International Energy Agency

Building Optimization and Fault Diagnosis Source Book

Energy Conservation in Buildings and Community Systems Programme. Annex XXV. Real Time Simulation of HVAC Systems for Building Optimisation, Fault Detection and Diagnosis

IEA ANNEX 25

Real Time Simulation of HVAC Systems for
Building Optimisation, Fault Detection and Diagnosis

Building Optimization and Fault Diagnosis Source Book

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Editors:
Juhani Hyvärinen and Satu Kärki
Technical Research Centre of Finland
Building Technology
B. O. Box 1804 (Lämpömiehenkuja 3)
02044 VTT (Espoo)
FINLAND

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P. O. Box 1804 (Lämpömiehenkuja 3)
FIN-02044 VTT (Espoo)

FINLAND

ABSTRACT

This source book describes the basic consepts and the fault detection and diagnosis approaches applied in Annex 25 collaboration. Annex 25, Real Time Simulation for Building Optimisation, Fault Detection and Diagnosis, was a part of the work of the IEA Energy Conservation in Buildings & Community Systems Programme.

A part of the book contain discussion of building optimisation, fault detection and diagnoisis, reasoning process, building optimisation and fault diagnosis system components, system structure, and system implementation. A major part of the source book is devoted to important faults of typical HVAC systems. Most of the annex research work is described in section discussing various fault detection and diagnosis approaches. Also a part of the book discusses general tools needed in building a fault diagnosis system.

Annex 25 reports consist of two volumes:

Volume I: Building opimization and fault diagnosis source book

Volume II: Technical papers of IEA Annex 25

Volume I, this source book, was written in collaboration and edited by Operating agent of the annex. Author of each separate section of the Source book took care and coordinated the writing of his section in such a way that the main results presented in the working papers and in the technical papers of volume II, and relevant to that section have been taken into account in a suitable way.

Volume II describes the technical and scientific work carried out in Annex 25, and the applications developed during the annex. It consists of three parts: system applications, method applications, and tools. The parts and sections in the volume are written as separate technical papers, reviewed and only published together without any further edition. Some of the papers are reprints of conferences and other publications and the purpose of reprinting them also here is that the major part of the research was carried out as contribution to Annex 25.

PREFACE

International Energy Agency

The International Energy Agency (IEA) was established in 1974 within the framework of the Organisation for Economic Co-operation and Development (OECD) to implement an International Energy Programme. A basic aim of the IEA is to foster co-operation among twenty-one IEA Participating Countries to increase energy security through energy conservation, development of alternative energy sources and energy research development and demonstration (RD&D) This is achieved in part through a programme of collaborative RD&D consisting of forty-two Implementing Agreements, containing a total of over eighty separate energy RD&D projects.

Energy Conservation in Buildings and Community Systems

The IEA sponsors research and development in a number of areas related to energy. In one of these areas, energy conservation in buildings, the IEA is sponsoring various exercises to predict more accurately the energy use of buildings, including comparison of existing computer programs, building monitoring, comparison of calculation methods, as well as air quality and studies of occupancy. Seventeen countries have elected to participate in this area and have designated contracting parties to the Implementing Agreement covering collaborative research in this area. The designation by governments of a number of private organisations, as well as universities and government laboratories, as contracting parties, has provided a broader range of expertise to tackle the projects in the different technology areas than would have been the case if participation was restricted to governments. The importance of associating industry with government sponsored energy research and development is recognized in the IEA, and every effort is made to encourage this trend.

The Executive Committee

Overall control of the programme is maintained by an Executive Committee, which not only monitors existing projects but identifies new areas where collaborative effort may be beneficial. The Executive Committee ensures that all projects fit into a pre-determined strategy, without unnecessary overlap or duplication but with effective liaison and communication. the Executive Committee has initiated the following projects to date (completed projects are identified by *):

I Load Energy Determination of Buildings * II Ekistics and Advanced Community Energy Systems * III Energy Conservation in Residential Buildings * IV Glasgow Commercial Building Monitoring * V Air Infiltration and Ventilation Centre VI Energy Systems and Designs of Communities * VII Local Government Energy Planning * VIII Inhabitant Behaviour with Regard to Ventilation * IX Minimum Ventilation Rates * X Building HVAC Systems Simulation * XI Energy Auditing * XII Windows and Fenestration * XIII Energy Management in Hospitals * XIV Condensation * XV Energy Efficiency in Schools * XVI BEMS - 1: Energy Management Procedures * XVII BEMS - 2: Evaluation and Emulation Techniques XVIII Demand Controlled Ventilating Systems * XIX Low Slope Roof Systems XX Air Flow Patterns within Buildings * XXI Environmental Performance XXII Energy Efficient Communities XXIII Multizone Air Flow Modelling * XXIV Heat, Air and Moistuire Transport XXV Real Time Simulation of HVAC Systems for Building Optimisation, Fault Detection and Diagnosis XXVI Energy Efficient Ventilation of Large Enclosures XXVII Evaluation and Demonstration of Domestic ventilation Systems XXVIII Low Energy Cooling Systems XXIX Daylight in Buildings XXX Bringing Simulation to Application

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This report has been produced in co-operation with all of the Annex 25 participants who took part in the working phase. The following countries, persons, and institutes have contributed to Annex 25. The authors of separate sections of the source book are indicated in the list of contents and in the beginning of each section or paper. The country contact person is mentioned first for each country then the rest participants are in alphabetical order.

BELGIUM
Dr Pierre NUSGENS, University of Liege Laboratory of Thermodynamics
Mr João M.D. PIMENTA, University of Liege Laboratory of Thermodynamics

CANADA
Dr. Alain LEGAULT, CANMET, Energy Diversification Research Laboratory
Dr. Darius NIKANPOUR, CANMET, Energy Diversification Research Laboratory
Mr Meli STYLIANOU, CANMET, Energy Diversification Research Laboratory

FINLAND
Mr. Juhani HYVÄRINEN, VTT Building Technology
Dr. Reijo KOHONEN, ABB Installaatiot Oy
Dr Jouko PAKANEN, VTT Building Technology

FRANCE
Dr J-C VISIER, C.S.T.B.
Mrs Ruxandra DUMITRU, Ecole des Mines de Paris, CENERG
Dr Xiaoming LI, C.S.T.B.
Dr Hossein VAEZI-NEJAD, C.S.T.B

GERMANY
Mr Michael BAUER, IKE University Stuttgart I.K.E., Abteilung HLK
Mr Klaus BAER, IKE University Stuttgart Wissensverarbeitung & Numerik
Mr Mathias HINKELMANN, IKE University Stuttgart Wissensverarbeitung & Numerik
Prof Gottfried KNABE, Technical University of Dresden Institut für Thermodynamik
Mr Madjid MADJIDI, University of Stuttgart I.K.E., Abteilung HLK
Dr.Ing F. SCHMIDT, IKE University Stuttgart Wissensverarbeitung & Numerik und Technische Gebäudeausrüstung

JAPAN
Prof Emeritus Nobuo NAKAHARA, Nagoya University
Prof Harunori YOSHIDA, Kyoto Univ. / Fac. Engineering, Div. of Global Environment Engineering
Prof Hisahiro ITOH, Mie University / Dept of Architecture, Faculty of Engineering
Mr Tatsuhiro IWAMI, Shinryo Reinetsu Co. Ltd.
Mr Kazuyuki KAMIMURA, Yamatake Honeywell Co. Ltd.

Mr Katashi MATSUNAWA, Nikken Sekkei Ltd.
Mr Tomoaki MIYAZAKI, Ohbayashi Corporation
Mr Masaharu NAKAMURA, Yokogawa Johnson Controls Corp.
Dr Hideharu NIWA, Nikken Sekkei Ltd.
Prof. Kazunobu SAGARA, Mie University / Dept. of Architecture, Faculty of Engineering
Mr Hiroaki TSUTSUI, Yamatake-Honeywell Co., Ltd
Mr Hideki YUZAWA, Nikken Sekkei Ltd.
Dr Minjie ZHENG, Sanko Kucho Ltd.
Dr Yi JIANG, Tsinghua University / Dept. of Thermal engineering
Dr Yingxin ZHU, Thsinghua University / Dept. of Thermal engineering
Dr Tianzhen HONG, Tsinghua University / Dept. of Thermal engineering

SWEDEN
Mr Per BLOMBERG, KTH (Royal Institute of Techn.) Div. Bldg Services Engineering
Prof T.G. MALMSTRÖM, KTH (Royal Institute of Techn.) Div. Bldg Services Engineering
Mr Svein RUUD, Swedish National Testing and Research Institute Energy Tech., HVAC and Sanitat

SWITZERLAND
Dr Jürg TOEDTLI, Landis & Gyr (Europe) AG
Dr Andrew S. GLASS, Ingenieurschule Luzern
Dr Peter GRUBER, Landis & Gyr Technology Innovation
Mr Henri van KUIJK, SEC Sulzer Energieconsulting SA
Dr Daniel MAURER, Ulrich Amman AG, Langenthal
Mr. Roger RAEBER, ETHZ, Energy systems laboratory
Mr Horst F. SCHIEL, H. F. Schiel Consulting Service, Winterthur
Dr Peter SPRECHER, Landis&Gyr (Europe) AG

THE NETHERLANDS
Mr Henk PEITSMAN, TNO Building and Construction Research, Dept. of Indoor Environment, Building Physics and Systems
Dr Lue L., SOETHOUT, TNO Building and Construction Research, Dept. of Indoor Environment, Building Physics and Systems

U.S.A
Dr George E. KELLY, NIST
Prof James BRAUN, Purdue University Ray W. Herrick Laboratories
Dr John M. HOUSE, NIST
Mr Les NORFORD, MIT
Dr Cheol PARK, NIST
Mr Todd ROSSI, Purdue University Ray W. Herrick Laboratories
Mr John SEEM, Johnson Controls Inc. Controls Research Dept
Dr Rex C. STRATTON, Pacific Northwest Laboratories BATTELLE Battelle Boulevard
Won-Yong LEE, Korea Instit. of Energy Research Taejean Yuseong Gu

UNITED-KINGDOM

Dr Arthur DEXTER, University of Oxford, Department of Engineering Science

Dr Philip HAVES, Loughborough University of Tech., Dept. of Civil and Building Engineering

Dr Mourad BENOUARETS, University of Oxford, Department of Engineering Science

Mr Richard FARGUS, Building Research Establishment

Mr Simon HEPWORTH, University of Oxford, Department of Engineering Science

Mr Newton MARUYAMA, University of Oxford, Department of Engineering Science

Mr Darius NGO, University of Oxford, Department of Engineering Science

Mr Tim SALSBURY, Loughborough University of Tech., Dept. of Civil and Building Engineering

Dr Jon WRIGHT, Loughborough University of Tech., Department of Civil and Building Engineering

LIST OF CONTENTS

1 INTRODUCTION

Hyvärinen, J. VTT Building Technology, Espoo, Finland

1.1 BACKGROUND

In the near future, energy savings will be obtained mainly through optimal control and early fault detection of building Heating Ventilation and Air Conditioning (HVAC) systems. Lowering of energy consumption and building operation cost with proper occupant comfort level will be reached together with well-organized maintenance, fast detection and correction of faults and best use of equipments' performances. Those aims are to be met partly through development of new systems but also by a selection of suitable control strategies as well as by predicting plant and building behavior and comparing those predictions (target performances) with actual performances.

The long-term strategy plan of the Executive Committee (ExCo) of IEA Energy Conservation in Buildings and Community Systems implementing agreement emphasizes the importance of research in building performance analysis, and the role of simulation tools in the evaluation of new products and technical solutions. Energy and comfort are not the only aspects in such evaluations, but also performance and reliability of the building system and its components are important criteria. The need for the development of methods to improve operation and maintenance of buildings and to correct malfunctions was stated in the Strategy Plan for the ExCo along with the need for closer collaboration with industry.

Simulation of HVAC-systems and processes has been used primarily for the design of equipment and to predict energy consumptions. As confirmed through the IEA Annexes on Building System Simulation, for most of these applications, steady state models of components are generally sufficient.

Further improvements of systems and the development and testing of local loop and supervisory controls require that dynamic models be considered. Optimal control (in terms of efficient use of energy and thermal comfort) was a fundamental aim of research efforts within IEA Annex 17 BEMS2: Evaluation and Emulation Techniques. Some new approaches in the field demand very fast responses from numerical simulation, because it should operate in real-time, directly coupled to physical devices. These approaches are emulation techniques (testing control algorithms) and process and fault diagnosis.

1.2 INTRODUCTION TO FAULT DIAGNOSIS IN BUILDING SYSTEMS

As technical systems develop, the processes and systems in a building get more difficult for the average operator to understand. Buildings get more intelligent but the users do not. Understanding the relationship between cause and effect is more difficult than in the past because of complex relationships in the building's processes.

Building' processes are normally supervised by a building automation system and suitable supervision or management software. The operator's task is mainly to initiate separate sequences and actions. When the process enters a failure state the supervisory programs currently available do not adequately assist in finding the underlying cause of the fault (the defect). Diagnosis of the defect is thus left to the operator.

The faults in a building may occur on many levels. Building's technical systems consist of subsystems which in turn consist of components. A fault in any of theses levels - component, subsystem, system or even building level - can cause degradation in the technical performance and technical availability of the building.

Faults may result in inefficient usage of energy and an uncomfortable working environment. To avoid this, the operator should continuously monitor the process and identify defective systems, subprocesses or components. When operating a complex building it is beneficial to provide the operator with tools which can help in decision making for building management and optimization, as well as recovery from a failure state. The tools should focus on the underlying defects and give instructions on corrective action to be taken in a simple and understandable way.

Various methods can be used to identify a fault in a process. As defects develop, they can be monitored with special condition monitoring instrumentation to obtain information on the need for maintenance. These systems are usually separate from building automation systems and need specific instrumentation of their own; for instance, vibration analysis systems which are used in industrial processes can be used for condition monitoring. Also various maintenance programs can be used to prevent serious defects and to schedule maintenance for maximum convenience. In maintenance programs, the process is inspected and maintained at fixed time intervals, independent of the true condition of the process. The main disadvantage of the present condition monitoring systems is that, because of the special instrumentation, they are expensive and/or that they cannot be operated in real-time applications.

The main purpose of a real-time fault diagnosis system is to monitor the operation of various process components and subprocesses and to detect, locate and, if possible, even predict the presence of the defects causing the faulty operation. Ideally, the system should resolve the primary defect and give instructions for undertaking corrective action. In practice this is seldom possible, and the fault diagnosis system should be considered more as a tool for obtaining information on the process and as an aid to help the operator identify the defects causing the faulty process operation.

1.3 MOTIVATION

The benefits for the "end user" of applying a Building Optimization and Fault Diagnosis (BOFD) system will be achieved through the following:

- energy and water savings; inefficiently operating processes can be detected earlier than otherwise

- increased quality of living; faults can be detected before they affect the indoor quality or the quality of other 'products' produced by the HVAC system, the maintenance work can be scheduled so that it does not cause unnecessary inconvenience to the occupant

- reduced maintenance costs when the maintenance work can be planned beforehand; faster location of faults, scheduling of work, usage of maintenance staff with right kind of skills, ordering of spare parts, and shorter process down time

- safety and health; detecting the faults early decreases the risk of personal injuries and equipment and property damage, improperly operating processes may cause a health risk.

The same difficulties encountered when assessing the benefits of any automation investment are also seen when assessing the benefits gained by BOFD system: BOFD system is a tool for an operator or an user and the benefits are gained only if the tool is accepted and used effectively. As a consequence to this, it is difficult to define on whose account the benefits should be put: on the operator's or on the tool's account.

The benefits are also difficult to measure in terms of economics. Energy utilization, water consumption and repair costs can be determined but it may be impossible to associate economic benefits directly to the BOFD system. Also, the benefit to the quality of living and health and safety are even more difficult to assess. It is a well known fact, however, that these qualitative benefits are more important for the end user today than in the past, and it can be foreseen that their importance is increasing.

The additional cost caused by BOFD system need not be big. New BEM systems are advanced and there are computing resources available for fault detection, diagnosis and user interface with relatively small additional cost. It can even be said that introduction of new features like fault detection and diagnosis might make the utilization of BEMS more effective than before.

One major source of costs in automation is process instrumentation which in modern BEM systems is already quite extensive. If the fault diagnosis system utilizes the normal process instrumentation as much as possible, and uses extra instrumentation only when really needed, the rise in instrumentation cost due to fault diagnosis methods can be small. In an ideal case a fault detection system can even reduce the amount of instrumentation needed by focusing the attention to those process measurements that really are needed.

Perhaps the largest cost class is introduced by development, design and commissioning of a BOFD system. The magnitude of this cost category can be reduced if the BOFD system and each procedure and method is first developed on a generic level and then only applied to specific instances like components and subprocesses. This way the BOFD system can be applied to a large set of process components and subprocesses so as to give the best possible benefit with lowest unit cost.

1.4 IEA ANNEX 25 [1.1]

The main goal of the annex was to develop methodologies and procedures for optimizing real-time performance, automating fault detection, and fault diagnosis in HVAC processes and to develop BOFD prototypes that can be implemented in BEM systems. These BOFD methods and system prototypes were called applications.

Partial objectives were:

- to evaluate the most suitable modeling approaches for the real-time simulation of HVAC systems
- to determine the basic approaches most suitable for fault analysis
- to create a database of the most important problems and faults in HVAC systems
- to demonstrate the implementation of the schemes in a real BEM system to facilitate and promote the technology transfer to industry
- to apply optimal control techniques to the problem of building optimization.

The Annex concentrated on monitoring the energy performance of the building and HVAC systems, and detecting faults in HVAC components and subprocesses. In general, however, other aspects such as indoor air quality and safety should also be taken into account.

Four phases were identified for Annex 25:

1. Preparation
2. Working
3. Reporting

(4. Demonstration).

Demonstration phase was in principle outside of the scope of the annex but in practice it was carried out in some participating countries in one way or another.

These participants demonstrated the results of the annex in a such a way which best suited the industrial and end users' needs and expectations in that country.

Annex 25 work was split into two main approaches: Building optimization, and component fault detection. Building optimization deals with the comparison of the actual state of a building and some defined target state. The target state is based mainly on building models. Deviations from the target state can be used to indicate the presence of a fault or faults within the building system. Instead of analyzing entire building, subsystems such as cooling energy production systems could be studied.

Component fault detection aims to find a faulty component by modeling the component according to physical laws and comparing the measured values of specific variables to the desired values. This approach could also be applied to a well defined relatively small subprocesses.

The two approaches were combined in the reasoning procedure for identifying the source of the deviations from the target performance/state of a building or a system, or when judging what is the consequence of component failure on the building level.

1.4.1 Preparation phase

The preparation phase dealt with process diagnosis, fault detection and real time simulation at an introductory level and defined the final work plan for the working phase. The outcome from the preparation phase was a 'system description' of a fault detection and building optimization system that was used as a framework during the working phase [1.1]. The description includes the basic concepts that were used as a starting point during the working phase.

Also the areas of application in which the system is intended to be used were described. This included

- the selection of components and processes
- the definition of the problems and the method approaches
- defining the areas where the component fault detection and building optimization is most needed.

1.4.2 Working phase

In the working phase the work was focused on selected components, subprocesses, and systems. The BOFD method approaches were selected by individual research groups.

The main steps followed in Annex 25 were:

Building optimization and fault diagnosis concepts

A general Building Optimization and Fault Diagnosis (BOFD) system description was developed and introduced. This served as the basis for the collaboration. The system description gave a concept (framework) into which the BOFD methods developed during working phase could fit along with appropriate terminology. Terminology was also considered.

HVAC system descriptions and an off-line data base on the typical troubles and faults in described systems

Functional descriptions of typical HVAC systems were prepared and analyzed. Heating systems, air handling systems, chillers and heat pumps, and thermal storage systems were considered. BOFD applications in the annex were made for these systems and their components.

During the working phase only some selected subprocesses or components were examined. To be able to focus on the most important problems, processes and components were selected according to the off-line database information gathered.

There are three main reasons for developing an off-line data base on typical faults in the Annex:

- effort can be concentrated on those components and subprocesses in which the failure is most serious or the proper functioning is most important. For instance, failure types considered in the Annex were chosen based on this data base.

- the data base can be used as a starting point in developing fault diagnosis algorithms and rules for identifying the cause, location and hazard class of the fault. The data base can give valuable information on the signature of certain faults and how that signature can be utilized for identifying the fault.

- the data base can be utilized in developing the user interface of a fault diagnosis system. For example instructions for recovering of the fault situation and for repairing it can be stored in the data base.

Description and selection of methods applicable to BOFD system

Methods for fault detection and building optimization in selected HVAC-systems and processes were studied and their applicability was considered.

The next few points affect the applicability of a method to a BOFD system:

- different fault detection and building optimization methods require different types of measurement signals (accuracy, filtering, etc.)

- some processes might require a certain type of method or some methods are not applicable to processes of a certain type

- the usage of the method; fault diagnosis, building optimization, modeling, parameter estimation, etc.

- additional measurements (if any) required by each method

- computational load of a method

Developing the methods for building optimization, fault detection and diagnosis of specific components and subprocesses of the HVAC-processes and development of a procedure for determination of the desired performance

One or more BOFD methods were developed for selected components, subprocesses or systems - to be used in a BOFD system. Developed methods either

- detect the faults or

- detect the faults and diagnose the location and cause of the fault

In the first case the method provides the BOFD system with a test signal or symptom which reflects the failure mode of that item. The symptom or test signal can later be used in diagnosing the location and cause of the fault. In the latter case the method performs both the detection and diagnosis at the same time and provides the system with information of the fault location and cause.

When the fault diagnosis or building optimization methods were developed the target performance of a process or subprocess were also considered. The target performance is described e.g. by a certain figure of performance, a value of a test signal, and the limits in which that value should remain in case there is no fault or process is in a target state.

Evaluation of the methods to detect and locate the fault in a process and to identify potential fault sources

The problem of diagnosing the location and cause of a fault was studied. Diagnosis is an essential part of the BOFD system because it binds together the building optimization and fault detection approaches (i.e. top-down and bottom-up approaches).

Reasoning was considered on relatively general level. One big obstacle in implementing reasoning is in presenting the knowledge related to diagnosis. There are several artificial intelligence (AI) tools with which the diagnosis could be implemented, but applying these tools requires system specific tailoring.

For each component or subprocess a specific description of reasoning was developed: namely which symptoms and disturbances are caused by which faults and what is the path of reasoning.

Development of procedures for decision making based on actions/measures/ alarms in order to reset the process to operate normally

A general user interface for purposes of fault diagnosis is an integral part of a BOFD system. As the first step, the emphasis should be on aiding the human user, not on any automatic correcting actions taken in case of failure. The user should get information regarding the reasoning and of the uncertainties inherent in the fault detection.

This step, however, was not trated in this annex.

1.5 THIS REPORT

This report - Annex 25 Source Book - is one of the reports documenting the work and achievements of Annex 25. This report is intended to be used as a source book for concepts in building a fault detection system.

Chapter two is a review of the basic concepts already published in [1.1]. Chapter three describes four typical HVAC systems and highlights the results of the fault analyses that were carried out for those systems. For fault analysis, various techniques and methodologies were applied. The tools used are described in chapter 5. Chapter four describes the approaches applied in developing BOFD methods. The approaches cover both fault detection and fault diagnosis methods and they are always applied to well defined process entities.

Chapter five presents generic tools that can be utilized in developing fault detection and diagnosis methods and BOFD systems. In chapter six some general aspects concerning BOFD systems are presented, and finally chapter seven concludes the report and the work carried out in the annex.

The Annex 25 Source Book was written by a number of contributing authors, the names of whose are given under titles of their topics. The list of contents was agreed upon by the Annex 25 participants, and the authors were selected for different sections and chapters in the expert meetings. Authors were responsible for writing the first draft, taking the reviewers' comments into account, and checking that all the relevant results from the working papers were dealt with in their topics. The source book was reviewed by the annex experts.

The other final report is a technical report that gives examples of applications of applying the concepts presented in the Source Book. The technical report includes papers on BOFD-system applications, BOFD-method applications, and some papers on BOFD-tools. There is only a slight difference between the method and system applications. Method applications concentrate on fault detection and diagnosis of a single component or process whereas system applications include the fault analysis of HVAC-system in question and the steps leading to development of BOFD-methods for specific components or subprocess of that system. The technical report is of proceedings type and it reports the detailed technical work carried out during Annex 25.

1.6 REFERENCES

1.1 Hyvärinen, J., Kohonen, R. (eds.) Building optimization and fault diagnosis system concept. Espoo: VTT, Laboratory of heating and ventilation, 1993. (IEA, Annex 25). ISBN 952-9601-16-6.

2 BUILDING OPTIMIZATION AND FAULT DIAGNOSIS SYSTEM CONCEPT

Juhani Hyvärinen, Vtt Building Technology, Espoo, Finland

2.1 INTRODUCTION

A building optimization and fault diagnosis system is used to detect and if possible to locate faults in a building's operation. A fault may give rise to unfavorable energy consumption or indoor environment, non-optimal operation of a subsystem or faulty operation of a component or a part (Fig. 2.1).

Building optimization starts with the detection of degradation in the performance of a building as a whole. For example, once it is noticed that the building consumes too much energy the immediate cause needs to be established, i.e. identify the non-optimally operating subsystem or the faulty component. In fault diagnosis, components or subsystems are monitored continuously and faults in their operation are detected after which the severity of the fault to building overall performance must be evaluated. Both approaches should be combined into one system and used in parallel.

A process fault is usually considered to cause an event (i.e. failure) where the required operation of the process suddenly halts. The process is assumed to operate in the required way when the "product" quality is within predetermined limits. In the context of fault diagnosis, this kind of definition of fault is inadequate. The requirements for the process operation should be stricter and, for example, the operating point deflection from the designed operation point (target)

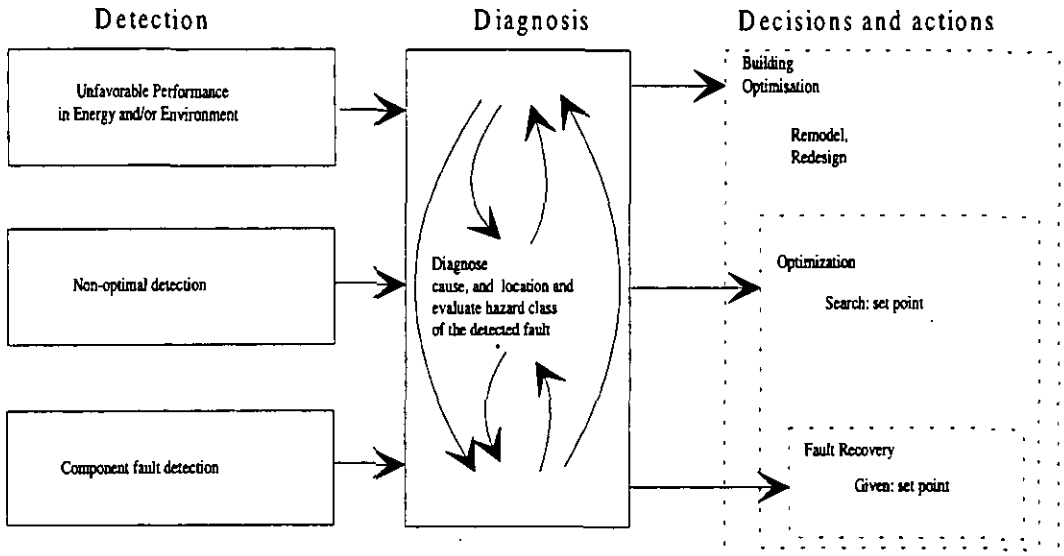

Figure 2.1. Tasks and objectives of building optimization.

should be considered as a process defect. A defect thus does not necessarily have to effect the product quality in any way because small deflections can be corrected automatically by controllers. This definition has the advantage that it considers the defect with regard to the process and its components themselves, not with regard to the product quality. It is then possible to detect defects before they effect the product quality and thus predict faults. In fault diagnosis, the emphasis should thus be put on monitoring the development of the defect and on minimizing the damages or losses caused by it.

A defect is a circumstance that changes some normal operating point of a process and may cause faulty operation that can be observed from the process measurements. Faulty operation may propagate to other parts of the process or to another subprocess due to changed operating points, or the effect of the fault may be eliminated by using controllers. From the process signals, some test quantities are generated, the variation of which is a symptom of defect. Once the test quantity reaches some predetermined level that reflects the seriousness of the defect, the test quantity is set into an alarm state (symptom) and reasoning is started to find the cause of the 'alarm - symptom - fault' chain. The alarm state is set once the seriousness of the defect requires corrective actions to take place.

An example of a defect is a slowly increasing blockage in a heat exchanger. This causes faulty operation (deviation of temperatures) of the heat exchanger. The defect and the fault are small in the beginning but they increase as the heat exchanger gets more dirty. The defect may result in changes in the inlet and outlet temperatures.

The purpose of the heat exchanger is to transfer heat between the primary and secondary circuits. The reduction in heat transfer between the primary and secondary circuits can be compensated for by increasing the flow rate or the primary circuit inlet temperature, both of which result in additional energy consumption. Once the dirt build up in the heat exchanger reaches a level that the rate of heat transfer cannot be kept at its required value through controlling the process variables, the defect becomes 'observable' to the user of the system and the fault starts to propagate. In real life this observability might mean that an occupant in the building feels too cold. Thus by monitoring the increase in dirt build up in the exchanger the fault can be detected earlyer instead of waiting for complains from the occupants; the increase in energy consumption can also be detected earlier.

In the previous example, the defect occurs when the exchanger starts getting dirty and the need for maintenance should be assessed from the value of the test quantity, i.e. from the amount of harm or loss of energy the defect causes to the user. If the development of the defect is rapid, the test quantity also rapidly reaches the alarm level and the 'prediction' of the defect is difficult. With slowly developing test quantities the prediction is easier.

2.2 DEFINITION OF BOFD [2.1]

2.2.1 Definition

Building optimization is the process of minimizing an overall objective function that includes all costs of building operation (e.g., energy maintenance, personnel) with the constraint of environmental condition. The building optimization can be performed with respect to both design and control variables.

When the substantial object of building optimization is reflected, the measures will even include manual operation using BEMS, the retrofit of building services engineering systems and thermal and optical performance of the building structure from the viewpoint of building management.

2.2.2 Optimization phase

Building optimization may be defined separately for design phase and operation phase. In a strict sense, these two phases cannot be separated, because the optimal design, which could be established after execution of load simulations and system simulations in a dynamic as well as static mode, should be followed by the optimal controls based on the same performance function, constraints and characteristic performance of equipment as used in simulations.

The total optimization in this sense, however, is so hard to realize, that a practical execution of buildings optimization may be separately performed at each phase of design and operation of a building, i.e. the architectural design of the wall structure, the heating and cooling load calculations, the building services system design, system simulations and operation after completion. As Annex-25 concentrated its objective study on the operation phase of the HVAC-system, the building optimization in this annex was limited only to the operation phase, which will actually result in a partial building optimization.

2.2.3 Premise of building optimization

Building optimization is accomplished only after establishing the optimal control and fault detection of the HVAC-system, as each equipment should be in a normal state and the each subsystem should be in an optimal state as defined in each routine.

An assembly of the optimal state of each subsystem, however, is not always an optimal state as a total. This may be called as the sub-optimal state from the viewpoint of the total system. This suggests that an optimal control may reduce to a building optimization when the scale of the optimized system becomes sufficiently large to include most of subsystems that can almost be called a total system.

A state resulting from the optimal control in which any faults are conceived in some equipment and/or subsystems is not an optimal state, because the calculated performance function and constraints may have resulted in a false optimal point.

For example, faulty measurements of the CO2 concentration may cause additional intake of the outside air which will result in a faulty predicted room condition, followed by a faulty lower set-point of outlet temperature condition of the delivery air from an air-conditioner and the chilled water from the refrigerating machine, resulting in an additional unnecessary energy consumption.

Figure 2.2 shows the concept and methodology of Building Optimization which reflects the optimization phase as described above and also defines its links with building optimization, optimal control and fault detection encompassing Annex 25.

2.2.4 Optimal control

The optimal control as well as the fault detection is closely linked with building optimization. Optimal control should therefore be considered in the context of the building optimization as defined above.

Optimal control applied to HVAC system is required in order to establish an optimal set-point for the feedback control loops included in each control subsystem. This way minimum energy consumption, as the performance criterion, with the requirements defined by the human comfort conditions can be met. As previously described, a system which is controlled in an optimal way should include several HVAC subsystems in order to establish real optimization.

Various kind of learning processes and feedforward routines for the load and status prediction and system identification may be applied which should be fed back anyway to satisfy the desired performance and setpoints of the objective variables. Figure 2.3 will assist in the interpretation of optimal control.

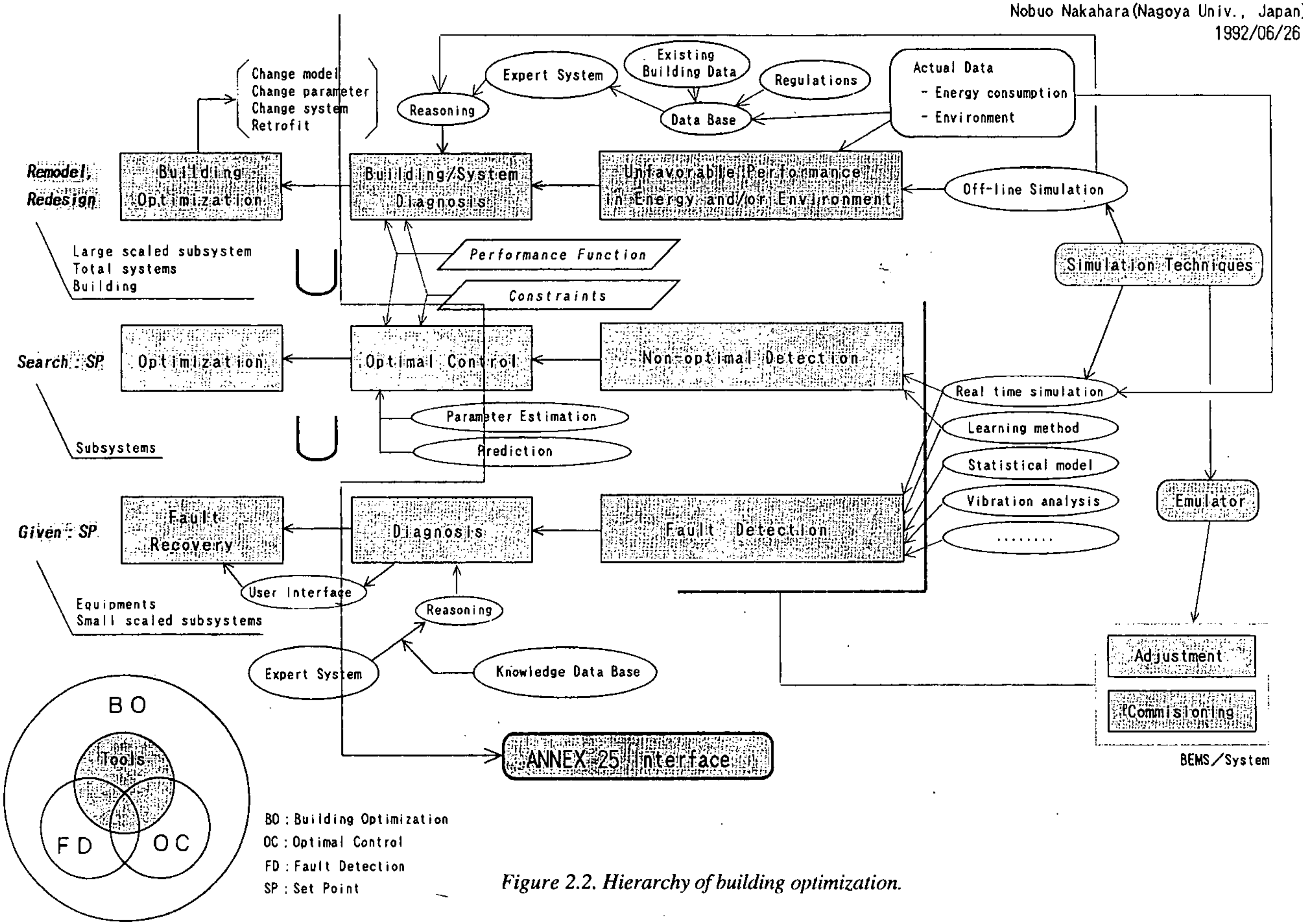

Figure 2.2. Hierarchy of building optimization.

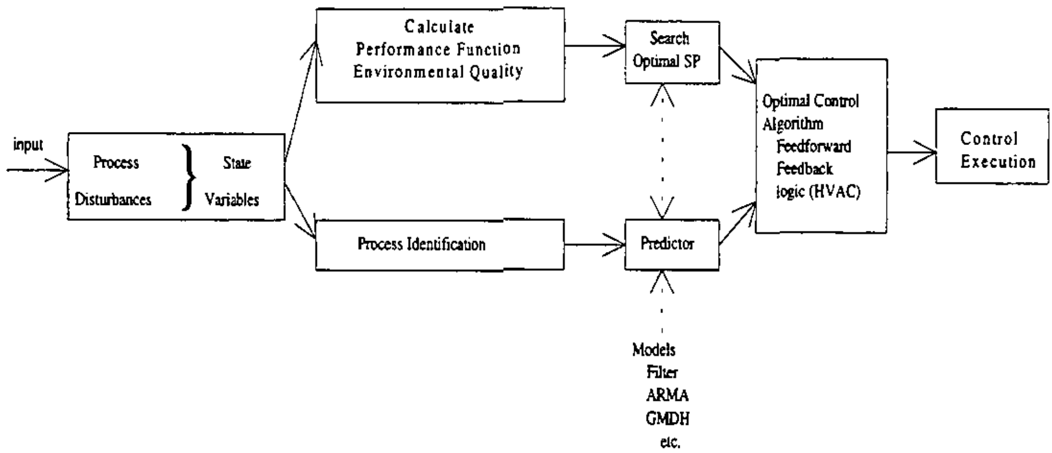

Figure 2.3. Structure of optimal control.

2.2.5 Methods of building optimization

The building optimization is performed by changing the control parameters which are not automatically adjusted through a learning process, as well as remodeling the algorithm of the optimal control and fault detection, and even by redesign of the HVAC-subsystems using off-line simulations. This may be followed by retrofitting some part of the system.

The performance function and requirements which need consideration in the optimization are the energy consumption, which should be minimized, and the environmental qualities, which should be kept within an allowable level. The reference data for energy consumption may be the designed value, as allowed by energy budget regulated by law or any other standards and/or database of energy consumption for other buildings. This includes sufficiently useful information on building type and HVAC-system for statistical analysis to be applied with reasonable confidence levels.

Off-line simulation is a useful tool not only at the design phase but also at the operation phase for building optimization. Various parameters describing building thermal characteristics as well as control gains may be identified in advance with the use of real-time simulation and learning methods. The off-line simulation will have sufficient precision to predict the air-conditioning load, energy consumption and the quality of indoor environment, thus allowing detection of any non-optimal state of performance by comparing with the actual normal data.

Other kinds of prediction models with the parameter estimation through real-time learning are also available. It may have the structure of the multi-inputs to describe important factors affecting the characteristic value as a single output. Parameters, which may be called the weighting factors of each input value, may be estimated by the filter model, auto-regressive model or any other data handling methods.

Expert systems for reasoning of non-optimal state are a practical method of diagnosis. Quite often, the expert system gives a good answer for remodeling, redesign and retrofitting of some HVAC sub-systems. In that case, the database should include the actual results of energy consumption and any other useful information about the building and system for statistical analysis. Knowledge database should also be compiled to allow a satisfactory solution to be reached in a short way. Questionnaires and listening to designers and engineers as well as maintenance personnel are also indispensable.

2.3 TOP-DOWN AND BOTTOM-UP APPROACHES TO REASONING

In implementing a reasoning process, the problem which arises when constructing a system to diagnose faults can be understood in terms of the following two central difficulties:

1) How can the original reason for and location of a fault observed in the functioning of the whole be decided?

2) How can information about a specific fault in a precisely delimited process be combined with the impact of that fault in the functioning of the whole?

The two problems can be presented in the following manner: When undesired operation is observed on the building level, what is the cause of the problem on the level of subsystems or components? When a fault is observed on the component level, what is the seriousness of that fault in terms of building performance on the level of the building as a whole? In Figure 2.4 the problems are represented by arrows. The tail of each arrow indicates an observation of a fault or undesired operation, while the head indicates the result of the reasoning. Instead the fault is detected in the building or in the component level it can as well be detected in the subsystem level. In the last case one must be able to deduce the impact of the fault in the subsystem level in a higher level (building level, for example), and on the other hand, be able to find the cause of the fault in a lower level (component level, for example).

Both two directions - top-down and bottom-up - must be considered when implementing a BOFD system. It has shown to be a difficult problem, on how best to present the knowledge related to both approaches in a consistent way. In section 5.1.5 a dendogram based on fault tree and symptom sets is presented. This allows to combine both approaches when presenting knowledge about upper level reasoning.

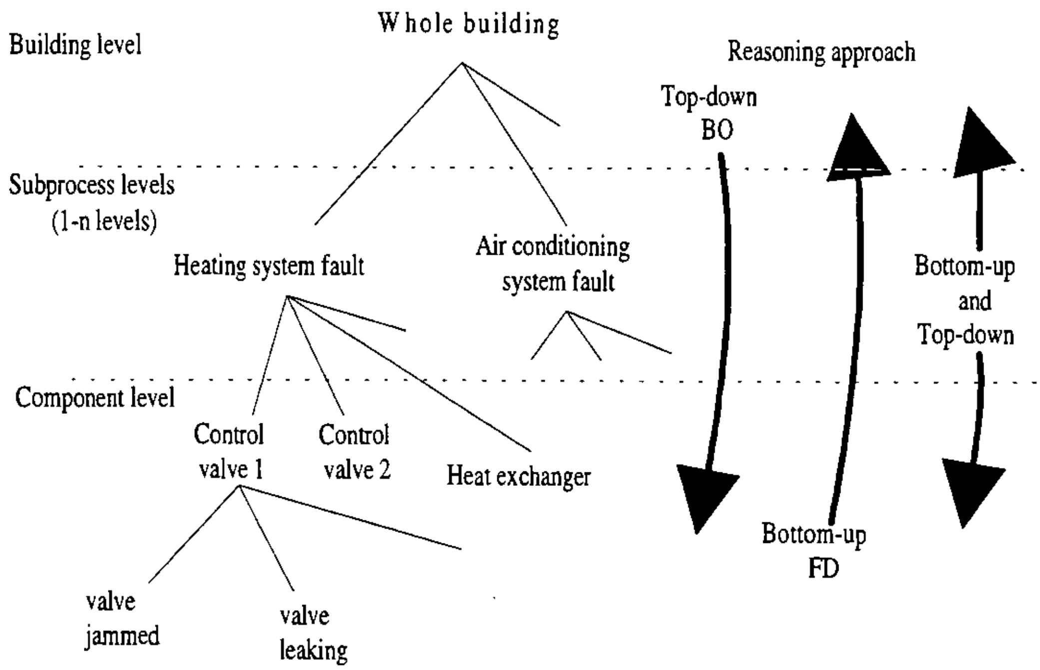

Figure 2.4. Main approaches in reasoning.

2.3.1 Building optimization - top-down reasoning, fault diagnosis - bottom-up reasoning

The problems can be named according to the principles used for their resolution. In the first - top down - approach the starting point is some performance property of a building which describes the function of the entire system, such as energy consumption, proceeding towards smaller details. In similar fashion, the other - bottom up - approach begins with some detail, the significance of which for the whole is not necessarily known, and ending up with the consequence of the fault from the standpoint of the whole. When starting form the subsystem level, both approaches must be utilized.

In Annex 25 the approaches have been designated as follows: the top-down approach is called building optimization, with the bottom-up approach correspondingly being called fault diagnosis. In this context, optimization does not mean strict mathematical optimization; instead, it is an attempt to attain a sub-optimal situation for the control of the system by applying various types of strategies to the subsystems and components of the overall system.

2.3.2 The top-down approach

In the top-down approach the observed phenomena becomes the objective function. The fact that the fault which is being examined has an undesired effect on the operation of the building is known right from the start. In this respect it is a more natural approach than the bottom-up approach. The top-down approach is well suited for use when there is a desire to locate a fault which has appeared in the system.

What becomes of a problem after the error has been observed, however, is in locating it in the many subsystems and constituent components of the building. How does localization of the error proceed, and to what degree should it be possible to explain the reason for its occurrence? It should be possible to arrange the reasoning so that it would proceed according to either the order of probabilities or some other corresponding order of importance. For example, if it is a question of how to reduce energy wasteing, the first thing that should be considered for inspection is the most probable subprocess which might have been damaged or, alternatively, the partial system which consumes the most energy. If the fault is found there, work should continue according to some preliminary determined system within the subsystem to its components or something similar.

Localizing the fault in the hierarchical tree would thus proceed to the level possible using existing process data which has either been obtained from measurements or requested from the user. If there is no control of reasoning of this type, implementation of the reasoning would be too difficult. This leads in practice to a situation in which no resolution of the problem is obtained.

2.3.3 The bottom-up approach

In the bottom-up approach an examination is made of the operation of individual components and small subsystems. A fault in a component or subsystem is not necessarily observable on the building level at the same time as on the lower levels. It can thus be said that bottom-up -approach can be used to predict the consequences which a fault in a specific individual process will have for the entire system.

Since the operation of all the components of the building cannot be monitored in practice, it is of essential importance that when the bottom-up approach is being used such components and faults are selected for investigation for which a failure is either probable or would have the greatest effect on the property or set of properties of the building which had been selected according to the order of importance selected.

2.3.4 Meta-knowledge

"A priori" knowledge (knowledge available in advance) of the operation of the process system to be diagnosed is of essential importance when designing the operation in both the top-down and the bottom-up approaches: in top-down approach a priori knowledge is needed for designing the reasoning process and in bottom-up approach it is needed for selecting the most important components (Figure 2.5). Determining the fault without any such prior knowledge would

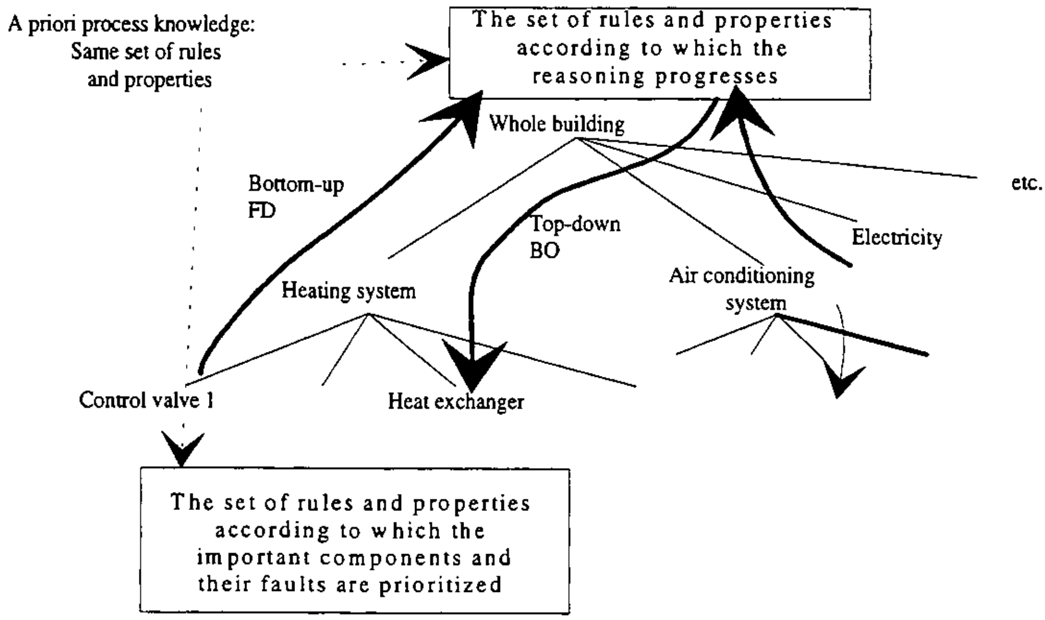

Figure 2.5. Using the prior knowledge in BOFD reasoning.

require a considerable calculation or involved reasoning, and is impractical in large systems. A priori knowledge is used in the top-down approach to expedite the reasoning process or to select the reasoning path which is most probable or best corresponds to observations. In the bottom-up approach prior knowledge is used for selection of the components and subprocess to be examined.

Since the knowledge concerning the behavior of the process consists of the set of rules for an expert system, the metaknowledge can correspondingly consist of rules which control the use of the rules providing information about the use of the process. Meta-knowledge may be used to change the priority of some rules to correspond to the state of the process under examination, to completely prevent the use of certain rules, or to change the information and facts to be used [2.2].

Use of the meta-knowledge describing the control of reasoning depicted above was particularly well suited for use in the top-down approach. In the bottom-up approach the utilization of meta-knowledge in reasoning is not so obvious, and it might not even be proper to speak of using metaknowledge for the control of reasoning. Instead, it is more appropriate to speak of the use of a priori knowledge in the construction of the system. If prior knowledge is used, the most important parts of the system can be selected in advance, and they can be provided with fault detection for the advance observation of faults. If such a method can be provided for each important part, the top-down approach is not needed at all. Instead, whenever a specific module leads to the detection of a fault, it is known that this will have an undesired effect on the operation of the overall system.

In the case of the bottom-up approach, prior knowledge consists of knowing which components are of central importance from the standpoint of the operation of the overall system, and what size or grade a fault has to have before it is regarded as undesirable. A concept laying down the basic principles to be used when selecting the components to be examined, from the totality of the components making up a large system, is presented in section 5.1 Qualitative availability analysis tools.

2.4 COMPONENTS OF A BOFD SYSTEM

2.4.1 Elementary functions of process supervision [2.3]

A fault is to be understood as a nonpermitted deviation of a characteristic property which leads to the inability to fulfill the intended purpose.

Figure 2.6 shows a block diagram for process supervision. If a process fault appears it has to be detected as early as possible. This can be done by checking if particular measurable or unmeasurable estimated variables are within a certain tolerance of the normal value. If this check is not passed, this leads to a fault

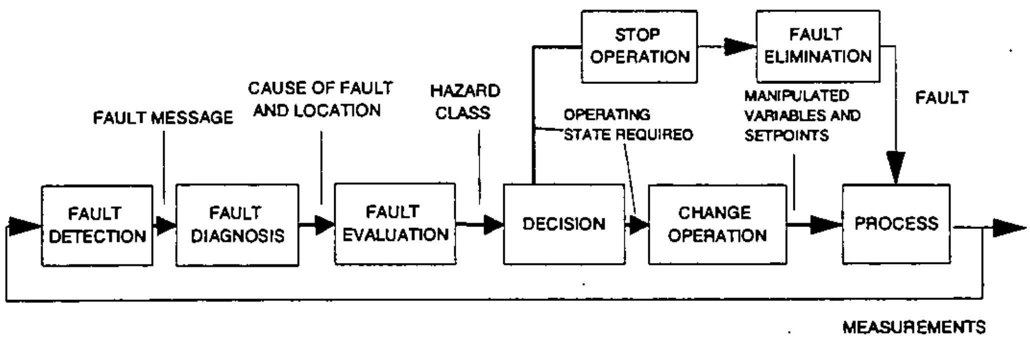

Figure 2.6. Supervision loop [2.3].

message. The functions up to this point are usually called monitoring, or as indicated in the first block of Figure 2.6, as fault detection. If necessary, this is followed by a fault diagnosis: the fault is located and the cause of it is established. The next step is a fault evaluation, that means an assessment is made of how the fault will affect the process. The faults can be divided into different hazard classes according to an incident/sequence analysis or a fault tree analysis. After the effect is known, a decision on the action to be taken can be made. If the fault is evaluated to be tolerable, operation may continue and if it is conditionally tolerable a change of operation has to be performed. However, if the fault is intolerable, the operation must be stopped immediately and the fault must be eliminated.

Figure 2.6 indicates that a looped signal flow exists in the supervision of processes in a similar way as in a closed loop control system. It is therefore possible to also refer to a supervision loop. This is only closed on the appearance of a fault and displays very different dynamic characteristics depending on the error. The time delay originates mainly in the blocks 'change operation', or 'stop operation' and 'fault elimination' and in the process itself.

2.4.2 Fault detection and diagnosis [2.4]

Figure 2.7 illustrates a FDD system. It transforms observations from a supervised process (e.g. HVAC system) into binary fault / no fault decisions indicating if the process is not operating normally (detection) and if not, then when and where the failure occurred (diagnostics). The decisions are vectors. The fault detection decision vector might indicate which fault effect was observed and the diagnostics decision vector indicates which component the fault has occurred in.

The fault detection and diagnostic sub-systems are modeled as separate devices with the same basic structure. In general, both sub-systems may be able to communicate with each other and with a central controller which might also be able to send control (test) signals to the supervised process to configure it for possible FDD tests. The controller or possibly even the diagnostic system may not be included in less sophisticated FDD systems.

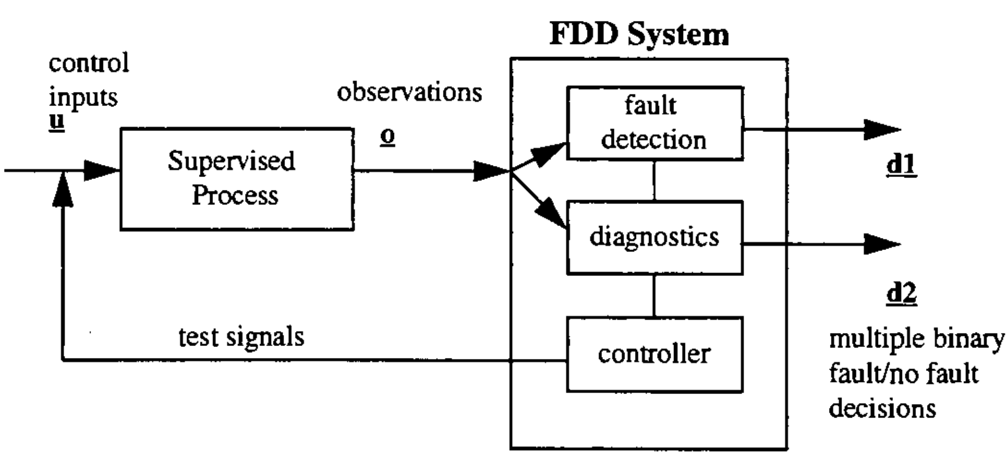

Figure 2.7. FDD system.

As illustrated in Figure 2.8, the observation preprocessor and classifier are two distinct components common to the fault detection and the diagnostics subsystems of a FDD system. The classifier is the essential component. It returns the decision appropriate for the region currently occupied by the inputs. A limit checker is a simple and typical example of a classifier. Predefined upper and lower limits establish the "no fault" region for an input variable. The "fault" region is defined as the complement of the "no fault" region.

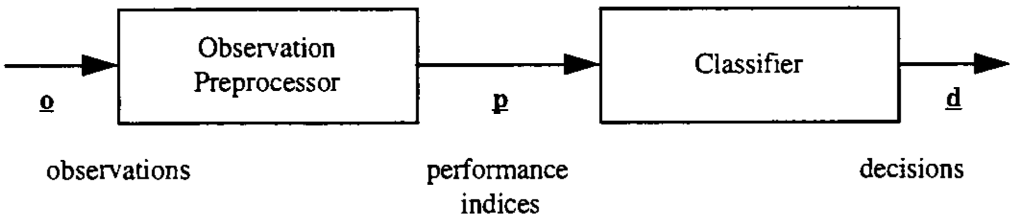

Figure 2.8. Components of both the fault detection and diagnostics sub-systems of a FDD system.

The observation preprocessor transforms observations into performance indices which are easier to classify. Analytical models of the supervised process, if they are used, are contained in the preprocessor. Using the input measures, the models can generate state-space innovations, parameter estimates, or characteristic quantities that are used as performance indices during classification. The performance indices should decouple the diagnostic information contained in the observations so that the classification regions are simpler to define.

An example of an observation preprocessor is the calculation of the volumetric efficiency of a compressor which is a characteristic quantity indicating flow rate performance for a measured pressure drop. It is defined as the actual flow rate divided by the maximum flow rate and is mostly a function of the inlet and outlet pressures: hv = f(Ph,Ps), where Ph and Ps are head (outlet) and suction (inlet) pressures respectively. The other parameters used to define the function can be specified or learned. In this technique, it is presumed that the volumetric efficiency is more directly indicative of compressor faults leading to flow rate degradation (e.g. leaking piston seals or valves) than the observations from which it is calculated. In this case, for example, a simple limit checking classifier can be used on the volumetric efficiency in place of a more complicated classifier which would be required to achieve the same diagnostic decision directly from the observations.

The two parts of both fault detection and diagnostic systems can further be broken down into several categories and subcategories according to following:

Preprocessor

simple functions

- time derivative function
- unity transformation which is used to describe a system that classifies observations directly

model-based transforms

- The sub-categories according to performance index are
    - innovations based on state estimates
    - parameter estimates
    - characteristic quantities

- The sub-categories according to way of determining the model structure are
  - Physical models
  - Black box models
- The sub-categories according to way of handling model dynamics are
  - Static models
  - Linear dynamic models
  - Nonlinear dynamic models

Classifier

Knowledge-based classifiers
- Rule-based deduction
- pattern recognition methods

Association-based classifiers.

For example, using the classification scheme shown above, a BOFD method could be classified to be a method the preprocessor of which
- uses characteristic quantities,
- is based on physical model and
- is based on static model

and the classifier of which
- is rule based.

2.4.3 Preprocessor [2.4]

The observation preprocessor generates performance indices from the available observations. These indices can be more easily and reliably classified than the observations themselves. The classifier generates the fault detection and diagnostic decisions based on the input performance indices.

Analytical models are the most interesting observation preprocessors. Process models relate measured process inputs and outputs. State-space innovations and parameter estimates are two performance indices generated by process models. Characteristic quantity models provide characteristic quantities as performance indices. These quantities can be defined to track how well the process is accomplishing its purpose. This makes classification easier and the results more relevant.

Process models can be derived in two ways. Physical models utilize the physical constraints inherent in the process to define the model structure. The analytical redundancy contained in this structure is a major advantage for FDD applications. Black box models use the simplest form capable of fitting the observations. Therefore, the structure does not contain physical analytical redundancy, but they can be much easier to compute. Black box models are efficient ways of storing observations for future comparison to new observations. This difference can be used as a performance index for fault detection.

Physical models are often nonlinear dynamic models. Steady-state and linear approximations can be used to simplify the models to enable easier computations. Steady-state models are valid when the process variables are constant. This occurs when input dynamics are slower than the system response time. The linear approximation allows the model to track dynamics in small ranges about a steady-state operating point. When neither of these approximations are valid the full nonlinear dynamic model must be solved, which can be a formidable and often prohibitive task.

2.4.4 Classifier [2.4]

The second component in a FDD system is the classifier. It makes the detection and diagnostic decisions based on the input performance indices from the observation preprocessor. Knowledge-based and association-based classifiers are two types. Knowledge-based classifiers separate the knowledge-base from the inference mechanism. Rule-base and statistical pattern recognition methods are two types of knowledge-based classifiers. They represent the more mature techniques which are most easily applied to various applications. Rule-based systems mostly utilize structural knowledge in the form of "IF", "THEN", "ELSE" statements. The inference mechanism evaluates the rules on the input performance indices and makes the appropriate decisions. Statistical pattern recognition methods use only probabilistic knowledge in the form of prior and conditional probabilities. Both of these knowledge-based methods have serious problems when the diagnostic problem becomes complicated. For these cases, associative models together with parsimonious cover theory create a more natural environment for classifying fault detection and diagnostic problems. However, the formalism is still in its infancy and many details still need to be worked out.

2.4.5 Evaluation

In Figure 2.6 the fault evaluation follows fault detection and diagnosis and in this part an assessment is made of how the fault will affect the process.

In buildings a fault in a component or in a lower level of component hierarchy need not necessarily affect the building performance at all. A sensitive fault detection method may detect faults that neither cause any immediate consequences on a higher level nor lead to an immediate failure state of any part of the building system. When this kind of fault is detected the consequences must be established and it must be decided how soon some actions must be taken in order to minimize the harms that could be caused.

If the fault is detected on a higher level of the component hierarchy the effect of the fault to the building performance is more obvious and evaluation may be easier. If, for example, a BOFD method monitors the energy consumption of a building the evaluation can be based on the criteria that are given for the performance requirements of that building.

Evaluation criteria should be the same as those used in evaluating the importance of components and subsystems of a building system. Some examples of these criteria are given in chapter 3 of this report.

A part of the evaluation can be performed already in the fault detection part and is related to the problem of setting the alarm limit for test signals. By setting the alarm limit suitably one can decide how sensitive a BOFD method is. Most of the method to determine the alarm limits are based on statistical analysis of the process model utilized but also some other criteria like economical and environmental in calculation of the alarm limit could be used (see sect. 5.4).

2.4.6 Decision and actions

The supervision loop of Figure 2.6 does not separate between automatic and "manual/human" interactions. The emphasis in automation of the process supervision has been on tasks of fault detection, diagnosis, and evaluation. Decision making of the required operation stage, and consequently, stopping or changing the operation of the process is more difficult to automate and has been left mainly to the operator.

The task of decision making is to solve what the operating state of the monitored process should be when a fault has been detected, its location and cause has been solved and severity has been evaluated. The decision is made on the basis of the information of the hazard classes of existing faults and possibly on the basis of the information of the process state. For example, a severe ignition fault of an oil burner may require immediate corrective actions but if heat is unconditionally needed, and if the burner runs continuously in a cold winter season, the operation may not be stopped unless the risk for safety is too big.

The actions consist of either

- stopping the operation of the process and eliminating the fault or
- changing the operation of the process

both of which need some intervention to the operation of the process. Stopping the operation is needed in any case if the fault has to be eliminated i.e. corrected. However, if the hazard class of the fault is low it may be possible to continue the operation for instance so long that the time and duration of fault elimination is convenient and as short as possible, respectively.

In a BOFD system the tasks preceding the decision should at least provide the operator information to back-up his or hers decision making. The information should be reliable and consistent. There may not be too much information and the information should be relevant in relation to process under supervision and the criteria that the process performance is judged.

In Annex 25, the scope of the work was restricted "passive" monitoring of the process. This means that automatic and thus active corrective signals from BOFD system to process were left out of the system concept. Only true feedback in system concept was the one through operator. This restriction was made with intention to focus the amount of work and, for example, optimal control was left out of the annex because of this reason. Test signals to the process in Figure 2.9 were "allowed" for the purpose of excitation of the process suitably when needed.

In Annex 25 BOFD concept, the decision and action blocks are left open in quite a large extent. These tasks would be taken care of mainly through the way the user interface is organized.

2.5 SYSTEM STRUCTURE

A number of the possible defects in a process, the fault that they cause or the way in which they develop is not known beforehand. As the process ages, new, unpredictable kinds of defects may also arise. To develop methods for fault detection is a time consuming and difficult task and it may take years for some special defect to occur. Instead of starting from one process unit and one defect type, the development work should be started with a set of methods applied to a set of process units. This requires the BOFD-system to allow a number of different kinds of methods. When a certain method appears to be efficient for some defect, the method should be applied to all other similar process units, which sets requirements for the expandability of the system.

A BOFD-system should be designed so that it does not restrict the number of different process units (buildings, subprocess, components) or the number of different methods. For developing new methods in a running system, the system structure should allow easy expansion of the set of fault detection and diagnosis methods and also the easy connection of new process units to the BOFD-system is easy. In addition the costs required to monitor a single component can not be high. These requirements can be fulfilled with a hierarchical and modular system structure (Figure 2.9).

The test quantities describing defects in process units are generated on the lower level BOFD-modules from the process signals. They are then passed to the upper level for reasoning. The test quantities may also include redundant information on faults. The test quantities are generated continuously or when required by an operator or the upper level reasoning. The inquiries for the generation of test signals are passed from the upper level to the lower level. A lower level module can use an additional test signal that is fed out to the process for generating suitable process variations for fault diagnosis purposes. A test signal might be a low amplitude random variation or a step in some control signal.

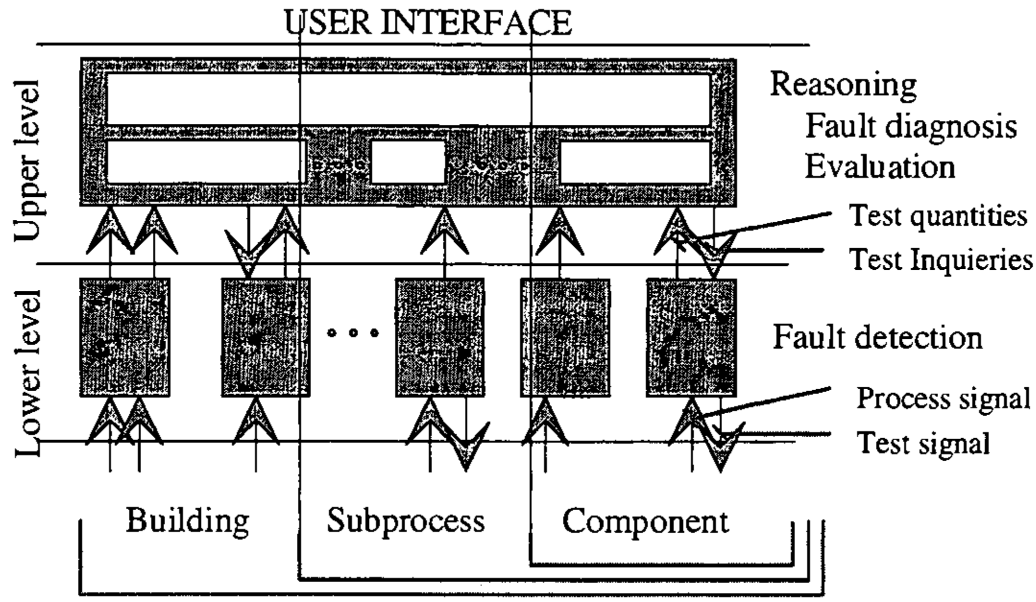

Figure 2.9. BOFD system structure.

For example, if the parameters of some subprocess are to be estimated, the operator or upper level software sends an inquiry to the lower level module of that subprocess that utilizes estimation techniques. The lower level module generates a suitable test signal and the subprocess parameters are estimated from the control signal and the process signals. The parameter estimates are then passed back to the upper level as test quantities.

2.5.1 Lower level

The methods on the lower level are modular and independent of other modules. Each module monitors a single, well defined, process unit (building, subprocess, component). For one process unit there may be several monitoring modules, each of which monitors a specific defect or uses a specific method. Because the modules operate in parallel, without interdepencies, there are no formal requirements for the methods used and several different kinds of methods can be used in the same system. If needed, the lower level can be divided into sublevels. In some fault diagnosis modules the lower level may consist of two sublevels: a method to find a faulty operating process unit and a method to generate a test quantity. Also, if needed, a process may be modeled in a hierarchical way which causes the lower level to consist of more than one sublevel.

Especially when dealing with the fault diagnosis, the methods do not have to describe the whole process exactly. The methods should only be exact enough to detect a fault in the monitored process unit. A method that describes the process exactly may be a waste of time because a simpler method could reveal most of the defects. Also, it is not so important to get two methods to describe the process exactly in a consistent way as long as the test quantities that the methods generate depend in a consistent way on the defects. If the methods are not accurate, it is not possible to have good absolute accuracy in generating the test quantities. When dealing with building optimization methods the accuracy requirements may be stricter.

In developing the fault diagnosis methods, one should at least aim for methods that give good relative accuracy so that relative changes in test quantities can be used for fault diagnosis.

2.5.2 Upper level

Each lower level module generates one or more test quantities or symptoms from the measured process signals. The test quantities are passed to the upper level reasoning. The reasoning aims at locating, sizing and finding the cause of the fault (diagnosing the defect). The output for the user are instructions and assistance in correcting the defect and the fault. The reasoning may in addition to generated test quantities also use direct process signals and information obtained from the user by dialogue. If there are mutually redundant test quantities, the reasoning may use only the most apparent test quantities, or alternatively a set of test quantities may be combined to give the best result. The upper level reasoning is easier if the test quantities generated on the lower level are as defect/fault selective as possible. This also implies that the number of test quantities needed in the reasoning is small.

The upper level reasoning can be realized by e.g. an expert system, by applying pattern recognition or statistical decision theory. Expert systems offer a user interface, reasoning and explanation parts and a system structure that allows for the expansion of the BOFD-system. Because the development of expert systems has been fast the BOFD-system should be such that the reasoning part can be replaced with newer versions or new kinds of programs if needed. In practice this means that passing the test quantities from the lower level to the upper level should be organized via some test quantity data base.

2.5.3 BOFD-system user interface

Because the BOFD-system primarily assists the operator in diagnosing process faults, much emphasis must be placed on designing the user interface of the BOFD-system. A building operator needs the BOFD-system to explain and reveal complex interdepencies in a simple way, not a technical system more complicated than he is already familiar with. On the other hand, the operator must be able to rely on the information the BOFD-system supplies him with, and that is why the operator must be able to check the reasoning the diagnosis is based on (explanation mechanism). In addition, the operator must be able to investigate all the variables and calculations the BOFD-system makes use of. The user interface thus has to meet the following mutually contradictory requirements: the user interface has to be clear and simple, but simultaneously it has to give thorough information on reasoning paths used. The defects should be diagnosed precisely but too detailed a diagnosis may cause the user not to notice the most obvious mistakes made by the BOFD-system.

2.6 BOFD-SYSTEM IMPLEMENTATION

An ultimate goal in implementing a BOFD system could be a system that is embedded in a building energy management system. This kind of system realization is shown in Figure 2.10. The BOFD system functions and features are added to the normal features and functions of BEMS. The BOFD modules might be a part of the normal routines in the BEMS outstations and the BOFD user interface and the reasoning might be realized as part of the operator station software. In a realization of this kind, the BOFD system would appear to the operator to be like, for instance, the alarm display and alarm functions in existing BEM system.

The functions and operation of a BOFD system can also be demonstrated with other kinds of realizations than the one presented above. In Annex 25, one objective was to demonstrate the implementation of the concepts in conjunction with a real BEM-system. This objective could be fulfilled with the realization shown in Figure 2.11.

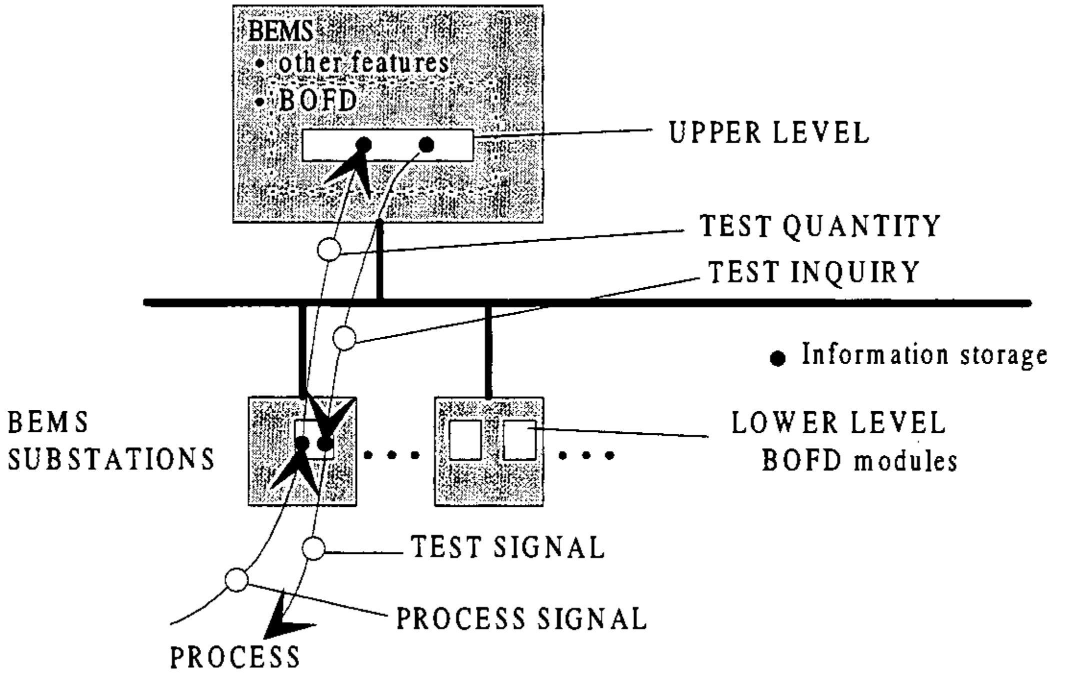

Figure 2.10. BOFD system as a part of a building energy management system (embedded).

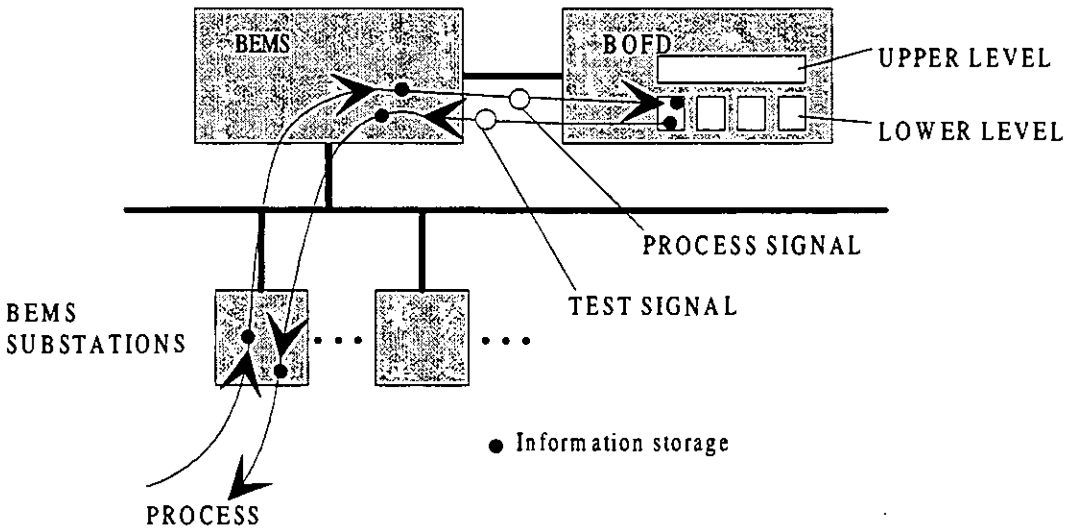

Figure 2.11. BOFD-system in conjunction with a BEMS. BOFD system uses the BEMS system process signal data base.

2.7 CONCLUSIONS

Building is a complex system that consists of subsystems and components. The building system can be described as a hierarchical structure in which, however, there may be some interactions between entities on the same level.

Ultimately, building optimization aims at finding some optimum state for that system by mathematical and conceptual tools of control and system theory. Due to system complexity this optimal state may not be understood in a mathematical sense but more from the practical point of view. This state could be described with words "sub-optimal" or "almost optimal" state which can be achieved when subsystems are used optimally and there are no faults in the system.

While fault detection and diagnosis forms an essential part of building optimization and while optimal control in buildings has been studied in other forums, it was decided to concentrate on fault detection and diagnosis in Annex 25.

A fault is an inadmissible or unacceptable property of a system or a component. There can be faults in a building as a whole, in its subsystems and its components. The methods to detect faults in all of these levels are fault detection methods. After detection of a fault the cause for it and its location must be diagnosed and the severity must be evaluated.

In case of a building, like also other systems, a single fault propagates to other parts of the system. A primary fault causes other related faults, secondary faults. As well there may exist several mutually unrelated or independent faults. The diagnosis should in addition to locating and finding the fault cause, but also aid the operator in separating between different independent faults and finding the basic faults.

Because of the reasons linked to special features of buildings and their systems the BOFD concept presented here aims to widen the existing concepts of process supervision with features applicable to this specific area of application. The main emphasis here and in the annex was on fault detection and diagnosis. Some general concepts on evaluation has been given but the tasks of decision making, and actions has been left out. The system structure for implementation and also two possible implementation plans have been presented.

Research in the field of fault detection has started in the advent of computers [2.5] and there is no need to develop any new concepts in the application area of building, building's systems and HVAC systems. The concept presented in this chapter is heavily based on the concepts and ideas used and applied in the industrial automation and processes and other fields of application. The new points of view that arise in buildings and their systems are that they are complex systems with non-linear characteristics, they are operated by uninformed operators and occupants, and efficient building management operation are at times in conflict with other constraints which are not easily measured.

2.8 REFERENCES

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3 TYPICAL FAULTS IN HVAC SYSTEMS

3.1 HEATING SYSTEMS

3.1.1 Overall Heating systems

Visier, J. C., CSTB, Paris, France

3.1.1.1 Introduction

This section deals with typical faults occuring in hydraulic heating systems.The approach followed to collect and rank the faults of heating systems includes three steps:

- a reference heating system was defined,
- discussion with a small number of experts enabled the definition of an extended list of faults of this heating system,
- ranking of faults was made in parallel with different approaches in Germany and France
- a list of symptoms for the most important faults was established.

The main results of these first three steps are described in this section. Results of the fourth step are presented in Appendix 3A in the end of this chapter.

DESCRIPTION OF THE REFERENCE SYSTEM

The reference system chosen is described in detail in the report of the preparation phase of Annex 25 [3.1]. Its main characteristics are summarized here.

The heating system is a typical hydraulic heating system used in medium to large size residential and non residential buildings for space heating as well as for domestic hot water heating.

The building is a multi-storey building.

The heat generation plant includes two gas boilers. The design departure temperature is around 90°C.

The distribution network is split into two circuits, one for the northern and one for the southern façade. The temperature of each circuit is regulated using a three-way valve.

The control system includes:

- boiler control and sequencing,
- scheduling of occupancy periods,
- adaptative control of the flow temperature setpoint of each secondary loop (weather compensation),

- adaptation of start/stop time prior to occupancy begin/end (optimum start/stop),
- flow temperature control observing the return flow temperature limitation signal,
- local temperature control of each zone by thermostatic valves.

The domestic hot water system is a nearly instantaneous system.

A schematic diagram and a control diagram of the reference heating system are given in Figures 3.1 and 3.2.

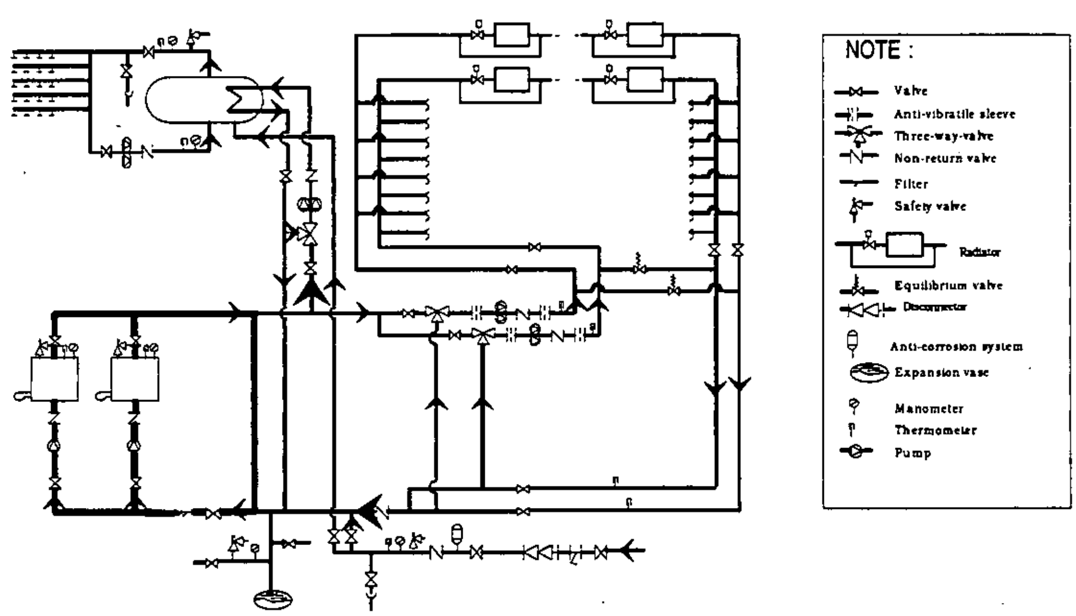
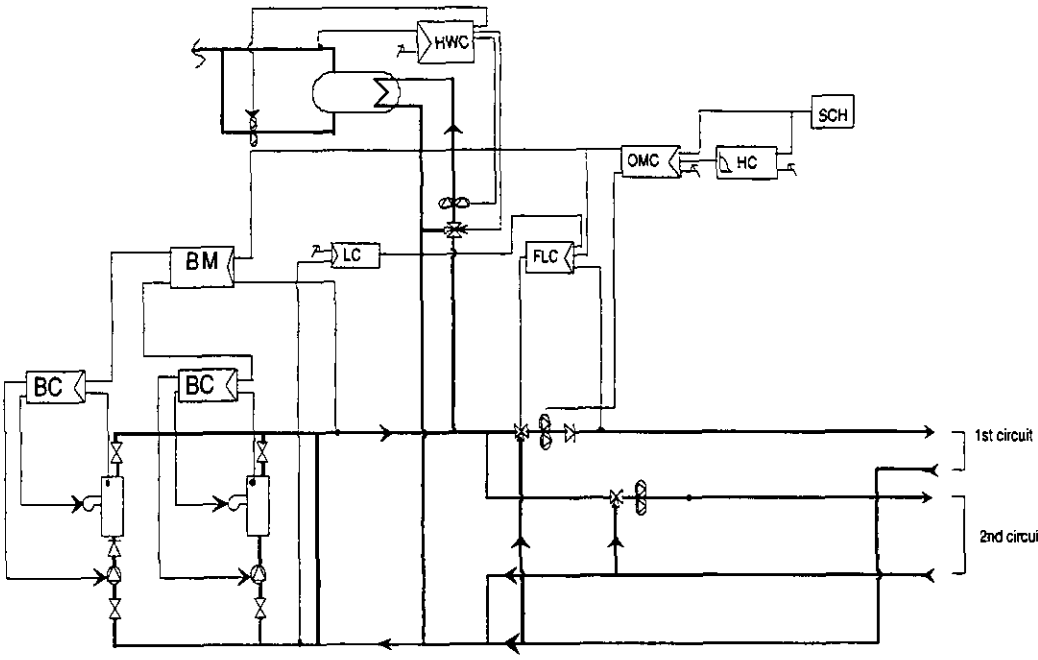


Figure 3.1. Schematic diagram of the reference heating system.



The control sheme of the second circuit is not represented.
It is equivalent to the control scheme of the first circuit.

NOTE

BM:	Boiler Master	defines the number of boilers to be used
BC:	Boiler Controller	on-off control of the boiler temperature
LC:	Limitation Controller	maintains the return flow temperature above a given limit
SCH:	Scheduler	defines the occupancy schedules
OMC	Operation Mode Controller	controls the intermittent heating (includes the optimal start stop)
HC	Heating Curve (= weather compensator)	defines the set point of flow departure temperature in normal mode
FLC	Flow Controller	control the flow departure temperature
HWC	Domestic Hot Water Controller	controls the temperature of the domestic hot water tank

Figure 3.2. Control diagram of the reference heating system.

3.1.1.2 List of faults of heating systems

From the description of the reference system a failure mode and effect analysis was performed. This lead to a detailed list of faults. A restricted list including faults which appears at first sight as the most important was defined. For each list in this fault the process variable deviation due to the fault and the associated symptoms were listed. Then the need to develop new fault detection methods was assessed. This restricted list is given in Appendix 3A.

3.1.1.3 Ranking faults

The faults are ranked to determine the important ones and the areas where the effort of Annex 25 should be focussed.

Two approaches were launched in parallel to perform this ranking. The first approach described below was led by IKE in University of Stuttgart and the second approach by CSTB.

1st APPROACH

This approach involved using 5 experts (2 service engineers and 3 heating experts) to rank a list of 60 faults chosen from the faults included in the detailed list.

The ranking procedure for each fault includes questions on 6 characteristics:
W: Availability of water for heating or domestic purposes
E: Influence on energy consumption
P: Probability of a fault
S: Ease of servicing, maintainability
Sp: Availability of spare parts
Sm: availability of service technician.

In order to catch various points of interest three different weighting approaches were considered to calculate the importance of a faults.

First weighting:

In this first weighting the availability of a service technician is not important. This wheighting is applicable to large buildings with integrated servicing where service technician are easily available. The faults with the highest importance appear to be:

- bad boiler efficiency
- defects of sensors (water flow, gas flow)
- defects of manometers (boiler, gas expansion system)
- leak of the gas tank.

Second weighting:

In the second weighting the service technician is very important. The assumption is that the building would be in a rural district. The most important faults are:
- boiler, radiator or pump size wrong,
- blockage of boiler pipes and heat exchangers,
- zone temperature too low,
- thermostatic valve defect.

Third weighting:

In the third weighting the availability of water for heating or domestic purposes is essential. This can be the case in hospitals. The most important problems are:
- leaks in pipes,
- defects in valves (three-way valve, non return valve),
- defects of manometers (boiler, expansion system),

2nd APPROACH

The second approach was based on a survey completed by 46 experts.

The questionnaire includes a list of the components in an hydronic heating system. For each of these components, a list of possible faults is given. A total of 106 possible faults have been listed.

The experts ranked the faults based on the following four characteristics:
- frequency of occurrence,
- degree of difficulty for the operating teams to detect it,
- impact on users comfort,
- impact on energy consumption.

The results obtained with 12 different classifications of faults are described in. These classifications are made according to the following criteria:
1) Frequency
2) Presence rate (design faults only)
3) Fault detection difficulty
4) Effect on comfort
5) Impact on energy consumption
6) Frequency of occurence and fault detection difficulty
7) Frequency of occurence and impact on occupants comfort
8) Frequency of occurence and impact on energy consumption
9) Effect on comfort and fault detection difficulty
10) Impact on energy consumption and fault detection difficulty
11) Impact on energy consumption and comfort
12) Frequency, fault detection difficulty, effect on comfort and impact on energy consumption.

The faults which appear to be the most important differ from one classification to another.The results of the last classification, which take into account all the characteristics and general comments obtained by analysing the other classifications, are summarised here.

The faults which appear to be the most important with regard to the 12th classification can be separated into design faults and operating faults.

Design faults:

- **fault 1:** heating imbalance between different parts of the building.
- **fault 2:** poor hydraulic balance between circuits.
- **fault 3:** over or under-dimensioning of radiator in certain rooms or specific parts of the system.
- **fault 4:** indoor temperature measurement sensors placed in a non-representative room.

Operating faults:

- **fault 5:** heating curve badly tuned.
- **fault 6:** incorrect calculation of the optimum start or stop by the operational mode controller.
- **fault 7:** poor combustion.
- **fault 8:** scaling and dirt accumulation in the boiler's heat exchanger.
- **fault 9:** leakage of the: three-way valves/two-way valves of the control of secondary circuits.
- **fault 10:** deposit of scale on the exchanger of domestic hot water.

The analysis of the results of the other classification leads to the following remarks:

- design faults that greatly affect comfort are generally detected at the start of the system's working life;
- design faults that have an important impact on energy consumption risk not being detected at the start of the system's working life;
- design faults are difficult to detect by maintenance teams;
- operating faults, i.e. faults other than design faults, which have a considerable impact on comfort, are generally well detected by operating teams;
- numerous operating faults that have a big impact on energy consumption are difficult to detect at present;
- numerous faults that affect both comfort and energy consumption are found in the secondary circuit control system, however, simple methods for detecting the faults do not exist;
- faults which occur in one single room are generally detected only through complaints of occupants.

3.1.1.4 Conclusions

A data base of faults of heating systems was obtained. The ranking procedure applied showed that different points of view can lead to a different ranking of faults. Moreover, a list of most important faults was obtained and was used as a basis for the work of the heating group in Annex 25.

3.1.1.5 References

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3.1.2 District heating subdistribution (DHS) system

Hyvärinen, J. VTT Building Technology, Espoo, Finland

3.1.2.1 Process

A simplified process and instrumentation diagram of a DHS system is given in Figure 3.3. The heat energy needed by a consumer is transferred from the district heating network to the radiator or domestic hot water network through heat exchangers (HE1 and HE2). Cooled district heating network water is returned to the return network and further to the power plant. The amount of heat transferred through the heat exchangers is controlled by varying the water mass flow (control valves TC1 and TC2) on the district heating network side of the heat exchangers.

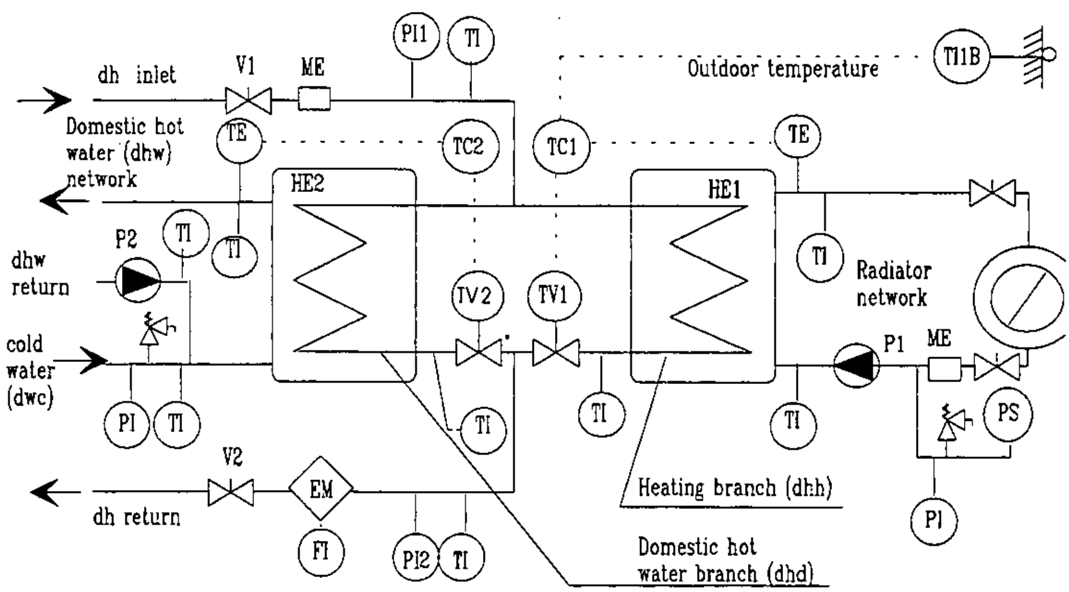

Figure 3.3. District heating subdistribution system process and instrumentation (PI) diagram.

The main subprocesses of the subdistribution system are:

Primary circuit

primary circuit, inlet (dh)
primary circuit, domestic water branch (dhd)
primary circuit, heating branch (dhh)
primary circuit, return (dh)

Secondary circuit, domestic water

domestic water, cold (dwc)
domestic water, circulated (cdw)
domestic water, hot (dwh)

Secondary circuit, heating (radiator) network (h)

Main functional entities in addition to the subprocesses mentioned above are

Control devices
Electrical devices, supply energy equipment

Electrical devices and supply energy equipment are not dealt with in this section.

3.1.2.2 List of typical faults

In Table 3.1 a list of typical faults of a DHS system is given.

Table 3.1. Typical faults of a DHS system.

No	Component	Fault
Domestic water		
318 (310)	• heat exchanger HE2 • (heat exchanger HE2 preheater, if exists)	• leak out from the water side • secondary circuit water leaks to the primary (dh) side, dh-water O_2 concentration increases • corrosion of HE2 exchanger • leak out to the environment from the heat exchanger • primary side (dh) water to the secondary side water network • heat exchanger partly stuck or dirty (scaled)
301 316	• main stop valve (and other stop valves) manual control valve	• erroneously closed • leaking when closed
311	• pipe	• domestic hot water network leaks out
313	• pump P2	• no heat load (no hot water demand) -> pump stopped • pump overdimensioned
302	• water meter	• (partly) blocked

No	Component	Fault
Primary circuits, district heating side of the process		
several	• flange joint	• leaking
116 122	• heat exchanger HE1 • heat exchanger HE2	• exchanger blocked because of poor district heating water quality • blocked • district heating water leaks to the secondary side water network • district heating pipe blocked, dirty
106	• mud separating device	• blocked or partially blocked
126 101	• pipe • pipe	• blocked • installation error, district heating pipes exchanged
125 133 103	• stop valve • stop valve • stop valve	• blocked, erroneously closed • quick closing of ball valve may cause high pressure impact
115 111	• stop valve, closed at summer • stop valve, closed at summer	• blocked, erroneously closed • quick closing of ball valve may cause high pressure impulse • (partly) blocked, erroneously closed • summer valve, open in summer
104	• throttle valve	• (partly) blocked
131	• water meter	• (partly) blocked
Room heating, radiator network		
211	• branch for filling	• filling up valve erroneously open
218	• discharge valve	• valve erroneously open
206	• expansion tank	• expansion system does not work correctly
208	• heat exchanger HE1	• district heating water leaks to the radiator water network
215	• manual control valve	• valve erroneously closed in radiator network
205	• pressure-relief valve	• overpressure expansion valve leaks • overpressure expansion valve jammed
213	• pump P1	• pump stopped • wrong movement direction • no heat load (-> pump stopped) • pump overdimensioned, water flow not justified • pump installed to wrong direction
Control circuit		
506 511	• actuating element, motor TV1 • actuating element, motor TV2	• control-unit does not operate correctly • control-motor broken
501 508 504	• controller TC1 (heating) • controller TC2	• control-unit does not operate correctly • control-curve oscillates • wrong control-curve • jammed open • controller/substation fault, valve TV1/2 erroneously closed
502 509	• outside air temp. sensor TI1B • sensor of domestic hot water temperature • temperature sensor of radiator network inlet water	• thermostat broken or false installation
510	• wires	• wire cut, broken, loose connection or installation error,...

3.1.2.3 Ranked list of components

The operation of a DHS system was analyzed in an expert group. The aim was to define those components for which a fault detection method should be developed. In the group, the typical faults of these components, and the symptoms from which each fault is usually noticed were listed.

The main emphasis in the analysis was on the consumer equipment in the district heating subdistribution room. Equipment owned by district heating and water suppliers was also considered because the equipment was installed in the consumer's rooms. The area of interest is the same as in Figure 3.3. The supplier equipment consists of main stop valves and energy and water measurement equipment. The supplier's district heating distribution network outside the consumer's building was considered as one component (subprocess). Faults in this subprocess reflect to the heat delivery, but the faults were not examined in detail. In addition to the subdistribution system, consumer's heating and domestic hot water networks were dealt with. As in the case of the district heating distribution network, the faults of the building networks were examined on a general level. The faults of process instrumentation equipment were examined. Faults in electric devices (230 V) were excluded.

On the basis of a detailed PI-diagram the components, each of which may have a number of faults, a large list of components was compiled. In order to concentrate only on essential components and their faults, the component list was evaluated against the district heating system properties important to the building owner. The properties, the evaluation scale, and the weights of individual properties used in the evaluation are listed in Table 3.2. The weights of the chosen characteristics were obtained by combining the opinions of experts.

Each component and its faults was considered with regard to each property, the evaluation scale, and weights of Table 3.2. For example, the importance of a heat exchanger is calculated in Table 3.3.

The result of the analysis is shown in Table 3.4 and in short it is, that the main effort in developing the FDD-methods should be concentrated on the following components and their faults:

- heat exchangers (leaks, blocks, dirtiness), especially domestic hot water heat exchanger
- control valves, controllers, actuators, related sensors
- pipes (leaks, blocks) and valves (leaks, blocks, erroneously closed or opened)

Table 3.2. Properties of a heating system.

Effect of a fault of a component to a chosen properties.			
Abbr.			Weight of the property
		Evaluation scale of the effect of a fault	
W	Hot domestic water and heat must be available		33
	habitant does not notice the fault	0	
	habitant may notice the effect later	1	
	habitant notices the effect within 1 day	2	
	habitant notices the effect within 10 minutes	3	
E	Energy consumption		20
	does not increase the energy consumption	0	
	energy usage is not optimal	1	
	wastes the money of habitant	2	
	wastes a lot of energy and money	3	
S	Ease of servicing, maintainability		12
	no tools needed, no break in domestic hot water or heating	0	
	tools needed + break in domestic hot water or heating longer than 30 min.	1	
	tools needed + break in domestic hot water or heating longer than 2 hours	2	
	tools needed + break in domestic hot water or heating longer than 2 days	3	
Sm	Availability of a serviceman		5
	no serviceman needed	0	
	a serviceman needed	1	
	a plumber or an electrician needed	2	
	an authorized serviceman (an expert) needed	3	
Sp	Availability of spare parts		5
	spare parts available at the building spare part stock	0	
	spare parts available within 2 hours	1	
	spare parts available within 2 days	2	
	spare parts available later (within 2 weeks)	3	
P	Probability of the fault		25
	mean time between failures (MTBF) $\geq$ 15 years	0	
	15 years > MTBF $\geq$ 7 years	1	
	7 years > MTBF $\geq$ 2 years	2	
	MTBF < 2 years	3	

Table 3.3. Calculating the importance of a heat exchanger.

Component HE2 heat exchanger		Component number 318	
charac-teristic:		evalua-tion	weight
W	Hot domestic water or heat must be available some fault occurs that habitant notices within 10 minutes	3	33
E	Energy consumption some fault occurs that a lot of energy to be wasted	3	20
S	Serviceability repairing of some fault requires tools and break of more than 2 days in operation	3	12
Sm	Service man available repairing some fault needs a special staff	3	5
Sp	Spare parts available getting the spare parts may take two weeks	3	5
P	Probability of fault fault occurs once a 15 years	1	25
total importance= 3x33 + 3x20 + 3x12 + 3x5 + 3x5 + 1x25 = 250			

Table 3.4. Ranking of DHS system components.

Subprocess.	Component	Priority	W 33	E 20	S 12	Sm 5	Sp 5	Fp 25
domestic water	heat exchanger HE2, secondary side	250	3	3	3	3	3	1
domestic water	heat exchanger HE2, primary side	245	3	3	3	2	3	1
domestic water	control valve TV2	238	3	2	2	3	2	2
heating, dh	control valve TV1	225	2	3	2	3	2	2
domestic water	controller TC2	213	3	2	2	3	2	1
domestic water	actuating element, motor TV2	213	3	2	2	3	2	1
domestic water	pipe	198	3	3	2	2	1	0
domestic water	sensor of dwh temp, TI2	196	3	2	1	3	1	1
heating	controller TC1 (heating)	180	2	2	2	3	2	1
heating	actuating element, motor TV1	180	2	2	2	3	2	1
heating network	heat exchanger HE1	177	2	1	3	3	3	1
heating, dh	heat exchanger HE1	172	2	1	3	2	3	1
inlet, dh	pipe	170	3	1	3	2	1	0
domestic water	wire for dwh sensor TI2	166	3	2	1	2	1	0
domestic water	wire for actuating element TV2	166	3	2	1	2	1	0
domestic water	pipe	158	3	1	2	2	1	0
outlet, dh	pipe	158	3	1	2	2	1	0
dw, cold	non-return valve	151	3	0	1	2	1	1
heating	sensor, radiator network inlet temp.	151	2	2	0	3	1	1
inlet, dh	stop valve	150	3	0	3	2	1	0
outlet, dh	stop valve	150	3	0	3	2	1	0

The importance of separate faults was not assessed.

3.1.2.4 Symptoms

In the following table some symptoms from which the faults are normally noticed are listed. The list is not exhaustive but gives an idea of how different faults can be detected with current practice on the field. Most of the symptoms can not be measured automatically and may require visual inspection.

Table 3.5. Symptoms for the most important faults.

Component		Fault	Symptoms or effects
heat exchanger HE2, domestic water circuit primary or secondary circuit	318 122	• Corrosion of HE2 exchanger --> domestic water leaks to district heating network	• big leak increases district heating flow which causes increased water and energy bills to the customer • district heating -water meter jams • district heating water O_2 concentration increases --> district heating pipe corrosion
		• Corrosion of HE2 exchanger --> district heating water leaks to the domestic water network	• decreased domestic water quality: taste, hygiene • decreased domestic water consumption (frequent checks of water consumption) • domestic water temperature increases • This fault can normally be detected only by using coloring of the district heating water or so called pressure test.
		• Corrosion of HE2 exchanger --> leak out from the domestic hot water exchanger	• outside corrosion of pipes • Measured domestic water amount increases. Damages due to water.
		• HE2 (or district heating pipe) blocked or dirty due to e.g. bad water quality	• domestic hot water not warm enough • pressure difference over the HE2 increases
control valve TV2	121	• (partly) blocked, erroneously closed (e.g. faulty controller operation) or jammed in close position	• decreased district heating flow • not enough domestic warm water or no warm domestic water at all
		• controller fault, valve in open position or jammed open	• district heating water temperature difference too small • domestic hot water temperature increased or too high (i.e. secondary circuit temperature increases) • high district heating water flow • flow meter damage
		• valve is oversized	• secondary circuit (domestic water) temperature fluctuates, period ca. 1 min. amplitude +-10'C • energy consumption increases

Component		Fault	Symptoms or effects
control valve TV1	117	• blocked, erroneously closed	• heat defect in radiator network (frost, corrosion)
		• valve continuously or erroneously in open position (e.g. due to controller fault) • valve jammed in open position	• heat exchanger corrosion due to too high flow • district heating water flow and energy consumption are too big • room heating water temperature increases • Noise due to high radiator network inlet water temperature. • Flow meter damage due to high water temperature.
		• jammed in closed position	• heat deficiency
		• TV1 valve does not close tightly	• overheating in some occasions
actuating element, motor TV2	511	• control-unit does not operate correctly	• TV2 valve closed
controller TC2, TV2 (same applies for TC1 and TV1)	508	• control-curve oscillates	• control valve wears quickly • waste on energy • long waiting periodes for domestic hot water
		• controller/substation fault, valve TV2 erroneously closed	• domestic hot water too cold
		• faulty controller pre-settings or tuning	• domestic hot water temperature fluctuates +- 10 °C, period 1 min.

3.1.3 Oil burner

Hyvärinen, J.
VTT Building Technology, Espoo, Finland

3.1.3.1 Process

An oil burner burns oil to warm the boiler water that is used for building and domestic hot water heating. The heat is generated in the process by burning light oil in the combustion chamber (No 501 see Figure 3.5) of the boiler. Oil is fed to the burner from the oil tank through oil feeding lines (305 - 313). The task of the burner is to produce a homogenous mixture of oil and combustion air. The mixture is fed to the chamber where mixing takes place as apart of the flame. The flue gas temperature in the chamber is about 1 400 °C. The heat from flue gas is transferred to the boiler water through chamber walls (504) prior to the flue gas passing up the chimney.

The boiler water temperature is kept within some predetermined limits or at some constant value by controlling the burner operation. The warm water is circulated to the heating and domestic hot water networks with circulation pumps. Cooled water returns from the heating circuits back to the boiler. The heating circuit departure temperature is controlled by mixing the boiler water and the heating circuit return water (control valve 106). A simplified PI-diagram of the process in consideration is shown in Figure 3.5.

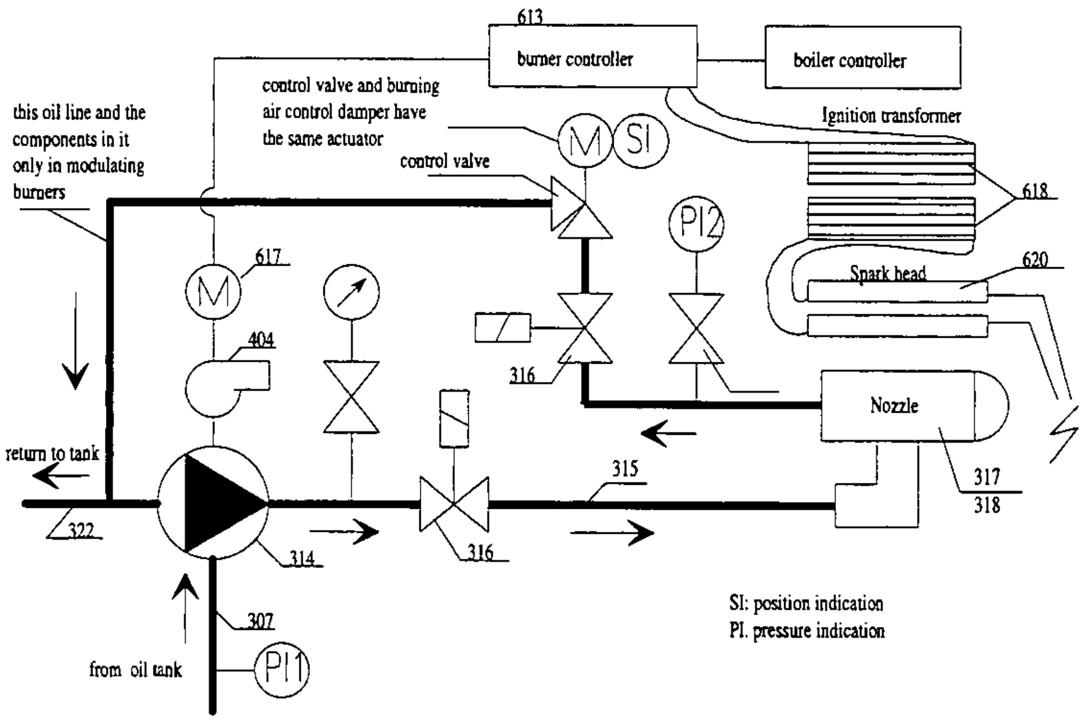

Figure 3.4. Oil circuitry of the burner.

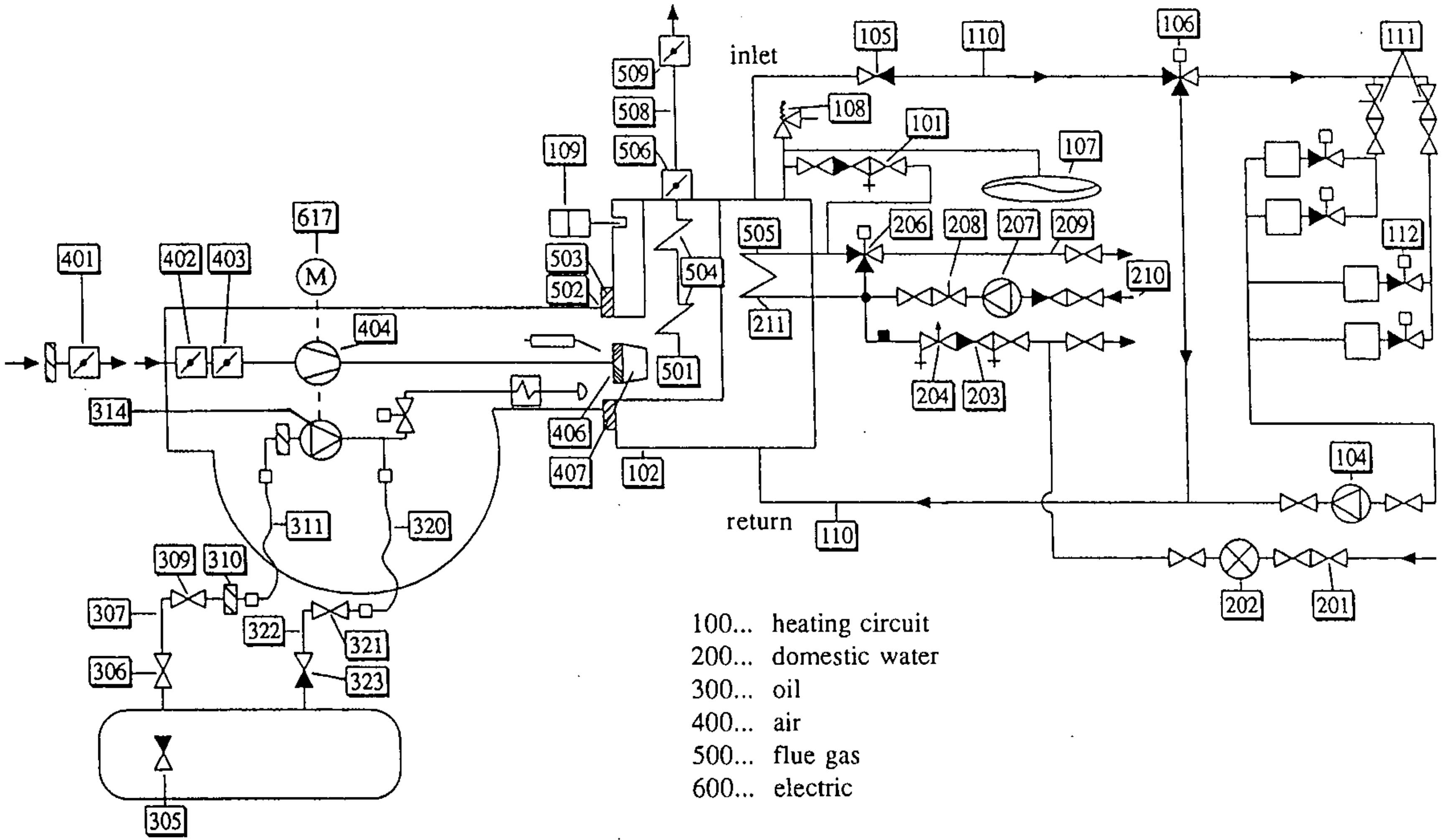

Figure 3.5. Burner/boiler process simplified PI-diagram.

The burner operation is controlled with burner control equipment which includes the equipment for preventing hazardous events. The complexity depends on the type of the burner used. In small burners, such as used in single family houses, the controller consists of so called control relay and safety equipment only. In bigger burners, modulating control is applied and the controller is more complex.

Oil burner/boiler system can be divided into seven functional groups:
- heating circuit
- domestic hot water circuit
- oil tank and oil circuitry (the latter in detail in Figure 3.4)
- air feeding circuit and the burner head
- furnace and the flue gas channels
- burner control equipment, electrical circuits (not in the process diagram)
- other control equipment, electrical circuits (not in the process diagram).

3.1.3.2 List of typical faults

In the following table a list of typical faults of a burner system is given. The list focuses on air and oil feeding, burner and flue gas channel. Other parts of the heating system of a building are covered elsewhere in this report.

Table 3.6. Typical faults of oil burner.

No	Component	Fault
oil circuit		
	• filling pipe	• filling cap removed letting water and impurities to tank
	• oil tank air exhaust pipe	• blocked due to ice or other material
	• oil storage tank	• water in tank • leakage • bad oil due to aging
305	• tank bottom non-return valve	• leakage due to dirtiness or wearing (oil runs back to tank leaving the feeding line empty)
  307 311 310	• oil feeding line components oil feed line oil hose, suction oil hose, couplings oil filter, feeding line	• leakage in: air or dust and impurities to oil, too little oil to burner • leakage out: oil to environment • blockage: due to impurities or too cold oil • •
	• filter in oil pump	• blockage due to impurities in oil
314	• oil pump	• pump not providing enough oil or no oil to nozzle due to gasket leakage, damaged pinion, corrosion, leakage to environment or some other reason
316	• solenoid valve and control valve in modulating burners	• partial or total blockage • valve not opening --> no oil • valve not closing (valve leakage) --> oil dropping to furnace • control valve faults

No	Component	Fault
317	• oil pre-heater	• blockage due to cracking of oil • electrical failure
318	• nozzle	• asymmetric flame due to nozzle wearing, partial blockage, dirt or mechanical damage in nozzle head • blockage due to cracking of oil at the nozzle due to high temperature during the burner halt
     320 322	• oil return line components • oil hose couplings • oil hose, return • oil return line	• leakage due to mechanical damage or incorrect installation: oil to environment • leakage due to wrong choice of material
air circuit		
401	• air inlet damper	• damper closed, not enough burning air • mechanical damage of the automatic air damper
402	• air control/adjustment damper	• mechanical damage: wrong air-oil ratio
403	• stand-by air restrainer	• mechanical damage or jamming: wrong air-oil ratio
404	• air fan	• mechanical damage, dirtiness: no or not enough burning air
406 407	• (air pressure tube +) mixing head • flame tube (burning head)	• soothing due to incorrect installation, air or oil leakages, air in oil, dirtiness • melting due to incorrect installation or existing circumstances •
flue-gas circuit		
501	• furnace	• corrosion due to moisture, wrong burner type or ashes in furnace
502	• burner flange	• gasket leakage or missing gasket: flue gas to environment or air to the combustion chamber
503	• boiler hatches	• gasket leakage or missing gasket: flue gas to environment
504	• convection tubes	• corrosion due to wrong burner sizing
505	• turbulators	• soothing
506	• flue regulating damper	• mechanical damage of the damper or joints
508	• chimney	• blockage due to ashes, surface disintegration
509	• stand-by flue restrainer	• mechanical damage or jamming

3.1.3.3 Ranked list of components

The process and its components were analyzed in an expert group. The aim was to define those components for which a fault detection method should be developed. In the group, the typical faults of these components, and the symptoms from which each fault is usually noticed were listed.

The main emphasis in the analysis was on the burner itself, however, the boiler, heating network, and domestic hot water network were also considered. The area of interest was the same as in Figure 3.5. Heating and domestic hot water network faults were dealt with on a general level. Also the faults of process instrumentation equipment were examined. Faults in electric devices (230 V) and controller were excluded.

The process was evaluated against the burner/boiler system properties important to the building owner. The properties, the evaluation scale, and the weights of individual properties used in the evaluation were the same as for district heating subdistribution system listed in Table 3.2. The weights of the chosen characteristics were obtained by combining the opinions of experts.

As a result a prioritized list of the components can be obtained. According to that list, in Table 3.7, the twelve most important components are all related to the oil burning or air feeding to the chamber. The 13th component in that list is the domestic hot water heat exchanger in the boiler water.

Table 3.7. The list of the most important components in an oil burner/boiler system.

Component No	Subprocess	Component	Relative importance
314	oil circuit	oil pump	266
406	burning air circuit	(air pressure tube +) mixing head	266
407	burning air circuit	flame tube (burning head)	266
318	oil circuit	nozzle	255
402	burning air circuit	air control/adjustment damper	246
316	oil circuit	solenoid valve (oil side)	241
317	oil circuit	oil pre-heater (oil side)	233
404	burning air circuit	air fan	233
615	electric circuit	oil pre-heater (electric coil)	233
621	electric circuit	solenoid (valve)	221
310	oil circuit	oil filter, feeding line	216
320	oil circuit	oil hose, return	215
211	domestic hot water circuit	dom. hot water heat exchanger	213
202	domestic hot water circuit	water meter	207
206	domestic hot water circuit	three-way valve	207
313	oil circuit	filter in oil pump	207
620	electric circuit	ignition electrodes	207
622	electric circuit	photocell	207
508	flue-gas circuit	chimney	204
507	flue-gas circuit	chimney connecting channel	199
201	domestic hot water circuit	main valve	197
203	domestic hot water circuit	non-return valve	197

3.1.3.4 Symptoms for the most important faults

Due to instrumentation practice in burner/boiler processes, and very detailed component list that was used in the prioritization, it is not practical to concentrate on single components but to some larger subprocess of the burner/boiler process instead. A list of issues that should be monitored in a burner operation is presented below. The three most important issues are:

- monitoring of combustion
- monitoring of ignition event
- monitoring of heat exchange surfaces (from flue gas to water).

Faults in the electric circuits are all "catastrophic faults" or complete failures that cause a halt of burner operation. Information for this kind of fault is usually available and needs no new methods. The problem is merely whether this kind of information is utilized effectively.

For the average user complete failures almost always require that a service man is called. Complete failures are also detected easily. When service man arrives the burner is in halt and he should find out the reason for the event. In that situation any information of quality of ignition or combustion prior to halt is very important. Without continuous monitoring or some other method this is impossible.

In normal operation the furnace and its convection surfaces soot. For the average user the correct point of time for cleaning the surfaces is difficult to judge and a method to detect that time would be useful.

In Table 3.8 a list of faults that usually lead to bad ignition and bad combustion are listed. Fast soothing is usually due to bad combustion and a symptom of some other fault. Otherwise soothing can not be considered a fault. It must, however, be detected also in that case.

In Table 3.8 the faults are prioritized in an unformal way. In the symptoms column there are references to process variables that can be measured from a burner process. The changes in these variables can be used when developing a method for burner fault detection.

Table 3.8. Faults to be monitored and components of oil burner/boiler.

Legend:
COLUMN symptom (symptoms in parenthesis are secondary symptoms)

A	oil pressure, pump suction side	F	temperature, boiler water
B	oil pressure, nozzle	G	temperature, flue gas
C	oil pressure, oil return line	H	temperature, burning air
D	oil pressure, tank	I	temperature, oil in the tank
E	pressure difference over the mixing head		

COLUMN Pr = priority (1 = the most important)

Component or event	Fault	Symptom	pr
oil	no oil water in oil	A,B,(D)	
oil feeding line	tightness - air leakage - oil leakage dimensioning blocked - oil viscosity too high - feeding line - oil tank bottom valve	A,B A,B A A I A A	5
oil filter	dirtiness air leakage oil leakage	A A,B	
oil pump	air leakage oil mass flow too low pump worn pump piston worn	A,B B,C,G,(E,F,H) A,B B	4
nozzle	worn, blocked wrong nozzle type	B,C,G,(E,F,H) E,B,C	
burner/boiler	incompatibility of the burner and the boiler ignition power of the burner too high	E,(B,C) E,(B,C)	2
burner head mixing plate	dirtiness damage (melting)	E,(B,C) E,(B,C)	1
ignition combustion	too much air --> flame escapes the burner head too little fresh air	E,(B,C)	3
air fan	wrong air/oil ratio due to - damper fault (actuator, or jamming) - air flap (if exists) - fan blade dirtiness	E,(B,C)	
combustion chamber/ chimney	wrong flow resistance due to - adjustment damper wrong position - heat exchanger dirtiness - sooty chimney	E,(B,C)	

3.2 CHILLERS AND HEAT PUMPS

Stylianou, M.,
EDRL-CANMET, Canada

3.2.1 Introduction

This section deals with typical faults occurring in either vapour compression equipment or equipment using absorption refrigeration, a combination that practically covers 100 % of the commercial refrigeration capacity.

3.2.2 Vapour compression refrigeration equipment

Vapour compression refrigeration equipment form the largest portion of the installed commercial refrigeration capacity. As shown in Figure 3.6, the basic vapour compression machine is composed of a compressor, a condenser, a thermal expansion valve, and an evaporator. The compressor, which is served by a lubrication subsystem, compresses the superheated refrigerant vapour. The compressed vapour is then condensed in the condenser, releasing its heat in a sink that can either be air or water. The condensed liquid is subsequently expanded at the expansion valve and evaporated at the evaporator to a superheated state. The heat for the evaporation is either supplied by air, water or a water-glycol solution, and the cycle is repeated.

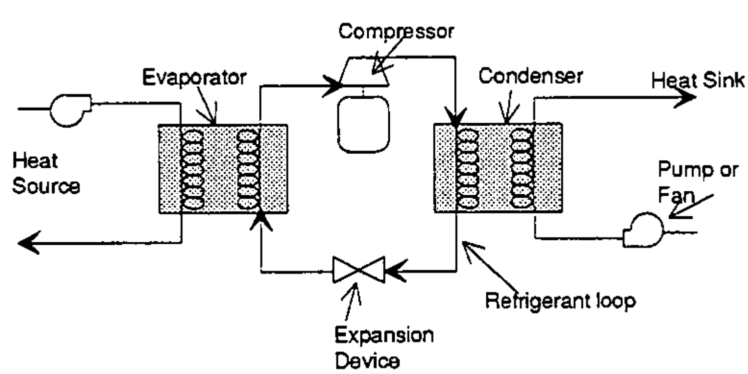

Figure 3.6. Basic vapour compression refrigeration cycle.

3.2.2.1 Typical faults

An extensive list of vapour compression cycle machine faults, including their causes and symptoms is in Appendix 3B in the end of this chapter. This section, however, will address the three faults that are deemed of highest priority due to their frequency and the adverse effects they have on equipment efficiency and mechanical integrity. These faults are:

1. Lack of refrigerant;
2. Presence of air in the refrigerating circuit;
3. Presence of refrigerant in the lubricating oil.

What follows is a discussion of the causes of these faults and their symptoms.

3.2.2.1.1 Lack of refrigerant

Lack of refrigerant is at the root of a number of serious failures encountered in the operation of vapour compression machines. Refrigerant losses have an adverse impact on the energy efficiency of the unit and its mechanical integrity, and also make up a significant portion of the global CFC emissions. Refrigerant losses occur during the normal operation of refrigerating machines, when component breakdowns occur and during maintenance work.

Causes

Refrigerant leaks in refrigerating systems are typically due to small holes in the refrigerant tubing, loose fittings or poor connections, typically caused by corrosion, vibration and poor workmanship. The shaft seal of the compressor, the tube plates in the condenser and the service valves of the compressor top the list of sites for significant leaks.

Symptoms

Refrigerant loss is, in general, gradual over a period of time and as such it is difficult to detect before a critical situation arises. Typically, When the refrigerant charge is low low suction pressure occurs and possibly a low discharge pressure. The low suction pressure, in turn, leads to low compressor capacity resulting in insufficient cooling. The low density of the vapour causes it to collect a higher level of heat per unit of refrigerant causing the refrigerant vapour to reach a higher and higher temperature. When this happens the compressor motor heats the vapour even more until, at the discharge of the compressor, the high discharge temperature may cause severe damage to the compressor. A more extensive list of indications or symptoms of the lack of refrigerant are displayed in Table 3.9.

Table 3.9. Symptoms and consequences ofrRefrigerant loss.

Apparent component failure	Component	Component defect	Symptom or effect
Instability of low pressure control		- Low pressure control differential too close (installation/commissioning)	
		- **Lack of refrigerant**	
System short of capacity	Strainers/filter-driers	- Blocked liquid strainer (outlet cooler than inlet)	High chilled water temperature
	System	- Load too high (Design)	
		- Liquid feed valve (txv) underfeeding evaporators	
		- Faulty control circuit	
		- Defective low limit thermostat controlling chilled water temperature	
		- Hot gas bypass valve defective	
		- **Low refrigerant level in receiver**	
Low discharge pressure	Compressor	- Compressor seized	
		- Motor overload tripped	
		- Compressor not pumping	
	Water-cooled condenser	- Water flow rate too high	Temperature of water leaving condenser too cold
		- Inlet water too cold	
	Air cooled condenser	- Fans running in low ambient	Condensing supply air too cold
	System	- **Lack of refrigerant**	Temperature of water leaving condenser too cold Bubbles in sight glass
Low suction pressure	Strainers	- Blocked Strainers and/or filter-drier/ Liquid line restriction	Compressor may shut down soon after starting
	Evaporator	- Wrong setting of evaporator controls	Compressor shuts down immediately after starting
		- Heater element open circuited	
		- Freeze-up or fouling (oil or product) of evaporator	
		- Chilled water thermostat set too low	
	Solenoid valve	- Liquid solenoid valves not working	Compressor shuts down soon after starting
	Expansion valve	- Faulty expansion valve (e.g. thermal element lost its charge)	Compressor shuts down soon after starting
		- Ice in expansion valve due to moisture in refrigerant	Chilled water temperature too high
		- Dirt blocking expansion valve	System short of capacity

Apparent component failure	Component	Component defect	Symptom or effect
	Condenser	- Restricted or too warm air to condenser	Compressor may shut down soon after starting
	System	- Excessive suction line pressure drop (Design/Installation)	Compressor shuts down soon after starting
		- Evaporator too small (Design/Installation)	(Compressor stops)
		- Float switch faulty (not usual on chillers)	
		- **Lack of refrigerant**	
		- Thermostat contacts stuck in closed position	
		- Capacity control range set too low	
		- Too much pressure drop in evaporator (Design)	
		- Low pressure control erratic in action	
		- TXV set for too high superheat	
	Compressor	- Compressor suction valve partially closed	
	System	- Capacity control pressure switch defective or set incorrectly	Compressor short cycles
		- Wrong refrigerant (service)	
		- Plant undersized (design)	
		- **Lack of refrigerant**	
High suction temperature	System	- **Lack of refrigerant**	Chilled water temperature too high
	Evaporator	- Short capacity of expansion valve (Installation/Design)	Large pressure drop across evaporator
		- **Low refrigerant**	
High oil temperature (High discharge temperature)	Lubricating system - Oil cooler (for water-cooled compressors)	- Water regulating valve requires adjustment or defective	Compressor shuts down soon after starting
		- **Low water supply**	
		- Dirty oil cooler	
		- Oil heater thermostat defective or oil heater too large	
	Lubricating system - Oil cooler (for liquid injection cooled compressors)	- Low refrigerant supply	Compressor may shut down during operation
		- Low liquid refrigerant in receiver	
		- Oil in liquid refrigerant supply	
	Lubricating System - Compressors without oil-coolers	- High suction temperature superheat	
		- Operation at high compression ratio	

3.2.2.1.2 Air in the refrigerating circuit

Air in the refrigerating circuit is another of the more frequently encountered faults, particularly in low pressure centrifugal chillers.

Causes

Air enters the refrigerant circuit during normal operation, equipment breakdown and maintenance work. Air, during normal operation, is admitted through loose fittings and poor connections, the same way refrigerant is lost. In the case of air, however, a negative pressure generally is required. Such a condition is present in the low pressure side of units operating with R-11 and R-123. Units operating using high pressure refrigerants do not, in general, experience gradual air intake but are more likely to have air present during ineffective evacuation and recharging of the refrigerant.

Symptoms

Air that is present in the refrigerating circuit usually collects in the condenser where it takes up space that would otherwise be occupied by refrigerant, thereby reducing the heat transfer surface. This leads to <u>high discharge pressure</u> since the air is non-condensible. In addition to this symptom, air in-leaks cause the admission of moisture into the circuit, the presence of which can lead to the blockage of the refrigerant flow control device by the formation of ice. This causes <u>low suction pressure</u> and possibly <u>low discharge pressure</u>, symptoms associated with reduced refrigerant flow. Finally, the presence of moisture can lead to acid formation that could damage the expansion valve and motor winding insulation.

3.2.2.1.3 Liquid refrigerant in oil

There are two possible modes by which refrigerant can be found in the crankcase oil: the first, called refrigerant floodback, occurs during the normal operation of the unit, while the second, called refrigerant migration occurs when the unit is off. In both cases serious damage can occur in the compressor since refrigerant will tend to remove the lubricating oil, thereby exposing moving components to excessive wear and causing premature failure of the compressor.

Causes

Liquid refrigerant floodback occurs due to an over-supply of refrigerant to the evaporator or possibly, low evaporator load. In both cases there is not enough heat to evaporate all the refrigerant present in the evaporator causing some of it to be entrained in the vapour and carried to the compressor. The over-supply of refrigerant can be due to any of the following:

· Expansion valve stuck open;
· Expansion valve bulb loose on suction line;
· Capillary tube system overcharged;
· Coil flooded after hot gas defrost.

Low evaporator load may be due to the environmental conditions or due to:
· Evaporator fans being inoperative;
· Air filters plugged;
· Evaporator coil plugged (dirt or frost).

Refrigerant migration occurs naturally due to the vapour pressure differential that exists between the refrigerant and the compressor oil. This problem is more prevalent during the off cycle when the oil temperature can fall due to a low temperature ambient conditions and/or a failed oil/crankcase heater. Consequently the higher vapour pressure of the refrigerant drives it to the compressor oil with which it is miscible. Any situation that drives the vapour pressure of the refrigerant up (higher ambient temperature for example) or that of the oil down worsens the situation.

Symptoms

Symptoms of liquid refrigerant floodback manifest themselves in a similar manner as refrigerant overcharge. Depending on the external conditions and the particular cause for its presence, refrigerant floodback may either result in <u>high suction pressure</u>, since if the ambient temperature rises more refrigerant will be available for evaporation, or <u>low suction pressure</u>, since not all the required refrigerant was evaporated as is the case with low evaporator loads. This could result in <u>high discharge pressure</u> and <u>low discharge temperature</u> respectively.

Since refrigerant migration occurs during the off cycle, the only symptom that can be observed is at start-up. When the unit is started, even a small drop in the suction pressure causes the rapid boiling of liquid refrigerant stratified on the compressor oil. This rapid boiling can clear oil and refrigerant out of the crankcase in a short period of time.

3.2.3 Absorption refrigeration machines

Contrary to vapour compression machines that use mechanical work, absorption refrigeration machines use heat to achieve the desired refrigeration effect. This is accomplished through the absorption and desorption of a (volatile) refrigerant into a solution. As can be seen in Figure 3.7 the typical unit includes a condenser, an expansion device and an evaporator. This type of chiller, however, substitutes for the compressor a system of two heat exchangers and a pump. Referring to Figure 3.7, the operation of a typical single effect absorption chiller using water as refrigerant and Lithium Bromide (LiBr) as the absorbant is as follows. The strong (in refrigerant) solution at the generator receives heat either directly by means of natural gas or indirectly by steam. The evaporated refrigerant is condensed in the condenser where it gives up its heat to the secondary liquid (water). The condensed refrigerant is then expanded and evaporated at the evaporator absorbing heat from the chilled water circuit. Subsequently the vapour is absorbed in the absorber which contains a weak (in refrigerant) solution. The pump then pumps the resulting solution to the generator which in turn returns the depleted solution to the absorber and the cycle is repeated.

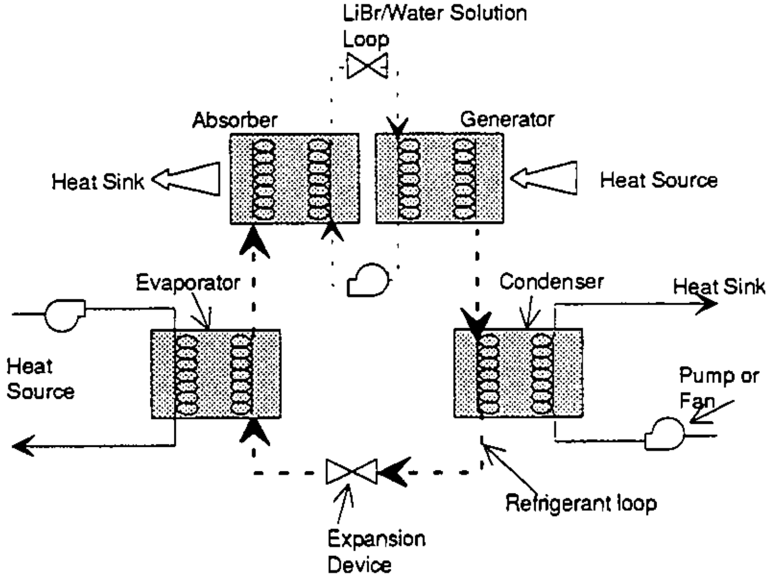

Figure 3.7. Basic absorption refrigeration cycle.

3.2.3.1 Typical faults [3.2] and [3.3]

Faults in absorption refrigeration machines are listed in and are reproduced in Appendix B. What follows are the three most common faults occurring in this type of refrigeration machine, namely:

1. Loss of vacuum
2. Clogging of condenser tubes
3. Clogging of evaporator tubes.

What follows is a more detailed discussion of the above faults, including their probable causes and symptoms.

3.2.3.1.1 Loss of vacuum

Absorption chillers are operated under vacuum (800 - 900 Pa). If this vacuum were lost, there is a COP reduction, corrosion and crystallization of solution.

Causes

Loss of vacuum is caused by imperfect welding at the manufacturing stage and degradation of the packing and/or of the O-rings. In addition, inefficient purging on non condensables (hydrogen) generated during the units normal operation decreases the vacuum, resulting in the above problems.

Symptoms

Non condensable gas causes a rise in saturated vapour pressure in the evaporator, resulting in higher saturated vapour temperature and eventually higher outlet chilled water temperature. This is followed by an increase of the thermal input, that is, the increased opening of the steam or the fuel valve to generator, in order to maintain the designated outlet chilled water temperature. The increased pressure of the generator then obstructs the return of the solution from the absorber, which causes the solution level in the generator to decrease. Low solution levels in the generator may lead to a concentration of the solution and possibly crystallization at the low temperature part of the chiller.

3.2.3.1.2 Clogging of the condenser tubes

Clogging of condenser tubes increases flow resistance, thereby decreasing cooling water flow. This leads to a pressure rise at the generator and a decrease in condensing water flow rate, thereby reducing the chiller's COP.

Causes

Clogging or scaling of the condenser tubes result from poor local water quality and poor maintenance practices.

3.2.3.1.3 Clogging of evaporator tubes

Evaporator tubes are usually clogged by frozen chilled water, although in an open circuit application, as is the case in a thermal storage system, scaling may be the cause of the clogged tubes.

Causes

In general, low chilled water temperature can cause the chiller protection circuit to shut off the unit. However, freezing of chilled water sometimes happens when there is a sudden decrease of the cooling water temperature due to low load conditions.

Symptoms

Under low load conditions, the delivery pressure of the circulating pump rises and the chilled water flow rate decreases. In such a case, the outlet chilled water temperature rapidly falls and the chiller stops due to the freeze protection circuit.

3 2.4 References

3.2. Personal communication with Prof. Nakahara.

3.3 Hyvärinen, J. and Kohonen, R. (Eds.). Building Optimization and Fault Diagnosis System Concept. October, 1993.

3.3 VAV AIR HANDLING UNIT

Yoshida, H.,
Kyoto University, Kyoto Japan

3.3.1 VAV System Description

The reference VAV air handling system used by most Annex 25 participants to evaluate various BOFD methods was the single-duct pressure independent system shown in Figure 3.8. The air handling unit has outdoor and return air dampers, cooling and heating coils, an air filter section, a supply air fan, a return air fan, and air plenum sections. The supply air is ducted to three VAV boxes which supply conditioned air to three different zones. The return air fan takes air from the conditioned space and discharges it into the mixing section and/or the outside through a motorized exhaust air damper. Both supply and return fans are fitted with variable frequency controllers for regurating static presure constant in air ducts.

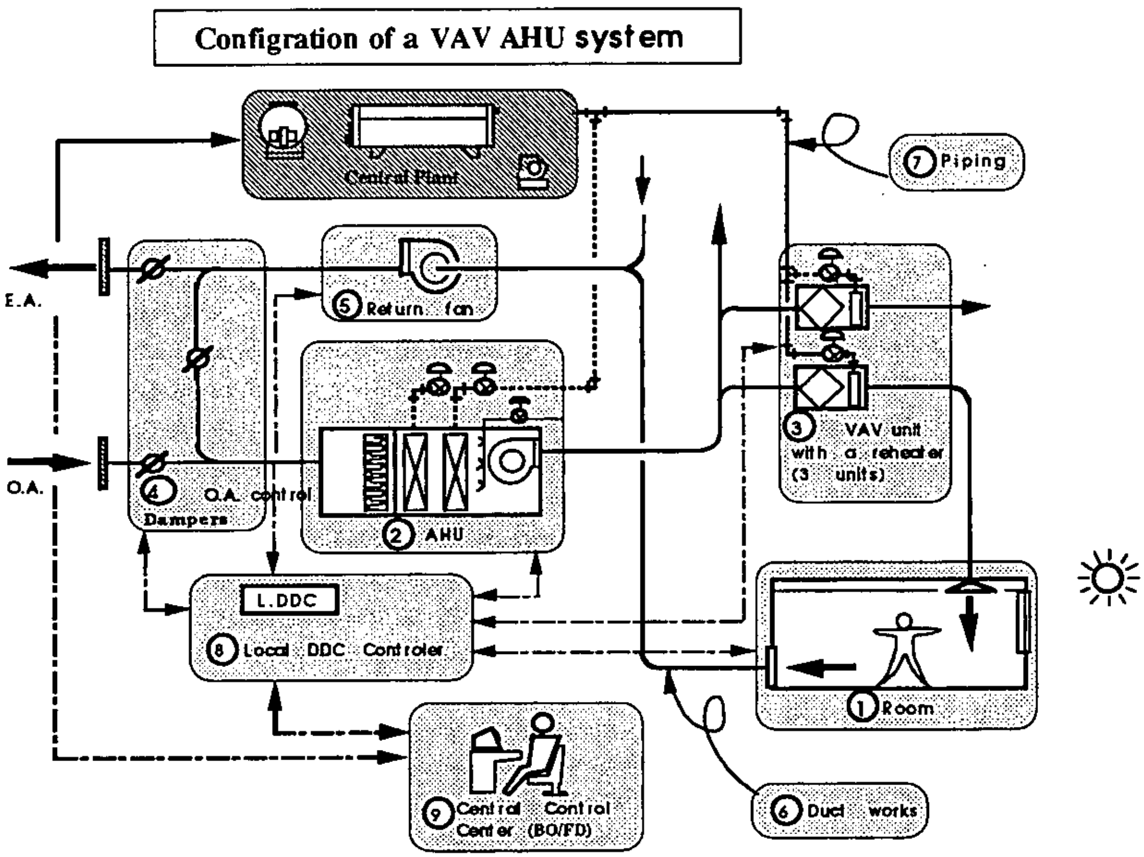

Figure 3.8. Reference air handling system.

The pressure independent VAV system attempts to maintain a constant static pressure at the VAV box inlets by sensing and controlling the static pressure in the supply duct. A static pressure controller with a PID algorithm sends a control signal to a variable frequency motor controller to vary the supply fan speed. The supply airflow rate is measured and the desired return airflow rate (supply air flow minus both the air flow through the exhaust air damper and the amount of air flow required for building pressurization) is calculated. The desired return flow rate is compared with the actual return rate and the difference (error signal) is used in a PID algorithm to set the return fan speed.

The reference system also employs a dry-bulb type economizer cycle to save energy through the use of outdoor air for "free" cooling. Details on the VAV reference system, its control strategy, and the operation of the economizer cycle are given in [3.4].

3.3.2 List of faults

A list of possible faults in the reference VAV air handling unit is given below. Faults are listed without regard to importance or frequency of occurrence for the air mixing section, filter-coil section, fan section(s), and VAV boxes.

AIR MIXING SECTION

- temperature or humidity (or dew point) sensors (return air, outdoor air, mixed air)
    - complete failure
    - incorrect reading (offset, wrong scale, drifting)
    - excessive noise
- damper and actuator (relief air, recirculating air, outdoor air, minimum air)
    - stuck (open, closed, intermediate position)
    - incorrect minimum positioning of outdoor air damper
    - air leakage past damper when closed
    - faulty indication of damper position
- mixed air controller
    - control signal (no signal, incorrect signal)
    - software error
    - improper tuning (unstable, sluggish)

FILTER - COIL SECTION

- temperature sensors (supply air, water entering or leaving preheating coil, water entering or leaving cooling coil, freeze protection)
    - complete failure
    - incorrect reading (offset, wrong scale, drifting)
    - excessive noise

- humidity sensor (supply air)
  - complete failure
  - incorrect reading (offset, wrong scale, drifting)
  - excessive noise
- filter
  - partially clogged
  - incorrect/malfunctioning DP sensor/signal
  - leakage through or around
- valve and actuator (preheat coil valve, cooling coil valve)
  - stuck (mechanical failure, actuator/motor failure)
  - water leakage past closed valve
  - faulty indicator of valve position
  - improper installation (installed backwards, mixing & diverter ports interchanged)
  - wrong valve installed
  - poor valve authority
  - clogged valve
- plumbing
  - pump failure (3-way preheating/cooling coil valve applications)
    - complete failure
    - cavitation
    - partially clogged
    - poor efficiency
    - wrong pump installed
  - piping
    - partially blocked
    - silted up
  - water pressure
    - too high/low pressure in hot/chilled water supply line
    - too high/low pressure in hot/chilled water return line
  - water temperature
    - too high/low hot water supply temperature
    - too high/low chilled water supply temperature
  - water leaks
- coil (preheat coil, cooling coil)
  - fouled coil
  - partially plugged coil
  - wrong coil installed (oversized, undersized)
  - water leaks
- supply air temperature controller
  - control signal (no signal, incorrect signal)
  - improper sequencing of valves and dampers
  - software error
  - poor tuning (unstable, sluggish).

FAN SECTION(S)

- fan (supply fan, return fan)
  - complete failure
  - stuck (full speed, intermediate speed)
  - inlet/outlet vanes (stuck, failed actuator)
  - wrong fan installed
- pressure sensor (supply duct)
  - complete failure
  - incorrect reading (offset, wrong scale, drifting)
  - excessive noise
  - improper location
  - poor resolution/accuracy
  - deterioration of sensor with time
- flow measurement station (supply duct, return duct)
  - complete failure of sensor signal
  - incorrect reading (offset, wrong scale, drifting)
  - excessive noise
- supply-return fan controller
  - control signal to fans (no signal/incorrect signal)
  - improper flow rate differential set point
  - improper pressure set point in supply duct
  - variable speed drive malfunction
  - software error
  - poor tuning (unstable, sluggish).

VAV BOXES

- damper and actuator
  - stuck (open, closed, intermediate position)
  - air leakage past closed damper
  - incorrect minimum position
  - faulty indicator of damper position
- reheat coil
  - fouled coil
  - partially plugged coil
  - wrong coil installed
  - water leaks
- plumbing
  - piping
  - partially blocked
  - silted up
  - water/pressure
    - too high in hot water supply line
    - too low in hot water supply line
  - water temperature
    - too high in hot water supply line
    - too low in hot water supply line
  - water leaks

- reheat valve and actuator
  - stuck (mechanical failure, actuator/motor failure)
  - water leakage past closed valve
  - faulty indicator of valve position
  - installed backwards
  - poor valve authority
  - plugged valve
- flow measurement station
  - complete failure of sensor signal
  - incorrect reading (offset, wrong scale, drifting)
  - excessive noise
- zone temperature sensor
  - complete failure
  - incorrect reading (offset, wrong scale, drifting)
  - excessive noise
- VAV box controller
  - control signal (no signal, incorrect signal)
  - improper sequencing of valve and damper
  - software error
  - poor tuning (unstable, over controlled, sluggish).

3.3.3 Ranking of faults

To determine the importance of the different faults in air handling systems, a preliminary survey was undertaken in Japan in 1992 among designers, construction engineers, and commissioning engineers. The system configuration shown in Fig. 3.8 was provided to each potential respondent and they were asked to select ten typical faults based on their experience.

The results from the preliminary survey are shown in Table 3.10. The responses obtained included a wide variety of faults, including faults related to the outdoor air dampers and VAV boxes. It was found, however, that selecting the ten most typical faults for the reference air handling system was a more difficult task than originally anticipated. This appeared to be due to the many different perspectives of the experts involved in the selection process.

Therefore, a follow-up questionnaire was developed to collect additional information on the types of faults and to allow a more complete analysis to be performed. The following tasks were included in the questionnaire:

1) Pick the most important faults for each section (subsystem) of the air handling unit using the table of faults-symptoms contained in the Appendix 3C in the end of this chapter.
2) Pick one reason for each fault from the seven reasons listed in Table 3.11.
3) Rank the ten most important faults that you selected.

Table 3.10. Ten typical faults of AHU systems selected by experts (preliminary study).

	Fault or symptom	Defect
1	too high or too low supply air temperature at AHU outlet	malfunction in control valve of heating or cooling coil
2	inadequate damper opening	malfunction in control signal to controller of air damper or mechanical break down
3	abnormal fan rotation speed	static pressure gauge in duct is deteriorated
4	room air temperature too high	too much internal heat generation (for example due to excessive number of people)
5	room air temperature too high or too low	malfunction in VAV controller
6	room air temperature too low	reheating coil in VAV unit is dirty
7	noise from AHU	wear of fan bearings
8	inefficient operation of AHU system	unbalanced volume control is established because several VAV units interfere with each other
9	inefficient operation of AHU system	window is open
10	room air temperature too high	no use of venetian blinds in spite of the existence of impinging solar radiation on windows

Table 3.11. Reason why a fault is important.

1	Environmental degradation and occupant complaints
2	Increased energy consumption
3	Serious secondary damage
4	Frequent occurrence
5	Difficult detection
6	Lengthy repair time
7	Costly repair

Participants were also asked to categorize each fault as resulting from:

- a failure in the design stage (D).
- a failure in the construction or fabrication stage (F).
- a failure in commissioning stage (C).
- a failure in proper maintenance (M).
- a failure by the users (U).
- a failure in the control hardware or software (S).
- a failure in the control algorithms (A).

Each cited fault was also categorized as to whether its importance, in the opinion of the expert, was related to it causing environmental damage, increasing energy consumption, causing additional secondary damage, its frequency of occurrence, the difficulty of detecting it, the difficulty of recovery from it, or the expenditure required to correct it.

Seventy-one responses were obtained. The professions, the number of experts and the average duration of their experience in years are summarized in Table 3.12.

Table 3.12. Professions of experts who responded.

Profession		Number of replies	Average duration in years of experience
A) design	- AHU system	23	
	- control system	4	17.3
B) construction	- construction	7	
	- commissioning	4	
	- control system	2	17.2
C) maintenance	- maintainance crew	28	
	- building owner	1	18.3
total number		71	

3.3.3.1 The most important faults

The ten most important faults as ranked by all the experts are shown in Table 3.13. Many of the faults do not involve mechanical break down or malfunctions. As indicated in the table, three of the faults originated in the design stage, seven in the construction stage, two are due to improper maintenance, and two are caused by users. Except for the two faults involving too little supply air from the VAV boxes and excessive pressure drop across the filter, the faults cannot be corrected by normal maintenance work. In addition, the clogged filter fault is a very simple fault that does not require a sophisticated detection system. Thus, almost all of the ten most important faults identified in this survey do not require an automated BOFD system for detection if effective commissioning and maintenance are performed.

In this context, a sophisticated BOFD system can not easily be justified and the investment in such a system may not be acceptable to building owners. On the other hand, it must be pointed out that many engineers and maintenance personnel do not understand the proper operation of building HVAC systems or the undesirable operating performance that can result from the occurrence of different faults. Thus the real benefit of automated BOFD systems may lie in their ability to reduce the need for highly qualified operating/maintenance personnel and to reduce building operating costs through proper HVAC operation.

Table 3.13. Most important faults selected by all professions.

Rank	Point	Sub-system	Process variable deviation	Component	Component defect	Stage
1	39	room	poor air quality	occupants	smoking	U
2	38	piping	water leakage	piping	condensation due to improper thermal insulation	F
3	37	room	room air temperature deviation	occupants	excessive internal heat generation	U
4	35	room	room air temperature deviation	air diffuser	inadequate air flow rate	F,E
5	31	VAV unit	too much or too little air volume	VAV unit damper	failure in adjustment	F,M,C
6	29	AHU	excessive pressure deference across an air filter	air filter	being clogged	M
7	27	air duct	abnormal noise or vibration	duct works	insufficient noise control	D,F
7	27	room	room air temperature deviation	air diffuser	inadequate positions of diffusers	D,F
7	27	local DDC control	false opening signal to a VAV unit	room air thermostat	improper location	D,F
10	23	piping	room air temperature deviation	piping	insufficient flow rate due to contaminated air in pipes	F,E

3.3.3.2 Differences between professions

The faults were sorted and ranked according to each profession. The most important faults selected by designers, construction engineers, and maintenance crews are shown in Tables 3.14 - 3.16. The results show that the importance of faults differ among profession. Investigations of the opinions of building owners were not, however, a part of the survey. They may have different view points. To develop an effective BOFD system, the interests and desires of building owners in BOFD systems should also be considered.

Table 3.14. Most important faults selected by designers.

Rank	Point	Sub-system	Process variable deviation	Component	component defect	Stage
1	19	room	room air temperature deviation	air diffuser	inadequate air flow rate	F,E
2	15	room	poor air quality	occupants	smoking	U
3	14	air duct	abnormal noise or vibration	duct works	insufficient noise control	D,F
4	13	room	room air temperature deviation	air diffuser	inadequate positions of diffusers	D,F
4	13	VAV	too much or too little air volume	VAV unit damper	failure in adjustment	F,M
4	13	room	room air temperature deviation	occupants	excessive internal heat generation	U
7	12	AHU	excessive pressure difference across an air filter	air filter	being clogged	M
8	11	piping	room air temperature deviation	piping	insufficient flow rate due to contaminated air in pipes	F,E
8	11	local DDC control	abnormal speed of a supply fan	static pressure sensor	improper location	D,F
8	11	local DDC control	false opening signal to a VAV unit	room air thermostat	improper location	D,F

Table 3.15. Most important faults selected by constructors.

Rank	Point	Sub-system	Process variable deviation	Component	Component defect	Stage
1	9	room	room air temperature deviation	occupants	excessive internal heat generation	U
1	9	piping	water leakage	piping	condensation due to improper thermal insulation	F
3	7	piping	water leakage	piping	failure in joints assembly	F
3	7	AHU	room humidity deviation	humidifier	mechanical failure	E,M
5	6	room	room air temperature deviation	air diffuser	inadequate air flow rate	F,E
5	6	air duct	abnormal noise or vibration	duct works	insufficient noise control	F
5	6	local DDC control	false opening signal to a VAV unit	room air thermostat	improper location	D,F
8	5	OA damper	abnormal OA damper opening	OA damper	mechanical failure	M
8	5	room	poor air quality	occupants	smoking	U
8	5	piping	room air temperature deviation	piping	insufficient flow rate due to contaminated air in pipes	F,E
8	5	AHU	excessive pressure difference across an air filter	air filter	being clogged	M
8	5	room	room air temperature deviation	air diffuser	inadequate positions of diffusers	D,F
8	5	VAV	too much or too little air volume	VAV unit damper	failure in adjustment	F,M

Table 3.16. Most important faults selected by maintenance crew.

Rank	Point	Sub-system	Process variable deviation	Component	Component defect	Stage
1	20	piping	water leakage	piping	condensation due to improper thermal insulation	F
2	19	room	poor air quality	occupants	smoking	U
3	15	room	room air temperature deviation	occupants	excessive internal heat generation	U
4	12	VAV	too much or too little air volume	VAV unit damper	failure in adjustment	F,M
4	12	OA damper	abnormal OA damper opening	OA damper	mechanical failure	M
4	12	AHU	excessive pressure difference across an air filter	air filter	being clogged	M
7	11	room	room air temperature deviation	occupants	excessive number of occupants	M,U
7	11	AHU	room air temperature deviation	cooling coil	fouling on coil fins	M
9	10	air duct	poor air quality	duct works	accumulation of dust inside of duct works	M
9	10	local DDC control	false opening signal to a VAV unit	room air thermostat	improper location	D,F

3.3.3.3 Reasons for choosing a fault

The experts were also requested to specify a reason for selecting a particular fault as being important using the seven possibilities listed in Table 3.11. The number of times ("points") each reason was specified is shown in Figure 3.9.

The reason related to room environment was cited the largest number of times, more than 30 % of the total number of responses recorded. The percentage of times that the reasons related to energy loss, frequency of occurrence, and difficulty of detection were cited were approximately 18 %, 13 %, and 12 %, respectively. The reason related to a fault causing additional secondary damage was considered least important (5 %). It is interesting to note that the order of importance hardly varies among the professions represented. In developing a BOFD system, it should thus be kept in mind that faults causing environmental degradation and energy loss appear to have the highest priority.

The ten most important faults associated with each of the different reasons cited by participants are shown in Tables 3.17 - 3.23. Most of the faults originated in the design and construction stages, although other stages are also represented in each table. The tables provide information which may prove useful in developing BOFD systems.

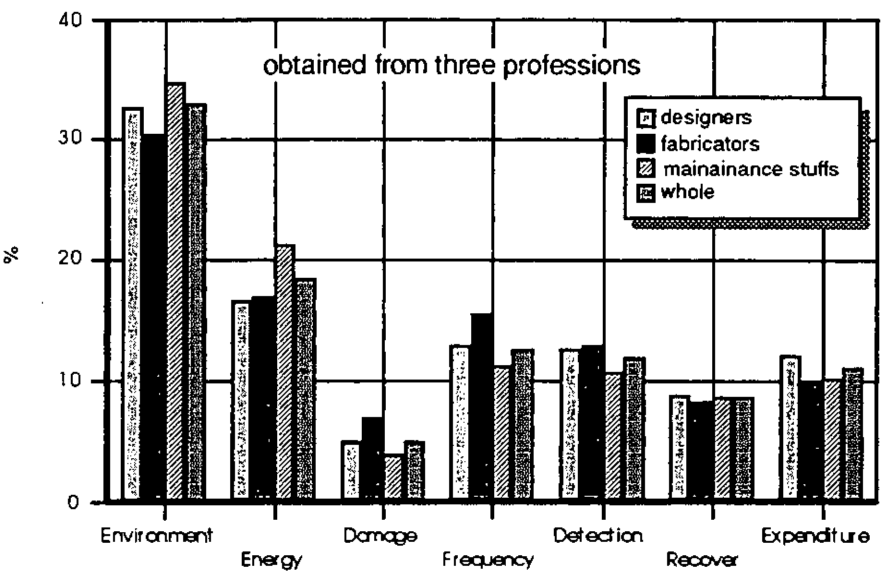

Fig. 3.9. Reasons given for fault importance.

Table 3.17. Most important faults causing environmental degradation.

Rank	Point	Sub-system	Process variable deviation	Component	Component defect	Stage
1	38	room	poor air quality	occupants	smoking	U
2	32	room	room air temperature deviation	air diffuser	inadequate air flow rate	F,E
3	30	room	room air temperature deviation	occupants	excessive internal heat generation	U
4	28	VAV	too much or too little air volume	VAV unit damper	failure in adjustment	F,M
5	27	room	room air temperature deviation	air diffuser	inadequate positions of diffusers	D,F
6	26	air duct	abnormal noise or vibration	duct works	insufficient noise control	D,F
7	25	local DDC control	false opening signal to a VAV unit	room air thermostat	improper location	D,F
8	21	AHU	excessive pressure difference across an air filter	air filter	being clogged	M
9	18	AHU	room humidity deviation	humidifier	mechanical failure	E,M
10	17	air duct	room air temperature deviation	air volume adjusting damper	lack of proper adjustment	F

Table 3.18. Most important faults causing energy loss.

Rank	Point	Sub-system	Process variable deviation	Component	Component defect	Stage
1	20	AHU	excessive pressure difference across an air filter	air filter	being clogged	M
2	16	AHU	supply air temperature deviation	cooling coil	fouling on coil fins	M
3	15	local DDC control	false opening signal to a VAV unit	room air thermostat	improper location	D,F
4	13	OA damper	abnormal OA damper opening	OA damper	mechanical failure	M
4	13	local DDC control	abnormal speed of a supply fan	static pressure sensor	improper location	M
4	13	VAV	too much or too little air volume	VAV unit damper	failure in adjustment	F,M
7	12	OA damper	abnormal OA damper opening	OA damper	failure in adjustment	F,M
7	12	piping	water leakage	piping	condensation due to improper thermal insulation	F
9	11	air duct	room temperature deviation	air volume adjusting damper	lack of proper adjustment	F
10	10	AHU	room air temperature deviation	cooling coil	scaling on inside surface of coil tubes	M
10	10	room	room air temperature deviation	occupants	no adequate use of solar shades	U
10	10	air duct	room temperature deviation	joints of ducts	air leakage	F
10	10	central control	room air temperature deviation	central computer	false setting of reference temperature	M

Table 3.19. Most important faults causing secondary damage.

Rank	Point	Sub-system	Process variable deviation	Component	Component defect	Stage
1	14	piping	water leakage	piping	condensation due to improper thermal insulation	F
2	13	central control	fail to alarm while a failure occurs	central computer	mechanical failure	E,M,C
3	11	piping	water leakage	piping	failure in joints assembly	F
4	6	local DDC control	false alarming on display	controller	mechanical failure	M,C
5	4	air duct	water leakage	duct works	carry of water from a humidifier	D,F
5	4	air duct	poor air quality	OA inlet	intake of polluted outside air	D
7	3	air duct	poor air quality	duct works	accumulation of dust inside of duct works	M
7	3	AHU	abnormal noise or vibration	fan motor	mechanical failure	M
7	3	central control	false alarming on a display	central computer	mechanical failure	E,M, C
7	3	room	poor air quality	occupants	smoking	U

Table 3.20. Most important faults based on frequency of occurrence.

Rank	Point	Sub-system	Process variable diviation	Component	Component defect	Stage
1	16	room	poor air quality	occupants	smoking	U
1	16	AHU	excessive pressure difference across an air filter	air filter	being clogged	M
3	14	room	room air temperature deviation	air diffuser	excessive internal heat generation	F,E
4	12	room	room air temperature deviation	occupants	excessive internal heat generation	U
4	12	VAV	too much or too little air volume	VAV unit damper	failure in adjustment	F,M
6	11	room	room air temperature deviation	air diffuser	inadequate positions of diffusers	D,F
6	11	piping	room air temperature deviation	piping	insufficient flow rate due to contaminated air in pipes	F,E
8	9	piping	water leakage	piping	condensation due to improper thermal insulation	F
8	9	local DDC control	false opening signal to a VAV unit	room air thermostat	improper location	D,F
10	8	air duct	room air temperature deviation	air volume adjusting damper	lack of proper adjustment	F

Table 3.21. Most important faults based on difficulty in detection.

Rank	Point	Sub-system	Process variable deviation	Component	Component defect	Stage
1	14	VAV	too much or too little air volume	VAV unit damper	failure in adjustment	F,C
2	13	piping	room air temperature deviation	piping	insufficient flow rate due to contaminated air in pipes	F,C
2	13	piping	water leakage	piping	condensation due to improper thermal insulation	F
2	13	central control	fail to alarm when a failure occurs	central computer	mechanical failure	F,E
5	10	local DDC control	abnormal speed of a supply fan	static pressure sensor	improper location	C
6	9	air duct	room air temperature deviation	fire damper	accidental shutting off	M
7	8	OA damper	abnormal OA damper opening	OA damper	mechanical failure	M
7	8	piping	room air temperature deviation	strainers	stuffing	M
9	7	air duct	poor air quality	duct works	accumulation of dust inside of duct works	M
9	7	AHU	room air temperature deviation	cooling coil	scaling on inside surface of coil tubes	M

Table 3.22. Most important faults based on restoration time.

Rank	Point	Subsystem	Process variable deviation	Component	Component defect	Stage
1	15	air duct	abnormal noise or vibration	duct works	insufficient noise control	D,C
1	15	piping	water leakage	piping	condensation due to improper thermal insulation	F
3	11	piping	water leakage	piping	failure in joints assembly	F
4	10	room	room air temperature deviation	air diffuser	inadequate positions of diffusers	D
5	9	air duct	poor air quality	OA inlet	intake of polluted outside air	D
6	8	room	room air temperature deviation	air diffuser	inadequate air flow rate	D,C
6	8	room	room air temperature deviation	occupants	excessive internal heat generation	U
8	7	AHU	abnormal noise or vibration	fan motor	mechanical failure	M
9	5	air duct	poor air quality	duct works	accumulation of dust inside of duct works	M
9	5	piping	room air temperature deviation	piping	insufficient flow rate due to contaminated air in pipes	F,C

Table 3.23. Most important faults based on restoration cost.

Rank	Point	Sub-system	Process variable deviation	Component	Component defect	Stage
1	17	air duct	abnormal noise or vibration	duct works	insufficient noise control	D,F,C
1	17	piping	water leakage	piping	condensation due to improper thermal insulation	F
3	15	room	room air temperature deviation	occupants	excessive internal heat generation	U
4	13	piping	water leakage	piping	failure in joints assembly	F
4	13	room	room air temperature deviation	air diffuser	inadequate positions of diffusers	D
6	12	room	room air temperature deviation	air diffuser	inadequate air flow rate	F,C
7	11	air duct	poor air quality	duct works	accumulation of dust inside of duct works	M
8	9	air duct	abnormal noise or vibration	duct works	insufficient noise control	F,C
9	9	room	poor air quality	occupants	smoking	U
10	7	air duct	poor air quality	OA inlet	intake of polluted outside air	D

3.3.3.4 Summary of survey results

In order to identify the most important faults occurring in a VAV air handling system, a survey of experts was conducted. The experts were selected from a wide variety of professions and included designers, construction engineers, and maintenance personnel. The following is a summary of the results obtained.

1) The results in Table 3.10 from the preliminary survey are interesting and useful. It was found, however, to be a difficult task to select the ten most typical faults for the reference air handling system because of the many different perspectives of the experts involved in the selection process. However, based on this preliminary survey, faults related to outdoor air dampers and VAV boxes appear to be fairly common.

2) From the questionnaires that were returned, it appears that most of the important faults originate in the design and construction stages. Therefore, if sufficient commissioning is performed, many faults will be eliminated and air handling systems will be more reliable. Even though commissioning is conducted with attention to detail and good professional skills, it is very difficult to perform effective commissioning in the short time usually available. Since air handling systems are becoming more sophisticated, this difficulty is likely to increase in the future. Therefore, BOFD systems should be designed to assist commissioning.

3) The kinds of faults chosen by experts as important are slightly different from profession to profession. This means that developing a universally acceptable BOFD system will be difficult. To design a BOFD system, one needs to decide for whom the system is provided, what kind of faults should be detected and diagnosed, and what are the desired benefits.

4) The order of importance of the faults was determined by counting the number of times a particular fault was selected on all the returned questionnaires. It was found that, in order of importance, the experts based their selection of faults on whether a fault: (1) caused environmental degradation, (2) increased energy consumption (3) occurred frequently, (4) was difficult to detect, (5) was costly to repair, (6) required a significant amount of time to repair, and (7) caused secondary damage. It is interesting to point out that this order is relatively insensitive to profession. Causing environmental damage, resulting in increased energy consumption, and frequent occurrence were always ranked first, second, and third in importance, respectively. This will be useful information for developers of BOFD systems.

5) Since the break down of an air handling systems in a building does not usually result in a life threatening situation, instantaneous fault detection may not be essential. Therefore, the aim of BOFD should be a) to predict possibility of deterioration of environmental conditions as quickly as possible, b) detect inefficient operations that increase energy consumption, and c) detect faults that occur frequently or ones that cannot be detected easily by maintenance personnel. An example of the latter would be a fault in a controller's software or a mechanical fault that does not have an immediate effect.

6) Finally, it should be noted that the ranking of important faults presented for VAV air handling systems were based on a survey done in Japan. While there are likely to be strong similarities, this ranking may not be entirely applicable to the design of BOFD systems for use in European or North American countries.

3.3.4 References

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3.4 THERMAL STORAGE SYSTEMS

K. Sagara (Mie University, Japan), representing the Thermal Storage System W.G.* of Japan BEMS/BOFD Committee
*K. Sagara, N. Nakahara (Nagoya Univ.), K. Kamimura (Yamatake-Honeywell Co., Ltd.), T. Miyazaki (Obayashi Corp.), and M. Nakamura (Yokogawa Johnson Controls Corp.)

3.4.1 Introduction

Thermal storage system are being widely used in Japan, the U. S. and other countries. They contribute to the effective use of energy, the peak shift of electrical demand, heat recovery, solar energy utilization system and seasonal storage.

Water, ice and other phase change materials are used as the thermal storage media. Water thermal storage has a long history in Japan and most of the large scale applications have used water. Ice storage is recently replacing a part of water storage in the U. S. as well as in Japan. Phase change materials are also being developed and utilized in practice.

The thermal storage tank is a kind of accumulator of the faults in HVAC as well as the thermal buffer. At the same time, faults in the thermal storage tank and/or system affect the performance of the HVAC system and human comfort. This suggests that fault detection in the thermal storage has two phase, one is as the tank subsystem, and the other is as the source of the faults in any subsystem and/or the total system.

3.4.2 Outline of thermal storage system

3.4.2.1 Process and instrumentation diagram (PI diagram, Figure 3.10)

Figure 3.10 shows the general diagram of the storage system to be used as a scale to make up any particular system diagram. Four subsystems included are as follows:

1. Thermal storage tank
2. Heat source/sink
3. Variable water volume (VWV) piping and controlled system
4. Constant water volume (CWV) piping and controlled system

The piping circuits are either open or closed. The open circuit is subdivided as -a and the other as -b.

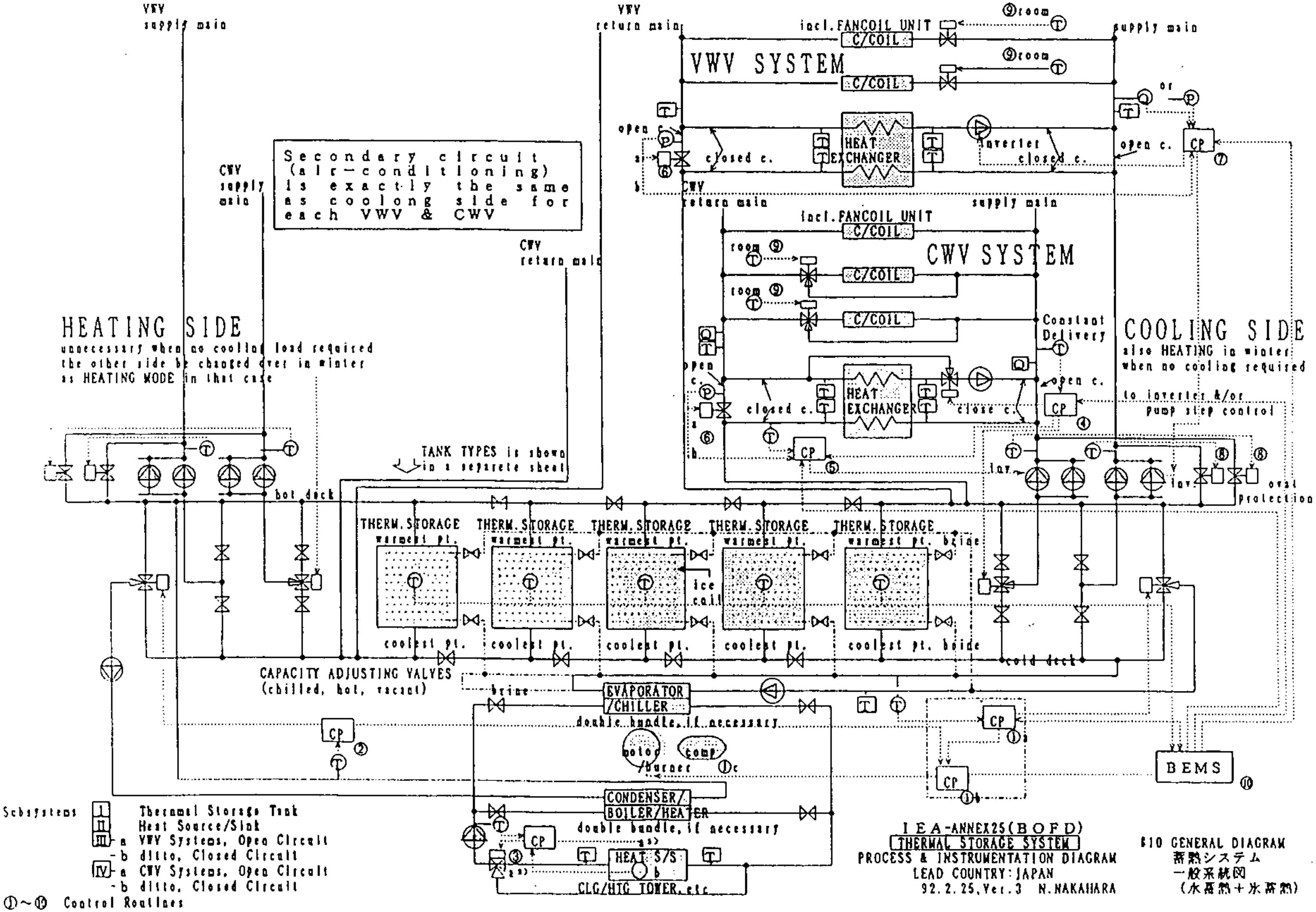

Figure 3.10. PI diagram (thermal storage, general).

3.4.2.2 Control policy of the thermal storage system

Control policy is the most important basics in interpreting the actual operating status and judging faults of the system whether they are inherent of the design, which should also be discovered during the BO process, or malfunctions. Typical and standard control method which makes the thermal storage system most effective is listed hereafter.

a. Heat pump control in cooling and heating mode
- Outlet chilled water temperature should be controlled with the sensor inserted at the exit of evaporator in order to keep the stored water temperature constant.
- Start/stop control of heat pump should be based on the predicted air-conditioning load and the actual heat stored in tank.
- Capacity control of heat pump should be based on the full power input in order to maintain the highest performance of heat pump operation.

b. Heat source/heat sink control
- Outlet temperature may be controlled with start/stop of tower fan or bypass of the inlet water depending on the kind of heat source/sink and on the kind of heat pump.
- Frost/freeze protection should be equipped for water freezing of the cooling tower or frosting on the fin surface of evaporator.
- Spray pump should be controlled either on or off in mid summer in case of spray type evaporative condenser/cooler.

c. Delivery water temperature control for constant water volume (CWV) system
- Delivery water temperature of the secondary water circuit may be preset either manually in remote mode or automatically by any other optimum delivery water temperature routine in order to keep the return water temperature constant.
- Variable water volume (VWV) control can be applied to the supply water pump with inverter motor in case of closed circuit because of the outlet water temperature control of the primary circuit of the heat exchanger.

d. Outlet water temperature control of heat exchanger primary circuit
- The set point temperature will be reset lower when the secondary supply temperature is not fulfilled due to the constant delivery temperature control.

e. Return water control in open circuit
- Pressure control at bottom of the return pipe should be used to avoid the vacuum pressure in pipe resulting in noises and vibrations.
- Power recovery turbine can be used to recover more than fifty percent of the power to pump up from the tank to the top of the water circuit, which can make the pressure control unnecessary.
- Open/close of return valve and interlock with pump operation should be used to avoid the water flush at the higher part of the pipe or the water falling into the storage tank resulting in cavitation, noises and vibrations.

f. Pump control for variable water volume (VWV) system

- When the water flow rate reduces at low cooling load, pump rpm should be changed by inverter or the number of operative pumps should be reduced in order to accomplish energy saving.

g. Pump protection control

- Bypass valves with small diameter should be equipped to avoid pump overheat at excessive small flow rate and the bypass water should be returned into the higher temperature side of the storage tank.

h. Room temperature control

- The high temperature differential type unit and individual on-off control with two way valve without fan speed control switch should be adopted.
- The two way valve control is always preferable because it decreases pump energy, keeps higher temperature differential in the low cooling load and increases the storage efficiency.

i. BEMS

- BEMS can monitor each control result, can contain control software, can implement the DDC and SCC, can supervise all control routines, can detect faults and can optimize the building energy and environmental performances.

3.4.2.3 Type of thermal storage tank

a. Water thermal storage

In the PI diagram shown in Fig. 3.10, the type of thermal storage tank is figured as the temperature-stratified one for convenience. Actually, however, several kinds of types are commercially used and some new ideas are proposed elsewhere.

Typical structures based on the Japanese practice and research are as follows:

1. Multi-connected complete mixing tank
2. Temperature-stratified tank
3. Multi-connected temperature-stratified tank
4. Self-balanced temperature-stratified tank.

b. Ice thermal storage

Ice thermal storage is more popular in the U. S. and it is not so popular in Japan due to the cost problems when compared with water thermal storage.

Typical classification are as follows:

1. Static ice on coils
2. Dynamic harvesting plate ice
3. Slurry ice generated from brine, sub-cooled water or direct contact.

3.4.3 Questionnaire to experts

An investigation to find out typical or important faults which should be detected by BOFD systems was carried out by the Japanese thermal storage sub-group in August 1992 by the way of questionnaires to experts. The aim of questionnaire was expressed to experts as follows:

1) We would like to know what are the most important faults in thermal storage systems for the development of automated fault detection systems and the simulation of thermal storage system under any fault conditions.

2) The faults should be listed up according to your whole experience rather than the on-going thermal storage systems in which you are currently involved.

The questions are:

No. 1: Please list important faults about each thermal storage system referring the attached tables of fault examples. If the fault that you would like to list cannot be found in the tables, please add it.

No. 2: Please pick up one reason from the following eight reasons why you select the fault as important one.

Table 3.24. Reasons of selecting faults being important.

	Abridged as
1) because it creates environmental degradation and occupants will complain	[environment]
2) because it causes energy loss	[energy]
3) because it causes serious secondary damage	[damage]
4) because it occurs frequently	[frequency]
5) because detection of it is difficult	[detection]
6) because it takes much time to fix it	[recovery]
7) because fixing it requires much cost	[cost]
8) because it causes credit loss for maintenance	[credit]

No. 3: Please select ten most important faults.

We received 25 replies. The professions and the numbers of the experts are as follows:

Table 3.25. Professions and numbers of experts.

Profession	Number of reply
Designer	19
Developer	2
Maintainer	4

3.4.4 List of faults on thermal storage system given to experts

1) The thermal storage system is divided into 4 subprocesses as follows:
   1) storage tank
   2) heat source/sink
   3) VWV system
   4) CWV system.

2) Typical faults were listed under configuration of a water thermal storage tank, a heat source/sink and a VWV/CWV secondary circuit in cooing mode.

3) Water thermal storage tank is a multi-connected complete mixing type or a temperature -stratified type.

4) Component defect were categorized as follows:
   (D) indicates a failure in the design stage.
   (F) indicates a failure in the construction or fabrication stage.
   (M) indicates a failure in the commissioning or maintenance stage.
   (U) indicates a failure by users.
   (C) indicates a failure in control hardware and software.
   (A) indicates a failure in algorithm of control.

3.4.5 Important typical faults

Twelve important faults which were selected from the questionnaire is summarized as shown in Table 3.26. Most faults are not so-called mechanical break down or malfunctions. As indicated at the right end, five of them are faults originating at design stage and four are maintenance stage. Percentage of design stage faults is larger than that of maintenance stage faults. These design stage faults cannot be fixed by normal maintenance works. Furthermore, such faults as "damage in water proofing" and "damage of insulation" are difficult to be detected, and are so tough that fixing these faults requires lots of time and cost. The too small tank volume and those faults in the controller and control valve also have a bad influence upon energy conservation through insufficient stored heat in thermal storage tank, while the insulation damage and duration of the partial capacity control of heat pump cause energy loss directly.

Table 3.26. Most important faults selected by experts.

Rank (point)	Subprocess variable deviation	Component	Component defect	Symptom or effect	Stage
	storage tank				
1 (11)	abnormal water level	water proofing	damage in water proofing	• increase of water supply • increase of overflow • deterioration in water quality	M
2 (10)	temperature in coolest side is too high or temperature in warmest side is too low	tank	tank volume is too small	• inlet water temperature of heat pump is too high • stored heat is insufficient • room temperature and humidity are too high	D
2 (10)	abnormal change of temperature in tank during off operation hours	insulation	damage of insultation	• condensation on slab • heat loss	M
	heat source system				
4 (9)	outlet/inlet water temperature difference of heat pump is small	heat pump	partial capacity control is working	• stored heat is insufficient • heat pump COP falls	D
5 (7)	flow rate of primary pump is too small	primary pump in pipe	water evacuation	• abnormal stop of heat pump • pump overheated • abnormal pump noise	D
5 (7)	temperature in coolest side of tank is too high	heat pump	outlet water temperature of heat pump is too high	stored heat is insufficient	C
5 (7)	temperature in tank at storage end time is too high	storage controller	control malfunction	stored heat is insufficient	C

5 (7)	temperature in tank at storage end time is too high	storage controller	overestimate of stored heat	stored heat is insufficient	A
	VWV secondary circuit				
5 (7)	supply water temperature is too high	tank	temperature in coolest side is too high	room temperature and humidity are too high	D
5 (7)	supply water flow rate is too much	piping	failure in piping	return water temperature is too low	D
5 (7)	supply water flow rate is too much	2 way valve	failure in valve or actuator	return water temperature is too low	M
5 (7)	supply water flow rate is too little	2 way valve	failure in valve or actuator	room temperature and humidity are too high	M

3.4.6 Reasons of selecting faults being important

Experts were requested to decide why a fault is important. The probable reasons were categorized into eight kinds and listed up as shown in Table 3.24. In the questionnaire experts were asked to select one reason for each fault.

Figure 3.11 shows how many points each categorized reason obtained. The reasons related to room environment and energy loss earned the highest point (nearly 30 %). The reasons related to difficulty of detection and cost of fixing rank to the next. Causing secondary damage and credit loss for maintenance were not evaluated very important.

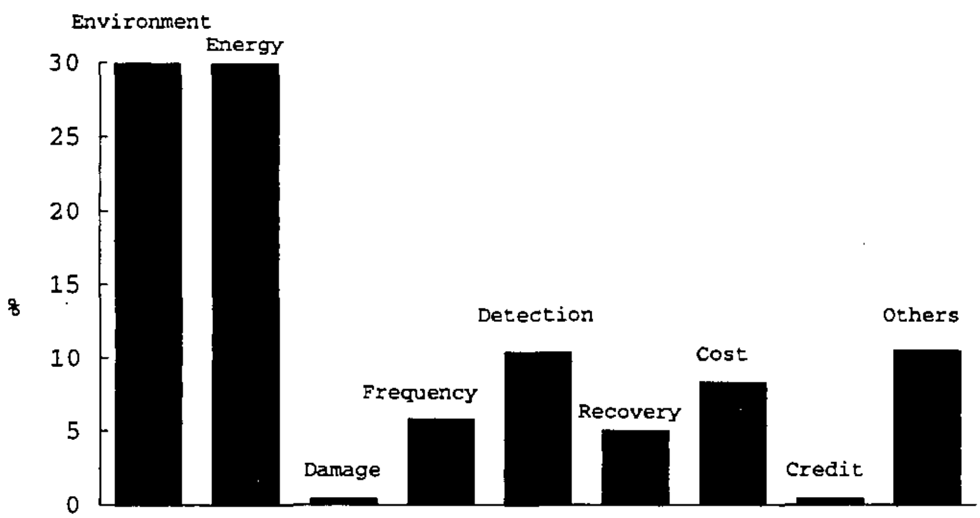

Figure 3.11. Reasons of important faults.

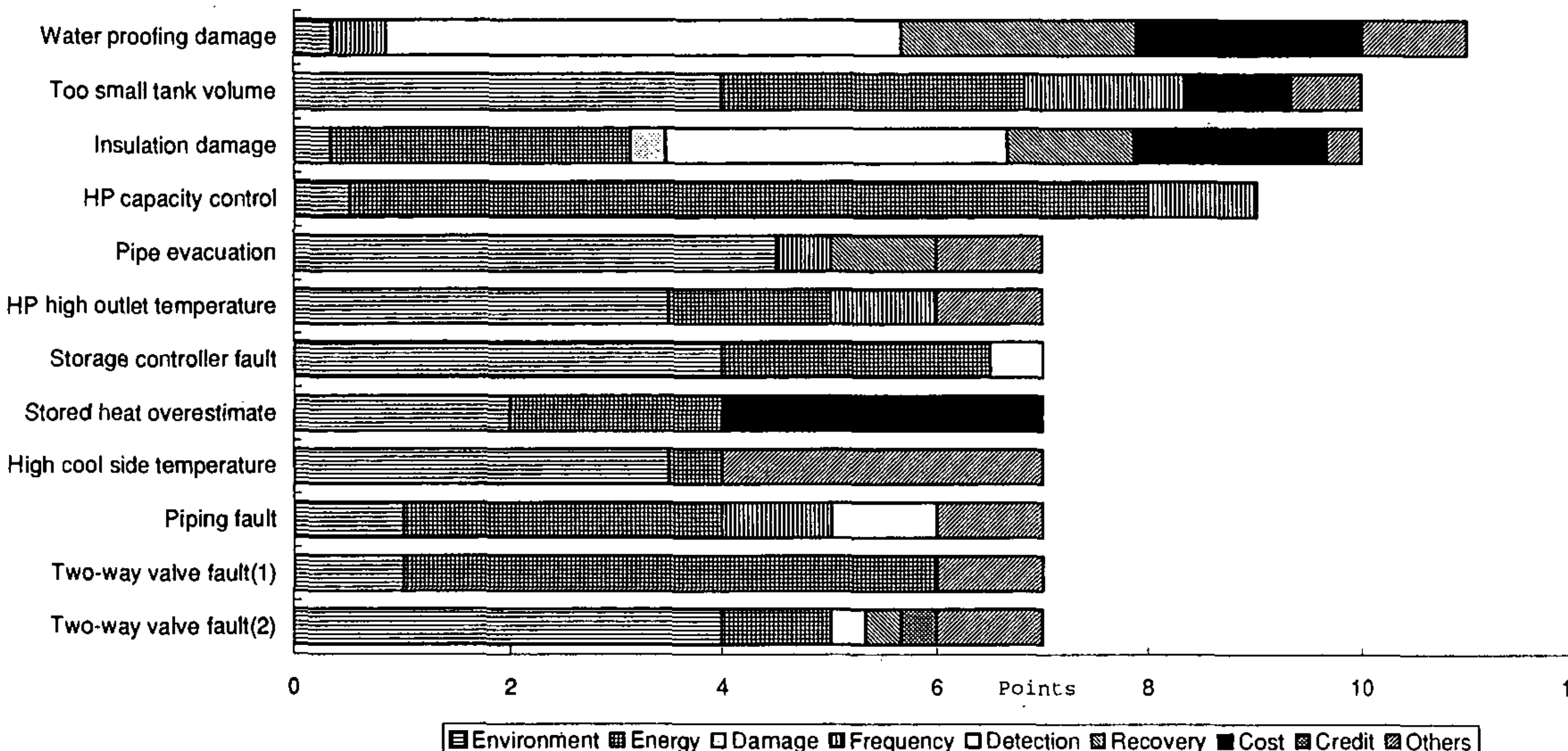

Figure 3.12. Important faults and reasons.

Figure 3.12 shows the twelve important faults and their reasons. The water proofing damage of the first rank is selected mainly because of three reasons; the difficulty of detection, the need for recovery time and the cost of fixing. It should be noted that the water proofing damage took the first place in important faults but that it does not include the environmental degradation and energy loss which are top reasons for the twelve important faults. The insulation damage which took the second place together with the too small tank volume is selected because of energy loss and difficulty of detection. The other important faults were selected because of environmental degradation and/or energy loss, and are considered to be easy to detect comparatively. Furthermore, it was found that faults concerning the control of the storage system are the biggest in point numbers when summed up. These results suggest that it is meaningful to detect the water proofing damage and the insulation damage automatically by BOFD systems [3.5] and control faults are also important in the BOFD of the thermal storage systems.

3.4.7 Conclusions

An investigation was carried out to find out typical faults in thermal storage systems based on a questionnaire to experts whose professions are ranging from system designers to maintenance engineers.
Following conclusions were introduced:

1) In the twelve important faults selected by experts, five of them are faults originating at design stage and four are maintenance stage. Percentage of design stage faults is larger than that of maintenance stage faults. These design stage faults cannot be fixed by normal maintenance works.

2) The water proofing damage and the insulation damage are difficult to be detected, and are so tough that fixing these faults requires lots of time and cost.

3) The too small tank volume and those faults in the controller and control valve also have a bad influence upon energy conservation through insufficient stored heat in thermal storage tank, while the insulation damage and duration of the partial capacity control of heat pump cause energy loss directly.

4) The reasons related to room environment and energy loss earned the highest point (nearly 30 %). The reasons related to difficulty of detection and cost of fixing rank to the next. Causing secondary damage and credit loss for maintenance were not evaluated as being very important.

5) The water proofing damage of the first rank is selected mainly because of three reasons; the difficulty of detection, the need for recovery time and the cost of fixing. It should be noted that it took the first place in the important faults but that it does not include the environmental degradation and energy loss which are top reasons for the twelve important faults. The insulation

damage which took the second place together with the too small tank volume is selected because of energy loss and difficulty of detection. The other important faults were selected because of environmental degradation and/or energy loss, and are considered to be easy to detect comparatively. Faults concerning the control of the storage system are the biggest in point numbers when summed up.

6) These results suggest that it is meaningful to detect the water proofing damage and the insulation damage automatically by BOFD systems and control faults are also important in the BOFD of the thermal storage systems.

3.4.8 References

3.5. Sagara, K. and Nakahara, N. Fault Detection in Thermal Storage Tank Using Physical Model. In: Hyvärinen, J. (ed.). Technical papers of IEA Annex 25. Espoo: VTT Building Technology, 1996. (IEA BCS Annex 25).

Appendix 3A. Restricted list of faults of heating systems.
Visier, J.-C. CSTB, Paris, France

Component	Fault	Symptom	New FDD method needed	Comment
Burner	Abnormally stopped	Internal boiler alarm ON (flow alarm, gas safety alarm, gas pressure alarm, over heating alarm, circuit breaker alarm).	No	FDD methods already exist.
	Bad combustion	Flue gas temperature deviation. Energy consumption increases, colour of flue gas, environmental pollution.	Yes	Possible detection by the O2 content of flue gas and flue gas temperature deviation.
Principal heat exchanger	Leak	Boiler flow alarm. Water in the combustion space.	No	Alarm on boiler flow already exists
	Scaling	Boiler outlet temperature too low. Bad efficiency of exchanger, increase of the energy consumption. Flue gas temperature too high.	Yes	
Pump	Complete failure	No water flow in the circuits. No heating of the building.	Yes	Fault easy to detect but not easy to locate.
	Dirtiness	Too low water flow in the circuits. Dirtiness in boiler pump: Too low departure water temperatures. Dirtiness in secondary circuits pumps: Low indoor temperature.	Yes	
	Cavitation	Too low water flow in the circuits. Noise. Defect in boiler pump: Too low departure water temperatures. Defect in secondary circuit pumps: Low indoor temperature.	Yes	
	Boiler pumps underdimensioned	Too low departure water temperature in some cases.	Yes	

Component	Fault	Symptom	New FDD method needed	Comment
Gas supply system	Abnormally stopped	No gas flow. Stop of the burner.	No	Burner control system signals an alarm.
	Leak	Too low gas flow, Too low gas pressure. Stop of the burner.	No	Burner control system signals an alarm.
Three-way valve (with drive unit)	Bad hydraulic authority	Fluctuation of the departure water temperature. Not stable indoor temperature, wear of valves.	Yes	
	Leak of the bypass way or unwanted limit of drive unit position	Too low departure water temperature when the set point is high. Low indoor temperature when the outdoor temperature is low, Indoor temperature cannot reach its set point at the start of the occupation period.	Yes	
	Leak of the direct way or unwanted limit of drive unit position	Too high departure water temperature when the set point is low (for example during stop period). Too high indoor temperature during the inoccupation period.	Yes	
	Closure of the bypass	Too high departure water temperature. Overheating of the building, increase of energy consumption, windows opening by the users.	Yes	
	Closure of the direct way	Too low departure water temperature. Underheating of the building.	Yes	
	Mechanical or electrical defect in the drive unit	Departure water temperature not close to its set point. Indoor temperature fluctuating.	Yes	
Heat exchanger of domestic hot water	Scaling	Too low flow of domestic hot water, or too low temperature of domestic hot water. User's complaint for the insufficiency of temperature and flow of domestic hot water, increase of energy consumption.	Yes	

Component	Fault	Symptom	New FDD method needed	Comment
Radiator	Bad authority of thermostatic valve.	Instability of indoor temperature. Complaints from the users.	Yes	
	Thermostatic valve in the pilot room.	Indoor temperature not equal to its set point (too high or too low). Complaints from the users. The free heat gains cannot be compensated.	No	Design fault, easy to find out.
	Air in radiator.	Too low indoor temperature. Noise, underheating of the building.	No	Fault easy to locate.
	Thermostatic valve breakdown.	Too high or too low indoor temperature. Bad heating of the building. The free heat gains cannot be compensated.	Yes	
Disconnector	Complete failure.	Possible negative flow of fresh water. Water in the heating circuits flows back into the distribution network of fresh water, pollution of fresh water.	Yes	
Expansion system	Leak of filling gas	Pressure of water circuits too high or too low.	Yes	
Flue gas duct	Corrosion	Not tight flue gas duct.	No	Fault should be discovered by chimney sweep.
Building and user	Window opened by the user	Rapid decrease of indoor temperature. Waste of energy, opening of thermostatic valve.	Yes	
	Large free heat gains in pilot room.	Quick variations of pilot room temperature. Indoor temperature too low in certain rooms.	Yes	

Component	Fault	Symptom	New FDD method needed	Comment
The entirety of the system of heating and domestic hot water	Bad balance between circuits.	Temperature difference between zones. Overheating and/or underheating in part of the building, waste of energy.	Yes	Different methods already exist, but are often not applied because being time consuming and therefore expensive.
	Leak	Too low water pressure and/or flow. Water in the building, permanent need of fresh water, increased corrosion in the system.	Yes	
	Clogged by mud	Too low indoor temperature. Underheating of the building.	Yes	
Temperature sensors	Sensors bias/drift	Measured value not equal to the real value. False alarms, discomfort, high consumption, controllers not properly working.	Yes	
	Immersion sensors not always irrigated	False measured values False alarms, discomfort, high consumption, controllers not properly working.	Yes	
	Sensor of the thermostatic valve influenced by the radiator	Discomfort of users.	No	Fault to be assumed based on visual inspection of positioning of thermostatic valve.
	Room temperature sensor in a bad position(free heat gains, zone with little air flow, room not representative)	Boost period too long, heating curve not well suited to the building, too low room temperatures in some rooms in the morning.	Yes	

Component	Fault	Symptom	New FDD method needed	Comment
	Flow temperature sensor too close to the mixing point	Bad control of flow temperature	No	Fault to be assumed based on visual inspection of sensor position.
	Electrical disturbances on sensor lines	Measured value not stable. Bad control.	Yes	
Weather compensator	Bad tuning of heating curve	Indoor temperature correlated to outdoor temperature. Discomfort, thermostatic valve nearly closed.	Yes	Autoadaptative heating curves are supposed to solve the problem.
Scheduler	Bad occupancy schedule defined by the user	Indoor temperature not following users needs. Complaints of users or waste of energy.	Yes	
	Scheduler not well timed (clock not well timed or schedule not coherent with occupation)	Indoor temperature not following users needs. Complaints of users/ waste of energy.	Yes	
Operational mode-calculator	Too late commutation between reduced heating(or off) and boost heating	Indoor temperature too low in the morning. Complaints of the users especially on cold mondays morning.	Yes	
	Too early commutation between reduced heating(or off) and boost heating	Boost heating finished before beginning of occupation, waste of energy.	Yes	

Component	Fault	Symptom	New FDD method needed	Comment
	Too early commutation between boost heating and normal heating	Indoor temperature too low, especially on monday morning. Complaints from users.	Yes	
	Too early commutation between normal heating and stop (or reduced) heating	Indoor temperature too low in the late afternoon. Complaints from the users.	Yes	
	Bad information on secondary circuits needs transmitted to the boiler master	Boiler outlet temperature too high or too low. Too low departure water temperature, waste of energy, discomfort.	Yes	
Flow temperature controller	Not adapted to the three-wayvalve	Fluctuation of departure water temperature. Wear of valves.	Yes	
	Not working	Departure water temperature different from its normal value. Three-wayvalve stays in the same position, discomfort, waste of energy.	Yes	
Boiler master	Bad choice of the number of boilers to be used	Working times of the boilers not correct. Bad efficiency of boilers, low mean load of the working boilers, too many start-stop of the burners.	Yes	

Appendix 3B. Refrigeration Equipment Faults

Stylianou, M., EDRL-CANMET, Canada

Vapour Compression Cycle Refrigeration

Apparent Component Failure	Component	Component defect	Symptom or effect
Complete unit stoppage		-General power failure	For open contacts: look at pump current low -->low flow
		-Control circuit breaker tripped out	
		-Blown fuse in control power feed disconnect	
		-Freeze protection trip	
		-Low flow protection trip (Open contacts in chilled water flow switch)	
Control circuit open	Compressor	-Protective switch tripped	Compressor will not start
		-Anti-recycle timer timing out (Part of system operation)	
		-No power supply to control circuit	
		-Compressor capacity control not in minimum position (not on reciprocating compressors)	
		-Emergency stop switch engaged	
		-Contactor not closing	
		-There is no call for compressor to start (Part of system operation)	
Compressor motor failure	Compressor	-Electronic/mechanical overload not reset	
		-Main circuit breaker tripped	
	Compressor	-Motor burned out	High amperage draw Fuses blown
		-Mechanical failure of compressor	
	Compressor	-Low voltage to the motor	Compressor motor hums but does not start
		-Compressor not unloaded	
		-Utility not supplying one phase of power	
	Compressor	-Burned-out holding coil or broken contacts	Compressor fails to start
	Compressor	-Blown line fuse or broken lead	
Non-optimal safety control		-Faulty protective switch	

Apparent Component Failure	Component	Component defect	Symptom or effect
Instability of low pressure control		-Low pressure control differential too close (installation/commissioning)	
		-Lack of refrigerant	
High temperature at stator and/or bearings	Compressor	-Anti-cycle timer set incorrectly	
		-Motor ventilation ports blocked (only open drive)	
		-Ambient temperature too high (only open drive)	
		- Bearings lubricated incorrectly	
		-Bearings worn or defective	
		-Motor drawing too much current. Unequal phase voltage/ Low voltage/Phase loss/Phase reversal	
High temperature in conditioned space/ High chilled water temperature	System	Excessive load (Design fault)	Compressor runs continuously at full load
Low temperature in conditioned space	Thermostat	- Room thermostat set too low or stuck in closed position	
Compressor noisy or abnormally high suction pressure and low discharge pressure	Compressor	-Leaking compressor valve (Reciprocating only)	Compressor runs continuously. Discharge temperature usually increases
Compressor operates unloaded but will not stop	Solenoid valve (during automatic shutdown)	-Solenoid valves leaks (outlet cooler than inlet)	Compressor runs continuously or cycles
System short of capacity	Strainers/filter -driers	-Blocked liquid strainer (outlet cooler than inlet)	High chilled water temperature
	System	-Load too high (Design)	
		-Liquid feed valve (txv) underfeeding evaporators	
		-Faulty control circuit	
		-Defective low limit thermostat controlling chilled water temperature	
		-Hot gas bypass valve defective	
		-Low refrigerant level in receiver	

Apparent Component Failure	Component	Component defect	Symptom or effect
High condensing temperature/ pressure	Condenser-air cooled	-Fans rotating in wrong direction (installation) /Phase reversal	Hot condenser Hot liquid line
		-Blocked air screens	
		-Blocked blades or dampers	
		-Blocked fins	
		-Air recirculation from exhaust to inlet	
	Condenser water-cooled	-Water inlet ball-cock jammed	Hot condenser
		-Water supply not turned on at mains	
		-Water supply at low pressure	
		-Water pump leaking	
		-Blocked water sprays	
		-Blocked strainer on inlet to pump	
		-Water temperature into shell and tube condenser too high	
Compressor vibrating	Compressor vibration	-Coupling or flywheel lose, out of alignment or unbalanced	
		-Key sheared or missing	
		-Loose belts	
		-Mounting or foundation loose or in disrepair	
		-Vibration mount rubbers sheared or springs worn	
Low discharge pressure	Compressor	-Compressor seized	
		-Motor overload tripped	
		-Compressor not pumping	
	Water-cooled condenser	-Water flow rate too high	Water leaving condenser too cold
		-Inlet water too cold	
	Air cooled condenser	-Fans running in low ambient	Condensing supply air too cold
	System	-Lack of refrigerant	Water leaving condenser too cold Bubbles in sight glass

Apparent Component Failure	Component	Component defect	Symptom or effect
High discharge pressure (High discharge temperature)	Compressor	-Discharge valve fully or partly closed (for manual valve)	Compressor shuts down immediately or soon after starting
	Compressor	-Liquid flood-back to compressor	Compressor may shut down immediately after starting
	Compressor	-High Pressure-control has cutout	Compressor stops
	Condenser (Water)	-No water in cooling tower	Compressor shuts down soon after starting
		-Insufficient cooling water flow across condenser	
	Condenser (Air)	-Fault in condenser selection	Compressor shuts down soon after starting (or Short-cycles) Hot Condenser
		-Dirty condenser heat exchanger	
		-Inoperative condenser fans	
	High pressure switch	-High-pressure erratic in action	Compressor stops until switch is manually reset
	System	-Too much refrigerant in system	Compressor may shut down soon after starting (or Short-cycles) Compressor runs continuously Exceptionally hot condenser
		-Air or non condensible gases in system	
	System	-Too much refrigerant in system	Exceptionally hot condenser
Low suction pressure	Strainers	-Blocked Strainers and/or filter-drier/ Liquid line restriction	Compressor may shut down soon after starting
	Evaporator	-Wrong setting of evaporator controls	Compressor shuts down immediately after starting
		-Heater element open circuited on liquid level control on flooded evaporators or faulty level control	
		-Freeze-up or fouling (oil or product) of evaporator	
		-Chilled water thermostat set too low	
	Solenoid valve	-Liquid solenoid valves not working	Compressor shuts down soon after starting

Apparent Component Failure	Component	Component defect	Symptom or effect
	Expansion valve	-Faulty expansion valve (e.g. thermal element lost its charge)	Compressor shuts down soon after starting Chilled water temperature too high System short of capacity
		-Ice in expansion valve due to moisture in refrigerant	
		-Dirt blocking expansion valve	
	Condenser	-Restricted or too warm air to condenser	Compressor may shut down soon after starting
	System	-Excessive suction line pressure drop (Design/Installation)	Compressor shuts down soon after starting (Compressor stops)
		-Evaporator too small (Design/Installation)	
		-Float switch faulty (not usual on chillers)	
		-Lack of refrigerant	
		-Thermostat contacts stuck in closed position	
		-Capacity control range set too low	
		- Too much pressure drop in evaporator (Design)	
		-Low pressure control erratic in action	
		-TXV set for too high superheat	
	Compressor	-Compressor suction valve partially closed	
	System	-Capacity control pressure switch set incorrectly or defective	Compressor short cycles
		-Wrong refrigerant (service)	
		-Plant undersized (design)	
		- Lack of refrigerant	
High suction pressure (High suction pressure)	Compressor	-Leakage of discharge valves	Compressor shuts down soon after starting
		-Refrigerant condensed in compressor	
	Recip. Compressor	-Suction valves worn or damaged	Rec. compressor vibrating or noisy Reduced capacity Low discharge pressure
		-Discharge valves worn or damaged	
		-Compressor damaged or worn internally	

Apparent Component Failure	Component	Component defect	Symptom or effect
	Screw Compressor	-Damaged or worn thrust bearings	Screw compressor vibrating or noisy
	Expansion valve	-Excessive capacity of expansion valve -Leakage of expansion valve -Expansion valve opens too far -Expansion valve stuck in open condition	Compressor noisy or knocking liquid in suction line
	System	-Superheated refrigerant condensed in suction line (installation) -Superheat setting out of adjustment	Compressor may shut down soon after starting
	System	-Excessive load on evaporator	Compressor runs continuously Chilled water temperature too high
	System	-Liquid refrigerant in suction line -Excessive refrigerant in evaporators -Liquid refrigerant in suction vapour	Compressor may be vibrating or noisy
	System	- Lack of refrigerant	Chilled water temperature too high
High discharge temperature	Compressor	-Operation at high compression ratio (Extremely low suction pressure or high discharge pressure)	Compressor may shut down soon after starting
	Evaporator	-Evaporator heat load too high, resulting in high suction superheat	Chilled water temperature too high
	System	-Superheat out of adjustment	Compressor runs hot
High suction temperature	Evaporator	- Short capacity of expansion valve (Installation/design) - Low refrigerant	Large pressure drop across evaporator
Low oil pressure	Lubricating system	- Defective start-up oil pump - Blocked oil strainer and/or filter - Start-up oil pressure switch incorrectly set or faulty	Compressor will not start

Apparent Component Failure	Component	Component defect	Symptom or effect
	Lubricating system	- Oil pressure relief valve and/or pressure regulating valve adjusted incorrectly or faulty	Compressor Shuts down soon after starting
		- Low oil level	
		- Worn or broken oil pump components	
		- Oil pump faulty or wired incorrectly	
		- Liquid refrigerant in oil	
		- Water in oil	
		- Vapour in oil (foaming)	
		- Wrong oil type (Service)	
		- Incorrect oil system piping (installation)	
		- Low discharge pressure on screw compressor	
Low oil pressure	Compressor	- Compressor bearings worn	Compressor vibrating or noisy
	Lubricating system	- Low oil level	
Low oil temperature	Lubricating system	- Refrigerant condensed in oil	
		- Crankcase or oil heaters not energized during shut-down	
High oil temperature (High discharge temperature)	Lubricating system- Oil cooler (for water-cooled compressors)	- Water regulating valve out of adjustment or defective	Compressor shuts down soon after starting
		- Low water supply	
		- Dirty oil cooler	
		- Oil heater thermostat defective or oil heater too large	
	Lubricating system- Oil cooler (for liquid injection cooled compressors)	- Low refrigerant supply	Compressor may shut down during operation
		- Low liquid refrigerant in receiver	
	Lubricating system - Compressors without oil-coolers	- Oil in liquid refrigerant supply - High suction temperature superheat	
		- Operation at high compression ratio	

Apparent Component Failure	Component	Component defect	Symptom or effect
High oil consumption (oil level in sight glass low)	Lubricating system	- Oil spillage	Oil not returning to sump
	Oil return system (flooded evaporator)	- Oil not returning from flooded evaporators	
	Oil return system (dry expansion evaporator)	- Oil not returning from dry expansion evaporators. Oil too thick or viscous	
		- Oil not returning from oil separator	
		- Suction piping incorrectly sized or laid out. Oil return poor, especially at low load.	
High oil consumption (High oil level)		- Coalester filter blocked	
	System	- Liquid refrigerant returning in compressor suction line	Oil not returning to sump
		- Oil vaporization because of high discharge temperature or high suction pressure	
		- Defective oil heater in sump	
		- Suction check valve	
		- Air in system causing oil to carbonize or vaporize	
Oil level too low	Lubricating system	- Insufficient oil charge	Compressor looses oil
Gradual drop of oil level		- Clogged filter dryer	
Visible oil leak		- Crankcase leaks	
Cuts out on oil pressure control		- Lack of oil	

ABSORPTION CHILLER

Process variable deviation	Component	Component defect	Symptom or effect
- Outlet chilled water temp. is too high			- [in general] - room temperature is too high
	- chiller	- insufficient capacity - insufficient evacuation of no condensing gas	
	-evaporator	- clogging in tube	- chiller COP falls - outlet/inlet pressure difference is too large
		- lowered vacuum	- insufficient vacuum
	- condenser	- clogging in tube	- chiller COP falls - outlet/inlet pressure difference is too large
	- absorber	- clogging in tube	- chiller COP falls
	- solution pump	- over current	- abnormal stop by thermal relay
- Chilled water temp. is too low	- evaporator	- flow rate is too small	- abnormal stop by thermoswitch - abnormal stop by flow switch
		- water volume in the system is too small	- abnormal stop by thermoswitch
- Pressure or temperature of regenerator is too high	- regenerator	- lowered vacuum	- abnormal stop by pressure switch
- Exhaust gas temp. is too high	- exhaust gas	- clogging in fire tube of regenerator - inadequate gas/air ratio	- abnormal stop by thermoswitch - abnormal stop by thermoswitch
- Ignition failure	- igniter	- failure in flame sensor	- abnormal stop by flame sensor - abnormal stop by pressure switch
- Cooling water temp. is too high			- [in general] - chilled water temperature is too high - chiller COP falls
	- cooling tower	- insufficient capacity	

Appendix 3C. Examples of faults and symptoms for the reference VAV Air handling system

Yoshida, H. Kyoto University, Kyoto, Japan

The following is a partial list of possible faults and their symptoms for the reference air handling system shown in Figure 3.3.1. In 1992, a more complete list was distributed along with a questionnaire to experts in Japan in the design, construction, and commissioning fields. They were asked to pick and rank the ten most important faults, to state when each fault was likely to have occurred (e.g., the design phase, the construction phase, etc.), and why a particular fault was important (e.g., caused environmental damage, increased energy consumption, etc.).

Process variable deviation	**Component**	**Component defect**	**Symptom or effect**
# subsystem (1) Room - room temperature is low in cooling mode			- [in general] - complaints by occupants <e> - alarming on a central control panel <e> - waste of energy <c>
	- air diffuser	- inadequate arrange (D,F)	- complaints by some occupants due to lack of uniform room temperature distributions or formation of cold draft <e>
		- inadequate direction of diffused air (C)	
	- {AHU}	- too low supply air temperature	- temperatures at some locations are out of the setting value <e, c, r>
	- {VAV unit}	- failure in air volume control	
	- {local control}	- too low supply air temperature setting - thermostat: inadequate locations as follows; * exposed to solar radiation (D,F) * exposed to the heat generated from OA facilities (M) * concealed by furniture (M)	- no alarming of abnormal temperature < e>
	- {central control}	- mode setting failure; cooling mode is selected despite cool outside. (S)	

Process variable deviation	Component	Component defect	Symptom or effect
- room temperature is high in cooling mode			- [in general] - complaints by occupants <e> - alarming on a central control panel <e>
	- air diffuser	- inadequate arrange (D,F) - inadequate direction of diffused air (M) - too little air flow rate (F,M)	- complaints by some occupants due to lack of uniform room temperature distributions <e>
	- building elements	- less wall insulation and/or too large windows than design values (F)	- temperatures at some locations are out of the setting value <e, c, r>
	- occupants usage	- keeping windows open (U) - no adequate use of shades (U) - excessive internal heat generation (M,U) - excessive number of occupants (M,U)	
	- {AHU}	- too high supply temperature	- require too much time for cooling down <r>
	- {VAV unit}	- insufficient supply air volume	
	- {OA control}	- failure in air volume control	- excessive opening of VAV units <r>
	- {local control}	- excessive OA intake - too high supply air temperature setting - thermostat: inadequate locations; supply air hit the thermostat (D,F)	- too high room air humidity <e> - no alarming of abnormal temperature <e>
# subsystem (2) AHU - supply air temperature is high in cooling mode	- cooling coil	- insufficient row number (D) - fouling on coil fins (M) - scale in coil tubes (M)	- room air temperature rise due to insufficient cooling capacity <e> - may cause of unfavorable smell of air <e>
	- {energy plant}	- too high chilled water temperature (D,C,M,S,A)	- waste of energy for fan operation due to handring excessive air volume <c>
	- {piping}	- too much pressure drop (D,C,M)	

Process variable deviation	Component	Component defect	Symptom or effect
	- {local control}	- failure in control algorithm for the control valve (A) - failure in the thermostat of supply air temperature control (S)	- room air temperature rise <e> - probable cause of a valve damage (ex. by hunting) <d>
	- {central control}	- mistake of supply air temperature setting (M) - electrical noise disturbing signals in wiring (S)	
- supply air temperature is low in cooling mode			- [in general] - waste of energy due to heat loss through duct works <c>
	- {local control}	- failure in control algorithm for the control valve (S) - failure in the thermostat of supply air temperature control (S)	- probable cause of room air temperature decrease <e> - cause to damage of valve (ex. hunting) <d>
	- {local control}	- failure in in control valve (D,M)	- probable cause of room air temperature decrease <e>
- supply air temperature is high in heating mode			- [in general] - waste of energy due to heat loss through duct works <c>
	- {local control}	- failure in control algorithm for the control valve (S) - failure in the thermostat for supply air temperature control (S)	- probable cause of room air temperature rise <e> - probable cause of a valve damage (ex. hunting) <d>
	- {local control}	- failure in control valve (D,M)	- probable cause of room air temperature rise <e>

4 FAULT DETECTION AND DIAGNOSIS METHODS

4.1 INTRODUCTION

Rossi, T. M., Braun, J. E. & Ray, W.
Herrick Laboratoires, Purdue University, West Lafayette, USA

Fault detection, diagnosis, and evaluation (FDDE) for heating, ventilating, air conditioning, and refrigeration (HVAC & R) systems have the potential to sustain performance, increase safety and reliability, and reduce operating costs [Isermann 1984, Usoro, Schick & Negahdaripour 1985, Kaler 1988, Wagner & Shoureshi 1988, Kaler 1990, Georgescu, Afshari & Bornard 1993a]. More spesifically, Usoro et al. [1985] argues that benefits obtained from improved controls with building energy management systems could be negated by poorly performing mechanical equipment if they are not supervised and maintained to a higher standard than is commonplace in buildings today. McKellar [1987] has shown that improved diagnostics of faulty HVAC systems can save money by reducing the frequency of replacing components that are not faulty.

Many authors [Willsky 1976, Isermann 1984, Frank 1987, Basseville 1988, Gertler 1988, Frank 1990] have offered excellent review papers on fault detection and diagnostic techniques. They were mainly motivated by critical processes such as aircraft engines [Onken & Stuckenberg 1979, Patton, Willcox & Winter 1987], nuclear power plants [Kitamura 1980], and the space shuttle main engine [Cikanek 1986, Duyar & Merill 1992]. With greater frequency, applications to HVAC & R systems are appearing due to the decreasing cost of the required hardware and the increased availability of data processing techniques. More specifically, there are applications to building envelops with generic components [Usoro & Schick 1985, Norford, Rabl & Spadaro 1987, Anderson, Graves, Reinert, Kreider, Dow & Wubbena 1989, Culp, Haberl, Norford, Brothers & Hall 1990, Pape, Mitchell & Beckman 1991, Georgescu et al. 1993a], air handling units [Usoro et al. 1985, Norford & Little 1993, Georgescu, Afshari & Bornard 1993b], refrigerators [McKellar 1987, Wagner & Shoureshi 1988, Stallard 1989, Wagner & Shoureshi 1992], and air conditioning equipment [Kaler 1988, Culp 1989, Yoshimura & Noboru 1989, Kaler 1990, Kumamaru, Utsunomiya, Yamada, Iwasaki, Shoda & Obayashi 1991, Hiroshi, Matsuo, Fujiwara, Yamada & Nishizawa 1992]. This introduction is a summary of classification techniques used for building fault detection, diagnostics, and evaluation systems for HVAC equipment. The techniques described in the following sections apply these techniques to specific FDDE system designs.

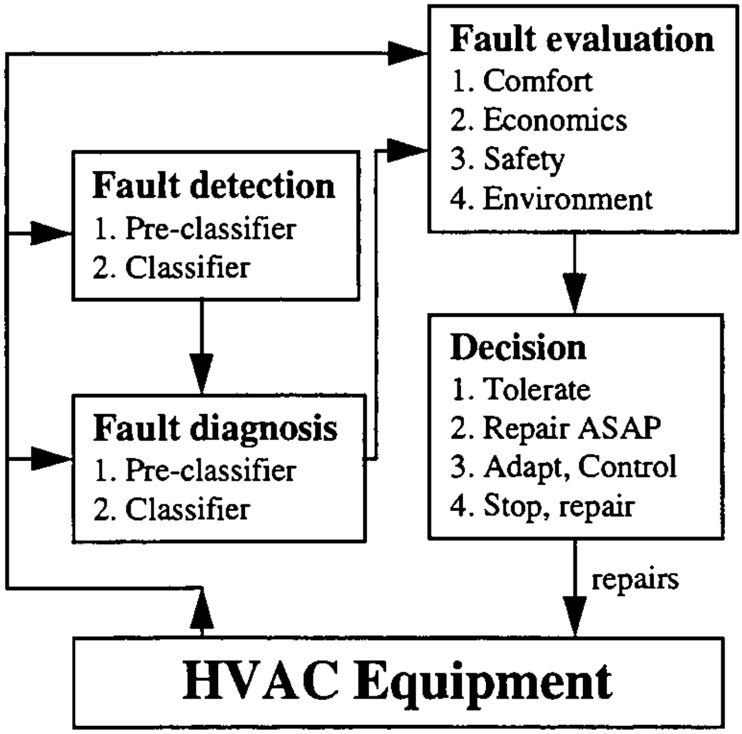

Figure 4.1. Supervision of HVAC & R equipment.

4.1.1 Classification of HVAC & R FDDE techniques

Process supervision has been described by Isermann [1984] and is illustrated in Fig. 4.1. It is a sequence of steps beginning with fault detection. Fault detection is an indication that the performance of a supervised system has deviated from expectation. The second step, diagnosis, determines which system component(s) are causing the fault. Following diagnosis, fault evaluation assesses the impact of the fault on system performance. Finally, a decision is made on how to react to the fault. Detection, diagnosis, and evaluation are based on measurements made on the HVAC & R equipment. The reaction decision effects the equipment by possibly changing its control or calling for service to repair broken components.

4.1.1.1 Fault detection and diagnosis

The first two steps in process supervision are fault detection and diagnosis (FDD). These two processes are similar and can be described using the same structure. Frank [1987] describes how information redundancy is required for FDD. Hardware or physical redundancy appeared first and is still common in critical processes. This involves the use of multiple sensors or actuators for the same purpose. A voting procedure is used to compare performance, and faults are detected by majority rules. This technique is expensive, bulky, and limited in ability. The alternative is analytical or functional redundancy which utilizes the inherent relationships existing between system inputs and outputs for FDD. These relationships can be described, for example, with mathematical models or less precisely with collections of rules.

HVAC & R applications are generally not critical processes and will not use physical redundancy because of economic constraints. The use of analytical redundancy can be divided into two steps: preprocessing and classification. This was described by Rossi & Braun [1993] and in a less general way by Frank [1990]. Preprocessing takes measurements from sensors and generates features for classification. This is where mathematical models, if used, are included. In general, preprocessing performs quantitative operations on measurements to simplify classification and improve overall FDD performance. Classifiers then operate on the features and make decisions about whether or not systems or components are faulty and may also provide reasoning explanations. Consider an important example of how preprocessing simplifies classification. All thermodynamic states in the vapor compression cycle (e.g. head pressure, suction line temperature, ...) are functions of external driving conditions (e.g. ambient temperature) as well as various faults. It is important in FDD not to mistake expected variations of the thermodynamic states with changes in the driving functions for faults. Without preprocessing, measurements are classified directly. Therefore, classification rules have to be complicated to consider the effect of external driving conditions [Stallard 1989]. This effect can be accounted for by using preprocessing. For example, a model can be provide the expected value of measured thermodynamic states as a function of measured external driving conditions. The difference between expected and actual measurement values (residuals) will always be zero mean when there are no faults (assuming no modeling errors). This is true independent of variations in the driving conditions. In this case, the classifier may not even need to consider the measurements of the driving functions, thereby simplifying it considerably.

4.1.1.2 Preprocessing

Simple transformations, characteristic quantities, and models are three types of preprocessors. Simple transformations include the unity transformation (no preprocessing) and trend generation (time derivatives). These were the first preprocessors to be used. Wagner & Shoureshi [1992] used this technique as a basis for comparison with a model-based approach. Characteristic quantities are features of a component or system that are determined directly from measurements. Examples include efficiencies and heat exchanger effectiveness. Model-based preprocessors utilize mathematical models of the monitored process to generate features for classification. These models, if well developed and evaluated, have great potential for making high performance FDD systems because they can generate easily classified features such as measurement residuals and physically relevant parameter estimates.

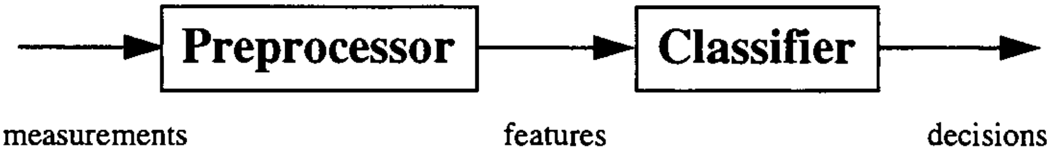

Figure 4.2. Preprocessing and classification are two sequential steps in both fault detection and diagnostics.

Current, nominal, and fault models are three types of models for FDD. The current model tracks the current performance characteristics of the system, a nominal model provides the expected performance of the system for the given inputs and no process faults, and fault models hypothesize how a system would respond to given inputs if a specific fault were present. Multiple fault models are possible. Fault detection can be achieved by comparing current and nominal models. Diagnosis can be done by selecting the fault model which provides features closest to current operation.

Residuals (or innovations) and parameter estimates are two types of features generated from model-based preprocessing. A residual is the difference between current and nominal or fault model-based state estimates. States can be measurable quantities (process outputs) or model-based estimates of non-measurable internal states. Innovations correct measured features for expected changes in model inputs. Model parameter estimates are derived by matching measured and calculated model outputs for given inputs. Variations in model inputs are therefore inherently considered. For example, Ohm's law provides a model for a resistor (V=I*R). An estimate of the resistance (R) can be made from measurements of current (I) and voltage (V) and the model equation. The estimate of R can then be used to detect and diagnose a failure of a resistor in a larger system.

Preprocessor models can have one of two structures: physical or black box. Physical models are based on equations derived from modeling fundamental physical processes (e.g. Ohm's law). Parameters in these models always have some physical significance (e.g. resistance), making them useful for diagnosis. Physical models are capable or extrapolating performance expectations well. However, physical modeling or complex systems (e.g. vapor compression cycle) can often involve large collections of nonlinear equations making it difficult to solve reliably with modest computational tools (e.g. small microcontroller). This problem can be overcome by using black box models. These models learn input/output relationships by adjusting internal parameters to match a training data set. These parameters have no physical significance.

Black box models can be easily evaluated, and depending on their exact structure (e.g. linear, quadratic, neural network), the parameters can be estimated with reasonable computational requirements. In contrast to physical models, they are not expected to extrapolate performance well, especially when high order polynomials are used.

In general, models of physical processes (physical or black box) are represented by nonlinear dynamic equations. It is often possible to reduce computational requirements by linearizing the model about a steady state operating point. In this case, the solutions to a set of linear differential equations can be obtained without iterative techniques using linear matrix operations. Some systems operate in steady state for significant portions of its run time. In this case, computations can be simplified to solving a collection of algebraic equations. If the dynamics are removed, then it often is possible to use limited computational power to solve for more nonlinearities.

4.1.1.3 Classifiers

Classifiers operate on features generated by the preprocessor to decide if a fault exists in the system (detection) and if so, then which component(s) are the cause (diagnostics). In a broad sense, the classifier is an expert system. An expert system is a machine that emulates the reasoning process of a human expert in a particular domain. It is comprised of two important parts: a knowledge base and an inference engine. The knowledge base contains expert knowledge about the domain. The inference engine combines data about a particular problem with the expert knowledge to provide a solution. The following paragraphs consider typical ways that knowledge bases and inference mechanisms are put together to make expert systems for fault detection and diagnostics. They can be as simple as a few rules or a complex reasoning system.

Expert knowledge can be represented as production rules (i.e. IF antecedents, THEN true consequences, ELSE false consequences). For example, IF the head pressure is greater than 425 psig, THEN threre is a fault in the vapor compression cycle. These rules are nonprocedural statements of fact used by a deductive inference engine. The simplest case is when the antecedents can be easily evaluated as TRUE or FALSE. Modifications to basic deductive logic have been made to consider uncertainty in the antecedents and rules. For example, the expert system MYCIN [Shortliffe 1976] assigns a numeric value to the antecedent between -1 (false) and +1 (true). Firing thresholds (e.g. -0.25) determine if the rule fires TRUE (e.g. > 0.25), FALSE (e.g. < -0.25), or not at all. Each rule has an associated confidence level represented by a number in the range [0,1]. The confidence in the conclusion is the confidence in the antecedent times the confidence in the rule. This is one of many examples of heuristic schemes to incorporate uncertainty into the evaluation of production rules. [Kandel 1992] describes fuzzy set theory-based techniques for handling uncertainty in production rule evaluation. [Peng & Reggia 1990] points out that production rule knowledge representation has several other limitations that can become a serious problem when the application becomes more complex. For example, domain expert knowledge is often not naturally available as production rules (and therefore require translation), antecedents can become complex to describe the rule's context, and it is difficult to construct hypotheses containing multiple causes. Therefore, production rules work well for relatively simple problems, but can become impractical for complex classifiers.

The deductive inference engine can be simplified if procedural knowledge can be obtained from the expert. Fault trees [Lee, Grosh, Tillman & Lie 1985] store procedural knowledge as well as production rules in the knowledge base. In this case, the inference engine simply propagates down the fault tree until the solution is found. This technique becomes bulky when the same rules are combined in many different ways. Each time they are combined, they add a node to the tree. Historically, this is a common classifier for diagnostic problems based on expert knowledge.

Knowledge can also be stored as a collection of a piori and conditional probabilities in statistical pattern recognition classifiers [Fukunaga 1990]. In most cases, Bayes theorem is used to calculate posterior probabilities in the inference mechanism. Analytical techniques are used to identify the boundaries between different classes that minimize the probability of making erroneous decisions based on training data. As an example, consider a problem where a statistical pattern recognition classifier is appropriate. The pattern of reflected sound waves from geological features beneath the ground are used to identify mineral resources. Learning the significance of the pattern is accomplished by comparing them to drilled cores before the system is commissioned. As this example illustrates, this technique is useful when large collections of quantitative training data identifies different classes. It does not lend itself well to rules obtained from domain experts. It is also only capable of operating in concurrent mode where all the input data is available at the beginning of the inference process. Furthermore, it is impossible to obtain explanations for the solution except that it matches the training data with minimum error. No physical insights are available.

Semantic networks can also be used to store expert knowledge. A semantic network is a knowledge representation formalism comprised of interconnected nodes. The nodes represent causes, manifestations, or intermediate results in the domain and connections represent the relationships (often cause and effect) that exist between them. Fig. 4.3 illustrates a semantic network used to diagnose a fault in an automobile. The casual associations (connections) between disorders (top) an manifestations (bottom) are shown. A hypothesize-and-test inference engine, based on parsiminous covering theory [Peng & Reggia 1990], can be used to find the disorder(s) that are most likely causing the currently observed manifestations. This theory finds the simplest solution that explains the observed mainifestations. This technique has many advantages including representing knowledge in a natural way, can easily reason explanations involving multiple simultaneous faults, and it includes a formalism based on probability theory to handle uncertainty.

Neural network classifiers include knowledge and inference together in a generic input/output model [Demuth & Beale 1992]. Neural networks are comprised of nodes with weighted connections followed by a summer and a transfer function as shown in Fig. 4.4. The transfer functions make decisions based on the level of the weighted sum from the input nodes. The weights are learned based on training data sets. This technique is similar to statistical pattern recognition because they both require a large collection of training data, not expert knowledge to work well.

Advantages of neural networks are rapid evaluation and versatility to learn arbitrary patterns. Disadvantages include no information for providing solution explanations is available and it can operate in concurrent mode only.

In conclusion, there are a large variety of classifier designs. Each has different levels of capability and complexity. Choosing which one to use depends on the characteristics of each particular problem.

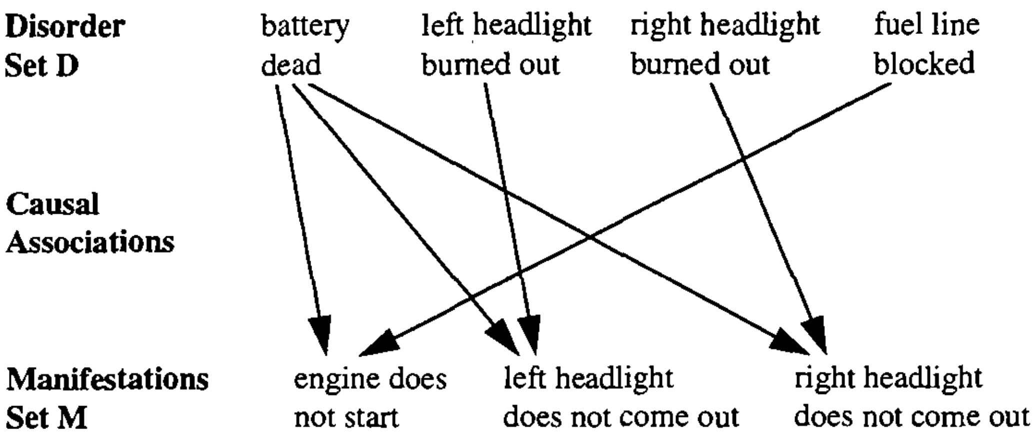

Figure 4.3. Semantic network used to diagnose a fault in a car.

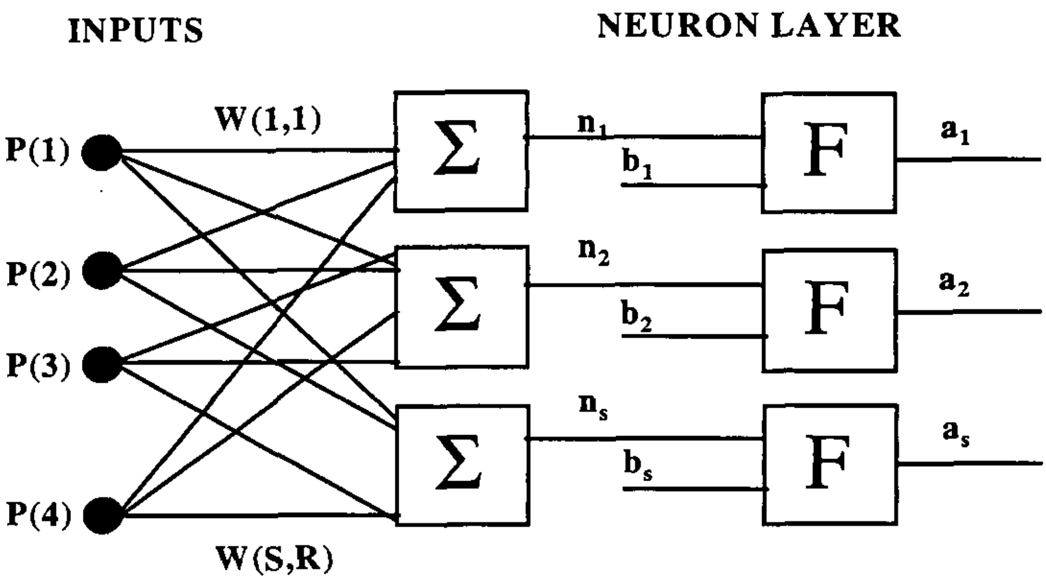

*Figure 4.4. Neural network. Symbols are: inputs (P), weights (W), bias (b), summer output (n), transfer function (F), and outputs (a). A = F(W * P + b).*

4.1.1.4 Evaluation

Fault evaluation assesses the impact of a fault on overall system performance. In simple FDD systems, only faults with an obviously severe impact on performance (eg broken fan belt) are considered to eliminate the need for this step. Without this step, it must be obvious that the benefit of servicing the fault justifies its expense. There are two types of faults: hard failures and performance degradations. Hard failures are severe and abrupt faults for which evaluation is often not necessary. Performance degradations are gradually evolving faults such as heat exchanger fouling. When these faults are considered, it is not obvious when they have become severe enough to justify the service expense. This is when fault evaluation is necessary to make this decision based on the impact of the fault on overall system performance.

Economic considerations alone can be used to determine if the cost of service is justified by minimizing lifetime operating costs. Important costs include service, energy, downtime (i.e. the cost of not maintaining comfort of refrigeration setpoint), safety hazards (e.g. slugging a compressor), and environmental hazards (e.g. refrigerant leak). The later three costs are difficult to quantify. It is possible to eliminate the need for these costs by assuming that the cost of servicing a fault that causes downtime, safety problems, or environmental hazards is small compared to the financial impact of the fault. Making this assumption leads to the following four fault evaluation criteria:

1. ECONOMIC - Service to minimize the combined costs of energy and sevice.

2. COMFORT - Service equipment when it is not capable of maintaining the control setpoint.

3. SAFETY - Service equipment when its operating state is leading to premature component ware (e.g. compressor slugging) or a personal safety hazard (e.g. high head pressure).

4. ENVIRONMENTAL HAZARD - Service equipment when there is a refrigerant leak that is harming the environment.

Separate subsystems can be designed to evaluate each of these criteria independently. Any one of them can justify service alone. Another way to visualize these criteria is as a constrained (comfort, safety, and environment) minimization of energy and service costs.

4.1.1.5 Reaction decision

Having detected, diagnosed, and evaluated a fault, a decision must be made on how to react to it. Four possible alternatives (in order of severity) are tolerate it, repair it as soon as possible, adapt the control, and stop operation until it is repaired. The fault should be tolerated if its impact on overall system performance is not severe enough as determined by the evaluation criteria. An example of a tolerable fault is mild heat exchanger fouling that may be detected by a sensitive FDD system. A fault should be repaired as soon as possible when it satisfies the economic, comfort, or environmental hazard criteria. However, if the fault is generating an unsafe condition, then the control can be adapted or the operation stopped until the fault can be repaired. Adaptive control (e.g. reducing compressor speed to prevent slugging when an evaporator fouls) is a sophisticated solution that may not become practical for a long time.

4.1.1.6 Learning techniques

Before they can be used for FDD, preprocessor models and classifiers must be taught what to expect under nominal and faulty conditions. This can be done in a controlled environment before commissioning the FDD system and/or on-line while the FDD system encounters naturally occurring faults. Controlled learning can be accomplished by experimentation (i.e. measuring the response of an actual piece of equipment) or observing the response of a detailed mechanistic model to imposed operating conditions and simulated faults. Controlled experimentation is the only type of learning process used in the literature. Mechanistic model-based learning has great potential for creating a good absolute reference for performance which does not assume that the unit being tested is operating properly at the beginning of the learning process. This technique can also be used to catch design errors. On-line learning occurs after the FDD system has been commissioned. When the system is expected to be performing well (e.g. immediately after commissioning or after a repair or cleaning), the current measurements can be used to learn nominal performance. Also, immediately before service, when the system is known to be faulty, fault models can be learned.

4.1.2 Performance criteria for evaluating FDDE systems

There are many different ways to design an FDDE system. Furthermore, there is no best solution to every problem because engineering designs always involve trade-offs between competing priorities. This section briefly describes some performance criteria for judging the relative qualities of FDDE designs.

Classically, FDD systems have been judged mainly by sensitivity, false alarm rate, and detection speed. Decision thresholds are determined by balancing these three criteria. Many design improvements are intended to provide better sensitivity and/or detection speed without increasing the false alarm rate. In HVAC&R applications, detection speed is generally not an important criteria. False alarm rate is critical because users will quickly abandon a system that calls for service needlessly. Given an acceptable false alarm rate, the best possible sensitivity should be obtained given the budget, available tools, and development schedule for the project.

Considering the problem of FDDE for HVAC&R applications, several more performance criteria have emerged.

1. Do the decision rules apply to a broad range of equipment or to only a specific piece of equipment or model that controlled experiments were conducted on?

2. Is the knowledge base static or self-learning?

3. Can the FDDE system detect multiple simultaneous faults well?

4. Does the FDDE system evaluate rules statistically to explicitly consider the effects of measurement noise?

5. Does the FDDE system use models to quantify the effect of changing independent variables?

6. Are model-based FDDE systems robust against modeling errors?

7. Are the impact of faults evaluated or assumed to be severe enough to require immediate repair?

Depending on the application, some of these criteria will be more important than others and they are all competing with cost and development time. From a research perspective, designs that score higher will certainly make a longer lasting contribution to the FDDE field.

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4.2 INNOVATION APPROACHES TO FDD

4.2.1 The use of physical models for FDD

Salsbury, T. I. & Haves, P.,
University of Technology, Loughborough, U.K.

4.2.1.1 Introduction

'Physical' models (also referred to as 'analytical', 'white-box' or 'first-principles' models) are quantitative mathematical models that are constructed using equations derived from a theoretical analysis of the physical processes occurring in a system (e.g. heat and mass balances). This analysis is used to determine the mathematical structure of the models and to define parameters that relate to measurable system properties. In practice, it is often necessary to supplement the physical equations with established empirical correlations. This is most beneficial when the complexity associated with describing a particular aspect of a system using a first principles analysis is excessive. In contrast to 'black-box' models (also known as 'empirical' models), physical models make as much use as possible of prior knowledge about the system being modelled.

Since the parameters of physical models relate to system properties, their values can, in principle, be measured directly from the real system, or obtained from system design and manufacturer's data. In practice however, accurate measurements of certain system properties, particularly the more empirical properties (e.g. heat transfer resistances) can be difficult to make, leading to uncertain parameter estimates. The use of design and manufacturer's data, although convenient, may lead to significant errors in the values of the parameters if the system as installed is significantly different from the system as designed.

A more reliable model can be obtained by using operational data gathered from the real system to refine the values of the parameters that have been calculated from system properties. The operational data ('training' data) consists of the inputs and outputs to the system measured at different points in the operating range. Parameter values that produce a good fit of the model to the data are then identified. The training data can also be used to evaluate the appropriateness of the model and estimate prediction accuracy thresholds.

Ideally, the training data should be collected over the whole of the operating range of the system in order to produce the most accurate parameter values and the most complete check of the adequacy of the structure of the model. For applications such as HVAC systems, which are primarily driven by the effects of weather and occupancy, it may be difficult or expensive to collect data that cover the whole of the operating range within realistic time frames. However, in cases where the coverage of the training data is incomplete, physical models are, by virtue of their predefined mathematical structure, likely to be more reliable than black box models for interpolation and extrapolation [Fargus and Dexter 94].

4.2.1.2 FDD schemes based on physical models

Model-based fault detection and diagnosis has been used in a wide range of applications, e.g. [Patton et. al. 95; Isermann 95; Benouarets et. al. 94; Gertler 88]. Models are used to detect changes in the relationship between the measured inputs and outputs of a system. Model-based fault detection requires a *reference* model of correct operation in order to detect changes in the operation of the system. Two ways in which the reference model can be used for fault detection and diagnosis are:

1. By using the reference model to predict the current outputs of the system and comparing these with measured outputs ('output innovations').

2. By comparing the parameters of the reference model with the parameters of another identically structured model representing the current observed behaviour of the real system ('parameter innovations').

Both of these approaches look for changes (termed 'innovations' since they signal the occurrence of something new). The first approach looks for changes in measurable variables, while the second approach looks for changes in properties that are not directly measurable. Each approach is described in more detail in the sections that follow.

Output innovations

One way to detect faults is to use a reference model of the correctly operating system to predict current system outputs. In this approach the predictions are compared with measured outputs and any discrepancies that occur are regarded as being due to the system deviating from its correctly operating condition. If the innovations exceed a predetermined threshold then a fault is deemed to have occurred [Usoro et. al. 85]. A diagnosis can be produced by analysing the way in which the innovations vary (e.g. by examining the variation with respect to operating point [Salsbury et. al. 95]). Any sort of quantitative model can be employed in this sort of scheme as the structure of the model is not important during operation. However, the way in which the reference model is configured initially *is* related to the type of model used. Physical models have meaningful parameters and their values can be estimated from design/manufacturers data. Although training data should also be obtained to validate the model and refine the parameter estimates if necessary, the amount of training data required is smaller than the amount required by black-box models. In HVAC applications, the gathering of training data can be difficult and the use of physical models can therefore help to alleviate this problem. An FDD scheme based on output innovations is depicted in Figure 4.5.

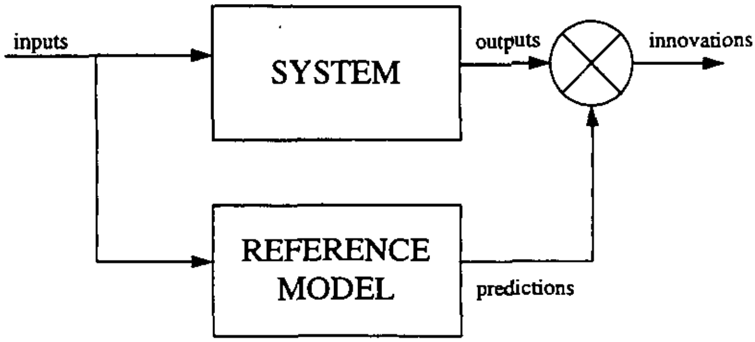

Figure 4.5. Output innovations-based approach.

The innovation-based approach can be a robust method for fault detection and it is capable of providing simple diagnostics. However, the potential to provide comprehensive diagnoses is limited, largely due to the difficulty associated with deriving rules that are able to distinguish between different types of faults, and different magnitudes of faults, purely from the innovations of the system outputs.

An alternative approach to diagnosis is to use models of faulty operation in parallel with the model of correct operation. A significant innovation with respect to any of the models, correct or faulty, indicates that the current state of the system is incompatible with that model. Those models that do not generate a significant innovation represent possible states of the system. As the system changes operating point, different models will generate significant innovations and the states of the system that correspond to these models will be eliminated from the list of possible states. If the operating points experienced by the system span the whole of the operating space, it should be possible to eliminate all possible states except the correct one. However, since faults may arise on shorter time-scales than the time-scale on which the operating range is covered, some form of forgetting is required, so that states that have been eliminated are gradually restored to the list of possible states. A further difficulty with this approach is the need to use multiple models to represent differing degrees of the same fault.

Parameter innovations

The parameter innovations approach involves estimating the values of model parameters from the measurements of system inputs and outputs. The parameters whose values are estimated during operation are those whose values are expected to change in the event of a fault occurring; these may be only a subset of the parameters of the model. If the structure of the model matches the behaviour of the system, the values of these parameters will be relatively constant when the system is operating correctly. A diagnosis is produced by analysing the way in which the estimated parameters vary from their initial reference values. If the parameters are physically meaningful, the diagnosis task is greatly simplified since the type and magnitude of fault can be inferred directly from the variations in the value of the parameters (e.g. a change in the heat transfer resistance of a heat exchanger may be attributed to a build-up of fouling). It is important that the model not be over-parameterised and that deficiencies in the structure of the model do not lead to the estimated values of the parameters being significantly different from the true values in order to compensate for these deficiencies, since it is the physical significance of the parameters that forms the basis of this FDD scheme. Figure 4.6 illustrates an FDD scheme based on parameter estimation.

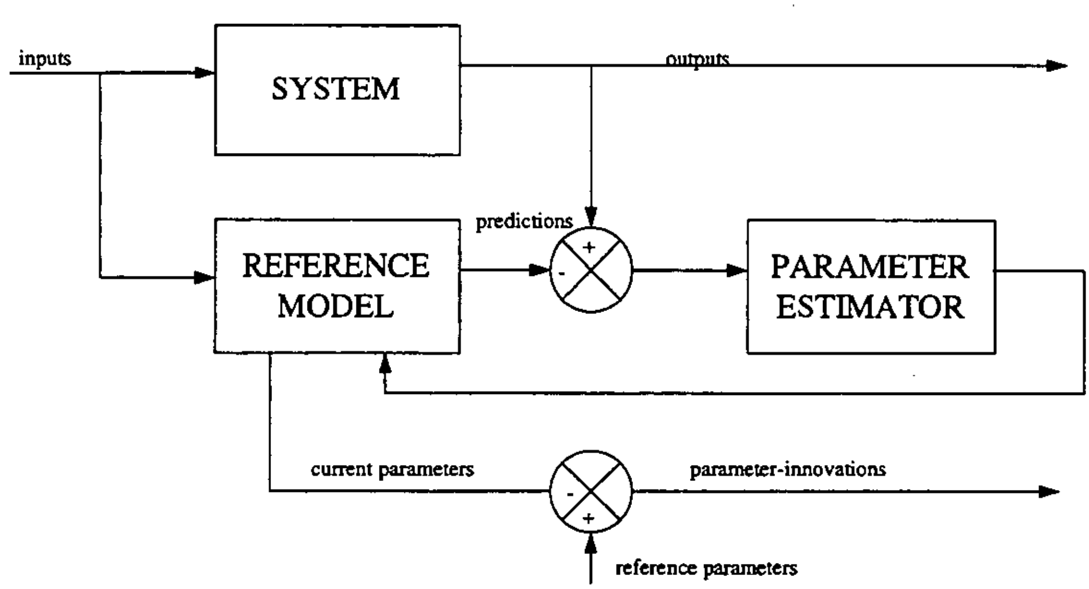

Figure 4.6. Parameter innovations-based approach.

One problem with using physical models as part of a parameter estimation scheme is that these models are not usually linear-in-the-parameters. Non-linear estimation methods are more expensive computationally and less robust than methods designed for linear systems. However, it has been found that slow changes in parameter values resulting from degradation faults can be tracked successfully using non-linear estimation techniques [Haves et. al. 96]. Robustness problems generally occur when there is a sudden, large, change in the parameter value(s) due to an abrupt, failure, fault. The parameter innovation approach is therefore not suited to the diagnosis of failure faults, although any estimator based (directly or indirectly) on the magnitude of the model prediction error will be capable of *detecting* such faults. (A broader problem that affects all fault diagnosis methods is that relatively little information is generated by a failed component, and hence it is difficult to produce a diagnosis without using test signals.)

4.2.1.3 Example: Physical models of air-water heat exchanger sub-systems

All FDD systems depend on measurements made by sensors in the target system. If an FDD system is to depend largely or exclusively on the BMS sensors, the division of the HVAC system into sub-systems will be determined by the control loops. In the case of heating and cooling coils, the sub-system will consist of the coil itself, the valve, the actuator and any temperature, flow rate or humidity sensors associated with either the air or the water streams flowing through the coil. Steady state physical models of these components have been developed for use in model-based FDD systems and are described in the sections that follow (see also [Haves 94]). The models treat the fault-free operation of a heating coil or dry cooling coil subsystem and also treat valve leakage and the direct thermal effects of coil fouling.

Actuator

Actuators affect both the dynamic and the steady state behaviour of coil sub-systems. The finite speed of travel affects only the dynamic behaviour. Hysteresis and positioner dead-band affect both the dynamic and the steady state behaviour, although the steady state behaviour is only affected to a modest extent unless their magnitude is large. The steady state performance is also affected by mismatches between the range of movement of the actuator and the range of movement of the valve. Such a mismatch may result in the valve failing to open or close fully or, particularly if the range of the actuator is deliberately selected to be larger than the range of the valve in order to avoid these problems, the valve may not start to move until the actuator has moved a significant distance from the end of its range. Whereas this behaviour may occur at either (or both) end(s) of the range, it has a greater effect on the performance of the coil at the closed end of the range, due to the significantly non-linear response of the coil to variations in flow rate and the common practice of over-sizing control valves. A simple model that treats such a mismatch at the closed end of the range is:

$$s = \left(\frac{u - v}{1 - v}\right) \tag{4.1}$$

where s is the valve stem position, u is the control signal (assumed to be equal to the actuator position in steady state) and v is the actuator position at which the valve starts to open. Both s and u lie in the range 0 - 1.

Valve model

All cooling coils and many heating coils are controlled by varying the water flow rate through the coil. Three-port mixing valves are most commonly used, although two-port valves are increasingly being used due to the availability of variable speed pumps. An exponential, or 'equal percentage' characteristic is used for the two-port valve and for the flow port of the three-port valve. The relationship between valve stem position and water flow rate through the coil (the 'installed characteristic') depends on the inherent characteristic of the valve and the authority of the valve (i.e. the ratio of the pressure drop across the valve to the total pressure drop across the valve and coil etc, measured when the valve is fully open).

Valves that have a nominally exponential characteristic and a high rangeability (i.e. a dynamic range of significantly more than 20:1 in flow rate) depart from a pure exponential characteristic in the lower part of their operating range (e.g. $s<0.33$). A simple approximation to such characteristic is provided by the modified exponential function:

$$f = \left(\frac{\exp(Ns) - 1}{\exp(N) - 1}\right) \tag{4.2}$$

where f is the fractional flow rate at constant pressure drop and N is a parameter that determines the shape of the characteristic.

Leakage may be incorporated in (at least) two different ways:

$$f = \max\left(\frac{(\exp(Ns) - 1)}{(\exp(N) - 1)}, C_L\right) \tag{4.3}$$

$$f = s\frac{(\exp(Ns) - 1)}{(\exp(N) - 1)} + (1 - s)C_L \tag{4.4}$$

where C_L is the fractional leakage flow.

Equation 4.3 is simpler, but Equation 4.4 has a continuous first derivative, which is advantageous if a gradient-based method of parameter estimation is used. Leakage may arise in a number of ways, including erosion of the valve seat and restriction of the movement of the plug due to the presence of foreign matter. The exact effect on the valve characteristic is unknown and can be expected to vary with both the cause of the leak and the design of the valve itself.

The installed characteristic is related to the inherent characteristic by:

$$f^1 = \left[Af(s)^{-2} + (1 - A)\right]^{-0.5} \tag{4.5}$$

where f^1 is the fractional flow rate when the pressure drop across the valve and coil is constant and A is the authority of the valve. The installed characteristic corresponding to Equation 4.4 is then:

$$f^1 = \left[A(s\frac{(\exp(Ns) - 1)}{(\exp(N) - 1)} + (1 - s)C_L)^{-2} + (1 - A)\right]^{-0.5} \tag{4.6}$$

Substituting Equation 4.1 into Equation 4.6 yields the relationship between fractional flow rate and control signal:

$$f^1 = \left[A(\frac{u - v}{1 - v})\frac{(\exp(N(\frac{u - v}{1 - v})) - 1)}{(\exp(N) - 1)} + (1 - \left(\frac{u - v}{1 - v}\right)C_L)^{-2} + (1 - A)\right]^{-0.5} \tag{4.7}$$

Approximate values of A and N can be obtained from manufacturers' data. These values can be used as initial estimates when estimating the parameters of the model using training data. Significant differences between the estimated and initial values may indicate faulty components or faulty installation. To avoid over-parameterisation, u and C_L should both be constrained to be positive since the effect of either one being negative is similar to that of the other being positive, at least for small magnitudes.

Heat exchangers

The outlet air temperature from a heating coil or a dry cooling coil can be predicted from the inlet air and water temperatures by calculating the air side approach using the appropriate effectiveness-NTU relationship. Although both heating and cooling coils generally have a cross-flow configuration, the performance of cooling coils approximates that of a counterflow heat exchanger when the number of rows of tubes exceeds about four.

Cooling coil:

$$T_{ao} = T_{ai} - \epsilon\frac{C_{min}}{C_a}(T_{ai} - T_{wi}) \tag{4.8}$$

where T_{ao} is the outlet air temperature, T_{ai} is the inlet air temperature, T_{wi} is the inlet water temperature, C_{min} is the lesser of the air capacity rate, C_a, and the water capacity rate, C_w, and the effectiveness, ϵ, is given by:

$$\epsilon = \frac{1 - \exp(-NTU(1-\omega))}{1 - \omega \exp(-NTU(1-\omega))} \tag{4.9}$$

where ω, the ratio of the capacity rates, is given by:

$$\omega = \frac{C_{min}}{C_{max}} \tag{4.10}$$

and NTU, the number of transfer units, is given by:

$$NTU = \frac{UA}{C_{min}} \tag{4.11}$$

where UA is the overall conductance of the coil.

Heating coil: A heating coil can be treated as a cross flow heat exchanger in which the air is unmixed and the water is unmixed *(in the direction of the flow of the other fluid)*. If the air has the greater capacity rate, the effectiveness is given by:

$$\epsilon = 1 - \frac{\exp(-(1 - \exp(-NTU\,\omega)))}{\omega} \tag{4.12}$$

If the water has the greater capacity rate, the effectiveness is given by:

$$\epsilon = \frac{1 - \exp(-\omega(1 - \exp(-NTU)))}{\omega} \tag{4.13}$$

The water side capacity rate is determined from the fractional flow rate, f^1 (Equation 4.7) and the maximum flow rate as measured during commissioning. The air side capacity rate is determined from the air flow rate, which is either measured during commissioning, in the case of constant air volume systems, or measured continuously, in the case of variable air volume systems.

In each case, a fixed value of UA may be used, or alternatively, UA can be treated as a function of the fluid flow rates in order to increase the accuracy of the model:

$$\frac{1}{UA} = \frac{1}{(\eta hA)_a} + \frac{1}{(hA)_w} + R_t \tag{4.14}$$

$$(\eta hA)_a = a \dot{m}_a^{0.8} \tag{4.15}$$

$$(hA)_w = c \dot{m}_w^{0.8} \tag{4.16}$$

where η is the fin global effectiveness, h is the convective surface heat transfer coefficient, A is the area and subscripts a and w indicate the air and water sides, respectively. R_t is the resistance of the tube wall, which can be considered negligible unless fouling is present. Parameters a and b are estimated from training data collected at commissioning time, with R_t=0. a and b are then fixed and the value of R_t is estimated from operating data in order to monitor the occurrence of fouling.

The parameters of the overall model of the actuator, valve and coil are listed in Table 4.1, together with the way in which their value is obtained.

Table 4.1.

Parameter	Meaning	Source
N	inherrent valve characteristic	manufacturer's data
$\dot{m}_{w,\max}$	maximum water flow rate	commissioning data
A	value authority	training data
u	valve-actuator mismatch	training data
a	coil air-side resistance parameter	training data
b	coil water-side resistance parameter	training data
C_L	valve leakage	Operating data
R_t	tube resistance (fouling)	Operating data

4.2.1.4 Parameter estimation

Depending on the method used, parameter estimation is required at two distinct stages:

1. At commissioning time, to determine the values of all the parameters required to predict behaviour of the sub-system in the absence of faults

2. During normal operation, to determine the values of those parameters that relate to faults.

Both the output innovation approach and the parameter innovation approach require estimation of the parameters of the fault-free system, which should be estimated from a comprehensive set of operational data collected over a short period of time when the system is supposed to be operating correctly. There is no need for the estimation to be recursive, and significant computational resources (e.g. a high performance PC) can be devoted to the process, since it is only performed once. A direct search technique, such as Box's Complex Method [Box 65], can be used if necessary. Initial values for the parameters may be obtained from design information and manufacturers' data. If the target sub-system is a mass-produced product, e.g. a VAV box, rather than a bespoke item, e.g. a built-up air handling unit, the parameters may be estimated by the manufacturer rather than on site. In this case it should only be necessary to estimate the parameters once for each model, rather than repeating the process for each item.

In the parameter innovation approach, the parameters relating to specific faults are estimated from data collected during normal operation. These parameters may either be estimated recursively or be re-estimated periodically from a comprehensive set of data collected from operating points that span the operating space.

4.2.1.5 References

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11

4.2.2 ARMAX model approach

'BLACK BODY'

Yoshida, H.,
Kyoto University, Japan

Of the various mathematical models which can produce inovations, the following ones are often used for fault detection (FD) because of their simplicity; an Autoregressive Exogenous (ARX) and an Autoregressive Moving Average Exogenous (ARMAX) model. The ARMAX is a more sophisticated model than the ARX, the number of the parameters is generally small. No knowledge of the inside system structure is considered in these models; namely the model is categorized as a black box type. Utilizing the obtained model fault detection can be achieved ~~by carrying~~ out statistical tests not only on the residuals but also on the model parameters (Fig. 4.7). A model that represents the system dynamics better can give high reliability and promptness of the fault detection.

Choosing an appropriate model type and incorporating a good parameter identification method is important. Many techniques assuring low computational cost and good stability are widely available ([4.48 - 4.50]) However, since the model is a black box type, if no information related to the system structure is given, diagnosing a fault is hardly possible. This is one of the limitations of this method. Many FD applications have been reported based on this method, however, very little is done in the field of HVAC systems. In Annex 25, applications can be found, for example, in [4.51 - 4.54].

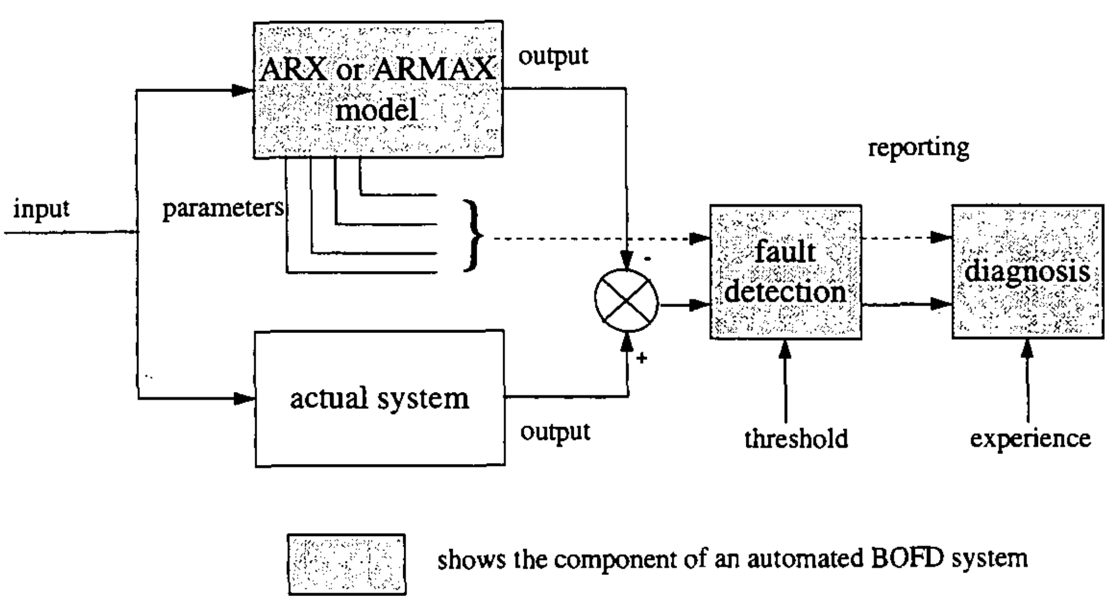

Figure 4.7. Fault detection and diagnosis with ARX and ARMAX model.

4.2.2.1 Mathematical expression of the model

The mathematical expression of the ARX and ARMAX models are as follows;

1) Autoregressive Exogenous (ARX) model

$$x_n = -\sum_{i=1}^{M} a_i \, x_{n-i} \quad + \quad \sum_{i=0}^{K} b_i \, u_{n-i} \quad + \quad e_n \tag{4.17}$$

where

x_n	: recorded output at time n
a_i	: autoregressive parameters
M	: order of an AR part
u_n	: recorded input at time n
b_i	: exogenous parameters
K	: order of an exogenous part
e_n	: residuals (considered to be white noise)

The above expression can be written as follows.

$$A(z^{-1})\, x_n = B(z^{-1})\, u_n + \quad e_n \tag{4.18}$$

where

$$A(z^{-1}) \;=\; 1 + a_1 z^{-1} + \;\cdots\; + a_M z^{-M}$$

$$B(z^{-1}) \;=\; b_0 + b_1 z^{-1} + \;\cdots\; + b_N z^{-N}$$

and z^{-1} denotes a shift operator for example $z^{-1} x_n = x_{n-1}$.

The predicted output $\hat{x}_n$ by the model is obtained as follows.

$$\hat{x}_n = [1 - A(z^{-1})\,]x_n \quad + \quad B(z^{-1})\, u_n \tag{4.19}$$

2) Autoregressive Moving Average Exogenous (ARMAX) model

$$x_n = -\sum_{i=1}^{M} a_i \, x_{n-i} \quad + \quad \sum_{i=0}^{K} b_i \, u_{n-i} \quad + \quad \sum_{i=0}^{N} c_i \cdot e_{n-i} \tag{4.20}$$

where

c_i	: moving average parameters
N	: order of a moving average part

An expression similar to Equation (4.18) is as follows.

$$A(z^{-1})\,x_n = B(z^{-1})\,u_n \quad + \quad C(z^{-1})\,e_n \tag{4.21}$$

where

$$C(z^{-1}) = 1 + c_1 z^{-1} + \cdots + c_N z^{-N}$$

The predicted output $\hat{x}_n$ by the model is written as follows.

$$\hat{x}_n = [1 - \frac{A(z^{-1})}{C(z^{-1})}]\,x_n \quad + \quad \frac{B(z^{-1})}{C(z^{-1})}\,u_n \tag{4.22}$$

A common criterion for determining the best model or the best parameter set is the least square criterion which requires minimization of the following value.

$$J = \sum_{n=1}^{L} (x_n - \hat{x}_n)^2 \tag{4.23}$$

Many types of identification methods are available: Least Square (LS) method, Recursive Least Square (RLS) method, Instrumental Variable (IV) method, Generalized Least Square (GLS) method, Extended Least Square (ELS) method, Maximum Likelihood (ML) method, Prediction Error (PE) method, etc. All the methods having recursive computation forms, such as the RLS, are useful because this form is suitable for on-line identification and can be easily employed in real time fault detection (4.55).

As mentioned before the model is categorized as a black box model, therefore, the model structure or the order of terms for an autoregressive, moving average and exogenous component is not fixed beforehand for a system. That is, the order has to be found during an identification process according to some criterion. An information theoretic criterion (AIC) proposed by Akaike is often used (4.56).

$$AIC(p) = L\log(\frac{J}{L}) \quad + \quad 2p \tag{4.24}$$

where

P	: number of parameters
L	: number of data

By minimizing the value of AIC , the best order is obtained. This means that a higher order model is not necessarily better than a lower order model. The AIC may also be used for residual test.

4.2.2.2 Implications in model building

Mathematically an ARX or ARMAX model represents a stationary linear model. In practice most actual systems have non-linear properties and are only more or less quasi-stationary. Therefore, when an actual system has significant non-linear and non-stationary characteristics, some considerations must be taken to perform good identification.

One approach is to introduce a forgetting factors into the identification process. The idea of this approach is that past data are not as important for present identification so reduce the contribution of the past data by multiplying by forgetting factor r. By doing so, model parameters can vary with time to fit the present state, namely, a non-stationary system can be identified. In addition, if the operating point of the system changes gradually, the identified model can be taken as the linearly approximated model of a non-linear system near the operating point.

When the RLS identification method for an ARX model is applied, the forgetting factor is implemented as follows.

$$\hat{\theta}_n = \hat{\theta}_{n-1} + h_n\,(x_n - \phi_n^T\,\hat{\theta}_{n-1})$$

$$h_n = \frac{P_{n-1}\,\phi_n}{\rho + \phi_n^T\,P_{n-1}\,\phi_n} \tag{4.25}$$

$$P_n = \rho^{-1}\,[I - h_n\,\phi_n^T\,]\,P_{n-1}$$

where

$\hat{\theta}_n$: vector of estimated parameters. i.e. $(a_1, a_2, \cdots a_M, b_1, b_2, \cdots b_K)^T$

ϕ_n^T : vector of input and output data.

i.e. $(-x_{n-1}, -x_{n-2}, \cdots, -x_{n-M}, u_{n-1}, u_{n-2}, \cdots, u_{n-K})$

The value of ρ is chosen empirically between 0.95 and 0.99. If ρ is set 1.0, the method becomes identical to the common RLS method.

Another way to cope with the non-linearity is a method using non-linear variables as input. This method is predicated on the fact that the non-linear characteristic of a system is given or the relation between output and input is formulated by a non-linear polynomial. Then ARX or ARMAX models can be applied taking the non-linear terms as input data.

As an example, an application to an air handling unit is shown. The output, Q of a heating coil is given by the following non-linear formula.

$$\dot{Q} = \alpha_0 + \alpha_1\,v_p + \alpha_2\,v_p^2 + \alpha_3\,\dot{m}_a + \alpha_4\,\dot{m}_a^2 + \alpha_5\,(\dot{m}_a\,v_p) \tag{4.26}$$

where

v_p : the heating valve position

$\dot{m}_a$: the mass flow rate of the air flowing through the coil

The ARX model of the system is formulated as follows.

$$\dot{Q}_n = -a_1\dot{Q}_{n-1} + \mathbf{c}_0\mathbf{u}_n + \mathbf{c}_1\mathbf{u}_{n-1} \tag{4.27}$$

where

c parameter vector of exogenous term. i.e.
c = $(c_1, c_2, \cdots\ c_5)$

u_n input data vector. i.e.
$u_n = \{(v_p)_n, (v_p^2)_n, (m_a)_n, (m_a^2)_n, (m\,v_p)_n\}^T$

4.2.2.3 Fault detection

The residuals obtained as the difference between actual output of a system and model output should become white noise if the model is well identified and no fault exists in the system. Therefore a fault can be detected by testing whether the residuals are white noise or not. The test is carried out statistically, for instance, testing the average of the residuals, the square mean, the variance, the auto-covariance and the summation of the square of auto-covariance. Generally the performance of the latter test is best. The auto-covariance function of residuals is defined by

$$\phi(\tau) = \frac{1}{L-\tau}\sum_{k=\tau+1}^{L} e_k e_{k-\tau} \quad . \tag{4.28}$$

where

$e_{k-\tau}$: the sequence e_k shifted by τ-steps

Using $\phi(\tau)$, the vector of residual auto-correlation becomes

$$r_{ee} = \frac{1}{\phi(0)}[\phi(1), \cdots, \phi(L)]^T \quad . \tag{4.29}$$

The 95%-confidence interval for asymptotic distribution of each component of the vector of residual auto correlations is given by

$$[-\frac{1.96}{\sqrt{L}}, \frac{1.96}{\sqrt{L}}] \quad . \tag{4.30}$$

If each component of the auto-corvariance, $\phi(\tau)$, is within this confidence interval, the condition of the k-th instant can be said to be normal. The method for testing auto-covariance, $\phi(\tau)$, is shown below. This method is often used because of its good performance and simplicity. If the following test fails:

$$|\phi(\tau)| \leq \frac{1.96}{\sqrt{L}}, \quad \tau \geq 1 \tag{4.31}$$

Then the probability of a fault occurring in the system is statistically significant.

Another method is based on the test of model parameters, deviation from the normal values. Namely, the occurrence of a fault is detected by testing whether the following value exceeds a threshold during identification.

$$S = (\bar{\theta} - \hat{\theta})(\bar{\theta} - \hat{\theta})^T \tag{4.32}$$

where

$\bar{\theta}$: parameter vector of normal operation

$\hat{\theta}$: parameter vector of test period

Several other methods can be used for fault detection, such as testing the AIC values (4.57).

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4.2.3 State estimation methods

Peter Sprecher
Landis & Gyr Building Control, Switzerland

4.2.3.1 Principle of fault detection via state estimation

Fault detection via state estimation is based on a plant model driven by the same inputs as the plant. The model is used to estimate the plant states and, based upon these, the plant outputs. The differences between the true outputs and the estimated ones, the so called residuals, are fed back into the model to achieve convergence with respect to initial conditions. This leads to an observer or Kalman filter. In the case of faults the true outputs will deviate from the estimated ones, leading to nonzero residuals. The residuals therefore serve as fault indicating signals and their evaluation leads to fault decisions. Fig. 4.8 illustrates this approach. For a survey about similar approaches see Frank [4.69].

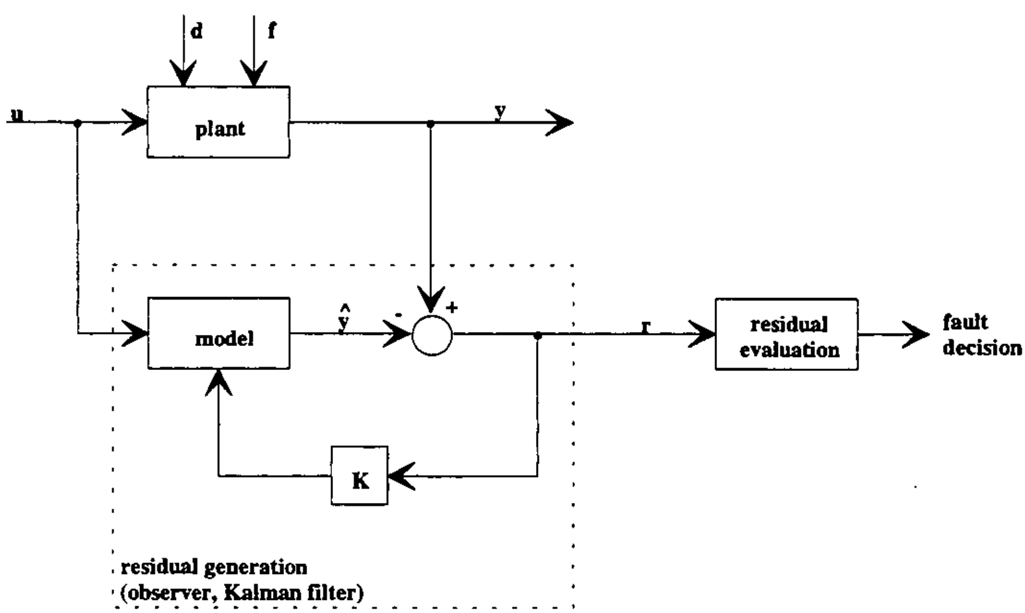

Fig. 4.8. Principle of fault detection via state estimation.

u: known input vector
y: output vector (measurements)
$\hat{\mathbf{y}}$:expected output
d: unknown input vector, disturbances
f: unknown fault vector
r: residual vector

4.2.3.2 Fault detection using Kalman filters and observers

There are two main state estimation based approaches to residual generation, the Kalman filter approach and the observer approach. Kalman filters are used to estimate the state of <u>stochastic</u> systems, i.e. systems with random disturbances. Observers originally were designed to reconstruct the state of <u>deterministic</u> systems, i.e. systems without or with known disturbances. Later observers have been generalized, enabling them to become robust against selected disturbances. The two approaches lead to rather different designs and properties of the underlying state estimator. Therefore they are treated separately in the following descriptions of the preprocessor and the classifier.

Preprocessor

Here the preprocessor is the residual generation block shown in Fig. 4.8.

Kalman filter approach

Assume that in the fault-free case the plant in Fig. 4.8 can be described as

$$\left.\begin{aligned} \mathbf{x}(k+1) &= \mathbf{A}\,\mathbf{x}(k) + \mathbf{B}\,\mathbf{u}(k) + \mathbf{v}(k) \\ \mathbf{y}(k) &= \mathbf{C}\,\mathbf{x}(k) + \mathbf{w}(k), \end{aligned}\right\} \tag{4.33}$$

where $\mathbf{x}$ is the state vector, $\mathbf{v}$ and $\mathbf{w}$ are linear transformations of the unknown disturbances $\mathbf{d}$, and $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{C}$ are <u>known</u> matrices of appropriate dimensions. For simplicity consider the discrete time case only. Assume further that:

$$\mathbf{x}(0),\ \mathbf{v}(0), \mathbf{v}(1), \ldots,\ \mathbf{w}(0), \mathbf{w}(1), \ldots \quad \text{are independent random variables} \tag{4.34}$$

$$E[\mathbf{x}(0)] = \bar{\mathbf{x}}_0,\ \mathrm{Var}[\mathbf{x}(0)] = \mathbf{P}_0 \tag{4.35}$$

$$E[\mathbf{v}(k)] = \mathbf{0},\ \mathrm{Var}[\mathbf{v}(k)] = \mathbf{Q}(k),\ k=0,1,.. \tag{4.36}$$

$$E[\mathbf{w}(k)] = \mathbf{0},\ \mathrm{Var}[\mathbf{w}(k)] = \mathbf{R}(k),\ k=0,1,.. \tag{4.37}$$

With these assumptions the Kalman filter can be set up (see Mehra and Peschon [4.66]):

$$\hat{\mathbf{x}}(k+1|k) = \mathbf{A}\,[\hat{\mathbf{x}}(k|k-1) + \mathbf{K}(k)\,(\mathbf{y}(k) - \mathbf{C}\hat{\mathbf{x}}(k|k-1))] + \mathbf{B}\,\mathbf{u}(k) \tag{4.38}$$

$$\mathbf{r}(k) = \mathbf{y}(k) - \mathbf{C}\,\hat{\mathbf{x}}(k|k-1) \tag{4.39}$$

$$\mathbf{P}(k+1|k) = \mathbf{A}\,(\mathbf{I} - \mathbf{K}(k)\mathbf{C})\,\mathbf{P}(k|k-1)\,\mathbf{A}^T + \mathbf{Q}(k), \tag{4.40}$$

where

$$\mathbf{K}(k) = \mathbf{P}(k|k\text{-}1)\,\mathbf{C}^T\,(\mathbf{C}\mathbf{P}(k|k\text{-}1)\mathbf{C}^T + \mathbf{R}(k))^{-1} \tag{4.41}$$

$$\hat{\mathbf{x}}(0|\text{-}1) = \hat{\mathbf{x}}_0\,, \quad \hat{\mathbf{x}} = \text{estimate of } \mathbf{x}$$

$$\mathbf{P}(0|\text{-}1) = \mathbf{P}_0\,.$$

In the fault-free case the residual sequence $\{\mathbf{r}(k)\}$ can be shown to be a zero mean <u>white</u> noise with variance $\mathbf{C}\mathbf{P}(k|k\text{-}1)\mathbf{C}^T + \mathbf{R}(k)$. If in addition to Eqs. (4.34 - 4.37) $\mathbf{x}(0)$, $\mathbf{v}(k)$ and $\mathbf{w}(k)$, k=0,1,..., are normally distributed, $\mathbf{r}(k)$ is also normally distributed. These properties greatly ease residual evaluation.

According to Tödtli [4.63, sect. 3.1.2 and 3.2], $\hat{\mathbf{y}}(k|k\text{-}1) = \mathbf{C}\,\hat{\mathbf{x}}(k|k\text{-}1)$ is the bias-free estimator of $\mathbf{y}(k)$, the error of which has the smallest norm among the linear estimators. Therefore $E[\mathbf{r}^T(k)\mathbf{r}(k)]$ is minimal and $\mathbf{r}(k)$ possesses some robustness against disturbances.

For extensions to nonlinear systems see Usoro et al. [4.64].

Observer approach

Assume that the plant in Fig. 4.8 can be described as

$$\left.\begin{aligned} \mathbf{x}(k+1) &= \mathbf{A}\,\mathbf{x}(k) + \mathbf{B}\,\mathbf{u}(k) + \mathbf{E}_d\,\mathbf{d}(k) + \mathbf{K}_d\,\mathbf{f}(k) \\ \mathbf{y}(k) &= \mathbf{C}\,\mathbf{x}(k) + \mathbf{E}_m\,\mathbf{d}(k) + \mathbf{K}_m\,\mathbf{f}(k), \end{aligned}\right\} \tag{4.42}$$

where all matrices are known and of appropriate dimensions. To generate the residuals, a full-order Luenberger observer for the <u>fault-free</u> and <u>undisturbed</u> system can be designed:

$$\left.\begin{aligned} \hat{\mathbf{x}}(k+1) &= \mathbf{A}\,\mathbf{x}(k) + \mathbf{B}\,\mathbf{u}(k) + \mathbf{K}(\mathbf{y}(k) - \mathbf{C}\hat{\mathbf{x}}(k)) \\ \mathbf{r}(k) &= \mathbf{y}(k) - \mathbf{C}\,\hat{\mathbf{x}}(k) \end{aligned}\right\} \tag{4.43}$$

A key problem of this observer is to choose the feedback matrix $\mathbf{K}$ such that the residuals $\mathbf{r}$ becomes insensitive to the disturbances $\mathbf{d}$. Instead of handling this problem directly Frank [4.59] and Wünnenberg [4.60] replace Eq. (4.43) by the generalized observer

$$\left.\begin{aligned} \mathbf{z}(k+1) &= \mathbf{F}\,\mathbf{z}(k) + \mathbf{J}\,\mathbf{u}(k) + \mathbf{G}\,\mathbf{y}(k) \\ \mathbf{r}(k) &= \mathbf{L}_1\,\mathbf{z}(k) + \mathbf{L}_2\,\mathbf{y}(k), \end{aligned}\right\} \tag{4.44}$$

offering more design freedom. For this observer scheme they develop so called optimal fault detection observers (OFDO), making the residuals $\mathbf{r}$ robust against the disturbances $\mathbf{d}$ and sensitive to the faults $\mathbf{f}$. As the design goal is no longer a good estimate $\hat{\mathbf{x}}$ of the state $\mathbf{x}$, the observer state is designated by $\mathbf{z}$ instead of $\hat{\mathbf{x}}$. Observing Eq. (4.42) and leaving out effects of initial conditions the residuals can be decomposed as

$$\mathbf{r} = \mathbf{r}_d + \mathbf{r}_f, \tag{4.45}$$

where $\mathbf{r}_d$ and $\mathbf{r}_f$ represent the residuals caused by the disturbances $\mathbf{d}$ and the faults $\mathbf{f}$ respectively. Replacing for simplicity the residual vector by a scalar residual, the design goal can be formulated as minimization of the performance index

$$J_r = \frac{E[r_d(k)^2]}{E[r_f(k)^2]}. \tag{4.46}$$

After choosing the order p and the characteristic polynomial N(s) of the observer, minimization of J_r leads to optimal observer matrices $\mathbf{F}$, $\mathbf{J}$, $\mathbf{G}$, $\mathbf{L}_1$, $\mathbf{L}_2$ (see Wünnenberg [4.60], section 3.3). However, the minimization procedure is not simple and it requires estimates of the matrices

$$\mathbf{C}_d = E[\ [\tilde{\mathbf{d}}^T(k),..\tilde{\mathbf{d}}^T(k-p)]^T \cdot [\tilde{\mathbf{d}}^T(k),..\tilde{\mathbf{d}}^T(k-p)]] \quad \text{and} \tag{4.47}$$

$$\mathbf{C}_f = E[\ [\tilde{\mathbf{f}}^T(k),..\tilde{\mathbf{f}}^T(k-p)]^T \cdot [\tilde{\mathbf{f}}^T(k),..\tilde{\mathbf{f}}^T(k-p)]], \tag{4.48}$$

where $\tilde{\mathbf{d}}$ and $\tilde{\mathbf{f}}$ are the disturbances and faults low-pass filtered by 1/N(s).

In certain cases $J_{r,opt} = 0$ independent of $\mathbf{C}_d$. The resulting observer is then completely insensitive to the disturbances $\mathbf{d}$ and is called 'unknown input fault detection observer' (UIFDO).

The residuals in Eq. (4.45) can be written in a form equivalent to one resulting from the parity space approach (see Gertler [4.61]).

Wünnenberg [4.60] extends his approach to the class of nonlinear systems described by Eq. (4.42) with the term $\mathbf{B}\,\mathbf{u}(k)$ replaced by $\mathbf{B}(\mathbf{u}(k), \mathbf{y}^*(k))$, where $\mathbf{y}^*(k) = \mathbf{N}_m\,\mathbf{y}(k) = \mathbf{N}_m\,\mathbf{C}\,\mathbf{x}(k)$, $\mathbf{N}_m\mathbf{E}_m = \mathbf{0}$ and $\mathbf{N}_m\mathbf{K}_m = \mathbf{0}$.

For another approach to the robustness problem see Patton and Chen [4.62].

Classifier

Here the classifier is the residual evaluation block shown in Fig. 4.8.

Residual evaluation is most simple if the residual sequence $\{\mathbf{r}(k)\}$ is a white Gaussian sequence with known mean and covariance. These conditions hold for a Kalman filter where the initial condition $\mathbf{x}(0)$ and the disturbances $\mathbf{v}(k)$ and $\mathbf{w}(k)$, $k=0,1,\ldots$, of the plant are normally distributed. For this case Mehra and Peschon [4.66] suggest simple parametric tests of whiteness, mean, and covariance. If the requirement for normality of $\mathbf{x}(0)$, $\mathbf{v}(k)$, and $\mathbf{w}(k)$ is dropped, $\{\mathbf{r}(k)\}$ is still white but has unknown distribution. In this case nonparametric tests are convenient [4.65, sections 5.6.3, 5.7.7, and 5.8.2]. The advantage of the tests mentioned so far is that they require only the H_0-distribution of $\{\mathbf{r}(k)\}$, i.e. the distribution in the fault-free case. However, they are often not robust with respect to deviations of the statistical properties of $\{\mathbf{r}(k)\}$ from the assumed ones (see [4.65], sections 5.6-8 and B.1.2.1). Due to this lack of robustness false alarms are to be feared.

Assume again that $\mathbf{x}(0)$, $\mathbf{v}(k)$, $\mathbf{w}(k)$, $k=0,1,\ldots$, and therefore also $\mathbf{r}(k)$ are normal. Willsky [4.67] considers as faults steps or jumps in the system Equations (4.33), e.g.

$$\mathbf{x}(k+1) = \mathbf{A}\,\mathbf{x}(k) + \mathbf{B}\,\mathbf{u}(k) + \mathbf{v}(k) + \mathbf{f}\,\varepsilon(k+1,k_F) \tag{4.49}$$

where $\mathbf{f}$ represents the fault size and direction, and $\varepsilon(k+1,k_F)$ is a unit step at time k_F-1. The residuals in the faulty case can be shown to be

$$\mathbf{r}(k) = \mathbf{G}(k, k_F)\,\mathbf{f} + \mathbf{r}_0(k)\,, \tag{4.50}$$

where $\mathbf{r}_0(k)$ is the residual vector in the fault-free case, and $G(k, k_F)$ is a failure signature matrix showing the effect of $\mathbf{f}$ on $\mathbf{r}(k)$. Now the generalized likelihood ratio (GLR) test can be set up (see Frank [4.59]):

$$l(k) = \max_{1 \le k_F \le k}\ \max_{\mathbf{f} \neq \mathbf{0}} \prod_{i=1}^{k} \frac{f(\mathbf{r}(i)|H_1,k_F,\mathbf{f})}{f(\mathbf{r}(i)|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \tag{4.51}$$

H_1 and H_0 represent the hypotheses 'fault $\mathbf{f}$ present' and 'no fault present' respectively. λ is a threshold to be selected. To simplifiy computations k_F can be constrained to a small subrange of $[1,k]$, and $\mathbf{f}$ can be given a fixed direction. According to Willsky [4.67] the GLR test is more powerful than the simple tests suggested by Mehra and Peschon [4.66].

Related to the GLR test is the Page-Hinkley test (see e.g. Basseville [4.68]). It is also a likelihood ratio test to decide which one of two probability laws can better describe a given sequence of observations. The Page-Hinkley test can drop old observations whereas the GLR test cannot.

For all tests mentioned so far thresholds are determined based on a selected false alarm probability. This is easy as long as the H_0-distribution of the test statistic can be determined. However, for the GLR test and the Page-Hinkley test the determination of this distribution can be difficult.

Evaluation of observer residuals

Residuals generated by the robust observers described in the preprocessor section have in general unknown statistical properties. Specifically they cannot be expected to be white.

The simplest evaluation method is to define some test quantity, e.g. an average residual across some moving time window, and to compare it with a fixed threshold. For proper threshold adjustment training data from the fault-free case are helpful.

Note that further filtering, e.g. whitening, of the residual $r = r_d + r_f$ generated by an optimal fault detection observer is not advisable, because the filtered components $\tilde{r}_d$ and $\tilde{r}_f$ would in general not be optimal in the sense of Eq. (4.46).

In spite of the robustification efforts described in the preprocessor section the residuals will usually still show some effects of disturbances. Assuming that the extent of these remaining effects will vary with changing plant inputs, Frank [4.59] suggests an input-dependent threshold. With this threshold control robustness is further increased without reducing the sensitivity to faults.

4.2.3.3 Discussion

Fault detection methods based on observers and Kalman filters make quite restrictive assumptions. The most restrictive one is that the plant can be described by a linear or some special nonlinear model in the state space. In addition they assume the model parameters to be known, which requires parameter identification. However, the parameters may be time varying. The Kalman filter approach is more restrictive in that it requires white disturbances **v** and **w** with no crosscorrelation. The robust observer approach allows serial correlations of the disturbances but requires them to be partially known (see Eq. (4.47)). The big advantage of the robust observers over the Kalman filters is that they simultaneously minimize the sensitivity to disturbances and maximize the sensitivity to faults. On the other hand their residuals are more difficult to evaluate than the ones of Kalman filters. Both approaches are very powerful if their rather stringent assumptions can be fulfilled.

Kalman filters and observers are also useful for fault diagnosis. To diagnose n possible non-simultaneous faults one can design a bank of n+1 Kalman filters, where each of them is the correct system description for one specific fault case and the fault-free case respectively. The one filter having residuals close to zero then indicates the specific fault case and the fault-free case resp. (see Willsky [4.67]). Similar approaches are given for observers by Wünnenberg [4.60].

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4.3 PARAMETER ESTIMATION APPROACHES TO FDD

4.3.1 Method based on Physical Models

Olsson, L.G. & Isakson, P.
Div. of Build. Services Engineering, KTH, Sweden

4.3.1.1 Background

Parameter estimation methods cover a broad range of applications in connection with system identification and model calibrations, cf. Söderström and Stoica [4.70] or similar literature. In the present work the aim is to study whether a simple, flexible and quantitative method for fault detection and diagnosis (FDD) can be developed on basis of parameter estimation using physical models. The parameters will thus serve as indicators for pre-defined faults.

Extensive comparisons of measured data and model predictions, with modified parameters, are the main characteristic of the present approach. The data acquisition is performed during operation (On-line mode) while the calculations are carried out on computer as batch runs (Off-line mode) by iterative procedures, in general. The physical models must be formulated so that they encompass correct as well as faulty behaviour of a component or subsystem function, in combination with a suitable parameterisation.

In the following, the underlying ideas concerning the fault detection and diagnosis procedures are briefly described and then applied to a simple case. It should be noted that there is no clear distinction between the detection and diagnosis routines. The level(s) of analysis is (are) set by the models used and the parameterisation.

4.3.1.2 Description of the Fault Detection/Diagnosis Method

a) General Aspects

The present method works on data sets of measured signals, one of which is taken as a response and the remaining ones as inputs. The objective is thus to find the model parameters, representative for the actual problem, that minimises the residuals between measured and calculated responses. The model must be a well-behaved function of its inputs. This is done in a computing process that is schematically shown in Fig. 4.9.

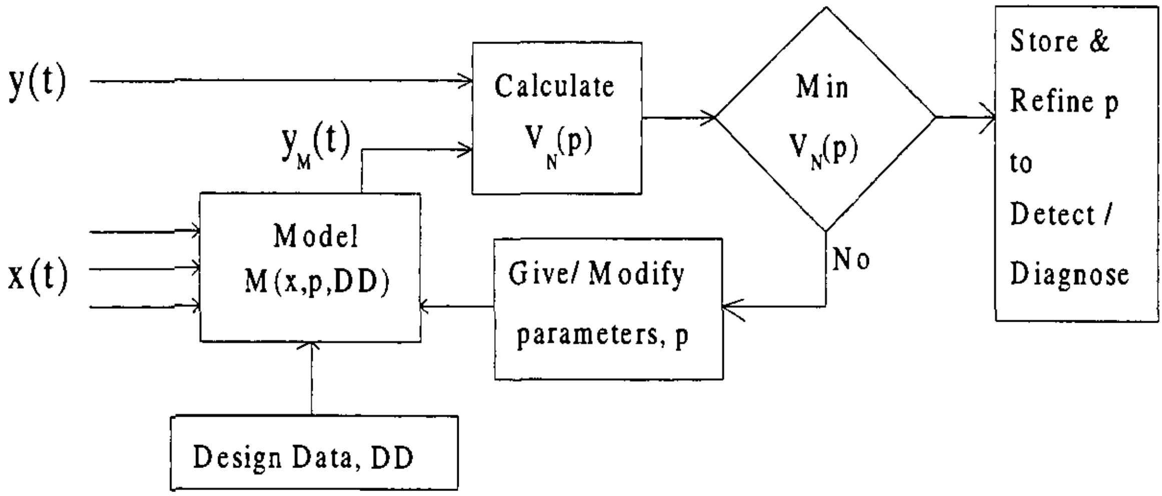

Figure 4.9. Block diagram for the FDD procedure. $V_N(p)$ is the objective function and remaining quantities are defined in the text.

The computer program can be divided in two parts:

a1) an administrative routine, which handles all the data files, information about the system being analysed, supplies the model to be used, starts the calculations and stores the results. The evaluation should also be controlled from this routine.

a2) a parameter search routine. Methods and software packages for such exist and in the present case a program developed by Spirkl is used [4.71], based on the Levenberg-Marquardt minimisation algorithm [4.72]. The analysed quantity is the objective function, defined as

$$V_N(p) = \sum_{t=1}^{N} \left| \frac{r(t,p)}{s_N} \right|^2 \tag{4.52}$$

$$r(t,p) = y(t) - y_M(t),$$

where

$r(t,p)$	= residual for element t
$x(t)$	= sets of input signals
$y(t)$	= set of responses
p	= set of free parameters
s_N	= normalisation constant, e.g. $\sqrt{N}$, measured standard deviation etc.
t	= number of element (timestep in unit scale)
N	= maximum number of time elements
M	= subscript for model values (including p and x).

The program has a number of facilities essential for the present application:

- provides statistical features for the estimated parameters,
- allows filtering of the residual,
- simultaneous minimisation of several sets of residuals.

The models serve also as basis for the pre-processor (cf. 4.1). There are no restrictions put on the models. They could be dynamic or static, linear or non-linear in the set of free parameters, first principles models or characteristic curves etc., but preferably of generic type. The models serve also as basis for the parameter choice and there are certain consideration to be taken:

- a fault should be identified with as few parameters as possible, the limits set by the chosen model structure,
- parameters can be applied on measured as well as calculated quantities and are defined as correction factors (or multipliers) to targeted quantities in the models,
- if each parameter can be related to a specific input signal the calculations will get more robust due to reduced risk for correlations.

The collection of parameters may be seen as the classifier in the FDD routines. Moreover, the characters of the faults are assumed to be rather constant during the measuring session; if not the spread in the parameter values will increase. In this respect short measuring periods with high sampling rates are an advantage.

b) Application Example

To illustrate the modelling and parameterisation a coil with control valve is selected. For practical reasons the steady state behaviour is used to define a set of parameters. Dynamic features are approximately included in the output signals. It is assumed that all inlet and outlet temperatures as well as the flow rates are measured.

- Actual coil temperature effectiveness $E_{act} = p_1 \cdot E_m(x, DD)$

  $E_m(x, DD)$ is the model value and changes in p_1 accounts for both fouling and flow rate errors, i.e. it has a detecting feature. Remaining denotations are given earlier,

- Actual pump flow rate $\dot{m}_{p,act} = p_2 \cdot \dot{m}_p$

  $\dot{m}_p$ is usually taken as a constant but may be measured or evaluated on basis of pump power and characteristic curves. p_2 does not give any further information about indicated flow rate changes, i.e. p2 has a detecting feature,

- Actual by-pass flow rate $\dot{m}_{by} = \dot{m}_{p,act} \cdot F(DD, p_3 \cdot A)$

  The function *F*(...) is numerically calculated for given valve characteristics, size and authorities. *A* is the valve stem position (input signal) and its multiplier p_3 accounts for the valve function, e.g. the leakage if A is small. Parameter p3 thus has a diagnostic feature.

Given this information the outlet temperatures for air and water can be calculated utilising the heat balance in steady state. However, it should be emphasised that correlations will occur with this definition, which can be reduced if dynamic analyses are carried out. To convert the responses to dynamic ones corrections are introduced for

- thermal capacitance using the one node approximation,

- fluid transport delays for the pipe circuit.

This is quite a crude model and the filter must be used to damp high frequencies in the residuals, the differences between the measured and calculated outlet temperatures (mean values over the pipe or duct cross sections). These quantities correspond to $y(t)$ and $y_M(t)$ in equations [4.52] or Fig. 4.9.

4.3.1.3 Description of the Fault Diagnosis/Evaluation Method

The basic aim with FDD procedures is to perform an evaluation, making it possible to take relevant decisions. As already mentioned there is no difference between detection and diagnosis routines and the parameters may carry both types of information. Sometimes it is possible by simple manipulations to refine detecting parameters to diagnostic ones, which is a necessary level for decision making. This procedure is indicated in Fig. 4.10. Throughout this subsection parameter estimates are discussed, omitting the symbol ^ normally used to distinguish them from their running values in the search process.

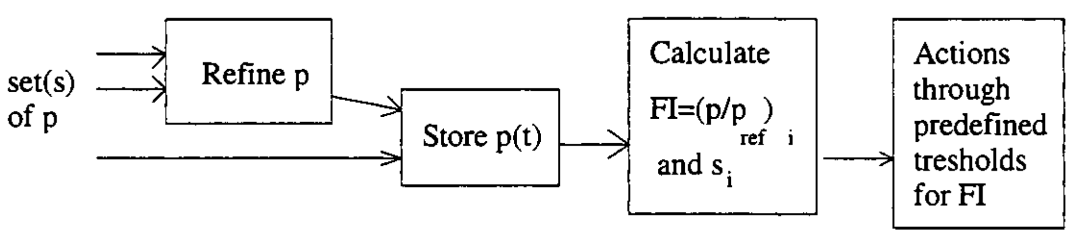

Figure 4.10. Block diagram for the diagnosis/evaluation routine. Subscripts ref indicates faultfree case, i parameter in the set and s denotes the overall spread in the fault indicator FI.

In principle a fault or degrading function of a component or subsystem should be possible to observe by tracing the time evolution of a parameter (set). Referring to the block diagram the following comments should be made:

- the processing or refinement of p depends on the chosen model and the parameterisation and may vary considerably from case to case, but the basic idea is that this should be a minor part in the diagnosis. Taking the previous coil example the ratio of p_1 for the water and air sides, respectively, detects the error in air flow rate (with E defined for the air side of the coil). If this is not too large p_1 for the water side diagnoses the fouling, while changes in p_2 will need additional information to carry out a diagnosis,

- reference values representative for the correct behaviour are needed. Such ones are best obtained when a system has been installed and just started, e.g. at commissioning. If the model description is realistic the reference parameters should stay around 1, according to the definitions. This is, however, not a requirement, rather a check of the relevance of the modelling or the system performance,

- the evaluation is performed by defining a fault indicator FI (cf. Fig. 4.10). Changes in FI>2*s are needed for safe observations of a component or subsystem fault or degradation, where s includes standard deviations and intercorrelations for both reference and actual parameters. Also the standard deviation itself contains information, e.g. sudden increases might indicate faulty sensors, a fluctuating fault, too low variability in the signals, fault case not well implemented etc. The statistical features of the parameters are thus of fundamental importance as they account for both modelling and measurement defects,

- it may be an advantage to combine the parameters from various subsystems in order to make the interpretation safer, particularly when more than one fault occur simultaneously and/or the parameters are of detecting type. This presents mostly no major problem since a lot of data sets are shared,

- the final step is to compare various FI with thresholds or a sequence of thresholds, possibly combined with rules, in order to take necessary measures. In this respect the time evolution of FI is important and the actions to be taken depend on a number of aspects, not further discussed here.

4.3.1.4 Summary of advantages and disadvantages with the method

The following features in the present method should be stressed regarding the previous description

a) Advantages

- works with dynamic states of the system
- simple interpretation of the results
- simultaneously occurring faults are allowed,
- quantitative method (suitable for degrading system function).

b) Disadvantages

- if many free parameters are used the system might need disturbances during measurements (to increase the variability of the data),
- for On-line applications there is a delay in the response (equal to the computing time for the parameter estimation),
- rapidly fluctuating faults may be difficult to resolve.

To get further insight in the pros and cons on applying this method, tests with different subsystem or components using both simulated and experimental information must be carried out.

4.3.1.5 References

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4.3.2 Characteristic curves

Madjid Madjidi,
University of Stuttgart, Germany

4.3.2.1 Introduction

Characteristic curves help to visualize models of physical processes. They are often used to explain empirical models in science and engineering. Also HVAC manufacturers publish characteristic curves to describe the properties of their products. Application of characteristic curves are, however, restricted to the design phase of a plant. But there are two basic reasons for propagating characteristic curves also to the phase of operating a plant and specially for implementation in a fault detection systems:

- the modelling task becomes easier by refering to design data of a plant and
- the process models become more comprehensible by visualizing the relationship between the process variables involved.

As characteristic curves are derived from physical models, they contain expert knowledge of the physics involved in the process. Unlike black box models, characteristic curves should be mathematically described with predefined structures. A calibration of characteristic curves on the basis of measured data requires less computational time, due to the smaller number of model characteristics requiring identification.

Furthermore, globally defined mathematical structures are more robust against inaccurate extrapolation. Often black box models are only capable to identify the structure in the range of the data used for training.

The requirement of visualization limits the number of variables involved in the basic function describing a characteristic curve mathematically. It is common to present characteristic curves in two dimensions (2-D-plots). Presentations in three dimensions (3-D-plots) require adequate computational tools.

Characteristic curves can be stored as tables or can be approximated by algebraic equations. The following basic relationships exist

for a 2-D-plot

$$y = f(x); \tag{4.53}$$

for a 2-D-parametrical-plot or a 3-D-plot

$$z = f(x; y) \tag{4.54}$$

and for a 3-D-parametrical-plot

$$w = f(w; x; y). \tag{4.55}$$

To implement a characteristic curve in an automatic fault detection and diagnosis system we shall know:

- what samples can be used
- the suitable type of equation which approximates the curve
- the best criterion for fitting data to the selected equation.

Design data are often idealised and may not accurately reflect the characteristics of the real plant. Furthermore, compromises may have been made during the installation process resulting in the plant no longer conforming to the original specification. This is a common phenomenum within the HVAC industry. Training the model using operational data leads to greater accuracy. But the application of operational data requires sufficient instrumentation of a process. For example to derive the characteristic curves of a fan, pressure sensors should be located before and behind the fan and the airflow rate should be also measured in some way.

The suitable type of equation which approximates the curve can be derived from the physical model or can be chosen by considering the shape of the curve. The following two approaches are most common because only two parameters (a and b) have to be estimated, but any other algebraic equation can also be applied:

straight line in a 2-D-plot:

$$y = a\,x + b \tag{4.56}$$

nonlinear curves in a 2-D-plot:

$$\log y = a \log x + b. \tag{4.57}$$

Other commonly used equations are polynomials. They can be generally described by

$$y = \sum_{i=0}^{n} a_i x^i \tag{4.58}$$

4.3.2.2 Description of the Fault Detection Method

Characteristic curves represent only static process models. Static models can be used if the process dynamic is neglectable (e.g. fans and pumps) or if the input dynamics are slower than the system response time. For example, an input change may be a result from turning on an air conditioning system.

The transient period will usually last only a few minutes followed by steady-state condition for a much longer period until the system is turned off again.

Static models are accurate if the steady state condition of a dynamic process gives enough information for fault detection. It should be understood that they are not applicable during transient conditions. Under these circumstances automatic fault detection systems should interrupt fault detection until the process returns to steady state conditions [4.73].

Figure 4.11 shows the block diagram of the fault detection principal based on characteristic curves. In a first step the characteristic curves are calibrated using measured signals of a faultless operation period. The signals of the calibration or training period should include partial and full load conditions and in each condition the signals should be steady state values.

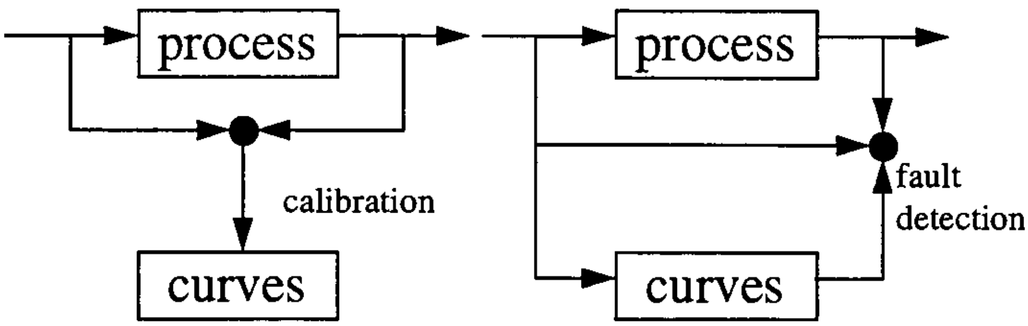


Figure 4.11. Fault detection principle based on characteristic curves.

To be able to identify the parameters of a function which describes the characteristic curves mathematically the number of samples must be equal (approximation) or higher (curve fitting, regression) than the number of parameters involved in the equations representing the charactersistic curves. Later faults can be detected by comparing the output(s) of a refererence model (calibrated during faultless operation) to the output(s) of the actual real process. For example a fouled coil could be detected by comparing the effectiveness predicted by the model to the actual effectiveness as demonstrated in Figure 4.12.

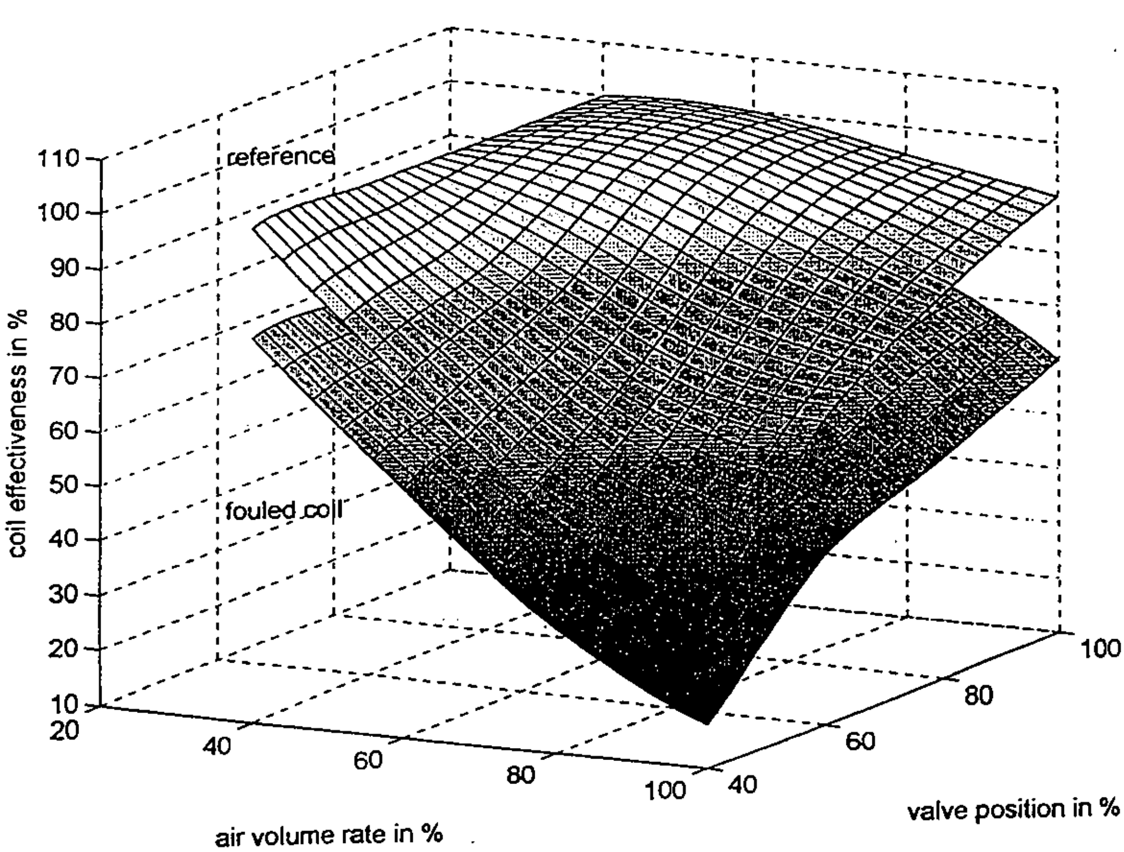


Figure 4.12. Example of fault detection (fouled coil) based on characteristic curves.

Curve fitting is needed in situations where there are much more data available than parameters so that exact matching is out of the question. Most of the curve fitting methods given in literature are based on the so called least-squares criterion [4.74 - 4.77]. Polynomials are most commonly used in least-squares matching, though any linear family (model class) will work about as well in practice. Least squares is very often regarded as smoothing the data or removing the noise. The principle of least squares states that for m observations the best estimate y_e of the true value y is that number which minimizes the sum of the squares of the deviations of the data from their estimate [4.77]:

$$\sum_{i}^{m}(y_i - y_e)^2 = MINIMUM \tag{4.59}$$

Least square is also applicable to functions with two variables (z=f(x,y)) [4.78].

A possible fault with least squares is that a single very wrong measurement will greatly distort the results because in the squaring process large residuals play the dominant part - one gross error 10 times larger than most of the others will have the same effect in the sum of the squares as will 100 of the others. Great care should be taken before applying any result to data blindly. At least even a quick check of the residuals, either by eye or by some suitable program, helps to find measurements which are wildly off. Another fault with least squares, if polynomial equations are to be matched, is that the error curve tends to have large errors at the end of the interval. This comes about because it is in the nature of polynomials to go to infinity for large values of the argument, and therefore the error is likely to be large at the ends.

Besides the method of least squares other methods are possible. We can also choose to minimize the sum of absolute values. This leads to the choice of the median or middle value. A third possible choice is to minimize the maximum deviation which leads to the midrange estimation of the best value and the so called Chebyshev criterion [4.77].

4.3.2.3 Examples for characteristic curves

Centrifugal Fans:

The total static pressure increase p in a specific centrifugal fan can be given as to be only a function of air volume flowrate $\dot{V}$ and revolving fan speed n. A biquadratic polynomial equation is applied to approximate the characteristic curve. Contrary to the following approach polynomial curve fitting gives more accuracy if the powers of fit of the variables are not predefined. But this requires much more computational effort, due to the higher number of parameters (polynomial coefficients) requiring identification.

The quadratic approach proposed here can be partly established by a simple physical model:

A basic pressure rise which is the total pressure rise across the fan at zero volume flow rate is assumed in the first step:

$$\Delta p_0 = c_6 \tag{4.60}$$

In a second step we subtract from the basic pressure rise a pressure drop due to fan resistance which can be shown to be a quadratic function of the volume flow rate. But we keep a general formula and set the substraction as an addition (the sign of c_5 will be automatically identified as a result of the curve fitting process):

$$\Delta p = c5\ \dot{V}2 + c6 \tag{4.61}$$

In a third step we consider the dependence to the revolving fan speed. Usually fan manufacturers give for various revolving fan speeds *n* curves of one fan in one 2-D-plot (p = f ($\dot{V}$), *n* parameter). We prefer a 3-D-plot representation and consider the nonlinear evolution of p with n again by choosing a quadratic approach and adding it to the previous equation:

$$\Delta p = c_1\, n^2 + c_5\, \dot{V}^2 + c_6 \tag{4.62}$$

Finally, we add linear and mixed components:

$$\Delta p = c_1 n^2 + c_2 n + c_3 n\dot{V} + c_4 n\dot{V} + c_5 \dot{V}^2 + c_6 \tag{4.63}$$

The main parameters of the model are the six polynomial coefficients of this equation.

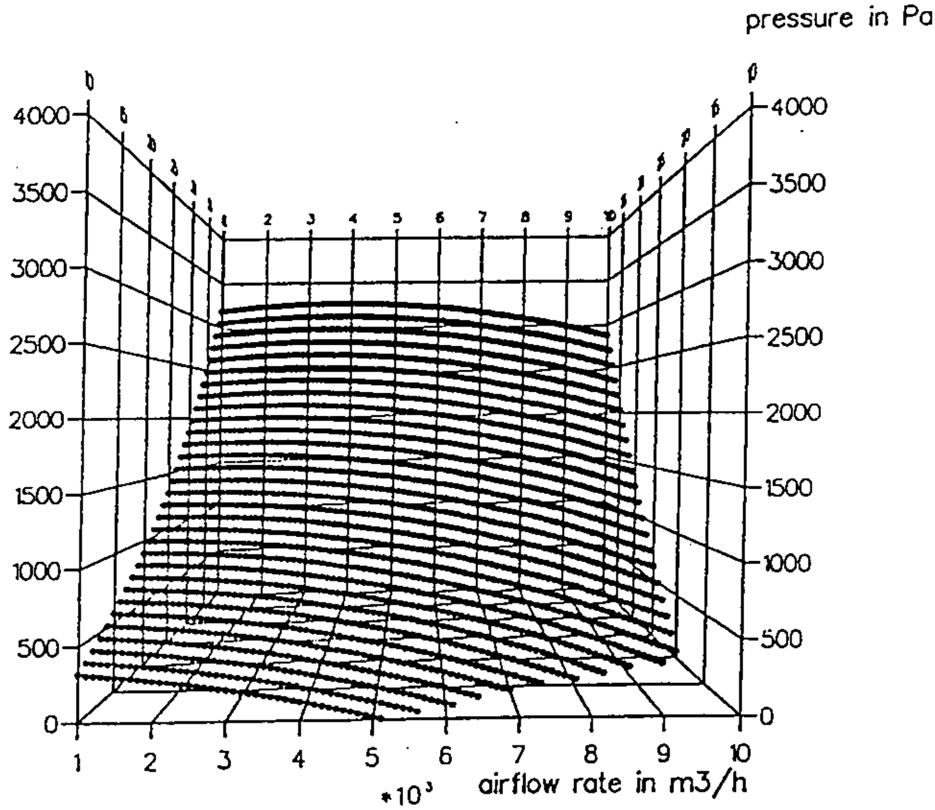
Figure 4.13 displays the curves of a centrifugal fan as measured by a fan manufacturer [4.79]. The same characteristic curves are shown as a 3D-space-surface. The curves can be obtained using the following polynomial coefficients:

$c_1 = +0.00019$, $c_2 = -0.01862$, $c_3 = +0.00003$,

$c_4 = -0.04369$, $c_5 = -0.00001$, $c_6 = +171.7724$.

Coils:

Within the IEA projects Annex 10 and 17 a detailed physical coil model was developed [4.80] and applied to system simulation applications. The majority of the parameters of this model are geometrical data of a coil, like fin thickness, fin spacing, tube diameters and so on. In this model the global thermal resistance is the sum of the thermal resistance on the waterside, the coil material resistance and the thermal resistance on the airside. Empirical relationships are given for the computation of the thermal resistances on both flow sides and are dependent on the flow velocity. Especially relationships given for the thermal resistance on the airside should be used with care. They often relate to various coil constructions, especially with different arrangements of water tubes [4.81, 4.82]. Furthermore, geometrical data are often not available or manufacturers regard these as a secret.



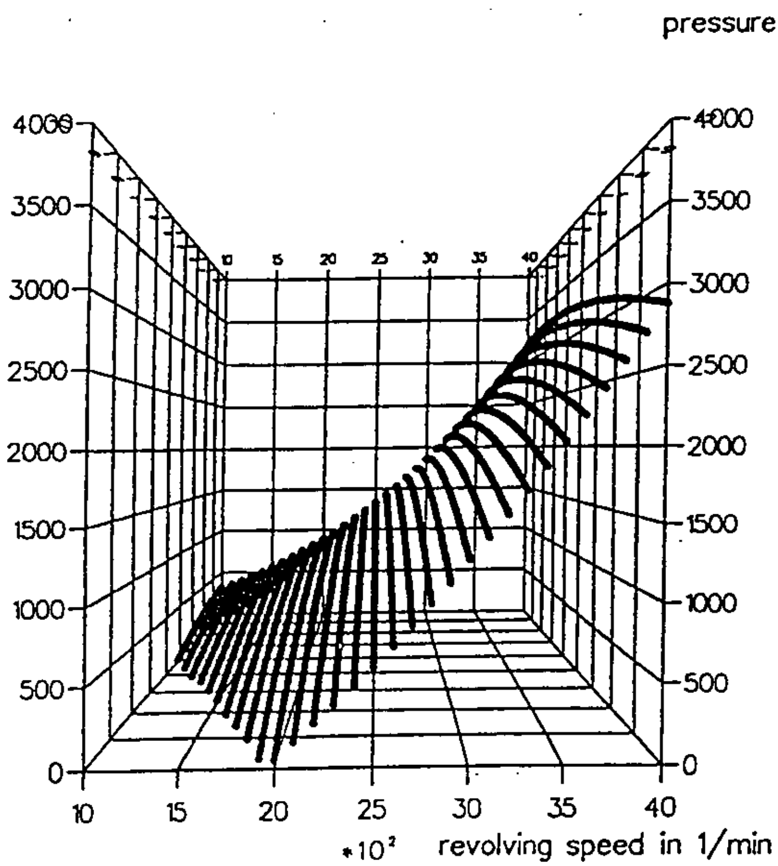


Figure 4.13. Characteristic curves for a centrifugal fan (based on manufacturer data).

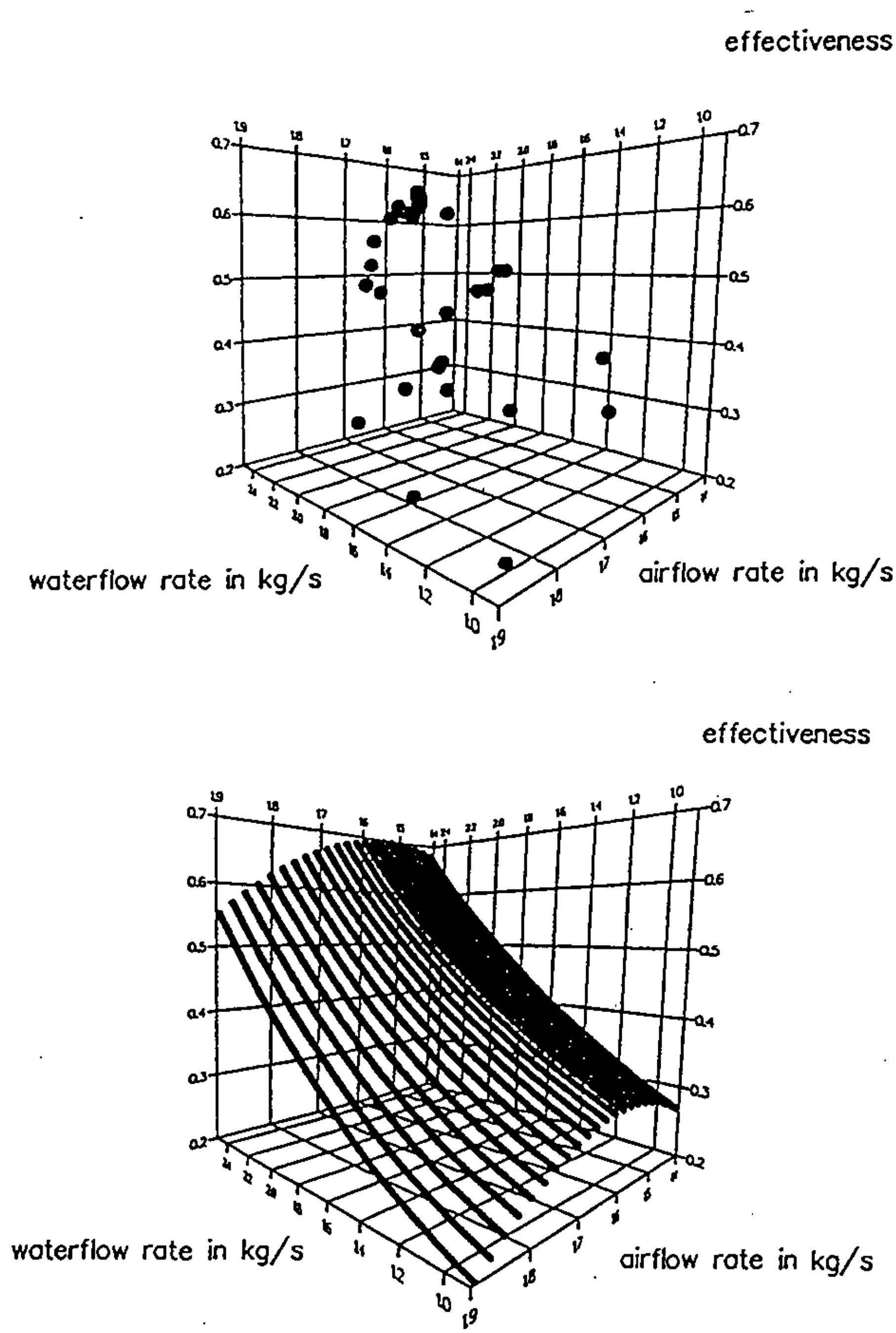


Figure 4.14. Characteristic curves for a cooling coil (based on measured data).

A more simplified way to roughly characterize the heat transfer in dry coils can be done with the so called coil effectiveness Φ. It is defined as the fraction of the total heat transfer to the maximum possible heat.

For example for an air/water cooling coil the definition leads to

$$\Phi = \frac{\vartheta_{Air,1} - \vartheta_{Air,2}}{\vartheta_{Air,1} - \vartheta_{Wat,1}} \tag{4.64}$$

If measured data are available (e.g. from catalogue or as cited in BEMS) the model of a specific coil can be easily calibrated. The result of a model calibration for dry air conditions will be a relationship between the effectiveness and the air and water flowrates:

$$\Phi = \Phi(\dot{m}_{Air} ; \dot{m}_{Wat}) \tag{4.65}$$

If such a relationship is available, the outlet air and water temperature can be computed by applying the energy balance.

Again a quadratic polynomial approach can be chosen:

$$\Phi = c_1 \dot{m}^2_{Wat} + c_2 \dot{m}_{Wat} + c_3 \dot{m}_{Air} \dot{m}_{Wat} + c_4 \dot{m}_{Air} + c_5 \dot{m}^2_{Air} + c_6 \tag{4.66}$$

Thus the parameters of the model are the six polynomial coefficients of this equation. Measurements in a real VAV system have been used for the calibration of a cooling coil model. Figure 4.14 displays measured values for the cooling coil in a 3-dimensional plot and the coresponding the calibrated characteristic curves achieved with the following coefficients

$c_1 = +0.06945$, $c_2 = +0.14889$, $c_3 = -0.08750$,

$c_4 = +3.45875$, $c_5 = -1.06667$, $c_6 = -2.561583$.

4.3.2.4 Fault detection example

The following example demonstrates how the coil model of section 4.3.2.3 can be applied to find an operational fault in a VAV system. The observed fault is a pump failure in a cooling coil water circuit and has occured in the VAV system of an office building near Stuttgart during a warm summer night.

Figure 4.15 shows the scheme of the HVAC system. It consists of a single-duct pressure independent VAV system with a central air handling unit and local terminals and an additional hydronic heating system equipped with radiators in each conditioned zone. The VAV-system consists of a mixing box, an air filter, finned tube preheating and cooling coils, centrifugal supply and return fans with speed control and finned tube reheating coils and VAV-boxes for each zone.

The system is controlled by a Direct Digital Control (DDC) unit and local controllers. A single controller is used to control both fans. It is set to keep a static pressure of 300 Pa at the measured point indicated in Figure 4.15 (Measured values in Figure 4.16). The air supply temperature set point is set constant (around 17 °C). The VAV and cooling systems run continuously (day and night) but the heating systems are shut down. Table 4.2 lists a selection of the recorded data. Massflow rates are estimated by using the magnitude of cooling coil valve position and revolving fan speed.

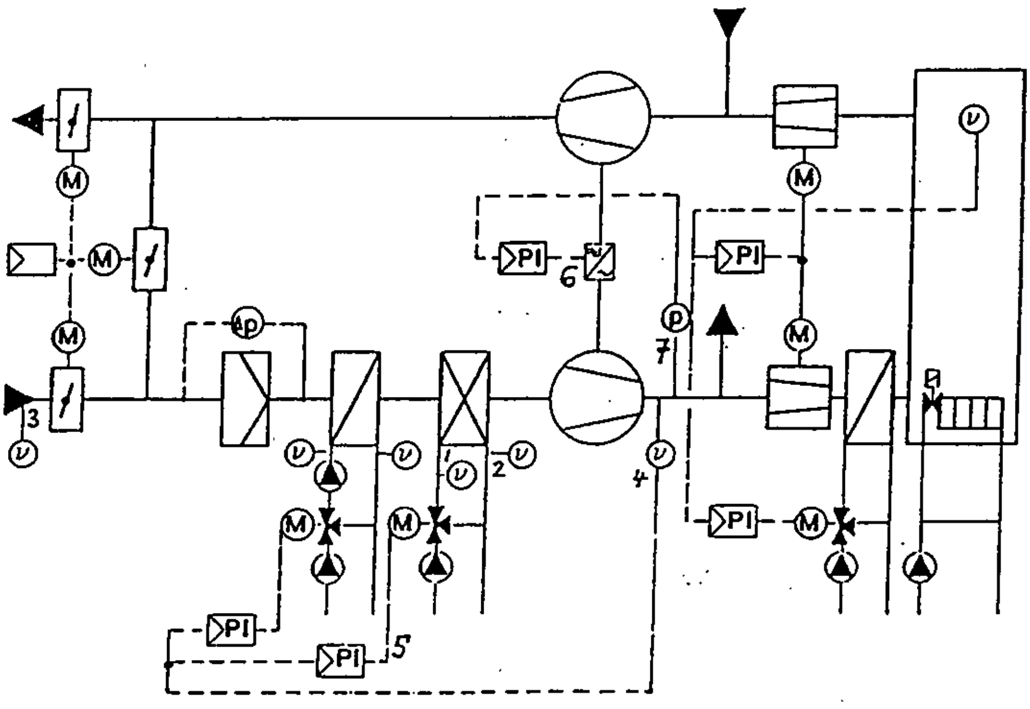


Figure 4.15. Scheme of a VAV system for a commercial building.

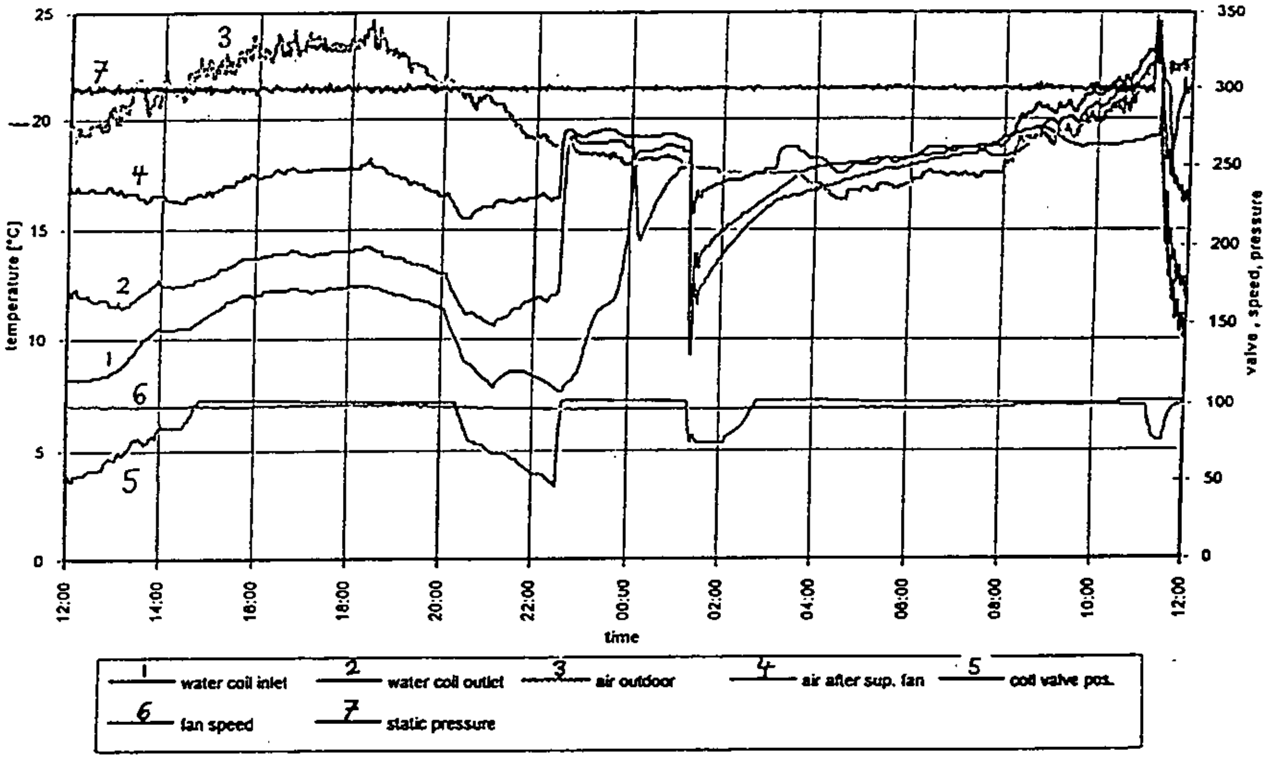


Figure 4.16. Measured process signals of VAV system.

Table 4.2.

time h	$\vartheta_{Air,1}$ °C	$\vartheta_{Air,2}$ °C	$\vartheta_{Wat,1}$ °C	$\vartheta_{Wat,2}$ °C	$\dot{m}_{Air}$ kg/s	$\dot{m}_{Wat}$ kg/s	Φ_{actual}	Φ_{model}	operation
14:00	22.3	16.5	10.4	12.4	1.9	2.11	0.48	0.43	normal
16:00	22.9	17.3	12.0	13.7	1.9	2.50	0.51	0.55	normal
18:00	23.6	17.8	12.4	14.0	1.9	2.50	0.52	0.55	normal
20:00	21.8	16.5	11.4	13.0	1.9	2.50	0.51	0.55	normal
22:00	19.1	16.4	08.4	11.8	1.9	1.37	0.25	0.26	normal
00:00	17.9	19.2	16.0	18.7	1.9	2.50	-0.67	0.55	alarm
02:00	17.5	17.1	13.7	14.9	1.9	1.87	0.11	0.37	alarm
04:00	17.0	18.2	16.7	17.8	1.9	2.50	-4.00	0.55	alarm

In an automatic fault detection system a failure alarm should be given as soon as the deviation between measured and computed effectiveness exceeds a certain threshold (in this example 50 %). Although the simple coil model neglects dehumidification and transient effects, the example demonstrates the applicability of such a model in an automatic fault detection system. The model can be used if the modelling assumptions are considered when defining the fault alarm threshold. Simplified modelling should be compensated with a generous choice of the threshold value.

4.3.2.5 References

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4.3.3 Characteristic parameters

Yi Jiang,
Tsinghua University, China

4.3.3.1 Introduction

The idea of the Fault Direction Space (FDS) method is to avoid the system performance learning and prediction process [4.83] as in a normal fault detection procedure and to try to use a global standard procedure to perform the FDD task. Based on the physical model of the system to be studied, some Characteristic Parameters (CP) are structured from measured data. The CP is selected such that it can be expressed by the structure of the system or component so that the value of CP should be constant during operation within a normal range of a fault free state. Based on this feature of CP, faults can be detected by watching the value of CP. If it remains constant or changes within a relatively small range, the system is in a normal state. When a big change in CP is observed, a fault has occurred in the system. The change of CP becomes an indicator of fault. There can be a number of CP in a system. Different types of faults may cause each CP to change in different manner. The Fault Direction Space consists of each CP for the system being studied. A normal state becomes a point or a small region in the FDS space. Each type of fault becomes a direction in the FDS. When a CP that is structured by measured data is out of the normal region, a fault state is indicated. The direction from the abnormal point of CP to the normal point can then indicate the type of fault. This is why this procedure is called Fault Direction Space procedure.

4.3.3.2 Basic approach of FDS

To illustrate the FDS approach, take a water-water heat exchanger, as shown in Fig 4.17, as a simple example. The heat balance equation for the heat exchanger at steady state is:

$$Q = UF\Delta T_M = m_1 C_p (T_{1i} - T_{1o}) = m_2 C_p (T_{2o} - T_{2i}) \tag{4.67}$$

where

$$\Delta T_m = \frac{T_{2i} - T_{1o} + T_{1i} - T_{2o}}{Ln\left(\frac{T_{2i} - T_{1o}}{T_{2o} - T_{1i}}\right)};$$

and m is the flow rate at each side and CP is the specific heat of water.

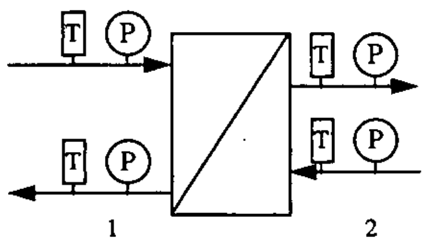

Figure 4.17. Heat exchanger.

If the pressure difference of water at each side is measured, the flow rate m can be replaced by the pressure difference as

$$m = S\sqrt{\Delta P} \tag{4.68}$$

where S is the water flow resistant coefficient of the heat exchanger. From Eq(4.67) and (4.68), two CP's can be defined as

$$CP_1 = \frac{S_2}{S_1} = \frac{T_{1i} - T_{1o}}{T_{2o} - T_{2i}} \frac{\sqrt{\Delta P_1}}{\sqrt{\Delta P_2}} \tag{4.69}$$

$$CP_2 = \frac{C_p S_2}{UF} = \frac{\Delta T_m}{T_{2o} - T_{2i}} \frac{1}{\sqrt{\Delta P_2}}$$

Although the heat transfer coefficient U changes with the temperature and flow rate, the CPs cannot change too much if the dynamic influence can be taken out.

CP_1 and CP_2 can be obtained from measured temperature and pressure data at each time interval. Fig 4.18 shows how the CP changes during normal operation and in some fault cases. These data are from real measurements. It can be found that the CP will undergo a big change when a fault occurs. The direction of the change in CP is also different for different types of faults.

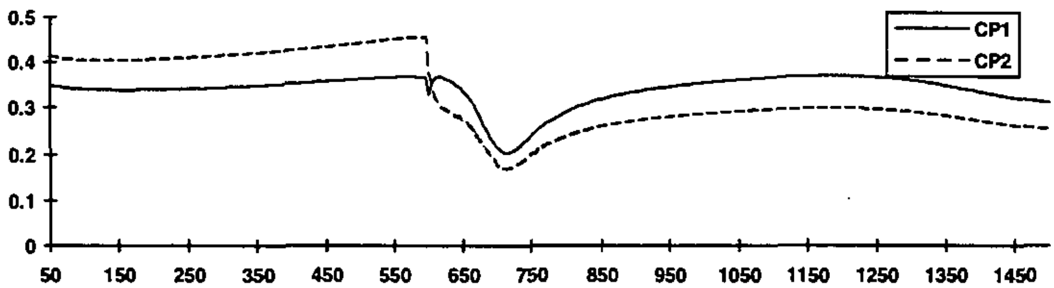

Figure 4.18. CP curve for heat exchanger. At time 600 second, a fault happen.

If the U value goes down due to fouling of the heat exchanger, CP_2 will go up and CP_1 will not change.

If side one is blocked, forcing the flow rate to get smaller, S_1 will go down thus causing CP_1 to go up. CP_2 will also go up a little as the heat transfer coefficient at side one decreases.

If side two is blocked, S_2 will go down and thus make both CP_1 and CP_2 go down.

If there is a leak between the two sides and water from side one leaks to side two due to the pressure difference, the temperature difference at side two will increase and the logarithmic mean temperature difference will decrease. The pressure difference at both sides will also change. The global effect will cause both CP_1 and CP_2 to go down, but in different trend from the trend of change when side two is blocked.

In the same way, the change of CP1 and CP2 can be analysed when there is a leak from side one or side two to outside. Taking the change of CP1 and CP2, that is ΔCP_1 and ΔCP_2, as the co-ordinator, the FDS (Fault Direction Space) can then be made as in Fig 4.19. ΔCP_1 and ΔCP_2 can be obtained from measured data during normal operation. At each time, the measured ΔCP_1 and ΔCP_2 becomes a point in the FDS. In a fault free state, this point should be at zero or within the normal region around zero due to the errors in measurement and the dynamic influence.

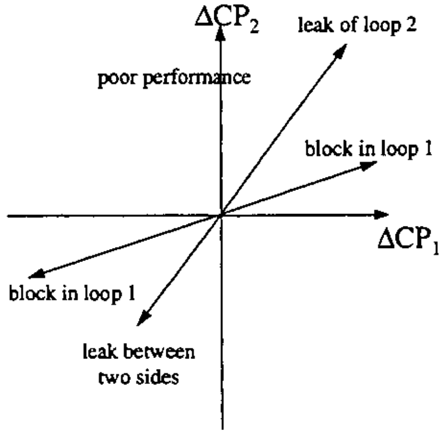

Figure 4.19. FDS for a heat exchanger.

If the point is far from the normal region in the FDS, there must be a fault. After a fault state has been detected, the location of the point indicates the type of fault. The distance from the point to the zero point shows how serious the fault could be. An uncertain region exists between the normal region and fault regions in the FDS. If the measured point is in the uncertain region, it may or may not be a fault. In this case, more measurements and longer observation may be needed to reach the final conclusion.

This is the general idea and basic procedure of the FDS method. However to make it implementable in a real system, the following questions need to be resolved:

How should the CP be structured for each HVAC component and system to make the FDS?

How to reduce the dynamic influence and obtain the steady-state value for CP? As the CP may change continually during operation, what does mean the ΔCP, how to calculate the ΔCP from the measurement?

There is no black and white answer for most types of fault. A slight fault may cause the value of CP change slightly from the normal value. However we do not care this level of fault. Certain level of errors may also exist in the measurement. This will cause CP deviate from the normal value. Therefore what should be the threshold of the ΔCP to distinguish serious faults from normal state?

To make this approach be easy used in practice, It is also very important to know if the direction of each type of fault in the FDS is dependent on the size and the operation state of the system. If so, an approach to make it independent needs to be developed.

These are the key points to be studied for the FDS method.

4.3.3.3 Structure CP

Finding a suitable set of CP is the key to making the FDS successful. The CP should have the following properties:

- It can be calculated from the measured data;
- It should be constant over the whole working range;
- It should form a complete set of parameters so that each type of fault will appear in a different direction in the FDS.

There are some examples of the selection of CP.

Water cooled air-conditioner

According to [4.84], when the condensation temperature and air flow rate are constant, the wet bulb temperature difference between inlet air and outlet air of the evaporator, ΔT_s, will be constant. ΔT_s is dependent on the air flow rate, m, and the condensation temperature. From this result, CP can be defined as

$$CP_1 = \Delta T_s m^k e^{n(T_C - T_{C0})}$$
$$CP_2 = m \ \ln\left(\frac{1-\varphi_2}{1-\varphi_1}\right) \qquad (4.70)$$

where ΔT_s, is the wet-bulb temperature drop from the inlet air to outlet air, m is the air flow rate, φ_1 and φ_2 are the relative humidity of the inlet and outlet air respectively and T_c is the average condensation temperature. T_{c0}, k, and n are parameters dependent on the type of the air-conditioning unit, k may be from 0.75 to 0.85; n may be from 0.01 to 0.02; T_{c0} is approximately around 35 °C. For a constant air flow rate system or for a VAV system with an air flow sensor, this CP is easy to measured. Many types of fault can be indicated by this set of CP.

Air handler unit

Fig. 4.20 is an air handler unit with constant air volume. Dampers 1, 2 and 3 are connected together so that they move simultaneously. They are regulated according to the enthalpy difference inside and outside so as to save energy. From the measurement point indicated in Fig. 4.20, the CP can be constructed as

$$CP_1 = \frac{T_3 - T_2}{T_1 - T_2}\frac{1}{r^k}$$

where the r is the position of the three dampers and k values from 0.5 to 1 depending on the performance of the dampers. k can be learnt on site.

$$CP_2 = \frac{h_4 - h_3}{\Delta h_m}$$

where h is enthalpy, Δh_m is the logarithmic mean enthalpy difference between enthalpy of air and the enthalpy related to the saturated air at the mean water temperature.

$$CP_3 = \frac{h_4 - h_3}{C_w (T_{w1} - T_{w2})\sqrt{r_{vc}}}$$

where the r_{vc} is the open ratio of the cool water valve.

$$CP_4 = \frac{1 - \varphi_4}{1 - \varphi_3}$$

if $d_4 < d_3$, that means if it is a dehumidify process otherwise CP_4 is not needed.

$$CP_5 = \frac{T_5 - T_4}{T_{w2} - T_{w4}} \frac{1}{\sqrt{r_{vh}}}$$

where r_{vh} is the open ratio of the water heater valve

$$CP_6 = \frac{T_5 - T}{\Delta T_m}$$

where the ΔT_m is the logarithmic mean temperature difference between air and hot water.

$CP_7 = \dfrac{d_6 - d_5}{\sqrt{r_{vhh}}}$ where r_{vhh} is the open ratio of the humidifier valve.

In above equations, T denotes air temperature, d denotes air absolute humidity in g/kg dry air and φ denotes relative humidity of air. r's are the open ratio of valves. When a valve is completely closed, the valve ratio is one and the relative CP value for the normal state should be zero.

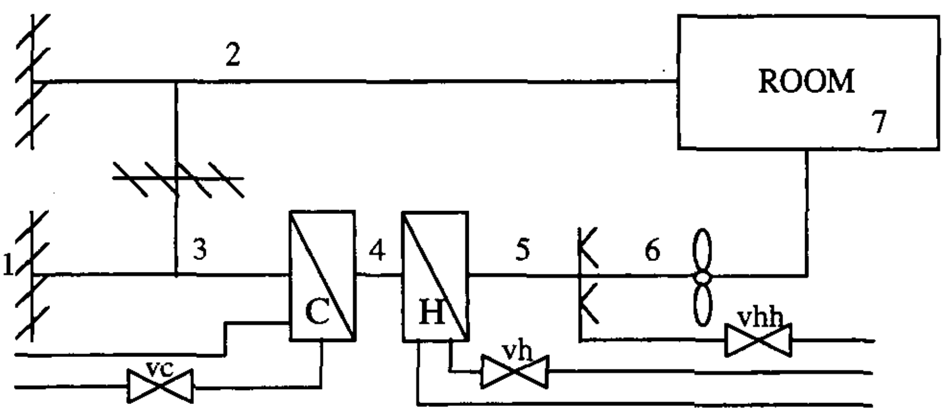

Figure 4.20. Shematic diagram of an air handler unit.

FDS consisting of the above CPs can be used to detect many kinds of faults in an air handler unit such as the speed of fan getting slower; the valve of humidifier cannot be completely closed; one of the dampers cannot move, and poor performance of heater or cooler due to fouling.

4.3.3.4 Staticizing of measured data and calculating of ΔCP

The CPs are based on the steady-state physical model of the system or components. However, the data to structure the CP are measured from a real system in a dynamic process. Therefore, finding the static solution from the dynamic data becomes very important for the FDS procedure. Moving average on the measured data before constructing CP's with them can then be used to staticize measured data and eliminate the dynamic influence:

$$X_m = \frac{1}{k}\sum_{i=1}^{k} X_{\tau-i} \tag{4.71}$$

where the $X_{\tau-i}$ is the directly measured data before i'th interval and the X_m is the moving-averaged value. X_m can then be used to calculate CP. While what is the suitable length k for computing of CP? If the k is too small the dynamic influence cannot be well filtered. If the k is too large, the CP may not be computed correctly as the operation state may change greatly during this k interval period and the relationship between input and output of a component is not a linear process normally. Analysis and practical test shows that the period of the moving-average on measured data for computing of the CP shall be 2 - 3 times of the time constant of the component.

The key of the FDS approach is to detect fault from the change of the CP, that is the ΔCP. Therefore, the moving-average filter cannot filter all the dynamic influence. Sensor may also produce some random errors so cause CP change. In this way ΔCP cannot be calculated simply by subtract the current value of CP from the previous one. The average value of CP over previous period may be used as the reference value. The ΔCP can then be calculated as:

$$\Delta CP = CP_\tau - \frac{1}{n}\sum_{i=1}^{n} CP_{\tau-i} \tag{4.72}$$

where CP_τ is the CP calculated from the current moving-averaged measured data and the $CP_{\tau-i}$ is the CP value before i'th interval.

The use of a long period (n) to computing ΔCP can avoid the influence of random change of CP causing by sensor error, dynamic influence and non-linear influence. However, some types of faults do not happen suddenly. They only become serious slowly, such as the fouling process, and cause the CP change slowly. The ΔCP may never become large value by using Eq (4.72) to compute ΔCP in this case.

Therefore what is difference between the change of CP due to random factors and the change due to the slowly happened fault? If the CP increase or decrease continuely, it shall be a type of fault. While if CP goes up and down around a reference value, it shall be considered as the random factors influence. According to this difference, the ΔCP can be computed in the follow procedure:

Assuming CP_0 is the reference CP through previous calculation, CP_τ is the CP calculated from current measured data and $\Delta CP_{\tau-1}$ is the ΔCP at last time interval, then

1. $\Delta CP_\tau = CP_\tau - CP_0$
2. if ΔCP_τ is the same direction as $\Delta CP_{\tau-1}$, CP_0 shall be kept up to next interval
3. if ΔCP_τ is the opposite direction of the $\Delta CP_{\tau-1}$, let $CP_0 \leftarrow rCP_0+(1-r)CP_\tau$. Where r=0.1-0.2, depending on the time interval, the non-linear behaviour of the component as well as the performance of fault it may involve.

4.3.3.5 Development of the FDS and the Diagnosis procedure

The threshold of the level of fault depends on the loss of energy and comfort caused by the fault and should be balanced against the cost of maintaining the fault. When the lost energy costs more than the cost of repair, the fault should be reported so that the repair can be carried on. This is described in the Section 5.4 and 5.5. Therefore, only a fault that is greater than the threshold level should be detected. Simulation can be made to decide the ΔCP when the fault is at the threshold level without any errors in measurement. The ΔCP is an n-dimensional vector as

$$\Delta CP = (\Delta CP_1, \Delta CP_2, \Delta CP_3, \ldots) \tag{4.73}$$

Standard direction R, for this type of fault in the FDS can then be obtained as

$$R = \Delta CP / (\Delta CP_1^2 + \Delta CP_2^2 + \Delta CP_3^2, \ldots) \tag{4.74}$$

During real operations, the measured ΔCP_m can be obtained from measurement. The projection P of the ΔCP_m on the direction of R, can then be calculated as

$$P = R\ \Delta CP_m \tag{4.75}$$

If there is this type of fault at the level of the threshold exactly without any errors in measurement, the P will have a value of unity.

If the P is greater than one, it may indicate significant fault.

However, the ΔCP_m may also change due to the follow reasons:

- errors in measurement;
- dynamic influence;
- non-linear behaviour of the component.

These influences can be considered as a deviation of the measurement, δM. The maximum possible ΔCP_m and the minimum possible ΔCP_m can then be calculated according to the δM. The maximum possible and minimum possible P when the fault is at the threshold level can also be calculated from the deviation of ΔCP_m. For instance, if

$$CP = \frac{T_1 - T_2}{P_1 - P_2},$$

where T_1, T_2, P_1 and P_2 are measurements with the deviation δT_1, δT_2, the deviation of ΔCP_m can be calculated as

maximum deviation $\delta_{max}\Delta CP_m$:

$$\delta_{max}\Delta CP = \frac{T_1 + \delta T_2 - T_2 + \delta T_2}{P_1 - P_2 - (\delta P_1 + \delta P_2)} - \frac{T_1 - T_2}{P_1 - P_2}, \tag{4.76}$$

$$\delta_{min}\Delta CP = \frac{T_1 - \delta T_2 - T_2 - \delta T_2}{P_1 - P_2 + (\delta P_1 + \delta P_2)} - \frac{T_1 - T_2}{P_1 - P_2}, \tag{4.77}$$

there the T_1 should be greater than T_2 and P_1 should be greater than P_2 respectively.

The deviation of P, that is the projection of the ΔCP_m on the direction of R can then be calculated as

$$P_{max}=1+R\ (\delta_{max}\Delta CP_1,\ \delta_{max}\Delta CP_2,\ \delta_{max}\Delta CP_3, \ldots\ldots)^T$$

$$P_{min.}=1-R\ (\delta_{min}\Delta CP_1,\ \delta_{min}\Delta CP_2,\ \delta_{min}\Delta CP_3, \ldots\ldots)^T \tag{4.78}$$

In this case, if there is a fault at the threshold level, the P cannot be greater than P_{max} nor less than P_{min}. Membership function can than be obtained as in Fig. 4.21.

$$Membership = \begin{cases} 0, & \text{if } P < P_{min} \\ (P-P_{min})/(P_{max}-P_{min}), & \text{if } P_{min}<P<P_{max} \\ 1, & \text{if } P> P_{max} \end{cases} \tag{4.79}$$

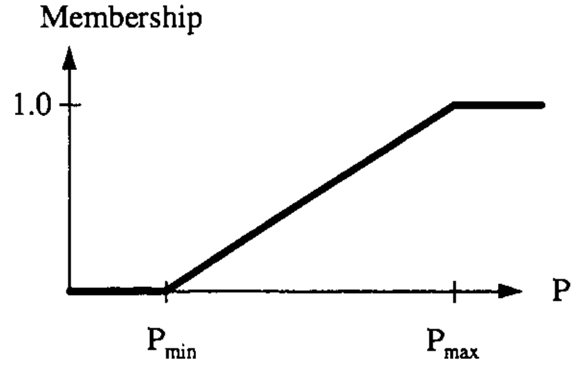

Figure 4.21. Membership function.

In real cases, if the membership function becomes one, there must be the fault at the level that more serious than the threshold level; if the membership function is zero, there cannot be a fault at or above the threshold level. When the membership function is between 0 and 1, there may be a fault possibly. The higher the membership value, the higher the possibility to be a fault.

In this way, fault direction, R, for each type of fault should be pre-calculated by simulation of the fault at the threshold level. During real operation, calculation the projection of ΔCP_m on each R, the membership for each type of fault can then be obtained. If there are more than one types of fault of which the memberships are between 0 and 1, the one with larger value of membership should be the first consideration.

In most cases the fault direction, R, is independent of the operation state and equipment size. Some types of fault cause very strong non-linear behaviour. Different levels of fault may appear different direction in the FDS. This type of fault can be considered as two or three types of fault. Each has their own direction. While the P_{max} and P_{min} for each type of fault is related the operation state strongly. From Eq. (4.77), when P_1-P_2 changes two times as the operation state changes, δP and δT will not change, then the $\delta_{max}CP$ and $\delta_{min}CP$ will change about 4 times so cause the P_{max} and P_{min} become very different. Due to this reason, the membership function should be calculated at each time step during operation.

4.3.3.6 Effectiviness and reliability

The effectiveness and reliability of the FDS approach involves issues such as:

- if there is a fault whose level is higher than the threshold, what is the probability of it being detected?
- if there is no fault or is a fault at the level that is less than the threshold, what is the probability of being mis-detected as a fault?

The uncertainty comes from the errors in measurement, the dynamic influence and the non-linear effect. If the uncertainty in CP causing by these three sources can be considered as Gaussian distribution with the deviation of δCP, then

$$\delta CP = \sqrt{\sum_M (\frac{\partial CP}{\partial M} \Delta M)^2} \tag{4.80}$$

where M indicates all the measurements consisting of the CP; ΔM is the deviation of the measurement causing by the sensor's errors, dynamic influence as well as non-linear effect. The value of δCP depends on the operation state.

If it is assumed that the δCP can be considered as Gaussian distribution, the projection P on each fault direction R should also be Gaussian distribution with the expected value P_e and deviation δP:

$$P_e=R(\Delta CP_1, \Delta CP_2, \Delta CP_3,....)^T$$

$$\delta P=R(\delta CP_1, \delta CP_2, \delta CP_3,....)^T \tag{4.81}$$

δP is about one sixth of P_{max}-P_{min} in Eq. (5.78). If the level of fault is higher than the threshold, the P_e will be greater than 1. Assuming $P_{max}-1 = 1-P_{min}$, the probability of membership being greater than a given value M_0 will be:

$$P(M > M_0) = \int_{-\infty}^{6(M_0-0.5)+(1-P_e)/\delta P} \frac{1}{\sqrt{2\pi}} \exp(\frac{x^2}{2})dx \tag{4.82}$$

Fig 4.22 shows the probability of membership being greater than 0.3, 0.5 and 0.7 respectively against different levels of fault in terms of $(P_e-1)/\delta P$. At the threshold level, that is $(P_e-1)/\delta P=0$, the membership will be greater than 0.5 for half cases and will be greater than 0.3 for 87 % of cases. While when the fault is more serious, the expected projector on the fault direction is δP longer than the threshold value, in the other words, when $(P_e-1)/\delta P=1$, the membership will be greater than 0.5 for more than 82 % cases. For more serious fault, that is $(P_e-1)/\delta P>2$, membership being greater than 0.5 will be the most fault cases. From the discussion above, it seems that the smaller membership value used as the threshold to decide whether it is a fault case, the higher the effectiveness that can be achieved. However, the smaller value used as the threshold of membership function, the higher probability of mis-detection of normal operation as a fault. Figure 4.23 shows the probability of mis-detection of normal operation state as a fault when 0.3, 0.5 and 0.7 are used as the threshold of the membership function. It is clear that the larger the uncertain part of the CP, the higher probability of mis-detection. If 0.3 is used as the threshold of the membership function to make the judgement wether it is a fault, the probability of mis-detection will be very high. When the size of uncertain part of the projection equal to 60 % of the threshold of fault level, the probability of mis-detection can be as high as 32 %. While if 0.7 is used as the threshold of membership to make the judgement, the mis-detection ratio can be quite low. However according to Fig. 4.22, the probability of discovering the fault during a fault case will also be quite low. Balancing of these two sides, 0.5 may be the best value as the threshold of membership to judge whether it is a fault case.

Fig. 4.22 and 4.23 also shows that effectiviness of the FDS approach depends on the portion of the uncertain part of the projection, that is δP/P, where P is the projection of the CP on the fault direction R when the fault is at the threshold level. The value of δP depends on the quality of sensors, the trend of the dynamics of the system and the non-linear behaviour of the system. While the size of P depends on the threshold of the fault level, that is the level of fault which should be considered. To increase the reliability and the effectively of the FDS approach, sensors and the statization procedure should be well selected according to the required fault threshold level, P.

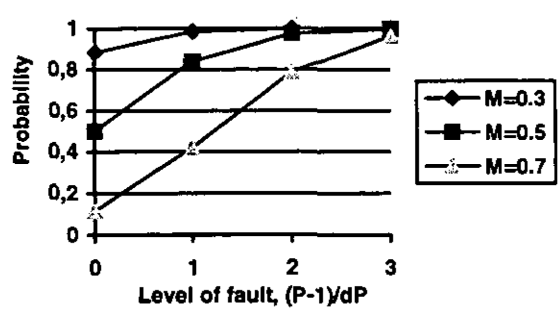

Figure 4.22. Probability of fault being detected when different thresholds are used as memberships.

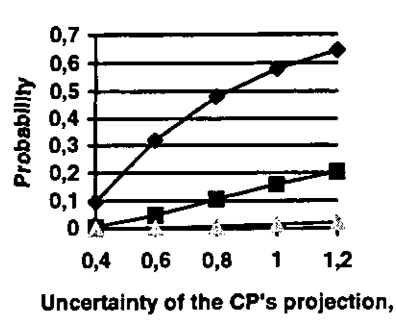

Figure 4.23. Probability of mis-detection as a fault during normal operation.

4.3.3.7 Summary

FDS method is based on the static physical model of the system to be studied. Instead of predicting the behaviour of a system on-line and comparing it with measured data, the FDS structures a set of CP and checks if the CP changes during operation. The change in CP indicates a fault. The direction in which the CP changes provides information about the type of fault.

A priori-knowledge required for the FDS method includes the definition of CP for different components and systems, the direction of each type of fault calculated at the threshold level of each type of fault. This knowledge can be produced by research work and provided to industry in the way of a database. In real applications, the FDS procedure can be built into a BAS (building automation system) system and work in a standard way to the extent that this knowledge is available. Commissioning of this procedure on site is almost eliminated.

The disadvantages of the FDS procedure compared to other methods are as follows:

First, it may need more sensors installed in the system to collect enough data for structuring the CP. Second, the FDS can only detect the change in the performance of components and systems due to physical defects. Some kinds of fault which are caused by outside influences rather than the system itself cannot be detected. For instance, a window in a conditioned space is opened such that the cooling load is too high. This needs an "if-then" procedure to be dealt with. Another example is that the temperature of chilled water is too high. The FDS method cannot report any fault within the air handler unit despite of the higher humidity or temperature of conditioned air. For this reason, an "if - then" rule may be needed to be combined with the FDS procedure to complete the fault detection and diagnosis.

4.3.3.8 Reference

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4.4 CLASSIFICATION APPROACHES TO FDD

4.4.1 Topological case based modeling

Hiroaki Tsutsui,
Yamatake-Honeywell Co., Ltd. Advanced Technology Center

4.4.1.1 Introduction

Several black-box modeling techniques [4.85 - 4.86] use historical data from the target system. Traditional black-box modeling techniques currently under vigorous investigation, such as neural networks and fuzzy modeling [4.87], are all well-known. These techniques are useful for modeling complex systems with relationships which are not easy to describe by physical equations or qualitative rules. These black-box modeling techniques convert modeling data to several model parameters, and it is therefore difficult for these models to show the qualitative relationship between new system states and the model [4.88]. That is, it is hard to decide whether the given data are sufficient for predicting system states. When attempting to apply these modeling techniques using insufficient data to build model parameters, the difference between actual measurement values of a system and the model output for the same input situation is hard to identify, and to cope with actual application problems becomes difficult.

For these problems, the idea of Case Based Reasoning (CBR) [4.89] is useful. CBR assumes that the input/output set implicitly contains the modeled system's internal mechanisms. Therefore, CBR does not require explicit statement of the input/output transfer function and its model parameters.

CBR infers a new case from stored cases and the relationship between new and recorded cases. However, CBR theory provides no general method to define the similarity (relationship) between cases. This paper proposes a definition of similarity as *the neighborhood in input space corresponding to a specified output closeness*. Closeness is arbitrarily set before constructing the model. This technique is named Topological Case Based Modeling (TCBM), and is described here.

4.4.1.2 Overview

The problems of traditional black box modeling techniques are inherent to modeling schemes which attempt explicit representation of the entire system. The paucity of theoretical bases for applying such approaches to complex nonlinear systems frequently results in time-consuming trial-and-error model development.

CBR operates using only localized system characteristics. CBR assumes that the modeled system's internal mechanisms are implicitly represented by measurable input/output relationships. Therefore, CBR does not require explicit statement of the input/output transfer function.

Previously, however, CBR theory has included no general method to define the relationship between cases recorded as discrete system states.

In this paper, it is assumed that the input/output data are extracted from historical data involving a certain continuous functional relationship. The concept of a topological continuous mapping is used to define a system of neighborhoods in the input space which map to neighborhoods in the output space with the specified closeness. The neighborhoods of input space are statistically converted to a single neighborhood. This method is referred to as Topological Case Based Modeling (TCBM).

Application of TCBM facilitates automated model construction from stored historical data, without regard to a formal model of the system. This basis in actually measured historical data represents internal mechanisms of the system implicitly.

For the statistically defined neighborhood of input space, a locally continuous mapping to the output is defined. A measure of similarity between these input cases is defined by the neighborhood, and interpolative and extrapolative methods are used to estimate the output of the new case against historical data from the case-base.

The use of a database of cases facilitates rapid update of the modeling system, as cases may easily be inserted or removed. This enables online adaptive learning.

TCBM's localized formalism of cases makes the approach highly descriptive.

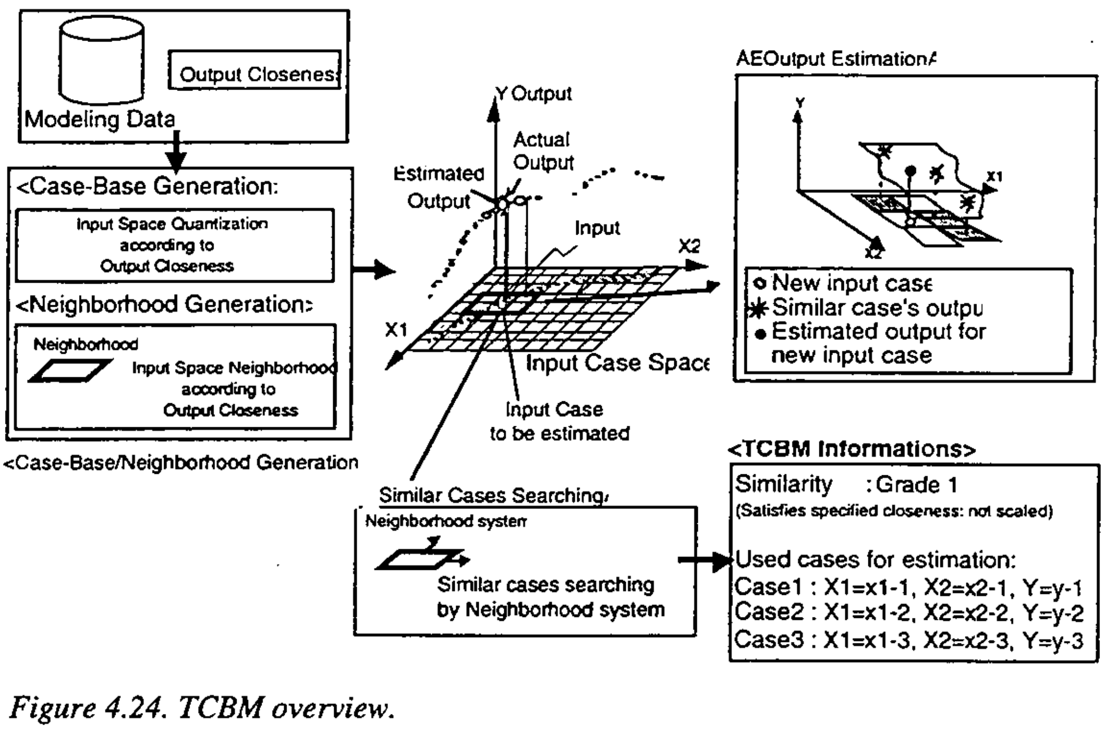

Figure 4.24. TCBM overview.

The procedures described in sections 4.4.2.3 to 4.4.2.5 are simply one implementation of the TCBM approach. There are many possible implementations, just as there are many ways of implementing techniques based on neural networks.

4.4.1.3 Case-base construction

4.4.1.3.1 Input/output variable definition

The first step of black-box modeling is to identify a set of input variables which together determine the system output. To achieve this, expert knowledge, statistical analysis, stepwise procedures, and other techniques are used.

From these analyses, input/output tuples are determined, and used for modeling.

4.4.1.3.2 Structure of the case-base

To construct the case-base, the input space is first partitioned into finite sets of input cases and quantized. The number of partitions is selected to give an output distribution for the same input case with the specified closeness. All cases within one quantization region are considered as "the same input case" in the following discussions.

The initial quantization number, m-initial, is defined as:

m-initial = whole range of output / specified closeness as defined.

The axes for the input variables are divided by the same initial quantization number.

The output distribution for the same input case is then calculated.

(1) If the whole output distribution for the same input case is within the specified output closeness, m-initial is decreased until the entire calculated output is within the specified closeness of output, to reduce case-base memory requirements.

(2) If any output for the same input case is not within the specified output closeness, m-initial is increased until the whole output distribution falls within the specified output closeness.

The input space is quantized by the final quantization number defined by this procedure. If no quantization number can be determined by steps (1) and (2), the input variable definition is assumed to be incorrect and is investigated again (as described in section 4.4.2.3.1).

A single case is generated by converting the input historical data to a single integer input case. Here, for 'n' inputs with partitioning number 'm', a single input case is symbolized in a m-adic manner.

Some historical data has been located in quantized input space and has the quantization number for each variables: N-x1, ..., N-xn.

The case indication of the historical data is:

$$N\text{-}x1 \cdot m^{n-1} + N\text{-}x2 \cdot m^{n-2} + N\text{-}xn$$

Case-base structure

(Input variables are X1,....,Xn, output variable is Y, number of recorded data which belong to the same input case is k)

Input case	{Xi}	(i=1,....,n)
Same input case number	k	
Average value of output for same input case	$Y = \sum_{j=1}^{k} \frac{Y_j}{k}$	
Average value of output differentiation for same input case	$\frac{\partial Y}{\partial Xi} = \frac{\sum_{j=1}^{k} \frac{\partial Yj}{\partial Xij}}{k}$,	*(i = 1, ... n)*

This equation is an approximation to simplify online calculation. The "t" in the

$$\left(\partial Yj / \partial Xij = [1 / \mid xij(t+1) - xij(t-1) \mid / \sum_{i=1}^{n} 1 / \mid xij(t+1) - xij(t-1) \mid] \cdot [yj(t+1) - yj(t-1)] / [xij(t+1) - xij(t-1)] \right)$$

equation is a timestamp. The smaller the variation of the i-th input, the greater the efficiency.

If the relationships between the infered case and a similar case in the case-base is the same as [xij(t + 1) - xij(t − 1)], (i = 1,..., n), the output of the similar case is revised as [yj(t + 1) - yj(t − 1)] by the Equation in 4.4.2.4 (see Phase 3 - Inferencing).

The $1/|xij(t+1) - xij(t-1)| / \sum_{i=1}^{n} 1/|xij(t+1) - xij(t-1)|$ is the i-th input weight of [yj(t + 1) - yj(t − 1)]/ [xij(t + 1) - xij(t + 1)].

The differentiation of the i-th input is the smaller, the efficiency to output is the bigger.

4.4.1.3.3 Topology, closeness and neighborhoods

Topology

In this paper *topology* is a concept which assures a continuous relationship between input and output spaces, and facilitates the definition of a concept of *closeness* for both input and output spaces. The set of values within a given closeness of a point constitutes the *neighborhood* of that point with the given closeness.

Continuous mappings

A mapping f: X->Y is continuous if and only if $f^{-1}(z)$ is in a neighborhood of X for all z in the neighborhood of Y.

From this definition, given a neighborhood of a given closeness in Y, and the existence of such a continuous mapping f:X->Y, it is possible to obtain the corresponding neighborhood in X.

In terms of TCBM, X corresponds to the set of input historical data, Y to the set of output data.

The absolute size of a single neighborhood in X (the input space), which is a statistical value according to neighborhoods of the specified closeness in Y (interpreted in TCBM as the *granularity* in Y), is a scalar quantity which may be used as a measure of the local correlation between the particular variables in question. A smaller value of this measure corresponds to a higher correlation between X and Y.

There are two procedures to calculate the neighborhood. The former is based on a statistical methodology, while the latter strictly assures a given closeness in Y.

(1) The regions in X according to neighborhoods of the specified closeness in Y are calculated. The regions are statistically averaged to define the absolute size of a single neighborhood in X. A sample case is shown in Figure 4.25. The absolute size of a single neighborhood (q-X) is q-x1=1 and q-x2=3.

$$q-x1 = \left[\sum_{i=1}^{n} Ri(q-x1) \; / \; n \right] = 1$$

(n=8, Ri (q-x1) is a quantization number of the region "i", []: Gauss's notation)

$$q-x2 = \left[\sum_{i=1}^{n} Ri(q-x2) \; / \; n \right] = 3$$

(n=8, Ri (q-x2) is a quantization number of the region "i", []: Gauss's notation)

(2) The regions in X according to neighborhoods of the specified closeness in Y are calculated (Figure 4.25). The minimum values of the regions are calculated to define the absolute size of a single neighborhood in X . A sample case is shown in Figure 4.25. In this example, the absolute size of a single neighborhood (q-X) is q-x1=1 and q-x2=2.

$$q - x1 = \min_{i=1}^{n}\{ Ri(q - x1) \} = 1$$

(n=8, Ri (q-x1) is a quantization number of the reagion "i")

$$q - x2 = \min_{i=1}^{n}\{ Ri(q - x2) \} = 2$$

(n=8, Ri (q-x1) is a quantization number of the reagion "i")

In this example, x1 is more strongly correlated to Y than x2 is to Y.

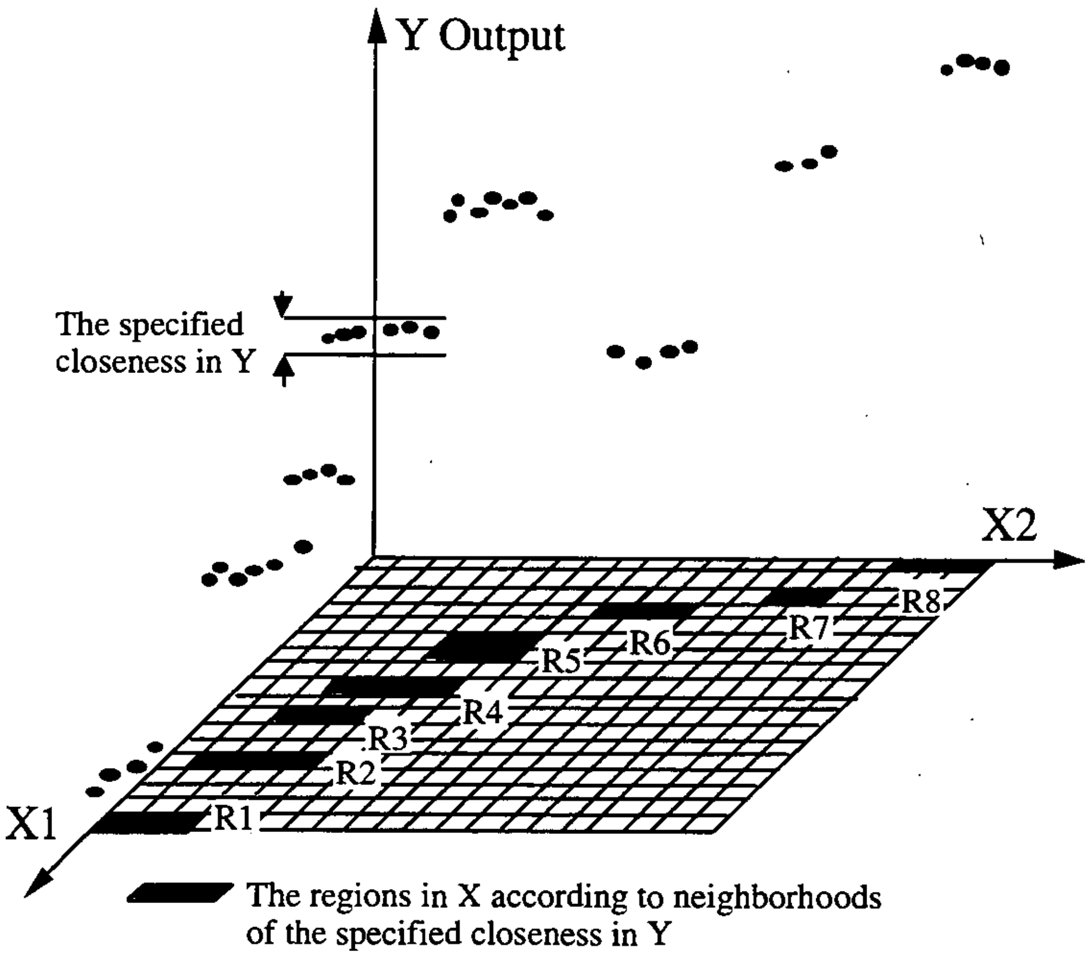

Figure 4.25. Neighborhoods.

The neighborhood system is generated by increasing or decreasing the quantization number of each variable of the neighborhood (Figure 4.24). The neighborhood system can thus select the cases which are used for inferencing.

4.4.1.4 Inferencing procedures

TCBM inferencing consists of 3 phases.

Phase 1 – Searching

New input cases are compared using cases stored in the case-base to determine similarities, using the neighborhood system.

If the system has n-inputs and one output, n+1 cases are selected. These n+1 cases can be represented by an n+1-dimensional local space.

Phase 2 – Significant weight calculation

The weight of the selected cases for the new situation is calculated as follows.

Two different equations may be used to calculate the weight, however their inferencing performance is almost the same.

1. Using topological distance:

Topological distance :

$$L = \sum_{i=1}^{n} \phi i \cdot | Xi^* - Xi |$$

Xi* is a new situation of Xi

$$\phi i = Ri / \sum_{i=1}^{n} Ri$$

(, where Ri is a correlation coefficient between Xi and Y)

and the significant weight : w = exp (-L)

2. Using neighborhoods:

$$w = w(x1, \ldots xn) = 1/(\sqrt{2\pi})^n \cdot 1/(\sigma x1, \ldots, \sigma xn) \cdot e^{-1/2(x1^2/\sigma x1^2 + \ldots + xn^2/\sigma xn^2)}$$

σxi : the statistical distribution xi is q-xi/2 to the specified closeness in Y

q-xi : the neighborhood of xi

Phase 3 – Inferencing

The selected n+1 cases are used for inferencing the new situation Y* from the new input set $X_1^*, ..., Xn^*$.

$$Y^* = \sum_{j=1}^{n+1} [wj \cdot \{Yj + \sum_{i=1}^{n} (\partial Yj / \partial Xij) \cdot (Xi^* - Xij)\}] / \sum_{j=1}^{n+1} wj \tag{4.83}$$

Xij : The value of i-th input variable for j-th selected case

Yj : Recorded value of output for j-th selected case

$\partial Yj / \partial Xij$: Recorded value of output differentiation for j-th selected case

wj : Significant weight of j-th selected case for new situation

4.4.1.5 TCBM characteristics

TCBM differs in several characteristics from generalized black-box modeling techniques. These differences are detailed below:

(1) TCBM defines the input space neighborhood according to the specified closeness of the output by topological continuous mapping. The neighborhood system, which is generated by zooming in on the defined neighborhood, can show the local relative relationship (similarity) between a new input case and recorded cases. The more the neighborhood has been scaled up, the more the inferred output becomes uncertain. Therefore, this zooming degree is a novel assurance index for inferred output according to input situation.

(2) TCBM regulates only input/output variables, without formalizing global input/output functional relationships.

(3) TCBM stores data as cases – historical data is not converted to model parameters.

(4) TCBM can identify the cases which are used for inferencing the new situation's output according to each new situation's input. Cases similar to the new input situation may be extracted from the case-base using the neighborhood system.

(5) Output estimation is performed locally by extracted cases using the neighborhood system.

These characteristics give the following advantages over generalized black-box modeling.

(i) General black-box models assure output certainty by only one statistical value, such as mean square error, which does not consider the input situation. If the current input situation data was not used for modeling, the inferred output is uncertain.

On the other hand, TCBM can evaluate output certainty according to the input situation. (by (1)) (Figure 4.26)

(ii) TCBM can check the basis for inference, showing the cases which are used for inferencing and their closeness by the zooming degree. (by (1), (3), (4))

(iii) TCBM can construct complex nonlinear models without investigating input/output transfer function parameters or networks. (by (2), (3))

(v) TCBM easily takes in new cases or improves the model simplifying online modeling. (by (2))

(iv) TCBM is suitable for modeling nonlinear systems. (by (5))

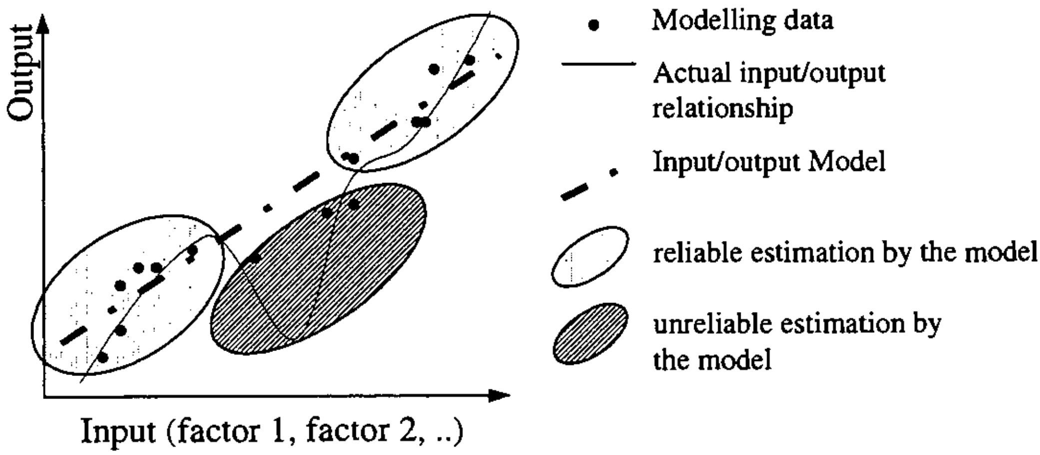

Figure 4.26. General black-box model by historical data.

4.4.1.6 FDD using TCBM

Faults are classified roughly into two classes. The first leads to breakdown and requires rapid treatment, whereas the second results in deterioration requiring treatment within the long term.

TCBM may be applied in situations involving:

(i) Multiple input/single output systems (ii) Nonlinear input/output relationships

(iii) Continuously changing inputs, outputs and relationships.

(1) Recognition of Breakdown Faults

In this case, there are two possibilities – the fault may be identified by a sudden change in system state, and may be due to an undetectable crack or other material failure. The second of these possibilities, material failure, may often only be detected by mechanical sensing, and is best tackled with other techniques.

In the first case, when a sudden divergence of output values between the model and the actual system for the same input state occurs, the question arises and has the problem whether or not the same or similar input states which might be another normal state exists in the modeling data.

In this situation, TCBM can judge continuing fault states by the presence of either:

(i) Absence of the same (or similar) current set of input variables from the case-base, or

(ii) A large difference between the current output value and the case-base output value corresponding to the same or the similar input.

These determinations are possible because TCBM uses cases without transformation, and uses a neighborhood of input space based on closeness in the output space.

(2) Recognition of long-term deterioration

When deterioration is occurring, change in the system state does not arise suddenly. Therefore, the existence of an input state similar to the current input state in the case-base is assumed. However, as the system changes slowly, a marked variance between the current state and the normal state does not arise. The model must be able to exactly describe this difference. If the relationship between inputs and outputs is globally formalized using the normal state data, the difference must be evaluated statistically to define the proper threshold. With such a technique, it is also difficult to assess whether the data quality is sufficient for state recognition. Given a sufficiently dense case-base, TCBM, however, can evaluate the current states individually under dynamically changing system conditions, can effectively analyze the differences between states with similar cases or the same case. TCBM is ideally suited for this kind of determination.

4.4.1.7 Conclusion

TCBM is a general method for black-box modeling which uses actual historical data obtained from a system. TCBM doesn't convert historical data information to model parameters which are used for global input/output functional relationships.

Therefore, model construction is easier than traditional black-box modeling, especially for constructing complex nonlinear models.

TCBM information, such as similarity and cases with estimated value, provides confidence in estimation. In this sense, TCBM is not a complete black-box model.

As TCBM can easily handle real time information, online modeling is easier.

The ease of use of TCBM, due to its simplicity and clearness, make it appropriate for actual application problems such as described in this paper.

4.4.1.8 References

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4.4.2 Artificial neural networks - approach

Vaezi-Nejad, H.
CSTB, France

4.4.2.1 Introduction

Man has always endeavoured to understand how the living world works, in particular the difficult process of cognition. Although intelligence can hardly be "defined", three essential faculties seem to be linked to any form of intelligence:

- the ability to store data acquired from experience. This means that perception and the ability to store and learn are required;

- the ability to structure these data. This requires judgment, logical reasoning as well as "good sense" and intuition etc.;

- the ability to develop, from these data, models to adapt to new situations.

What else can be required of a complex system diagnosis process? For instance, the human brain is considered to be one of the best systems in terms of performance, most likely to perform this task. The neuron or nerve cell is, as we all know, the basic functional element of the brain. It is therefore easy to understand the interest aroused by connectionist methods. Why not be inspired by biological principles to develop algorithms and machines that are better in terms of performance than those developed up to now?

In 1943, McCulloch and Pitts [4.91] proposed a model which proved to serve as a basis for present neural networks. Based on neurobiological knowledge, they developed a Boolean human neural model. In the meantime, the work carried out by Hebb [4.90], a neurophysiologist, underlined the importance of synapses to the learning process. In 1949, he proposed a qualitative synaptic modification rule.

Thanks to the above-mentioned work, models started to develop. In 1958, Rosenblatt's perceptron [4.92], the first network model, was able to learn some simple functions by progressively modifying the strength of synaptic links between neurons. Meanwhile, Widrow and Hoff, two electronics engineers carried out research into particular network architectures for adaptive signal filtering: Adaline and Madaline.

This work was highly debated in 1969 by Minsky and Papert who showed the perceptron's limits [4.93], thus resulting in a slowing down of the research into networks. The craze for networks started again in the eighties. Hopfield's research (stemming from physics) and in particular the development of a learning algorithm for multi-layer networks (backpropagation of the derivative of the error) by different research teams (Le Cun, Rummelhart) opened up new horizons for connectionist models.

Today, the field of application of networks is already widespread: signal processing (image, words), data pre-processing, pattern recognition, process identification and diagnosis etc.

4.4.2.1.1 Formal neural networks

The term "neural network" refers to a very rich field because of the variety of formalisms that coexist under this designation. This paragraph is aimed at defining a general framework within which all the models that we are going to present may lie.

Definition:

> *A neural network is defined as a set of processing units (or neurons, cells or automatons) in which all of the units are in contact with one another or with the outside by means of axonal or synaptic ramifications.*

Generally speaking, a network can only be perfectly defined if we know:

- the nature of the cells it is composed of;
- its architecture;
- its propagation rule;
- its learning method.

4.4.2.1.2 Neuron model

Each cellular automaton (Figure 4.27) receives from other automata or from the outside, a number of activating signals x_i by means of a synapses. It then carries out a weighed summation of these signals to calculate an activation potential p_i.

$$p_i = \sum_j w_{ij} x_j \tag{4.84}$$

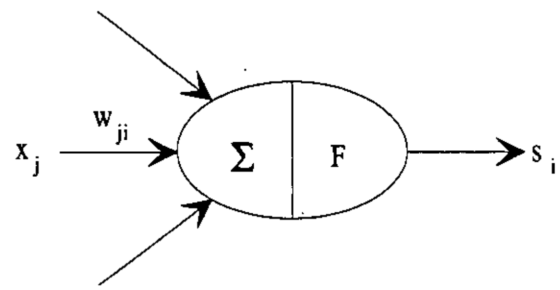


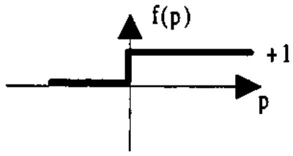
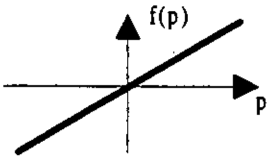
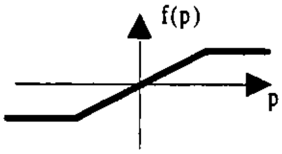
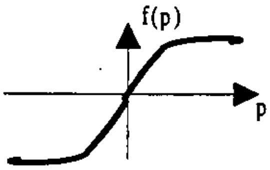
Figure 4.27. A formal neuron.

Weighting is carried out by means of a weight w_{ji} associated to each synapsis. A transfer function or activation function F then generates, by comparison with a threshold w_o, an output signal s_i which itself is sent to other neurons.

$$s_i = F(p_i + w_0) \tag{4.85}$$

We may observe that threshold w_o is frequently considered as the weight associated to an additional input set to 1. Depending on the type of inputs and the type of activation function, we may notice several types of cells. Examples of the most commonly used activation function are listed in Table 4.3.

Table 4.3. Examples of transfer functions.

	inputs/outputs	**activation function**
Threshold transfer function (McCulloch and Pitts)	binary or continuous inputs binary outputs	 step
Linear transfer function	actual inputs and outputs	 linear
Saturation transfer function	actual inputs bounded outputs	 bounded linear
Continuous automaton	actual inputs and outputs	 sigmoïd
Probabilistic transfer function	any type of inputs binary outputs	stochastic function

4.4.2.1.3 Network architecture

Different types of architecture are used: networks that are totally connected, locally connected, arranged in successive layers, etc. Nevertheless, the choice of connections facilitates the use of the network and the interpretation of weights. Various types of network architecture are depicted in Figure 4.28.

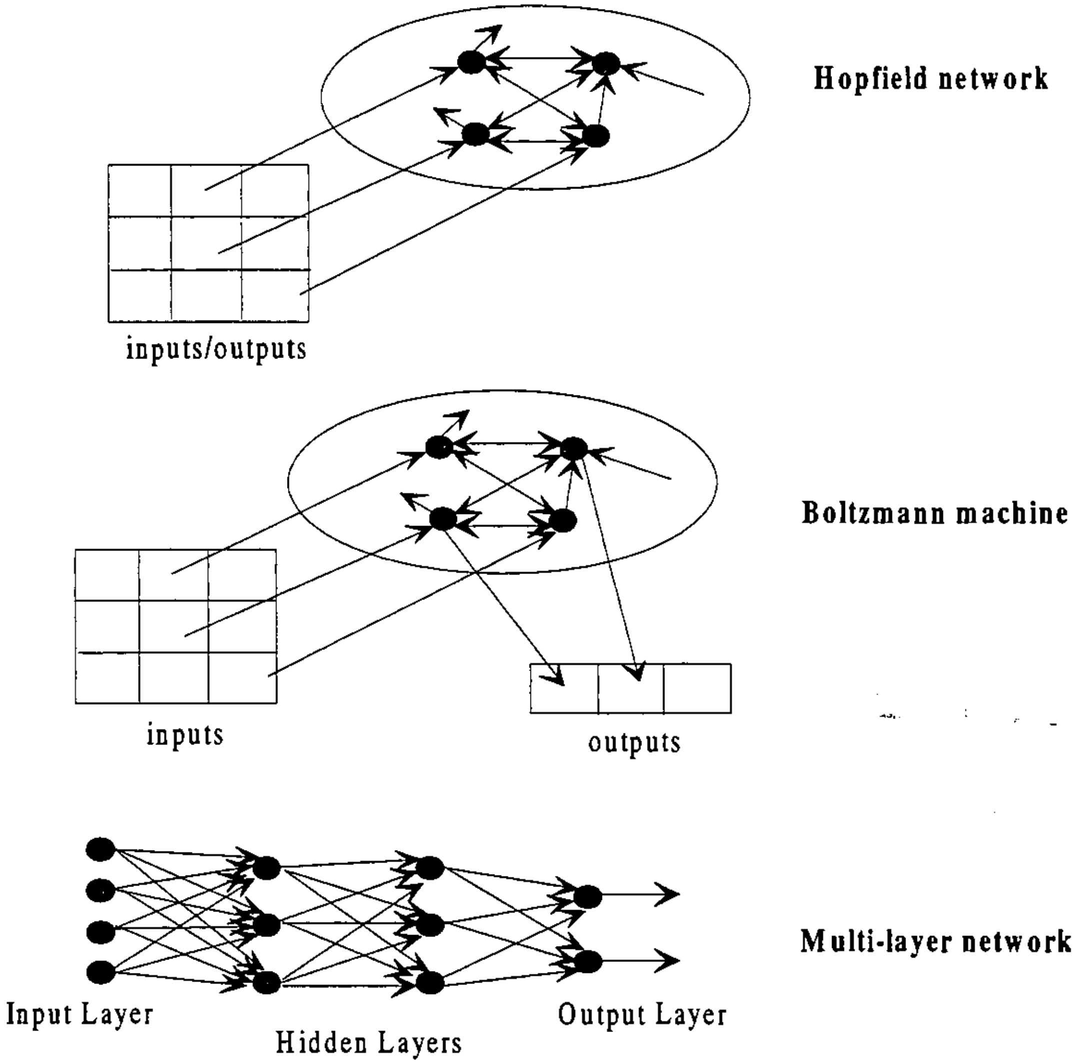


Figure 4.28. Different types of network architecture.

4.4.2.1.4 Learning

The most interesting property of networks, inspired by the nervous system, is obviously their faculty for learning, that is their ability to acquire and store knowledge thanks to experience. This information is fully contained in synaptic weights w_{ij}. From a connectionist's point of view, learning means:

- removing existing connections,
- developing new connections,
- modifying the strength of connections.

Even if studies are now undertaken on the first two points mainly devoted to the forgetting phenomenon, the third point is of course most frequently used (and can be considered as the generalization of the two others). Without getting deeper into this learning notion, it should be mentioned that we usually distinguish two types of learning:

- supervised learning which consists of determining weights so as to impose on each input a desired output (a *teacher* is required),
- unsupervised learning, done without any teacher thanks to a self-organization process based on competition between cells.

Some authors mention a third learning category referred to as "learning *by reinforcement*", which is close to supervised learning in the sense that instead of having a desired output associated to an input, we have a note qualifying the output quality. We will go into detail about learning algorithms in a later section.

4.4.2.2 Studying several models

4.4.2.2.1 From the automaton by McCulloch and Pitts to the multi-layer network

This part describes the process which has led to the development of a high-performing network model: multi-layer networks.

Geometrical interpretation of a neuron

Consider the simple neuron by McCulloch and Pitts [4.91] represented by Figure 4.29. The output of this neuron, for an input $x = [x_1,x_2]^t$ of R^2 is expressed as follows :

$$s(x) = F(p) = F(w_0 + w_1x_1 + w_2x_2) \qquad (4.86)$$

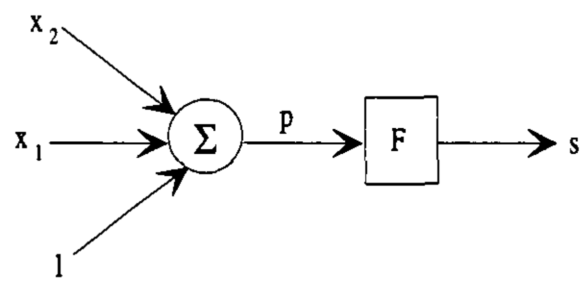


Figure 4.29. McCulloch and Pitts' neuron in R^2.

The transfer function F of the neuron is here chosen as a signal function generating a (+1) or (-1) value depending on the sign of the calculated summation. F is the identity function.

$p = 0$ defines the equation of a straight line in the plane $[x_1,x_2]$ which divides the space into two half-planes, the sign of s(x) defining x membership of either of the two half-planes (Figure 4.30).

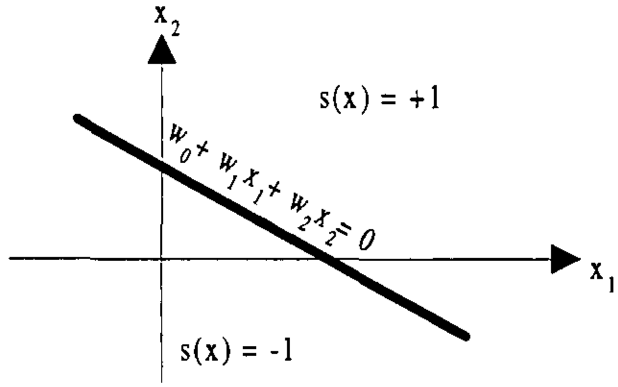


Figure 4.30. The neuron represented as a linear separator.

A neuron with d+1 weights $w = [w_0, w_1, \ldots, w_d]^t$ can be regarded in the same way as a separating hyperplane in R^d. The application to the linear discrimination into two classes is then immediate.

Perceptron

The weight learning algorithm proposed by Rosenblatt [4.92] consists of sequentially presenting the forms and progressively modifying the weights as follows:

<u>*Algorighm.:*</u> **Perceptron**

i) Initialize *w*

ii) Until all the forms are well classified

. presentation of a form x
. calculation of $s(x)$
. adaptation of weights
$w_j = w_j + \alpha\big(s(x) - t(x)\big)x_j \;\; \forall j = 0, d$

End until

t(x) is a target output (or desired output) imposed on the neuron. Here t(x) will be equal to +1 if x belongs to w_1, and to -1 in the opposite case. α is called the adaptation step. If the form is correctly classified, weights are not modified at all. If not, the adaptation of weights consists of adding or taking away a certain proportion of the input vector from the weight vector. w modifications shall be considered as the progressive positioning of a separating hyperplane between the two classes. Unfortunately, it is possible to show that the algorithm can only converge if there is a linear separation between the classes, which restricts the application area (see [4.94].

Adaline

The Adaline model (ADAptive LInear NEuron) is the result of the work by Widrow and Hoff [4.95]. The interest of the model lies in the weight adaptation rule called Widrow-Hoff rule, which can be expressed in the following form:

$$w_j = w_j + \alpha\left(\sum_{k=0}^{d} w_k x_k - t(x)\right)x_j \quad \forall j = 0, d \tag{4.87}$$

The Widrow-Hoff rule differs from the perceptron rule in the sense that the synaptic modification is made depending on the non-threshold neuron output and the desired output, and not on the output value (with threshold) and the target value. The difference is huge since each time a form is presented, the weights are modified. Each form of the learning set will result in "pushing away" the separation area if it is well classified, and if not, in "removing" it. A more median separating hyperplane can thus be found.

Multi-layer networks

Multi-layer networks can be regarded generally as a tool for the numerical modelling of a function, permitting the passage of some space or other into another one. This can be achieved without a priori information on the form of the function by using an example basis, also called *"learning basis"*, i.e. a set of data couples (input space/output space) which will permit network learning. The primordial advantage of neuron networks in general and particularly of multi-layer networks, is their capacity for *generalization* (or interpolation), i.e. their ability to correctly react to an input which does not belong to the learning basis. In order to test this capacity for generalization, we generally use a second set of data called *"testing basis"*. Multi-layer networks have expanded only recently (in the eighties) since from the beginning arose the delicate problem of their learning capacity. The weight adaptation methods described above require a *"teacher"*, which means that for each neuron from the output layer, a target value is specified. If we introduce several hidden layers, specifying a target value at the exit of the hidden neurons appears to be impossible. So we need a new algorithm in order to modify weights of the hidden layers using only the output error. We need also a derivability property for f(i). Using the sigmoïd function (differentiable) allows a new learning algorithm to be developed, the *backpropagation of the gradient's error*, which refers to the simple properties for the derivation of compound functions [4.96 - 4.98].

Backpropagation of the gradient

The network learning algorithm consists of determining the weights from a set of couples (inputs/outputs) in order to minimize a criterion of the least square type measuring the gap between the outputs observed and the ones imposed on the network.

The transfer functions of the cell layers are called "sigmoïd functions". These functions are often calculated as follows:

. sigmoïd [0;+1] : $f(x) = \frac{1}{1+exp(-ax)}$

. sigmoïd [-1;+1] : $f(x) = -1 + \frac{2}{1+exp(-ax)}$

Parameter a has an effect on the slope of the function in the *"non saturating"* part of the sigmoïd. The higher a, the closer the sigmoïd approximates a step function.

Algorighm.: **Backpropagation of the gradient**

i) **Initialize** ***w***

ii) **Until** the stop criteria is satisfied

For all forms of the learning bases

. presentation of a form x
. calculation of the network output
. calculation of the error according to the target
. calculation of the network output layer derivative error
. backpropagation of the derivative error and adaptation of weights

End For

End Until

Modifying synaptic weights

We obtain according to the gradient algorithm a general formulation for modifying weights of the layer k (w_{ij}^k) expressed as follows:

$$w_{ij}^{(k)} = w_{ij}^{(k)} - \alpha \frac{\partial E}{w_{ij}^{(k)}} \quad \forall k = 1, r \ \forall i = 1, n_{k+1} \ \forall j = 1, n_k \tag{4.88}$$

where α is the adaptation step, r is the number of layers and n_k is the number of neurons of the layer k.

Stop criteria

There may be several stop criteria. The most commonly used are the following:

- stop if the number of iterations is higher than a given limit,
- stop if the sum of errors at the exit of the networks for all the learning forms is lower than a given threshold,
- stop if the error progression between two iterations is lower than a given threshold.

This last stop condition is recommended since, in practice, we do not know beforehand the minimal value of the cost function associated with the problem.

Each multi-layer network user is naturally induced to ask himself the delicate question of network architecture: number of layers, number of cells per layer. As regards the number of layers, a significant result was obtained by Funahashi [4.97] who showed that any continuous function could be approached by a network with one hidden layer, with linear transfer functions for input and output, and with bounded increasing monotonous transfer functions (sigmoïd for instance), provided that the number of neurons in the hidden layer is sufficient. The choice of the number of cells in the hidden layer is guided by the following observation: the higher the number of neurons in the hidden layer, the lower the overall error of the network on the *learnt* forms (Figure 4.31). This observation also applies to the number of iterations to be carried out (Figure 4.31). After a number of iterations, whereas the learning error is still decreasing, the test error which was diminishing significantly at the beginning of the learning process, begins to increase. We observe a learning *"by heart"* phenomenon according to which the network is even able to learn noise. The weights value for which the overall error for the test forms is minimal should be save. In the case of a huge volume of data, it is possible to divide the original set into three parts: one part intended for network learning, another one for testing its power of generalization and the last one for a testing set. We then refer to cross-validation.

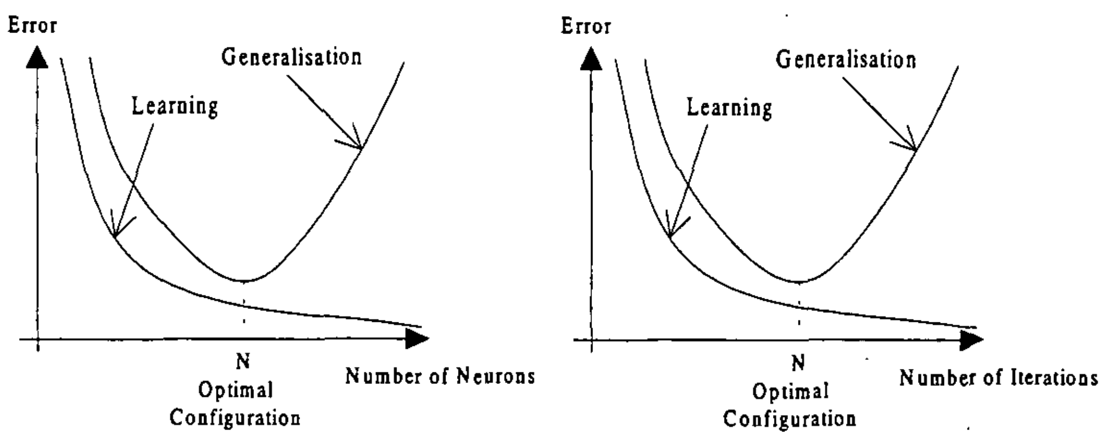


Figure 4.31. Learning "by heart" phenomenon.

4.4.2.2.2 Competitive learning models

The previous paragraph was focused on the functioning of supervised learning algorithms whose principle lies in minimizing a cost function by measuring the gap between the actual output from the network and an output that we want to impose. This part of the document will be devoted to unsupervised algorithms called : "competitive learning" algorithms. The general description of this type of algorithm is as follows:

- we start with a set of units, all of them being identical to within a random factor, which enables them to respond slightly differently to a set of input data (patterns); a set of weights of the input space is associated with each cell. The cell response is a function of a dissimilarity measurement between the input form and the weights of the cell;

- units are allowed to compete in a certain way in order to obtain the right to respond to certain forms. During the learning process, weights are modified in order for similar input forms to generate the same outputs.

Following the learning process, each cell appears in the form of a characteristic detector, that is a prototype for the input space.

Simple competitive learning

The simple competitive learning rule, whose principle is at the root of Kohonen's algorithm of topological cards, is a widely used rule. It does not refer to any neighbouring notion; the weight adaptation is only carried out on the winning cell:

$$w_c = w_c + \alpha(t)(x - w_c) \tag{4.89}$$

It was shown [4.100] that weights converge in probability towards the centre of gravity of the forms which activate them if the sequence $\alpha(t)$ conforms to the following:

$$\lim_{t \to \infty} \alpha(t) = 0$$

$$\lim_{T \to \infty} \sum_{t=1}^{T} \alpha(t) = \infty$$

Conclusions on competitive learning

This type of network is rarely used alone in practice; it usually forms an efficient pre-processing layer for networks operating in a supervised mode.

4.4.2.2.3 Varying architecture models

Up to the present time, we have studied network models whose overall architecture is determined before the learning process and does not vary in the meantime. Some research scientists took an interest in cell incremental recruitment algorithms. Besides the fact that this strategy avoids the crucial and often tedious problem in selecting the number of cells, it has the advantage of not having to question any previous learning when new data are inserted in the network.

RCE networks

Specialized in classification tasks, the RCE network, which operates in a supervised mode, is the precursor of a whole generation of networks which differ only slightly from RCE network.

An RCE network (whose name derives from its authors: Reilly, Cooper and Erlbaum) [4.101] is composed of three layers:

- a first layer which receives input data,
- an internal layer which represents a space prototype,
- an output layer which classifies the form.

A cell j on the internal layer computes the Euclidean distance between the input vector x that comes from the previous layer and the weight vector w_j which is associated with it. This distance is then compared to a threshold Y_j to generate either a positive (active cell) or negative signal :

$$A_j = f\big(Y_j - \sum_{i=1}^{d}(x_i - w_{ji})^2\big) \qquad \text{f: signal function} \qquad (4.90)$$

The representation of a cell in R^2 is given in Figure 4.32. Generally speaking, a cell belonging to the internal layer may be regarded as a hypersphere with a radius Y_j centred on a space prototype.

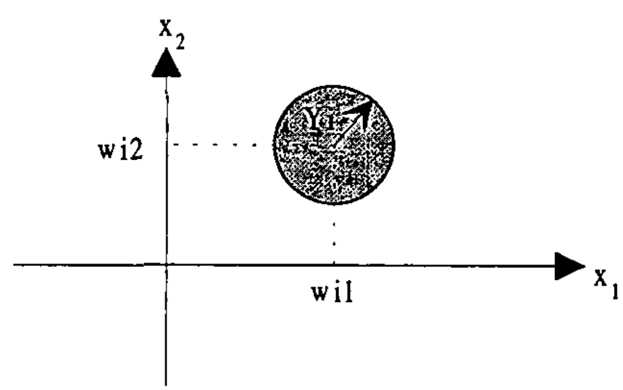


Figure 4.32. Representation of a cell in the internal layer in the plane.

Each output cell corresponds to a class. It is active if at least one of the cells in the internal layer connected to it is active. The main advantage of this learning algorithm is the ability to proceed by a dynamic construction of the network.

Among the advantages of RCE, its very high learning speed and its ability during testing to reject forms located far from the learning zones (distance rejection), are worth mentioning. However, two drawbacks penalize RCE:

- the system does not assure the absence, inside classes, of "holes" that can lead to the rejection of a point in a class,
- the system is not able to quantify the degree of closeness of a rejected point.

4.4.2.3 Conclusion

At the present time, the human brain is assumed to contain between 10^{10} and 10^{11} neurons; and each neuron is supposed to be able to receive or emit from 10,000 to 100,000 signals. Although it seems easy to prove that the term "neuromimetic" network and other terminologies are formal neural networks or artificial neural networks, computer models are, for the time being, of course far from the performances of their renowned model. Still this field, which is in full expansion , opens up new research axes, parallel processing and possible dedicated material achievements, which prove to be the major assets of these techniques.

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4.5 EXPERT SYSTEM APPROACHES TO FDD

4.5.1 BOFD rule-based method

Kamimura, K., Yamatake-Honeywell, Japan

4.5.1.1 Introduction

A fault detection and diagnosis system which applies rule-based knowledge is also known as an expert system. If any fault occurs in a system it covers, it first detects the fault manually or automatically from a knowledge base of measured data or from a fault detection program. It then notifies the manager or operator of the result. Further, from a knowledge base of multiple faults and their causes, it automatically infers the cause of a fault and notifies the manager or operator of the diagnostic result (Fig. 4.33). Based on the diagnostic result, the manager or operator proceeds to take necessary steps such as eliminating the cause of the fault or reviewing the values set for the control system.

This section explains the technology behind the expert system and describes a particular fault detection and diagnosis expert system.

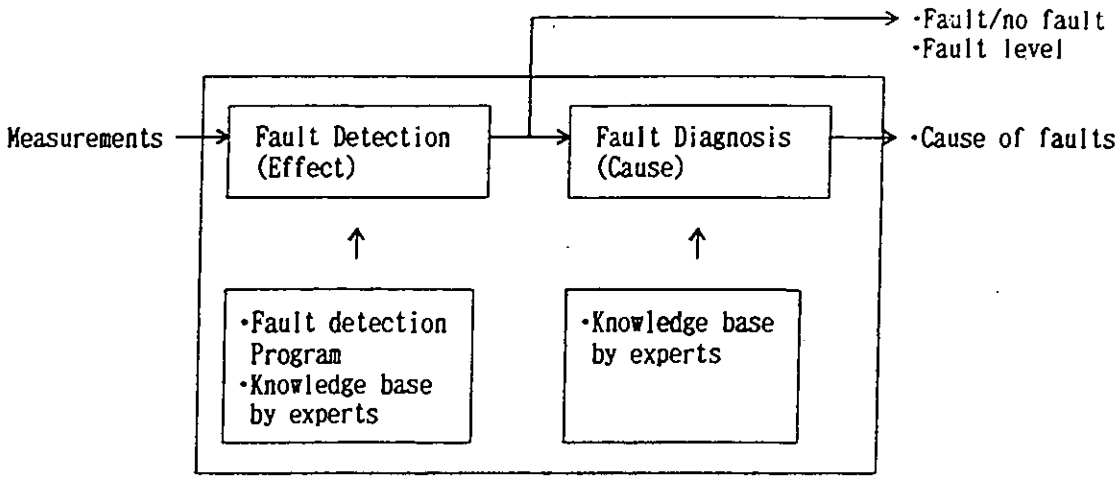

Figure 4.33. Fault detection diagnosis system.

4.5.1.2 Expert System Technology

The structuring of a fault detection and diagnosis expert system requires that the relationship attributes and hypotheses, e.g., the relationships between the level of measured data and the occurrence of faults or between faults and the causes of faults, and their combinations, can be properly reduced to a knowledge base in advance. Such a knowledge base is often developed through interviews with highly experienced experts. Major technical considerations in the efficient development of an expert system are how to acquire knowledge from the experts or actual cases histories (the acquisition of knowledge), how to express the knowledge (expression of knowledge) and how to implement the diagnosis (method of reasoning).

Acquisition of Knowledge

Methods of acquiring knowledge include interviews or other contact with experts to obtain knowledge, the extraction of knowledge from past case histories which provide precise data on symptoms and the causes of faults, and the acquisition of knowledge from related design and simulation data. The process of knowledge acquisition consists of actually acquiring the knowledge, sorting it, and expressing it in the form of a knowledge base. The efficient execution of this process requires cooperation between experts in the aspects of the system question and knowledge engineers who have acquired adequate knowledge and experience in the development of expert systems. It is said, however, that this process is more difficult than generally considered, requiring a tremendous amount of time, money, and effort.

The need has thus arisen for an expert system construction tool that facilitates the speedy and inexpensive development of expert systems by making it possible for experts in their respective fields to describe knowledge bases easily on their own.

Expression of Knowledge

The "IF-THEN" expression of knowledge has long been used as one of the forms of expressing rule-based knowledge, which is described as a knowledge base for sorting knowledge of for an expert system construction tool. Forms of expression used more recently include visual ones such as graphic expression, fault trees, and decision tables. In our case study, the same knowledge is expressed in these various forms. In the expression of knowledge in actual cases, it will lead to the efficient acquisition of knowledge to sort and describe it as a knowledge base in the form of an expression that best fits the characteristics of the problem in question.

(1) IF-THEN Expression

Fig. 4.34 shows an example of IF-THEN expression in the case of a fault detection and diagnostic knowledge base for an air-conditioning system. The description is made according to the rules in which attributes (symptoms, test results, and measured values) make up the IF part and conclusions (causes) make up the THEN part. The first rule expresses the knowledge "if the room is warmer

```
IF Room is Warmer AND Supply temperature is Too high THEN Valve is malfunctioning

IF Room is Warmer AND Supply temperature is Too high THEN Size of coil is insufficient

IF Room is Cooler AND VAV air volume is Too much THEN Controller is malfunctioning
```

Figure 4.34. Example of IF-THEN expression in HVAC cooling process.

(the fault learned from a resident) and the supply air temperature is too high (the fault learned from a measured value), then the cooling water valve is malfunctioning (the cause of the fault) or the size of cooling water coil of AHU is insufficient (the cause of the fault)". This is a case in which there are two possible causes. Rules must be added in order to specify each of the causes. This form of knowledge expression has the advantage of being highly descriptive but it also has the disadvantage of being difficult to understand when too many rules have to be described.

(2) Graphic Expression

Fig. 4.35 gives a graphic expression of the rule mentioned above. The left side corresponds to the condition part of the rule and the right side to the conclusion part. It is shown here than AND links the multiple conditions to the conclusion part. OR conditions can also be described with a slight change in the form of expression. If either of the two possible causes of the fault is to be specified, rules can be easily added. Such visual expression facilitates the making and revision of knowledge and rules.

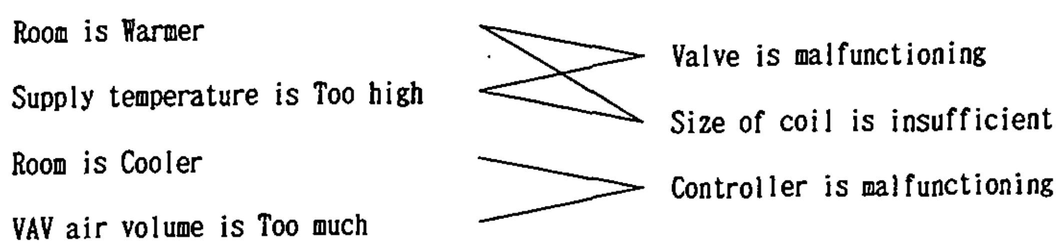

Figure 4.35. Example of graphic expression in HVAC cooling process.

(3) Fault Tree Expression

Fig. 4.36 shows a fault tree. In this form of expression, knowledge is expressed by a tree-like graph in which questions about attributes constitute nodes and choices about the attribute values constitute arcs generated from these nodes. Leaves of the tree represent conclusions. For example, if attributes are the "room" is "warmer", the arc is traced to the question about the attribute "air supply

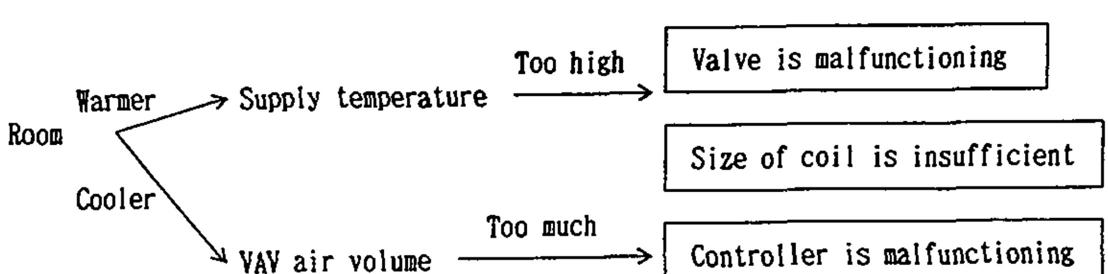

Figure 4.36. Example of fault tree expression in HVAC cooling process.

temperature". If the answer to the question is "too high", then the "malfunction of the cooling water valve" or the "insufficient number of rows cooling water coils of the airconditioner" is the conclusion. This is a case in which there are two possible causes. Rules must be added in order to specify each of the causes. This form of expressing knowledge is much like the form of troubleshooting charts often seen in equipment maintenance manuals and the like. Checking based on the chart leads you to the conclusion. In this respect, it is a form of expression easy to understand, but it is not very descriptive of the combination of complex rules, such as their addition.

(4) Decision Table Expression

Fig. 4.37 shows an example in which the same knowledge as mentioned above is expressed in the form of a decision table. In this type of expression, the relationships between attributes and conclusions are arranged in order in a two-dimensional table and these relationships are described by using symbols. If, for example, attributes are the "room" is "warmer" and the "air supply temperature" is "too high", they correspond to the first and second lines. Thus, the conclusion obtained is the "malfunction of the cooling water valve" or the "insufficient number of rows of cooling water coils of the air-conditioner". In this form of expression, it is easy to verify the rules, but it gives only a poor approximation of the sequence of the diagnosis.

	Room		Supply air temperature	VAV air volume
	Warmer	Cooler	Too high	Too much
Valve is malfunctioning	○	×	○	×
Size of coil is insufficient	○	×	○	×
Controller is malfunctioning	×	○	×	○

Figure 4.37. Example of decision table expression in HVAC cooling process.

<u>Inference Method</u>

Either forward or backward inference has often been used in rule-based knowledge bases. With the calculation of the degree of confidence. Some other methods of inference have recently been proposed [4.102] The inference engine provided by expert system construction tools is usually used as the program for making inferences.

(1) Forward Inference

Forward inference is a method of reasoning in which questions are first made about the condition part of rules, followed by inferences to the conclusion part with those rules which meet the conditions used. A question is first made about the "room", for example, followed by a question about the "air supply temperature". The rules that match the result are applied and the conclusion part becomes true. In the fault diagnosis of the air-conditioning system shown in Fig. 4.34, if the "room" is "warmer" and the "air supply temperature" is "too high", then the "malfunction of the cooling water valve" or the "insufficient number of rows of water cooling coils of the airconditioner" becomes true and is drawn as conclusion. In this example, the conclusion is not drawn in a single stage. In the case of multi-stage rules, however, rules are applied one by one before a final conclusion is reached.

(2) Backward Inference

Backward inference is the opposite of forward inference. That is, an inference is started with the conclusion part of the rules, followed by questions about the condition part. It is first assumed, for example, that the conclusions is the "malfunction of the cooling water valve". Questions about the room and the air supply temperature are made as the conditions for these assumptions to hold true. The hypothesis for which all conditions are met is found true and thus becomes a conclusion.

(3) Certainty Factor

For the sake of simplicity, the example of inference mentioned above is set free from the vagueness of attributes and conclusions. In actual cases, a degree of confidence, ranging from 1 to minus 1, is used to make as accurate inferences as possible from vague or incomplete attributes, knowledge, and conclusions. With regard to the degree of confidence, 1 indicates that an event or conclusion is true without any doubt. Minus 1 indicates that it is false without any doubt. Some other methods include the use of probability values or the use of fuzzy inference. It is necessary to choose the optimal method for the problem in question.

4.5.1.3 Fault detection and diagnostic expert system

The BOFDD fault detection and diagnostic expert system for thermal storage air-conditioning system in a demonstration site (a hospital in Japan) is furnished with optimization software, fault detection software, and fault diagnosis software. This section describes the fault diagnosis software, which provides the main functions of the expert system and uses a rule-based knowledge base.

<u>Fault Diagnosis Software for Thermal Storage Systems</u>

Described here are the acquisition of knowledge, the expression of knowledge, and the method of inference, which together make up the core of fault diagnosis software for thermal storage systems.

(1) Acquisition of Knowledge

The knowledge base concerning faults and their causes is a general-purpose knowledge base developed by the Heat Source and Thermal Storage Subcommittee of Japan based on the results of questionnaires and interviews about diagnosis (see sect. 3.4) through the use of an Annex 25 Failure mode and effect analysis (FMEA) sheet (see sect. 5.1) a survey among experts was conducted on thermal storage air-conditioning systems, that is, designers, contractors, system managers, and operators.

(2) Expression of Knowledge

Table 4.4 shows an example of the knowledge base concerning faults related to a thermal storage tank and the causes of the faults. Because the thermal storage tank is in the center with a heat source and air-conditioners connected in parallel, the volume of hierarchical knowledge is small, making efficient graphic expression easier. This example shows 15 faults, 11 causes of faults, and the relationships between the faults and their causes. This knowledge base features the compound interaction of the relationships between faults and their causes. In addition, many of the faults that constitute the condition part of rules are linked by OR to the causes of faults, that is, the conclusion part. The relationships of AND and OR must be therefore reviewed based on the method of inference used and the results of diagnosis.

(3) Method of Inference

The method of inference used in this trial is simple forward inference that uses relational database software. The knowledge base features the compound interactions of multiple faults and multiple causes of faults. Making inferences has, therefore, caused a problem in that so many possible causes of faults are chosen that it is impossible to narrow them down to the most probable cause or causes. In order to solve this problem, it is necessary to consider a method suitable for the inferences of compound rules. Abductive reasoning (see sect. 4.5.2) is one such possible candidate method.

Fault Diagnosis Software for Air-Conditioning Systems

This section describes the acquisition of knowledge, the expression of knowledge, and the method of inference, which together make up the core of the fault diagnosis software for air-conditioning systems.

(1) Acquisition of Knowledge

The knowledge base concerning faults and their causes is a general-purpose knowledge base developed by the Air-Conditioning Subcommittee of Japan based on the results of questionnaires and interviews (see sect. 3.3) through the use of an Annex 25 FMEA analysis sheet a survey was conducted among experts on VAV air-conditioning systems, that is, designers, contractors, system managers, and operators.

Table 4.4. Example of causes of faults - faults knowledge base for thermal storage tank in cooling process.

```
1) Cause :Temperature sensor in tank malfunction
       Fault 1) Abnomal change of temperature in tank during off operation hours
             2) Temperature in coolest side of tank is too high
             3) Room temperature and humidity are too high
             4) Inlet water temperature of heat pump is too high
             5) Heat storage efficiency is insufficient
2) Cause :Damage of insulation
       Fault 1) Abnomal change of temperature in tank during off operation hours
             6) Heat loss
             7) Condensation on slab
3) Cause :Water level sensor malfunction
       Fault 5) Heat storage efficiency is insufficient
             8) Increase of overflow
             9) Increase of water supply
            16) Abnomal water level
            10) Temperature in tank is too high
4) Cause :Water supply unit malfunction
       Fault 5) Heat storage efficiency is insufficient
             8) Increase of overflow
             9) Increase of water supply
            16) Abnomal water level
            10) Temperature in tank is too high
5) Cause :Damage in water proof
       Fault 5) Heat storage efficiency is insufficient
             8) Increase of overflow
             9) Increase of water supply
            18) Abnomal water level
            10) Temperature in tank is too high
            11) Deterioration in water quality
6) Cause :Scale on heat pump evaporater
       Fault 11) Deterioration in water quality
             12) Heat pump COP falls
7) Cause :Scale in heat pump inlet 3-way valve
       Fault 11) Deterioration in water quality
             12) heat pump inlet 3-way valve malfunction
8) Cause :Scale in primary and secondary water heat exchanger
       Fault 11) Deterioration in water quality
             14) Heat exchanger efficiency is insufficient
9) Cause :Scale in piping and foot valve
       Fault 11) Deterioration in water quality
             15) Water leakage piping
             16) Flow rate of primary pump is too small
             17) Water evacuation
10) Cause :Tank volume is too small
       Fault 2) Temperature in coolest side of tank is too high
             3) Room temperature and humidity are too high
             4) Inlet water temperature of heat pump is too high
             5) Heat storage efficiency is insufficient
11) Cause :Connection pipe size between tanks is too big
       Fault 2) Temperature in coolest side of tank is too high
             3) Room temperature and humidity are too high
             4) Inlet water temperature of heat pump is too high
             5) Heat storage efficiency is insufficient
```

(2) Expression of Knowledge

Fig. 4.38 shows an example of a knowledge base for one fault (the deviation of the room temperature from a set value in a VAV air-conditioning system) and the possible causes of that fault. Because the room, the VAV unit, the air-conditioners, dampers, and return fans were connected in a series, there was so much hierarchical knowledge that it was most successfully and efficiently expressed by a fault tree. However, because more than one cause of a fault is linked to one fault, rules must be added in order to identify the more specific causes of the fault. In this case, the fault tree becomes more complex.

Top Event:Room temperature deviation from set point   to A1

- A1
  - Lack/excess of VAV supply air volume   to B1
  - Inadequate VAV supply air temperature   to B2
  - AHU start is too late
  - Inadequate position of air diffuser
  - Window/door is open
  - Inadequate use of shade
  - Excessive internal heat generation
- B1
  - Lack/excess of static pressure in fan control   to C1
  - Failure in VAV damper control   to C2
  - VAV unit is too small
  - Degradation of VAV damper
  - Deterioration of VAV damper actuator
  - Air leaking from duct
- B2
  - Inadequate AHU supply air temperature   to C3
  - Poor insulation of duct
- C1
  - Failure in fan control   to D1
  - Insufficient size of fan
  - Deterioration of fan
- C2
  - False wiring connection
  - Inadequate parameter setting
- C3
  - Inadequate mixed air temperature   to D2
  - Coil water temperature deviation   to D3
  - Failure in AHU valve control   to D4
  - Insufficient size of coil
  - Scale on coil
  - Degradation of AHU valve
  - Deterioration of valve actuater
- D1
  - False wiring connection
  - Deterioration of controller
  - Inadequate parameter setting
- D2
  - Failure in OA/EA/RA damper control
  - Outside air temperature is high/low
  - Degradation of OA/EA/RA damper
  - Deterioration of damper actuater
- D3
  - Temperature deviation of water from primary side
- D4
  - False wiring connection
  - Deterioration of controller
  - Inadequate parameter setting

Figure 4.38. Example of faults knowledge base for VAV air-conditioning system.

(3) Method of Inference

In fault detection, the data related to a fault is first displayed on the data display screen of the expert system. Based on the data displayed, the operator judges the occurrence of the fault. In fault diagnosis, it is necessary to consider many of the same points mentioned above in the case of the thermal storage air-condition system.

4.5.1.4 Summary

The conventional method used in the development of expert systems required programming techniques for the preparation of rules and thus required knowledge engineers who are versed both in expert system construction tools and in the problems to be dealt with. Because knowledge engineers are not specialists in the operations to be covered by the systems in question, however, they had to learn a lot to understand what operation specialists tell them and to complete practical diagnosis systems. Even if the knowledge engineers successfully developed practical systems, however, there then arose the question of how to maintain the knowledge bases. One of the features of diagnosis systems is that they can flexibly cope with changing subjects through revisions in their knowledge bases. If the knowledge bases are developed by knowledge engineers, however, it is often only the knowledge engineers who know the system who can make such revisions easily.

These facts indicate the need to develop an environment in which specialists in field operations can make and maintain knowledge bases by themselves. The need will be met by developing an expert system construction tool furnished with a way of expressing of knowledge and a method of inference that can be easily used by specialists in field operations, by summarizing the methods of acquiring knowledge suitable to the diagnosis of air-conditioning systems and by accumulating the related knowledge bases.

4.5.1.5 References

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4.5.2 Associative networks

Klaus Baer, Mathias Hinkelmann, Martin Schöckle,
University of Stuttgart, IKE, Stuttgart, Germany

4.5.2.1 Introduction

A traditional and very successful application of expert systems is fault diagnosis in complex systems [4.103]. One of the best known experts systems of this domain, called MYCIN, supports medical diagnosis of meningitis and other bacterial infects. It was the first large expert system reaching the level of human experts and had a strong impact on further development of expert systems [4.104].

Characterizing for expert systems is the strict separation of expert knowledge of a given domain and general knowledge about problem solving. Main issue is the knowledge base, which represents domain specific knowledge in a well prepared and formalized form. The evaluation of the knowledge - the process of problem solving - is done by an inference engine, which links the knowledge of the knowledge base and the input in a suitable way, draws conclusions upon it and tries to achieve step by step the solution. As pointed out in sect. 4.5.1, major technical considerations are how to express and formalize this knowledge and how to select the most suitable method for reasoning about the given knowledge.

Following the separation of fault detection and fault diagnosis as proposed by [4.105], the fault detection is done through a preprocessing program. One approach for the preprocessing program is to compare simulated data to measured data, where the simulated data is taken as reference. The result of the preprocessing program is a set of detected symptoms. Symptoms are the noticeable or measurable effects of faults. A fault manifests itself in one or more symptoms. Therefore, the question how to express the knowledge is reduced to the question how to represent the symptom/fault relation and how to infer from the detected set of symptoms to the causing fault(s).

4.5.2.2 General Description

Rule-based approaches typically describe the knowledge through conditional rules

IF < premise(s) > THEN < conclusion(s) >

and an inference mechanism, which might be characterized in its simplest form by modus ponens:

Given fact "A" and rule 'if A, then B', infer "B"

An instantiation of such a rule could look like the following:

IF DomesticWaterConsumptionTooHigh is true

THEN or { LeakInDomesticWaterPipe is true

LeakInHeatExchangerForDomesticWater is true }

In the case of fault diagnosis, the presence of a fault may but need not result in the occurrence of some of the symptoms. Deductive systems usually try to overcome this through adding certainty factors to rules. Another approach is to use abductive inference of the form

Given fact "B" and association 'if A, then B', infer "plausible A"

Rule-based approaches are normally not able to draw such conclusions, although they are quite obvious for humans. Knowledge based systems[1]) are able to deal with such an abductive inference mechanism, but there is no well developed theoretical foundation available.

The technique of associative networks is an approach to fill this gap. An associative network is inherently abductive and Reggia et al. [4.106] gives a theoretical foundation for the reasoning algorithm. In an associative network, the above mentioned symptom/fault relation is stored in form of direct links between symptoms and faults (see Fig. 4.39). Symptoms are pointing to faults which are able to cause this symptom. Given a set of symptoms, the reasoning process tries to find minimal sets of faults that are able to explain the occurrence of the observed symptoms. In this reasoning model, uncertainty is included from the very beginning. In pointing to faults, symptoms invoke faults as possible explanations for the occured symptoms. A diagnosis is the minimal set of faults explaining all observed symptoms. The more symptoms point to the same fault the more likely it is, that this fault will be included in the diagnosis. For details on how the term "minimal" may be defined more exactly, see [4.106, 4.107].

4.5.2.3 Illustrative example

A small associative network describing symptoms and faults associated with a heat exchanger in the heating reference system was derived from a fault list of section 3.1.2 and is shown in Fig. 4.39. As a first example, suppose the pre-processing program has shown the two symptoms "DistrictHeatOutletFlowTooLow" and "DomesticWaterConsumptionTooLow" to be present. As can be easily verified out considering Fig. 4.39, there are three faults capable of causing the detected symptoms, while only one fault ("HeatExchangerLeak") is capable of causing both symptoms. This fault is therefore chosen as the diagnosis result [4.107].

If a third symptom is detected in the system, "DomesticWaterTemperature-TooLow" for example, the symptom set is extended by one more fault

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[1] The term 'knowledge based systems' summarizes all systems using additional knowledge representation schemes than just facts and rules. Often they are also called 'frame based systems'. Information in the knowledge base is generally represented in object-oriented models and a sequential hypothesize-and-test inference process is used. This leads to very powerful tools, because all advantages of object-oriented programming can be used (classification, hierarchies, (multiple) inheritance, message passing, polymorphism, ...) and in addition, declarative programming (rules) can be closely intermixed with procedural programming (methods). Therefore, the best fitting paradigm can be chosen for a given subtask (e.g. calculations by methods, diagnosis by rules). In general, those systems are often explicit attempts to model the underlying reasoning of the human diagnostician.

("LeakInDomesticWater Branch"). As can be verified out considering Fig. 4.39, no single fault is capable of causing all symptoms present in the plant. The diagnosis result therefore consists of three fault tuples ("BlockedDistrictHeatPipe", "HeatExchangerLeak") or ("LeakInDomesticWater Pipe", "HeatExchangerLeak") or ("ValveStuckClosed", "HeatExchangerLeak") each of which is capable of causing all symptoms in the plant.

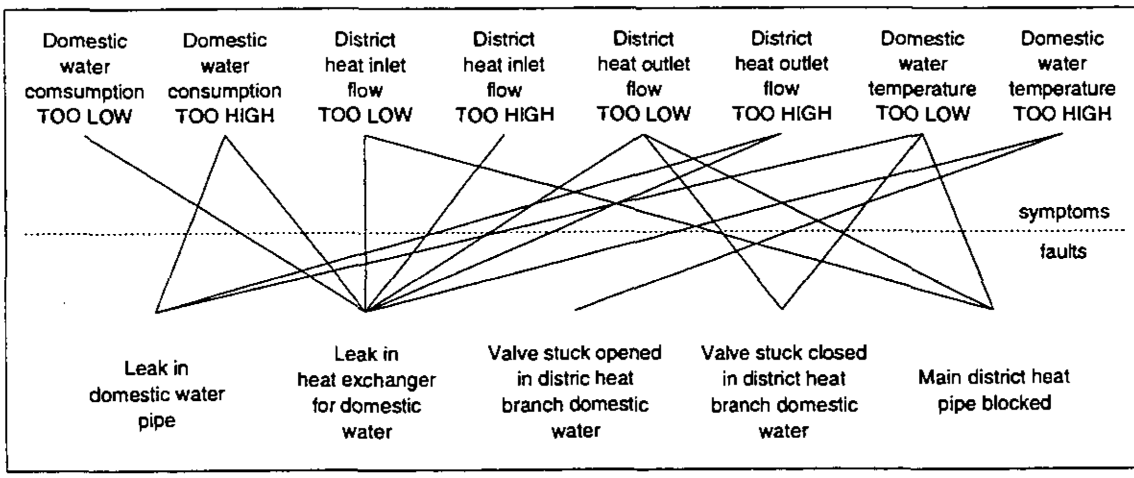

Figure 4.39. Associative network for diagnosis of faults in a district heat sub-dsitribution system.

4.5.2.4 Advantages and Disadvantages

The associative network approach offers several advantages. The representation of the diagnostic knowledge in terms of symptom/fault associations is a very natural format which can be directly inferred from text books and fault lists [4.105]. Therefore, coding of diagnostic knowledge as symptom/fault associations is more easily achieved in comparison to the implementation of a rule base.

While rules have to be interpreted, the reasoning process dealing with an associative network is much faster, because only links have to be processed that may be stored and accessed efficiently. An algorithm performing an associative diagnosis can be easily implemented on the basis of a description of such an algorithm in [4.106].

As already pointed out above, the associative reasoning model is an abductive model [4.106] and is able to deal with uncertainty. In addition, also the handling of multiple faults is inherently included in this approach.

Disadvantages in general of expert systems are that it is difficult to ensure completeness and correctness and to check consistency in the underlying knowledge bases. Besides that, the associative network approach has to be setup for each HVAC-system seperatly. Each HVAC-system is a unique system. Because a lot of special knowledge about faults and symptoms in a plant is included implicitly in the associative network, for each unique plant a unique associative network has to be built. Therefore, a single fault diagnosis tool that applies to all HVAC plants cannot be built using the associative reasoning model.

Another important drawback is the missing explanation facility. In principle it is not possible with associative networks to produce an other explanation than just listing the faults identified by the system as cause for the symptoms. All knowledge is compiled in the network and the algorithm. So, there is no way for a human expert to duplicate the inference process.

Table 4.5. Summarized advantages and disadvantages.

Advantages	Disadvantages
- easy to implement	- difficult to ensure completeness and correctness
- fast algorithm	- difficult to check consistency
- inherent uncertainty	- individual setup for each HVAC system required
- handling of multiple faults	- no explanation facility
- theoretical foundation	

4.5.2.5 References

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4.6.1 Formal qualitative models in fault detection and diagnosis

A.S. Glass, *
Landis & Gyr, CH-6301 Zug, Switzerland

4.6.1.1 Introduction

Among diagnostic methods available to the planner of fully automated **FDD** systems, by far the best make use of *explicit* diagnostic information provided by individual **HVAC** components themselves: for example, actuators which signal their position. It is only when this information is not provided that more sophisticated diagnosis using *implicit* evidence is required.

A general strategy for computer-based diagnosis using implicit information is illustrated schematically in Fig. 4.40. The observed behaviour of a system is compared with expected behaviour as predicted by suitable models. Discrepancies between the two generally lead to the supposition that a fault is present. In a feedback process, further assumptions may be added to the model concerning possible faults, thereby allowing one to draw conclusions about the nature of the fault. An automaton performing these steps is referred to as a general diagnostic engine [4.113]. In applying this approach to **FDD** systems for **HVAC** plants it is hoped to obtain a full or partial diagnosis of the *location* and *nature* of any faults detected.

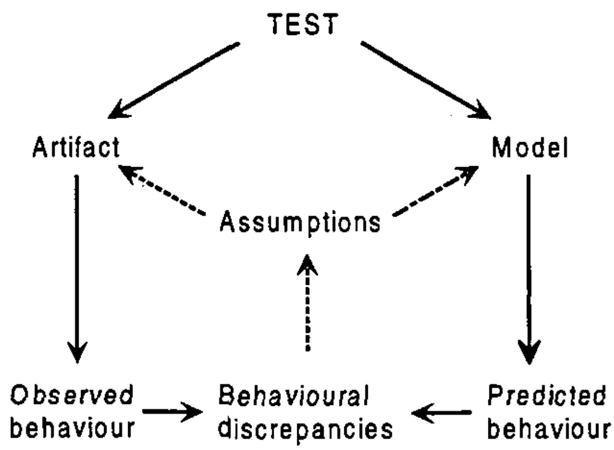


Figure 4.40. General diagnostic engine.

Such methods generally presuppose that the normal, prescribed behaviour of the **HVAC** components and the associated control systems can be accurately *modelled*. However, in practice, it is extremely difficult if not impossible to model the whole system accurately. Even supposing the mathematical models themselves

* current address Zentral Schweizerisches Technikum, CH-6340 Horin-Luzern, Switzerland.

are correct, many of the relevant parameters will be unknown and might only be obtainable by means of difficult and time-consuming measurements. This is particularly true of building dynamics, for instance. Nevertheless, it is well known that experienced service engineers can diagnose many faults without knowing all the system parameters.

They often identify problems on the basis of *qualitative* appraisals of malfunctioning systems. Might it not therefore be possible, when confronted with a system whose description in terms of models is incomplete, to apply this qualitative approach methodically? One could thereby ensure that the **FDD** system is capable of diagnosing those faults which are detectable in spite of an incomplete quantitative knowledge.

Broadly speaking, a qualitative description differs from the quantitative one in *reducing* the amount of *information* relevant to the description. The typical quantitative model used in **HVAC** applications involves a description in terms of *continuous* state variables which satisfy systems of well determined differential equations. A *qualitative* description, on the other hand, either involves non-quantitative attributes, such as "liquid", "vapour", "mechanism jammed", etc., or involves *coarsely quantized* numerical quantities, such as "temperature above 100°C", "temperature below 0°C", etc.

Although models of **HVAC** systems need not be directly derivable from physical principles, we shall stress those aspects of qualitative modelling involving formal derivations via *qualitative physics*. Additional qualitative models describing **HVAC** systems may be developed from expert knowledge of the domain or from experimental or simulation data.

Furthermore, in situations in which qualitative physics by itself yields unacceptably ambiguous results, it may be useful to apply methods based on *fuzzy sets*. Zadeh [4.133, 4.134] states in his *principle of incompatibility*: "As the complexity of a system increases, our ability to make precise and yet significant statements about its behaviour diminishes until a threshold is reached beyond which precision and significance (relevance) become almost mutually exclusive characteristics." The application of such methods to fault detection & diagnosis in HVAC systems is discussed in detail elsewhere [Reference 4.114 & section 4.6.2 in this book]. This article will be confined to the description of orthodox qualitative methods which involve crisp boundaries between qualitative states.

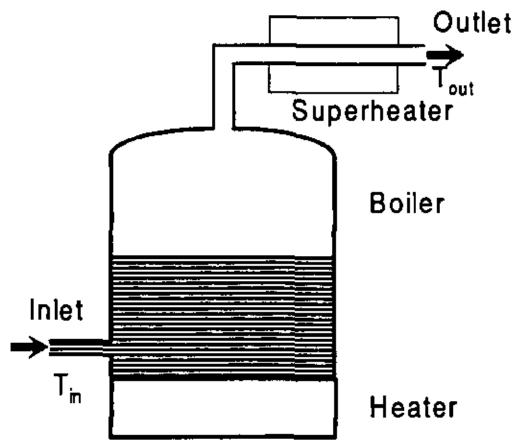
Qualitative descriptions based on a limited number of qualitative values or on fuzzy sets are useful in situations when little precise information on a system exists or its behaviour is prone to disturbances which make accurate measurements and modelling impossible. The term **qualitative physics** is used to describe predictions based on first principles about possible behaviour which may be observed in terms of such a qualitative description.

A strategy is envisaged in which these methods are integrated into an overall **FDD** concept including more conventional, quantitative models. In the first instance, explicit diagnostic data would be used whenever it is available in a given **HVAC** system. Failing that, diagnoses would be made on the basis of a comparison between observed and modelled behaviour: accurate, quantitative models are to be preferred, but in adverse situations in which essential quantitative information is missing or difficult to obtain, qualitative methods would be exploited. The result would be a **FDD** system that is *robust* by virtue of qualitative reasoning and, at the same time, *sensitive* in discerning more subtle problems with the aid of available quantitative models.

4.6.1.2 Qualitative physics

4.6.1.2.1 Qualitative analysis based on physical intuition

A classic example of qualitative analysis applied intuitively to a practical physics problem occurs in a naval training school examination question [4.117]. Consider a ship's boiler as depicted in Fig. 4.41 supplied with feed water at a certain temperature $\mathbf{T_{in}}$, which is turned into steam and superheated before reaching the outlet at $\mathbf{T_{out}}$. Sufficient water is supplied to maintain constant level in the boiler. Steam is produced at a constant working pressure. The question asked is: if the temperature of the feed water is increased, what happens to the temperature at the outlet?

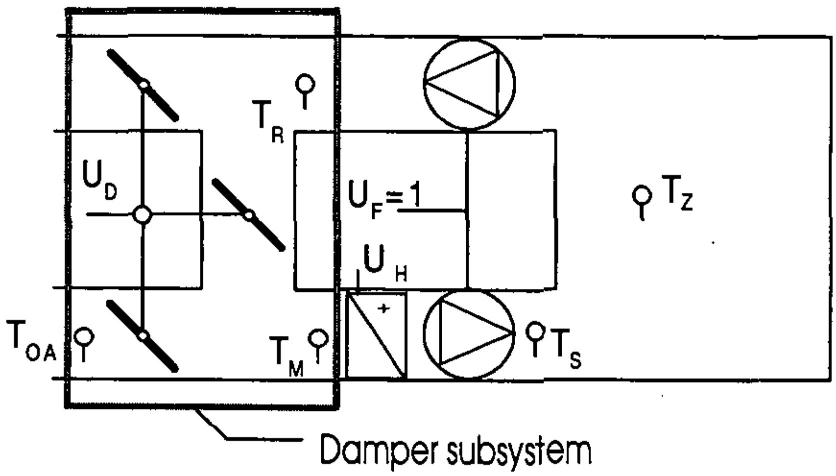


If $\mathbf{T_{in}}$ is increased, what happens to $\mathbf{T_{out}}$?

Figure 4.41.

The analysis goes roughly like this: assuming a steady state in which the level of water in the boiler is constant, the heat absorbed by each drop of water entering the boiler suffices to raise it to boiling temperature and to evaporate it (at the boiler working pressure). If $\mathbf{T_{in}}$ is increased, less heat is required to raise each drop to boiling, so that an increased amount of steam will be produced for the same amount of energy supplied by the primary heater. Because the steam now flows more rapidly through the superheater, each drop will absorb less energy there. Consequently the output temperature $\mathbf{T_{out}}$ is lowered!

A second, illustrative example concerns the bypass section in an air-conditioning system [4.124, 4.125]. The three dampers shown in Fig. 4.42 are operated simultaneously (parameter U_M) to vary the proportion of recirculated air. The extreme settings are no recirculation – bypass damper closed and fresh air and exhaust dampers open – or total recirculation – bypass damper open and fresh air and exhaust dampers closed. A typical fault occurs if one of the dampers is unable to open or close in response to the signals received by the actuators.



Example of a rule

IF $T_{OA} = const.$ **AND** $T_R = const.$ **AND** $T_{OA} < T_R$ **AND** U_M *increasing* (i.e. ↑)

AND ($T_M = const.$ **OR** T_M *increasing*) **THEN** fault in damper subsystem.

Figure 4.42.

Ideally, for diagnostic purposes one would like to have measurements of either the damper settings or the air flows. However, under some circumstances, a damper fault can be detected qualitatively by monitoring temperature *changes*. Assuming cool outside air, suppose, for example, the damper actuators are instructed to reduce the volume of recirculated air. The temperature of the mixed air in front of the heating coil should drop owing to the increased proportion of cool fresh air. If, however, the temperature in fact remains constant or rises, it may be concluded that the dampers are not responding as expected, or that there is some blockage in the fresh air intake.

In both of these examples the essential point is that the only quantitative information required concerns whether the increments are positive or negative. Precise knowledge of the actual quantities is unnecessary.

4.6.1.2.2 Theoretical approaches in qualitative physics

Qualitative physics (QP) is a relatively new field and is the subject of active, on-going research. Consequently, there is not yet a general consensus as to the approach and methods used. One approach views **QP** as a *projection* of a quantitative reality onto a description with reduced quantitative resolution. A second approach is to develop a completely *self-contained formalism* based on qualitative descriptions.

Generally speaking, the various qualitative physics theories attempt to take the following features into account [4.132]:

- Physical or descriptive attributes assume a *finite* set of values.
- Qualitative values should encompass the *full range* of behaviour being modelled.
- It must be possible to *interpret* the results of qualitative analysis in a meaningful way.
- Qualitative values (**QV**) should be non-overlapping. Otherwise the results of QP might be ambiguous.
- A theory should offer adaptable, adequate granularity. For example, intervals used for temperature ranges should be relevant to the phenomenon at hand.
- The various possible values assumed by a **QV** should be naturally ordered.
- A **QP** theory must include as part of its overall formalism both a *description* of the relevant phenomena and a set of *operations* to obtain solutions.

A number of general approaches – termed *ontologies* by many authors – have been investigated. The most significant are the *device structures* ontology [4.111, 4.112], *process theory* [4.115, 4.116] and *constraint propagation* [4.126 - 4.128].

Device structures are analogous to circuit diagrams, or, for that matter **HVAC** layouts, in which a number of components are interconnected in a system. Each component occupies a fixed position and responds to given inputs by yielding certain outputs. *Process theory* is closer to conventional dynamical systems in physics: rigid bodies, flows, etc. One thinks of an entity, the process, which undergoes various physical transformations throughout its history. For example, a more radical transformation might involve a change of phase from liquid to gas. *Constraint propagation* is a mathematical model for tracing the propagation of mathematical constraints (algebraic equations) from one part of a complex system to another.

In addition, a number of other approaches have been investigated, such as order-of-magnitude reasoning, naïve physics. However, though frequently very useful as intuitive approaches, they have proved persistently difficult to implement as computer aids.

In the qualitative fault detection method developed for a central air-handling unit, a *device* approach has been used in which the **HVAC** plant is viewed as a system of interconnected components.

4.6.1.2.3 Essential features of a QP theory

In analogy to various examples of systems in physics and engineering, QP deals with *states*, *transitions*, and *behaviour*. In a conventional model of an air-conditioning systems, the states might involve a complete description of temperatures, pressures and air flows. The rules governing transitions would be the differential equations describing the evolution of the states, and "behaviours" would correspond to legitimate solutions of the system differential equations.

In qualitative physics continuous time is replaced by a sequence of discrete times. The intervals between them are of varying length, in general. The transitions between states occur at times belonging to the sequence. Between transitions, the system remains in a particular qualitative state. A behaviour is a sequence of transitions and states.

Among all describable states, those states which are in fact *permissible* within the physical context must be selected. *Allowable* transitions must be identified, and on that basis *consistent* sequences of transitions and states can be derived.

The state itself may be truly qualitative in nature or it can involve reduced quantitative resolution – i.e.. some sort of interval scheme. In the version developed by Kuipers [4.126 - 4.128], so-called *landmark* values are used. Landmark values ought to be physically significant. Typical examples are the freezing and boiling temperatures of water. In that type of situation the qualitative temperature would be deemed to be in one of five possible states: below 0°C, at 0°C, in the interval (0°C, 100°C), at 100°C or above 100°C. In addition, *trends* of functions may be identified: constant, increasing or decreasing. *Constraints* consisting of linear, multiplicative or differential relationships between variables may be identified, and *monotonicity* of functions may be taken into account.

In the approach favoured by Forbus [4.115 - 4.117], qualitative values are positive, negative or zero. The concept of *Q-proportionality* is introduced. Depending on the sign of the derivative of the functional relationship between two quantities one may be Q-proportional to the other in a positive or negative sense. For example, the differential pressure at a damper is normally negatively Q-proportional to the damper opening: as the opening increases, the differential pressure is reduced. *Functional specifications* are permitted without necessarily specifying the formula of the function. If it turned out, for instance, that the functional dependence between differential pressure and damper opening for two mechanically different dampers were the same, then this fact would be noted. The information regarding Q-proportionality is further extended by *correspondences*: for example, it may be noted what the differential pressure at the damper is when the damper is fully open.

The evolution of a system – the analogue of a trajectory in conventional dynamics – consists of a sequence of states separated by transitions as depicted in Fig. 4.43.

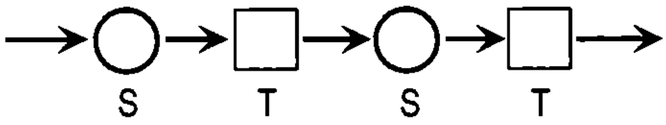


Figure 4.43. Sequence of states and transitions.

Table 4.6. Comparison of approaches used in various types of physics.

	Classical physics	Quantum physics	Statistical physics	Qualitative physics
Evolution of state	deterministic DE's initial conditions	deterministic state vector	many outcomes stochastic DE's Markov chains, etc.	many outcomes (behaviours)
Observables	identical with state	projected from state (interpreted probabilistically)	averages over distributions	qualitative variables (including ambiguities)

4.6.1.2.4 Correspondence between quantitative and qualitative models

Qualitative physics is most directly related to classical quantitative physics, although it shares some features of quantum physics and statistical physics in describing systems in terms of *discrete* values and allowing for more than one *possible outcome* given particular qualitative initial conditions (cf. Table 4.6). Like classical physics, however, qualitative physics describes the time evolution of *directly observable* quantities such as temperature or position without resorting to hidden variables or states.

When comparing qualitative and quantitative methods describing the same physical phenomenon, there are three important features which are desirable in a qualitative theory, completeness, soundness and stability.

- *Completeness*: in a theory which is complete, every quantitative solution should correspond to at least one qualitative one.
- *Soundness*: in a theory which is sound, every qualitative solution should correspond to a valid quantitative one.
- *Stability*: in a stable theory, legitimate mathematical transformations (e.g. rescaling variables, or shifting the time axis) should not result in radically altered solutions.

Completeness is to some extent self-evident, provided correct descriptions are used for qualitative states and transitions. Indeed, it is theoretically known that interval-based qualitative modelling methods do not miss quantitative solutions.

However, with regard to mathematical manipulations, the *only* qualitative modelling method preserving arithmetical associativity simply allows {-,0,+} as possible qualitative values. This means that the Forbus scheme remains self-consistent in this regard. The Kuipers scheme, on the other hand, does not preserve associativity unless only zero were allowed as a landmark. However, any problems of consistency this might pose could well be offset by the advantages of using landmark values.

Rather sobering however, is the theoretical result that *no qualitative modelling method is sound* [4.132]. This means that in many situations, qualitative modelling techniques will inevitably yield at least some *extraneous solutions*.

This suggests that qualitative methods used in FDD systems may not be expected to yield reliable results for *all* situations. However, as seen in the examples there are still many situations in which the methods may be expected to yield conclusive results.

4.6.1.3 Fault detection and diagnosis

As mentioned in the introduction, computer-based diagnostic methods compare predicted behaviour of a system with observed behaviour, taking note of any discrepancies that may occur (cf. the general diagnostic engine in Fig. 4.40 [4.113]). The models used to predict system behaviour may be conventional *quantitative* ones, they may consist of rules in a *knowledge-based expert system*, they may be derived from *qualitative physics*, or they may involve *fuzzy identification* [cf. section 4.6.2].

In all of these approaches, effective diagnosis requires extending models of normal behaviour to take certain known types of faults into account. Thus, in a kind of feedback process, once a fault has been detected, predictions based on various hypothetical faults will be compared with observed behaviour. Moreover, once a fault is suspected, it may be useful – perhaps even necessary – to augment the observations by running specific tests and capturing additional data.

In addition, in order to apply qualitative methods, it is necessary to transform conventional physical measurements into the *qualitative attributes* envisaged in the models being used. This task is not be underestimated: for instance it may be necessary to identify time-dependent temperature data as "increasing", "decreasing", or "constant" in the presence of noise affecting the measurements. Such questions of *state estimation* (cf. section 4.2.3) will not be elaborated here.

This general strategy can be applied to FDD systems for HVAC plants [4.131]. An effective goal of computer-based diagnostic systems is the focusing of attention to a particular subsystem within a complex layout. Thus the first step in fault-diagnosis of an **HVAC** system would be to *locate* the fault to within a particular subsystem (cf. Fig. 4.42). The second step is to attempt to *diagnose* the nature of the fault itself, possibly with the aid of specific diagnostic tests [4.124].

4.6.1.4 Qualitative methods in FDD

Two basic approaches were envisaged for the work to be done during the Annex. A third was envisaged as a long-term goal of this type of research.

The first is a pragmatic one, in which general qualitative rules are derived from expert knowledge (including *analytic* methods) and incorporated as built-in rules in an **FDD** system (Column 1 in Figure 4.44).

The second approach makes use of formal qualitative modelling methods to *generate* rules suitable for incorporation in the same type of **FDD** system as before

Qualitative Methods for Fault Detection & Diagnosis
(Three possible approaches)

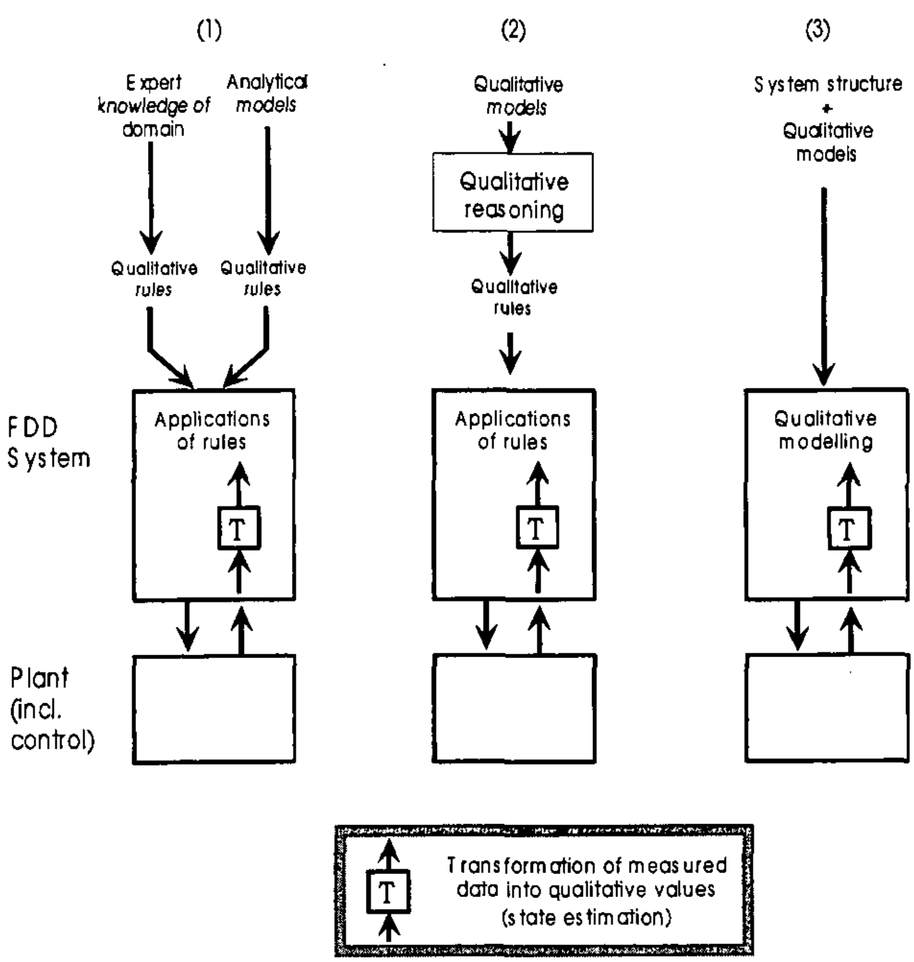


Figure 4.44.

(Column 2 in Figure 4.44). In one variant, a qualitative physics approach based on first-principles will be researched. In this case a device ontology seems appropriate and the methods of constraint propagation should provide useful diagnostic support. The rules would be derived from information about the system layout and qualitative-physics models of the individual components.

A long-term goal would be to integrate qualitative methods into the **FDD** system itself (Column 3 of Figure 4.44), with the aim of providing a system capable of *robust* diagnosis, using qualitative methods in situations which do not lend themselves to the application of more precise methods, as well as *differentiated* diagnosis when more sophisticated quantitative methods are required.

4.6.1.4.1 Work carried out

A fault detection method using the second approach was successfully devised and tested in laboratory conditions [4.118 - 4.120]. The behaviour of a central air-handling plant was studied under steady state conditions. It proved feasible to relate the controller behaviour to temperature conditions in such a way that component faults in the air-handling unit could be detected on the basis of qualitative information.

The behaviour of the system is modelled analytically. The device approach is used for qualitative modelling: the air-handling unit is viewed as a system of components and connections. In addition, it proved particularly useful to identify suitable "landmarks", although they were not applied to model the dynamical evolution of the system [4.126 - 4.128]. The sequential controller operates the heating coil, the dampers and the cooling coil in sequence so as to attain the desired supply-air temperature, and the landmarks used were transitions between heating and damper operation, in the one instance, and damper operation and cooling, in the other.

These landmarks are associated with particular combinations of the outside-air temperature together with the supply and return temperatures and allow discrepancies between the associated qualitative temperature states and the sequential-controller states to be detected. Individual component faults can be analysed to obtain the *rules* leading to the detection of each particular fault. The results can be tabulated to aid fault diagnosis. In general, however, each "signature" of qualitative fault symptoms can be associated with more than one type of fault. One would need quantitative fault models to distinguish between them.

Some work is currently being done along the lines of the first approach, in which a purely pragmatic approach of capturing expert knowledge is used to obtain rules. For example: "IF the zone temperature remains significantly below its set point for more than 3 hours after the HVAC system was switched on THEN there must be a fault".

The third approach was pursued both in [4.118, 4.119] and in collaborative work carried out by the Swiss Federal Institute of Technology, in which attempts was made to qualitatively model the air-handling unit directly in PROLOG and in LISP. The latter model was linked directly to an assumption-based truth maintenance system (ATMS). In the work described in [4.118], the PROLOG environment was able correctly to detect at least some of the faults predicted in the steady-state analysis. In the collaborative work using LISP, the formal qualitative models used did not lead to unambiguous fault detection. However, quantitative models were also used, and these successfully demonstrated the ability of the ATMS to localize the possible source of the fault [4.121].

Of the methods attempted, the most promising has been the analytic approach to qualitative modelling used to define rules that can be applied in practice. With a view to applications, an essential component of a qualitative fault detection strategy is the pragmatic approach of implementing commonsense qualitative rules.

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4.6.2 Fuzzy model-based approaches

Dexter, A.L. & Benouarets, M.
University of Oxford, Department of Engineering Science

4.6.2.1 Introduction

Many of the model-based fault detection and diagnosis (FDD) methods use quantitative models to define the behaviour of the system when it is operating correctly and when faults are present. In practice, a qualitative treatment is usually required for fault diagnosis, since it is very difficult to obtain adequate representations of the complex and often highly non-linear behaviour of faulty plant using quantitative models. The use of fuzzy qualitative models can take more realistic account of the uncertainties associated with describing the behaviour of the HVAC plant and more easily incorporate what expert knowledge is available about the symptoms of faults [4.151].

Fuzzy FDD schemes have been proposed that use both implicit, shallow knowledge models [4.147, 4.141, 4.143, 4.144, 4.150, 4.137] and explicit, deep knowledge fuzzy models [4.152, 4.142, 4.135]. Implicit fuzzy models are sets of fuzzy rules which relate symptoms to faults, whereas explicit fuzzy models are linguistic descriptions of the behaviour of the plant. The models can be based on expert knowledge or learnt from training data. Either the experts' opinion of `what should occur' (the design specification), or `what in practice would occur' (the achievable specification), can be used.

4.6.2.2 An innovations approach to fuzzy model-based fault detection

An explicit fuzzy model is used to describe the behaviour of the correctly operating plant. Expert knowledge is used to choose the structure of the model that is best suited to describing the relationship between the measured variables. The main issues that need to be considered are whether a dynamic or steady-state relationship is most appropriate and what level of precision is required. An important aspect is the confidence that can be placed in the model prediction.

To avoid the problems which can arise when the model is based on incomplete training data (for example, when normal operating data must be used), the reference model is distributed in structure; consisting of a coarse-grained set of fuzzy rules and a finer-grained fuzzy model, trained on-line using measured data from the plant [4.141]. The fuzzy rules are generic, describing the behaviour of a class of plant of this type, and are based on expert knowledge or identified from data generated by simulating plants of similar design. The fuzzy model is specific, describing the observed behaviour of a particular plant, and is generated using a recursive parameter estimator, or a simple fuzzy identification scheme (for example, [4.154]), and normal operating data from the fault-free plant. A measure of the local density of training data can be used to decide which of the two models offers the most credible prediction. In common with all innovations based schemes, faulty operation is detected by comparing the observed behaviour with the predictions of the fuzzy reference model using a threshold which takes account of the estimated modelling errors [4.148].

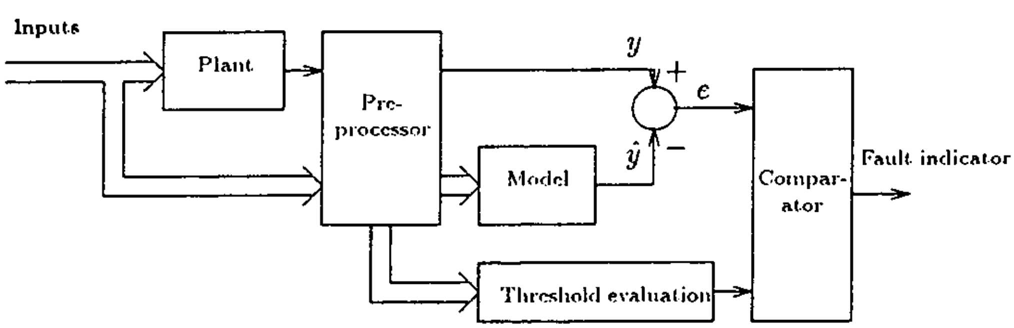

Figure 4.45. Fuzzy fault detection scheme.

4.6.2.3 A parameter estimation approach to fuzzy model-based fault diagnosis

Explicit fuzzy models based on predefined fuzzy reference sets [4.153] are used as the reference models describing the symptoms of faulty and fault-free behaviour at all possible operating points. Design information is used to normalise the measured data so that all values are in the range 0.0 to 1.0 or -1.0 to 1.0. The membership functions for the reference sets are usually triangular in shape and are equally spaced with 50 % overlap over the normalised range. A particular model is defined by specifying the values of the elements of an associated fuzzy relational array. Each element of the array is a measure of the credibility or confidence that the associated rule correctly describes the behaviour of the system around that operating point. Fuzzy identification is used to generate a partial fuzzy model (describing the behaviour around the current operating point) from operating data collected on-line from the actual plant under test. The degree to which a particular fault, or correct operation, is present is determined by comparing the rules of the partial fuzzy model with the rules of the reference models [4.138] (see Figure 4.46). A steady-state detector is used to detect and reject any transient test data in cases where the reference models describe only the steady-state behaviour of plant.

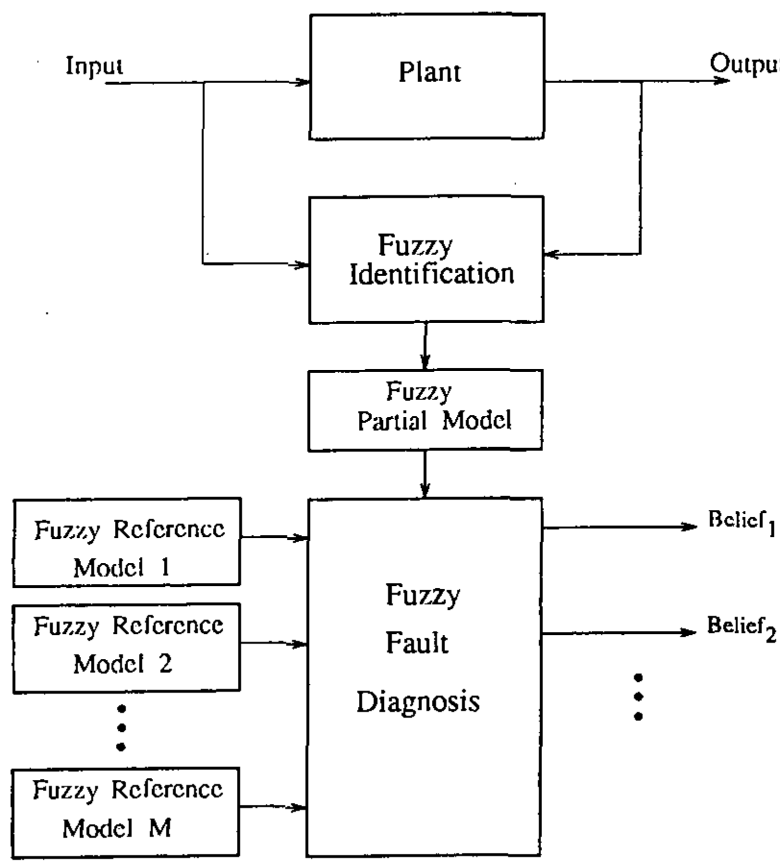

Figure 4.46. Fuzzy fault diagnosis scheme.

The fuzzy reference models are based on expert knowledge or generated off-line from training data produced by computer simulation of typical plant, with and without the faults. The operation of several different plant designs must be simulated to generate representative training data so that the fuzzy reference models are sufficiently generic to capture the underlying characteristics of the behaviour of the actual plant [4.139]. The approach:

- avoids the problems associated with on-line training on the actual plant (for example, the assumption that the plant has been fully commissioned and is initially working correctly);
- can be used when it is impossible to train on data collected from the actual plant (for example, when the training data must be representative of faulty behaviour);
- requires little modification to be used to identify faults in different designs of the same class of plant.

4.6.2.4 Fuzzy Matching

A fuzzy measure of similarity [4.146] is used to compare the fuzzy models. The fuzzy models are considered as level-two fuzzy sets whose membership values are the credibilities of the rules C. A measure of the similarity $Sim_{S,Si}$ between the partial fuzzy model representing the current state of the system S and the fuzzy reference model representing the behaviour of the system if it were in state S_i is given by,

$$Sim_{S,Si} = \frac{\sum_{n=1}^{N} MIN[C_S(n), C_{Si}(n)]}{\sum_{n=1}^{N} C_S(n)} \tag{4.91}$$

where $C_S(n)$ is the credibility of the nth rule in the partial fuzzy model, $C_{Si}(n)$ the credibility of the equivalent rule in the ith fuzzy reference model describing the behaviour of the system when it is in state S_i, and N is the number of rules that are compared. Since a partial model can only describe the symptoms of operation around the current operating point, the rules of the partial fuzzy model are only compared with those rules in the fuzzy reference models that have the same antecedents as rules with non-zero credibility in the partial model, and the result is normalised to the sum of the credibilities in the partial fuzzy model.

Since most physical systems are non-linear to some extent, situations may occur where, for example, two or more reference models exhibit common symptoms at some operating points. In this case nearly equal degrees of similarity are associated with more than one state and it becomes practically impossible to distinguish between different faults or between correct and faulty operation at those operating points. To avoid this problem, additional sensors can be introduced to discriminate between different faults [4.152]. However, for economic and technical reasons, the installation of additional or different sensors is often not feasible in practice, and alternative solutions must be considered. The approach proposed here is to evaluate the levels of ambiguity by calculating the maximum degree of similarity between the partial model and a particular reference model, and each of the other reference models [4.138] The unambiguous strength of evidence $m(\{S_i\})$ that the plant is in state S_i can be obtained by subtracting the ambiguous component from the degree of similarity. Thus,

$$m(\{S_i\}) = Sim_{S,Si} - Amb_{Si} \tag{4.92}$$

where

$$\mathrm{Amb}_{\mathrm{Si}} = \frac{\sum_{n=1}^{N} \min\left[C_S(n), C_{Si}(n), \max_{j=1, j\neq i}^{K} C_{Sj}(n)\right]}{\sum_{n=1}^{N} C_S(n)}$$

is the total ambiguity associated with the state S_i.

The values of the unambiguous strengths of the evidence $m(\{S_i\})$ can be used as basic assignments since the method of evaluation ensures that the values are in the range 0.0 to 1.0, where $m(\{S_i\})$ = 0.0 indicates no evidence and $m(\{S_i\})$ = 1.0 indicates complete evidence, and that the sum of the basic assignments is always less than 1.

The measure of belief (**Bel**) in the system being in a particular state is the sum of the basic assignments for all subsets of that state [4.145]. The plausibility (**Plaus**) of the system being in a particular state is equal to one minus the sum of the belief committed to the system being in any of the other states. Thus the lower bound on the level of belief that the system is in state S_i is given by,

$$\mathrm{Bel}_{\mathrm{Si}} = \mathrm{m}(\mathrm{S_i}) \tag{4.93}$$

and the upper bound on the level of belief that the system is in state S_i by,

$$\mathrm{Plaus}_{\mathrm{Si}} = \sum_{S \cap S_i \neq 0} \mathrm{m}(\mathrm{S}) \tag{4.94}$$

The measures of belief in the presence of particular faults or combinations of faults are updated using the Dempster rule of combination to combine new evidence generated at the current sample time with the evidence generated from data already collected [4.136].

The fuzzy diagnosis scheme, which generates a confidence interval for each of the possible diagnoses, is computationally efficient, since the on-line identification of a partial fuzzy model and the fuzzy matching of the models require relatively little processing power, and is suitable for on-line implementation in an out-station. Tests have demonstrated that the scheme can successfully identify the presence of faults if the symptoms are sufficiently pronounced. Results have shown that the fuzzy FDD approach can diagnose correct operation of the mixing box of an experimental air-conditioning rig, and identify faulty operation of a simulated heating system in a large building, and incorrect tuning of a supply air temperature controller, and water-side fouling and valve leakage in the cooling coil, of a simulated AHU.

It should be noted that the fuzzy diagnosis scheme will be sensitive to the presence of design and/or commissioning faults.

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5 GENERIC BOFD TOOLS

5.1 QUALITATIVE AVAILABILITY ANALYSIS TOOLS FOR KNOWLEDGE ACQUISITION

Hyvärinen, J. VTT Building Technology, Espoo, Finland

This section provides a brief presentation of some tools that can be utilized for knowledge acquisition and presentation. In [5.1, 5.2] the methods are described in detail and this section is only a brief compilaton of those methods that have been applied at least to some extent in the annex 25 work (sect. 4.5.1, 3.1, 3.2, 3.3 and 3.4).

Essential matters that must be resolved in building a fault detection and diagnostic system are

- to identify those central entities (subprocesses and components) on which the development of a fault detection methods and related methods should focus,
- to collect data on the practical ways in which faults are detected as well as
- to collect data on how possible faults are remedied.

This information can then be used in various stages of designing and building a fault detection and diagnosis system.

The methods of analysis for availability performance offer a good starting point for these tasks. Stages of availability analysis are briefly described in section 5.1.2. The methods of assessing availability performance can be divided into two main groups: qualitative and quantitative. Quantitative methods require statistical data on the occurrence of defects and faults in the systems to be studied. This data can be collected or it may already exist. If no quantitative data is available, qualitative methods offer a relatively fast means of obtaining information on the operation of the process under consideration and on features connected with the occurrence of faults. In this section only qualitative methods are considered.

Qualitative methods are applicable to the collection of expert data. Typically, they involve a discussion in which a group of experts analyses the system in question according to an agreed model and the results of the discussion are recorded in tabular form. In subsection 5.1.3 two useful qualitative availability analysis metods are described.

When using qualitative methods, the amount of data recorded tends to become very large. This is why it is a further requirement of qualitative systems that the experts indicate which items that have been recorded are most important for the total operation of the system. If no quantitative information is available on the ways in which defects and faults arise and on the defects of system components, attention must be directed at a specific part of the database or data corpus in some other way. A method for classifying the entries in the database according to some subjective evaluation criteria is proposed in subsection 5.1.4 Method for prioritizing.

In addition to the two methods of qualitative availability analysis methods, and the method for prioritizing, a tool for presenting the knowledge concernig faults and their causal relationships in a manner that could be utilised in diagnosis. In section 5.1.5 a fault tree is suggested for this purpose.

5.1.1 Availability performance [5.1.2]

The ability of a system to perform the task for which it is intended (Operational performance) depends just as much on technical performance as it does on availability performance. Both can be studied and engineered analytically and both are subject to control actions in the same manner. Availability performance can be further divided into reliability performance, maintainability and supportability (Figure 5.1).

Availability (A) is the measure of availability performance and describes the system's ability to perform a task without downtime or production interruptions. For example, 95 % availability means that the system is impaired by a fault for 40 hours if the period of operation is 800 hours.

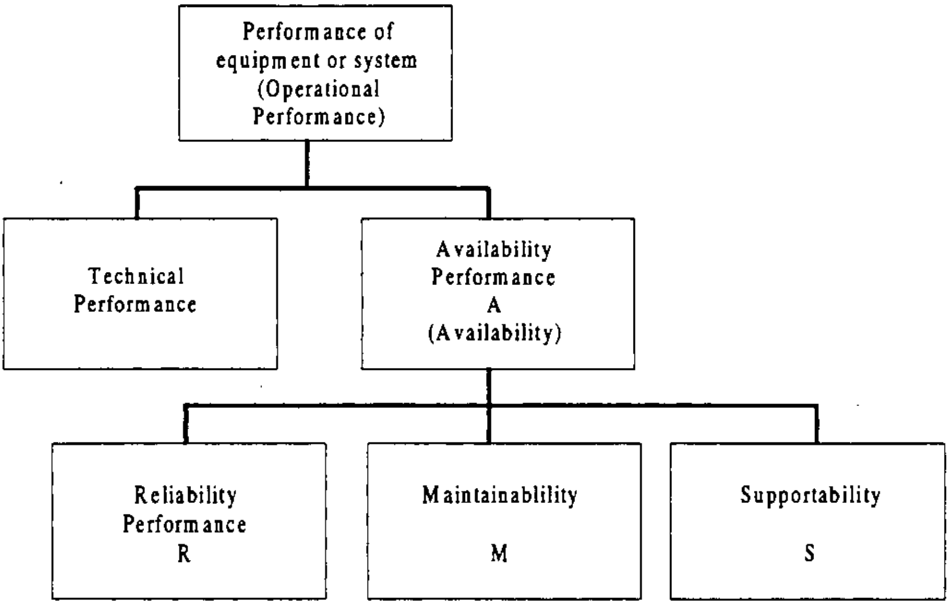

Figure 5.1. Operational performance of a technical system consists of technical and availability performances.

Reliability performance (R) describes the ability to operate without defects or faults for a given time. Reliability performance is an extension of the quality concept into the time dimension and it is of particular interest when an unrepaired system is involved, say, in space technology and in electronics.

Maintainability (M) describes how soon after a failure the faulty equipment can return to operating condition after maintenance has been carried out. In many cases maintainability is just as important a factor as reliability performance (R). For example, it is a reasonable expectation that a car requires maintenance only once a year, but the availability would not be satisfactory if the repair took 11 months. On the other hand, the maintainability of, say, an unmanned satellite is not of great significance, whereas reliability performance (R) is the factor that demands attention.

Supportability (S) describes the maintenance organization's ability to organize, as needed, the requirements for system maintenance (spare parts, apparatus, personnel, documentation). The lead time needed before undertaking repairs is a typical factor that describes supportability.

5.1.2 Stages of analysing reliability performance [5.3]

The characteristics of the system's reliability performance are mapped out by making a systematic reliability performance analysis. Figure 5.2 shows the different stages of the analysis[5.4]. The kind of system involved and purpose of the analysis determines which stages are given greater or lesser emphasis or are omitted entirely. In this section the quantitative methods are left without attention.

When **delineating the** plant, it must be decided which chains of events, failure modes or effects the analysis will be directed at. This stage also involves delineating the requirements on the operation and reliability performance of the plant as well as the degree of detail which the examination should strive to attain. It must be decided whether, for example, reliability performance or maintainability will be paramount in the analysis.

The "ingredients" of a functional description include

- a breakdown of the system into functional groups based on system descriptions, diagrams and lists of components.
- descriptions of modes of use and functions
- a description of the usage profile (eg, permanence curves, shutdowns)
- possible capacity or output level requirements.

The analysis of reliability performance can be carried out either qualitatively (left path of in Figure 5.2) or quantitatively (right path in Figure 5.2). Qualitative, ie, **identification methods** (section 5.1.3), enable one to address the fault and

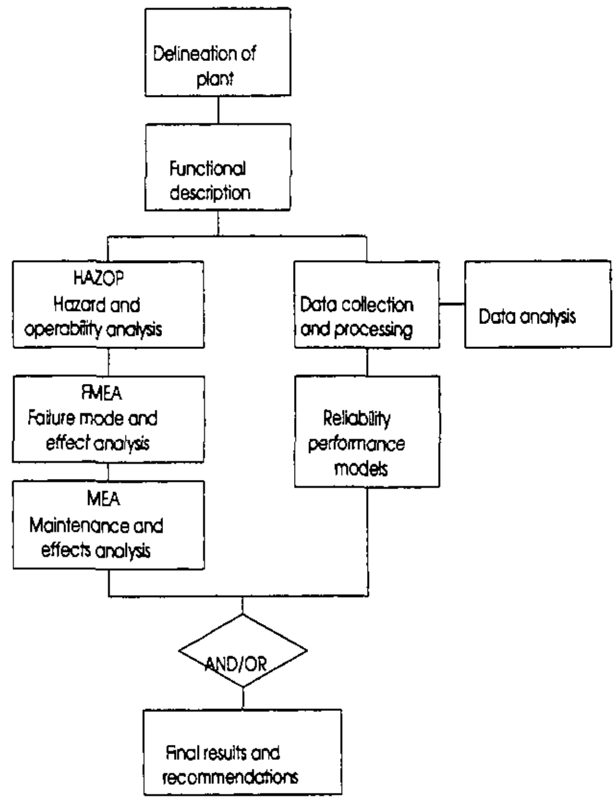

Figure 5.2. Order of drawing up an analysis of reliability performance [5.4].

maintenance characteristics of the equipment as well as their consequences. In qualitative analyses, which include identification methods, non-numeric methods are used to determine the possible states of the system as well as the causes and chains of events leading to them. Qualitative methods include Hazard and Operability Analysis, HAZOP, Failure Mode and Effect Analysis, FMEA, and Maintenance and Effects Analysis, MEA.

Quantitative analysis utilizes information and data gathered from existing plants and equipment. As result it gives numerical information of the availability performance, such as failure probability, and mean time between failures. The quantitive analysis comprises of **collection and processing of reliability performance and maintenance data, data analysis**, and analyzing the data using **reliability performance models**.

The last stage of availability analysis is to draw conclusions of the data produced with qualitative and/or quantitative methods. This is usually done in the form of recommendations to system design, operation and maintenance. The data is classified according to measures that can be taken to improve the availability of the system under consideration. Thes measures comprise traditionally of giving guidelines to design, operation and maintenance, but developing fault detection and diagnosis methods for selected process entities could be one of the measures as well.

In addition to pinpointing the feasible components and subprocesses for developing fault detection and diagnosis methods, the analysis produces information of the ways how the faults effect the system operation, in what way the faults are normally detected, and other kind of information for developing the FDD system or method.

5.1.3 Methods of identification [5.3]

In carrying out design work, it is important to identify concealed or latent risk and problem points at the earliest possible stage and to find better solutions for them before the plant is installed or commissioned. Best adapted to this stage of analysis are so-called methods of identification, the most important of which are

- Hazard and Operability Analysis (HAZOP)
- the analysis of the causes and effects of process disturbances Failure Mode and Effect Analysis (FMEA)
- the effects of equipment defects and faults on the system Maintenance and Effect Analysis (MEA)
- the effect of repairs and maintenance on the system.

Especially HAZOP and FMEA are well suited for pinpointing the important components of a HVAC system. MEA concentrates more on what happens after the fault has been diagnosed and the process should be repaired without too much down time. For these reasons only HAZOP and FMEA are described below.

The limitation of methods of identification is that faults, disturbances and defects are examined in a piecemeal manner. When seeking to sort out combinations of several events (e.g multiple faults), methods intended for the modelling of chains of events must be used - ie, reliability performance models. In practical design work, methods of identification have proved to be very useful thanks to the systematic approach they offer. In addition, they provide for careful documentation of factors that are important for the efficient operation of the plant.

Owing to the nature of the methods, it is recommended that they be used so that they supplement one another, thereby decisively improving the degree of identification. The final result also depends on the accuracy of the initial data.

Methods of identification can be assimilated relatively easily and their use does not call for in-depth reliability performance training, since a good knowledge of the process will suffice. One requirement is that persons who are familiar with the part of the process being studied are brought together at regular intervals around the same table for a discussion led by a designer who has received practical experience of using the methodology.

5.1.3.1 Hazard and operability analysis

One of the qualitative methods is Hazard and Operability Analysis (HAZOP) [5.2], which has been developed within the chemical industry to identify risks. It is best suited to auditing disturbances due to changes in the operating parameters or to defective design, and it is useful in mapping out the resultant risks of accident. Furthermore, it can also be used to good effect in seeking out the causes of smaller events (fault occurrences).

To carry out a Hazard and Operability Analysis, a group of people familiar with the process to be examined is formed and, led by a facilitator, they go through a preprepared list of key words and deviations (Table 5.1). The participants reflect on the causes of the deviations, their effects and possible actions that can be taken to reduce the risks, and the results are recorded on a specific form (Figure 5.3).

Table 5.1. Process quantities and auxiliary functions with their related possibilities of deviation. The example relates to a continuous, ongoing process [5.5].

PROCESS QUANTITY	DEVIATIONS
Flow	large, small, none, opposite, incorrect feed ratio
Temperature Pressure pH Viscosity	high, low
Level, volume	high, low, zero
Content	excessive, too little (for each component separately*), impurity
Phase content	incorrect, extra phase
etc....	
*) Can also be dealt with in the form "incorrect mixing ratio" with its different possibilities.	
AUX FUNCTION	DEVIATIONS
Mixing Heating CoolingWater feed Compressed air feed Steam feed Inert gas feed Other aux. feeds	none, too little, too much
Electrical supply	none, high/low voltage
Vacuum	too large, too little

HAZARD AND OPERABILITY ANALYSIS PROJECT: AN25

HAZARD AND OPERABILITY ANALYSIS VTT BUILDING TECHNOLOGY PROCESS: AIR-CONDITIONING UNIT SUBSYSTEM: L1			PROJECT: AN25 CREATOR: JHy DATE: 8.8.1995 PRESENT: JHy, MM, NN	
ANOMALY DEVIATION	PLACE	CAUSE	EFFECT OR MODE OF DETECTION	ACTION/ REMARK
no flow	LI01	LITV02 jammed	drop in temperature, danger of freezing	lower limit alarm from LI03
too high flow	LI01	LITV02 jammed open	etc.	

Figure 5.3. Form used in hazard and operability analysis.

A good size for the group is 3 - 6 people and a facilitator assisted by a secretary who is familiar with the objectives of the analysis and records in detail its results. The group is made up of designers of the system as well as operating and upkeep personnel. The composition depends on whether the analysis focuses on a system that is in the design stage or one that is in operation.

The material required for the Hazard and Operability Analysis group includes piping and instrumentation diagrams as well as data on the constructions of the machinery and equipment, the process materials and the layout solutions. The parts of the process stages and the system are coded and the facilitator can prerecord the deviation lists for them on forms [5.5].

The records of the Hazard and Operability Analysis can serve as the basis for various reports containing, for example, the following matters:

- process description
- data on sources used (PI diagrams, operating instructions, manuals)
- summary of data records
- suggestions for improvement in order of importance
- descriptions of harmful chains of events with their initial events.

The Hazard and Operability Analysis supports the design effort and it can be used to compare different alternative designs and to define the requirements to be set for equipment suppliers. The documentation furthermore serves the need to train future users of the system and to prepare them for commissioning.

5.1.3.2 Failure and mode effect analysis

Failure and Mode Effect Analysis (FMEA) [5.6] provides a systematic audit of the system's faults, the causes of them and their effects, by mode of failure, on the reliability performance and safety of the machine, system or plant. The purpose of FMEA is thus to identify all the components and system parts that are important in causing unavailability. FMEA can be mapped out on a form such as that shown in Figure 5.4 [5.6], which provides sufficient documentation also for subsequent analyses.

FAILURE MODE AND EFFECT ANALYSIS PROJECT: AN25

FAILURE MODE AND EFFECT ANALYSIS PROJECT: AN25
VTT BUILDING CREATOR: JHy
PROCESS: HEAT GENERATION DATE: 8.8.1995
SUBSYSTEM: BURNER PRESENT: JHy, MM, NN

LOCATION/ COMPONENT	FAULT	CAUSE	EFFECTS	MODE OF DETECTION	ACTIONS/ CLASSIFICATION	REMARK
flame plate	melting	wrong material	wrong air/oil ratio and distribution, sooting, burner halt	no heat	new flameplate or burner	

Figure 5.4. Form for failure mode and effect analysis [5.6].

The Failure Mode and Effect Analysis is set forth in a document drawn up by a single individual if the analysis is carried out in detail. This person may need to check the information with experts and he must be well familiar with the operation of the system being examined. If the analysis focuses on subsystems or equipment entities, the FMEA analysis can also be carried out as groupwork. The group then concentrates only on the essential hazard and unavailability factors.

After a short period of instruction, carrying out FMEA analysis does not call for any preliminary information on reliability technology per se. The analysis is suited as a design tool because it is the design engineer who best knows the causes and effects related to equipment faults.

A large process system is divided into process stages that are examined as independent subsystems. It makes sense to devote the needed attention to defining the boundaries between systems and mapping out functions. A list of component types is drawn up for the systems and it is used to obtain data on reliability performance. On the basis of the component list, a component analysis is carried out which yields a list of the fault modes for each component in all the different operating situations.

The faults are classified depending on the plant analysed and the objectives of the analysis. The following criteria, among others, may be relevant.

- the significance of the fault from the standpoint of reliability performance and safety (priority)
- deferrability of the repair
- detectability (latency) of the fault, mode of detection and situation
- permissible output of the system or possibility of operation during repair.

The abbreviations (marks) to be used in making the classification should be unambiguous and clear. Quantitative data, such as fault frequency, repair time and various delays are usually not needed unless it is intended to prepare a model of the reliability performance of the system later on.

The restrictions on FMEA are the following:

1. By itself, FMEA is intrinsically a qualitative method, and quantitative data cannot be obtained on the system's overall reliability performance (although the analysis can be utilized in building a reliability performance model itself).
2. In studying the safety of a system, data that are not essential from the standpoint of its safety are also examined.
3. FMEA does not encompass an examination of the effect of combinations of faults.

5.1.3.3 Methods of identification in building BOFD system

The methods of identification as also the other qualitative availability methods have been utilised primarily in process or plant design phase. However, they could effectively be utilised also for other purposes. In cases where qualitative availability analysis is already now a common practice the additional work of analysing the results from the wievpoint of fault detection and diagnosis is small.

Designing and building an fault detection and diagnosis system requires a lot of ingormation of the process for which the FDD system is being built. In building sector, availability analysis is not a common practice but qualitative availability analysis methods provide a system designer with an existing and well documented disipline to this task of knowledge acquisition. Though the analysis methods are not developed for this purpose they can quite easily be applied for this task only.

However, to get the best benefit out of the analysis, the results should be utilized broader than only for BOFD system construction.

5.1.4 Method for prioritizing

Qualitative analysis methods lead easily to a large amount of fault data. Especially when a system is studied in a detailed level, the component list may consist of a large number of components. Each component may then have a number of different faults. To be able to concentrate only to essential components and their faults the system component list and sytems faults must be evaluated against the characteristics important with respect to correct operation of the system.

In principle, an evaluation procedure of a component or a fault comprises of the following stages:

1. definition of evaluation criteria and the evaluation grid

2. definition of the relative weights of the evaluation criteria.

3. assessment of components's effect to the system characteristic in case of fault using the evaluation grid defined in the preceding stage

4. calculation of an index that describes the priority, importance or similar kind of result

Stage 1: First the characteristics that are important for correct operation of the system are listed and an evaluation grid for each of these characteristics is defined. The characteristics and their grids should be unambiguous. For example, in Table 5.2, a list of characteristics and their evaluation grid are presented. In Table 5.2, the 'Energy consumption' -characteristic is ambiguous: its grid number 2 is concerned with money - not energy. Other characteristics are quite clear.

Stage 2: The weights of the characteristics can be gained in an expert group by combining the opinions of experts, and using, for example, a method a weighed levels.

In the method of weighed levels, the characteristics are first grouped according to some hierarchy (see Table 5.3 as an example). Each expert gives his weights to the characteristics on each level. The sum of weights given on one level by one expert is normalised suitably or agreed in the group. The weights given to a single characteristic by experts are summed in the end and then normalised so that the sum of the weights on each hierarchy level is 1 (or 100%).

In Table 5.3 there is an example of calculating the weights of a system's characteristics. Instead the method of weighed levels also other methods can be used. One, Analytical Hierarchy Process, is presented in [5.1.7].

Table 5.2. Properties of a heating system and an assessment grid for it (= scaling of significance).

System characteristic to be assessed		
	Assessment grid for the significance of the effect	
1	Heat and warm water (Sufficiency of heating)	
	0	no effect (nothing)
	1	some effect
	2	effect within 24 h
	3	immediate effect (within 10 min.)
2	Energy consumption	
	0	no effect on energy consumption
	1	consumption is not optimal (dT is smaller)
	2	wastes the housing corporation's money
	3	wastes a lot of energy
3	Maintainability (Ease of maintenance)	
	0	no tools, heating not interrupted
	1	tools + interruption 30 min
	2	tools + interruption 2 hours
	3	tools + interruption 48 h
4	Supportability 1 = Service man availability	
	0	standby
	1	caretaker / maintenance company man can perform
	2	plumber / electrician needed
	3	special repair person / authorized personnel (control device, etc.)
5	Supportability 2 = spare parts availability	
	0	spare parts on site
	1	takes no more than 2 hours
	2	takes no more than 48 hours
	3	takes no more than two weeks
6	Probability of fault occurrence (any fault)	
	0	Probably will never malfunction (> 25 yrs)
	1	malfunctions seldom (once in 15 years)
	2	malfunctions in normal use (once in 7 years)
	3	very probable (once in 2 years)

Table 5.3. Calculating the weights of system properties.

hierarchy level 1	integer weight	weight 1	hierarchy level 2	integer weight	weight 2	hierarchy level 3	integer weight	weight 3		total weight: total weight	100*total weight
technical characteristics 4+5+6+6	21	0.525	heat and warm water 7+8+5+5	25	0.625				W	0.33	33
			energy consumption 3+2+5+5	15	0.375				E	0.20	20
			summa	40	1						
availability performance 6+5+4+4	19	0.475	reliability=probability of fault 7+8+8+9	32	0.533				P	0.25	25
			maintainability 4+4+4+3	15	0.25				M	0.12	12
			supportability 4+3+3+3	13	0.217	availab. spare parts 6+4+4+5	19	0.475	Sp	0.05	5
						availab. of serviceman 4+6+6+5	21	0.525	Sm	0.05	5
sum	40	1	sum	60	1	sum	40	1		1.00	100

integer weights given by experts 4+5+6+6=21

19/40=0.475

calculation of total weight from level weights 0.525*0.375=0.20

Stage 3: After having defined the criteria, their assessment grid and weights the evaluation continues with assessment of the value of a component's effect to the system characteristics in case of a fault. Each component or fault is assessed by asking "What effect does a fault in this component or a specific fault have to the system?" The result is analysed and given a number from the assessment grid.

Stage 4: Last step in evaluation procedure is the calculation of the some index that is then used in priorisation. In Table 5.4 there is an example of assessment and calculation of the total index.

Table 5.4. Importance of heat exchanger 2.

Component: HE2 heat exchanger		Component number: 318	
Characteristic:		Evaluation	Weight
W	hot domestic water or heat must be available some fault occurs that habitant notices within 10 minutes	3	33
E	energy consumption some fault occurs that a lot of energy to be wasted	3	20
S	maintainability (ease of maintenance, serviceability) repairing of some fault requires tools and break of more than 2		
Sm	Service man available repairing some fault needs a special staff	3	5
Sp	Spare parts available getting the spare parts may take two weeks	3	5
P	Probability of fault fault occurs once a 15 years	1	25
total importance= 3*33 + 3*20 + 3*12 + 3*5 + 3*5 + 1*25 = 250			

The priorization method described above is one of many that can be utilized. Common to all of them is that the final prioritized list is only a suggestion. Varying the weights of the chacteristics different lists can be obtained and different points of view can be emphasised.

The methodology above gives a good tool for group work. The result combines the opinions of the group members. After the list is formed, the weights, characteristics, and the list itself must be analysed again in the group in order to get the group final opinion. In this analysis stage there may be some changes in the priorization.

5.1.5 Fault tree

Fault tree analysis method [5.9] has been developed during 1960's for analyzing systems having a net topology. In [5.10] there is a thorough review of fault tree analysis methods and applications.

Fault trees can be used qualitatively or quantitatively. When using them quantitatively a probability of some event (so called TOP-event) is calculated starting from the probabilities of known basic events. For instance, in a building, a component fault or alike is a basic event and excessive energy consumption a TOP event. When utilized qualitatively fault trees can be effectively used for documenting cause-effect relationships on the system level. Furthermore, the weakiest points of the systems and the fault combinations that might not be noticed will be mapped [5.3].

Information concerning a fault in the process is usually broken down into components using a fault tree. Underlying it is the so-called TOP event, which constitutes the root of the tree, and the reasons which contributed to the event taking place are depicted by the branches.

The precondition to constructing a fault tree is that the operation and behaviour of the system under examination is well known in different modes. After the operation of the system is defined the most important system level faults and risks are found out (TOP events). Then, a fault tree is constructed for each of these TOP events. The primary faults causing the TOP event are found out. Then the secondary faults causing each primary fault are defined and so on until the level of basic events. The events mapped out this way are then connected using logical AND and OR functions. The usability of a fault tree depends much on how well the basic events can be defined.

5.1.5.1 Fault tree in fault diagnosis

Fault trees can be utilised both qualitatively and quantitatively. In fault diagnosis fault trees are well suited to the top-down approach since the events which have had an undesired effect on the operation of the entire building are suitable to be used as their TOP events. Consequently, such phenomena as an increase in energy consumption or a decline in the comfort of the building as a result of a decrease in heat can serve as the TOP events.

No standard practice exists for describing the bottom-up approach. One proposal has been to use a set of symptoms or associative networks to describe the symptoms of a fault and their relation to that fault.

The fault tree and set of symptoms can be combined relatively easily. A fault tree consists of a hierarchical structure in which one fault can explain one or several faults on a lower level. For example, increased energy consumption at a district heating station could be the result of a leak in a heat exchanger, valve, or some other similar fault. A fault tree allows the concept 'leak in a heat exchanger' to be further subdivided into internal and external and external leaks.

The fault tree should have information added to it which would indicate that a specific fault has occurred. A set of symptoms could be used for this purpose (see Figure 5.5). The set of symptoms would be the signs of the presence of the fault. One particular symptom could be a part one or several symptom sets.

A fault can be detected from the symptom set assosiated with the fault in question. The symptoms are formed from the test quantities calculated or measured from the process. The information concerning symptoms may be uncertain and can be dealt with by classification of test quantities together with classical logic systems. Some non-classical logic systems such as fuzzy logic, for example, can be used for deduction using uncertain information.

In addition to containing the set of symptoms, the fault tree can also include information on what the primary direction of searching the TOP event cause is at each node in top-down decision making. This information might be deduced analytically by evaluating the different branches of the search paths on each level using the same criteria for evaluation as were used in the selection of the components. Nevertheless, a method considerably closer to practice is to ask an expert about the order of progression at each node. In this manner the evaluations and estimations used by experts concerning the orders of probability of faults in the system could later be taken into consideration in efforts to implement such improvements as automatization of reasoning using an expert system.

Figure 5.5 represents one proposal for marking a fault tree. The faults are described in the boxes, and their sets of symptom are given in lists below the boxes. The boxes are combined with one another using the logical AND and OR operators. Logical operators are used in reasoning, and symptom sets are used for detection of each individual fault. The set of symptoms can also be the empty set.

In addition, the order of the branches in the fault tree might be useful information. The branches can be drawn in the order of examination, or they can be marked with labels to indicate the search priority.

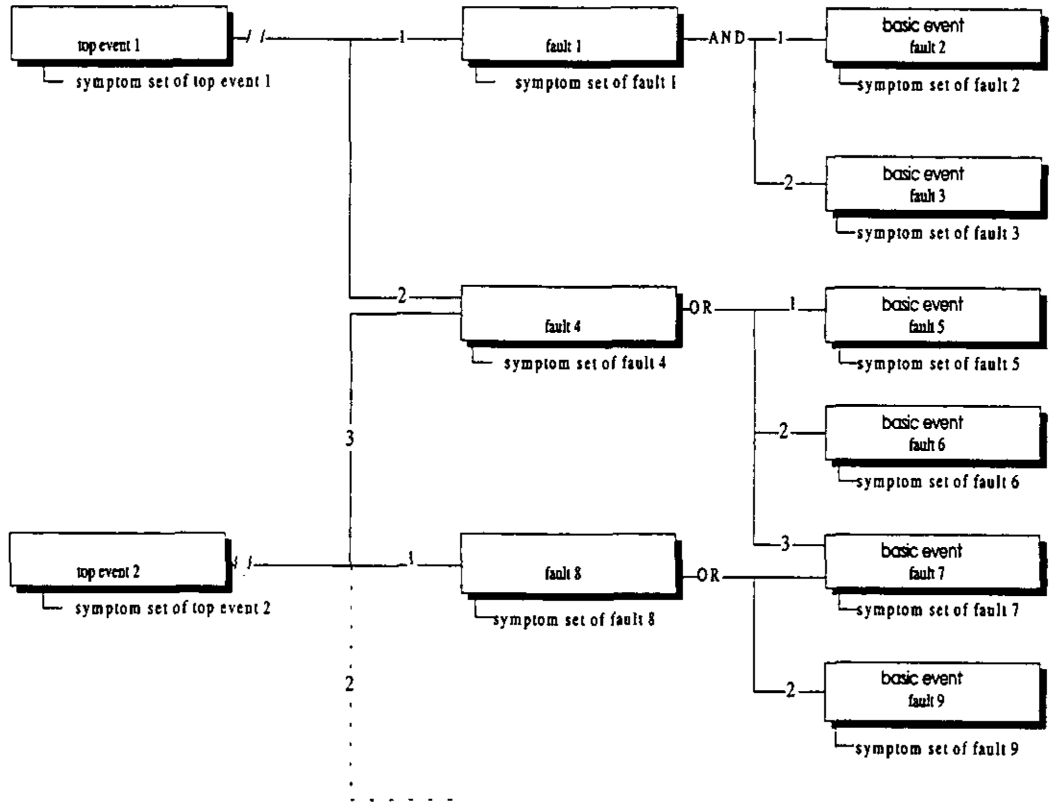

Figure 5.5. The markings on the fault tree.

5.1.5.2 An example

Figure 5.6 depicts a part of a fault tree and the symptom sets for its faults. The example used in the picture is a fault in an oil burner. The TOP event was that the oil burner stopped functioning. The fault tree is constructed using the TOP event as the starting point, and it ends with different types of other faults (i.e. basic events) which explain the TOP event. For example, too cold temperature of the oil explains why the disturbed burning of the burner led to its stoppage.

Each fault has one or several symptoms assosiated with it. Different faults can be distinguished from each other if the set of symptoms describing each fault is typical to that specific fault only. At the "No oil in the tank" fault, Figure 5.6 indicates that the symptom is "user checks", which means that the symptom cannot be measured or observed automatically. Instead, the user must visually inspect the symptoms that indicate the fault in question. The faults "flame won't light" and "disturbed burning" can be distinguished from one another on the basis of different sets of symptom: the fault "flame won't light" has the set of symptoms "maintenance man checks" while "disturbed burning" has a symptom generated with fault detection method 1.

At any given moment a valid set of symptoms can simultaneously trigger several faults. A situation arises if the faults share common symptoms. In such cases the structure of the fault tree can serve as a means of determining whether the faults are completely separate or in a relationship of mutual dependency. For example, the fault "cold oil" explains the fault "disturbed burning". In practice this situation arises if only fault detection method 1 is indicating a fault. In contrast to this, if both fault detection method 1 and 2 were simultaneously valid, the faults "cold oil", "worn-out pump", and "solenoid valve not functioning" would have to be interpreted as separate faults, because they cannot be reliably distinguished from one another. At most it can be pointed out that clarification of the fault situation should begin with "worn-out pump", because this would explain the largest number of symptoms.

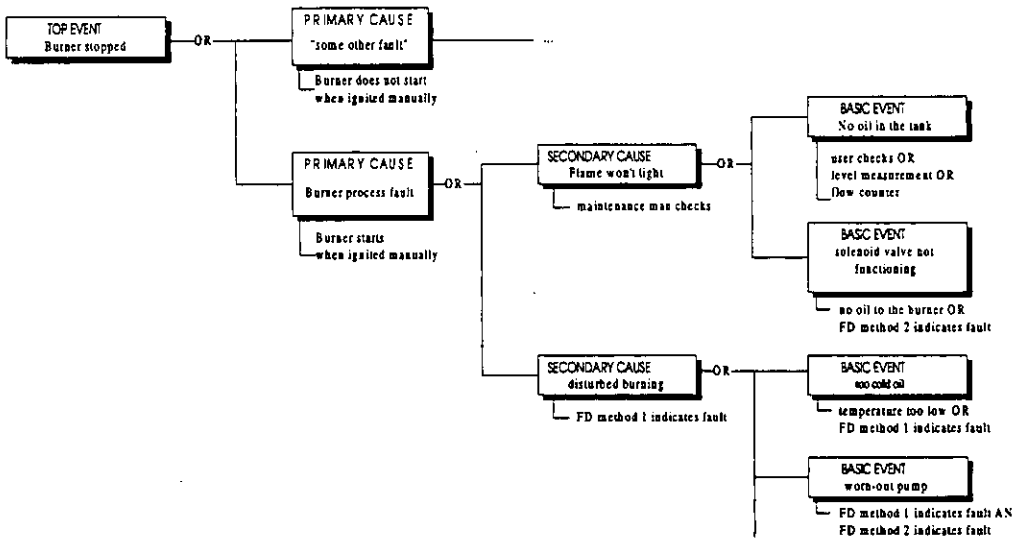

Figure 5.6. An example of a fault tree. A part of a fault tree of an oil burner.

5.1.6 Summary

Two identification methods, HAZOP and FMEA, that can be used for knowledge acquisition when designing and building a building optimisation and fault diagnosis systen, have been described briefly. Hazard and Operatibility Analysis and Failure Mode and Effect Analysis methods are both well suited to the collection of data for a fault diagnosis database. These methods alone give valuable information of faults, their effects and symptoms, and how the faults are remedied. Moreover, however, there are other reliability engineering tools that can be utilized according to data available of the process under consideration.

In addition to identifying faults and fault-sensitive items, the database must be structured modularly in such a way that when planning follow-up actions, attention can be focused on the most important parts of the database and thereby of the system being studied. To aid prioritization, a procedure based on a method of weighed levels and a generally used scoring method were presented.

A fault tree is one of the reliability performance methods and it is generally used in a quantitative mode. In building a fault diagnosis system, it would nevertheless seem more natural to make use of fault trees as a qualitative method alongside Hazard and Operability Analysis and Failure Mode and Effect Analysis. A fault tree can, in this case, be utilised as a formal presentation of inferential rules presented by experts, cause and effect relationships and metainformation describing how the reasoning process unfolds.

5.1.7 References

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5.2 PARAMETER ESTIMATION

Olsson, L. G. Div. of Build. Services Engineering, KTH

5.2.1 Introduction

Parameter estimation covers a very broad range of methods and applications, and in the present section the discussion is restricted to those areas described in chapter 4. Parameters can be seen as specific quantities in given models and their values are estimated on the basis of experimental information. Models could be complex, physically derived equations solved numerically, as well as a simple expression for direct calculation of a parameter. The problem may be illustrated as follows:

$$y = f(x,p) \tag{5.1}$$

where,

y = output signal (or data sequence)
x = input signal (or a set of such ones)
p = set of parameters (to be estimated)
$f(.)$ = model.

In FDD applications there are basically two ways in which the models are used, namely:

- parameter estimations are done repeatedly during the monitoring phase and changes in p are subject to analysis. In order to associate changes in the parameters with faults in a system, reference data for fault-free cases are required. Choice of the model and parameterisation are strongly dependent on the particular application.

- parameters are estimated once and then kept constant. In general they are used to define some important system features, like fault-free states. The difference between measured and modelled y, the residuals, are generally of main interest in fault detection.

It seems practical to distinguish between these two approaches in this section because the requirements on the parameters are quite different. In the latter case the choice of suitable model is the important task while in the former case there are further aspects to consider, such as

- sensitivity of parameters to changes in the system or component behaviour

- statistical features of parameters due to modelling and measurement errors.

In analysing the usefulness of parameter estimation techniques as a BOFD tool, the focus here is placed on the statistical features of the parameter estimates because they have a direct impact on the possibility to detect and diagnose faulty or degrading performance of systems or components.

5.2.2 Parameter estimation during monitoring phase

The behaviour of a system or component is described by models. Depending on the applications the modelling differs considerably, but the parameters are always defined in such a way that they are sensitive to changes in behaviour of the system or component being studied. Models can be simple linear models or empirical combinations of measured signals as well as systems of differential and/or algebraic equations. Changes to individual parameters or groups of parameters can be used as fault indicators. The methods also differ considerably in evaluation procedures. For example, the methods may consider:

- overdetermined problems using minimisation methods to estimate parameters (regression or iteration routines). Examples are FDD approaches using physical models with parameters targeting features to be studied (sec. 4.3.1). Also blackbox models might be included in this group in the sense that they are a minimisation problem.

- Fully determined problems where all signals are measured at a certain time or during a short time interval to evaluate time averages. The parameters are directly calculated from this data and the given models, i.e. $p = g(x,y)$ in terms of Eq. (5.1). In general the model g(.) is a rather simple expression and this approach could be seen as a special case of parameter estimation. Such methods are here called explicit calculation methods, and an example is given by the characteristic parameter approach (sec. 4.3.3).

a) Minimization methods

Minimisation methods are used in treating time sequences of signals, one is taken as output or response and the other ones as inputs to the model. The quantity of interest is the objective or cost function, usually defined by the sum of quadratic residuals (cf. sec. 4.3.1). The parameters are modified until the objective function reaches a minimum and the corresponding parameter values are called estimates. This is the least square method for computing the best agreement between measurements and model predictions. Often the residuals (or signals) are filtered to suppress or emphasise certain features of the models and/or measurements which may have a direct impact on the result. Filters constitute an important part of the pre-processing.

Minimisation routines result in parameter estimates which will be affected by uncertainties due to the statistical nature of the problem. Information about the uncertainties may be obtained from the covariance matrix for the parameter estimates, however, the derivation of this covariance matrix is an elaborate task [5.11], even for models with linear parameterisation. In non-linear cases further approximations are necessary, as carried out by Spirkl [5.12], involving linearisation of the model around its estimated value (with respect to the parameters). This is carried out numerically by the computer program and valuable information about the accuracy of the parameter estimates can generally be obtained as standard deviations (STDs) and correlations between various pairs of parameters (mutual dependence of two estimated parameters).

In analysing the results, STDs are simply attached to the estimates while correlations, possibly normalised with the corresponding STDs, are merely used for informative purposes. In such cases estimates for a parameter *i*, as obtained at two different measurement sessions, should fulfil the following condition in order to be deemed different (i.e. indicate a fault):

$$\left|\hat{p}_{i,ref} - \hat{p}_i\right| > 2 \cdot \left(s_{ii,ref} + s_{ii}\right) \tag{5.2}$$

where,

$\hat{p}_{i,ref}$ = estimate of parameter i from calibration measurement (e.g. at commissioning or model validation)

$s_{ii,ref}$ = STD corresponding to $\hat{p}_{i,ref}$

$\hat{p}_i$ = estimate of parameter i from measurements during monitoring phase

s_{ii} = STD corresponding to $\hat{p}_i$.

The factor 2 is chosen so that the probability for the two estimates of parameter i being different (defined as the amount of non-overlapping areas), is at least 95 % if normal distributions are assumed. In the present applications this should be considered as a statistically safe observation. Replacing the factor 2 with 1 decreases the probability to 71 % and a fairly large risk for false alarms. Conversely, for same estimates there is a 50 % risk for a fault to occur within the STDs. How serious this is depends on the size of STDs and determine realistic values of the STDs is clearly a very urgent matter. Systematic under-estimation of the uncertainties may occur when the impact of correlations is omitted.

In an automatic analysis procedure it will thus be an advantage to include correlations in the uncertainty limits. For cases of normalised parameters, as defined in section 4.3.1, the following expression is tentatively introduced to calculate an overall uncertainty or equivalent STD for each estimated parameter in the model. Thus, for $\hat{p}_i$:

$$s_i = \sqrt{s_{ii}^2 + \left|\sum_{j=1}^{d}\left[P_N\right]_{ij}\right|} \tag{5.3}$$

where

P_N = the covariance matrix (diagonal elements give the variance of the parameters, s_{ij}^2)

s_i = overall uncertainty of parameter

i, j = running index

N = number of time intervals in the data sets

d = number of free parameter

The summation should exclude index i. Adding the STD and correlations quadratically is simply made in analogy with how experimental error limits are usually combined. Moreover, correlations between parameter pairs not including parameter i are neglected. This might place restrictions on how correlations are added when d > 2. A rigorous treatment of this problem is given by Norton [5.13]. A statistically safe (to 95 %) change of the parameter estimates must then fulfil the condition:

$$\left|\hat{p}_{i,ref} - \hat{p}_i\right| > 2 \cdot \left(s_{i,ref} + s_i\right) \tag{5.4}$$

The overall uncertainty for the reference case is calculated similarly and it is important that the signals cover a major part of the normal operation range to get meaningful results. If in the continued analysis some parameters are combined to get new ones, the overall uncertainties will increase, which may be considered by calculating the corresponding root square sums.

Inclusion of the correlations in such a way implies that $s_i > s_{ii}$, as long as the correlations do not completely cancel, and s_i should serve as a more realistic index of the quality of the modelling and measurements. It is essential for the usefulness of these FDD methods that the STDs for all parameters are kept small, particularly if system degradation is of main interest or if more than one fault occur simultaneously. Large correlations need not be dangerous if the STDs are small but they are warning flags. Realistic models, relevant parameterisation and signals of high richness ensure good accuracy. Sudden changes of STDs may indicate violation of these prerequisites (or faults like sensor malfunction). Such aspects must be considered in the diagnostic routine. In practice it might be useful to normalise each parameter or the inequality (5.4) with its reference value. This provides a direct measure of changes in system or component behaviours compared to fault-free cases.

b) Explicit calculation methods

On the basis of measured data, parameters are directly calculated according to given models. An example of this type of method is the fault direction space (FDS) approach with characteristic parameters (*CPs*, cf. section 4.3.3). These are defined in such a way that they are (nearly) constant in fault-free cases for normal operation ranges but change when faults occur.

The definition of the parameters may be based on physical models as well as empirical knowledge about the component or system behaviour (in steady-state). Measured data are used to calculate relevant values of the parameters, with and without faults. Sets of these parameters then serve as predefined fault indicators. Uncertainties entering these parameter values may originate from

- sensitivity of the parameters in fault-free and faulty cases
- evaluation of steady-state data from measurements in monitoring phase
- non-linear effects in modelling
- measurement errors,

which must be combined to form an overall uncertainty ascribed to each parameter. This implies that the calculated parameter values can be seen as mean values with uncertainty limits (or STDs), i.e. a kind of estimate. Correlations do not occur in this case since the parameters are not coupled. To avoid false alarms, the values of the parameters that are sensitive to the fault must change more than the uncertainties involved, which may be illustrated for parameter i by the following relations:

$$\Delta CP_i = CP_i - CP_{i,ref} \tag{5.5}$$

$$\Delta CP_i > 1.5 \cdot (s_i + s_{i,ref}) \approx 3 \cdot s_{i,ref}$$

where

s_i = overall uncertainty of parameter i during monitoring

$s_{i,ref}$ = overall uncertainty of parameter i for the fault-free (reference) case

and assuming that these uncertainties are nearly equal. Subscript *ref* indicates fault-free cases. The factor *1.5* is set somewhat arbitrarily and should correspond to a probability of 87 % that the change is in fact due to a fault. All ΔCP_i *s* from a measurement are collected to a fault vector which is subjected to the continued analysis, where the uncertainties play an important role.

Firstly, identification of a fault type may be made by systematically searching to fulfil the condition:

$$1 - \cos(\varphi) < 0.5 \tag{5.6}$$

$$\cos(\varphi) = \mathbf{V_f} \cdot \mathbf{V_{CP}} / |\mathbf{V_f} \cdot \mathbf{V_{CP}}|$$

where

$\mathbf{V_f}, \mathbf{V_{CP}}$ = observed and predefined fault directions, respectively (sets of ΔCPs).

This might be an elaborate task if the fault vectors contain many components (cf. further 4.3.3). Secondly, for an assessment of how serious a fault might be ($\mathbf{V_f}$ and $\mathbf{V_{CP}}$ are almost parallel), the amplitudes of $\mathbf{V_f}$ and $\mathbf{V_{CP}}$ are compared and the result is again affected by the overall uncertainties of the fault vectors.

The uncertainties of the characteristics parameters play a significant role in the FDS approach and much effort is required to estimate these, e.g. by measurements in laboratory, simulations, analytical considerations etc. Also the definition of the parameters is essential.

5.2.3 Parameter estimation during calibration phase

Parameters are used in the modelling but they are kept constant to represent certain features of the system/component behaviour, i.e. referring to Eq. (5.1) the signal (or variable) y is of interest. Other quantities, like residuals, are utilised as fault indicators. Examples of methods in which the parameters are constants are given below.

Characteristic curves (sec **4.3.2**): The correct behaviour of a component or subsystem is represented by characteristic curves which have been obtained by curve fittings (usually with the least square method). The parameters are estimated based on steady-state data, measured in situ or in a laboratory. In this way relevant physical quantities are efficiently stored for later comparison with similar quantities calculated using measured data from normal operation (in nearly steady-state). The evaluation of data from this monitoring phase is probably the most sensitive part in this approach.

State estimation methods (sec. **4.2.3**):The modelling is carried out in the state space representation and the residuals between measured and model data are fed back into the model. Observers or Kalman filters using parameters, independent of time, are used to identify faulty behaviours.

In both these cases the statistical features of the parameters play a minor role. The main purpose is to provide an accurate value of y for given input signals x, cf. Eq. (5.1). Moreover, as the conditions for estimating the parameters may be well controlled the uncertainties can be kept small.

5.2.4 Summary

Parameter estimation is a generic modelling method. However, for FDD application involving cases where parameters are used as fault indicators, further conditions must be fulfilled in order to make the procedures a generic FDD tool, such as:

- the sensitivity and the statistical features of the parameter estimates together set the limits for fault detection and diagnosis, i.e. form a kind of resolution power for the FDD method. This resolution power combined with experience of how faults affect the behaviour of a system create the basis for decision making procedures. A high resolution power is thus essential and it is given by the modelling, parameterisation and measurement performance.
- parameter estimation may not work with too many undefined signals in the data sequences, e.g. when the system is off during long periods or sensors are failing

completely. Checks have to be made in order to avoid such situations in an automatic analysis.

5.2.5 References

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5.3 STEADY STATE DETECTION

Glass, A.S., Gruber, P. Landis & Gyr, Zug, Switzerland

5.3.1 Introduction

Many fault detection and diagnosis methods developed in the course of Annex 25 require the HVAC system to be more-or-less in *steady state*. In some of the methods this requirement is explicitly stated (e.g. Fornera et al [5.14, 5.15]). In other FDD techniques, transient behaviour is prohibited, which is effectively equivalent.

Consequently the ability to identify steady-state conditions is essential to the successful application of many FDD techniques. In addition, it is also useful in acquiring and verifying performance characteristics of HVAC system components, such as fans, which are often specified in terms of steady-state models.

In practice, however, controlled HVAC systems responding to changes of weather conditions cannot be expected to be found in steady states in the strictest sense of the definition. What is needed are practical criteria for determining when a given HVAC system is *quasi-stationary* - i.e. in a sufficiently *close approximation* of steady state that the FDD method in question can be expected to yield *reliable* results. Filtering the BEMS data in order to identify such quasi-stationary states can be a key aspect of the generic *pre-processing* described by Rossi & Braun (cf. [5.16, 5.17]).

Conceptually, as shown in Figure 5.7, a set $\mathbf{y}_n$ of inputs and outputs of the process or plant to be monitored are collected and pre-processed and then fed to a fault detector where decisions are made on correct and faulty behaviour of the plant. If these decisions are based upon the steady state behaviour of the plant, the overall fault detector (FD) must incorporate a steady state detector (SSD), which outputs a steady-state decision $d_{1,n}$, and a steady-state fault detector (SSFD), which outputs a decision $d_{2,n}$. The SSD forms part of the pre-processing phase, and the SSFD includes the classifier.

$$d_{1,n} \in \{NSS, SS\} \qquad d_{2,n} \in \{F, NF\} \tag{5.7}$$

where NSS denotes "Non Steady State", SS "Steady State", F "Fault" and NF "No Fault".

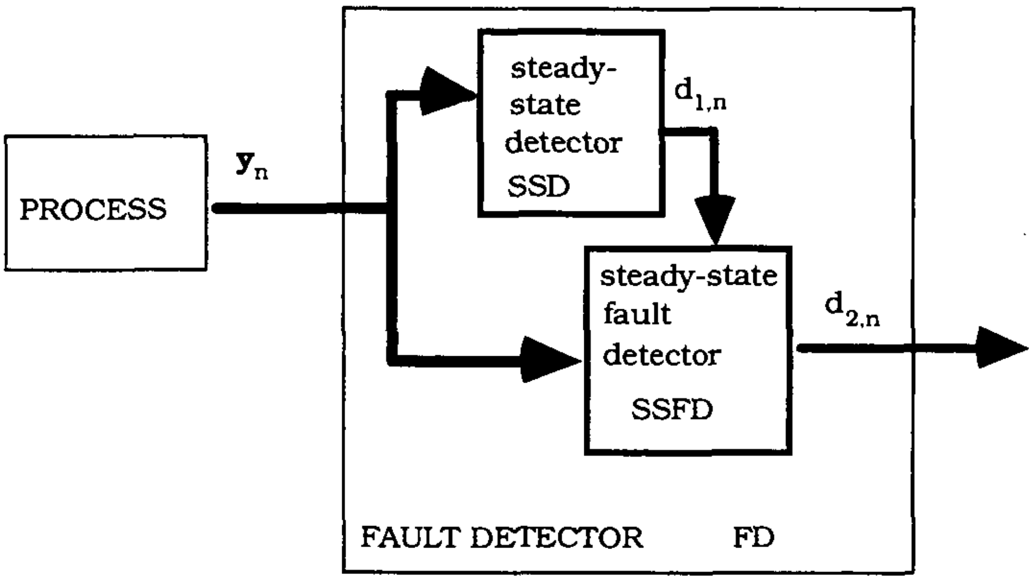

Figure 5.7. Block diagram of the fault-detection process.

A classic problem in designing a successful fault detector is the necessity of striking a balance between two conflicting goals:

- Maximum *sensitivity*: the probability that a genuine fault should remain undetected should be minimal.

- Maximum *reliability*: the probability of false alarms should be minimal.

An analogous problem applies to the design of a steady-state detector needed to identify those quasi-stationary states appropriate for a given fault-detection procedure:

- Those *non-steady-state* conditions under which the FDD method might yield *false alarms* ought to be excluded by the steady-state detector.

- Steady-state conditions should not be interpreted so strictly that they *scarcely ever occur* in practice. Otherwise the FDD procedure would almost always *fail to detect* faults that might be present.

Choosing a happy medium between these two requirements involves *tuning* the relevant parameters in relation to the HVAC system and the FDD method being considered. The steady state detectors explicitly described in IEA Annex 25 work comprise three processes and corresponding tuneable parameters.

- The raw data from a particular sensor is subjected to low-pass filtering to yield some sort of *moving average*. The tuneable parameter is the effective *time-window* used in the averaging procedure.

- The available data is processed to obtain a measure of *fluctuation*. The tuneable parameter is an effective *time-window*, which may be chosen independently to that used in averaging.

- The third parameter is a *threshold*. Whenever the fluctuation measurement falls below the threshold the sensor signal is deemed to be quasi-stationary.

In addition, the SSFD itself must be tuned in terms of thresholds. Both types of thresholds may incorporate *hysteresis* if it is desirable to avoid all too rapid changes of the outputs $d_{1,n}$, and $d_{2,n}$. For instance, the steady-state detector can be programmed to switch on at a slightly lower threshold and switch off again at a somewhat higher value.

The three stages described above are shown in Figure 5.8.

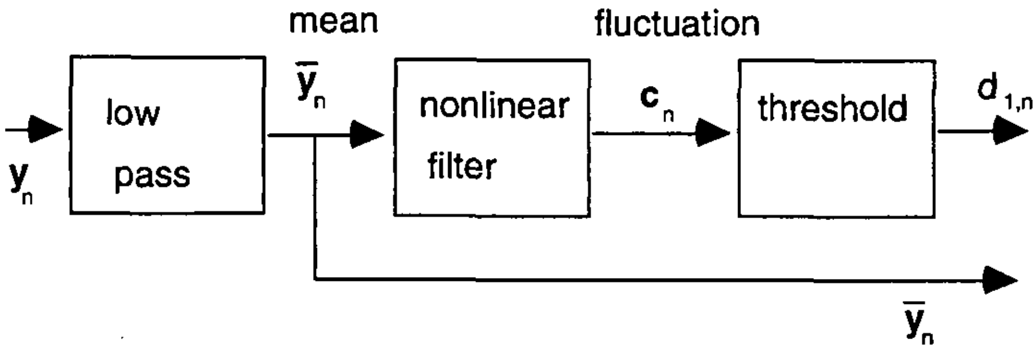

Figure 5.8. Signal Processing chain for steady state detection.

Two types of moving average have been the subject of continued investigation in Annex 25:

- moving averages using time-windows of fixed length

- geometrically weighted moving averages.

Three principal measures of fluctuation have been used.

- moving average of the functional *variation* (integral of the *absolute value* of the derivative).

- moving *variance* using a time-window of fixed length
- moving *geometrically weighted* variance.

In the steady-state detector developed by Glass [5.18] both a geometrically-weighted average and a geometrically weighted variance are used. In the one developed by Dexter & Benouarets [5.20] the signal is first filtered using a fixed-window moving average and the functional variation of the *filtered* data is computed.

Depending on the filtering techniques used, the quasi-stationarity decision $d_{1,n}$, and correspondingly the fault decision $d_{2,n}$, can be interpreted in two different ways.

- They may be deemed to apply to the current time point $n\Delta T$.
- They may be considered to apply to the whole time interval T_W.

In the sections below, an example is introduced in which moving fixed time-window averages and variances are computed. This is followed by the scheme introduced by Dexter & Benouarets [5.20], in which functional variation is computed. The last example is the scheme introduced by Glass [5.18], which uses a recursive averaging procedure. The last differs from the first two in that the quasi-stationarity property is necessarily a time-dependent function.

Gruber [5.21] also addressed the question of tuning the steady-state detector used in conjunction with the qualitative FDD applied to the central air-handling unit [5.18]. Dexter & Benouarets [5.20] describe the tuning of their steady-state detector in terms of its response to a ramp change of the signal.

A related issue, not addressed directly in the above work, is the assessment of steady *trends* in the BEMS data being observed. It is possible to generalize the steady-state detection concept to identify both rates-of-change in the BEMS data, and whether the rates-of-change themselves are stationary. This approach can be adapted to steady-state detection by requiring the system variables to have stationary rates-of-change sufficiently close to zero.

5.3.2 Steady-state detection using fixed-window moving variances

5.3.2.1 Description

A classical measure of fluctuation in a signal is obtained by estimating the mean and variance of a stochastically varying signal by averaging over samples in time with a *fixed time-window length*. The concept is illustrated schematically in Figure 5.9.

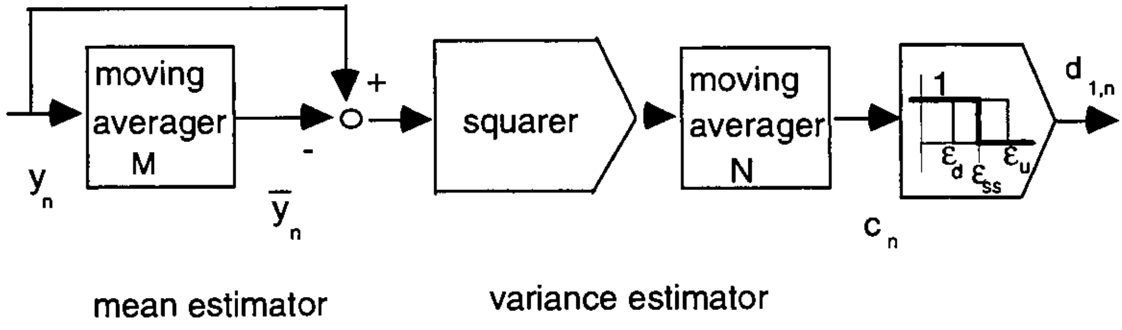

Figure 5.9. Steady state detection scheme using fixed window moving variances.

Denoting the sequence of data by

$$\{y_0, y_1, y_2, \ldots, y_n\}, \tag{5.8}$$

recorded at constant time intervals ΔT, the moving average over a fixed time $T_F = M\Delta T$ is defined

$$\bar{y}_n(T_F) = \frac{1}{M} \sum_{k=n-M+1}^{n} y_k \, . \tag{5.9}$$

The corresponding variance can be formally defined with a time window $T_W = N\Delta T$:

$$S_n^2(T_F, T_W) = \frac{1}{N} \sum_{k=n-N+1}^{n} \left(y_k - \bar{y}_n(T_F)\right)^2 . \tag{5.10}$$

The variable x_n is deemed to be in steady state whenever the weighted *deviation* S_n falls below a pre-determined threshold ε_{SS} [or, equivalently, the variance S_n^2 falls below ε_{SS}^2]

$$S_n(T_F, T_W) \leq \varepsilon_{SS} \, . \tag{5.11}$$

The effect of using *differing* parameters T_F & T_W is summarized in the equation:

$$S_n^2(T_F, T_W) = S_n^2(T_W, T_W) + \left(\bar{y}_n(T_F) - \bar{y}_n(T_W)\right)^2 . \tag{5.12}$$

The conventional variance is increased by the square of the difference between the averages calculated using the two different time-window lengths.

The design parameters are the two averaging lengths $T_F = M\Delta T$ and $T_W = N\Delta T$ and the threshold ε_{SS}. It is interesting to note that this detector differs from the one described in section 6.4.3 in that it has no differencing part as in the functional variation measurement. The difference computed here is between $\bar{y}_n(T_F)$, the estimate of the mean of y_n, and the signal y_n itself. Thus there is no amplification of high frequencies as in the activity measurement and consequently no need for an additional, separate low-pass filter.

5.3.2.2 Tuning

The following tuning scheme is proposed. First of all the two averaging lengths are set equal to $T_F = T_W = N\Delta T$. Then T_W is chosen dependent on the dominant time constant of the system monitored. If the signal considered, denoted y, is a controlled variable, then the settling time $T_{settle,sp}$ to a 5% error with respect to a set point step change is taken as the time window. If y is acting as a disturbance on some control loop, the same settling time $T_{settle,sp}$ as before is taken as time window, because usually the disturbance input settling time is faster than the set point settling time. The time window length can thus be approximated by

$$T_W = T_{settle,sp} = 3\tau_D \tag{5.13}$$

τ_D is either the dominant time constant for real poles or the absolute value of the inverse of the real part of the dominant poles for a complex conjugated pole pair.

The choice of the height of the threshold for the variance or standard deviation is based on two contributions: one on noise and one on low frequency components (ramp-like behaviour). The variance S^2_{noise} of the noise can be estimated from old data, which appear to be in steady state. If the signal is acting as disturbance input to a controlled system, it is possible to derive a relation between the input noise variance and the output noise variance. Normally a greater input noise variance is acceptable due to the filtering effect of the control loop. for the low frequency part a ramp signal is superposed. Its variance S^2_{ramp} is proportional to the square of the product KT_W where K is the gradient of the ramp. The threshold ε_{SS} is then found via the relation

$$\varepsilon_{SS} = \sqrt{S^2_{noise} + \frac{K^2T^2_W}{12}}\ . \tag{5.14}$$

The threshold is a positive value in the physical units of the signal being processed.

An example of the tuning of these parameters is given in Gruber [5.21] for a controlled central air handling unit.

K is chosen depending on the examination of old data of the plant to which the FDD method is being applied, on T_W and on the desired frequency with which the steady state detector detects steady states.

5.3.3 Steady-state detection using functional variation of filtered signals

5.3.3.1 Description

Given a data sequence as above, an alternative to using a moving variance (or standard deviation), the average *functional variation* can be used, defined as

$$\overline{V}_T(t) = \frac{1}{T}\int_{t-T}^{t} |y'(\tau)| d\tau , \tag{5.15}$$

namely the integral of the absolute value of the derivative of the signal being processed. In practice it is computed as the averaged sum of the absolute values of the differences between neighbouring points with the sampling time ΔT. For a fixed time interval $T_W = N\Delta T$ it may be defined

$$\overline{V}_n(T_W) = \frac{1}{N}\sum_{k=n-N+1}^{n} |y_k - y_{k-1}| . \tag{5.16}$$

This approach is used in the steady-state detector introduced by Dexter & Benouarets [5.20] the functional variation of the filtered signal being termed the "activity" *act.* The variation was chosen because it provides a measure of fluctuation which is proportional to both the *amplitude* and *frequency* of the changes in the signal being measured.

The fact that a differentiation in time is being performed means that noisy components of the signal are enhanced. Consequently, such components must be eliminated at the outset by applying a low pass filter. In the paper cited this is accomplished by a moving average using a fixed time-window length $T_F = M\Delta T$, as in Equation (5.9). The averaged variation $\overline{V}_n(T_W)$ is then compared to a threshold, which can be time-dependent as is indicated in the schematic diagram in Figure 5.10.

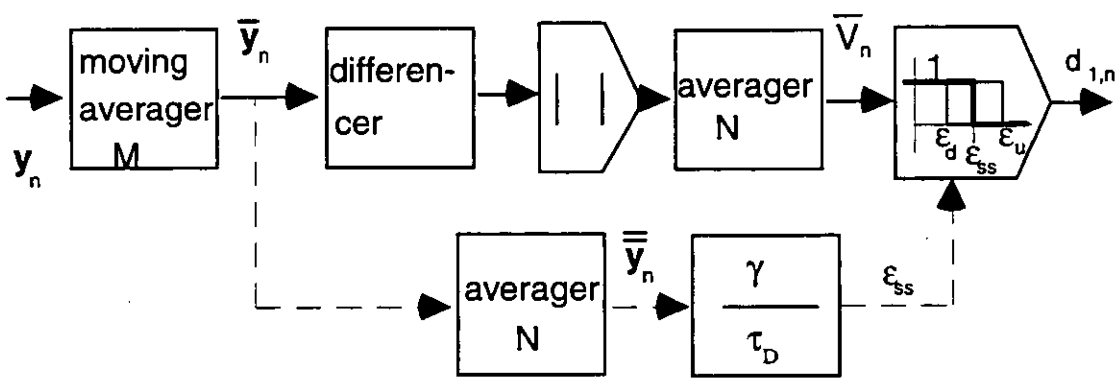

Figure 5.10. Steady state detection scheme with measurement of functional variation.

In particular, it might be noted that the subsequent averager (with time window $T_W = N\Delta T$) can be applied in a number of different ways.

- It can be a moving fixed time-window average - like the front-end averager, but in general with a separate time window.
- Subsets of the pre-filtered sequence can be down-loaded for secondary averaging. For example, feeding the decimated subsequence

  $$\{\bar{y}_0, \bar{y}_M, \bar{y}_{2M}, \ldots\} \quad (5.17)$$

  to the secondary averager can significantly reduce the processing complexity.
- Arbitrary intervals can be extracted from the pre-filtered sequence for subsequent testing. In this case the property of quasi-stationarity is considered to apply to the whole interval rather than just the time point $n\Delta T$.

The steady-state detector introduced by Dexter & Benouarets is, for example, applied to whole intervals of pre-filtered data. In conjunction with their fuzzy-logic fault detector, data must be collected in such a way that *independent* tests of stationarity are made. This requires comparing evaluations of non-overlapping intervals.

In general the design parameters of this scheme are:

- the averager length $T_F = M\Delta T$
- the averager length $T_W = N\Delta T$
- the dominant time constant τ_D
- the relative prediction error γ.

Because the fuzzy-logic fault detector used by Dexter & Benouarets evaluates stationarity for whole intervals, there is no need to use a hysteresis-type threshold, and a single value ε_{SS} determined by γ / τ is used.

5.3.3.2 Tuning

There are three parameters $T_F = M\Delta T$, $T_W = N\Delta T$ and a threshold parameter (either ε_{SS} or γ) which must be tuned in relation to the system at hand.

T_F must be chosen so as to remove those high frequencies which could adversely affect the performance of the system. It may not be too short, or otherwise high frequency components would not be sufficiently suppressed. It may not be too long, since otherwise the pre-filtered signal would end up being too smooth to detect any non-stationary behaviour.

The averager length $T_W = N\Delta T$ must be longer than the dominant time constant τ_D

The threshold ε_{SS} can be tuned to match an acceptable absolute error, or it can be related to a parameter γ, which is defined as the *acceptable relative prediction error*. The latter, which is chosen arbitrarily, can be related to the absolute error between the value y predicted by a simple linear first-order model for the system dynamics and the corresponding steady state value $\hat{y}$ according to the formula

$$\gamma = \frac{y - \hat{y}}{\bar{\bar{y}}} = \frac{\tau_D}{\bar{\bar{y}}}\frac{dy}{dt}, \tag{5.18}$$

where $\bar{\bar{y}}$ is the average of y in the time period T_W being investigated.

In general, the computed functional variation is not less than the *averaged time derivative* of the signal, and the two are identical (in absolute value) whenever the signal is *monotonic* in the time interval being considered (for example, ramp-like behaviour).

$$\widetilde{V}_{T_w}(t) = \frac{1}{T_W}\int_{t-T}^{t}|y'(\tau)|d\tau \geq \left|\frac{1}{T_W}\int_{t-T}^{t} y'(\tau)d\tau\right|, \tag{5.19}$$

Thus, if the derivative in (5.18) is replaced by its interval average, combining (5.18) & (5.19) leads to the relation

$$\widetilde{V}_{T_w}(t) \geq \frac{\bar{\bar{y}}}{\tau_D}\gamma, \tag{5.20}$$

so that a for a particular interval and given γ the threshold:

$$\varepsilon_{SS} = \frac{\bar{\bar{y}}}{\tau_D}\gamma \tag{5.21}$$

is adopted.

An open question at the present time is a detailed procedure for choosing appropriate values of T_F and γ (or ε_{SS}) in relation to the plant to which the FDD method is being applied.

5.3.4 Steady-state detection using geometrically weighted moving variances

5.3.4.1 The algorithm

The prototype detector used by Glass *et al* [5.19] replaces the fixed-length mean and variance estimates of §6.4.2 with a geometrically weighted running variance with respect to a geometrically weighted running average. It was chosen in preference to a fixed-window moving average because:

- the computations are recursive, requiring a minimum of memory
- it is sensitive in reacting promptly whenever the current data depart from their steady-state values.

Barring the use of differing "on" & "off" threshold values, fixed-window detectors experience exactly the same time delays before identifying entry into, or departure from steady state. The decisions output from fixed-window detectors can be deemed to apply either to the current time point or to the whole window being tested. For this recursive detector, however, the output decision applies to the *current time point* $n\Delta T$.

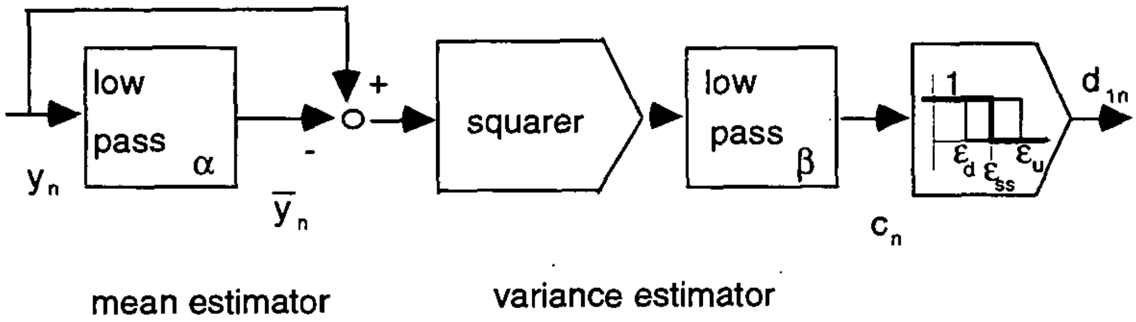

Figure 5.11. Steady state detection scheme using geometrically weighted moving variances.

The geometrically weighted average is defined

$$\bar{y}_n(\alpha) = \frac{\sum_{k=0}^{n} \alpha^{n-k} y_k}{\sum_{k=0}^{n} \alpha^{n-k}}, \tag{5.22}$$

where α is the (constant) geometric weighting factor $(0 < \alpha \leq 1)$. The geometrically weighted variance can be formally defined with a different weighting factor β $(0 < \beta \leq 1)$:

$$S_n^2(\alpha, \beta) = \frac{\sum_{k=0}^{n} \beta^{n-k} \left(y_k - \bar{y}_n(\alpha)\right)^2}{\sum_{k=0}^{n} \beta^{n-k}}. \tag{5.23}$$

The above can be computed recursively in terms of running moments $X_n^{(m)}(\alpha)$:

$$Y_n^{(m)}(\alpha) = \sum_{k=0}^{n} \alpha^{n-k} \left(y_k\right)^m; \qquad Y_{n+1}^{(m)}(\alpha) = \left(y_{n+1}\right)^m + \alpha Y_n^{(m)}(\alpha); \tag{5.24}$$

$$S_n^2(\alpha,\beta)=\frac{Y_n^{(2)}(\beta)}{Y_n^{(0)}(\beta)}-2\frac{Y_n^{(1)}(\beta)}{Y_n^{(0)}(\beta)}\frac{Y_n^{(1)}(\alpha)}{Y_n^{(0)}(\alpha)}+\left(\frac{Y_n^{(1)}(\alpha)}{Y_n^{(0)}(\alpha)}\right)^2. \tag{5.25}$$

The variable y_n is deemed to be in steady state whenever the weighted *deviation* falls below a pre-determined threshold ε_{SS} [or, equivalently, the variance falls below ε_{SS}^2]

$$S_n(\alpha,\beta)\le\varepsilon_{SS}. \tag{5.26}$$

The effect of using *differing* parameters α & β can be summarized in the equation:

$$S_n^2(\alpha,\beta)=S_n^2(\beta,\beta)+(\bar{y}_n(\alpha)-\bar{y}_n(\beta))^2. \tag{5.27}$$

In the simulation tests carried out, the geometrically weighted variance has been used with a *single* parameter $\alpha=\beta$. At the moment, the merits of using differing weighting parameters are not apparent.

The (single) parameter α can be related to an effective time "window" of length τ_{SS} by means of the weighted average

$$\tau_{SS}=\frac{\sum_{k=0}^{\infty}\alpha^k(k\Delta T)}{\sum_{k=0}^{\infty}\alpha^k}. \tag{5.28}$$

where ΔT is the time increment between measurements. Thus

$$\alpha=\frac{\tau_{SS}}{\tau_{SS}+\Delta T}, \tag{5.29}$$

In general, the design parameters are the two filter factors α and β (or the corresponding time-window lengths) and the threshold ε_{SS}. The filter factors are smaller than but close to 1. As in the case of fixed window-length averaging there is no need for an additional, separate low pass filter.

5.3.4.2 Tuning

We consider only the SSD for which α and β are set equal. Tuning involves adjusting both the threshold ε_{SS} and the effective time window τ_{SS}. The latter is set to match the typical relaxation times of the test system and the former must be set according to how much "noise" is to be tolerated when the system is deemed to have reached a steady state. In the simulations and laboratory tests, a hysteresis-type threshold was used to avoid rapid fluctuations of the steady-state signal.

The effective time window τ_{SS} is basically the time constant of the exponential transient behaviour of the low pass to a step input. Its is related to the settling time $T_{settle,sp}$. Therefore, in order to achieve a 5% error against the steady state after the settling time, one can conclude that the effective time window is equivalent to the dominant time constant, that means

$$\tau_{ss} \cong \tau_D = \frac{T_{settle,sp}}{3} \tag{5.30}$$

$$\alpha = \frac{\tau_D}{\Delta T + \tau_D} = \frac{T_{settle,sp}}{T_{settle,sp} + 3\Delta T} \tag{5.31}$$

The determination of the threshold is done in the same way as in the fixed time window case. The contribution of the ramp signal to the noise variance is now approximately

$$S^2_{ramp} \cong K^2 \tau^2_{ss} \tag{5.32}$$

and therefore the threshold is given by

$$\varepsilon_{SS} = \sqrt{S^2_{noise} + K^2 \tau^2_{SS}} \tag{5.33}$$

K is chosen depending on the examination of old data of the plant to which the FDD method is being applied, on τ_w and on the desired frequency with which the steady state detector detects steady states.

5.3.5 References

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5.4 THRESHOLDS FOR FAULT DETECTION, DIAGNOSIS, AND EVALUATION

Braun, J., E., Ray W. Herrick Laboratories, Purdue University, West Lafayette, USA

As described in Chapter 4, an FDD system should include the following steps: fault detection, fault diagnosis, and fault evaluation. Fault detection indicates a deviation of performance from expectation, diagnosis determines the cause of the fault, and evaluation assesses whether the impact is significant enough to justify service. In each of these steps, it is necessary to define criteria or thresholds for establishing appropriate outputs. The outputs would be fault or no fault for fault detection, the type of fault for diagnosis, and repair or don't repair for fault evaluation. Each of the thresholds associated with these outputs is unique and require different estimation methods. This section describes the types of thresholds appropriate for fault detection, diagnosis, and evaluation and gives an overview of issues relevant to threshold selection.

5.4.1 Fault detection thresholds

Fault detection methods compare measurements with expectations to identify faults. The simplest methods involve range checking, where the measurements are "expected" to be within certain fixed bounds. These bounds must be set rather "loosely" so as to limit the number of false alarms. As a result, range checking can only be used to detect large changes in performance. The range checking bounds (or thresholds) for fault detection are normally established based upon heuristics, but can be determined using statistical methods. In a statistical approach, the standard deviation of a measurement about its mean could be estimated under normal operation. Assuming the measurements are normally distributed about the mean, the bounds for range checking could then be established based upon a specified confidence level that the measurement will fall within the bounds (e.g., 3 standard deviations for 99.5 % confidence).

The sensitivity for detecting faults can be dramatically improved through the use of models for expected performance. The model predicts the outputs of a process for normal operation for given measured inputs. A fault is indicated when the difference between predicted and measured outputs (i.e., residual) is greater than a threshold. Even under normal operation, the residuals are nonzero due to unmodeled inputs, dynamics, and measurement noise. Figure 5.12 depicts probability distributions for normal and faulty behavior for a single measurement residual. The normal distribution has a zero mean, while the fault distribution moves away from zero as the fault severity increases. The shaded area, formed by the overlap of the two distributions, represents the probability that a faulty diagnosis will be in error. The threshold should be set such that the shaded area is a small fraction of the total area under the distributions. For instance, a 99.9 % confidence level for a correct fault diagnosis would be achieved when the shaded area is 10^{-3} of the total area. A Bayes classifier for a normal distribution (Fukunaga, 1990) could be used to estimate the classification error (i.e., the probability of incorrectly diagnosing the fault).

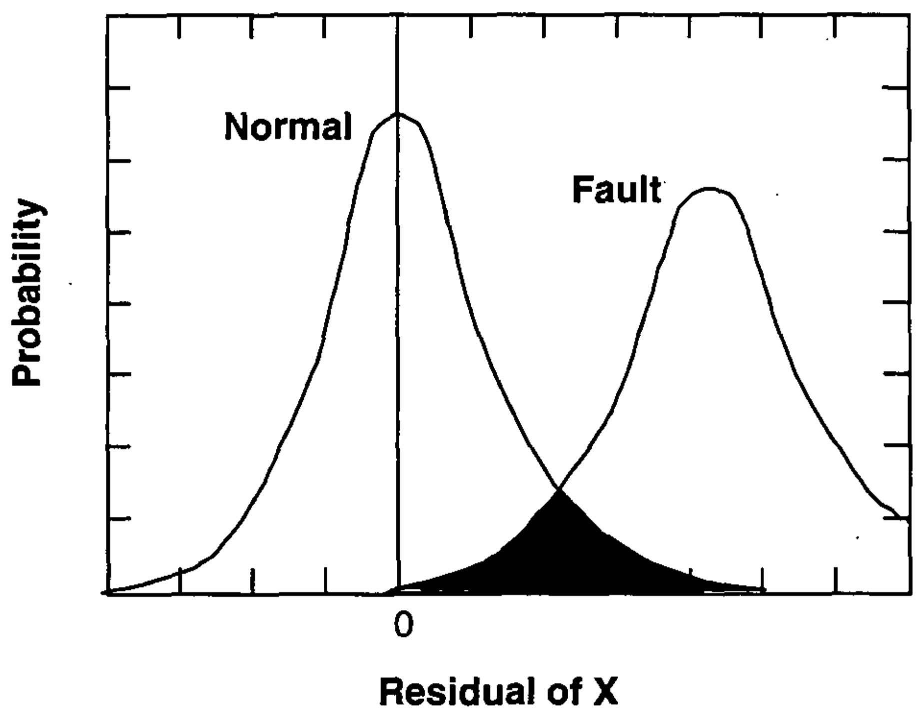

Figure 5.12. Fault detection example.

5.4.2 Fault diagnosis thresholds

There are several different approaches to diagnosis once a fault has been detected. One of the simplest approaches involves fault isolation. Fault isolation is simply fault detection applied on a component level. In this case, the fault is diagnosed as soon as it is detected and no additional thresholds beyond the fault detection thresholds are necessary. The disadvantage of fault isolation is the large number of measurements required. For instance, diagnosis of heat exchanger fouling would require measurements of all states entering and leaving the heat exchanger.

Another diagnostic approach involves comparing physical parameters determined from measurements with "expected" values for normal operation. For instance, heat exchanger conductance could be estimated from entering and leaving conditions and used to diagnose fouling. Here again, fault detection and diagnosis is combined and thresholds could be estimated through statistical analysis of the normal variation in the estimates of the physical parameters.

A more common diagnostic approach that requires fewer measurements involves the use of fault models. For each type of fault to be diagnosed, a fault model predicts the "expected" outputs associated with the occurrence of that fault for a current set of inputs. The fault is diagnosed through the use of a classifier that attempts to find the fault model that gives the smallest error between predictions and measurements. With fault modeling, thresholds are generally necessary for evaluating whether the confidence in a particular diagnosis is strong enough to make a diagnostic decision. One approach would be to set a minimum acceptable limit on the probability that a correct diagnosis had been achieved. A second approach could be to set a minimum acceptable limit on the ratio of fault probabilities for the two most likely faults.

5.4.3 Fault evaluation thresholds

In general, service should not be performed unless the benefit justifies the expense. For abrupt faults, such as a motor failure, the benefit of service is often obvious and no additional thresholds are necessary for fault evaluation. In this case, the fault should be repaired after it is detected and diagnosed. However, for performance degradations such as heat exchanger fouling, a service decision should be based upon economic considerations.

In theory, economics alone could be used to determine if the cost of service is justified for all possible faults. Important costs include service, energy, downtime (i.e., the cost of not maintaining comfort or refrigeration set point), safety hazards (equipment or personnel), and environmental hazards (e.g., a refrigerant leak). The costs associated with faults that lead to downtime, safety hazards, and environmental hazards are difficult to quantify, but are generally much larger than the service costs required to repair them. With this assumption, the following four fault evaluation criteria may be used to identify the need for service:

1. **Comfort** - Service whenever the equipment cannot maintain comfort conditions.
2. **Safety** - Service whenever equipment or personnel safety is compromised.
3. **Environment** - Service whenever the environment is adversely affected.
4. **Economic** - Service at intervals that minimizes the combined costs of energy and service.

The thresholds associated with the first three criteria are relatively straightforward to specify. For comfort, the difference between the space temperature and controller setpoint should be between bounds dictated by the "expected" controller performance. These bounds could be specified based upon heuristics or determined statistically based upon measurements under normal operation. For safety, thresholds would be established based upon experience for the particular equipment under consideration. Examples of conditions in an air conditioner that lead to safety problems include liquid entering the compressor (compromises compressor life) and high head pressure (compromises both compressor life and personnel safety). An expert would establish limits on minimum acceptable suction superheat and maximum allowable head pressure necessary to avoid these safety problems. The environmental criteria was included in order to consider refrigerant leakage. In general, a refrigerant leak should be fixed when it can be reliably detected and diagnosed. Therefore, no additional evaluation thresholds are necessary for this particular fault.

Thresholds associated with the economic evaluation criteria are much more difficult to specify. Recently, Rossi and Braun (1996) developed a simplified method for estimating the optimal service times that minimizes combined energy and service costs for cleaning condensers and evaporators in air conditioners. They also compared the costs associated with optimal maintenance scheduling with those associated with regular maintenance and with a procedure where service was performed based only on the comfort and safety criteria (constrained service). Figure 5.13 shows sample results for evaporator fouling. The operating costs, plotted on the vertical axis, are normalized using the base operating cost with no fouling. The base cost is the total annual energy cost with no fouling for cooling. The normalized cost is the actual cost of service and energy minus the base cost divided by the base cost and represents the fractional extra cost due to reduced efficiency and increased service associated with the fouled heat exchangers. The horizontal axis is a characteristic fouling time defined as the calendar time required for the evaporator to completely foul. All the results in Figure 5.13 were generated for service costs of $60 per cleaning and energy costs of $0.10 per kWh.

The results in Figure 5.13 demonstrate there are significant cost savings associated with utilizing an economic criteria for performing service as compared with basing service on comfort and safety criteria or utilizing a regular service schedule. The regular maintenance schedulers always provide excessive service whenever the service interval is short enough to ensure that comfort conditions are maintained. Constrained only service results in excessively high energy costs as compared with optimal scheduling. The savings associated with optimal maintenance scheduling increase with fouling time. For a fouling time of 5 years in Figure 5.13, the minimum operating costs are about a third of those for twice/season service and about two-thirds of those for once/season and constrained service.

The simplified maintenance scheduler could be used to determine thresholds for evaluating heat exchanger fouling faults in air conditioners. The average difference between the optimal and simplified scheduler costs is less than 0.2 % for all results presented in Figures 5.13. Additional research is necessary to develop methods for estimating economic thresholds for other applications.

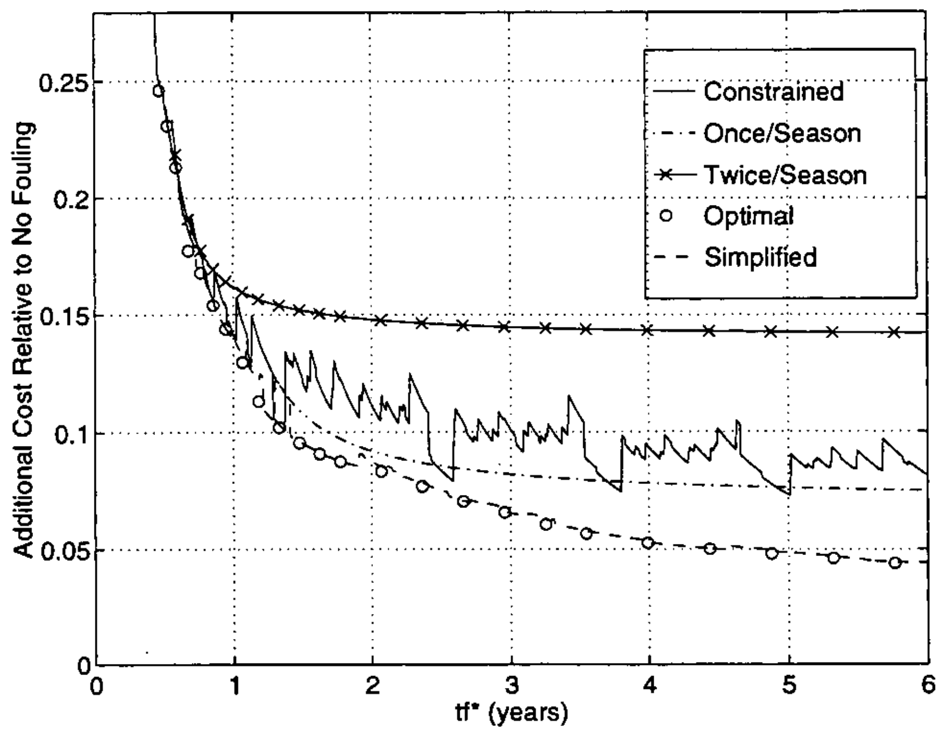

Figure 5.13. Cost comparisons for alternative maintenance strategies.

5.4.4 Summary

Fault detection, diagnosis, and evaluation are steps that are necessary to properly supervise a process. Each of these steps requires different thresholds that are used to make decisions (fault / no fault, type of fault, repair / no repair). Fault detection and diagnostic thresholds are often determined based upon heuristics, although better performance (lower ratio of false alarms to correct diagnoses) is achieved when statistical thresholds are employed. For comfort, safety, or environmental problems, fault evaluation thresholds would normally be set based upon experience. However, there are examples associated with degradation faults (e.g., heat exchanger fouling) where an economic criteria would dictate earlier service than would occur for the other three evaluation criteria. For the economic criteria, the threshold for service should be based upon minimizing the combined costs of service and energy.

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5.5 COST BENEFIT ANALYSIS AND ECONOMIC & ENVIRONMENT EVALUATION

K. Matsunawa & H. Iizuka, Nikken Sekkei Ltd
H. Itoh, Mie University
F. Miyasaka, Yamatake-Honeywell Co., Ltd
T. Takase, Mitsubishi Estate Co., Ltd
N. Nakahara, Nagoya University

5.5.1 Introduction

The Cost/Benefit analysis is required for decision making whether or not to introduce the BOFD system. Only when the Cost/Benefit assessment has shown positive results an introduction of the BOFD system can be justified. This section summarizes the various methods of the Cost/Benefit analysis, which were classified into two categories, the conventional methods and advanced methods, for convenience. The latter is concerned especially with the decision-making procedures. The last section refers to the significance of the Cost/Benefit analysis referring to an actual example of the BEMS/BOFD system.

The typical method of Cost/Benefit analysis is to evaluate whether the monetary benefits justifying the investment can be obtained or not, which is most simply expressed by the Payback Year among the conventional methods. Other conventional methods called as the Annual Cost Method and the LCC method, or the Present Worth Method, are mainly used for evaluating alternatives. The Vector Diagram Method included in the advanced method is used for technology assessment from the economical, energy and environmental viewpoint in system design and retrofit. In terms of economic benefit, the priority order of A>B>C shown in Fig.5.14 should be given for adopting the BOFD system.

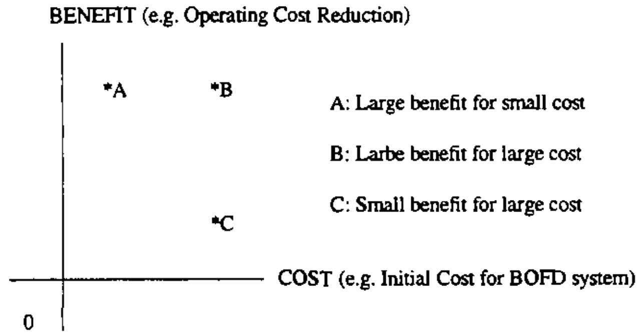


Figure 5.14.

All the benefits are not always converted into monetary values, among which are improved indoor environment, environmental contamination and work efficiency. Energy savings is primarily converted to monetary value, but the fundamental importance of energy conservation is difficult to evaluate in money as same as the environment.

The Fault Transmission Probability Method included in the advanced method is a theoretical development of deciding optimal timing of repair and/or retrofit or the optimal life of equipments and/or subsystems. It also converts all the benefits, including the damages in terms of negative benefits, into monetary values. The AHP Method is the method of making comprehensive assessment for decision making with a hierarchical structure by weighting various kind of benefits which have different criteria of evaluation.

5.5.2 Conventional methods

5.5.2.1 Simple payback method [5.24]

The simplest method of Cost/Benefit analysis is the Simple Payback Method. Saving energy and manpower is expected in the introduction of the BOFD system, which results economic benefits in annual energy cost and personnel cost. On the other hand, introduction of the BOFD system requires capital investment, or the construction cost. The Simple Payback Method is a method of determining the number of years necessary for paying back the investment by reduced annual expense. The payback year is calculated by the following formula:

$$\text{Payback Year} = \frac{\text{Construction Cost for BOFD}}{\text{Amount of Annual Operating Cost Saved by the BOFD System}} \qquad (5.34)$$

As is evident from the formula, this method ignores interest rates. Therefore, this simple method is only applicable when the payback is expected in a few years, where the interest, inflation and other time dependent parameters could be ignored. The method is quite often used for assessing the introduction of the mechanical and electrical (M/E) systems, especially for industrial investment, and it is applicable to evaluate introduction of the BOFD system, too.

5.5.2.2 Annual cost method

The BOFD system alternatives will be compared on the construction cost and the operation cost in its introduction to a certain BEMS system. The Annual Cost Method makes it possible to evaluate both kinds of cost in a single index called as the annual cost during its life. The following formula is applied for calculating the Annual Cost.

* Annual Cost = Annual Fixed Cost + Annual Operating Cost
* Fixed Cost = Capital Recovery Cost, or Depreciation Cost & Interest + Tax & Insurance
* Operating Cost = Energy & Resource Cost + Personnel Cost + Maintenance & Repair Cost

The Capital Recovery Cost is calculated by the following formula. The depreciation year, or the life, is usually determined on the basis of the service years of the BOFD system, however, it is sometimes strategically determined as the pay back year of intention.

Annual Capital Recovery Cost = CRF (Initial Investment - Scrap Value)

$$CRF = \frac{i}{1-(1+i)^{-n}} \tag{5.35}$$

where

CRF = Capital Recovery Factor

n: Depreciation year, i: Interest Rate.

Note: Different formulae should be applied in case the rate of interest and inflation are subject to change. The amount for Tax and Insurance are calculated by multiplying the ratio of tax and insurance by the price when necessary.

The Energy Cost is calculated by the change of the energy consumption due to introduction of the BOFD system. The Personnel Cost is calculated from the change on the number of the maintenance personnel due to introduction of the BOFD system. The costs for maintenance and repair are also the cost change resulting from the BOFD introduction, in which early findings of malfunction an faults are performed.

When the Annual Cost (with BOFD) < Annual Cost (without BOFD), then the proposed BOFD system is recommended to be introduced.

5.5.2.3 LCC method

(1) **Present value LCC method**

The Life Cycle Cost, or LCC, is the sum of the total expenses during the building life, expressed by the Present Worth or the Future Worth. The LCC includes those cost for the design, construction, tax, insurance, energy, personnel, maintenance, repair or renovation and demolition. The variation of the interest rates and inflation rate is easily taken into account in the LCC analysis.

The LCC method is convenient when the life of the building is far longer than the HVAC system components and the periodic expenditures for renewal of them are necessary. When the LCC is assessed with the present worth, it is called the Present Worth LCC Method. The calculation formulae of present worth are as follows.

$$\boldsymbol{P_{de}} = \boldsymbol{F_p} \cdot \boldsymbol{F_d} \cdot \boldsymbol{Q} \tag{5.36}$$

$$\boldsymbol{F_p} = \frac{w^m\left(1-w^{nm}\right)}{(1+e)\left(1-w^m\right)}, \qquad w = \frac{1+e}{1+i} \tag{5.37}$$

If $i=e$, then $\boldsymbol{F_p} = \frac{n}{1+e}$

$$\boldsymbol{F_d} = \frac{r\left(1-(b/a)^{n1}\right)}{(1-b/a)} + \frac{b^{n1}}{a^{n2}}, \qquad a=1+i,\ b=1-r, \tag{5.38}$$

where

$\boldsymbol{P_{de}}$ is present worth of the asset to be periodically renewed,

$\boldsymbol{F_p}$ periodic present worth factor,

$\boldsymbol{F_d}$ present worth factor at the time of periodic investment for the fixed rate depreciation,

$\boldsymbol{Q}$ investment on an asset at the current price, which shall be renewed periodically at,

$\boldsymbol{m}$ period (every m year) and **n** number of payment (n times) and with,

$\boldsymbol{n_1}$ number of depreciation year=the smaller one between the depreciation term in years and $\mathbf{n_2}$,

$\boldsymbol{n_2}$ planed life in years=number of service years on which LCC is based,

$\boldsymbol{r}$ fixed depreciation rate

$\boldsymbol{e}$ inflation ration,

$\boldsymbol{i}$ interest rate.

(2) Simplified LCC evaluation diagrams

A simplified diagram to evaluate LCC will serve as a useful tool when making decisions on introduction of the BOFD system at the time of building plan. It must be particularly convenient if the sensitivities of the LCC factors, that is, the initial cost, maintenance cost, energy-saving cost, etc., can be evaluated. The Figure 5.15 shows some examples of sensitivity.

$$LCC = LCC<i> + LCC<m> + LCC<e> \qquad (5.39)$$

where

$LCC<i>$ initial cost in LCC

$LCC<m>$ maintenance cost in LCC

$LCC<e>$ energy cost saving in LCC.

The life cycle of 99 years was tentatively adopted in these examples. It was also assumed that the BOFD is replaced every 15 years and interest rate is 4 %. The upper, middle and lower parts of the diagram indicate the impact on the Initial Cost, Maintenance Cost, and the Energy-saving Cost, respectively. Each graph incorporates the inflation rate as a parameter.

When LCC (with BOFD) < LCC (without BOFD), BOFD system introduction is justified. Then,

1. It is easy to make assessment from the viewpoint of LCC.

2. In a long-term perspective, the impact of the Maintenance Cost and Energy-saving Cost is the most dominant, and that of the Initial Cost is small.

3. The Inflation Rate has a major impact on the LCC. The Initial Cost, Maintenance Cost and Energy cost saving increase drastically following the higher inflation.

4. The impact of the Interest Rate is also large as same as the inflation rate, though no space was given to show the fact.

5.5.3 Advanced methods

5.5.3.1 Vector diagram method

This method can illustrate which kinds of alternatives should be taken with the reasonable cost/benefit effect on a two dimensional plane. The horizontal axis is the capital cost, or the fixed cost, difference, ΔF, and the vertical one is the operating cost, or the variable cost, difference, ΔV, among the two alternatives, while the inclined lines correspond to the depreciation period. If the period is infinitive and the system is actually used infinitely, the depreciation line coincides with the fixed cost axis. To the contrary, if the capital should be paid back very shortly, it approaches the variable cost axis. With the use of the average interest method for calculating the fixed cost, the depreciation lines are calculated as follows.

$$\Delta F\{1+i(T+1)\}/2 = \Delta V\{(1+j)^T - 1\}/j \qquad (5.40)$$

where

T = depreciation period,

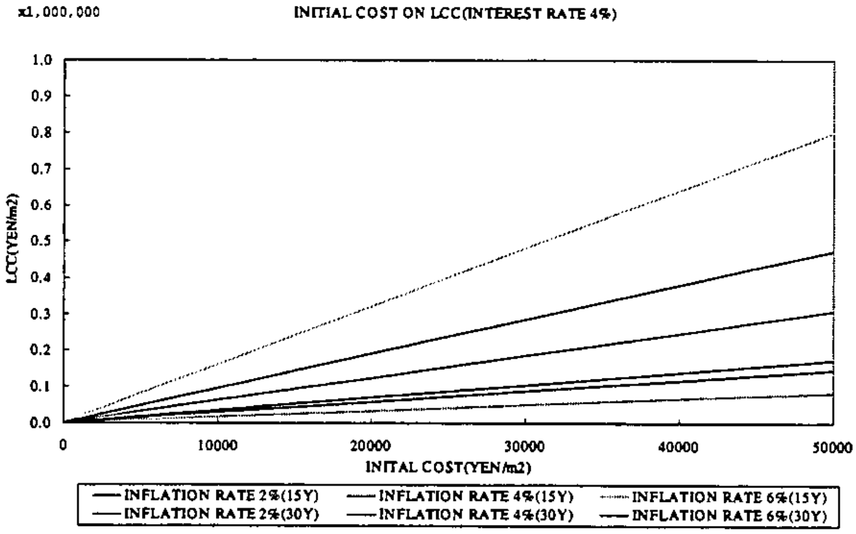
I = interest rate,

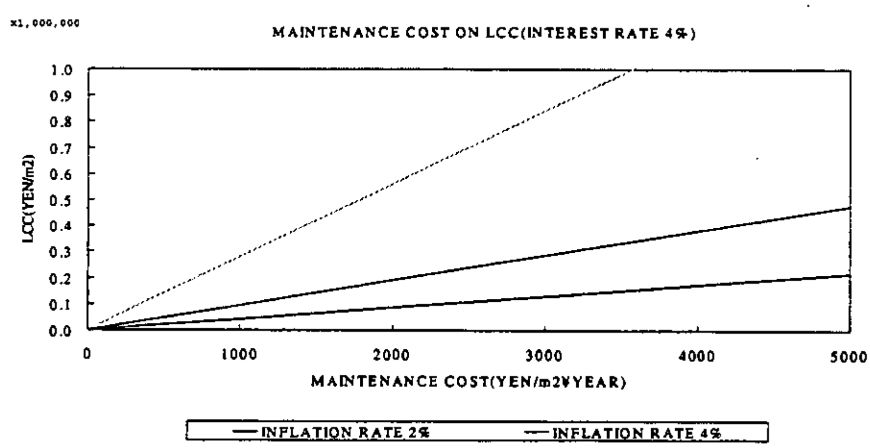
j = annual escalation rate of energy price.

(N.B.: In the vertical axis, which represents the benefit values, the same graduations have been employed for all the charts to facilitate comparison among the charts. As a result, graduations on the horizontal axis (indicating the costs)had to be adjusted for each chart so that they accommodate the required order of the values.)

The idea of this method was presented by Nakahara [5.25] and was first applied to the decision making of energy conservation measures in HVAC and the building structure to be selected for Ohbayashi Research Laboratory, which achieved less than a third of normal energy consumption in office building by Sakai [5.26]. It is also introduced in the Annex 16 report by Hyvärinen [5.27]. This is also useful for decision making in the Building Optimization and retrofit after BOFD measures diagnosed that some way should be taken but which ones have the priority to be taken is not uncertain.

The advantage of this method is that managers can easily understand the relationships among the kind of technology to be taken, fixed cost which mainly depends upon the investment, variable cost which mainly depends upon the energy cost, depreciation period or payback period, the escalation status in energy prices and strategy for optimal selection.





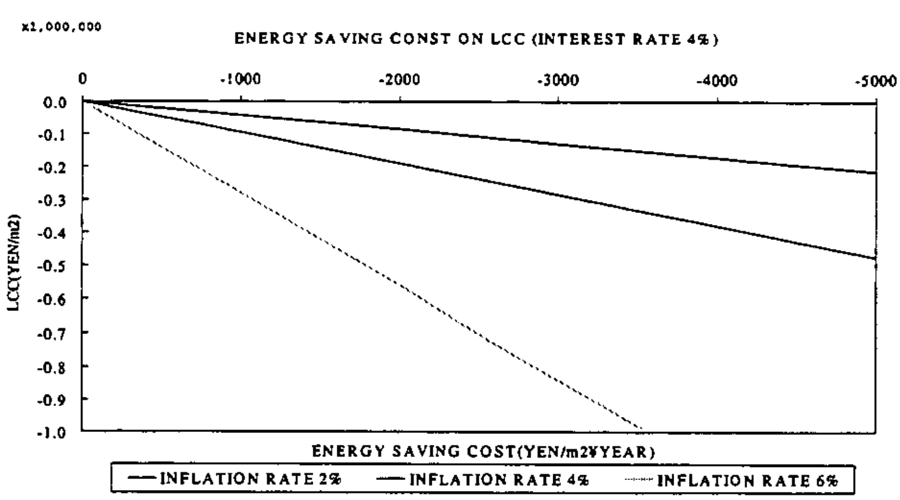


Figure 5.15. Examples of decision making support chart.

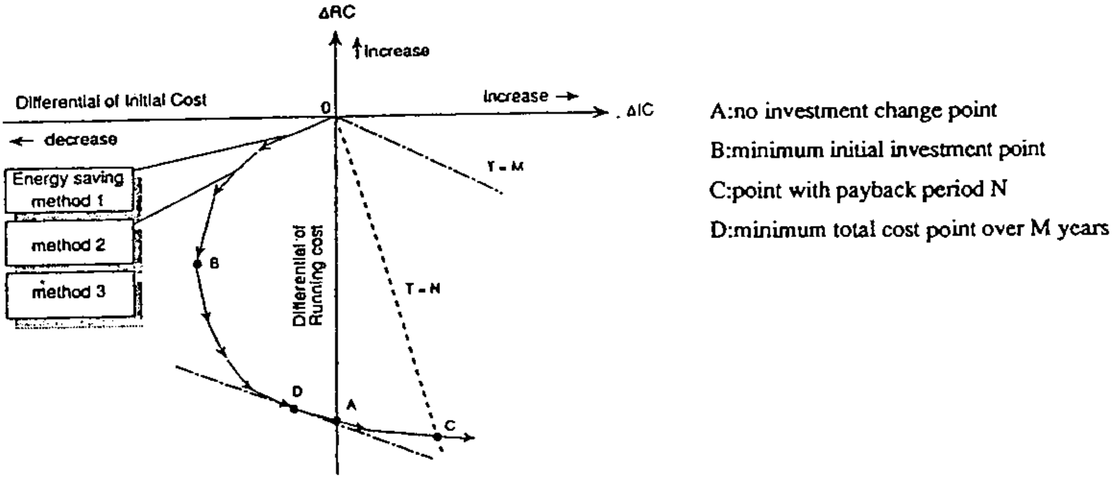


Figure 5.16. Vector diagram method.

5.5.3.2 Fault transmission probability method

The principle of the building management is to pay minimum cost in life cycle of the building. real life cycle should mean the life including design, construction, maintenance and salvage cost. However, it is not realistic to overview whole building life at the time of building decision making. Therefore, the BOFD, maintenance and retrofit cost will be taken into account hereafter in this section, which will set up the following strategy.

minimize: $I_s+I_r+E_a+E_e+E_d+E_r = LCD$ (5.41)

where

I_s = initial cost of BOFD,
I_r = life cycle cost for maintenance of BOFD system itself,
E_a = life cycle damage of environmental aggravation,
E_e = life cycle damage of energy wastefulness,
E_d = life cycle cost for the preventive maintenance with fault detection,
E_r = life cycle cost for post maintenance with failure,
LCD = life cycle damage.

The following hypothesis is believed rational in BOFD system and faulty state transmission. Refer Fig. 5.17.

1. Fault state is described as L_i at the ith year, where L_0 means normal state and L_h means just before failure level.

2. Define the faulty level transmission probability from L_i to L_j as p_{ij} at each yearly time step, where $\Sigma p_{ij}= 1$ ($j= i$ to c) and $p_{ij}= 0$ for $j<i$.

3. At any higher level than L_e waste of energy, which can be expressed by money as D_{ei}(\$/h), will take place.

4. At any higher level than L_a, IAQ is degraded, which is also converted by money loss as D_{ai}($/h), will take place.
5. The FDD process is also probabilistic and is expressed as qi for the probability of successful FDD at L_i level.
6. Suppose the L_d is the threshold level of repairing with the cost of D_{di} at the ith year, after that the state returns to L_o.
7. The L_c is the failure state level in which system cannot operate any more and the cost for repair is expressed as D_c.

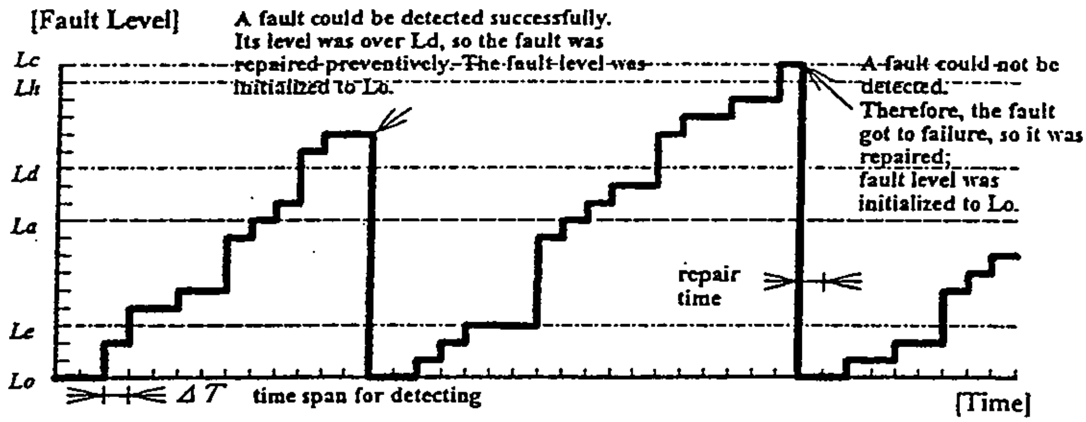


Figure 5.17. Progress of the faulty state, the relation between the fault level and time.

Thus it is easily imagined that the I_s is the function of the qi and that the I_r, the hardware as well as the software of maintaining BOFD system, is also the function of q_i and T_l, the life of the system, and T_r and D_r, the mean time interval and cost for maintaining BOFD hardware and software, respectively, both of which will depend on q_i. A mathematical development lead the following equations, after which, putting the partial differentiation of LCD by L_d as zero, an optimum L_d can be obtained, if all the probabilities could be identified. Refer the case study in the reference[5.28].

$$LCD = I_s + I_r + \sum_{n=0}^{L} (E_{a,n} + E_{e,n} + E_{d,n} + E_{r,n}) \tag{5.42}$$

$$E_{e,n} = (q_{d,n-1} + q_{r,n-1}) \sum_{i=e}^{h} p_{0i} D_{ei} \Delta t + (1 - qsubd, n - 1 - q_{r,n-1}) \sum_{i=e}^{h} \sum_{j=0}^{i} p_{j,n-1} p_{ji} D_{ei} \Delta t \tag{5.43}$$

$$E_{a,n} = (q_{d,n-1} + q_{r,n-1}) \sum_{i=a}^{c} p_{0i} D_{ai} \Delta t + (1 - qsubd, n - 1 - q_{r,n-1}) \sum_{i=a}^{c} \sum_{j=0}^{i} p_{j,n-1} p_{ji} D_{ai} \Delta t \tag{5.44}$$

$$E_{d,n} = q_{d,n} D_d, \qquad E_{r,n} = q_{r,n} D_r \tag{5.45}$$

5.5.3.3 Application of AHP method to cost-benefit analysis

The Analytical Hierarchy Process (AHP) was developed in 1971 by Professor Thomas L. Saaty of the University of Pittsburgh as a decision making tool for the use in the uncertain situations involving multiple criteria [5.29]. In applying this method to cost-benefit analysis, a hierarchical chart should be first prepared according to the benefit evaluation criteria, followed by an overall evaluation based on the paired comparison. Then, with respect to the same subjects of evaluation, another hierarchical chart should be prepared according to the cost evaluation criteria, and the weight of each subject is obtained. Lastly, the benefit per unit cost is calculated by dividing the weight of the benefit of each evaluation subject by the weight of cost. It is judged that a larger quotient means greater investment effect. AHP features the following steps:

1) Break down the elements of the problem into a hierarchical structure with regard to final targets, criteria, and alternatives. Fig. 5.18 shows a sample hierarchical chart concerning benefit.

2) Assign a weight to each element at every level. Each pair of elements is then compared based on the criteria of the related element one stage higher. Letting n be the number of comparison elements, n (n-1)/2 in number will be compared using a marking system of 1/9, 1/7, 1/5, 1/3, 1, 3, 5, 7, 9 as shown in Table 5.5. For example, if C1 (the scholar's opinion) is slightly more important than C2 (the company's opinion) for the purpose, give a score of 3. Likewise, if C2 (the company's opinion) is not very important compared to C3 (the committee s opinion), give the reciprocal of 7, or 1/7. Complete the table of paired comparisons shown in Table 5.6 in this way From this table, weight W is calculated by the power method of eigen value, which results,

   $W^T = (0.118, 0.055, 0.565, 0.262)$

3) Calculate the weights between the elements on each level, then use the results in an overall evaluation of alternatives for the target involved. Table 5.7 shows a list of the weights calculated at the respective levels, and Table 5.8 shows an example of hierarchical overall evaluation values. When the weight is represented by X:

   $X^T = (0.283, 0.263, 0.034, 0.078, 0.087, 0.253)$

   The results indicate that the economy, energy and the effects of faults have been assigned weights as high as 25 % or more for the subjects of cost-benefit analysis in BOFD, while the global environment, indoor environment and the system reliability are not given as much significance. Because this has only been done by the author to explain how to use the AHP method, the results themselves have no meaning as such.

4) Following the method of the above, another hierarchical chart that has cost evaluation criteria is prepared as shown in Fig. 5.19. Following the same steps as described in 2) and 3), perform the overall evaluation of cost. When this weight is represented by Y, the following result is obtained:

Table 5.5. Meaning of paired comparison values.

Score	Definition (Comparison of former and latter)
1	equally important
3	weakly important
5	strongly important
7	very strongly important
9	absolutely important

Table 5.6. Paired comparison at Level 2 Table.

Ci \ Cj	C1	C2	C3	C4
C1		3	1/5	1/3
C2			1/7	1/5
C3				3
C4				

Table 5.7. Totalized tabulation of weights.

	C1 0.118	C2 0.055	C3 0.565	C4 0.262 (weights for Level 2)
A1	0.025	0.446	0.439	0.025
A2	0.340	0.273	0.211	0.340
A3	0.044	0.027	0.028	0.044
A4	0.166	0.099	0.055	0.085
A5	0.085	0.055	0.055	0.166
A6	0.340	0.099	0.211	0.340
	weights on C1 for Level 3	weights on C2 for Level 3	weights on C3 for Level 3	weights on C4 for Level 3

Table 5.8. Overall evaluation.

	C1	C2	C3	C4	Overall evaluation
A1	.025×.118 0.003	.446×.055 0.025	.439×.565 0.248	.025×.262 0.007	0.283
A2	.340×.118 0.040	.273×.055 0.015	.211×.565 0.119	.340×.262 0.089	0.263
A3	.044×.118 0.05	.027×.055 0.001	.028×.565 0.016	.044×.262 0.012	0.034
A4	.166×.118 0.020	.099×.055 0.005	.055×.565 0.031	.085×.262 0.022	0.078
A5	.085×.118 0.010	.055×.055 0.003	.055×.565 0.031	.166×.262 0.043	0.087
A6	.340×.118 0.040	.099×.055 0.005	.211×.565 0.119	.340×.262 0.089	0.253

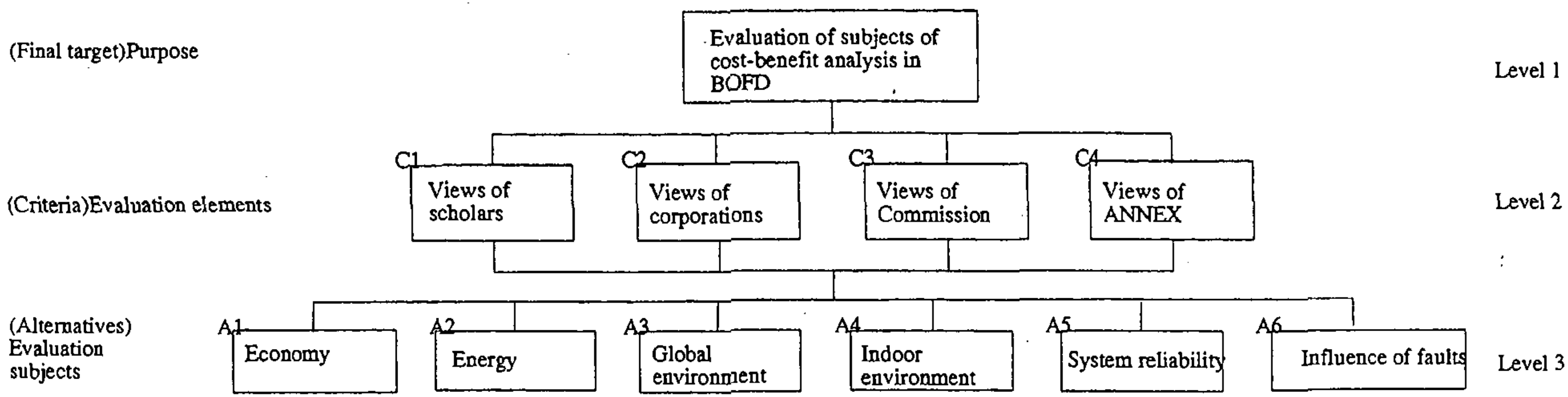


Figure 5.18. Hierarchy concerning to the benefit.

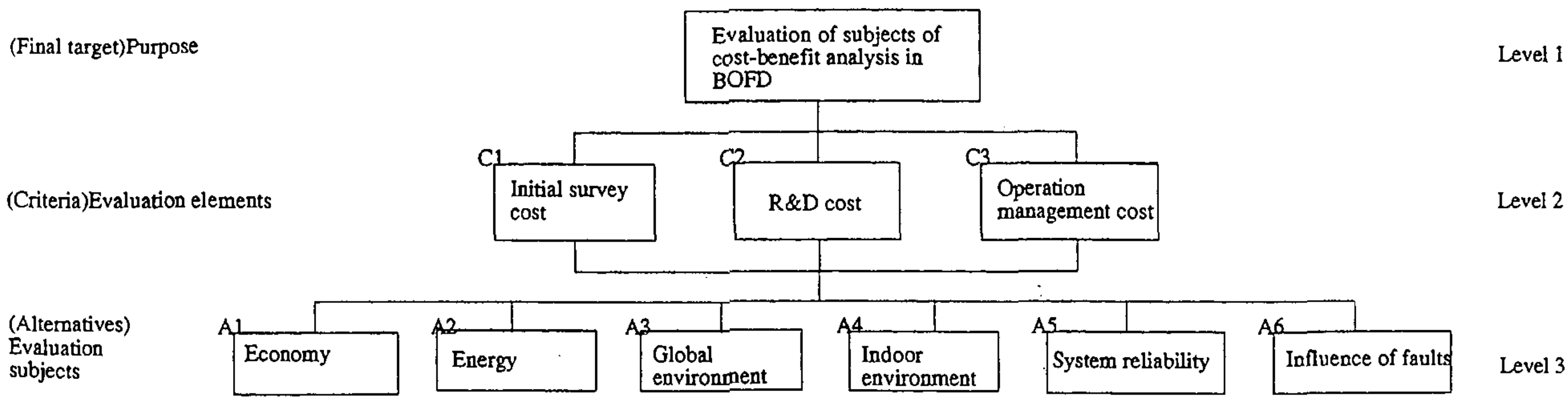


Figure 5.19. Hierarchy concerning to the cost.

$Y^T = (0.264, 0.057, 0.102, 0.028, 0.184, 0.367)$

Then, cost-benefit overall evaluation, the benefit per unit cost (Z) yields as follows. It is judged that A2 and A4, which have large values, are valuable enough to be selected. Note, however, that since these values are hypothetical paired comparison values given only for explaining this method, the calculated values themselves have no practical meaning.

$$Z = \begin{bmatrix} 0.283/0.264 \\ 0.263/0.057 \\ 0.034/0.102 \\ 0.078/0.028 \\ 0.087/0.184 \\ 0.253/0.367 \end{bmatrix} = \begin{bmatrix} 1.072 \\ 4.614 \\ 0.333 \\ 2.786 \\ 0.473 \\ 0.689 \end{bmatrix}$$

5.5.4 Actual application of cost benefit analysis by LCC method

Case study-The cost benefit analysis of the BOFD system installed in a computer center

5.5.4.1 Subjects and conditions for the cost benefit

(1) Composition of the BOFD system

Figure 5.20 shows the composition of the BOFD system in this case study model. This system consists of the Fault Detection and Diagnosis system (FDD) and the Optimal Control system (OC). The FDD System corresponds to the expert system and the OC system corresponds to the energy management support system. The subject of the BOFD system described in this section is the heat source equipments installed in a computer center building. The analysis is based on the following assumptions.

(2) Calculation of the investment cost

The investment cost for the BOFD system includes every cost relating to the installation of this system other than the cost for the development of the BOFD system.

(3) Calculation of the operating cost

The followings are the subjects for the operating cost analysis of the BOFD system.

a) Additional maintenance cost for the BOFD system

b) Cost reduction of maintenance manpower

c) Reduction of energy cost

(4) The Method of cost-benefit analysis

In this case study, the Present Worth LCC method is used, which is described in the section 5.5.2.3 and regarded as the most suitable for this kind of analysis. In calculation, 6 % the interest rate, 1.5 % of the inflation rate for energy price and thirty years of the projected life was assumed.

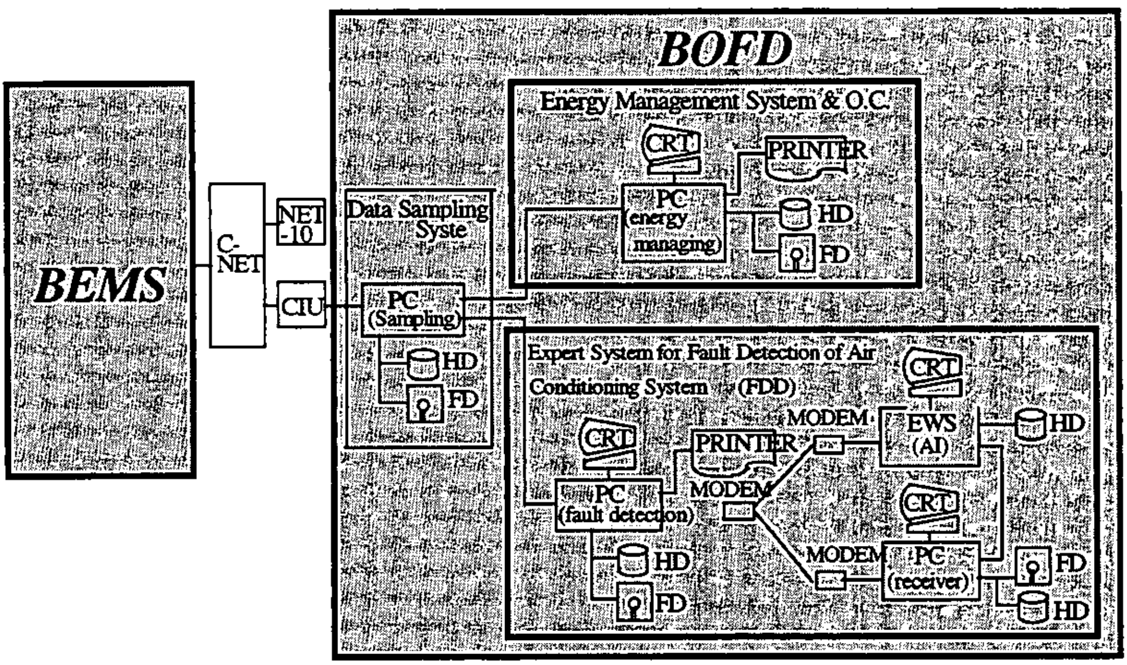


Figure 5.20. BOFD system diagram.

5.5.4.2 Actual application results

(1) Actual application results of the energy management support system

The followings contribute to achieve the reduction of operating cost effectively.

1) The relation between the operating time of absorption refrigerating machines and their operating cost was supervised based on the system advise. The time and energy consumed by the absorption machines were reduced.

2) The optimal thermal storage for demand shift to the nighttime of the electric-driven centrifugal refrigerating machine was achieved, resulting in the cost reduction and effective use of electricity through cheaper nighttime rate.

3) Optimal heat recovery operation of the centrifugal refrigerating machine with the double-bundle condenser was properly performed.

(2) Actual performance of the refrigerating machine through the fault detection system

According to the field data for three years since the systems was installed, the COP of refrigerating machines have kept a stable value. The efficiency of heat exchange at the evaporator has been also kept stable, whereas that of the condenser is slightly deteriorating due to the slight scaling.

5.5.4.3 Investment cost and benefit

(1) Investment on BOFD system

a) Energy management support system	\ 40,000,000.-
b) Fault detection system	\ 60,000,000.-
c) Instrumentation	\ 50,000,000.-
d) Software	\ 40,000,000.-
Total	\ 190,000,000.-

(2) Benefit Analysis, the operating cost of BOFD system per annum

a) Additional costs caused by maintenance of the BOFD system	\ 1,000,000.-
b) Savings in users' maintenance staff cost	\-16,000,000.-
c) Savings in energy expense	\ -40,000,000.-

(Costs and benefits in Japanese yen. 1 ECU ~ 140 Yen
1 \$ ~ 110 Yen)

5.5.4.4 LCC analysis

As It is difficult to achieve a LCC analysis of the BOFD system based on the field date of only three years, we assumed four cases of cost saving, from CASE-A to Case-D, brought about by the BOFD system on the basis of LCC for 30 years. Table 5.9 and Fig. 5.21 give estimated LCC by the present worth method.

Table 5.9. Estimated LCC of 30 years with present worth method.

CASE-A: All the benefit, energy and manpower saving are brought about by the BOFD system only.

CASE-B: Half of the benefit are supposed being brought about by the BOFD system and another half are by the BEMS functions and maintenance efforts.

CASE-C: Ten millions yen of energy cost saving per year and only one of the maintenance personnel saving is caused by the BOFD system and the other most saving are due to the BEMS system and maintenance efforts.

CASE-D: Ten millions of energy cost saving per year only is due to the BOFD system and the other most saving are caused by the original BEMS and maintenance efforts.

Parameters: project life length=30 years, inflation ratio=6%, energy escalation ratio=1.5%/year,

(1) Investment cost	CASE-A	CASE-B	CASE-C	CASE-D
Energy management system	43,108	43,108	43,108	43,108
FD system	64,642	64,642	64,642	64,642
Instrumentation	57,249	57,249	57,249	57,249
Software	48,545	48,545	48,545	48,545
Sub Total	213,564	213,564	213,564	213,564
(2) Operating Cost				
Maintenance Cost of BOFD	16,174	16,174	16,174	16,174
Energy cost saving	-646,979	-323,490	-161,745	-161,745
Manpower cost saving	-258,792	-129,396	-129,396	-,-
Sub Total	-889,597	-223,147	-274,966	-145,570
Total	**-676,032**	**-223,147**	**- 61,402**	**67,994**

It is observed that, if half of energy expense and maintenance manpower savings in the field data are brought about through the BOFD system introduction, it would be profitable to install the system in this building.

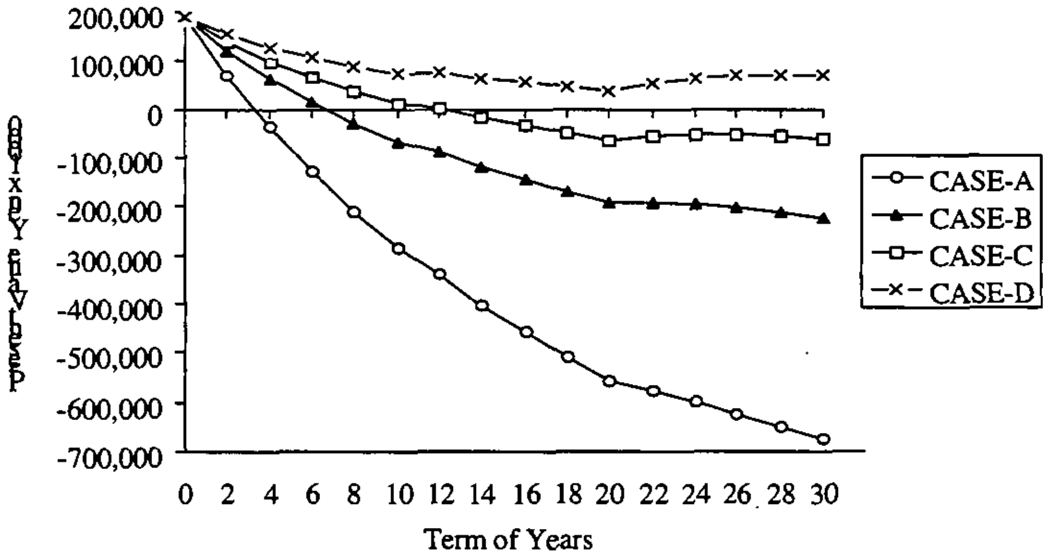


Figure 5.21. Estimated LCC in every term of years by Present worth method.

5.5.4.5 Conclusion

It is not easy to estimate the effect of the BOFD system in this case study, but it is defined that the BOFD system can contribute to the cost savings by using the energy management support system. Therefore the BOFD system can be very useful for the buildings like a computation center which are consuming much more energy than general office buildings in terms of energy cost savings.

5.5.5 References

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6 ASPECTS FOR IMPLEMENTATION

6.1 COST BENEFIT

Matsunawa, K., Nikken Sekkei Ltd
Representing the Cost Benefit Working Group of Japan BEMS/BOFD Committee

The introduction of the BOFD (Building Opimization & Fault Detection) System is expected to be considerably important in terms of cost benefit. It is anticipated to bring about the benefit of reducing energy cost which will compensate the invested amount for the system.

However, neither the definition of C/B (Cost Benefit) nor the method of its evaluation has been clarified up until the present. Therefore, review of C/B is essential for the widespread use of the BOFD system. Building owners will be able to rationally determine whether or not to adopt the BOFD system if they were able to evaluate its anticipated costs and benefits. Therefore, this section aims to explain the framework of C/B analysis for teh BOFD system.

6.1.1 Scope of BOFD cost and benefit evaluation

Before the discussion of costs and benefits of the BOFD systems, it is vital to determine the scope of evaluation. For the sake of convenience, discussions below will base on Fig. 6.1 where evaluations will be on the costs and benefits of the BOFD functions being added to the BEMS (Building & Energy Management System).

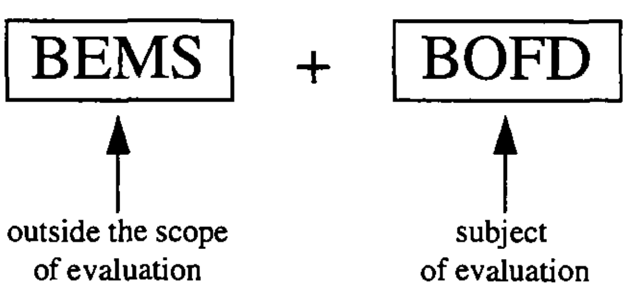

Figure 6.1. Costs and benefits subject to evaluation.

6.1.2 Recipients of the benefits

It is also necessary to determine the recipients of the benefits, since the benefits enjoyed are assumed to be different to each beneficiary. Beneficiaries include the Occupants, Tenants and Building Owners. In a wider sense, the general public can also be viewed as beneficiaries. Building owners would concern about the benefit gained from savings in energy cost, whereas occupants would be interested in improved indoor environment. Energy conservation and decrease of environmental loads would be major concern to all relevant parties as well as general citizens. It is therefore essential to identify who the beneficiaries are before carrying out the cost/benefit evaluation. Table 6.1 summarizes the main beneficiaries assumed for cost/benefit evaluation undertaken from various view points.

6.1.3 Clarification of the applicable evaluation period

In defining the applicable period for the cost/benefit evaluation, the following three concepts are generally applied.

1) *Evaluation term of several years:*

   In this case, evaluation is applied during a period of several years, beginning from the time of investment to the adoption of BOFD system. This concept is extensively used when one wishes to know the simple pay-back period for the amount invested.

2) *Evaluation term equivalent to the assumed service years of BOFD*

   In this case, evaluation is conducted on the expected costs and benefits for the assumed service years of the BOFD system. Costs for overhaul and replacement are not taken into consideration. This method is popularly used for selecting a single system from multiple systems.

3) *Evaluation term equivalent to the entire lifetime of the building*

   In this case, evaluation is conducted on the expected costs and benefits for the entire lifetime of the building. Consequently, not only the initial installation cost but also additional costs for overhaul, maintenance, repair, and replacement are taken into account. Compared with methods (1) and (2), this method is more popularly used when long-term and comprehensive analysis is required. The disadvantage of this method is that it is somewhat difficult to forecast precisely with the rise of interest rates and inflation rates over a long period of time.

In anly case, the most appropriate of the three methods described above should be adopted, in order to comply with the purpose of the cost/benefit evaluation.

6.1.4 Definition of costs and benefits

The costs and benefits of the BOFD system should be clearly defined. The following assumptions are made to facilitate the understanding of what the costs and benefits are. First of all, the case of BOFD not being applied to the HVAC system is assumed. Next, the case of the BOFD system being applied to the HVAC system is assumed. It is expected that the latter case will bring about decreased energy consumption and lower energy cost compared to the former case. On the other hand, the latter case requires investment for the adoption of the BOFD system. The relationship between the costs and benefits is summarized in Fig. 6.2. It represents the most basic and easy ways to understand relationship between costs and benefits. There are other ways to understand the relationships between costs and benefits, and they are shown in Table 6.1.

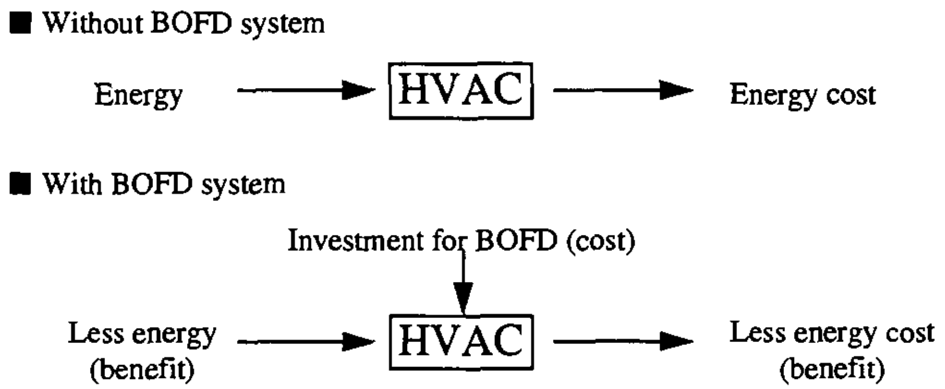

Figure 6.2. Examples of Costs and Benefits in BOFD.

1) *Costs*

The costs include investments required for introducing the BOFD system. In general, they are referred to initial installation cost, maintenance cost, and replacement cost. In another sense, the costs also include the depreciation cost of the BOFD system appropriated in the yearly operating expenses. The total investment amount (converted into current value) for installation and replacement of the BOFD system throughout the life of the building is also viewed as one of the costs. The definition of "costs" is subject to change, depending on whether the period of investment is regarded as temporary, fixed, or lifelong. The interrelations among these factors are given in Table 6.1.

2) *Benefits*

There are two types of benefits: one that can be converted into monetary values and another that cannot easily be, or prefer had not be, converted into monetary values. The former includes reduction in energy cost and/or running cost. The latter includes reduction in energy consumption volume, decrease of environmental loads, improved indoor environment, reduction of various damages and increased productivity. As for the case with costs, different definitions are applied to benefits depending on whether the benefits are regarded as temporary, fixed-period or lifelong. Table 6.1 summarizes the benefits expected, viewing from different standpoints.

Table 6.1. Summary of various costs and benefits.

Basic concept	Applicable period	Costs	Benefits	Main beneficiaries			
				B	T	O	C
Simple Playback Method	For several years after installation	· Initial installation cost	· Energy cost saving	○	○		
		· Replacement cost	· Running cost saving	○	○		
			· Reduction of energy consumption volume	○	○	○	○
			· Reduction of environmental loads	○	○	○	○
			· Improvement of indoor environment	○	○	○	
			· Minimizing of loss	○			
			· Improved productivity	○	○		
Annual Cost Method	Period during the service life of equip-ment	· Depreciation of the amount invested	· Annual energy cost saving	○	○		
			· Annual running cost saving	○	○		
			· Annual operating expenses saving	○	○		
			· Reduction of annual energy consumption volume	○	○	○	○
			· Reduction of annual environmental loads	○	○	○	○
			· Improvement of indoor environment	○	○	○	
			· Minimizing of loss	○			
			· Improved annual productivity	○	○		
LCC Method	Throughout lifetime of the building	· Lifelong investment amount (costs for initial installation, replacement, overhaul, etc.)	· LCC saving	○			
			· Lifetime energy consumption volume saving	○	○	○	○
			· Reduction of lifetime environmental loads	○	○	○	○
			· Improvement of indoor environment	○	○	○	
			· Minimizing lifetime loss	○			
			· Improved lifetime productivity	○	○		

B: Building
T: Tenants
O: Occupants
C: Citizens

6.2 DESIGN FAULTS

Nakahara, N.
Nagoya University, Japan

6.2.1 Introduction

The design faults should not be overlooked in the BOFD process. Many fault-like phenomena occur during operation and are not always due to the operational faults in components, controls, setting of system parameters, energy performance and/or environmental satisfaction, but rather due to the design faults such as over- or under-estimates of sizing or capacity rating and improper zoning and/or control systems. Sometimes an appropriate design may have been changed into a faulty design during construction. Proper building commissioning should bring to light the latter kind of faults before delivery to the customer.

In the beginning the compsition of HVAC subsystems is shown in Fig. 6.3. It is important to recognize that each subsystem is often evaluated separately for obtaining suboptimal operation in the total system.

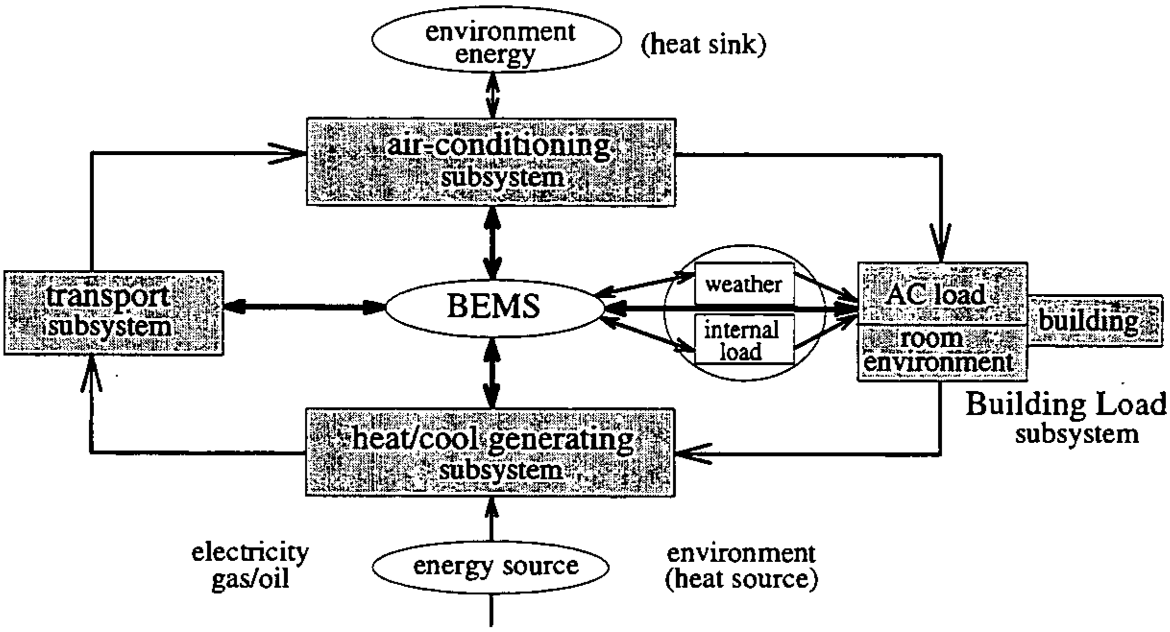

Figure 6.3. Composition of HVAC subsystems [6.1].

According to the definition of Building Optimization [6.2], the fault detection in the component level and the optimal control without any faults in the components, as well as the subsystems, are not enough. However optimized the operation could be, there are few chances to attain the Building Optimization based on the reference performances consisting of both energy and environmental performances. Fig. 6.4 shows the total BOFD structure including production stage.

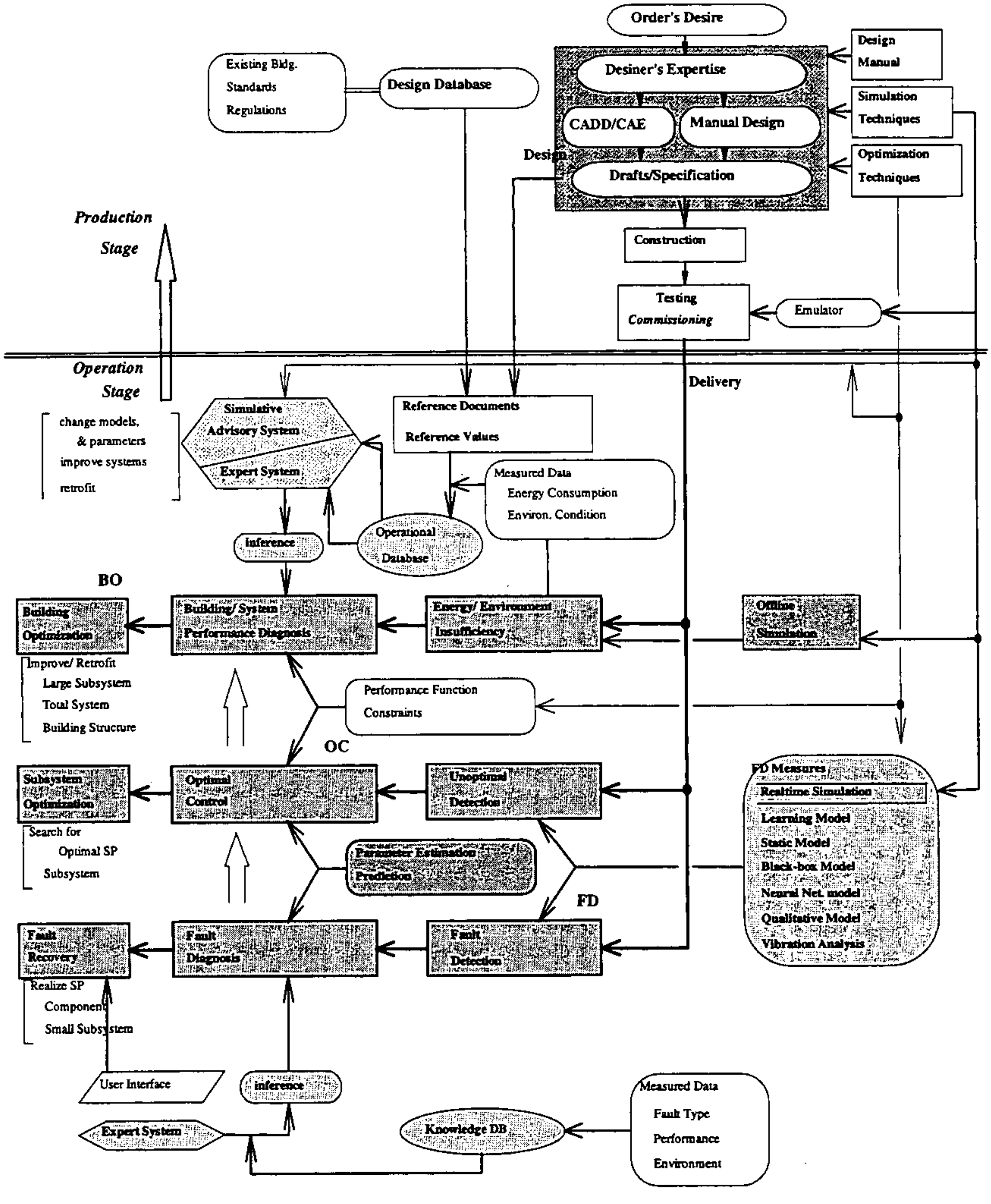

Figure 6.4. Design faults and the structure of BOFD.

6.2.2 Cause of design faults

It is important to recognize that there are no system design which are free from design faults. Many kind of causes are thought of where a certain design fault come from. For example,

1) mistake in computer input or miscalculation of the air-conditioning load, improper selection of the duct and/or pipe size and any components included in the HVAC system, which result in too much energy and/or bad environment,

2) improper air-conditioning zoning and/or improper sensor location due to unskilled design, which results in bad environmental condition,

3) overrating of the HVAC components such as coils, control valves, control dampers and heat generating plant due to excessive safety factors, which results in too much energy, bad controllability and/or short life cycle,

4) selection of improper characteristics for components such as the control valves, control dampers, fan and pumps control system, heat pump control system, etc., which result in bad energy performance, environmental dissatisfaction and short life cycle.

5) misdesign in thermal storage system, which results in energy loss due to heat loss from the tank wall in case of overrating, or which results in environmental dissatisfaction due to impossibility of heat pump operation caused by bad temperature profile, which means low storage efficiency in case of underrating. In either case the financial loss will be enormous.

6) improper system design due to lack in designers experience and the use of improper computer program for the system design and components selection.

6.2.3 Detection of the design faults

Two kinds of approaches, the top-down and the bottom-up, are available for detecting design faults. Both of these approach are common for detection of design faults and operationa faults. It is no wonder that the same symptoms may sometimes come from either design faults or operational faults. Environmental dissatisfaction, for example, is very common symptoms of many kinds of faults. However, design originated faults may be discriminated by the continuity of the symptom from the other one which will show a discontinuous change.

6.2.3.1 Top-down approach

This approach shown in Fig. 6.5 detects the macroscopic performance of either total system or any subsystems as follows.

1) Energy performance, which is compared with the data base about the reference performance,

2) Environmental performance, which is judged by the statistically analyzed claims from occupants and compared with the physical data plotted on the comfort index such as PMV or on the comfort chart shuch as ET*

3) Some typical indices for evaluating overall performance of subsystems such as the temperature profiles of thermal storage tanks, the coefficient of energy consumption, or CEC, defined as the energy consumption of any subsystems divided by the corresponding heat transferred, delivered or generated.

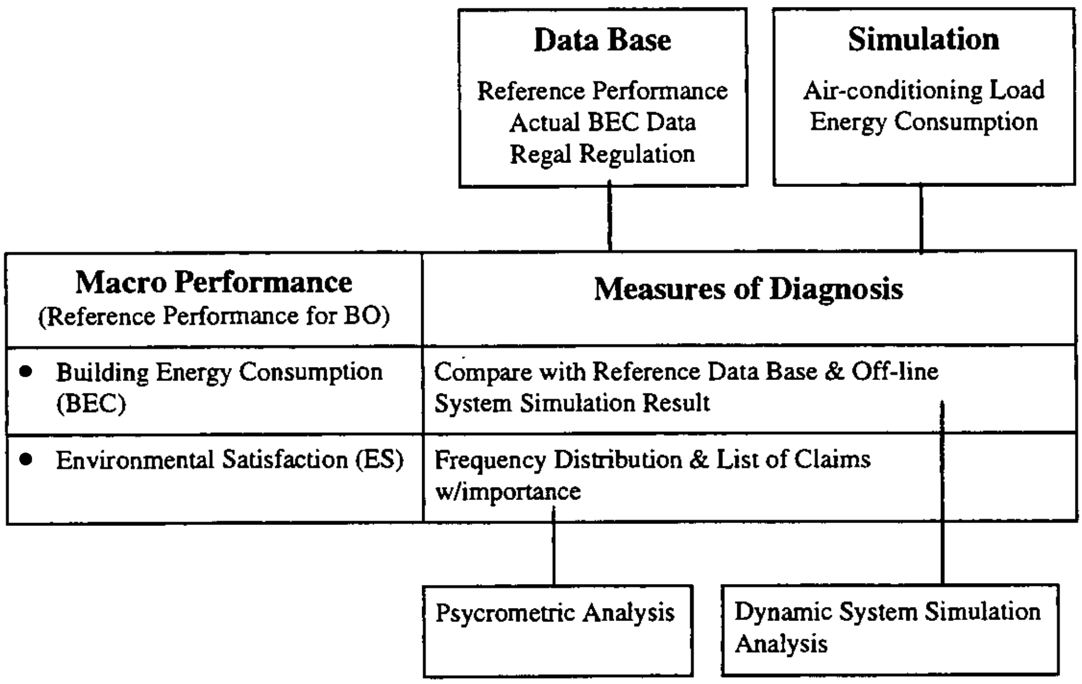

Fig.6.5. Procedure of top-down approach [6.3].

6.2.3.2 Bottom-up approach

This approach usually follows the detection of defects in macro performance. Knowledge database is useful for localizing faults. The database should be prepared before and during the design, and then added by operators in the course of operation. Examples of typical processes are shown in the following.

a) Energy Performance database for subsystems

The reference value of energy consumption budget or the CEC, for example, is calculated following a certain predetermined procedure and/or with the system simulation program in order to agree with the initial goal of design. Data from existing buildings of same kinds and the similar scale in the database should be referred, too. After operation, actual data will be summed up from the direct reading or indirectly calculated performance of the logged data. Statistical treatment of these data, such as moving average or regression analysis, will generate more detailed and real data.

b) Reference tables of the cause-effect relationships

Experts' knowledge and simulated test results on subsystem faults are combined into knowledge database which clarifies the qualitative cause-effects relationships among HVAC variables. Then one can easily find out the candidates of improper components and/or a localized symptom as the top incident for the fault tree analysis. Table 6.2 and Table 6.3 shows an example of reference table and cause-effect relationships [6.3].

Table 6.2. Reference table to localize design faults.

	Too bad Environment	**Excessively cool and/or warm Environment**
Too much Energy Consumption	Inadequate System Design I ③⑧, II ②④⑨⑩, III ② System Element Malfunction or Failure I ⑤⑧, II ①②⑨ Control Malfunction or Failure I ⑦⑧, II ②, III ⑥ Change of Building Use or Usage I ⑧⑨, II ②④, III ①, IV ①④⑨	Too large Design Capacity I ③⑨, II ②⑦⑨⑩, III ②, IV ④ Erroneous Control Policy or Set-point I ⑦, II ⑥⑨⑩, III ③, IV ④⑥ Change of Building Use or Usage I ⑨, II ⑦, III ②, IV ④⑥⑨
Too small Energy Consumption	Too Small Design Capacity I ③⑧⑨, II ①②⑤⑥⑦, III ①, IV ①②④ Too Short Operation Time System element Malfunction or Failure I ①②③⑥, II ①③⑤⑧, III ⑤⑥, IV ②③⑤⑥⑦⑧⑨ Control Malfunction or Failure I ⑦, II ②⑥, III ③④⑥③④	Superior Design Extraordinary Weather or Interior Load Change of Building Use or Usage I ③⑧⑨, II ②, III ②, IV ④

note:Symbols as I ,① should be referred
to the List of Principal Causes in Table 2.3.2

Table 6.3. Cause-effect relationships in subsystem faults.

I Air Handling Unit	
②	Air Filter Malfunction
③	Too Large or Too small Fan Selection
④	Fan Malfunction
⑤	Air Leakage through AC Unit and/or Damper
⑥	Inadequate Allocation of Elements in the Unit
⑦	Local Control Malfunction, Failure or Improper Set-Point in Intelligent AC Unit
⑧	Too much or too small Outside Air Volume Intake
⑨	Too large or too small Capacity
II Duct/Pipe and Air/Water Distribution System	
①	Air Leakage and/or Insufficient Insulation, including damage
②	Too large or Too small Pressure loss, or duct/pipe size
③	Damper/Valve Malfunction, Inadequate Position
④	Inbalance of Duct Sizing
⑤	Inadequate Allocation of Air Supply Units
⑥	Inadequate Allocation of Temperature/Humidity Sensors or Improper Set-Point
⑦	Bad Zoning or lack of Indivisual Control
⑧	Air Intrusion or Cavitation in Pump or Pipe System
⑨	Mixing Energy Loss in Systems
⑩	Mixing Energy Loss in Rooms
III Heat Generating Plant	
①	Too small Capacity
②	Too large Capacity and Inadequate Capacity Control
③	Local Control Malfunction, Failure or Inproper Set-Point
④	Malfunction or Failure in Operation
⑤	Reduced Output Capacity due to Insufficient Maintenance
⑥	Malfunction or Insufficient Capacity in Peripheral System Elements such as Cooling Tower, Pumps, Piping System, Insulation, Electricity, Controler, etc.
IV Thermal Storage	
①	Insufficient Volume
②	Insufficient Insulation or Water-proof, including damage
③	Bad Temperature Profile, Insufficient Storage Efficiency a) Design Failure in Temperature Control Policy in Water Piping b) Design Failure in Tank Structure against Temperature Blending c) Control Malfunction, Failure or Improper Set-Point in Water System
④	Inadequate Optimal Control in Load Prediction and On-off Control
⑤	Insufficient or Reduced Performance of Heat Exchanger due to Insufficient Maintenance
⑥	Pump oversizing or Undersizing
⑦	Pipe/Valve Malfunction or Failure such as Foot-valve Clogging due to Water Quality
⑧	Lack of Water Quality Control or Closed Circuit Policy
⑨	Inadequate Capacity Control for Pumps

c) Fault Tree Analysis

Once the top incident is fixed, then FDD expert system based on the fault tree analysis shall be followed [6.4].

6.2.3.3 Simulative advisory expert system

When the target of retrofit is determined, all the existing system data are input into a computer program and adjust parameters in order to output similar results as obtained from the actual system. The simulative advisory expert system then interactively displays the frequency distribution of energy and comfort indices of the subsystem for alternatives and the existing design with faults.

Fig. 6.6 shows the system diagram and the diagnostic procedure of design faults with the simulative advisory system. Fig.6.7 is an example of display showing the comparison of energy performance among alternatives.

Fig.6.8, which is common to both design faults and operational faults, explains the relationships between the top-down and bottom-up procedures.

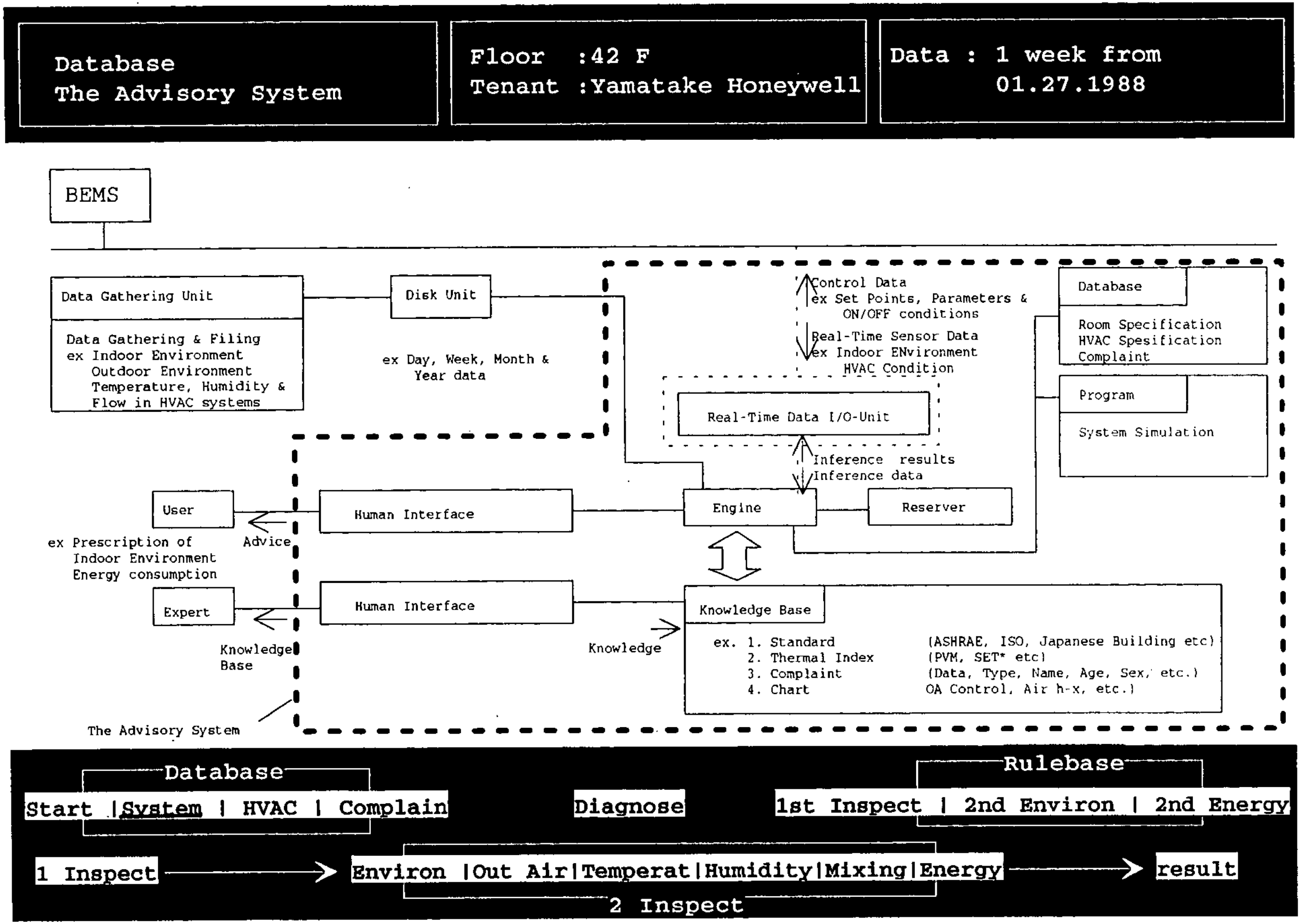

Figure 6.6. Procedure of simulative advisory system.

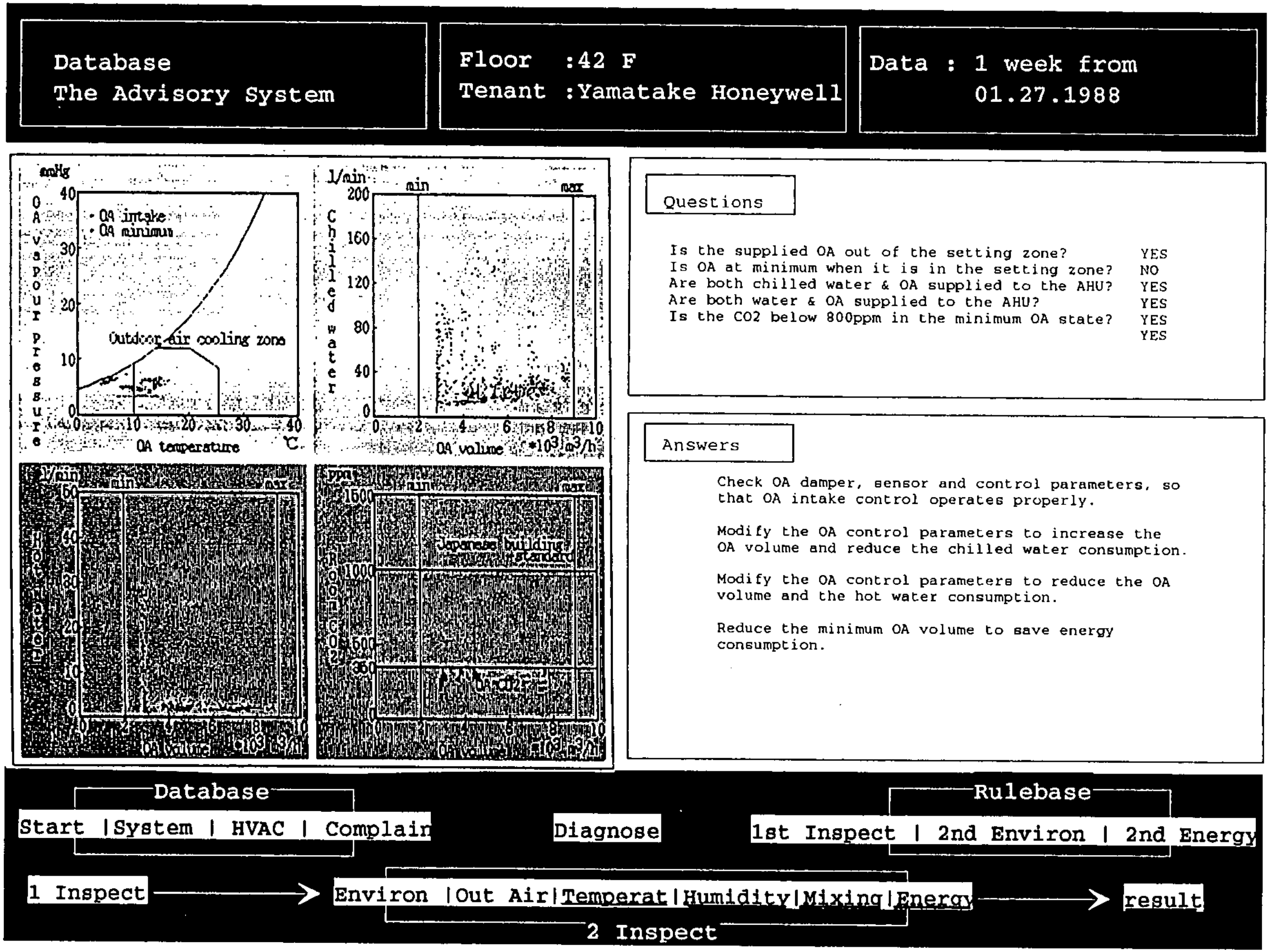

Figure 6.7. Example display of energy performance.

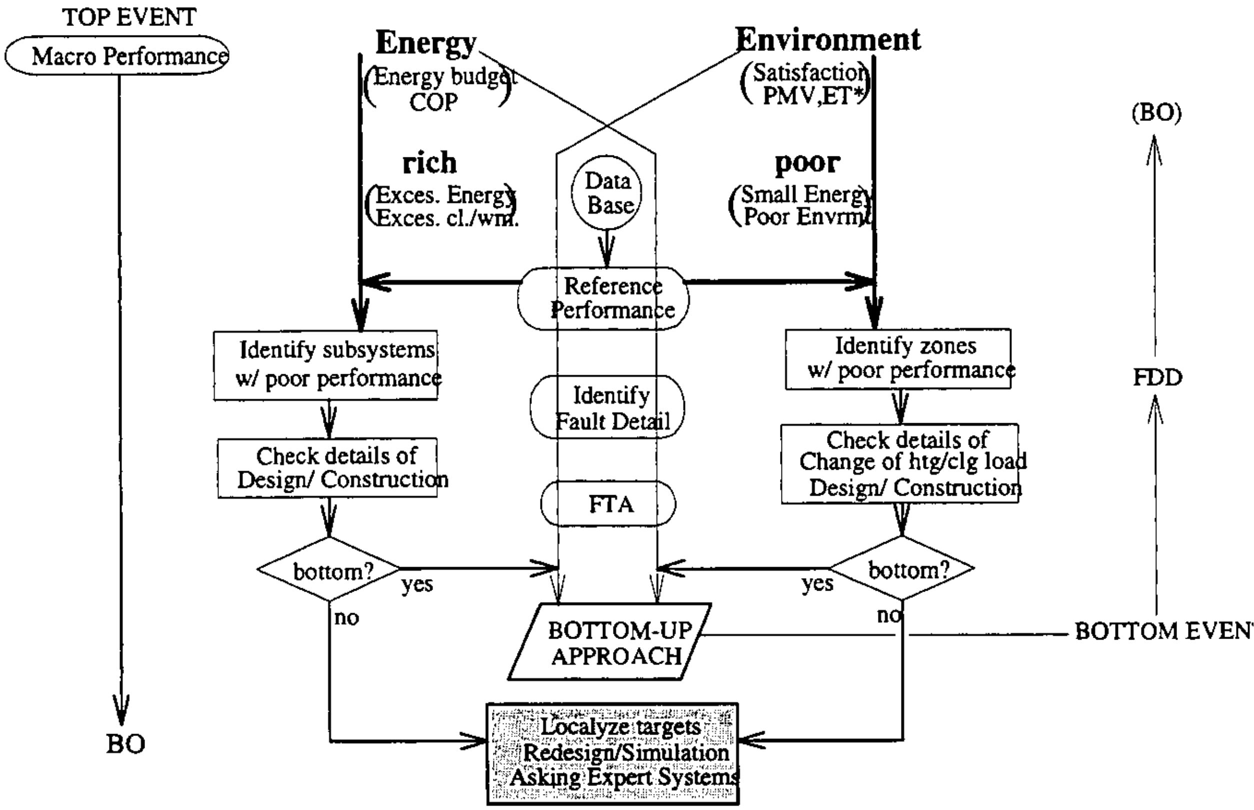

Figure 6.8. Relationships between top-down and bottom-up [6.5].

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6.3 CONFIGURATION AND PARAMETER SETTING AS A CRITICAL ISSUE FOR PRACTICAL APPLICATION

Tödtli, Jürg,
Landis & Gyr (Europe) Co, Zug, Switzerland

A fault detection and diagnosis method is usually designed for a class of HVAC systems or components. In order to apply it to a specific system or component, some adaptation of the method is needed. Adaptation in this broad sense usually consists of configuration and parameter setting (parameter adjustment, parameter tuning). Parameters to be set include parameters of a model in a model-based method, filter parameters, probabilities in a Bayesian approach, parameters characterizing a membership function in a fuzzy method, threshold values or upper limits for false alarm probability.

Do we not have enough problems with the configuration and tuning of control systems? Do we not make the situation even worse if we add fault detection and diagnosis functions which have to be adapted as well? Without good solution to the adaptation procedure, there is no chance for an FDD method to be broadly applied. The motivation to find good solutions was one of the major challenges in the Annex 25 project.

What is a good solution? Or in other words: what are the requirements to be met by an adaptation procedure? First of all it must result in a fault detector and diagnostic system with good performance, e.g. with acceptable false alarm probability, high probability for detecting faults, robustness with respect to specific parameters, etc. Secondly there are requirements for the adaptation procedure itself. To discuss these requirements, we consider three typical application cases.

Application case 1: A large number of identical HVAC plant components with an integrated control and an integrated detection and diagnosis system is industrially manufactured. The configuration of the control and the fault detection and diagnostic system, and the setting of their parmeters has to be done only for one plant component and may be copied for the others. It is conducted in the R&D department of the industrial company. Therefore it might be expensive: it might be time consuming, requiring expensive tools and requiring highly skilled specialists in areas like control theory, simulation, artificial intelligence, HVAC systems or building sciences.

Application case 2: Fault detection and diagnosis will be applied in a customized installation with a standard structure. The configuration of the control system and of the fault detection and diagnosis system for this structure is done before the customer specific project starts. Setting the parameters of the control system and of the fault detection and diagnosis system is partially done during engineering and partially during commissioning and operation. Because parameter setting is therefore conducted within the customer specific project, it must be cheap.

Application case 3: Fault detection and diagnosis will be applied in a customized system with nonstandard structure. In contrast to application case 2, configuration of the control system and of the fault detection and diagnosis system is part of the engineering within the customer specific project. Thus also configuration must be cheap, additionally to parameter setting.

The requirements are summarized in Table 6.4. We see from the table that configuration must be cheap in application case 3 and parameter setting must be cheap in application cases 2 and 3.

Table 6.4. Requirements which configuration and parameter setting must meet.

Application case	Requirements for		
	result of adaptation:	adaptation procedure itself:	
	Good performance	Cheap configuration	Cheap parameter setting
1	x		
2	x		x
3	x	x	x

Different solutions to the problem of adapting an FDD system have been proposed in the Annex 25 project. Some typical solutions are discussed in the following.

There are FDD methods with very good performance, but for which configuration as well as parameter setting is expensive. Such methods are suitable only for application case 1. An example of such a method is the optimal fault detection observer discussed in section 4.2.3. It is not based on a model with parameters which have a physical meaning. All their parameters are optimized to give a good performance, in particular to make the method insensitive with respect to some specific disturbances.

There are several circumstances and approaches which can contribute to make parameter setting cheap. One of them we find in model-based FDD methods which have *model parameters with physical meaning*. As examples two fault detectors for a district heating substation are mentioned [6.6]. In the first example (the "model output error method") a model is used to estimate on the basis of some measurements (two pressures and the valve position) the square of the primary water flow. If the deviation of this estimate from the square of the measured flow exceeds some threshold value, the fault detector indicates the detection of a fault. The model is described by three parameters: two describing the valve characteristics and one describing the flow resistance of the primary side of the heat exchanger. The values of the three parameters could be obtained from data sheets supplied by the valve and heat exchanger manufacturer or could be determined by performing a measuring experiment. The second example of a fault detector for the district heating substation described in [6.6] (the "parameter error method") uses a model to estimate two model parameters and then calculates the deviation of these estimates from reference values. If the deviations exceed some threshold values the detection of a fault is indicated. The reference values of the two parameters can be calculated in advance from three parameters with physical meaning using simple formulas. The three parameters with physical meaning are the same as in the first example and can be obtained in the same way.

If a detailed physical model (models whose parameters have a physical meaning) were used for monitoring a whole building including its HVAC installations, the number of model parameters would be immense and the work to set all these parameters could be prohibitively expensive today. A future possibility to reduce the costs of this approach could be to integrate the engineering of the monitoring system in an *integrated design process* which integrate the architectural as well as the HVAC installation design and which is based on a *common data base* from which all model parmeters can be obtained in an efficient way [6.7].

A very direct way to make parameter setting cheap is *self-adaptation of parameters during a reference phase of operation*. In case of a fault detector based on a quantitative model - whether it is a physical model or a black-box model - the reference phase of operation would be a phase for which it is assumed that the monitored system has no faults. It could be a phase during commissioning or a first time period during operation after commissioning. Perhaps active tests are performed to improve the self-adaptation. In case of a fault diagnosis system based on quantitative fault models it would be required to have reference phases of operation where specific faults are present, a requirement which rarely could be fulfilled in practice. Typical representatives for self-adaptation of parameters during a reference phase of operation are methods based on an ARMA model (see section 4.2.2) and methods based on ANN (see section 4.4.2). It is important to note that some of the self-adaptation algorithms also have parameters which must be set. The setting of these parameters should not be more difficult for the user than that of the original parameters which now are adapted automatically. If it is not obvious how to set them, the user should be supplied with a step-by-step procedure which tells him or her how to set these parameters or with a proposal for a robust setting of these parameters which he or she can use for a whole class of systems. The approach described here can also be applied to certain threshhold values. P. Sprecher designed a method for energy consumption of buildings (energy signature) [6.8] with a self-adaptive threshhold. The only parameter to be set by the user is an upper limit for the false alarm probability which he or she is willing to accept. The rest is done automatically.

Another direct way to make parameter setting inexpensive is to *supply parameter settings which are robust for a whole class of systems* and which are determined as part of the design of the method. If a user wants to apply the FDD method to a specific system belonging to a specific class of systems, he or she can use the parameter setting prepared for that class. Typical for this approach is the FDD method based on normalized fuzzy models described in [6.9].

A completely different solution to the problem of making parameter setting cheap is to *eliminate parameters which are expensive to set*, i. e., to develop FDD methods which do not contain such parameters. Typical examples are the *qualitative methods* (based on crisp logic as opposed to those based on fuzzy logic) described in section 4.6.1. The desire to avoid parameters which are usually difficult to be set was actually the driving force to develop qualitative fault detectors, and in particular to develop the qualitative fault detectors for the central air handling unit with a standard structure but a customized sizing [6.10]. The elimination of some parameters by applying a qualitative method also has a price: less faults can usually be detected than with a quantitative method. Similar to the methods with self-adaptation of parameters during a reference phase, the problem of parameter setting is usually not completely eliminated but shifted to the (hopefully easier) problem of setting other parameters. In the case of the qualitative methods described in [6.10], these new parameters to be set are those of the transformation unit which transforms quantitative signals to qualitative values. One of these parameters is the threshhold value which is used to determine when a temperature difference is considered to be "zero". Another typical example of the solution by eliminating parameters which are expensive to be set is the use of *static models*. By using static models instead of dynamic models, all parameters describing transient behaviour (for example time constants or heat capacities) are eliminated. But here again, by eliminating some parameters, new parameters which must be set are introduced: parameters of a steady-state detector or parameters of any kind of averagers. Whether the setting of the newly introduced parameters is easier than that of the eliminated ones, must be carefully examined. A method to determine parameters of a steady-state detector used in a fault detector is described in [6.11].

In application case 3 parameter setting and configuration of the FDD system must be inexpensive. One general approach to make the configuration of the FDD system inexpensive (i.e. to make the adaptation of the FDD system to a given structure of the monitored system cheap), is to use an *FDD method which is based on an explicit description of the system's structure*. Then the configuration of the FDD system consists mainly of formally describing this structure. An approach going in this direction is the already mentioned building monitoring system, which is engineered as part of an integrated overall design process based on a common data base [6.7]. Another approach of this kind is the qualitative fault detector incorporating a *deep model* described in [6.10] (fault detector 2 in [6.10]). In addition to qualitative descriptions of all components or subsystems the deep model contains an explicit description of the system structure (i.e. how the components and subsystems are linked together to the system). In order to configure the FDD system it must therefore be supplied with the description of the system's structure.

Another approach to make the configuration inexpensive is to supply tools which accept formal descriptions of the system structure as input. An example of this approach is fault detector 3 in [6.10]. The same deep model as was used in fault detector 2 (mentioned above) is used in the tool, which automatically compiles it to a flat model in the form of a table, that is used in the fault detector.

The main purpose of this section was to make the reader aware of, and sensitive to, the problem of adaptation and to invite him or her to consider all methods also from the viewpoint of this problem.

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6.4 PRACTICAL ASPECTS FOR ON-LINE FAULT DETECTION & DIAGNOSTICS

Seem, J. Johnson Controls, USA

The performance of HVAC systems degrade over time. For example, heat exchangers become fouled, chillers lose refrigerant, valves for heating and cooling coils can leak. Currently, simple test, such as range checking, are used to detect faults. Early detection and correction of faults in HVAC equipment will result in decreased energy consumption, longer equipment life and improved comfort and safety for building occupants. After detecting a fault, manual inspection or an on-line diagnostic system can be used to diagnose the cause of the fault. It is critical to identify and correct the true cause of the fault. Next, we describe a case that demonstrates the importance of identifying and correcting the true cause of a fault.

Fictitious Case: Unstable control of heating valve in air handling unit

Figure 1 is a block diagram for a variable-air-volume air handling unit that has a single supply duct. The purpose of the air handling unit controller is to supply conditioned air to the building. The controller has two main objectives. First, the controller attempts to maintain the supply air temperature at setpoint by adjusting the control signals to the cooling coil, and damper motors. Second, the controller tries to maintain static pressure at setpoint by adjusting the control signal to the supply air fan. A number of different types of air handling units exist. Most air handling units have some common components, e.g., fans, valves, dampers, controllers, temperature sensors, and heat exchangers for cooling or heating air. Air handling systems can fail in a number of different ways. For example, a damper could break, a heating or cooling coil could become fouled, a valve for the heating or cooling coil could leak, or the control signals to the coils and dampers could be cycling.

Valves are commonly used to control the flow rate of water through heat exchangers on air handling equipment. There are control systems where the heating system is tuned too aggressively. Consequently, the heating valve may cycle continuously in an attempt to maintain the discharge air temperature at setpoint. Opening and closing the heating valve will cause the valve seat to prematurely wear out. Eventually, the heating valve will leak when it is closed.

We could use on-line fault detection system to detect the leaky valve. After a leak is detected, we should repair the valve and tune the control system. However, if we only repair the valve and do not diagnose the unstable control system, then the valve will prematurely wear out again. In summary, it is important to identify and correct the true cause of faults.

Following is a list of desirable features for an on-line fault detection and diagnostic system.

1) *Commissioning time should be small.*

The time for commissioning an on-line fault detection and diagnostic system should be small. This will help reduce installed cost of the system.

2) *Eliminate false alarms.*

It is important to not have too many false alarms. If there are an excessive amount of false alarms, then the building operator or maintenance person will begin to ignore both real and false alarms.

3) *Reasonalble computational and memory requirements.*

Ideally, the computational and memory requirements of the fault detection system should be reasonable. This will allow us to use the fault detection and diagnostic system with today's digital control systems.

4) *Detect faults before occupants comfort and safety is sacrificed.*

It is important to detect faults before the occupant's comfort or safety is sacrificed.

5) *Consider economic impact of detecting and correcting energy related faults.*

When detecting faults related to energy consumption, consider the economic benefits of detecting and correcting the fault.

6) *Quickly detect CFC and HCFC refrigerant leaks.*

7) *Identify and correct true cause of fault*

7 CONCLUSIONS

Hyvärinen J., VTT Building Technology, Espoo, Finland

The main goal of IEA Annex 25 was to develop methodologies and procedures for optimizing real-time performance, automating fault detection and fault diagnosis in HVAC processes and to develop BOFD prototypes that can be implemented in BEM systems.

Part objectives were:

- to evaluate suitable approaches for the real-time simulation of HVAC systems
- to determine the basic approaches suitable for fault analysis
- to create a database of the most important problems and faults in HVAC systems
- to show that the BOFD schemes are suitable for implementation in a real BEM system and
- to develop a procedure for joint evaluation of BOFD-methods.

All these objectives have been achieved and can be presented in the following lists describing concrete and less tangible results.

- A general BOFD system concept
- Reference systems (Air handling unit, heating system, chillers and heat pumps, and thermal storage); list of faults, ranking of faults, symptom sets
- Applications of selected BOFD methods to components, subsystems, systems, and buildings
- Laboratory test rigs: District heating subdistribution system, Air handling unit, Chiller, Thermal energy storage
- Data sets: simulated and measured data sets for BOFD-method development and testing.
- New component and component fault models
- BOFD software development tools: e.g. prototype expert system (RICE, KAPPA), fault tree presentation (MSAccess), HVACSIM+ and TRNSYS modules, MATLAB/SIMULINK modules
- Application of generic tools to BOFD: e.g. Qualitative availability analysis methodology for expert knowledge acquisition, steady state detection method, cost benefit assessment methods, parameter estimation methods, system simulation
- some preliminary applications in real buildings
- joint evaluation procedure and performance criteria.
- Final reports.

Some major intangible achievements can also be listed:

- An international network of experts has been established.
- A new technology has been introduced to the sector of building and community systems

- Prototypes of several BOFD methods which are close to practical demonstration
- Strong industrial involvement.

This report can describe only a small part of the results which were obtained and which were dealt with and evaluated in meetings of experts held twice a year. Part of the technical and scientific work is set forth in the technical reports to be published in the second part of the programme. This source book and the technical reports of the second part are based on the more than 200 work reports that were prepared for the meetings.

An indication of the success of the project is the active participation also of industrial companies from the start of the project to its conclusion. This kind of collaboration has traditionally been closely associated with research institutes and universities and their methods of working.

7.1 SYSTEM CONCEPT AND METHOD DEVELOPMENT

In developing fault diagnosis methods, a system concept was adhered to, which was defined when the annex was in preparation phase and is also described in its essential aspects in this report. The concept comprises two main approaches. One is a broad approach that is based on monitoring an entire building or large system, detecting faults and diagnosing them. In the project, this approach was called optimizing building use. The second main approach deals with the detection of a fault in an individual component, device or system. The approaches nevertheless lead to the utilization of the same methods in detection and diagnosis, and the difference between them is probably philosophical in the last analysis.

The bulk of the work in connection with the annex involved the development of methods of detecting faults in components using process data obtained from the system simulation. To some extent development work was carried out based on measurements made with test rigs on a laboratory scale and obtained from actual processes. Fault detection methods have been developed, for example, for industrial processes and airplanes for a long time, and the new feature in the methods developed in connection with the annex is the application of the methods to a new area, monitoring the energy consumption of buildings, and in obtaining experiences of how the methods function in this area. Some 50 new methods for HVAC processes were developed or applied in the annex project.

The fault detection methods studied are based on the use of a process model, i.e. the detection methods are model-based. There was a good deal of discussion on the classification of fault diagnosis methods, but a clear-cut recommendation was not reached in this matter. In this report, a classification is discussed at least in section 4.1and one result of the classification discussion is the table of contents of Chapter 4, which is a compromise result of a number of discussions. An attempt at classification was thus made at least on the basis of the structure of the fault detection method, the structure and dynamics of the process model as well as the approach to fault detection.

Apart from fault detection, a number of the methods developed also embody diagnostic features. These methods can be termed more appropriately fault diagnosis methods and they involve a combination of fault detection and establishment of the location, cause and seriousness of the fault. The methods used for diagnosis, i.e. the classification of faults detected, were rule-based approaches, conventional and fuzzy logic, neural networks, pattern recognition, associative networks and qualitative inference.

Both the fault detection methods and the fault diagnosis methods that were developed in the project can be used as part of a more extensive fault diagnosis system. Individual fault detection and diagnostic methods can each be applied to the fault diagnosis of process entities at different levels. For example, the method based on the Armax model can well be applied to a valve, air-conditioning plant or the monitoring of the energy consumption of an entire building.

Joint evaluation exercises were conducted to apply BOFD methods in identical fault free and fault containing HVAC applications to identify their strenghts and limitations and to extend and enhance these methods for reliable fault detection and diagnosis. Detailed reports were generated by each of participant. In case of AHU and Thermal storage systems a summary report was produced for each joint exercise.

A type of inference by means of which the user tries to establish the effect of individual faults on the operation of a more extensive entity or the entire building, or an inference by means of which the user tries to establish the causes that have led to the malfunction of a more extensive subsystem were referred to in the annex as building optimization.

The building optimization approach came up frequently throughout the annex project, but it accounted for a smaller share of the work papers presented and publications completed than did fault detection and fault diagnosis methods. The reason for this may be that buildings are extensive and complex systems whose fault diagnosis does not lend itself to clear-cut and systematic approaches or examples from other typical applications. In this respect, the building optimization approach describes a set of problems whose solution and study could be of significance also in other areas of application than energy systems for buildings.

7.2 SYSTEM ANALYSES AND TOOLS

Apart from method development per se, the annex project led to the development of tools and the obtaining of information for developing a fault diagnosis system and methods. Procedures for the analysis of availability performance have traditionally been applied to the analysis of the malfunctioning of critical processes and systems. In the annex, these methods were applied to the identification of typical faults of different systems. In addition to the procedures, this yielded lists, arranged according to four typical systems, of the important faults at which detection actions should be directed, and information was also collected on the ways in which faults showed up and how they were remedied. The systems analysed were: the heating system, the cooling system and the heat pump, the air-conditioning system as well as the thermal energy storage system.

The availability performance analyses also indicated that in evaluating the significance of a malfunction, attention should also be paid to other factors than the energy consumption alone. Other important system characteristics are the quality of the indoor air, the safety of property and human beings, hygiene, the environment and the use of consumables, consequential faults and effects as well as system availability, maintainability and supportability.

For carrying out system analyses, so-called reference systems were defined and these were used as cases. In addition to the availability performance analyses, part of the reference systems were modelled and data simulated on the basis of the model were used in method development and in testing the methods that were developed. Four different series of test data were produced. The series of test data are necessary for the development of methods, but producing them is a time-consuming process. The cooperation yielded the benefit that the data series produced could be exploited more widely than in the development of a single method alone. In addition, the data series produced could be used in comparing the methods with each other.

In addition to methods of analysing availability performance, the annex project involved the development and application of other general tools, too. The tools are described to some extent in this source book, but also in the technical reports. The majority of the detection methods are based on the use of a process model whose parameters can be estimated before the model is used. The methods of estimating parameters are one significant part of the tool box that is needed in developing fault diagnosis methods.

As regards the process models, it always pays to stick to highly simple models. One way to achieve this is to confine the modelling to models that describe the behaviour of the process in its stationary state. Models of the stationary state do not provide a sufficiently accurate description of fast change situations. Accordingly, when applying them, it should be possible to determine the instance when the process is in nearly a stationary state. For this purpose, the annex project involved the development of methods for detecting the stationary state.

One of the central problems in model-based fault diagnosis is the setting of alarm limits, i.e. the question of when the outputs of the process and the model describing the operation of the process differ from each other so much that the difference can be assumed to be due to a malfunction. The problem was explored during the development work on virtually all of the methods, but general guidelines could not be laid down. The practical side of setting alarm limits was examined in a number of work papers which are published in the technical reports.

The setting of alarm limits can be facilitated by means of statistical methods, but even when using them there is no guarantee that the method will function flawlessly and detect all the faults with no false alarms. A practical solution is to permit several alarm limits within the method, these being set based on different types of criteria and being user-setable. Amongst the criteria mentioned were statistical, functional, absolute and economic criteria.

System simulation can also well be considered a tool. System simulation has previously been studied a good deal and the results of the research work were one of the starting points for the Annex 25 work. In the Annex 25 project, additional information and methods have been obtained for system simulation. This information consists of new component and system models for both processes that are in good working order and those that are malfunctioning. This information has been utilized in method development and in setting alarm limits on functional grounds.

7.3 SUMMARY

The research subject, i.e. applying fault diagnosis to the monitoring of the operation of the technical systems of buildings, is new in that it has not previously been implemented as an extensive cooperation project. The research work of Annex 25 was carried out within the framework of the IEA's research agreement Energy Conservation in Buildings and Community Systems and the participants in it included 11 countries and a total of more than 50 experts from these countries. These figures indicate the wide interest in the subject. The intensity of the research work and the activity of the participants remained high throughout the time the project was run and even became stronger towards the end of the project.

It is part of the nature of IEA cooperation that the participant countries and also individual experts each have their own research objectives. The cooperation for Annex 25 was more diversified than traditional project cooperation, and within its framework it was possible to achieve both joint objectives set for the entire Annex and the objectives of individual participants. In addition, in the course of the project the work expanded to a greater scope than had been defined in the original objectives, and this further increases the value of the results obtained in the Annex 25 work.

As a conclusion to the annex and to this Source book it can be said that co-operation has been fruitfull. All the essential objectives for the annex have been met and the results have been excellent. The next step would be the utilization of the results in practical applications. Hopefully this step will be seen already in the near future also in international collaboration forum.

GLOSSARY

George E. Kelly, NIST

PRIMARY DEFINITIONS

system	an interacting collection of discrete components. A system may be broken down into subsystems consisting of interacting collections of discrete components.
component	A component is an entity that is not further divided in the analysis being considered. (In another analysis, this component might itself be regarded as a system or subsystem.)
failure	there are two major types of failures: complete failures and malfunctions.
complete failure	a complete cessation of operation of a system or a component.
malfunction	a cessation of functional performance of a system of a component, whereby operation is ensured to some extent.
degradation	a deterioration in performance which can lead to a failure.
functional performance	operation of a component or system within some specified limits.
fault	an inadmissable or unacceptable property of a system or a component. A property is inadmissable if it is itself a failure or if it causes one directly or causes one indirectly through subsequent faults. In general, all failures are faults, but not all faults are failures. (e.g.: If a relay fails to close when a proper voltage is applied, it is a "relay failure". However, if the relay closes at the wrong time due to the improper functioning of some upstream component, it is not a relay failure but a fault since it may cause improper operation of a downstream component.) Faults may be classified by severity, physical location within the system or level (e.g.: fault cause or fault effect) within the system (SEE ATTACHED COMMENT ON FAULTS AND FAULT PROPAGATION.)
defect	an undesirable property of a system or a component. A property is undesirable if it is itself a degradation or if it causes one directly or causes one indirectly through subsequent defects. If a defect exceeds a certain level, the defect becomes a fault.

fault detection	the process of recognizing fault effects (i.e.: fault symptoms) using available measured data.
fault diagnosis	the process of searching "fault causes" for the detected fault effect(s).
fault tree analysis	involves identifying system level faults and their constructing a logic diagram showing all possible combination of failures and conditions which lead to each. Failure mode probabilities can then be computed from basic fault data.
fault cause	the fault just below the system resolution boundary that leads to a failure either directly or indirectly through subsequent faults. (The fault cause(s) identified will depend on the selection of the resolution boundary of the system. SEE ATTACHED COMMENT ON FAULTS AND FAULT PROPAGATION.)
fault effect or	an effect of a fault or defect or the fault just above the system boundary
fault symptom	that is detectable using measured data. (SEE ATTACHED COMMENT ON FAULTS AND FAULT PROPAGATION.)
input signals	control (input) signals to the process. It may or may not be possible or feasible to manipulate all of them.
output signals	measurement (output) data that provides information on the state of a process.
driving signals or	control (input) signals that are manipulated so as to "excite" the system
test input signals	during an experiment involving either system identification or fault detection.
dependent test signals	measurement (output) data that provides information on the state of a
or test output signals	process during an experiment involving either system identification or fault detection.

ADDITIONAL DEFINITIONS

fault isolation	the process of determining the location of a fault to the extent necessary to effect repairs.
fault localization	the process of determining the appropriate location of a fault.

failure mode	a fault, usually on the part/component level or the consequence of the mechanism through which failure occurs (e.g., the valve stuck closed, the valve failed open, the relay failed to release).
failure mechanism	the physical, chemical, electrical, thermal, or other process which results in failure .
failure analysis	subsequent to a failure, the logical systematic examination of an item, its construction, application, and documentation to identify the failure mode and determine the failure mechanism.
failure mode and	a systematic process whereby faults at the part/component level are
effect analysis	identified and their effect at the system level is determined using failure rates for thespecific stress levels.
failure state	the condition of an item or system that is characterized by its lack of ability to perform the required function.
primary failure	is failure of a part or a function that directly causes cessation of operation of functional performance.
associate failure	is a failure induced by the primary failure (e.g., burn-out of a transformer caused by failure of a current limiting component).
common cause failure	the coincident failure of two or more independent items as the result of a single cause.
failure rate	the number of failures of a part, component or system per unit time (e.g., per hour, cycle, operation, etc.). This can be applied to:
	(1) observed failure rate: as computed from a sample
	(2) assessed failure rate: as inferred from sample information
	(3) extrapolated failure rate: projected to other stress levels.
corrective maintenance	the action associated with the repair of faults and defects.
dependability	a measure of the degree to which a part, component or system is operable and capable of performing its required function at any (random) time during a specified period.
down time	the time during which an item is not able to perform to specifications.

fail soft — a failure in the performance of a system component that neither results in immediate or major interruption of the system operation as a whole nor adversely effects the quality of the product.

functional test — an empirical test routine designed to exercise an item such that all aspects of the item are brought into use.

maintainability — the probability that a failed part, component, or system will be restored to operational effectiveness within a given period of time when the repair action is performed in accordance with prescribed procedures.

maintenance, scheduled — preventive maintenance performed at prescribed points in the item's life.

maintenance, unscheduled — corrective maintenance required by item's condition.

mean time between failure (MTBF) and mean time to fail (MTTF) — the total cumulative functioning time of a population divided by the number of failures. As with failure rate, this applies to Observed, Assessed, and Extrapolated MTBF. MTBF is used for items which involve repair. MTTF is used for items with no repair.

mean time to repair (MTTR) — the mean time to carry out a necessary maintenance action.

preventive — the actions, other than corrective maintenance, carried out for the purpose

maintenance — of keeping an item in a specified condition.

redundancy — the provision of more than one means of achieving a function. Active: parts running parallel with the failed component have enough capacity that there is no adverse effect on the quality of the product. Standby: replicated parts or components do not operate until needed.

reliability — the probability that a part, component, or system will perform a required function, under stated conditions, for a stated period of time. Observed reliability is defined as the ratio of items which perform their function for the stated period to the total number of items in the sample.

repair rate — the reciprocal of MTTR.

repair time — the time during which an item is undergoing diagnosis, repair, checkout, and alignment.

diagnostic message — an output message signaling a problem and providing information as to its cause.

on-line diagnostics — diagnostic messages that are output to an operator or user console during normal system operation.

diagnostic test — execution of a diagnostic routine by sending a test input signal to determine ifthe system or a component is operating within acceptable limits.

fallback — a mode of operation in which manual or special operating procedures are usedto maintain some level of system performance.

fault tolerant — software or a system that continues to operate properly even after faultsoccur.

COMMENT ON FAULTS AND FAULT PROPAGATION

The definition of 'fault' as the immediate cause of a failure is considered as too restrictive, because it does not allow to express fault propagation across several stages. It is argued that any inadmissible property of a component of system can be regarded as a fault. A certain fault f_k can then cause another fault f_{k+1}, which again can cause a further fault f_{k+2}, etc. The fault propagation can also be traced back. The following example concerning a flow temperature control illustrates fault propagation (arrows indicate causal links):

Clearly some boundaries must be established when tracking fault propagation. The choice of a resolution boundary limits the detail of the diagnosis. The resolution boundary chosen in an automatic diagnosis system will be different from the one chosen in a manual failure analysis (defined as in draft). The choice of a system boundary stops tracking of fault propagation where faults are found that are detectable using the available process data. The faults just below the resolution boundary can be considered as fault causes, where as the ones just above the system boundary can be considered as fault effects or symptoms.

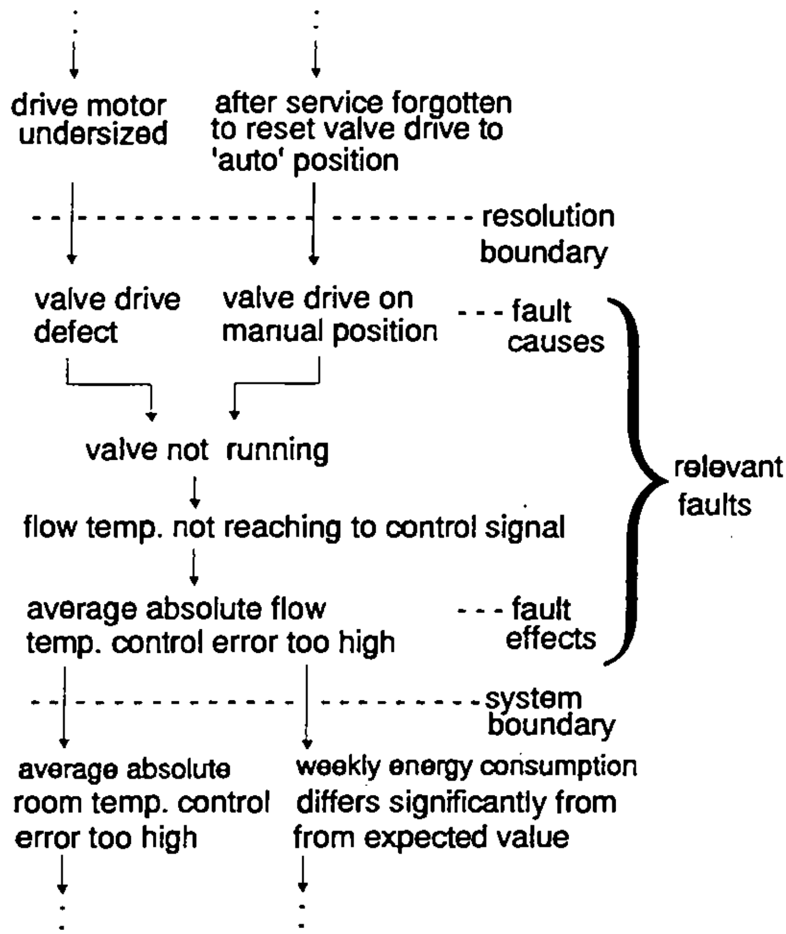

Figure A.1. Fault propagation.

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