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Fault diagnosis methods for district heating substations

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ABSTRACT

A district heating substation is a demanding process for fault diagnosis. The process is nonlinear, load conditions of the district heating network change unpredictably and standard instrumentation is designed only for control and local monitoring purposes, not for automated diagnosis. Extra instrumentation means additional cost, which is usually not acceptable to consumers.

That is why all conventional methods are not applicable in this environment. The paper presents five different approaches to fault diagnosis. While developing the methods, various kinds of pragmatic aspects and robustness had to be considered in order to achieve practical solutions. The presented methods are: classification of faults using performance indexing, static and physical modelling of process equipment, energy balance of the process, interactive fault tree reasoning and statistical tests. The methods are applied to a control valve, a heat exchanger, a mud separating device and the whole process. The developed methods are verified in practice using simulation, emulation or field tests.

PREFACE

This paper is a collection of fault diagnosis methods to be applied in district heating substations. The objective of the research was to develop practical fault diagnosis in cooperation with HVAC companies. The work is part of the Finnish contribution in IEA Annex 25, which concerns real-time simulation of HVAC systems for building optimization, fault detection and diagnosis. The research was financed by Technology Development Centre of Finland (TEKES), Technical Research Centre of Finland (VTT) and the following companies: Halton Oy, Oilon Oy and Stenfors Ky.

The paper presents five different approaches to fault detection and isolation. The methods were developed and written during the years 1992 - 1994 and most of them have not been published before. Some changes were made afterwards in order to update the contents. The method presented in chapter 4 is written by Juhani Hyvärinen and that in chapter 5 by Markku Ahonen & Juha Kuismin. Chapters 3, 6 and 7 present methods written by Jouko Pakanen.

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NOMENCLATURE

$E(x)$	Expected value of x
$D^2(x)$	Variance of x
$\boldsymbol{F}$	Feature vector
H_0	Null hypothesis
H_1	Alternate hypothesis
J	Performance index
K	process amplification
P	Probability
Q	heat power [kW]
S	Finite set
T	temperature [°C]
ΔT	Temperature difference [°C]
U_{a}	Absolute limit
U_{d}	Dynamical limit
U_{s}	Saturation limit
X	Estimator of a mean
Z_s	Constant flow resistance of a heat exchanger and pipeline

a	Parameter
b	Parameter
c	Coefficient, number of fault grades
c_p	Specific heat capacity [kJ/kg°C]
dp	Pressure difference
dt	Time differential [s]
e	Residual
f	Coefficient
g	Coefficient
k	Sample time [s], step size of a predictor
kr	Reliability coefficient
kv_c	Manufacturer specific parameter for a valve kv-value
n	Sample size
n_e	Manufacturer specific parameter for a control valve characteristics
n_p	Manufacturer specific parameter for a control valve characteristics
p	Parameter
q_m	Mass flow [kg/s]
q_v	Volume flow [dm^3/s]
r	Residual
s	Laplace operator
t	Time variable, test parameter
tau	Time constant [s]
th	Threshold
u	Input of a process, control signal

$\hat{u}$	Predicted value of u
y	Output of a process
z	Test parameter
x	Variable, random variable, feature component
$\boldsymbol{x}$	Feature vector
Ω	Set of fault grades
η	heat transfer efficiency
λ	Deviation
μ	Mean
σ	Standard deviation
σ^2	Variance
ω	Fault grade

subscripts

1	primary side of heat exchanger
2	secondary side of heat exchanger

1 INTRODUCTION

1.1 BENEFITS OF FAULT DIAGNOSIS

Fault detection and isolation (FDI) methods applied in buildings result in several benefits. One benefit is reduced energy consumption. Excessive energy consumption of buildings caused by fouling dampers, sticking valves, drifting controls and other faults may be considerable if the faults are not detected and repaired in time. Besides energy savings other benefits are also obvious. These include: water savings, reduced maintenance costs, lower safety and health risks and increased quality of living.

Generally, a real-time fault detection system can be used to monitor the process in a building and to detect, isolate and even predict faults that may exist or develop in them. In an ideal case, the system should isolate the original fault and issue instructions on how to eliminate it. A natural solution would be to provide a building automation system or an energy management system (BEM) with on-line diagnostic methods and procedures. However, this kind of FDI system has been only partly attained in practice. This is also true for the benefits mentioned above.

1.2 APPLIED PRINCIPLES

Although some diagnostic methods and procedures are already included in automated processes, their extensive and effective utilization has not yet begun. This is also true for processes in buildings. One reason is the lack of robustness of FDI methods. Due to modelling uncertainties and disturbances, the robustness problem is always present in diagnostic systems. Something can be done to alleviate the problems by careful design of the FDI method. Such solutions and suggestions for model-based methods are presented by Gertler (1988), Frank (1994) and Patton (1994). However, the robustness problem concerns not only the diagnostic method but the whole diagnostic system. Concentrating only on diagnostic methods does not solve the problem. Robustness can be partly improved by choosing correct alternatives during system design. These include, for instance, the diagnostic method, the level of automation and instrumentation, the role of the user, etc. The final solution is a compromise which also positively influences robustness. The robustness problem is difficult to solve, but when practical diagnostic methods are targeted, robust solutions must be the first choice.

Besides robustness, pragmatic aspects (Kurki 1995, Steels 1990, Leitch & Gallanti 1992) of the HVAC process and its environment also need to be considered when the objective is practical implementation of FDI. These basic issues are seldom presented in FDI publications, although they definitely have an influence on FDI method development.

A brief definition of a practical FDI system is difficult, but some general, qualitative properties can be stated. A practical FDI system has more or less the following properties. Such a system

- Needs only a few input data submitted by the user.
- Needs only domain knowledge for initiation or updating.
- Adapts easily to new faults.
- Does not disturb normal operation of the process.
- Needs no human assistance during detection or isolation.
- Causes no additional energy/fuel consumption.
- Requires only a short training period/a few training data.
- Applies to many kinds of HVAC processes; generic over processes.
- Applies to many kinds of faults; generic over faults.
- Supports both fault detection and isolation.
- Needs only an uncomplicated process model.
- Is easy to configure to new applications.
- Is easy to embed and integrate in a BEM.
- Requires only a minimum or moderate amount of work/costs for development and implementation.
- Requires no additional instrumentation.

The list is not exhaustive and some aspects may be changed or omitted, depending on the application. However, it is obvious that these requirements can be only partly fulfilled. Some methods follow the design guidelines more carefully than others, but the final solution is still a compromise for all diagnostic approaches. Although the requirements are demanding, it is reasonable to analyze and compare diagnostic methods and systems using the above aspects before proceeding to design and implementation.

1.3 SELECTED APPROACH

This paper presents several FDI methods to be applied in a district heating substation. A starting point for their design is to achieve robustness and to follow the guidelines set by the pragmatic aspects.

Most of the methods are proven by simulating, emulating or field testing. But none of them has been implemented in an automation system or a BEM. So, the following description clarifies concepts, restrictions and requirements of the methods more than their detailed implementation procedures. Although many of the methods are not yet directly applicable in practice, the diversity of approaches illustrates different solutions and reveals diagnostic problems in the district heating environment.

2 DISTRICT HEATING SUBSTATION

2.1 SYSTEM DESCRIPTION

The main function of a district heating substation is to transfer heating energy from a district heating network to a domestic hot water and heat distribution network of a building (Figure 1). Transferring is performed by two heat exchangers (HE1 and HE2). Cooled leaving water is circulated back to the district heating network. The setting for the hot water temperature coming from the district heating network is 115 °C, and for the leaving water, 45 °C. Corresponding settings for the secondary side inlet and outlet temperatures are 70 °C and 40 °C.

Figure 1 presents standard instrumentation of a substation. Besides manual control and monitoring, the instrumentation provides for automated control and supervision of the process. The latter function requires interfacing to a local controller or a BEM. Consumer energy consumption is measured by a separate device (EM) using data from a water meter and a temperature difference measurements between inlet and outlet waters. A mud separating device (mud filter) collects any mud and rubbish that may be present in the inlet water.

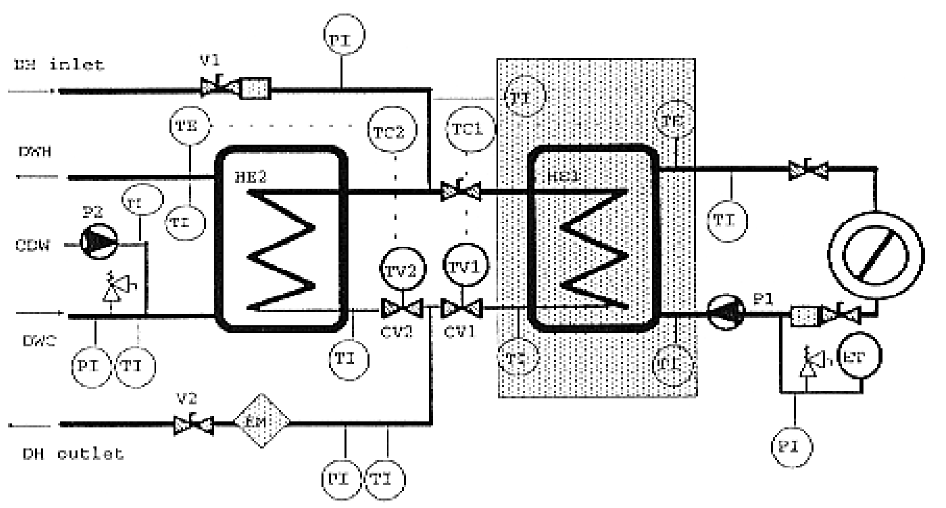

Figure 1. Schematic of a district heating substation.

2.2 DOMESTIC HOT WATER

Domestic hot water temperature is continuously kept at 55 °C. Variations caused by changing load conditions are minimized by a control circuit. This is rather difficult due to the short time constant of the heat exchanger. The instrumentation of the control circuit consists of a temperature sensor TE, a controller TC2 and a control valve TV2, which mixes cold and hot water. A water pump P2 runs day and night, recirculating the water through the domestic water network. Local pressure and temperature instruments PI and TI enable monitoring of the cold water supply.

2.3 HEATING NETWORK

The heat distribution network consists of the components on the right of Figure 1. Besides the heat exchanger, the system includes a radiator network, a circulating pump P1, an expansion tank ET, a pressure relief valve and a control circuit with two temperature sensors, a controller TC1 and a control valve TV1.

The expansion tank is necessary to smooth out the pressure and volume variations in the water due to changing water temperature. Additional pressure relief is possible by means of the pressure relief valve. If the water level of the radiators is low, they are filled with water through a pipe (FI).

The heat supply through the radiator network is controlled by TC1 using an actuator combined with a control valve (TV1) and two measurements, one from the outdoor air and the other from the network inlet temperature. The control strategy differs from the control of the hot water. The set point of the water temperature depends on the outdoor temperature. The measurement from the inlet water is required to keep the outlet temperature at the desired level. Typically, changes in set point values and loads are slow. That is why temperature control of the heating water is uncomplicated.

2.4 TYPICAL FAULTS IN A SUBSTATION

According to Hyvärinen & Karjalainen (1993) the main effort in developing FDI-methods for a district heating substation should be directed to the components: heat exchangers, valves, controllers, actuators, sensors and pipes. Each of these components generates faults characteristic of the component, its function and the surrounding process environment. However, similar components in similar functions give rise to faults which are peculiar to the component regardless of the process. Thus, the mentioned components have typical faults presented in Table 1. A district heating substation consists of over one hundred components. Each of them may have a fault. Emphasis is placed on the listed components because of their assumed high failure rate and their significant role in the operation of the substation.

Table 1. Examples of typical faults found in components of a district heating substation.

COMPONENT	FAULTS
Heat exchanger	- leakage - blockage - dirtiness
Valve	- stuck or binding - failure open or close - leakage
Controller	- drift - bias - hunting - faulty electronics - faulty computer program
Actuator	- shaft seizure or binding - failure open or close - bent or disconnected linkage
Sensor	- bias - drift - poor location
Pipes	- clogging - leakage - faulty insulation

2.5 PROBLEMS IN FAULT DIAGNOSIS OF A SUBSTATION

The structure and operation of a district heating substation is straightforward. However, the environment contains several characteristic features, which make diagnosis difficult. One of them is a poor instrumentation level. Standard instrumentation of a substation is designed only for control and local monitoring purposes, not for automated fault diagnosis. Extra instrumentation means additional cost, which is not acceptable to the consumers. If extra instrumentation is allowed, at most it is one or two temperature sensors or corresponding low-cost instruments. The demand for economical solutions also means that diagnostic methods must be included in local controllers or in BEMs. No separate diagnosis system, parallel to an existing controller or BEM, is allowed.

The consequences of insufficient instrumentation are clearly seen by monitoring the water pressure of the district heating network. The pressure variation is totally unpredictable and changes in the pressure directly effect every piece of equipment in the primary side. Thus, without interfaced pressure measurements, which is a normal situation, modelling of the process is inaccurate and model-based fault diagnosis is demanding.

Some of the typical faults in substation components are difficult to detect. One of them is internal leakage in the hot water heat exchanger. In such a failure, district heating network water is mixed with domestic hot water. Measurable symptoms are minimal and operation of the process seems to be normal. But contamination of the hot water may cause health risks. Another typical fault is accumulation of dirt on the inner surfaces of the heat exchangers. The phenomenon occurs gradually, but can finally cause blockages and a total breakdown of the equipment. Due to the above mentioned problems, these kinds of faults are very difficult to detect. This is the reason why the following FDI methods concentrate only on faults causing distinct and abrupt changes in the operation.

3 CLASSIFICATION OF FAULTS AS A METHOD TO ELIMINATE PROBLEMS OF THRESHOLD ADJUSTMENT

3.1 INTRODUCTION

A typical problem in fault detection is the threshold adjustment. Optimal threshold adjustment is difficult to achieve, which is seen in practice as unreliable or unrobust operation of diagnosis systems, i.e. false alarms or undetected faults. One possible solution to the problem is to classify detected faults in several hazard grades. The benefit is that alarm messages need not be sent too early, if the fault is insignificant. Thus, at least part of the false and unnecessary alarms can be neglected. This kind of performance classifier can operate as an independent fault detector and/or classifier, parallel to another fault detection method, or embedded in a diagnosis system. The method is appropriate for applications in which performance of the process is easily categorized quantitatively and/or qualitatively. Typically it can be used as a supplement to a fault diagnosis system. The method is illustrated by classifying faults of sensory instruments. Further applications are presented in the following chapters.

3.2 PROBLEMS OF THRESHOLD ADJUSTMENT

Every fault detector makes decisions based on some threshold or limit value. Thresholds may be set according to a-priori knowledge but usually they are set by utilizing measured data, gathered during normal operation of the process, and by applying a statistical estimation procedure. Statistical estimation methods do not ensure 100% probability and finite limits at the same time. Degradation or small changes in the process may also effect the probability limits and the thresholds (Pakanen 1992). Sometimes disturbances contain noise components, which are not consistent with the assumed probability density functions. The effect is directly seen on threshold levels.

The proper level of an alarm may also be set by the user. But without good knowledge this easily leads to intuitive adjustments. The result is non-sensitive or even inoperative fault detection caused by too many false alarms and a frustrated user. In addition, threshold adjustment also depends on performance requirements set on the fault detection. If early detection is required the method and limits will differ from fault detection, that is executed over a longer time period. Also, a fault of minimum magnitude needs more effort and different tools than a distinct and abrupt change in process operation.

3.3 INCREASING THE ROBUSTNESS OF FAULT DETECTION

Threshold adjustment is one way to increase the robustness of fault detection. If threshold adjustment is reliable, it has a positive effect on overall fault diagnosis. One alternative for increasing robustness is to apply several independent methods, and thus utilize several threshold levels to detect the same fault. This is identical to increasing analytical redundancy of the detection. If most methods indicate an alarm condition, an actual fault is probable. Another alternative is to apply the user and his/her knowledge in the decision of the possible fault. Then, the fault detection and needed decisions are based on wider knowledge than a single threshold level. But the decisions and actions of the user must be based on real information of the process, not on intuition. Such a solution easily leads to an expert system or to interactive fault tree reasoning (chapter 6).

Threshold adjustment of fault detection has received the attention of many researchers. For example, Halme et al. (1994) proposes a method based on qualitative reasoning and temporal constraints. Frank (1994) suggests threshold adaption using fuzzy logic. Many of the presented methods are based on adaptive thresholds. Patton (1994) gives a survey of several techniques.

The approach presented in this paper differs from those above. The classification concept is based on the performance of the observed signals (Pakanen 1993). In this scheme, fault size is defined according to its effect on process performance, especially on process output. Numerical values given to a performance measure or index allows classification of faults into different hazard grades. This approach is convenient when early detection is not the primary objective. In this scheme, the decision of the fault grade requires monitoring of several limits. But there is no need to accurately adjust them because the hazard grade of the fault is known. Estimation of the hazard grade allows more thorough consideration of the right time of alarm messages, decisions and actions are to be made. This makes it possible to prevent at least some of the false and unnecessary alarms and still maintain sensitivity of fault detection.

3.4 PERFORMANCE INDEX

A central idea in the classification concept is the performance index, denoted as $J_i(\boldsymbol{x})$, which is defined in the following way. Let W = $\{w_1, w_2, ..., w_c\}$ be a finite set of classes, representing fault grades. A classifier finds the best category w_i, i = 1,2,3,...,c for the data, i.e., the most probable fault grade, by computing a discriminant function $J_i(\boldsymbol{x})$, where $\boldsymbol{x}$ is a vector-valued variable. The classifier assigns the feature vector $\boldsymbol{x} = (x_1, x_2, ..., x_d)^T$ to class w_i if

$$J_i(\mathrm{x}) \;>\; J_j(\mathrm{x}),\ \forall\, j \neq i\,. \qquad (1)$$

Each feature component x_j defines a quantitative or qualitative property typical of the fault grade. The performance index $J_i(\boldsymbol{x})$ attaches one numeric or symbolic value for each feature component x_j, which together specify a valid region for the fault grade.

Equation 1 sets only a few requirements for $J_i(\boldsymbol{x})$ and allows numerous ways to realize the function in practice. One alternative is to define $J_i(\boldsymbol{x})$ as a logic function which is consistent with the rule-based programming techniques. If all numeric or symbolic values concerning one fault grade w_i and one feature component x_j are included in a set $S_{i,j}$, then the performance index is easy to represent as

$$J_i(x) \;=\; \begin{cases} 1,\ if\ x_j \in S_{i,j}\,,\ \forall\, j = 1,2,\ldots,d \\ 0,\ if\,\exists\ x_j \notin S_{i,j}\,,\ j = 1,2,\ldots,d\,, \end{cases} \qquad (2)$$

where number 1 denotes a value true and 0 a value not true. According to the equation 1, only one of the performance indices $J_i(\boldsymbol{x})$, i=1,2,...,c can have the value true each time.

The performance index can be set to any or all monitored signals of the process. But process output is a natural alternative because targeted performance and allowable fluctuation of the output are usually defined during system design.

3.5 FEATURES

Each fault category contains features which are characteristic to the process and the application. Feature selection is based on a-priori knowledge of the observed process. Features can be quantitative or qualitative in character. A process with one continuous output $y(t)$ might have features concerning the size of deviation, average frequency of fault appearance and duration of failure. Similarly, limits can be set for required minimum activity of $y(t)$ during a prescribed time period, or tolerances of dy/dt, i.e. derivative of $y(t)$. A controlled process signal might provide features like magnitude of overshoot, settling time and number or existence of overshoots. The last one represents an example of a qualitative feature.

3.6 PRACTICAL FAULT GRADES

In practice, the number of fault grades must limited to a few categories. If faults are classified in three hazard grades, they would be: *tolerable*, *conditionally tolerable* and *intolerable* faults (Isermann 1984). A tolerable fault means that the operation of the process can continue but an indication of an exceptional situation is recorded. Process output is slightly changed but performance of the process is still satisfactory. It is not known whether the change in the operation is due to a disturbance or a fault. A conditionally tolerable fault requires a change in the operation. Clearly, a failure has occurred and the operating time of the faulty process is limited. Performance of the output is somewhat degraded, which cannot be tolerated for a long time. The fault is reported to the operator. If the fault is intolerable, the operation is stopped or radically changed, if possible and an alarm message is immediately sent to the operator.

3.7 APPLICATION OF THE PERFORMANCE CLASSIFIER

The classification concept described above is not a conventional fault detection method. The primary intent is to classify performance of the process. But when the size of a fault is defined according to its effect on prescribed, measured signals of the process, then the confirmed hazard grade also helps in fault detection and fault size evaluation. Figure 2 presents a case where the performance of the process output is measured using the procedure. The method *operates independently* as a fault detector/classifier.

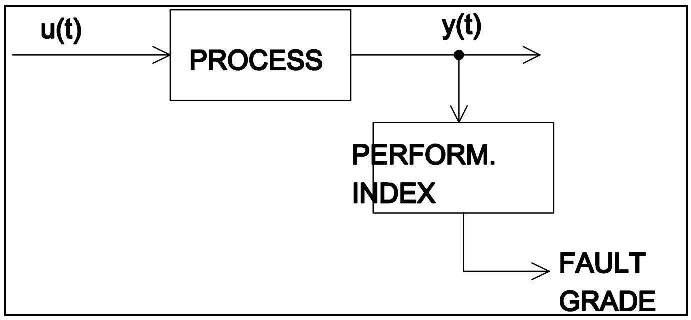

Figure 2. Performance monitoring and classification of a process output as an independent operation.

The performance classifier can also *operate parallel* to a conventional fault diagnosis method. In this case, the procedure serves as a supplement to the diagnosis, because it is able to evaluate the size of the detected and isolated fault. This is a common objective of fault diagnosis, but it is rarely achieved in practice. Figure 3 illustrates a case where performance monitoring and fault classification operates parallel to a model-based fault detection system. The residual *r(t)* makes it possible to indicate the type of the fault and its occurrence time while the performance classifier reveals the size of the fault.

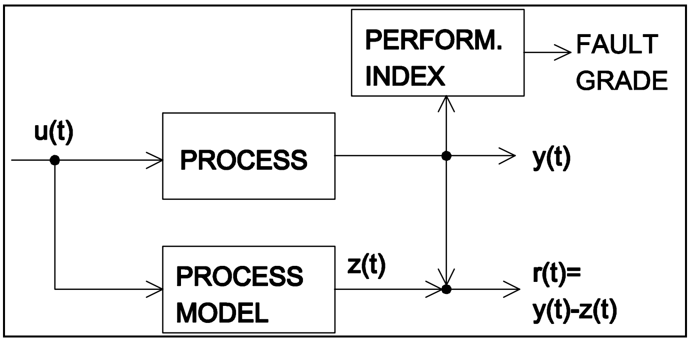

Figure 3. Parallel operation of a performance classifier and model-based fault detection.

A third alternative for using the performance classifier is *embedded operation*. In this case, the indexing procedure is hidden in a fault diagnosis system. Figures 4 and 5 present an example of a pattern recognition system, which is applied in fault diagnosis of input signals $u(t)$. Recognition requires learning of fault features from the input signals. As shown in Figure 4, all extracted features are combined with a performance measurement of the output $y(t)$. Then, the classifier can link a fault to its effect on the process output, i.e., the fault grade. After the learning phase, faults and their hazard grade in the input $u(t)$ are directly detected and classified without the performance classifier, as shown in Figure 5.

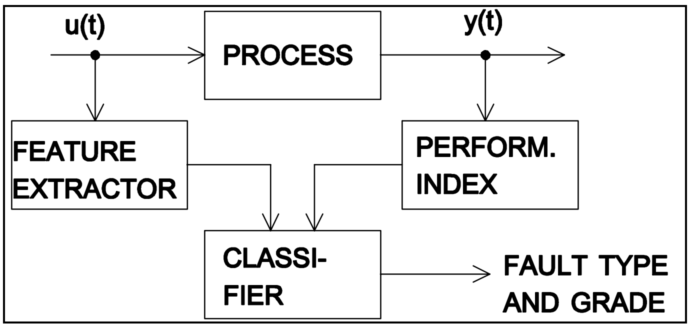

Figure 4. Learning phase of a pattern recognition system combined with a performance classifier.

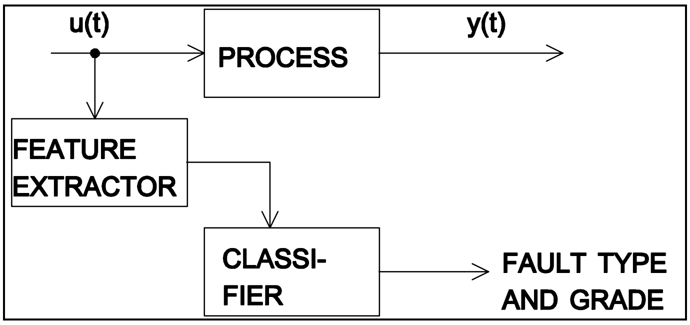

Figure 5. Fault detection and classification of a pattern recognition system with embedded performance indices.

3.8 AN EXAMPLE: FAULT DETECTION OF SENSORY INSTRUMENTS

System description

The following example concerns fault detection of sensory instruments of an HVAC controller. Analog signals coming from the sensors are analyzed and possible faults are detected using performance index methodology.

Sensors and their interface to a controller may contain several types of faults. Typical is a loose or broken contact or connector, which may cause a sudden and large change in the measurement signal of a resistive sensor. The phenomena can be temporary or irregularly repeated. A cold solderjoint or corrosion may change the scale and cause larger instabilities in the measurement. External inductive or capacitive noise, which may be temporary or permanent, cumulates as noise of variable magnitude in the measurement. Aging or the temperature of the surroundings are often the reason for drift in the measurement signal. The proposed method is planned to detect all these faults except the last one, which is usually found during calibration of the measurement.

Features

The sensory instrument produces an analog signal which is continuously monitored. The signal is assumed to go through several tests, which extract certain features and their proportional magnitudes. The features together form a feature vector ***F***. The following features described by feature variables are included:

Size of deviation (x_1)
duration of fault (x_2)
Average frequency of fault appearance (x_3).

A definition of each feature is given later in this chapter. Thus, the feature vector of the faults is defined as $\boldsymbol{F} = (x_1, x_2, x_3)^T$. The problem is to partition the three-dimensional feature space into regions where all the points in one region corresponds to one fault grade. Similarly to fault grades, the regions of feature variables are also qualified in three categories, which describe their magnitude or intensity. Although the feature category may have a qualitative name, the limits of each region will be specified quantitatively.

The size of deviation (x_1) could be partitioned like the other features. However, the following partition, which comes from natural behavior of the input signal, is applied. In this scheme, the size of deviation includes three type of limits on both sides of the signal. The closest limit is called the dynamical limit U_d which is given as a result of signal prediction. The analog signal is first modelled with an ARMA-model, which combines both deterministic and stochastic features of the signal in one model. The model is identified during the normal operation period and then applied as a predictor. A *k*-step predictor is written as

$$\hat{u}(t+k/t) = -\sum_{i=1}^{m} c_i \hat{u}(t+k-i/t-i) + \sum_{i=0}^{m-1} g_i u(t-i) . \qquad (3)$$

At time t the above equation gives the predicted value of the real signal $u(t+k)$, where k is the number of sampling periods. The dynamic limit of the signal is achieved when a probability limit is calculated for the prediction. For example, when the 95% probability limit is applied

$$U_d = \hat{u}(t+k/t) \pm 1.96\sigma\sqrt{1 + f_1^2 + f_2^2 + \ldots + f_{k-1}^2} \qquad (4)$$

where f_k is a coefficient of a polynomial related to the ARMA-model.

The saturation limit U_s describes the extreme values of the sensory signal when the output quantity of the controller gets its physically realizable maximum or minimum value. Similarly to the dynamic limits, the saturation limits locate both sides of the signal as an upper and lower limit. The dynamic limits are usually closer to the real signal than the saturation limits. For analog measurement signals, the saturation-limits are prescribed using a-priori information or a test sequence of the process.

The absolute limit U_a is the extreme value of the sensory instrument where analog measurements give sensible results. The absolute limit may be located far away from the other limits. The absolute limits are defined from the characteristics of the sensory instruments and an A/D-converter of the controller. The absolute limit and the preceding limits are normally related as

$$U_{a\,\max} > U_{s\,\max} > U_{d\,\max} > U(t) > U_{d\,\min} > U_{s\,\min} > U_{a\,\min} \qquad (5)$$

The duration of the fault (x_2) combined with the size of the deviation effectively indicates the character of the fault. A small deviation of a short period may be filtered out, but larger and longer ones can cause damage to the system. The duration of the fault is defined as the time period during which the signal exceeds one of the above specified limits during consecutive sampling instants.

In order to relate the duration of the fault to the corresponding hazard grades, one must use both a-priori information and experimental results. Abnormal deviation of the analog measurement signal has an effect on the output or the main function of the system. When noise of variable variance and duration in the input is added their common effect on the output can be categorized in the three hazard grades previously mentioned. These kinds of experiments could be performed by the manufacturer of the controller.

The average frequency of the fault appearance (x_3) is also a meaningful feature. A rarely appearing short deviation in the measurement, exceeding the low limit hardly causes any trouble to the system. It can be assumed to be cumulative random noise and is easy to filter out. If it appears frequently, the situation is different. In this case, it may refer to a loose or broken connection. The average frequency of fault appearance, and the size and duration of the deviation are closely related to each other. That is why determination of frequency limits for different hazard grades must be performed together with the other limits.

An illustration of classification

Tables 2, 3 and 4 illustrate a case where three type of faults are classified according to the features and their values. The tables illustrate the way how the results of classification could be presented. They are not based on any real data or measurements. The intensities of each feature in the tables are described qualitatively but in practice all categories must also be defined numerically. They are prescribed during the preliminary tests. The tables form a three-dimensional system that defines the class of the fault in all grades of intensities of the features.
When the fault is classified the system can choose the necessary actions to be taken after fault detection. A tolerable fault is perhaps not a good reason to send an alarm message to the user, but the time of appearance and the class of the fault may be worth recording. A conditionally tolerable fault may require some actions to be taken in addition to the alarm message, and an intolerable fault could stop or change the operation of the process.

3.9 SUMMARY

Classifying faults into several hazard grades gives new possibilities of avoiding false alarms, because fault detection is not based on one threshold level. The three hazard grades: tolerable, conditionally tolerable and intolerable fault permit more thorough estimation of the effect of the fault on the process and the right time to send an alarm message. The classification concept is based on the performance index, which can be set to any or all monitored signals of the process. The procedure based on performance indexing can operate independently as a fault detector/classifier, parallel to another fault detection method, or embedded in a diagnosis system.

Table 2. Classification of a fault according to the three types of features. Frequency of the fault appearance low.

Size of deviation	Fault of very short duration	Fault of short duration	Fault of notable duration
Exceeding absolute limit	conditionally tolerable	intolerable	intolerable
Exceeding saturation limit	tolerable	conditionally tolerable	intolerable
Exceeding dynamical limit	tolerable	tolerable	conditionally tolerable

Table 3. Classification of a fault according to the three types of features. Frequency of the fault appearance moderate.

Size of deviation	Fault of very short duration	Fault of short duration	Fault of notable duration
Exceeding absolute limit	intolerable	intolerable	intolerable
Exceeding saturation limit	conditionally tolerable	intolerable	intolerable
Exceeding dynamical limit	tolerable	conditionally tolerable	intolerable

Table 4. Classification of a fault according to the three types of features. Frequency of the fault appearance high.

Size of deviation	Fault of very short duration	Fault of short duration	Fault of notable duration
Exceeding absolute limit	intolerable	intolerable	intolerable
Exceeding saturation limit	intolerable	intolerable	intolerable
Exceeding dynamical limit	conditionally tolerable	intolerable	intolerable

4 FAULT DETECTION METHOD FOR SUB-STATION PRIMARY FLOW ROUTE AND CONTROL VALVE

4.1 INTRODUCTION

In this section, a method is described that was developed as a part of technical work carried out for developing fault detection methods (Hyvärinen 1994a, Hyvärinen 1994b) for two typical heat production units: district heating subdistribution system (Hyvärinen & Karjalainen 1993) and oil burner (Hyvärinen et al. 1993). The method is based on a simple physical first principles static process model and on the use of analytical redundancy (Frank 1990) of the system under consideration. In other words, the redundancy contained in the static relationships among the system inputs and measured outputs is exploited for fault detection. The procedure of evaluation of the redundancy given by a mathematical model of some system equations can be roughly divided into two steps: generation of residuals, and decision and isolation of the faults. Here the residuals are generated based on static parallel model approach, and on parameter estimation approach in which the consistency of the mathematical equations of the system is checked by using actual measurements. Because of the static process model, direct redundancy relations can be used. The decision is based on a simple threshold. The cause of the fault can be diagnosed based on parameter estimates of the process.

The main emphasis in the development work has been on simplicity and on practical rather than on theoretical aspects of the method. The reason for this is that it is assumed that in the near future field level application specific controllers will be capable of simple diagnostic tasks but with limited computational recources only. For example, the computational speed, numerical and measurement accuracy, and amount of memory are limited for practical and, in the end of the day, for economical reasons.

Practical application of a fault detection method requires that the model structure is known and its parameters can be estimated reliably. Also it is required that the threshold values and parameter deviations from their nominal values for fault detection can be determined before the method is taken into use. For these purposes and especially for processes with linear control valve least squares estimation algorithms provide a good methodology and applying the method is quite straightforward. For processes with exponential control valve also the unlinearity must be modelled before the required model parameters and threshold values can be solved.

4.2 OUTLINE OF THE PROCESS AND THE METHOD

The simplified process can be approximated to consist of control valve and a flow route the flow of which the control valve affects (Figure 6). The control valve represents a varying flow resistance. The flow route consists of a pipeline and other components, and it represents a constant flow resistance. The process is connected to an outside network which generates the pressure difference over the process. In an oil burner the pressure is generated with an oil pump in the burner, and in a district heating subdistribution system the distribution network can be seen as a constant pressure source.

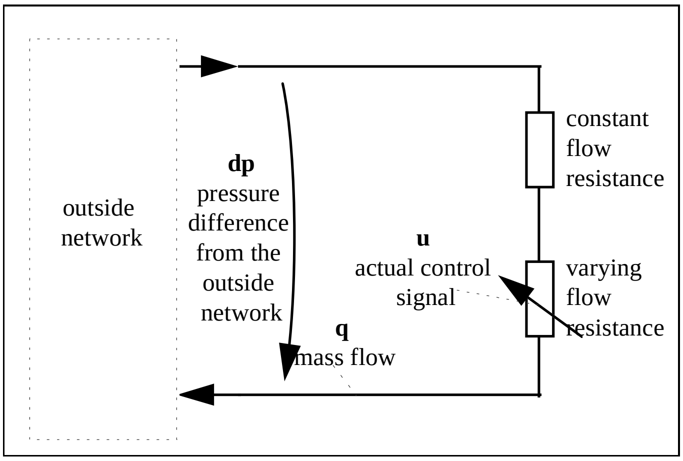

Figure 6. Electrical circuit analogy of the flow route and control valve.

The control valve can be described as a flow resistance the value of which changes as a function of actual control signal. The structure of the function of the varying flow resistance is usually known for each specific valve and it is typically characterised either by exponential or linear valve equation. In case of water or oil as media the process is fast and it can be considered to be in a steady state condition all the time. The process dynamics need not to be considered.

The basic idea of the method is to use a process model that relates the three variables: pressure difference *dp*, mass flow *q*, and actual control signal *u*. Process faults can then be detected either by calculating one of the process variables from the others, and comparing the calculated value to actual measured value, or by estimating the process model parameters and comparing them to nominal values. The threshold values and nominal parameter values are estimated from a non faulty process condition.

4.3 FAULT DETECTION METHOD

Process model

The flow and pressure equations of the simplified subprocess are

$$q^2 = kv^2 * dp_v \tag{6}$$

$$dp = dp_s + dp_v \tag{7}$$

$$dp_s = Z_s * q^2 \tag{8}$$

where Zs is constant flow resistance of the heat exchanger and pipeline
The dependency of the valve kv-value from the shaft position in general can be modelled with the following equation

$$kv = kv_c * g(u) \tag{9}$$

where the function *g(u)* describes the valve unlinearity.

Applying equations 7, 8 and 9 to 6 the following equation is obtained

$$\underline{q^2} = kv_c^2 * \underline{g(u)^2 * dp} - kv_c^2 * Z_s * \underline{g(u)^2 * q^2} \tag{10}$$

and further when arranging for $g(u)^2$

$$g(u)^2 = \frac{q^2}{kv_c^2 * dp - kv_c^2 * Z_s * q^2} \tag{11}$$

Taking a derivative of 10 with respect to *u* and supposing that *dp* does not change as a function of *u*, the following equation is obtained.

$$\frac{\partial q^2}{\partial u} = kv_c^2 * dp * 2 * g(u) * g'(u) - kv_c^2 * 2 * g(u) * g'(u) * Z_s * q^2 - kv_c^2 * g(u)^2 * Z_s * \frac{\partial q^2}{\partial u} \tag{12}$$

If the valve unlinearity is characterised with the following equation

$$g'(u) = C * g(u) \tag{13}$$

the equation 12 can the be presented as below

$$\frac{\partial q^2}{\partial u} = kv_c^2 * dp * 2 * C * g(u)^2 - kv_c^2 * 2 * C * g(u)^2 * Z_s * q^2 - kv_c^2 * g(u)^2 * Z_s * \frac{\partial q^2}{\partial u} \tag{14}$$

By applying equation 11 to 14 and solving it with respect to $dp*d(q^2)/du$ the following is obtained

$$\underline{dp*\frac{\partial q^2}{\partial u}} = 2*C*\underline{q^2*dp} - 2*C*Z_s^2*\underline{q^4} \qquad (15)$$

Now, equations 10 and 15 form the equation set that models the subprocess. In case of a linear valve is utilised instead of an unlinear one, equation 10 alone forms the model. The underlined parts represent signals that are measured and calculated from process signals and the other parts represent model parameters that are estimated during tuning and operation phase.

Unlinear valves that fulfils the requirement of equation 13 are, for example exponential valves characterised with following equations.

$$g(u) = e^{n_e * u} \quad C = n_e \qquad (16)$$

$$g(u) = \left(1 - \frac{n_p}{100}\right)^{(100-u)} \qquad C = \ln\left(1 - \frac{n_p}{100}\right) \quad (17)$$

where n_p and n_e are manufacturer specific parameters used to describe the unlinearity.

Finally the subprocess model is

$$q^2 = \frac{kv_c^2 * g(u)^2 * dp}{1 + kv_c^2 * Z_s g(u)^2} \qquad (18)$$

Table 5. The process quantities that have to be measured.

quantity	computation/ measurement	unit	meaning
dp	PI1-PI2	kPa	pressure difference
q	FI	m^3/h	water volumetric flow
u	TV	%	valve shaft position

Often, the valve position is not measured and only the control signal value is known. This causes extra work during the tuning of the method because the valve shaft position as a function of control signal must be modelled. The control signal value from the controller can not be used in place of shaft position because the control signal changes stepwise and position rampwise and there is a difference between these two signals. The valve position must be used instead.

The measured values (Table 5) must be instantaneous values and they may not be filtered or averaged in any way. The sampling time does not play any role. It can be of varying length and chosen arbitrarily. The signals (underlined terms) in equation 10, however, can be filtered with any linear filter. They can, for example, be cumulated over some time interval.

Method description

Process faults can be detected either by using a model output error (Figure 7) or parameter deviations from their nominal values (Figure 8). The model output error is the residual between the model output, q^2 , given by equation 18, and the actual measured value. If the parameter deviations are used for fault detection the parameters of equations 10 and 15 are estimated periodically and compared to those estimated during tuning phase.

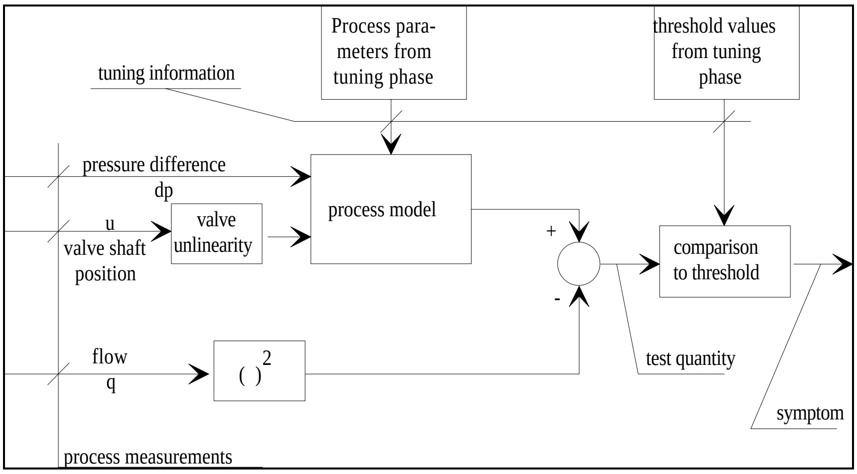

Figure 7. *Block diagram of the output error method.*

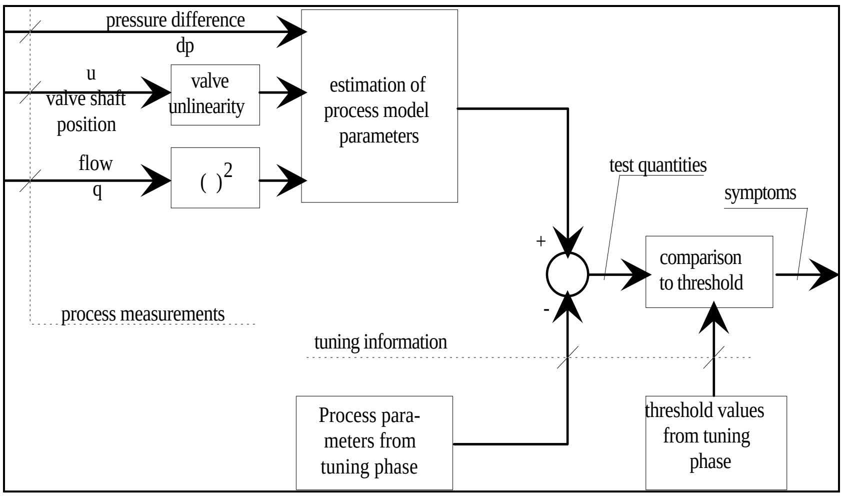

Figure 8. *Block diagram of the parameter error method.*

The square of flow given by equation 18 is compared to the square of the flow measured and calculated from the process. The value of the function *g(u)* is calculated using equation 20 or 21. The parameter values of equations 10 and 15 and the threshold values for fault detection are estimated during the tuning phase and fixed during the operation phase.

When parameter deviations are used for fault detection, the parameters of the process model (equation 10) are estimated periodically and the results are compared to values estimated during the tuning phase. The parameters of the model describing valve unlinearity (equation 15) are estimated only during tuning phase and are fixed during normal operation period.

If the subprocess is linear i.e. there is no such a component that causes some unlinear feature like the unlinear valve does, then the parameters can be estimated on-line instead of periodical estimation.

The method is tuned following the steps below

1. Measuring the tuning data
2. Prehandling of the measurement data
3. Parameter and threshold value estimation.

It is important that the input signals to the process vary in a large enough area i.e. the input signals must be exciting enough. It would be best if each of the normal operation point could be measured during the tuning phase for a long enough time. For practical reasons this is usually not possible and the tuning must be done with less information. The process is assumed to be in non-faulty condition during the measurement of tuning data. The method is “taught” the non-faulty operation of the process during tuning phase. When, at the operation phase, the measured process operation deviates from the taught (modelled) operation, it can be assumed that there is a fault in the process.

In the DHS, the valve control signal can be varied freely. One has to take care that no harm is caused to the other parts of the process or user. For example, the domestic hot water temperature may not rise too high if the water is used during the tuning period. The control signal should be varied between 0 % and 100 % if possible. The changes should be slow enough so that the valve actuator and real position of the valve have enough time to travel to each operation point.

The pressure difference over the subprocess can not be affected by the operator. The pressure difference varies according to the heating load of the external district heating network. At a minimum, one should get measurement data for one pressure difference value over all the valve position values.

During the tuning and operation phases only unfiltered raw data are utilised. Outliers should be removed if possible. Also those operation points where the process has clearly operated erroneously should be removed. For example, in a near open and close situation the process may saturate due to erroneous tuning of the actuator causing erroneous information of the process operation.

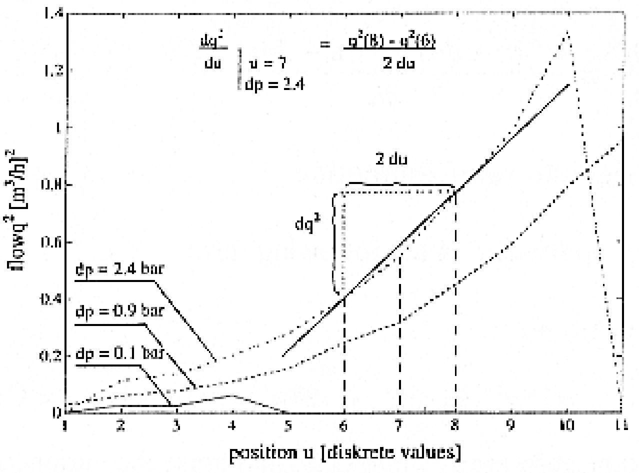

Figure 9. Process characteristic curves and calculation of partial derivative of q^2 with respect to valve shaft position.

In equation 15 the output signal (regressed variable) is the partial derivative of the square of flow with respect to the valve position. Solving this on-line from measurements is sensitive to measurement noise which causes the result to be unreliable. For this reason the partial derivative is calculated off-line from a characteristic curve of the process (Figure 9).

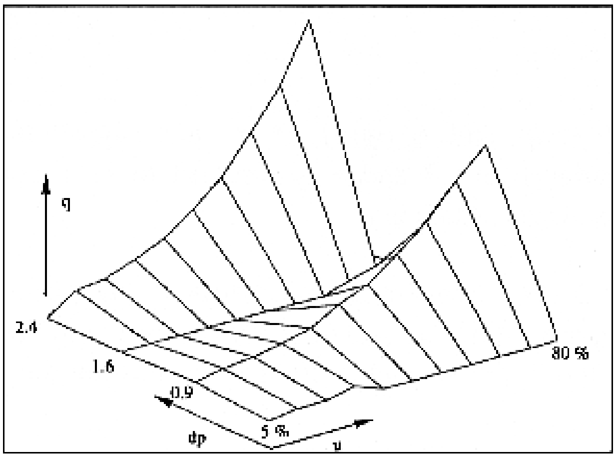

Figure 10. Process characteristic curves of figure 8 plotted as a surface (mesh-plot). The flow value remains in zero at dp value 1.6 because there has not been any measurements at that value. In reality the value of q increases continuosly with value of dp.

A characteristic curve is formed from the process (Figures 8 and 10), in which the valve position u is on the x-axis and square of the flow on the y-axis. The different curves in Figure 8 are isoclines having different values of pressure difference. The partial derivative is calculated for each discretized position of *u* on each isocline curve using the following equation.

$$\frac{\partial q^2}{\partial u} = \frac{q^2(u + du) - q^2(u - du)}{2 * du} \qquad (19)$$

Parameter and threshold value estimation

Equation 15 can be represented in the following form

$$y = x_1 * a_1 + x_2 * a_2 + e \qquad (20)$$

where $y = dp \frac{\partial q^2}{\partial u}$, $x_1 = 2*q^2*dp$, and $x_2 = 2*q^4$ are signals a_1 = C and a_2 = $-C*Z$ and $\boldsymbol{e}$ is assumed to be zero-mean white Gaussian noise the variance of which is λ^2

The parameter values a_1 ja a_2 are estimated using least squares method (Söderström 1989). Using parameter a_1 the parameter describing the valve unlinearity n_e or n_p can be solved.

Because the partial derivative of square of the flow is solved from a characteristic curve the parameters must be estimated off-line. Furthermore, the estimation result is better if the averages are removed before the estimation. This, too, requires an off-line estimation method to be used.

Equation 10 can be represented in the following form

$$y = x_1 * b_1 + x_2 * b_2 + e \qquad (21)$$

where $y=q^2$, $x_1 = g(u)^2*dp$, and $x_2 = g(u)^2 * q^2$ are signals b_1 and b_2 are parameters, with covariance of P and *e* is assumed to be a zero-mean white Gaussian noise the variance of which is λ^2

The parameter values b_1, b_2, their covariance matrix *P*, and the estimate of the variance l^2 of noise *e*, are estimated using the least squares method. In this case, too, the result is better if the averages are removed from the signals before estimation.

It is not possible to choose a threshold value for fault detection that gives 0 % false alarm rate. The thresholds are chosen in such a way that an alarm does not necessarily mean a fault but may be caused by normal measurement noise, too. After an alarm occurs, it must be decided if the alarm is caused by a fault.

Fault detection method output is the residual between subprocess model and corresponding measurements. As a threshold for this residual a value calculated from the variance l^2 of the noise *e* is used. The threshold values are chosen in the same way as in case of oil burner.

Applying the method requires reasoning in two ways. Firstly, the way the threshold values are selected does not guarantee a 0% false alarm rate and thus the decision of the fault situation must be done for example using a classifier presented in chapter 3. Secondly, the method produces a set of test quantities the changes of which indicate some faults in the process. The test quantities that can be used in addition to the residual, are the parameters a_1, a_2 , b_1 and b_2.

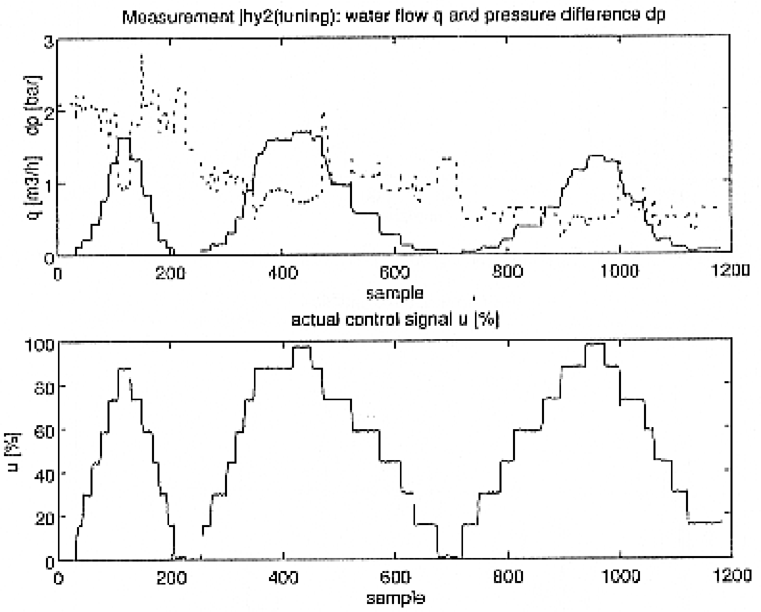

Figure 11. DHS Tuning data.

4.4 RESULTS

The tests shown in Figure 11 were done with the subprocess to tune the model parameters. The measurements were used to build the characteristic curve, and for parameter estimation. In the upper half of the figure both the flow (solid line) and the pressure difference (dashed line) are presented. In the lower half of the figure the valve shaft position is presented.

Figure 12 shows the simulated square of the flow (dashed line), the corresponding value calculated from the measurements (solid line), and the confidence limits. Only those operation points are included where the valve position has been in the interval of [5% - 80%]. The simulation model of equations 16 and 18 has been used and parameters shown in Table 6 were obtained. The error of the simulation is shown in Figure 13.

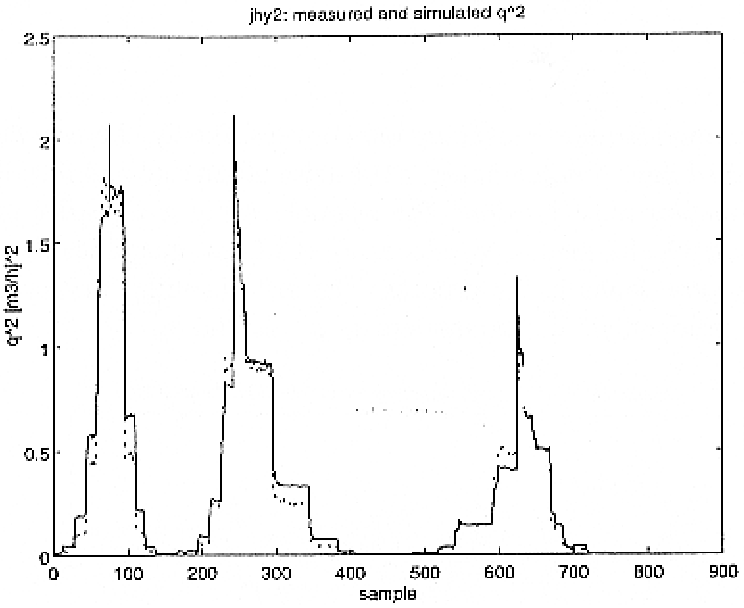

Figure 12. Simulation of q^2. Simulation done with tuning data.

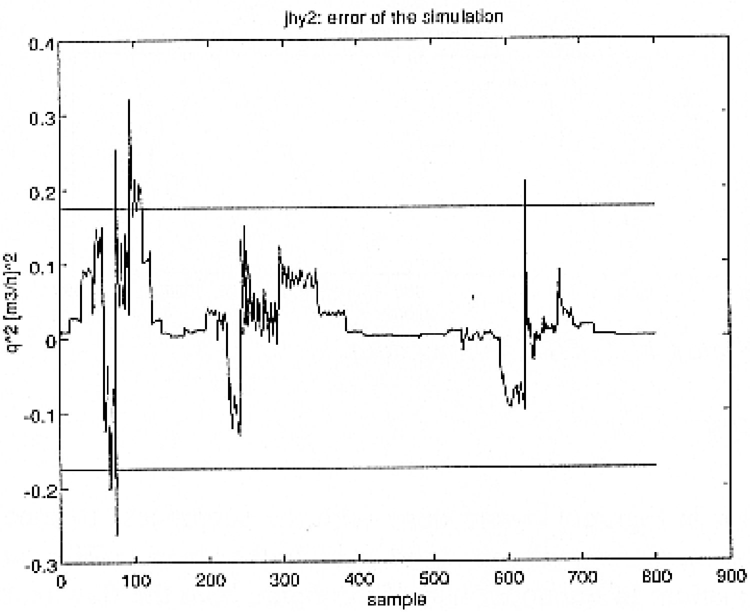

Figure 13. Error of the simulation using tuning phase data.

The results of applying the method to a non-faulty process are shown in Figures 14 and 15. In 14 simulated (solid line) and measured (dashed line) q^2 are presented. In Figure 15, the model residual (i.e. the error between measured and simulated process output) and its thresholds are presented. In the testing phase, only those measurements where the actual control signal remained in an interval of [5% - 70 %] were taken into account. The other measurement values were considered to be out of the valid area of the method.

Table 6. Parameter estimates obtained from tuning phase.

Equation 20	
b_1 b_2	1.0e-3*0.3528 0.1054
λ^2	0.0046
P	1.0e-9*0.65 0.67 0.67 0.71
n_e	0.0558

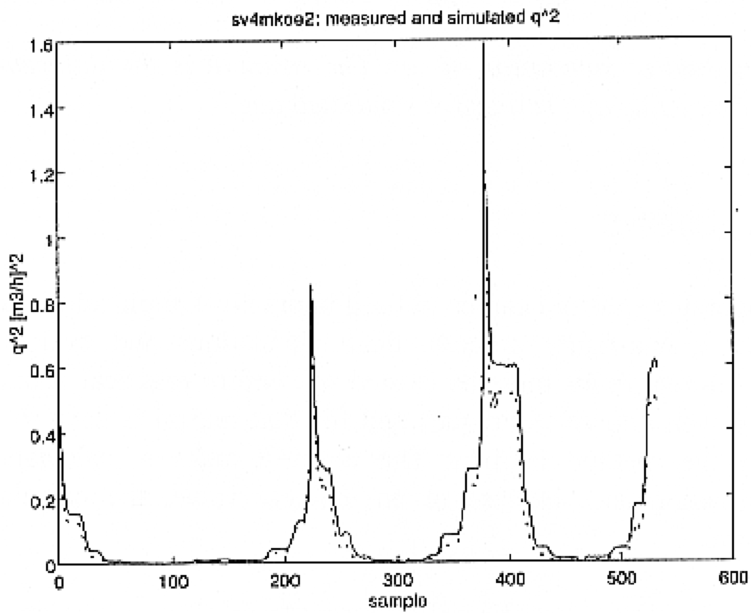

Figure 14. Simulation of q^2 using testing phase data.

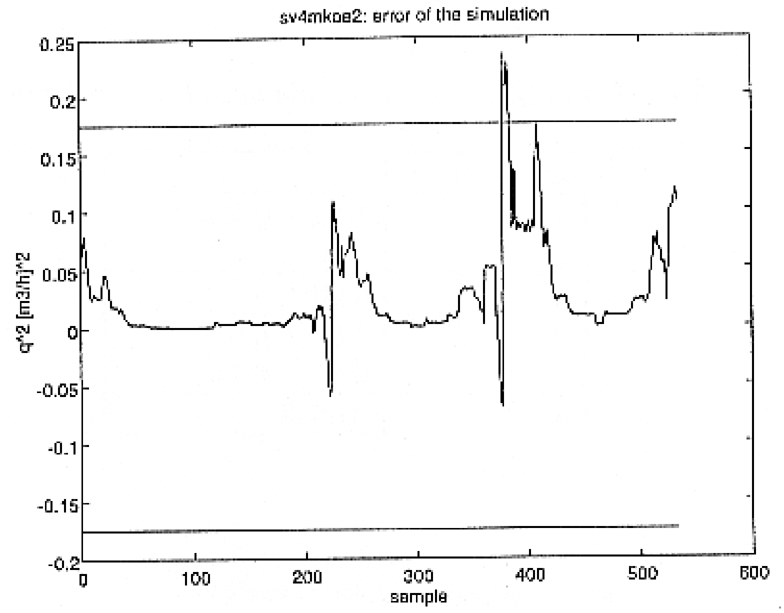

Figure 15. Residual of simulation of q^2. *The residual is the difference between measured process value and respective simulated one.*

4.5 CONCLUSIONS

The method operates well and can be utilised in practical applications according to test results for a non-faulty process. Fault simulations and evaluation of the sensitivity to different faults must be carried out before practical application. The method utilises well known techniques and for that reason is easy to implement. Calculationally the method is light. The heaviest tasks in calculation are the parameter estimation and, in case of an unlinear valve, the calculation of an exponential term.

The method copes with a specific unlinear processes. The unlinearity assumed is typical in district heating systems and in HVAC applications. The unlinearity causes the performance of the method, if measured in terms of output error whiteness, to decrease, and the complexity of the method to increase. With a linear valve the method gives better results is less complex, and needs less calculations and memory.

The method does not give 0% false alarm rate but requires an additional classifier to make the decision whether the alarm is caused by a fault or not. The Method produces several test quantities, which all can be used in diagnosing the fault or in improving the fault detection. By combining the information from different test quantities the method gives relatively fault selective information of the process operation.

5 FAULT DETECTION METHOD OF A HEAT EXCHANGER

5.1 INTRODUCTION

The aim of this paper is to describe one approach to detecting a leak in a heat exchanger. Leakage is chosen as an example because it is one of the most common faults and has an obvious effect on the operation of the heat exchanger. This method is based on continuously evaluating the heat power difference between the primary and the secondary side of the heat exchanger. The method is based on both steady state and dynamic models.

5.2 DESCRIPTION OF THE METHOD

Process

The process being examined is limited to heat exchangers and temperature sensors of district heating subdistribution system (Figure 1). Therefore the method depicted, which is based on the heat power balance, is limited to the diagnostics of faults occurring in heat exchangers and temperature sensors. This method is applicable to the operation of heat exchangers for heating and for domestic hot water heat exchangers. Here, only one heat exchanger is examined. The operation of the district heating subdistribution system is shown by Hyvärinen & Karjalainen (1993).

Faults detected by the method

The heat power balance method for a heat exchanger calls for flow measurements which are generally not installed in district heating subdistribution system (Figure 1). These flow measurements are substituted by other components' such as control valves' and pumps' characteristic curve methods or using some more economical measuring method than flow measurement, such as measuring the pressure difference over a constant flow resistance. This way the number of faults found by the method increases. Using only the exchanger's heat balance method, the following faults can be identified:

a) An internal or external leak in the heat exchanger.
b) The malfunction of a temperature sensor.

This method does not isolate a faulty component or direct the user to corrective steps; instead, it only detects the fault or sends the information to the reasoning system installed in the building's upper level automation system.

Calculation model of the method

This method is based on the continual observance of the heat exchanger's calculated static heat power balance (Q_2 = hQ_1). The heat exchanger's primary flow transfers heat through the heat surface to the secondary flow. Part of this heat is transferred through the heat exchanger's casing into the environment. This heat loss is taken into account in a heat transfer efficiency h (equation 22). The heat transfer efficiency is supposed to be constant all the time, which is not exactly correct. Nevertheless, the heat loss is insignificantly small in an insulated heat exchanger. The heat exchanger's primary and secondary heat power is calculated using measured or calculated flows from other models and with the help of measured temperatures (equations 23 and 24). The operating point of the heat exchanger under varying conditions causes errors in the stady state calculation model. It has been attempted to reduce the error by changing the static model of the heat power balance to an dynamic ARX-model (equation 25). Figure 16 shows the principles of the calculation model of the method.

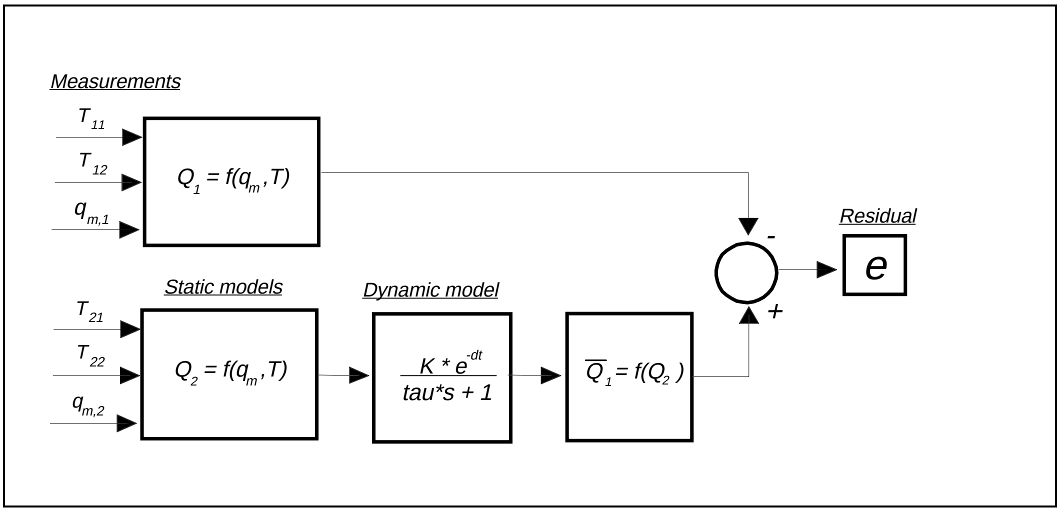

Figure 16. The calculation model of the heat power balance method. Subindex 1 corresponds to the heat exchanger's primary side, and 2 to the secondary side.

The dynamic model is used to calculate the primary side's heat power from the secondary side's heat power while taking into account the varying conditions of the heat exchanger and the slow response of the measuring devices. The heat loss into the environment is included in the dynamic ARX-model's parameters *a* and *b* (equation 25), which in the tuning phase of the method are determined from the heat powers of the primary and secondary side which are calculated with the static model by means of the least squares method. In the steady state conditions the constant heat transfer efficiency is determined from the dynamic model's parameters ($\eta = (1-a)/b$). Based on experience of the measurements the heat transfer efficiency can also be over one because of inaccurate of the measuring devices and the calculated fluid properties. The determined heat transfer efficiency indicates also how successful the parameter's tuning has been. For example, the typical heat transfer efficiency varies between 0,9 - 1,0. In continuously monitoring the operation of a heat exchanger, the relative error of the heat power of the calculated primary side and the heat power determined from the measurement quantities are compared (equation 26).

Static models:

$$Q_1 = \frac{1}{\eta} Q_2 \tag{22}$$

$$Q_1 = q_{m,1} c_{p,1} \Delta T_1 \tag{23}$$

$$Q_2 = q_{m,2} c_{p,2} \Delta T_2 \tag{24}$$

Dynamic models (k = sample time):

$$\overline{Q}_1(k) = a\overline{Q}_1(k-1) + bQ_2(k) \tag{25}$$

$$e(k) = \frac{Q_1(k) - \overline{Q}_1(k)}{Q_1(k)} \tag{26}$$

The heat power balance error e (residual), is thus the relative error of the primary side's heat power calculated using two different approaches, and in the continuous state of an unimpaired process it is approximately zero. In a fault situation the error in the heat power balance diverges more from zero than the predefined alarm limits, and the user is accordingly warned of the fault.

Measurements

Figure 1 shows typical measurements of a district heating subdistribution system. The heat exchanger's power balance method needs additional primary and secondary flow measurements. If the flow measurements are replaced by the calculation models of other components (i.e., control valve and pump) the method can examine the operation of more components than before.

Although the flows are replaced by the calculation models of other components, the flows must also be measured at the tuning phase. This way the flows calculated from the model can be compared to the actual flows and the heat exchanger's dynamic computation model can be tuned using the actual flows for calculating the heat powers. The flow can be measured in the tuning phase by using ultrasonic measurements, for example.

The sample measurement data should be an instantaneous value. The test interval should be sufficiently frequent (< 5 seconds) if the model is to perform satisfactorily in the changing conditions of the process. It does not matter how frequently samples are taken while observing continuous operations.

5.3 THRESHOLD CALCULATION

It is not possible to define a threshold for the faulty process using analytical methods to attain a zero per cent rate of false warnings. The thresholds for the process must be selected in such a way that when a quantity describing a malfunction exceeds the limit selected, this does not necessarily imply a malfunctioning of the process, since instead the exceeding may be due to measurement noise or to some other statistical phenomena. After the threshold has been exceeded, it must be deduced how significant the exceeding is and whether the exceeding has caused by the faulty process. This is determined by a reasoning system.

The threshold for the error of the heat power balance method is calculated in the tuning phase of the method, while the dynamic model's parameters *a* and *b* are defined using the least squares method. The threshold *th* is determined by means of equation 27 as the product of the deviation η of the relative heat power balance error (Figure 16) and the selected coefficient k_r.

$$th = k_r * \lambda \qquad (27)$$

While the heat power balance is at its normal distribution, the coefficient k_r can be used, for example, to calculate the thresholds of the following heat power balance error's reliability limits:

k_r = 1,65 -> 90% of the calculated values within the thresholds
k_r = 1,96 -> 95% of the calculated values within the thresholds and
k_r = 2,58 -> 99% of the calculated values within the thresholds.

5.4 TUNING OF THE METHOD

In the phase when the method is tuned, the parameters *a* and *b* which take into account the dynamics of the calculation model, are determined as well as the threshold *th*. The tuning of the parameters is most successful when the heat exchanger's loading is varied within a wide operating range using large step-like changes of secondary side flow. In practice, this is not always possible. For example, in small buildings the load of a heat exchanger for domestic hot water can be changed easily over a wide operating range, but in large buildings it is more difficult to make sufficiently large changes in the load. In this case, it is a good idea to do the tuning during a time when the load varies a good deal owing to normal consumption.

If the threshold is tuned by using the same measuring data as for tuning parameters, it must be taken into consideration that changes in the operating point will increase the threshold. If the threshold is tuned in the steady state conditions, the calculated threshold is error limit of measurement noise. The changes in the operating point of heat exchanger will increase the threshold. The greater the changes made to the operating point, and the more frequent they are, the higher the threshold is. Tuning the threshold changes should be done in the normal process having characteristics of normal use so the threshold can be set as low as possible. In tuning the threshold, it is necessary to use different data than for the parameters in the calculation model if the loading changes in the process are values from normal operation.

Tuning and commissioning according to the method are done by phases as follows:

1. Measuring the temperatures and flows and recording data if necessary.
2. Carrying out loading changes and calculation of the parameters of the dynamic model.
3. Calculation of the threshold value from the measurement data stored previously or from separately measured data.
4. Setting the parameters and threshold for the calculation model.
5. Starting the on-line calculation model.

5.5 UPPER LEVEL REASONING

If the threshold is exceeded, the cause must be deduced and it must be decided if an alarm signalling this error should be sent. The reasoning system can be implemented in the building's so-called upper level automation system, in which a final assessment can be made of the seriousness of the exceeding the threshold values for the error of the heat power balance and the necessity of registering an alarm. If a reasoning system connected to the upper-level automation system is not available, this should be taken into account in determining the alarm limit. In this case a larger coefficient must generally be used than the one which was used to determine the threshold in Section 5.3.

When the process's components are operating correctly, the threshold is exceeded owing to rapid changes in the heat exchanger's operating point or momentary rough measurement and data transmission errors. The reasoning system can be based, for example, on an assessment of the magnitude, duration and frequency of occurrence of the exceeding of the threshold of the calculation value indicating a fault, as shows in Chapter 3. The seriousness of the exceeding of the threshold for an error in the heat power balance can be classified, for example, according to Tables 7 and 8 on the basis of the duration and the magnitude of the exceeding or the frequency of occurrence and magnitude of the exeeding. Reasoning according to Table 8 is facilitated if, say, a signal commanding a control valve is used as an aid in the reasoning. A signal commanding the control valve can be used to deduce whether the process is in a state of change or not. When the signal commanding the control valve changes, it does not make sense to use inference rules for the frequency of occurrence of the exceeding.

In Tables 7 and 8 a model-related calculation error means a calculation error due to a program error or to inaccurate tuning or a calculation error due to states of change within the process; a measurement error means an error in measurement or data transmission.

Table 7. An example of classifying the exceeding of the threshold and deduction of the seriousness of the exceeding on the basis of the duration and magnitude of the exceeding (Chapter 3).

Duration and value of exceeding	Exceeding < 10 sec	Exceeding < 10 min	Exceeding > 10 min
Large (4*threshold)	Model-related calculation error or measurement error or process fault -> alarm	Model-related calculation error or process fault -> alarm	Model-related calculation error or process fault -> alarm
Medium (2*threshold)	Model-related calculation error or measurement error -> no alarm	Model-related calculation error or process fault -> duration over 10 sec -> alarm	Model-related calculation error or process fault -> alarm
Small (1*threshold)	Model-related calculation error or measurement error -> no alarm	Model-related calculation error or measurement error -> no alarm	Model-related calculation error or process fault -> duration over 10 min -> alarm

Table 8. An example of classification of the exceeding of the threshold and deduction of the seriousness of the exceeding on the basis of the frequency of occurrence and magnitude of the exceeding. A signal commanding the control valve is used as an auxiliary quantity in the reasoning.

Exceeding frequency and magnitude	Seldom (< 10 times / 10 min and control unchanged)	Quite frequently (< 60 times / 10 min and control unchanged)	Frequently (> 60 times / 10 min and control unchanged)
Large (4*threshold)	Model-related calculation error or measurement error or process fault -> alarm	Model-related calculation error or process fault -> alarm	Model-related calculation error or process fault -> alarm
Medium (2*threshold)	Model-related calculation error or measurement error -> no alarm	Model-related calculation error or process fault -> alarm	Model-related calculation error or process fault -> alarm
Small (1*threshold)	Model-related calculation error or measurement error -> no alarm	Model-related calculation error or measurement error -> no alarm	Model-related calculation error or process fault -> alarm

Tables 7 and 8 show examples of inference rules whose alarm limits are suitable mainly for a heat exchanger for domestic hot water. In the case of a heat exchanger for heating, the alarm limits can be stricter, at least as far as the magnitude of the exeeding is concerned, since the changes in load due to the process's dynamics do not cause an error in the calculation model to the same extent as they do with a heat exchanger for domestic hot water. Alarm limits of the reasoning system cannot be determined analytically, but instead they must be set to the correct level on a trial and error basis.

5.6 RESULT EXAMPLES

Presented in the following are results of operational tests made with the heat power balance method for a heat exchanger in laboratory conditions. The process examined is shown in Figure 17. The process is subprocess shown in Figure 1 except for the flow measurements of the primary and secondary side and in addition it shows the pipe describing a leak in the heat exchanger. The heat exchanger in the process is a soldered plate heat exchanger having a nominal power of 30 kW. The demonstrated leak in the heat exchanger occurs between the district heating (DH) inlet fit of the flow primary side and the outlet fit of the flow of the secondary side. The direction of the leak is from the primary side to the secondary side.

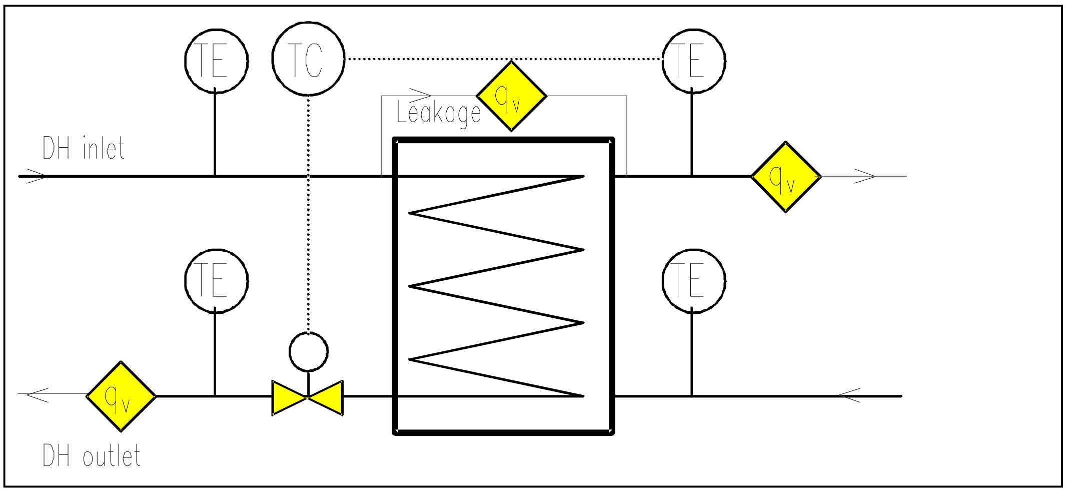

Figure 17. The demonstration process of the method.

Tuning example

The calculation model of the power balance method for a heat exchanger is tuned according to the phases shown in Section 5.4. Figure 18 shows an example of tuning of the parameters and tuning data, i.e., the heat powers calculated from the measured values. Figure 19 shows an example of tuning the threshold. The threshold is determined with a 95% reliability limit (k_r =1.96).

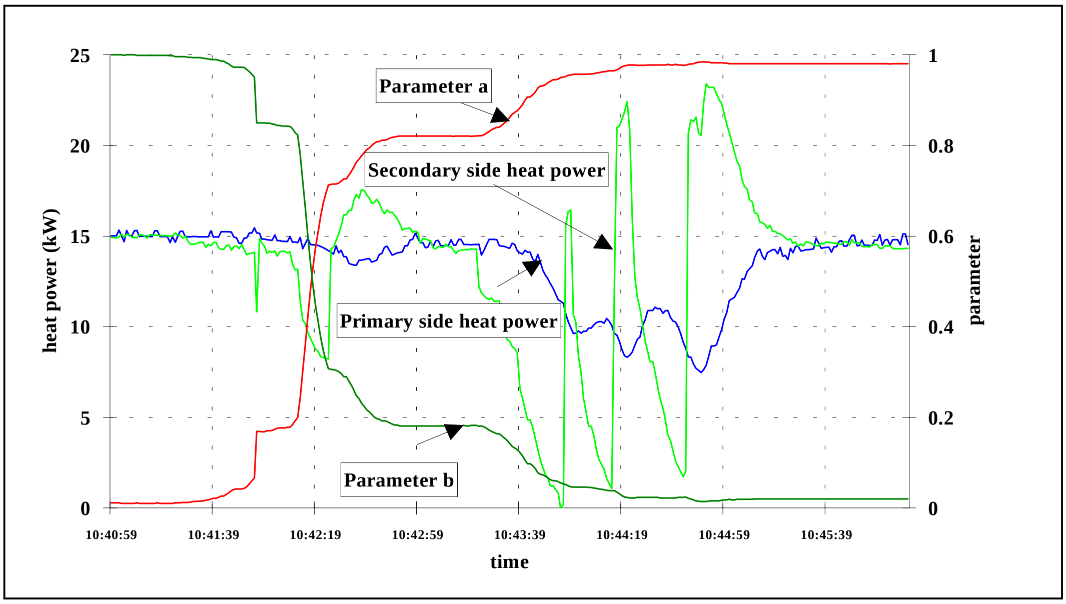

Figure 18. Tuning of parameters a and b of the dynamic calculation model according to the method as well as the heat powers of the primary and secondary side which were used as tuning data. The heat powers have been calculated from measured values. The values of the parameters at the end of the tuning are a =

0,981 and b = 0,020.

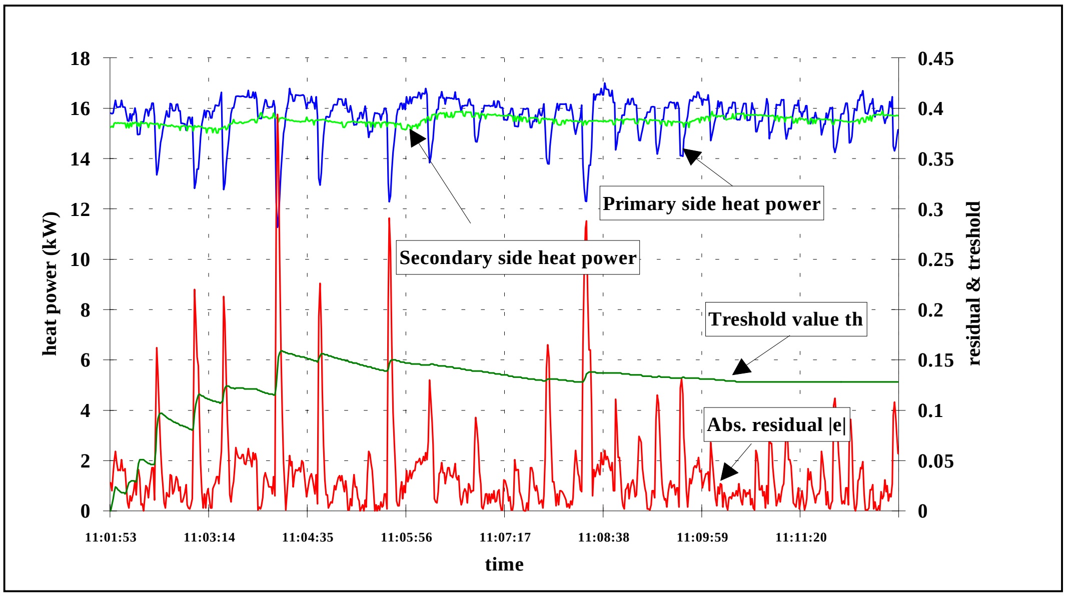

Figure 19. Tuning of the threshold according to the method. The tuning data used are the residual, which is the relative error of the primary side's heat power determined from the measured values and calculated with the dynamic model. A value of 0,128 (95% reliability limit) was obtained as the threshold.

Operation example

Figure 20 shows an example of an operating heat exchanger's measured heat power and calculated primary side heat power. Figure 21 shows the corresponding relative error.

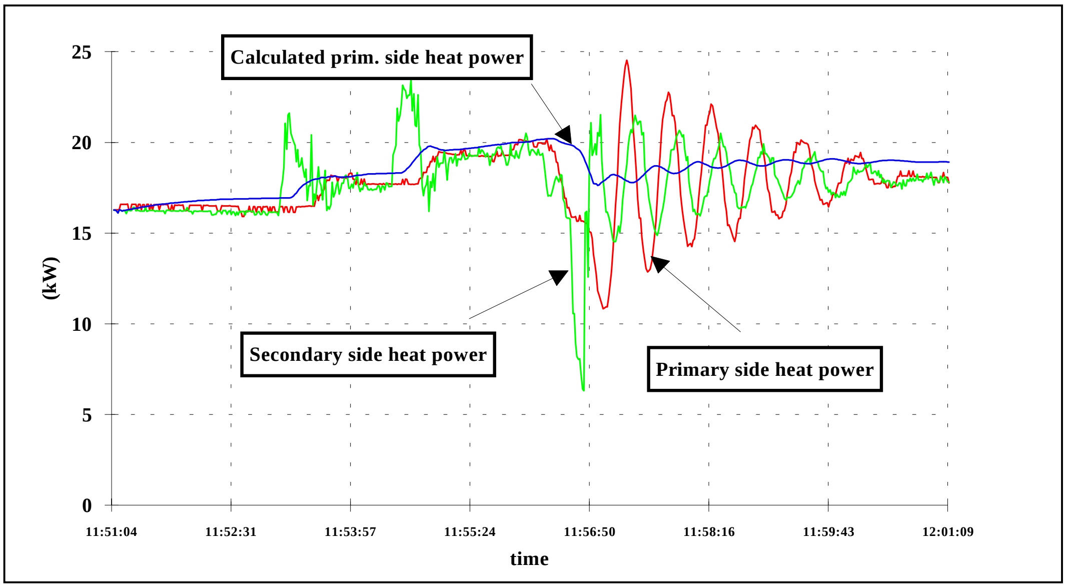

Figure 20. The heat powers of the primary and secondary side calculated from the heat exchanger's measured operating values. The figure also shows the primary side's heat power calculated with the model according to the power balance

method.

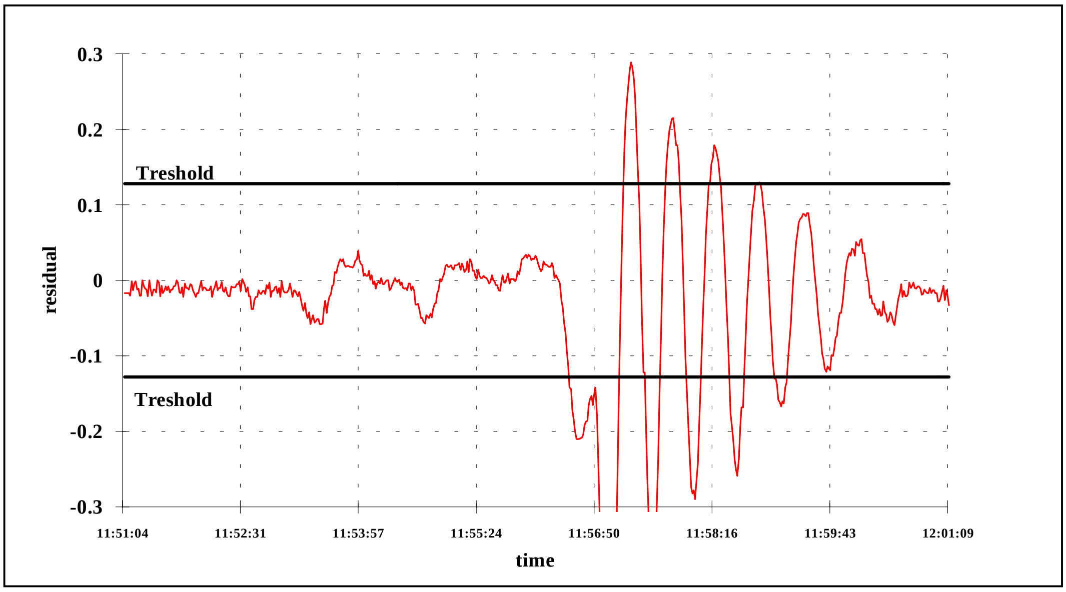

Figure 21. The relative error e of a heat exchanger's measured and calculated primary side heat power with the load period according to Figure 20.

Figure 22 shows an example of a leaking heat exchanger's measured heat powers as well as the calculated primary side heat power. The leak from the heat exchanger's primary side to the secondary side was an average of about 20% of the primary flow and about 15 % of the secondary flow. Figure 23 shows the corresponding relative error.

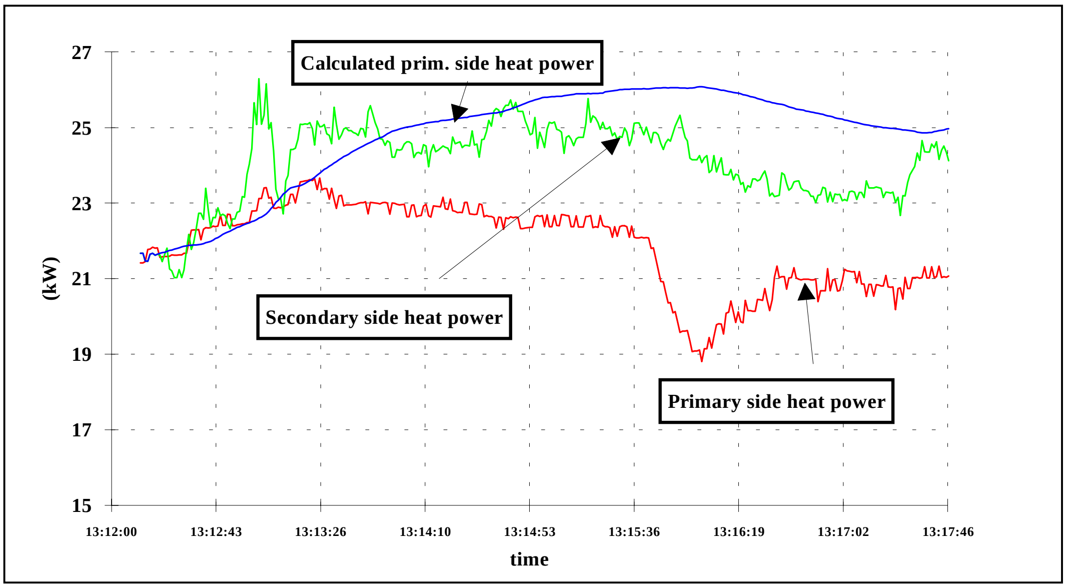

Figure 22. The primary and secondary side heat powers calculated from a heat exchanger's measured operating values as well as the primary side heat power

calculated with the model according to the power balance method.

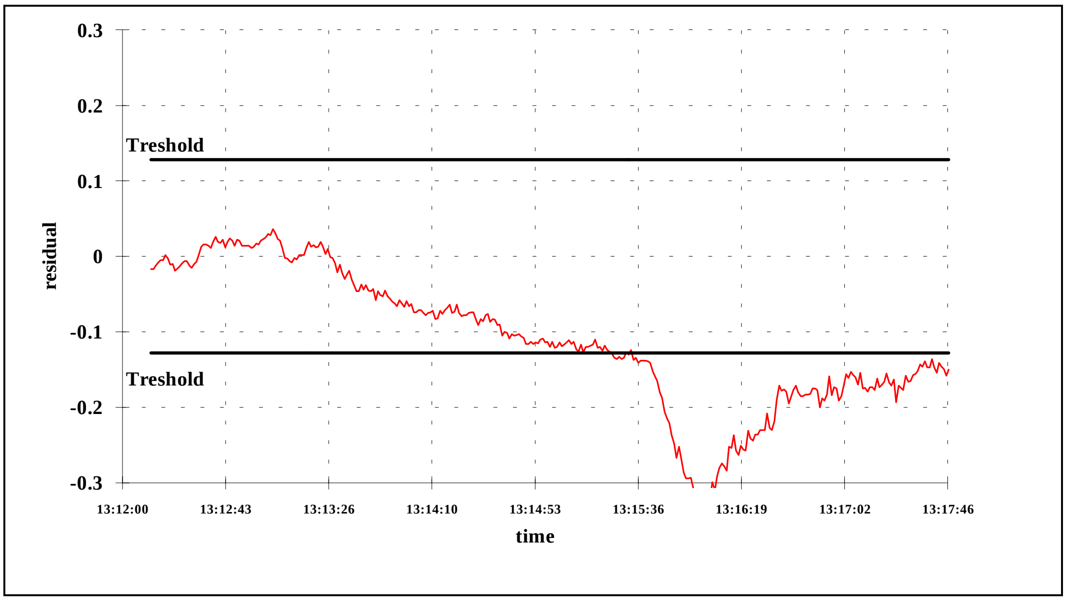

Figure 23. The relative error e of a heat exchanger's measured and calculated primary side heat power with the load period according to Figure 22.

5.7 CONCLUSIONS

In developing a heat power balance method for a heat exchanger, the assumption was that the flow measurements required for the method can be replaced by computational models of other components such as the control valve and the pump. The developed calculation model of control valve (Chapter 4) can be utilised by using the calculated flow instead of the measured primary side flow. For a pump, it is also possible to determine the characteristic curve model of the flow as a function of the electrical power drawn by the motor. Measurement of the electrical power should nevertheless be highly precise, which means that the measurement is as expensive or even more expensive than measurement of the flow. In addition, a characteristic curve model of the pump cannot be utilised in a district heating subdistribution system other than in determining the flow of a heating-related heat exchanger's secondary side. Accordingly, notwith standing the original objective, it was not possible to avoid so-called added instrumentation in implementing the method.

It is probably cheapest to implement the problematic secondary side flow of the heat exchanger by measuring the pressure difference of the flow across a constant resistance. For example, in a heat exchanger the resistance of the flow is nearly a constant. The pressure difference of the flow across a heat exchanger also makes it possible to deduce whether the heat exchanger is affected by a large amount of grime or blocking. Measurement of the pressure difference of the primary side flow across several components is also used in the calculation model for a control valve (Chapter 4). In this case, if the heat exchanger has a large amount of grime or is severely blocked, this is also detected on its primary side, providing that the model for a control valve is in use.

In the development phase of the method, all the analyses were done on a soldered plate heat exchanger. The method nevertheless functions in a similar manner in all types of exchangers, because the principle of the process is the same. On the basis of the simulations and laboratory measurements made, the method acts as a means of detecting leaks occurring in a heat exchanger. Furthermore, on the basis of simulations, a fault in the temperature sensor can also be detected. In the laboratory measurements the leakage point in the heat exchanger was not varied; rather, the leak was always between the heat exchanger's inlet fit of the district heating flow and outlet fit of the secondary side flow or out from either of the fittings.

When the process is in the static state, the method can be used to detect relatively small leaks. In the laboratory measurements the smaller leaks detected with the method were about 5 % of the measured primary side flow. A problem is nevertheless the errors which the process's dynamics cause in the computational quantity indicating a fault, since this quantity raises the final alarm limits. Accordingly, the amount of measurement data available for the reasoning system and the way in which the reasoning system is implemented largely determine how small the leaks can be in order to be detected with the method. On the basis of analyses made in the laboratory, it can be observed that a simplified dynamic computational model according to the method does not function sufficiently well in order to manage the changes in load of a heat exchanger in the desired manner. The problem is mainly in tuning the model to provide sufficient sensitivity as well as the complicated dynamic behaviour of the process, which is comprised of a heat exchanger and control devices. This aspect is dealt with in the source (Ahonen & Kuismin 1993), among others. Thus, the above-presented method is best suited to monitoring a process which remains in the static state for long periods and in which the changes in load are slow.

Another problem occurring in a heat exchanger, and one which in practice is perhaps more troublesome than a leak, is the accumulation of grime on the heat transfer surfaces. The above-presented method, which has been supplemented by measurements of the pressure difference of the primary and secondary side flows across the heat exchanger, has not been tested and thus there is no first-hand experience of its suitability for detecting the accumulation of grime. The grime that builds up on the heat transfer surfaces of heat exchangers is often very finely divided. The grime presumably does not have a very significant effect on the frictional resistance of the flow but, on the other hand, it has a considerably greater effect on the heat transfer ability of the heat surfaces. Thus, the accumulation of grime on the heat transfer surfaces could be defined better by means of the heat transfer coefficient of the heat surfaces or with some other corresponding quantity than with the flow resistance. The approach in question calls for a detailed knowledge of the construction of a heat exchanger and precise tuning of the computational models so that they operate well with the object to which they are applied. An approach of this type is used in the fault diagnosis method of a static model of a heat exchanger, which is described by Blomberg et al. (1992).

6 INTERACTIVE FAULT TREE REASONING

6.1 INTRODUCTION

Fault diagnosis of small HVAC-controllers needs special attention, because of their limited memory, computing capacity and demand for cost-effective implementation. Sophisticated methods may be unreliable and multiply the need for memory and computing capacity of the controller. This paper suggests a method called interactive fault tree reasoning. The method activates the user and the controller to co-operation, which simplifies the fault localization procedures and reduces the need for extra instrumentation. The method is a natural way to implement a reliable, cost-effective diagnostic system of a district heating substation with moderate additional hardware and software requirements.

6.2 FAULTS LOCALIZED BY AN EXPERT USER

Fault localization is a problem of HVAC-controllers and other local building automation devices. A typical controller gives an alarm signal or outputs a code or short message to a display unit when a possible fault is detected. Fault detection is usually based on limit or trend monitoring instead of more sophisticated methods (Sprecher 1992). However, an alarm signal or message rarely identifies the real fault location, confusing an inexperienced user. Such a system needs an expert user, who knows the process and can make measurements and search for the location of the fault. A separate reasoning method to point out the actual fault and its hazard grade is not a common feature of such devices.

This is also true for controllers of district heating substations. The level of instrumentation, limited memory and computing capacity of the controllers together with insufficient knowledge of process characteristics and demands for cost-effective implementation do not support development of complicated fault localization methods. Thus, due to the lack of practical procedures, the actual fault can only be found by an expert user or experienced serviceman.

6.3 FAULTS LOCALIZED BY AN EXPERT CONTROLLER

The other extreme is achieved if the controller contains a real-time embedded expert system. After fault detection the cause of the problem is automatically identified. Only the fault and its location and hazard grade are reported to the user. In this case, the user need not be an expert. All knowledge including facts and problem-solving rules are stored in the data base. Unfortunately, an embedded expert system needs a tenfold or even hundredfold memory capacity compared with the original process control program. Technically it is possible to increase the memory capacity. Also, the need of extra computing capacity to maintain both process control and expert system functions can be satisfied. However, the situation reveals a problem often encountered in applying fault detection and localization methods. The memory and computing capacity of the diagnostics exceeds many times those of the main function of the system. Still they are needed only a few times during the life cycle of the device. In addition, the system inevitably needs extra instrumentation in order to simplify the diagnostic procedures. All these features increase the costs and/or decrease the reliability of the system.

6.4 AN INTERMEDIATE FORM OF THE TWO METHODS

The above methods represent two extreme approaches of reasoning, where the role and expertness of the controller and the user are opposite (Figure 24). A practical method can probably be found somewhere between these two extremes. A good method allows cost effective implementation of the controller with an ordinary level of instrumentation. The method must be easy to apply and lead to reliable operation of the main functions and diagnostics.

A practical reasoning method for a district heating substation is suggested, which benefits the co-operation of an inexperienced user and non-expert controller. The method is an intermediate approach of the above two methods and later referred to as interactive fault tree reasoning. In this method, the dialoque is controlled and the reasoning is supervised by the HVAC-controller and it follows a fault tree procedure, which is a conventional fault localization method (Pau 1981). The basic idea is to activate the user to interactive co-operation with the controller. This is not just answering questions but reading instruments, reporting symptoms and performing manual control actions supervised by the controller. Thus, the size of the necessary knowledge-base is reduced and the reasoning rules can be implemented with an ordinary programming language. Symptom-oriented fault tree reasoning with logical reduction rules (Visuri 1986, Lautala et al. 1989) make procedures short and selective. Interactivity and the special role of the user also minimizes the need for extra instrumentation and multiplied memory and computing capacity. A drawback is the reduction in flexibility compared with the expert system approach and the need of a versatile user interface.

6.5 INSTRUMENTATION REQUIREMENTS

Implementation of the interactive fault tree reasoning only requires ordinary process instrumentation, local and interfaced. Sometimes it is possible to reduce the complexity of the fault tree procedure by adding a new instrument. If the instrument is not essential to the main process, a cost effective choice may be to add a local instrument without any connection to the controller. There may appear faults that are difficult to detect and locate with ordinary methods and instrumentation. In such a case, visible symptoms recognized by the user may be crucially important for localization of the fault.

Because the user is inexperienced and not familiar with the process, it may be necessary to label the instruments the user is going to touch or check. The same symbols are output in the instructions of the controller.

Because the controller does not include an expert system, the extra memory and computing capacity are moderate. However, the new method needs a good user interface that outputs clear messages and instructions to the user. Interactivity also requires fluent data inputting capabilities. Although technical prerequisites for such user interfaces have been available for a long time, practical, cost effective solutions are products of recent years.

6.6 DIAGNOSTIC TESTS

Fault evaluation and localization will be more straightforward if the controller performs diagnostic tests (Pakanen 1996). A diagnostic test is a sequence of control actions, measurements and mathematical algorithms that check the condition of one machine or piece of equipment. The test may be accomplished by the controller alone or assisted by the user. Because the instrumentation supervised by the controller is limited, co-operation of the user can simplify the test procedures. Tests can be performed without significantly disturbing the main functions of the process.

6.7 MORE SPECIFIC FAULT DETECTION

Alarm signals and messages of commercial controllers are results of relatively simple fault detection methods, which may refer to several faults. However, the controller is able to collect data and perform many kinds of algorithms and calculations that are not complex and time consuming, such as calculation of statistical parameters, fault frequencies, maximum and characteristic quantities (Isermann 1984). The information may help to design more specific fault detection methods. A detection method decreasing the number of alternative choices also simplifies the fault localization.

6.8 SELECTION OF THE FAULT TREE PROCEDURE

A single fault can easily cause several different alarm signals to be sent to the display. This is a serious problem in supervising large processes. Attempts have been made to solve the problem with alarm analysis and logical reduction rules (Visuri 1986, Lautala et al. 1989). They sort the alarm signals and allow only relevant ones to propagate to the user. The same rules are also useful in smaller systems with interactive fault tree reasoning. But now these rules are applied to sort the right fault tree procedure to be followed. When several alarms originate from one fault, the essential alarm signal can be solved with the aid of timing and the logical relationship of the alarms. The chosen alarm signal points to a fault tree that reveals the most probable origin of the fault. If the logic cannot discern the right alarm from a wrong one, the user may have to go through several fault trees.

6.9 DEALING WITH UNCERTAIN INFORMATION

While reporting the tasks to the controller, the user makes decisions and performs reasoning in his mind, which reduces the handling of uncertain information. Because all of the information is not numerical, the controller must have a procedure for handling uncertain information. This is also a general aspect of a good user interface. On occasions when qualitative information must be handled, it can be presented with fuzzy variables or certainty factors. The rules may be similar to expert systems, but presented with ordinary programming language.

6.10 APPLICABILITY

The above method is appropriate for small, uncomplicated applications, where reliable fault diagnosis would require heavy instrumentation and/or complicated methods without the aid of the user. Although the user is not an experienced serviceman, it is helpful if he is familiar with the basic operation of the process and knows the names and locations of the equipment. Such a situation is common in residential HVAC-systems. Occupants who constantly observe the behavior of heating or air conditioning easily recognize possible changes in the process.

6.11 THE METHOD APPLIED IN A DISTRICT HEATING SUBSTATION

A district heating substation (Figure 1) is a proper system for interactive fault tree reasoning. Ordinary instrumentation interfaced to the controller is not versatile enough to ensure fault detection and localization with usual methods and the requirement of cost-effective implementation does not allow for extra instrumentation. The problems of fault detection and localization are due to the nonlinear processes and unstable characteristics of the district heating supply. However, the interfaced and local instrumentation makes it possible to successfully apply interactive fault tree reasoning. User tasks are easy to perform, because all the equipment and instrumentation of the substation are installed in one compact space. Table 9 presents typical user tasks when the method is applied in a district heating substation.

Table 9. Typical user tasks applicable in a fault localization procedure.

- close or open a valve - check the position of a valve - check the condition of a fuse - check the position of a switch - read a thermometer - read a pressure gauge	- check the condition of a safety valve - check the operating condition of a pump - manual on-off control of a pump - check if a heat exchanger has an outside leak

Table 10. Typical faults located using the interactive fault tree reasoning.

- mud filter dirty - temperature of the district heat water is low - flow rate of the district heat water is low - heat exchanger of the heating system is leaking - control valve of the heating system out of order - temperature measurement of the heating water out of order - set point temperature curve of the heating water needs adjustment - circulating pump of the heating water out of order - outdoor temperature measurement out of order - temperature control of the heating water out of order - temperature measurement of the domestic water out of order - control valve of the domestic water out of order - temperature control of the domestic water out of order - set point temperature of the domestic water needs adjustment - circulating pump of the domestic water out of order - heat exchanger of the domestic water is leaking - pipe blockage in the heat exchanger of the domestic water - pressure level of the heating pipe is low

Figure 25 represents a flowchart of a fault tree procedure starting from a water temperature alarm. The procedure shares tasks between the user and the controller. Actions taken by the user are presented using darkened boxes. The user inputs the requested information or certifies a performed task. The interactivity requires that the controller informs the user of all decisions and achieved results. The flowchart does not present all details of the communication. The total number of symptom-oriented fault trees is ten to fifteen, which is enough to the most common faults to be located. Table 10 presents typical faults that are possible to locate with the method.

The fault tree procedures may take several forms, depending on instrumentation, user tasks and the characteristic of the faults. One must optimize the costs, user tasks, reliability and complexity of the fault diagnosis procedure. The interactive communication must not be too long and complex or the user will get bored. It may be better to point out several possible faults rather than make the procedure too long. Another way to shorten the procedure is to avoid a too detailed specification of the fault. There are also situations, where it is not possible to solve and locate the fault. In such a case the fault may be temporary or the symptoms are non-visible and/or non-measurable.

6.12 CONCLUSIONS

Interactive fault tree reasoning represents a competitive choice for fault localization of a district heating substation. In spite of non-linearities and variation in process characteristics, the method is applicable for reliable localization of many kinds of faults. The method can be implemented without adding extra instrumentation. Extra hardware and software requirements are also moderate. These features make the method a cost-effective and practical solution for district heating substations and other small HVAC-processes.

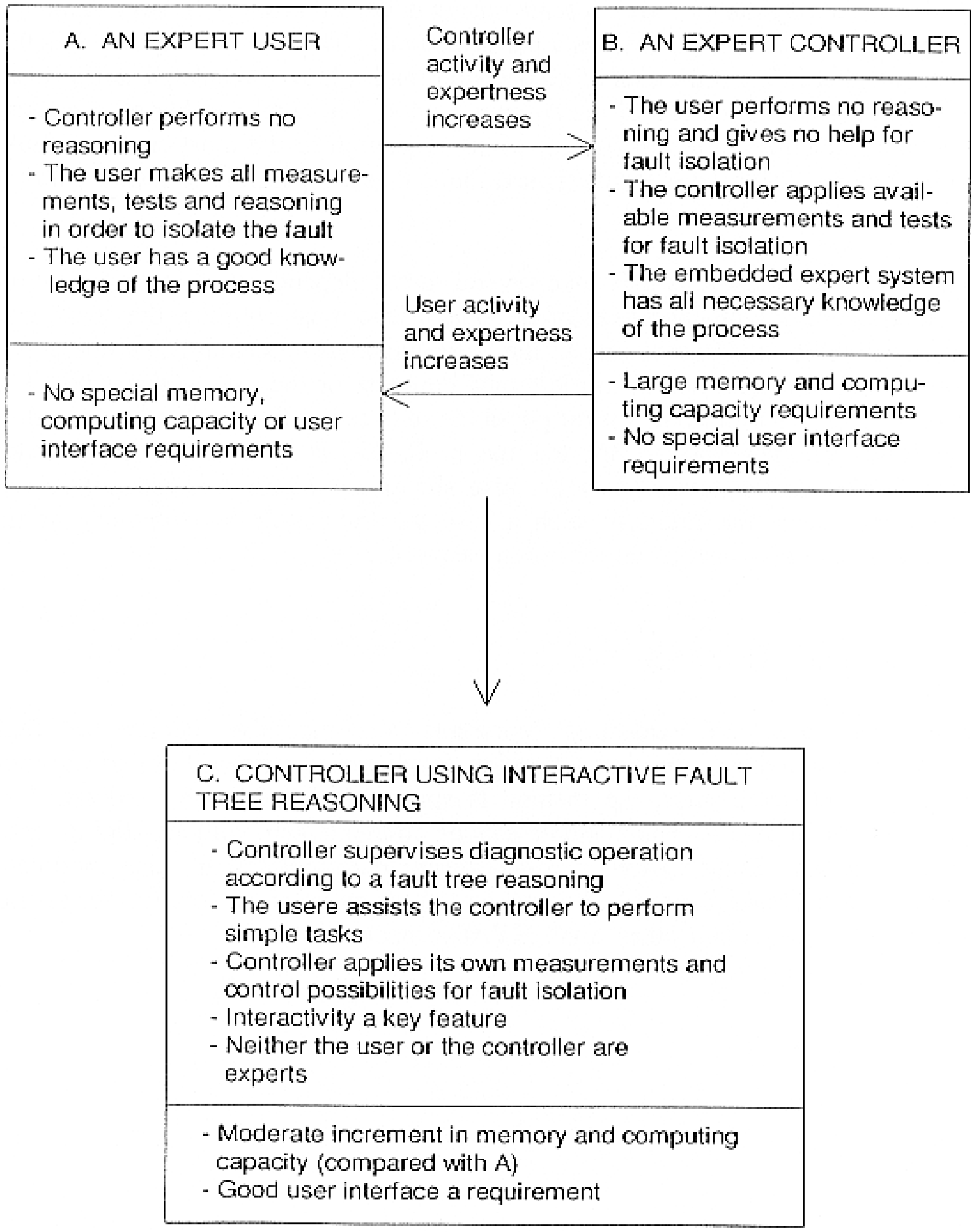

Figure 24. Interactive fault tree reasoning as a combination of two extreme approaches.

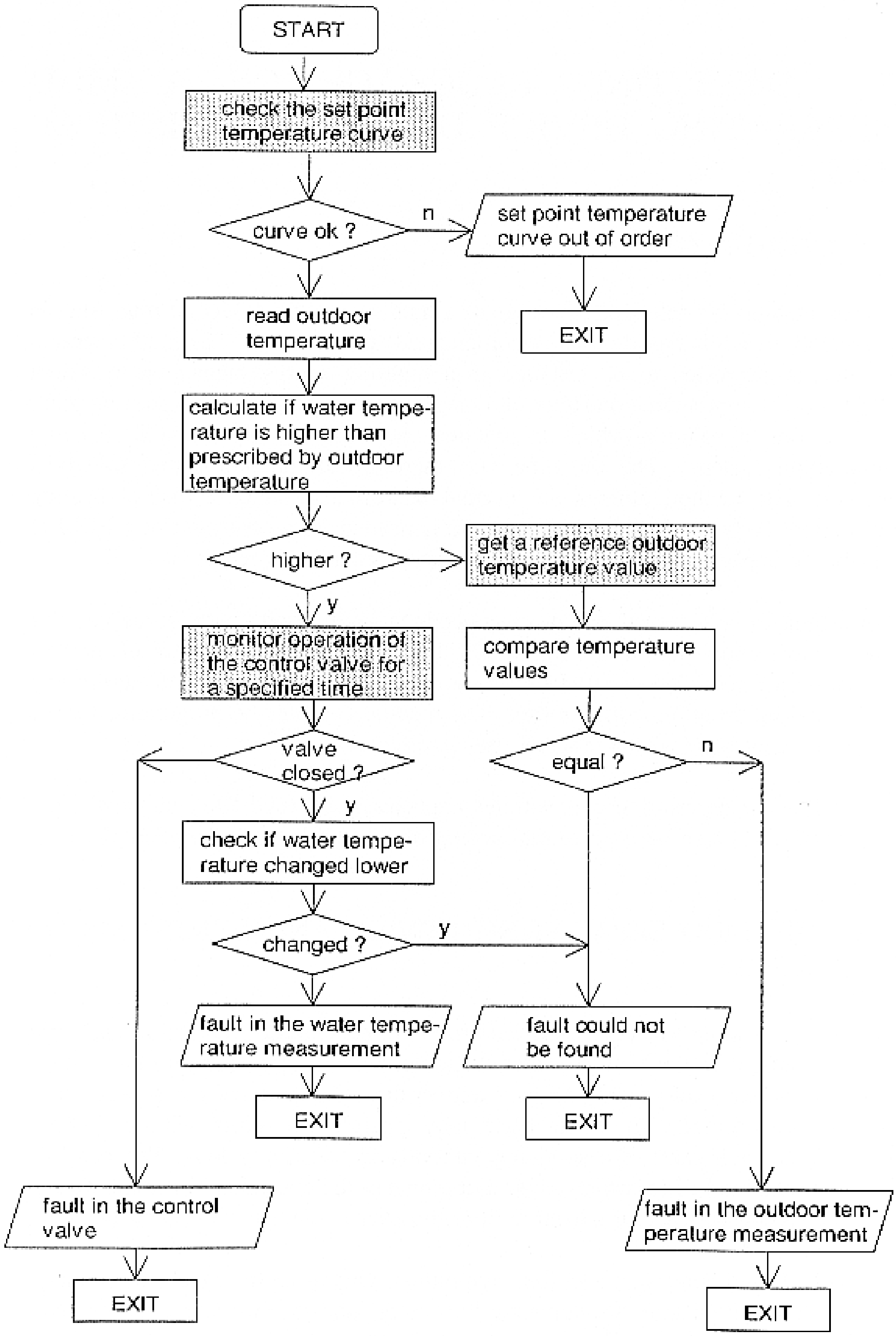

Figure 25. A flowchart of the fault localization procedure. The procedure finds a fault when the symptom is high heating water temperature. Darkened boxes refers to actions taken by the user.

7 DETECTING BLOCKAGE OF A MUD SEPARATING DEVICE USING A STATISTICAL TEST

7.1 INTRODUCTION

A new method for detecting blockage of a mud separating device or mud filter is presented, which is based on an uncomplicated statistical test. The fault detection method is suggested to be installed in a building energy management system (BEM) or a temperature controller of a district heating substation. A starting point was to find a solution which is practical and directly applicable in existing automation systems. The outcome was therefore an uncomplicated statistical method. The method utilizes the normal instrumentation of a district heating substation. Only some additional software is needed for a controller or a BEM to be able to apply the method. No further instrumentation is required.

For a fault to be detected, the process needs to be in good condition at least for the identification period during which the characteristic features of normal operation are recorded. Apart from these data, the method does not require any additional information from the user. The method can thus be programmed to be used in a controller with a reduced user interface.

The following description concentrates exclusively on mud filter diagnosis, but the method can also be used to monitoring of a control valve, for example.

7.2 THE MUD SEPARATING DEVICE AND SYMPTOMS OF BLOCKING

In a district heating substation, the mud filter collects all the mud and rubbish that may be present in the heating water. It prevents them from entering the control valves and heat exchangers and thus allows the other parts of the substation to operate undisturbed. The mud filter may operate for years without getting blocked. In such cases, the servicing intervals are relatively long. The possible blocks in the mud filter, which cause symptoms in the operation of the substation, are often a consequence of a local fault or disorder in the district heating network.

A blocked mud filter gives various symptoms. Owing to the block, not enough heat is transmitted into the domestic hot water, and the hot water temperature therefore tends to drop. The return water also has a lower than normal temperature. Because the temperature is inadequate, the control valves usually open abnormally into a nearly or fully open position.

7.3 MONITORING OPERATION AND SYMPTOMS OF THE MUD FILTER

It is possible to detect blocking of a mud filter by observing the above symptoms. To be able to detect a fault, one must be aware of the normal temperatures fluctuations and valve opening patterns. The fault detection method to be described below collects information from a normally operating process during an identification period and uses this as reference data in detecting faults. The duration of the identification period and the amount of information must be chosen in such a way that the observed signals are persistently existing and that the amount of information collected is statistically sufficient. While monitoring system operation to detect a possible fault, the diagnostic system starts a "reference period" every now and then. The data collected during this period are analyzed and compared to the data collected previously during an identification period. The emerging residual includes information on a possible fault. For the data to be reliable, however, it must be possible to decrease the effect of disturbances and noise from the residual signal before any decision is made concerning the possible fault. This can be achieved by means of statistical testing.

7.4 STATISTICAL TESTING

Statistical testing and fault diagnosis

Statistical testing is part of the fault detection procedure in most diagnostic methods (Isermann 1984, Gertler 1988, Pau 1981). If the residual is structured (Patton 1994), it is possible to apply direct parallel testing, multivariate testing or sequential likelihood ratio testing. In the present case, the data consist of scalar signals, to which univariate probability distributions and statistical tests can be applied. One alternative would be to apply sequential tests to detect changes in means as Basseville (1988), but their use does not involve any essential benefits. Reliance on conventional and well-known procedures is useful from the viewpoint of the systems designer, who is probably only familiar with the basic methods. This is a pracmatic aspect, sometimes pointed out by automation manufacturers.

Test of means

Consider first how the expected values of hot water temperature can be tested. The values measured for the signal are recorded at regular intervals during the identification and reference periods. The results obtained during the identification period give an estimated mean, which is written as m_1. According to the null hypothesis of the test, the mean m_2, measured later during the reference period is identical to that measured during the identification:

$$H_0:\ \mu_1 = \mu_2 \ . \tag{28}$$

According to the alternative hypothesis:

$$H_1:\ \mu_1 > \mu_2 \ . \tag{29}$$

In a failure, the mean is expected to be higher than normal. The test result shows whether the mean has changed significantly. The estimators of the mean are

$$X_1 = \frac{1}{n_1}\sum_{i=1}^{n_1} x_{1i} \ , \quad X_2 = \frac{1}{n_2}\sum_{i=1}^{n_2} x_{2i} \ , \tag{30}$$

where x_{1i} and x_{2i} are single measurements. The difference between the estimators X_1-X_2, on the other hand, is the estimator of the difference m_1-m_2. Assuming that the samples are mutually independent, the variance of the difference between the means is written as

$$D^2(X_1 - X_2) = D^2(X_1) + D^2(X_2) = \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2} \ , \tag{31}$$

where s_1 and s_2 are the standard deviations of the measurements X_1 and X_2. Since s_1 and s_2 are unknown in practice, they can be estimated by using the sample variances:

$$s_1^2 = \frac{1}{n_1 - 1}\sum_{i=1}^{n_1}(x_{1i} - X_1)^2 \tag{32}$$

$$s_2^2 = \frac{1}{n_2 - 1}\sum_{i=1}^{n_2}(x_{2i} - X_2)^2 \ . \tag{33}$$

The actual test parameter t is thus

$$t = \frac{X_1 - X_2}{\sqrt{\dfrac{s_1^2}{n_1} + \dfrac{s_2^2}{n_2}}} \ , \tag{34}$$

which is distributed approximately as $N(0,1)$ when the null hypothesis is valid and the sample sizes n_1 and n_2 are large.

The null hypothesis is rejected at a 5 % significance level if

$$t > 1.645 . \tag{35}$$

The limit value of the test parameter is obtained at a 5 % significance level of the normal distribution $N(0,1)$.

Test of relative proportions

The mean value test does not necessarily give reliable information on mud filter blocking, if the loading is increased for a long period or permanently. The blocking of the mud filter causes a change in the valve opening. This is seen as an increasing number of positions, in which the valve is fully open. So, the relative time for the fully open position is longer than normally and can be determined with a one-sided statistical test. The fully open position can be measured with a limit switch or applying driving time of the actuator.

The testing of relative proportions is usually accomplished by using a binomial distribution. But when the sample size is large, a normal distribution may become more appropriate. This is due to the fact that a binomial distribution approaches normal distribution when the sample size is increasing. A necessity is that, the original relative proportion must be nearly 0.5. In practice, this presents no problem. Another benefit of the normal distribution are the uncomplicated coefficients for large sample sizes, contrary to the the binomial coefficients.

It is assumed that parameter $p=P(A)$ is the unknown probability of the event A. The event A refers to the relative proportion of fully open valve positions after a blocking of the mud filter. The fully open position refers to positions involving angles larger than the given opening angle. The valve opening angle or the stem position is measured at regular sampling intervals for a predefined period. Parameter p is compared to the given probability p_0, which represents the probability in a normal situation and is measured during the identification period. Hence, the normal and faulty situations can be presented in terms of the following hypotheses.

$$\begin{aligned} H_0 &: p = p_0 \\ H_1 &: p > p_0 . \end{aligned} \tag{36}$$

The random variable x represents the frequency of occurrence of event A in a sample of n events, of which it is known that

$$x \_ \ Bin(n, p) \qquad (37)$$

A random variable with a known binomial distribution has

$$\begin{aligned} Ex &= np \\ D^2 x &= np(1 - p) \,. \end{aligned} \qquad (38)$$

The indicators corresponding to the relative frequency $\underline{P}=x/n$ of event *A* are

$$\begin{aligned} E(\underline{P}) &= p \\ D^2(\underline{P}) &= \frac{p(1 - p)}{n} \,, \end{aligned} \qquad (39)$$

in which case the test parameter *z* with a nearly *N*(0,1) distribution is

$$z = \frac{x - n\,p_0}{\sqrt{n\,p_0(1 - p_0)}} \,. \qquad (40)$$

A situation accordant with the null hypothesis is considered to be rejected at a 5 % significance level if

$$z > 1.645 \,. \qquad (41)$$

7.5 MEASUREMENTS

Measurements with an emulator

The data for the statistical testing were gathered using two different methods. Some of the measurement data come from laboratory tests performed with the VTT emulator system. The operation of the emulator was set to resemble the hot water plant of a district heating substation, including a control valve with a control circuit, a heat exchanger and a manual valve simulating the mud filter of a district heating substation. Persistent load variations were generated with a combination of a slow sine wave and a white noise signal. The system has been described in more detail by Laitila et al. (1992).

The measurements are from four different phases. At first, the identification phase was started, during which the data of a normally operating system was recorded. After that, the position of the manual valve was changed to make the pressure differential across the valve greater than normal. This corresponds to a situation where the mud filter is partly blocked. After these settings, the measurements of the first reference period were made. Then the pressure differential across the manual valve was set to be even greater, and the same measurements were repeated. The measurements of the reference period were recorded with three different pressure differentials.

The key signals measured in the statistical tests were the hot water temperature and the position of the valve stem. Measurements of flow rates and temperatures at both sides of the heat exchanger were also made to ensure that the testing situation met the predefined criteria of loading and temperature fluctuation. Each period included 150 - 500 measurements. Some characteristics of the measurement period are shown in Table 11.

Table 11. Emulator measurements to simulate gradual blocking of mud filter.

Measurements n:o	Incoming pressure of the district heating water [bar]	Pressure loss at valve [bar]
1	0.80	0.2
2	0.45	0.1
3	0.30	0.07
4	0.30	0.04

Measurements at a district heating substation

Apart from making emulator tests, the method was also tested by performing measurements at a district heating substation of a sports hall. During the experiments hot water consumption was normal or higher than normally. The measurement periods were longer than above. The measured signals consisted of the control valve stem position and the hot water temperature. Mud filter blocking was simulated by using a manual ball valve, which was part of the substation installation. Measurements were made during two days.

During the reference period, the incoming flow at the substation was limited sufficiently to achieve distinct changes in the process water temperature, but to prevent any excessive drops in temperature during maximum loads. Experimentally, a ball valve position was found which resulted in a 10 - 15 % change in the reading of the manometer when compared with the normal situation. With this adjustment of the ball valve, however, the control valve was seldom in a fully open position and the process can be interpreted as slightly faulty.

7.6 ALARM LIMITS

The alarm limits are determined by comparing the calculated value of the test parameter to the critical values of the probability distribution. For example, the critical values of a standardized normal distribution in a one-sided test at different significance levels are as shown in Table 12.

Table 12. Critical values of a standardized normal distribution at different significance levels.

Significance level	5 %	1 %	0.1 %	0.01 %
Critical value	1.65	2.33	3.09	3.72

7.7 TUNING AND START UP OF THE METHOD

The hypotheses are set on the basis of data acquired during the identification phase. During the identification, estimates are given for the mean and the relative proportion, which are then applied during the actual testing. According to an analogous method, a sample parameter corresponding to the identification measurements is chosen to be used as the estimate.

The length of the identification phase and the number of measurements must be chosen according to the test. While testing the means of the hot water temperature, the length of the identification period probably need not be longer than a few hours to 24 hours, depending on loading fluctuations.

In the tests of the relative proportion of the valve opening angle, the identification period must be longer or the time must be chosen with more care, because the pressure variations in the district heating network also influence the average position of the valve stem. A long-term change in loading may also alter the relationship.

The sampling interval between the measurements must be sufficiently long in both cases to make the measurements mutually independent. In practice, the measurement interval must be longer than the driving time of the actuator.

7.8 FAULT SELECTIVITY

Both of the above methods have been designed to detect symptoms that are typical of mud filter blocking, but neither of the above statistical tests are able to isolate the fault exclusively. If the pressure or temperature of the district heating network is abnormal relative to the loading, both tests may trigger an alarm. The same is also true of faults in the hot water controller, which causes changes in the operation. Separate fault diagnosis and reasoning methods are needed for testing the operation of both district heating network and hot water controller, to allow differentiation between blocking of the mud filter and other faults.

7.9 TEST RESULTS

The above statistical test results suggest that the hypothesis h_0 should be rejected if the value of the test parameter is higher than 1.65. This corresponds to a 5 % significance level. If the test parameter is higher than 2.33, a situation accordant with hypothesis h_1 is probable at a 1 % significance level.

Tables 13 - 16 show the test results for both the test of means and the test of relative proportions when data measured in the emulator experiment and at the district heating substation were used.

Both the test of means and the test of relative proportions applied to the emulator experiments clearly imply that the hypothesis h_0 should be rejected. The identification data shown in Table 14 consist of the results of measurement period 3, to minimize the pressure difference between the measurement periods. In this case, too, the tests yield results parallel to those shown in Table 13, but with slightly lower numerical values.

Table 13. The results of the test of means applied to data measured in the emulator experiment. The results shown on the first line were obtained by using measurement period 1 (Table 1) as the identification data, while measurement period 3 was used for the results shown on the second line. Measurement period 4 was used as the reference material in both cases.

Value of test parameter	Variance in identification data	Variance in reference data	Mean of identification data	Mean of reference data
8.04	11.28	46.74	39.48	34.49
4.49	30.73	46.74	37.71	34.49

Table 14. The results of the test of relative proportions applied to data measured in the emulator experiment. The results on the first line were obtained by using measurement period 1 (Table 1) as the identification data, while measurement period 3 was used for the results presented on the second line. Measurement period 4 was used as the reference material in both cases.

Value of test parameter	Relative proportion, identification data	Relative proportion, reference data
7.19	0.51	0.80
4.26	0.52	0.69

Table 15. The results of the test of means applied to data measured at the substation. The results shown on the first line were calculated for a reference data sample of 100 measurements, while the results shown on the second line were calculated for a sample of 30 measurements.

Value of test parameter	Variance in identification data	Variance in reference data	Mean of identification data	Mean of reference data
2.54	0.97	0.51	53.64	53.39
2.27	0.97	0.87	53.64	53.22

Table 16. The results of the test of relative proportions applied to data measured at the substation. The results shown on the first line were calculated for a reference data sample of 100 measurements, while the results shown on the second line were calculated for a sample of 30 measurements.

Value of test parameter	Relative proportion, identification data	Relative proportion, reference data
2.19	0.44	0.55
1.38	0.44	0.57

The test results of the substation measurements are not so conclusive as those of the emulator experiment. Most of the test parameter values suggest the rejection of hypothesis h_0, but the numerical values of the test parameters only reach the 5 % significance level. The uncertainty is further increased by the test parameter value 1.38 obtained in the test of relative proportions, which suggests that the null hypothesis is still valid. This result was obtained using a smaller sample size.

7.10 CONCLUSIONS

On the basis of the experiment, the process water test of means and the valve stem position test of relative proportions appear to be relatively good indicators of mud filter blocking. For the detection to be reliable, however, the blocking must cause measurable changes in the signals. The dimensioning of district heating substations and the quality of loading vary. The test must be designed to take into account these differences, for there may be differences in mud filter symptoms in even mutually similar conditions.

Since the methods are able to detect blocking of the mud filter, but unable to isolate selectively the fault caused by it, they are best suited to be used in combination with another or some other diagnostic methods. The actual fault should then be isolated by reasoning.

In practice, both tests can be easily integrated with the software of the substation control instrument or the controlling system. The procedure for detecting a fault is simple. The need for memory and data processing capacity is small. Nor is any additional instrumentation needed at the substation.

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