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EVALUATION OF FAULT DETECTION AND DIAGNOSIS TECHNIQUES FOR APPLICATION IN HVAC SYSTEMS

Meli Stylianou and Alain Legault
Energy Diversification Research Laboratory
1615 Mtee Ste-Julie
Varennes, Quebec
J3X 1S6

INTRODUCTION

HVAC systems in commercial buildings account for about 65% of the total building energy requirements. Significant savings can be achieved through improved operation of these systems, all the while ensuring the comfort and well-being of the occupants and using the least amount of energy possible. The aim of Fault Detection and Diagnosis (FDD) of HVAC systems is to ensure the proper operation of the system through the timely detection of system problems and correct diagnosis of their causes. FDD has been receiving increasing attention from researchers in the field of control systems. This interest has been spurred by stricter standards on building energy utilization efficiency (1) and indoor air quality (2). In addition, recent developments in the fields of control systems and computer science have opened up new possibilities for improving commissioning and operation of the HVAC systems.

Presently, Building Energy Management Systems (BEMS) provide simple checks for the occurrence of faults. These include checking: (a) the limits of critical parameters, (b) whether a point is operational or not and (c) the status of equipment (ON/OFF). No capability exists to detect errors in sensors, degradation in equipment performance and problems with actuators. The responsibility for the detection and diagnosis of faults rests with building operators whose knowledge of the underlying principles of building operation and whose familiarity with the building system's performance enable them to detect, diagnose and ultimately correct problems. Despite the best intentions of the operators, lack of support in terms of training as well as the overwhelming flow of information from the BEMS often limit the operators' ability to adequately respond to faults of the type described above (3). Consequently, it is desirable to develop tools for the detection and diagnosis of HVAC system faults without imposing additional information processing tasks on the operators. Such a system would actually reduce the operator's load since it would automate the fault detection, diagnosis and evaluation parts of the procedure shown in Figure 1. The system would report to the operator either the information necessary to proceed with an alternative operating strategy (A) or that which is necessary to eliminate the fault (B).

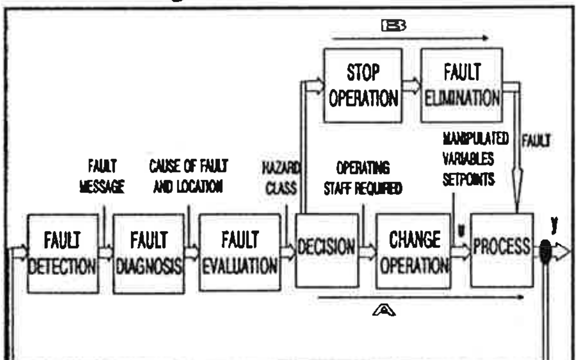

Figure 1 Conceptual sequence of events in an FDD procedure

TYPES OF FAULTS IN HVAC SYSTEMS

HVAC systems, like any dynamic system, can be considered to consist of three major subsystems: the sensors, the process and the actuators. Consequently, faults can be categorized accordingly into sensor failures, process failures or actuator failures. Sensor failures can have a substantial effect on system performance. Kao and Pierce (4) and Kao (5), have shown through simulation of an office building, that in certain cases a 5.5°C (10°F) error can increase the annual energy requirements by 50%. These failures may be subdivided into two types: sensor bias and sensor drift. In the former case the sensor, although still operational yields incorrect readings, while, in the latter, the sensor bias continually changes with time. Sensor drift, which is more prominent in pneumatic systems, poses serious problems for the controllers. This type of failure often leads to instabilities which may in turn cause indoor air quality problems, early deterioration of equipment as well as waste energy. Actuator faults can also substantially diminish the efficiency of building system operation. Valves or dampers that are not opening or closing properly will not deliver the desired flow rates leading to problems similar to the ones mentioned above. Process faults include the malfunctioning of equipment and of the air and water distribution systems. These types of faults may be either easy to detect, as in the case of a tripped motor, or very difficult to detect as in the case of fouled heat exchangers. Regardless of the origin or type of fault, continued system operation without detection, diagnosis and correction of the fault, will inevitably lead to further system degradation, excessive energy use and, possibly, indoor air quality problems.

FAULT DETECTION AND DIAGNOSIS METHODS

Hardware redundancy, an FDD method primarily used in the aerospace and process industries is a technique that uses a set of three or more sensors to measure one variable. The signals are then examined and majority vote ensures that the proper reading is taken. This approach however, has not been and is unlikely to be applied to the FDD of HVAC systems largely because it is prohibitively expensive

Current FDD procedures for HVAC systems are operator dependent. Automation of the these procedures for these systems has received limited attention until recently. Alternative approaches are being developed based on analytical redundancy and Artificial Intelligence (AI) techniques (3, 6, 7). Brief descriptions of these techniques follow.

ANALYTICAL REDUNDANCY METHODS

Various methods for FDD using analytical redundancy have been reported in the past two decades. As the name implies, these methods make use of the inherent redundancy contained in the static and dynamic relationships among the system inputs and measured outputs. In other words they make use of a mathematical model of the system, an aspect that has both advantages and disadvantages for the application of these methods in HVAC systems. The main advantage being the significant number of HVAC equipment models already available (8), while the disadvantage being the non-linear characteristics of the processes involved in HVAC systems.

A schematic of the overall procedure used in analytical redundancy techniques is shown in Figure 2. Two basic techniques exist for generating the difference between the expected and actual system observations (residuals) using analytical redundancy: 1. state estimation and 2. parameter identification.

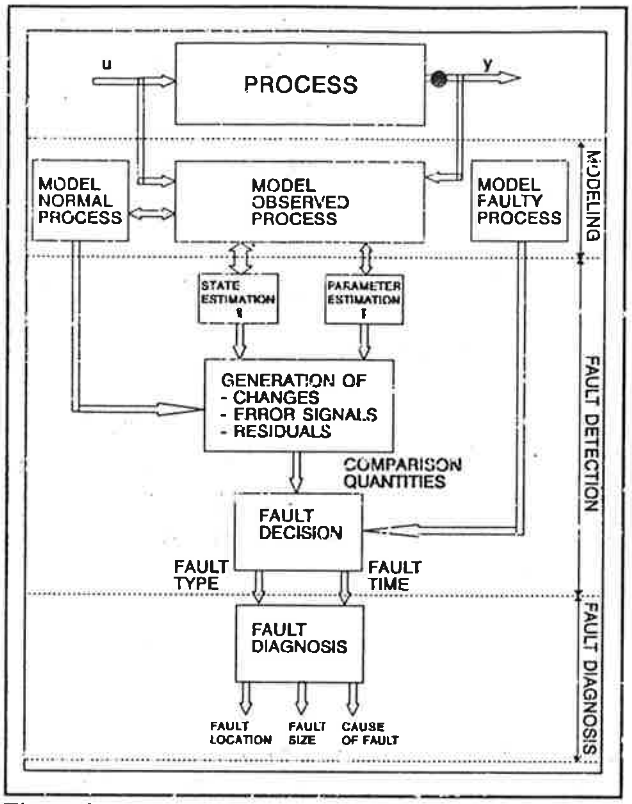

Figure 2 Procedure for FDD using analytical redundancy methods

1. State Estimation Techniques

In order to facilitate the description of the characteristics of state estimation techniques let us consider the linear system given by the following state equations:

$$\dot{x}(t)=Ax(t)+Bu(t)+Ev(t)+Kf(t) \quad (1)$$

$$y(t)=Cx(t)+Fv(t)+Gf(t) \quad (2)$$

where **x** is the state vector, **u** the known input vector, **v** the unknown inputs vector, **f** the fault vector and **y** the measured outputs vector. The matrices **A**, **B**, and **C** are known matrices. **Ev**(t) models the unknown inputs to the actuators and to the dynamic process, **Kf**(t) actuator and component faults **Fv**(t) the unknown inputs to the sensors and **Gf**(t) the sensor faults. The model is then used to evaluate the redundancy relationships through the generation of residuals for fault isolation and diagnosis.

The state estimation techniques require the reconstruction of the system state based on measurable input and output signals. The reconstruction is achieved with the aid of observers or Kalman filters. The fundamental configuration of a linear full order estimator is shown in Figure 3 (9). It consists, in effect of a parallel model of the process with a feedback (**H**) of the estimation error. It can be shown from equations 1 and 2 that the estimated state $\hat{x}(t)$ and estimated output $\hat{y}(t)$ are governed by the following two equations:

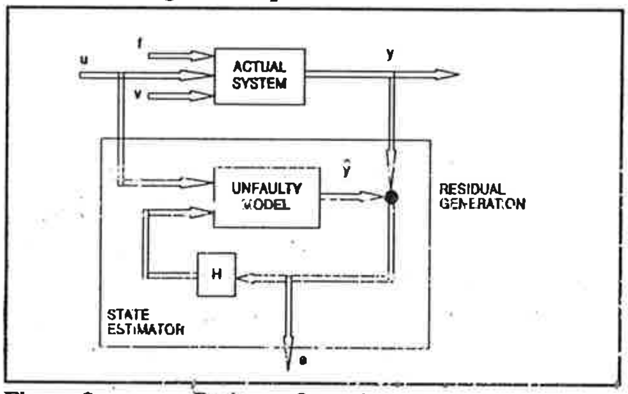

Figure 3 Basic configuration of residual generation through state estimation

$$\dot{\hat{x}}(t)=A\hat{x}(t)+Bu(t)+H[y(t)-C\hat{x}(t)] \quad (3)$$

$$\hat{y}(t)=C\hat{x}(t) \quad (4)$$

where **H** is the feedback gain matrix that has to be chosen properly to achieve the desired performance of the observer. Using equations 1 through 4 the state estimation error $\epsilon(t)=x(t)-\hat{x}(t)$ and the residuals or output estimation error $e(t)=y(t)-\hat{y}(t)$ are derived:

$$\dot{\epsilon}(t)=A\epsilon(t)+Ev(t)+Kf(t)-H[C\epsilon(t)+Fv(t)+Gf(t)] \quad (5)$$

$$e(t)=C\epsilon(t)+Fv(t)+Gf(t) \quad (6)$$

It can be seen from these equations that the output estimation error **e** is a function of the fault vector **f** and the vector of unknown inputs **v** but not of the actual input **u**. This vector can therefore be used for detecting faults. The degree to which the residual generation is affected by the unknown inputs, i.e. its robustness, is one measure by which the technique's performance is assessed.

Fault decisions can subsequently be made through special testing methods:

(a) *Generalized Likelihood Ratio* test which results in the correlation of the observed residuals with the precomputed filter responses due to faults.
(b) *Fault Detection Filters* which are full order state estimators with special choice of **H**.
(c) *Statistical tests* of the residuals of a Kalman filter.

State estimation methods have been studied extensively. However, the non-linearities inherent in the physical processes involved in HVAC and the fact that the faults are difficult to separate from unknown inputs, make the use of these techniques problematic. More detailed descriptions of methods using state estimation may be found in Ref. 10.

2. Parameter Identification Techniques

Parameter identification techniques detect faults via estimation of the model parameters through the following procedure (11).

1. Development of the empirical process model. This model may be in the form of a polynomial equation in the case of a static model:

$$y(u)=\beta_o+\beta_1 u+\beta_2 u^2\ldots \tag{7}$$

   or of a differential (or difference) equation in the case of a dynamic model:

$$y(t)+a_1\dot{y}+a_2\ddot{y}+\ldots.+a_n y^{(n)}=b_o u+b_1\dot{u}+b_2\ddot{u}+\ldots.+b_m u^{(m)} \tag{8}$$

   The process model parameters $\theta^T=[\beta_o,\beta_1,\beta_2,\ldots]$ or $\theta^T=[a_1,\ldots,a_n|b_1,\ldots.,b_m]$ represent relationships of several process coefficients.

2. Determination of the relationships between the model parameters Θ_i and the physical coefficients p_j

$$\theta=f(p) \tag{9}$$

3. Identification of the model parameter vector θ using the input vector **u** and output vector y

4. Calculation of the process coefficients

$$p=f^{-1}(\theta) \tag{10}$$

5. Calculation of the vector of deviations Δp_j from its nominal value taken from the nominal model.
6. Location of faults by the use of a library of fault signatures in which the relationships between faults and changes in Δp_j has been established. This step may require the use of statistical decision theory and pattern recognition.

This technique may be particularly useful for the detection of slowly developing (incipient) faults, for example sensor drift and fouling of heat exchangers.

PROBLEMS WITH ANALYTICAL REDUNDANCY

These methods require advanced information processing techniques and depend heavily on the quality of the system models. Since HVAC system models would require model order reduction and some degree of linearization to make them computationally efficient, the requirement for high quality models would pose problems in the implementation of an FDD system based on analytical redundancy (11). Such FDD systems suffer in general, from the practical limitations imposed by the approximate nature of the model used. This leads to problems of robustness with respect to (a) parameter uncertainties, e.g., heat transfer coefficients (b) non-linearities, e.g., radiation heat transfer (c) uncertain dynamics, e.g., combustion and (d) fault types, e.g., actuator or sensor failure.

These limitations may be overcome by the use of thresholds in order to distinguish a fault from modelling errors and signal noise. Choosing appropriate thresholds, however, is not a trivial task. Thresholds that are set too low often result in false alarms while thresholds that are set too high can reduce the sensitivity of the FDD system in detecting real faults.

Although several robust techniques, i.e., techniques that are aimed at reducing the effect of the above mentioned limitations, have been developed, problems still remain which limit significantly the practical application of analytical redundancy-based techniques. Other techniques, namely ones that use the developments in AI such as qualitative modelling and the use of artificial neural networks may prove to be more advantageous.

ARTIFICIAL INTELLIGENCE-BASED METHODS

The use of AI in process control as well as fault detection and diagnosis is spreading rapidly albeit with varying degrees of success. Three major areas of on-going research include:

1. Rule based expert systems;
2. Deep knowledge expert systems and
3. Artificial neural networks (ANN).

1. Rule Based Expert Systems (RBES)

Pioneering efforts at using AI methods in process control and diagnosis made use of rule based expert systems. These systems constitute the AI applications currently in use. Their mode of operation is intuitively simple, although creating practical applications is far from trivial. Process measurements or alarms are explicitly linked to causes or consequences in the process behaviour through the use of a compiled knowledge database, as illustrated by the following example:

EXAMPLE
RULE 2055: Examine effect of wind on economizer
IF wind speed > 45
AND NOT control OF Outside Air Damper IS full outside air
AND Reading OF Mixed Air temp sensor = Reading OF Ambient temp sensor
THEN State OF Mixed Air temp sensor IS Faulty

The main advantage of these systems is that knowledge of human experts can be translated to this form without any in-depth understanding about the dynamics of the process, i.e, rules of thumb can suffice. Other advantages of RBES-based methods include the fact that they are relatively easy to follow and that incremental increases of the scope of the system are easily done by the knowledge engineer. These advantages clearly address the limitations cited earlier for analytical redundancy techniques. However, RBES-systems do have several disadvantages. First, situations not described explicitly in the database cannot be recognized and/or treated (this is sometimes referred to as brittleness). This may be a major impediment for large systems, as is the case with large HVAC systems, where the number of rules required to cover all situations may rapidly increase with size. Second, finding optimal strategies for the activation of rules (referred to as "firing" of rules) becomes increasingly difficult with size. Finally, a relatively slow response time in the case of large systems may limit their on-line application.

2. Deep Knowledge Systems

Deep knowledge systems address the inability of KBES to treat novel situations by providing models of reasoning that can lead to fault detection/diagnostic decisions. In this sense one can view the rule based systems as the topmost layer of the deep models. Among others, the relatively new "qualitative physics" or "qualitative modelling" approach is currently generating a lot of interest for cases where computational difficulties or the lack of detailed knowledge about the dynamics of a system renders analytical redundancy impossible (12). The basic idea here is that the traditional description of a system with state variable and algebraic or differential equations is replaced with one where only part of the information of the state variable is retained and where formal equations are replaced with *qualitative constraint equations.*

addition
[x] + [y]

[x] \ [y]	-	0	+
-	-	-	?
0	-	0	+
+	?	+	+

[x]=sign(x)
[y]=sign(y)

Figure 4 Truth table

As an example consider a system in which only the sign of a variable X and the sign of its derivative with respect to time X' are retained. The algebra governing the system is then defined through "truth tables" for "operations" on the variable as shown in Figure 4. A question mark indicates that any of the outcomes (+,-,0) is acceptable. With the operations defined, one can construct qualitative constraint equations from physical models and any assignment of variables (and derivatives) satisfying the constraints are deemed to represent valid states (i.e., physical states). A simple valve configuration shown in Figure 5 will be used to illustrate this. Rates of change in flowrate, pressure drop and orifice area are constrained by the following constraint equation:

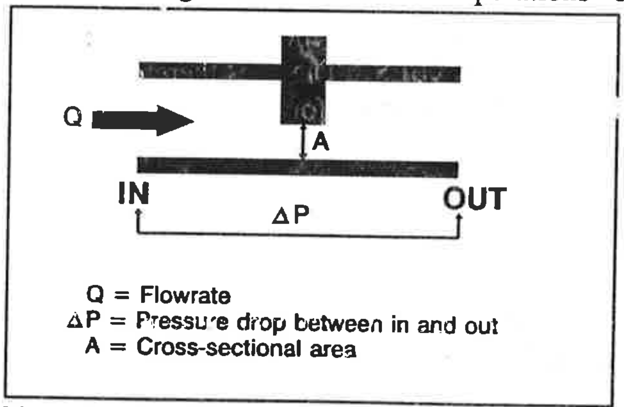

Figure 5 Valve model

$$[dP] + [dA] + [dQ] = 0 \qquad (11)$$

The requirement that the flow be in the same direction as the pressure drop leads to:

$$[P] - [Q] = 0 \qquad (12)$$

Given these equations, one then tries to evaluate the possible outcomes of the system.

3. Artificial Neural Network Systems

Whereas KBES store their information explicitly (rules, symbols, models), ANN's, an example of which is given in Figure 6, are an implicit realization (13) of the information contained in a system: synaptic weights and neuron biases contain all the knowledge one has about a given system. This "storing" of information is achieved in the following way: a set of input/output vectors I_i and O_k is used to "train" the network. "Train" in this context means the adjustment of synaptic weights and neuron biases at every node so that error (e.g., the norm of the difference (P_k-O_k) between the predicted (P_k) and actual output (O_k)) is minimized. If training is successful, the net will not only be able to correctly estimate the output for the original set of inputs but will also be able to generalize the relationship to correctly estimate the output for inputs never encountered before.

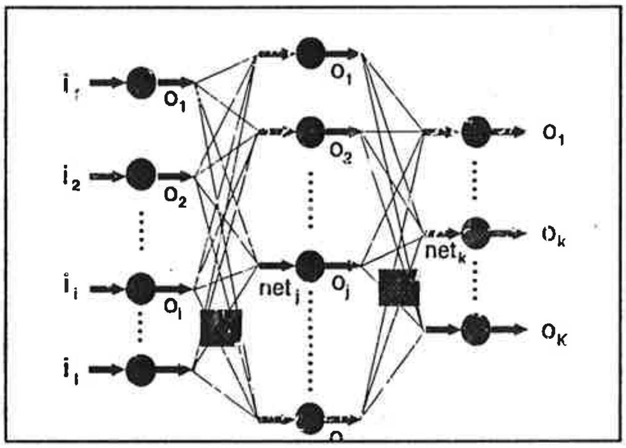

Figure 6 An artificial neural network

In the case of fault detection, one can train the net (or nets) with regular operating data. Once this has been done, the net should correctly report situations which are outside the defined regime of operations as "faulty". An interesting feature here is the ability to incrementally expand the training set by re-assigning situations which are incorrectly labelled "faulty" to the set of "operational" data. Since nets are inherently black box systems and cannot "explain" why a fault has occurred, their applicability to diagnosis is limited.

CONCLUSION

The use of any one of the techniques reviewed in large HVAC systems poses several problems, robustness being the most important. This is especially so for the fault detection aspect of FDD systems. The problems described with respect to analytical redundancy techniques seem to point in the direction of methods that are more tolerant of modelling approximations. The use, therefore, of AI-methods appears to be preferred. The black box models developed through ANN do not lend themselves to fault diagnosis where knowledge of the reasoning is often important. This aspect of FDD has long been the domain of KBES. The use, therefore, of a hybrid AI-based technique would seem to offer the flexibility required for the development of an HVAC Fault Detection and Diagnosis system.

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