An Innovation-Based Methodology for HVAC System Fault Detection

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Although Energy Management and Control Systems (EMCS) have since the early 1970's contributed significantly to the reduction (20-40 percent) of energy use in buildings without sacrificing occupants' comfort, their full capabilities have not been completely realized. This is in part due to their inability to quickly detect and compensate for failures in the Heating, Ventilation and Air Conditioning (HVAC) system. In fact, no matter how good the control scheme for the HVAC system might be, the presence of undetected faults can completely offset any expected savings. This paper presents a methodology for detecting faults in an HVAC system using a nonlinear mathematical model and an extended Kalman filter. The technique was implemented in a computer program and successfully used to detect "planted" faults in simulations of the air handler unit of an HVAC system. Test results are presented to demonstrate the effectiveness of the methodology.

1 Introduction

Since their introduction in the early 1970s, Energy Management and Control Systems (EMCS) have contributed significantly to the reduction of energy use in buildings without sacrificing occupants' comfort [1]. The energy use reduction by many of these systems, when fully utilized by knowledgeable operators, is reliably reported to be on the order of 20 to 40 percent per year as compared to building operation without such systems. Fundamental requirements for effective energy usage are properly operating equipment—both the Heating, Ventilation and Air Conditioning (HVAC) system and EMCS—as well as operator knowledge and the application of this knowledge. In both of these areas there are significant problems. Proper operation of equipment both as installed and over time cannot be assumed. Examples of this include a recent National Bureau of Standards (NBS) study of instrumentation sensor error experience with the Park Plaza Building in Newark [2] and experience reported by the U.S. Army's Construction Engineering and Research Laboratory [3]. These and many other industry documents and general user experience indicate that much of the potential energy savings that can be realized in HVAC systems is lost due to the condition of the process and monitoring.

It has been estimated that further energy savings can be achieved by using all the available information correctly in controlling building energy processes. An American Society of Heating, Refrigeration and Air Conditioning Engineers (ASHRAE) survey article [4] estimates that an additional 10 to 15 percent energy savings can be obtained. The opportunity therefore exists to pursue these potential improvement areas by utilizing current mathematical and computer processing methods. While the process control industry has taken advantage and benefited from the application of some of the latest developments in modern system engineering and control theory, the building HVAC industry has not taken effective advantage of these techniques.

Much of the work done in the area of enhancing the performance of HVAC systems followed the OPEC oil embargo of 1973-1974 (which lead to a dramatic increase in energy cost) and has focused on system optimization [5-10, among others]. Unfortunately, not nearly as much work has been done in the area of Fault Detection and Diagnosis (FDD), thus creating a gap in the overall effort. At present, only the simplest checks are performed with respect to diagnostic methods. Essentially, these include checking upper and lower limits of nominal sensor values, checking whether the point is still communicating to the CPU, and checking whether certain binary points are on or off. Also, an operator who understands the processes and thermal relationships in a building and who is able to recognize degraded performance of the processes is essential to the efficient utilization of energy in the building. Unfortunately, such operators are hard to come by [11]. An improved and more sophisticated detection, diagnosis, and correction procedure is clearly desirable and needed in the HVAC system so that impending sensor faults and problems can be anticipated before they happen and noise corrupted measurements can be dynamically and optimally estimated on an on-line basis. In fact, without satisfactory fault detection and isolation capability, the goal of improved control strategies can be completely defeated.

Several surveys of failure detection methods exist. Willsky [12] is a classic paper, discussing many of the techniques available at the time. Himmelblau [13] gives a broad treatment of FDD in chemical processes. Pau [14] and more recently Isermann [15] survey many methods for FDD in various applications. A Kalman filter-based approach to this problem is presented in this paper. The methodology utilizes a nonlinear mathematical model of the process in conjunction with an extended Kalman filter to compute certain features of the process which can be used to detect the occurrence of faults and to identify them. In order to provide a basis for the testing of the

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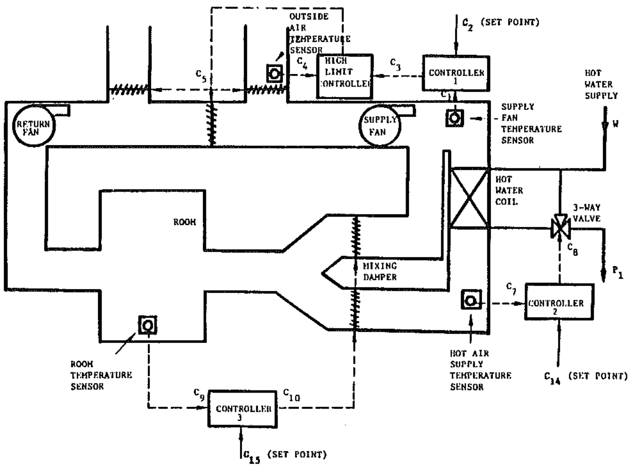

Fig. 1 Schematic diagram of a typical HVAC (heating only) air handler unit

fault detection methodology, a simulation model of an HVAC system air handler unit was used as the process. Known fault conditions were planted in the system and the ability of the detection algorithm to use the outputs of the model to quickly detect the occurrence of the faults without raising false alarms was tested.

The remainder of this paper is organized as follows: In Section 2, a mathematical model of an HVAC system Air Handler Unit (AHU) is described. Section 3 identifies typical fault modes in the HVAC system and describes some of the practical problems in their detection. The fault detection approach is presented in Section 4. A description of the algorithm which was implemented in a computer program and simulation test results are presented in Section 5. Conclusions are provided in Section 6.

2 HVAC Air Handler System Model

A typical HVAC system consists of several subsystems: (i) Water Chiller, (ii) Air Handler, and (iii) Heating and/or Cooling Load Subsystems. Each of these subsystems exhibit dynamic interactions with each other and with the environment. These interactions range from the relatively slow changes in the thermal state of the building in response to the external environment to the very fast changes of some of the internal control systems. Although it is desirable to study the HVAC system as a whole, the focus of this paper is on the Air Handler Unit (AHU).

A schematic diagram of a typical single-zone air handler system is shown in Fig. 1. A mathematical model for the system was developed based upon first principles and a lumped parameter approach. The system was identified as comprising several components, each of which being treated as a lump. Models for each of these components were developed separately and then combined to provide the necessary representation for the entire system. Model parameters for the simulation were obtained from Johnson Controls, Inc. [16].

Overall, the HVAC air handler system model includes nonlinear differential equations that represent the dynamics of the thermal system, sensors, controllers, and actuators, as well as nonlinear algebraic equations that relate the pressures to the flow(s) through each component. The resulting model corresponds to a system of stiff nonlinear algebraic differential equations, of the form:

$$\dot{\mathbf{x}} = \tilde{\mathbf{f}}(\mathbf{x},\mathbf{u},\mathbf{z},\mathbf{w}) \tag{1}$$

$$\mathbf{0} = \mathbf{g}(\mathbf{x},\mathbf{u},\mathbf{z}) \tag{2}$$

$$\mathbf{y} = \tilde{\mathbf{h}}(\mathbf{x},\mathbf{u},\mathbf{z},\mathbf{v}) \tag{3}$$

where $\mathbf{x}$ is an n-vector representing the system state; $\mathbf{u}$ an m-vector representing controller set-points and externally prescribed inputs; $\mathbf{z}$ a p-vector of pressures and flows; $\mathbf{w}$ a q-vector of process noise; $\tilde{\mathbf{f}}$ an n-vector of nonlinear functions representing system dynamics; $\mathbf{g}$ a p-vector of nonlinear algebraic functions representing constraints relating pressures and flows; $\mathbf{y}$ an r-vector of sensor outputs; $\mathbf{v}$ an r-vector of sensor noise; and $\tilde{\mathbf{h}}$ an r-vector of nonlinear functions representing the measured response. The detailed equations and model parameter values are not provided here but can be found in [17]. For the HVAC/AHU system illustrated in Fig. 1, $n=20$, $p=24$, and $r=3$. The observations are the supply fan outlet temperature, hot air supply temperature, and room temperature.

Observe that the model specified by equations (1)–(3) is not in a conventional state-space form because of the presence of the set of algebraic equations (2) and the associated vector $\mathbf{z}$. However, if one assumes that the set of simultaneous algebraic equations (2) can be solved for $\mathbf{z}$ in terms of $\mathbf{x}$ and $\mathbf{u}$, at least at times t_i, $i=1,2,\ldots$, then $\mathbf{z}$ can be substituted for in equations (1) and (3), so that $\mathbf{x}$ and $\mathbf{y}$ become dependent on $\mathbf{x},\mathbf{u},\mathbf{v}$, and $\mathbf{w}$ only. This manipulation reduces the system model to a conventional state-space structure of the form:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x},\mathbf{u},\mathbf{w}) \tag{4}$$

$$\mathbf{y} = \mathbf{h}(\mathbf{x},\mathbf{u},\mathbf{v}) \tag{5}$$

This is the model structure used for the detection problem discussed below. Note that the noise vectors $\mathbf{v}$ and $\mathbf{w}$ typically enter the model additively, and this assumption is made in this study.

3 Problem Discussion

One of the fundamental aims of FDD is to detect and identify changes in the structure and parameters of a given system in order to take compensatory or corrective action to maintain operation at some desired point. This capability is crucial to enhancing the reliability and safety of operating equipment, and to ensuring efficient operation of the system [18]. Examples of AHU faults include: (i) fan stall and resulting surge behavior, (ii) coil flow occlusion, (iii) valve failures, (iv) damper failures, (v) sensor hard failures (both high and low limits; these are important for both pneumatic and electrical transducers, but often easy to detect), (vi) sensor soft failures (including biases or drifts, which are more critical and difficult to detect), (vi) actuator motor failures (including shaft seizure or binding on both pneumatic and electric actuators, and leakage in pneumatic motors), (vii) control failures (including drift and bias, leakage and occlusion of modules or their connecting lines), and (viii) miscellaneous process failures (including occluded filters, broken equipment, pipe clogging, pipe leakage, boiler leakage, etc.).

A practical problem regarding HVAC fault detection is the computation time requirements. Fault detection and diagnosis algorithms are often computation intensive. This problem is compounded by the fact that HVAC systems are generally modeled by very high dimensional nonlinear systems of equations. However, in order for the FDD algorithm to be suitable for HVAC applications, two important capabilities must be present: (i) The ability to quickly detect the occurrence of a failure condition within a very short period following its occurrence; and (ii) the ability to determine not only the fact that a fault has occurred, but also its identity. For instance, it is important to know the value of the bias in a specific sensor in order for the control system to take adequate compensatory actions. These considerations call for an innovative approach to solving the problem and has, in fact, motivated the methodology presented below.

4 Fault Detection Methodology

The basic approach to fault detection presented here relies on using a statistical criterion as an indicator of fault occurrence. The criterion is based on certain "features" of the system behavior which are monitored during system operation and compared with the corresponding *a priori* estimates based on the no-failure model of the system. Statistically significant disagreements between the monitored and *a priori* features are used to indicate the occurrence of failures and to determine their identity. The overall approach consists of three primary steps:

(i) Residual Generation: estimates of the system states are utilized to compute the difference between the expected and actual observations. These give a measure of the distance between the actual system and the model prediction;

(ii) Feature Computation: the residuals cannot be used in raw form, but must be used to compute certain quantities with known statistical properties (at least under no failure conditions). A typical such quantity is the normalized squared residual, which can be shown to be related to the likelihood function under certain conditions;

(iii) Decision making: the information collected is used by means of comparisons with known values (threshold tests) or pre-established classification in making a decision on the presence or absence of a failure, as well as possibly its nature and location.

Each of these steps as applied to the present problem is discussed below.

Residual Generation. The generation of residuals requires estimates of system states. The sequential optimal Bayes linear estimator, also known as the Kalman Filter, is most often used for this purpose. The problem at hand, however, is rendered more complex by the following factors:

(i) The system is nonlinear and subject to complex nonlinear constraints relating the state variables, pressures and flows. Thus, while it can be linearized at various points along the trajectory by solving sets of simultaneous nonlinear equations and computing first-order Taylor approximations, these computations are costly and the resulting linear model is time-variant.

(ii) Although the system is continuous, it is sampled discretely. While this does not ordinarily cause any difficulties, the complexity and time-variance of the model result in a highly complicated procedure in which numerical stability and computational economy are serious considerations.

These properties necessitate the use of an extended Kalman Filter approach [19, 20], as discussed below.

Let the model of the HVAC system be given by

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t),\mathbf{u}(t),\theta,t) + \mathbf{w}(t) \tag{6}$$

$$\mathbf{y}(t_i) = \mathbf{h}(\mathbf{x}(t_i),\theta,t_i) + \mathbf{v}(t_i) \tag{7}$$

where $i = 1,2, \ldots$ denoting sampling times, the state vector $\mathbf{x}(.)$ is subject to the initial conditions

$$E[\mathbf{x}(t_0)] = \mathbf{x}_0 \tag{8}$$

$$E[(\mathbf{x}(t_0) - \mathbf{x}_0)(\mathbf{x}(t_0) - \mathbf{x}_0)^T] = P_0 \tag{9}$$

θ is a parameter vector, and the disturbances $\mathbf{v}(.)$ and $\mathbf{w}(.)$ are zero-mean normal. Note that (6) and (7) are a special case of equations (4) and (5), with the disturbances occurring additively and linearly.

Assuming the model structure specified in equations (6)–(9), then, the state estimates are given by

$$\hat{\mathbf{x}}(t|t_{i-1}) = \hat{\mathbf{x}}(t_{i-1}|t_{i-1}) + \int_{t_{i-1}}^{t} \mathbf{f}(\hat{\mathbf{x}}(\tau),\mathbf{u}(\tau),\theta,\tau)d\tau \tag{10}$$

for $t_{i-1} \le t \le t_i$, where $\hat{\mathbf{x}}(t_1|t_2)$ is the estimate of $\mathbf{x}(t_1)$ given all information available at t_2, and

$$\hat{\mathbf{x}}(t_i|t_i) = \hat{\mathbf{x}}(t_i|t_{i-1}) + K(t_i)[\mathbf{y}(t_i) - \mathbf{h}(\hat{\mathbf{x}}(t_i|t_{i-1}),\theta,t_i)] \tag{11}$$

with

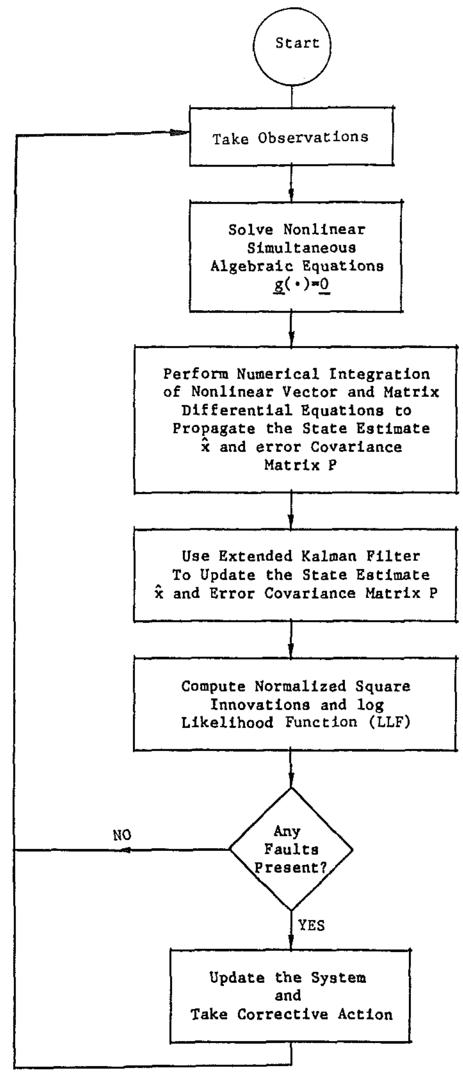

Fig. 2 A flow chart of the detection algorithm

$$\hat{\mathbf{x}}(t_0|t_0) = \mathbf{x}_0 \tag{12}$$

and $K(.)$, the gain matrix, obeys the following relation:

$$K(t_i) = P(t_i|t_{i-1})H^T(t_i|t_{i-1}) \bullet [H(t_i|t_{i-1})P(t_i|t_{i-1})H^T(t_i|t_{i-1}) + R]^{-1} \tag{13}$$

$P(.|.)$ is the state estimate covariance matrix, $H(t_i|t_{i-1})$ corresponds to a linearization of $\mathbf{h}(.)$ at the point $\hat{\mathbf{x}}(t_i|t_{i-1})$, and R is the observation noise covariance matrix. In turn, the state estimate covariance matrix obeys

$$P(t_j|t_{i-1}) = \Phi_j(t_{j-1},t_j)P(t_{j-1}|t_{i-1})\Phi_j^T(t_{j-1},t_j) + Q \tag{14}$$

for $t_{i-1} \le \ldots < t_{j-1} < t_j < \ldots \le t_i$ for small enough time increments (which may be determined automatically by the linearization procedure), where Q is the process noise covariance matrix and $\Phi_j(. \, , .)$ is the state transition matrix corresponding to a pointwise linearization of $\mathbf{f}(.)$ along the trajectory $\hat{\mathbf{x}}(t_j|t_{i-1})$. The covariance update is given by

$$P(t_i|t_i) = [I - K(t_i)H(t_i|t_{i-1})]P(t_i|t_{i-1}) \tag{15}$$

and finally

$$P(t_0|t_0) = P_0 \tag{16}$$

This formulation gives a first-order approximation to the problem of tracking a nonlinear, time-varying, continuous-time system observed discretely, as described by equations (6)–(9).

Equations (10)–(16) describe the "best" estimate of the state vector and other related quantities. These estimates are used to compute residuals, or "innovations," given by:

$$\gamma(t_i) = \mathbf{y}(t_i) - \mathbf{h}(\hat{\mathbf{x}}(t_i \mid t_{i-1}), \boldsymbol{\theta}, t_i) \tag{17}$$

Under the null hypothesis of "no failure," i.e., assuming that the model corresponds to reality, and assuming normal noise, the innovations will be distributed approximately as zero-mean normal random numbers, with covariance

$$\Gamma(t_i) = H(t_i \mid t_{i-1}) P(t_i \mid t_{i-1}) H^T(t_i \mid t_{i-1}) + R \tag{18}$$

This behavior is used to test for failures by checking whether or not the model does, in all likelihood, correspond to the true system; this is described in the next section.

Feature Computation. The method discussed above generates a sequence of random numbers which have known statistical properties under the null hypothesis. These numbers, called innovations, are accumulated over a period of time, and used to compute certain quantities to be utilized in the decision making process.

One of the simplest statistics that may be used for this purpose is the sum of normalized squared innovations, given by

$$l_W(t_i) = \sum_{j=i-W+1}^{i} \gamma^T(t_i) \Gamma^{-1}(t_i) \gamma(t_i) \tag{19}$$

where W is a window length to be determined [21]. Under the null hypothesis, $l_W(.)$ is χ^2-distributed, with Wr degrees of freedom (where $r = dim\ \gamma(.)$). Thus, a critical value for threshold tests can easily be found. It must be noted that small values of W would cause $l_W(.)$ to be very sensitive to noise, while large values of W would cause excessive smoothing and thus make the detector insensitive or slow to react. Consequently, the choice of W must be made with care. In the test case presented below $r = 3$ and $W = 10$.

The criterion $l_W(.)$ defined in (19) is essentially the negative log-likelihood function assuming normal noise, minus some terms. This gives an intuitive justification not only for using it in failure detection but also for formulating a combined detection/ diagnosis scheme in a likelihood ratio setting [22]. Such an approach would consist of including in the Kalman Filter models for various possible failures, estimating their parameters (e.g., value of the sensor bias) by a maximum likelihood approach, and then choosing that model for which the likelihood is maximum

Decision Making. Once the information needed to detect and possibly diagnose faults has been accumulated, it is necessary to interpret the information in various ways: whether or not there is a failure, the probability of a failure occurrence, the most likely failure to have occurred, and so on. While very complicated logic could be designed to take into acount the past history of the system as well as various factors possibly external to the system, simple tests are often satisfactory.

For example, in the case of $l_W(.)$, defined by equation (19), the test can be as simple as comparing the value of the statistic with critical values for a χ^2 distribution at a predetermined significance level α (e.g., .05, .01, etc.). As seen in the results presented below, this approach is satisfctory when the only question asked is whether or not a failure has occurred. It must be noted, however, that even in the absence of failure, the model used in the extended Kalman filter, given in equa-

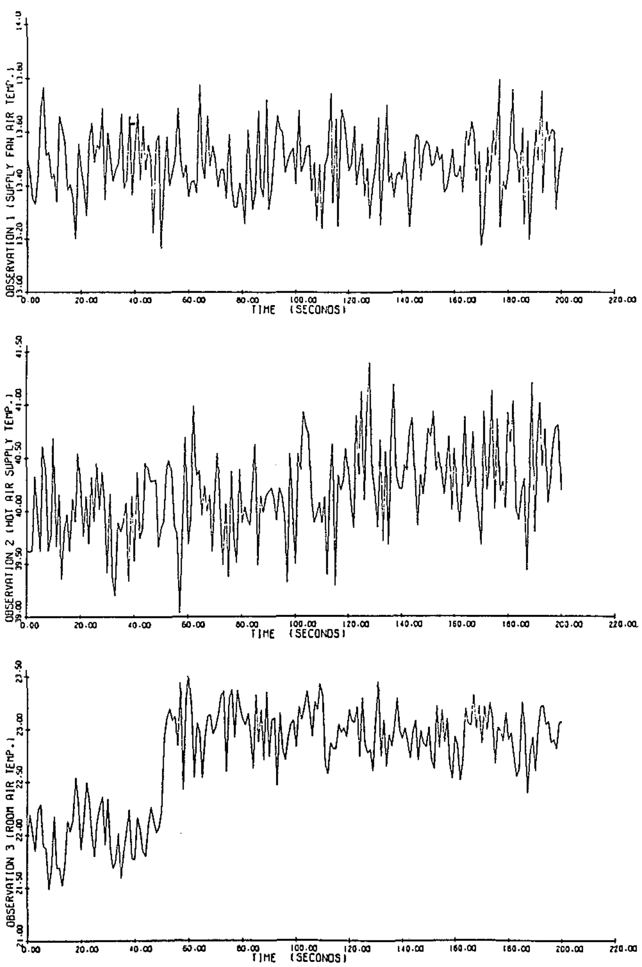

Fig. 3(*a*) Detection of step bias in room temperature sensor at 50 seconds: system response

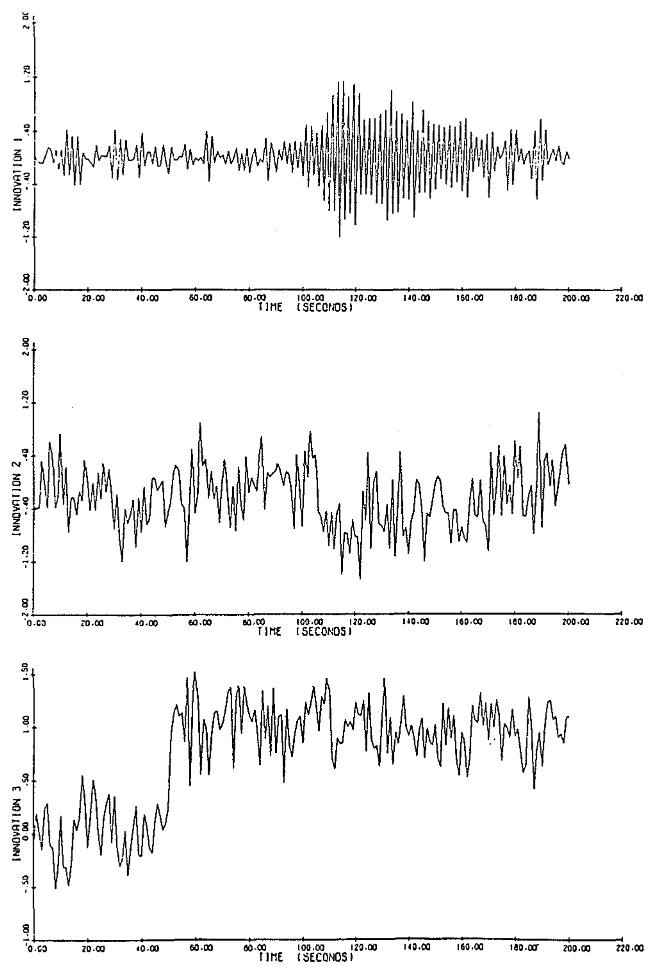

Fig. 3(*b*) Detection of step bias in room temperature sensor at 50 seconds: innovation process

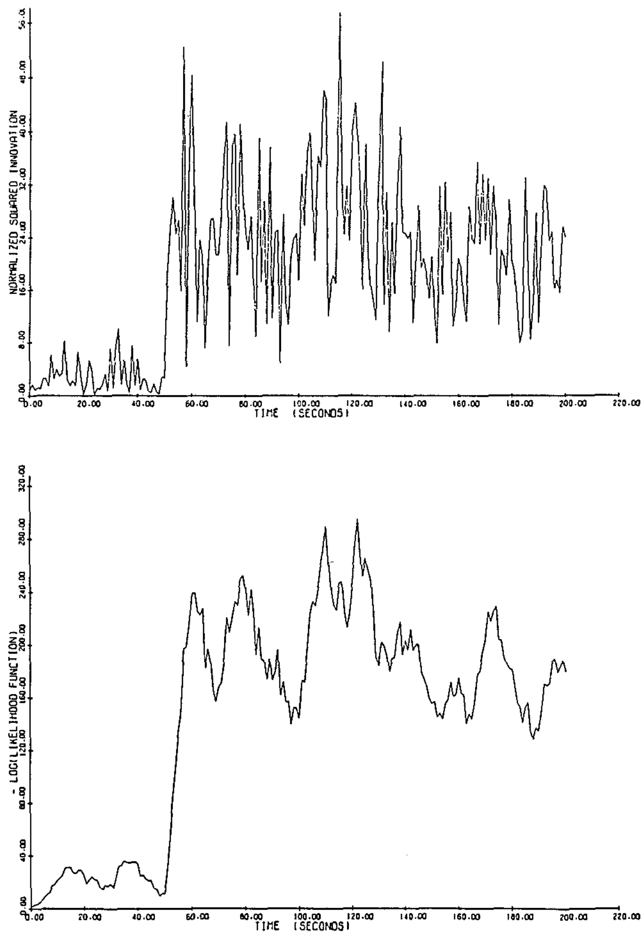

Fig. 3(c) Detection of step bias in room temperature sensor at 50 seconds: normalized squared innovation and test criterion

tions (10)–(16), is only approximate. Thus, it would be wrong to religiously test for innovation normality; rather, one must watch for sudden and large changes in the value of $l_W(.)$. With that slightly relaxed approach, the failure detector based on (19) gives very good results, as shown below.

5 Implementation and Test Results

Implementation. The fault detection program performs three major tasks: first, it propagates the state of the system and the error covariance matrix from a given initial time to a final time (two consecutive observation times); second, it updates the estimates of the system state and error covariance matrix after a new measurement is taken; lastly, it performs a test to determine whether or not a fault has occurred. The propagation is performed by numerical integration of the model differential equations, while the updating is done using an extended Kalman filter, described in the previous section. The innovations and their covariances are used to generate the likelihood function for a moving time window of selected size. The likelihood function is then compared with a critical value (as described previously) and a fault condition is determined to be present if the negative log likelihood function exceeds the critical value for a selected period of time. A flow chart of the detection program is presented in Fig. 2.

The continuous-time nonlinear differential equations for the system model are used to propagate the state of the system from one observation time to the next, by using Gear's algorithm [23]. However, the error covariance matrix is propagated by using a linearized model of the system. The Jacobian computed in the linearization process is used to compute the transition matrix for that time interval in order to propagate the error covariance matrix. Using an extended Kalman filter, the updated estimate of the state and the error covariance matrix are computed and used as initial conditions for the next interval. The filter also computes the innovation covariance matrix which is used to compute the terms in the likelihood function. The simulation was run "off-line" on a VAX 11/780.

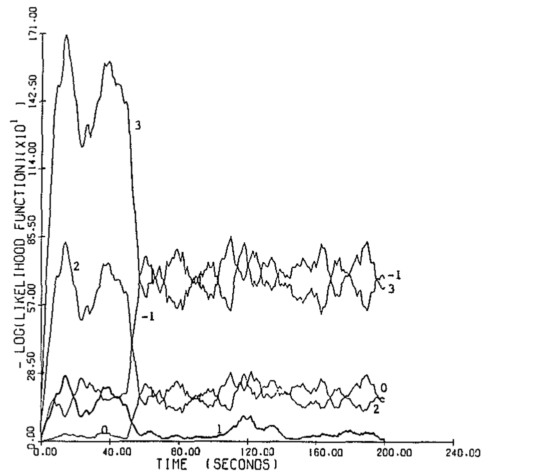

Fig. 4 Plate of negative log likliehood function assuming −1, 0, 1, 2, and 3°C biases. (True value is 1°C.)

Test Results. In order to evaluate the failure detection methodology presented here, several test cases were run [17]. In general, for each of the test examples, the system was simulated with sensor noise included, and a selected fault condition was imposed starting at a selected time. Sensor readings from the simulation were then processed by the failure detection software. The aim was to assess the ability of the detector to accurately determine the presence of a fault within a short time following the actual occurrence of the fault, as well as the reliability of the detector in not raising false alarms. As discussed in Section 4, the detector essentially uses an extended Kalman filter to compute the innovations for the system. By computing the associated likelihood function and monitoring its excursions, the presence of a fault is determined.

A test case is presented below to demonstrate the ability of the fault detection program to detect room temperature sensor bias. In the test, the supply fan outlet temperature, hot air supply temperature, and room air temperature were observed. Also, zero mean white sensor noise was added to all the sensors. The root mean square values of the noise for each sensor represented approximately one percent of typical sensor readings. Although process noise was not explicitly added to the system, the sensor noise feeds into the system through the controllers, so that the process itself was in fact subjected to noise. Detailed plots of the process response to the fault condition are not provided here, the focus being on the available sensor observations and the ability to detect the presence of faults.

Detection of a Step Bias in the Room Temperature Sensor. In this test the model was started at a normal operating condition and the states were propagated for 50 seconds before a +1°C bias was added to the room temperature sensor (refer to Fig. 1). The overall simulation lasted for 200 seconds. Two hundred observations were taken at a sampling rate of 1 sample per second. Figure 3(a) shows the observations for this simulation. The room temperature measurement shows the jump in the temperature reading at around 50 seconds.

Using the measurements taken from this simulation, a fault detection test was performed. The innovations, normalized squared innovations and negative log likelihood function computed by the detection program are presented in Figs. 3(b) and

3(c). The large jump in the likelihood function value after 50 seconds is an indication that a fault has occurred within the system. If the threshold for the negative log likelihood function is set at 50, (approximately, the critical value of a χ^2 distribution with 30 degrees of freedom for a 0.01 confidence level), this implies that the fault can be detected within a few seconds of its occurrence. (The threshold should be selected judiciously based upon extensive analysis of a variety of failure modes and operating conditions.) Overall the sensitivity of the likelihood function to a $+1°C$ bias (in this case) in room temperature sensor signal implies that such a bias can be easily detected by the algorithm.

Determining the Level of a Step Bias in the Room Temperature Sensor Signal. Figure 4 illustrates the results of a test similar to that described above, where a 1°C bias is added to the room temperature sensor signal after 50 seconds, but for cases where the Kalman filter assumes different values of bias for the sensor. Different curves corresponding to different assumed bias values (−1°C, 0°C, 1°C, 2°C, and 3°C) are shown. The idea is that at any given "instant" of time the curve with the lowest negative log likelihood function yields the correct bias. Clearly, the lowest curve in Fig. 4 corresponds to no bias until about 54 seconds, after which time the 1°C bias curve is minimum. This clearly provides a good indicator of the true status of the system. Not only can the bias be detected rapidly in this case, but it can also be accurately estimated. In practice, the bias would of course be estimated, *via* maximum likelihood, rather than deduced from such comparisons.

6 Discussion and Conclusions

A methodology for detecting faults in an HVAC system using a nonlinear mathematical model of the system plus an extended Kalman filter has been presented. This methodology has been implemented in a computer program and successfully used to detect a variety of simulated faults in the HVAC system. Simulation test results show that by sampling measurements every second, a 1°C room temperature sensor bias can be detected within 5–10 seconds of occurrence. Such early detection capability for faults, would greatly enhance the economic operation of the HVAC system. For one, the control system could be adjusted to compensate for soft failures such as biases and drifts, or to ignore faulty sensor readings in the case of hard sensor failures. On the other hand, the system could be made to stop operation in such cases as when a major process failure or a condition which is not easily correctable is detected. Such "stop operation" enforcement can protect the system against the occurrence of a potentially hazardous or catastrophic event, which might be very expensive to repair.

Acknowledgments

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