Fault Detection in an Air-Handling Unit Using Residual and Recursive Parameter Identification Methods

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ABSTRACT

A scheme for detecting faults in an air-handling unit using residual and parameter identification methods is presented. Faults can be detected by comparing the normal or expected operating condition data with the abnormal, measured data using residuals. Faults can also be detected by examining unmeasurable parameter changes in a model of a controlled system using a system parameter identification technique. In this study, autoregressive moving average with exogenous input (ARMAX) and autoregressive with exogenous input (ARX) models with both single-input/single-output (SISO) and multi-input/single-output (MISO) structures are examined. Model parameters are determined using the Kalman filter recursive identification method. This approach is tested using experimental data from a laboratory's variable-air-volume (VAV) air-handling unit operated with and without faults.

INTRODUCTION

Fault detection and diagnosis of heating, ventilating, and air-conditioning (HVAC) systems is an important part of maintaining proper performance, reducing energy consumption, and increasing the reliability and availability of the system. One of the main purposes of on-line monitoring and diagnosis is the early detection of failures of equipment and sensors used in the control of HVAC systems.

Studies on fault detection are extensive and various approaches have been proposed. Willsky (1976) examined statistical techniques for the detection of failures in stochastic dynamic systems. Isermann (1984) surveyed existing fault-detecting and diagnosing methods based on the estimation of unmeasurable process parameters and state parameters. Patton et al. (1989) also provided an overview of various fault-detecting and diagnosing methods by presenting research that included many references to application case studies. Frank (1990) reviewed state-of-the-art fault detection and isolation in automatic processes using analytical redundancy.

In recent years, several schemes for fault detection in HVAC systems have been investigated. Liu and Kelly (1989) proposed a rule-based diagnostic method for fault detection. Anderson et al. (1989) studied statistical analysis preprocessors and rule-based expert systems to monitor and diagnose HVAC system faults. Pape et al. (1991) developed a methodology for fault detection in HVAC systems based on optimal control. In order to detect faults in system operation, deviation from optimal performance was sensed by comparing the measured system power with the power predicted using the optimal control strategy. Norford and Little (1993) presented a method for diagnosing fault in HVAC systems using the parametric models of consumed electric power.

In this paper, faults and symptoms were studied using changes in physical quantities, such as the deviation of temperature, pressure, or flow rate, from their normal operating points. When a process operates under normal conditions, the process parameters should be at their normal values. A fault in the system can be detected by observing the residual value, which is the difference between the normal (or expected) data and the abnormal operating data. If some physical change in the equipment causes a deviation from the normal state, the model parameters of the process will also deviate from their normal values. These parameters can be estimated for fault-free and fault-containing systems using parameter-identification methods.

Faults are detected when a specified threshold is exceeded. The threshold can be determined by using statistical methods. A three-sigma limit (three standard deviations) is often used as a threshold value (Montgomery et al. 1994; Rose et al. 1993; Farnum 1992; Fasolo and Seborg 1992).

There are two types of faults: complete (or abrupt failures) and performance degradations. Complete failures are severe and abrupt faults. Performance degradations are gradually evolving faults. Although there are many kinds of potential faults in an air-

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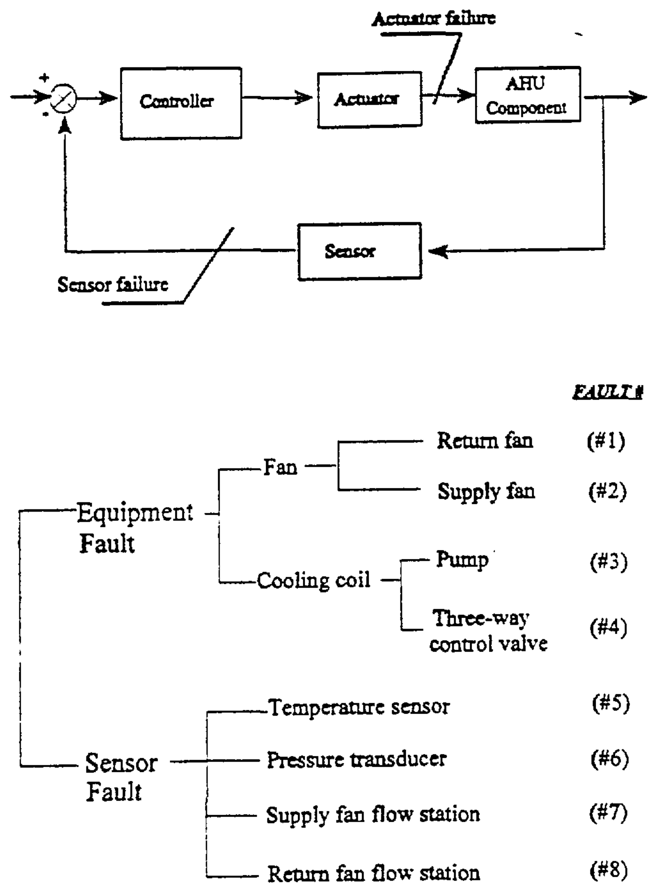

Figure 1 *Fault situations.*

handling unit, the eight different equipment and instrumentation faults shown in Figure 1 were considered in this study, based on experimental testings.

SYSTEM UNDER TEST

Air-Handling Unit

The variable-air-volume (VAV) system used in this study was based on a reference system (Kelly 1992) developed by the International Energy Agency (IEA) Annex 25. A simplified system layout diagram of the air-handling unit (AHU) is shown in Figure 2. The unit consists of fans, dampers, a cooling coil, sensors, and controllers. The static pressure in the main supply duct is controlled to maintain a constant static pressure at each VAV box inlet by sensing the static pressure and controlling the speed of the supply fan. The flow difference between the return fan and the supply fan is controlled by a return fan with variable speed. The supply air temperature is controlled by the chilled-water control valve to maintain a constant reference temperature. Heating and preheating of the outdoor air are not considered in this study.

Controllers

A proportional-integral-derivative (PID) controller using the velocity algorithm was designed to control the supply air

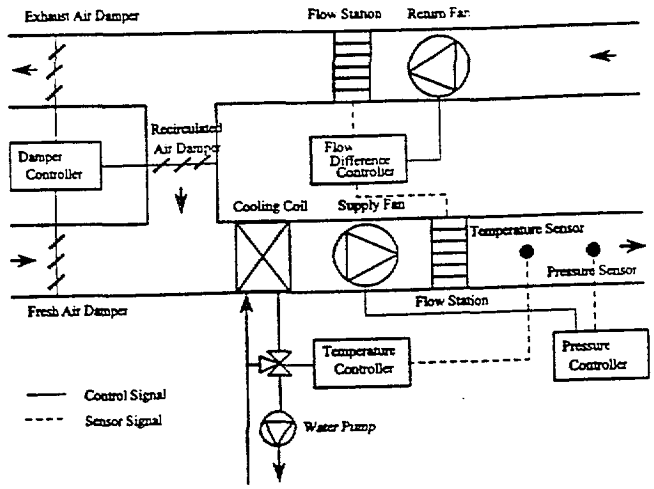

Figure 2 *System layout diagram.*

temperature. Two other controllers were designed to control the static pressure in the supply duct and the difference between the supply fan and return fan flow rates. The PID velocity control algorithm is expressed as

$$U(i) = U(i-1) + K_P[E(i) - E(i-1)] + K_I T_S E(i) + \frac{K_D}{T_S}[E(i) - 2E(i-1) + E(i-2)] \tag{1}$$

where $U(i)$ denotes the control signal at the ith sampling instant, $E(i)$ is the error at the ith sampling time (defined by the difference between the setpoint value and the measured value), and T_S is the sampling period. The parameters K_P, K_I, and K_D are the proportional, integral, and derivative gains of the PID velocity control algorithm, respectively. The sampling period was 10 seconds.

The supply air temperature was controlled at 14.5°C (58°F) using a three-way control valve. The supply duct static pressure controller maintained the static pressure at 249 Pa (1.0 in. H_2O) in the supply duct by modulating the supply fan speed. The return fan speed was controlled to maintain the return airflow rate at 0.472 m^3/s (1,000 cfm) below the supply airflow rate.

In the present study, the controller gain was approximately determined using a simple first-order transfer function for the system with the delay term obtained from a step change in the setpoint. The transfer function is given by

$$T(S) = \frac{K_S}{1 + T_C S} e^{-T_D S} \tag{2}$$

where K_S is the system gain, T_C is the time constant, T_D denotes the dead time, and S is the Laplace variable. From the experimental data, the K_S, T_C, and T_D values for the supply air temperature controller were determined to be 1.02 K/V (1.836 °F/V), 80 seconds, and 20 seconds, respectively. Using this approximate transfer function, the PID controller gains were first adjusted to minimize the integral absolute error over time (Dorf 1980) and then modified by experiments on the actual system. The final PID gains used for this three-way valve controller were K_P = 1.5 V/K (0.8333 V/°F), K_I = 0.0157 V/s·K (0.0087 V/s·°F), and K_D = 10.6 V·s/K (5.8889 V·s/°F), respectively. The controllers for the static pressure and the airflow rate difference did not use derivative terms due to the fast response of the controlled variables. The proportional and integral (PI) controller gains were also determined by computer simulations and then modified by experiments (Lee et al. 1994). Normal operating conditions for the controller tuning and the fault detection tests are given in Table 1.

TABLE 1 Nominal Operating Conditions

Variables	Description	Nominal Values
Q_s	Supply airflow rate (m^3/s)	1.5
T_{WI}	Inlet water temperature of the cooling coil (°C)	10.2
T_M	Mixed air temperature (°C)	22.0
H_M	Mixed air humidity (dew-point temperature, °C)	12.5

To smooth the measured data and reduce the effect of random noise, smoothing filters were applied to the measured supply duct pressure, the measured flow rates, and the supply air temperature. The smoothed values were then used by the controllers. The following equation was employed:

$$M_{SS}(i) = \alpha M_S(i) + (1-\alpha)M_{SS}(i-1) \tag{3}$$

where M_{SS} is the smoothed measurement, α is the smoothing weight factor, M_S is the actual measurement, and i is the current sampling instant. A value of 0.7 was employed.

TECHNIQUE OF FAULT DETECTION

Residual Method

Faults in a broad sense result in symptoms that involve the deviations of measured values from their normal operating points. A fault can be detected by observing residual values, which are defined as the differences between actual measured values under a fault condition and the expected values under normal operation.

The residual of the supply air temperature, R_T, was defined as

$$R_T = T_S - T_{S,SP} \tag{4}$$

where T_S is the supply air temperature and $T_{S,SP}$ is the supply temperature setpoint.

The residual of the supply duct static pressure, R_P, was defined as

$$R_P = P_S - P_{S,SP} \tag{5}$$

where P_S is the measured static pressure value and $P_{S,SP}$ is the static pressure setpoint value.

The residual of the flow difference between the supply and return fans, R_Q, was defined as

$$R_Q = Q_D - Q_{D,SP} \tag{6}$$

where Q_D is the difference between the measured supply and return airflow rates and $Q_{D,SP}$ is the setpoint value.

The residual of the cooling coil control signal, R_U, was defined as

$$R_U = U_{CC} - U_{CC,SP} \tag{7}$$

where U_{CC} is the control signal for the cooling coil valve (as determined by Equation 1) and $U_{CC,SP}$ is the setpoint value or reference value at a normal condition.

The value of U_{CC} controls the supply water temperature for a three-way valve or the supply water flow rate for a two-way valve. Under normal operation, U_{CC} is the same as $U_{CC,SP}$. However, when a fault occurs, U_{CC} will deviate from $U_{CC,SP}$. A problem, however, arises because $U_{CC,SP}$ is not a fixed value but varies with the load on the AHU. One possible way of handling this difficulty is to calculate the mean value and standard deviation of $U_{CC,SP}$ every sampling time using a number of data points (e.g., 20 data points) from previous time steps. This works well for systems subject to slowly varying loads and for quickly developing (complete) faults.

Another approach for determining $U_{CC,SP}$ is to use a reference model that is developed under normal conditions. The reference model is a function of load change and environmental conditions, such as outdoor air temperature and humidity. The residual is the calculated difference between the measured value and the estimated value from the reference model. If there is no fault, the measured and estimated values should be the same. Deviations between the measured and the estimated values indicate the presence of faults. This reference model approach is essential for detecting long-term performance degradation, such as the fouling of heating and cooling coils.

The residuals for the actuators are defined as the difference between the input control signal and the measured positions of the actuators or speed signals of the fans. The residuals of the supply fan speed, R_{NS}, and the return fan speed, R_{NR}, are given by

$$R_{NS} = N_S - U_S \tag{8}$$

and

$$R_{NR} = N_R - U_R \tag{9}$$

where N_S and N_R are the measured values of the supply and the return fan speeds, and U_S and U_R are the control signals for the supply and return fans, respectively.

The residual of the cooling coil valve position was defined as

$$R_V = V_P - U_{CC} \tag{10}$$

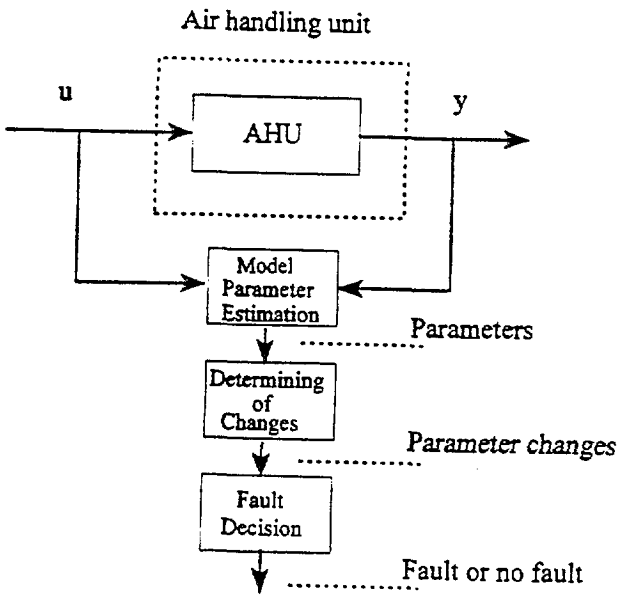

Figure 3 *Fault detection using parameter estimation.*

where V_P is the three-way cooling coil valve position determined by monitoring a variable resistor on the valve stem. At normal operation, R_{NS}, R_{NR}, and R_V are approximately zero. However, these values deviate from zero when an actuator fault occurs.

Parameter Identification Methods

When a process operates under normal conditions, the parameters in a continuously updated model of the process will be at their normal values. If some physical changes in the system cause deviation from the normal state, some or all of the model parameters will deviate from these normal values. The fault condition can then be detected as shown in Figure 3.

The parameters of a model can be estimated by employing a system identification method. In this study, multi-input/single-output (MISO) and single-input/single-output (SISO) autoregressive moving average with exogenous input (ARMAX) models and autoregressive with exogenous input (ARX) models were used, and model parameters were recursively identified using Kalman filters.

The general structure of the SISO or MISO ARMAX models (Ljung 1987) is given by

$$A(q)y(t) = B(q)u(t-nk) + C(q)e(t) \tag{11}$$

where n is the number of time-step delays from input to output. $A(q)$ and $C(q)$ are polynomials in terms of the time delay operator q^{-1}:

$$\begin{aligned} A(q) &= 1 + a_1 q^{-1} + \ldots + a_{na} q^{-na} \\ C(q) &= 1 + c_1 q^{-1} + \ldots + c_{nc} q^{-nc} \end{aligned} \tag{12}$$

$$B(q) = \begin{bmatrix} b_{11} & b_{12} & \cdots & . \\ b_{21}q^{-1} & b_{22}q^{-1} & \cdots & . \\ . & . & \cdots & . \\ b_{nb1}q^{-nb+1} & b_{nb2}q^{-nb+1} & \cdots & b_{nbnu}q^{-nb+1} \end{bmatrix} \tag{13}$$

where $B(q)$ is an $nb \times nu$ matrix. The quantities na, nb, and nc are the orders of the polynomials, and nu is the number of input variables. For the SISO model, $nu = 1$.

For the first-order MISO model with a delay of two sampling times, Equation 11 becomes

$$\begin{aligned} y(t) &= -a_1 y(t-1) + b_{11}u_1(t-2) \\ &+ b_{12}u_2(t-2) + \ldots + b_{1n}u_n(t-2) \\ &+ e(t) + c_1 e(t-1) \end{aligned} \tag{14}$$

where n is the number of input variables.

As a special case of the ARMAX model, the ARX model structure is given by

$$A(q)y(t) = B(q)u(t-nk) + e(t). \tag{15}$$

This equation can also be written explicitly for a first-order model with a delay of two sampling times as

$$\begin{aligned} y(t) &= -a_1 y(t-1) + b_{11}u_1(t-2) \\ &+ b_{12}u_2(t-2) + \ldots + b_{1n}u_n(t-2) + e(t). \end{aligned} \tag{16}$$

Recursive Parameter Estimation Using Kalman Filter

The typical recursive parameter identification algorithm (Ljung 1987, 1991; Johansson 1993) is given by

$$\theta(t) = \theta(t-1) + K(t)y(t) - \hat{y}(t)) \tag{17}$$

$$y(t) = \psi(t)^T\theta_0 + e(t). \tag{18}$$

and

$$\theta_0(t) = \theta_0(t-1) + w(t) \tag{19}$$

where $\theta(t)$ is the parameter estimate at time t, $\psi(t)$ is the regression vector that contains old values of observed inputs and outputs, $y(t)$ is the observed output at time t, and $\hat{y}(t)$ is the prediction of the value $y(t)$ based on observations up to time $t-1$ and the current model at time $t-1$. θ_0 represents the true description of the system, $e(t)$ is the noise source with the variance, $R_2 = E[e^2(t)]$, and $w(t)$ is assumed to be white Gaussian noise with covariance, $R_1 = E[w(t)w^T(t)]$.

The gain $K(t)$ determines how the current prediction error, $[y(t) - \hat{y}(t)]$, updates the parameter estimate. It is typically chosen as

$$K(t) = Q(t)\psi(t). \tag{20}$$

The Kalman filter algorithm is given by

$$\hat{y}(t) = \psi^T(t)\theta(t-1), \tag{21}$$

$$Q(t) = \frac{P(t-1)}{R_2 + \psi^T(t)P(t-1)\psi(t)}, \tag{22}$$

$$P(t) = P(t-1) + R_1 - \frac{P(t-1)\psi(t)\psi^T(t)P(t-1)}{R_2 + \psi^T(t)P(t-1)\psi(t)}. \tag{23}$$

An optimal choice of $Q(t)$ is computed from Equations 17 through 23.

Threshold Checking

The proper choice of the threshold values is important for detecting faults. The thresholds can usually be determined from statistical properties of the process. The concept of statistical method is very straightforward. If a measurement is greater than an upper limit threshold limit or is lower than a lower threshold limit, the process is said to be out of the normal state and a fault is presumed to have occurred.

In this study, a three-sigma limit was used as the threshold value. If the measurable characteristic, x, of an item is normally distributed with the mean, $\bar{x}$, and the standard deviation, σ, it is possible to find the probability that x will lie within a fixed interval. The probability that x will fall within the interval $[\bar{x}-3\sigma, \bar{x}+3\sigma]$ is 0.9973. The threshold for a measured variable x was specified as $|x-\bar{x}| = 3\bar{\sigma}$, where $\bar{x}$ denotes the assumed mean and $\bar{\sigma}$ denotes the assumed standard deviation. Typically, $\bar{x}$ and $\bar{\sigma}$ are calculated from a set of test data (Fasolo and Seborg 1992; Farnum 1992). When the residual method is used, $|x-\bar{x}|$ is the value of the residual, and when the parameter identification method is used, $|x-\bar{x}|$ is the difference between the estimated value and the mean value at normal condition.

TEST RESULTS AND DISCUSSION

As previously mentioned, a fault in the system can be detected by observing the residual values. When an input-output model is used for the system description, a fault can be detected by looking for changes in the model parameters, which are estimated by using model identification methods.

The first-order system models were used in this study to estimate the model parameters before and after a fault occurs. Pseudo-linear ARMAX equations and linear ARX equations were employed. The structure of the multi-input ARMAX system model is given by

$$\begin{aligned} P_S(t) &= -a_{P1}P_S(t-1) + b_{P1}U_P(t) \\ &+ b_{P2}U_Q(t) + b_{P3}\theta(t) + e(t) + c_{P1}e(t-1), \end{aligned} \tag{24}$$

$$\begin{aligned} Q_D(t) &= -a_{Q1}Q_D(t-1) + b_{Q1}U_P(t) \\ &+ b_{Q2}U_Q(t) + b_{Q3}\theta(t) + e(t) + c_{Q1}e(t-1), \end{aligned} \tag{25}$$

$$\begin{aligned} T_S(t) &= -a_{T1}T_S(t-1) + b_{T1}U_{CC}(t-2) \\ &+ b_{T2}Q_S(t-2) + b_{T3}T_M(t-2) \\ &+ b_{T4}H_M(t-2) + e(t) + c_{T1}e(t-1), \end{aligned} \tag{26}$$

where P_S is the static pressure at the supply duct, Q_D is the flow difference between the supply and return fans, and T_S is the supply air temperature. The variable θ is the angle that the recirculating air damper makes with a plane perpendicular to the direction of flow, Q_S is the supply airflow rate, T_M is the mixed-air temperature, and H_M is the mixed-air humidity ratio. The subscripts P, Q, and T denote the supply air static pressure, the flow difference between the supply and return fans, and the supply air temperature, respectively.

If noise is not explicitly taken into account, Equations 24 through 26 become an ARX model. A disturbance influences the output, and this output changes the feedback signal to the controller, which, in turn, changes the controller output. Since the control signal includes information on disturbances in the SISO model, only the control signal and the output need to be considered. The structure of the simplest SISO ARX model becomes

$$P_S(t) = -a_{P1}P_S(t-1) + b_{P1}U_P(t) + e(t), \tag{27}$$

$$Q_D(t) = -a_{Q1}Q_D(t-1) + b_{Q1}U_Q(t) + e(t), \tag{28}$$

$$T_S(t) = -a_{T1}T_S(t-1) + b_{T1}U_T(t-2) + e(t), \tag{29}$$

where $e(t)$ is the equation error.

Four different identification methods were compared by using average absolute errors (AAE) defined by

$$\mathrm{AAE}(y) = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{30}$$

where y and $\hat{y}$ are the observed and the predicted values.

The HVAC system was tested for the parameter identification method under the load condition shown in Table 1. It is important to note, however, that system identification parameters may change with load changes. Since load conditions often vary slowly in actual building systems, one might expect that dramatic changes in the identified parameters would indicate quickly developing (complete) faults.

Table 2 shows the AAEs of T_S, P_S, and Q_D calculated for four ARMAX and ARX models. It can be seen that all the estimated values are close to each other for the case of a constant load on the AHU and no external disturbances. Since the result of the SISO ARX model is almost the same as the other results, only the results from the model corresponding to Equations 27 through 29 will be discussed below.

For system parameter identification, normalized input values are used. The supply air temperature is divided by room air temperature, and the control signals and actuator signals are

TABLE 2 AAE Comparison of ARMAX and ARX Models (Pump Fault Condition)

Model Structure		AAE (T_s) (°C)	AAE (P_s) (kPa)	AAE (Q_D) (m^3/s)
ARMAX	MISO	0.0243	0.0028	0.0988
	SISO	0.0282	0.0030	0.0997
ARX	MISO	0.0256	0.0028	0.0976
	SISO	0.0256	0.0030	0.1010

normalized to make their maximum value unity. All the faults were introduced after 1,500 seconds in operation. If complete faults occur, the control and the measured signals change significantly. To detect these kind of faults, it is necessary to use feedback signals from the system and the controllers. It should be noted that those signals that were *momentarily* out of bounds of the given thresholds during the observation periods were ignored in this study.

Fault 1 is a complete failure of the return fan. The return fan was changed from normal operation to an abruptly shut-off condition. Since the return fan was controlled to maintain the return fan airflow rate below the supply airflow rate by a fixed amount, the return fan fault caused the return fan flow to change dramatically. The best variables for detecting this fault are the return fan rotational speed and the airflow rate difference between the supply and return flow rates. Figure 4a shows system variables such as supply air temperature, airflow rate difference, and pressure at the supply air duct. Figures 4b through 4h show the residuals of the supply air pressure, the flow rate difference between supply and return air fans, the supply air temperature, the three-way valve control signal, the supply fan rpm, the return fan rpm, and the three-way valve position, respectively. Residual values in Figure 4c show that the return fan failure causes the flow rate difference to jump suddenly, while the supply air pressure and temperature are maintained constant. The significant fault signature can be seen in the residual values of the return fan speed (Figure 4g). If the return fan is stopped, the controller attempts to compensate by increasing the

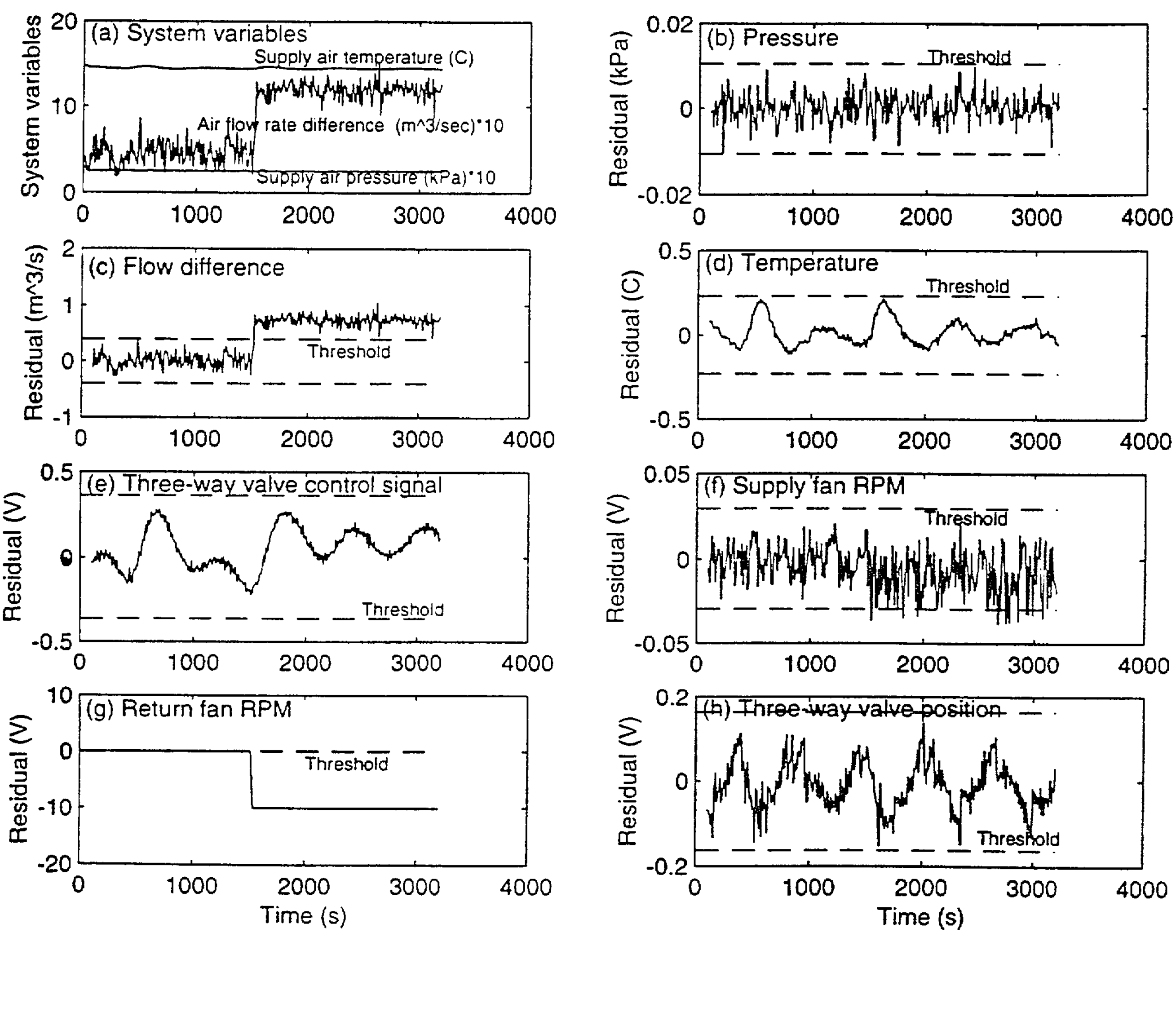

Figure 4 *Residuals for fault no. 1.*

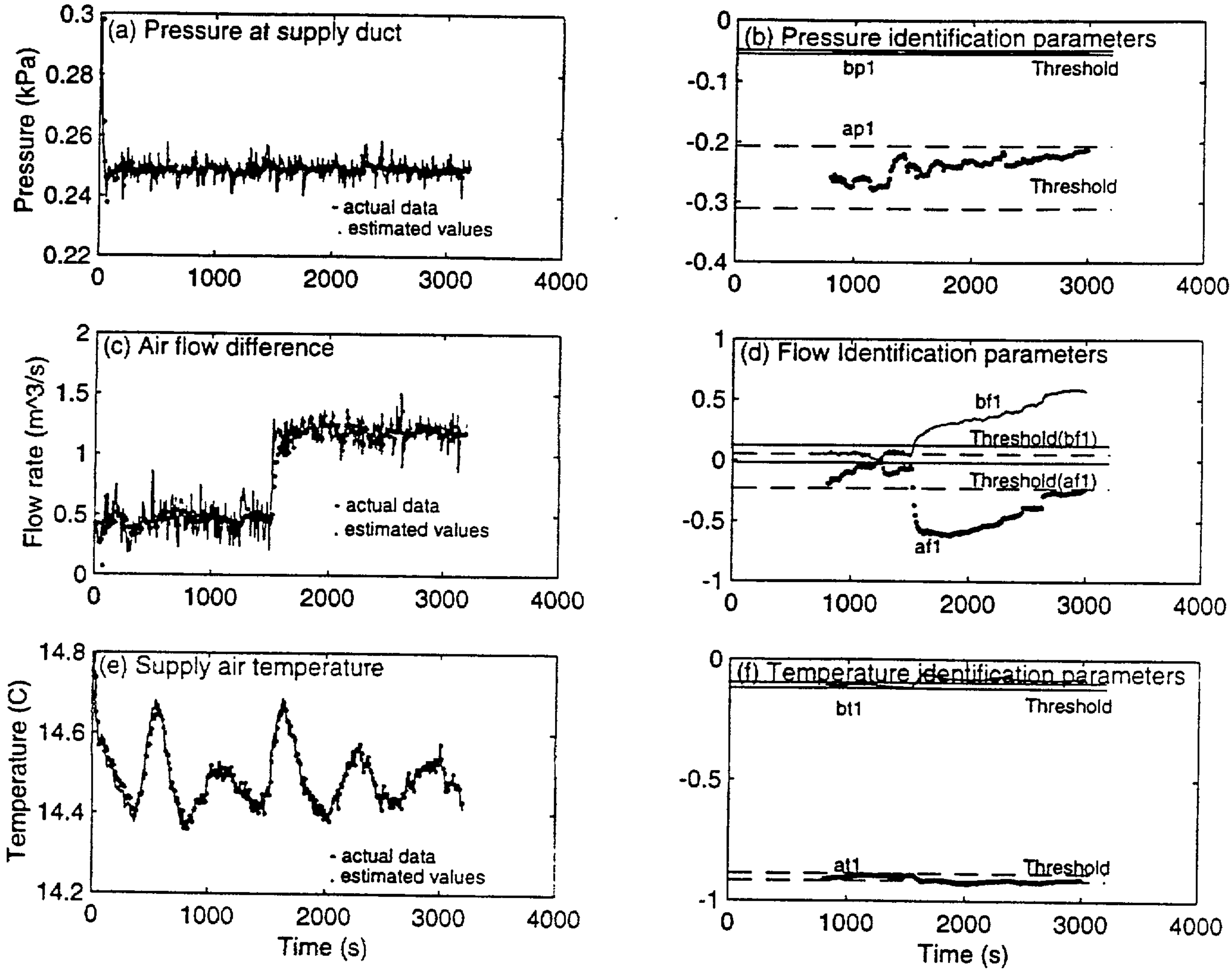

Figure 5 *System identification result and identification parameters for fault no. 1.*

control signal. However, the fan is not controlled and the fan failure generates a big change in the residual value of the fan rotational speed.

As shown in Figure 5, this fault can also be detected by the parameter identification method. The identification parameters of the flow difference are greatly changed and deviated significantly from the threshold due to the return fan fault (Figure 5d), while the parameters of supply air pressure stay within the threshold range (Figure 5b) and the parameters of the supply air temperature deviate only slightly from the threshold (Figure 5f).

The residual values and the changes in the model parameters for this fault and the other seven faults given in Figure 1 are summarized in Tables 3 and 4, respectively.

Fault 2 is a complete failure of the supply fan. The supply fan was changed from normal operation to an abruptly shut-off condition. Since the static pressure at the supply duct is controlled at a certain value by modulating this supply fan speed, the failure in the supply fan significantly influences the static pressure at the supply duct. From Table 3, it is seen that the supply pressure abruptly decreased to a zero value (residual value −0.249 kPa [−1.0 in. H_2O]) and the flow rate difference is decreased to a zero value. This failure causes the supply fan controller to increase the output control signal to its maximum value in an attempt to increase the static pressure in the main supply duct.

To keep the flow difference between the supply and return fan flows positive, the return fan rotational speed is also

TABLE 3 Residual Values After Faults

	R_P (kPa)	R_Q (m³/s)	R_T (°C)	R_U (V)	R_{NS} (V)	R_{NR} (V)	R_V (V)
Fault No.1	0	0.7256	0	0	0	−10.0	0
Fault No.2	−0.249	−0.47	1.766(r)	4.9(r)	−10	0	0
Fault No.3	0	0	1.5(i)	1.66	0	0	0
Fault No.4	0	0	0	−0.06	0	0	0.11
Fault No.5	0	0	−14.5	5.0(i)	0	0	−6.0(i)
Fault No.6	−0.249	0.55(i)	1.2(i)	1.33	−1.0(i)	0	0
Fault No.7	0	−0.8	0	0.25	0	0	0
Fault No.8	−0.65(i)	1	0	0	0	0	0

Note that (r) and (i) mean ramp and impulse responses after faults and other residual values are step changes.

TABLE 4 Changes in Identification Parameters After Faults (SISO ARX)

	a_{T1}	b_{T1}	a_{P1}	b_{P1}	a_{Q1}	b_{Q1}
Fault No.1	0	-0.03	0	0	−0.4	0.42
Fault No.2	−0.1797	−0.0427	−0.8432	0.0305	−0.954	0
Fault No.3	−0.1778(i)	−0.05	0.05	0	0	0
Fault No.4	−0.0551	−0.044	0.0713	0	0	0
Fault No.5	0.7(i)	−3.586	.05	0	0	0
Fault No.6	−0.25(i)	−0.05	−0.77	0.01	0	0
Fault No.7	−0.05	0.05	0.05	0	−1.0	−0.15(i)
Fault No.8	−0.04	0	0.2	−0.06(i)	−0.6	0.6

decreased to zero. Since there is no airflow through the cooling coil, the air temperature in the supply duct slowly increases and thus the cooling coil control signal also increases. The best variables chosen for detection of this fault are the supply fan rotational speed residual and the static air pressure residual. The fault can also be detected through the parameter identification scheme, as shown in Table 4. The identification parameters of pressure and flow rate difference are greatly changed, but those for supply air temperature changed little.

Fault 3 is a complete failure of the chilled-water circulation pump. The pump was changed from normal operation to an abruptly shut-off condition as might result from mechanical or electrical problems. From Figure 6, it is seen that the supply air temperature is changed temporarily and then returns to normal. If the pump fails, the mixed water flow rate through the three-way valve is immediately decreased and thus the supply air temperature is increased and the error signal to the controller is increased. This error signal is reduced by increasing the three-way valve opening position. From Figure 6e and Table 3, it is seen that the cooling coil valve control signal is increased above the threshold value to compensate for the pump failure. The identification parameters of the supply air temperature are changed due to the pump fault, while the parameters of supply pressure and flow difference are within the thresholds, as seen in Figure 7.

Fault 4 is the fault condition where the cooling coil control valve sticks in a certain position. In this case, the residual values after the fault do not change significantly in spite of fault occurrence. If there is no external disturbance, the output condition should be unchanged. But there is a small difference between the normal or expected signal and the measured value. In the case of noise and external disturbances, such as the load change and fresh air temperature change, the supply air temperature may be slightly changed. As time goes by, this small change of temperature and the small difference between the setpoint value in the normal case and the measured value cause the control signal to change continuously due to the integral term of the controller. It can be said that it is difficult to detect this fault from the supply air temperature residual, but this fault can be detected over time from the change of input control signal. From Table 3, the profile of the control signal residual of the cooling coil valve can be seen to be slightly different from the one without the fault. However, the residuals related to the supply air pressure and the airflow difference are not changed. From Table 4, it can be seen that the parameters for the supply air temperature change slightly, while the parameters of the flow difference do not change. The parameters of the supply air pressure are within the thrshold values.

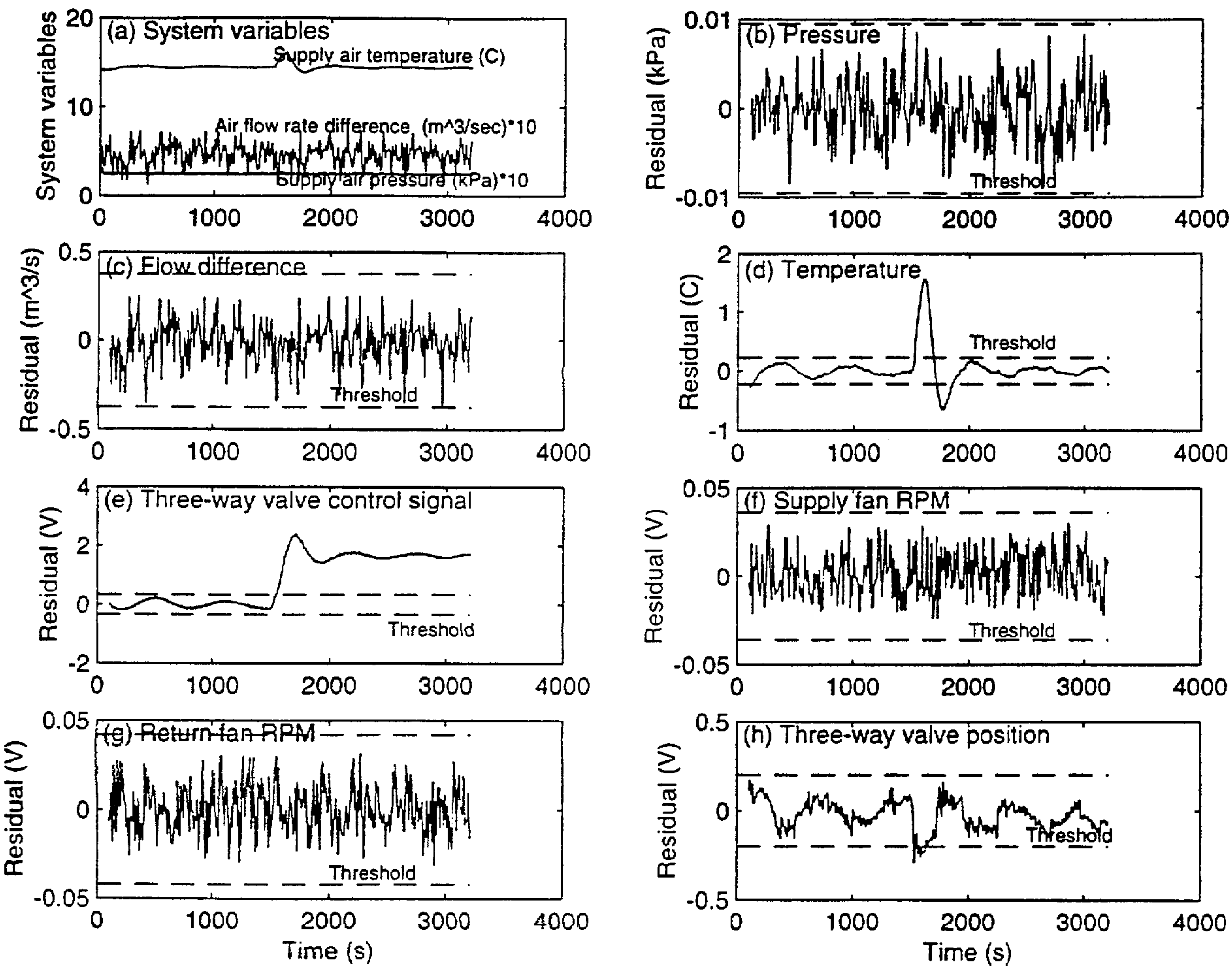

Figure 6 Residuals for fault #3.

Fault 5 is the case when a temperature sensor undergoes a complete failure. From a given set of sensor readings, a normal operating range for each temperature sensor can be established based upon expert knowledge about the process, sensor characteristics, and historical databases. Once the range of each measurement is selected, it can be determined whether the measurement is within a normal range or not.

If the temperature sensor is disconnected, sometimes the measured temperature oscillates randomly. If the supply air temperature range is out of the normal operating range, typically between 0°C (32°F) and 40°C (104°F), when the system operates in the cooling mode, the temperature sensor is known to be at fault. The temperature signal can be set to zero to make the output signal constant at the fault condition. The input signal is abruptly changed and the controller attempts to compensate by increasing the control signal. However, the temperature signal is not changed and the temperature sensor fault generates a large change in the cooling coil valve control residual, while the supply air pressure and the flow difference residuals are not changed as seen in Table 3. It is seen from Table 4 that this results in the parameters for the supply temperature changing greatly, while the parameters of the flow difference are unchanged. The parameters of the supply air pressure are within the threshold values.

Fault 6 is a complete failure of the static pressure transducer in the air supply duct. For this fault, the output of the pressure transducer is abruptly changed to zero due to electrical or mechanical problems. The pressure transducer generates the feedback signal to the supply fan controller. The failure in the pressure transducer significantly influences the static pressure in the supply duct. From Table 3, it is seen that the pressure residual is greatly changed, but the supply temperature and the flow difference due to step change are not significantly changed. The impulse response values in Table 3 can be ignored, since for fault detection, it is best to consider only step and ramped values. Because the feedback pressure signal is zero (actual value is not zero), this controller makes the supply fan control signal maximum in an attempt to maintain the feedback pressure signal at the reference value. Unlike the supply fan failure, the supply fan operates at its maximum rotational speed and the flow difference and the supply temperature are controlled normally after some transient changes.

This fault can be detected through the parameter identification scheme, as shown in Table 4. The identification parameters of the pressure are significantly changed, while those of the flow rate difference are not changed. The parameter changes of the supply air temperature are insignificant.

Fault 7 is a failure of the supply fan flow station. The output signal is abruptly changed from its normal value to zero due to a differential pressure transducer failure or mechanical fitting problems. Since the return fan was controlled to maintain a constant flow difference using the flow station signal, the flow station failure causes the return fan control signal to change, which is proportional to rotational speed. Residual values in Table 3 show that the supply fan flow station failure causes the flow rate difference residuals to jump suddenly, while the supply

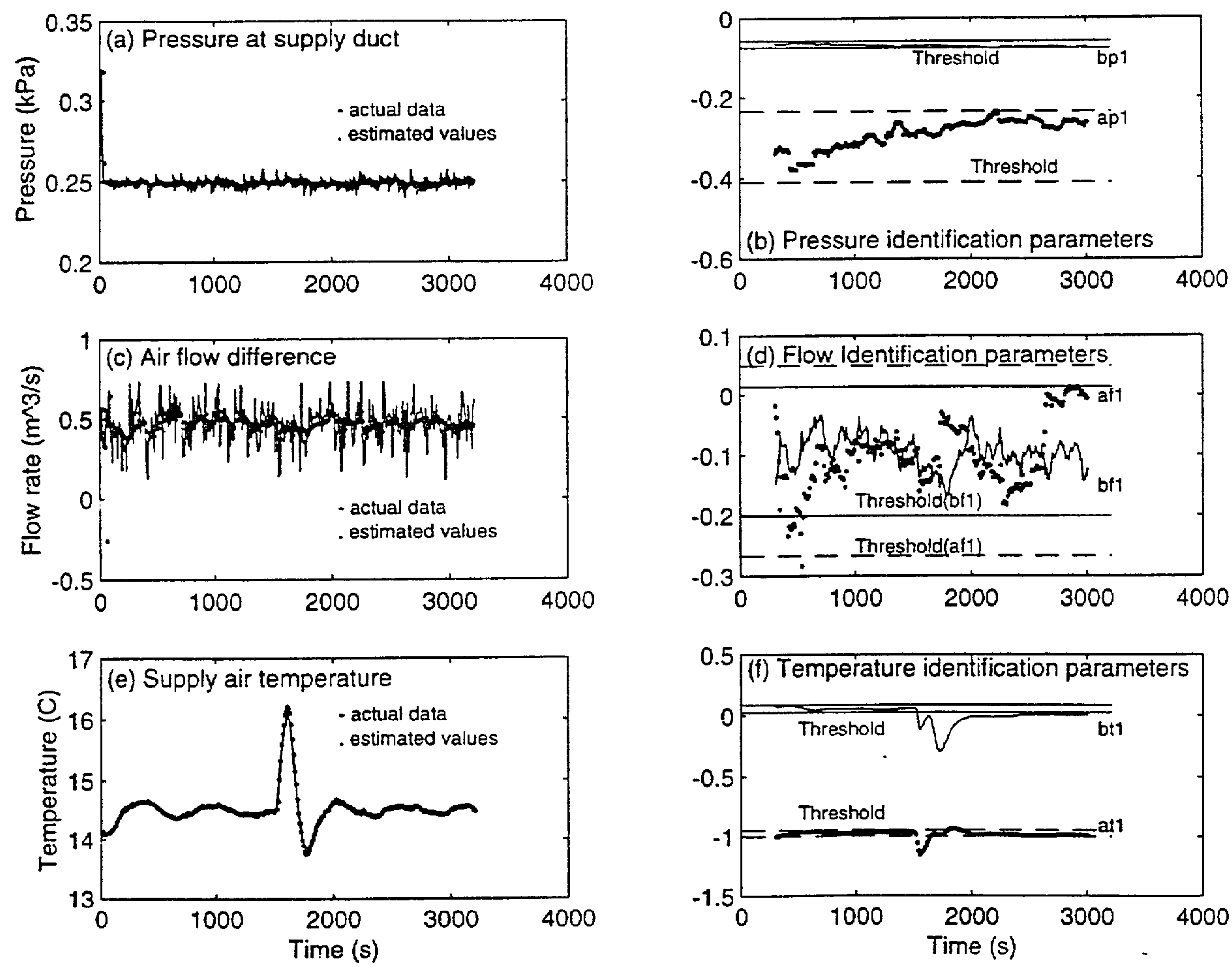

Figure 7 *System identification results and identification parameters for fault #3.*

air pressure and temperature residuals are constant. The significant fault signature appears in the residual values of the flow rate difference. As the supply flow station output signal is zero, the return fan controller attempts to compensate by sending a lower control signal to decrease the return fan flow rate, which decreases the fan speed. Unlike the return fan fault, the actuator residual values are not changed.The actuator residual values are not changed.

As shown in Table 4, the fault can also be detected through the parameter identification method. The identification parameters of the flow difference are greatly changed due to the supply flow station fault, while the parameters of the supply air temperature are slightly changed. The parameters of the supply air pressure are within the threshold values.

Fault 8 is a failure of the return fan flow station. The output signal is changed abruptly from its normal value to zero due to the same problems as in fault 7. If the return flow station output signal is reduced to zero, the flow difference signal is increased and the return fan controller attempts to compensate by sending a higher control signal to increase the return flow and reduce the flow difference. Compared with fault 7, this fault has the opposite effect on the residual values. As shown in Table 4, the fault can be detected through the parameter identification method. The identification parameters of flow difference are greatly changed due to the return fan flow station fault, while the parameters of the supply air pressure and temperature are slightly changed. The parameters of the supply air pressure are changed but not nearly as much as those of the flow difference.

For the eight complete faults discussed above, the two fault detection methods can be used to detect the faults of a VAV air-handling unit. The residual method requires less computing time to calculate the residuals but requires more sensors than parameter identification methods. The residuals change after the faults display the unique fault signatures seen in Tables. Thus, not only fault detection but also fault diagnosis is possible. The latter is the subject of a companion paper (Lee et al. 1996).

SUMMARY

Residual and parameter identification methods were employed for fault detection in an air-handling unit of a building HVAC system. For parameter identifications, ARMAX and ARX models were employed with MISO and SISO structures to estimate model parameters recursively using the Kalman filter. Eight complete faults of equipment and sensors were tested under constant load conditions and for short periods. These faults were examined using both residual and parameter identification methods using the laboratory-measured data. The test results show that both methods can be used to detect the presence of faults in the air-handling unit.

Faults were detected when residuals and identification parameters changed significantly and thresholds were exceeded. Momentary indication of a fault was not accounted for, but continuous presence of fault signature for a reasonable period was considered. The work was done for one load on the AHU. If building loads change rapidly, these methods may not detect the faults.

The proposed approach can be applied to practical problems when observation is made in a short period under the assumption that the load remains constant. However, further investigation is needed for the load-change cases. Fault signatures were developed for eight complete faults. The use of these signatures to diagnose a particular fault is the subject of a second paper.

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