REVIEW ARTICLE

Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems— A Review, Part II

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This paper is the second of a two-part review of methods for automated fault detection and diagnostics (FDD) and prognostics whose intent is to increase awareness of the HVAC&R research and development community to the body of FDD and prognostics developments in other fields as well as advancements in the field of HVAC&R. The first part of the review focused on generic FDD and prognostics, provided a framework for categorizing methods, described them, and identified their primary strengths and weaknesses (Katipamula and Brambley 2005). In this paper we address research and applications specific to the fields of HVAC&R, provide a brief discussion on the current state of diagnostics in buildings, and discuss the future of automated diagnostics in buildings.

INTRODUCTION

Poorly maintained, degraded, and improperly controlled equipment wastes an estimated 15% to 30% of energy used in commercial buildings. Much of this waste could be prevented with widespread adoption of automated condition-based maintenance. Automated fault detection and diagnostics (FDD) along with prognostics provide a cornerstone for condition-based maintenance of engineered systems. Although FDD has been an active area of research in other fields for more than a decade, applications for heating, ventilating, air conditioning, and refrigeration (HVAC&R) and other building systems have lagged those in other industries. Nonetheless, over the last decade there has been considerable research and development targeted toward developing FDD methods for HVAC&R equipment. Despite this research, there are still only a handful of FDD tools that are deployed in the field.

This paper, which is the second of two parts, provides a review of fault detection, diagnostics, and prognostics (FDD&P) research in the HVAC&R field and concludes with discussions of the current state of applications for buildings and likely contributions to operating and maintaining buildings in the future. In the first paper (Katipamula and Brambley 2005), we provided an overview of FDD&P, starting with descriptions of the fundamental processes and some important definitions, and then identified the strengths and weaknesses of methods across the broad spectrum of approaches.

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FDD RESEARCH IN HVAC&R

In this section we review FDD research relating to refrigerators, air conditioners, chillers, and air-handling units (AHUs), which represent most of the HVAC&R FDD research completed to date. This review is an update to the review previously published by Katipamula et al. (2001) and includes recent FDD publications. For information on FDD for other building systems refer to Pape et al. (1990), Dexter and Benouarets (1996), Georgescu et al. (1993), Jiang et al. (1995), and Han et al. (1999) for HVAC&R plants; Fasolo and Seborg (1995) for HVAC&R control systems; Li et al. (1996, 1997) for heating systems; Isermann and Nold (1988) and Dalton et al. (1995) for pumps; Noura et al. (1993) for large thermal plants; Isermann and Ballé (1997) for applications for motors; and Dodier and Kreider (1999) for whole-building systems.

Refrigerators

One of the early applications of FDD was to vapor-compression-cycle-based refrigerators (McKellar 1987; Stallard 1989). Although McKellar (1987) did not develop an FDD system, he identified common faults for a refrigerator based on the vapor-compression cycle and investigated the effects of the faults on the thermodynamic states at various points in the cycle. He concluded that the suction pressure (or temperature), discharge pressure (or temperature), and the discharge-to-suction pressure ratio were sufficient for developing an FDD system. The faults considered were compressor valve leakage, fan faults (condenser and evaporator), evaporator frosting, partially blocked capillary tubes, and improper refrigerant charge (under and over charge).

Building upon McKellar's work, Stallard (1989) developed an automated FDD system for refrigerators. A rule-based expert system was used with simple limit checks for both detection and diagnosis. Condensing temperature, evaporating temperature, condenser inlet temperature, and the ratio of discharge-to-suction pressure were used directly as classification features. Faults were detected and diagnosed by comparing the change in the direction of the measured quantities with expected values and matching the changes to expected directional changes associated with each fault.

Air Conditioners and Heat Pumps

There are many applications of FDD to air conditioners and heat pumps based on the vapor-compression cycle. Some of these studies are discussed below (Yoshimura and Ito 1989; Kumamaru et al. 1991; Inatsu et al. 1992; Wagner and Shoureshi 1992; Rossi 1995; Rossi and Braun 1996, 1997; Breuker 1997; Breuker and Braun 1998b; Ghiaus 1999; Chen and Braun 2000). Breuker and Braun (1998a) summarized common faults in air conditioners and their impact on performance. In addition, the frequency of fault occurrence and the relative cost of service for various faults were estimated from service records.

Yoshimura and Ito (1989) used pressure and temperature measurements to detect problems with condenser, evaporator, compressor, expansion valve, and refrigerant charge on a packaged air conditioner. The differences between measured values and expected values were used to detect faults. Expected values were estimated from manufacturers' data, and the thresholds for fault detection were experimentally determined in the laboratory. Both detection and diagnosis were conducted in a single step. No details were provided as to how the thresholds for detection were selected.

Wagner and Shoureshi (1992) developed two different fault detection methods and compared their abilities to detect five different faults in a small heat pump system in the laboratory. The five faults included abrupt condenser and evaporator fan failures, capillary tube blockage, compressor piston leakage, and seal system leakage. The first method was based on limit and trend

Table 1. Symptom Patterns for Selected Faults (Grimmelius et al. 1995)

Fault Modes	Compressor Suction Pressure	Compressor Suction Temperature	Compressor Discharge Pressure	Compressor Discharge Temperature	Compressor Pressure Ratio	Oil Pressure	Oil Temperature	Oil Level	Crankcase Pressure	Compressor Electric Power	Subcooling of Refrigerant	ΔT Refrigerant and Cooling Water	ΔT Cooling Water	Inlet Temperature at Expansion Valve	Filter Pressure Drop	Evaporator Outlet Pressure	Superheat	ΔT Chilled Water	Evaporator Outlet Temperature	Number of Acting Cylinders
Compressor, Suction Side, Increase in Flow Resistance	↓	→	→	→	→	↓	→	→	↓	↓	→	→	→	→	→	↑	↑	↓	→	→
Compressor, Discharge Side, Increase in Flow Resistance	↑	→	↑	→	→	↑	→	→	↑	→	→	→	→	→	→	↑	↑	↓	→	→
Condenser, Cooling Water Side, Increase in Flow Resistance	→	→	↑	→	→	→	→	→	→	↑	↓	→	↑	→	→	→	→	→	→	→
Fluid Line Increase in Flow Resistance	→	→	→	→	→	→	→	→	→	↓	→	→	→	↓	→	→	↑	↑	→	→
Expansion Valve, Control Unit, Power Element Loose from Pipe	↑	→	→	→	→	↑	→	→	↑	↑	→	→	→	→	→	↑	↓	↑	→	→
Evaporator, Chilled Water Side, Increase in Flow Resistance	↓	→	→	→	→	↓	→	→	↓	↓	→	→	→	→	→	↓	↑	↑	→	→

checking (qualitative model-based), and the second method was a simplified physical model-based approach. In the second approach, differences between predictions from a simplified physical model and the monitored observations are transformed into useful statistical quantities for hypothesis testing. The transformed statistical quantities are then compared to predetermined thresholds to detect faults.

The two fault detection strategies were operated in parallel on a heat pump in a psychrometric room. The qualitative method was able to detect four of five faults that were introduced abruptly, while the simplified physical model-based method was successful in only detecting two faults. Because the selection of thresholds for both methods is critical in avoiding false alarms and reduced sensitivity, Wagner and Shoureshi (1992) provide a brief discussion of how to trade off diagnostic sensitivity against false alarms. Their implementation is only capable of detecting faults and does not include diagnosis, evaluation, and decision making.

Rossi (1995) described the development of a statistical rule-based fault detection and diagnostic method for air-conditioning equipment with nine temperature measurements and one humidity measurement. The FDD method is capable of detecting and diagnosing condenser fouling, evaporator fouling, liquid-line restriction, compressor valve leakage, and refrigerant leakage. In addition to the detection and diagnosis, Rossi and Braun (1996) also describe an implementation of fault evaluation. A detailed explanation of the fault evaluation method can be found in Rossi and Braun (1997). The methods were demonstrated in limited testing with a rooftop air conditioner in the laboratory.

Breuker (1997) performed a more detailed evaluation of the methods developed by Rossi (1995). The detailed evaluation relied on steady-state and transient tests of a packaged air conditioner in a laboratory over a range of conditions and fault levels (Breuker and Braun 1998b). Seven polynomial models (ranging from first to third order) were developed to characterize the performance of the air conditioner (evaporating, condensing, and compressor outlet temperatures, suction line superheat, liquid line subcooling, temperature rise across the condenser, and temperature drop across the evaporator) using steady-state data representing normal (unfaulted) operations. The steady-state normal data are also used to determine the statistical thresholds for fault detection, while transient data with faults were used to evaluate FDD performance. Breuker and Braun (1998b) concluded that refrigerant leakage, condenser fouling, and liquid line restriction were detected and diagnosed before 8% reduction in capacity or COP occurred. The technique, however, was less successful in detecting evaporator fouling and compressor valve leakage. The authors also concluded that increasing the measurements from 6 (2 inputs and 4 outputs) to 10 (3 inputs and 7 outputs) and using higher order polynomial models improved the performance by a factor of two.

Ghiaus (1999) presented a bond-graph model for a direct-expansion vapor-compression system and applied it to diagnosing two faults in an air conditioner. The author states that this qualitative approach of modeling faults does not need *a priori* knowledge of possible faults as long as the bond model is complete and accurate.

Chillers

Several researchers have applied FDD methods to detect and diagnose faults in vapor-compression-based chillers; some of the studies are summarized below (Grimmelius et al. 1995; Gordon and Ng 1994, 1995; Stylianou and Nikanpour 1996; Tsutsui and Kamimura 1996; Peitsman and Bakker 1996; Stylianou 1997; Bailey 1998; Sreedharan and Haves 2001; Castro 2002). Comstock et al. (1999) and Reddy et al. (2001) provide a detailed review of FDD literature relating to chiller systems up to their respective times. Comstock et al. (2002) presented a list of common chiller faults and their impacts on performance.

Grimmelius et al. (1995) developed a fault diagnostic system for a chiller, in which fault detection and diagnostics are carried out in a single step. The FDD method uses a reference model based on multivariate linear regression that was developed with data from a properly operating chiller to estimate values for process variables for a healthy (unfaulted) chiller. These estimates are subsequently used to generate residuals (i.e., differences between actual measured values and the values from the reference model). Patterns of these residuals are compared to characteristic patterns corresponding to faulted conditions, and scores are assigned indicating the degree to which the patterns match the pattern corresponding to each fault mode. Fault modes with good fits (high scores) are judged as probably existing in the chiller. Fault modes with poor fits (low scores) are judged as unlikely to exist in the chiller, and faults with intermediate scores are labeled as possibly existing. Twenty different measurements are used including

Table 2. Scoring of Fault Modes for a Highly Idealized Example

Fault Mode/ Score	Symptom 1	Symptom 2	Symptom 3	Symptom 4	Total Score	Normalized Score
F1	↓	→	↓	↑		
Scores	10	10	10	10	40	1.0
F2	↑	→	↑	→		
Scores	0	9	0	3	12	0.3
Measurement-Based Pattern	↓	→	↓	↑		

temperatures, pressures, power consumption, and compressor oil level. In addition to the measured variables, some derived variables, such as liquid subcooling, superheat, and pressure drop, are used. The inputs to the model also include the outdoor ambient temperature and load conditions.

To identify potential fault modes, the chiller is classified into seven components: compressor, condenser, evaporator, expansion valve, liquid line immediately downstream of the condenser and including a filter drier, liquid line with solenoid and sight glass between the other liquid line and the evaporator, and the crankcase heater. Fault modes are associated with any component that is serviceable, which leads to 58 different fault modes. A cause and effect study of the 58 fault modes helped establish the expected influence of the faults on the components, measured variables, and subsequent chiller behavior. Symptoms are defined as a difference in any measured or derived variable from its expected value for normal unfaulted operation (i.e., the value given by the reference model). Symptoms associated with all 58 fault modes were generated and arranged into symptom patterns. Fault modes having identical symptom patterns were aggregated into a single fault mode, reducing the total number of fault modes from 58 to 37. These symptom patterns are arranged in a symptom matrix as shown in Table 2, with each row giving the symptom pattern associated with a particular fault. A symptom (cell in the matrix) shown by an arrow pointing up, ↑, indicates a value for the variable greater than that given by the reference model. Likewise, an arrow pointing down, ↓, indicates a symptom corresponding to a value for the variable less than the value from the reference model, and a horizontal arrow, →, indicates the fault has no effect on the corresponding variable.

To diagnose a fault, a symptom pattern corresponding to a set of measurements is compared to the symptom patterns for all of the fault modes. Scores are assigned to each fault mode indicating the probability that its symptom pattern matches the measured symptom pattern as follows. For each fault mode, each symptom is compared to its corresponding measured symptom and assigned a score between 0 and 10. If the symptom for the fault mode matches the measured symptom very well, it is assigned a high score (close to 10). If it weakly matches, it is assigned a score around 5, and if it does not match well at all, it is assigned a score close to zero. A total score for each fault mode is generated by adding the individual scores of all symptoms and dividing the total by the maximum possible score per pattern (i.e., the number of symptoms in the pattern multiplied by 10) to obtain a normalized score. These normalized scores are then classified into three categories. A normalized score of 0.9 or higher indicates a probable fault, a score between 0.5 and 0.9 indicates a possible fault, and scores lower than 0.5 indicate that the fault is likely not present.

A highly simplified example is shown in Table 2. Symptom patterns for two faults, F1 and F2, are shown along with a symptom pattern derived from measurements. Each pattern consists of symptoms based on four variables. Scores have been assigned to the symptoms in each pattern based on how well the symptom shown in the symptom matrix corresponds to the symptom based on measurements. For example, Symptom 1 for fault mode F1 corresponds identically to Symptom 1 in the pattern derived from measurements, so it is assigned a score of 10. The normalized scores in this example lead to the conclusion that fault F1 with a score of 1.0 probably exists in this system and fault F2 with a score of 0.3 is likely not present. In actual implementation, this methodology accounts for uncertainty in measurements by establishing threshold bands around numerical values of measured and derived variables and using the proximity to them in assigning scores to symptoms. The exact algorithm for assigning numerical scores, however, is not available in the paper.

Although the method proved effective in identifying faults in systems before the chiller system failed completely, faults with only a few symptoms tended to get high scores more often. Because the reference model is a simple regression model developed with data from a specific test chiller, the same model cannot be used on other chillers but instead new models would need to be developed for each chiller. Nonetheless, this generic approach provided a foundation for diagnostic work that followed.

Stylianou and Nikanpour (1996) used the universal chiller model developed by Gordon and Ng (1995) and the pattern matching approach outlined by Grimmelius et al. (1995) as part of their FDD system. Like Grimmelius et al. (1995), Stylianou and Nikanpour also perform detection and diagnosis in a single step. The methods used in the FDD system included a thermodynamic model for fault detection and pattern recognition from expert knowledge for diagnosis of selected faults. The diagnoses of the faults are performed by an approach similar to that outlined by Grimmelius et al. (1995). Seventeen different measurements (pressures, temperatures, and flow rates) were used to detect four different faults: refrigerant leak, refrigerant line flow restriction, condenser water-side flow resistance, and evaporator water-side flow resistance.

The FDD system is subdivided into three parts: one used to detect problems when the chiller is off, one used during chiller start-up, and one used at steady-state conditions. The off-cycle module is deployed when the chiller is turned off and is primarily used to detect faults in the temperature sensors. The temperature sensor readings at different locations on the system are compared to one another after the chiller is shut down and reaches steady state (under the assumption that the temperature of refrigerant will reach equilibrium conditions and reach the ambient state when the chiller is shut down overnight). The differences are then compared to the difference observed during commissioning (if the sensors are calibrated during commissioning, the differences should be zero). The monitored rate of change of a sensor value is used to check whether a particular sensor has reached steady state or not before comparing measurements across sensors.

The start-up module is deployed during the first 15 minutes after the chiller is started. The module uses four measured inputs (discharge temperature, crankcase oil temperature, and refrigerant temperatures entering and leaving the evaporator) scanned at five-second intervals to detect refrigerant flow faults, which are easier to detect before the system reaches steady state. To detect faults, the transient trends in measured variables during start-up are compared to the baseline trend from normal start-up. For example, a shift (in time or magnitude) in the peak of the discharge temperature may indicate liquid refrigerant flood back, refrigerant loss, or a refrigerant line restriction. Because ambient conditions affect the baseline response, the baseline response has to be normalized before a comparison is made.

The steady-state module is deployed after the chiller reaches steady state (steady-state condition is established by monitoring the rate of change of the sensor values just as in off-cycle analysis) and stays deployed until the chiller is turned off. In this mode, the module performs two functions: (1) verifies performance of the system and (2) detects and diagnoses selected faults.

Table 3. Fault Patterns Used in the Diagnostic Module (Stylianou and Nikanpour 1996)

Fault	Discharge Temperature	High Pressure Liquid Line Temperature	Discharge Pressure	Low Pressure Liquid Line Temperature	Suction Line Temperature	Suction Pressure	ΔT_{cond}	ΔT_{Evap}
Restriction in Refrigerant Line	↑	↓	↓	↓	↑	↓	↓	↑
Refrigerant Leak	↑	↓	↓	↓	↑	↓	↓	↑
Restriction in Cooling Water	↑	↑	↑	↓	↓	↓	↑	↓
Restriction in Chilled Water	↑	↓	↓	↓	↓	↓	↓	↓

Performance is verified using the thermodynamic models developed by Gordon and Ng (1995). For fault diagnostics, linear regression models are used to generate estimates of pressure and temperature variables that are then compared to actual measurements in an approach similar to that described by Grimmelius et al. (1995). The estimated variables are compared to the measured values, and the residuals are matched to predefined patterns corresponding to the various faults using a rule-base (as shown in Table 3).

Although Stylianou and Nikanpour (1996) extended the previous work of Gordon and Ng (1995) and Grimmelius et al. (1995), their evaluation of the FDD systems was not comprehensive and lacked several key elements including sensitivity and rate of false alarms. In addition, it is not clear whether the start-up module can be generalized easily.

Stylianou (1997) replaced the rule-based model used to match the patterns shown in Table 3 with a statistical pattern recognition algorithm. This algorithm uses the residuals generated from comparison of predicted (using linear regression models) and measured pressures and temperatures to generate patterns that identify faults. Because this approach relies on the availability of training data for both normal and faulty operation, it may be difficult to implement in the field. Only limited testing of the method was presented in the paper.

Tsutsui and Kamimura (1996) developed a model based on a topological-case-based reasoning (TCBR) technique and applied it to an absorption chiller. Case-based reasoning is a knowledge-based problem-solving technique that solves new problems by adapting old solutions. It is based on defining neighborhoods that provide the needed measure of similarity between cases. In contrast, TCBR defines “the neighborhood theoretically, based on the assumption that the input/output relationship is locally continuous” (Tsutsui and Kamimura 1996). Tsutsui and Kamimura (1996) also compared the diagnostic capabilities of TCBR with a linear regression model. The authors state that although the linear regression model had a better overall modeling error (mean error) than the TCBR model, the TCBR model was better at identifying abnormal conditions.

Peitsman and Bakker (1996) used two types of black-box models (artificial neural networks [ANNs] and auto regressive with exogenous inputs [ARX[1]]) to detect faults in the system and at the component level of a reciprocating chiller system. The inputs to the system models included condenser supply water temperature, evaporator supply glycol temperature, instantaneous power of the compressor, and flow rate of cooling water entering the condenser (for the ANN only). The choice of the inputs was limited to those that are commonly available in the field. Using these inputs with both the ANN and ARX models, 14 outputs were estimated. For the ANN models, inputs from the current and the previous time step and outputs from two previous time steps were used.

Peitsman and Bakker (1996) compared diagnostic capabilities of two types of models—a multiple input/output ARX model and ANN models. They used a two-level approach in which system-level models were used to detect "faulty" operation and component-level models were used to diagnose the cause of the fault. They developed 14 system-level models and 16 component-level models to detect and diagnose faults in a chiller; however, only one example (air in the system) is described in their paper. ANN models appeared to have a slightly better performance than the ARX models in detecting faults at both the system and the component levels. The authors also note that it is critical to find a global minimum when using ANN models. If an incorrect initial state is chosen, it may lead to a local minimum rather than the global minimum.

Bailey (1998) also used an ANN model to detect and diagnose faults in an air-cooled chiller with a screw compressor. The detection and diagnosis were carried out in a single step. The faults evaluated included refrigerant under- and overcharge, oil under- and overcharge, condenser fan loss (total failure), and condenser fouling. The measured data included superheat for heat exchanger circuits 1 and 2, subcooling from circuits 1 and 2, power consumption, suction pressure for circuits 1 and 2, discharge pressures for circuits 1 and 2, chilled water inlet and outlet temperatures from the evaporator, and chiller capacity. Each heat exchanger circuit has its own compressor. The ANN model was applied to normal and "faulty" test data collected from a 70-ton laboratory air-cooled chiller with screw compressor.

Sreedharan and Haves (2001) compared three chiller models for their ability to reproduce the observed performance of a centrifugal chiller. Although the evaluation was meant to find the most suitable model for chiller FDD, no FDD system was proposed or developed. Two models were based on first principles (from Gordon and Ng [1995] and a modified ASHRAE Primary Toolkit from Bourdouxhe et al. [1997]) and the third was an empirical model. While each model has some distinct advantages and disadvantages, they concluded that the accuracies of all three models were similar. Hydeman et al. (2002) reported that the three models compared by Sreedharan and Haves (2001) were not accurate in predicting the power consumption of chillers with variable condenser water flow and centrifugal chillers operating with variable-speed drives at low loads. They reformulated the Gordon and Ng model and found that it performed better than the three models described above.

Castro (2002) used a physical model developed by Rossi (1995) along with a k-nearest neighbor classifier to detect faults and a rule base to diagnose five different faults (condenser and evaporator fouling, liquid line restriction, and refrigerant under- and overcharge) in a reciprocating chiller. The FDD implementation detected and diagnosed condenser fouling, refrigerant undercharge at faults level of 20% or greater, and evaporator fouling and liquid line restriction at fault levels of 30% or greater.

[1]Refer to Box and Jenkins (1976) for more details on ARX type models.

Air-Handling Units

There are several studies relating to FDD methods for air-handling units (both the airside and the waterside); some of these are summarized in this section (Norford and Little 1993; Glass et al. 1995; Yoshida et al. 1996; Haves et al. 1996; Lee et al. 1996a, 1996b; Lee et al. 1997; Peitsman and Soethout 1997; Brambley et al. 1998; Katipamula et al. 1999; House et al. 1999; Ngo and Dexter 1999; Yoshida and Kumar 1999; Seem et al. 1999; Karki and Karjalainen 1999; Morisot and Marchio 1999; House et al. 2001; Dexter and Ngo 2001; Kumar et al. 2001; Salsbury and Diamond 2001; Carling 2002; Norford et al. 2002; Wang and Chen 2002; Pakanen and Sundquist 2003).

Norford and Little (1993) classify faults in ventilating systems, consisting of fans, ducts, dampers, heat exchangers, and controls. They then review two forms of steady-state parametric models for the electric power used by supply fans and propose a third, that of correlating power with a variable-speed drive control signal. The models are compared based on prediction accuracy, sensor requirements, and their ability to detect faults.

Using the three proposed models, four different types of faults associated with fan systems are detected: (1) failure to maintain supply air temperature, (2) failure to maintain supply air pressure setpoint, (3) increased pressure drop, and (4) malfunction of fan motor coupling to fan and fan controls. Although the paper by Norford and Little (1993) lacks details on how the faults were evaluated, error analysis and associated model fits were discussed. The results indicate that all three models were able to identify at least three of the four faults. The diagnosis of the faults is inferred after the fault is detected.

Glass et al. (1995) use a qualitative model-based approach to detect faults in an air-handling unit. The method uses outdoor, return, and supply air temperatures and control signals for the cooling coil, heating coil, and the damper system. Although Glass et al. (1995) mention that the diagnosis is inferred from the fault conditions, no clear explanation or examples are provided. Detection starts by analyzing the measured variables to verify whether steady-state conditions exist. Then, the controller values are converted to qualitative signal data and, using a model for expected values and measured temperature data, qualitative signals are estimated. Faults are detected based on discrepancies between measured qualitative controller outputs and corresponding model predictions based on the temperature measurements. Examples of qualitative states for the damper signal include “maximum position,” “minimum position,” “closed,” and “in between.” When the quantitative value of the damper signal approaches the maximum value, the corresponding qualitative value of “maximum” is assigned to the measured controller output. The results of testing the method on a laboratory AHU were mixed because the method requires steady-state conditions to be achieved before fault detection is undertaken. Fault detection sensitivity and ability to deal with false alarms are not discussed.

Yoshida et al. (1996) use ARX and the extended Kalman filter approach to detect abrupt faults with simulated test data for an AHU. Although the fault diagnosis approach is clearly described, the authors note that diagnosis is not feasible with the ARX method but that the Kalman filter approach could be used for diagnosis. Fault detection sensitivity and ability to deal with false alarms are not discussed.

Haves et al. (1996) use a combination of two models to detect coil fouling and valve leakage in the cooling coil of an AHU. The methodology was tested with data produced by the HVACSIM+ simulation tool (Clark 1985). A radial bias function (RBF) models the local behavior of the AHU and is updated using a recursive gradient-based estimator. The data generated by exercising the RBF over the operating range of the system are used in the estimation of the parameters for the physical model (UA and percent leakage) using a direct search method. Detection is accomplished by comparing estimated parameters to fault-free parameters.

Lee et al. (1996a) used two methods to detect eight different faults (mostly abrupt faults) in a laboratory test AHU. The first method uses discrepancies between measured and expected variables (residuals) to detect the presence of a fault. The expected values are estimated at nominal operating conditions. The second method compares parameters estimated using autoregressive moving average with exogenous input (ARMX) and ARX models with the normal (or expected) parameters to detect faults. The faults evaluated included complete failure of the supply and return fans, complete failure of the chilled-water circulation pump, stuck cooling-coil valve, complete failure of temperature sensors, complete failure of the static pressure sensor, and failure of the supply and return air fan flow stations. Because each of the eight faults has a unique signature, no separate diagnosis is necessary.

Lee et al. (1996b) used an ANN to detect the same faults described previously (Lee et al. 1996a). The ANN was trained using the normal data and data that represented each of the eight faults. Inputs to the ANN were values for seven normalized residuals, and the outputs were nine values that constitute patterns that represent the normal mode and the eight fault modes. Instead of generating the training data with faults, idealized training patterns were specified by considering the dominant symptoms of each fault. For example, supply fan failure implies that the supply fan speed is zero, the supply air pressure is zero, the supply fan control signal is maximum, and the difference between the flow rates in the supply and return ducts is zero. Using similar reasoning, a pattern of dominant training residuals was generated for each fault (see Table 4). A dominant symptom residual is assigned a value of +1 if the residual is positive and –1 if the residual is negative; all other residuals are assigned a value of 0. The ANN was trained using the pattern shown in Table 4. Normalized residuals were calculated for faults that were artificially generated in the laboratory AHU. The normalized residuals vector at each time step was then used with the trained ANN to identify the fault. Although the ANN was successful in detecting the faults from laboratory data, it is not clear how successful this method would be in general because the faults generated in the laboratory setting were severe and without noise.

Lee et al. (1997) extended the previous work described in Lee et al. (1996b). In the 1997 analysis, Lee et al. (1997) used two ANN models to detect and diagnose faults. The AHU is decomposed into various subsystems such as the pressure control subsystem, the flow-control subsystem, the cooling-coil subsystem, and the mixing-damper subsystem. The first ANN model is trained to identify the subsystem in which a fault occurs, while the second ANN model is trained to diagnose the specific cause of a fault at the subsystem level. An approach similar to the one used in Lee et al. 1996b is used to train both ANN models. Lee et al. (1997) note that this two-stage approach simplifies generalization by replacing a single ANN that encompasses all considered faults with a number of less complex ANNs, each one dealing with a subset of the residuals and symptoms. Although 11 faults are identified for detection and diagnosis, fault detection and diagnosis are presented for only one fault in the paper.

Peitsman and Soethout (1997) used several different ARX models to predict the performance of an AHU and compared the predictions to measured values to detect faults. The training data for the ARX models were generated using HVACSIM+. The AHU is modeled at two levels. The first level is the system level, where the complete AHU is modeled with one ARX model. The second level is the component level, where the AHU is subdivided into several subsystems such as the return fan, the mixing box, and the cooling coil. Each component is modeled with a separate ARX model. The first level ARX model is used to detect a problem and the second level models are used to diagnose the problem. Most abrupt faults were correctly identified and diagnosed, while slowly evolving faults were not detected. There is a potential for a conflict between the two levels with this approach; for example, the top-level ARX model could detect a fault with the AHU, while the second-level ARX models do not indicate any faults. Furthermore, there is a potential for multiple diagnoses at the second level. Peitsman and Soethout (1997)

Table 4. Normalized Patterns for AHU Fault Diagnosis Used in ANN Training (Lee et al. 1996b)

Fault Diagnosis	**Network Inputs – Residuals: Supply Pressure**	**Difference in Supply and Return Airflow**	**Supply Air Temperature**	**Control Signal to Cooling Coil**	**Supply Fan Speed**	**Return Fan Speed**	**Cooling Coil Valve Position**	**Network Outputs**								
Normal (no fault)	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Supply Fan	–1	–1	0	1	–1	0	0	0	1	0	0	0	0	0	0	0
Return Fan	0	1	0	0	0	–1	0	0	0	1	0	0	0	0	0	0
Pump	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0
Cooling Coil Valve	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0
Temperature Sensor	0	0	–1	–1	0	0	0	0	0	0	0	0	1	0	0	0
Pressure Transducer	–1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Supply Fan Flow Station	0	–1	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Return Fan Flow Station	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1

indicated that some of this multiple diagnosis could be discriminated by ranking of diagnoses according to their improbability; however, no details were provided on how to implement such a scheme.

House et al. (1999) compared several classification techniques for fault detection and diagnosis of seven different faults in an AHU. The data for the comparison were generated using an HVACSIM+ simulation model. Using the residuals, as defined in Lee et al. (1996a, 1996b), five different classification methods are evaluated and compared for their ability to detect and diagnose faults. The five classification methods include: ANN classifier, nearest neighbor classifier, nearest prototype classifier, a rule-based classifier, and a Bayes classifier.

Based on the performance of classification methods, the Bayes classifier appears to be a good choice for fault detection. For diagnosis, the rule-based method proves to be a better choice for the classification problems considered, where the various classes of faulty operations were well separated and could be distinguished by a single dominant symptom or feature.

Ngo and Dexter (1999) developed a semi-qualitative analysis of measured data using generic fuzzy reference models to diagnose faults with the cooling coil of an AHU. The method uses sets of training data with and without faults to develop generic fuzzy reference models for diagnosing faults in a cooling coil. The faults include leaky valve, waterside fouling, valve stuck closed, valve stuck midway, and valve stuck open. The fuzzy reference models describe in qualitative terms the steady-state behavior of a particular class of equipment with no faults present and when each of the faults has occurred. Measured data are used to identify a partial fuzzy model that describes the steady-state behavior of the equipment at a particular operating point. The partial fuzzy model is then compared to each of the reference models using a fuzzy matching scheme to determine the degree of similarity between the partial model and the reference models. Ngo and Dexter (1999) provide a detailed description of fault detection sensitivity and false alarm rates.

Yoshida and Kumar (1999) evaluated two model-based methods to identify abrupt (sudden) faults in an AHU. They report that both ARX and adaptive forgetting through multiple models (AFMM) seem promising for use in on-line fault detection of AHUs. They report that ARX models require only a minimal knowledge of the system, and the potential limitation of the technique is that it requires long periods to stabilize its parameters. On the other hand, Yoshida and Kumar (1999) report that the AFMM method requires long moving averages to suppress false alarms. When this is done, faults of lesser magnitude cannot be easily detected. Implementation details are not provided, and only one example of fault detection is provided.

Morisot and Marchio (1999) use an ANN-based approach to detect degradation of performance of a cooling coil in an AHU. The ANN network includes an input layer (six inputs), a hidden layer (four nodes), and an output layer (two outputs). The inputs include entering air temperature and humidity, entering and leaving water temperatures, fan-control signal, and cooling-coil-valve-control signal. The outputs are the leaving air temperature and humidity. The authors highlight the difficulties of using ANNs with real measured data, which include a need for an exhaustive training data set and the inability of the ANNs to extrapolate values outside the range of the training data. The proposed alternative is to use a simulation model to generate the training data for the ANN. Using this alternative approach, the authors test the ability of the ANN to detect two faults (air-side fouling and a sensor fault).

Dexter and Ngo (2001) outline a multi-step fuzzy model-based FDD approach to detecting and diagnosing faults with AHUs. This approach involves classifying measured data with fuzzy rules and comparing them to a set of fuzzy reference models for normal and faulty operations. The fuzzy reference models for a specific system are developed from data that are generated from simulations. Each rule is assigned a rule-confidence in the range from zero to one, where zero indicates no confidence and one indicates complete confidence in the rule correctly describing the behavior. Rule-confidence values are estimated from the data. The authors state that this method prevents false alarms because it accounts for major sources of uncertainty. The multi-step approach is shown to be capable of detecting and isolating faults in a cooling coil (leaking valves and fouling).

Kumar et al. (2001) propose a method based on an auto regressive exogenous model and a recursive parameter estimation algorithm to detect faults with AHUs. They conclude that changes in parameter estimates from real data cannot be directly used to detect faults; instead a statistical analysis of the frequency response of the model parameters is needed to detect faults.

Salsbury and Diamond (2001) develop a simplified physical model-based approach to both control and detect faults in AHUs. Results from a field test on a single AHU demonstrate the fault detection capabilities but also highlight some of the practical implementation difficulties including selection of model parameters, reliability of sensor signals, and difficulty in establishing a baseline of “correct” operation of the AHU.

Carling (2002) assesses the performance of three fault detection methods for AHUs: (1) qualitative model-based approach outlined in Glass et al. (1995), (2) rule-based approach outlined in House et al. (2001), and (3) simplified steady-state model-based. The normal and "faulty" data used for the assessment were collected from real systems for an offline analysis. The "faulty data" were collected by introducing artificial faults in the AHU. The qualitative model was easy to set up, generated few false alarms, but also detected fewer faults. The rule-based method detected more faults but required some analysis and customization during setup. The third method detected more faults but also generated more false alarms and took considerable time to set up and customize. It also required installation of additional sensors.

Norford et al. (2002) present results from controlled field tests for detecting and diagnosing faults in AHUs. These tests were part of an ASHRAE research project (RP-1020), which was to demonstrate FDD methods for AHUs. The first FDD method used a first-principles model-based approach, and the second one was based on semi-empirical polynomial correlations of submetered electrical power with flow rates or process control signals generated from historical data. Although data representing faulty operation were based on blind tests, the faults were selected from a predefined set for an agreed set of conditions and magnitudes. The criteria used in the evaluation of the two FDD methods were sensitivity, robustness, the number of sensors required, and ease of implementation.

Both methods were successful in detecting faults but had difficulty in diagnosing the actual cause of the fault. The first principles-based method requires more sensors and more training data and misdiagnosed more often than the semi-empirical method.

CURRENT STATE FOR DIAGNOSTICS IN BUILDINGS

During the 1990s, significant growth occurred in research on the development of fault detection and diagnostic methods for HVAC&R systems. Still, very few commercial FDD products exist today, and the ones that do are very specialized or not fully automated. There are several reasons for lack of widespread availability and deployment of FDD systems: lack of demand by the building operations and maintenance (O&M) community, possibly as a result of insufficient information on the improvements possible from automated FDD, lack of adequate sensors installed on building systems, reliable sensors being too costly, high perceived cost-to-benefit ratio of deploying FDD systems with current sensor technologies, lack of acceptable benchmarks to quantify the potential benefits from deploying FDD systems, lack of easy access to real-time data unless FDD is built directly into building automation systems, and lack of infrastructure to gather data from existing building automation systems (BASs) for add-on applications.

Most papers reviewed for this study did not cover the evaluation and decision stages of a generic O&M support system using FDD; yet to be useful in the field FDD must be embedded in complete building management and decision support systems. Katipamula et al. (1999), Rossi and Braun (1996), and Breuker and Braun (1998b) have addressed the evaluation aspect of the O&M support system, and Katipamula et al. (2002) and Brambley and Katipamula (2003) proposed a decision step for AHUs. Furthermore, many of the FDD methods have only been tested in laboratory or special test environments (Castro et al. 2003). Some FDD tools have been tested in the field (Katipamula et al. 2003; Castro et al. 2003; Braun et al. 2003). The detection sensitivity of the methods and occurrence rates for false alarms have not been thoroughly investigated in real buildings yet. Although the R&D reviewed is focused on methods for automating FDD, most papers do not address the automation itself in sufficient detail. Efficiently and cost-effectively creating the code that implements these methods represents an important aspect of creating usable tools based on these methods.

A significant number of papers address FDD methods based on process history. In most cases, models based on process history are specific to the system from which the training data are collected. In order to make these methods broadly applicable, the models need to be developed in factory settings for equipment model lines or automatically online in an as-installed setting. Automation of the model development process is critical to controlling the costs of FDD systems. Preliminary work on online modeling has been done by Reddy et al. (2001), but more work is needed in this general area.

Another major limitation of most FDD methods developed to date is that they work well when a single dominant fault is present in a system, but if multiple faults occur simultaneously or are present when FDD is done initially, many of the methods fail to properly detect or diagnose the causes of the faults. Braun et al. (2003) extended the previous work by Rossi and Braun (1996) and Breuker and Braun (1998b) to diagnose multiple simultaneous faults. More work is needed in development of methods that can reliably handle multiple faults.

FUTURE FOR AUTOMATED DIAGNOSTICS IN BUILDINGS

The application of automated FDD to building HVAC&R is still in its infancy. Key technical problems still requiring solutions include:

- eliminating the need to handcraft FDD systems
- automating generation of FDD systems
- selecting the best FDD method for each type of HVAC&R application and the constraints applicable to it
- developing the balance of system for operation and maintenance support tools—evaluation and decision support
- development of prognostics to transform HVAC&R maintenance from corrective and preventive to predictive condition-based maintenance
- lowering the cost of obtaining data for FDD and O&M support

To the extent that FDD requires handcrafting for each installation, costs will likely be prohibitive. Three generically different solutions for this problem exist: (1) deploy FDD in service tools with databases sufficient to cover many equipment model lines, (2) deploy FDD as part of on-board equipment control packages, and (3) develop methods for automatically generating FDD tools. The first approach has already been introduced to the market in a hand tool for air-conditioning service providers (Honeywell 2003). More tools of this type, embedding automated FDD, are likely to evolve. The second approach of embedding monitoring and safety controls capabilities in on-board equipment control is already underway to some extent by manufacturers of equipment and equipment control packages (such as chillers for safety reasons but not for system performance). Capabilities deployed to date appear limited and details of methods are difficult to obtain because of their proprietary nature, but FDD deployment is beginning to emerge via this route. The third approach involving rapid generation, possibly in an automated manner, requires further research not only into the methods for FDD but also for automated code generation (in the fields of software development, adaptive systems, genetic systems, etc.).

Additional R&D is needed in the field of FDD itself to further develop fundamental methods for FDD, selection and specialization of methods to the constraints of the built environment (e.g., pressure to keep costs low and a data-poor environment in buildings), application and testing of FDD to the various systems, equipment, and components used in buildings, and development and application of FDD for building systems of the future, which are likely to include integration with on-site electricity generation, management of electric loads, real-time purchasing of electricity, and other interactions with the electric power grid of the future, and transition to new fuels (e.g., energy carriers such as hydrogen). All provide rich areas for research and development that will improve the performance and efficiency of commercial and residential buildings.

Prognostics are critical to transitioning building equipment maintenance as practiced today to condition based so that it accounts for the expected remaining life of equipment and its performance degradation over time. Only with this information can decisions be made regarding the optimal scheduling of maintenance. The field of prognostics presents a rich area of investigation and development for the HVAC&R research community. Little has been published to date on prognostics for HVAC&R.

Beyond research into FDD methodologies and their application to building systems, the HVAC&R field is faced with the opportunity to develop an entirely new class of tools and to add them to building automation systems. FDD methods may provide a core capability for enhanced operation and maintenance support systems of the future, but the balance of those systems must be developed. Packaging is critical to success in the market. Tools must be developed that meet the needs and fit into the environment of building operators and maintenance service providers and provide them value.

Probably the most constraining of all problems facing the application of FDD&P to HVAC&R is the dearth of data. Relatively small numbers of sensors are generally installed in building systems and the quality (accuracy, precision, and reliability) of the sensors that are installed is inadequate for many uses. Sensors frequently fail or drift out of calibration and remain that way for long periods of time until fortuitously discovered. Performance, cost, and durability need to be addressed to promote better sensing in buildings.

With the development of low-cost reliable sensor technology (Kintner-Meyer and Brambley 2002; Kintner-Meyer et al. 2002), a major hurdle to commercial deployment of FDD systems would be overcome. This would potentially speed the deployment of third party FDD tools and integration of FDD into individual equipment controllers and building automation systems to provide continuous monitoring, real-time fault detection and diagnostic information, and recommendations for maintenance service and would lead to much improved maintenance of HVAC&R systems. Ultimately, as networking infrastructure matures, the use of automated FDD systems should enable a small support staff to operate, monitor, and maintain a large number of different systems from a remote, centralized location. Local FDD systems could communicate across a network to provide reports on the health of the equipment that they monitor. Failures that lead to loss of comfort could be identified quickly before significant impacts on comfort or equipment damage occurs. In many cases, degradation faults could be identified well before they lead to loss of comfort or uneconomical operation, allowing more efficient scheduling of (and lower costs for) maintenance service.

At present, no fully automated FDD systems have been integrated into individual controllers for commercial HVAC&R equipment. In general, larger equipment applications (e.g., chillers) can absorb more add-on costs than smaller ones (e.g., rooftop units) and, therefore, automated FDD will probably appear first in larger equipment.

Open communication standards for building automation systems are catching on, and use of Internet and intranet technologies is pervasive. These developments enable FDD systems to be deployed more readily. In addition, the structure of the industry that provides services for the operations and maintenance of buildings is changing; companies are consolidating and offering whole-building operations and maintenance packages. Furthermore, as utilities are deregulated, they will begin to offer new services, including complete facility management. With complete and distributed facility management, the cost-to-benefit of deploying FDD systems will improve because the cost can be spread over a large number of buildings (Katipamula et al. 1999). To benefit from these changes, facility managers, owners, operators, and energy service providers are challenged to acquire or develop new capabilities and resources to better manage this information and, in the end, their buildings and facilities.

Although the incentives for application of FDD systems for HVAC&R and other building systems have never been greater, there still are several obstacles to their development and deployment. Beyond research and development, there is a need to quantify the benefits, to establish benchmarks for acceptable costs, and to provide market information. Assessing and demonstrating value for these technologies is an opportunity for public/private partnerships. Public agencies can help reduce risk to facility owners and operators while promoting and accelerating transition to a more efficient buildings sector by demonstrating the value of these technologies and transforming the market to accelerate adoption where public benefits warrant. FDD&P promises to help transform the buildings sector to a new level of energy and operational performance and efficiency.

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REFERENCES

Bailey, M.B. 1998. The design and viability of a probabilistic fault detection and diagnosis method for vapor compression cycle equipment. Ph.D. thesis, School of Civil Engineering of University of Colorado, Boulder, Colorado.

Bourdouxhe, J.P., M. Grodent, and J. Lebrun. 1997. *HVAC1 Toolkit: Algorithms and Subroutines for Primary HVAC Systems Energy Calculations*. Atlanta: American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.

Box, G.E.P., and G.M. Jenkins. 1976. *Time Series Analysis, Forecasting and Control*. San Francisco: Holden-Day.

Brambley, M.R., R.G. Pratt, D.P. Chassin, and S. Katipamula. 1998. Automated diagnostics for outdoor air ventilation and economizers. *ASHRAE Journal* 40(10):49-55.

Brambley M.R., and S. Katipamula. 2003. Automating commissioning activities: An update with an example. In *Proceedings of 11th National Conference on Building Commissioning*.

Braun, J.E., T. Lawrence, K. Mercer, and H. Li. 2003. *Fault Detection and Diagnostics for Rooftop Air Conditioners*. P-500-03-096-A1, California Energy Commission, Sacramento, California.

Breuker, M.S. 1997. Evaluation of a statistical, rule-based fault detection and diagnostics method for vapor compression air conditioners. Master's thesis, School of Mechanical Engineering, Purdue University, Purdue, Indiana.

Breuker, M.S., and J.E. Braun. 1998a. Common faults and their impacts for rooftop air conditioners. *International Journal of Heating, Ventilating, Air Conditioning and Refrigerating Research* 4(3):303-318.

Breuker, M.S., and J.E. Braun. 1998b. Evaluating the performance of a fault detection and diagnostic system for vapor compression equipment. *International Journal of Heating, Ventilating, Air Conditioning and Refrigerating Research* 4(4):401-425.

Carling, P. 2002. Comparison of three fault detection methods based on field data of an air-handling unit. *ASHRAE Transactions* 108(1).

Castro, N.S., J. Schein, C. Park, M.A. Galler, S.T. Bushby and J.M. House. 2003. *Results from Simulation and Laboratory Testing of Air Handling Unit and Variable Air Volume Box Diagnostic Tools*. National Institute of Standards and Technology, Gaithersburg, MD, NISTIR 6964.

Castro, N. 2002. Performance evaluation of a reciprocating chiller using experimental data and model predictions for fault detection and diagnosis. *ASHRAE Transactions* 108(1).

Chen, B., and J.E. Braun. 2000. Evaluation the potential on-line fault detection and diagnostics for rooftop air-conditioners. *Proceedings of the 2000 International Refrigeration Conference, Purdue University, W. Lafayette, IN.*

Clark, D.R. 1985. *HVACSIM+ Program Reference Manual.* NBSIR 84-2996, National Institute of Standards and Testing, Gaithersburg, Maryland.

Comstock, M.C., B. Chen, and J.E. Braun. 1999. *Literature Review for Application of Fault Detection and Diagnostic Methods to Vapor Compression Cooling Equipment*. HL 1999-19, Report #4036-2, Ray Herrick Laboratories, Purdue University.

Comstock, M.C., J.E. Braun, and E.A. Groll. 2002. A survey of common faults in chillers. *ASHRAE Transactions* 108(1).

Dalton T., R.J. Patton, and P.J.H. Miller. 1995. Methods of fault detection for a centrifugal pump system. *On-Line Fault Detection and Supervision in the Chemical Process Industries, IFAC Workshop*, Newcastle Upon Tyne, UK. New York: Pergamon Press.

Dexter, A.L., and M. Benouarets. 1996. Generic Approach to Identifying Faults in HVAC Plants. *ASHRAE Transactions* 102(1):550-556.

Dexter, A.L., and D. Ngo. 2001. Fault diagnosis in air-conditioning systems: a multi-step fuzzy model-based approach. *International Journal of Heating, Ventilating, Air Conditioning and Refrigerating Research* 7(1):83-102.

Dodier, R.H., and J.F. Kreider. 1999. Detecting whole building energy problems. *ASHRAE Transactions* 105(1).

Fasolo, P.S., and D.E. Seborg. 1995. Monitoring and fault detection for an HVAC control system. *International Journal of Heating, Ventilation, Air-Conditioning and Refrigeration Research* 99(1):3-13.

Georgescu, C., A. Afshari, and G. Bornard. 1993. A model-based adaptive predictor fault detection method applied to building heating, ventilating, and air-conditioning process. *TOOLDIAG' 93*. Organized by Département d'Etudes et de Recherches en Automatique, Toulouse, Cedex, France.

Ghiaus, C. 1999. Fault diagnosis of air-conditioning systems based on qualitative bond graph. *Energy and Buildings* 30:221-232.

Glass, A.S., P. Gruber, M. Roos, and J. Todtli. 1995. Qualitative model-based fault detection in air-handling units. *IEEE Control Systems Magazine* 15(4):11-22.

Gordon, J.M., and K.C. Ng. 1994. Thermodynamic modeling of reciprocating chillers. *Journal of Applied Physics* 75(6):2769-74.

Gordon, J.M., and K.C. Ng. 1995. Predictive and diagnostic aspects of a universal thermodynamic model for chillers. *International Journal of Heat and Mass Transfer* 38(5):807-18.

Grimmelius, H.T., J.K. Woud, and G. Been. 1995. On-line failure diagnosis for compression refrigerant plants. *International Journal of Refrigeration* 18(1):31-41.

Han, C.Y., Y. Xiao, and C.J. Ruther. 1999. Fault detection and diagnosis of HVAC systems. *ASHRAE Transactions* 105(1).

Haves, P., T. Salsbury, and J.A. Wright. 1996. Condition monitoring in HVAC subsystems using first principles. *ASHRAE Transactions* 102(1):519-527.

Honeywell. 2003. Advanced portable AC diagnostics: The HVAC service assistant. Number 63-9178 Rev 5/03. Honeywell, Golden Valley, Minnesota. Available on the Web at http://hbctechlit.honeywell.com/request.cfm?form=63-9178.

House, J.M., W.Y. Lee, and D. R. Shin. 1999. Classification techniques for fault detection and diagnosis of an air-handling unit. *ASHRAE Transactions* 105(1):1087-1097.

House, J.M., H. Vaezi-Nejad, and J.M. Whitcomb. 2001. An expert rule set for fault detection in air-handling units. *ASHRAE Transactions* 107(1).

Hydeman, M., N. Webb, P, Sreedharan, and S. Blanc. 2002. Development and testing of a reformulated regression-based electric chiller model. *ASHRAE Transactions* 108(2):1118-1127.

Inatsu, H., H. Matsuo, K. Fujiwara, K. Yamada, and K. Nishizawa. 1992. Development of refrigerant monitoring systems for automotive air-conditioning systems. *Society of Automotive Engineers*, SAE Paper No. 920212.

Isermann, R., and S. Nold. 1988. Model based fault detection for centrifugal pumps and AC drives. In *11^{th} IMEKO World Congress. Houston, USA*, pp. 16-21.

Isermann, R., and P. Ballé. 1997. Trends in the application of model-based fault detection and diagnosis of technical process. *Control Eng. Practice* 5(5):709-719.

Jiang, Y., J. Li, and X. Yang. 1995. Fault direction space method for on-line fault detection. *ASHRAE Transactions* 101(2):219-228.

Karki, S., and S. Karjalainen. 1999. Performance factors as a basis of practical fault detection and diagnostic methods for air-handling units. *ASHRAE Transactions* 105(1):1069-1077.

Katipamula, S., R.G. Pratt, D.P. Chassin, Z.T. Taylor, K. Gowri, and M.R. Brambley. 1999. Automated fault detection and diagnostics for outdoor-air ventilation systems and economizers: Methodology and results from field testing. *ASHRAE Transactions* 105(1).

Katipamula, S., R.G. Pratt, and J.E. Braun. 2001. Building systems diagnostics and predictive maintenance. Chapter 7.2 in *CRC Handbook for HVAC&R Engineers*, (Ed: J. Kreider), CRC Press, Boca Raton, Florida.

Katipamula, S., M.R. Brambley, and L. Luskay. 2002. Automated proactive techniques for commissioning air-handling units. *Journal of Solar Energy Engineering* 125:282-291.

Katipamula, S., M.R Brambley, N.N Bauman, and R.G Pratt. 2003. Enhancing building operations through automated diagnostics: Field test results. In *Proceedings of 2003 International Conference for Enhanced Building Operations*, Berkeley, CA.

Katipamula, S., and M.R. Brambley. 2005. Methods for fault detection, diagnostics and prognostics for building systems—A Review, Part I. *International Journal of Heating, Ventilating, Air Conditioning and Refrigerating Research* 11(1):3-26.

Kintner-Meyer, M., and M.R. Brambley. 2002. Pros & cons of wireless. *ASHRAE Journal* 44(11):54-61.

Kintner-Meyer M., M.R. Brambley, T.A. Carlon, and N.N. Bauman. 2002. Wireless sensors: Technology and cost-savings for commercial buildings. In *Teaming for Efficiency: Proceedings, 2002 ACEEE Summer Study on Energy Efficiency in Buildings*: Aug. 18-23, 2002, Vol. 7; Information and Electronic Technologies; Promises and Pitfalls., pp. 7.121-7.134. American Council for Energy Efficient Economy, Washington, D.C.

Kumamaru., T., T. Utsunomiya, Y. Iwasaki, I. Shoda, and M. Obayashi. 1991. A fault diagnosis systems for district heating and cooling facilities. *Proceedings of the International Conference on Industrial Electronics, Control, and Instrumentation*, Kobe, Japan (IECON '91), pp. 131-136.

Kumar, S.S. Sinha, T. Kojima, and H. Yoshida. 2001. Development of parameter based fault detection and diagnosis technique for energy efficient building management system. *Energy Conversion and Management* 42:833-854.

Lee, W.Y., C. Park, and G.E. Kelly. 1996a. Fault detection of an air-handling unit using residual and recursive parameter identification methods. *ASHRAE Transactions* 102(1):528-539.

Lee, W.Y., J.M. House, C. Park, and G.E. Kelly. 1996b. Fault diagnosis of an air-handling uni using artificial neural networks. *ASHRAE Transactions* 102(1):540-549.

Lee, W.Y., J.M. House, and D.R. Shin. 1997. Fault detection of an air-handling unit using residual and recursive parameter identification methods. *ASHRAE Transactions* 102(1):528-539.

Li, X., V. Hossein, and J. Visier. 1996. Development of a fault diagnosis method for heating systems using neural networks. *ASHRAE Transactions* 102(1):607-614.

Li, X., J. Visier, and H. Vaezi-Nejad. 1997. A neural network prototype for fault detection and diagnosis of heating systems. *ASHRAE Transactions* 103(1):634-644.

McKellar, M.G. 1987. Failure diagnosis for a household refrigerator. Master's thesis, School of Mechanical Engineering, Purdue University, Purdue, Indiana.

Morisot, O., and D. Marchio. 1999. Fault detection and diagnosis on HVAC variable air volume system using artificial neural network. *Proc. IBPSA Building Simulation 1999, Kyoto, Japan*.

Ngo, D., and A.L. Dexter. 1999. A robust model-based approach to diagnosing faults in air-handling units. *ASHRAE Transactions* 105(1).

Norford, L.K., and R.D. Little. 1993. Fault detection and monitoring in ventilation systems. *ASHRAE Transactions* 99(1):590-602.

Norford, L.K., J.A. Wright, R.A. Buswell, D. Luo, C.J. Klaassen, and A. Suby. 2002. Demonstration of fault detection and diagnosis methods for air-handling units (ASHRAE 1020-RP). *International Journal of Heating, Ventilating, Air Conditioning and Refrigerating Research* 8(1):41-71.

Noura, H., C. Aubrun, D. Sauter, and M. Robert. 1993. A fault diagnosis and reconfiguration method applied to thermal plant. *TOOLDIAG' 93*, Organized by Département d'Etudes et de Recherches en Automatique, Toulouse, Cedex, France.

Pakanen, J., and T. Sundquist. 2003. Automation-assisted fault detection of air-handling unit; Implementing the method in a real building. *Energy and Buildings* 35:193-202.

Pape, F.L.F., J.W. Mitchell, and W.A. Beckman. 1990. Optimal control and fault detection in heating, ventilating, and air-conditioning systems. *ASHRAE Transactions* 97(1):729-736.

Peitsman, H.C., and V. Bakker. 1996. Application of black-box models to HVAC systems for fault detection. *ASHRAE Transactions* 102(1):628-640.

Peitsman, H.C., and L.L. Soethout. 1997. ARX models and real-time model-based diagnosis. *ASHRAE Transactions* 103(1):657-671.

Reddy, T.A., D. Niebur, J. Gordon, J. Seem, K.K. Andersen, G. Cabrera, Y. Jia, and P. Pericolo. 2001. Final report: Development and comparison of on-line model training techniques for model-based FDD methods applied to vapor compression chillers, ASHRAE Research Project 1139-RP, ASHRAE, GA.

Rossi, T.M. 1995. Detection, diagnosis, and evaluation of faults in vapor compression cycle equipment. Ph.D. thesis, School of Mechanical Engineering, Purdue University, Purdue, Indiana.

Rossi, T.M., and J.E. Braun. 1996. Minimizing operating costs of vapor compression equipment with optimal service scheduling. *International Journal of Heating, Ventilating, Air Conditioning and Refrigerating Research* 2(1):3-26.

Rossi, T.M., and J.E. Braun. 1997. A statistical, rule-based fault detection and diagnostic method for vapor compression air conditioners. *International Journal of Heating, Ventilating, Air Conditioning and Refrigerating Research* 3(1):19-37.

Salsbury, T.I., and R.C. Diamond. 2001. Fault detection in HVAC systems using model-based feedforward control. *Energy and Buildings* 33:403-415.

Seem, J., J.M. House, and R.H. Monroe. 1999. On-line monitoring and fault detection. *ASHRAE Journal* 41(7):21-26.

Sreedharan, P., and P. Haves. 2001. Comparison of chiller models for use in model-based fault detection. *International Conference for Enhanced Building Operations (ICEBO)*, organized by Texas A&M University, Austin, TX.

Stallard, L.A. 1989. Model based expert system for failure detection and identification of household refrigerators. Master's thesis, School of Mechanical Engineering, Purdue University, Purdue, Indiana.

Stylianou, M., and D. Nikanpour. 1996. Performance monitoring, fault detection, and diagnosis of reciprocating chillers. *ASHRAE Transactions* 102(1):615-627.

Stylianou, M. 1997. Classification functions to chiller fault detection and diagnosis. *ASHRAE Transactions* 103(1):645-648.

Tsutsui, H., and K. Kamimura. 1996. Chiller condition monitoring using topological case-based modeling. *ASHRAE Transactions* 102(1):641-648.

Wagner, J., and R. Shoureshi. 1992. Failure detection diagnostics for thermofluid systems. *Journal of Dynamic Systems, Measurement, and Control* 114(4):699-706.

Wang, S., and Y. Chen. 2002. Fault-tolerant control for outdoor ventilation air flow rate in buildings based on neural networks. *Building and Environment* 37:691-704.

Yoshida, H., T. Iwami, H. Yuzawa, and M. Suzuki. 1996. Typical faults of air-conditioning systems, and fault detection by ARX Model and extended kalman filter. *ASHRAE Transactions* 102(1):557-564.

Yoshida, H., and S. Kumar. 1999. ARX and AFMM model-based on-line real-time data base diagnosis of sudden fault in AHU of VAV system. *Energy Conversion & Management* 40:1191-1206.

Yoshimura, M., and N. Ito. 1989. Effective diagnosis methods for air-conditioning equipment in telecommunications buildings. *INTELEC 89: The Eleventh International Telecommunications Energy Conference*, October 15 – 18, 1989, Centro dei, Firenze, 21:1-7.