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A review of fault detection and diagnostics methods for building systems

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The current article provides a summary of automated fault detection and diagnostics studies published since 2004 that are relevant to the commercial buildings sector. The review updates a previous review conducted in 2004 and published in 2005, and it categorizes automated fault detection and diagnostics methods into three groups. The examples of automated fault detection and diagnostics in the primary category are selectively reviewed to identify various methods that are suitable for building systems and to understand the strengths and weaknesses of the methods. The distribution of studies based on each automated fault detection and diagnostics method and heating, ventilation, and air-conditioning system is also described. Researchers and industries can use the current article as a guideline for selecting an appropriate automated fault detection and diagnostics method.

Introduction

Commercial buildings consume almost 20% of the total primary energy used in the United States (CBECS 2012). As much as 30% of the energy consumed by commercial building HVAC and lighting systems results from inadequate sensing and controls and the inability to fully and properly use the capabilities of existing building automation systems (BASs). In 2004, Katipamula and Brambley (2005a, 2005b) conducted a detailed review of automated fault detection and diagnostics (AFDD) studies of building systems and published a two-part review that summarized the AFDD and prognostics methods. The review of over 120 articles, of which about 90 focused on the AFDD of building systems, was completed in 2004. Their intent was to increase research and development community awareness of the body of AFDD 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 AFDD and prognostics, provided a framework for categorizing methods, described them, and identified their primary strengths and weaknesses. The second part of the review focused on research and applications specific to the fields of HVAC&R, briefly discussed the current state of diagnostics in buildings, and discussed the future of automated diagnostics in buildings.

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Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/uhvc.

AFDD studies associated with HVAC&R have increased in number since 2004—an additional 118 new studies in the past decade were identified and are reviewed in the current article. The present article categorizes all AFDD studies (including those before 2005) and reviews the AFDD articles relevant to the commercial buildings sector published since 2004. The articles are classified by one of three types of AFDD method: process history-based, qualitative model-based, or quantitative model-based. Some representative publications in each category are summarized to highlight how each method was applied to certain building systems. The selection of the appropriate method for successful and practical implementation requires a mathematical understanding of each method and an understanding of its strengths and weaknesses.

The current article provides a classification of each AFDD study based on the method and building system and then identifies the strengths and weaknesses of the approach across the broad spectrum of methods. The assessment of energy and cost impacts of faults is critical, but many methods do not account for them. The present article highlights the methods that identify energy and cost impacts and then concludes with a discussion of the current state of applications in buildings. It can be used as a good guideline for selecting an appropriate AFDD method, identifying gaps in current methods, and determining enhancements needed for the current methods. It also compares the conclusions drawn in 2005 with the conclusions drawn in 2016. It does not provide detailed description of the methods used; for that please refer to the Katipamula and Brambley (2005a, 2005b).

Classification of AFDD based on method

While conducting the survey in 2004 to classify the AFDD methods used in fault detection and diagnostics, the

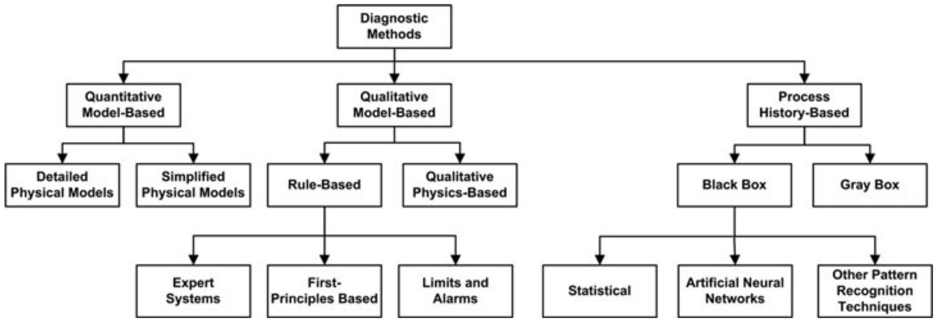

Fig. 1. Classification scheme for AFDD methods (adopted from Katipamula and Brambley 2005a).

classification scheme shown in Figure 1 was created. Although the classification developed previously had some limitations, it provided a convenient way to organize the methods (Katipamula and Brambley 2005a). Therefore, the same classification has been used to summarize the combined literature review (including those before 2005).

Over the past three decades, a number of AFDD methods have been developed for building systems. Katipamula and Brambley (2005a, 2005b) provided a summary of over 90 AFDD studies related to building systems; the summary included work published before 2005. Since 2004, over 100 more AFDD studies associated with building systems have been published. Figure 2 categorizes the 197 AFDD publications (both pre-2004 and post-2004) that relate to building systems based on the three fundamental methods used to classify them—the process history-based, qualitative model-based, and quantitative model-based methods. Process history models derive behavioral models from measurement data obtained from the process over time. Qualitative models consist of qualitative relationships derived from knowledge of the underlying physics. Quantitative models are sets of quantitative mathematical relationships based on the underlying physics of the process (Katipamula and Brambley 2005a). Of the 197 publications, 62% of the AFDD methods were process history-based, 26% were qualitative model-based, and 12% were quantitative model-based. The process history-based AFDD methods have been the most popular because they rely on historical data to train models and because of their reduced modeling complexity.

AFDD methods based on models derived from process history

Depending on the formulation of a model, process history-based methods may be classified as gray box or black box models. The black box model relies on parameter estimation to identify faults in the system, although in many cases the physical meaning of the parameter deviation is not known. The gray box model is formulated such that the parameter estimates used for AFDD can be traced to actual physical parameters (e.g., estimate of the coefficient of performance of a vapor-compression system) that govern the system or the component. As shown in Figure 3, of the 123 studies that used the process history-based methods, 72% of them were based on the black box model, 12% were based on the gray box model, and the rest were based on a combination of these methods. In some cases, black box models were combined with other methods to handle multiple faults or to further isolate faults.

Black box models

A black box model is formulated based on a relationship between inputs and outputs of a process or a system, but does not consider any physical significance. A black box model consisting of behavioral models is derived from process history data. Black box models can be further sub-classified based on the modeling technique used: statistical, artificial neural networks (ANNs), and pattern recognition. As shown in Figure 4, of the 110 studies that used the black box methods, the most common technique is statistical (63%), which include techniques such as polynomial regression,

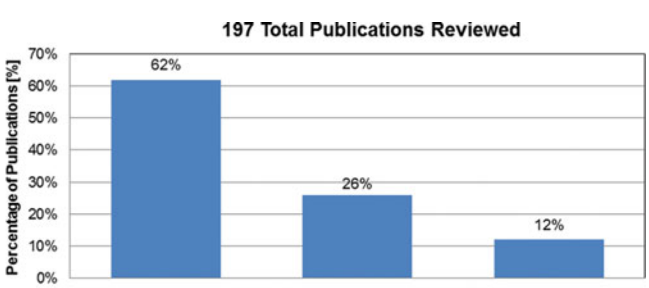

Fig. 2. Classification of AFDD literature based on process history-based, qualitative model-based, and quantitative model-based classification.

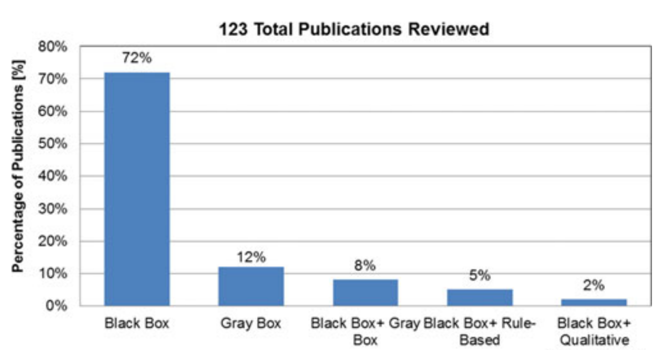

Fig. 3. Classification of process history-based methods.

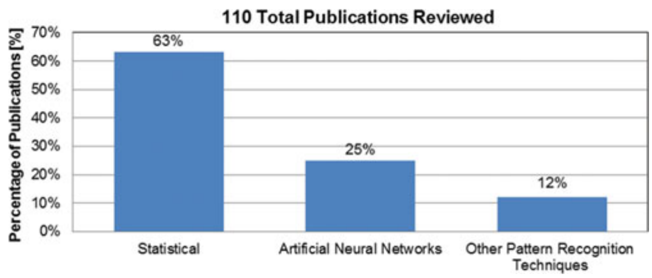

Fig. 4. Classification of black box methods.

autoregressive (AR), principal component analysis (PCA), logistic regression, and partial least squares.

The black box statistical model depends on polynomial regression, which is a form of linear regression, to describe the relationship between the operating conditions and the expected output states in normal operating system. The estimated coefficients are assumed to be a constant and independent of the operating conditions. Recent (post-2004) examples of studies of polynomial regression models applied to building system include Cui and Wang (2005), Radhakrishnan et al. (2006), Prakash (2006), Namburu et al. (2007), Zhou et al. (2009), Wang et al. (2010), Fisera and Stluka (2012), and Jacob et al. (2010).

Cui and Wang (2005) present an on-line AFDD method based on a polynomial regression black box model to indicate the health condition of a centrifugal chiller system. Six polynomial models are developed and trained to use regression analysis applied to normal experimental data. The models used two temperatures and cooling load as inputs, and estimated six different performance indices as output states. Residuals are formed as the differences between the monitored performance indices and those predicted by the steady-state regression models. The calculated residual values are used to determine whether the operation is faulty or normal. After a fault is detected, a rule-based classifier identifies the most likely cause of the faulty behavior using a rule-based pattern chart that relate each fault to the direction of residual change corresponding to each type of the fault. A polynomial regression model is very simple in form and easy to use, but has limitations in regard to statistical modeling. The rule-based classifiers take only a limited number of shapes and are particularly ill-suited to modeling asymptotes.

The AR model, a type of black box statistical model is widely used for modeling and forecasting time series data. It uses a stochastic difference equation that predicts the present value of a time series using its own previous observations in time. The optimization techniques (e.g., least-squares method) minimize the overall error between the AR model output and observed input–output data. The AR black box model and moving average model are sometimes combined to make a special case of a key component of the more general autoregressive-moving-average (ARMA) black box model, which has a more complicated stochastic structure. Some of these studies (Armstrong et al. 2006; Hou et al. 2006; Jin et al. 2005; Ploennigs et al. 2013; Wu and Liao 2010; Yiu and Wang 2007; Yoon et al. 2011; Yuwono et al. 2015) are discussed below.

Yiu and Wang (2007) use an ARMA, a type of black box statistical model for detecting the faults in an air-handling unit (AHU). Under their method, the parameters of the ARMA model are estimated based on the performance data derived from available normal test data. The output of the ARMA model is used as the expected performance and is compared with the current performance to determine whether service is needed due to an existing fault. Performance degradation higher than a threshold indicates that the fault impact is sufficiently severe to require service. After the performance model detects a fault, another ARMA model diagnoses the cause of the fault in each component separately. Typically, it is necessary to assign reasonable thresholds for deviations between actual and normal performance that constitute faults. Overall, the ARMA black box models can provide excellent mappings to nonlinear behavior, but require a great deal of data to train the models. These models cannot be used to extrapolate beyond the training data.

Armstrong et al. (2006) developed a fifth-order AR black box model with one input to detect faults in rooftop units (RTUs). Under this method, the AFDD implementation requires a current sensor and measurement of all three phases of voltage of the RTU. During start-up transient operation, voltage is used to detect liquid ingestion in the compressor, compressor valve leakage, and refrigerant undercharge. The steady-state power of each fan is also used to detect airflow faults in either the condenser or the evaporator.

PCA method based black box statistical models have been found to be useful in detecting sensor faults in various industrial and engineering processes because of its capability to reduce a higher dimensional space into a lower dimensional space (Wang and Xia 2004a). PCA-based AFDD methods are based on the premise that anomalous sensor readings are very different from the normal data. Therefore, faults can be detected by finding sensor data that are "far away" from the median of the principal components of the sensor data. For fault diagnosis, however, PCA becomes less useful because of the noncausal relationship of the data. In the noncausal relationship, it is hard to identify whether changes in one variable will result in changes in another variable. Therefore, PCA is more appropriate for fault detection than for fault diagnosis. PCA method-based black box statistical models have been extensively applied for detecting faults in AHU systems (Du et al. 2007; Hao et al. 2005; Li and Wen 2014a; Wang and Qin 2005; Wang and Xia 2004b; Wu and Sun 2011a; Xiao et al. 2006).

Xiao et al. (2006) proposed a PCA-based AFDD method for real-time monitoring of the sensor status in an AHU system. PCA models require fault-free history data to develop and train models and use transient operating data to detect and diagnose faults. PCA models are updated using a condition-based adaptive scheme to learn the normal shifts in the process due to the change in operating conditions. The Q-statistics[1] derived from the PCA model are compared with their thresholds based on chosen normal test data. However,

[1]Q-statistics is a test statistic output used in statistical hypothesis testing that provides better small-sample properties.

Xiao et al. (2006) reported that Q-statistics was too weak to identify complex sensor faults because the sensor faults in the AHU are propagated to other parts of the system. The sensor fault symptoms could be hidden due to the feedback of the other fault symptoms. To improve the accuracy of PCA, Du et al. (2007) proposed a PCA method based on black box statistical model using joint angle analysis (JAA) to detect and diagnose both fixed and drifting biases of sensors in variable-air volume (VAV) systems. JAA was used to isolate the complex faults by comparing them with the corresponding vector directions of known faults from a fault library based on expert rules. The use of the JAA method requires prior knowledge of a fault signature library for all known faults.

Xu et al. (2008) proposed a PCA based on black box model using wavelet analysis for sensor AFDD in a centrifugal chiller system. PCA is used in combination with wavelet analysis to extract the approximations of sensor measurements by separating noise and dynamics. Through the application of the wavelet transform method, high-frequency noise as well as sharp spikes in the data are removed without smoothing out the important features in the measurement data. The thresholds were experimentally determined based on the measurement of the training matrix. The difference between the calculated residual values and the threshold value is used to determine whether the operation is "faulty" or normal. However, a separate method is required to diagnose the cause of the fault. To overcome this limitation, other methods, such as JAA, wavelet analysis, or other pattern recognition techniques, can be combined with PCA to enhance the performance of the AFDD method.

Other black box modeling AFDD techniques used ANN (25%) and pattern recognition (12%). ANN black box models are good at establishing a complex functional relationship between a set of network inputs and outputs, which is achieved by using a network training procedure. When sufficient data are available for training, ANN black box models can learn patterns for normal and "faulty" behavior and provide direct classification of raw measurements. A number of researchers have used an ANN black box model for AFDD (Du et al. 2014; Fan et al. 2010; He et al. 2011, 2012; Hou et al. 2006; Jones 2015; Kim et al. 2008; Mavromatidis et al. 2013; Rueda et al. 2005; Yunwono et al. 2015; Zhu et al. 2012).

Kim et al. (2008) developed and evaluated an AFDD method for a residential air-conditioning system. Under this method, seven ANN black box models are used to describe the relationship between the driving conditions and the expected output state in a normally operating system. The residuals are formed as the differences between the measured output states and those predicted by the ANN black box models. If the standard deviation of the difference exceeds three times the standard deviation of the normal difference, the system is considered to be "faulty." The probabilities of a residual being positive, negative, or neutral are calculated, allowing for the determination of a fault probability relative to normal probability. When the fault probability is greater than the no-fault probability, the AFDD system flags a fault.

Fan et al. (2010) applied a two-stage back-propagation neural network (BPNN) black box model using wavelet analysis and fuzzy logic to detect and diagnose faults in an AHU. Back-propagation is a method of training the ANN model that is used in conjunction with a gradient descent. The first BPNN model is trained to detect abnormal conditions using data from a freshly calibrated sensor. In the first stage, the BPNN model is used for generating the residuals between the measured output states and those predicted by the first model. A fault can be detected when residuals exceed a threshold established for normal operation. Sensitivity analysis for the first BPNN black box model can determine which input variable has the most influence on prediction precision. The second BPNN black box model is constructed on the basis of the sensitivity analysis of the first BPNN model. After a fault is detected, a fault diagnosis is performed to identify sensor faults using a wavelet analysis and a recurrent neural network (RNN). The wavelet analysis is used to reduce the dimension of the input data for the RNN.

Pattern recognition, a type of black box models, is a branch of machine learning. Pattern recognition-based AFDD is used to perform nonlinear correlations between data patterns and fault classes. It is based on analyzing the observed behavior of a system and comparing it with a set of behavioral patterns generated based on various faulty conditions. Pattern recognition includes techniques such as support vector machine (SVM), Gaussian mixture model, and Bayesian network. Examples of studies of the pattern recognition method applied to building systems include those by Ren et al. (2008), Sharifi and Dagnachew (2012), Han et al. (2011a), Najafi et al. (2012a, 2012b), Guo et al. (2013), and Srivastav et al. (2013).

Ren et al. (2008) applied black box SVM model for pattern classification to evaluate whether a fault is present in a refrigerant system. SVM is a supervised learning algorithm based on finding the hyperplane that gives the largest minimum distance to the training examples. Ren et al. (2008) used SVM to find the best pattern for matching faults based on different operating patterns including a normal state and six fault states.

Najafi et al. (2012b) proposed a diagnostic method for AHU AFDD using a Bayesian network, which is a type of pattern recognition method. The method is based on analyzing the observed behavior of the system and comparing it with a set of behavioral patterns generated based on various "faulty" conditions to find the best representation for the current behavior. They presented how such a pattern-matching problem can be formulated as an estimation of the posterior distribution of a Bayesian probabilistic model.

Gray box models

Gray box models use physical knowledge or first principles to specify the mathematical form of terms in the model, and measured data are used to empirically determine the model parameters. The parameters of the gray box models are estimated using a training data set. The training data can be obtained from the equipment manufacturer, laboratory tests, or the field when the unit is operating normally. A number of researchers have proposed using gray box models for building systems (Nassif et al. 2008; Sun et al. 2014; Yu et al. 2011a, 2011b; Zogg et al. 2006). Zogg et al. (2006) proposed a gray box model with a vector clustering method for a heat pump system. Under this method, the parameters that capture key characteristics of the heat pump are considered the state variables. The data from 12 different sensor measurements are obtained and used to estimate the model parameters. The model parameters are tuned online by minimizing the error between measured and estimated performance data. The vector clustering is used for classifying gradual faults.

Yu et al. (2011) proposed a gray box model based on energy balance or a mass balance equation. Under this method, the gray box model is used for estimating the steady-state response and detecting dirty indoor filters. The airflow-rate model can be formed with outdoor-air damper state, supply-air, and outdoor-air temperature sensor. The model parameters are adjusted by a genetic algorithm-based optimization method to reduce the residual between the predicted and known airflow rate using all available data over a range of operating conditions. The gray box model has been proved to be accurate for a large number of AHU types and sizes.

Sun et al. (2015) proposed a Kalman filtering-based gray box model along with statistical process control (SPC) for robust system-level fault detection. Under this method, the parameters of a gray box model for chillers and cooling towers are obtained from historical measured data using the least-squares method. The Kalman filter employs a state dynamic model to predict the posterior probability density function of the state. The filter is used to predict the time evolution of the parameters of a gray box model based on measured variables. SPC is used for measuring and analyzing the gray box model parameters' variations caused by faults.

Summary of process history-based AFDD models

One of many strengths of process history-based models is that the methods are well suited to problems for which theoretical models of behavior are poorly developed or inadequate to explain observed performance. The models are also ideal when training data are substantial or inexpensive to create and collect. Black box models in particular are easy to develop and do not require an understanding of the physics of the system. Although computational requirements can vary, they are generally manageable. Finally, there is a wealth of documented information available on the underlying mathematical methods. Most models, however, cannot be used to extrapolate beyond the range of the training data. A large amount of training data are required to make accurate conclusions. The models are specific to a system for which they are trained and rarely applicable to other systems. Due to the requirement of a large amount of data, these methods are applicable when no other method is available. Although these methods are rarely used in the field for this reason, they have potentials for wide usage with the growing data storage technology.

The ANNs-based models have an advantage in that they model complex nonlinear relationships between dependent and independent variables without detailed knowledge of the physics of the system. Like other black box approaches, ANNs are not good at predicting behavior that is not present in the training set, and they require a vast amount of data to be adequately trained. The advantages of the pattern recognition-based models include their ease of implementation, the need for very little modeling effort, and they do not require *a priori* knowledge.

Gray box models that are based on first principles also require a thorough understanding of the system and expertise in statistics. Using a gray box model has some advantages over using a black box model. In particular, when using a gray box model fewer data are required to obtain an acceptable fit and there is better confidence that the model extrapolates well for operating conditions outside of the range used to obtain the parameters.

Unlike the black box models that only use measured inputs and outputs to represent characteristics of a device, the gray box models combine partial physical principles with process data to complete the model. Therefore, gray box models are more robust than black box models for AFDD and online control applications, and they can also provide insight into and understanding of faults for fault diagnosis. Although a gray box model is derived from measured data, it can be used for limited extrapolation outside of the data range used to obtain the correlations because they are formulated from first principles. However, use of a gray box model requires a high level of user expertise both in formulating the appropriate form for the model and in estimating model parameters.

Qualitative model-based methods

Figure 5 shows the sub-classification of the 50 studies that used qualitative model-based AFDD methods. Qualitative model-based methods rely on *a priori* knowledge to draw conclusions about the state of a system; they include both rule-based AFDD techniques and qualitative physics-based AFDD techniques. The most commonly used qualitative model-based technique is the rule-based technique (78%), which employs a large set of if–then-else rules and an inference engine to identify the process condition from a previously defined set of potential states. Sometimes, a black box model technique such as pattern recognition is also combined to identify and isolate specific faults. Qualitative physics-based methods, which allow for conclusions to be drawn about a process without exact expressions governing the process and precise numerical inputs, are used by only 10% of the studies.

Rule-based systems

Rule-based modeling techniques use *a priori* knowledge to derive a set of rules (e.g., if–then construct) and an

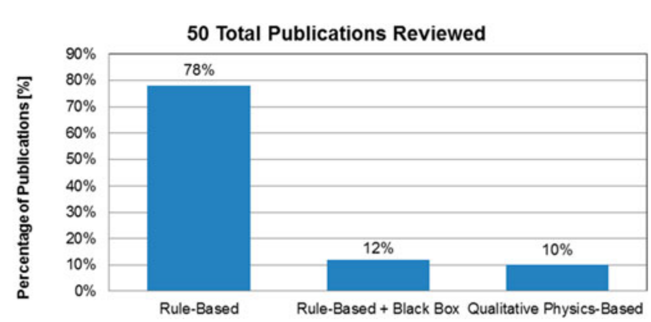

Fig. 5. Classification of qualitative model-based methods.

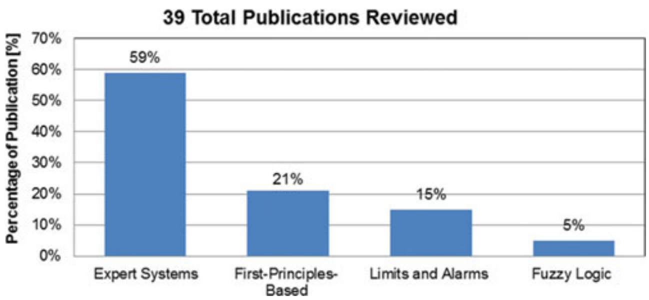

Fig. 6. Classification of rule-based techniques.

inference mechanism that searches through the rule space to identify fault symptoms. The rule-based method relies on expert analysis of specific building systems and the setting of thresholds or alarms, which are derived from analysis of the historical sensor data. A sub-classification of the 39 studies that used rule-based methods is shown in Figure 6; the sub-classifications include expert systems (59%), first-principles-based techniques (21%), limits and alarms (15%), and fuzzy logic (5%).

Rule-based model depend on expert systems, which are computer-based applications that simulate the performance of human experts in a given field. The insights, knowledge, and/or guidance from experts are encapsulated into a database (often referred to as a knowledge base). Rules are then formulated as *if* conditions and *then* consequences. Expert systems are widely used for AFDD of building systems because of their simplicity to develop and apply in real systems (Bruton et al. 2014; Cho et al. 2005; Choinière 2008; Schein and Bushby 2006; Schein et al. 2006; Song et al. 2008; Yang et al. 2008).

Schein et al. (2006) extended an earlier study that proposed a rule set for AHUs by House et al. (2001). The AFDD method provides 20 rules using expert knowledge of the four operating modes commonly used to control supply air temperature and pressure. In each rule, a threshold value is computed by considering the measurement uncertainties of controlled variables and control signals. Therefore, it is very important to define reasonable thresholds for appropriate fault detection. Schein and Bushby (2006) also propose a hierarchical rule-based expert system based on knowledge acquisitions of experts and the collection of real cases when the building system is complex and has a large number of operating modes. To overcome this limitation, three hierarchical levels were distinguished: the building, system (e.g., AHU), and component (e.g., return fan, cooling coil) level. For example, the rule-based chart based on the system level is used to detect faults. After a fault has been detected, the cause of the fault is diagnosed on the component level to obtain specific information about which part of the system is defective.

Cho et al. (2005) also described a ruled-based expert system for an AHU. They proposed a rule-based chart method based on the variation of system features for analysis of the faults occurring in an AHU system. Their method uses transient data at start-up from five measured inputs (outdoor and indoor air temperature, outdoor damper position, and supply-air temperature and pressure). The transient trends in measured variables during start-up are compared to the baseline trend from normal start-up. Because operating conditions affect the baseline response, the baseline response must be normalized before a comparison is made.

Bruton et al. (2014) presented a Cloud-based AFDD method for AHUs using a rule-based expert system. A generic data extraction process is incorporated with an AFDD method to facilitate the transmission of data from the client's BAS to a Cloud-based Web server. Expert systems are a popular diagnostic method because they can be applied when the relationships between operational variables and threshold values are known. However, as the building systems become more complex, the number of expert rule sets dramatically increases and they fail to generalize and detect new faults with unknown signatures. To overcome these limitations, the machine learning technique has been used to automatically extract knowledge from various data by using advanced statistical techniques such as decision tree models and a Kernel machine model.

The second category under rule-based methods uses rules derived from first principles, which are implemented in a tree structure (Brambley et al. 2011; Fernandez et al. 2009; Wang et al. 2012a). A first principles-based model is typically generated by using laws governing system behavior, such as mass and energy balance. A steady-state algorithm is used to filter out transient data, because the first-principles method is based on steady-state operating conditions.

Fernandez et al. (2009) developed rule-based methods based on first principles model to detect sensor, economizer damper, and damper actuator faults in an AHU. In this case, the rules derived from separate first-principle models are implemented for the economizer, cooling coil, and fan duct system. The economizer and cooling-coil models are coupled with the mixed-air measurement predicted from the economizer model. The predictions from the first-principles model are used to generate (if–then) rules that are evaluated by an expert system using information about the actual process.

The limits and alarms method is widely used as rule-based AFDD model to prevent or highlight potentially harmful operations (Alsaleem et al. 2014; Freddi et al. 2013; Li et al. 2012; Wang et al. 2011; Wang et al. 2012b). This method, also commonly supported by BASs, relies on comparing raw outputs that are directly measured using sensors that have expected values. The method is appropriate in data-rich environments that feature redundant sensors. A fault can be indicated if the comparison residual between the actual value and expected value exceeds the limits that would cause an alarm condition. Therefore, reasonable limits for an AFDD system must be defined.

Wang et al. (2011) proposed a rule-based AFDD method based on residual cumulative sum (CUSUM) control charts to detect faults in VAV terminals. The CUSUM control chart is one of the most popular techniques used with limits and alarms. An alarm is triggered when at least one of the multiple CUSUM statistics reaches the corresponding control limit. To use this method, the user needs to specify a causal relationship between all of the control variables and their controlling components. Based on the real-time monitored data, a CUSUM statistic is calculated for each control variable and a fault counter is then updated based on an automatic count mechanism.

Freddi et al. (2013) proposed a simple rule-based limits check method for lighting systems based on system health monitoring. In this case, AFDD is performed through a limit and alarm algorithm based on the trend of the temperature rate of the heat sink. Data gathered during the steady operation allow for navigating the decision limits of the lighting system's behavior. Faults are detected and diagnosed by comparing the change in the direction of measured quantities with expected values and matching the changes to expected directional changes associated with each fault.

The rule-based methods that use fuzzy logic for AFDD rely on fuzzy rule sets to account for the uncertain, nonlinear behavior of a HVAC system. A set of inputs are converted into fuzzy representations that can be compared with the fuzzy rule sets that describe the relationship between a set of inputs and outputs in qualitative terms. Only a few fuzzy rule sets are normally required, compared to an expert system, because one fuzzy rule can replace a number of conventional rules. The fuzzy systems have been used in several studies of building systems (Cimini et al. 2015; Lauro et al. 2014; Lianzhong and Zaheeruddin 2014; Marino et al. 2014).

Lauro and Moretti (2014) proposed a fuzzy model to detect abnormal electric consumption when fan coils are improperly used. Fuzzy logic consists of a set of production rules that define the relationship between the input (people presence data, time, and electric power) and output variables. Rules are of the form "*if* X is A *then* Y is B", where A is a fuzzy set over the input domain X and B a fuzzy set over the output domain Y. For example, "*if* a fault in fan coil electric consumption occurs *and* occupancy on the floor is low *and not* during working hours *then* the diagnostics index is high."

Cimini et al. (2015) presented an AFDD method based on fuzzy logic for a light-emitting diode (LED) lighting system. Under this method, the LEDs are controlled by using proportional integral and derivative (PID) logic, which generates the control signal on the basis of the reference generated by the fuzzy logic. This method requires three input variables (temperature sensors, light sensors, and motion sensors) and two output variables (fan power and reference current of the LED) to monitor system health. AFDD is achieved by employing both hardware redundancy and control signal-based methods.

Qualitative physics-based models

The qualitative physics-based models contain models contain qualitative equations derived from qualitative descriptions of relationships among the process variables or knowledge about the fundamental behavior of the system (Katipamula and Brambley 2005a). Fault detection is performed by comparing the predicted qualitative behavior of a system based on a model with the actual observation. AFDD research using these methods includes that conducted by Müller et al. (2013), Bonvini et al. (2014a), and Sterling (2015).

Müller et al. (2013) described a model-based qualitative method to performing AFDD on an AHU. In this case, the qualitative model of a heat exchanger determines the probability that a subsequent condition might occur. The air outlet temperature is defined as a state value. The inputs and outputs are the valve control signal, the air mass flow rate, and the air- and water-side temperatures. Faults are detected on the basis of discrepancies between the states of the real process and the corresponding expected state of faultless behavior. When an observed mismatch occurs indicating the presence of faults, the rule-based table is used to diagnose the fault.

Sterling (2015) proposed an AFDD method for an AHU based on a transformation of first-principles models into a qualitative representation of the components' behavior. Under this method, the controller signals for the pre-heating coil, dampers, and cooling coil are collected. The controller outputs are converted to some predefined qualitative values (e.g., "closed," "open," and "between"). Faults are detected when there is a deviation between the measured qualitative controller outputs and the corresponding model-based predictions based on temperature measurements. The qualitative physics-based model is simple to develop and apply because accurate numerical knowledge (accurate measurement or physical description of the system) and time-consuming mathematical models are not needed. However, this method only can apply to a specific system and process, and only offers solutions in cases where high numerical accuracy is not needed.

Summary of qualitative AFDD models

One of the biggest strength of qualitative models is that they are simple to develop and apply. The models are ideal for data-rich environments and noncritical processes because the models can assess a process without precise numerical inputs and exact expressions that governs the process. In fact, some methods can perform AFDD without precise knowledge of the system or exact numerical values for inputs and parameters. Furthermore, the rationale is transparent and the models provide explanations for the suggested diagnoses based on the cause–effect relationships.

The biggest weakness of qualitative model is that the methods are specific to a system or a process, which makes it difficult to ensure that all rules are always applicable especially for complex systems. If new rules are added to extend the existing rules or accommodate special circumstances, the simplicity gets jeopardized. Finally, the models depend on the expertise of the developer. Based on these strengths and weaknesses, these qualitative AFDD models provide shortcuts for field application and may offer the most expedient way to meet analytical needs where more rigorous approaches are time or cost prohibitive.

Quantitative model-based methods

Quantitative model-based methods use an explicit mathematical model of the monitored plant or a system to achieve analytical redundancy to detect and diagnose the cause of faults. The mathematical equations to represent each component of the system can be developed and solved to simulate the steady and transient behavior of the system. The quantitative model-based methods need to be properly validated with experimental data for both fault-free and "faulty" operation before any credibility can be placed on their prediction

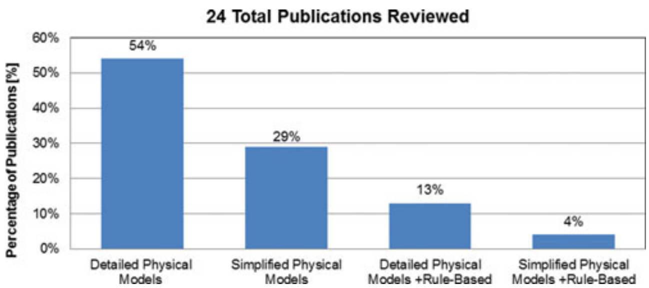

Fig. 7. Sub-classification of quantitative model-based methods.

accuracy and usefulness. These models can be further subclassified as detailed physical and simplified physical models, as shown in Figure 7. The quantitative model-based methods require detailed knowledge of the system.

Of the 24 studies that are associated with quantitative model-based methods, 54% are detailed physical models. These models are generally derived from detailed knowledge of the physical relationships that govern the behavior of the system (Keir and Alleyne 2006; O'Neill et al. 2014; Thumati et al. 2011; Weimer et al. 2012).

Keir (2006) proposed detailed physics-based models for vapor-compression systems based on residuals using dynamic model outputs. The study used an experimental vapor-compression system that had a variable-speed compressor and electronic expansion valve as the expansion device. The possibility of using more complex moving-boundary models for fault detection and diagnosis in vapor-compression equipment was explored. A linearized form of the model was used to explore the sensitivity of each output to fault conditions of evaporator frosting, refrigerant leakages, and compressor valve leakages.

Thumati et al. (2011) proposed a detailed physical model governing system behavior such as mass and energy balance in terms of dynamic models. Under this method, a fault is detected if the generated detection residual, which is defined as the error between the observer outputs and HVAC system states, exceeds a threshold. The thresholds are chosen to minimize false alarms.

Simplified physical models constituted 29% of the quantitative model-based studies reviewed. The simplified physical models calculate a physical quantity using a lumped parameter approach with limited assumptions. In contrast to the detailed physical modeling, this approach is computationally simpler because coupled space partial differential equations are transformed into ordinary differential and algebraic equations. A number of researchers have used simplified physical models for AFDD of building systems (Haves et al. 2007; Mele 2012; Papale 2012; Provan 2011).

Provan (2011) described a reduced-order systems model for an AHU derived from a thermodynamic principle. To diagnose selected faults, a physical model was transformed to a diagnosis model using model transformation methods, which mapped the physical relations into a set of transformation rules based on expert knowledge.

Papale (2012) presented a simplified physical model for detecting actuator failures in HVAC systems that dynamically estimates the model parameters while performing detection. Under this method, a first-order heat-equation model is assumed to model interactions between adjacent rooms, which are used to formulate a hypothesis testing problem assuming known inter-room thermal parameters. The method is formulated to provide performance that asymptotically bounds both the probability of misses and the probability of false alarms.

Summary of quantitative AFDD models

One of the most noteworthy strengths of quantitative models is that they are based on sound physical or engineering principles, which provide the most accurate estimators of output when they are well formulated. The detailed models based on first principles can model both normal and faulty operation, which makes "faulty" operation distinctive from normal operation. In addition, only detailed physical models can capture the transients in a dynamic system.

There are also some weaknesses of quantitative models. Due to the complexity of equations and quantity of data, they can be not only computationally intensive but also a significant level of effort is required to develop a model. Often the data required for modeling is not available in the field and these models cannot be generalized to other similar systems easily without a lot of effort. The extensive user input has a potential to create opportunities for poor judgment or input errors that can contribute to a significant impact on results. Furthermore, the method needs adequate and reliable sensors for data acquisition, and hence, may not be cost-effective. Therefore, these models are more ideal for critical industrial processes than for building systems. However, simplified quantitative models can play major roles for building AFDD application.

AFDD methods based on the combination of various methods

Some of AFDD methods use a combination of techniques to handle multiple simultaneous faults to improve (e.g., accuracy, robustness, and reliability) fault diagnosis as shown in Figures 3, 5, and 7. AFDD methods need to be able to accurately distinguish the fault from the list of possible faults. To isolate specific faults when there are multiple simultaneous faults, numerous studies have combined black box models with gray box or qualitative models (Fontugne et al. 2013; Bynum et al. 2012; Li and Braun 2007b; Lin and Claridge 2015; Wang and Cui 2006; Wang et al. 2013; Yang et al. 2013; Zhao et al. 2014).

Wang and Cui (2006) combined a qualitative model with a statistical black box model, PCA, to detect and diagnose faults in a centrifugal chiller. Under this method, the condition of the centrifugal chiller system is characterized by six performance indices used as benchmarks for comparison with monitored performance indices. The residuals between measured and expected values are used to detect faults. The sensor AFDD method uses a PCA-based black box model to capture the correlations among the measured variables. The Q-statistics between the approximation coefficients of new

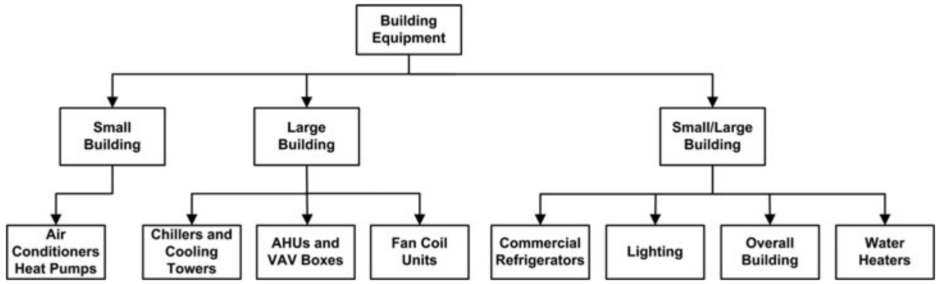

Fig. 8. Categorizing of the building systems based on building size.

data and cluster centers of the known sensor fault data are calculated. These Q-statistics are used to isolate "unknown" sensor faults from the new data.

Li and Braun (2007b) present an integrated AFDD algorithm based on a combination of gray box and black box statistical polynomial regression models. The AFDD methodology uses features that uniquely isolate individual faults, and, therefore, readily handles multiple faults for RTUs. To realize a cost-effective method, they also developed a number of gray box and black box polynomial regression models that provide high-value decoupled features using a combination of low-cost measurements and models for the compressor, expansion valve, condenser, evaporator, and refrigerant charge.

The quantitative model-based methods can be combined with a black box model, which increases robustness and reduces disturbance, noise, and modeling uncertainty (Arseniev et al. 2009; Kocyigit 2015; Liang and Du 2007; Qin and Wang 2005; Wu and Sun 2011b). For example, statistical techniques such as PCA, JAA, and wavelet analysis are used to analyze the results obtained by the qualitative model-based method to diagnose and isolate faults.

Liang and Du (2007) used an AFDD method that combined a quantitative model obtained from first-principles with a SVM, a type of black box model. Under this method, the first-principles model of a single zone HVAC system is developed first, and then the characteristics of three major faults are investigated by computer simulation. The SVM black box model is used to design a fault classifier, which is based on the statistical learning theory that transforms the signal to a higher dimensional feature space for optimal classification. The diagnostics are achieved by comparing the residuals between the outputs and model predictions at one or more operating points.

Wu and Sun (2011b) also used a combination of AFDD methods based on a quantitative model obtained from first-principles and a PCA method to track the system status for VAV systems. In this case, the PCA black box model is used first to reduce a high-dimensional data volume into the useful information of a lower dimensional space. Then, the airflow rate and energy consumption are estimated using the energy balance and pressure-flow balance to diagnose faults existing in VAV systems. Overall, the combined method can reduce the modeling requirements, but it requires more memory to store data.

Classification of AFDD methods based on building system

Although none of the studies explicitly stated whether the AFDD method described in the study is applicable to small (<50,000 sf) or large commercial buildings, it can be implicitly inferred based on the type of building system. Small buildings typically use RTUs, while large buildings typically use AHUs, chillers, cooling towers, and fan coil units. Some AFDD methods associated with the whole building energy consumption, lighting, hot water heaters, and commercial refrigerators apply to both small and large buildings, as shown in Figure 8.

Figure 9 breaks down the AFDD literature by building system. Of the 197 studies, 42% were associated with VAV-AHUs, 17% were for chillers and cooling towers, 16% for RTUs, 12% for overall building (whole building application), 4% for water heaters, 3% each for commercial refrigerators and lighting, and 2% each for other HVAC and fan coil units. Based on the review, 87% of the current research is focused on the development of AFDD methods for a handful of buildings systems: VAV-AHUs, chillers and cooling towers, RTUs, and overall building.

AHUs and variable-air-volume boxes

VAV-AHUs provide both heating and cooling for multiple zones and are generally used in large commercial buildings. These systems along with distribution terminals (VAV boxes) are controlled using a BAS to meet occupant comfort requirements. Eighty-three AFDD studies reviewed are

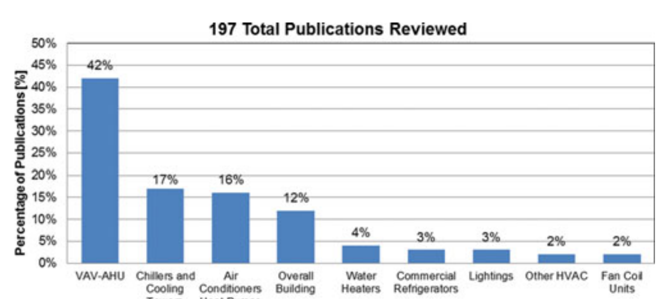

Fig. 9. Classification of AFDD literature based on building system.

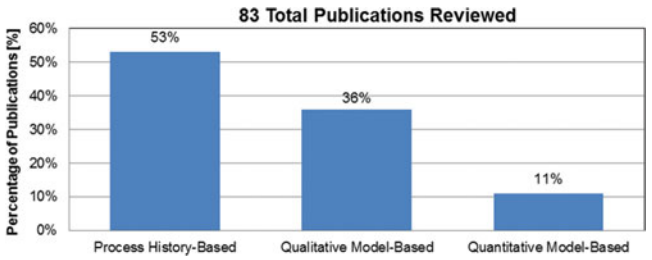

Fig. 10. Methods used for VAV-AHU based on process history-based, qualitative model-based, and quantitative model-based classification.

related to VAV-AHU; they are broken down based on the first level of classification, as shown in Figure 10. The most popular method is process history-based (53%), followed by qualitative model-based (36%) and quantitative model-based (11%).

These studies can be further sub-classified based on the AFDD method used, as shown in Figure 11, where it can be seen that 80% of the studies used either black box (52%) or rule-based (28%) AFDD methods. The remaining studies used simplified physical models (7%), qualitative physics-based models (6%), detailed physical models (4%), gray box models (2%), and fuzzy logic (1%). A few of these studies are summarized below (Bashi et al. 2011; Jones 2015; Dehestani et al. 2011; Du et al. 2009; Guo et al. 2013; He et al. 2015; Jin and Du 2006; Lee et al. 2004; Li and Wen 2014b; Sterling et al. 2014; Wang and Xiao 2006; West et al. 2011; Xiao et al 2014; Yang et al. 2011).

Lee et al. (2004) described four general regression neural network (GRNN) models that use a simple rule-based method for AFDD in an AHU system. The GRNN model is a regression technique that uses a memory-based feed-forward network to produce estimates of continuous variables. In this case, four GRNN models were used to generate estimates of sensor values (mixed-air temperature, return-airflow rate, and supply-air static pressure) and control signals (cooling-coil control valve signal) that were then compared to actual values to produce residuals. The residuals of four system variables were used to quantify the dominant symptoms of fault modes based on if–then-else rules.

Wang and Xiao (2006) presented a condition-based adaptive statistical method to detect degradation sensor faults in AHUs. Under this method, a PCA technique is used to transform a number of related process variables to a smaller set of uncorrelated variables. Two PCA models are built corresponding to the heat balance and pressure-flow balance. Sensor faults can be detected based on Q-statistics and diagnosed using the Q-contribution plot and expert system. The adaptive scheme updates PCA models with different operating conditions and stores the PCA models generated in the adaptive process in a model database. The outdoor-air temperature and humidity are selected to represent the changing operating conditions. The set of rules, based on directional changes, are used to identify the unique cause of each sensor fault.

Du et al. (2009) proposed combining wavelet analysis with neural networks for use in diagnosing the faults in a VAV system. The wavelet transformation method can be used to decompose the data collected from BAS into different scales of decreasing level of detail or resolution. Three-level wavelet decomposition is used to process the original data collected from BAS and then the characteristic data representing the main operational information of the system are obtained. Employing the decomposed data, the neural networks are trained and used to identify the operational condition and isolate the source of the fault in the VAV system.

Chillers and cooling towers

Several researchers have applied AFDD methods to detect and diagnose faults in vapor-compression chillers and cooling towers (Bonvini et al. 2014b; Han and Gu 2011; Au: Han et al. 2011, 2011b; Magoules et al. 2013; Navarro-Esbri et al. 2006; Rueda et al. 2005; Xu et al. 2008). Figure 12 classifies the studies based on process history-based, qualitative model-based and quantitative model-based classification. For the 34 studies related to the chillers and cooling towers, 79% used a process history-based method followed by studies that used quantitative model-based (15%) and qualitative model-based (6%) methods.

These studies can be further sub-classified based on the AFDD method used, as shown in Figure 13, where it can be seen that 68% of the studies used either black box (50%) or a combination of black box and gray box (18%) AFDD methods. The remaining studies used detailed physical (12%),

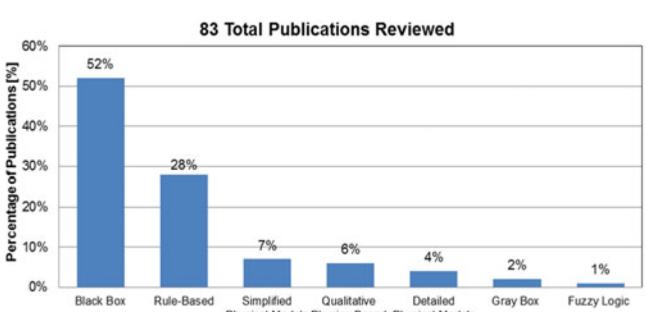

Fig. 11. AFDD methods used for VAV-AHU.

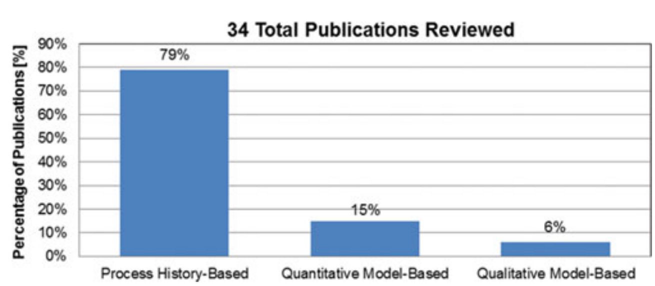

Fig. 12. Methods used for chillers and cooling towers based on the process history-based, qualitative model-based, and quantitative model-based classification.

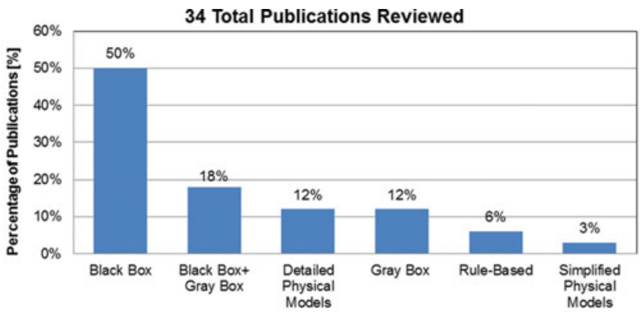

Fig. 13. AFDD methods used for chillers and cooling towers.

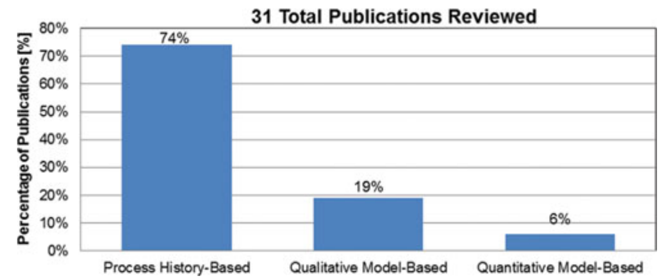

Fig. 14. AFDD methods used for air conditioners and heat pumps.

gray box (12%), rule-based (6%), and simplified physical (3%) models.

Rueda et al. (2005) used a steady-state black box model for a liquid chiller system that had a thermostatic expansion valve and a fixed-speed compressor. The AFDD method uses a set of 10 ANNs to predict the fault-free steady-state condition of 10 refrigeration system parameters. The transient data from the measurements is filtered out using a steady-state detection algorithm. The ANNs receive the current coolant inlet temperatures for the evaporator and condenser as input and each ANN calculates the expected fault-free condition of the 10 parameters that consist of the coolant outlet temperatures for the 2 heat exchangers and 8 refrigerant conditions. Residual values between the measured output states and those predicted by the output of the ANN model are used with an expert system to determine whether the system is operating under low-, normal-, or high-charge conditions.

Navarro-Esbri et al. (2006) suggested an AR model and an extended Kalman filter to track abrupt faults with the system states for a reciprocating chiller system. In this case, the inputs to the system models include the inlet temperature of the secondary fluids to the evaporator and condenser and the compressor rotation speed. The suction pressure is selected as output for the system model. If thresholds are set too close to normal conditions, the AFDD system is too sensitive and this leads to false alarms. If thresholds are set too far from normal conditions, the AFDD system might miss faults that potentially reduce system performance. Therefore, the dynamic thresholds for residuals are determined based on different operating conditions during the model initialization period. The Kalman filter generated a minimum error estimation of states to determine time-varying parameters of AR models. The refrigerant charge fault is identified if the residuals exceed a given dynamic threshold.

Han et al. (2011a, 2011b) developed a statistical AFDD method for a centrifugal chiller that had a fixed-speed compressor and a thermal expansion valve. Under this method, five types of individual faults (refrigerant leakage and overcharge in chiller, excessive oil in chiller, condenser fouling in chillers, evaporator fouling in chiller, noncondensable gas in refrigerant in chiller) with different levels are simulated in the field and used for the evaluation. A black box model based on an ANN algorithm is developed for the expected reference value. The fault is detected by a multi-layer SVM classifier based on residual rules by comparing chiller system measurements with the black box model outputs. The design of the multi-layer SVM classifier accounts for the normal and chiller fault output conditions.

Air-conditioners and heat pumps

The third most popular building system used by AFDD researchers is the electrically driven vapor-compression air-conditioner or heat pump systems (31 studies). Figure 14 classifies the studies based on the process history-based, qualitative model-based, and quantitative model-based classification. Process history-based methods and qualitative model-based methods were used in 74% and 19% of the studies, respectively.

These can be further sub-classified based on the AFDD method used, as shown in Figure 15, where it can be seen that 74% of the studies used either black box (55%) or rule-based (19%) methods. The rest of the studies used gray box (10%), black box in combination with gray box (10%), detailed physical models (3%), and simplified physical models (3%). Some of these studies are discussed below (Armstrong et al. 2006; Hjortland 2014; Li 2012; Li and Braun 2007a).

Li and Braun (2007a) presented improvements to the original statistical rule-based AFDD algorithm for RTUs that have a fixed-speed compressor and a fixed orifice. Under this method, six different faults are imposed on the RTU: (1) compressor/reversing valve leakage; (2) improper outdoor airflow; (3) improper indoor airflow; (4) liquid-line restriction; (5) refrigerant undercharge/overcharge; and (6) presence of noncondensable gas. Refrigerant overcharge results from improper charging by a service technician. Refrigerant undercharge may result from improper charging or from a leak. Improper refrigerant charge causes problems

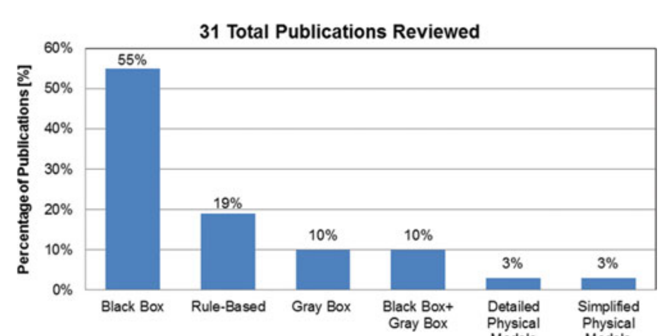

Fig. 15. AFDD methods used for air conditioners/heat pumps.

in the field, such as compressor damage and could lead to a significant increase in energy consumption. Noncondensable gases raise the condensing pressure, which degrades the compressor efficiency and increases energy consumption. The long-term operation of a compressor may cause discharge and suction valve leakage due to valve wear and tear. Also, when the system is overcharged or when the evaporator is fouled, the compressor suction chamber may be damaged by liquid refrigerant flooding. The condenser heat exchanger without service for several years may become dirty, thereby inhibiting heat transfer from the refrigerant side to the air-side. Improper indoor airflow may be caused by an improper duct design, a fouled heat exchanger, or a fouled air filter with an excessive loading. The liquid-line restriction fault is meant to represent a dirty filter/dryer. The role of the filter/dryer installed in the liquid line is to remove moisture and any tiny particles due to improper refrigerant charge service or piping connections. The accumulation of these substances blocks the filter/dryer, causing a degradation of refrigerant mass flow.

Li (2012) proposed an electrical signal-based AFDD method that can be applied to RTUs that have a variable-frequency-drive (VFD) for both the indoor fan and compressor. There are four steps to implementing this method. The first step is to develop the performance baseline by trending the variable frequency drive speed, power, supply air, outside air, and space air temperatures under normal conditions. The measured values are referenced to the rated values. The second step is to conduct real-time monitoring of the system operations. An increase in the residual value between actual performance and the baseline performance indicates a fault. The next step is to identify one or multiple faults using unique signatures. The last step is to estimate the impact or severity of the fault. Steady-state tests are performed to train the baseline for normal operation and to determine statistical thresholds for fault detection. The impact of the thresholds for fault detection and fault diagnosis is also evaluated.

Whole building

Research on whole building diagnostics has been a subject of interest over the past decade (Bynum et al. 2012; Capozzoli et al. 2015; Costa et al. 2013; Lin and Claridge 2015; Liu et al. 2010; Miller et al. 2015; Narayanaswamy et al. 2014; Seem 2007). AFDD methods associated with whole building energy are classified based on the process history-based, qualitative model-based, and quantitative model-based classification, as shown in Figure 16. Of the 24 studies in this category, the process history-based method is used by 63% of the studies, followed by the qualitative model-based (21%), and quantitative model-based (17%) methods.

These studies can be further sub-classified based on the AFDD method used, as shown in Figure 17, 38% of the studies used black box, followed by gray box (25%), detailed physical (21%), and rule-based (17%) models.

Narayanaswamy et al. (2014) presented a statistical method that is able to detect anomalies by automatically modeling and clustering similarities in an HVAC system. They present black box models using sensor data that correspond to each zone. They also use a clustering technique to

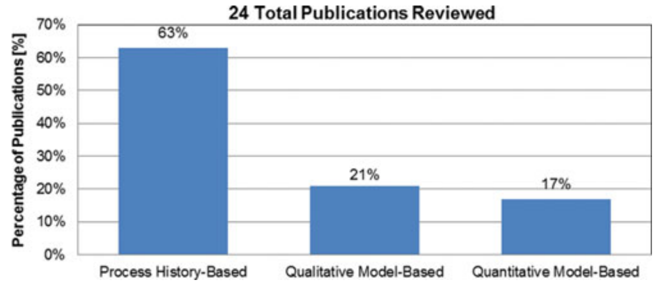

Fig. 16. Methods used for overall building based on the process history-based, qualitative model-based, and quantitative model-based classification.

automatically identify zone categories within a building, and use data driven methods for comparing zones to flag anomalous zones while limiting false alarms. Based on the outputs of model-compare and cluster, the rule-based methods are used to detect faults in the larger data.

Miller et al. (2015) presented a pattern recognition method that uses symbolic aggregate approximation (SAX), motif and discord extraction, and clustering to detect the underlying structure of building performance data. The SAX method can convert time series data with an equivalent symbolic representation for identifying relevant patterns by comparing strings. The authors present how the SAX method can be implemented to detect the schedules using total building power measurement. Two different power measurement time series data are analyzed in order to find the similarity between two data sets and discover meaningful patterns to identify excessive consumption. Because most whole building methods cannot easily isolate the cause of the fault, the building operations staff need to do a deeper analysis of the HVAC system to identify the cause.

Energy and cost impact assessment of faults

Fault evaluation (or impact assessment) is one of the major steps in the AFDD process described previously in the generic AFDD process section. The severity of the fault and its impact on energy consumption is essential for prioritizing the repair. However, assessing the impact (energy and cost) or the severity of the fault is difficult because in many cases the information needed to make the assessment is not easily

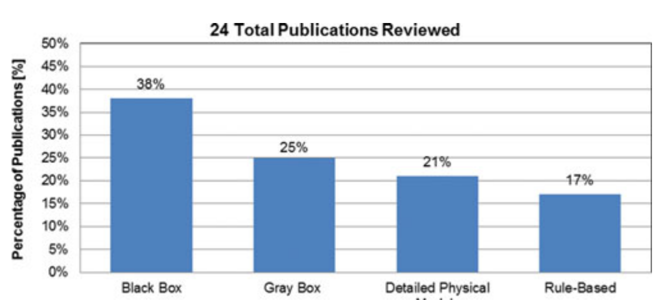

Fig. 17. AFDD method for the whole building.

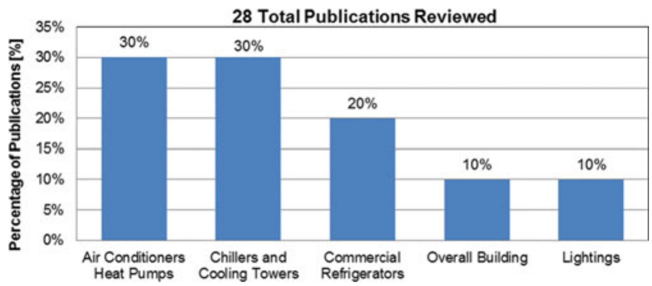

Fig. 18. Breakdown of AFDD studies that report fault impact.

available. Therefore, only 28 of the 197 studies estimated the energy/cost impact from faults. The fault impact can be used to prioritize the repairs, which will result in reduced energy and costs, improved comfort and equipment life, and reduced service costs. A breakdown of studies based on building systems is shown in Figure 18, where it can be seen that 80% of the studies that report fault impacts are associated with RTUs, chillers and cooling towers, and commercial refrigerators (Kim 2013; Lee and Lu 2010; O'Neill et al. 2014; Prakash 2006; Sutharssan et al. 2012; Wichman and Braun 2009).

Lee and Lu (2010) presented six different empirical models for predicting chiller energy performance at different operating conditions: (1) linear regression model; (2) bi-quadratic regression model; (3) multivariate polynomial regression model; (4) Gordon-Ng universal model; (5) simplified physics model; and (6) gray box models. Under their method, the empirical coefficients of the performance models are estimated based on performance data from available normal data or test data using least-squares regression. The predicted output of the models is compared with the measured energy performance. Their results indicate that the multivariate polynomial regression model had the best prediction capabilities.

Sutharssan et al. (2012) used an AFDD method for monitoring the faults of lighting systems. The AFDD method uses the light intensity sensor to measure the approximate level of the light and its statistical distribution. The detection thresholds are identified at the point where the output of light intensity sensors starts to decrease. Furthermore, real-time health monitoring is conducted based on input current, input voltage, and board temperature to predict the light output power degradation of an LED in real-time.

Kim (2013) developed an AFDD method for RTUs that have a fixed-speed and a variable-speed compressor. Under this method, five different faults are detected: (1) loss of compressor performance; (2) low or high refrigerant charge; (3) fouled condenser or evaporator filter; (4) faulty expansion device; and (5) liquid-line restriction. The performance models for capacity and power consumption for normal conditions are developed to estimate the expected reference value. A comparison between current estimated performance and normal expected values is used to determine whether a fault, when detected, is severe enough to justify service. The impact of faults on system performance were assessed using capacity, efficiency, and operating cost using data for air-conditioners and heat pump systems tested in the laboratory and using data obtained from manufacturers. Based on the results of this study, it is estimated that a refrigerant undercharging in the range of 25% can lead to an average reduction of 20% in cooling capacity and 15% in energy efficiency. Furthermore, an undercharge of about 25% would cause an average penalty in seasonal energy efficiency ratio (SEER) of about 16% and a cost penalty of US \$60 per year per ton of rated capacity. These penalties could be considered cost savings associated with improving refrigerant charge levels and are very significant. For evaporator fouling, a reduction in airflow of 50% decreases the average capacity by 14%, whereas the energy efficiency decreases by 12%. The average SEER value decreases by 10% and annual cost increases by US \$24 per ton. For condenser fouling, a 50% reduction in airflow decreases the average capacity by 9%, whereas energy efficiency decreases by 22%. The SEER value decreases by 20% and annual cost increases by US \$80 per ton. Evaporator fouling has more influence on capacity than on efficiency, while condenser fouling has more impact on efficiency.

O'Neill et al. (2014) proposed a whole building energy performance monitoring and diagnostics method. In this case, the diagnostic tool applies data mining and anomaly detection methods to identify building faults using real-time building measurements and building reference model predictions (DOE 2010). The expected performance models based on quantitative method are used to quantify deviation from the current measurements, as well as determine whether the current fault is severe enough to warrant service.

Current state of diagnostics in buildings

In the 2005 review (Katipamula and Brambley 2005b), it was noted that there were very few commercial AFDD products and the products that do exist are very specialized or not fully automated. In 2016, there are more commercial AFDD products and services available in the market. However, the penetration is not as widespread as one would expect. There are a number of reasons for this, as was noted in the 2005 study, which still holds true. Access to real-time data and infrastructure to gather data from BAS has been addressed to some extent by research and development efforts funded by the U.S. Department of Energy (DOE) and also by the private sector. The DOE's open source VOLTTRON^{TM} platform was funded in part to address the above need. However, configuring AFDD tools with the right data from BAS is still a manual process and takes significant amount of time. Lack of automated tools and processes to automatically map data sources to AFDD tools impedes scaling AFDD services and also increases the cost of deployment. Many researchers have recognized this as one of the key challenges to overcome. Low-cost reliable sensing for some type of measurements (airflow, pressure, power, etc.) are still lacking, although DOE has made some concerted effort to develop low-cost power meters and the industry has made some progress in development of nonintrusive power meters. However, low-cost power measurement is still a myth because it still can cost several hundred dollars per measurement, which is not cost-effective. The DOE also has made some progress in developing low cost multi-sensor (temperature, humidity, and light level) wireless sensing (Joshi et al. 2015a, 2015b, 2015c; Noh et al. 2015).

One of the key areas of improvement in the last decade is the development of low-cost AFDD algorithms that reduce the number of sensors necessary to detect a set of faults or degradation of the performance of a system. These studies have relied mostly on techniques to create analytical redundancy or "virtual" sensing (derived parameters, for example, outdoor-air fraction). Some gray box models also used low-cost measurements to estimate parameters that are expensive to measure (pressure and power). For example, the saturation pressure is estimated using saturation temperature measurements and thermodynamic state property relations.

Some recent studies (Han et al. 2011a; Li and Braun 2007) have also been able to detect multiple simultaneous faults. It is important to note that the earlier AFDD methods did not handle multiple faults that occur simultaneously. Occasionally, the faulty component causes faults in other system components and the AFDD method must be able to diagnose all fault sources simultaneously. For example, when a refrigerant charge fault and condenser fouling exist at the same time, sub-cooling at the liquid line is decreased with increasing condenser fault levels. This interaction between the faults could lead to large errors in refrigerant charge predictions. If only one fault is diagnosed and repaired, the system will continue to operate with an undiagnosed fault that could cause the repaired component(s) to fail again. Some AFDD algorithms (Kim 2013; Yu et al. 2011b) developed over the last decade were able to analyze a given set of fault levels and identify which faults are affecting the system at any given point in time.

The history-based method has received remarkable attention with the development of sensor and computer technologies. Various researchers (Fan et al. 2010; Najafi et al. 2012b; Ren et al. 2008) have identified history-based methods that are suitable for building HVAC systems. Regardless of the amount of the research, this method is still in its infancy due to the rarity of commercial products that embed the AFDD method into building systems.

Some methods (Kim and Payne 2008) proposed after 2004 focused on the selection of a suitable threshold to prevent frequent fault alarms. High false alarm rates and a lack of good threshold selection strategies prevent building industry from embracing the latest AFDD strategies. If thresholds were set too close to normal conditions, the AFDD system would be too sensitive, which would lead to false alarms. If thresholds were set too far from normal conditions, the AFDD system would miss faults that potentially could reduce system performance. Therefore, it is important to define reasonable thresholds so that the presence of fault is detected.

In the 2005 review article (Katipamula and Brambley 2005a, b), it was noted that most studies did not cover the evaluation and decision stages of the generic AFDD systems (Figure 1). Despite some improvement during the past decade, many studies still do not estimate the impact of the fault that are detected. Widespread field-testing and validation of the AFDD tools is still not a common practice. Like most studies before 2004, the studies after 2004 were mostly focused on air conditioners, heat pumps, and AHUs. Most studies before 2004 did not create a complete AFDD system. These studies focused on the development and validation of detection and diagnostic algorithms without examining the methods of implementing the automated tools in the field. Many of the more recent studies described an AFDD tool. In some cases, these studies give users the nature of the fault and the performance impact resulting from the fault, but there are still very few real-time implementations of AFDD tools in the field.

Conclusions

Over the past three decades, close to 200 AFDD studies related to building HVAC systems have been published. These studies have made significant contributions to the advancement of AFDD in the building sector; however, there are significant gaps as well. The current article categorized all AFDD studies (including those published before 2005) and reviewed AFDD articles relevant to the commercial buildings sector published since 2004. AFDD methods in HVAC areas were categorized into three main categories—process history-based, qualitative model-based, and quantitative model-based methods. A few AFDD methods in each category are selectively reviewed in the present article to highlight their strengths and weaknesses. The distribution of studies based on the AFDD method and HVAC system is summarized. New AFDD researchers can use the current article as a guideline for selecting an appropriate method. Some concluding remarks are presented below.

- Of the three categories, process history-based AFDD methods were most commonly used. This method is best suited for applications where theoretical models of system behavior are inadequate to explain the system behavior or are difficult to create.
- The black box AFDD technique, which relies on process history, is the most common technique used because of its simplicity. The second most common AFDD technique is rule-based, which is one of the qualitative model-based methods.
- The combination of various methods has been used to enhance the efficiency of individual methods and detect simultaneous faults in the system. For instance, the rule-based method can be combined with the statistical method to reduce disturbance, noise, and modeling uncertainty.
- The quantitative model-based method, which requires an explicit mathematical model of the system/plant, is the least popular because of its complexity.
- Most studies have focused on a few types of HVAC systems (air conditioners/heat pumps and VAV-AHUs). Many other HVAC systems and challenges need to be considered in future work.
- A number of studies focused on improving the effectiveness, reliability, and implementation cost of AFDD algorithms.
- Most studies focused on detection and diagnoses of the faults and not operational problems or opportunities for advanced controls. However, one of the main reasons why buildings consume excess energy is because of lack of penetration of advanced controls and lack of use of best operational practices (e.g., measures associated with re-tuning and retro-commissioning). Furthermore, maintaining

persistence of building performance over time requires continuous monitoring and identification of operational problems, unfortunately, very few studies focused on this aspect.

- Detection of faults and diagnosing the cause of the faults are two important steps in the AFDD process. However, without an estimate of fault severity and of the energy and cost impact building operators lack the knowledge to prioritize whether or not to address and/or repair the fault. Many studies have focused on the identification of faults and diagnosis of their causes. There appears to be a relative void in studies that have focused on estimating the fault impact.
- While demonstrating AFDD tools for the whole building and AHUs in the late 1990s and early 2000s, researchers found that even when the building operators were given clear guidance on the fault and the impact associated with it, it was difficult to get their attention to respond to that fault. There are many reasons for that, including lack of incentives to make building operations more efficient, a culture that only tries to address problems or react to “fires” when an occupant makes a complaint and the whole issue of split incentives (owners who are not occupants of the building).
- To address the previous issue, in late 1990s, researchers started developing proactive diagnostics and self-correcting controls. These methods take AFDD beyond providing actionable information; they can isolate the cause of the fault and in some cases even correct the fault.
- Most AFDD techniques, especially rule-based ones, rely on thresholds to identify faults. If the thresholds are not properly selected or are not general enough, too many false alarms may be generated or faults may be mis-identified. Some studies have identified this as an issue, but much more work is needed in this area.
- Very few studies focused on small- and medium-size commercial buildings, and these studies were associated with AFDD methods for air conditioners and heat pumps only.
- The primary reasons for the lack of widespread deployment of AFDD systems are the high initial costs of additional sensors and the need for customization of software solutions for each specific building.
- Like most studies before 2005, the studies after 2004 were mostly focused on air conditioners, heat pumps, and VAV-AHUs. Most studies before 2004 did not create a complete automated FDD system. These studies focused on development and validation of detection and diagnostic algorithms but not how to implement them in the field as an automated tool. Many of the more recent studies describe fully automated FDD tools. In some cases, these studies provide the user with information related to the nature of the fault and the performance impact resulting from the fault. However, there are still very few actual real-time implementations of AFDD tools in the field.
- Future work should include the improvement of methods that eliminate the need for manual model identification or algorithm training and provide the flexibility for adapting the methods to the change in the configurations of HVAC systems.

Nomenclature

AFFD	= automated fault detection and diagnostics
AHU	= air-handling unit
ANN	= artificial neural network
AR	= autoregressive
ARMA	= autoregressive-moving–average
BPNN	= back-propagation neural network
CUSUM	= cumulative sum
GRNN	= general regression neural network
HVAC	= heating, ventilation, and air conditioning
HVAC&R	= HVAC and refrigeration
LED	= light-emitting diode
JAA	= joint angle analysis
PCA	= principal component analysis
PID	= proportional integral and derivative
RNN	= recurrent neural network
RTUs	= rooftop units
SPC	= statistical process control
SAX	= symbolic aggregate approximation
SEER	= seasonal energy efficiency ratio
SVM	= support vector machine
VAV	= variable-air volume

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