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Review

A review of fault detection and diagnosis methodologies on air-handling units

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ABSTRACT

Faults occurring in improper routine operations and poor preventive maintenance of heating, ventilating, air conditioning, and refrigeration systems (HVAC&R) equipment result in excessive energy consumption. An air-handling unit (AHU) is one of the most extensively operated equipment in large commercial buildings. This device is typically customized and lacks of quality system integration, which can result in hardware failures and controller errors. This paper aims to provide a systematic review of existing fault detection and diagnosis (FDD) methods for an AHU therefore inspire new approaches with high performance in reality. For this goal, the background of AHU systems, general FDD framework and typical faults in AHUs, is described. Ten desirable characteristics used in a review of FDD in chemical process control are introduced to evaluate the methodologies and results. A new categorization method is proposed to better interpret the different and most recent approaches. The main FDD methodologies and hybrid approaches are described and commented to illustrate the use of evaluation standard parameters for improving the performance of FDD on AHUs.

Contents

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Nomenclature

ANN	artificial neural network
AHU	air-handling unit
AFDD	automated fault detection and diagnosis
APAR	air handling unit performance assessment rules
BAS	building automation system
BPNN	back-propagation neural network
CAV	constant air volume system
CV	cooling coil valve
CVA	canonical variate analysis
DC-1	damper controller
D-1	damper of a VAV box
DWT	discrete wavelet transform
EA	exhaust air
ENN	Elman neural network
F	flow sensor
FDD	fault detection and diagnosis
FTC	fault tolerant control
FC-1	return air flow rate controller
FC-2	flow rate setpoint controller
FC-3	flow rate controller
FDA	Fisher discriminant analysis
FFT	fast Fourier transformation
HV	heating coil valve
H	humidity sensor
HMM	hidden Markov model
JAA	joint angle analysis
M-1	damper motor
MA	mixing air
OA	outdoor air
P	pressure sensor
PC-1	supply air static pressure controller
PV	preheating coil valve
PCA	principal component analysis
PLS	partial least squares
Q	air flow rate
RA	return air
RTU	rooftop unit
RF	return air
SA	supply air
SF	supply fan
SDG	signed directed graph
TC-1	supply air temperature controller
T	temperature
ΔT	temperature difference
UIO	unknown input observer
u	control signal
VAV	variable air volume
VFD	variable speed drive

Greek symbols

ε_t	threshold parameter for errors of temperature measurements
ε_{cc}	threshold parameter for the control signal of the cooling coil valve
ε_{hc}	threshold parameter for the control signal of the heating coil valve
ε_f	threshold parameter for errors relayed to airflows

Subscripts

cc	cooling coil valve
co	changeover switch between modes 3 and 4
hc	heating coil valve
i	count number
MA	mixing air
min	minimum
OA	outdoor air
RA	return air
rf	return fan
SA	supply air
sa,s	supply air set point
sf	supply fan

1. Introduction

According to U.S. Department of Energy, building HVAC systems, included space heating, space cooling and ventilation, consumed nearly 40% of the total energy used in commercial-building sector at 18.35 Quads (quadrillion Btu) [1]. This issue significantly challenges the current status of energy efficiency in buildings. Even building automation system or advanced controllers are applied to enhance system efficiency, faults can develop during the installation, routine operations or scheduled preventive maintenances in systems and result in excessive energy waste. In a survey of UK buildings, the data showed 25–50% of energy wasted from faults in building HVAC systems. This range could be reduced below 15% whenever those faults could be detected and identified early in the premature stage before unacceptable damages occur [2]. These fault problems will be more difficult to examine in complex systems without applying smart technologies.

To tackle these problems, automated fault detection and diagnosis (AFDD) as the automated procedure of investigating faults and identifying the location and causes of abnormal symptoms has been developed in fields such as chemical process controls, automobiles and power plants. Also, this application has been applied to HVAC&R for detecting and evaluating fault occurrence and improper operations of equipment. AFDD has been included in control systems through building automation system (BAS) or embedded into HVAC equipment such as rooftop air-conditioning units (RTUs) [3]. Along with the evolvement of energy-efficient HVAC in commercial buildings, the broad scope of FDD in HVAC fields has been increased continuously because various computer-aided techniques with low-cost installation have been improved and developed for enhancing real-time fault diagnosis over the years. A number of AFDD studies have been conducted not only in vapor compression equipment (i.e. RTUs and refrigeration systems) for small and medium commercial buildings, but also in chillers and AHUs for large-scaled buildings. Fault tolerant control (FTC) with AFDD incorporated with advanced control systems has also been introduced but still in infancy for on-line assessment in HVAC areas. This advanced control research could maintain the robust system performances in acceptable ranges in the event of failure or of some of its components. The solid background of collaborative researches composes of the systematical understanding of FDD, modeling of a dynamic plant and control system fundamentals.

This paper presents a systematic study of various AFDD methods in an AHU by using a set of desirable characteristics, which was set up in a review of FDD in chemical process controls [4], to evaluate the existing methodologies for the development of an advanced online AFDD implementation. Although a good review associated with an AHU had been conducted [5], this prior paper mainly concerned the overview of FDD in generic HVAC equipment. The discussion on AHUs was short and not instructive in regards of selecting and evaluating suitable AFDD techniques for AHUs. Also, a systematic evaluation method based on a standard technique for developing more advanced and feasible technologies such as hybrid FDD approaches and FTC was not covered in the prior paper.

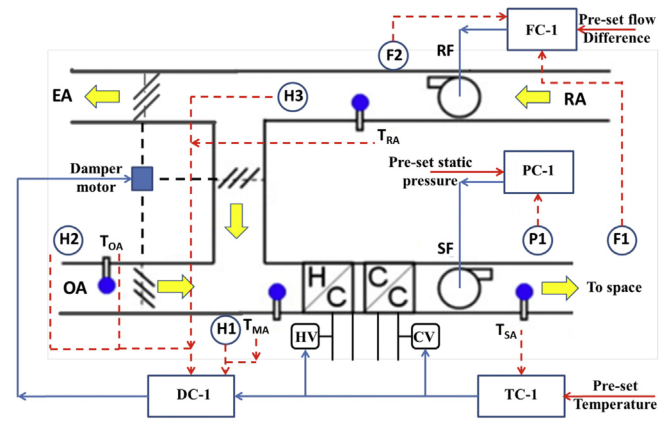
2. General FDD framework for an AHU

This section introduces the fundamentals relating to FDD of an AHU. Firstly, an AHU system and its control on the unit and a single variable air volume (VAV) box are described. After that, the general FDD framework of an AHU system indicating the typical faults and malfunctions at different locations is detailed. The framework composes of AHU actuators, an AHU dynamic plant, sensors and a feedback controller. The aforementioned fault occurrences are examined and the corresponding location is identified by an FDD system. Understanding of this relation between the AHU system and the FDD framework is critical for systematically evaluating each FDD approach with the 10 desirable characteristics introduced in Section 3.

2.1. System description

An AHU is one of the most important equipment in HVAC systems. Especially, large-scale buildings use this equipment for providing both heating and cooling for multiple zones. Also, it is controlled together with distribution terminals to satisfy human comfort by maintaining appropriate humidity and amount of ventilation air in each conditioned space. Two common types of AHU system are constant air volume system (CAV) and variable air volume system (VAV). The main difference between these two systems is that a VAV system modulates the air flow according to the variation of a building load condition. The supply fan equipped with variable frequency drive (VFD) can adjust the air flow when the load condition changes, whereas a CAV system supplies constant air flow to a conditioned zone regardless the building load is changed or not. Fig. 1 depicts a typical single-duct VAV system, including the control diagram consisting of four subsystem controllers: TC-1, DC-1, PC-1 and FC-1.

As shown in Fig. 1, a VAV system typically maintains the supply air temperature (T_{SA}) to the terminals for air-conditioning. This temperature is measured and compared with pre-set temperature of TC-1. The control is linked to DC-1 in order to automatically



TC-1: Supply air temperature controller
DC-1: Damper controller
PC-1: Supply air static pressure controller
FC-1: Return air flow rate controller
HV: Heating coil valve
CV: Cooling coil valve
SF: Supply fan
RF: Return fan
T: Temperature sensor; H: Humidity sensor; P: Pressure sensor; F: Flow sensor.

Fig. 1. A typical VAV air handing unit (AHU) system.

operate OA damper and RA damper for appropriately mixing temperature (T_{MA}) before entering a heating or cooling coil. Regarding the control of a mechanical cooling (Modes 3 and 4) and heating mode (Mode 1), the heating and cooling coil valves are sequentially programed to synchronize with the damper control as shown in Fig. 2.

As in Fig. 2, in the heating mode (Mode 1), HV is controlled for hot water supply from a boiler (or the input to an electrical heater in that case) to maintain T_{SA} meanwhile CV is closed and the minimum outdoor fraction of mixing box dampers (OA, RA and EA dampers) is operated to satisfy the minimum ventilation requirement. When the outdoor air temperature increases, this sequential operation switches from the heating mode to the cooling mode (Mode 2). Both HV and CV are closed, whereas the mixing dampers are controlled to maintain T_{SA} at the setpoint. Eventually, OA and EA are positioned at 100% (fully open) and a RA damper is fully closed. As the cooling load continually increases, this free cooling using outdoor air is not adequate to maintain the setpoint. Then, the mechanical cooling is triggered on by opening only CV to maintain the setpoint temperature meanwhile mixing box dampers can be positioned either 100% (Mode 3) or minimum outdoor air fraction (Mode 4) to meet ventilation requirements. The methodology used to select the appropriate mixing box dampers positions depends on the programs. For example, if OA temperature (or OA enthalpy) is larger than or equal to RA temperature (RA enthalpy), a fully opened OA damper is required to minimize mechanical cooling demand and partial free cooling is used by the operation of Mode 3.

For the operation of PC-1 and FC-1 controller in Fig. 1, a VAV system can adjust SF to meet the loads variation in off-design condition by operating PC-1 controller. This controller handles the motor speed of SF by maintaining the supply air static pressure at its setpoint. As a result, the different flow rate between SF and RF may change and affect the operations of mixing box dampers. To keep this different flow rates constant, flow sensors at supply air location (F1) and at return air location (F2) are used as the inputs of FC-1 to regulate the motor speed of RF. Similar to a VAV system, DC-1 and TC-1 are operated by the same sequences for a CAV system; however, it does not include PC-1 and FC-1 to manipulate the system performance since SF nearly keeps constant air flow rate leading to the constant flow of RF.

In the application of multiple zones, a VAV box connected to the supply air duct is applied to each zone. This unit regulates the

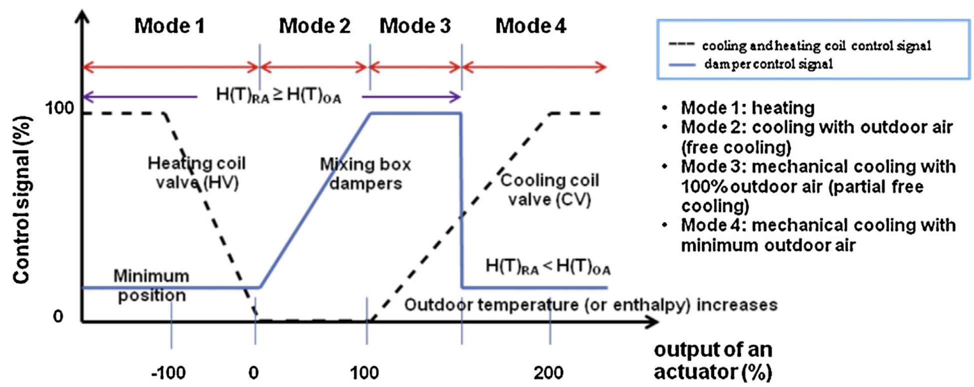


Fig. 2. Sequential control of operational modes in an AHU.

temperature and the amount of supply air to maintain the zone temperature in cooling and heating seasons. This device can be divided into two types in terms of mechanism. Firstly, a pressure-independent VAV box (Fig. 3a) is composed of the flow setpoint controller (FC-1) and the flow controller (FC-2). FC-1 is used to compute the setpoint of supply air flow rate according to the variation of cooling load which is measured by the temperature sensor (T1) in Fig. 3b. If the supply flow varies due to the change of the static pressure sensed by the flow sensor (F1), the measured flow of F1 and the set point of FC-1 is used as inputs for FC-2 to regulate the damper position (D1) to satisfy the required air flow rate in the zone. This type of VAV box is generally used together with a reheating coil as auxiliary heat when overcooled air or reduced cooling occurs in a zone. Secondly, a pressure-dependent VAV box (Fig. 3b) uses the temperature control (TC-1) instead of FC-1 and FC-2 in Fig. 3a. In this application, D-1 is directly controlled by TC-1 using a zone temperature ($T1$) to measure the variation of cooling load.

2.2. Faults in an AHU system

FDD system is applied to modern engineering fields to detect and diagnose abnormal conditions, faults or malfunctions occurring in the routine operations of a system before these situations lead to severity or additional damage to the system. This technique can be illustrated as a general framework, as depicted in Fig. 4. This framework is appropriate to analyze and evaluate a complicated system such as multiple devices with multiple feedback controllers in HVAC or chemical process systems. In the application of an AHU, the four different sources of failures can be systematically incorporated with the FDD system to indicate causes and locations of faults. Faults with sensors and controllers are considered as one type since feedback controllers are typically applied to modern engineering systems that mainly guarantee stability if the controller gains are suitably selected. As a result, the problems of feedback controller are practically influenced by the effect from faulty sensors.

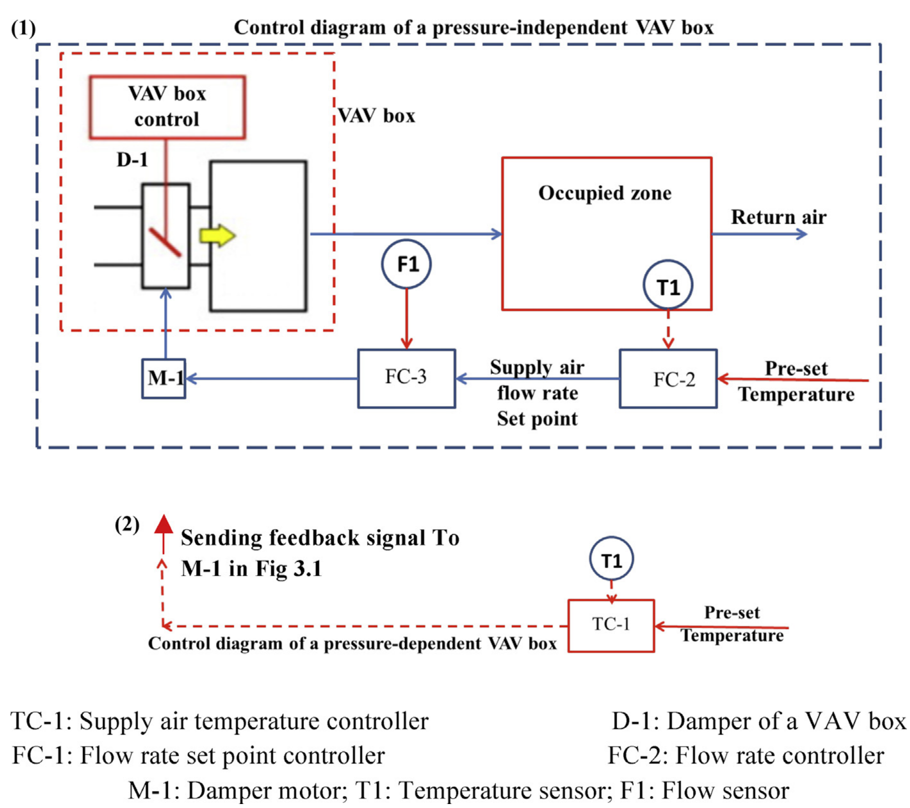


Fig. 3. (a) Control diagram of a pressure-independent VAV box. (b) Feedback control signal of a pressure-dependent VAV box.

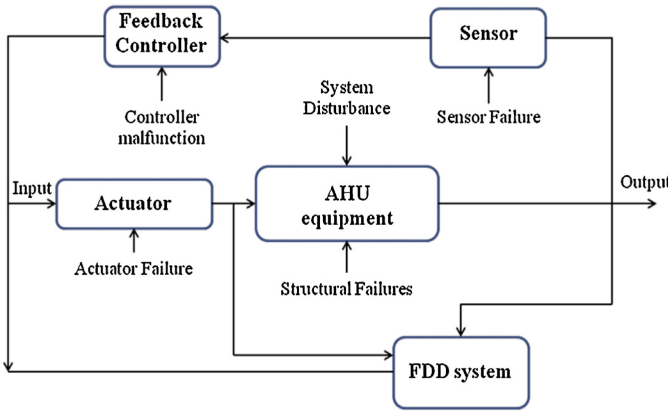


Fig. 4. A general FDD framework.

2.2.1. Failures in AHU equipment

In Fig. 4, faults occurring in AHU equipment can be separated into two causes. First cause is from system disturbance which normally interacts with a modeling approach such as a simplified model. The model could have sorts of uncertainties if essential terms are excluded or neglected from the plant. The uncertainties could result in uncontrollable parameters and be sensitive to system disturbance, and eventually lead to parameter failures. These failures perform as independent variables and the system controller cannot handle the uncertainties. Second cause is structural failures that involve malfunctions in the equipment of an AHU. The structural changes lead to the variation of the process. When the equipment is in incomplete status such as air leakage in duct, failures could occur in a system in terms of insufficient heating/cooling or increasing infiltration. Other example is a dirty coil that leads to the change of heat coefficient resulting in reduced thermal conditioning capacity. Table 1 tabulates typically possible faults that occur in the equipment of an AHU resulting in the degradation of system performance.

2.2.2. Failures in AHU actuators

Actuators (on devices, such as dampers and valves) directly interact with an AHU plant for modulating the system inputs. When failures exist in actuators, these situations could cause the deviation of the plant outputs beyond acceptable limits unless these failures can be detected instantly and can be solved in time. Also, faults in these instruments could practically degrade the performance of the control system since they affect the overall output with the feedback signal to the controller. As a result, the system outputs could be changed from the expectation or design conditions. For instance, if an OA damper is stuck, the efficiency of a temperature controller could be reduced in terms of longer rise and settling time and/or waste energy by using mechanical cooling instead of free cooling from outdoor air. Other faults of actuators are shown in Table 2.

Table 1
Typical faults occur in equipment affecting AHU equipment.

Category	Device	Typical faults
Equipment	Fan	Pressure drop is increased Overall failures of supply and return fans [6,7] Decrease in the motor efficiency [8] Belt slippage [9,10]
	Duct	Air leakage
	Heating coil	Fouling (fin and tube) leads to reduced capacity
	Cooling coil	Fouling (fin and tube) leads to reduced capacity [9,10]
	Preheating coil	Fouling and reduced capacity

Table 2
Typical faults occur in AHU actuators.

Category	Device	Typical faults
Actuator	OA, RA and EA dampers	A damper is stuck or a faulty position is operated [11,12] Air leakage occurs at fully open and closed positions [12,13]
	Heating coil (HV), cooling coil (CV) and preheating coil valve (PV)	A valve is stuck, broken or wrong operated position [8,9,11,12,14] Leakage occurs at fully open and closed positions of the valve [8,11,12,14–16]

2.2.3. Failures in sensors and feedback controllers

Sensors are used to measure state variables in a system and then send the feedback signals to the controllers maintaining the setpoints of state variables and reducing the errors between the setpoints and measured values. As a result, controller performance practically depends on sensor performance. If faults occur in sensors such as drifting and offset, the performance of controllers will gradually degrade. For example, the temperature sensor drifts about 2 °C higher than an actual value in a zone. The controller will automatically open a cooling coil valve to supply more chilled water to the cooling coil, so the room temperature will be lower than the actual value incurring energy waste. Typical faults in sensors and controllers are given in Table 3.

3. Desirable characteristics of a FDD system for an AHU

This study not only presents previous FDD approaches for an AHU; it also applies 10 desirable characteristics for the systematic evaluation [4]. One of the key intellectual merits of this research is the new application of these characteristics as the standard evaluation of FDD approaches in an AHU. Although previous review papers in HVAC area evaluated each FDD methodology in terms of limitations and advantages, the methods for evaluation were not systematic to benefit the selecting of suitable approaches for real implementations in buildings. With the application of these desirable characteristics with the general structure of diagnostic framework, the proposed criteria can be used to systematically evaluate the limitation of each FDD approach and to select appropriate FDD approaches for enhancing the real-time FDD of AHUs in commercial buildings.

While the 10 desirable characteristics are defined for a well-designed diagnostic approach, in practice, each proposed approach never satisfies all characteristics. Selection of FDD methodology is dependent on the behavior and feature of applications. For example, HVAC systems require the completeness (a fault prediction being a subset of actual faults) of a diagnostic classifier rather than

Table 3
Typical faults in AHU sensors and controllers.

Category	Device	Typical faults
Sensor	SA, MA, OA and RA temperature	Failures of a sensor are offset, discrete or drift [6–8,12,13,16]
	MA, OA and RA humidity	Failures of a sensor are offset, discrete or drift [17]
	OA, SA and RA flow rate	Failures of a sensor are offset, discrete or drift [13,17,18]
	SA and zone pressure	Failures of a sensor are offset, discrete or drift [8]
Controller	Motor modulation	Unstable response
	Sequence of heating and cooling coil valve	Unstable response
	Flow difference	The system sticks at a fixed speed [9]
	Static pressure	Unstable response
	Zone temperature	Unstable response

the resolution (fault sets being as minimal as possible) of a fault prediction, which is required in chemical reactor process. Therefore, there is a trade-off between completeness and resolution in terms of accurate faulty predictions.

3.1. Quick detection and diagnosis

This feature is fundamental for a typical diagnostic system; however, the system designed for rapid detection and diagnosis is sensitive to noise leading to frequent false alarms in even normal operations since some noise effect could be over the threshold. This one should be trade-off between the performance of a diagnostic system and robustness (noise, false alarm or threshold). This ability is satisfied by the general categories of FDD approaches (analytical-based, knowledge-based and data driven approaches).

3.2. Isolability

This characteristic shows the capability of a diagnostic system to distinguish multiple failures; these failures sometimes overlap with modeling uncertainties in terms of residuals. For example, if a diagnostic system, such as analytical-based or rule-based methods, requires multiple models in the procedures, rejecting modeling uncertainties will frequently occur and isolability will gradually decline for each step of multiple modeling processes. Therefore, there is a trade-off between isolability and the rejection of modeling uncertainties in an appropriate diagnostic system.

3.3. Robustness

If a diagnostic system satisfies robust feature, its performance should be insensitive to the effect of various noise and modeling uncertainties. The robustness should be traded-off between noise and the selection of a suitable threshold to prevent frequent fault alarms for normal operations. The approach such as state estimation for a dynamic system called unknown input observer (UIO) can satisfy this feature because of its characteristic, which is not sensitive to the unknown inputs (disturbance and noise).

3.4. Novelty identifiability

It is used for considering whether a system is in a normal or malfunction operation and, if an abnormal condition occurs, whether the causes are from known or novel unknown malfunction. Normally, some historical data processes cannot satisfy this criterion because most of them are modeled based on the abnormal regions which are covered by the used patterns; however, PCA (principal component analysis) can fulfill this feature. It is capable of reducing the dimensions of data in terms of essential information from originally huge data. So, this technique will bound only the significantly abnormal regions.

3.5. Classification error estimate

The evaluation of a diagnostic system can be performed through this feature in terms of accuracy and reliability to encourage the confidence of users. The feature of error estimate shows the efficiency of diagnostic decisions. Practically, single FDD approach such as an analytical approach cannot eliminate residual errors. Even UIO observer, which is insensitive to unknown inputs or disturbance, tries to track the system until the residuals from disturbance are as small as possible; however, the errors from the estimation still occur in the process due to noise, modeling uncertainties or linearization techniques. The range of confidence for error measurement can be analyzed by using accurate sensors or virtual calibration sensor techniques and virtual sensors. For example, Yu et al. [20] developed the airflow virtual sensor with the virtual calibration technique [21,22] for the heating mode in a rooftop unit. This innovative sensor can identify the accuracy of supply air temperature within $\pm 0.8\,^{\circ}\mathrm{C}$.

3.6. Adaptability

This term involves the adaptable capability of a diagnostic system to automatically response with system changes due to external inputs or structural changes. If the diagnostic system satisfies adaptable capability, the structural changes, such as structural failures given in Table 1, will gradually develop as new environments. Generally, diagnostic systems designed by historical data or knowledge-based approaches do not possess this feature since the limited scopes of data or approaches are specific or unchangeable. However, the technique called recursive parameter identification methods in analytical-based methods can be used as an adaptable diagnostic system in AHU systems [6,23].

3.7. Explanation facility

Not only can an FDD approach identify malfunctions, but also it should explain where and how faults occur in a system. This feature is significantly required for on-line decision applications of diagnostic classifiers. It is useful for building operators to examine a system according to the explanations or recommendations of a FDD approach. The diagnostic system modeled with priori experiences or first-principles equations has the ability of explanation.

3.8. Modeling requirements

Number of modeling methods of FDD should be as minimal as possible for quick and easy implementations; otherwise, the method will be not suitable to apply in real-time applications. Rules-based and process historical methods generally require no modeling process, whereas the detailed first-principle model based method may hardly satisfy this feature. However, the novel model-based approach called decoupling-based features [3] can tackle this barrier by using models obtained from manufacturer's data and virtual sensing technologies in rooftop units for reducing computational processes embedded into micro-controllers.

3.9. Storage and computational requirements

This criterion is specifically required for the fast real-time implementation of diagnostic classifiers. Then, the systems should be reasonably balanced between high storage capacities and less computational complexity.

3.10. Multiple fault identifiability

This feature is one of the most difficult and significant requirements for isolating simultaneous faults. Naturally, the combination of several faults typically occurs in nonlinear or larger systems, leading to the difficult separation of individual fault. An UIO observer, which is in the form of state space equation and independent to disturbance, can capture uniquely fault signature and decouple faults. Moreover, the decoupling-based feature is another approach that is developed to specially isolate multiple faults. However, these two techniques have not been implemented in an AHU system.

4. Classification of diagnostic algorithms in AHU systems

The classification of FDD systems depends on the area of consideration and the embedded innovations. Fig. 5 provides a general

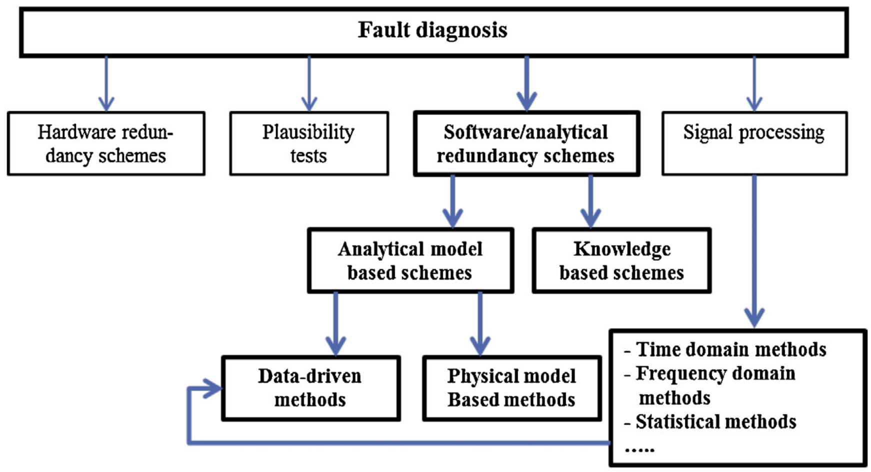


Fig. 5. Classification of fault diagnosis methods [24].

classification by Chiang et al. [24]. In this illustration, four areas were classified for technical fault diagnosis since the early 70s based on automated processes. Hardware redundancy schemes were firstly developed to detect faults in hardware components using the identical hardware components. Although this method is of high reliability and can directly isolate faults, using redundant hardware leads to costly and time-consuming processes. After computer science community has developed continuously, computational techniques have become the main potential innovation in terms of software forms on computers applied in automated processes. As a result, most hardware redundancy approaches have been substituted by analytical redundancy schemes to tackle the aforementioned barriers. Meanwhile plausibility test is based on the investigation of some physical laws used in process components. Also with computers generalization, this technique can be fulfilled by software programs and included in knowledge-based schemes of software redundancy diagnosis. Similar to plausibility test, signal processing, which is mainly used for detecting the steady-state condition of certain process signals such as sensors in automated processes, can be analyzed and discussed in terms of data processing for analytical model. In this review, signal processing methods will be included in data driven approaches since the main process is based on data processing by sensors.

In the modern engineering systems, with the continuous development of software forms in computer community, feedback control systems influence on all automated engineering processes for optimizing energy consumption and efficient productivity. Although efficient control system has been developed continually, there are still many factors that result in improper operations and commissioning in systems. For example, improper designs lead to the inappropriate selection of equipment and controller. Specifically, complex systems such as HVAC systems in medium- and large-scaled commercial buildings, the unsuitable selection of equipment cannot be fully compensated by only feedback controllers. To increase and improve the efficiency of building energy performance, the developed techniques of fault diagnosis in terms of innovative software forms have been continually applied to HVAC systems. Previous researchers have developed smart systems embedding fault diagnosis techniques into HVAC controllers for early detecting and diagnosing their abnormal operations before these conditions could develop severity to overall system performances. From past to 2005, FDD approaches in HVAC areas were categorized into three classes by Katipamula and Brambley [5,9], as shown in Fig. 6. This classification is similar to the analytical redundancy schemes and powerfully satisfies most HVAC areas; however, some developed methods were recently proposed after these reviewed papers were published. For instance, at least four data-driven approaches such as PCA [25,26], FDA (Fisher discriminant analysis, [27]), JAA (joint angle analysis, [18,28]) and DWT (discrete wavelet transform [29]) were applied to AHU systems. Advantages of those new data-driven approaches can be used to reduce a high dimensional data volume into a lower dimensional space, in which the low space contains most of the useful information, for large-scaled data.

To reflect most recent FDD approaches for AHU applications, analytical-based techniques combine all modeling methods to generate parameter residuals (parameter estimation) and/or output residuals (observers and parity relations). Physical models, black-box and gray-box methods are classified into parameter estimation of analytical-based methods. They all fundamentally rely on the residual analysis between the nominal model parameters and the estimated model parameters for FDD. Meanwhile, ANN is newly categorized in knowledge-based techniques since it is a model-free method being one of machine learning approaches using online and/or historical data. Methods having the feature of reducing data dimension, such as the application a filter in signal-based techniques, are considered as data-driven methods.

Following aforementioned reasons and description, modified diagnostic methods can be classified into three domains to fulfill all previously studied FDD approaches for AHU systems as illustrated in Fig. 7. The three techniques are software redundancy schemes and can be categorized as (1) analytical-based, (2) knowledge-based and (3) data-driven methods. They are briefly described as follows.

4.1. Analytical-based methods

Analytical-based methods mainly use the difference between measured data of a plant and a modeling process (mathematical model) in terms of residuals to detect and diagnose faults. If residuals are zero, the system is regarded as fault-free. Conversely, these residuals could be large when faults occur or they could be small if the residuals are in the form of noise, disturbance and/or modeling errors. To avoid frequent fault alarms and stopped operations, the appropriate selection of a threshold is computed from these forms of residuals to detect the presence of faults in systems. Based on the means of residual generation, FDD methods can be further categorized as parameter estimation based methods and output residual based approach. In the first type, estimation techniques typically use the residual generation based on parameter errors between the nominal model parameters and the estimated model parameters by minimizing output error.

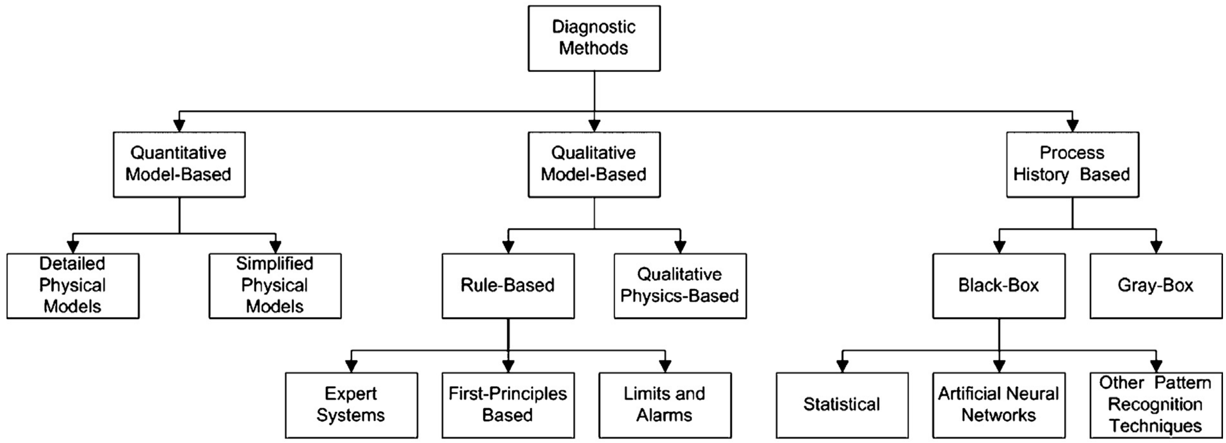


Fig. 6. Diagnostic methods in HAVC areas [19].

Depending on the modeling approaches, for dynamic or steady-state, the parameter estimation methods can be first-principle, gray-box or black-box. Meanwhile, output residual based methods include observers and parity relations. They are theoretically distinguished by the structure of residual output errors. The details of each analytical-based diagnostic approach are further described in a separate paper.

A first-principle model is typically generated by physical principle laws governing system behavior such as mass and energy balance in terms of static and dynamic models. Although the strengths of this category can explain the dynamic behavior of a system and perform as an accurate estimator, it is non-convenient for real-time computation and requires a good and fast-response controller that can shortly stabilize the system performance for detecting and diagnosing sudden faults. For instance, if the controller performs slowly with long rise time and settling time, the system requires long-term period to reach a steady-state condition for generating residuals. As a result, some sudden faults cannot be detected when its response is faster than the system performance [30]. To reduce the computational cost, simplified physical models have been developed for enhancing model-based FDD [31] and real-time HVAC control [32,33].

To tackle the limitations, a gray-box model has been developed for tracking the steady-state response and detecting abrupt faults. The pattern of these models combines the physical parameters referring to system characteristics with regression techniques in terms of a static model. The non-complex models can reduce computational process for remaining the system performance. There were a number of researchers proposing gray-box models for FDD in AHUs [13,31,34,35]. In contrast to using system characteristics, dynamic black-box models use system identification techniques for mathematical models which cannot govern system characteristics because the estimated variables have no physical significance. However, a black-box model may be appropriate for on-line FDD when recursive identification techniques are used to continuously estimate the parameters. Additionally, it can perform unique faults in terms of state-space equations. As a consequence, it does not require fault diagnosis process [6]. To enhance the performance of black-box models for AFDD and real-time intelligent control, Wu and Sun [36,37] proposed physical-based parametric and multi-stage regression linear parametric models, respectively, for predicting room temperature in office buildings. These equations were developed by the combination of energy balance in rooms and multiple inputs and multiple outputs of autoregressive moving average (ARMAX) model, called physical-based ARMAX (pbARMAX). Scotton [38] developed physical-based models for predicting temperature, humidity and CO_2 concentration in rooms. These mentioned examples can enhance the performance of black-box

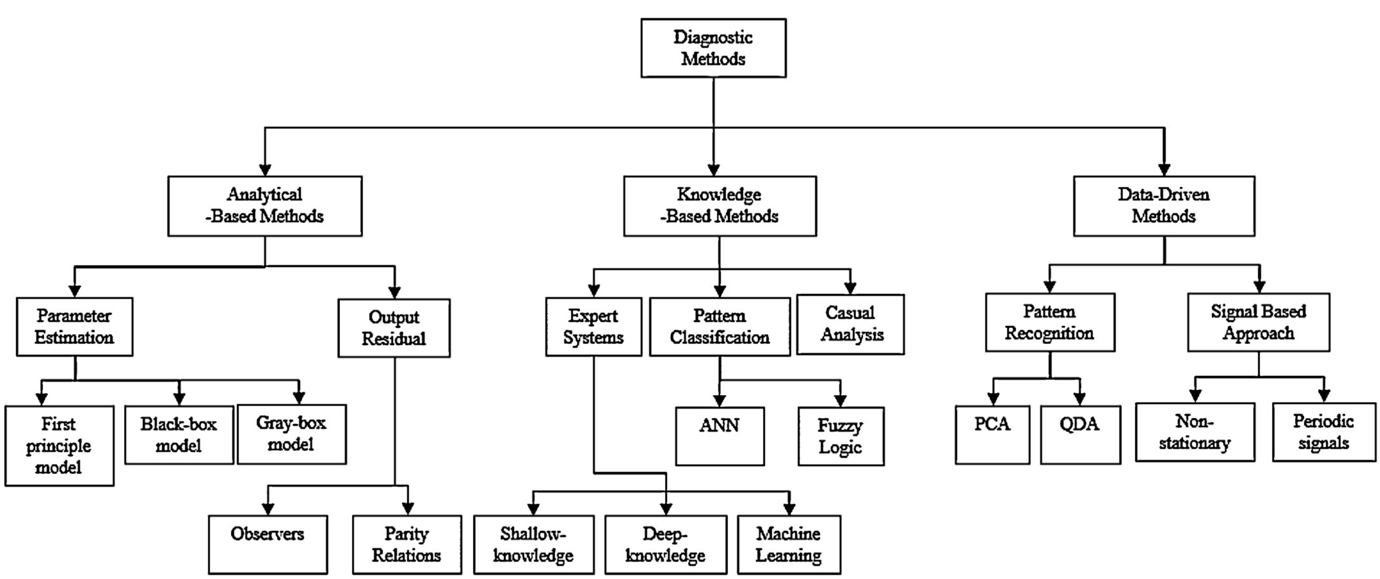


Fig. 7. Basic diagnostic methods for AHU systems is based on industrial systems.

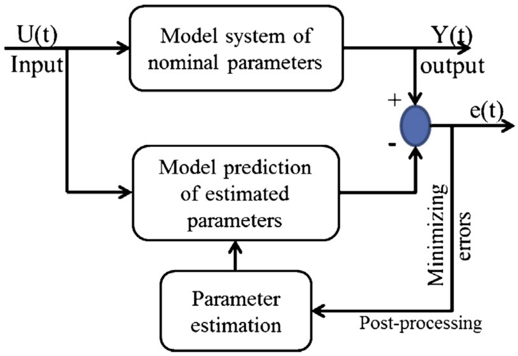


Fig. 8. Schematic description of the parameter estimation scheme.

model for describing the physical meaning of estimated parameters.

In the process of parameter estimation as illustrated in Fig. 8, the aforementioned techniques are used to compute parameter estimator block in different mathematical models for estimating parameter outputs from process inputs and measured outputs. The parameter estimator is computed by the correlation between the measured input and output variables of a process by minimizing output errors between the measured outputs and predicted outputs. Non-zero residuals from the plant and the model can be caused by faults, or the modeling uncertainties, noise from measurement and disturbance. In these situations, the parameter estimation performs as fault diagnosis or post-processing used to diagnosing and isolating faults from noise or disturbance. When the change of estimated parameters is out of the selected thresholds of the parameters, these parameters show fault signature. Suitable thresholds (lower and/or upper bounds) can be selected by two major approaches: statistical testing and norm-based residual evaluation [39].

Unlike parameter estimation in terms of post-processing or residual evaluation, output residual based methods are based on the difference between the estimated states and the real input–output data. For example, observer methods are mainly based on output residuals, so they have no requirement for estimating the variation of parameters; they use input signals and the measured signals of state variables for reconstructing linear or non-linear mathematical models. The structure of linear observer (full observer or Luenberger observer) is depicted in Fig. 9. The state-space equation of the linear observer will track the state outputs by using feedback errors through feedback gain (L). The residual

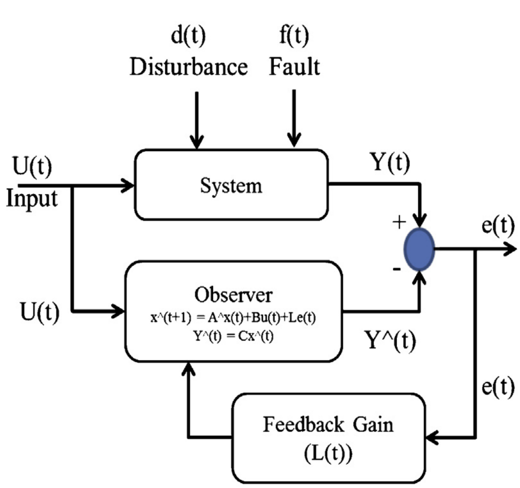


Fig. 9. Structure of the full observer-based fault detection (Luenberger observer).

evaluation of the observer is performed by residuals threshold. The selection of the threshold is similar to a parameter estimation approach. The four main types of observers are a full-order observer, unknown input observer (UIO), Kalman filter observer and non-linear observer. Since an observer mainly in state-space methods, it is useful for allowing a frequency-based design in terms of transfer function that can minimize sensitivity because of model uncertainties [24]. However, the physically-meaningful states are lost due to simplified model or linearization approach.

Similar to observers but simpler to design the structure, parity relations are presented in form of algebraic equations with state-space equations. Also, it can check the consistency of system framework with the measurements. Thus, most problems regarding to FDD can be solved by linear-algebraic framework. The residual matrix of parity-based FDD is straightforward obtained by the instruction and recommendation of references [24,39,40]. By these reasons, FDD system can easily design parity space FDD framework without solid knowledge of the advanced control theory and complex mathematical algorithms.

4.2. Knowledge-based methods

For large-scaled systems, if information relating to generate mathematical models are not available or are too costly and time-consuming, knowledge-based methods are alternative approaches to solve these problems for fault diagnosis. These techniques are based on qualitative models that can be generally obtained through causal modeling or detailed description of systems, expert knowledge, or typical fault symptoms [24]. The three approaches in this domain have already been applied to AHU systems, namely, expert systems, pattern classification and casual analysis. For casual analysis, signed directed graph (SDG) is used for diagnosis systems since the procedures in these two methods can reflect the behaviors of systems modeled by fault symptoms without the requirement of first-principles. The fault decision of each node connection (node variable) can be computed by defining low and high thresholds. A node is defined by 0 when the measured variable is normal. For FDD, symbol + is assigned if the measure variable is higher than the high threshold, whereas symbol "−" is assigned when the value is less than the low threshold. The relations between cause nodes (+ and −) are used to identify whether the cause and effect change in the same or the opposite directions. One of casual analysis techniques applied to an AHU system was SDG [41].

In the second method of knowledge-based domain, the procedures can consist of an existing expert knowledge, an inference engine, or an expert system interface which can combine with the knowledge from first principles or structural description of the system in terms of rules. Meanwhile, an expert systems approach can be classified into: (1) shallow-knowledge expert systems using the formulation of IF–THEN rules for generating rule-based methods; (2) deep-knowledge expert systems including functional reasoning or first-principles expert systems for diagnosing faults and (3) machine learning methods.

With the combination of shallow-knowledge (IF–THEN) and deep-knowledge expert systems (functional understandings of control system), Schein et al. [42] developed the rule set for air handling units (APAR) by using IF–THEN and the four mode operations of sequential control in an AHU as tabulated in Table 4, which provides the 20 rules of four modes form the total 28 rules of five modes and occupied mode operations. In each rule, a threshold value, ε_t was computed by considering the measurement uncertainties of controlled variables and control signal (U_{cc}) from AHUs. APAR was transferred into computational algorithms embedded into BAS or AHU control as manufacturers' standard program libraries and was successfully tested in real buildings [43,44].

Additionally, Schein and Bushby [45] developed hierarchical rule-based FDD; the results were tested and evaluated by simulation. However, expert approaches are difficult to design when knowledge acquisitions of experts and collecting of real cases are not available. A possible solution to solve this problem is to use machine learning approach, through which knowledge is automatically extracted from data by using advanced statistical theories such as hidden Markov model (HMM) and Kernel machines [46]. For an AHU application, West et al. [47] developed AFDD using statistical machine learning based on HMM; the proposed method was successfully tested in a real building.

Lastly, without explicit model structures as well as analytical-based approaches, pattern classification techniques can perform non-linear correlations between data patterns and fault classes. Even though these techniques can be usefully applied to systems, where expert knowledge or certain model structures are unavailable or costly for obtaining, they essentially require robust and accurate rich data for computing potential and reliable patterns for FDD. At least four available methods of this domain applied to AHUs are (1) artificial neural networks (ANN) [7,9,13,48]; (2) fuzzy logic [49]; (3) support vector machine (SVM) classifier [50] and (4) Bayes classifier [9].

4.3. Data-driven methods

Another method that also uses the relation between data patterns and fault classes in terms of modeling process is data-driven methods. These methods differ from pattern classifications since they are dimensional reduction techniques based on rigorous multivariate statistics, whereas pattern classifications learn the pattern of fault performance using entire data. According to the strength of this feature, its ability can transform high dimensional data into a lower dimension for only interested domains of data, so this approach is suitable to modern engineering systems with large-scale domains. For example, HVAC systems of medium and large commercial buildings are composed of many sensors applied to feedback control systems. These devices possibly cause drift or offset errors from true values resulting in the main drawback of these methods because their proficiencies depend on the quantity and quality of the process data from sensors. The two main groups of data-driven methods applied to AHU systems are signal based FDD and multi-variable statistics based FDD. First one is signal processing methods consisting of: (1) periodic signals (e.g. band-pass filtering, Fourier analysis, spectral estimation and correlation functions); (2) stochastic signals; and (3) non-stationary signals which include wavelet transformation and short-time Fourier analysis [40]. However, only wavelet transformation was presently combined with PCA for fault diagnosis in AHU systems [29]. For multi-variable statistics based FDD, PCA has been extensively applied to detect faults in large systems because of the key concept that can reduce a high data volume into the useful information of a lower interested space; however, this extensive method does not use direct relation of data or tells the cause–effect relationships. As a result, it is more appropriate for fault detection rather than fault diagnosis. To solve its limitation, other methods such as FDA, JAA, PLS (partial least squares), CVA (canonical variate analysis) or other pattern recognition techniques can be combined with PCA to enhance the efficient performance of fault diagnosis for on-line FDD applications in large buildings.

5. Combination of various techniques

To enhance the performance of an individual diagnosis approach, the combination of various techniques has been developed in terms of hybrid FDD approaches. The fundamental concept of these developed approaches is to improve the fault diagnosis efficiency of each methodology in terms of accuracy, robustness and reliability. In this section, the four hybrid approaches are briefly introduced and explained how to improve the performance of a single FDD method by using the evaluation standard parameters as mentioned in Section 3.

5.1. Analytical-based and knowledge-based approaches

Generally, analytical-based FDD are considered by generating residuals from the difference between measured parameters and estimated values by model references. After that, faults, noise and disturbance in terms of residuals are evaluated and isolated by computing suitable thresholds. However, the essential barriers of fault diagnosis isolated by model-based FDD are classification error, modeling requirement, novelty identifiability and computational requirements. A knowledge-based approach is useful to tackle some mentioned limitations which are computational requirements, and modeling requirement; meanwhile it enhances the performance in terms of reducing classification error and increasing robustness due to noise and disturbance, but it cannot eliminate all errors. The combination method of these two approaches was developed by ASHRAE 1020 project as illustrated in Fig. 10. First-principle models were used for fault detection, whereas fault diagnosis was processed by expert knowledge. In this process, a steady-state detector was employed to guarantee the stability of steady-state outcomes for diagnosing faults. Furthermore, expert rules combined with an analytical-based approach can elevate the explanation facility by identifying rules which are similar to Table 4. The computation of selected residuals and the modeling process of complex or large-scale systems can be reduced and replaced by using the knowledge rules.

5.2. Analytical-based and data-driven approaches

Typically, an analytical-based method or data-driven method such as PCA or FDA can appropriately and conveniently detect faults in terms of residual generation. Although model-based approach can provide physical understanding for residuals, the residuals may include disturbance and noise due to measurement and control signals leading to the degradation of detection robustness. With the combination of PCA based on a first-principle model for fault detection, the combined approach can reduce the effect of noise and disturbance because PCA can perform as a dimensionality reduction tool for producing lower-dimensional representations of the interested data from the originally large-scale data. Additionally, the feature of the first-principle model can refer the physical understanding to the residuals. Wu and Sun [51] combined energy flow balance with PCA-based method, the statistical analysis, PCA was used to reduce the dimensional data and the flow energy consumption was used to detect faults existing in VAV systems. With PCA-based approach, the combined method can perform novelty identifiability and reduce modeling requirement feature; however, the combined approach requires more memory to perform storage and computation for off-line training process.

5.3. Knowledge-based method and data-driven approaches

For large systems without knowledge rules or with complex models leading to costly and time-consuming process, a data-driven approach can be used to decrease high-dimensional data into the interested information of lower-dimensional space. After that, a classification technique or expert rule in knowledge-based domains can be used for modeling instead of an analytical-based method. For instance, fuzzy logic, ANN or SVM can map the relations between inputs and outputs in terms of non-linear models. Fan

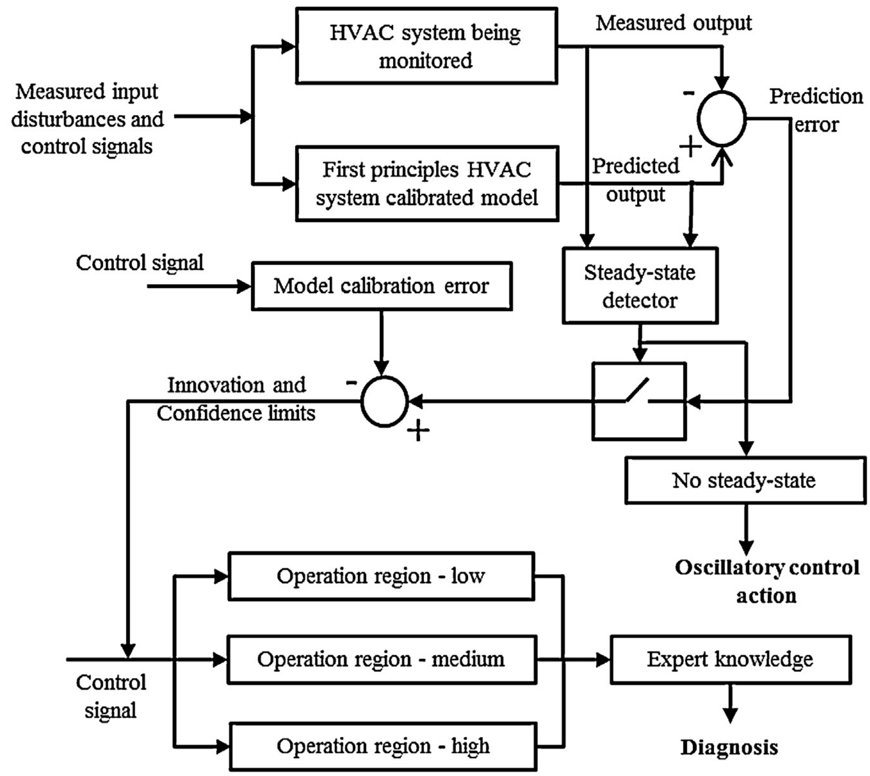


Fig. 10. Method for fault detection and fault diagnosis using first-principle models and expert knowledge [10].

et al. [52] proposed the hybrid strategy (multi-level classification techniques and a non-stationary signal) composing of two-stage process. In the first step, the first back-propagation neural network (BPNN) model was trained by the fault-free data from normal HVAC operations and the second BPNN model was trained to analyze the first BPNN model due to the sensitivity of the prediction reliability. These two-stage BPNN models provided accurate fault detection process rather than one-stage BPNN. In the second step to diagnose sensor faults, wavelet analysis in signal-based methods was used to reduce the dimension of the input data for training non-linear model by Elman neural network (ENN). Then, ENN was used to identify sensor faults. The combination between wavelet analysis and ENN improved the ability and precision of the sensor faults diagnosis. The combined techniques increase the efficiency of FDD in terms of robustness and precision.

5.4. Analytical-based, knowledge-based and data-driven approaches

With the concept of reducing or eliminating the drawbacks and utilizing the advantages of each method according to Section 5.2, the combination of analytical-based and data-driven approaches can enhance fault detection performance and meet more desirable characteristics. However, for the well-designed diagnosis feature, it should demonstrate explanation facility for automatically identifying fault locations and causes to building operators in order

Table 4
Rule set of air handling unit performance in four modes [42].

Mode	Rule #	Rule expression for four model operations in Fig. 2
Heating (Mode 1)	1	$T_{SA} < T_{MA} + \Delta T_{sf} - \varepsilon_t$
	2	For $\lvert T_{RA} - T_{OA}\rvert \ge \Delta T_{min}$; $\lvert Q_{OA}/Q_{SA} - \left(Q_{OA}/Q_{SA}\right)_{min}\rvert > \varepsilon_t$
	3	$\lvert u_{hc} - 1\rvert \le \varepsilon_{hc}$ and $T_{SA,S} - T_{SA} \ge \varepsilon_t$
	4	$\lvert u_{hc} - 1\rvert \le \varepsilon_{hc}\rvert$
Cooling with outdoor air (Mode 2)	5	$T_{OA} > T_{SA,S} - \Delta T_{sf} + \varepsilon_t$
	6	$T_{SA} > T_{RA} - \Delta T_{rf} + \varepsilon_t$
	7	$\lvert T_{SA} - \Delta T_{sf} + T_{MA}\rvert > \varepsilon_t$
Mechanical cooling with 100% outdoor air (Mode 3)	8	$T_{OA} < T_{SA,S} - \Delta T_{sf} - \varepsilon_t$
	9	$T_{OA} > T_{CO} + \varepsilon_t$
	10	$\lvert T_{OA} - T_{MA}\rvert > \varepsilon_t$
	11	$T_{SA} > T_{MA} + \Delta T_{sf} + \varepsilon_t$
	12	$T_{SA} < T_{RA} - \Delta T_{rf} + \varepsilon_t$
	13	$\lvert u_{hc} - 1\rvert \le \varepsilon_{cc}$ and $T_{SA} - T_{SA,S} \ge \varepsilon_t$
	14	$\lvert u_{hc} - 1\rvert \le \varepsilon_{cc}$
Mechanical cooling with minimum outdoor air (Mode 4)	15	$T_{OA} < T_{CO} - \varepsilon_t$
	16	$T_{SA} > T_{MA} + \Delta T_{sf} + \varepsilon_t$
	17	$T_{SA} > T_{RA} - \Delta T_{sf} + \varepsilon_t$
	18	For $\lvert T_{RA} - T_{OA}\rvert \ge \Delta T_{min}$; $\lvert Q_{OA}/Q_{SA} - \left(Q_{OA}/Q_{SA}\right)_{min}\rvert > \varepsilon_t$
	19	$\lvert u_{cc} - 1\rvert \le \varepsilon_{cc}$ and $T_{SA} - T_{SA,S} \ge \varepsilon_t$
	20	$\lvert u_{cc} - 1\rvert \le \varepsilon_{cc}$

Table 5
Comparison of various diagnostic approaches.

Desirable characteristics	Parameter estimation	Rule-based	Data-driven	Combination techniques			
	1st principle	APAR	PCA	Method 5.1	Method 5.2	Method 5.3	Method 5.4
Quick detection and diagnosis	√	√	√	√	√	√	√
Isoability	√	√	√	√	√	√	√
Robustness	√	√	√	√	√	√	√
Novelty identifiability	?	×	√	?	√	√	√
Classification error	×	×	×	×	×	√	√
Adaptability	√	×	×	×	×	√	√
Explanation facility	√	√	×	√	√	√	√
Modeling requirement	×	√	√	?	√	√	?
Storage and computation	×	√	√	√	×	×	?
Multiple fault identifiability	×	×	×	?	×	?	?

Note: √ satisfies the characteristic feature; × indicates that the property is not satisfied and ? means case dependency. Method 5.1 combines first principle with rule-based approach. Method 5.2 utilizes first principle and PCA approach. Method 5.3 uses ENN and wavelet analysis approach and method 5.4 is the combination of first principle, rule-based and PCA approach.

to decrease costly and time-consuming preventive maintenances. To meet this essential requirement and capability, a knowledge-based approach or expert rule practically provides reasonable fault explanation. By the combination of these three approaches, they are suitable for detecting, isolating and diagnosing faults in large-scaled systems such as large-scaled building operations, industrial systems and monitoring chemical processes.

5.5. *Hybrid method evaluation*

In Table 5, we evaluate the performance of the three main methods and four hybrid approaches by utilizing the 10 desirable characteristics mentioned in Section 3. In this section, each single method is evaluated and improved in terms of a hybrid approach. For example, the parameter estimation based on first principle equation is shown in Fig. 10. The limited performances of this single method are classification error, model requirement, storage and computation and multiple fault identifiability. If the first principle equation is used since it has advantages in quick detection, explanation facility and adaptability via recursive system identification, the diagnosis performance can be enhanced by combining with a rule-based technique. With prior experiences and operational routine information, the combined method 5.1 could reduce modeling requirement with if–then rules and could diagnose multiple fault identifiability by constructing potential rules from the prior experiences to isolate simultaneous faults; however, the performance of this combined approach depends on the efficiency of the system routine operations and previous knowledge for designing powerful rule-based diagnosis. As a consequence, they are case dependent. For another case, if novel identifiablity is mainly considered in a diagnosis process, the PCA technique can satisfy this feature. Therefore, this feature can be improved by utilizing PCA combining with the first principle approach as method 5.2 since PCA reduces high dimensional data to lower dimension for only interested domains of data. Consequently, PCA is a good method for fault detection; however, the weakness of PCA is diagnosis for multiple fault situations. If method 5.2 is applied in a large-scaled system, it can detect novel faults; but it cannot diagnose simultaneous faults. A researcher can improve this hybrid method by utilizing PCA for only detecting faults and appropriately select another method which has a unique fault feature such as an UIO observer and decoupling-based feature [3].

For reducing classification error and eliminating model requirement feature, method 5.3 [52] uses a BPNN, which is one of model-free methods. Two BPNN are utilized to map historical and online data. The BPNN model can be adaptable for training online data. In the second stage for fault diagnosis, wavelet analysis being one of variable window technologies is used to analyze raw data at frequency domain. The fast response can well extract the approximation of measurement data coefficients for further training data by ENN. The combination of wavelet analysis and ENN can well diagnose the specific cause of fault sensor in the control loop. This combination of diagnosis can improve the capability and reliability of fault diagnosis in sensors. To further reduce classification error, another ENN is also used to train new online data to search and recheck new unknown faults. However, this combined technique mainly use historical data in multi steps, resulting in high storage and computation; it may be costly and time-consuming for large-scaled systems and it requires to be further tested with other faults in AHUs for ensuring multiple fault identifiability feature.

6. Conclusion

This review article presents essential information of FDD on AHU systems. Firstly, the configuration of AHU systems with VAV boxes conventional operations are introduced. Then, the typical faults in AHUs and the general structure of FDD for dealing with the faults investigated in the existing literature are summarized. Later on, 10 desirable characteristics applied to chemical processes are introduced and discussed for developing consensual standard evaluation of FDD on HVAC systems. The evaluation framework can also be used as a guideline for generating hybrid FDD approaches to enhance the efficiency of current approaches, or for suitably selecting FDD methods by new researchers.

Upon these, a classification method, which divides FDDs into three main categories, namely analytical-based methods, knowledge-based methods, and data-driven methods, is proposed to interpret the various FDDs on AHUs. Examples of the FDDs in each category are selectively reviewed to understand the pros and cons. To enhance the diagnosis performance of residual evaluation or fault isolation, the combination of various techniques might be used. For instance, knowledge-based or data-driven approaches can be combined with an analytical-based approach to elevate the robustness of an analytical-based approach against disturbance, noise and modeling uncertainty. To demonstrate the use, three main methods and four hybrid methods are evaluated based on the 10 desirable characteristics.

Since analytical-based techniques are generated based on physical principles or mathematical models, they have attracted remarkable attention in modern intelligent building energy systems to enhance system efficiency by reducing errors during routine operations and preventive maintenances. Additionally, they can be continuously developed in terms of passive, active or hybrid fault tolerant control that can maintain the efficiency of overall control performance when faults occur in systems; however, this area as part of intelligent building technologies is still at its infancy with rare real-time implementations.

For these reasons, we will further review intensively essential methods of analytical-based methods through the necessary theories and the examples of AHU applications or relating areas in a separate paper. The examples can be used by researchers for developing advanced analytical-based approaches and intelligent control system in HVAC areas.

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