A Review of Fault Detection and Diagnosis Methodologies for Air-Handling Units

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Abstract: HVAC (Heating, Ventilation and Air-Conditioning) systems for space heating, space cooling and ventilation of buildings consume nearly 40% of the world energy demand and present the least expensive opportunities for reducing the greenhouse gases emission.

Fault Detection and Diagnosis (FDD) methods could monitor the operation of various processes and/or components allowing to detect and, if possible, even predict the presence of defects (deviations from normal or expected operation) as well as ideally identify (diagnose) the fault and/or its location, giving instructions for undertaking corrective actions.

FDD techniques could be successfully used for managing the predictive maintenance and/or optimizing the energy/economic/environmental performance of HVAC units while assuring the comfort of occupants.

This paper examines the current state of the art of the research on the development and implementation of FDD systems when applied to Air-Handling Units (AHUs), the main and most important device of HVAC systems. This paper describes the existing methodologies, approaches and tools for the utilization of FDD techniques, summarizes the most important findings available in current literature in reference to several case studies where FDD systems have been applied with reference to AHUs and indicates the main gaps to be further investigated.

Keywords: Heating, Ventilation and Air-Conditioning systems; Air-Handling Units; Fault Detection and Diagnosis systems; Predictive maintenance.

1. INTRODUCTION

According to the United Nations [1] and World Resources Institute [2], HVAC (Heating, Ventilation and Air-Conditioning) systems for space heating, space cooling and ventilation of buildings are one of the major contributors to the world's energy use (consuming nearly 40% of the total energy demand) and present the least expensive opportunities for reducing the Greenhouse Gases (GHG) emission.

Even when building automation systems or advanced controllers are applied to enhance the performance of HVAC systems, faults can develop during the installation or routine operation, resulting in excessive energy waste or inefficient usage of energy as well as uncomfortable environment, unless corrective action is taken. In addition, it should be highlighted that the premature component failure of HVAC plants increases the direct costs through the embodied energy and material resources in replacing the equipment as well as the indirect costs associated with the repair process [3, 4]. In a survey of United Kingdom buildings, the data showed 25-50% of energy waste due to faults in HVAC units; this range could be reduced below 15% in the case of the faults could be detected and identified early in the premature stage before unacceptable damage occur [5].

When operating a complex HVAC system, it is beneficial to provide the operator with tools which can help in decision making for the system management and optimization as well as recovery from a failure state; the tools should be able to detect the defects and give instructions on corrective actions to be taken in a simple and understandable way. However, understanding the relationship between causes and effects is more difficult than in the past due to both increased complexity of HVAC plants as well as current supervisory strategies used by energy management systems which do not explicitly optimize performance and cannot respond to the occurrence of faults that cause it to deteriorate.

Companies follow different maintenance programs in order to guarantee the reliability of systems and reduce the costs; generally, a reactive or preventive maintenance is adopted. In the case of reactive maintenance, a system is used up to its limits and the repairs are performed only after the system failure; this kind of approach is not convenient with reference to complex systems mainly due to the fact that repairing the damaged parts after failure could (i) be extremely

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expensive and (ii) cause safety issues. For this reason, it could be useful to prevent the failures by performing regular checks on the equipment by means of a preventive maintenance; in this case , the systems are inspected and maintained at fixed time intervals, independent of their actual condition; however, one of the main challenges of this approach is to determine when the maintenance has to be performed; it has to be conservative in order to prevent safety issues as well as reduce the costs of failures, but scheduling the maintenance very early could mean wasting system life that is still usable. The above-mentioned critical points associated to both reactive and preventive maintenance programs highlight how "predicting" the failures of components could be extremely important in minimizing the related costs, optimizing the performance as well as avoiding safety issues.

Fault Detection and Diagnosis (FDD) methods can monitor the operation of various processes and components as well as detect and predict the presence of the defects (deviations from normal or expected operation) causing a faulty operation. Ideally, FDD systems could also resolve (diagnose) the type of problem and/or identify its location, giving instructions for undertaking corrective actions; in practice, this is seldom possible and FDD systems should be considered more as a tool for obtaining information on the process/component as well as an aid to help the operators in identifying the causes of the faulty process operation [6-8].

FDD methods are based on the use of controllers. From the process signals, some test quantities are generated, the variation of which in comparison to a "nominal/healthy" trend is assumed as a symptom of defects; once the test quantity reaches some predetermined levels that reflects the seriousness of the defect requiring corrective actions to take place, the test quantity is set into an alarm state (symptom) and reasoning is started to find the cause of the "alarm - symptom – fault" chain [9, 10].

FDD techniques have been used for decades in aerospace, nuclear and industrial applications, and their use in building operation and control applications is becoming more widespread. In the building sector, they have been commonly used for HVAC systems, but are in principle applicable to all the sub-systems of buildings [11].

In order to apply FDD methods to HVAC units or components, it is necessary to compare real behaviour of the systems to the "nominal/healthy" operation without faults that can be modeled by means of simulation softwares and/or artificial intelligence techniques.Simulation softwares represent a useful approach not only in design phase, but also in combination with FFD methods thanks to the fact that they could have the required accuracy to predict thermal/cooling loads, energy consumption and quality of indoor environment of buildings, thus allowing for the detection of any non-optimal states of performance by comparing the simulation results with the normal data. However, accurate mathematical models of HVAC units or sub-systems are sometimes difficult to realize since (i) most HVAC designs are unique, (ii) financial considerations restrict the amount of time and effort that can be put into deriving the model, (iii) detailed design information are seldom available, and (iv) measured data from the actual operation of plants are often a poor indicator of overall behaviour since the buildings are subject to seasonal disturbances, with transient behaviour generally occurring. In these cases, other approaches are also available, such as using artificial intelligence techniques [12]. Artificial Neural Networks (ANNs), for example, gather knowledge by detecting the patterns and relationships in data and learn (or are trained) through experience, not from programming; once the network is trained and tested, it can be given new input information to predict the output. Therefore, ANNs represent a promising modeling technique, especially for data sets having non-linear relationships which are frequently encountered in a number of processes; in terms of model specification, ANNs require no knowledge of the data source but, since they often contain many weights that must be estimated, they require large training sets; in addition, ANNs can combine and incorporate both literature-based and experimental data to solve problems.

Efficient FDD methods could detect faults before the building occupants notice the effects, which would reduce the strain on heating, ventilation and air-conditioning service industry. Furthermore, they would reduce the repair and maintenance costs of the plants. In addition, these methods could provide the manufacturers and dealers with feedback about the design and sales of systems in order to identify where any improvements could be made, and which systems have a history of reliability. Moreover, improving the operation of HVAC systems could provide significant benefits to the environment by reducing the energy consumption and related GHG emissions [13-15].

Finally, integrating FDD systems into modern HVAC plants naturally fits into the future retrofit projects to enhance theefficiency, comfort and reliability of buildings; lowering the energy consumption and building operation costs with a proper occupant comfort level could be reached together with well-organized maintenance, fast detection and correction of faults and best use of the equipment.

One of the main disadvantages of FDD approach is that it could require a continuous monitoring with specifically devoted instrumentation and, therefore, the above-mentioned benefits alone could fail in justifying the cost of implementing FDD methods [15]. As a consequence, to achieve a widespread adaptation of FDD systems, the benefits of this approach throughout the value chain have to be assessed in greater detail. In addition, someone has to pay for higher costs of the FDD system, and multiple parties may share the costs if these benefits are realized; for example, electric-grid operators could provide an incentive in the form of a cash rebate for customers who adopt the FDD techniques; moreover, manufacturers could offer an FDD-enabled system to the dealer at a discounted price; the dealer, installer, and service company could also pay for access to the FDD data, in order to receive feedback on their services [15].

The prediction of faulty operation is also problematic since some types of faults cannot be introduced in a realistic manner, and the deliberate insertion of faults may lead to an unacceptable increase in energy costs or occupant discomfort; an additional problem is that many variables cannot be measured accurately and some measurements are not available. Finally, it should be highlighted that there is a real risk of an incorrect diagnosis having to respond to a false alarm, for example due to the limited accuracy/high uncertainty of the instrumentation [16, 17].

Therefore, additional studies have to be carried out in order to better highlight and assess the potential applications and benefits/drawbacks associated to FDD techniques.

The very first efforts on creating and applying FDD methods were seen in the 1980s, thanks to the rise of microcomputers and direct digital control [18, 19]. A number of methodologies and procedures for optimizing fault detection and diagnosis methods were developed in the Annex 25 of the International Energy Agency (IEA)'s Energy Conservation in Buildings and Community System (ECBCS) [20]; many of these methods were later demonstrated in real buildings in the IEA ECBCS Annex 34 [21]. Furthermore, since 2010 studies on FDD systems steadily increased.

Several reviews are already available on the literature. However, the reviews of Katipamula and Brambley [14, 22] mainly concerned the overview of FDD methods in generic HVAC equipment; the discussion on AHUs was short and not instructive with reference to the selection and evaluation of suitable FDD techniques for AHUs. Yu *et al*. [5] presented a systematic study of various FDD methods focusing on AHUs by using a set of desirable characteristics to evaluate the existing methodologies for the development of an advanced online FDD implementation; however, the main results of related studies available in literature as well as the existing gaps in the research field were not indicated and discussed in detail.

This paper firstly presents in brief the fundamental theories and classifications of FDD methods; then, a systematic and detailed analysis of various FDD methods applied to AHUs is carried out in order to (i) highlight the existing methodologies for FDD implementation, (ii) summarize the most important findings available in literature and (iii) indicate the main gaps in research.

2. BASICS OF FDD SYSTEMS

This section provides a concise introduction to the fundamentals of FDD techniques; for greater detail, it is worth referring to the works by Ding [23], Isermann [24], Himmelbleau [8], De Dkleer and Williams [25].

According to Himmelblau [8], a fault is "a departure from an acceptable range of an observed variable or a calculated parameter associated with a process" [26]. Faults can be further categorized by their time dependency into (i) abrupt faults (stepwise), (ii) incipient faults (drift-like), and (iii) intermittent faults [27]. As a general rule, abrupt faults are the easiest to detect, while incipient faults and intermittent faults are more difficult to identifiy due to their dependency on time. Rogers [15] distinguished between soft and hard faults; soft faults result in degraded performances without affecting occupant comfort, whereas hard faults result in uncomfortable occupant conditions. With respect to the development of FDD systems, the distinction between hard and soft faults is that hard faults may be detected by analyzing the indoor conditions, whereas some insights to the system operation is necessary for detecting soft faults.

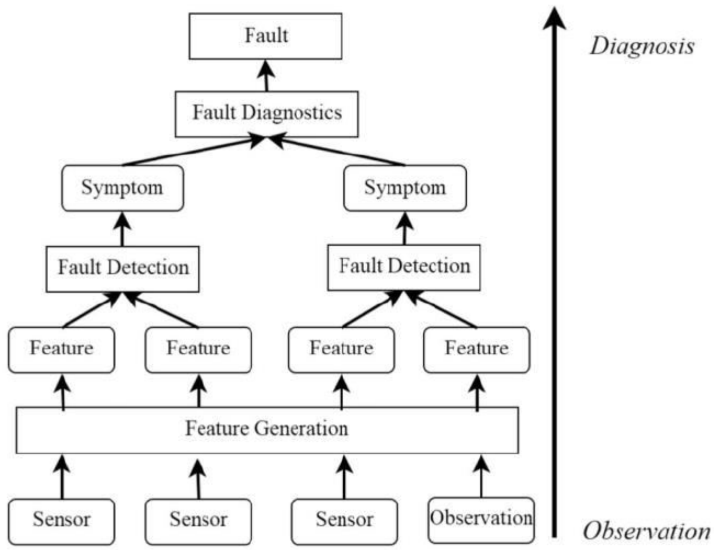

Figure 1: Overview of FDD systems [12].

A typical outline of FDD systems is shown in Figure **1** [12]. The data sources for FDD applications include mainly sensors and control data from the building automation system and energy management system; these data are then typically sent to a feature generation procedure such as expert rules and/or process models. Then, the system can perform a complete fault diagnosis process [12].

Most of the modern FDD methods are based on several measured variables. If any significant discrepancies are detected between the experimental data and "nominal/healthy" operation, a fault is detected. This decision of whether a fault has truly occurred can be reached by using simple threshold values, discriminant function, or other more complicated decision models [12]. Besides identifying abnormal operations, symptoms generated from fault detection can be later used in the fault diagnostics [28, 29].

Networking is yet another hurdle when preparing a working FDD infrastructure. A large commercial building may have thousands of controllers and pieces of equipment interfacing with each other at high frequency. Thus, providing a functioning and robust network infrastructure is one of the fundamental requirements for implementing an advanced FDD system [30-32].

3. CLASSIFICATIONS OF FDD METHODS

In current literature, there are multiple classifications of FDD methods [12, 15, 22, 27, 33-35].

One of the most recent and used classifications of FDD methods distinguishes (1) *quantitative model-based methods*, (2) *qualitative model-based methods*, and (3) *process history-based methods* [12, 15, 22, 35]. This classification scheme is shown in Figure **2**.

Quantitative model-based methods are sets of quantitative mathematical relationships based on the underlying physics of the processes; they include those based on detailed physical models as well as those based on simplified models of the physical processes [22]. Qualitative model-based methods are models consisting of qualitative relationships derived from knowledge of the underlying physics; these approaches include rule-based systems and models based on qualitative physics. For rule-based systems, Katipamula and Brambley [22] further distinguished between (i) those based on expert rules (i.e., expert systems) for which there may, in some cases, be no underlying first principles from physics, (ii) rules derived from first principles, and (iii) simple limit checks (which serve as the basis for alarms). Quantitative model-based as well as qualitative model-based methods are also known as white-box models [23]. These models are usually developed in the cases of precise representations of underlying physical process, they are able to simulate fault states and they are good in representing transient states [36]. However, they are often too complex to implement and compute, require a lot of data input which may not always be available, and are very hard to calibrate/recalibrate due to a high degree of freedom [22]. These models are usually used as forward models in which the parameters are predefined based on design information and

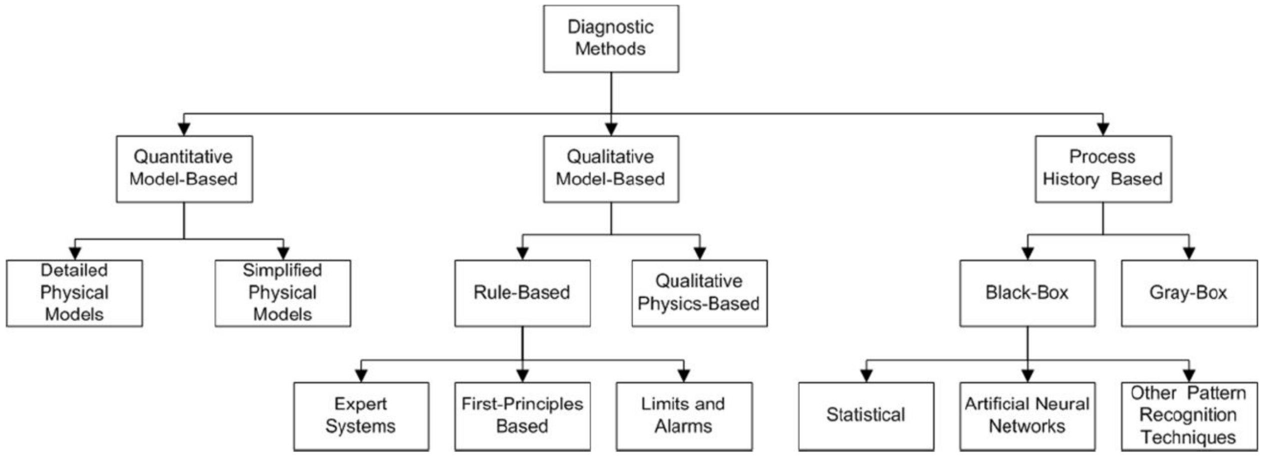

Figure 2: Classification scheme for FDD methods [22].

recalibration is usually limited to a small parameter space. However, while implemented properly, features generated from white-box models could achieve higher accuracy [36] compared to alternative models; however, researchers noted that the expertise and time required to implement and maintain such models are significant [37, 38].

In contrast to the first two groups where a priori knowledge of the process is assumed, the third group (process history-based models) is based solely on process history, i.e. a large amount of historical data is assumed to be available. This category includes black-box methods for which the models are derived purely from the data and gray-box models that use first principles or engineering knowledge to specify the mathematical form of terms in the model for which parameters are determined from process data.

Some of the shortcomings of white-box models are addressed by gray- and black-box approaches.

Black-box modelling requires no knowledge of internal processes and should only be developed in terms of its inputs and outputs. Gray-box modelling is unaware of the detailed specifics of a system, but a certain model can be created with some insights and experimental data.

In particular, black-box methods include statistically derived models (e.g., regression), artificial neural networks (ANNs), and other pattern-recognition techniques; they use operation data to train internal parameters, but as their name suggests, in most cases black-box models can only act as observers since the estimated parameters have little relevance to the actual physical process, thus making it difficult to pinpoint the fault cause [39]. Black-box models are more effective with respect to HVAC systems and their components since those systems are usually equipped with enough sensors to be compared with the observer [40, 41]. The fast-growing statistical learning (machine learning) field has led to a growing trend of research works using black-box models in FDD applications [35].

Gray-box models are analytical models loosely based on first principles, in which the model parameters can still be traced to the process physical response [14]. A lower number of parameters used in these models often makes them less prone to over-fitting issues [39]. Compared to white-box models, they are faster to compute and easier to calibrate and construct; in comparison to black-box models, they are more robust and can be used for parameters estimation. On the other hand, formulating gray-box models requires expert knowledge and extensive measured data to train the model parameters [14], and may be less accurate than black-box and white-box model counterparts. Since most of the processes inside buildings or zones are structurally similar, common gray-box models can be formulated relatively easily. Some of the reasons why gray-box approach is often preferred over black-box is the lack of the physical interpretation of the results in the latter [42]. The gray-box models also have better generalization capabilities when the test data deviates considerably from the training data [43].

Katimapula and Brambley [22] described the above-mentioned categories of FDD methods in terms of strength, weakness and suitability, as summarized in Table **1**.

Afroz *et al*. [43] compared white-box, black-box and gray-box models with reference to prediction accuracy,

Table 1: Strengths, Weaknesses and Suitability of FDD Techniques [22]

FDD Technique	Strengths	Weakness	Suitability
Quantitative model-based methods	They are based on sound physical or engineering principles. They provide the most accurate estimators of output when they are well formulated. They can model both normal and "faulty" operation.	They can be complex and computationally intensive. The effort required to the development is significant. They generally require many inputs to describe the system, some of which values may not be readily available. Extensive user input creates opportunities for poor judgment or input errors that can have significant impacts on results.	They are unlikely to emerge as the method of choice in the future
Qualitative model-based methods	They are well suited for data-rich environments and noncritical processes. They are simple to develop and apply. Their reasoning is transparent, and they provide the ability to reason even under uncertainty. They possess the ability to provide explanations for the suggested diagnoses because the rely on cause-effect relationships. Some methods provide the ability to perform FDD without precise knowledge of the system and exact numerical values for inputs and parameters.	They are specific to a system or a process. It is difficult to ensure that all rules are always applicable and to find a complete set of rules, especially when the system is complex. They depend on the expertise and knowledge of the developer.	They may offer the most expedient way to meet analytical needs where more rigorous approaches are time or cost prohibitive.
Process history-based methods	They are well suited to problems for which theoretical models of behaviour are poorly developed or inadequate to explain observed performance They are suited when training data are plentiful or inexpensive to create or collect. Black-box models are easy to develop and do not require an understanding of the physics of the system being modeled. Computational requirements may vary, but they are generally manageable.	Gray-box models based on first principles require a thorough understanding of the system and expertise in statistics. Most models cannot be used to extrapolate beyond the range of the training data. A large amount of training data is needed, representing both normal and "faulty" operation. They are specific to the system for which they are trained and rarely can be used on other systems.	They are suitable for virtually any kind of for which significant amounts of measured data are available.

generalization capability, training data requirement and complexity level; the results of this comparison are summarized in Table **2** [43] where the methods are ranked by taking into account that prediction accuracy and generalization capability should be high leveled, while a low level is desirable for the other two performance criteria.

4. LITERATURE REVIEW: DISCUSSION AND CONSIDERATIONS

The whole structure and operation of HVAC plants is quite complex, taking into account that timevarying system dynamics, slow-moving processes with time delays and non-ideal behaviuor of actuators prevail. The AHU is one of the main components of HVAC systems. Two common types of AHU system are (i) Constant Air Volume (CAV) and (ii) Variable Air Volume (VAV). The most important difference between these two systems is that a VAV system modulates the air flow according to the variation of building loads, whereas a CAV unit supplies a constant air flow to a conditioned zone regardless of whether the building load has been changed or not. An AHU system typically maintains the supply air temperature (T_{SA}) to the aeraulic terminals equal to the desired target (T_{SA_SP}), according to the outdoor air temperature (T_{OA}) as well as the return air temperature (T_{RA}); the system is controlled in order to automatically operate the outdoor air damper (U_{Damper_OA}), the exhaust air damper (U_{Damper_EA}) as well as the mixed air damper (U_{Damper_MA}) for appropriately regulate the air temperature (T_{MA}) before entering the heating and/or cooling coils; the operation of the heating and/or cooling coils is managed by the control signals of the heating valve (U_{HValve}) and cooling valve (U_{CValve}). Other parameters generally monitored in AHUs are the supply airflow rate ($\dot{m}_{SA}$ or Q_{SA}), supply air pressure (p_{SA}), outdoor relative humidity (RH_{OA}), return air relative humidity (RH_{RA}), supply air relative humidity (RH_{SA}), and control signal of fans (U_{Fans}).

Table 2: Comparison of FDD Techniques Based on Performance Criteria [43]

Modeling Technique	Prediction Accuracy	Generalization capability	Train data Requirement	Complexity Level
White-box	Low	High	Low	High
Black-box	High/Medium/Low	Low/Medium	High	Low
Gray-box	High	Medium	Medium	Medium

Table 3a: Descritpion of White-Box Models under Analysis

Modeling Technique	Type of building	Year	Location	Type of AHU	Component of AHU object of study	Reference
White-box models	Office building	1996	Varennes (Canada)	VAV	All sub-systems	[44]
	Commercial building	1996	Zug (Switzerland)	VAV	All sub-systems	[45]
	Laboratory building	1999	-	VAV	All sub-systems	[46]
	Laboratory building	2001	-	VAV	All subsystems	[47]
	College building	2006	Washington D.C. (USA)	VAV	All sub-systems	[48]
	Various buildings	2006	Various sites	VAV	All sub-systems	[49]
	-	2014	-	-	All sub-systems	[50]
	University building	2017	Chang'an (China)	VAV	All sub-systems	[51]
	University building	2019	Boston (USA)	VAV	All sub-systems	[52]

Table 3b: Descritpion of Black-Box Models under Analysis

Black-box models	Laboratory building	1999	-	VAV	All sub-systems	[46]
	Commercial office building	1999	Kawasaki (Japan)	VAV	All subsystems	[53]
	Laboratory building	1999	Paris (France)	VAV	Cooling coil	[54]
	-	2004	-	VAV	All subsystems	[55]
	-	2008	-	VAV	All subsystems	[56]

Table 3c: Descritpion of Gray-Box Models under Analysis

Gray-box models	Office building	2001	Steinhausen (Switzerland)	CAV	All subsystems	[57]
	Laboratory building	2001	-	VAV	All subsystems	[47]
	University building	2016	Ottawa (Canada)	VAV	All subsystems	[39]
	Office building	2017	Ottawa (Canada)	VAV	All subsystems	[29]
	University building	2018	Ottawa (Canada)	VAV	All subsystems	[58]
	University building	2019	Shenyang (China)	-	All subsystems	[59]

In this paper eighteen papers available in current literature referring to the application of FDD systems to AHUs are analyzed; they are summarized in the following Tables **3-7**. In particular, Tables **3a**, **3b** and **3c** report the type of FDD technique (white-box, gray-box or black-box), year of the study, type of building, location, type of AHU (VAV or CAV) and components of AHU under investigation. Table **4** shows the number and type of parameters monitored by the FDD systems, purpose of the study (fault detection/diagnosis and/or optimization), investigation approach (experimental and/or simulation), adopted software in the case of simulations. Tables **5**, **6** and **7** indicate the main results as well as the weakness of the studies using white-box

Table 4: Monitored Parameters, Purpose and Approach of the Studies under Analysis

Modeling Technique	Reference	Monitored parameters	Number of detected faults	Purpose	Approach (Simulation and/or Experimental)	Software
White-box models	[44]	T_{OA}, T_{RA}, T_{SA}	3	Fault detection	Simulation	Simulink [60], MatLab [61]
	[45]	T_{OA}, T_{RA}, T_{SA}, T_{SA_SP}	3	Fault detection	Simulation and Experimental	PROLOG [62]
	[46]	p_{SA}, Q_{RA}, Q_{SA}, T_{MA}, T_{RA}, T_{SA}	6	Fault detection	Simulation and Experimental	Non-commercial software
	[47]	Q_{MA}, Q_{RA}, Q_{SA}, RH_{OA}, RH_{RA}, RH_{SA}, T_{MA}, T_{OA}, T_{SA}, U_{CValve}, U_{Damper_EA}, U_{Damper_OA}, U_{Damper_RA}, U_{Fans}, U_{HValve}	7	Energy efficiency and fault detection	Simulation	Non-commercial software
	[48]	Operation mode of the plan, RH_{OA}, RH_{RA}, T_{MA}, T_{OA}, T_{RA}, T_{SA}, T_{SA_SP}, U_{CValve}, U_{Damper_MA}	8	Fault detection	Simulation and Experimental	Non-commercial software
	[49]	T_{OA}, T_{SA}, T_{RA}, T_{SA_SP}, T_{MA}, RH_{OA}, RH_{RA}, U_{Damper_MA}, U_{CValve}, U_{HValve}, U_{HValve}	4	Energy efficiency and fault detection	Simulation	Non-commercial software
	[50]	Q_{RA}, Q_{SA}, RH_{MA}, RH_{RA}, RH_{SA}, T_{MA}, T_{OA}, T_{RA}, T_{SA}, U_{CValve}, U_{Damper_EA}, U_{Damper_MA}, U_{Damper_OA}, U_{HValve}	3	Fault detection	Simulation and Experimental	Non-commercial software
	[51]	Q_{CW}, Q_{SA}, T_{Room}, T_{SA}	5	Energy efficiency and fault detection	Simulation	TRNSYS [63]
	[52]	T_{MA}, T_{OA}, T_{RA}, T_{SA},	2	Energy efficiency and fault detection	Simulation and Experimental	Non-commercial software
Black-box models	[46]	p_{SA}, Q_{RA}, Q_{SA}, T_{MA}, T_{RA}, T_{SA}	7	Fault detection	Experimental	-
	[53]	Q_{CW}, Q_{HW}, Q_{SA}, T_{CW}, T_{HW}, T_{Room}, T_{SA}, U_{Damper_EA}, U_{Damper_OA}, U_{Damper_MA}	4	Fault detection	Experimental	-
	[54]	RH_{RA}, RH_{SA}, T_{CW}, T_{RA}, T_{RCW}, T_{SA}, U_{CValve}, U_{Fans}	2	Fault detection	Simulation and Experimental	Non-commercial software
	[55]	p_{SA}, Q_{RA}, Q_{SA}, RH_{MA}, T_{MA}, T_{OA}, T_{RA}, T_{SA}	6	Fault detection	Simulation and Experimental	Non-commercial software
	[56]	$\dot{m}_{CW}$, $\dot{m}_{OA}$, $\dot{m}_{RA}$, $\dot{m}_{SA}$, RH_{OA}, RH_{RA}, T_{CW}, T_{OA}, T_{RA}, T_{RCW}, T_{SA}	8	Energy efficiency and fault detection	Simulation	Non-commercial software
Gray-box models	[57]	Operation mode of the plan, T_{OA}, T_{RA}, T_{room}, T_{room_SP}, T_{SA}, T_{SA_SP}, U_{CValve}, $U_{Heat\ recov}$, U_{HValve}	4	Energy efficiency and fault detection	Experimental	-
	[47]	Q_{MA}, Q_{RA}, Q_{SA}, RH_{OA}, RH_{RA}, RH_{SA}, T_{MA}, T_{OA}, T_{SA}, U_{CValve}, U_{Damper_EA}, U_{Damper_OA}, U_{Damper_RA}, U_{Fans}, U_{HValve}	7	Energy efficiency and fault detection	Simulation	Non-commercial software
	[39]	E_{Lux}, p_{SA}, T_{OA}, T_{room}, T_{SA}, U_{Rads}	6	Fault detection	Simulation and Experimental	EnergyPlus [64]
	[29]	$\dot{m}_{SA}$, T_{OA}, T_{RA}, T_{room}, T_{SA}, U_{CValve}, U_{Damper_EA}, U_{Damper_MA}, U_{Damper_OA}, U_{Fans}, U_{HValve}	6	Energy consumption and fault detection	Experimental	-
	[58]	p_{SA}, T_{room}, T_{room_SP}, T_{SA},	5	Energy efficiency and fault detection	Simulation and Experimental	EnergyPlus [64]
	[59]	$\dot{m}_{SA}$, RH_{OA}, T_{CW}, T_{HW}, T_{OA}, T_{room}	4	Energy efficiency and fault detection	Simulation and Experimental	EnergyPlus [64], MatLab [61]

Table 5: Main Results and Weaknesses of the Analyzed White-Box Methods

Reference	Main results	Weakness
[44]	A white-box/qualitative model for detecting faults based on logical programming was proposed and applied to a VAV AHU. The predictions of the qualitative model were compared with numerical simulations. The comparison highlighted that it is possible to define a fault detector for a VAV AHU only based on qualitative observable features.	The qualitative approach required only a minimal knowledge of the system parameters, even if it was not always able to discern faults that quantitative methods might identify. Only three faults were considered. The assumed steady-state operation of the system might occur very infrequently during normal operation.
[45]	A white-box/qualitative model was applied to the AHU of a commercial building. The measured values were used to predict corresponding qualitative values of the controller outputs. The model assumed that the system is operating under conditions approaching steady-state. The qualitative fault detection has proved its worth both in laboratory tests and on building data. The advantage of such method was that it is independent of quantitative system parameters. The same method could be applied to systems of widely different sizes.	The limitations of the proposed method were typical of qualitative methods, i.e. although faults might be present, qualitative discrepancies were not observed in all operating states. Moreover, not all types of faults could be detected. Finally, once a fault was detected, the qualitative symptoms might often be insufficient to diagnose the cause unambiguously.
[46]	The object of this study was to demonstrate the application of several classification techniques to the problem of detecting and diagnosing faults in data generated by an AHU of a laboratory building. In particular, two different white-box/qualitative methods were used and seven different types of failure were considered. With reference to six faults (except that one related to the cooling coil valve stuck), the results highlighted a very good performance of both methods together with a negligible difference between the two proposed approaches.	A not negligible percentage of misdiagnoses were found, even if it was believed to be faults associated with the malfunctioning of some sensors. Furthermore, the rules on which the two methods were based were not sophisticated enough to handle more complex plants. The conclusions of this work were drawn from a single study not fully exhaustive in terms of number and type of faults.
[47]	Results are presented from controlled field tests of two FDD methods (a white-box and a gray-box models) for detecting and diagnosing faults in HVAC equipment. The tests were conducted in a unique research building that featured three air-handling units. Faults were introduced into the air-mixing, filter-coil, and fan sections of each of the three air-handling units. Both methods detected nearly all of the faults in the two matched air-handling units but fewer of the unknown faults in the third air-handling unit. Fault diagnosis was more difficult than detection.	The white-box method misdiagnosed several faults and it required a larger number of sensors than the gray-box model, although the latter method required power meters that are not typically installed. The white-box model required training data for each subsystem model to tune the respective parameters so that the model predictions more precisely represent the target system.
[48]	This paper presented an expert rule set to identify eight fairly obvious AHU operation problems and examined the performance of the rule set using simulation and field data. The rule set was structured in accordance with the discrete modes of operation of typical AHUs and was fairly intuitive to individuals familiar with the operation of AHUs. The results were encouraging.	Field testing of the rules is needed to identify appropriate values of user-selected parameters and to ensure the validity of the rules. This paper did not attempt to thoroughly assess the false alarm rate.
[49]	An FDD method consisting of a set of expert rules, derived from energy and mass balances, was tested in both an emulation study and a field study. The results highlighted the proposed FDD method is effective in detecting a variety of common mechanical and control faults and it is suitable to be embedded in commercial HVAC equipment controllers	A relevant amount of information must be provided. The performance of the method was greatly dependent on the threshold values of monitored parameters for setting the alarms.
[50]	This paper presented a comparison between two white-box models (one quantitative and the other qualitative) that can be used to detect and diagnose various faults that occur in AHUs. Comparative results of both methodologies on an air handling unit are presented and thoroughly discussed using as a benchmark the rule-based approach known as air-handling unit performance assessment rule-set.	Both model based diagnostics approaches produced very similar results in terms of diagnostics power and robustness of the solutions. The main difference between both approaches is the time at which the highest amount of computational resources was needed. For the qualitative approach this was at set-up time in order to generate the qualitative diagnostic's models. In the case of the quantitative one, more power was needed during operation time as a higher amount of simulations are run for each diagnostics event.
[51]	A white-box/qualitative model in a VAV AHU was proposed and five typical faults were investigated in cooling mode. The results showed that the trends of specific variables caused by different faults could be used to distinguish one fault from others. It was an efficient method to optimize the operation of AHU, allowing to determine the influence of different faults by comparing the actual value with the optimized energy consumption of the equipment.	Although the method showed positive results, it was only a prototype version of the FDD system. Moreover, it focused on an AHU system operating under simplified control logics by considering only 5 typical faults.
[52]	This paper presented an expert rule-based fault detection in a VAV AHU with minimal non-intrusive measurements able to check one or multiple faults at the same time.	Simple models were usedm not able to provide a detailed insight about the origin of faults. Only two faults were considered.

Table 6: Main Results and Weaknesses of the Analyzed Black-Box Methods

Reference	Main results	Weakness
[46]	The object of this study was to demonstrate the application of several classification techniques to the problem of detecting and diagnosing faults in data generated by an AHU of a laboratory building. In particular, three different black-box methods were used and seven different types of failure were considered. The results highlighted a very good performance of all three methods together with a negligible difference between the two proposed models.	A not negligible percentage of misdiagnoses were found, but it was believed to be faults associated with the malfunctioning of some measurers. The good conclusions of this work were drawn from a single study that was by no means exhaustive in terms of the number and type of faults, complexity of the methods considered and training data used.
[53]	A real-time black-box tool for a VAV AHU was developed using a signed directed graph as a qualitative model of the system. The signed directed graph model was more compact than rules-based model so that the engineering effort can be minimized. It was able to detect the symptoms of the faults and find the cause of the faults. Good results were obtained.	The good performance of the method depended on the thresholds setting. If the thresholds were not set properly, the diagnosis system would have made wrong diagnosis. Moreover, threshold setting was difficult and time-consuming. Finally, the number of the causes was too low (between 3 and 6).
[54]	The method consisted in comparing the real behaviour of a cooling coil of a VAV AHU to a normal/healthy behaviour given by an ANN trained during a preliminary phase. Theremore, a physical model was developed and tested to produce training data for the ANN. The resulting detector was tested on normal behavior as well as faulty operation; no false alarm appeared and the faults are detected.	The performance of the detector was linked to the quality of these data. The database for fouling detection was too poor. The experiments have to be completed to really conclude on this side.
[55]	The FDD scheme consisted in process estimation, residual generation and fault detection and diagnosis. General regression neural network models were used for generating estimates of sensor values and control signals that were then compared to actual values to calculate the residuals. Faults were detected when the residuals exceed the threshold values established for normal operation. The main advantage of the method was that a detailed mathematical model was not needed.	The good performance of the method was affected by the thresholds setting. If the thresholds were not set properly, the diagnosis system would have made wrong diagnosis. The model was based on steady-state equations and approximate first-order dynamics. Moreover, it focused on an AHU system operating under simplified control logics by considering only 7 typical faults.
[56]	A data-driven method based on principal component analysis and Fisher discriminant analysis to detect and diagnose multiple faults including fixed bias, drifting bias, complete failure of sensors, air damper stuck and water valve stuck occurring in AHU was proposed. Multi-level strategies were developed to improve the diagnosis efficiency.	-

Table 7: Main Results and Weaknesses of the Analyzed Gray-Box Methods

Reference	Main results	Weakness
[57]	The Performance Audit Tool, based on an expert system, had the goal of fault detection and diagnosis. A gray-box model was applied to a CAV air-conditioning system. The number of rules and the complexity of the system were important factors influencing the performance of the FDD system.	The prototype version of the model was not further developed to a full product. Setting up at several new sites was too costly. The lessons learned was used to avoid similar difficulties with a new version.
[47]	Results are presented from controlled field tests of two FDD methods (a white-box and a gray-box models) for detecting and diagnosing faults in HVAC equipment. The tests were conducted in a unique research building that featured threeair-handling units. Faults were introduced into the air-mixing, filter-coil, and fan sections of each of the three air-handling units. Both methods detected nearly all of the faults in the two matched air-handling units but fewer of the unknown faults in the third air-handling unit. Fault diagnosis was more difficult than detection.	The method demonstrated great success in diagnosis, although the limited number of faults addressed in the tests contributed to this success. The white-box method required a larger number of sensors than the gray-box model, although the latter method required power meters that are not typically installed.
[39]	A linear fault detection algorithm for VAV AHU was implemented using Kalman filter-based methods with a reduced order energy balance model; its performance was tested using both simulation and experimental data. The method was able to detect most of the fault cases.	A multiple fault caused the method to perform poorly. Only limited cases of faults were created. Further tests with more faults can further validate the performance of this method.

(Table 7). Continued.

Reference	Main results	Weakness
[29]	An inverse gray-box modelling-based automated commissioning approach was put forward for VAV AHU to detect and diagnose both hard and soft faults. By using a dataset, several hard and soft faults were identified.	Comprehensive fault-symptom datasets were needed to establish cause-effect relationships between model parameters and common building faults. It was unsure whether or not the method was able to diagnose multiple faults affecting the model parameters simultaneously. Fault prioritization was not studied.
[58]	A gray-box model using probabilistic representations for faults and symptoms was applied in a VAV AHU. The fault diagnostic agent used a novel technique based on a dynamic Bayesian network. This enabled the detection of minor persistent faults as well as transient faults, while keeping a good performance of the FDD system. The structure of the proposed model allowed the integration with other fault detection methods. The fault evaluation task was performed using both simulation-based and statistical-driven methods using evidence gathered from the fault detection agents.	Construction of the conditional probabilities between the faults and symptoms is still manual and relies on expert knowledge. In addition, even if the model reduced the number of required inputs, the number of values to be defined might still become unbearable when the FDD system became sufficiently large. Many complicated faults, that were not measured directly and nonlinear parameters that were difficult to estimate, could not be evaluated unless more advanced modeling or sensing techniques were adopted.
[59]	The results showed that this method can detect the fault of an AHU as well as effectively reduce the rate of false alarm.	The study was not fully exhaustive in terms of number and type of faults. Only limited cases of faults were created.

models, black-box models and gray-box models, respectively.

The data reported in the tables highlight that:

- white-box methods are generally the most common, even if in the last years the application of both black-box and gray-box methods has increased;
- white-box methods are characterized by some drawbacks, such as a relevant complexity due to the need of a detailed knowledge of the physical laws governing the processes as well as the significant number of parameters to be taken into account (sometimes a steady-state operation and/or a simplified scheme is assumed in the development of white-box methods in order to deal with this complexity); in addition, it can be noticed that white-box methods developed for a specific AHU is not general, so that they cannot be also used for a different AHU;
- once fully developed, white-box methods are simple to be used; in addition, it should be considered that they need no experimental data or only a few measurement points. Finally, it could be highlighted that white-box methods could obtain an accuracy level similar to that one of black-box and gray-box methods;
- black-box models are more flexible with respect to the white-box models mainly thanks to the fact that they do not require a detailed knowledge of the physical laws governing the process; this is the main reason why they are becoming more and more popular. In addition, it can be noticed that they can be also applied to AHUs different with respect the one used for the development of the model;
- due to the limited knowledge of the process behind black-box models, they are generally not able to diagnose/identify the causes of faulty operation; in addition, their performance is usually significantly dependent on the amount of experimental data used for the development;
- gray-box models have been recently developed; they represent a sort of mix between black-box and white-box models, highlighting intermediate benefits/drawbacks;
- in general, the analyzed papers highlight encouraging results in terms of the capability to detect and diagnose the defects (whatever the modeling technique is); however, the number of defects that can be recognized is usually low (between 2 and 8) together with a reduced possibility to identify several faults simultaneously. These aspects have to be further investigated in the future studies.

5. CONCLUSION

In the first part of this review, a classification scheme for FDD methods was described and the strengths and weaknesses of each approach was identified.

In the second part of the paper, eighteen scientific works concerning the application of FDD methods to Air-Handling Units were analyzed. In particular, the type of FDD technique (white-box, gray-box or black-box), year of the study, type of building, location, type of AHU (VAV or CAV), components of AHU under investigation, number and type of parameters monitored by the FDD systems, purpose of the study (fault detection/diagnosis and/or optimization), investigation approach (experimental and/or simulation), adopted software in the case of simulations were identified for each paper.

In addition, the main results and potential of all the studies were described in detail, highlighting the main gaps in research to be further investigated.

The main results of the review can be summarized as follows [14, 22]:

- although quantitative model-based FDD methods are most accurate and reliable, they are generally more complex and computationally intensive compared to models based on other approaches; therefore, these are unlikely to be the methods of choice in the near future, especially for real-time applications;
- qualitative model-based FDD methods are well suited for data-rich environments and non-critical processes; they may represent the most expedient way to meet analytical needs where more processing-intensive approaches are time and cost prohibitive;
- FDD methods based on process historyare easy to develop and use and, therefore, suitable for virtually any kind of problem for which significant amounts of measured data are available;
- the application of FDD mehods to HVAC units is still in its infancy with key technical HVAC systems is the dearth of data. Relatively small numbers of sensors are generally installed in building systems and the quality (accuracy, precision, and reliability) of the sensors that are installed is inadequate for many uses. Furthermore, that there is currently little guidance in terms of minimal sensors for FDD systems. Performance, cost, and durability need to be addressed to promote better sensing in buildings.

NOMENCLATURE

Acronyms

AHU	air-handling unit
ANN	artificial neural network
CAV	constant air volume system
ECBCS	Energy Conservation in Buildings and Community System
FDD	fault detection and diagnosis
GHG	Greenhouse Gases
HVAC	heating, ventilation and air conditioning
IEA	International Energy Agency
VAV	variable air volume system

Parameters

E_{Lux}	luminance measured from the ceiling	(cd/m^2)
$\dot{m}_{CW}$	mass flow rate of water entering the cooling coil	(kg/s)
$\dot{m}_{OA}$	outdoor air mass flow rate	(kg/s)
$\dot{m}_{RA}$	return air mass flow rate	(kg/s)
$\dot{m}_{SA}$	supply air mass flow rate	(kg/s)
p_{SA}	supply air pressure	(bar)
Q_{CW}	volumetric flow rate of water entering the cooling coil	(m^3/s)
Q_{HW}	volumetric flow rate of water entering the heating coil	(m^3/s)
Q_{MA}	mixed volumetric air flow rate	(m^3/s)
Q_{RA}	return volumetric air flow rate	(m^3/s)
Q_{SA}	supply volumetric air flow rate	(m^3/s)
RH_{MA}	mixed air relative humidity	(%)
RH_{OA}	outdoor air relative humidity	(%)
RH_{RA}	return air relative humidity	(%)

RH_{SA}	supply air relative humidity	(%)
T_{CW}	temperature of water entering the cooling coil	(°C)
T_{HW}	temperature of water entering the heating coil	(°C)
T_{MA}	mixed air temperature	(°C)
T_{OA}	outdoor air temperature	(°C)
T_{RA}	return air temperature	(°C)
T_{RCW}	return chilled water temperature	(°C)
T_{Room}	room temperature	(°C)
T_{Room_SP}	setpoint room temperature	(°C)
T_{SA}	supply air temperature	(°C)
T_{SA_SP}	setpoint of supply air temperature	(°C)
U_{CValve}	cooling valve control signal	(-)
U_{Damper_EA}	exhaust air damper control signal	(-)
U_{Damper_MA}	mixed air damper control signal	(-)
U_{Damper_OA}	outdoor air damper control signal	(-)
U_{Damper_RA}	return air damper control signal	(-)
U_{Fans}	fans control signal	(%)
$U_{Heat\ recov}$	heat recovery control signal	(-)
U_{HValve}	heating valve control signal	(-)
U_{Rads}	radiant panel control signal	(-)

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