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Fault detection and diagnosis of large-scale HVAC systems in buildings using data-driven methods: A comprehensive review

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ABSTRACT

Abnormal operation of HVAC systems can result in an increase in energy usage as well as poor indoor air quality, thermal discomfort, and low productivity. Building automated systems (BAS) collects a massive amount of data related to the operation of each component of HVAC systems. Although BAS has been implemented in many buildings over the past decade, the collected data have not been analyzed thoroughly. Some studies have relied on data-mining methods to predict, detect, and diagnose faults in HVAC systems. This paper critically reviews the existing literature and identifies the research gaps in data-driven data mining fault detection and diagnosis (FDD) methods studies on HVAC systems. In this review, data-driven based FDD methods are classified into three classes, namely supervised, unsupervised, and hybrid-learning methods. The hybrid approaches are introduced as the preferred methods among the existing approaches to be used in online FDD processes. Furthermore, some components of HVAC systems and their potential faults are discussed in detail. The outcome of this review shows that data-driven based approaches are more promising for the FDD process of large-scale HVAC systems than model-based and knowledge-based ones. Moreover, an optimal approach could involve both supervised and unsupervised learning (hybrid methods).

Contents

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Nomenclature

AFDD	Automated fault detection and diagnosis
AHU	Air-handling unit
ANN	Artificial neural network
ARM	Association rule mining
BAS	Building automated systems
CART	Classification and regression tree
DBSCAN	Density-based spatial clustering of applications with noise
DD	Data-driven
DNN	Deep neural network
DM	Data mining
EANN	Ensemble neural networks
FDD	Fault detection and diagnosis
FDI	Fault detection and isolation
GAN	Generative adversarial network
GESD	Generalized extreme standard deviate
GRNN	General regression neural network
KNN	K-nearest neighbor
LDA	Linear discriminant analysis
LS	Least-squares
MC	Multi-class
ML-SVM	Multi-label support vector machine
PCA	principal component analysis
PLS	Partial least squares
RDP	Recursive deterministic perceptron
RNN	Recurrent neural networks
RS	Rough set
SVM	Support vector machine
SVR	Support vector regression

1. Introduction

The building sector is responsible for 36% of the total global energy consumption [1]. This consumption is estimated to increase annually over 1.5% for the next 20 years [2,3]. Of this amount, HVAC systems consume approximately half of the energy used by commercial buildings [4]. Poor maintenance, improper performance of components, installation faults, and control errors significantly affect the efficiency of HVAC systems. It has been reported that a considerable percentage of HVAC systems components operate below optimal levels [5]. The main causes were an unbalanced airflow, malfunctioning operation of dampers, insufficient evaporator airflow, stuck valve and valve leakages, and air-cooled condenser fouling [6]. On the other hand, it has been reported retrofitting of the existing commercial building controls infrastructure could lead to 4–5% of national energy saving [7]. Khudhair et al. [8] reported that one-third of residential chillers were not operating at their optimum operational level in the last decades.

Some faults in building HVAC and its distribution systems (e.g., foaling) may occur gradually. The gradual faults may not produce a significant effect on the operation at the time; nonetheless, these faults can lead to considerable energy waste without the operator's/owner's knowledge of the source of the problem. Mills [6] reported that only duct leakages (as a gradual fault) in commercial buildings could result in approximately an extra 1 $billion/year energy costs in the US.

An HVAC system contains numerous simultaneously interacting sub-systems, which makes the controlling system complicated. Automated fault detection and diagnosis (AFDD) methods can be easily applied to modern HVAC systems, and accurate diagnostic of the system faults can help fault-tolerant and self-healing of the system in the next stages. Accurate diagnostic could directly affect operating and maintenance costs of the buildings, especially those which have large scale HVAC systems [9,10]. Based on the literature review, fault detection and diagnosis (FDD) methods in HVAC systems are categorized in diverse ways. Yang et al. [4] classified fault detection and diagnosis methods into data-driven (DD) models, gray box models, and prior knowledge-based (rule-based) methods (Fig. 1).

Katipamula el al. [11] categorized all the studies prior to 2005 on the subject of AFDD process on building HVAC system into history-based, qualitative model-based, and quantitative model-based methods (Fig. 2).

Precise modeling is vital for FDD. However, it is very challenging and time-consuming to model a complicated and non-linear system such as large scale HVAC system by mathematical functions or physical models (e.g., gray box and model-based and rule-based methods) [13]. Nonetheless, data-driven (DD) approaches have shown great potential in characterizing system operations and developing accurate system models because of their independency on modeling and only exploiting the system data [14]. In addition, Kim et al. [15] claimed that DD approaches as history-based AFDD methods are best applied to complicated systems or where the theoretical system behavior of the model is insufficient to clarify the performance of the system. The DD approaches need historical data through the use of HVAC sensors and actuators signals to reveal the components' interdependencies based on the inter-correlations among their features.

Building automated systems (BAS) receives enormous sensor data from various HVAC components to regulate the operational quality of the components/sub-systems and control the operation of each sub-system [16]. However, raw data collected by BAS are not in an understandable format and commonly are of poor quality (missing values and frequently containing noise) [17]. From a technical point of view, achieving acceptable results from the knowledge extraction process requires the raw historical data to be of high-quality. Therefore, any DD process run without data pre-processing may lead to misleading results. In addition, high dimensionality and a large volume of the raw data and redundancy in attributes data would be a serious obstacle for a proper fault detection process. Moreover, using operationally unrelated and/or redundant attributes within massive dataset results in overfitting [18]. Therefore, feature evaluation and feature selection may be needed as another step. From the initial extraction of the data, feature selection chooses high-quality attributes, removes co-linear features, and selects the optimal subset from the original dataset [19]. Thus, the optimized dataset is prepared for the DM approach to extract interesting rules and information. On the other hand,

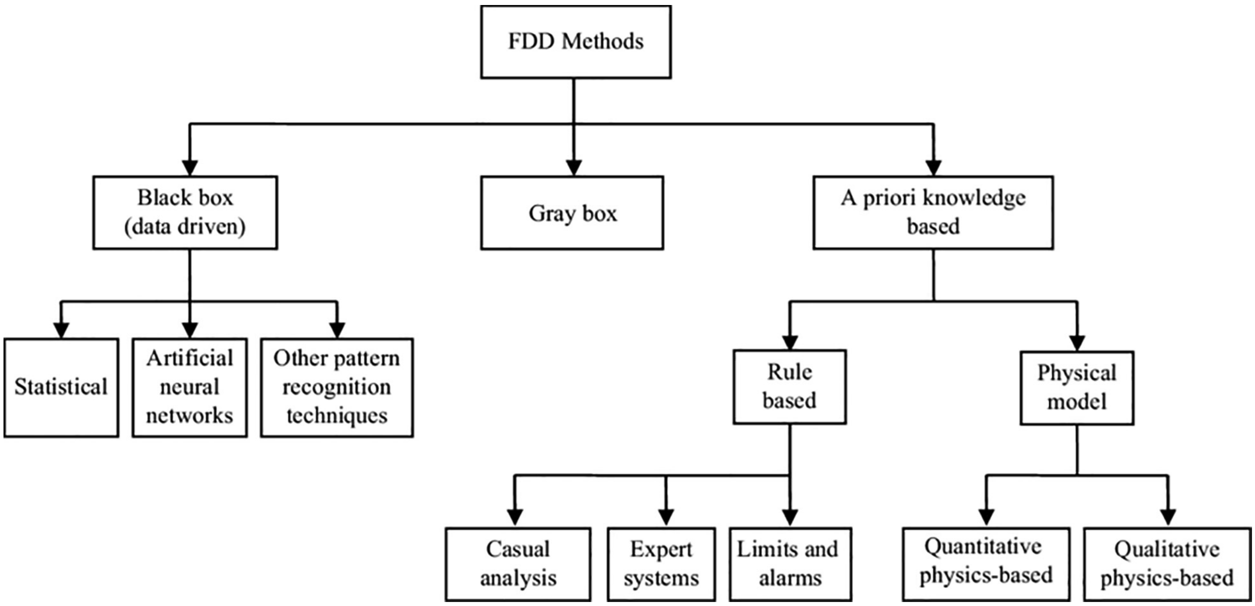

Fig. 1. Classification of FDD methods based on the study of Yang et al. [4].

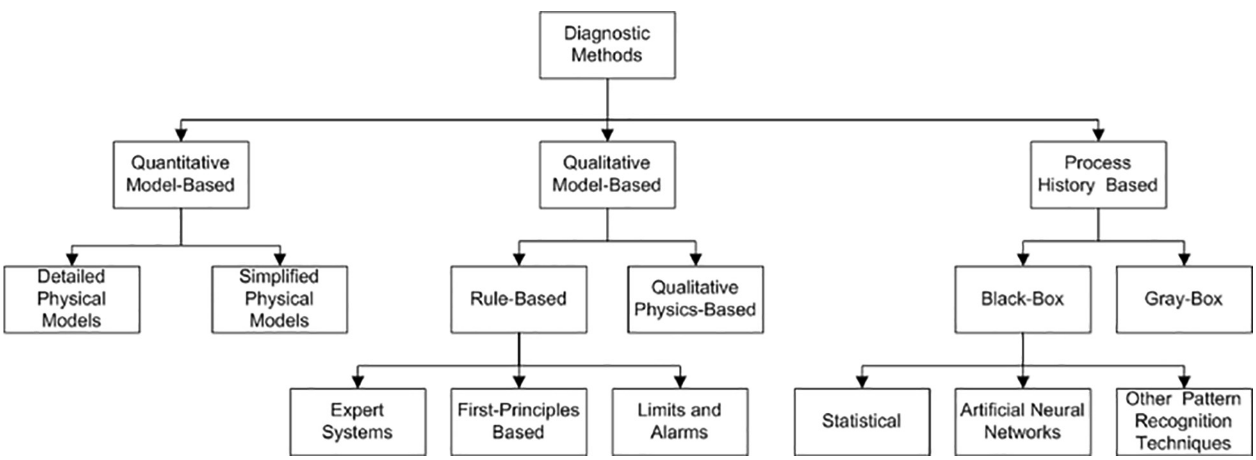

Fig. 2. Classification of diagnostic methods based on the study of Katipamula et al. [12].

earlier works have failed to address that feature selection method should carefully be chosen based on the type, quality, and distribution of data to prevent data loss.

The DD (history-based) approach is based on intra-attribute intrinsic correlations and patterns [20]. As can be seen in Fig. 3 DD method holds data mining (DM) methods and statistical methods under its branches. Although statistical methods have the advantage over the model training step —because it requires fewer samples to find faults [21,22] — they only provide the general estimate for the entire data. However, they have a key role in the heart of DM methods. DM method as an interdisciplinary method is mixed of statistical methods, machine learning and artificial intelligence, pattern recognition, and visualization. As a result, DM methods themselves contain preprocessing, knowledge discovery, and visualizing of the obtained results. Thus, these methods are able to discover surprising and previously unknown knowledge from the data.

Principal component analysis (PCA) is a statistical method that works based on the least square technique and is widely used for the FDD process in HVAC systems. The exclusive use of PCA methods is not capable of finding all kinds of HVAC faults and is very probable to get missed alarms. Especially, they may fail in detecting small magnitude faults in a system [23]. For instance, it is assumed that the nodes in Fig. 4-(a1) are related to an evaporator operation. The figure reveals a diagram of the evaporator outlet temperature versus pressure. And the diagram in Fig. 4-(b1) represent the flow rate versus velocity of the supposed chiller system. In Fig. 4-(b1) when the directions of the flow velocity are opposite, it is assumed that the flow rates should never take any amount of zero or near to zero. As can be seen in Fig. 4-(a1 & b1) by applying PCA to the dataset, all the nodes are projected on the a2 and b2 axis. As a result of the projection of data to the lower dimension, faulty nodes are lost between the non-faulty projected nodes, and there is no chance to distinguish between them. Thus, in recent years the combination of PCA with other methods are more exploited to achieve PCA with higher accuracy in FDD processes in HVAC systems [23–25].

DM-based algorithms commonly use statistical methods during pre-processing to reduce the dataset dimensions [26,27]. DM techniques could enhance the energy-saving potential of HVAC systems by providing multifaceted insight into the energy-use patterns of HVAC components and offering means of improvements to this

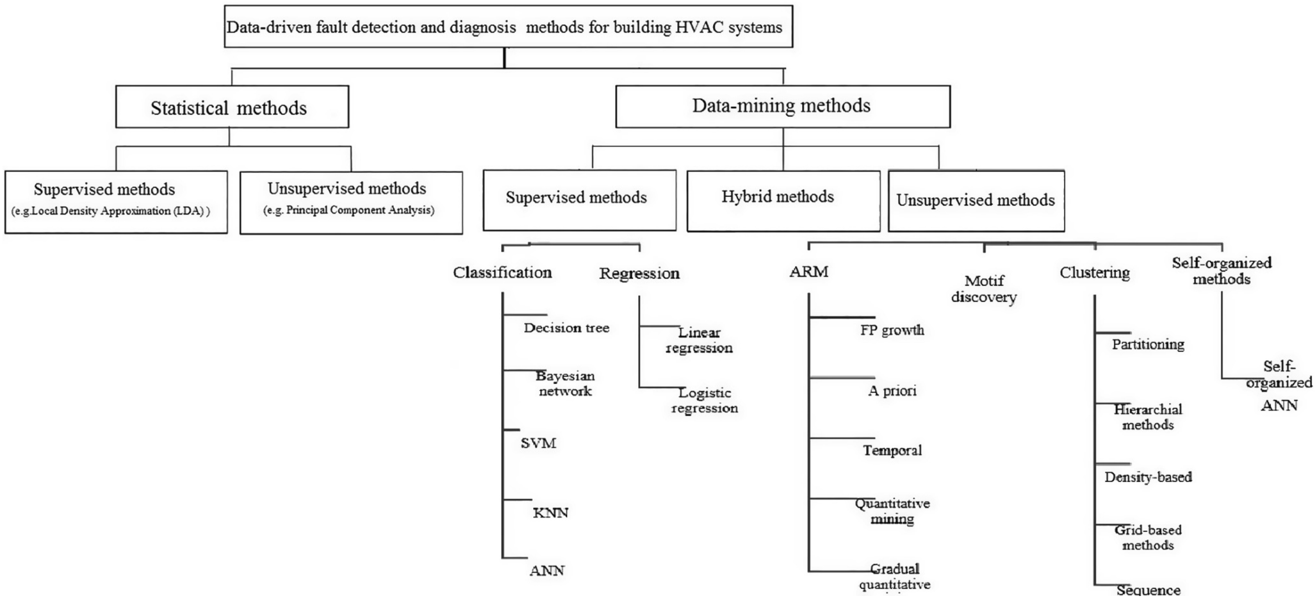

Fig. 3. FDD categorization for building HVAC systems.

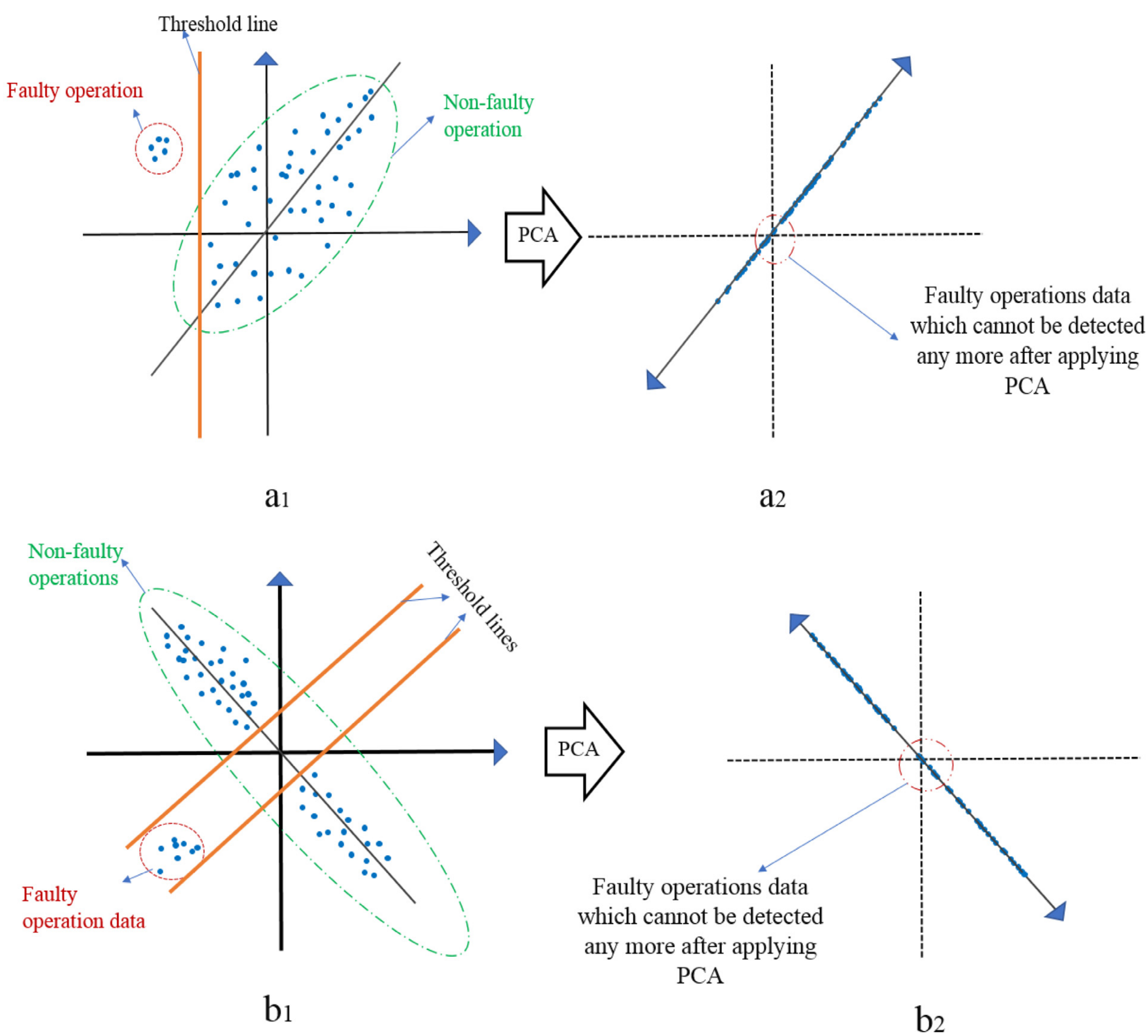

Fig. 4. a1 and b1 are the normalized data containing faulty and non-faulty operational data of a cooling sub-system component based on pre-defined thresholds. Figures b1 and b2 are representor of projected data on the optimum line to the lower dimension. As can be seen, the PCA method can lose some valuable information, including occurred faults by projecting the nodes.

energy use [28]. These methods can also be applied when modeling is very costly and computationally expensive.

DM based FDD methods have not extensively been done in the last decades. Thanks to the growth of the DM-based methods in the last 15 years, more than 100 papers have been published in this area. A recent literature review clearly shows that a limited number of artificial intelligence-DD-based works have been done on HVAC systems as well as on their components [5].

Although some other review papers have discussed the fault detection and diagnosis methods, they mostly provided only a general review of the available studies. However, in the current paper, authors have made the general review, provided a comparison of methods, and recommendations for the best available approaches based on their limitations and advantages. In summary, in this paper, three main FDD methods (knowledge-based, model-based, and DD methods) have compared for large-scale HVAC systems, and all limitations and advantages related to each technique are discussed. Then, DD as the most proper FDD method for large scale HVAC systems is recommended. After a brief comparison between the sub-categories of DD methods (statistical methods and DM methods), DM methods were suggested as the preferred DD method for handling large scale HVAC systems. Then in the field of DM based FDD, a comprehensive review of supervised, unsupervised, and hybrid DM methods is provided. Semi-supervised (a subcategory of supervised method) and hybrid DM were recommended as the best DM approaches to handle large scale HVAC systems. Also, the most important HVAC system components which are more probable to get faults and cause energy wastage are introduced, and the methods which are used to handle the faults are discussed.

2. Fault detection

Anomaly detection and fault detection, which are widely used in several studies to find the HVAC system faults, [29–34] are interesting approaches to find the faults and diagnosis in the HVAC systems. However, anomaly detection fails to take event-based anomalies and transient states into account. For example, faults may happen just for a short period and then be resolved automatically. The aim of the fault detection process is to discover failure and faulty operations in a system. Despite all interests, many attempts to propose a practical algorithm with very low false-alarm rate/false positives and missed-alarm rates/false negatives were not successful. The major problem is that the thresholds are commonly chosen to create a balance between the chance of receiving false-positive and false-negative results. Therefore, it is highly probable that some faulty conditions remain hidden. The fault detection step can only reveal if something is wrong in the system; it cannot discover the source of the fault (when detection and diagnosis cannot be made in one step).

3. Fault diagnosis

Fault diagnosis is defined as the process of locating the physical fault factors in the systems (type, location, severity, and time). Inference methods and classification methods are the two main approaches for fault diagnosis [35]. Inference methods like fault-trees are based on a decision tree and multiple binaries of if-statements. These methods are time-consuming and may highly be depended on domain expertise. Classification methods are much faster, and they train the model based on provided data contains faults and their symptoms [36]. Many of the previous studies preferred more interpretable methods like Bayesian networks than uninterpretable black-box models for the diagnosis process [35–38]. Finding a fast and reliable fault diagnosis method is a prominent issue for complicated HVAC systems, and remains challenging to achieve. Based on the study by [39], fault diagnosing of HVAC systems would usually lead to more than 90% accuracy when applied on cooling systems data, which is more accurate in comparison with heating systems. Thus, handling temporal data and developing an accurate online FDD process for sensor-based HVAC systems by the operator has been rarely successful and needs more attention and effort [40].

4. Fault detection and diagnosis methods

4.1. Model-based methods

Model-based methods develop mainly by applying a dynamic process to estimate signals and parameters [41,29]. The most well-known approaches for estimating parameters are the first principle method and gray box [30,34,13]. The first-principle method is used to model both dynamic and static systems based on the system's physical characteristics. However, this approach is not suitable for an online FDD process as the time response is slow, and it only works for steady-state conditions. To address the slow response issue, exploiting the gray-box method can help stabilize the system by having a swift response to abrupt faults. However, the use of gray-box models still requires a highly-precise physical model coupled with the regression techniques, and there may be a problem of uncertainty from oversimplifying the complicated HVAC system models [42]. In case of any modification on the system, the previous models are not usable.

4.2. Data-driven methods

Based on detailed categorization by Zhang et al. [43], DD approaches can be divided into qualitative and quantitative methods. Expert systems, fuzzy logic, pattern recognition, frequency analysis are examples of the DD qualitative-based methods. And, statistical methods and neural networks are subcategories of the DD quantitative-based methods.

DD approaches are using operational data collected for the system under the study. In contrast with the model-based approach, DD methods are more practical for applying FDD to complicated HVAC systems as these methods do not have the concern for system complexity and depend only on historical or online data. DD method does not require any intervention of human knowledge or physical models, and it only needs real system operational data [44,20]. As mentioned in Section 1 (Fig. 3), a DD method holds DM methods and statistical methods under its branches. The DD methods also are flexible with dimensionality reduction (employing statistical methods) to reduce the amount of data and consider the high weighted or manually selected features for the FDD process.

Previous DD-DM FDD studies are utilized different data-mining approaches to detect abnormal behaviors of the HVAC systems by studying the relationships between input and output data [42]. A DD-FDD process may be developed by DM methods or in combination with statistical ones [45]. However, based on the study by Ebrahimifakhar et al. [46], the overall accuracy of the DM classification method such as SVM is higher than statistical methods such as linear discriminant analysis in finding fault in a cooling system. DM methods are divided into supervised—where the data patterns are recognized based on the training set —and unsupervised methods—where underlying relations in data are summarized. In recent years, the FDD of various parts of HVAC systems in buildings has been performed via the application of DD supervised, semi-supervised, and unsupervised DM techniques, as well as their combination (hybrid methods) which are discussed in the Sections 5.3.1 to 5.3.3.

4.3. Knowledge-based methods

Based on Fig. 5 FDD classification adopted from the study by Alzghoul et al. [47], the knowledge-based method can be defined as the combination of a qualitative part of the model-based method, including structural graphs, fault trees, or qualitative physics, and DD qualitative subcategory including fuzzy logic or expert systems. Knowledge-based methods are mainly used when the physical or mathematical modeling of the system is too costly and computationally expensive. Also, these methods are utilized when there are a small number of inputs, outputs, and states for modeling of the system or when modeling of the system requires special domain knowledge [34,48]. Thus, they work well only when applying to the data of a small-scale system with limited operational states. Moreover, achieving deep knowledge of the physical features of the system to create rules is very challenging [49,40].

4.4. Combination of FDD methods

Different couplings of three main FDD methods are used to get higher accuracy [50]. Ding [51] and Khorasgani et al. [52] used combined supervised DD methods and model-based methods to find the system faults in the HVAC systems. The combination of the two main methods may initiate the new model structure built up. For instance, two layers of a Bayesian network that can contain fault layer and fault symptoms layers can be developed based on previous knowledge about faults and symptoms of related systems [36]. The combination of DD and model-based methods in FDD can help to decrease the number of requirements of attributes for modeling. However, physical modeling in combination with DD or knowledge-based methods, has some limitations. For instance, it is probable to get modeling errors and a high rate of false positives as a result of the over-simplifying the modeling of large-scale HVAC systems. This type of combined method needs big data storage, and the process of simulating various faulty conditions is very time-consuming [53]. Besides, when knowledge-based method be combined with DD or model-based method, it will reveal its limitations in regard to the provision of the insights which are beyond the engineers' general knowledge [47]. It is mostly true when a previously known fault happens in a system that cannot be diagnosed by the engineers' general knowledge or pre-defined rules.

5. Fault detection and diagnosis process

5.1. Data pre-processing

Data pre-processing must be carried out before running any FDD process. However, this critical step for FDD is often neglected or not mentioned in the literature [29]. Pre-processing involves the cleaning, integration, transformation, and reduction of the data [54]. Monitored data are usually multi-dimensional and may contain outliers. Data cleaning is essential when the dataset contains many missing values or consists of noise created by sensor faults; without data cleaning, results of the FDD process would not be reliable and could cause false alarms. Data integration prevents redundancy in the data; for instance, Hou et al. [55] implemented a rough set (RS) method before FDD to decrease redundant and irrelevant variables. Data integration is also used to convert seconds or minutes into hourly or half-hourly data. Integration thus produces smoother data and decreases the number of false alarms. Data transformation is implemented to transform data into a more consolidated form that is preferable for information mining. Data transformation may involve normalizing the data as well as the scaling and weighting of variables based on their importance [29]. Data reduction is commonly used for decreasing the dimensions of data [56]. Linear discriminant analysis (LDA) [26] and PCA [57] are the most common methods used to reduce the dimensionality of the data. LDA works based on minimizing the distance of the same class spreading data while trying to separate the different classes. LDA highly needs well-normalized distributed data. PCA can reduce the number of dimensions by mapping the data from a high-dimensional state to a lower-dimensional one [27].

5.2. Feature selection

The accuracy of DD classification methods highly depends on the quality of the training dataset. Using all the attributes within a massive dataset will cause the model to be overfitted [18]. Thus, the FDD process requires a careful selection of the most relevant features and a consideration of the correlation among these features. Choosing an optimal subset of attributes offers a greater chance that faults will be found in a system, prevents an excessive number of correlations and false alarms, decreases the chances of model overfitting, and reduce model complexity [58]. Furthermore, feature selection reduces the heavy computational load of the FDD process. Thus, it is functional for the online FDD and isolating process in complicated systems [18].

Chandrashekar et al. [19] divided feature selection methods into three main groups, namely, filter, wrapped, and embedded methods. They ranked the features based on the confidence levels of the training set, which are calculated based on the general characteristics of their features. The principle of the wrapper method is based on the functionality of the predictor based on the selected features. This method is computationally expensive and is not suitable for a large amount of data. Embedded methods use feature selection during the training process before separating the dataset into training and testing sets, which is faster than the wrapper

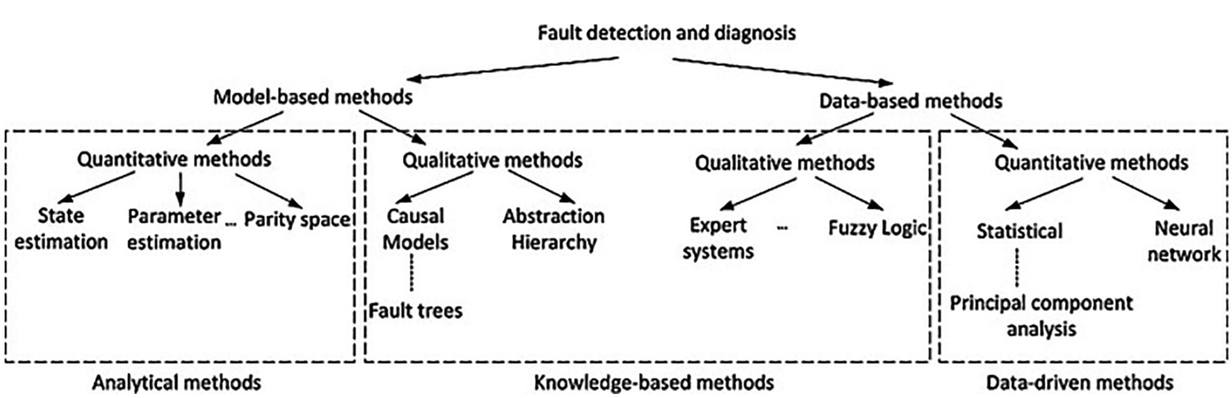

Fig. 5. FDD classification adopted from a study by Alzghoul et al. [47].

method and more efficient than the filter one [19]. Feature selection can be performed with supervised [59], unsupervised, and semi-supervised [60,61] approaches. In the FDD process, it is essential to choose the variables accurately to prevent the loss of important data.

Some previous studies implemented simple, sensitive analyses for choosing the most relevant features for the FDD process [62,63]. Furthermore, Yan et al. [64,65] used two different feature selection methods for detecting faults in a chiller system. Before starting an SVM-based FDD process, Yan et al. [65] used a filter-based method (ReliefF) to select the optimal feature subset, a selection process similar to the other studies [66,67]. They argued that the approach works well with the SVM method, and their algorithm can be applied to similar chiller plants.

It is sometimes probable that a noticeable number of the nominated features be equally important for the task at hand in a large-scale HVAC system. However, earlier works have failed to address that data loss may occur during feature selection of data when the number of attributes is large. Furthermore, despite many efforts that have been made over the last decades to identify the best subset of attributes (to be deployed to each component of HVAC systems for the FDD process), this remains a debating problem in the field.

5.3. Data mining -based fault detection and diagnosis

5.3.1. Supervised fault detection and diagnosis

In the off-line supervised learning process, each observation in the training set contains both input and output values (labels). Then, the unseen data is classified based on the model learned from the training set. Supervised learning works well in training, and it can guide the FDD process by providing feedback regarding the accuracy and leaning results. As it uses the pre-defined output model, this method is categorized as a backward approach in the DM process. Moreover, the accuracy of the training data and domain expertise have crucial roles in this method [68].

In contrast, with the off-line learning processes, online processing involves both training and testing phases being performed at the same time for each dataset. Consecutive rounds of learning contain two steps: label prediction and correction of the label. Therefore, instead of separating the data pool from the training and testing sets, each round attempt to predict each sample, and in the next step, the correct label is found. The corrected labeling thus improves future predictions [69]. Supervised learning may be classified into two main categories (Fig. 3): classification (for discrete target values) and regression. Decision trees, Bayesian networks, and SVM are the conventional algorithms used by classification methods. However, other methods such as supervised neural networks, lazy learners (e.g., K-nearest neighbor (KNN)), and ensemble methods are also classified within the regression category. Decision-tree methods follow the top-down approach. Thus, in the first stage, associated class labels of tuples are developed, and these are then applied to classify the unseen data.

SVM is a powerful classifying tool that can search for the optimal separating hyperplane by using support vectors. By these means, SVM can find large margin separators to boost the generalization and minimize error, which includes training error and confidence level [54]. Because of its ability to solve non-linear problems and its relatively high accuracy, SVM has been used in several types of research. Namburu et al. [70] used a genetic algorithm to determine the best sensor for fault diagnosis in a chiller system and then developed a DD-based generic FDD method. In the first step, they implemented SVM, PCA, and partial least-squares (PLS) to find the fault. Then, fault severity was assessed using PLS. Multi-label SVM (ML-SVM) was studied by Han et al. [71] to assign labels to more than two classes at the same time. From this study, they could identify simultaneous faults occurring in the system. They did two other similar SVM-based FDD studies for chillers [72,73].

Non-linear support vector regression (SVR) can also be applied to recognize patterns and detect faults. Linear regression functionality is not promising in non-linear FDD problems. To resolve this issue, using logistic regression is suggested. Anh et al. [74] enhanced the least square support vector regression (LSSVR) model to increase the accuracy of the method for finding faults in a chiller system. Likewise, Anh et al. [75] investigated the performance of different regression algorithms in fault detection of a chiller system. Then they, as well as Han et al. [76], proposed a least square-SVM (LS- SVM) regression-based method to find the faults in chillers. The study showed that both LS-SVM and SVM methods are highly dependent on the quality and quantity of labeled data. However, LS-SVM showed more accuracy than SVM in the FDD process when a small sample size of faulty data is available.

Some studies have used a neural-network approach to find faults in systems; the Application of kernel-based partial least square regression in FDD of heat exchangers is studied by Wang et al. [77], Bailey et al. [78] used SVR to detect and diagnose faults in a chiller. They defined 28 inputs for the artificial neural network (ANN) algorithm and worked on seven outputs to achieve a good result using two hidden layers. Hou et al. [55] applied FDD to an air-conditioning system. Their strategy adopted an RS method for omitting redundant attributes and ANN for fault detection and diagnosis.

Bayesian networks function is based on the conditional probabilities theorem to predict the response value of a set of observations. For FDD, the response values are the fault labels. Bayesian networks also can work well even if complete information about the system is not available [78]. These models usually do not properly work for finding the indirect effects from faults, as the naïve Bayesian assumption is based on independence between observations. Therefore, in the case of dependencies, some degree of error may be revealed in the network. Some authors are exploited the Bayesian network in combination with The Gaussian naïve Bayesian network assumes a normal distribution for the response value, and the weight of all classes is identical. Zhao et al. [79,80] used Bayesian belief networks to deal with dependencies for FDD in an Air-handling unit (AHU) system. Regression is used mostly for prediction. Logistic and linear regression are binary and numerical forms of regression method, respectively [54]. Discretized and abnormal intrinsic mathematical relationships between different attributes are the most effective factors for discovering and diagnosing faults [27].

ANN has been used widely for FDD in building HVAC components [81,82]. Finding faults and diagnosing them employing ANN are mostly based on residuals and thresholds. Residuals show how far the actual system has deviated from its normal operating conditions and can be defined as the difference between the measured and predicted value [74,83–85]. Furthermore, when an estimate of the severity of a fault is required, a calculation of the residuals is essential. ANN methods, which are used for isolating or diagnosing faults, are divided into two main methods based on the residuals. The first groups of ANN methods that isolate the faults are based on generating residuals and their comparison with the thresholds. The second group ranks ANN classification methods that categorize abnormal residuals in their related fault groups [78]. The threshold, in the latter group, is usually chosen based on a trial-and-error method [86] or domain knowledge [81]. Besides, statistical testing and norm-based residuals are two means of determining the most appropriate threshold (using the appropriate threshold is necessary to avoid frequent false alarms) [87]. When there are some different types of faults in the system, ANN is applied to every residual to verify those residuals that are representative of the fault. Then, ANN isolates the faults in their related fault group [88].

Deep learning, as a new generation of ANN-FDD, may receive increasing attention in the upcoming years as they might provide more accurate results than other supervised FDD methods when a limited number of labeled data are available [89]. To date, limited studies have applied deep neural network (DNN) methods to HVAC systems for fault detection and diagnosis [90]. Shahnazeri et al. [91] applied a recurrent neural network (RNN) to find faults in an HVAC system. Although their method did not require the existence of fault history to isolate faults, the accuracy of their results is limited by the ability of the identification technique to capture the process nonlinearity. Another factor that may affect the accuracy of the result when using DNN is that these methods do a feature selection step automatically inside its process. Automatically feature selection may result in the loss of some essential data that mathematically gained low weight in the process.

The problem which is common among all the supervised training based FDD methods is that faulty samples that are using for training the model may be collected from older components (this is true in most applications); this can decrease the accuracy of the results markedly. Furthermore, when FDD processing is performed over the first months or year of the operating period of the component, there is no systematic routine to adjust the training inputs to the actual condition [92]. Finally, another limitation of the supervised FDD method is that this approach is more applicable to steady-state conditions and is not functional for transient states [93].

5.3.1.1. Semi-supervised fault detection and diagnosis. A complete training dataset is necessary for supervised learning in the first stage of the FDD process. However, for the FDD process in HVAC systems, there is usually not adequate or varied fault data available for training. Semi-supervised learning can help deal with this issue. An FDD process is named semi-supervised learning when only non-fault class labels are provided for the training process [93]. Specifically, when a limited number of faulty training samples are available, semi-supervised learning performs better than supervised learning.

The semi-supervised learning method compares each observation with a nonfaulty class and adds new faults to the training set after each iteration update. By updating the training set, the training set of faulty samples becomes larger, and the remainder of the testing data is evaluated. However, semi-supervised learning has a higher computational cost than supervised learning.

Yan et al. [64] implemented semi-supervised SVM for an FDD process of an AHU system and then compared this method with four other machine-learning techniques (semi-supervised KNN, semi-supervised classification and regression tree (CART), semi-supervised, and random forest). They found that a semi-supervised SVM produced a greater accuracy than other semi-supervised methods. Semi-supervised SVM had 93% accuracy using only 6.66% faulty samples in the training set; adding a more significant number of faulty samples to the training set did not increase the accuracy. They tried to improve the accuracy level of semi-supervised FDD in their recent study [94] using generative adversarial network (GAN) extensions. These GAN extensions are implemented to the different supervised FDD methods to increase the number of faulty training samples of the AHU system synthetically. Although their methodology obtained high accuracy in comparison with classical supervised methods, the optimized parameter should be changed for different configurations of the systems.

5.3.2. Unsupervised fault detection and diagnosis

When there are no labeled classes in the input data, the process of learning is unsupervised [54]. Via this method, indirect correlation and the construction of formerly hidden data can be disclosed. Furthermore, unsupervised learning is a forward approach for discovering interesting knowledge and structure from unlabeled data. The most promising methods in this category are clustering [54,95,96], association rule mining (ARM) [68,97,98], motif discovery [99,100], and self-organized neural networks [68]. Fig. 3 presents the categorization of the various unsupervised DM methods.

ARM methods can find frequent patterns and associations among variables, and it is a useful tool for finding the inherent regularities in data. Also, informal structures between attributes can be extracted [97]. Yu et al. [83] implemented ARM to discover faults in mechanical ventilation system performance using daily and yearly data and then compared the extracted rules and found the faults [83].

Clustering represents another practical unsupervised approach for FDD. Clustering groups a set of objects into classes of similar objects so that intra-group members are most likely to each other, and inter-cluster members are less similar to one another. The clustering method can be quite helpful for understanding the timing of each specific behavior in a building's elements and extracting useful knowledge from their intra-cluster relationships. Reddy et al. [84] applied cluster analysis solely on hourly energy consumption in order to adjust models that are most appropriate for short-term energy consumption prediction in the building. Xue et al. [101] employed a combination of ARM and clustering to find faults in a district heating system. They used clustering to categorize different seasonal patterns of operation in the heating system. Then, ARM was applied to each cluster to find faults from the associated rules.

There are some limitations to using unsupervised methods. The results obtained from unsupervised learning methods (e.g., rules from ARM) are usually massive and have a large amount of redundancy. Thus, post-mining methods such as active methods are needed to automatically extract interesting results and mine the correlations from these massive sets of results. In addition, in some cases, when clustering is applied to the system operational data, the number of clusters is defined based on known fault groups by domain expertise [26]. Thus, all new faults that are not recognized as a member of these groups cannot be diagnosed properly by this clustering method. Besides, in the post-mining step, the complicated relationships among multiple features would be challenging for clustering and ARM, in comparison with the supervised methods [102].

Krarti et al. [103] carried out an extensive review of unsupervised ANN methods. Self-organized ANN algorithms can be implemented into the FDD process to create an unsupervised model. The use of a self-organized ANN can significantly reduce the number of iterations in the training process and simplify the process [104]. Thus, a self-organized ANN can speed up the FDD process.

Pattern recognition and motif discovery FDD have also received more attention in recent years. They are mostly exploited as a pre-processing step or in combination with PCA methods as a semi-supervised method [105]. For instance, the combination of symbolic aggregate approximation (SAX) pattern matching with PCA is used in [94] to detect the fault in the whole building without considering single-components faults. In the feature selection stage, regression coupled with generic algorithms is applied to the data to find the key features, which later are used in PCA. SAX provided a weather-based pattern baseline as a threshold to compare it with the historical data pattern to find the faults. However, pattern recognition and motif finder methods have great potential for an online study of time series data, and more studies and investigations are needed to exploit them in the process in large scales HVAC system AFDD process.

5.3.3. Hybrid fault detection and diagnosis

The sole application of supervised/semi-supervised learning or unsupervised learning in the FDD process has widely been examined in the literature. However, the obtained results were not generally precise enough for large-scale applications and for generating low false alarms. The integration of the unsupervised and supervised learning techniques to improve the accuracy of the FDD process has extensively been done in the last decade. Du et al. [27] implemented DD fault detection via coupling subtractive clustering analysis with a combined neural network (two consecutive neural networks) to detect the abnormities in the AHU and to enhance the energy efficiency and occupants thermal comfort. The first neural network, a basic neural network, was utilized for feature selection by detecting the sensitivity of attributes. These selected variables were later considered as a target of both the basic neural network and auxiliary neural network (the second neural network). PCA was also applied to determine the weight of each target variable of each neural network. These weightings were used to obtain a combined relative error. A combined relative error that exceeded the threshold was considered a fault. In the final stage, fault diagnosis, subtractive clustering diagnosed the faults in the new data.

In another study [82], a combination of clustering, CART, and EANN identified anomalies and faults by detecting outliers in a total active electric power and electricity dataset. CART and K-means models found outliers in the first stage using a generalized extreme standard deviate (GESD). They then compared the results of the k-means, CART, and GESD methods with those of density-based spatial clustering of applications with noise (DBSCAN) in order to find the best fault detection algorithm and reduce the number of false anomalies in total active electric power in a building. Clustering using DBSCAN was more appropriate than the k-means for grouping data, and the single neural network was not as robust as ensemble neural networks (EANN). Dey et al. [106] used a multi-class-SVM (MC-SVM) on data from fan-coil units to create an automated fault detection method. In their study, in addition to the supervised algorithm, x-means clustering (an extended form of the k-means method) was also applied to the fan-coil units' data of a building to diagnose system faults. Multiple clusters were chosen automatically by Bayesian information criteria. The validation and assessments of the number of clusters were fulfilled by Davies–Bouldin and silhouette techniques, and the results were compared to hierarchical clustering and a Gaussian mixture model.

Nonetheless, the number of studies that have focused on the hybrid data-mining approach for the FDD process remains limited. There are also only a few studies that have applied a hybrid method for prediction purposes. For instance, Naseri et al. [107] used a hybrid model by combining a neural network and clustering to predict the daily electric peak load. Their results showed that the DM-based approach had a greater potential for producing accurate predictions than statistical methods did. Piscitelli et al. [39] studied an AHU operational data throughout the transient and non-transient periods. They applied temporal ARM algorithm to detect the faults during the non-transient period and then utilized classification models to detect the severity of the faults.

A hybrid model, a combination of both supervised and unsupervised techniques, may contain the limitations of both. However, choosing an appropriate combination of supervised and unsupervised learning methods can increase the accuracy and decrease the time of FDD [108]. Table 1 presents a summary of some of the research literature and a rendered methodology for the FDD process.

6. The potential application of FDD in an HVAC system and its sub-systems

Some factors, such as poor operations of HVAC systems, delay in diagnosis source of malfunction or failure, and the time is taken during their service operation may violate thermal comfort conditions [110]. Diagnosis source of non-catastrophic faults would be challenging when a fault occurs in complicated sub-systems of the large-scale HVAC system where the system has a large number of sensors, setpoints, controllers, and mechanical parts. For instance, a HAVC system may contain the following components: chiller, AHU system, VAV system, heat storage, air ducts, pipes, pumps, air filters, cooling towers, humidifiers, dehumidifiers, valves, fans, heat exchangers, and diffusers. Of these components, the chiller and the AHU system are the energy-using components most likely to cause serious and costly problems in buildings. Table 2 illustrates some component faults and their DM-data-driven FDD results based on the literature.

6.1. Chiller

Several studies used DM methods to detect faults in the chiller system [26,70,71,74,109]. Table 3 illustrates that not all potential faults were taken into consideration, and the synergetic effects of simultaneous faults were mostly neglected. Furthermore, all data-driven DM approach studies focused on compression chillers, and there is a lack of DD studies for FDD of absorption chillers. Relative to the simple structure of compression chillers, absorption chillers are built with a larger capacity, have more complicated structures, and require more attention to provide precise AFDD systems. Because of the intricate structure of absorption chillers and a high chance of error in modeling or an oversimplification of the developed model, a DM -DD approach may be a better choice for finding actual-scale faults in these types of applications.

6.2. AHU system

Numerous studies have shown how to detect faults in an AHU system. The most common faults relate to; 1) actuator malfunction, 2) faulty sensors, 3) blocked ducts and restricted lines, 4) air filtration issues, 5) improper fluctuation of a pressure setpoint, 6) motor failure, 7) fan operating malfunction, and 8) coil fouling [12,42]. However, various FDD methods could only find single major faults in systems, and they were unable to find simultaneous multiple faults, determine any synergetic effect between these faults, or diagnose the source of the faults. Few studies have implemented DM-based DD approaches for finding faults in AHU systems [27,56,64,83].

7. Discussion and recommendations

Although many efforts have been made to develop online FDD methods to achieve the optimal efficiency for HVAC systems, online methods remain mostly in their developmental stage. There remains a shortage of reliable, fast, computationally affordable, and comprehensive solutions for controlling faults in HVAC systems. Table 4 highlights the advantages and disadvantages of three main FDD methods. An extensive literature review shows that training supervised ANN and deep learning may not be accurate enough to diagnosis the novel faults with a low rate of false alarms in the online FDD process. Moreover, defining a suitable threshold that can preserve the FDD process from false and missed alarms for ANN and DNN methods is challenging. Although more sophisticated DNN based methods such as generative adversarial networks can overcome this issue, they are usually time-consuming for large scale HVAC systems. In contrast, the use of unsupervised methods, such as self-organized ANN, can speed up this process, but it is a cluster-based ANN, and still, there could be the problem of inaccuracy in the results and the occurrence of false alarms. In addition, this method is not suitable for application to all sorts of HVAC data

Table 1
Summary and categorization of the existing literature based on methods and techniques.

Refs.	Method	Building component	FDD isolation technique	Threshold/cluster distance	Inference
[71]	Supervised learning	Chiller	ML-SVM	By calculation bias (threshold) for the specified function[1]	Survey of AFDD of multiple-simultaneous faults in the chiller system.Multi-labeled SVM works well for FDD when multiple faults occur simultaneously.
[88]	Supervised learning	HVAC system and interior building equipment	ANN	Specified by expert domain knowledge (author)	Use of recursive deterministic perceptron (RDP) for a neural network that has good capacity detection to diagnose faults.
[70]	Supervised learning	Chiller	SVM, PLS, PCA (PLS)	Specified by expert domain knowledge	A chiller data-driven model is developed to predict system response under new loading conditions.
[81]	Supervised learning	VAV system	ANN	Specified by expert domain knowledge	ANN applied to the VAV system data to extract faults occurring in the system, based on training data.
[63]	Supervised learning	Chiller	ANN	Not mentioned	Decreased performance of a chiller detected by ANN and classified based on the faults.
[56]	Supervised learning	AHU	GRNN	Set at three standard deviations of the related residuals based on benchmark operating data.	The process of FDD in AHU is adopted via the following steps: residual generation and FDD. Creation of a general regression neural network (GRNN) models for estimating residuals.
[109]	Supervised learning	Refrigerator leak detection	ANN	Specified by expert domain knowledge	FDD is applied on the refrigerant system to detect leakage of the system based on the ANN model. Patterns of faulty operations, steady-state, and transient operation, leakage, and overcharge conditions are distinguished by the method.
[74]	Supervised learning	Chiller	LSSVR	Based on estimating the mean and variance of observations	Least squares support vector regression applied to the data; the accuracy of the model was high.
[91]	Supervised learning	HVAC	Deep learning	Estimating based on a trial-and-error	Recurrent neural networks (RNN) applied for fault detection and isolation design in the HVAC system. This method does not require the existence of plant fault history, mechanistic models.
[55]	Supervised learning	Air-conditioning system	ANN	Specified by expert domain knowledge (author)	ANN trained in the first stage and then performance indices based on residues for sensors FDD.
[26]	Unsupervised learning	Chiller	LDA for preprocessing, Cluster (Used severity level cluster)	Manhattan distance	The DD-FDD approach is applied in two stages for the chiller system. Firstly, LDA was used to reduce the dimension of the data. Then clustering was asked to find seven common chiller fault types. Finally, the severity level of the fault was determined.
[83]	Unsupervised learning	Air-conditioning system	ARM	80% support and at a 95% confidence level	The method proposed to extract all associations between air-conditioning system operational data to find the fault in the system.
[106]	Unsupervised learning	Total energy consumption	Clustering	Not mentioned	Adopted the clustering model to hourly data for detecting anomalies and finding the faults of energy usage in the building.
[82]	Hybrid	HVAC	MC-SVM (clustering (X-Means))	Silhouette value	MC-SVM classifier is used for fault detection, and x-means applied for diagnosis fault in the HVAC system.
[27]	Hybrid	Total active electric power	EANN (CART, clustering (K-means and DBSCAN))	Based on a trial-and-error method	The method utilized the coupling of three outlier detection methods (CART and k-means and DBSCAN) and used EANN to detect faults.

[1] $b = y_i - w^T * x_i$ where x_i is any support vector and y is -1 or 1, and w is the weight vector.

for the FDD process. For instance, ANN ANN does not work well when it is applied on valves binary time series data.

Considering all the supervised-based FDD studies, the absence of adequate labeled data, simplified modeling, and the complexity of the synergetic effects of faults in the complicated HVAC systems, make diagnosing the source of faults quite difficult. Faulty sample data in the training step is labeled based on domain knowledge and known faults. Therefore, algorithms are unable to identify novel faults. As the entire supervised process is based on the accuracy and generality of the labeled data, training labeled data does not usually support novel faults. Besides, most studies rely on the test data collected from older systems for their analysis; this test data may not contain novel system faults. Thus, having missed alarms when a new system fault is occurring is highly probable. Another challenge is collecting accurate training data. This process is typically costly and time-consuming, and datasets may contain labeling errors. Furthermore, gradually occurring faults that decrease the system's efficiency progressively (e.g., fouling, scaling) may be recognized by monitoring residuals in a supervised approach with delay. Thus, the mentioned challenges can affect the operational quality of the whole system and may violate users' comfort conditions as well as energy efficiency. Occasionally, some sources of faults have an indirect effect on the malfunction of other components that cannot be detected by supervised methods. However, unsupervised and semi-supervised learning methods can be used for fault detection when faulty labeled data are limited or inaccessible. To tackle the issue of detecting new faults and assessing the synergetic effects of simultaneous faults, unsupervised learning methods such as motif discovery, and clustering methods can be applied.

Moreover, associated rule mining can be used to detect the relation between different component malfunctions. On the other hand, supervised methods like classification methods do not need a long post-mining process, in contrast with the unsupervised methods like ARM, which contain massive amounts of data and have numerous redundant results. As a result, implementing both approaches to use a hybrid method shows more promise for FDD processes in HVAC systems. However, future research should be devoted to the development of unsupervised methods with minimum post-processing time. Furthermore, more efforts are needed to develop the feature selection methods, which can handle attributes with a rarely faulty operation, which inherently are equally important as the other one. Making the entire online FDD system unsupervised and trying to evolve fast and accurate approaches

Table 2
Component faults and their DM-data-driven FDD results.

Refs.	System	Faults	Diagnosis/isolation algorithm	Technique	Quantitative Factors
[88]	HVAC system and interior building equipment	• Decreased performance of some equipment by 35% • Fan inefficiency • Motor inefficiency • Design of water flow rate • Reference COP	A model developed to categorize faults. Then, based on the accuracy of the model predictions, the most probable faulty equipment was determined.	ANN	Accuracy: Up to 97% FDD speed: 8–13.7 sec
[27]	HVAC system	• Fixed/drifting biases for the following variables: • Return water temperature • Supply air temperature • Failure for the supply air temperature • Jammed chilled water valve	Faulty operational data used to train the classification model for isolating the faults.	Dual ANN (clustering)	False alarm ratio: 6–7.5% Missing alarm ratio: 0–8.3% (8.3% is related to drifting bias) FDD speed: 1–29 min(the worse is related to diagnosis the complete sensor failure)
[74]	Chiller	• Refrigerant overcharge • non-condensable gas • Refrigerant leakage • Condenser fouling	DE[1]-LSSVR[2]-EWMA[3] was used for diagnosis.	DE-LSSVR-EWMA RBF[4]-EWMA SVR-EWMA	Accuracy: 99.73% FDD speed: not mentioned
[26]	Chiller	• Condenser fouling • Excess oil • Decreased condenser water flow rate • Decreased evaporator water flow rate • Refrigerant undercharge and overcharge or non-condensable	Data was monitored to discriminate similarities to any specific cluster. The severity of faults was diagnosed based on pre-defined severity clusters.	Cluster (used severity level cluster)	Accuracy:87–98.8% FDD speed:2–75 min based on sample sizes
[71]	Chiller	• Decreased condenser water flow rate • Decreased evaporator water flow rate	SVM trained based on four different severity conditions for both the condenser and evaporator.	ML-SVM	Accuracy: more than 99.9% FDD speed: not mentioned
[70]	Chiller	• Fault in sensor operation	Isolation of the fault was carried out using a classification model trained using known faulty operation data; its severity was estimated by PLS.	SVM, PLS, PCA	Accuracy: more than 95% FDD speed: not mentioned
[83]	Air-conditioning system	• The low-temperature output from the air-conditioning system on cold days • Fresh air temperature increases after the heating coil and significantly decreases after the humidifier • Contradictory fan airflow rates in two different years	Comparison of yearly data.	ARM	Highly accurate result, but time-consuming

[1] Differential evolution.
[2] Least squares support vector regression.
[3] Exponentially weighted moving average.
[4] Radial basis function.

Table 3
Predicted chiller faults of some previous studies.

Ref. / Chiller fault	Refrigerant undercharge	Refrigerant overcharge	non-condensable gas	Refrigerant leakage	Condenser fouling	Undercharged oil	Excess oil	Decreased condenser water flow rate	Decreased evaporator water flow rate	Fault in sensor operation	Fan loss
[74]		*	*	*	*						
[26]	*	*	*		*		*	*	*		
[71]								*	*		
[70]										*	
[109]		*		*							*
[78]	*	*			*	*	*				

will likely be a key in future attempts to overcome delays, find simultaneously novel faults, and get less false alarms and missed alarms.

8. Conclusion

Compared with model-based and knowledge-based approaches, the DD approach is considered as a more promising approach for the FDD process of complex systems. Based on the literature, combining DD methods can be applied to non-linear systems- like complex HVAC systems- that creating mathematical functions or physical models is challenging and time-consuming. Moreover, DD methods can detect the faults that are beyond the engineers' experience.

This paper carried an extensive review of the application of DD-DM in fault detection and diagnosis, and the advantages and limitations of FDD methods within the supervised/semi-supervised, unsupervised, and hybrid learning categories. Moreover, it concluded that the ability of the supervised learning approaches is limited in finding new and simultaneous faults in large-scale HVAC

Table 4
Advantages and limitation of main FDD methods.

Method	Advantages	Limitation
Model-based	1. works properly when a good HVAC physical model is available	1. It is not proper for large-scale and complex HVAC systems 2. The performance would be limited because of modeling and linearization error [34]
Knowledge-based	1. the detailed mathematical model is not needed available 2. Suitable for the system with a small number of inputs, outputs, and states	1. It highly relies on domain expertise while a wide range of faulty and failure cases are beyond engineers' experiences 2. Not capable of detecting novel failures which are not flagged in the historical data 3. Cannot work well for complex and large scale HVAC systems [47]
Data-driven	1. Less model development time and cost 2. No dependency on the model 3. Easy to retrain 4. Efficient use of system data 5. High accuracy 6. Good performance in works with large-scale and complex systems 7. minimizing cognitive errors which are beyond the engineers' knowledge	1. Need to collect the high quality and sufficient training data for supervised models 2. High dependency on the quality and the quantity of the collected data

systems. Furthermore, the synergetic effects of the faults cannot be detected with high accuracy. Unsupervised FDD methods, in which no prior knowledge of known/previously unknown faults are required, can address this issue of synergistic faults. However, post-mining steps of applied unsupervised methods are usually very time-consuming, and the earlier research demonstrated that unsupervised learning has rarely been applied to the cases involving online knowledge discovery in buildings. Thus, optimal results are obtained through the development of a methodology that combines both supervised and unsupervised learning approaches. An example of this combined approach is hybrid methods. Furthermore, literature shows that more efforts are needed to develop:

- reliable, fast, computationally affordable, and comprehensive solutions for detecting online faults in large-scale HVAC systems;
- online methods that can detect and diagnosis non-catastrophic novel faults occurrence in large-scale HVAC systems, and detect their synergetic effect with minimum false and missed alarms;
- accurate algorithms that consider data type and its distribution to choose the most appropriate feature selection method. Especially in large-scale HVAC systems with different types of data and a noticeable number of features that can be equally important for the task at hand.
- approaches that are flexible with renovations or exchange of HVAC mechanical system components without the need to retrain the model for the FDD process.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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