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Artificial intelligence-based fault detection and diagnosis methods for building energy systems: Advantages, challenges and the future

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ABSTRACT

Artificial intelligence has showed powerful capacity in detecting and diagnosing faults of building energy systems. This paper aims at making a comprehensive literature review of artificial intelligence-based fault detection and diagnosis (FDD) methods for building energy systems in the past twenty years from 1998 to 2018, summarizing the strengths and shortcomings of the existing artificial intelligence-based methods, and revealing the most important research tasks in the future. Challenges in developing FDD methods for building energy systems are discussed firstly. Then, a comprehensive literature review is made. All methods are classified into two categories, i.e. data driven-based and knowledge driven-based. The data driven-based methods are abundant, including the classification-based, unsupervised learning-based and regression-based. They showed powerful capacity in learning patterns from training data. But, they need a large amount of training data, and have problems in reliability and robustness. The knowledge driven-based methods show powerful capacity in simulating the diagnostic thinking of experts. But, they rely on expert knowledge heavily. It is concluded that new artificial intelligence-based methodologies are needed to be able to combine the advantages of both kinds of methods in the future.

1. Introduction

Buildings are responsible for approximately 39.8% of energy consumption in the United States [1], 40% in the European Union [2], and 20% in China [3]. In general, building energy systems are quite complex which consist of thousands of sensors, actuators, controllers and devices. They always suffer from various malfunctions and degradations which lead to uncomfortable indoor environment, poor indoor air quality, occupant complains and serious energy wastes. For instance, Qin and Wang found that 261 of 1251 variable air volume (VAV) terminals (20.9%) were ineffective in a commercial building located in Hong Kong [4]. Katipamula and Brambley estimated that poorly maintained, degraded, and improperly controlled equipment could contribute to 15%–30% of energy waste in commercial buildings [5]. Roth et al. found that thirteen key faults could waste about 4%–18% of the energy consumed by heating, ventilation and air conditioning (HVAC) systems, lighting systems and refrigeration systems in U.S. commercial buildings [6].

Building energy management systems (BMS) have been widely implemented in modern buildings. A large number of data are monitored from building energy systems in real-time. A question arises about how to improve building energy efficiency using the monitoring data. Monitoring-based commissioning was demonstrated to be one of the most effective ways [7]. Automatic fault detection and diagnosis plays a crucial role to reduce equipment downtime, energy penalty, and service costs in the monitoring-based commissioning. Fig. 1 summarizes the contribution of fault detection diagnosis (FDD) tools in the monitoring-based commissioning based on Mills' work [8].

In the last decades, a considerable amount of FDD methods have been developed for building energy systems, such as for economizers [9,10], chillers [11–16], air handling units [17–23], variable air volume terminals [24–29], and HVAC system level [30–35]. However, there is still a lack of reliable, affordable and scalable solution. It is important to recognize the major barriers. Katipamula and Brambley made a comprehensive literature review in 2005 [5,36]. They classified FDD methods into three subcategories, i.e. quantitative model-based methods, qualitative model-based methods and process history-based methods. The dominant methods relied on physical models. There were few studies about artificial intelligence-based methods at that time. In the last decade, there were more and more studies about artificial intelligence-based FDD, such as for air handling units [37–40], chillers [41–43], cooling/heating systems [44–47], variable refrigerant flow systems [48–51], and HVAC system level [52–56]. Although some literature reviews were published about air handling unit FDD [17],

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Abbreviation and nomenclature

ANN	Artificial neural network
BMS	Building energy management systems
EKF	Extended kalman filter
FDD	Fault detection and diagnosis
HVAC	Heating, ventilation and air conditioning
OCSVM	One-class support vector machine
PCA	Principle component analysis
RCMAC	Recurrent cerebellar model articulation controller
ROSVM	Recursive one-class support vector machine
SPE	Squared prediction error
SMDS	Smart monitoring and diagnostic system
SVDD	Support vector data description
SVM	Support vector machine
SVR	Support vector regression
VAV	Variable air volume
VRF	Variable refrigerant flow

building energy system FDD [57] and fault modeling [58], there is still a lack of comprehensive review about the artificial intelligence-based FDD methods. Therefore, this paper aims at making a comprehensive literature review of artificial intelligence-based FDD methods for building energy systems in the past twenty years from 1998 to 2018, summarizing the strengths and shortcomings of the existing artificial intelligence-based methods, and revealing the most important research topics in the future.

2. Challenges in developing FDD methods for building energy systems

It would be better to make clear the challenges in developing FDD methods for building energy systems first. FDD is usually a complex inference process to map the symptoms to faults. In most cases, one fault may result in multiple symptoms, and meanwhile different faults may result in similar symptoms. In the field of building energy system FDD, sensor faults and component faults were always treated separately because they have different natures. The term 'sensor FDD' refers to detect and diagnose faults in sensors, and the term 'component FDD' refer to detect and diagnose faults in controllers, controlled devices and equipment.

In the last decade, researchers have recognized that *incomplete information* and *uncertainty* are of the major challenges [59]. The term *incomplete information* refers to the lack of sensors, normal data, faulty data and physical parameters, which makes it difficult to develop physical models. The term *uncertainty* refers to measurement errors, probabilistic relations among symptoms and faults, as well as inaccurate knowledge. To be specific, challenges in diagnosing faults of building energy systems are as follows:

- There are generally few sensors equipped in building energy systems. Most building owners are very sensitive to initial costs. Only sensors essential for controls are installed. Actually, there are very few flow rate, pressure and power sensors which are relatively expensive. In most cases, existing sensors are insufficient for fault detection or/and diagnosis.
- Sensors are always of poor accuracy due to the limitations of initial costs and poor maintenance. The consideration of sensor faults with component faults together would increase the difficulty of FDD exponentially.
- Existing building automation systems are mainly developed for regular operations. Generally, a significant portion of measurements are utilized in controller level only. They are not uploaded to and saved in building automation systems. What is worse, operation data are often stored temporarily. Therefore, long-term historical data of sufficient variables are always unavailable. Also, historical data are often not complete due to network communication failures etc.
- Some faults could be propagated by control loops, which lead to complex relationships between faults and symptoms. For instance, if the supply air temperature sensor in an AHU has a positive bias, the fault will be propagated to the cooling coil. The openness of cooling coil valve will be larger to maintain the measurements of supply air temperature at its set-point.
- Building energy systems are generally equipped with a large amount of sensors, controllers, controlled device and equipment from various manufactories. There is a lack of standardized sensor installments and control logics. It is much more difficult to develop general FDD methods [60].

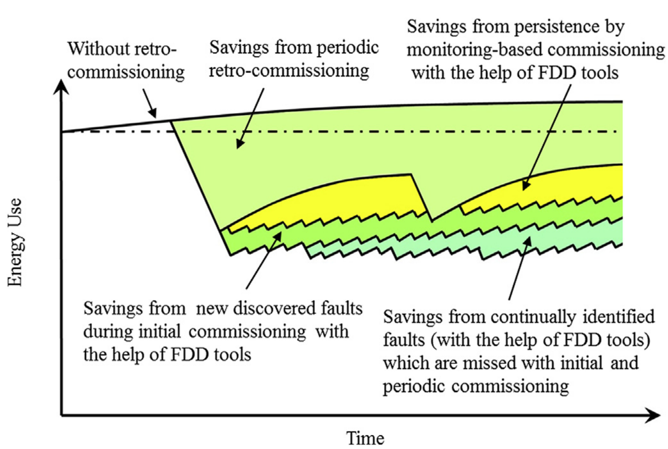

Fig. 1. The role of FDD tools in monitoring-based commissioning (inspired by Mills [8]).

In summary, it is still a difficult task to develop reliable, affordable and scalable FDD tools for building energy systems. To overcome the challenge of *incomplete information*, the most effective way is to introduce prior knowledge such as first principles and expert experience. To overcome the challenge of *uncertainty*, it is very important to handle the problem of uncertainties properly in the mathematic descriptions of diagnostic information and the inference processes.

3. Classifications of building energy system faults and FDD methods

In general, a FDD method has two parts, i.e. fault detection and fault diagnose. Fault detection is to check whether a fault has occurred. Fault diagnosis is to identify the type of a fault and its location. Some methods can handle the two parts simultaneously, such as most of the data driven-based methods. Some methods can detect faults only such as regression-based methods (Section 4.3). Some methods can diagnose faults only such as Bayesian networks-based methods (Section 5.1). Therefore, some methods should combine the two parts in sequence, such as most of the knowledge driven-based methods. It is reasonable to discuss fault detection methods and fault diagnosis methods separately.

3.1. Fundamental fault detection methods

Specified to the field of building energy systems, fault detection methods can be classified into two subcategories: data driven-based and knowledge driven-based, as shown in Fig. 2.

The classification in Fig. 2 mainly depends on the nature of domain knowledge used in the development of fault detection methods.

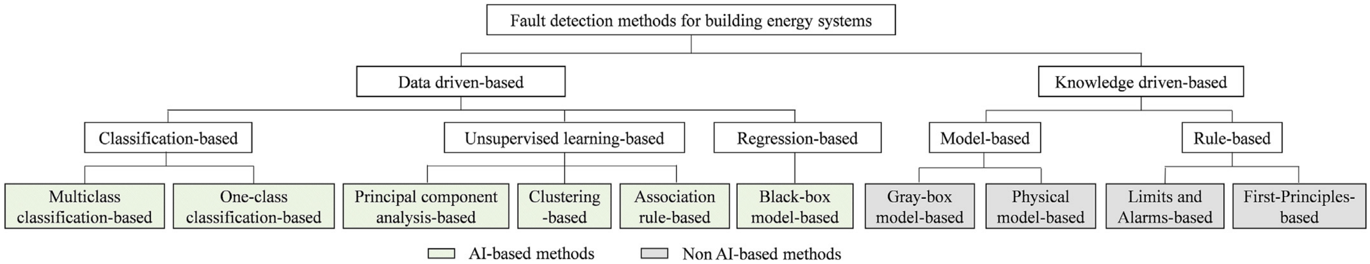

Fig. 2. Classification of the fault detection methods for building energy systems.

Methods in the knowledge driven-based subcategory rely heavily on domain knowledge. Every fault detection rule or model is developed based on prior knowledge which generally has clear physical meanings. On the contrast, methods in the data driven-based subcategory do not use fault detection rules or models. They detect faults through finding the changes of patterns in the measurements of selected variables. Patterns are extracted using data driven algorithms automatically which do not have any physical meanings in most cases. The knowledge driven-based methods had been dominant in the field of building energy system FDD from 1980s to around 2005 [5]. The data driven-based methods started from the end of 1990s and became more and more popular in the last decade.

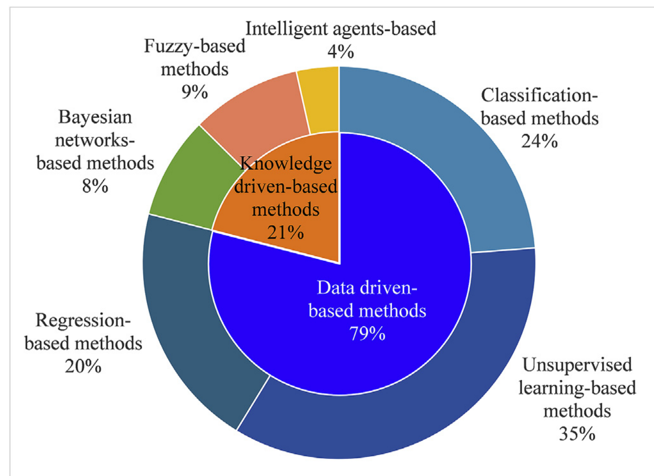

Fig. 4. Classifications of the papers about the artificial intelligence-based FDD methods for building energy systems by categories.

3.2. Fundamental fault diagnosis methods

Fault diagnosis methods can also be classified into two major subcategories: knowledge driven-based and data driven-based, as shown in Fig. 3.

The classification mainly depends on the nature of the domain knowledge and the nature of inference approaches introduced in fault diagnosis methods. Methods in knowledge driven-based subcategory simulate the diagnostic thinking of domain experts. On the contrast, methods in data driven-based subcategory mainly rely on the similarities of patterns. In the recent years, there are more and more studies about data driven-based diagnosis methods in the building energy system field with the growth of artificial intelligence.

It is worth noting that detection methods of the knowledge driven-based subcategory in Fig. 2 can work with any fault diagnosis methods of the knowledge driven-based subcategory in Fig. 3 in principle. However, for the data driven-based category, a fault diagnosis method should be of the same kind as the fault detection method. For instance, a one-class classification-based fault diagnosis method in Fig. 2 works with a one-class classification-based fault detection method in Fig. 3 only [61].

3.3. Summary of the literature

A comprehensive literature survey is made using all available search engine such as Web of Science (www.webofknowledge.com), Scopus (https://www.scopus.com) and google scholar (http://scholar.google.com/). Various combination of keywords are utilized including fault, detection, diagnosis, HVAC, building, energy system, chiller, air handling unit, etc. Besides, references of every paper are also checked manually to find new papers which are related to this topic. Finally, 135 papers are found where were published in the last twenty years from 1998 to 2018. The classifications of these papers are as shown in Fig. 4. Most papers were about the data driven-based methods (79%). Few papers were about the knowledge driven-based methods (21%).

Fig. 5 shows the distribution of artificial intelligence-based FDD publications in the past 15 years. In recent year, more and more studies focused on developing FDD methods using artificial intelligence algorithms, especially data driven-based methods.

As shown in Fig. 6, some papers were about component level FDD, such as AHU FDD, chiller FDD, and heat pump FDD. The other papers were about system level FDD methods, such as cooling/heating system FDD, VAV system FDD, variable refrigerant flow (VRF) system FDD, HVAC systems FDD, and building system FDD.

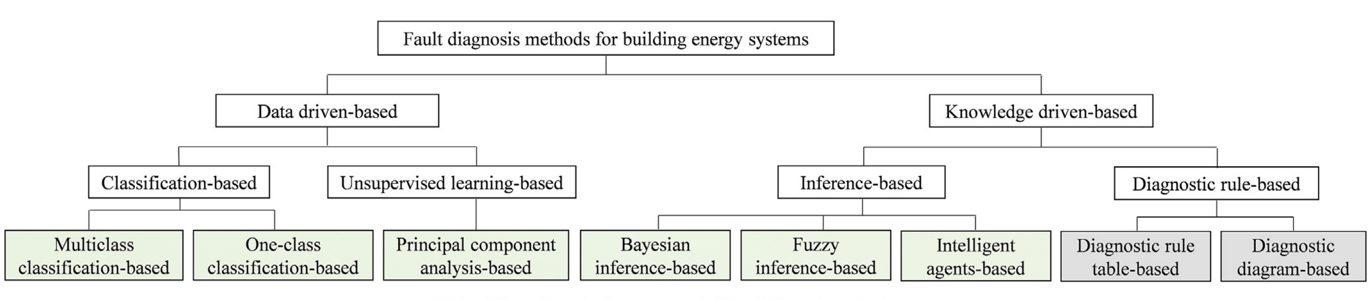

Fig. 3. Classification of the fault diagnosis methods for building energy systems.

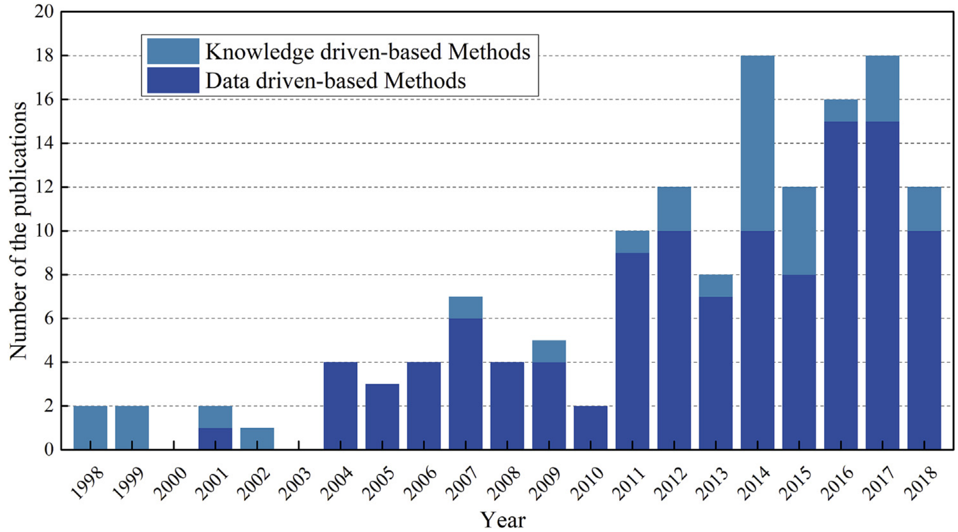

Fig. 5. Distributions of the papers about the artificial intelligence-based FDD methods for building energy systems from 1998 to 2018.

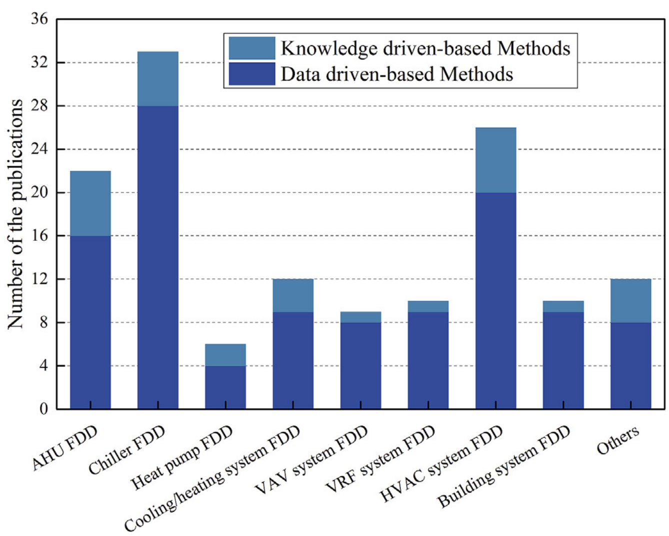

Fig. 6. Classifications of the papers about the artificial intelligence-based FDD methods by targets.

4. Data driven-based methods

Machine learning is a field of computer science that gives computers the ability to learn without being explicitly programmed. A fault detection/diagnosis problem in building energy systems can also be regarded as a pure machine learning problem. With sufficient training data, the task of fault detection is to distinguish whether the patterns of monitoring data are similar to those of the normal training data. The task of fault diagnosis is to determine which fault class the monitoring data is the most similar to. In this way, the field of building energy system FDD can benefit from the powerful algorithms from machine learning field. The data driven-based methods can extract patterns for FDD automatically. Therefore, they need limited prior knowledge. As shown in Fig. 7, the data driven-based FDD methods can be further classified into classification-based (30%), unsupervised learning-based (44%) and regression-based (26%).

4.1. Classification-based methods

In machine learning, classification is the task of identifying which fault class a new monitoring data belong to. Similarly, fault detection can be considered as the task of identifying whether the monitoring data belong to the normal class or not. Given each set of data measured in various fault conditions as an individual class respectively, fault diagnosis can be considered as the task of identifying which fault class the monitoring data belong to. The classification-based FDD can be further classified into two subcategories, i.e. multiclass classification-based and one-class classification-based.

4.1.1. Multiclass classification-based methods

Multiclass classification-based FDD is to classify a series of sampling data into a set of the classes which includes a normal class and several fault classes. Both fault detection and fault diagnosis are processed at the same time. A general scheme of multiclass classification-based FDD methods is as shown in Fig. 8. In the model training process, a multiclass classifier is trained using training data set including normal data and faulty data. In the online FDD process, the monitoring data are classified by the trained multi-class classifier. The classifier can tell which class the data belong to. The multiclass classification-based methods can also be further classified into two subcategories, i.e. support vector machine-based and artificial neural networks-based.

4.1.1.1. Support vector machine -based methods. Support vector machine

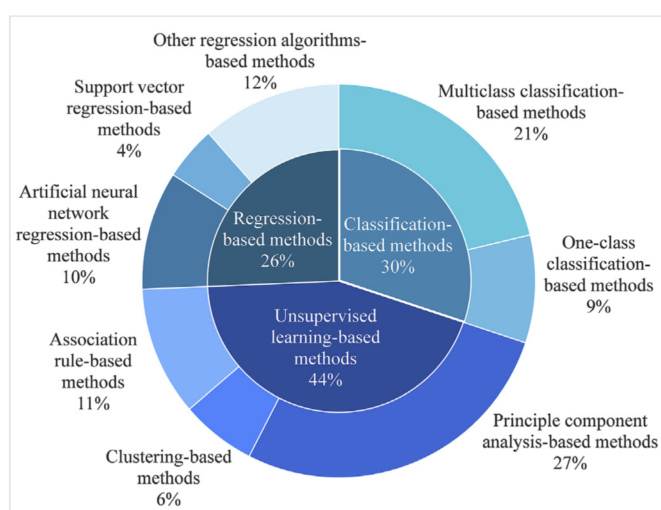

Fig. 7. Classifications of the papers about the data driven-based FDD methods for building energy systems by categories.

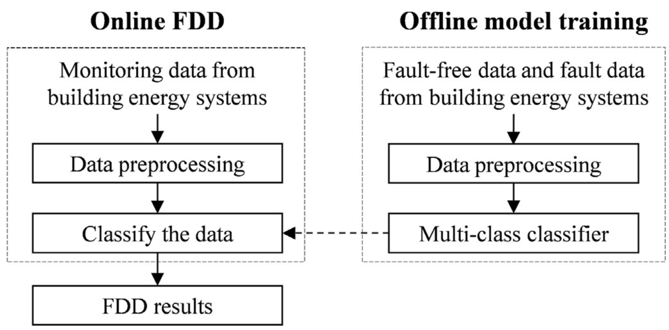

Fig. 8. A general scheme of the multiclass classification-based FDD methods.

(SVM) is based on the structural risk minimization principle rooted in the statistical learning theory [62]. Fig. 9 shows a simple illustration of *One vs One SVM-based* FDD methods. In the training process, an optimal hyperplane in a higher dimensional feature space is found which maximizes the margin between the data of a fault class with these of the others. In the FDD process, the hyperplane determine whether the monitoring data belong to the fault class or not.

Liang and Du developed a multi-layer SVM-based FDD method for chillers [63]. The first SVM classifier was used to detect whether a fault occurred or not. If not, a set of SVM classifiers, which were trained for classifying each fault respectively, were processed one by one in sequence to isolate the fault. Evaluations were made on a lumped simulation platform. The method was effective to diagnose the faults of recirculation damper stuck, cooling coil fouling/block and supply fan speed decreasing. Dehestani et al. extended Liang and Du's work by training SVM classifiers incrementally using online monitoring data [64]. Han et al. developed a SVM-based FDD method for water-cooled centrifugal chillers [65–67]. The method achieved 95% correct ratio of fault diagnosis for all seven typical chiller faults on ASHRAE RP-1043 data set.

Data preprocessing can improve the FDD performance of multiclass classification-based method. Han et al. introduced PCA to preprocess data for the SVM-based chiller FDD method [68]. Yan et al. introduced an auto-regressive model with exogenous variables algorithm to construct a high dimensional parameter space before training the SVM classifier for chiller FDD [69]. Dehestani et al. utilized artificial neural network to generate residuals firstly, and trained SVM classifier based on the residuals [70]. Sun et al. combined wavelet de-noising algorithm to improve the performance of SVM-based FDD method for multi-split variable refrigerant flow systems [71]. Yan et al. employed a back-tracing sequential forward feature selection algorithm to select the most important features before training the SVM-based chiller FDD model [72].

4.1.1.2. Artificial neural network classifier-based methods. Artificial neural network (ANN) classifier is a supervised multi-classifier composed of one input layer, one or more hidden layers and one output layer. Each layer contains several nodes named artificial neurons which are connected with other nodes in adjacent layers. Each connection has a weight that adjusts as model training process to minimize the difference between the targets and the outputs. Fig. 10 showed a four-layer artificial neural network classifier for fault detection and diagnosis.

Lee et al. introduced artificial neural network to learn the relationships among the dominant symptoms and the faults for air handling unit fault diagnosis [73]. Zhou et al. developed fuzzy models to quantify the residuals of key chiller performance indices under various fault conditions. Based on the fuzzy models, they trained artificial neural network models to diagnose chiller faults [74]. Sun et al. employed independent component analysis to reduce the original data amount firstly, and then trained a back-propagation neural network for variable refrigerant flow system FDD [75]. Similarly, Kocyigit developed a fuzzy inference system to detect sensor faults firstly. Based on the outputs of the fuzzy inference system, an artificial neural network was trained to diagnose faults in a vapor compression refrigeration system [76]. He et al. developed a hierarchical adaptive resonance theory-based neural network to detect faults in solar hot water systems [77,78]. Magoulès et al. proposed a recursive deterministic perceptron neural network-based method for the building energy system level FDD [79]. Guo et al. trained a deep belief network to diagnose faults in variable flow refrigerant system [80]. They found that the FDD performance would not be improved much using more layers.

In general, possible faults in building energy systems are numerous. For instance, ASHRAE Project 1043-RP reported that a typical water-cooled centrifugal chiller has more than twenty types of common faults [81]. ASHRAE Project 1312-RP reported that a typical air handling unit has 68 types of common faults [82]. It is very costly to get sufficient training data for every faults. Generally, only eight types of chiller faults were took into account in most of data driven-based chiller FDD methods. Most of multiclass classification-based methods classify monitoring data into one of the known fault classes only, such as the SVM-based and the ANN-based. They shall report wrong FDD results definitely if a new type of fault existed, as discussed by Khan and Madden [83].

4.1.2. One-class classification-based methods

One-class classification algorithms show advantages in avoiding the misclassification problem of the multiclass classification-based methods in principle. They are able to identify data of a specific class amongst all data, by learning from a training set containing only the data of that class. The task of fault detection is to detect whether the monitoring data belong to the normal class. Similarly, the task of fault diagnosis is to find which fault class the data belong to. One-class classification-based methods could be more reliable compared with the multiclass classification-based methods. Generally, normal data are sufficient but faulty data are rare in the field of building energy systems. The one-class classification-based methods show advantages in developing fault detector using normal data only. If faulty data are available, one-class classifiers can be trained for each types of faults respectively for fault diagnosis. Therefore, each classifier can diagnose a specific fault only.

A general schema of the one-class classification-based methods is as shown in Fig. 11. In the training stage, one-class normal classifier and fault classifiers are trained respectively. The normal classifier can detect whether a fault exists. The fault classifiers determine the fault type. The one-class classification-based methods can also be further classified into two subcategories, i.e. support vector data description-based and one-

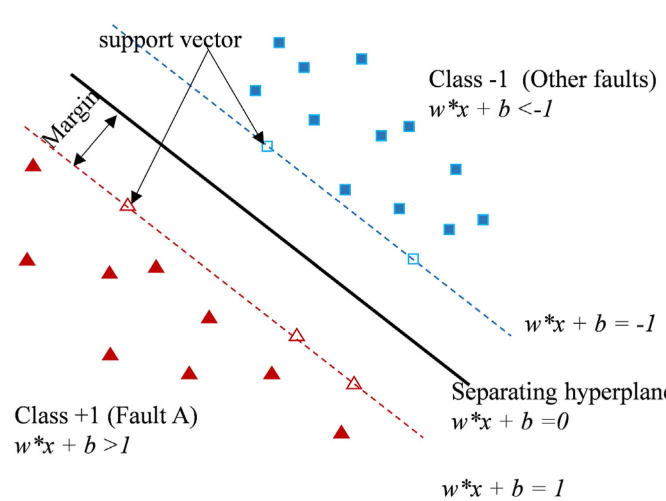

Fig. 9. Illustration of a support vector machine-based fault detection and diagnosis method.

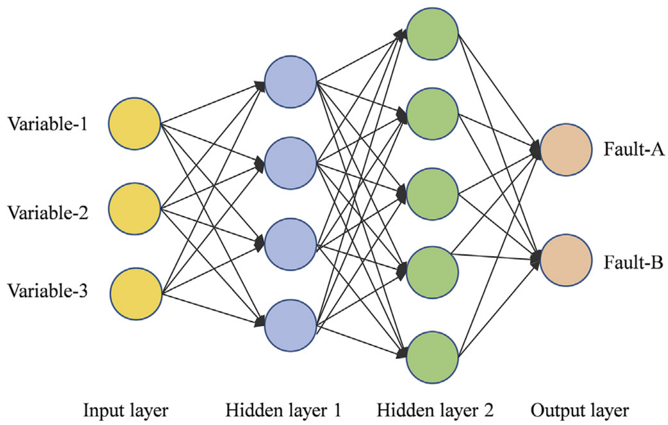

Fig. 10. Illustration of the artificial neural network-based fault detection and diagnosis methods.

class support vector machine-based.

4.1.2.1. Support vector data description-based methods. Support vector data description (SVDD) is a typical one-class classifier algorithm [84]. The basic idea of SVDD is to find a minimum-volume hypersphere in high dimensional space to enclose most of the objects. An illustration of SVDD sketch map in two dimensions is as shown in Fig. 12. Given Fault A is the target class, a hypersphere is trained to contain most of training data of Fault A, and keep most of the training data which do not belong to Fault A outside of the hypersphere.

Zhao et al. trained a SVDD-based fault detector for a centrifugal chiller using historical normal data [61,85]. Evaluation results showed that the method improved fault detection capacity significantly. It could detect incipient faults including condenser fouling, reduced evaporator water flow rate and refrigerant leakage, which were challenging for other fault detection methods. Zhao et al. further proposed a SVDD-based method to diagnose centrifugal chiller component faults [86]. Li et al. introduced SVDD for screw chiller sensor FDD [87]. A distance variation-based contribution plot was employed to diagnose sensor faults. Gu et al. found that the density distribution of training data in operating condition space was a determining factor in the false alarm rate of the SVDD-based method [88]. They developed a density weighted SVDD-based method for chiller fault detection with a consideration of density distribution. Evaluation results showed that the method can reduce the false alarm rate by about 30% on the RP-1043 data set. Li et al. developed the SVDD model in the residual subspace of the principle component analysis modeling residual data [89,90]. The method was demonstrated to be much more sensitive to the incipient centrifugal chiller faults.

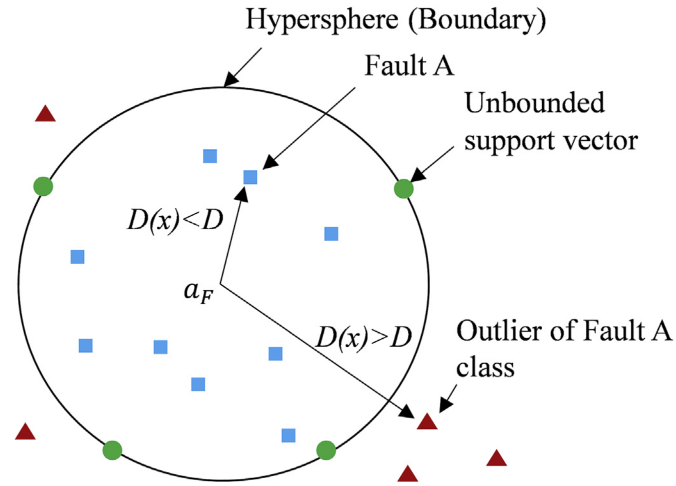

Fig. 12. Illustration of SVDD sketch map in two dimensions for FDD.

4.1.2.2. One-class support vector machine-based methods. The basic idea of one-class support vector machine (OCSVM) is to find a hyperplane to separate data of a class from data of the others with maximum margin in the higher dimensional feature space. The OCSVM-based methods are not different from the SVDD-based ones for the purpose of FDD.

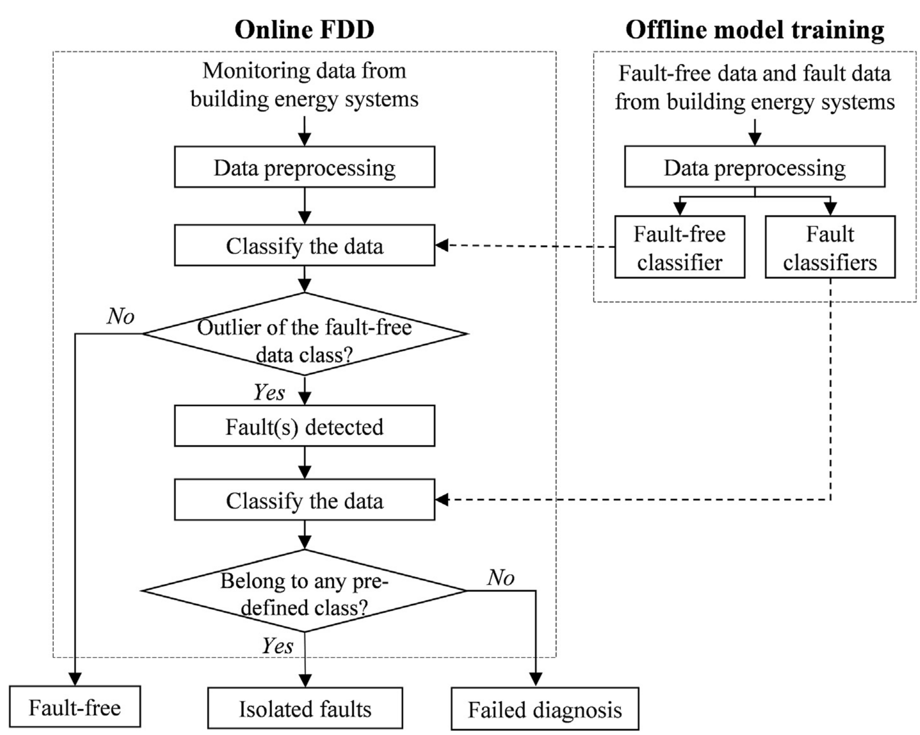

Fig. 11. A general schema of the one-class classification-based FDD methods.

Beghi et al. developed a PCA and OCSVM-based fault detection method for centrifugal chiller [91]. The data were preprocessed using PCA to discard the variability related to usual operating conditions changes. The OCSVM algorithm was used to train a fault detector. Yan et al. developed a chiller fault detection method by combining extended kalman filter (EKF) and recursive one-class support vector machine (ROSVM) [92]. The EKF was used to preprocess data. The ROSVM refines the hyper-planes in high dimension by absorbing normal training data. Results showed that the method had significantly higher detection rates with less feature variables.

4.2. Unsupervised learning-based methods

4.2.1. Principle component analysis-based methods

Principle component analysis (PCA) is one of the most popular algorithm in the field of building system FDD. It transforms a group of correlated variables into a new group of variables which are uncorrelated or orthogonal to each other. An illustration of the PCA-based fault detection method is as shown in Fig. 13. It classifies the measuring space into two orthogonal subspaces named principal component subspace and residual subspace. They represents normal condition and faulty condition respectively. Fault detection is carried out with the help of the Hotelling's T^2 and Q-statistic, also known as the squared prediction error (SPE). Fault diagnosis can be realized by using the Q-statistic and Q-contribution plot.

The PCA-based methods had been applied in the air handling unit sensor FDD [93–98], variable air volume system sensor FDD [99–105], variable refrigerant flow system FDD [106–108], heat pump component fault detection [109,110], chiller sensor FDD [111–114] and component FDD [115], system level sensor FDD [116–120] and so on. Wang and Xiao proposed a PCA-based sensor FDD method for air handling units [94,95]. Sensor faults were detected using the *Q*-statistic. The faults were further diagnosed using *Q*-contribution plot supplemented by simple expert rules. Evaluations showed that the method was effective to detect and diagnose sensor faults of air handling unit under various operating conditions. Xiao et al. further improved the method using a condition-based adaptive scheme to overcome the shortcomings of the time-based adaptive scheme [116]. It showed improvements in detecting slowly developing faults. Yu et al. proposed a PCA-based fault detection method for the sewage source heat pump system [109]. Chen and Lan found that the PCA-based fault detection method is effective to detect component faults in air-source heat pump water chiller and heaters [110]. Wang and Cui developed two PCA models to capture the correlations among the major measured variables in centrifugal chillers [111]. Du et al. combined T^2 and *SPE* to isolate the faults of monitoring-type and controlling-type sensors in vapor compression systems [119].

Researchers also recognized the shortcomings of the PCA-based methods gradually. Zhao et al. found that the SVDD-based method had better FDD performance than the PCA-based method for centrifugal chiller component faults [61,85]. They pointed out that the Gaussian distribution and linear assumptions of the PCA algorithm were the main reasons. Li and Hu found that the PCA-based method was not good in sensor FDD under a wide range of screw chiller operation conditions [113]. Due to the pure data-driven nature, the PCA-based sensor FDD methods cannot avoid false diagnosis when component faults occur or in the cases that the sensors are adopted in control loops.

4.2.2. Clustering-based methods

Clustering algorithm divides measurements concerned into several clusters according to the geometric distances between them. Data in a cluster have similar statistical characteristics. Data in different clusters have quite different statistical characteristics. In general, the statistical characteristics of faulty data are different from that of normal data. They should belong to different clusters.

House et al. utilized c-means clustering algorithm to group the operational data of an air-handling unit into three clusters, i.e., normal, unknown and faulty [121]. Zogg et al. found several clusters of faults in heat pumps using clustering methods [122]. Du et al. introduced subtractive clustering analysis to find the clustering centers of normal data and faulty data of various type respectively [123]. Therefore, the method could also screen out the unknown faults. Capozzoli et al. proposed a fault detection method using a density-based clustering algorithm for office buildings [124]. They found that the method was effective in putting all the faulty data into an individual cluster. Li and Hu also used a density-based spatial clustering of applications with noise method to recognize the corresponding operation conditions [113]. Wall et al. adopted the agglomerative clustering algorithm to group the calculated fault detection indicators into normal cluster and faulty cluster [125]. Narayanaswamy et al. introduced clustering algorithm to detect the control loop configuration faults of HVAC systems [126]. Chen and Wen employed a symbolic aggregate approximation approach to cluster days with similar weather patterns in historical database, based on which a PCA model was trained to detect building system faults [127].

4.2.3. Association rule-based methods

Association rule algorithm is powerful in discovering relations between various measurements. The discovered relations could reveal the system operation patterns. But, it needs domain experts further analyze the patterns for fault detection [128]. Yu et al. proposed an association rule mining-based method to discover abnormal occupant behavioral patterns using the end-use power consumption data [129]. Yu et al. further compared the association rules extracted from two different periods of a VAV air-conditioning system. Based on the extracted rules, they discovered some operation faults and component faults manually [130]. Similar works can also be found in the detection of abnormal energy usage in building lighting systems [131], faults in variable refrigerant flow systems [132] and operation faults in district heating substations [133]. Xiao et al. [134] and Fan et al. [135] proposed building operation data mining frameworks for discovering abnormal operations in building energy systems. The frameworks showed powerful capacity in detecting abnormal building operations and faults [135,136].

Recently, researchers realized that dynamic relations were helpful in detecting temporal and gradual anomalies. Fan et al. proposed a temporal association rule mining method to detect temporal anomalies [137]. They further proposed a gradual pattern mining method to

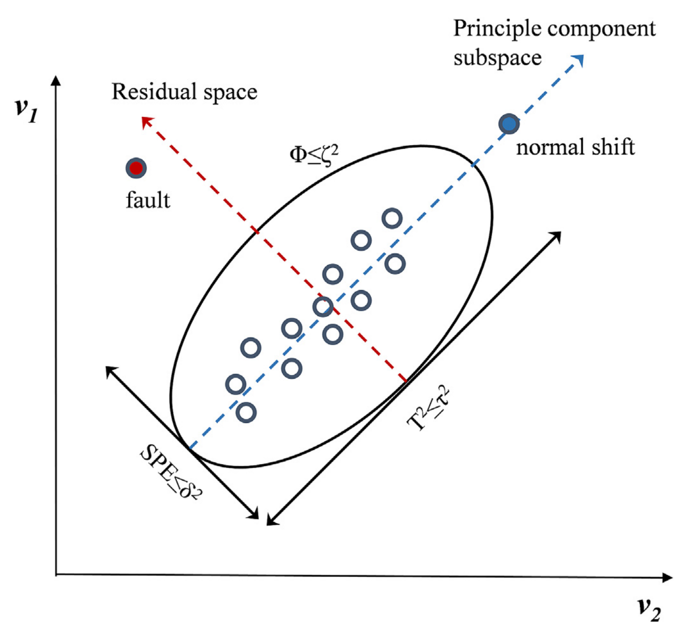

Fig. 13. Illustration of the PCA-based fault detection method.

detect gradual anomalies [138].

4.3. Regression-based methods

Regression-based methods become more and more popular in developing benchmarking models for fault detection. There are two types of regression models, i.e. gray box models and black box models. Gray box models combine a partial theoretical structure from prior knowledge with data to complete the models. Black box models do not rely on any physical/scientific laws and prior knowledge. The regression-based FDD can be further classified into three subcategories, i.e. artificial neural networks-based, support vector regression based and other regression-based. Fig. 14 illustrates the flow chart of the regression-based fault detection.

4.3.1. Artificial neural network regression-based methods

Artificial neural network also can be applied to build a regression model. Different form the artificial neural network classifier, the output of an artificial neural network regression model is a continuous variable such as energy consumption, temperature and so on. Wang and Jiang trained a recurrent cerebellar model articulation controller (RCMAC) neural network to monitor the performance degradation of valves in air handling units [139]. Lee et al. utilized the general regression neural-network algorithm to regress a set of benchmarking models respectively for air handling unit fault detection [140]. Each benchmarking model was sensitive to one or more faults, including a supply-air temperature control model, a mixed-air temperature control model, and a static-pressure control model. Evaluation showed that the method could detect abrupt faults and performance degradation faults in air handling units effectively. Mavromatidis et al. trained an artificial neural network to predict the energy benchmarking values for abnormal detection of supermarket energy consumption [141]. Du et al. introduced a dual-neural-network structure to improve fault detection capacity [123]. A basic neural network was regressed using a back-propagation neural network to predict the supply air temperature of an air handling unit. Based the model, they found that the return water temperature is the most relevant variable to the basic neural network. An auxiliary neural network model was trained to predict the return water temperature. PCA was utilized to calculate weights to combine the two neural networks together. Du et al. trained neural networks for detecting sensor faults in ventilation systems based on the data decomposed by three-level wavelet [142–144]. Similar work can also be found from Fan et al. [145] and Zhu et al. [146]. Yan et al. introduced the back-propagation neural network algorithm to predict the performance of ground source heat pump system [147]. Tran et al. reported that radial basis function-based regression models had better performance than multiple linear regression-based and Kriging-based [148]. Swider et al. also found that the generalized radial basis function neural network had good performance in chiller performance prediction [149].

4.3.2. Support vector regression-based methods

Support Vector Regression (SVR) is derived from the SVM for regression [150]. Its basic idea is to find a hyperplane which maximizes the margin and minimize the errors which are outside of the margins. Zhao et al. proposed a SVR-based FDD method suitable for the detection and diagnosis of centrifugal chiller faults at low severity levels [151,152]. The SVR was adopted to develop a reference performance index model for calculating the benchmarks of the performance indexes. Then the residuals between the current performance indexes and benchmark values were calculated to detect the faults. Based on this work, Tran et al. further utilized the least squares SVR, a reformulation of SVR with better generalization performances, to develop the reference performance index model of chillers [153].

4.3.3. Other regression algorithms-based methods

Van Every et al. utilized the Gaussian process regression algorithm to estimate air handling unit sensor measurements [154]. The algorithm can offer a posterior distribution over the prediction rather than a prediction only. Therefore, it is possible to compute the prediction error and its variance. The ratio between the error and its standard deviation, as well as the inputs of the regression model, are then fed into a one-class SVM classifiers for fault detection. Wang et al. employed the kernel-based partial least square algorithm for fault detection and performance tracking of a heat exchanger [155]. Karami and Wang introduced an adaptive Gaussian mixture model regression method to estimate benchmarking values of a system performance index [156]. It was integrated with an Unscented Kalman filter to adjust the parameters of the model. Chung proposed a fuzzy linear regression-based method to generate benchmarking value of the energy efficiency of commercial buildings [157]. Similar works could be found in Ref. [158]

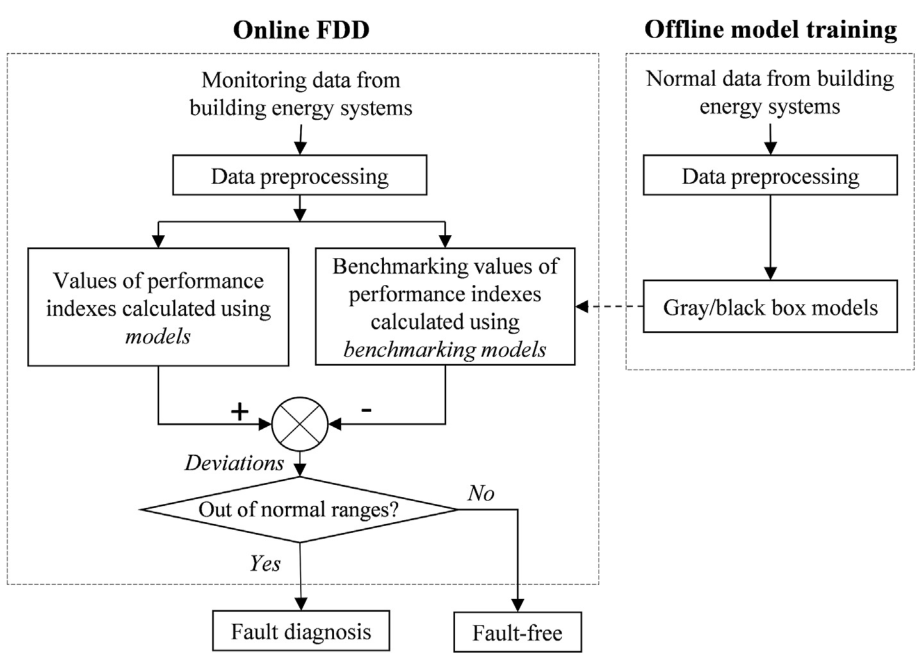

Fig. 14. Illustration of the regression-based fault detection methods.

using a recursive least-squares-based algorithm.

4.4. Discussions

4.4.1. Strengths of the data driven-based methods

In summary, based on the above analysis, we can conclude that the data driven-based methods have the following strengths:

- They do not require a deep understanding of the causal relationships among faults and symptoms of the building energy systems. They do not need physical models since they can learn patterns from data automatically. Therefore, it would be simple to implement the data driven-based methods.
- They generally have higher fault detection and fault diagnosis accuracy than the knowledge driven-based methods. They are very sensitive to the changes of patterns in monitoring data. Therefore, they can also detect and diagnose faults of low severity levels.
- They can still work even if some crucial variables are missing. It is because patterns from the measurements of limited variables could be still distinguishable to isolate faults. It also can reduce the amount of required sensors significantly though the optimisation of sensor installations.
- They can benefit from the field of artificial intelligence which is growing rapidly with a bright future. Most of artificial intelligence algorithms are open sourced with a wealth of documented information. Developers can focus on the applications of the algorithms rather than coding the algorithms themselves.

4.4.2. Shortcomings of the data driven-based methods

Based on the above analysis, we can conclude that the data driven-based FDD methods have the following shortcomings:

- They need a large amount of labeled faulty data for training diagnosis models. However, it is quite costly to get faulty data. For instance, in ASHRAE Project 1312-RP, it cost a year to conduct faults and measure faulty data of 19 types of air handling unit faults in laboratory. Even so, the data did not cover a wide range of operating conditions. In practices, it is almost impossible to conduct so many faults in real building energy systems widely. It is also unrealistic for manufactories because the combination number of fault types and operating conditions is quite large. Even so, it is still doubtful that whether machine learning models trained from an equipment/system can work well in others.
- They cannot extrapolate beyond the range of training data. A serious problem is that, most faults actually could be at a wide range of severity levels from slight severity levels to serious severity levels. In principle, machine learning models trained using faulty data of a certain severity level could not diagnose the same fault at other severity levels. Another serious problem is that, generally building energy systems work under quite wide operating conditions. In general, training data cannot cover all operating conditions. Data driven-based methods could not be able to detect new operating conditions, or be robust to new operating conditions.
- They could not provide more meaningful information other than fault detection and fault diagnosis results only. Technicians cannot understand the reasons or mechanisms based on the results, which are essential for them to make further decisions.
- The reliabilities of data driven-based methods are still doubtful. The models are trained to have the best performance on training data set. There are no effective approach to detect the over-fitting problems. Therefore, the performance of models is not guaranteed in practical applications. They would alarm faults in the cases of normal performance degradations/changes, regular maintains and component replacements. But, they cannot tell the reasons behind the results for further analysis.

4.4.3. Discussions about the existing studies

In the field of building energy systems, studies about the data driven-based FDD methods are still in an early stage. Here are common problems of the existing studies:

- Generally, the evaluations were inappropriate and not rigorous. The evaluation approaches of most data driven-based methods were employed from artificial intelligence field directly. But researchers ignored the characteristics of the FDD problems in building energy system filed. A major characteristic is that the training data cannot cover all possible cases. However, in existing studies, training data and test data were randomly selected from the same data set. It was not possible to distinguish whether the excellent FDD performance was obtained through over-fitting or not. What is worse, most of the existing methods were evaluated using simulation data or experimental data only. It is not reasonable to conclude that the same performance can be obtained in practical applications.
- There is a lack of reliable and effective approaches to tune model parameters for developing building energy FDD models. Almost all parameters of machine learning algorithms do not have any physical meanings. In the existing studies, the parameters were optimized to get the best performance on test data and training data. It is doubtful that the models could have an acceptable generalization capability in practical applications for building energy system FDD.
- Too much attentions were paid on introducing much more powerful artificial intelligence algorithms. Although there were a lot methods, the methodologies of them were very similar. Few attentions were paid on how to improve the methodologies based on a deep understanding of the nature of building energy system FDD process.

5. Knowledge driven-based methods

Experts can detect and diagnose faults more effectively and reliably than most of the existing FDD methods, especially in the cases that diagnostic information is incomplete and uncertain. Researchers realized that the major reason was that experts had sufficient prior knowledge and powerful inference capacity [159]. Therefore, simulating the diagnostic thinking of experts became another way to solve the FDD problems in the last decade.

Compared with the data driven-based methods, the knowledge driven-based methods rely on prior knowledge heavily. Experts play a crucial role in the development of knowledge driven-based methods since the models cannot be developed automatically. Compared with the conventional knowledge driven-based FDD methods, the artificial intelligence-based ones introduce intelligence approaches to describe prior knowledge and to reason with the prior knowledge and facts. They show advantages in fully utilizing all kinds of diagnostic information to overcome the problem of incomplete information. A variety of information resources besides sensor measurements are helpful for fault diagnosis, e.g. maintenance records, status of related equipment, and even expert experiences. The knowledge driven-based methods also show advantages in powerful capacity in probabilistic reasoning and fuzzy reasoning to overcome the problem of uncertain information. As shown in Fig. 15, the knowledge driven-based methods can be further classified into Bayesian networks-based (40%), fuzzy-based (42%) and intelligent agents-based (17%).

5.1. Bayesian networks-based methods

Bayesian network is a probabilistic graphical model that represents the relationships of probabilistic dependence within a group of variables [160]. A Bayesian network is defined by two components, i.e., structure and parameters. Specified for fault diagnosis, the structure of a Bayesian network is a graphical and qualitative illustration of the relations among the faults and symptoms. The parameters of a Bayesian

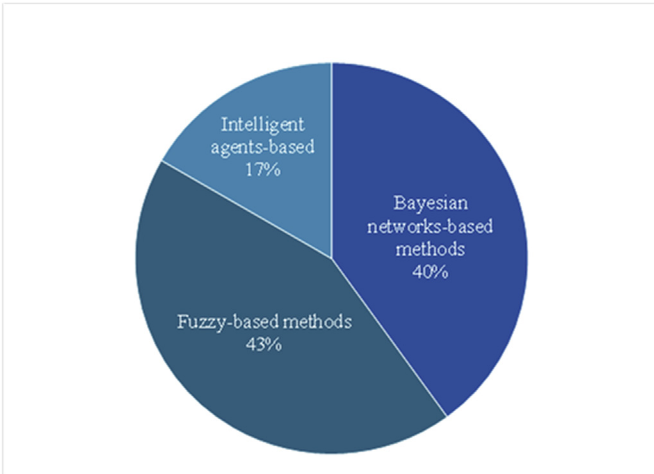

Fig. 15. Classifications of the papers about the artificial intelligence and knowledge driven-based methods for building energy systems by categories.

network represent the quantitative probabilistic relationships among the faults and symptoms. It is a powerful tool to represent and to reason about complex systems with uncertain, incomplete and even conflicting information. Both structure and parameters can be determined depending on prior knowledge or learning from training data.

Zhao et al. proposed a general Bayesian networks-based fault diagnosis method which was mainly based on prior knowledge [59]. Each Bayesian network had three layers, including an additional information layer, a fault layer and a symptom layer, as shown in Fig. 16. The additional information layer made it possible to take factors that affected the probabilities of faults into considerations, such as the repairing service, abnormal operation records and routine maintenances. The structures were developed manually according to the causal relationships. Noisy-MAX was introduced to reduce the number of parameters needed to be estimated. Evaluations were made on centrifugal chiller FDD. Results showed that the method was still powerful in the cases that diagnostic information was incomplete, uncertain and conflicting. There were similar FDD methods for variable air volume terminal [161], ground-source heat pump [162] and air handling unit [163,164].

The parameters can also be learned from training data. Wang et al. integrated PCA with Bayesian networks for chiller sensor fault detection. The score matrixes in the residual subspace decomposed by PCA were introduced to train the conventional probabilities [165]. Liu et al. introduced the back-propagation neural network to impute the missing data firstly, and then learnt the parameters of Bayesian networks using the maximum likelihood estimation algorithm, for fault diagnosis of solar assisted heat pump systems [166].

Bayesian networks can also work as a classifier. He et al. developed a Bayesian network-based multiclass classifier for chiller FDD [167]. The Bayesian networks had a class node in which every state presented a type of fault, except of a state which presented the normal case. The conditional probability distributions among the class node and symptom nodes were learned from the training data using the maximum likelihood estimation algorithm. The FDD results depended on the posterior probabilities of every state in the class node. Wang et al. further merged a distance rejection approach into Bayesian network to identify new types of faults [168], and developed a feature selection approach to reduce the amount of sensors needed [165]. Wall et al. utilized dynamic Bayesian network to learn the behaviours of air handling units under faulty and normal operation conditions [125]. Similarly, Najafi et al. formulated FDD as an estimation of the posterior distribution of a Bayesian probabilistic model. They trained statistic Bayesian networks based on normal and faulty data of air handling units [169]. Compared with SVM-based and ANN-based methods, the method showed advantages in having clear physical meanings in the structure and parameters of Bayesian networks. Therefore, it is possible to merge prior knowledge into the trained Bayesian networks.

5.2. Fuzzy-based methods

Fuzzy rules are usually utilized within fuzzy logic systems to reason about output variables according to input variables. They are usually in the form of “IF-THEN” statement. They could be used for fault diagnosis so long as the outputs of the fuzzy rules are faults and the inputs of the fuzzy rules are symptoms.

Dexter and Ngo developed a multi-step fuzzy model-based FDD method for air handling unit [170–174]. Fuzzy rules were identified from the real-time monitoring data to describe the behavior of the equipment concerned in the current operating condition [170]. Then, a fuzzy matching scheme was introduced to calculate the overall similarity of the fuzzy reference models to the identified fuzzy rules respectively [170,174]. A fault was isolated if its corresponding similarity was high. This method allowed the combination of prior knowledge with the learnt knowledge from data, since the learnt fuzzy models could be interpreted linguistically. Haves et al. reported that it was convenient to apply linguistic rules to continuous variables of air handling units using fuzzy logic, such as temperature and control signal [175]. Wang and Haves further introduced Monte Carlo analysis to improve the FDD robustness and reduce false alarms [176]. Besides, Twiddle and Jones developed a fuzzy model-based condition monitoring and fault diagnosis method for a diesel engine cooling system [177]. Kocyigit developed a fuzzy inference system for detecting sensor faults of vapor compression refrigeration systems [76]. Lauro et al. introduced fuzzy sets and fuzzy logic for diagnosing abnormal building fan coil electric consumption [178]. Zhou et al. introduced a fuzzy modeling method to quantify residuals of performance indices using the Gaussian membership functions [74]. The parameters of each fuzzy set were determined by the training data and prior knowledge. It overcame

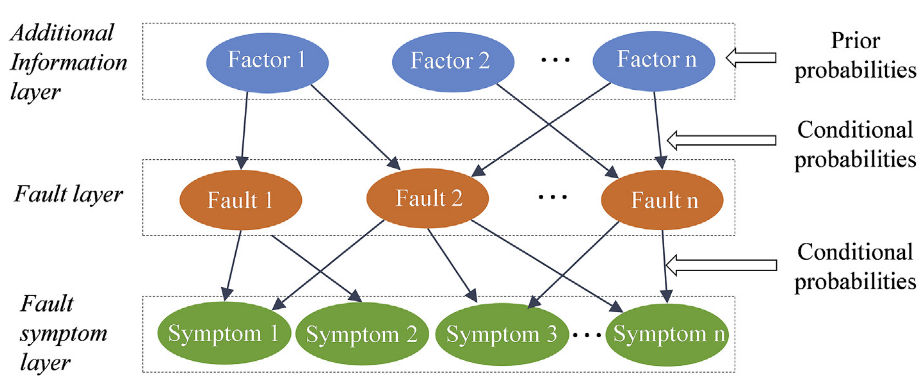

Fig. 16. A general structure of the Bayesian diagnostic network-based fault diagnosis method.

the problem faced by classical qualitative rule-based fault diagnosis methods in the cases that different faults had the same linguistic rule patterns. Zhou et al. developed a neuro-fuzzy sliding mode observer to estimate the magnitude of incipient faults [179].

Researchers also realized the shortcomings of the fuzzy logic-based diagnosis methods. Najafi et al. pointed out that as the problem complexity grows, a large number of fuzzy sets and fuzzy rules are required, which lead to the difficulty in adjusting and tuning fuzzy sets [169].

5.3. Intelligent agents-based

In artificial intelligence, an intelligent agent is an autonomous entity which observes through sensors and acts upon an environment using actuators and directs its activity towards achieving goals. Intelligent agents know or can learn the performance and status of the systems and equipment they monitor. An agent can also collaborate with other agents to achieve a common goal. Building energy systems always have a large number of interacting components with nonlinear and self-organized activities. Intelligent agents-based FDD methods have the potential to utilize the advantages of multi-agent properties such as autonomy, sociality, reactivity and pro-activity. Kelly and Bushby pointed out that such features made intelligent agents ideally suited for detecting and identifying faults in building energy systems [180–182]. Since the development of agents relays on prior knowledge heavily, in this review the method is classified into the subcategory of the knowledge driven-based methods.

Papadopoulos et al. developed a multi-agents-based method for isolating actuator and sensor faults in a multi-zone HVAC system [183,184]. It considered a HVAC system as a network of interconnected subsystems. Every subsystem was represented by a monitoring agent. An agent communicated with its neighboring agents to exchange diagnostic information to perform distributed fault detection and local fault identification. Therefore, it could solve FDD problems that are difficult or impossible for an individual agent. Studies about this method are still at an early stage.

5.4. Discussions

5.4.1. Strengths of the knowledge driven-based methods

In summary, based on the above analysis, we can conclude that the knowledge driven-based methods have the following strengths:

- They show advantages in overcoming the problem of incomplete information. On the one hand, they can take more diagnostic information of various kinds into account which cannot be used by the data driven-based methods, including maintenance records, on-site measurements, and even symptoms observed by technicians. On the other hand, they can introduce domain knowledge and expert experience into the FDD process, especially in the cases that information is insufficient.
- They show advantages in overcoming the problem of uncertain information. On the one hand, algorithms like Bayesian networks and fuzzy logic can describe uncertainties in domain knowledge, expert experience, relationships among faults and symptoms, physical/regression models and measurements. On the other hand, they have very strong capacity in reasoning with uncertain and even conflicting information. Therefore, the knowledge driven-based method can simulate the reasoning process of experts.
- They show advantages of generalization. In principle, they can extrapolate beyond the range of training data since the models are developed based on first principles. They can work correctly at any severity levels of faults under wide operating conditions.
- They are understandable since the whole FDD processes have clear physical meanings in detail. Technicians can understand the reasons or mechanisms of the results. The over-fitting problem can be avoided easily as well. Through adjusting model parameters, the knowledge driven-based models can still work when the patterns of monitoring data are changed by normal performance degradations, regular maintenances and component replacements.
- They do not need a large amount of labeled faulty data. Without labeled faulty data, the qualitative and even quantitative relationships between faults and symptoms can still be obtained with the help of domain knowledge based on a deep understanding of the systems.

5.4.2. Shortcomings of the knowledge driven-based methods

In summary, based on the above analysis, we can conclude that the knowledge driven-based methods have the following shortcomings:

- They require a deep understanding of the causal relationships between faults and symptoms of the building energy systems. Therefore, it would be quite challenging for most of technicians to implement the prior-knowledge methods.
- In general, the accuracy of knowledge driven-based methods is lower than the data driven-based methods. Because the accuracy of physical models are generally not as good as those of the data driven-based models.
- Comprehensive adjustments are always necessary if the sensor installments are different from the required ones. In most of time, adjustments need professional knowledge and skills to change equations and parameters. Actually, the sensor installations in real building energy systems are generally different from the ones required by the standard FDD methods.

5.4.3. Discussions about the existing studies

In the field of building energy systems, studies about the artificial intelligence and knowledge driven-based FDD methods are also in an early stage. Here are common problems of the existing studies:

- Most knowledge driven-based FDD methods were developed for typical equipment of building energy systems currently. Although the methodologies are general, it is quite time consuming to develop models for equipment/systems even of the same types with different installed sensors or control logics.
- There is still a lack of automatic approaches to improve the efficiency in developing knowledge driven-based FDD solutions. They rely on experts' knowledge heavily. They still needs professional knowledge and skills to develop models.

6. A survey of finished FDD projects

According to the survey, there were 13 reported research projects about FDD for building energy systems. Most of the projects were supported by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE), U.S. Department of Energy (DOE) and U.S. Department of Commerce. Some projects made very comprehensive field surveys, laboratory tests or performance evaluations. For instance, ASHRAE Project 1312-RP listed about 68 types of air handling unit faults. Some projects got valuable experimental data. ASHRAE Project 1043-RP project employed a 90-ton centrifugal water-cooled chiller to conduct 8 typical faults. For each type of fault, four severity levels were considered. Each experiment was tested under 27 operating conditions for about 864 min. After this project, more than 70% publications about chiller FDD were evaluated using the experimental data. Table 1 lists the finished FDD projects in public for building energy systems.

7. Important research tasks in the future

7.1. How to distinguish sensor faults and component faults?

The influences of sensor faults and component faults are always

Table 1
A list of fault detection and diagnosis projects for building energy systems.

No.	Target	Project Title	Project name	Supporter /Organizer	References
1	Chiller	Development of analysis tools for the evaluation of fault detection and diagnostics in chillers	1043-RP	ASHRAE	Comstock and Braun (1999) [81]
2	Chiller	Evaluation and assessment of fault detection and diagnostic methods for centrifugal chillers	1275-RP	ASHRAE	Reddy et al. (2006) [185]
3	Chiller	Development and comparison of on-line model training techniques for model-based FDD methods applied to vapor-compression chillers	1139-RP	ASHRAE	Reddy et al. (2001) [186]
4	Chiller	Fault detection and diagnosis for centrifugal chillers: online implementation	1486-RP	ASHRAE	Li and Zhao (2011) [187]
5	HVAC system	Demonstration of fault detection and diagnosis methods in a real building	1020-RP	ASHRAE	Norford et al. (2000) [188]
6	Air handling unit	Tools for evaluating fault detection and diagnostic methods for air-handling units	1312-RP	ASHRAE	Wen and Li (2011) [82]
7	Air handling unit and variable air volume box	Results from Simulation and laboratory testing of air handling unit and variable air volume box diagnostic tool	NISTIR-6964	U.S. Department of Commerce	Castro et al. (2003) [26]
8	Air handling unit and variable air volume box	Results from field testing of embedded air handling unit and variable air volume box fault detection tools	NISTIR 7365	U.S. Department of Commerce	Schein (2006) [60]
9	Air handling unit	Self-correcting HVAC controls: algorithms for sensors and dampers in air-handling units	PNNL-19074	U.S. Department of Energy	Fernandez et al. (2010) [189]
10	Packaged air-conditioners and heat pumps	Field testing and demonstration of the smart monitoring and diagnostic system (SMDS) for packaged air-conditioners and heat pumps	PNNL-24000	U.S. Department of Energy	Taasevigen et al. (2015) [190]
11	Variable air volume system	Self-correcting controls for VAV system faults filter/fan/coil and VAV box sections	PNNL-20452	U.S. Department of Energy	Brambley et al. (2011) [191]
12	HVAC system	Real time simulation of HVAC systems for building optimisation, fault detection and diagnostics	IEA ANNEX-25	International Energy Agency	Hyvarinen et al. (1997) [192]
13	HVAC system	Demonstrating automated fault detection and diagnosis methods in real building	IEA ANNEX-34	International Energy Agency	Dexter and Pakanen (2001) [193]

different. Most of sensor faults affect the readings of sensors only, expect in the case that the sensors are utilized as control inputs. Most of component faults affect the readings of more than one sensor. Therefore, in the field of building energy systems, most of FDD methods considered sensor faults or component faults only, ignoring the possibilities of the other one. For instance, classifier-based FDD methods always considered component faults only. A wrong classification would made if a sensor was faulty. PCA-based FDD methods always consider sensor faults only. A sensor fault would be identified wrongly if component faults occurred.

Researchers tried to utilize Bayesian networks to consider both kinds of faults in the meantime [59]. Each fault was treated equally as a fault node. Therefore, the relationships of sensor faults to symptoms and the relationships of component faults to symptoms were able to be described together in the same Bayesian network. However, it relied on expert knowledge heavily and, it was quite time consuming to develop such a Bayesian network. More elegant and powerful methods are needed to be proposed in the future.

7.2. How to balance accuracy and reliability?

Most of literature demonstrated their improvements through comparing FDD accuracy with those of others only. However, the improvement would be meaningless without the consideration of reliability. For the FDD problems in building energy systems, a higher FDD accuracy on training data set would increase the risk of over-fitting, as well as a higher risk of a loss of reliability and robustness in practical applications.

In essence, it might be unnecessary to get very high FDD accuracy. In the field of building energy systems, most of faults should neither be removed immediately nor be removed at small severity levels due to the maintenance costs. Before a fault should be alarmed, there should be plenty of sampling data already. Therefore, it is not necessary to alarm fault at every time slide. The authors believe that the improvements of reliability, robustness and generalization of FDD methods are more valuable than the improvement of accuracy only.

7.3. How to evaluate the FDD performance more comprehensively?

Most studies introduced the Type I error and Type II error to evaluate the performance of FDD methods. A Type I error occurs when the method incorrectly rejects the true null hypothesis that a series of normal data are in fact normal [151,193]. A Type II error occurs when the method fails to reject the false null hypothesis that a series of faulty data are normal. However, it is far from enough to evaluate whether a FDD method is suitable for practical applications quantitatively. To the best of the authors' experiments, we think the following errors should also be considered at least:

(1) The method incorrectly rejects the true null hypothesis that a series of faulty data of a known type belongs to an unknown type of fault. In which, the term unknown refers to a type of fault which is not considered in the FDD method. The term known refers to the contrast meaning.
(2) The method fails to reject the false null hypothesis that a series of faulty data of an unknown type belongs to a known type of fault.

Since the amount of types of faults are various, most methods took a portion of important ones only. Both (1) and (2) are therefore introduced to reduce false alarms/reports. And, there are some suggestions for developing new evaluation criteria:

- The ability in overcoming the problem of incomplete information which is mainly caused by missing sensors and poor sampling systems.
- The ability in overcoming the problem of uncertainty which is

mainly caused by sensors of low quality.
- The reliability at operating conditions which are out of the range covered training data.
- The feasibility of implementing into other equipment/systems of the same model or similar model.

7.4. How to compare various FDD methods uniformity?

According to this review, most studies utilized experimental data from laboratory tests. For instance, ASHRAE Project 1043-RP data were widely used in chiller FDD studies. Since the data preprocessing approaches were different, the Type I error and Type II error could be quite different even using the same dataset and the same algorithm. In some studies, faulty data were obtained through conducting faults on simulation platforms, especially for sensor FDD studies. But, open source simulation models were rare. In artificial intelligence, there are some public databases for comparing the performances of various algorithms like ImageNet [194]. However, in the field of building energy systems, there is a lack of public databases including normal data and faulty data of some typical buildings. It becomes one of the major barriers for future studies.

Yuill and Braun reported that it is necessary to use simulation data to evaluate performance of FDD methods [195]. Zhang and Hong developed a feature in EnergyPlus to model operational faults that are common in HVAC systems of existing buildings [32]. More details about how to model faults refer to the review by Li and O'Neill [58]. Simulation data are of very low cost and standard. In the near future, it shall be efficient and effective to compare various FDD methods quantitatively. But, measurements from real building energy systems are still needed as supplements in the long run.

7.5. How to combine the advantages of both data driven-based methods and knowledge driven-based methods in a method?

In essence, data driven-based methods are difficult to utilize prior knowledge to reasoning over the models and data. Knowledge driven-based methods are difficult to find hidden patterns from data automatically. The authors believe that a perfect FDD method should have advantages of both data driven-based methods and knowledge driven-based methods. This review has not found any effective solutions so far from literature. The authors believe that, narrowed to a specific equipment/system, it is possible to design a proper algorithm to combine advantages of both kinds of methods in the near future.

7.6. How to transfer knowledge?

Experts can detect and diagnose various types of equipment and building energy systems using incomplete and uncertain information. Because, they have very strong capacity of generalization. They can transfer knowledge/experiments learnt from an individual cases to other cases even if the similarity among them is low. FDD models are always adjusted for specified equipment/systems. In general, different equipment/systems have different parameters, operation patterns, and sensor installations. It is still challenging to apply a FDD model developed for one equipment/system to another directly. This is one of the major barriers for the practical application of FDD methods. In the field of artificial intelligence, knowledge transfer in an open world is still a very challenging task. But, the authors believe that the knowledge transfer in the field of building energy systems are possible using current artificial intelligence algorithms. Because the range of problems is much more narrowed and simplified.

8. Conclusions

A comprehensive literature review is provided in this study about the artificial intelligence-based fault detection and fault diagnosis methods for building energy systems. All methods are categorized into two classes including the data driven-based methods and the knowledge driven-based methods.

The data driven-based methods rely on the training data heavily. They could obtain a very high fault detection and diagnosis accuracy and could work in the cases that some sensors are missing. They are feasible to be trained and applied automatically. But, the models should be trained using a large amount of normal data for fault detection and faulty data for fault diagnosis. They cannot extrapolate beyond the range of the training data. Knowledge-based methods show advantages in simulating the diagnostic thinking of experts and fully utilizing all kinds of diagnostic information. They have very strong capacity in reasoning with uncertain, incomplete and even conflicting information. They only need a small number of training data and can extrapolate beyond the range of training data. But, they rely on expert knowledge too much. The FDD performance depends the understanding of the nature of the building energy systems.

This paper also summarizes the most important research tasks in the future. Both sensor faults and component faults should be took into account together in an individual FDD method. New evaluation approaches are necessary to estimate the actual FDD performance in practical applications. New methodologies should be developed in the future to combine advantages of both data driven-based methods and knowledge driven-based methods. It is no doubt that artificial intelligence-based methods have great potential to solve the FDD problems of building energy systems. Further studies are in great need to develop effective, efficient, scalable and reliable FDD methods for practical applications.

Declarations of interest

None.

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