International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 11 Issue 3 ǁ March 2023 ǁ PP. 61-74

Review Article: Fault Detection and Diagnosis of Air-conditioning System Based on Data-driven Method

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Abstract: *In recent years, extensive building equipment automation has contributed to the accumulation of a large amount of air conditioning system operation data, which can be used to research air conditioning system Fault Detection and Diagnosis (FDD). A data-driven approach based on intrinsic correlation and regularity of data is more advantageous for FDD modeling of air conditioning systems. The relevant literature indicates that data-driven FDD models require input training samples. A literature review is conducted in separate sections based on whether the training samples have labels, such as fault labels, and whether the data-driven methods are supervised or unsupervised. Among the supervised data-driven methods are classification and regression. Data-driven methods that do not require supervision include cluster analysis, association rule mining, and Principal Component Analysis (PCA). An analysis and summary of the advantages and disadvantages of supervised and unsupervised methods has been conducted from the perspectives of diagnostic accuracy, scope, model applicability, and calculation. An overview of the related literature on data-driven fault detection in HVAC is presented in this paper, as well as a brief discussion of the fault types found in HVAC systems and the application of data-driven fault detection in AHU, Chiller, and HVAC systems. In light of the difficulties in developing data-driven methods, this paper provides some suggestions and further research directions, such as developing hybrid FDD approaches.*

Keywords: FDD ; Data-driven ; HVAC ; Supervised method ; Unsupervised method

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Date of Submission: 25-02-2023 Date of acceptance: 06-03-2023

I. Introduction

As a percentage of total global energy consumption[1], the building sector accounts for 35% of the total, while HVAC systems account for 50-60% of the totalbuilding energy consumption[2]. There are a number of components in HVAC systems that operate below optimal levels [3]. A study conducted by Qin and Wang found that 261 out of 1251 Variable Air Volume (VAV) terminals in a commercial building in Hong Kong were operating abnormally [4]. In commercial buildings in the United States, Roth et al. [5] found that 13 critical failures account for approximately 4-18% of the energy consumption of lighting systems, HVAC systems, and refrigeration systems. In the event of an HVAC system failure, energy can be wasted, equipment can be shortened, indoor environment can be uncomfortable, and many other issues may arise. The efficiency of HVAC systems may be adversely affected by poor equipment maintenance, improper component performance, installation failures, and control errors[6-9]. Therefore, it is imperative to detect HVAC system failures as soon as possible in order to create a comfortable indoor environment and prevent energy losses.

With the advancement of technology, artificial intelligence fault diagnosis technologies have become increasingly prevalent. There have been many FDD methods applied to building energy systems over the past few decades. The HVAC system includes interconnected air supply, fresh air, chilled water, and cooling water systems, making the air conditioning control system more complex. The FDD method is easily incorporated into HVAC control systems. Detecting and diagnosing faults accurately can improve the self-healing capabilities and fault tolerance of the air conditioning control system while reducing its operating and maintenance costs. The literature review by Katipamula et al. in 2005 and 2018 categorizes FDD methods into three categories: quantitative model-based, qualitative model-based, and process history-based methods [10-12]. According to Yu et al.[13], FDD methods can be divided into analytical-based methods, knowledge-based methods, and data-driven methods.

With the maturation of building automation systems and all kinds of system data, a data-driven (DD) analysis method based on the intrinsic correlation and regularity of data has become one of the most promising tools for analyzing a wide range of building operation data. Using large amounts of historical data on various operation conditions (including normal and fault conditions), a data-driven method was used to investigate the correlation between variables and parameters[14].DD methods cannot rely on expert knowledge or physical models, but only require data regarding the operation of the system [15, 16]. In comparison with the analytical-based method of diagnosis, the DD method has a greater advantage in the model training step since fewer samples are required to find the fault. The DD method differs from the knowledge-based method in that it is no longer a "customized" model of the system, and its applicability is more broad than the knowledge-based method. There are a number of DD techniques, including artificial neural network [17], Bayesian network [18], decision tree [19], principal component analysis [20], support vector machine [21, 22], cluster analysis [23], and Association Rule Mining (ARM) [24].

A HVAC system consists of a number of components, including an air handling unit, cold and heat source equipment, a water system, an air system, and an air conditioning terminal, as well as variables such as ambient air temperature, humidity, volume of air, wind speed, ambient temperature, solar radiation, and meteorological information. The HVAC system is a complex system composed of many nested subsystems, and each subsystem may fail independently or simultaneously, making fault diagnosis and detection extremely challenging.

Poor HVAC system operation and delayed or incorrect fault diagnosis will result in air conditioning operations failing and will result in an increase in energy consumption of about 5-30%[10]. It is more difficult to diagnose non-catastrophic failures (soft failures) in HVAC systems when sufficient sensors, controllers, and mechanical components fail. The most common components of HVAC systems that fail are air handling units, cold and heat source equipment, air supply terminals, fans, pumps, filters, cooling towers, valves, and sensors.

Based on a literature review and combing, data-driven methods are divided into supervised and unsupervised ones based on whether the training samples have labels, as well as reviewing relevant literature on FDD. This research summarizes and analyzes the progress in comprehensive fault diagnosis and detection of AHU, chillers, and air conditioners.

II. Supervised data-driven method

The supervised data-driven method represents the mapping relationship between multiple variables by training the model with a certain number of data samples, which is usually used for prediction and classification tasks [24]. The method consists of two parts: supervised classification and regression.

2.1 Supervision classification method

Based on the data collected under different fault conditions, the supervised classification method is capable of learning the mapping relationship between fault and data in order to achieve fault diagnosis. There are a number of classification-based supervision methods, including linear discriminant analysis, support vector machines, artificial neural networks, and Bayesian networks.

Using Linear Discriminant Analysis (LDA), also known as Fisher linear discriminant, high-dimensional data is projected into low-dimensional space while preserving multi-class difference information. After projection, it ensures that the sample has the maximum inter-class and minimum intra-class distances in the new subspace, resulting in maximum class identification[25]. However, in a study conducted by Ebrahimifakhar et al. [17] on cooling system fault detection, it was found that the overall accuracy of the LDA method alone was lower than that of the SVM and other methods of classification.

The Support Vector Machine (SVM) is a generalized linear classifier that can avoid model overfitting and is capable of handling nonlinear and high-dimensional pattern recognition challenges. The SVM model is used in the FDD training process to find an optimal hyperplane in a higher-dimensional3 feature space. Monitoring data is compared with the hyperplane in order to determine whether they belong to the fault class or not. According to Fig.1[26], fault A is separated from other fault data. An SVM-based FDD method has been proposed by Han et al. [27] in which the ML-SVM method includes over two types of labels and is capable of diagnosing multiple faults in a system simultaneously. In two studies of chiller failures, four SVM classifiers were developed for the detection of no-failure conditions and three different types of failures[28, 29].Liang and Du [30] proposed the use of a four-layer SVM classifier in order to detect and diagnose faults. The first layer of the classifier determines whether or not the system is failing, and the remaining three layers determine the type of fault. According to Sun et al. [31], a hybrid Refrigerant Charge Amount (RCA) fault diagnosis model is proposed based on Wavelet De-noising (WD) and support vector machine (SVM).

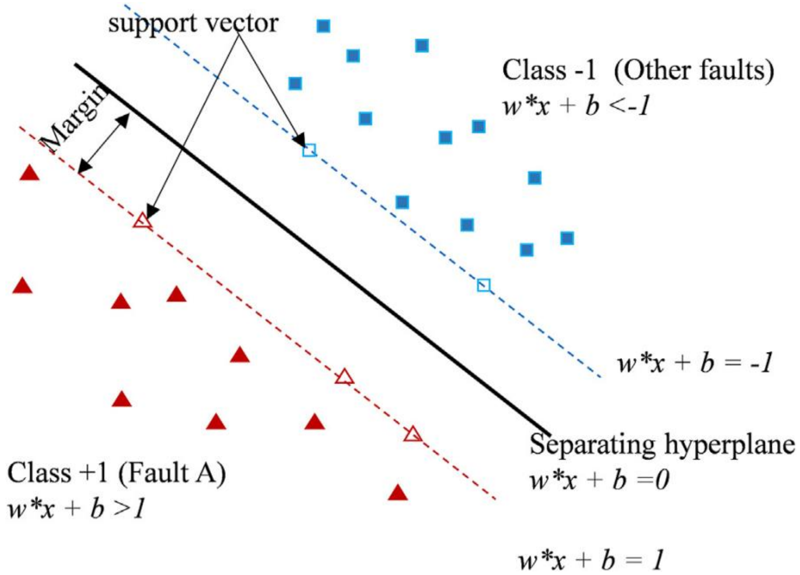

Fig. 1 Description of fault detection and diagnosis method based on support vector

Artificial neural network (ANN) comprises an input layer, one or more hidden layers, and an output layer, and weight matrices connect the layers. In ANN model training, minimize the difference between the target value and the model output value by adjusting the weight matrix. In the fault diagnosis and detection process, the trained ANN model is used to calculate the residual and determine the type and severity of the fault by comparing the residual with the threshold [32-34]. Fig.2 indicates a four-layer artificial neural network structure for fault diagnosis [26]. Neural network methods for detecting or diagnosing faults through residuals include those based on the comparison of residuals with thresholds and those based on the comparison of abnormal residuals with thresholds after classification and ranking [35, 36]. Kocyigit proposed a fault diagnosis and detection model based on a fuzzy inference system (FIS) and ANN to diagnose the faults of a vapor compression refrigeration experimental setup [37]. Sun et al. [38] proposed a fault diagnosis method combining independent component analysis (ICA) and a back-propagation neural network (BPNN). Before BPNN training, ICA is used to reduce the dimension of the original data to realize the fault detection and diagnosis of the VRF system. Guo et al.[39] established a VRF system fault diagnosis model using the deep belief network (DBN) method. They found that increasing the number of hidden layers can improve the fault diagnosis accuracy of the model and proposed a parameter selection strategy to optimize the model. Taheri et al. [40] applied deep recurrent neural networks (DRNNs) to fault diagnosis and compared and optimized seven DRNN models with different depths to make the model more accurate. Shahnazari et al. [41] proposed a recurrent neural network (RNN) fault diagnosis model for HVAC systems, which can fault diagnosis without historical data.

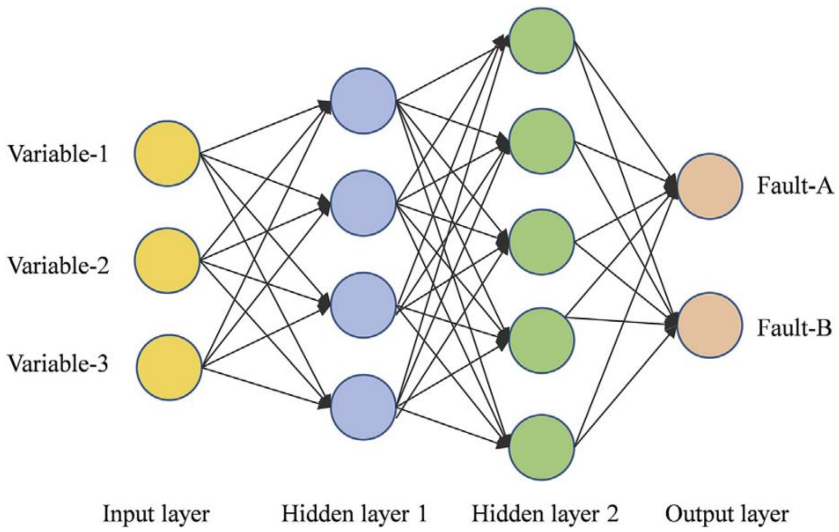

Fig. 2 Schematic diagram of a four-layer ANN structure for fault diagnosis

Bayesian networks (BNs) are a method for predicting the response value of a variable based on the conditional probability theorem. BNs can discretize continuous variables to obtain nonlinear relationships between variables, and Dynamic Bayesian networks (DBNs) can consider the time factor in the data [42]. In the FDD process, the response value is the desired fault tag. Bayesian networks can fault detection and diagnosis even without complete system information [36]. Hu et al. [24] proposed a model based on PCA and Gauss naïve Bayes (GNB) to realize the detection and diagnosis of four faults of the VRF system. Zhao et al. [43] proposed a diagnostic Bayesian network (DBN)-based method for detecting and diagnosing 18 typical faults in heating/cooling coils and sensors and faults in secondary supply chilled water/heating water systems in AHU. Wang et al. [44, 45] proposed two hybrid methods based on the Bayesian network, one is to integrate Bayesian networks with fused reference model methods, and the other is to combine BNs with PCA. The hybrid method overcomes the limitations of a single method, thus improving the performance of FDD.

2.2 Supervised regression method

Using sample data, a supervised regression method trains a model according to the regression principle and predicts the data using the model. The gray box model and the black box model are two types of regression models. The gray box model was developed by combining partial theoretical structures derived from prior knowledge with data. Data can be processed using the black box model without relying on physical/scientific laws or prior knowledge [26]. In order to calculate the benchmark test value and the confidence interval, the FDD benchmark model based on the regression method is used. It is possible to detect a fault by comparing the actual measurement value with the confidence interval, as shown in Fig.3[46]. There are three categories of supervised regression methods: artificial neural network-based methods, support vector-based methods, and other regression methods.

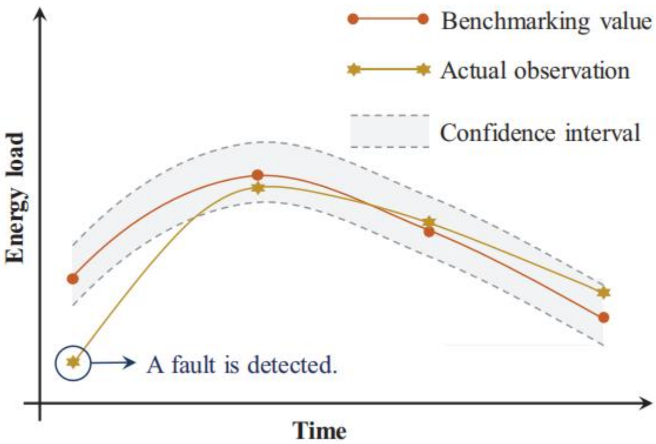

Fig. 3 Illustration of the regression-based FDD method

The ANN regression method comprises an input layer, one or more hidden layers, an output layer, and a weight matrix connecting the layers. However, the difference between the classification method is whether the output variable is continuous. Mavromatis et al. [47] proposed a model based on ANN regression to diagnose and detect the faults in supermarket systems. Du et al. [48] proposed a double neural network combination method combined with the principal component analysis method, the basic neural network of the control relationship between variables and the auxiliary neural network of the correlation analysis between variables to detect the sensor fault in the AHU supply air temperature control loop. Combined with data monitoring and clustering analysis of supply air temperature and return water temperature, a combination of two back propagation neural networks was used to detect the failure of the AHU[49].

The support vector regression (SVR) method calculates a relevant feature space and output variables through a nonlinear mapping function, maps the input data to a high-dimensional feature space, and finds a hyperplane in which the edge is maximized, and the error is minimized, which is used to solve complex regression problems [50]. Zhao et al. [51] proposed a combined model based on Exponentially Weighted Moving Average (EWMA)control charts and SVR to detect and diagnose refrigeration system faults. Tran et al. [52] proposed a combined model of the nonlinear least squares support vector regression (LSSVR) and the exponentially weighted moving average (EWMA) control charts to diagnose the fault of centrifugal chillers of building air conditioning systems.

III. Unsupervised data-driven method

An unsupervised method is a forward-looking approach to discovering useful knowledge and structure from unlabeled data. Unsupervised methods aim to discover a data's intrinsic structure, correlations, and associations [24, 53]. Clustering analysis [54, 55], Association Rule Mining (ARM) [56], Principal Component Analysis (PCA) [57, 58], and self-organizing neural networks [24] are examples of unsupervised methods.

Based on the distance between variables, cluster analysis divides the data into multiple clusters. As a result of selecting the appropriate distance index, the distance between the data and the cluster has similar characteristics. The purpose of clustering is to group together objects that are similar and dissimilar to those belonging to other clusters. A Multivariate Statistical Process Analysis (MSPA) method referred to as weather Pattern Matching (PM) and Principal Component Analysis (PCA) was proposed by Chen and Wen et al. [59]. The Symbolic Aggregate Approximation (SAX) method is used to detect system faults by identifying similar weather patterns in historical databases and generating a dynamic baseline dataset for the PCA model to use. In an attempt to improve the building energy management system (BEMS), Capozzoli et al. [32] proposed a Density-Based Spatial Clustering of Applications with Noise Clustering (DBSCAN) method that detects abnormal energy consumption in building energy systems. According to Li and Hu et al. [60], an improved method for combining the DBSACN with PCA was proposed, which uses DBSCAN to classify and identify the low and high chilled-water flow operation conditions of the chiller, and then uses the PCA model to diagnose and detect the sensor fault in the chiller. According to Du et al. [49], fault conditions in AHUs were classified adaptively using subtractive clustering analysis, which divided different faults into different space zones in the data space. In addition to identifying the known faults in the library, this method can also identify new unknown faults and adaptably supplement them with the fault library. Clustering and correlation analysis were used by Xue et al. [61] to detect faults in district heating systems. First, they used the clustering method to determine the operating patterns of the heating system during different seasons, and then they used correlation analysis for each pattern to determine if there were any faults.

Association rule mining [ARM] can extract the correlation between variables and express knowledge discovered in a rule format [24]. Fan et al. [62] proposed a general framework for knowledge mining in Building Automation System (BAS) data. First, the analysis of variance (ANOVA) method was used to identify the most significant variables affecting the total power consumption and determine the typical working patterns by cluster analysis. Then the quantitative association rule mining (QARM) method is used to detect and diagnose faults. Like the above pattern, Li et al. [63] used clustering analysis to classify data and used association data mining to detect and diagnose faults in VRF air conditioning systems.

PCA is a statistical method based on the least square method, widely used in the FDD process of HVAC systems. The FDD method of single PCA is suitable for the steady-state process of the dynamic system. However, the actual monitoring data is the complex data of nonlinear control, so the adaptability and low accuracy of the PCA model need to be considered in practical application [64, 65]. To solve the problems mentioned above, we proposed a fault diagnosis method combining PCA with other methods. Li et al. [66] proposed a combined PCA and support vector data description (SVDD) model for chiller fault detection. In addition, considering the adaptive problem of the PCA model in fault diagnosis, Zhang et al. [64] proposed a model based on subtractive clustering, k-means clustering, and the PCA method for sensor fault detection and diagnosis.

IV. Discussion

Based on the above literature review and analysis, the advantages and disadvantages of supervised and unsupervised data-driven methods are summarized, as shown in Table 1 below.

Table 1 Comparison of advantages and disadvantages of supervised and unsupervised data-driven methods

	Supervised data-driven methods	Unsuperviseddata-driven methods
Advantage	1. Strong modeling ability for complex system 2. The input and output variables in the training samples have a clear corresponding relationship 2. Bycombiningdomain expertise to improve the accuracy of the model output	1. It can be used when the sample data is less 2. Mining the internal relationships in the data may lead to the discovery of unknown rules 3. Does not rely on domain expertise and high-quality labeled training data, making the economic cost low
Shortcoming	1. The training model needs label data, and the amount of data required is enormous 2. The model's input and output data are labeled, and the ability to mine new knowledge and rules is limited. 3.The reliability and robustness of the model are affected by the quality of training data	1.The time required for data preprocessing depends on the quality of the original running data 2. Using unlabeled data may cause the model to output incorrect results 3. The amount of knowledge found is large, and it is not easy to screen helpful knowledge

V. Application of Data-Driven FDD Technology in the HVAC System

Between 2004 and 2018, 197 FDD-related publications were published, which mainly focused on VAV-AHU, water chillers and cooling towers, air conditioning and heat pumps, and general building applications, as shown in Fig.4[12]. This paper reviews and analyzes relevant research on the FDD of HVAC systems after 2018. In particular, they concentrate on the diagnosis and detection of AHUs, chillers, air conditioning systems, and HVAC. The following is a literature review and analysis of the aspects of AHUs, chillers, and overall air conditioning systems.

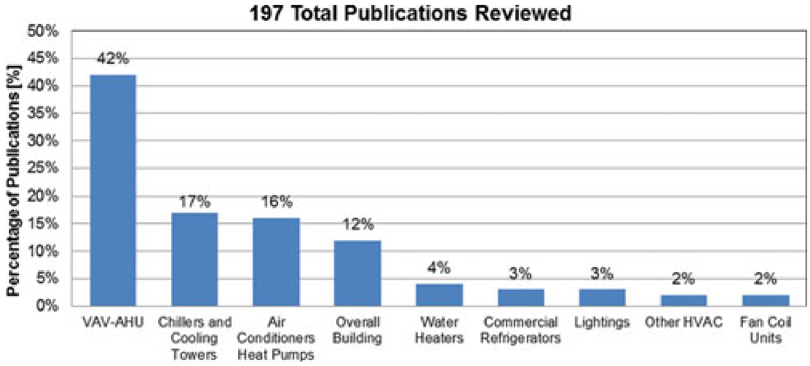

Fig. 4 Classification of FDD documents based on the building system

5.1AHU

In large commercial buildings, Air Treatment Units (AHUs) are used primarily to heat and cool the air. As shown in Table 2, AHU faults can be divided into AHU equipment faults, AHU actuator faults, AHU sensor, and feedback controller faults [13, 67].

There are two types of faults associated with AHU equipment: system disturbances and equipment structure faults. When modeling the AHU system, the fault diagnosis model may be too simple or critical information may be ignored, which leads to uncertainty in the model, which results in the system disturbance fault. The term "equipment structure failure" refers to the failure of a particular structure of an equipment, which results in the inability to perform the entire process, such as an air leakage in a duct. System failures may occur due to insufficient heating or cooling or increased infiltration. As another example, a dirty coil will change the heat coefficient, resulting in a reduction in thermal conditioning[13, 67]. In their study [43], Zhao et al. used diagnostic Bayesian networks to diagnose coil fouling, heating coil stuckness, cooling coil valve leakage, and other AHU faults.

In addition, the actuator failure may affect the feedback signal received by the controller, thus affecting the overall output and reducing the control performance of the system. For example, OA dampers are stuck, reducing the efficiency of the temperature controller so that temperature regulation requires longer rise and fall time, and mechanical cooling rather than free cooling of outdoor air increases energy consumption. Dey et al. [68] proposed a model combining the Air handling unit Performance Assessment Rules (APAR) and the Bayesian Belief Network (BBN) method to diagnose and detect faults such as AHU damper leaks or stuck and supply fan/return fan faults. Provide diagnosis when multiple different faults occur. Yan [69] and Piscitelli [70] used data-driven FDD models to diagnose and detect valve and damper faults.

Faults of the AHU sensor and feedback controller will degrade the overall performance of the AHU. Sensors are used to measure the state variables of each part in the AHU as input signals, send the input signals (input values) to the controller and compare them with the set values. It applies sequencing logic and then produces output signals transmitted to the actuators. The AHU schematic is shown in Fig.5. The performance of the controller depends on performing the sensor. If the sensor has drifted, offset, and other faults, it will affect the controller's performance. Du et al. [48, 49] used a double neural network combination method to detect and diagnose supply air temperature sensor faults, water valve stuck faults, unreasonable control set points, and other faults in the AHU.

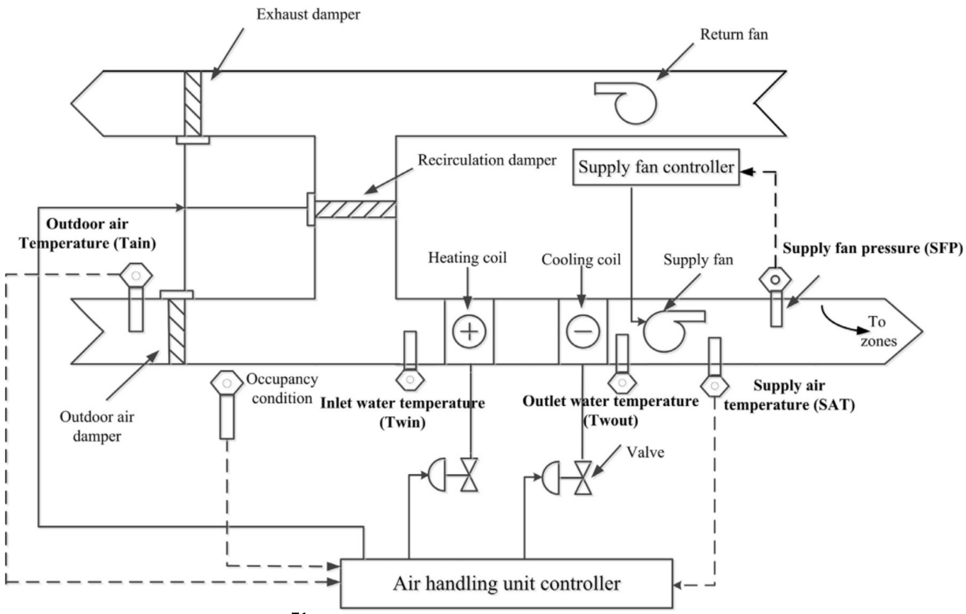

Fig. 5 Schematic of an AHU [71] (The sensors used in this work are indicated using bold font)

Based on the above classification method, the above documents summarize the unelaborated and typical literature, as shown in Table 5.

Table 2 Faults of AHU

Typesof AHU component faults	Device or cause	Fault type
Equipment failure	System disturbance	Model uncertainty leads to sensitivity to perturbations.
	Equipment structure failure	Air leakage from the duct Coil contamination [72]
Actuator failure	OA, RA, and EA dampers	A damper is stuck or a fault the position is operated[73, 74] Air leakage occurs at fully open-and-closed positions[75]
	Heating coil (HV), cooling coil (CV) and preheating coil valve (PV)	A valve is stuck, broken, or wrong operated position[74, 76] Leakage occurs at fully open-and-closed positions of the valve[72, 76, 77]
Faulty sensor	SA, MA, OA and RAtemperature	Failures of a sensor are offset, discrete, or drift[75, 77, 78]
	MA, OA, and RAhumidity	Failures of a sensor are offset, discrete, or drift[79]
	OA, SA, and RA flow rate	Failures of a sensor are offset, discrete, or drift[79]
	SA and zone pressure	Failures of a sensor are offset, discrete, or drift[77]
Feedback controller failure	Motor modulation	Unstable response
	The sequence of heatingand cooling coil valve	Unstable response
	Flow difference	The system sticks at a fixed speed[72]
	Static pressure	Unstable response
	Zone temperature	Unstable response

5.2 Chiller

The main components of the chiller are the evaporator, condenser, expansion valve, and compressor. The refrigeration cycle in chillers can be illustrated: After removing the building's heat, the chilled water enters the evaporator and transfers the heat to the refrigerant at a lower temperature. The refrigerant evaporates, and the refrigerant vapor enters the compressor, where the vapor with low pressure and low temperature is compressed into the vapor with high pressure and high temperature. Flowing out of the compressor, the refrigerant vapor enters the condenser and rejects the heat to the cooling water. In the condenser, the refrigerant vapor condenses into the liquid. The liquid refrigerant with high pressure and high temperature is expanded into the liquid with low pressure and low temperature through the expansion valve. Then, the refrigeration cycle repeats. Fig.6 indicates the simple schematic of a chiller system with four main components[80]. There are seven typical failures in chillers, as shown in Table 3[45, 81-84].

Reviewed relevant research literature, and for the 34 studies related to chillers and cooling towers, 79%

adopted data-driven methods[12]. Han et al. [27] diagnosed multiple-simultaneous faults (MSF) in water chillers, including FWC and FWE faults, using an FDD model based on SVM and multi-label(ML). Wang et al. [45] proposed an FDD model based on BN and PCA to diagnose seven typical faults in the chiller in Table 3 and divided each fault into four severity levels. They detected and diagnosed each fault at each severity level under 27 operating conditions. Zhao et al. [51] proposed a combined model based on the EWMA control chart and SVR to diagnose six typical faults except for Excess oil in Table 3 of the chiller, and Tran et al. [52] proposed a combined model of LSSVR and EWMA control chart. It diagnoses RO, CF, NC, and RL faults in centrifugal chiller systems. In addition, most of the research focuses on the compression chiller, and there is little research on the absorption chiller. The absorption chiller has a larger construction capacity and a more complex structure, so it needs a more accurate FDD model to detect and diagnose faults.

Based on the above classification method, the above documents summarize the unelaborated and typical literature, as shown in Table 5.

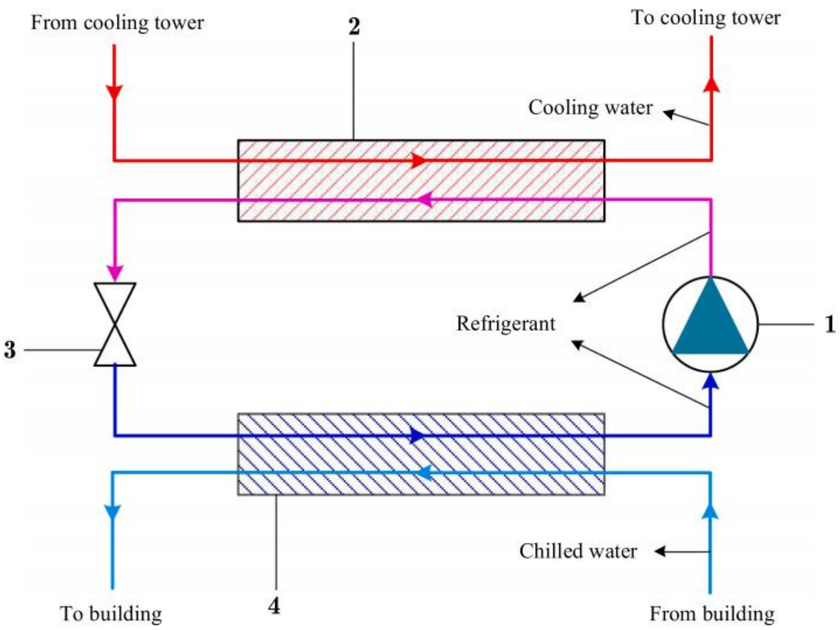

Fig. 6Schematic diagram of a chiller system with four main components: 1—Compressor, 2—Condenser, 3—Expansion Valve, 4—Evaporator

Table 3 Fault of chiller

Number	Fault type
1	Reduced condenser water flow (FWC)
2	Reduced evaporator water flow (FWE)
3	Condenser fouling (CF)
4	Non-condensable gas (NC)
5	Excess oil
6	Refrigerant overcharge (RO)
7	Refrigerant leak/undercharge (RL)

5.3 HVAC system

The HVAC system consists of a VAV, a VRF, a heat pump, a residential air conditioner, and a vapor compression refrigeration system (VCRS). There are several types of faults that may occur in each system, resulting in poor operation, increased energy consumption, and reduced indoor air quality, such as sensor and actuator faults[85, 86], valve leakage, and RCA faults. The fault types are shown in Table 4 below.

For faults in VAV air conditioning systems, Shahnazari et al. [41] proposed an FDD model based on RNN to detect multiple simultaneous faults in the system. Yan et al. [87] used a model based on kernel principal component analysis (KPCA) with a double-layer bidirectional long short-term memory (DL-BiLSTM) to detect minor soft faults of sensors. Wang et al. [88] proposed an FDD model based on a self-adaptive model and layered random forest to diagnose sensor faults, reduced airflow and hardware failure.

For RCA faults in VRF air conditioning systems, Sun et al. [31] proposed a hybrid FDD model based on WD and SVM to diagnose and detect faults, and Sun et al. [38] used a combined model of independent component analysis (ICA) and BPNN to detect them. Wang et al. [89] proposed a model detection method based on PCA and Gaussian naive Bayesian to diagnose RCA faults, compressor liquid floodback, and Four-way valve failure in VRF air conditioning systems.

Chintala et al. [90] proposed a method based on Thermostat driven algorithm to diagnose duct-leak faults, indoor airflow faults, and refrigerant undercharges in Residential Air Conditioners. Kocyigit et al.[37]used the model based on a fuzzy inference system (FIS) and artificial neural network (ANN) to diagnose and detect compressor valve leakage, improper refrigerant charge, evaporator fan failure, and other faults in VCRs. Sun et al.[91] proposed a model based on the Convolution- sequence model and Convolutional neural network (CNN) to diagnose fouling and refrigerant leakage faults in air source heat pumps (ASHP).

Based on the above classification method, the above documents summarize the unelaborated and typical literature, as shown in Table 5.

Table 4 HVAC Faults

Equipment	Fault type
VAV	Sensor and actuator failure [41, 87, 88, 92]
	The damper stuck [92, 93]
	Hardware failure[88]
	Reduced or improper airflow[88, 93, 94]
VRF	RCA faults[31, 38, 89]
	Four-way valve failure[89]
	Condenser and evaporator fouling[95]
	Compressor liquid floodback[89]
Residential Air Conditioner	Condenser and evaporator fouling[96]
	Reduced or improper refrigerant charge[90, 96]
	reduced airflow[90, 96]
VCRS	Compressor valve leakage[65, 97]
	Refrigerant Undercharge/Overcharge [65, 97, 98]
	Evaporator low indoor airflow [97]
	Condenser low outdoor airflow [97]
Heat pump	refrigerant leakage[91]
	Fouling[91]

5.4 Summary of research on data-driven FDD in air conditioning system

As shown in Table 5, the diagnostic methods, method classification, and diagnostic effects used in various components of air conditioning systems in the current relevant literature are summarized after summarizing common faults and research status for air conditioning system components.

Table 5 Summary of faulty components, diagnostic methods, and results

System	Classification of methods	Diagnostic method and principle	Diagnostic results
AHU [49]	Hybrid methods	Double neural network and subtractive clustering analysis； The double neural network detects the abnormality of the AHU, and different faults can be divided into different spatial zones in the data space through subtractive clustering analysis.	The double neural network has better detection efficiency than every single neural network.
AHU [68]	Supervised method	APAR rule and Bayesian belief network; Use APAR for fault diagnosis, and BBN prioritizes the faults when multiple rules are satisfied simultaneously. Information can also be derived from historical data to provide a diagnosis.	It effectively overcomes the problem that the APAR rule can not provide the source diagnosis of the fault.
AHU [69]	Supervised method	Classification and regression trees(CART) ; The decision tree is induced by the CART algorithm and validated by both testing data and expert knowledge	The results show that the strategy has good diagnostic performance, and the average F-measure is 0.97.
AHU [70]	Unsupervised method	Temporal Association Rules Mining (TARMs) and classification trees； Use TARM for fault detection during the start-up period of transient operation, and use the decision tree for fault diagnosis during the non-transient period	The model showed an overall accuracy of 90%
AHU [99]	Supervised method	ANN and supervised auto-encoder (SAE); Using the reconstruction error of SAE, the fault diagnosis can be carried out only when the FDD model can provide inference for the input variables. Otherwise, perform the retraining of the FDD model input.	The retrieval probabilities are 98.7% and 95.6%, respectively.

AHU [100]	Hybrid method	Enhanced kernel slow feature analysis (SFA)； To identify the fault, the SFA model calculates the similarity between the existing fault direction and the historical fault direction.	The experimental results show that performing the proposed model is significantly improved compared to the traditional model.
Chiller [52]	Supervised method	DE-LSSVR-EWMA； Most little squares support vector regression is performed on the data and diagnose the fault based on the estimation of the average and variance of the observation.	Accuracy: 99.73% The accuracy of this model is high.
Chiller [80]	Hybrid method	Semi-generative adversarial network; Moreover, effectively use that unlabeled data to improve the fault diagnosis performance.	The diagnostic accuracy was 84%. Compared with the neural network, the number of samples required is reduced by approximately 60%.
Chiller [81]	Hybrid method	LDA and predefined fault clusters; Divide the FDD process into two stages. First, LDA is used to reduce the dimension, and then the predefined fault clusters are used to detect the fault type.	Accuracy: 87–98.8%
Chiller [82]	Unsupervised method	generative adversarial networks; Using the variational auto-encoder (VAE) and the GANomaly to select high-quality synthetic fault data samples with the generative adversarial networks.	Experiments show that the model has high FDD accuracy with only a tiny amount of accurate fault data.
VAV air conditioni-ng [87]	Hybrid method	KPCA-DL-BiLSTM; Detect Soft faults by comparing the output data with the actual value of the sensor	Accuracy was 43% higher than KPCA and 18.33% higher than Long Short-Term Memory (LSTM).
VAV air conditioni-ng system [88]	Hybrid method	self-adaptive model and layered random forest； Self-adaptive zone air-temperature model is used to detect faults, and expert rule-based fault diagnosis layer and random forest-based are developed to isolate faults.	The FDD method is a reliable and practical technique for processing multiple faults of VAV terminals.
VAV air conditioni-ng [101]	Unsupervised method	ARM; Extract all correlations between air conditioning system operation data to find system fault	Results are accurate but time-consuming
VRF air conditioni-ng system [102]	Hybrid method	PCA and Gaussian mixture model; Fault Diagnosis Using Gaussian Mixture Model	Reduce the running time from 176.78s to 15.18s, and the fault diagnosis accuracy is over 99%.
VRF air conditionin-g system [89]	Hybrid method	PCA, Gaussian naive Bayesian, RUSBoost algorithm; PCA is used to reduce the dimension of the data, the Gaussian naive uses the Bayesian model to diagnose the fault, and the RUSBoost algorithm solves the problem of unbalanced data sets.	98.6% accuracy
VCRS [37]	Hybrid method	Fuzzy logic and artificial neural network； Using the FIS diagnostics fault of the refrigeration system from the sensor data. ANN was used for the prediction of the fault condition when it was trained to identify the fault.	The FIS and ANN-based diagnosticsystemseffectively detected the problems and classified the faults in the study.
Heat pump [91]	Supervised method	Convolution-sequence model and CNN； Convolution-sequencemodelfor general fault diagnosis, the CNN with an optimized convolution kernel is used todiagnose the specific failure of ASHP systems	the method proposed in this paper is a workable and practical diagnosis method for gradual fault in ASHP systems

VI. Future research suggestions

Based on the literature review and analysis, we concluded that data-driven methods have great potential in the field of fault detection and diagnosis (FDD) for air-conditioning systems. However, most of these approaches are not yet ready for practical application, and many aspects need to be improved. In light of this, the following suggestions are made for future research:

- There are advantages to both the supervised and unsupervised methods. However, there are limitations to the single diagnosis method in terms of accuracy, range of diagnosis, speed of diagnosis, model applicability, and calculation. Both methods can be combined in the future to complement each other.
- Currently, there is little research being conducted on multiple simultaneous faults and enhancing the development of models in this area.
- The HVAC system consists of a number of subsystems. At present, each subsystem has its own FDD model. To improve the efficiency of the FDD, we need to strengthen the correlation between multiple subsystems of the FDD in the future.

- Domain knowledge plays a crucial role in enhancing the intelligence of data-driven methods, and domain knowledge should be used to develop new data-driven methods.

VII. Conclusion

In this paper, a comprehensive literature review is presented regarding fault detection and diagnosis methods in HVAC systems, as well as classifications and analyses of data-driven methods. This paper summarizes and compares the advantages and disadvantages of supervised and unsupervised data-driven methods, and identifies typical HVAC subsystems and faults. Furthermore, the data-driven FDD method will be applied in each subsystem in a practical manner.

The supervised methods are insufficient to detect new faults and multiple simultaneous faults, and they cannot detect their synergistic effects with high precision. Unsupervised methods usually require a lot of time and effort to calculate data. It is also easy to obtain incorrect results when using unsupervised methods. Compared to the unsupervised method, the supervised method is more accurate and capable of modeling. Using the unsupervised method, faults and unknown patterns in the data can be effectively identified without the need for high-quality training data. There are advantages and disadvantages to both methods. In order to improve the accuracy, range, speed, and applicability of model diagnosis, hybrid methods are developed and combined with the advantages of different methods so as to avoid the defects of a single method and overcome its limitations.

A great deal of potential has been demonstrated by data-driven methods for detecting and diagnosing HVAC system faults. In spite of this, most data-driven methods are not suitable for practical applications, and in the near future, it will be imperative to develop general and intelligent methods.

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