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A review of data-driven fault detection and diagnostics for building HVAC systems

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ABSTRACT

With the wide adoption of building automation system, and the advancement of data, sensing, and machine learning techniques, data-driven fault detection and diagnostics (FDD) for building heating, ventilation, and air conditioning systems has gained increasing attention. In this paper, data-driven FDD is defined as those that are built or trained from data via machine learning or multivariate statistical analysis methods. Following this definition, this paper reviews and summarizes the literature on data-driven FDD from three aspects: process, systems studied (including the systems being investigated, the faults being identified, and the associated data sources), and evaluation metrics. A data-driven FDD process is further divided into the following steps: data collection, data cleansing, data preprocessing, baseline establishment, fault detection, fault diagnostics, and potential fault prognostics. Literature reported data-driven methods used in each step of an FDD process are firstly discussed. Applications of data-driven FDD in various HVAC systems/components and commonly used data source for FDD development are reviewed secondly, followed by a summary of typical metrics for evaluating FDD methods. Finally, this literature review concludes that despite the promising performance reported in the literature, data-driven FDD methods still face many challenges, such as real-building deployment, performance evaluation and benchmarking, scalability and transferability, interpretability, cyber security and data privacy, user experience, etc. Addressing these challenges is critical for a broad real-building adoption of data-driven FDD.

1. Introduction

1.1. Background

Building systems, including heating, ventilation and air conditioning (HVAC) systems, are usually subject to faults that can lead to undesirable performance, such as excessive energy waste, high maintenance costs, uncomfortable indoor thermal environments, and poor air quality. These faults refer to sensor failure, equipment failure, or faulty system operation. Studies have shown that 15%–30% of energy may be wasted due to building system faults and improper controls [1]. Therefore, fault detection and diagnostics (FDD) or automated fault detection and diagnostics (AFDD) as it is also commonly referred to, is crucial to ensure reliable system operation and avoid energy waste. To be specific, fault detection is defined as "determination that the operation of the building is incorrect or unacceptable in some respect" and fault diagnostics is defined as "identification or localization of the

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cause of faulty operation" [2]. It is reported that FDD users in the office and higher education market sectors of the United States were able to achieve 10% median energy savings annually with two-year simple payback period [3]. It demonstrates the high competitiveness of FDD systems as a profitable investment option in the building sector.

Over the past decades, many FDD methods have been developed. With the advancement of data science and the wide adoption of building automation systems (BAS) or other smart building technologies, data-driven FDD is gaining increased attention. Compared to the traditional expert knowledge/rule based approaches that are typically seen in commercial-off-the-shelf FDD products, data-driven FDD requires little or no *a priori* knowledge and has the potential to achieve high detection and diagnostic accuracy at relatively low cost [4].

Despite the rapid development of machine learning techniques, the market is slowly adopting data-driven FDD as an alternative or complement to the traditional rule-based approaches. A recent systematic survey of fourteen FDD tools in the United States showed that pure expert knowledge-driven methods for fault detection and diagnostics continue to dominate the market, though a few vendors are beginning to use data-driven methods [5]. In Australia, Wall and Guo [6] performed a survey of five FDD tools, two of which claimed to be equipped with machine learning techniques. Yet, details of the data-driven methods were not fully disclosed.

1.2. Data-driven FDD definition

Before a further discussion, it is necessary to provide a definition of the term "data-driven FDD" on the basis of existing literature. During the past two decades, more than twenty review articles concerning FDD in building energy system have been published, and many of them focused on classifying existing FDD approaches. However, the scope of what data-driven FDD encompasses varies. In the classical two-part review by Katipamula and Brambley [1,7], FDD studies were classified into quantitative model-based, qualitative model-based, or process history (data-driven) — based depending on how they approach the problem of fault diagnosis. This classification is loosely based on the classification employed by Venkatasubramanian et al. [8,9,10]. Generally speaking, quantitative and qualitative model-based approaches require *a priori* knowledge of the physical process, while process history-based approaches do not. Although this classification provided a good standing point at that time, Venkatasubramanian et al. [8] acknowledged that it can be confusing sometime as some methods were not one or the other. For example, some physical models require process data to tune the parameters (e.g., grey-box model) and some process history-based methods are quantitative (e.g., neural network) [11]. Despite its shortcomings, this classification scheme was adequate at the time when most methods were based on physical models. It is commonly adopted by other reviewers, such as Chen et al. [12]. With the rapid growth of data science in recent years, a number of recent FDD review articles have focused on data-driven FDD. Zhao et al. [13] conducted a review on artificial intelligence-based (AI-based) FDD methods for building energy systems. They proposed two classification schemes for fault detection and fault diagnosis, respectively. In both schemes, studies were classified into data-driven-based or knowledge-driven-based. For fault detection, data-driven-based methods included classification-based, unsupervised learning-based, and regression-based methods, while knowledge-driven-based methods included model-based and rule-based methods. For fault diagnosis, data-driven-based methods included classification-based and unsupervised learning-based, while knowledge-driven-based methods included inference-based (e.g., Bayesian network, fuzzy logic) and diagnostic rule-based methods. Upon this classification, they further labeled a part of the methods as AI-based. For fault detection, the AI-based methods overlapped with the data-driven-based methods. For fault diagnosis, in addition to data-driven-based methods, inference-based methods from the knowledge-driven-based side were also labeled as AI-based. Mirnaghi and Haghighat [14] conducted a review on FDD of large-scale HVAC systems using data-driven methods. They classified FDD into model-based, data-driven, or knowledge-based. Model-based methods included first principle models and grey-box models. Data-driven methods were further divided into qualitative and quantitative methods. According to Mirnaghi and Haghighat [14], expert systems, fuzzy logic, pattern recognition, frequency analysis were data-driven qualitative-based methods. And statistical methods and neural networks were data-driven quantitative-based methods. Knowledge-based methods were defined as the combination of a qualitative part of the model-based method, including structural graphs, fault trees, or qualitative physics, and data-driven subcategory including fuzzy logic or expert systems.

From the literature, we have not seen any classification scheme that can perfectly classify the wide variety of FDD methods, especially if an FDD method includes multiple techniques. One of the main reasons is that there are no uniform definitions for terms such as data-driven, knowledge-driven, and model-based. In fact, (1) data often contains some levels of knowledge; (2) knowledge is typically presented as data; (3) the term model is often used to express a mathematical relationship between inputs and outputs (which may or may not be based on first principles). Another difficulty is that data could come from various sources, like real building systems, laboratory testing, or even simulation models. In addition, newly proposed methods are often combinations of techniques belonging to different categories. Therefore, in this paper, we will not focus on the categorization of various data-driven FDD methods, but rather on the process, systems studied, and evaluation metrics of data-driven FDD. We hope that this breakdown allows the readers to have a more holistic understanding of data-driven FDD to foster the development and market introduction of data-driven FDD products.

In most publications, the terms data-driven and machine learning are often used interchangeably and machine learning often is not strictly differentiated with multivariate statistical analysis. Therefore, we refer to those FDD methods that have at least one component, such as baseline modeling, fault detection, or fault diagnosis, which are built or trained from data via machine learning or multivariate statistical analysis methods, as data-driven FDD [15]. The effectiveness of the data-driven model is often limited by the training dataset. Therefore, the data quality, resolution, completeness, extensiveness (i.e., whether the data accounts for a variety of operating conditions), and uncertainty (i.e., measurements errors) are particularly important for data-driven FDD methods [1,13].

1.3. Literature gaps and organization of the paper

Despite extensive literature on FDD, a comprehensive review focusing on data-driven methods is still missing, especially one that meets the above definition and the scope. To further advance the development and market adoption of data-driven FDD, this paper provides a comprehensive review of the state-of-the-art data-driven FDD technologies from three main aspects: process, systems studied, and evaluation metrics. The goal of this review is to provide a comprehensive introduction for researchers and practitioners who are new to the topic. It also offers a systematic framework that can be used to categorize these methods, as well as research gaps and future work directions for experienced practitioners.

The content of the article is organized as follows. Section 2 presents the literature collection methodology and provides an overview of the collected papers. Section 3 describes the data-driven FDD process and summarizes the methods used in each step. In addition, it describes studies that have compared different FDD methods. Section 4 summarizes the systems that the data-driven FDD methods are applied to. These systems include, among others: air handling units (AHU), variable air volume (VAV) systems, chiller systems, variable refrigerant flow (VRF) systems. This section also lists the faults that have been identified in these systems and the different data sources. Section 5 discusses typical metrics for evaluating data-driven FDD methods. Section 6 discusses challenges and opportunities for future advancement of data-driven FDD. Section 7 concludes the review.

Fig. 1. Wordcloud of the reviewed papers' keywords.

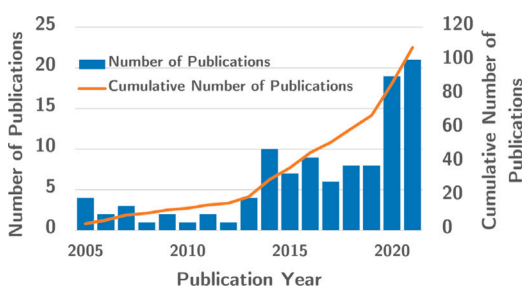

Fig. 2. Breakdown of publications by publication year.

2. Literature identification and screening

The literature reviewed in this paper was collected mainly using a Google scholar based methodology known as Sub-keyword Synonym Subtopics Searching (SSSS: https://github.com/lz356/SSSS). This method aims to exhaust relevant papers by multiple searches with synonyms and subtopics sub-keywords. This method has been proven successful in other review papers, such as Zhang et al. [16,17]. Three sub-keyword groups were used to collect papers from 2005 to 2021. The first group contains: "fault detection", "fault diagnostics". The second group contains: "data driven", "data mining", "AI", "black-box model", "anomaly detection", "data cleansing". And the third group contains: "building", "HVAC". For each search, SSSS took one word from each sub-keywords group to form a new keyword, and searched it in Google scholar. Besides the papers collected through SSSS, relevant papers from the authors' own collections and papers cited in the reviewed studies were also investigated. Fig. 1 shows a visual summary of the keywords contained in the reviewed literature.

Fig. 2 illustrates the number of published technical papers focusing on data-driven FDD from 2005 to 2021, with a detailed breakdown on the year of publication. The blue bars show the total number of papers published per year while the orange line displays the cumulative number of publications from 2005. The figure shows a gradual increase of the number of publications with a more noticeable rise in the last ten years. Fig. 3 illustrates the breakdown of the number of publications for the different journals. In particular, only the journals with at least 3 publications are included in this figure. The journal Energy and Buildings ranks the first with 32 papers. These figures, while they may not include every relevant article, generally reflect the current trends of data-driven FDD development.

3. Main steps of data-driven FDD process

Based on the reviewed literature, a data-driven FDD process can be broadly generalized as illustrated in Fig. 4. The first step is the data collection process, in which data are collected from the BAS, meter, or other data sources (e.g., IoT network). Following this, initial data cleansing such as missing data imputation and outlier detection are often performed. The data cleansing process can be carried out before or after the data are sorted into the data pool, depending on the framework of each individual FDD method. Besides data from a real building, simulated data from a digital twin or a simulation model can also be stored in a data pool for model training purposes. Before data is used for FDD development, additional preprocessing (e.g., feature selection, data reduction, data scaling) is often required to improve training performance. Section 3.3 reviews feature selection techniques in more details, as they are crucial for data-driven applications. For real-time implementation, a data-driven FDD method often compares incoming data (also referred to as snapshot data in the literature) with a baseline, which is further discussed in Section 3.4. Here a baseline refers to data or model that represent normal operation. In some cases, a baseline is not necessary. For example, a distributed method was applied to faulty sensor detection which referred to neighbor sensors instead of baselines [18,19]. The final steps of an FDD process are fault detection, fault diagnostics and fault prognostics. It should be noted that some FDD methods can perform fault detection and diagnostics simultaneously, whereas, some methods only perform fault detection without isolating the root causes [13]. Therefore, it is reasonable to discuss fault detection and fault diagnostics methods separately. Besides fault detection and diagnosis, one may also perform fault prognosis. Although this field is relatively underdeveloped, it is meaningful to include it in a general process discussion as it is closely related to detection and diagnosis. Methods used in each FDD step are discussed in the following subsections.

3.1. Data collection

Increasing advancements in building digitization, smart sensing and metering technologies have allowed a large amount of data to be collected and saved for monitoring, analyzing, and controlling of building systems. While modern buildings have considerably more sensing and actuation points than ever before, using them for better data-driven decisions is challenging both on a scientific and an engineering level [20]. Collecting data from a BAS is often the most time-consuming and labor-intensive process due to the fact that an individual building may have its unique BAS configurations, database structures, and datapoint naming conventions [21]. The use of standardized communication protocols, e.g., Building Automation and Control Network (BACnet), and metadata schemas, e.g., Project Haystack, Brick, and the recent ASHRAE 223P standard [22–24], can effectively ease the data collection process. Nevertheless, FDD applications that utilize metadata or semantic graph are still very few and underdeveloped [25].

3.2. Data cleansing

Often, datasets obtained from the BAS or other sources may be incomplete due to sensor and equipment failures, communication or transmission issues, data corruption, or inconsistencies due to sensor noise, thus, leading to loss of valuable information [26]. These issues exist in almost all kinds of sensors/automation systems and can significantly affect the FDD outcomes since most data analysis and statistical tools are not designed to handle incomplete data. Therefore, in this section, literature reported methods for missing data imputation are mainly discussed. Existing literature on data imputation methods for building data has been focused on univariate time series data using statistical methods [27–29] as well as nonlinear machine learning and deep learning [21,30–32]. More recently, ensemble methods that utilize

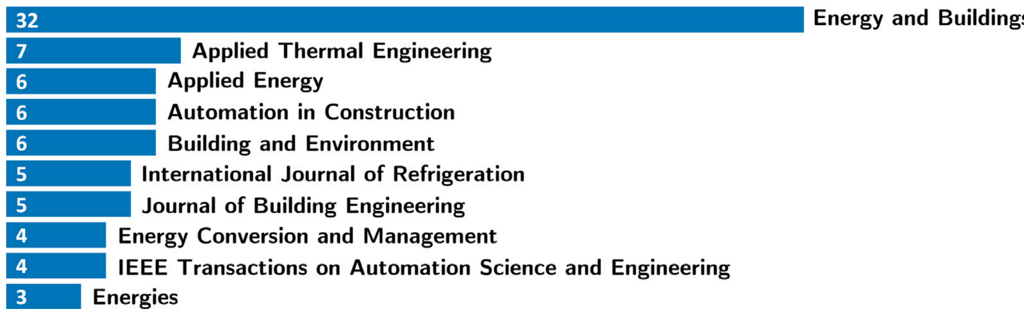

Fig. 3. Number of papers for journal.

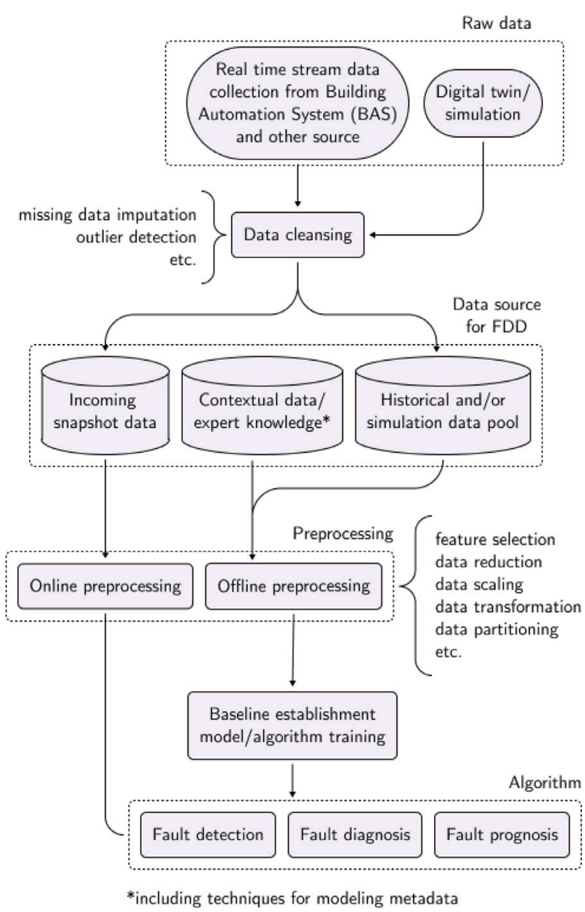

Fig. 4. A general data-driven FDD process.

multiple imputation methods to make an improved prediction of the missing values have also been developed [33,34]. Their research on ensemble methods have shown good performance compared to single imputation methods for building system data. While most of the techniques reported for missing data imputation are focused on generic data-driven applications, there are few studies addressing the missing data issue for FDD purposes. For instance, Li et al. [35] proposed a filtering technique that uses both temporal and spatial information to reconstruct missing values, resulting in an improved FDD performance. Similarly, Wang et al. [36] utilized expectation–maximization (EM) algorithm to impute missing data prior to fault diagnosis. Their comparative study showed significant improvement when adding data imputation to their fault diagnosis model.

3.3. Data preprocessing

Data used for training FDD algorithms often need to be preprocessed beforehand to achieve desired training performance. This step may include feature selection, data reduction, data scaling, data transformation, data partitioning, etc. [37]. Typically, this step is performed offline (e.g., selecting some relevant features from historical data), and then the results of the preprocessing (e.g., the selected features), are applied to the snapshot data. This section mainly reviews the feature selection techniques.

Considering that there are hundreds or thousands of sensors from a BAS, often consisting of redundant measurements, the selection of informative and representative features strongly affects the performance of a data-driven FDD method [38]. Using all the features available within a massive dataset would cause models to be overfitted and increases the model complexity and computational cost [38,39]. Therefore, feature selection processes are often used to find the key inputs for a data-driven model used for the FDD process. Using only selected features instead of the entire dataset reduces the model complexity and model overfitting issues.

Different categories of feature selection methods such as filter, wrapper, embedded, and hybrid methods have been reported for FDD applications [40]. For instance, Li et al. [41] developed a novel filter method named information greedy feature filter (IGFF) to efficiently select and identify the most informative features from the AHU measurements based on mutual information. The selected method showed good performance when applied to the ASHRAE RP-1312 dataset [42,43]. Filter methods are computationally fast and less prone to overfitting; however, it may fail to find the subset of features that results with the highest model accuracy [39]. On the other hand, wrapper method is an exhaustive searching method that trains and evaluates a specific model with different feature combinations, then selects the optimal combination with the best performance. Namburu et al. [44] implemented a simple genetic algorithm (SGA)-based wrapper to determine the optimal feature set for chiller FDD applications. Similarly, Yan et al. [45] and Mulumba et al. [46] incorporated auto-regressive models with exogenous variables (ARX) and Support Vector Machine (SVM) for chiller FDD application. Chen et al. [47,48] developed a partial least square regression and genetic algorithm (PLSR-GA) wrapper method to identify candidate features that represent the system performance under different operational modes. In their method, the GA searching process is used to facilitate the process of searching candidate features which are iteratively fitted to the PLSR model to evaluate the model performance. Although wrapper methods have shown good model performance, they are computationally expensive and susceptible to overfitting since multiple models are trained and evaluated [38]. Embedded methods that combine both the filter and wrapper methods are usually incorporated into a specific learning algorithm such as decision trees (DT) and random forest (RF). Yan et al. [49] applied a DT-based fault diagnostic for AHUs using a classification and regression tree (CART) algorithm where the features are automatically selected when training the model. Embedded methods that are not incorporated into the learning are categorized as hybrid methods. Han et al. [50, 51] used mutual-information-based filter and genetic-algorithm-based wrapper method to search for the important sensors in data-driven chiller FDD applications.

More recently, feature extraction methods directed at identifying and extracting interesting "localized" patterns within a timeseries to guide the feature selection process have also gained attention. For example, Zhang et al. [38] developed a novel framework that integrated feature extraction and selection for whole building FDD. Statistical feature extraction techniques are first employed in this framework to actively extract features from raw sensor data using various window sizes and statistical measures. Then, a hybrid feature selection algorithm that combines the filter and wrapper method is used to select the best feature combination. This framework achieves high model generalization since it considers diverse durations of fault behavior among different fault types. However, it should be noted that using a wrapper method may increase the computation time significantly if the number of features extracted is too high.

3.4. Baseline establishment

In order to enable FDD, a baseline which represents the normal system operation is often needed. Here, a baseline is defined as a status at which the building's operation is considered to be satisfactory, for instance, when the building has just gone through a commissioning process [47,48]. It is well-recognized that most existing buildings do not operate the way they are supposed to. For a real building, a true fault-free status is hardly achievable. Hence, a more realistic fault detection process is to detect when a building's status is significantly different from its baseline status [47,48]. Such baseline can either be generated by simulation [52] or constructed from historical (normal) data collected from a building.

Building HVAC systems present significantly different system dynamics under different operation modes (heating, cooling, etc.). For example, the components and their parameters engaged in a heating mode for an HVAC system is very different from those in a cooling mode. Both weather and internal loads could trigger the HVAC system to change its operation mode (e.g., from economizer control to cooling when outdoor air temperature increases). Hence, it is often challenging to differentiate system parameter/behavior variations triggered by weather and/or internal conditions from abnormalities triggered by faults in the system [47,48]. Since most data-driven FDD methods detect and diagnose faults by comparing real-time or quasi real-time operation data (snapshot data) with the baseline, it is important that the baseline is under the same operation mode as the snapshot data. The majority of the existing baseline studies focus on pattern recognition and motif discovery strategies to construct a baseline using outdoor weather conditions, daily internal load profiles and temporal association rules to ensure that the constructed baseline is under the same operation mode as the incoming snapshot data [47,48,53–58].

In addition to being a function of the HVAC system modes (e.g., heating, cooling), the baseline is also influenced by the specific control strategy (i.e., the detailed sequence of operation) implemented. A baseline model would ideally be able to incorporate and learn these changes instead of detecting them as faults.

3.5. Fault detection

Data-driven fault detection strategies that determine whether the HVAC system has failures or abnormal operations have shown great potential in efficiently characterizing system operations and developing accurate system models that are scalable, while also reducing engineering time and labor cost. A wide range of fault detection methods have been studied in the literature that can be categorized as supervised, semi-supervised or unsupervised methods [12–14].

Supervised methods for fault detection are trained using both normal operation and labeled fault data to identify whether the incoming data is faulty or fault-free. Supervised methods can be further categorized into classification methods or regression methods based on the type of model output. While classification methods such as SVM [44, 45,59–64] and DT [56,65–71] are used to predict whether the incoming data belongs to the fault or fault-free class, regression methods such as support vector regressions (SVR) [72,73] and neural networks (NN) [52,69,74–81] typically predict continuous variables, representing the system operation status, which is then compared to the baseline to identify any occurring faults. Both types of supervised methods have been widely used for fault detection in building HVAC systems. However, the challenge with supervised methods is in obtaining sufficient labeled fault data for training the models, often leading to imbalanced classes. Given the difficulty and the cost to label data, models used by supervised methods are often trained using data collected from older components or simulation models which can lead to lower detection accuracy and higher false alarm rates.

Alternatively, semi-supervised methods are more suitable when only limited labeled fault data is available [14]. Semi-supervised methods transfer unlabeled data into labeled classes by comparing the incoming data with normal operation, and updating the training set iteratively [82]. Although semi-supervised methods perform better when limited labeled fault data is available, semi-supervised methods have a higher computational cost than supervised learning [14].

Lastly, unsupervised methods that do not require fault labels have also been reported in the literature. These methods are helpful in discovering hidden correlations within a building's dataset and allow fault impact analysis to be made during the detection process. Some of the popular methods in this category are clustering algorithms [54, 65,68,75,83–91] and principal component analysis (PCA) [44,47,48,63, 92–102] which are used typically with pattern recognition and motif discovery methods. Since only fault-free data is required for deploying unsupervised methods, these methods are easier to develop and deploy for fault detection purposes.

3.6. Fault diagnosis

Identifying or localizing the root cause of a fault or anomaly is typically more challenging than detecting the anomaly, since different faults (e.g., malfunctioning hardware, software errors) can lead to the same symptom. Correctly diagnosing the root cause of a fault often requires a detailed knowledge of the HVAC configuration and control strategies, both of which are specific to a building. The literature has reported several inference and classification methods for fault diagnosis. Bayesian network (BN) models based on the conditional probability theorem that predicts the fault beliefs based on a set of observations are popular [103]. BN models can incorporate the system structure information through probabilistic conditional relations between faults and their symptoms. These probabilities can be updated after new observations (evidence) of the system are obtained. Further, by adding uncertainty factors for reasoning, the BN model can avoid incorrect diagnosis by avoiding under-responsiveness or over-responsiveness to evidence [104]. Successful implementation of BNs for both component-level and system-level fault diagnosis has been demonstrated in the existing literature. For instance, Zhao et al. [104, 105] proposed a component-level diagnostic BN for different faults in AHUs and chillers. These BNs were developed based on the fault patterns found in projects including NIST 6964, ASHRAE projects RP-1020 and RP-1312. Similarly, Xiao et al. [106] developed a BN based FDD method for diagnosing faults in VAV terminal units. At the system-level, Verbert et al. [107] developed a model-based BN method to diagnose system-level HVAC faults which included interdependencies between different components to carry out continuous fault diagnosis. More recently, Chen et al. [108] developed a discrete BN-based method for cross-level faults diagnosis in commercial buildings. Unlike continuous BNs which use continuous probability distributions in each node of the network, the continuous variables are discretized to represent fuzzy events in a discrete BN [109]. This makes modeling the BN parameters easier and more efficient, especially when obtaining parameters from expert knowledge and incomplete field data [110]. Alternatively, dynamic BN models that describe the temporal relationship of the fault states within each time slice have shown to be effective for fault diagnosis as well. Shi et al. [111] employed a dynamic BN using simulated data which successfully identified persistent as well as transient faults with reduced false positive rates. By carrying past information, a dynamic BN allows fault beliefs to accumulate over time, thus helps eliminate measurement errors and improve diagnosis accuracy [112].

Other diagnostic inference methods such as fault-trees that are based on a decision tree and multiple binaries of if-statements are usually time-consuming and may be highly dependent on domain expertise [14]. Alternatively, classification methods such as SVMs [46,113–116] and ANNs [52,74,75] are also popular. These methods generally require a large amount of labeled data for model training, which can be challenging to obtain in real-world applications. To overcome the challenge of insufficient labeled data, Miyata et al. [52] proposed a NN-based method using convolutional neural network (CNN) trained on dynamic system simulation data of various fault types. Their method demonstrated good performance in learning fault behaviors from simulated data to identify both equipment-level and system-level faults in real data. Overall, NN-based methods have received increasing attention in recent years and show more accurate results than other classification methods [117]. However, the inference process behind the diagnosis of such black-box models often lacks transparency and interpretability [118].

3.7. Fault prognosis

Fault identification and diagnosis through FDD may not be sufficient in cases where critical functions of the systems may have already failed before the fault symptoms are observed, leading to excess operation and maintenance cost [119]. Additionally, some faults in building HVAC occur gradually and although do not produce a significant effect on the operation at the time, they may lead to considerable energy waste over time [14]. For example, if the zone temperature sensor drifts resulting in a higher than actual value, the controller will supply more chilled water to the cooling coil to reduce the zone temperature incurring in energy wastage. Other examples of gradual faults include coil fouling, duct leakage, decrease in fan efficiency, etc. It is estimated that over 20% of HVAC systems are running under early stage of gradual faults resulting over 15% in energy waste [120]. Therefore, data-driven fault prognosis approaches, which refers to identifying impending faults ahead of time and estimating how soon a fault may occur by analyzing historical or real-time measurements for predictive maintenance and repair schedules, is essential for ensuring the safety, stability and for increasing the lifespan of HVAC systems. As an example for predictive maintenance, the maintenance program could be based on the performance degradation of a heat pump system. Typical key performance indicators for such an approach are the coefficient of performance (COP) of the heat pump or the system efficiency index (SEI), which is the ratio of the measured COP and the maximum COP at the same specified reference temperatures [121,122].

Data-driven fault prognosis methods have been gaining attention from different industrial sectors in recent years [119], however, development of fault prognosis strategies for HVAC systems is still in its infancy. Of the existing literature, Yang et al. [123] employed a text mining approach based on operator logbooks to produce multiple high-level metrics such as failure probabilities and mean-time to failure. Similarly, Yang et al. [124] developed regression tree models for estimating time-to-failure for chillers and boilers in a central heating and cooling plant. Ahmad and Atta [125] studied motor failures using electric current predictions and Wang et al. [126] developed an algorithm based on particle filters to estimate the remaining useful life (RUL) of heat exchangers. Their proposed method demonstrates its effectiveness in predicting both natural and transient degradations. Using their method, about half of the modeled failure events were accurately predicted in the distributed control system of the plant. Using typically available BAS data, Yan et al. [127] developed a Hidden Semi-Markov Model (HSMM)-based method to efficiently estimate the RUL of an AHU and its component. Their approach was evaluated using ASHRAE RP-1312 data for both single and multiple fault cases.

The strength of data-driven models for fault prognosis has been demonstrated in many industrial sectors. For example, Recurrent Neural Networks (RNNs) that can exploit temporal correlations in the data by using a feedback loop enables accurate predictions of time series. Such data-driven models for fault prognosis have been investigated in process operations [128] and predictive maintenance of machines [129,130]. Besides RNN, Autoencoder (AE) [131] and Restricted Boltzmann Machine (RBM) [132] approaches are also applied in recent data-driven models for fault prognosis. Those architectures show great potential for fault prognosis of building HVAC systems.

3.8. Summary of data-driven FDD methods

Table 1 presents ten data-driven methods used for fault detection and diagnosis that are commonly seen in the reviewed papers. These methods are: Clustering, Decision Tree (DT), Principal Component Analysis (PCA), Support Vector Machine (SVM), Support Vector Regression (SVR), Neural Network (NN), Bayesian Network (BN), Hidden Markov Model (HMM), Generative Adversarial Network (GAN), and Ensemble Learning. Notice that the papers listed for each method serve as examples and are not all-inclusive.

Among all the reviewed papers, some compared different data-driven FDD algorithms in their studies. These comparison studies are illustrated in Table 2. For each comparison study, Table 2 presents information about (1) whether the study focuses on fault detection or fault diagnosis; (2) whether the studied method is supervised or unsupervised; (3) the HVAC system/component that the FDD method is applied to; and (4) the specific algorithms being compared. It can be seen that most compared algorithms belong to the same category. For example, Amruthnath and Gupta [133] applied and compared unsupervised methods for early fault detection in exhaust fans. Asgari et al. [80] compared two supervised models, CNN and RNN, to predict multiple simultaneous failures in the data center cooling units. There are limited studies that compare the performance between different categories (e.g., expert rule-based vs data-driven, supervised vs unsupervised).

4. Systems studied with data-driven FDD

Data-driven FDD methods have been reported to be applied to many HVAC components and subsystems for various types of faults. This section summarizes (1) the systems that data-driven FDD have been applied to; (2) the identified faults associated with the systems; and (3) the main data source utilized when developing and evaluating a data-driven FDD method. Table 3 presents the detailed information that is being discussed in this section.

4.1. Faulty systems and identified faults

Several studies discussed HVAC fault categories [120,183,184]. Based on these discussions, HVAC faults can be categorized as hardware and software faults by the types of component. Hardware faults further include equipment faults, sensor faults, and controlled device (including actuator) faults. Software faults further include controller faults (e.g., unstable control), human faults (operator faults) and control logic errors. Fig. 5 illustrates the workflow of these categories. Reviews

Table 1
Commonly used data-driven methods for fault detection and diagnostics.

Method	Reference
Clustering	Capozzoli et al. [65], Du et al. [75], Narayanaswamy et al. [134], Fan et al. [83], Miller et al. [54], Cheng et al. [84], Li et al. [35,85], Dey et al. [86,87], Aguilar et al. [88], Gunay and Shi [89], Xu et al. [90], Zhou et al. [91], Liu et al. [68]
DT	Capozzoli et al. [65], Yan et al. [49], Li et al. [135], Capozzoli et al. [66], Piscitelli et al. [56], Tesfay et al. [67], Liu et al. [68], Piscitelli et al. [69], Chiosa et al. [70,71]
PCA	Wang and Qin [92], Namburu et al. [44], Du and Jin [93,94], Hu et al. [95], Li and Wen [96,97], Cotrufo and Zmeureanu [98], Hu et al. [99], Yan et al. [136], Shi et al. [100], Li and Hu [101], Montazeri and Kargar [63], Zhou et al. [102], Chen et al. [47,48]
SVM	Namburu et al. [44], Liang and Du [59], Li et al. [113], Han et al. [51], Dehestani et al. [60], Yan et al. [45], Beghi et al. [61], Beghi et al. [114], Mulumba et al. [46], Fan et al. [115], Madhikermi et al. [62], Montazeri and Kargar [63], Li et al. [64], Lee et al. [116]
SVR	Zhao et al. [72], Liu et al. [73]
NN	Cho et al. [137], Hou et al. [138], Du et al. [139], Magoulès et al. [74], Dehestani et al. [60], Du et al. [75], Jones [76], Guo et al. [140], Shi et al. [100], Madhikermi et al. [62], Lee et al. [77], Shahnazari et al. [141], Sipple [78], Xu and Chen [79], Miyata et al. [52], Piscitelli et al. [69], Asgari et al. [80], Han et al. [142], Liu et al. [143], Taheri et al. [144], Liao et al. [81]
BN	Wall et al. [145], Zhao et al. [146], Dong et al. [147], Xiao et al. [106], Zhao et al. [104,105], Verbert et al. [107], Taal et al. [148], Wang et al. [149], Li et al. [118], Chen et al. [108]
HMM	West et al. [150], Yan et al. [127,151]
GAN	Zhong et al. [152], Yan et al. [82,153], Li et al. [154]
Ensemble learning	Araya et al. [155], Fan et al. [156], Zhong et al. [152], Han et al. [157]

Table 2
A collection of the comparison studies using different data-driven FDD algorithms.

References	Detection	Diagnosis	Proposed FDD type	System	Algorithm comparison
Namburu et al. [44]		x	Supervised	Chiller	SVM, PCA, PLS
Capozzoli et al. [65]	x		Unsupervised	Whole building	CART, K-Means, DBSCAN
Yan et al. [45]		x	Supervised	Chiller	ARX+SVM, LinReg+SVM, ARX+NN, SVM
Jones [76]	x	x	Supervised	AHU	Detection: ART, LAPART, NN, SVM, Rule-based; Diagnosis: SVM, LAPART
Mulumba et al. [46]		x	Supervised	AHU	NB, BN, RBF, MLP, SVM, RF
Li et al. [158]		x	Supervised	Chiller	SVM, DT, NN, AB, QDA, LogReg
Guo et al. [159]		x	Supervised	VRF	DBNs w/ various settings
Amruthnath and Gupta [133]	x		Unsupervised	Exhaust fan	PCA, T2 statistic, Hierarchical clustering, K-Means, Fuzzy C-Means
Li et al. [135]		x	Supervised	VRF	CART, RF, GBM
Li and Hu [101]	x	x	Unsupervised	Chiller	PCA, DBSCAN
Dey et al. [87]		x	Supervised	FCU	SVM, NN
Zhou et al. [160]		x	Supervised	VRF	DT, SVM, clustering, SNN, DNN
Ebrahimifakhar et al. [161]		x	Supervised	RTU	LogReg, LDA, QDA, KNN, Bagging, RF, AB, XGB, SVM
Yan et al. [82]	x	x	Semi-supervised	Chiller	SVM, RF, DT, BN, KNN, LogReg w/ and w/o GAN
Yan et al. [153]	x	x	Semi-supervised	AHU	RF, SVM, MLP, KNN, DT w/ and w/o GAN
Shohet et al. [162]	x		Supervised	Boiler	KNN, DT, RF, SVM
Han et al. [157]		x	Supervised	Chiller	Ensemble learning, KNN, SVM, RF
Li et al. [163]		x	Semi-supervised	Chiller	Semi-GAN, NN, DBN, LS-SVM
Asgari et al. [80]	x	x	Supervised	AC unit	CNN, RNN
Wang et al. [164]		x	Supervised	Chiller	SVM, BN, SVM+BN
Taheri et al. [144]		x	Supervised	AHU	deep RNN, RF, GB

on the impact of faults in each category are out of the scope of this paper. For interested readers we recommend the following studies on impact of faults: equipment faults from Mirnaghi and Haghighat [14] and Rogers et al. [11], sensor faults from Zhang et al. [185], controlled device faults from Weimer et al. [186], human faults from Torabi et al. [187], and fault impact evaluation framework from Lu et al. [188]. Most published papers focus on single fault, despite the fact that simultaneous faults could occur in real systems. Some recent studies such as Hu et al. [189], Hu and Yuill [190] start to discuss impacts from simultaneous faults.

Fault detection and diagnostics can be implemented at the building level, system/subsystem level (e.g., an air handle unit), and/or component level (e.g., a damper) [183]. Building-level FDD aims to detect and diagnose the occurrence of non-optimal operational patterns by identifying anomalous energy trends in the building energy consumption time series [54,66]. At this scale, classification, regression and pattern recognition techniques are employed to estimate the baseline for the detection of anomalies while sub-meter load data are used to infer the root cause of anomalies at whole-building level [70,71].

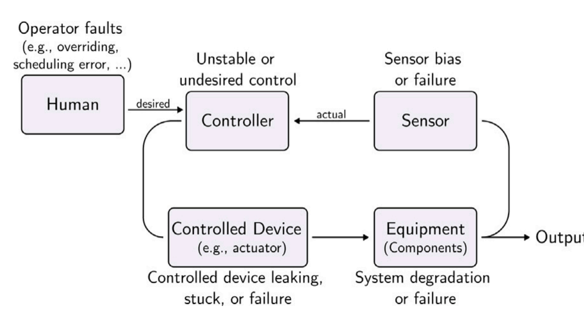

Fig. 5. Fault distribution in an HVAC system.
Source: Expanded from Yu et al. [120].

Table 3
Summary of systems studied with data-driven FDD and associated data sources.

System	Data source	Reference
AHU or AHU-VAV	lab data	Cho et al. [137], Hou et al. [138], West et al. [150], Wall et al. [145], Dehestani et al. [60], Li and Wen [96,97], Mulumba et al. [46], Zhao et al. [105], Yan et al. [49], Zhao et al. [104], Yan et al. [127], Zhong et al. [152], Li et al. [35], Piscitelli et al. [56], Yan et al. [153], Dowling and Zhang [165], Li et al. [118], Taheri et al. [144], Liao et al. [81]
	real data	Wang and Qin [92], West et al. [150], Dong et al. [147], Narayanaswamy et al. [134], Cheng et al. [84], Madhikermi et al. [62], Gunay and Shi [89]
	sim data	Wang and Qin [92], Liang and Du [59], Du and Jin [93,94], Li et al. [113], Du et al. [75,139], Xiao et al. [106], Jones [76], Yan et al. [127,136], Verbert et al. [107], Turner et al. [166], Shahnazari et al. [141], Lee et al. [77], Yan et al. [151], Montazeri and Kargar [63]
Chiller	lab data	Choi et al. [167], Namburu et al. [44,168], Han et al. [50,51], Zhao et al. [146], Yan et al. [45], Zhao et al. [169], Beghi et al. [61,114], Li et al. [85,158], Beghi et al. [170], Fan et al. [115], van de Sand et al. [171], Wang et al. [149], Han et al. [157], Liu et al. [172], Yan et al. [82], Li et al. [64], Yan [173], Li et al. [163], Han et al. [142], Li et al. [154,174], Wang et al. [164], Liu et al. [143], Gao et al. [175]
	real data	Hu et al. [95], Zucker et al. [176], Dong et al. [147], Cotrufo and Zmeureanu [98], Cheng et al. [84], Hu et al. [99], Li et al. [177], Li and Hu [101], Lee et al. [116]
	sim data	Du and Jin [93], Zhao et al. [72], Miyata et al. [52]
Boiler	sim data	Verbert et al. [107], Shohet et al. [162]
AC unit	sim data	Asgari et al. [80]
RTU or RTU-VAV	lab data	Li et al. [154]
	sim data	Ebrahimifakhar et al. [161]
FCU	real data	Dey et al. [86], Dey et al. [87]
VRF	lab data	Guo et al. [140], Shi et al. [100], Li et al. [135], Guo et al. [159], Liu et al. [73,178], Zhou et al. [160], Zeng et al. [179], Zhou et al. [102]
Heat pump	lab data	Zogg et al. [180], Tesfay et al. [67]
	real data	Taal et al. [148]
District heating	real data	Xue et al. [181]
Whole building	real data	Jacob et al. [182], Capozzoli et al. [65], Fan et al. [83], Miller et al. [54], Araya et al. [155], Capozzoli et al. [66], Fan et al. [156], Gunay and Shi [89], Sipple [78], Xu and Chen [79], Aguilar et al. [88], Zhou et al. [91], Xu et al. [90], Piscitelli et al. [69], Chiosa et al. [70], Liu et al. [68], Chen et al. [47], Chiosa et al. [71], Chen et al. [48,108]
	sim data	Magoulès et al. [74]

Not all potential faults are studied in the existing research papers and reports, and different HVAC systems are focused for different building sizes. For large size buildings, FDD is often applied to AHU-VAV systems, fan coil units (FCU), chillers, and boilers. Yet for small and medium sized buildings, FDD is usually applied to heat pumps and window air conditioners. From the reviewed papers, the most popular research subjects are secondary AHU-VAV systems (35%) and chillers (32%), followed by whole-building studies (17%) and VRFs (7%). The top two faulty systems (i.e., secondary systems and vapor compression systems) and the corresponding classification of the faults in these systems (summarized from the references listed in Table 3) are illustrated in Fig. 6. Secondary systems can provide required heating and cooling for multiple zones. Its actuator faults and equipment faults are typically studied, including OA/RA/SA/VAV dampers, cooling/heating coil valves, SA/RA fans, and air ducts. Vapor Compression Cycle (VCC) systems, consisting of a set of components (compressors, heat exchangers, and expansion devices), are included in a wide range of equipment, from small split air conditioners that are usually used in residential houses, to large central systems such as chillers that provide significant cooling/heating capacity to serve an entire office building, hospital, or campus buildings. Among them, chiller faults are the most widely studied with regards to data-driven methods. Those faults can be classified as local faults (e.g., condenser fouling, reduced condenser water flow, non-condensable in the refrigerant, reduced evaporator water flow, etc.) and system faults (e.g., refrigerant leak/undercharge, refrigerant overcharge, excess oil, etc.) [149]. Furthermore, a proper time resolution of the measurement data should be chosen depending on which system level is of interest. For example, determining the COP of a heat pump with on/off control might only need data with 15-minute resolution, whereas higher resolution (e.g., 1-minute) can reveal operational issues, such as too frequent heat pump cycling or an unreasonable defrost cycle schedule. These control logic issues can lead to a poor energy performance even though all components work properly.

Although most of the literature on FDD focuses on the system/component level, FDD at whole-building level has increasingly attracted the interest of researchers. The influence of several factors such as building dynamics, external climatic conditions, system operating schedules and occupant comfort requirements can determine the occurrence of numerous building energy consumption patterns that are not always easy to be recognized. In addition, in most of the real-life applications, only few and aggregate variables pertaining to the whole-building and main sub-loads energy consumption are available, which increases the complexity in conceptualizing FDD processes at the building level. In this context, the main objectives of a building-scale FDD process are (1) the recognition of typical patterns in the whole-building energy consumption time series, (2) the detection of infrequent/anomalous patterns, and (3) the diagnosis of the detected anomalies by inferring the presence of anomalous patterns at the sub-load level. All three objectives require expert domain knowledge on how the building and its energy systems work and are operated. Different from applications at the system level, anomalies at a higher level of analysis are difficult to be classified and generalized due to the lack of ground-truth datasets for conducting both detection and diagnosis. As a consequence, for applications at whole building level, unsupervised learning through pattern recognition techniques is the most employed approach [47,48,108].

4.2. Data source

For data-driven FDD method development, data, such as labeled normal and fault data, are needed for training and method evaluation purposes. These data can be supplied from simulation, laboratory experiments, and field measurements from a real building. Among the papers reviewed, excluding those in which the data source was not

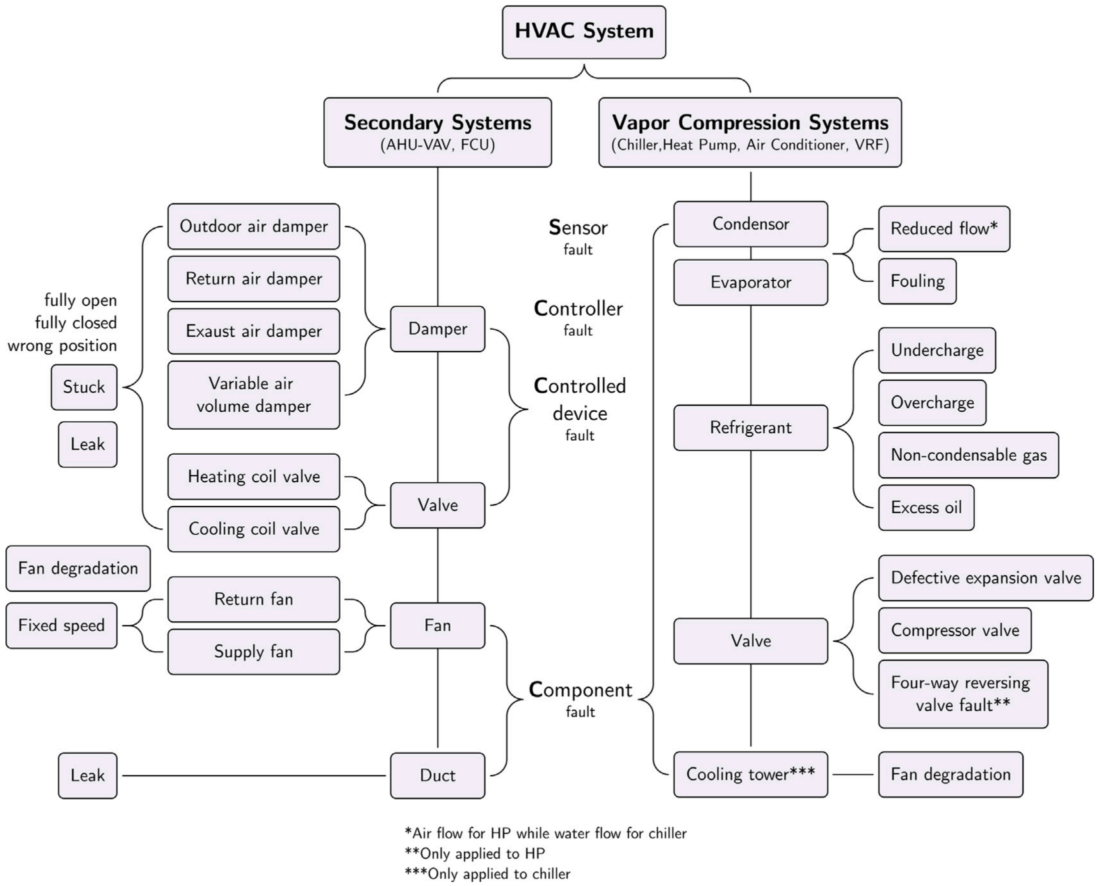

Fig. 6. Fault classification of HVAC systems.

explicitly stated, 48% use lab experiment data, 20% use simulation data, 32% use real building data. The coupling between the data source and the system type is further analyzed in Fig. 7 which shows that the majority of whole building applications rely on real field measurement data while system-level VRF, AHU and Chiller applications mainly rely on laboratory data.

Among all the reviewed studies, lab experiment data were most commonly adopted. They had been applied in tree-structured learning FDD of chillers [158], GAN-based FDD of AHUs [153], deep learning-based FDD of VRF systems [159] and so on. However, there are limited examples of publicly available datasets that have verified ground-truth information on the presence and absence of faults. Based on the reviewed studies, four research projects offer valuable public available experimental data. The first two are ASHRAE Project 1043-RP data and ASHRAE Project 1312-RP data, which have been widely used in chiller and AHU FDD studies, respectively. The third is the building fault detection data to aid diagnostic algorithm creation and performance testing. The fourth is the LBNL fault detection and diagnostics datasets [191]. Notice that in many cases, a laboratory testbed is a real building with real HVAC system, but it is not occupied and is solely used for testing purposes, such as the ASHRAE 1312 testbed [192]. Details about these four datasets are further discussed below.

- ASHRAE Project 1043-RP data [193]: The experiments were conducted on a R134a refrigerant centrifugal chiller with 90 tons (316 kW) cooling capacity. Nine typical chiller faults were artificially implemented to the test chiller, including reduced evaporator water flow fault, reduced condenser water flow fault, a combination of these two faults, condenser fouling fault, refrigerant leakage fault, refrigerant overcharge fault, excess oil in the compressor fault, non-condensables in refrigerant fault, and a defective pilot valve fault. Each fault was implemented

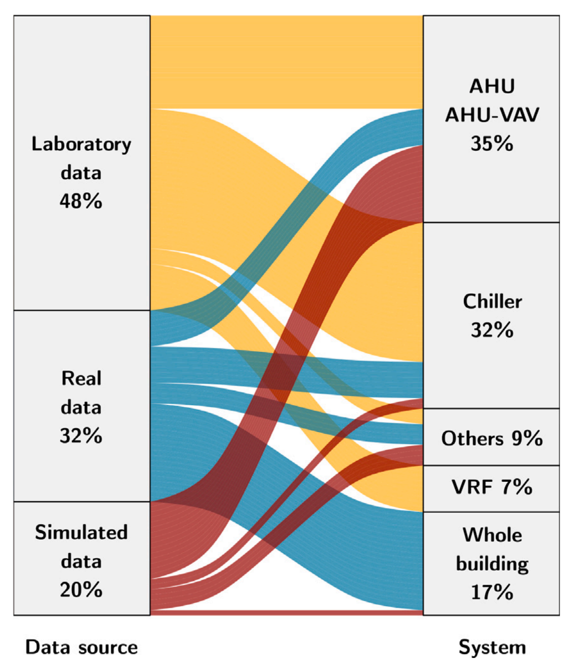

Fig. 7. Alluvial plot for the analyzed literature classified by data source and system type.

at four severity levels ranging from 10% to 40%. At each level of each fault, the experiment was conducted under 27 different operating conditions for about 14 hours. The operational data of 64 variables (e.g., temperature, pressure, rate of flow, power) were collected at 10 seconds and 2 minutes intervals. In each operating condition, the experimental test was first carried out to reach the steady state for about 30 minutes. Next, the steady state test was continuously performed for 15–25 minutes for each operating condition.

- ASHRAE Project 1312-RP data [42,43,192]: A series of experiments were performed on two identical systems (system A and B). Each system includes a multizone AHU-VAV (AHU-A and AHU-B) that serves four building zones (three external and one internal). The AHU-VAV and building zones from each system are exactly identical to the other system. AHU-A was always operated under normal conditions while AHU-B was used to implement different faults. Seventeen faults were tested, including equipment faults, control device faults, sensor faults, and controller faults. Each fault was tested at multiple fault intensity levels in three seasons — spring, summer, and winter. At each level of each fault, the experiment lasted for one day and the operational data of 160 variables were collected at 1-min intervals.
- Building fault detection data to aid diagnostic algorithm creation and performance testing [194]: Two experimental test datasets were created for a single-zone AHU-CAV and a single-zone AHU-VAV serving a real building zone. The experiments include the following AHU faults at multiple fault intensity levels: outside air damper stuck fault, heating/cooling coil valve stuck/leakage fault, and outdoor air temperature sensor bias fault. Another experimental test dataset was generated for RTU-VAV system faults: condenser fouling, HVAC or lighting system setback error (delayed onset or early determination), excessive infiltration, no overnight HVAC or lighting setback, and thermostat temperature bias. In all three datasets, 24 hour operational data of normal and fault test cases were collected at 1-minute intervals.
- LBNL fault detection and diagnostics datasets [191]: The project includes an RTU experimental test dataset, covering faults of incorrect economizer setpoint, outside air damper stuck, and supply air temperature sensor bias. The experiments were performed in spring, summer, fall, and winter seasons and all data use 1-minute measurement frequency.

Simulated data generated from non-proprietary physical model-based simulation software were also used in the reviewed studies. A detailed review of current state-of-the-art for the fault modeling of HVAC systems in buildings, including fault model, fault occurrence probability, and fault simulation platform, was provided in Li and O'Neill [195]. For instance, Du et al. [75] validated a combined neural networks algorithm to detect AHU abnormities using a TRNSYS-based simulation testbed. Lee et al. [77] employed EnergyPlus software to generate different types of fault operation behavior data to serve as references for a deep-learning FDD algorithm for AHUs. Montazeri and Kargar [63] used simulated data from HVACSIM+ software to train and test SVM and PCA FDD methods. Shahnazari et al. [141] modeled an AHU-VAV system using Modelica to demonstrate the ability of recurrent neural networks-based FDD algorithm. In Lu et al. [188], a comprehensive fault impact analysis and robustness assessment of the high-performance control sequences from ASHRAE Guideline 36 was conducted using a Modelica-based fault modeling framework, where 359 fault scenarios, including faults of sensor, duct and pipe, valve and damper, HVAC equipment (e.g., coil fouling, fan mode degradation, etc.), control, design and construction, were simulated. Since these simulation software are originally designed to simulate fault-free operations, fault generators or similar means are needed to simulate faulty operations. Simulating faults using these simulation software sometimes results in unexpected numerical difficulties such as long simulation time, inaccurate results, or even crashing of the simulation program. When modeling faults, it is important to avoid some common causes of numerical difficulties, such as numbers that are beyond the computer precision [196] and discontinuous functions [197]. When it comes to the generation of simulation data for large-scale HVAC systems, an advanced numerical solver that is both efficient and robust shall be considered. For example, when simulating the HVACSIM+ model developed for the ASHRAE Project 1312-RP [192], an advanced nonlinear equations solver [198] can reduce the simulation time by about 70% while maintaining the same level of robustness as the default solver, and even more for larger scale systems. In terms of open-sourced simulation datasets, LBNL FDD datasets [191,199,200] include large simulated datasets with verified information on the presence and severity of faults spanning seven HVAC systems and configurations: a single-duct AHU, a RTU, a dual-duct AHU, a series fan-powered VAV unit, a parallel fan-powered VAV unit, a fan coil unit, a chiller plant, and a boiler plant. HVACSIM+ and Modelica-EnergyPlus co-simulation were employed to carry out simulations of more than 250 faulted or fault-free condition states (e.g., mechanical faults, control sequence faults, sensor faults, etc.) over a full year of operation. Each dataset includes from 20 to more than 100 data points which are described with the Brick schema [22].

Although 32% of the reviewed studies use real building data, half of the studies focus on the detection of energy anomalies that only require energy consumption data. For example, Zhou et al. [91] tested a hierarchical clustering method to identify anomalies in daily energy consumption with the chiller plant power consumption data. Publicly available power consumption datasets that can be used to validate anomaly detection algorithms are rare. The competition "Power Laws: Detecting Anomalies in Usage" offers a few datasets with hand-labeled anomalies corresponding to different types of building sites from different geographies [201]. Field measurements with labeled faulty operation data are more challenging to obtain since manual investigation and/or maintenance record are typically needed to confirm the occurrence of a naturally occurred fault. LBNL FDD datasets [191] also include months of field measured RTU data for a compressor control fault and a refrigerant undercharging fault. Measurements from the commissioning phase of a real building often contains faults and can thus be a valuable part of a training dataset. Documentation of changes in the system throughout the commissioning process is of utmost importance to understand what was a normal or faulty operation. Among studies that utilized real building operation data, Gunay and Shi [89] demonstrated a cluster analysis-based anomaly detection method with a year's worth of BAS data from 247 thermal zones and an air handling unit. Lee et al. [116] implemented AI-FDD on 14 chillers for a 1 year test to obtain the real-world false alarm rejection rate. Chen et al. [47,48] developed a weather and schedule information-based pattern matching (WPM) and feature-based principal component analysis (FPCA) method to detect whole building level faults using 30 day BAS data from a multi-used campus building.

In addition to the labeled time-series system operation or energy use data under normal and fault conditions, other data sources have also been utilized to support the data-driven FDD algorithms. For example, expert knowledge, maintenance records, building information models (BIM), and real-time occupancy data. Expert knowledge has been integrated into data-driven FDD approaches to (1) detect outliers in the data preprocessing step [83], (2) develop, select, and interpret the characteristic features of faults [107,170,181,202], and (3) support the selection of layers, nodes, and parameters in the BN-based or tree-structured FDD algorithms [108,146,158]. Maintenance records were utilized to label the ground truth of field measurements, i.e., whether the collected data contain faults or not [116,148]. The BIM was integrated into model-based FDD to provide building design information (e.g., architecture geometry and building equipment information) [147,203,204]. Real-time building occupancy data from internet of things sensors were employed as an additional data stream to detect the degraded building operation performance [84].

Table 4
Summary of evaluation metrics for data-driven FDD.

Evaluation metrics	References
General evaluation metrics (e.g., Eqs. (1)–(8))	Zogg et al. [180], Jacob et al. [182], Shohet et al. [162], Hu et al. [95], Zhao et al. [72], Sun et al. [205], Zhao et al. [146], Yan et al. [45], Du et al. [75], Narayanaswamy et al. [134], Jones [76], Beghi et al. [114], Li et al. [177], Araya et al. [155], Turner et al. [166], Verbert et al. [107], Guo et al. [140], Liu et al. [73], Guo et al. [159], Shi et al. [100], Zhong et al. [152], Liu et al. [172], Zhou et al. [160], Li et al. [163], Guo and Rasmussen [206], Zhou et al. [102], Piscitelli et al. [69], Chen et al. [47,48,108]
Classification problem metrics	Choi et al. [167], Namburu et al. [168], Du and Jin [93], Namburu et al. [44], Liang and Du [59], Li et al. [113], Dehestani et al. [60], Magoulès et al. [74], Mulumba et al. [46], Yan et al. [49], Li et al. [158], Yan et al. [127], Li et al. [135], Lee et al. [77], Liu et al. [178], Fan et al. [115], Li et al. [35], Montazeri and Kargar [63], Ebrahimifakhar et al. [161], Yan et al. [153], Zeng et al. [179], Aguilar et al. [88], Yan et al. [82], Dowling and Zhang [165], Dey et al. [87], Gao et al. [175], Yan [173], Lee et al. [116], Chiosa et al. [70], Li et al. [154,174], Wang et al. [164], Liu et al. [143]; Beghi et al. [61], Sipple [78], Asgari et al. [80]
Statistical significance tests	Han et al. [157], Dey et al. [86]

5. Evaluation metrics for data-driven FDD

It is critical to evaluate and quantify the performance and effectiveness of data-driven FDD methods by using dedicated metrics. In this section, evaluation metrics adopted from the reviewed literature for data-driven FDD are summarized and discussed. Corresponding studies for each evaluation metric are illustrated in Table 4. The collected metrics can be broadly classified into three categories: general evaluation metrics for FDD applications, evaluation metrics for data-driven classification problems, and statistical significance tests that assist the evaluation of classification problems.

General evaluation metrics

Lin et al. [207] summarized the evaluation metrics for general FDD applications. To assess the performance of a fault detection problem, the evaluation metrics include the true positive rate (TPR), true negative rate (TNR), false positive rate (FPR), false negative rate (FNR), and no detection rate (NDR), which are shown in Eqs. (1)–(5). To assess a fault diagnosis method, the evaluation metrics often include the correct diagnosis rate (CDR), the misdiagnosis rate (MDR), and the no diagnosis rate (NDgR), as listed in Eqs. (6)–(8). Note that each evaluation metric mentioned above focuses on a specific aspect of the FDD problem, and thus relying solely on one metric can be misleading. For example, in a dataset with a large number of fault-free samples and a small number of fault samples, TNR can be misleading, since an algorithm that simply predicts fault-free for all samples can still achieve a high TNR. Therefore, it is important to evaluate these metrics together. To provide a clear understanding of these metrics, Fig. 8 visualizes the relationship of the terms used in these equations in a confusion matrix, which will be further discussed in the section below.

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{1}$$

$$\mathrm{TNR} = \frac{\mathrm{TN}}{\mathrm{TN+FP}} \tag{2}$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{TN+FP}} \tag{3}$$

$$\mathrm{FNR} = \frac{\mathrm{FN}}{\mathrm{TP+FN}} \tag{4}$$

$$\mathrm{NDR} = \frac{\mathrm{ND}}{\mathrm{TP+TN+FP+FN}} \tag{5}$$

$$\mathrm{CDR} = \frac{\mathrm{CD}}{\mathrm{TP+FN}} \tag{6}$$

$$\mathrm{MDR} = \frac{\mathrm{MD}}{\mathrm{TP+FN}} \tag{7}$$

$$\mathrm{NDgR} = \frac{\mathrm{NDg}}{\mathrm{TP+FN}} \tag{8}$$

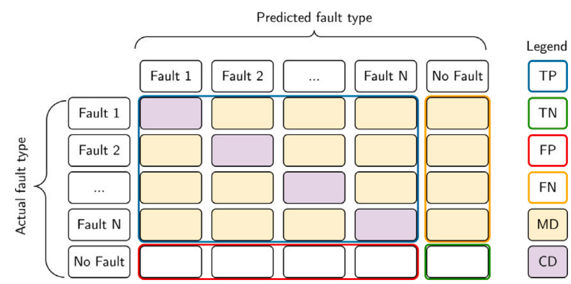

Fig. 8. Example of a confusion matrix. Given the predicted fault types on the columns and the actual fault types on the rows, the matrix shows the correct diagnosis (CD), misdiagnosis (MD), true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN).

Classification problem metrics

An FDD problem is essentially a classification problem; fault detection is a binary classification problem, while fault diagnosis is a multi-class classification problem. The general metrics described above are often combined visually or quantitatively into a classification problem metric for a more in-depth evaluation of data-driven classifiers. These classification problem metrics include confusion matrix, accuracy of correct predictions, F-measure (or F-score), Receiver Operator Characteristic (ROC), and Area Under the Curve (AUC).

Confusion Matrix. A confusion matrix is a visualization of prediction results for a classification model [208]. It depicts the degree of algorithm confusion within different classes and is independent of a concrete classification algorithm [157]. Each matrix element represents the test observations, with the actual (true) class in rows and the predicted class in columns. The diagonal elements show the correct predictions while the off-diagonal elements show the incorrect predictions and how they were misclassified. For a 2 by 2 confusion matrix, two rows and two columns report the number of true positive, false negative, false positive, and true negative. Ebrahimifakhar et al. [161] visualized the classification performance of different algorithms in diagnosing faults for packaged rooftop units.

Accuracy of Correct Predictions. The overall accuracy of correct predictions is defined as the number of correct predictions (i.e., the diagonal elements of the confusion matrix) divided by the total number of observations, as shown in Eq. (9). Montazeri and Kargar [63] compared the diagnostic results of the proposed FDD method (i.e., KPCA and RBF neural network) and previous studies by visualization of the confusion matrix and using the accuracy. Overall, it is a simple and intuitive measure, yet it may fail on classification problems with a skewed class distribution.

$$\mathrm{Accuracy} = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \tag{9}$$

F-Measure. F-measure [209] is a comprehensive performance metric to evaluate the quality of a classifier which considers the class-specific performance, as shown in Eq. (10). F-measure ranges from 0 to 1. The larger the F-measure is, the better the comprehensive performance of the classification model is [210]. In the equation, "Precision" refers to the proportion of correctly diagnosed samples in all positive samples, while "Recall" refers to the proportion of correctly diagnosed samples in the true samples.

$$F = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{11}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{12}$$

ROC and AUC. The ROC curve is a graph showing the performance of a classification model at all classification thresholds [211] which plots two parameters: TPR and FPR. One potential drawback of the ROC curve is that it can be difficult to interpret if there are many decision thresholds. This is because each point on the curve represents a different tradeoff between the TPR and FPR, and it may not be immediately clear which point represents the best overall performance of the algorithm. AUC measures the entire two-dimensional area underneath the entire ROC curve from (0,0) to (1,1). A higher AUC [212] indicates that the model performs better in distinguishing between positive and negative classes. Sipple [78] used AUC to compare the anomaly detection performance of various models on predicting failures of HVAC equipment.

Statistical significance tests

Statistical significance (or hypothesis) tests can aid in comparing the performance of different classification models. The purpose of statistical significance testing is to help gather evidence of the extent to which the results returned by the aforementioned evaluation metrics are representative of the general behavior of the classifiers. However, it is noted that significance testing never constitutes a proof that the observation is valid. It provides added support for the observations. Ultimately, demonstrating that a new FDD algorithm performs better than a reference algorithm requires a combination of statistical tests, evaluation metrics, and validation experiments. The frequently used significance tests, for data-driven FDD, include the t-test [213], McNemar's Test [214], Wilcoxon's signed-Rank Test [215], Friedman Test [216], Nemenyi Test [217], etc. Han et al. [157] used Friedman Test and Nemenyi Test to evaluate the performance of different classification models on diagnosing the chiller faults.

6. Future challenges and opportunities

Although research on data-driven FDD has made great advancements in recent years as discussed above, its broad market adoption remains limited [5]. In this section, we discuss some of the ongoing efforts and challenges to further the development and market adoption of data-driven FDD.

Real-building deployment

As discussed in Section 4.2, although much research has been conducted to develop and implement data-driven FDD methods for building systems, most of the studies developed or validated their data-driven methods in simulated environments, in laboratory settings, or using small-scale HVAC systems. Online and real-time implementations of data-driven FDD methods in large-scale systems in real buildings, that can demonstrate the method's performances under various weather conditions, are still rare and in its infancy stage. Despite this limitation, some real-building deployments have been reported in the literature. Here real-building deployment refers to using a strategy for real-time FDD. For example, Lee et al. [116] deployed an SVM-based AI-FDD system to reject false alarms on 14 chillers in a data center for a year. Their results showed that the AI-FDD system achieved 100% correct false alarm rejection rate and the operational cost of investing in the AI platform can be recovered in three months. Wall and Guo [6] presented case studies using five different FDD tools in Australia, some of which reported to employ machine learning techniques. Blanes et al. [218] reported a CASCADE Implementation Kit that integrates FDD tested in two major European airports. The FDD tool employs the SVM method to detect sensor faults. Although the authors implemented pilot tests through 2013 to 2014, a complete performance evaluation was not found.

In general, reliable, fast and computationally affordable solutions that are readily deployable in the field have not been explored sufficiently [14]. Real-building deployments are challenging due to incomplete information and uncertainty [13]. The main factors contributing to this challenge are lack of sensors, poor sensor accuracy, imbalance of fault and fault-free training data, ad-hoc naming conventions for data points, non-standardized sensor installation and control logic, and missing data [13]. A recent study has shown that data uncertainty has a significant impact on the performance of SVM algorithms for chiller fault diagnosis [64]. Validation of data-driven FDD in terms of not only accuracy but also decision-making with real-world uncertainty is needed to overcome market barriers.

Performance evaluation, benchmarking, and fault impact analysis

In the literature, there are limited studies that compare the performance between FDD methods, especially under different categories (e.g., data-driven vs rule-based, supervised vs unsupervised). More comparison studies are needed to demonstrate the performance of and identify the weakness of data-driven methods. On the other hand, establishing common FDD datasets with validated ground-truth is needed to facilitate the assessment of different FDD methods. Lawrence Berkeley National Laboratory has released large FDD datasets, including experimental, simulated, and real building data, to support this effort [191].

In building HVAC systems, there are faults that generate relevant effects while others have negligible symptoms. However, the performance evaluation process of an FDD method is mostly based on the calculation of classification accuracy metrics without considering the importance of prioritizing faults with most adverse impacts. The impact assessment through novel weighted multi-criteria key performance indices (KPIs) is thus needed to put the right attention on different faults considering their effects in terms of energy consumption, greenhouse gas (GHG) emissions, energy costs, thermal comfort and indoor air quality (IAQ) according to their severity and occurrence frequency. For example, Chen et al. [219] developed a simulation-based framework for evaluating the fault effects in FCU. They also proposed a metric, namely the fault symptom occurrence probability (SOP), to assist the fault prioritization. Lu et al. [188] conducted a comprehensive fault impact analysis and robustness assessment of the high-performance control sequences from ASHRAE Guideline 36 using Modelica-based simulation with key performance indexes to evaluate fault impacts from the aspects of energy consumption and energy cost, control quality factor, thermal comfort, ventilation, and the power system.

Scalability and transferability

HVAC systems in large commercial buildings are typically designed and constructed in a unique way for each building. Each building may have its own unique boundary conditions, such as weather, occupancy, and internal load schedules that vary daily. As a result, data-driven FDD method developed for one building may not be applicable to another building. The following research areas may be considered to improve the scalability and transferability of a data-driven FDD method.

Hybrid approach. Data-driven FDD methods require a considerable amount of data to exploit enough reliable and robust extracted knowledge. However, data-driven FDD methods generally cannot extrapolate well beyond the range of training data related to specific boundary conditions, limiting then the scalability and transferability of detection and diagnosis logics among different systems [220]. The expert-based approach, in contrast, has a strong capability for replicating and transferring expert diagnostic reasoning, especially in cases where initial information is not enough for deploying a data-driven process. Integration of both approaches may significantly improve the robustness, accuracy, and generalizability of FDD tools designed for building energy system applications.

Transfer learning. Besides the hybrid approach, transfer learning is being investigated as a fully data-driven solution to address the scalability issues of FDD strategies. Transfer learning [221], can effectively reduce the time to re-collect labeled data and re-train FDD algorithms, and thus reducing developmental costs. Recently, there has been some discussions about transfer learning in the building FDD field. For example, Dowling and Zhang [165] demonstrated a transferable Bayesian classifier for detecting supply fan degradation fault due to fouling filters in a VAV system. Miyata et al. [222] demonstrated transfer learning on convolutional neural networks (CNN) for fault diagnosis of central chilled water plants. Liu et al. [143] developed a transfer-learning-based CNNs for fault diagnosis of chillers. More studies are needed to further explore the potential of using transfer learning to improve the scalability of data-driven FDD.

Metadata schemas. Metadata schema or semantic data model allows data from different buildings to be described in a consistent and standardized manner. Using a common metadata schema not only eases the data collection process (as mentioned in Section 3.1), but also makes a data-driven FDD method more generic. Without a common metadata schema, a data-driven FDD method must be hard-coded to a specific data source of a specific building, thus limiting its scalability and transferability. In addition, metadata schemas can provide well-organized information about the nature of the data (e.g., type of sensor, causal relationship between points), which allows expert knowledge to be incorporated into a data-driven method more effectively. Project Haystack, Brick, and the recent ASHRAE 223P standard [22–24] are good options of metadata schema for building energy systems.

Interpretability

For a market-oriented FDD product, its interpretability (i.e., the ability to explain how a fault is detected or diagnosed) is very important. In fact, building professionals tend to be suspicious of the output of data-driven processes because they are unable to fully understand the model inference mechanism [223]. It is becoming more and more important to develop FDD tools that are capable of providing feedback about the reasons behind a certain detection or diagnosis result with robust indication of the supporting and conflicting evidences towards it.

In this respect, hybrid approaches, such as BNs that incorporate causal relationships between faults and symptoms, show great advantages. However, for pure black-box approaches, such as ANN, users are often unable to explain how they make decisions due to the models non-intuitive and non-transparent nature. The development of an explainable framework can help increase user confidence in such models. While interpretability continues to be a challenging task, a few studies have focused on this issue in recent years. For example, Madhikermi et al. [62] used Local Interpretable Model-agnostic Explanations (LIME) to explain behaviors of SVM and ANN in detecting AHU heat recycler fault. Li et al. [174] developed an explainable CNN-based FDD by utilizing Gradient-weighted Class Activation Mapping and validated it using the ASHRAE 1043-RP data.

Cyber security and data privacy

Modern BAS are typically connected to internet or enterprise network to reduce operational cost and increase automation. There are many benefits that a BAS can gain through the network connectivity, such as remote management, cloud computing, and data sharing [224,225]. However, a network connectivity also makes BAS and the associated systems and devices potential targets of cyber attacks, leading to comprised systems and loss of credential information. For building energy systems, cyber attacks can disrupt the normal operation and result in serious consequences, such as occupant discomfort, energy waste, equipment downtime, and disruption of grid operation [225]. Therefore, there is a need for an FDD framework that takes cyber security and data privacy into account. For example, researchers are currently developing a Cyber Defense and Resilient System (CYDRES) that employs fault detection, fault diagnostics, fault prognosis, and cyber-resilient control scheme to enhance Grid-interactive Efficient Buildings (GEBs) tolerance to both cyber-related and physical faults [225,226].

Overall speaking, cyber security and data privacy is an important topic for any data-driven product in modern smart buildings. Further reading on this topic of can be found in Habibzadeh et al. [227].

User experience

Each of the previously mentioned future challenges will to some extend affect the user acceptance of data-driven FDD services. The user/client is usually the one paying for the service, thus creating a successful user experience will also benefit user acceptance of FDD as a service and ease a widespread implementation in real buildings. A positive user experience depends on how information is presented to the user to be able to understand what is happening in the building/system and why. In this regard, dedicated dashboards for different building users (facility managers, building owners, building tenants) are of utmost importance [228,229]. A proper visualization of measurement data, predicted data from data-driven models and case-specific key performance indicators all contribute to a better user experience and thus higher acceptance of data-driven methods among clients/users. A proper indication of the severity of a fault is important for the person, usually the facility manager, who has to repair the faulty systems. Clustering and ranking faults/alarms based on their severity and criticality for the operation of the system/building is a time-saving measure for the facility manager in an often hectic workday. More research is needed to understand how to improve the user experiences for data-driven FDD methods.

7. Conclusion

This paper provides a comprehensive review of the process, systems studied, and evaluation metrics for data-driven FDD. Existing literature provides promising methods and frameworks for implementing data-driven fault detection and fault diagnosis, step by step from collecting data to detecting anomaly to isolating root causes. Data-driven fault prognosis remains to be further developed. In terms of system studied, many studies exist that apply data-driven FDD methods to typical building HVAC systems (e.g., AHU-VAV and chiller). However, most of the studies are based on simulated or lab experiment data. Many types of evaluation metrics have been reported in the literature which are sufficient for data-driven FDD performance evaluation. Overall speaking, existing literature has laid a solid foundation to demonstrate the feasibility and benefit of using data-driven FDD. Yet significant challenges still remain for a wide market adoption of data-driven FDD methods. These challenges include real time and real-building implementation that is subject to data uncertainties; method performance benchmarking in real buildings; fault impact analysis; method scalability and transferability; fault interpretation; cyber security and data privacy; and user experience. It is our hope that this review would provide insights and directions for practitioners and researchers to develop the next generation data-driven FDD products.

Acronyms

AB	Adaptive Boosting
AE	Autoencoder
AHU	Air Handling Unit
AI	Artificial Intelligence
ANN	Artificial Neural Network
ART	Adaptive Resonance Theory
ARX	Auto-Regressive model with eXogenous variables
AUC	Area Under the Curve
BAS	Building Automation System
BIM	Building Information Model
BN	Bayesian Network
CART	Classification And Regression Tree
CAV	Constant Air Volume
CNN	Convolutional Neural Network
COP	Coefficient of Performance
DBN	Deep Belief Network
DNN	Deep Neural Network
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DT	Decision Tree
FCU	Fan Coil Unit
FDD	Fault Detection and Diagnostics
GA	Genetic Algorithm
GAN	Generative Adversarial Network
GB	Gradient Boosting
GBM	Generalized Boosted regression Model
GHG	GreenHouse Gas
HMM	Hidden Markov Model
HVAC	Heating, Ventilation and Air Conditioning
IAQ	Indoor Air Quality
IGFF	Information Greedy Feature Filter
KNN	K-Nearest Neighbors
KPCA	Kernel Principal Components Analysis
LAPART	Lateral Priming Adaptive Resonance Theory
LDA	Linear Discriminant Analysis
LinReg	Linear Regression
LogReg	Logistic Regression
LS-SVM	Least Squares Support Vector Machine
MLP	MultiLayer Perceptron
NB	Naive Bayes
NN	Neural Network
OA	Outdoor Air
PCA	Principal Component Analysis
PLS	Partial Least Squares
PLSR	Partial Least Square Regression
QDA	Quadratic Discriminant Analysis
RA	Return Air
RBF	Radial Basis Function network
RBM	Restricted Boltzmann Machine
RF	Random Forest
RNN	Recurrent Neural Network
ROC	Receiver Operator Characteristic
RTU	RoofTop Unit
RUL	Remaining Useful Life
SA	Supply Air
SGA	Simple Genetic Algorithm
SNN	Shallow Neural Network
SVM	Support Vector Machine
SVR	Support Vector Regression
VAV	Variable Air Volume
VRF	Variable Refrigerant Flow
XGB	eXtreme Gradient Boosting

Declaration of competing interest

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

Data availability

No data was used for the research described in the article

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