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Review

Development and implementation of automated fault detection and diagnostics for building systems: A review

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ABSTRACT

This article reviews the current research on the development and implementation of automated fault detection and diagnostics (AFDD) technology for building systems. This article first examines the fundamentals of AFDD and its special requirements on building systems to provide a theoretical formulation of the problem. Some infrastructural barriers for scalable AFDD implementation are discussed. Then it reviews various methods used by previous researchers and real-life products in a typical AFDD workflow. The article compares different methods for feature generation and fault detection and fault diagnostics, and proposes ways to improve their current limitations from other research disciplines. The authors also discuss potential research topics to inspire further developed of new AFDD methodologies and make them more applicable, including: 1) fault assessments and improved information delivery; 2) benchmarking AFDD performance; 3) better interoperability of AFDD methods; and 4) cases of fault propagation and simultaneous faults.

1. Introduction

According to the United Nations [1] and World Resources Institute [2], buildings are one of the major contributors to the world's energy use and present the least expensive GHG emission reduction opportunities. Over the last few decades building systems have become more complex to meet the demand for higher energy efficiency and indoor environment comfort. However, complex systems do not guarantee reliability and often create complex operation challenges. One survey as early as 1975 reported that 19%–64% of various building types have defects or faults [3]; another survey in California based on 13,000 air conditioning systems indicated 65% residential units need repair and 71% of commercial units need repair [4]. These challenges lead to the need for automated fault detection and diagnostic (AFDD) in building engineering systems. Extensive research has concluded that timely diagnosis and correction of faults could significantly decrease energy waste and improve indoor environment quality [5–7]. As the problems of aging building stock in developed countries become more apparent, integrating modern AFDD systems naturally fits into the future retrofit projects to enhance buildings' efficiency, comfort and reliability. The very first efforts on creating AFDD systems for buildings were seen in the 1980s, thanks to the rise of microcomputers and direct digital control [8,9]. Since the 2010s, research on building AFDD has seen a steady increase with an increasing focus on black-box models.

Several literature reviews on AFDD were published over the last two decades, including the classical two-part review by Katipamula and Brambley [6,7] and a follow-up study by Kim and Katipamula [10]. Katipamula and Brambley [6,7] used the same classification scheme as Venkatasubramanian et al.'s review [11] on process engineering AFDD by classifying AFDD methods into quantitative model-based, qualitative model-based and process history-based methods. This classification scheme has been widely adopted by subsequent reviews, such as a review on air handling unit (AHU) FDD tools by Bruton et al. [12], and Yu et al.'s review [13] on AHU AFDD. This classification scheme does not separate the tasks inside an AFDD workflow or review the methods applied for each task. While this approach is suitable to process engineering and developing individual AFDD tools, it limits the interoperability of various techniques especially when a lot of the feature extraction techniques can be applied complementarily. The authors hope to provide a modern take on the building AFDD problem through this review article by separating the tasks of an AFDD process, comparing different methods among these tasks and discuss ways to improve them. Furthermore, fundamentals of the problem based on theoretical AFDD research and data science are formulated. The authors also present the underlying infrastructure requirements for a functioning building AFDD system and their implications on AFDD methodologies. Finally, this review summarizes future challenges of building AFDD research and suggests some solutions by examining other related disciplines such as machine learning and reliability engineering.

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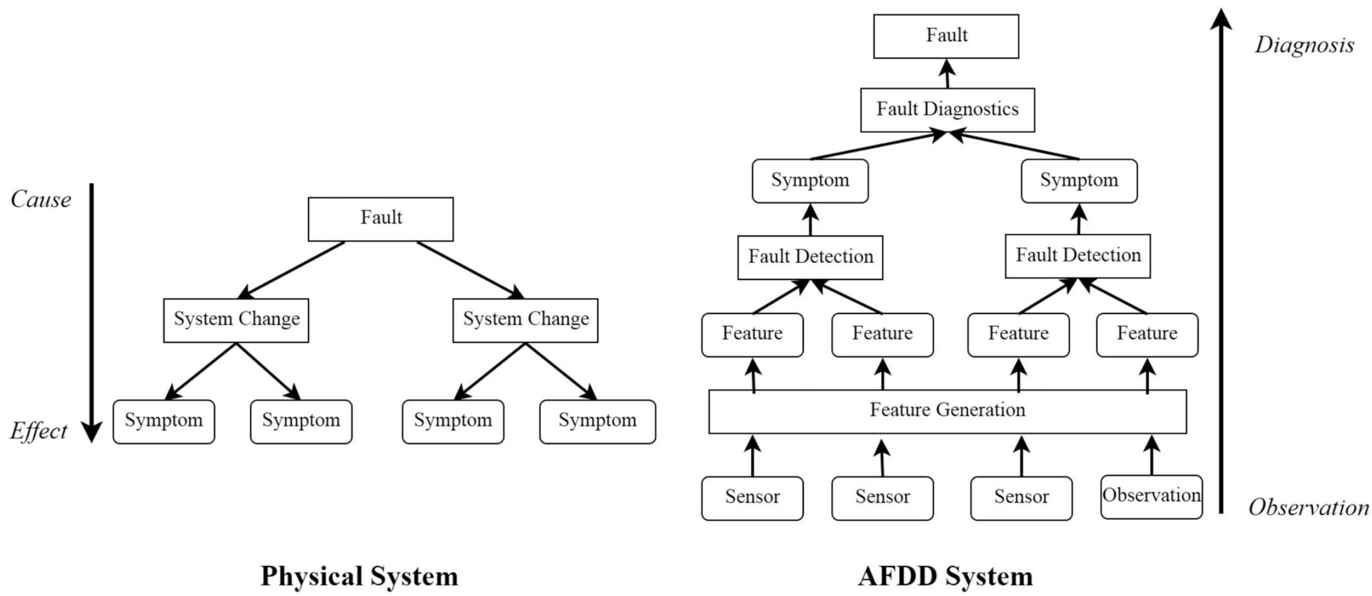

Fig. 1. Overview of an AFDD system – from observation to diagnosis.

1.1. Scope of paper

This review article addresses some of the research needs mentioned above by first separating the tasks of feature generation, fault detection and fault diagnostics instead of treating them as an integrated process. This separation allows researcher to apply different combinations of approaches and provides fundamental abstractions for these tasks. Various methods inside each of the three components are examined, with their limitations discussed. Ways to improve the reviewed methods from other relevant disciplines are also discussed by the author. Below is a brief description of the three components inside an AFDD process:

1. Feature generation. Since building systems are complex and often under-monitored, operational data alone may be insufficient for reliable decision-making. Feature generation, discussed further in Section 4, uses physical relationships, domain expert knowledge and statistic models to extract more information from operation data.
2. Fault detection and symptom generation. This component involves using operation data and features for detecting anomalies. Anomaly detection, discussed further in Section 5, is typically carried out with simple methods such as linear discriminant analysis and rules. Some anomalies can be further identified as symptoms for further diagnosis or evaluation.
3. Fault diagnostics. This step uses the existing operation data as well as features and symptoms generated from the previous steps to locate and isolate the root cause of the fault. It can be performed by using complex rules, statistical inference or classification models. It is also possible to perform this step using solely operation data, and the authors will discuss these options in detail in Section 6.

At the start of this article, the authors also introduce the fundamentals of FDD theory and review the requirements for real AFDD implementations for building systems to help formulate the problem in a clearer way. In addition, the authors will also cover some of the issues affecting the implementation of a functioning AFDD system discussed by other researchers. These challenges include data communication, data quality issues, metrics for evaluating AFDD performance, model training, data availability, etc. Finally, some of the future challenges to expand the building AFDD discipline will also be discussed.

1.2. Paper organization

These authors reviewed over 250 papers from the last two decades on building AFDD and other related topics. The paper starts with a brief review of the fundamental theories from classical FDD in Section 2, followed by a summary to building AFDD in Section 3. Section 4 discusses feature generation and methods employed from previous research. Section 5 looks at fault detection methods, and possible symptoms generated from fault detection results. Section 6 looks at fault diagnostic methods, and ways to improve their performance. Section 7 provides an outlook to the future development to this research topic as well as discusses some new subtopics. Finally, Section 8 provides a closure to this review.

2. Fault detection and diagnostics fundamentals

Fault detection and diagnosis of a technical process ensures the safety, efficiency, and quality of the process. Conventional FDD systems often use a knowledge-based approach [14,15]. The processing of measured variables by instruments requires *analytical knowledge,* and the evaluation of observed variables by human operators requires *heuristic knowledge* [16]. This section provides a concise introduction to the fundamentals of FDD, for more depth the readers may refer to the work by Ding [17], Isermann [16], Himmelbleau [18], De Dkleer and Williams [19]. An overview of the AFDD workflow adopted in this review is provided in Fig. 1.

2.1. Faults

According to Himmelblau [18], a fault is "a departure from an acceptable range of an observed variable or a calculated parameter associated with a process" [11]. Faults are states within the system that can lead to failures and malfunctions. There are two types of fault causes: external causes F_e are environmental influences outside the technical process and internal causes F_i are inside the technical process. Faults can be further categorized by their time dependency into abrupt fault (stepwise), incipient fault (drift-like), or intermittent fault [20]. As a general rule, abrupt faults are the easiest to detect; while incipient fault and intermittent fault are more difficult to detect due to their dependency on time. Faults can also propagate within the system through their process hierarchy. Because most building systems are composed of complex and interconnected processes, this makes FDD

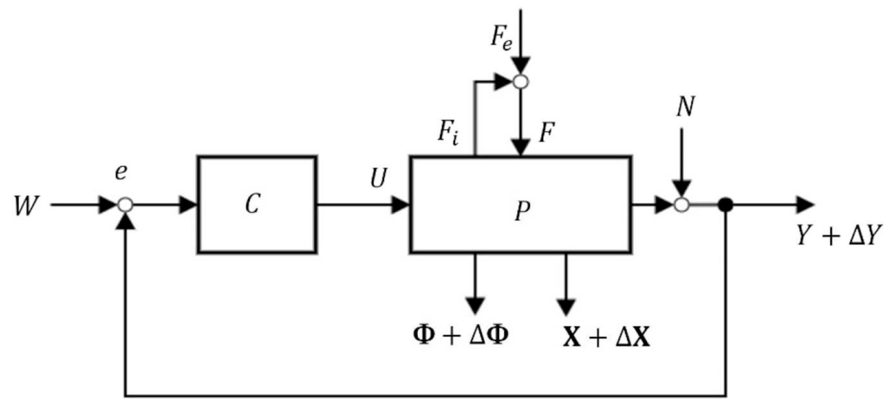

Fig. 2. A technical process with faults.

applications in buildings especially challenging.

An example of an engineering system is shown in Fig. 2. Faults F first affect internal process parameters Φ by $\Delta\Phi$ and/or internal states X by ΔX. Eventually, faults affect measurable outputs Y by a change of Δy. Note that Y is also affected by measurement noise N. In building systems, most processes are closed loop with proportional integral derivative (PID) controls C which often make the change Δy vanish over time while causing a shift in the control variable U. Therefore, for building FDD applications ideally states X, control variables U (e.g. supply air pressure), output variables Y (e.g. indoor air temperature) and control deviation e (e.g. difference to target supply air pressure) should *all* be measured and recorded for the FDD purposes, while parameters Φ should be estimated if possible. This measurement constraint leads to elevated building automation system (BAS) infrastructure requirements, which the authors will discuss in detail in Section 3.3.

2.2. Feature generation

Since most building systems involve several concurrent engineering processes with limited sensors, the available operation data are usually not enough for AFDD decision-making. For example, a typical room involves heat, mass and light transfer with the outdoor environment, its occupants, neighbouring spaces, and various building systems. Yet such a complex system is often only monitored through a thermostat. Additional *features* such as estimated parameters $\widehat{\Phi}$, predicted states $\widehat{X}$ and outputs $\widehat{Y}$ need to be generated from process models could greatly aid the FDD process [17]. For example, change-model using degree-days (DD) is often used to estimate expected monthly or daily energy consumption ($\widehat{Y}$) for operation fault detection purposes [21]. Besides conventional statistical features such as mean and standard deviation used by data scientists [22], there are two main types of process models capable of generating additional features: quantitative models and qualitative models. This review only focuses on quantitative models since the use of qualitative models in building AFDD is rarely discussed [10]. Still, one important qualitative feature is to determine the operation mode of the equipment, such as the ones used in APAR rules to determine the heating/cooling mode of AHU [23]. The authors further classify quantitative models into three categories: white-box (first-principle) models, black-box models, and grey-box models. All three models could be used to represent the technical process shown in Fig. 2 and calculate $\widehat{X}$, $\widehat{Y}$ and $\widehat{U}$. However, only white-box models are capable of estimating physical parameters $\widehat{\Phi}$. Black-box models use pure arithmetic parameters A, while grey-box models may predict reduced parameters Ψ with certain degrees of physical meaning. In addition, residuals between the observed and predicted pairs such as state residuals X^- can be used as additional features. More detailed discussion of feature generation and quantitative models for building AFDD will be discussed in Section 4.

2.3. Fault detection

According to Ding [17], the purpose of fault detection is the "detection of the occurrence of faults in the functional units of the process, which lead to undesired or intolerable behaviour of the whole system". Most of the modern automated fault detection methods are model-based, be it first principle models, rule-based models (if-then rules), or machine-learning models based on several measured variables. Since in this review, the authors explicitly separated the feature generation step, we define automated fault detection step as follows: Apply change detection on features and measured variables referencing nominal values, for example comparing X and X^- against $\overline{X}$ and $\overline{X}^-$. If any significant discrepancies are detected, a fault is detected. This decision of whether a fault has truly occurred can be reached by using simple threshold values, discriminant function, or other more complicated decision models. These decision functions can be set static before operation or updated dynamically to reflect system changes overtime.

Fault detection can also be carried out manually. In fact, conventional complaint-driven maintenance can be regarded as a form of manual fault detection-based maintenance, as complaints are derived from observed state X such as temperature or parameter Φ such as window operability from the occupants.

Besides identifying abnormal operations, fault detection can provide valuable information for further fault diagnostics. Symptoms generated from fault detection can be later used in the fault diagnostics [24,25]. Two kinds of symptoms, denoted by S, can be generated once a fault is detected: *analytical symptoms* S_a are generated from automated fault detection algorithms such as low indoor air temperature; and *heuristic symptoms* S_h are generated through human observations such as cold indoor comfort.

2.4. Fault diagnostics

Fault diagnostics is also called fault identification, fault isolation, or fault analysis by many researchers [20]. This can help isolate the fault and provide enough information to perform corresponding maintenance actions. In this research, fault diagnostics means explicitly the process to characterize the fault in as much detail as possible regarding type, location, size and time. Besides manually performing fault diagnosis through heuristic reasoning, there are two types of automated fault diagnosis methods: classification methods and inference methods [20]. Inference methods such as binary reasoning can only be used when the fault-symptom causalities could be well defined. Otherwise, classification methods without prior structure knowledge such as statistical classification and machine learning models have to be trained based on experimental data. Note machine learning techniques can be applied to inference methods, which can perform partial structural (causality) learning [26]. However, full structural learning is still an ongoing research topic [27].

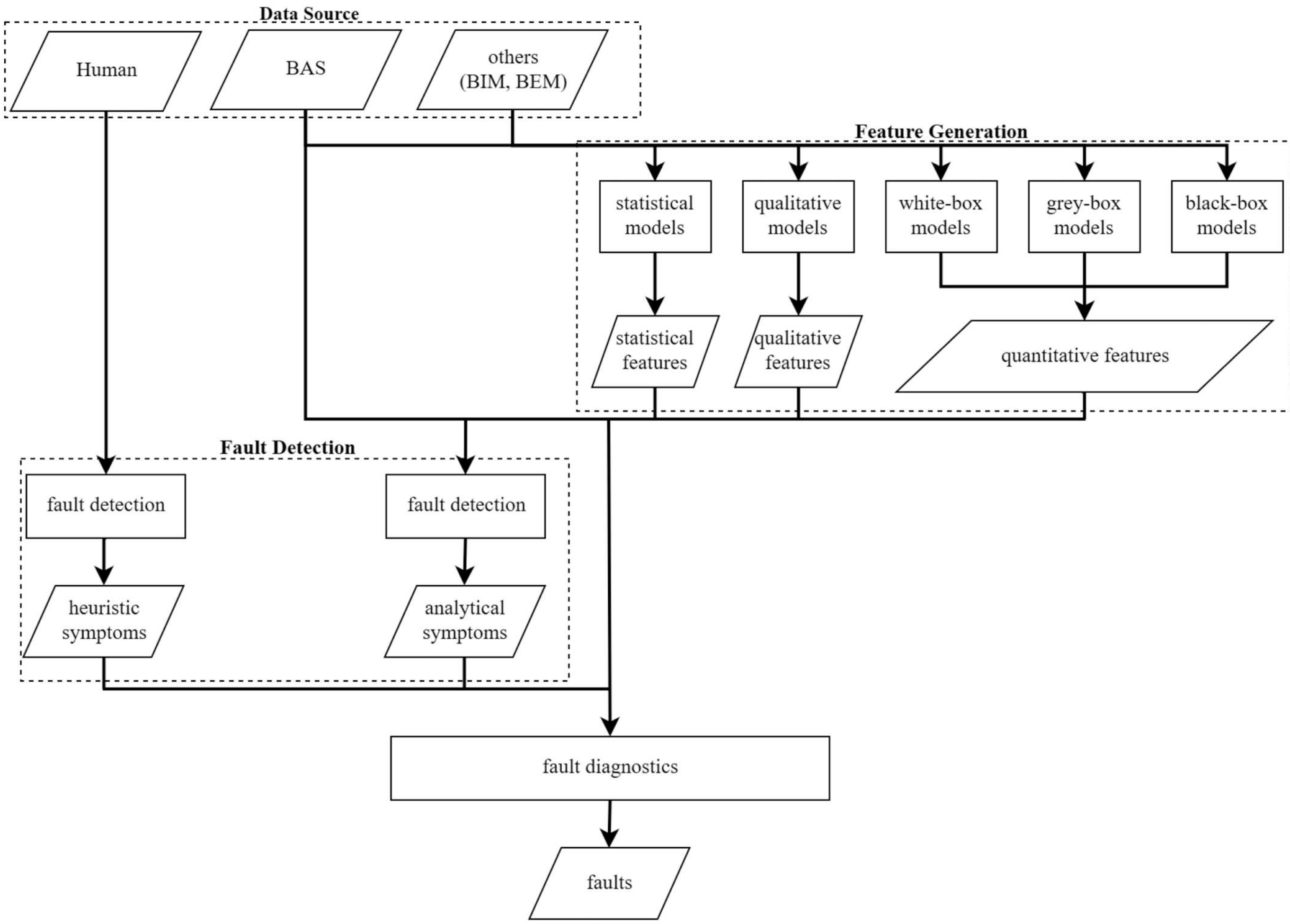

Fig. 3. Outline of a building AFDD system.

In addition to operation data, both features and symptoms discussed previously can be used in fault diagnostics. It is advantageous to use a unified symptom representation for both analytical and heuristic symptoms. This way, fault diagnostic is natural to conduct [28] and can be integrated with different fault detection systems. Unfortunately, such representation has rarely been discussed in building AFDD research [29].

3. Introduction to building AFDD

Based on the review on AFDD fundamentals, a typical outline of an AFDD system for buildings is shown in Fig. 3. The data sources for a building AFDD system includes sensor and control data from the building automation system (BAS) and building energy management system (BEM), design information from the BAS and building information system (BIM), as well as observations from the occupants and operators. These data are then typically sent to a feature generation procedure such as expert rules and process models. Then the system can perform fault detection only or a complete fault diagnosis process. Of all the building AFDD articles reviewed in this article, approximately one third are focused on fault detection only, while the rest proposed complete fault detection and diagnostics methods. It is noteworthy that feature generation, fault detection and symptom generation are not mandatory for a diagnostic system, although they are beneficial to extract more data from the raw data. In fact, some AFDD research for building systems chose to use BAS data directly for diagnostics by incorporating feature generation into deep machine learning models [30]. The authors will discuss this further in Section 6.4.

3.1. Ideal characteristics of a building AFDD system

An ideal AFDD system should have those following characteristics from previous research [6,7,16]:

1) Low cost. Since nowadays computation and sensing resources have become relatively economical, the main cost barrier for AFDD system is the human resource required to setup and maintain a proper AFDD system.
2) Reliable. Reliability is currently less problematic than the past, still, network issues and sensor reliability still present infrastructure challenges to the current building AFDD systems.
3) Low false diagnosis rates. False diagnoses such as false positives and false negatives are often costly, since they lead to waste in operation resources. In addition, it reduces the trustworthiness of an AFDD system to the degree of being totally ignored.
4) Have no need for handcrafted AFDD algorithms. Many of the existing rule-based AFDD systems need to be updated manually once system characteristic changes, this severely limits the scalability of the AFDD system.
5) Becomes automatically configured. Since buildings contain many identical or similar systems, it is possible to use model selection and fitting to create AFDD models adaptively.
6) Has improved evaluation and decision support capabilities. Most AFDD research is focused on diagnosis which provides little fault evaluation for decision-making. Improved decision support capabilities can greatly enhance the usability of the AFDD systems.

The authors also propose additional favourable characteristics for building AFDD systems in this review:

7) Uses heuristic observations as evidence. Observation from the occupants and the operators are often valuable for diagnosing faults that are difficult to capture through analytical means.
8) Interoperability to communicate with other AFDD tools. This allows the AFDD system to consider the effect of fault propagation and use the outcomes of other AFDD tools as evidence.

3.2. Preparing a functioning AFDD infrastructure

Reliable AFDD cannot be achieved without proper infrastructure. Functioning AFDD infrastructure requires several fundamental components: sufficient sensing capability, a reliable network, and adequate computational resources. Several exogenous data sources may also help improve the performance of an AFDD system, such as building information modelling (BIM) [31], occupant feedback system, and operation and maintenance (O&M) integration [13,32].

Sensing capability not only includes sensing availability, but also the correct configuration of these data sources. ASHRAE has published several guidelines for measuring building systems [21], however multiple authors [33–35] have identified that there is currently little guidance in terms of minimal sensors for AFDD systems, and insufficient number and/or range of sensors for AFDD is a common problem. With the development of wireless and self-powered sensing technologies, sensor abundance may be achieved economically for new constructions and retrofits in the future [34,35]. Besides sensors, almost all information from the BAS can be used for AFDD, such as control inputs, control variables and schedules.

Another major issue related to building sensing capability is appropriate data tagging [33,36]. An appropriate tagging system should provide a consistent naming convention to all the building sensors, equipment and control variables. To combat this, project Haystack [37] and Brick Schema [38] have been created in an attempt to unify the naming convention of building data points. Haystack [37] provides a flat tagging system, while Brick [38] treats BAS objects hierarchically with directed graphical relationships. At the time of writing, ASHRAE Standard 223P is an ongoing effort to standardize semantic information for building data based on Haystack and Brick [39]. Still, these conventions are not yet widely adopted in new constructions or retrofits. To combat this issue, several authors have investigated automated and semi-automated sensor identification in the past [40–42], Wang et al. provided a review on this topic recently [43]. Other issues related to sensing capabilities include sensor calibration, data cleaning and noise elimination [36], which the authors will not discuss in detail in this review.

Networking is yet another hurdle when preparing a working AFDD infrastructure. A large commercial building may have thousands of controllers and pieces of equipment interfacing with each other at high frequency. Conventionally, a building automation system operates in its own localized network, but the fast growth of internet of things (IOT) devices further complicates existing networks. As noted by some researchers, BAS is prone to network congestions [34,36]. So, if an AFDD system requires remote data access, it may not perform its tasks on-time simply because the data cannot transmit fast enough. This is critical for cloud-driven AFDD systems that currently dominate the market [44]. Thus, providing a functioning and robust network infrastructure is one of the fundamental requirements for implementing an advanced AFDD system. Another strategy to reduce network overhead is to move some of the data-heavy work to the local controller and then send extracted information for remote AFDD applications. However, if an AFDD algorithm is to be implemented locally on a controller device, the designer still has to consider limited computational power and scan rate requirement on controllers [45].

Besides BAS data, other data streams such as metered data from BEM systems, user feedback, expert knowledge, and event log and design information can all be used for AFDD purposes [33,46]. This data fusion approach has gained attention in recent years. Dong et al. established a BIM-enabled infrastructure to integrate design information as part of the AFDD data [31]. Several other authors have also demonstrated the usage of BIM for building AFDD [47–49]. A few researchers explored using event logs as part of AFDD knowledge discovery [50], but have not yet implemented them into an AFDD system. Integration of occupant's feedback could also provide heuristic data for AFDD, but is rarely examined by previous researchers [33]. Other researchers have worked on cloud data aggregation to increase the training data set for AFDD models, but this development is still quite recent [51,52].

Ideally an AFDD system needs to be fully integrated with the O&M system to effectively improve building operation. Yet the problem of how to meaningfully convey AFDD results to the operators has rarely been researched. The authors will examine this issue in more detail in Section 7.

3.3. Validating AFDD performance

Once an AFDD method is developed, its performance needs to be evaluated and compared against other methods on the same tasks [53]. The rule-based APAR system [54] has been used a few times as benchmark for AHU AFDD comparison [55,56]. In order to quantitatively compare the performance of AFDD methods, the authors propose the use of three metrics: false positive rate (FPR), false negative rate (FNR) and detection time (DT). Besides FPR, FNR and DT, other metrics such as precision and recall sometimes are also used for evaluating AFDD performance [57,58]. The equations below provide a concise definition of major metrics used for evaluating AFDD methods.

$$\text{False Positive Rate (FPR)} = \frac{FalsePositive}{FalsePositive + TrueNegative} \tag{1}$$

$$\text{False Negative Rate (FNR)} = \frac{FalseNegative}{FalseNegative + TruePositive} \tag{2}$$

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} \tag{3}$$

$$\text{True Positive Rate (TPR) or Recall} = 1 - FNR = \frac{TruePositive}{FalseNegative + TruePositive} \tag{4}$$

$$\text{Detection Time (DT)} = Time_{FirstTruePositive} - Time_{FaultStart} \tag{5}$$

The reason the authors propose FPR, FNR and DT as the main metrics is their synergy with optimization when model training is required. Most optimization processes are for minimization or convex optimization [59], and an ideal AFDD system should have FPR, FNR and DT at zero –always correctly reporting faults instantaneously after occurring. However, data takes time to measure, transmit and process, so it is impossible to have DT at zero. Furthermore, there is an inherit trade-off between false positive and false negative due to model sensitivity. When an AFDD model is more sensitive, it becomes easier to identify or detect faults but at the same time more likely to produce false alarms and false diagnoses due to uncertainties such as modelling error and sensor error [60].

There is no clear-cut method in determining which of the metrics is more important than another, and researchers should establish different priorities for different fault based on its characteristics. For example, a minor fault with localized impact should prioritize minimizing false positive rates; for a critical fault on a plant equipment needs to prioritize minimizing false negative rates while keeping the occurrences of false positives below an acceptable frequency; and for a safety-related fault both detection time and false negative rate should be minimized. This differentiation of metric importance naturally leads to the question

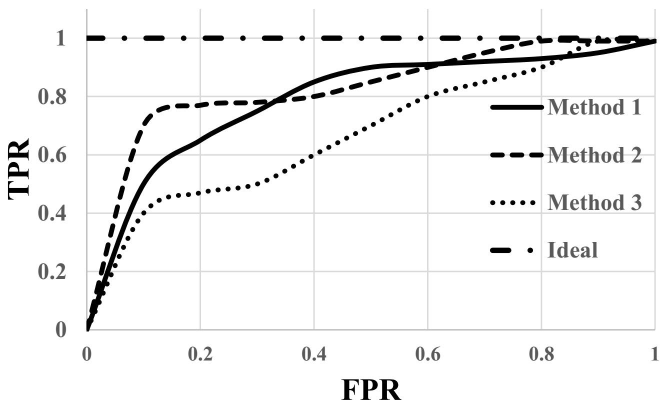

Fig. 4. Example of a ROC curve for characterising AFDD model.

of customizing cost function when training data-driven AFDD models for different objectives and faults, which the authors will discuss in detail in Section 6.3.

In many AFDD research disciplines, the reporting of false positive rate and false negative rate has become common practice. The reporting of detection time has also become important for time-critical tasks. Still, these metrics are still not regularly reported by building AFDD researchers. If these performance metrics are published, other researchers could quantitatively compare different AFDD methods. One visualization technique called a receiver operator characteristics (ROC) curve [61] is often used to investigate the effectiveness of an AFDD model, which has only been used by a few building AFDD articles [62–65]. An example ROC curve in Fig. 4 demonstrates the trade-off between true positive rate and false positive rate. An ideal AFDD model on the ROC curve has a TPR of one while the FPR is zero. By using the ROC curve, we could compare the performance of different AFDD models. In addition, ROC curves could also tell us when increasing the sensitivity of an AFDD method starts to give out diminishing returns, and where to constrain the maximum false positive rate or maximum model sensitivity.

4. Feature generation

Feature generation helps the AFDD system to obtain more information through different process models. Some researchers have used statistical features such as exponential moving average and autocorrelation [45,66–68]. For most researchers, these features are generated from process models as discussed in Section 3.3, such as estimated parameters their residual pairs calculated from comparing observed/expected values. Before illustrating different model types for feature generation, according to Wen et al. [69], process models used for building AFDD and control applications should have the following characteristics:

1. Use commonly available measurement sources. Some novel sensors such as camera-based occupant count sensors and infrared cameras can provide much-needed insight into the operation of a building. Since they are not widely available yet, reliance on these sensors could limit the applicability of the fault detection method.
2. Be easy to update. Characteristics of a building system can change over time, repurposing of a room, change of sensor location, or change of AHU components can make existing AFDD process outdated. So, it is crucial for the AFDD process to be quickly updated to keep functional.
3. Be capable of predicting states in the near future. The functionalities of AFDD and model predictive controls (MPC) are often intertwined, they both use process models, for AFDD is to compare parameters and state outputs, for MPC is to predict future states given different control inputs. Thus, if the AFDD model and MPC model can be integrated, the data processing load can be significantly reduced.

Table 1 summarizes a list of quantitative features available for building AFDD. Three main types of process models – white-box models, black-box models and grey-box models are abbreviated as WB, BB and GB. These process models are described in greater detail next.

4.1. White-box models

White-box models are quantitative analytical models based on first principles [11]. Those models are usually developed for simulation with precise representation of its underlying physical process. They are able to simulate fault states and are good at representing transient states [70]. However, they are often too complex to implement and compute, require a lot of data input which may not always be available, and are very hard to calibrate/recalibrate due to a high degree of freedom [6]. These models are usually used as forward models in which the parameters are predefined based on design information and recalibration is usually limited to a small parameter space. While they are useful for equipment-level process models, the parameters inside a constructed building may vary from design, thus requiring periodical model calibration for building-level models [71].

Numerous detailed physical models have been adopted for building AFDD, namely for chillers [72–74], HVAC components [47,75–77] and AHU [78]. For whole building and zone level AFDD, most of the white-box models are based on existing building performance simulation programs such as EnergyPlus [71,79–81]. While implemented properly, features generated from white-box models could achieve higher AFDD accuracy [47,71,73] compared to alternative process models. However, researchers noted that expertise and time required to implement and maintain such models are significant [71,81], and extra interfacing between the BAS and the model may be required [71]. Most of the white-box model implementations produces estimated input and output states ($\widehat{X}$ and $\widehat{Y}$) of a building system, while the use of parameter estimations from white-box models for AFDD is still unknown to the authors.

4.2. Black-box models

Black-box models are statistical or machine learning models in which the model parameters convey no physical meaning [7]. These models can be compelling due to model flexibility and easiness to construct. They use operation data to train internal parameters, but as

Table 1
List of quantitative features for building AFDD.

	Sources of expected values	Sources of predicted values
States X	Sensors, first principle equations	WB, BB, GB
Outputs Y	Sensors, first principle equations	WB, BB, GB
Control U	Controller inputs	WB, BB, GB
Physical parameters Φ	Design, commissioned model	WB
Reduced parameters Ψ	Commissioned model	GB
Arithmetic parameters A	Commissioned model	BB

their name suggests, in most cases black box models can only act as observers since the estimated parameters has little relevance to the actual physical process. A well curated black-box model can achieve high accuracy in state prediction. The fast-growing statistical learning (machine learning) field has led to a growing trend of research work on using black-box models in FDD applications [10]. Some common examples of the black-box models include curve fit [66], artificial neural network (ANN) [82–84], principal component analysis (PCA) [85–87], support vector machine (SVM) [87,88] and others. Note parameters from black-box models have not been used as features for building AFDD. Methods based on signal processing such as wavelet analysis [89–91] have also been widely used. Black-box models are more effective in HVAC and its components since those systems are usually equipped with enough sensors to compare with the observer [92–97], while as in other building systems and zones they are often applied in fault detection systems with limited capabilities for automated fault diagnosis [68,98–101]. Interestingly, usually there is little discussion in how the cost function is set up when black-box models are trained. Furthermore, few authors have discussed the potential of over-fitting when applying these black-box models [102], which is one of the major concerns when applying these methods [103]. Finally, some black-box models are directly used to diagnose faults without detecting them first. These methods are called "one step diagnostics" in this review and will be discussed in Section 6.4.

4.3. Grey-box models

Grey-box models are analytical models loosely based on first principles, in which the model parameters can still be traced to the process's physical response [7]. Compared to white-box models they are faster to compute and easier to calibrate and construct; while compared to black-box models they are more robust and can be used for parameter estimation. On the other hand, formulating grey-box models requires expert knowledge and extensive measured data are required to train their model parameters [7], and may be less accurate than the black-box model and white-box model counterparts. Since most of the processes inside buildings or zones are structurally similar, common grey-box models can be formulated relatively easily. Grey-box models have seen numerous implementations in both control applications and FDD systems for building systems and are typically implemented as inverse models in which the parameters are learned and updated from operation data. While many of the grey-box models that have been developed for HVAC systems and its components [104–106], some research has been performed in the whole building and building zone grey-box models [107–110]. Some of the grey-box models used to represent a whole building or zone thermal behaviours are based on the work done by Braun and Chaturvedi [108] and have been proven very effective in both FDD and model predictive control applications [111–115]. Besides quantitative grey-box models discussed above, qualitative grey-box models can also be established to extract features qualitatively. This is particularly useful when the general behavior pattern of the system is of interest, or the sensors are less reliable [15]. However, only a few qualitative grey-box models have been developed for building systems [116,117]. Examples of the usage of grey-box models in building AFDD for feature extraction includes air conditioner models [118,119], air handling units [53,120–122], chillers [123–126], VAV terminals [127] and general HVAC applications [128–136].

4.4. Trend in feature generation

Fig. 5 shows types of feature generation method used by articles reviewed in this paper. The number of articles using black-box models to detect faults has significantly increased since 2010, while the popularity of other methods remains relatively consistent. This can be explained by the increasingly powerful statistical models and machine learning algorithms, which became generalized enough to be applied to building systems. Among these black-box models, the most popular ones are PCA (17 papers), variations of autoregressive models (AR) (5 papers) and variations of ANN (4 papers). The popularity of these models agrees well with the FDD research from other disciplines [70] due to their flexibility and robustness. While black-box models cannot provide meaningful parameter estimations, they can be used to generate symptoms in fault detection for fault diagnostic purposes. The use of black-box process models however, brings some unique challenges due to its heavy reliance on operation data, some of which has been discussed in Sections 3.1 and 3.3. The authors will further expand on the usage of black-box models, namely machine learning models for building AFDD in Section 7.2.

5. Fault detection and symptom generation

The task of fault detection is to detect faults within building systems without necessarily identifying and isolating them. Automated fault detection on its core is a binary classification problem: determine if the operation condition is normal or abnormal. Due to this nature, fault detection is usually easier to implement than fault diagnostic. In a generalized FDD framework, fault detection process is also responsible for generating symptoms for the fault diagnosis process [20]. Many researchers use key metrics obtained from feature extraction for fault detection, such as equipment efficiency and energy usage patterns to identify operation anomalies. In some applications feature generation and fault detection are not explicitly separated, such as rule-based fault detection methods [54] where residual generation and decision on residual are often carried out in the same step.

5.1. Fault detection

Conventionally fault detection is performed deterministically using discriminant analysis [20]. Preprocessed data and features are mapped into a model space, then linear or polynomial functions describing the boundary between normal and abnormal operation are used to determine if the observation is outside the model space. Limit checking is a common discriminant fault detection method built-in inside building controllers using predefined threshold and is one of the first fault detection method employed in building systems [137]. Trend checking is similar to limit checking, but uses first order derivatives to detect anomalies. Combined with sensor measurements, trend checking and limit checking are simple to implement and fast to respond, which provides excellent performance for critical failures such as fire alarm and carbon monoxide alarm [20]. Examples of using limit checking in building system fault detection include usage of statistical models to establish limit thresholds [92], and thresholds created using expert knowledge [138]. Some researchers have also adopted dynamic generation of limit checking thresholds. Moving average and exponential weighted moving average (EWMA) has been used by numerous researchers to update limit checking thresholds [57,66,67,139]. Other authors used statistical models to update fault detection thresholds [73].

However, discriminant analysis falls short for more complicated fault detection tasks, especially when a direct indicator of abnormal operation is not available for detecting less obvious faults, such as minor defects in AC motors. While it is possible to generate residual feature to describe this deviation through complex process models [140], as demonstrated by some researchers with PCA [141–143]. Many other authors decided to improve the decision models directly, such as fuzzy logic [144,145], pattern recognition or clustering-based methods [142,146–148], or simply use black-box models such as ANN for detecting abnormal states [145,148].

5.2. Symptom generation

If a fault detection decision is based on physical relationships such

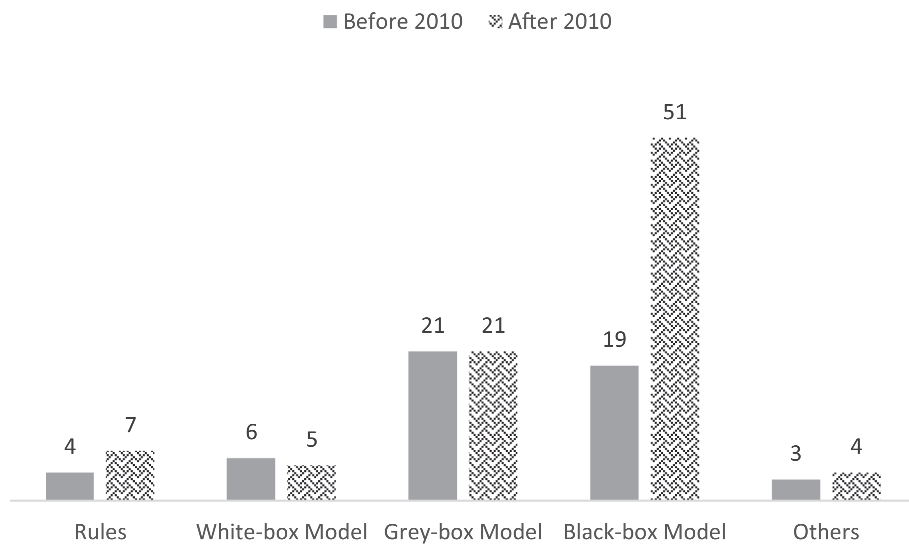

Fig. 5. Comparison of different feature generation methods before and since 2010.

as rule-based method or discriminant analysis, it can also determine the state of a physical symptom related to this discovery [24]. This symptom can be used as an additional feature to the fault diagnostics problem. For example, if a fault detection method determines the supply air flow of an air handling unit is too low, a symptom of low supply air flow can be produced. Since symptoms are direct causes of faults, by combining causality the combined information can make the fault detection problem easier. The symptoms can be described either deterministically or probabilistically depending on the fault detection method described above. An example of the usage of deterministic symptoms is the integration of APAR rules in a few of the previous research [56,149]. Deterministic symptoms are then used as hard evidence and probabilistic symptoms are used as soft evidence for fault diagnostics [150]. Although the hard evidence can be treated as special cases of soft evidence, only a limited number of algorithms could process soft evidence natively. The distinction between soft evidence and hard evidence is detailed by Bilmes [150]. Shi et al. [29] discussed the possibility of applying soft evidence for building AFDD applications. Other authors have explored the possibility of adopting probabilistic AFDD models [56,96]. However, the discussion of symptom generation from fault detection used for fault diagnostics is still rare in building AFDD research.

6. Fault diagnostics

Fundamentally the task of fault diagnostics is to determine the states of all potential faults based on measurements, features symptoms and other available information. According to Isermann [20], the fault diagnosis approaches can be classified into two categories: inference methods and classification methods. Inference methods are applicable when the causalities between faults and symptoms can be expressed explicitly, while classification methods can be trained experimentally when the causalities are not apparent [20]. However, the distinction between the two categories has started to blur recently due to the growth of structure learning in classification research [26].

6.1. Inference method

The most basic form of the inference method is a fault tree based on a decision tree and multiple binary if-statements. An AFDD system composed of multiple decision trees is often called "expert" systems, and has been widely researched [54,149,151,152]. It typically uses predefined fault trees based on cause-effect relations between the symptoms and faults to perform the fault diagnosis task [54,153], and in many cases fault detection and symptom generation are integrated as part of the AFDD package [92,93,98]. However, several authors did not the constraints of expert system, including heavy reliance on expert knowledge, requirement for manual configuration and lack of generalizability to different system configurations ("brittle") [7,152]. These limitations are similar to those computer science researchers faced in the 1980s when expanding the capabilities of expert systems [154].

Fault trees only work in the manner of discrete-event; for continuous faults such as incipient faults and intermittent faults, approximate reasoning can be used. Approximate reasoning can be carried out by fuzzy logic or probabilistic reasoning in the form of forward chaining or backward chaining. Several building FDD applications have used fuzzy logic [93,155,156] to diagnose faults. More recently other inference methods include manually structured Bayesian Network which has been applied to AHU [29,56,157], VAV terminals [29,158], and chillers [96,159].

Due to the requirement of prior knowledge, the inference method may not be suitable for all AFDD systems, but it is still very powerful for building systems since most of the fault-symptoms relationships can be derived from first principles or expert knowledge. Furthermore, the structured information between faults, symptoms and features can be served as guidelines when an operator is manually diagnosing a fault [160]. This makes the inference method the more popular in the survey articles, as 64 out of the 104 surveyed papers chose this approach, dominated by expert systems. Yet this does not mean the inference method is the superior choice, as larger building systems such as AHU may have an enormous amount of fault-symptom causal relationships that need to be manually defined. Fortunately, thanks to the recently development in computer science, it is possible to perform partial structural learning on the inference models for both the expert system [27,161] and Bayesian Network [26]. Furthermore, parameters inside inference models can be updated through operator feedback on false diagnosis. However, only few authors have tried to use operation data to improve the accuracy of inference models [73,159]. While the limitations mentioned above hinder the usability of the inference methods, but ease to use, no training data requirement and intuitiveness mean they are often the first choice when developing new AFDD systems.

6.2. Classification method

Classification methods can be used when the structural knowledge between the faults and symptoms is unknown or very hard to manually define. Operation data including fault cases as well as prior knowledge can be used to train the classification algorithms. This means unlike inference methods, classification-based AFDD models can be created quickly without a lot of manual definitions. This approach has gained lots of attention recently thanks to the advancement of machine learning research [10].

Common classification methods used in FDD systems include decision tree, geometrical classifier and artificial neural network classifier. In the 40 surveyed articles which used classification methods, the most commonly used classifiers in building FDD is the artificial neural network classifier (ANN) and its variations [82,90,124,162,163]. Geometrical classifiers have also been used in many fault diagnosis applications [88,164]. Some other classifiers applied in building AFDD include support vector machine (SVM) [88,141] and classification tree [151]. Most of these classifiers have been proven very effective in FDD research [11,20]. However, one of the major shortcomings when using classifiers is the requirement for a large set of data for training. This training data set also requires data from faulty operations, which may hard to obtain since not all faults can be easily recreated without causing damage to a building system. Thus, for the near future classifiers may be suitable for individual equipment since its faults can be emulated and analyzed before its production.

Besides the requirement for faulty data, other limitations of classification-based AFDD method includes hard to generalize and AFDD system trained from one system to another [11], and difficulty to extract meaningful insight from its trained parameters. Some solutions to these limitations include collaborative AFDD, which will be discussed in Section 7.2. It is also possible to simulate the faulty operations along with normal operation through building performance simulation, which the authors will discuss briefly in Section 7.1.

6.3. Improve model training

As mentioned in Section 3.3, there is an inherent trade-off between false positive rate and false negative rate based on how sensitive a fault diagnostic model is trained [60]. And for different faults these rates should be prioritized differently. Thus, when a fault diagnostic model is trained, its loss function needs to be modified accordingly to reflect this requirement, since by most default loss functions used by classification algorithms does not discriminate false negatives and false positives.

In general, there are multiple ways to formulate cost functions for classification errors, and not all of them can be customized to penalize a certain false outcome. In the following sections the authors will use a common classification loss function called cross entropy(log) loss function [165] to demonstrate how to prioritize false positive or false negative rate. The formulation for cross entropy loss function is as follows:

$$L = -\sum_{c=1}^{M} w_{o,c}\log(p_{o,c}) \tag{6}$$

where M denotes the number of fault states to be classified, o is the actual fault state, c is the predicted fault state, p is the probability observed fault state o is of predicted state c, and w is the weight term for correct/incorrect fault state classification. For correct classification the weight term is always zero. To further illustrate, Table 2 shows a matrix of w for a single fault diagnostic with three states: **Positive, Fault Free (FF) and Negative**. For this particular fault, false positive is penalized more than false negative and false diagnosis, in turn the trained fault diagnostic model should have a lower false positive rate than a model trained with an equally weighted loss function. While the customization of loss function is relatively common in other classification research disciplines, few paper [166] attempted to discriminate false positive or false negative diagnosis in building AFDD research.

Table 2
Example of different weight terms for fault diagnostics model training.

		Actual state		
	w	Positive	FF	Negative
Diagnosed state	Positive	0	2	1
	FF	1	0	1
	Negative	1	2	0

Alongside with weighted loss function is the issue of class imbalance in the data [167]. Since faults in building tend to occur sparsely in the temporal domain, there could be an imbalance between the number of faulty observations and non-faulty observations. If there is very few cases of faulty observations and the cost function does not discriminant incorrect diagnosis, an AFDD system can simply conclude no fault can happen while still maintain superficial high accuracy, thus gaining a high false negative rate but zero false positives. On the other hand, if a training set is filled with too many fault cases, the AFDD system can become biased towards false positives. Besides using different weights covered above, researchers could also stratify the data set to mitigate instances of class imbalance [168], or use algorithms designed for class-imbalance [169].

Another important factor to consider when training classification model is the possibility of overfitting. Machine learning models are prone to overfitting due to their high nonlinearity. Common approaches to avoid this issue are to apply cross validation and regularization [103,170–172]. Details of cross validation and regularization can be referenced from theoretical research [103,170–172]. While most of the building AFDD research adopted cross-validation by splitting training data and testing data, only few of the building AFDD research used [102,141] k-fold cross-validation. k-Fold cross-validation further reduces overfitting risks by segmenting the data into k folds, and then randomly selecting them for training and testing for k times. The models generated from this process are then averaged to avoid overfitting from individual training sets. The main challenge with k-fold cross-validation for building AFDD is that many times there is a need to preserve temporal continuity. So instead of randomly selecting data points, data should be segmented into days/weeks/months based on its application. Another way to reduce overfitting is through model regularization. Regularization reduces the risk of overfitting by introducing additional terms to the loss function to penalize model complexity [20,171]. In other words, regularization makes the model prefer less model complexity at the cost of lower accuracy. Many machine learning tools provide regularization by default, but only limited number of researchers explicitly stated its usage in past building AFDD research [173].

6.4. Direct vs indirect diagnostics

In many theoretical FDD papers, the tasks of fault detection and diagnostics are often separated to ensure the modularity and expandability of the system [19,28,174]. Several current building AFDD articles do not explicitly separate these two components, especially for methods using statistically driven models such as ANN [175,176], as they directly classifies the fault states from sensor measurements. Direct approach has become more popular in recent years as classifier methods become the dominant choice for fault diagnostics, as shown in a comparison in Fig. 6.

The direct approach can simplify the fault diagnostic process and potentially increasing its accuracy by avoiding modelling error incurred during the symptom generation step. However, this approach can cause several issues include limited generalizability, as well as lacking interoperability with other peer AFDD systems [29]. This might change given the development of collaborative AFDD system and reinforced deep learning. On the contrary, the indirect diagnostics approach follows the classic fault detection – symptom generation – fault diagnostics

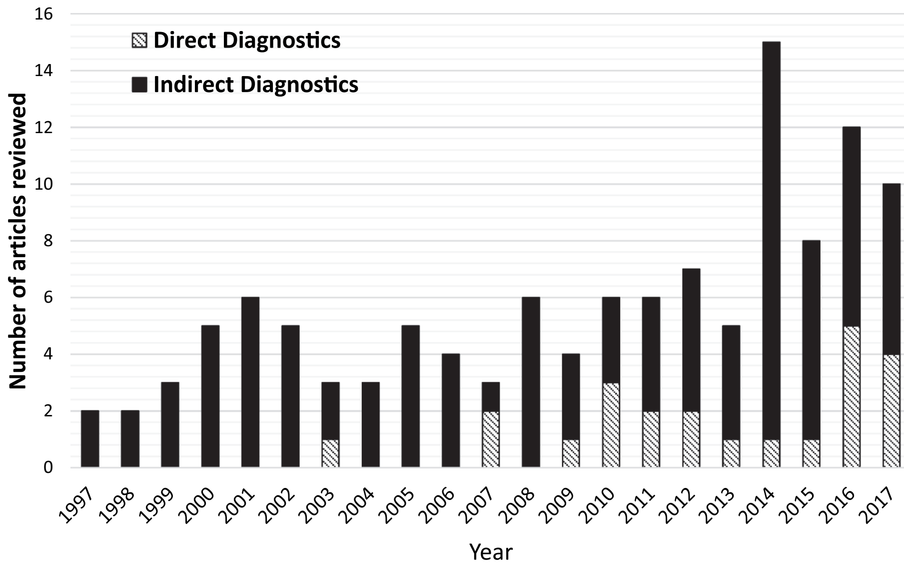

Fig. 6. Comparison of direct and indirect diagnostics approach by year.

procedures proposed by Isermann [20], as described in Section 2. This allows the possibility of integrating other fault detection or fault diagnostics methods by using symptoms to transport information between different methods. This indirect two-step approach was used by most of the researchers. However, potential problems of modelling errors introduced by the fault detection process may decrease the overall AFDD reliability, and how to quantify or quality symptoms are the problems still need to be addressed [86]. Still, if implemented properly with reliable process models, the fault detection step inside an indirect approach can be treated as an additional process to generate more features for direct fault diagnostics [20]. Thus, future research should look at the potential of applying additional feature generation used by other researchers to improve AFDD performance.

7. Future challenges

This review discovered several challenges facing the current development and implementation of AFDD technology for building systems, including improving decision-support for AFDD, ensuring functioning infrastructure for AFDD, improving the existing inference-based and classification-based fault diagnostics methods, and integration of existing AFDD methods from previous research. Over the rest of this section the authors will discuss some ongoing efforts and potential future research topics to tackle these challenges.

7.1. Fault assessment and decision support

As concluded in the reviews by Katipamula and Brambley (2005a, 2005b), researchers developing AFDD methods often overlook their implications on fault management – how to meaningfully present AFDD results to the building operators to make decision-making faster. Katipamula and Brambley (2005a, 2005b) proposed to include fault impact assessment in AFDD systems to provide quantitative metrics to the operators, which can help the operators prioritize their work schedule. Still after over a decade, according to the recent survey by Kim and Katipamula (2017), only 28 out of the 197 articles provided fault impact estimations regarding energy and cost. Moreover, more than 80% of the 28 articles reporting fault impacts were focused on individual mechanical equipment such as heat pumps and cooling towers. A couple of the commercial AFDD products offer fault impact assessment [44], but they mostly rely on rule-based approximation.

Encouragingly, recent years have seen the development of numerous fault models inside building performance simulation (BPS) tools [177]. For instance, a comprehensive list of fault models was developed with OpenStudio Measures [178], and additional new fault models are becoming available in EnergyPlus [179]. Combined with the versatility of BPS tools to change their numerous inputs, this presents a unique opportunity to utilize BPS to simulate and assess fault impacts in buildings in an adaptable manner. O'Neill et al. [71] included whole building fault impact assessment as part of their study with BPS, while another study by Cheung and Braun focused on chiller fault assessment [180]. The development of fault models also brings up an opportunity to pre-simulate fault cases and use simulation outcomes to train and test AFDD models, this eliminates the need to artificially generate or assume these faults in order to create a training dataset. However, caution needs to be exercised when using simulation data for training and validation, which this review will discuss further in the next section.

Another approach to evaluating fault impacts is to directly compare measurable metrics before and after the fault. Those methods can be created based on existing retrofit analysis procedures such as ASHRAE Guideline 14 [21] since they both analyze the effect of a parameter change within a system by directly comparing the measured metrics. If the metric of interest is directly observable, this approach can provide reliable analysis. However, it requires sufficient data to be collected after the fault event, and this data cannot be used to reasonably predict future impacts if the fault is not remedied.

7.2. Collaborative and cloud-driven AFDD

The development of cloud computing provided enhanced capabilities to conduct large-scale data storage and analytics [181]. Many authors have explored the possibility of cloud-driven real-time AFDD services for buildings [51,52,149]. Several commercial products have also become available to the market [44]. For cloud-driven AFDD, besides fundamental infrastructure challenges mentioned in Section 3.3, another important issue is how to assimilate data from different buildings for another layer of mutual information [51,182]. Since faults in buildings occur sporadically and buildings tend to share similarities, using data from other buildings could speed up the training process of a new AFDD program to achieve accurate and exhaustive fault models [51], as discussed in Section 6.2. However, cloud-driven AFDD requires a reliable network infrastructure, since a malfunctioning network connection cannot deliver enough data to the cloud on time. Furthermore, it is inevitable to have data quality issues on the cloud side, and inadequate data quality produces poor AFDD outcomes due to the "garbage in, garbage out" (GIGO) principle. Data cleaning or data preprocessing has been widely researched in statistical analysis [183,184]. While some research has been done on cleaning sensor data [185,186], its applications in building AFDD or building data analytics still await more systematic investigation.

Even for offline AFDD applications, several researchers have raised the importance of data collaboration. While many researchers have relied on using simulation to generate fault cases [75,100,110,132,135,187], they may not be sufficient for real-life applications since actual measured data contains sensor noise, missing data and other operation complications which can result in model stability issues [188,189]. Although some datasets are available publicly, such as ASHRAE RP-1020 and RP-1312 [190,191], they are still limited in scope. A collaborative dataset containing many building systems with verified ground-truth would allow researchers to develop and benchmark various AFDD methodologies easily [192]. Some data sharing models based on buy-in program or open access repository like UCI ML Repository [193] can be established for this purpose.

High quality data, especially labelled ground-truth data with fault instances are critical to machine learning models. Historically ground-truth data for developing and evaluating AFDD tools has been difficult to obtain. One potential method to improve this is to combine data from building audit/recommission and building automation system to produce ground-truth fault data set. Another option is to take advantage of the maintenance log book and use text mining techniques to identify past faults and match them to the automation data [32]. These topics still await more comprehensive studies.

7.3. Benchmarking AFDD performance

Common testing procedures should be established in order to evaluate the performance of AFDD systems comparatively. Some authors have used a common data set such as ASHRAE RP-1020 [255], but it does not consider the effect of different climate and system configuration. Yuill and Braun have proposed a novel method for evaluating AFDD performance for air conditioning systems [58]. However, for other building systems or whole building AFDD, these benchmarking methodologies are lacking. Furthermore, there is no standard requirement for reporting different performance metrics such as false negative rate, false positive rate and detection time. At the time of writing, the authors are aware of one whole building AFDD testing procedure currently in development by the Lawrence Berkeley National Laboratory [192], who have published a report on AFDD installation and operation costs [194]. In addition, ASHRAE is developing a laboratory testing standard for evaluating AFDD for air-cooled packaged systems [195]. As more and more building owners start to utilize AFDD products with the intention of improving efficiency and comfort, it is imperative for the academia and policy-makers to ensure the effectiveness of various AFDD products and methods so that the end-users do not lose confidence in this technology in the near future. Furthermore, there is no current guideline determine which fault should have prioritize lowering false positive or false negative rates. Some authors have attempted to collect lists of potential faults in building systems [25,56], but priorities of FNR or FPR for different faults are yet to be formalized.

7.4. Fault propagation and simultaneous faults

The research on fault propagation and multiple simultaneous faults is still underdeveloped [10]. An AFDD system without considering the effect of fault propagation may raise redundant alarms since affected building systems could also exhibit anomalies. This could lead to the confusion of building operators, especially when no assessment of the fault is provided and the faults are not prioritized. Dibowski et al. [196] have explored using BIM to generate rules in order to determine fault propagation paths using qualitative presentations. However, without the support of communications between AFDD systems, passing fault information from one equipment to another could still be challenging unless all AFDD programs are centralized.

On the other hand, the impacts from multiple simultaneous faults are two-fold [19,139,197]: first without assessing fault impacts the building operators have to rely on their experience to prioritize maintenance tasks; second simultaneous faults may augment or mask the same symptoms on a building system, making them very hard to diagnose thus causing some AFDD methods fail to respond. For example, a biased thermostat sensor combined with insufficient heating/cooling may appear normal on the surface until an occupant complains, leading the operators revert to complaint-driven maintenance. Some researchers have considered the issue of multiple faults diagnosis as part of AFDD research [83,198–200], while a few other authors have explicitly developed AFDD methods for simultaneous faults [139,197]. Still, this area of research has lots of potential to be explored [10,139].

7.5. Improving AFDD interoperability

Unlike BAS, BEM, BIM or other building-related technologies, there is yet a standard communication protocol for building AFDD systems. As mentioned many times in this review, a standard protocol can greatly help an AFDD system to tackle fault propagation, simultaneous faults and obtain additional knowledge from its fellow AFDD agents. This can enable a distributed AFDD system which reduces network traffic and provides a faster fault diagnosis rate. Such a system would require schemas for describing symptom and fault, a standardized list of building faults as well as ways to convey causalities of fault propagation. An example of such interfaces in other discipline can be seen in communication networks [201] and computer engineering [202].

7.6. Other related research

On a broader perspective, AFDD is part of reliability engineering which contains many other aspects of research that can maintain an engineering system's reliability and robustness [203]. Prognostics – predicting faults in advance, has rarely been researched for building related applications [6,204]. Another related topic is self-correcting or robust control, which has been investigated by a few authors [153,205]. Other topics include robust designs [206], fault management and other related topics.

8. Conclusion

Over the last decade research on AFDD for building systems have gained a great deal of attention thanks to the increasing need for higher efficiency and productivity. This review first examined the fundamentals of AFDD for building systems, then separated the tasks of feature generation, fault detection, symptom generation and fault diagnostics inside a typical AFDD process. Methods for each of these tasks are categorized and compared with their current trend of research discussed. Advantages and disadvantages of various AFDD methods are examined, and the authors have also proposed several ways to improve the existing techniques employed in building AFDD research. Yet there are still many challenges facing the current researchers, including the gap between research and real-life applications, the integration of various AFDD methods and the need for more collaboration. This review hopes to bring insight from building AFDD and other related disciplines to inspire other researchers expanding this field.

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