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Evaluation of HVAC & refrigeration system fault behaviors and impacts: A systematic review

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ABSTRACT

Achieving the goals of green buildings critically depends on the fault-free operation of heating, ventilation and air conditioning and refrigeration (HVAC&R) systems. However, faults frequently occur in these systems, causing a range of negative consequences, including increased energy consumption, diminished operational performance, compromised indoor environmental quality, higher operational costs, and shortened system lifespan. The evaluation of fault behaviors and impacts plays a critical role in revealing fault characteristics and consequently supports many research areas, including the design of the high-performance equipment, development of fault detection and diagnostics (FDD) and robust control approaches, as well as the enhancement of maintenance decision-making activities. This paper systematically reviews 112 research publications that reported the analysis and evaluation of fault behaviors and impacts in HVAC&R systems over the past thirty years. We designed a review approach to address five crucial research questions, namely: 1) the objectives of analysis and evaluation of fault behaviors and impacts, 2) data sources, 3) equipment/system types and fault types, 4) evaluation methods including evaluation measures and associated metrics, and 5) challenges and future directions in the research on evaluating of fault behaviors and impacts. In-depth discussions on these questions help bridge the gap between the evaluation of fault behaviors and impacts and their practical applications, such as the development of high-performance systems, fault models, FDD methods, and maintenance decision-making tools within the HVAC&R FDD domain.

1. Introduction

Buildings consume a substantial portion of energy. According to the Energy Information Administration [1], combined end-use energy consumption by buildings (including both residential and commercial buildings) accounts for 27.6% of total end-use energy consumption in the U.S. Heating, ventilation, air conditioning, and refrigeration (HVAC&R) systems are responsible for 38% of energy consumption in buildings [2]. To enhance energy efficiency, various types of high-performance HVAC&R systems and equipment, along with advanced control strategies, have been developed and are being increasingly deployed in the market in recent years.

In HVAC&R systems, numerous faults and instances of malfunctioning equipment have been identified. Faults and malfunctioning equipment can cause a range of negative impacts, including increased energy consumption, reduced thermal comfort, elevated maintenance costs, and shortened system lifespan. For example, it is estimated that 15%–30% of energy is wasted due to faults, poorly maintained equipment, degraded performance, and improperly controlled equipment in commercial buildings [3,4]. Therefore, fault-free control and operation are essential to achieving desired operational performance, enhancing energy efficiency, and reducing carbon emissions in HVAC&R systems.

To ensure fault-free control and operation performance, extensive research has been conducted on fault detection and diagnostics

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(FDD) of HVAC&R systems. In recent years, many review papers have summarized research achievements in various research directions in the FDD area, including FDD method development, HVAC&R system fault modeling, fault types and fault occurrence distributions, and fault tolerant control. For example, numerous studies have reviewed the development of different FDD methods (e.g., physical model-based, machine-learning-based and data-driven methods) applied to varied types of HVAC&R systems [5–10]. Li et al. summarized methods and accomplishments in fault modeling research [11]. HVAC system fault occurrence characteristics were investigated in Refs. [12–14]. The development of fault-tolerant control systems was studied in Refs. [15,16]. A comprehensive review of studies on the influence of maintenance strategies on building energy performance was conducted in Ref. [17]. Nonetheless, none of the aforementioned review publications has specifically examined one fundamental research direction, i.e., the evaluation and analysis of fault behaviors and impacts in HVAC&R systems within buildings. While many studies acknowledge that such faults can cause consequences like increased energy consumption and deteriorating thermal comfort, they often do so without providing detailed analysis.

The analysis and evaluation of fault behaviors and impacts are critical in the FDD area. Fault behaviors in HVAC&R systems often refer to changes in relevant measurements (e.g., sensors and control signals), which can be captured by building automation systems (BAS). Fault impacts can represent high-level effects caused by faults, such as increased energy consumption or deteriorated thermal comfort. This research area aims to understand the operational behaviors and performance of equipment or systems under faulty operations, and consequently uncover the characteristics and effects of these faults. The analysis can serve multiple purposes, including the assessment of system degradation, control system robustness, energy waste, indoor environment deterioration, and increased operational and maintenance costs associated with faults.

Although research on the evaluation of fault behaviors and impacts in HVAC&R systems is vital and active, few efforts have been made to systematically review this research topic. A handful of reviews have focused on particular types of HVAC&R systems. For example, Bellanco et al. reviewed research on the fault behavior of heat pumps [18]. However, to the authors' best knowledge, no studies have comprehensively reviewed research efforts across the entire spectrum of HVAC&R systems. This substantial gap results in a limited understanding of fault characteristics in HVAC&R systems, which in turn hinders progress in key FDD research directions, such as the successful development and implementation of effective FDD approaches and maintenance strategies. To bridge this gap, this paper systematically reviews the current state of knowledge and identifies gaps in the analysis and evaluation of fault behaviors and impacts in HVAC&R systems. Specifically, five critical research questions related to this research direction are addressed. They are:

1) What research objectives are targeted?
2) What data source is used?
3) What types of HVAC&R equipment/system and what types of faults are investigated?
4) What measures and metrics are used?
5) What are the challenges and gaps?

The contributions of this work include:

- Data sources and HVAC equipment types are identified to support fault behavior and impact analysis
- The framework for evaluating fault behaviors and impacts is summarized
- Measures and associated metrics for evaluating fault behaviors and impacts are systematically reviewed and compared
- Research gaps are identified and future directions are proposed

The subsequent sections of this paper are organized as follows: Section 2 delineates the research objectives derived from prior publications. Section 3 presents the data sources utilized for fault impact analysis. In Section 4, a concise discussion is provided on the equipment or system types, and fault types previously examined in fault impact analyses. Section 5 systematically reviews diverse metrics and associated methodologies from existing literature. Section 6 delves into challenges and suggests potential research directions for future explorations. Section 7 concludes the paper. A detailed literature search strategy is described in Appendix I.

2. Research objectives

Research objectives affect both the research methods employed and the engineering applications related to fault behaviors. In this study, we identified four primary research objectives based on previous research efforts. They are: i) analysis and modeling of component or system performance, ii) development of resilient control systems and equipment installation, iii) development of FDD and value proposition, and iv) guidance for maintenance decision-making.

2.1. Analysis and modeling of component or equipment performance

When developing or modeling a component or piece of equipment, it is imperative to analyze its performance under faulty conditions to obtain comprehensive insights into its functionality across all operational scenarios. Several studies have explored this aspect [20–24]. Additionally, fault impact models for specific components, which have been integrated into various software simulation tools, have been developed [25,26].

2.2. Development of resilient control system and equipment installation

Fault impact analysis plays a pivotal role in supporting the development of resilient control systems and providing guidance for equipment installations. Understanding how faults influence system operation is crucial for designing resilient control strategies capable of mitigating negative impacts. For instance, a holistic fault impact analysis approach aimed at designing high-performance control sequences for HVAC systems in medium-sized office buildings was proposed [27]. Furthermore, some studies have investigated the impacts of installation faults to develop best practice guidelines. For example, energy waste and associated costs caused by two installation faults of air conditioners and heat pumps in single-family homes in the U.S. were investigated [28].

2.3. Development of FDD and value proposition

Numerous FDD approaches, including expert systems and rule-based methods, rely on elucidating relationships between faults and their associated symptoms. For example, various rules for detecting air handling unit (AHU) faults by evaluating fault impacts on different measurements were developed [29,30]. A rule-based statistical FDD method was proposed after analyzing the impacts of five faults to detect faults in vapor compression air conditioners [31]. In rooftop units (RTUs), rules extracted from fault impact analysis were used to detect faults [32]. Transient patterns during faulty operation were analyzed to enhance FDD performance [33].

Additionally, some studies have investigated the value proposition of FDD solutions in enhancing building energy efficiency and mitigating fault impacts. For example, Gunay et al. evaluated the energy and comfort performance benefits derived from early detection of building sensor faults and actuator faults [34]. Lee et al. quantified the energy penalties associated with typical variable air volume (VAV) system faults, underscoring that FDD implementation might not receive attention in buildings until building owners recognize the benefits it offers [35].

2.4. Guidance for maintenance decision-making

Fault impact analyses are crucial in enhancing maintenance activities for two key reasons. First, when multiple faults occur, facility managers need an optimized decision-making approach to prioritize maintenance activities. Various metrics of fault impacts, such as their impacts on energy consumption, economics, and the indoor environment, can support maintenance decision-making. Additionally, the consideration of the fault impact severity levels, comprising the magnitude and spatial scale, is paramount. Therefore, fault impact analyses have been performed to promote HVAC&R maintenance activities [36,37]. For instance, fault impacts based on factors like energy consumption, thermal comfort, and costs across various equipment types were ranked [21,38,39]. Secondly, maintenance costs, including both labor costs and financial costs, can be evaluated based on various fault characteristics such as severity levels and occurrence frequency. For example, a quantitative approach was developed for scheduling service and planning following an analysis of fault impacts in an HVAC system [40].

3. Data sources

Data serves as the cornerstone for conducting analyses of fault behaviors and impacts. Furthermore, the process of data generation can dramatically influence the accuracy and scalability of the analysis. In this study, we identified and compared three principal sources of data from existing literature, including: i) experimental and field data, ii) software simulation data, and iii) interview surveys.

3.1. Experiment and field data

Operational data collected from laboratory experiments or field operations can provide a more accurate reflection of the system's real-world operations under faulty conditions. In laboratory experiments, faults can be deliberately injected into the HVAC equipment while operating under typical conditions. Operational interval data can be gathered using a Supervisory Control and Data Acquisition (SCADA) system or a BAS.

Table 1
Publications using experimental and field data and system or equipment types investigated.

Equipment/system type	Publication
HVAC systems (Combined various equipment that may include AHU, VAV box, RTU, chiller plant, and boiler plant)	[41,42]
Refrigeration systems (including VRF systems, vapor compression systems)	[23,31,43,43–45,45–50]
Residential air conditioner	[51–54]
Chiller/chiller plant	[20,25,55–60]
AHU	[26,29,30,33,61–64,64–67]
FCU	[68]
RTU	[21,23,32,67,69–71]
VAV box	[67]
Heat pump	[22,72–83]
Heat exchanger	[84,85]

A total of 62 publications employed experimental and field data to evaluate fault behaviors and impacts, as listed in Table 1.

In the early stages, the analysis of fault behaviors and impacts was carried out to model either HVAC&R equipment or components or to generate fault-inclusive data sets for specific types of HVAC&R systems through laboratory experiments. For example, fault impacts on a centrifugal chiller under various load conditions in a laboratory environment were studied [20]. The authors developed the chiller fault data set (i.e., ASHRAE RP1043), which serves as a resource for FDD development and equipment design. Experiments across various operational seasons in the laboratory were carried out to analyze fault behaviors on particular measurements (e.g., damper control signals and supply air temperature), and to develop models for single-duct AHUs and variable air volume (VAV) boxes [26]. The results produced the single-duct AHU and VAV box datasets (i.e., ASHRAE RP1043). Experimental data was employed to model fault behaviors and develop an FDD tool for a fan coil unit [68].

Additionally, several research endeavors have focused on investigating fault impacts on high-performance HVAC equipment using various experimental setups. For example, psychrometric chambers were used to investigate fault impacts in variable refrigerant flow (VRF) systems [86,87]. Laboratory experimental platforms were established to investigate fault impacts in heat pump systems [51,77,78,82]. Various laboratory tests were performed to analyze fault impacts in commercial RTUs [21,69].

While experiments conducted in laboratory or field settings can generate high-quality data that closely mirrors actual fault behaviors, the associated costs of constructing such testing environments are typically substantial. As a result, most studies that used experimental and field data focused on fault behavior analysis at the component- or equipment-level. The analysis of fault behaviors and impacts at the system-level through experiments is rare due to the prohibitive costs involved. Moreover, the analysis based on the data collected from limited operational conditions may overlook certain fault behaviors and impacts during the evaluation process.

3.2. Software simulation data

Since 2010, an increasing number of studies have used software simulation tools to evaluate fault impacts. This is for three main reasons. First, there are an increasing number of HVAC&R component models available in software tools, making it much easier to simulate system operations without conducting physical tests. Secondly, using software simulation is more cost-effective compared to experiments and field tests. With simulation tools, there is no need to set up a complex experimental environment or deploy sophisticated sensor networks. Furthermore, simulation tools can generate a large amount of faulty and fault-free data within a very short time frame. Lastly, system-level simulations of fault-free and faulty operation can be performed using software tools. Hence, a complete evaluation of fault impacts can be conducted to enhance the understanding of faulty operations of an HVAC system.

A total of 40 publications utilized software simulation data to evaluate fault behaviors and impacts. Typical software simulation tools used are summarized in Table 2.

Although using software simulation tools can efficiently evaluate fault impacts at various scales with respect to the system complexity and operation durations, there are two challenges associated with using software tools to generate fault-inclusive data. First, the analysis relies heavily on various factors such as accurate equipment models, correct software settings (e.g., various control sequences), and fault imposition approaches. Secondly, when evaluating system-level fault impacts, validating faulty behaviors of an HVAC&R system under various operational modes can be a very time-consuming process and requires sufficient experience from model developers.

Table 2
Publications using software simulation data and system or equipment types investigated.

Software tool name	System/equipment	Publication
TRNSYS	HVAC systems (Combined various equipment that may include AHU, VAV box, RTU, chiller plant, and boiler plant)	[39,88]
	AHU	[89]
	Heat pump	[90,91]
EnergyPlus	HVAC systems (Combined various equipment that may include AHU, VAV box, RTU, chiller plant, and boiler plant)	[27,35,92–102]
	AHU	[34,103,104]
	Heat pump	[28,105,106]
HVACSIM+	HVAC systems (Combined various equipment that may include AHU, VAV box, RTU, chiller plant, and boiler plant)	[107]
	FCU	[38,131]
Modelica	HVAC systems (Combined various equipment that may include AHU, VAV box, RTU, chiller plant, and boiler plant)	[108–112]
MATLAB	AHU	[113]
Co-simulation (EnergyPlus and Modelica)	Chiller/chiller plant, boiler/boiler plant	[24]
Co-simulation (MATLAB and TRNSYS)	HVAC systems (Combined various equipment that may include AHU, VAV box, RTU, chiller plant, and boiler plant)	[114]
	AHU	[115]
	Chiller/chiller plant	[116]
Tools not indicated	AHU	[117]
	Chiller/chiller plant	[37]
	Heat pump	[118]

3.3. Interview surveys

In addition to experiments and software simulations, 10 studies collected data from interview surveys and service records to understand fault impacts. Table 3 summarizes the publications using interview surveys based on the systems or equipment investigated.

For example, Comstock et al. carried out a survey to investigate common faults and associated maintenance costs for chillers [123]. In the study, they interviewed four U.S. chiller manufacturers. From the manufacturers, 170 service records for centrifugal chillers, 228 service records for water-cooled screw chillers, and 111 service records for air-cooled screw chillers were collected. Breuker et al. investigated 6,000 service records from an RTU service company to identify common faults and their impacts on breakdown costs [21]. Bassetto et al. analyzed 600 reports of failure in the reciprocating compressor of refrigeration systems to understand failure modes caused by certain faults [126]. Thompson et al. analyzed AHU and condenser failure and maintenance data to enhance the design of equipment and support preventive maintenance [125].

Compared to experimental and field data and software simulation data, interview surveys and service records reflect real operations of HVAC&R systems and equipment, and hence they are very valuable for understanding HVAC&R fault behaviors and impacts under real operations. However, carrying out a large-scale interview survey or collecting service records is very challenging. Meanwhile, quantifying fault impacts using interview surveys or service records is difficult because of the high variety of HVAC&R systems and applications, and no guideline can be followed. Therefore, only a small number of studies have carried out interview surveys in recent years to evaluate fault behaviors and impacts.

4. HVAC&R systems or equipment and fault types

A multitude of HVAC&R equipment and systems is employed in today's commercial and residential buildings. Moreover, the spectrum of fault types across these diverse equipment and systems is extensive. In this study, we conducted a thorough review that encompasses the classification of equipment and systems, as well as an examination of the various fault types associated with them.

According to when an HVAC&R fault may occur, faults can be classified into three categories: 1) design stage, 2) installation and commissioning stage, and 3) operating stage. At the design stage, equipment and system hardware or software are wrongly designed. At the design stage, equipment size and model can be incorrectly specified, causing malfunctioning operation. For example, the chilled water pump may be oversized, causing excessive energy consumption, or undersized, causing failure to provide enough cooling [116, 127]. At the installation and commissioning stage, the equipment or system is improperly installed or commissioned, causing malfunctioning equipment. For example, the installation faults commonly found during commissioning of the air-source heat pump were studied [91]. It was found that heat pump installation faults can lead to increased annual end-use energy waste in buildings. Most reported faults happen during the system's operation. Various operational conditions, such as continuous operation, extreme operational conditions, as well as insufficient maintenance can cause failure of certain components, and lead to operational faults. There are typically four categories of faults at the operating stage. They are actuator faults (e.g., a broken damper linkage causing the damper to get stuck), sensor faults (e.g., a failure of an electronic chip causing the sensor reading to freeze), stationary part faults (e.g., cooling coil fouling or coil leakage), as well as communication and control software programming faults (e.g., disconnected communication wire, wrong schedule setting, or improper PID parameter setting) [107].

Fig. 1 lists the fault categories. The green blocks indicate the fault categories that the previous research efforts have covered.

In this review, faults occurring in 10 types of HVAC&R equipment and systems studied in previous research are examined. They are AHU, VAV box, RTU, chiller/chiller plant, boiler/boiler plant, heat pump, FCU, residential air conditioner systems, refrigerant systems (including VRF systems and vapor compression systems), and heat exchanger. The previous research identified 138 fault types occurring in those types of equipment or systems. We provide a list of systems or equipment studied and fault types in Appendix II.

5. Fault behavior and impact evaluation method

In the past, many methods have been used to understand fault behaviors and their subsequent impacts. Various approaches may result in a wide range of quantitative fault impact outcomes from the same type of faults in the same or similar equipment. However, in this study, we did not focus on reporting and comparing the quantitative outcomes in terms of specific faults or specific systems or equipment reported by previous research efforts side-by-side. Instead, we systematically reviewed and categorized the methods, primarily focusing on the measures and metrics used in previous research endeavors.

In this section, we first review the analysis framework that was developed to evaluate fault behaviors and impacts in Section 5.1.

Table 3
Publications of fault impact using interview surveys and system or equipment types investigated.

System/equipment	Publication
HVAC systems (Combined various equipment that may include AHU, VAV box, RTU, chiller plant, and boiler plant)	[36,40,119–122]
Chiller/Chiller plant	[123,124]
AHU	[124,125]
FCU	[124]
Refrigeration systems (including VRF systems, vapor compression systems)	[125,126]

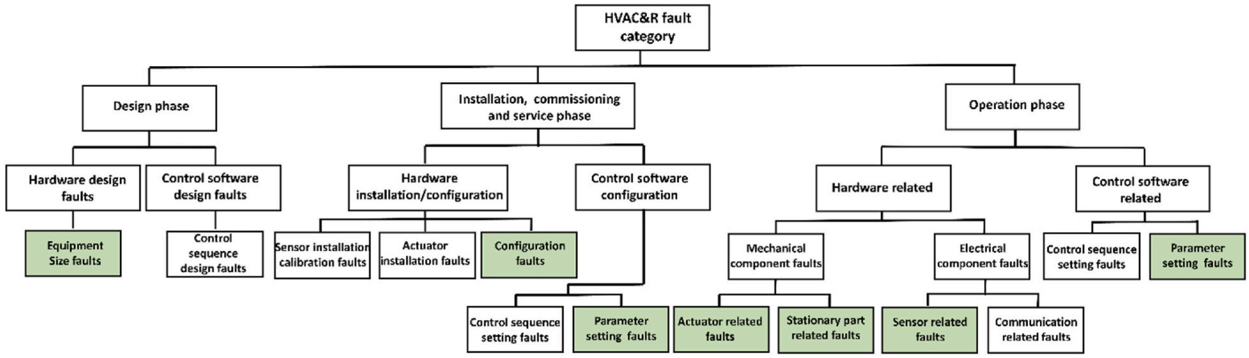

Fig. 1. Fault category.

Then, in Section 5.2, we review various methods (including measures and metrics) that were employed to evaluate fault behaviors and impacts. We focus on the description and comparison of evaluation approaches instead of quantitatively comparing the impact results of specific faults.

5.1. Analysis framework

Several studies have explicitly proposed frameworks for analyzing and evaluating fault behaviors and impacts. For instance, Lu et al. proposed a holistic method to analyze fault impacts when the HVAC system operates using an advanced control sequence [27]. In the method, various key performance indexes (KPIs), including operational cost, source energy, site energy, control loop quantity, thermal comfort, ventilation, and power system metrics were employed to comprehensively evaluate fault impacts. Li et al. developed a fault impact analysis framework, which includes three aspects during fault impact analysis as: fault construction, fault simulation, and fault impact analysis [99]. Chen et al. proposed a bottom-up framework to analyze HVAC system fault impacts [38]. In the framework, fault impacts on various measurements, which are commonly accessible in the BAS, are first analyzed. Then, a high-level impact analysis using other metrics such as indoor thermal comfort and energy consumption was performed.

From a handful of studies, we generalized a framework for evaluating fault behaviors and impacts as shown in Fig. 2. The

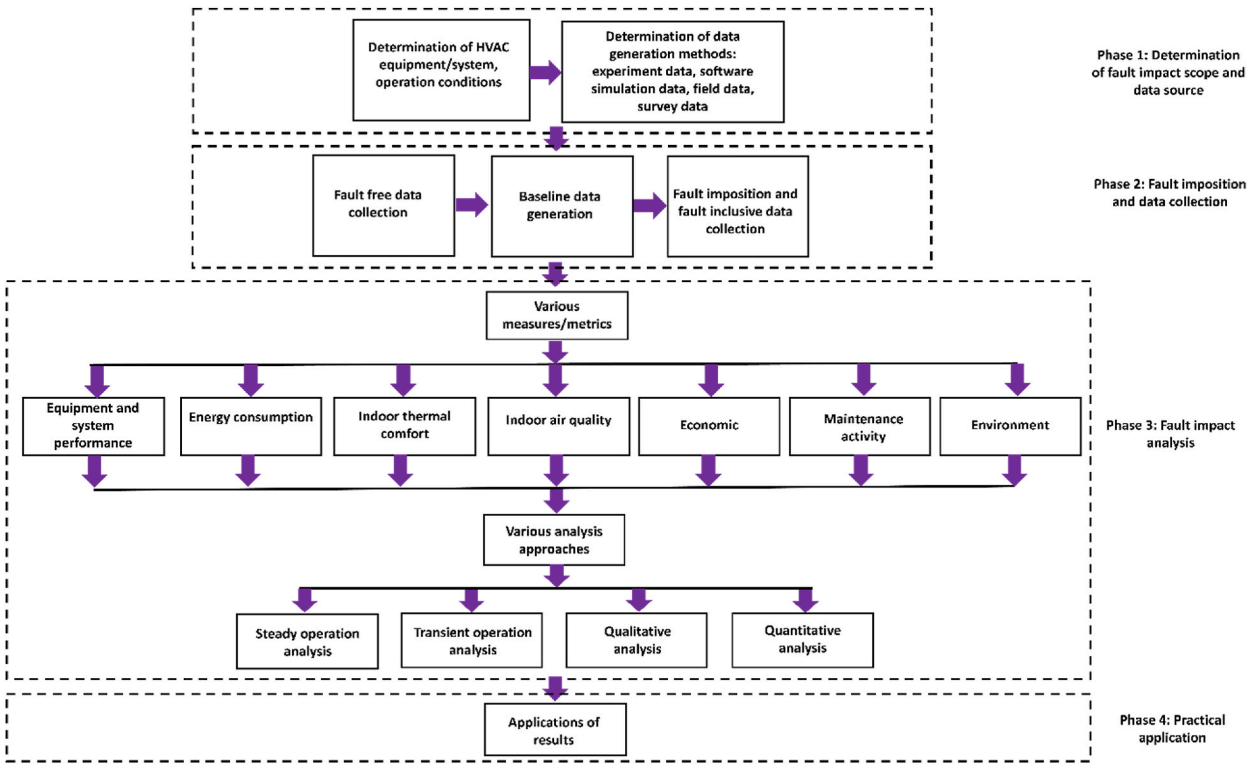

Fig. 2. Framework for evaluating fault behaviors and impacts.

framework includes four phases in the fault impact analysis. The first phase is to determine the fault impact scope and data source. In this phase, the targeted HVAC&R equipment and system, and operation conditions need to be identified. In addition, the data source and data generation method are determined. The second phase is to impose the designed faults and collect data (including both fault-free data and faulty data). Furthermore, the baseline data needs to be generated during this phase. In the third phase, various methods including measures, metrics, and approaches are employed to perform the fault impact analysis. The primary measures used in the existing studies include seven types: 1) equipment and system performance, 2) energy, 3) thermal comfort, 4) indoor air quality, 5) economic cost, 6) maintenance activity, and 7) environment. Under each measure, various metrics were developed to evaluate the impact magnitude caused by various types of faults. Additionally, different approaches are used. They are mainly divided into steady operation analysis, transient operation analysis, qualitative analysis, and quantitative analysis. The definition of each approach is given below.

- Steady operation analysis: The analysis uses data collected during the system's steady operation after a fault occurs. Most studies use this approach to analyze fault impacts in terms of various measures and metrics.
- Transient operation analysis: The analysis uses data collected before the system reaches steady operation. The data in the transient operation can better capture the system's dynamic characteristics caused by faults. However, due to the low sampling rate of the BAS (normally at a 5–15-min sampling rate) in real practice, dynamic characteristics in the transient operation of systems/equipment cannot be captured. Therefore, very few studies have used this approach.
- Qualitative analysis: The analysis result reflects the trend of the fault impacts but does not numerically quantify the magnitude. Some studies use this approach to analyze fault impacts on various measurements and equipment operation performance.
- Quantitative analysis: The analysis quantifies the fault impacts on various measures using different metrics such as absolute deviation, percentage of change, percentage of unmet time, and duration of unmet time. Most studies perform quantitative analyses. However, the results vary significantly for the same type of fault in the same system or equipment.

In the fourth phase, the applications of the analysis are discussed to guide the use of the results for various purposes.

5.2. Review of measures and associated metrics

In this section, we illustrate HVAC&R fault impact analysis based on various measures and their associated metrics. The primary measures include equipment and system performance, energy consumption, thermal comfort, indoor air quality, economic costs, maintenance activities, and the environment, as presented in Sections 5.2.1 to 5.2.7.

5.2.1. Equipment and system performance

The evaluation of equipment and system performance changes due to faults can be performed in two ways: 1) the analysis of fault symptoms on various measurements (e.g., sensor readings and control signals), and 2) the analysis of certain control performance criteria (e.g., control stability and equipment efficiency). These changes directly reflect faulty characteristics.

In the studies, observable fault symptoms are first identified by comparing the measured operation interval data under faulty operations to fault-free operation (i.e., the baseline), or by comparing the measured operation interval data under faulty operations to the reference values (i.e., setpoint values or nominal values) when a fault occurs and lasts for a certain period until the operation can reach a steady state under the faulty condition. Typically, there are two analysis approaches, such as qualitative analysis and quantitative analysis, to assess fault symptoms and uncover symptom patterns.

5.2.1.1. Qualitative analysis of fault behaviors

5.2.1.1.1. Fault and symptom relation. When a fault occurs, certain measurements can present symptoms. The relations between fault and associated symptoms can indicate fault behaviors; hence, they were adopted by early FDD developers, who tried to generalize the relations to establish rules. Consequently, rule-based or expert system-based FDD tools were developed to identify the HVAC&R fault. For example, Schein et al. developed a set of expert rules, which includes 28 rules to detect faults in AHUs [29]. The rules were derived from mass and energy balances. The violation of the rule (i.e., an exposure of a certain fault symptom) can be observed and hence indicates certain faults. For example, if the difference between the outdoor air (OA) temperature and mixed air (MA) temperature is higher than a threshold (i.e., rule #10), it indicates the OA damper-related faults or OA temperature sensor-related faults, or MA temperature sensor-related faults. Kaldof et al. established a rule set to develop an expert system-based Performance Audit Tool for detecting faults in the chiller plant [59]. In each rule, it contains a fault and a set of conditions to reveal associated symptoms.

Although the research results can indicate fault behaviors on specific measurements, the research did not quantify the magnitude, making it difficult to employ the results to understand fault severity levels.

5.2.1.1.2. Symbolized representation. Many studies have used symbols to qualitatively evaluate the fault symptom patterns once the deviation for a specific measurement is determined. Here, symbols denote the direction and magnitude of the deviation. For example, when the deviation is positive (i.e., the measured value exceeds the threshold above the reference value), a positive symbol (e.g., ↑, +) is used to represent the positive symptom. If the deviation is negative (i.e., the measured value falls below the threshold above the reference value), a negative symbol (e.g., ↓, -) is used to indicate the negative symptom. If the deviation is neutral (i.e., the measured value lies within the threshold of the reference value), a neutral symbol (e.g., no change, (●)) is used. Furthermore, researchers have used a varying number of the symbols to indicate symptom strength (i.e., fault impact level). For example, "+" may indicate that the fault impact is light, and "+++" may indicate that the fault impact is severe. This approach has been used to evaluate the impacts caused by faults in RTUs, chillers/chiller plants, refrigeration systems, and heat pumps [20,21,31,32,46,55,75,87,88].

Although qualitative analyses of fault impacts provide intuitive results on fault impact magnitudes and explicitly uncover symptom patterns, there are some shortcomings. First, there is no clear boundary between various levels. For example, it is hard to distinguish the impacts between the level of "+" and the level "++". Secondly, the symbolic results of fault impacts can hardly be translated into practical applications such as the development of FDD approaches, where quantitative results are programmed. Thirdly, the analysis does not consider the uncertainty in fault behaviors and impacts due to changing operation conditions.

5.2.1.2. Quantitative analysis of fault behaviors

5.2.1.2.1. Magnitude of deviations. It is straightforward to use the magnitude of deviations to quantify the fault impacts. When a fault causes a higher magnitude of deviation (i.e., the deviation from the baseline or the reference value is higher), it means that the symptom is strong and more observable.

Hu et al. quantified impacts caused by single faults, double faults, triple faults, and quadruple faults on a heat pump by showing the magnitude of deviations on various measurements [75]. For example, the combination of the evaporator airflow fault (at an intensity of 60%) and insufficient refrigerant charge fault (at an intensity of 70%) can reduce the subcooling temperature by 5°C. In addition, the same approach was used to investigate single or simultaneous fault impacts on various measurements on the heat exchanger, air conditioner, condensers, fixed-orifice (FXO) expansion device, RTUs, AHUs, VRF systems, and heat pumps, respectively [52,53,61,72,75–77,84,85,128,129].

In addition, some studies have developed sensitivity indices, which can better reflect the magnitude of deviations. For instance, Comstock et al. developed a sensitivity factor, which quantifies the measurement deviation for the worst fault when evaluating fault impacts on chiller performance [20]. The sensitivity factor contains the maximum experimental uncertainty at the upper limit of the range of uncertainties and can be analogous to a signal-to-noise ratio as given in Eq. (1).

$$Sensitivity = \frac{Residual\ of\ Given\ Measurement\ at\ Fault\ Level\ 4\ (\%)}{Maximum\ Experimental\ Uncertainty\ of\ Given\ Measurement\ (\%)} \tag{1}$$

Similarly, Gao et al. developed a total sensitivity index to quantify chiller fault impacts on various measurements [57]. The index contains the influence (i.e., the magnitude of the deviation) on a single measurement, and the comprehensive influence caused by the interaction between multiple measurements. Consequently, a four-level sensitivity classification was developed to evaluate the fault impacts.

5.2.1.2.2. Probabilistic distribution analysis. Some studies investigate probabilistic distributions to quantify the relations between faults and associated symptoms. In the analysis, the conditional probability distributions are established between faults and associated symptoms due to uncertainties. For example, if an outdoor damper stuck fault occurs in an AHU, what is the likelihood that the cooling coil valve signal increases (indicating an increased cooling supply) being observed? The analyses considered the uncertainty of fault behaviors and impacts caused by varied operational conditions in HVAC&R systems.

For instance, Zhao et al. calculated the conditional probability distributions between faults and associated symptoms for chiller and AHU fault diagnostics [58,64,130]. In the studies, the authors used the experimental data of each fault at one level of one severity to calculate the conditional probabilities. For example, for the condenser coil fouling fault, there is a 75% probability that it causes the condensed water to increase. Chen et al. quantified each fault symptom into three levels (i.e., minor, moderate, and severe) based on the assigned conditional probability distribution for each pair of the fault and associated symptoms in an HVAC system when developing a BN-based fault diagnosis method [122]. In another study, Chen et al. developed a weather pattern matching method to calculate the fault symptom occurrence probability (SOP), which quantifies the range of fault impact on various measurements [131]. The SOP uncovered the fault symptom occurrence pattern under various operational conditions as given in Eq. (2).

$$P(fault\_sym|OP_{OAT}) = \frac{\sum num\_fault\_sym}{\sum OP\_time} \tag{2}$$

where, *num_fault_sym* is the number of times the fault symptom is observed, and *OP_time* is the total operational duration within each binned OAT window.

Using the SOP distribution, Rosato et al. assessed the impact caused by the seven faults in AHUs when validating the AHU fault models [62,63].

5.2.1.2.3. Transient analysis. It is noted that most studies, as reviewed in (1) and (2), performed steady operation analyses on fault behaviors and impacts, i.e., when a fault exists for a certain period and operation reaches a steady state, the deviation can be steadily observed on various measurements. Nonetheless, evaluating transient impacts on measurements when a fault occurs may provide additional information for characterizing the fault. There is very little literature investigating what incipient impacts can be observed and how to quantify them. Cho et al. proposed a transient analysis to quantify fault transient impact patterns [33]. The method compares the time required to reach steady state after the fault is present. It was found that it can take at least 10–60 min for the system to reach a stable state for different types of faults in AHUs and VAV boxes. For example, when the outdoor damper is stuck at a 30% position, it can take the system 60 min to reach a steady state. Dooley investigated transient impacts due to three types of faults (i.e., system cycling, improper evaporator airflow, and coil fouling) in residential split system air conditioners [54]. The research indicated that the moisture removal rate was negative during the first 3–30 s after startup due to a cycling fault.

5.2.1.3. Control performance. Some studies used the developed control criteria to evaluate fault impacts on the control system performance. For example, Lu et al. used Sobol's index to analyze sensor error impacts in a demand-controlled ventilation system [96]. Ji et al. developed a systematic analysis method to understand sensor and actuator fault propagation and impact in chilled water systems [88]. It was found that the pump control performance is more sensitive to three types of sensors, i.e., the supply air temperature sensor, the indoor air temperature sensor, and the valve opening signal sensor of the terminal at the critical hydraulic loop.

Additionally, cooling capacity and coefficient of performance (COP) are often used to evaluate fault impacts on operational performance in various types of HVAC components or equipment. Table 4 lists the COP impact analyses from previous literature.

Meanwhile, several studies used annual COP and seasonal COP to fully evaluate fault impacts in long-term operations. For example, Motomura et al. evaluated the yearly impact caused by faults on the system COP and ranked 35 faults in a chiller plant [37]. The change in the system COP can be calculated by Eq. (3).

$$RC_{SCOP,Fn} = \left\{ \left(SCOP_{year,Fn} - SCOP_{year,F0} \right) / SCOP_{year,F0} \right\} \times 100 \tag{3}$$

It was found that the impact of annual system COP (SCOP) due to a fault related to condensers was significant. For example, the pressure loss in condenser water can decrease the SCOP by 7.86%.

Pelella et al. evaluated the combined impacts of both the refrigerant leakage fault and the fouling fault on air-source heat pump performances in cooling mode [118]. They used the seasonal COP to analyze faults in three typical climate zones. It is found that the refrigerant leakage fault can cause a decrease of seasonal COP by more than 25%, whereas the heat exchanger fouling fault can downgrade the seasonal COP by approximately 15%. Similarly, Palmiter et al. evaluated the COP change due to improper airflow and refrigerant charge on the seasonal performance of a typical residential heat pump with a thermostatic expansion valve [73].

5.2.2. Energy

Energy consumption is one of the most important measures that is commonly evaluated to unveil HVAC&R system fault impacts. There are two approaches used to analyze fault impacts on energy consumption. The first approach is to quantify energy consumption variation caused by faults at various spatial levels (i.e., equipment-level, system-level, building-level, and nation-level) and at different temporal levels (i.e., daily, monthly, and yearly). The second approach is to measure the peak power impact caused by faults.

5.2.2.1. Energy consumption. To quantify fault impacts on energy consumption, the relative or absolute energy consumption changes between faulty and fault-free operation can be calculated. For example, the relative energy consumption change for a piece of equipment under faulty operation can be obtained by calculating the percentage change of energy consumption as illustrated in Eq. (4). Here, the energy consumption change can be represented by various units such as electricity consumption (i.e., kWh), Btu, Joule, and so on.

$$\text{Energy\_change\%} = (\text{Energy\_faulty - Energy\_fault-free}) / \text{Energy\_fault-free} * 100 \tag{4}$$

After the energy consumption impact is calculated by analyzing one piece of equipment, it can then be extrapolated to the whole system level or whole building level and even larger scales.

The evaluation of fault impacts on energy consumption has been carried out for multiple types of faults in various types of HVAC systems and equipment. It is observed that energy consumption changes caused by the same type of a fault in the same type of HVAC

Table 4
Summary of literature reporting fault impact on COP.

HVAC equipment/system type	Fault type	% Change in COP	Publication
RTU	Refrigerant leak, compressor valve leakage, liquid-line restriction, condenser fouling, evaporator filter fouling	−2.7 to −23.8	[21]
Chiller/chiller plant	Evaporator tube fouling, condenser tube fouling, compressor internal faults, motor/transmission faults, condenser water flow change, chilled water flow change	Qualitative result	[55]
Refrigerant systems (including VRF systems, vapor compression systems)	Condenser air flow blockage	−6 to −7.6	[47]
	Compressor valve leakage, liquid line restriction, presence of non-condensable, low or high refrigerant charge, heat exchanger fouling	~ −15 to −17[a]	[43,132]
	Indoor unit fouling fault, outdoor unit fouling fault, non-condensable gas, refrigerant overcharge, Refrigerant undercharge, multiple simultaneous faults	<-3 to −47.6	[86]
	Indoor unit fouling fault, outdoor unit fouling fault, refrigerant overcharge, refrigerant undercharge, electronic expansion valve stuck	−12.67 to −22.29	[129]
Residential air-conditioner	Multiple simultaneous faults	3 to −38	[53]
Heat pump	Improper refrigerant charge	−4.8 to −16.1[b]	[81]
	Heat pump sizing, duct leakage, indoor coil airflow, refrigerant overcharge, refrigerant undercharge, excessive refrigerant subcooling, non-condensable gas, electronic expansion valve sizing, multiple simultaneous faults	<-3 to > -30	[80]
	Multiple simultaneous faults	5 to −34	[79]

[a] This range is for the non-condensable fault.
[b] The baseline COP ranges from 2.35 to 3.15 at different temperatures.

equipment or system can be very different across the literature. There are three major reasons, such as 1) the different physical configurations of the equipment and systems (e.g., various sizes), 2) different control sequences and approaches in operation conditions (e.g., climate zones, operational schedules, and fault duration), and 3) the different fault intensity levels examined. Table 5 lists the literature reporting the energy consumption impacts on various types of HVAC equipment or systems. However, we do not list the quantified energy consumption caused by specific faults in each type of equipment due to a wide range of faults investigated.

At the same time, it is worth noticing that when calculating the annual energy consumption, some factors, such as fault occurrence frequency and fault persistence, need to be considered to better evaluate fault energy impact in real practice. For example, Gunay et al. used the average annual energy use intensity (EUI) as a metric to evaluate long-term (i.e., a 50-year simulation period) energy consumption impact caused by five types of faults [34]. They also included three factors: the fault recurrence period, fault repair period, and discomfort threshold for simulated complaints. The results indicate an increased EUI ranging from 16% to 62% for the simulated faults.

The energy consumption from one piece of HVAC&R equipment can be extrapolated into a large scale of energy consumption impact, such as at the national level. Roth et al. carried out a large-scale investigation on the energy consumption impacts caused by HVAC system faults [119,120]. In the study, the annual national energy impacts of 13 types of faults in HVAC equipment and systems were investigated. For each type of fault, the annual energy consumption was calculated by Eq. (5).

$$AEC_{Fault} = AEC_{RE} \cdot Frequ_{Fault} \cdot \ Degradation_{Fault} \tag{5}$$

where, AEC_{Fault} is the national energy consumption potentially impacted by these faults. $Frequ_{Fault}$ is the fault frequency in the relevant equipment and system type. The fault frequency is measured by how often the fault occurs and consequently leads to an increase in energy consumption. $Degradation_{Fault}$ is the average percent increase in energy consumption due to the fault.

Additionally, Qian et al. estimated the national energy consumption penalty in the U.S. due to five typical faults in HVAC systems [97].

5.2.2.2. Peak demand. Another type of fault impact on energy usage is the impact on peak demand. Due to the increasing penetration of HVAC systems into the smart grid, fault impacts on the grid and power demand have attracted attention. A few studies have investigated fault impacts on peak demand.

Motomura et al. evaluated the percent change in the annual peak demand caused by 22 faults in chiller plants [37]. The percentage change of the annual peak demand can be calculated using Eq. (6):

$$RC_{PP,Fn} = \left\{ \left(PP_{year,Fn} - PP_{year,F0}\right) / PP_{year,F0} \right\} \times 100 \tag{6}$$

where Fn is a fault label, $RC_{PP,Fn}$ is the percent change in annual peak demand due to the fault, and $PP_{year,Fn}$ is the annual peak demand of Fn.

The one-year operation simulation results indicated that the setpoint of chilled water flow fault, the sensor of chilled water flow fault, and performance of chiller faults were identified as the top three faults having the largest annual peak demand impacts. The fault impact on the annual peak demand due to these three faults can increase by 32.37%, 31.73%, and 8.82%, respectively.

Lee et al. evaluated the peak demand penalty caused by air-side system faults in a VAV HVAC system in a 40-storey office building model [35]. They found that five types of faults may affect peak demand ranging from −11.7% to 1.51% considering the fault occurring on all floors in the building.

5.2.3. Thermal comfort

The analysis of fault impacts on thermal comfort includes two primary metrics. The first metric uses certain indices (e.g., the predicted percentage of dissatisfied (PPD) index) to quantify the impact. The second metric calculates the duration or percentage of unmet time of thermal comfort to assess the magnitude of the fault impact on thermal comfort. From the literature reviewed, the evaluation of the comfort impact is often carried out using simulation software tools.

5.2.3.1. Thermal comfort index. Some studies have used the PPD index [134] to quantitatively predict the percentage of thermally dissatisfied occupants who feel too cool or too warm as a result of degrading zone conditions due to faults.

Table 5
Literature reporting fault energy consumption impacts.

HVAC equipment/system type	Publication
HVAC systems (Combined various equipment that may include AHU, VAV box, RTU, chiller plant, and boiler plant)	[45,65,94,95,100,108,109,112,114,133]
AHU	[45,61,93,101]
VAV box	[35,45,93,102,111]
Chiller/chiller plant	[24,56,88,93,105]
Boiler/boiler plant	[24,93,101,105]
RTU	[45,70,108,133]
FCU	[38]
Heat pump	[28,80,88,90,105]
Refrigerant systems (including VRF systems, vapor compression systems)	[48,86,105,129]

Lu et al. proposed using the PPD index to assess the cumulative thermal comfort impacts under faulty operations in the HVAC system [27]. From the research, it was found that the PPD does not significantly increase under 11 sensor bias faults in the chiller plant, AHU, and zones during cooling seasons. Other fault categories (i.e., damper- and valve-related faults, control-related faults, HVAC equipment-related faults, and schedule setting-related faults) can cause substantial impacts on the PPD index.

Li et al. used the PPD index to rank building faults based on their impacts on occupant thermal comfort [99]. The cumulative thermal comfort impacts were evaluated and ranked using the monthly PPD index in June and December, respectively. The study showed that the top impactful faults differed among the four climate zones. Furthermore, Li et al. used the PPD index to analyze RTU fault impacts on thermal comfort [98]. In the study, they simulated faults on RTUs in secondary schools in four cities representing four climate zones in the U.S. and calculated the monthly averaged PPD index under faulty operation of RTUs. The results showed that the effectiveness of water loops and air loops can significantly affect thermal comfort. For example, faults in chiller-fouling and boiler-fouling have significant impacts on thermal comfort for buildings in Atlanta and Miami, whereas for buildings in San Francisco, the chiller fouling fault and the fan motor worn fault have more severe impacts.

Similarly, Shi et al. evaluated the PPD impact caused by the VAV reheat valve stuck fault [102]. Gunay et al. analyzed the annual PPD impact in an HVAC system using a 50-year simulation period to evaluate the value proposition of the FDD tool [34]. They found that faults can cause an 11%–38% increase in annual PPD if the faults are not addressed. Zhong et al. ranked faults based on the PPD impacts in the VAV HVAC system [94]. In the study, the authors evaluated the average yearly PPD deviation percentages caused by 14 faults in the HVAC system.

It is noted that none of the studies considered the fault occurrence frequency and fault occurrence duration when evaluating fault impacts. In reality, some faults, which cause significant impacts on the PPD index, may be quickly addressed after occupants' complaints are received by the facility team. As a result, those faults may not persist long enough to cause long-term impacts in real practice.

5.2.3.2. Duration or percentage of setpoint unmet. Another approach to quantify the zone thermal comfort impact is to analyze how the zone temperature setpoint is unmet. This can be achieved by comparing the actual zone temperature under faulty operation with the zone temperature setpoint. Two metrics are often adopted to quantify the unmet setpoint. The first metric is to evaluate the magnitude of the deviation from the setpoint when it is unmet. The second metric is to evaluate the duration of the unmet setpoint, e.g., how many hours or what percentage of hours the setpoint is not met due to the fault.

Ji et al. found that the indoor air temperature sensor bias fault (at a negative 10% error level) can result in a degraded indoor temperature increase by 11.11% (in Celsius) [88]. Zhang et al. simulated the integrated thermostat/humidistat offset fault and the heating coil fouling fault in HVAC systems and quantified the thermal comfort impact based on the annual number of hours the heating/cooling setpoint was not met [110]. The one-year simulation results showed that the heating/cooling setpoint was not met for a range of 5–700 h for the integrated thermostat/humidistat offset fault and 50–360 h for the heating coil fouling fault, respectively. Chen et al. ranked the fault impacts in terms of annual zone setpoint unmet in FCUs [38]. The study showed that the heating coil valve stuck fault may cause significant zone thermal comfort impacts. For example, when the fault is at a 100% intensity level, the annual zone temperature setpoint unmet time reaches 63% of total operation time. Yoon et al. evaluated the setpoint unmet hours in VAV HVAC systems caused by a single temperature sensor fault or simultaneous temperature sensor faults [93]. Rosato et al. studied the reduced annual thermal comfort time due to six types of faults in the VAV HVAC system [61].

5.2.4. Indoor air quality

Faults in some components (e.g., outdoor air dampers or airflow sensors of AHUs) can affect ventilation performance, subsequently causing impacts on indoor air quality (IAQ). Some research has been carried out to evaluate how HVAC system faults may affect IAQ in buildings. The outdoor air ratio and CO_2 concentration were used to evaluate fault impacts.

5.2.4.1. Outdoor air ratio. The ventilation components in an HVAC system should be properly operated to provide the desired fresh air to zones. However, some faults occurring in the ventilation assembly can dramatically reduce the intake of outdoor air. Lu et al. studied the outdoor air ratio (OAR) impact caused by faults in Modelica-based HVAC system simulations [27]. The authors proposed two metrics, namely mean OAR (OAR_{ave}) and OAR met ratio (Met_{OAR}), to evaluate how a fault may affect the ventilation performance. OAR_{ave} is the mean OAR value during the defined operation time period. The larger the OAR_{ave} value, the better the ventilation performance. Met_{OAR} is the ratio of the operation hours when the OAR is larger than 0.9 during the total operation hours. The results indicated that the AHU outdoor air damper stuck fault can cause significant impacts on the OAR in terms of the two metrics developed. For example, when the outdoor air damper is stuck at a 5% position, OAR_{ave} is −36.1% in the cooling season and −43.6% in the shoulder season, indicating a substantial lack of OAR during operation.

5.2.4.2. CO_2 rate. CO_2 concentration is one of the important indicators of ventilation performance in an HVAC system and should be maintained to ensure IAQ. Studies show that higher indoor CO_2 concentration may significantly affect occupants' health and working performance [135]. Several faults in HVAC systems can affect the ventilation operation and hence increase the indoor CO_2 concentration. Ginestet et al. used the CO_2 rate to quantify the IAQ impacts of three AHU faults: incorrect fresh airflow, decreased supply airflow, and leak flow [113]. They found that both the incorrect fresh air fault and decreased supply airflow fault had a significant impact on the CO_2 rate, while the leak flow fault had minor impacts on the CO_2 rate. Marigo et al. analyzed the CO_2 concentration inside the building to evaluate fault impacts on indoor air quality. In the study, they calculated the annual percentage of hours in terms of various CO_2 concentration levels due to faults in CAV systems [112].

5.2.5. Economic cost

Faults can affect economic costs in HVAC&R systems in two primary aspects:1) operational cost, and 2) maintenance and repair cost.

5.2.5.1. Operational cost. Fault impacts on operational cost stem from two aspects:1) energy cost, and 2) equipment life-cycle operational cost due to faults.

5.2.5.1.1. Energy cost. The energy consumption changes caused by faults can be calculated as illustrated in Section 6.2.2, and then the energy cost can be calculated by multiplying the energy consumption by the utility cost for each type of energy source, as given in Eq. (7).

$$Energy_{cost} = EC_{change} \cdot Utility_{rate} \tag{7}$$

Deshmukh et al. estimated the monthly increased energy consumption cost when simultaneous heating and cooling faults occur in AHUs [117]. The energy waste in cooling provided by chillers and heating provided by gas boilers was calculated. Then, the monetary loss associated with the energy loss was calculated using the local electricity rate and gas price. They found that there were around $22, 500 in extra energy costs per month due to the simultaneous heating and cooling fault in AHUs in a large hospital.

5.2.5.1.2. Equipment life-cycle cost. Faults can reduce the equipment lifespan or increase the life-cycle costs because of degraded equipment performance. In addition, for some faults (e.g., schedule setting faults), the HVAC&R equipment and systems need to operate for a longer time, resulting in increased life-cycle costs.

Li et al. developed an overall economic performance degradation index (EPDI), which can be used to quantify the performance degradation caused by faults in direct expansion cooling equipment based on economic factors [44]. In the study, three factors, namely, COP, cooling capacity, and sensible heat ratio (SHR) degradations, are used to calculate the EPDI as given in Eq. (8).

$$EPDI = \frac{1}{1 - r_{\Delta SHR}} \left(\frac{1}{1 - r_{\Delta COP}} \frac{\underline{C}_{utility}}{\underline{C}_{utility} + \underline{C}_{equip}} + \frac{1}{1 - r_{\Delta cap}} \frac{r_{equip}\underline{C}_{equip}}{\underline{C}_{utility} + \underline{C}_{equip}} \right) - 1 \tag{8}$$

where $r_{\Delta SHR}$ is the SHR degradation ratio, $\underline{C}_{utility}$ is the average utility price ($/kWh), $\underline{C}_{equip}$ is the average equipment price ($/kWh), $r_{\Delta COP}$ is the COP ratio, r_{equip} is the ratio of average equipment price for faulty operation to the normal value, $r_{\Delta cap}$ is the capacity ratio.

A severe fault can increase the value of EPDI. For example, the analysis results show that the combination of the compressor valve leakage fault, the condenser fouling fault, and the evaporator fouling fault can lead to an EPDI of 0.5, indicating that the operating cost has increased by 50%.

In addition to the economic cost impact at the equipment or system level, several studies investigated the economic costs at a larger scale, i.e., at the national level. Kim et al. studied the national financial impacts of common faults in small commercial buildings [36]. The calculation of the annual economic impact of faults (AFI_{fault}) considered both the utility cost increase and equipment life-cycle cost increase due to faulty operation as given in Eq. (9).

$$AFI_{fault} = AFI_{utility,fault} + AFI_{LCC,fault} \tag{9}$$

where, $AFI_{utility,fault}$ is the increased utility cost, and $AFI_{LCC,fault}$ is the increased equipment life-cycle cost.

The annual financial impact on the utility cost ($AFI_{utility,fault}$) can be estimated by converting the excessive energy usage (including energy impacts of electricity, natural gas, fuel oil, and the associated nationwide average prices) due to a fault, as given in Eq. (10).

$$AFI_{utility,fault} = \sum_{j}^{energy} \left(\sum_{i}^{fuel} \alpha_j \beta_i FC_i AEI_{fault} \right) \tag{10}$$

where α_j is the fraction of different energy usages in category j, j is an index representing one of the uses—heating, cooling, ventilation, lighting, or refrigeration—that corresponds to each fault's equipment type. β_i is the different fuel fractions in category i, i is an index representing each energy-usage type (e.g., electricity, and natural gas). FC is the unit cost of each fuel. AEI is the annual energy consumption change due to the fault.

The annual financial impact of faults due to the increased life-cycle cost can be calculated by Eq. (11).

$$AFI_{LCC,fault} = AFI_{base} \left\{ \frac{1 + r_{load}}{(1 - r_{cap})(1 - r_{SHR})} - 1 \right\} = \left(\sum_{i}^{equip} C_i \cdot AEC_i \cdot COP_i \right) \left\{ \frac{1 + r_{load}}{(1 - r_{cap})(1 - r_{SHR})} - 1 \right\} \tag{11}$$

where C_i ($/kWh) is ith equipment's average hourly cost per unit of cooling capacity determined by dividing the total equipment cost per kW of capacity (including costs associated with unit purchase and installation) across the unit life span. r_{load} is the load ratio, r_{cap} is the capacity ratio, r_{SHR} is the sensible heat degradation ratio. AEC is the annual energy consumption.

5.2.5.2. Maintenance and repair cost. The equipment repair cost refers to the financial expense incurred to fix a fault or failure (e.g., labor costs for replacing failed components and the component costs) in a system. A few studies have investigated the repair costs due to HVAC&R system faults.

Based on the relative costs to repair the faults, Comstock et al. ranked 21 faults found in water-cooled screw chillers using 228 service records, as well as 15 faults found in air-cooled screw chillers using 111 service records [123]. It is found that the refrigerant leakage fault in water-cooled screw chillers and the control box/starter fault in air-cooled screw chillers have significantly higher frequency of occurrence and associated repair costs, respectively. Breuker et al. evaluated the total repair cost of various RTU faults using service records from 1989 to 1995 [21]. In the study, they ranked the compressor-related failure based on the overall repair costs. Carlo et al. investigated preventive maintenance costs due to faults in AHU filters [41]. The authors concluded that the preventive maintenance cost reaches the lowest point when the interval between maintenance activities is approximately 4500 h.

5.2.6. Maintenance activity

Faults occurring in HVAC&R systems may significantly affect the system maintenance activities such as maintenance schedule, duration, and planning. Therefore, studying how to enhance the HVAC&R system maintenance decision-making process when various faults are present, and how to implement predictive maintenance when fault symptoms are observed, is important. However, there is very little research investigating how faults may affect maintenance activities.

Khan et al. proposed using a risk analysis method to evaluate maintenance inspection scheduling and planning for HVAC systems [40]. In the study, the authors proposed a risk-based maintenance (RBM) approach to reduce the overall risk of downtime in HVAC systems. They also quantified the risk using risk factors to show the fault impacts on system operation performance as well as the potential maintenance duration.

Additionally, severe faults in the HVAC&R system can cause system failure, i.e., the system cannot operate at all. In such a condition, downtime needs to be considered. Although there is no literature investigating the financial cost due to HVAC&R system fault-caused downtime after a thorough investigation, some studies investigated the downtime caused by faults. Thompson et al. used the mean downtime (MDT) to quantify the average downtime caused by five failures in AHUs and two failures in condensers [125]. Additionally, they also illustrated the mean time to repair (MTTR) for the failures. The results provided support for equipment predictive and preventive maintenance. For example, it is reported that the MDT and MTTR for failure in propeller type fans with coils in condensers can reach 4.9 h and 8.18 h, respectively.

5.2.7. Environment

Because faults can cause increased energy consumption in HVAC&R systems, their impacts on the environment can be evaluated using environment-related measures such as carbon emissions. However, very few studies have investigated this topic. Pelella et al. developed a total equivalent warming impact (TEWI) index to quantify environmental impacts due to three faults (i.e., the refrigerant leakage fault, condenser fouling fault, and evaporator fouling fault) in electric heat pump systems [118]. The TEWI can be calculated by Eq. (12).

$$TEWI = m_{leak} \cdot GWP + W_{el,tot} \cdot f_{ee}\left(kgCO_{2,equiv}\right) \tag{12}$$

where m_{leak} is the refrigerant charge due to the leakage fault, $W_{el,tot}$ is the total electric energy consumption, f_{ee} is the conversion factor for electricity production.

The authors used TRNSYS to simulate environmental impacts for the 12-year lifetime of the equipment, considering ordinary maintenance actions in three typical climate zones. It was found that a lower maintenance interval of the equipment can significantly increase CO_2 emissions when a fault occurs.

6. Challenges and future directions

In this section, we proceed to delineate challenges and research gaps within existing research efforts, while also outlining avenues for future research.

6.1. Intricacies of analyses

The analysis of HVAC&R system fault behaviors and impacts is challenging in six key aspects.

(1) Numerous factors affect fault behaviors and impacts. HVAC&R fault behaviors are affected by many factors, such as fault severity levels, system configuration, control sequences, and operation conditions. As a result, the same type of fault may generate completely different behaviors and consequent impacts under different conditions. For example, in an AHU, a cooling coil valve stuck at a 50% position may cause supply air temperature to be too low in a shoulder season, when there is no need for mechanical cooling. However, this fault can cause the supply air temperature to be too high when the AHU operates in a hot summer, when the zones require significant cooling [136,137]. Hence, fault impact analysis becomes more intricate.
(2) A diversity of HVAC&R equipment and systems exist. Fault impact analysis can cover a wide range of scopes in terms of spatial scope, such as the component-level or equipment-level, system-level, and higher levels (e.g., climate zones or the national level), and the temporal scope, such as transient impacts, steady impacts, and cumulative (e.g., monthly and annual) impacts. Moreover, with the increasing complexity of the HVAC&R system, accurately identifying fault behaviors and impacts becomes

very challenging. This is especially true for system-level analysis, where various types of equipment are highly coupled, and system operation is affected by many factors.

(3) Single faults and simultaneous faults. The operational behaviors and impacts of a single fault vs. simultaneous faults may be completely different. Some simultaneous faults may cause more severe impacts on the system, but others may not, because fault impacts may be compensated. For example, a single improper evaporator airflow (at 60 % of fault free level) fault can cause the discharge air temperature to increase, but the simultaneous evaporator airflow (at 60% of the fault free level) fault and a refrigerant undercharge fault (at 70% of the fault-free level) can cause the discharge air temperature to decrease in a heat pump [75]. This challenge enhances the complexity of accurately evaluating fault behaviors and impacts.

(4) Increasing fault types. In HVAC&R systems, fault types keep growing due to a rapidly increasing deployment of new technologies (e.g., new types of sensors and actuators). It requires more assessment of impacts caused by faults in such technologies. For instance, the integration of occupancy sensors can significantly enhance HVAC&R system operation in the context of occupant-centric control. However, if such sensors malfunction, the entire control system will be affected. At the same time, faults in some types of HVAC&R systems, such as cool thermal storage systems, have been seldom investigated.

(5) Comparison of evaluation results. Quantitatively comparing the side-by-side analysis on outcomes across various studies is difficult, even though the reported fault type and associated components/equipment/system types are the same or similar. For example, for the supply air temperature sensor negative bias fault in AHU, Lee et al. reported a 0.29% energy consumption increase in a cooling season at a negative 4 °C bias fault [35]. However, Gopalan et al. reported a 5.71% energy consumption increase in a cooling season at a negative 2 °C bias fault (the fault severity is minor compared to Lee's study) [104]. This is due to multiple factors (e.g., fault severity levels, system configurations and sizes, as well as operational conditions) that can influence the magnitude of fault impacts. Additionally, the metrics used may not be exactly the same. This challenge can cause difficulties in using the fault impact analysis results in practical work, e.g., effectively maintaining HVAC&R systems in building portfolios.

(6) Different contributing causes. In HVAC&R systems, faults happening in various stages have completely different characteristics but similar impacts on the system. For example, an improper installation of a discharge air temperature sensor in a VAV box may produce fault impacts similar to a temperature sensor bias fault. As a result, it is crucial to thoroughly examine and understand contributing fault causes and associated impacts.

6.2. Needs for real data and high-quality fault models

Three primary data sources are identified to evaluate fault behaviors and impacts in previous studies. As illustrated, most studies use simulation data or laboratory data to perform fault impact analysis. However, there is a lack of field data or survey data to support a more comprehensive understanding of fault impacts. Using simulation data and laboratory data is cost-effective, but there are some shortcomings, such as an incomplete understanding of fault behaviors and consequent impacts. Additionally, some characteristics of faults (e.g., actual fault occurrence, fault persistence, fault intensity levels, and equipment maintenance status in real practice) are often not considered during the impact evaluation process. The omission may affect the accurate evaluation of fault impacts, especially for cumulative impacts such as monthly and annual energy consumption.

6.3. Practical applications

How to effectively translate the results from the evaluation of fault behaviors and impacts into real applications remains a challenge. Although we identified four major objectives of evaluating fault behaviors and impacts in previous research efforts, we found that there are a few gaps, which may hinder the smooth translation of research results into two major practical applications, such as: 1) the development of FDD approaches, and 2) the development of data-driven maintenance strategies.

6.3.1. Challenges in the development of FDD approaches

A thorough analysis of fault behaviors can significantly improve the development of different FDD approaches, particularly those based on machine learning (ML). However, there are two key challenges in this regard:

(1) Encoding fault behaviors into the development of ML-based FDD approaches presents a significant challenge. Developing ML-based FDD approaches typically involves training models to perform tasks such as classification, feature extraction, and fault behavior prediction. As such, accurate analysis of fault behaviors serves as a critical foundation. However, a substantial gap remains in clearly linking the insights from fault behavior analysis to the development of machine learning-based FDD methods. For example, certain ML techniques, such as those based on Bayesian Networks (BN), require both qualitative results (i.e., relations between faults and associated symptoms) and quantitative results (i.e., likelihood of symptom occurrence) to construct network structures and parameter models. Translating fault behaviors across diverse operating conditions into such model components demands significant efforts. In addition, many ML-based approaches rely on fault-inclusive datasets, which are often generated by imposing faults on systems under the assumption that all fault behaviors are present (i.e., fault symptoms are observable). In reality, fault behaviors can vary significantly depending on multiple factors, such as fault severities, operation conditions, and system sizes. Consequently, even when applying the same ML method to the same type of fault, the resulting models may differ due to these behavioral variations. Therefore, establishing a clear association between fault behavior variability and the performance or structure of ML-trained models remains a critical and unresolved issue.

(2) Enhancing the interpretability of ML-based FDD methods using fault behavior insights remains a significant challenge. For instance, when a neural network-based FDD method demonstrates a high detection rate, it is often unclear whether this is due to the method's effectiveness or simply because the fault symptoms are particularly strong and easy to detect. This ambiguity makes it complicated to interpret and compare the performance of different machine learning-based FDD methods, and consequently, to improve them. Furthermore, field engineers and operators often struggle to relate the FDD outcomes to the fault behaviors they observe in practice. This disconnect may ultimately hinder both the refinement and real-world deployment of ML-based FDD solutions.

6.3.2. Challenges in the development of data-driven maintenance strategies

The significance of fault impacts is a key factor in guiding system maintenance decision-making. Computerized maintenance management systems (CMMS) use fault impact information to prioritize and schedule maintenance tasks effectively [138,139]. However, current approaches to evaluating fault impacts exhibit several limitations that reduce their reliability and practical value.

(1) Key factors, such as fault occurrence frequency and fault occurrence duration, are often overlooked when evaluating fault impacts. This may lead to inaccurate assessments in real-world applications. For example, several studies evaluated fault impacts in one year while assuming that faults persist throughout the entire year—an assumption that can significantly overstate the actual impact. As a result, incorporating these overlooked factors into fault impact models remains a critical challenge, particularly for improving the accuracy and usefulness of models implemented in CMMSs.
(2) Existing fault impact evaluations often suffer from low scalability, as they are typically based on limited systems and narrowly defined operational conditions. In practice, however, the significance of fault impacts can vary widely depending on numerous contextual factors. For example, a fouled heating coil fault in an AHU located in a cold climate zone may result in higher cumulative energy waste than the same fault in an AHU located in a hot climate zone, due to extended heating operation periods. Therefore, a major challenge lies in developing evaluation approaches that account for diverse operational conditions to improve the scalability and generalizability of fault impact results.

6.4. Future directions

To address the above challenges, we outline six directions for the evaluation of fault behaviors and impacts for HVAC&R systems in the future.

(1) It is worth developing guidelines or frameworks to streamline fault impact evaluation processes. In this paper, an initial analysis framework is proposed in Section 5.1. However, we believe the framework can be enhanced in the future with more efforts focused on identifying fault characteristics at certain severity levels in various systems/equipment. We hope this work can address challenges #1, #2, and #5 in Section 6.1.
(2) It is worth investing in studying more simultaneous faults in HVAC&R systems. Specifically, some simultaneous faults (e.g., cooling water coil valve stuck too high and outdoor damper stuck too high in an AHU) can mitigate fault impact on thermal comfort but cause hidden energy waste. How to evaluate such simultaneous faults is worth studying. We hope this work can address challenge #3 in Section 6.1.
(3) It is necessary to evaluate the impacts of faults happening in new technologies and in a wider range of HVAC&R systems to ensure the operational performance of such HVAC&R systems in the future. For example, impacts caused by the temperature sensor fault or the coil fouling fault happening in thermal energy storage systems are worth studying. To identify the faults that are worth studying, more real operational data and interview surveys should be collected and analyzed. We hope this work can address challenge #4 in Section 6.1.
(4) It is worth providing a detailed classification of fault characteristics before analyzing fault impacts and supporting practical applications (such as the development of FDD). In this study, we propose a fault characteristic category based on the fault occurrence phases as given in Section 4. In the future, a full fault list, which includes various systems or equipment, should be created under each phase. We hope this work can address challenge #6 in Section 6.1.
(5) There is an urgent need for more field data or survey data, which can accurately reflect fault behaviors and impacts from real practices. In addition, it is necessary to develop high-quality fault models so that more complex fault impact analysis based on the simulation of system-level HVAC&R operations, or during various control sequences, can be effectively performed. We hope this work can address the challenge uncovered in Section 6.2.
(6) It is worth developing innovative metrics or analysis methods that can enhance the translation of fault behavior and impact results into practical applications, such as the development of FDD approaches and informative maintenance strategies. For example, in the development of FDD approaches, quantifying fault behaviors under diverse operations can support the development and validation of ML-based FDD approaches. Furthermore, additional research is needed to identify and incorporate key factors—such as fault occurrence frequency and duration—that influence the severity and significance of fault impacts. We hope this work provides a meaningful step toward resolving the challenges identified in Section 6.3.

7. Conclusion

The evaluation of fault behaviors and impacts is pivotal in many research areas in HVAC&R systems because it provides insights into a better understanding of fault characteristics and consequently supports many practical applications. For instance, performing a thorough evaluation of fault behaviors can significantly strengthen the development and validation of various FDD approaches, resilient HVAC&R control strategies, as well as high-performance equipment. Furthermore, conducting a sufficient assessment of fault impacts facilitates improved maintenance strategies, including the design of CMMSs that require such information to assist in efficient and data-driven maintenance decisions. However, there is no systematic review of previous studies in the evaluation of fault behaviors and impacts in HVAC&R systems, causing a significant knowledge gap in the research direction. To bridge this gap, this paper comprehensively reviews the existing publications reporting the evaluation of fault behaviors and impacts in HVAC&R systems. The main findings of the review are summarized as follows:

- Four research objectives for the evaluation of fault behaviors and impacts from previous research efforts were identified. This helps to better understand the advantages and disadvantages of methods used during the analysis and evaluation.
- Three data sources, such as: 1) experiment and field data, 2) software simulation data, and 3) interview and survey data, used for performing evaluations and analyses, were outlined from previous research efforts. We found that there is a lack of interview and survey data, which can offer engineering insights on fault behaviors and impacts in real practices. This may not only hinder the accurate evaluation of fault impacts but also prevent the translation of the research results into practical applications.
- 138 fault types in 10 types of HVAC&R systems, which were previously investigated to evaluate fault behaviors and impacts, were summarized. However, due to the differences (e.g., system physical configurations, sizes, operational conditions, and fault severity levels), it is difficult to compare the research results for the same type of fault in the same type of system. Additionally, there is a lack of research efforts on the evaluation of fault behaviors and impacts on emerging HVAC&R technologies and solutions such as thermal energy storage systems.
- Seven measures, including 1) equipment and system performance, 2) energy, 3) thermal comfort, 4) indoor air quality, 5) economic cost, 6) maintenance activity, and 7) environment, as well as associated metrics from previous publications, were concluded. We did not quantitatively compare fault impacts obtained from the same measure or metric side by side. Instead, we categorized and compared measures and metrics to uncover the limitations of each method.
- Three major challenges in previous research efforts on the evaluation of fault behaviors and impacts were revealed. These challenges include 1) the intricacies of analyses, 2) the requirement of real data and high-quality fault models, and 3) practical applications.
- Following the identification of challenges, we outlined six research directions, which will pave the way to enhance the research efforts and engineering applications of fault behaviors and impacts in the future.

Overall, this review serves as a guide for future research efforts, highlighting current challenges and directions that will improve research and accelerate the practical applications of the evaluation of fault behaviors and impacts in the HVAC&R domain.

CRediT authorship contribution statement

Yimin Chen: Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Yifeng Hu:** Writing – review & editing, Methodology, Formal analysis. **Guanjing Lin:** Writing – review & editing, Methodology, Formal analysis. **Yun Zhang:** Writing – review & editing, Formal analysis, Data curation. **Shi Ye:** Writing – review & editing, Validation, Data curation. **Bo Shen:** Writing – review & editing, Formal analysis.

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.

Appendix I. Review methodology

We introduce our methodology for conducting the literature review. Specifically, in Appendix 1.1, we illustrate the framework formulated to guide our literature review endeavors. In Appendix 1.2, we detail the approach employed to search for relevant publications.

Upon establishing the literature review objectives and formulating the research questions, we performed a rigorous literature search strategy using Google Scholar and major academic databases. In this study, publications from 1995 to 2024 were considered for two reasons: 1) this period aligns closely with the development of various HVAC system FDD techniques, and 2) this period effectively illustrates the research progress and highlights the challenges in this field.

In this review, we adopted four steps in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) statement [19]. Fig. 1 shows the literature search.

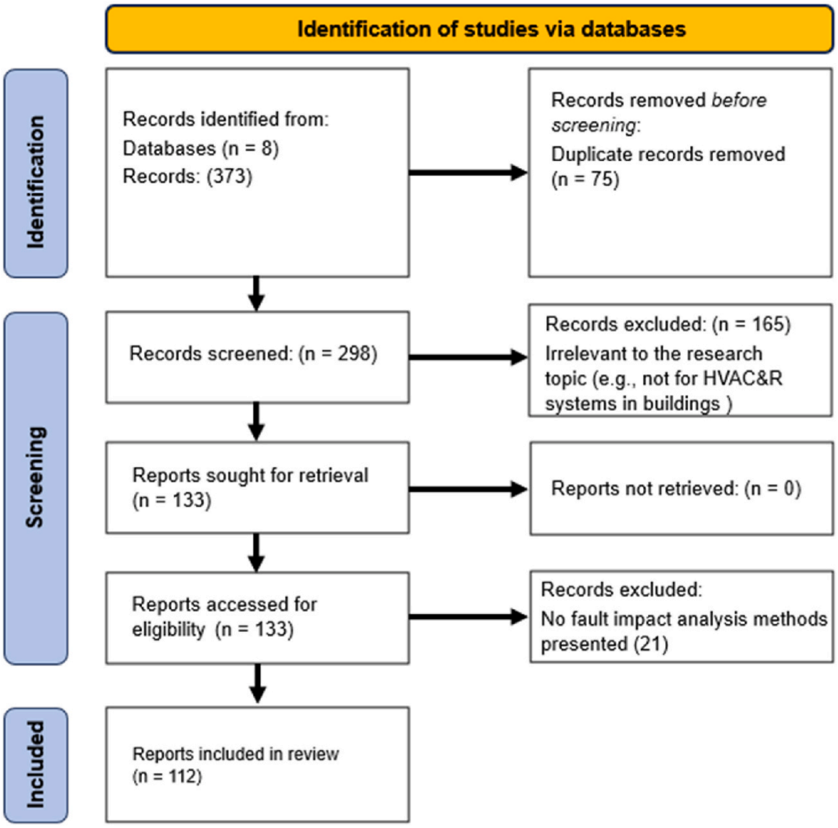

Fig. A1. Literature search strategy.

First, we identified nine databases, including Scopus, Web of Science, Elsevier, Emerald Insight, IEEE, ProQuest, EBSCO, Sage, and Taylor & Francis. These databases cover most publications relevant to the FDD research area. Additionally, we used Google Scholar to search for research reports that addressed fault impacts and facility maintenance. At the same time, we determined a set of keywords, such as "HVAC", "refrigeration system", "fault detection", "fault diagnosis", "fault diagnostics", "FDD", "fault behavior", "fault impact", "fault effect", "sensitivity", "fault model", "maintenance", "fault tolerant", and "prognostics", to retrieve relevant literature. A wildcard was used with several keywords to avoid missing records. Table 1 illustrates the search strategy based on the keywords used.

Table A1
Searching strategy.

Keyword	Boolean logic	Keyword	Boolean logic	Keyword
HVAC * OR refrigeration *	AND	fault OR fault detection OR fault diagnostic* OR fault diagnosis OR maintenance OR tolerant OR FDD	AND	behavior?r* OR fault impact* OR fault effect* OR prognostic* OR model* OR sensitivity*

In this step, we received 373 publication records and removed 75 duplicates.

Secondly, we screened 298 publications. We excluded 165 publications whose contents were irrelevant to the research topic (e.g., HVAC systems not used for buildings, or fault behaviors or impacts were not discussed). We retrieved 133 publications and confirmed all were available for review. Then, we filtered out 21 publications that did not present methods for fault behavior or impact evaluation analysis. This resulted in 112 publications included for detailed review.

Finally, for the 112 publications, we created a spreadsheet to systematically document the findings pertaining to the identified research questions. The publications include academic articles, conference papers, research reports, and dissertations. Table 2 shows the distribution of publications by type.

Table A2
Number of publications by type.

Publication type	Number	Percentage (%)

(continued on next page)

Table A2 (*continued*)

Publication type	Number	Percentage (%)
Journal article	77	68.8
Conference paper	22	19.6
Research report	10	8.9
Dissertation	3	2.7

Fig. 2 shows the chronological distribution of these publications. The annual publication numbers were generally consistent, except for the Years 2021, 2022, and 2024.

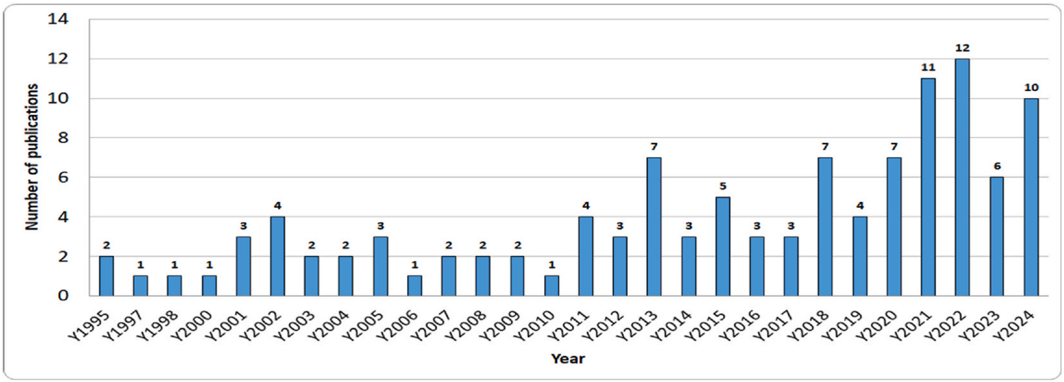

Fig. A2. Publication chronological distribution.

Appendix II. List of system/equipment and associated faults

System/equipment	Component	Fault type
Chiller/chiller plant	Refrigerant	Overcharge
		Undercharge
		Refrigerant leak
		Non-condensable
	Oil	Excess oil condition
	Evaporator tube	Fouling
	Condenser tube	Fouling
	Condenser motor	Failure
	Compressor gate valve	Failure
	Compressor bearings	Failure
	Compressor motor	Burnout
	Compressor transmission	Failure
	Compressor control system	Failure
	Liquid line	Restriction
	Expansive valve	Defective expansion valve
	Water flow sensor	Primary chilled water flow sensor offset
		Secondary chilled water flow sensor offset
	Outdoor relative humidity sensor	Outdoor relative humidity sensor offset
	Water temperature sensor	Secondary chilled water inlet temperature sensor offset
		Chilled water inlet temperature sensor offset
		Condenser water outlet temperature sensor offset
		Condenser water flow control lower limit
	Heat exchange	Efficiency lower
	Lube box	Fault
	Oil pump	Fault
	System	Low delta-T
		Oversize
Boiler/boiler plant	Boiler water tube	Fouling
	Boiler steam pressure sensor	Bias
	Boiler inlet temperature sensor	Bias
	Boiler outlet air temperature setpoint	Offset
	Isolation valve	Leakage
AHU	Outdoor air temperature sensor	Bias
	Supply air temperature sensor	Bias
	Supply air temperature sensor	Frozen

(*continued on next page*)

(*continued*)

System/equipment	Component	Fault type
	Return air temperature sensor	Bias
	Mixed air temperature sensor	Bias
	Supply air relative humidity sensor	Bias
	Return air relative humidity sensor	Bias
	Outdoor airflow sensor	Bias
	Supply airflow sensor	Bias
	Return airflow sensor	Bias
	Supply air static pressure sensor	Bias
	Supply air static pressure sensor	Frozen
	Outdoor air damper	Stuck
		Leakage
	Return air damper	Stuck
	Mixed air damper	Leakage
	Heating coil valve	Stuck
		Leakage
	Cooling coil valve	Stuck
		Leakage
	Fan	Failure
		Stuck
	Fan belt	Loose
	Fan filter	Blockage
	Heat recovery wheel	Failure
	Indoor air temperature (thermostat) sensor	Bias
	Duct	Leakage
	Discharge temperature setpoint	Incorrect
		Unstable
	Supply air temperature setpoint	Low
	Schedule	Wrong setting
	Control	Unstable
	System	Heating failure
		Cooling failure
		simultaneous cooling and heating
RTU	Supply air temperature sensor	Bias
	Compressor	Compressor performance loss
		Compressor wear
	Refrigerant	Overcharge
		Undercharge
		Non-condensable
	Condenser	Tube fouling
		Tube leakage
		Airflow reduction
	Condenser fan	Cycle
	Evaporator filter	Blockage
	Thermal expansion valve	Failure
	Liquid line	Liquid line restriction
FCU	Fan	Failure
		Blockage
	Heating coil	Airside fouling
		Water side fouling
	Cooling coil	Airside fouling
		Water side fouling
	Filter	Filter restriction
	Zone temperature sensor	Offset
	Outdoor air damper	Stuck
		Leakage
	Heating coil valve	Heating coil valve stuck
		Heating coil valve leakage
	Cooling coil valve	Cooling coil valve stuck
		Cooling coil valve leakage
	Control	Control unstable
		Heating control reversed
		Cooling control reversed
Air terminal (VAV box)	Control	Airflow setpoint setting
		Schedule setting
	Thermostat temperature sensor	Zone thermostat temperature sensor bias
	Reheat coil	Fouling
	Reheat electric heater	Stuck
Heat pump	Condenser	Condenser heat transfer fault
	Compressor	Compressor leakage

(*continued on next page*)

(*continued*)

System/equipment	Component	Fault type
	Evaporator	Fouling
	Liquid line	Restriction
	Refrigerant	Non-condensable
		Overcharge
		Undercharge
		Leakage
	Thermal expansion valve	Undersize
	Coil	Coil fouling
	Indoor unit	Improper airflow
	Outdoor unit	Improper airflow
	Thermostat temperature sensor	Bias
	Duct	Leakage
	System level	System cycling
		Installation fault
		Size
Heat exchanger	Heat exchanger	Fouling
	Airside coil	Fouling
Residential air conditioner	Refrigerant	Overcharge
		Undercharge
		Refrigerant leak
		Non-condensable
	Liquid line	Restriction
	Evaporator	Airflow improper
	System	Cycle
Refrigeration systems (including VRF systems, vapor compression systems)	Refrigerant	Overcharge
		Undercharge
		Leakage
	Compressor valve	Leakage
	Condenser	Fouling
	Evaporator	Fouling
	Vapor compression	Fouling
	Liquid line	Restriction
	Indoor unit	Fouling
	Outdoor unit	Fouling

Data availability

The authors do not have permission to share data.

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Nomenclature

List of abbreviations

HVAC&R: Heating ventilation, air conditioning and refrigeration
AHU: Air handling unit
VAV: Variable air volume
CAV: Constant air volume
VRF: Variable refrigerant flow
RTU: Rooftop unit
FCU: Fan coil unit
COP: Coefficient of performance
SCOP: System coefficient of performance
FXO: Fixed-orifice
SOP: Symptom occurrence probability
EUI: Energy use intensity
OA: Outdoor air
MA: Mixed air
FDD: Fault detection and diagnostics
KPI: Key performance index
BAS: Building automation system
SCADA: Supervisory Control and Data Acquisition
OAT: Outdoor air temperature
PPD: Predicted percentage of dissatisfied
IAQ: Indoor air quality
OAR: Outdoor air ratio
MetOAR: OAR met ratio
EPDI: Economic performance degradation index
SHR: Sensible heat ratio
AFI: Annual economical impact
TEWI: Total equivalent warming impact