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Sensor impact evaluation and verification for fault detection and diagnostics in building energy systems: A review

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ABSTRACT

Sensors are the key information source for fault detection and diagnostics (FDD) in buildings. However, sensors are often not properly designed, installed, calibrated, located, and maintained, which negatively impacts FDD performance. Several sensor-related FDD topics have been widely studied, covering a wide range of fault types and applications. However, it is difficult to get a clear picture of the technical development of sensor-related topics in FDD. A systematic review of sensor topics is needed to summarize the existing research in a logical way, draw conclusions on the current development, and predict the future development of sensors in building FDD. To address this gap, we conducted a comprehensive literature review of more than 100 FDD-sensor-related papers. In this article, we subdivide the FDD tasks into building-level, system-level, and component-level FDD, and review sensor-related topics in each category. Our major conclusions are: (a) current data-driven FDD research focuses more on FDD algorithms than sensors, (b) sensor "hardware" research topics are less studied than sensor "software" topics, (c) very few papers focus on sensor engineering as an integral aspect of FDD development, and (d) some important sensor topics, such as sensor cost-effectiveness and sensor schema/layout/location, are not well studied. Finally, we discuss the need for a systematic framework of FDD sensors and models to integrate sensor design/selection, sensor data analysis/mining, feature selection, physics-based or data-driven algorithm development, sensor fault detection, sensor calibration, and sensor maintenance. Finally, expert interviews are conducted to validate the above findings and conclusions.

1. Introduction

The building sector consumed 32% of primary energy in the U.S. in 2019—13% in the commercial buildings sector and 19% in the residential sector [1]. Equipment and system faults and control errors are pervasive in today's commercial buildings [2], and building faults waste 0.3 to 1.8 quadrillion BTU of primary energy each year in the United States [3]. This equates to 5% to 15% of energy used in the commercial buildings sector [4].

Fault detection and diagnostics (FDD) detects operational faults (fault detection) and identifies the fundamental causes (fault diagnostics). FDD can improve both thermal comfort and energy efficiency, and ultimately improve building performance.

In terms of modeling methodology, FDD models can be categorized into qualitative, quantitative, and process history-based (or history-data-driven, hereafter referred to as "data-driven") [2, 5]. FDD can be categorized into three levels: building, system, and component. For any FDD modeling method and at any level, FDD always depends on sensor measurements—sensors are the key information source for building FDD.

However, sensors are not perfectly designed, installed, calibrated, located, and maintained. Poor sensor installation, calibration, and maintenance cause sensor inaccuracy. And in building heating, ventilation, and air-conditioning systems (HVAC), sensor network architectures are not necessarily designed and optimized solely for FDD applications [6]. Sensor problems result in biased or erroneous information and obscure understanding of equipment/system control and operations, leading to inaccurate FDD, including increased false alarms and failed detection.

Several sensor-related FDD topics have been widely studied:

- *Sensor fault* detects bias, drift, precision degradation, and complete failure of sensors.
  Sensor fault can be divided into four types: bias, drift, precision degradation, and complete failure [7]. Dai and Gao [8] noted that detecting sensor/actuator faults via data-driven modeling may be

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Nomenclature

FDD:	fault detection and diagnostics
HVAC:	heating, ventilation, and air conditioning
PCA:	principal component analysis
RTU:	rooftop unit
VAV:	variable air volume
VIC:	virtual in-situ sensor calibration
VRF:	variable refrigerant flow

complicated, because sensor/actuator faults may influence model input/output in the same way as process faults; when factoring in input and sensor noise, it is even more challenging to detect sensor faults.

- *Feature selection from available sensors* applies machine learning or information science to extract, generate, and select features (inputs, or variables) from available sensor data for FDD models.
  In an FDD process, data are collected from the components of the HVAC system. The data may include sensed data from various sensors within the system and feedback data from various components of the system. Additional data from external sources can also be collected, such as weather data. Consequently, the dimensionality and volume of these data can be enormous [9]. Selecting an optimal sensor set is a crucial step in a data-driven FDD process. The benefits of selecting the minimal number of sensors providing critical information include correlation removal, computational complexity reduction, as well as optimizing the number of sensors to be installed.
- *Additional and built-in/existing sensors* relates to whether FDD solutions require additional sensors or can perform well using built-in/existing sensors.
  Using built-in sensor is most cost-effective, and how to maximize the information from existing sensors are important for researchers and building operators. Using additional sensor is key to extend the information source and further improve FDD performance. Beside the common sensors from BAS, many researchers are exploring installing new sensors for better FDD performance.
- *Sensor data analysis/mining* applies data-driven techniques to extract information from sensor data to improve FDD performance.
  Analysis and application of real-time operational sensor data from buildings is important for energy management. However, raw data inevitably contain a number of outliers and usually have a significant negative impact on performance of data-based models [10]. Many researchers apply data analysis to improve data quality. Principal component analysis, or PCA, is a widely applied technique in this field. PCA is a statistical procedure to reduce dimension in large data tables by transforming them to a smaller set of summary indices that still contains most of the information in the large set and can be more easily visualized and analyzed. PCA is a widely applied data analysis/mining technique to improve FDD performance.
- *Virtual sensors* provide feasible and economical alternatives to costly or impractical physical sensors to improve FDD models or reduce cost.
  Virtual sensors are logical sensors that provide economical alternatives to costly physical sensors, and a virtual sensing system uses information available from other physical sensors to estimate a quantity of interest [11].
- *Sensor calibration* relates to actively adjusting and tuning sensors and removing structural sensor errors and faults, which is part of sensor maintenance and a follow-up step for sensor fault detection.
- *Sensor layout/location* discusses the impact of sensor layout and location on sensor accuracy and efficiency. It is an important topic which can have a significant impact on sensor cost-effectiveness, effectiveness, and efficiency.

Many existing FDD studies cover the sensor topics mentioned above. Those sensor topics are discussed in the context of a wide range of fault types and applications, however, making it difficult to get a clear picture of technical development in the field of sensor-related FDD topics. A systematic review of sensor topics in FDD is needed to summarize the existing research in a logical way, identify research gaps, and predict the evolution of sensors in building FDD. The practical value of this paper is not only to inform the researchers from the building industry who would be exposed to cutting-edge sensor research and development, but also those from the sensor industry who could gain the understanding of potentials and challenges of sensor application in building FDD and how it will further impact building energy efficiency and robustness. It is worth mentioning that the listed sensor topics are limited to the research about direct sensor impact on FDD performance and accuracy. Where sensor-related FDD topics are covered in literature, some evaluation of performance is typically provided, in terms of FDD detection and diagnosis accuracy, or impact on energy cost, maintenance cost, or thermal comfort. In some cases, performance is quantified; in others, it is discussed qualitatively. Because quantified estimates of performance vary widely with respect to both metric and application, we do not attempt to report them here. The value in this review as it relates to performance impact is captured by qualitative summary of findings. It is expected that project-specific analysis is required to derive meaningful quantitative estimates of performance impact. As a result, their further impact on building energy efficiency and thermal comfort is not considered in this review paper.

To address the need for a comprehensive summary of sensor-related FDD topics, we conducted a comprehensive literature review of more than 100 sensor-related FDD papers which span the full range of sensor topics and the FDD domain. We categorize FDD research and applications as building-level, system-level, or component-level (or equipment-level) FDD, and review sensor-related topics in each category. Section 2 introduces the paper-searching methodology used for this review paper. Section 3 summarizes existing review papers addressing sensor topics. Section 4 reviews technical papers, and groups findings according to FDD level (building, system, or component). The sensor topics include sensor fault, feature selection from available sensors, additional and built-in/existing sensors, sensor data analysis/mining, virtual sensor, sensor calibration, and sensor layout/location. Section 5 introduces an expert interview on current sensor configuration practice in FDD. Section 6 presents conclusions, identifies research gaps, and predicts future development in this field.

2. Paper searching methodology

To exhaust the impactful literature, we used a searching methodology called “sub-keyword synonym searching” for this review paper which is introduced in [12]. This methodology exhausts relevant papers by performing multiple searches with synonym sub-keywords [12]. Taking FDD sensor-related topics as an example, some researchers use “FDD, sensor, in buildings” instead of “AFDD, sensor in HVAC” (AFDD: automated fault detection and diagnostics) to describe their research, but these combinations of terms essentially represent the same research field. Hence, it is necessary to develop a mechanism to systematically search similar keywords to ultimately identify all relevant papers [12]. In the sub-keyword synonym searching methodology, each search is defined by a set of sub-keywords for which there are multiple synonyms. The set of searching keywords is made up of the combination of every possible value of each sub-keyword [12].

In this paper, we use keywords that consist of three sub-keywords. The first sub-keyword narrows the search to papers focused on FDD: “AFDD,” “FDD,” “fault detection,” “fault detection and diagnostics,” and “automated fault detection and diagnostics.” The second sub-keyword defines the sensor topic: “sensor,” “sensor impact,” “sensor importance,” “sensor selection,” “sensor fault,” “virtual sensor,” “sensor design,” and “sensor calibration.” The third sub-keyword narrows the search to pa-

Table 1
Parameters of sub-keyword synonym searching for sensor-related FDD research.

Parameter	Values
Sub-keyword 1	AFDD, FDD, fault detection, fault detection and diagnostics, automated fault detection and diagnostics
Sub-keyword 2	Sensor, sensor impact, sensor importance, sensor selection, sensor fault, virtual sensor, sensor calibration, sensor design
Sub-keyword 3	In buildings, HVAC, energy system in buildings
Citation threshold	5
Number of papers per search	10
Year from	2010
Year to	2021

pers focused on building energy systems: "in buildings," "HVAC," and "energy systems in buildings." We used Google Scholar to deploy the methodology. As a result, the full list of search keywords in Google Scholar is the full combination set of each sub-keyword. Example keywords include "FDD, sensors, in buildings," "fault detection, sensor impact, HVAC." The total number of search keywords is $5 * 8 * 3 = 120$.

Table 1 summarizes the parameters of the sub-keyword synonym searching methodology used in this paper. The total number of papers searched is: 120 keywords * 10 papers/keywords = 1200 papers; after filtering out duplicates, 712 unique papers in the field of sensor-related topics in building FDD remained. The 712 papers are further reviewed, categorized, and organized by authors' domain knowledge according to the paper structure introduced in Section 1. During this process, many papers were removed from consideration due to irrelevancy or poor quality; ultimately, over 100 papers were selected for review. Our summaries of review papers (Section 3) and technical papers (Section 4) are based on that down-selected set.

3. Summary of review papers

In this section, review papers related to sensor topics in FDD are summarized. The topic of sensor measurement constraints caused by incompatible sensor network architectures is discussed in some review papers. In Najafi's dissertation [6], he summarized the current status of sensors in FDD applications by pointing out that measurement constraint is a challenging issue in building HVAC diagnostics. In building HVAC systems, sensor network architectures are not necessarily designed for diagnostic purposes. As a result, it is common to have one or more components monitored via only a single sensor (or a single set of sensors). Measurement constraint can significantly expand the complexity of building HVAC diagnostic problems. To improve the diagnostic result, people either need to reduce modeling/measurement error or include other measurements—additional sensors—in the diagnostic process. A reliable solution to this problem is to develop a framework to analyze the effect of new measurements on diagnostic strength, thereby leading to better design and optimization of sensor network architecture from a diagnostic perspective. The author developed an algorithm to quantify the impact of measurement constraints on diagnostic capability using model-based and non-model-based diagnostic algorithms. The algorithm can deal with modeling and measurement constraints more effectively. The developed algorithm and framework can trace the measurement constrains and optimize the architecture of sensor networks from a diagnostic perspective [6].

The topic of data science as applied to sensor data is reviewed by many papers. Molina-Solana et al. [13] reviewed how data science has been applied to address the most difficult problems faced by building energy management (including FDD). They summarized that data science can help verify operational status and detect faults within building infrastructures. By continuously monitoring a building, data science techniques can detect when a fault has occurred and how it affects other equipment via correlation analysis. Pattern recognition and regression techniques are extremely useful to implement countermeasures to increase building resilience and prevent costly incidents. Fugate et al. [14] discussed the topic of sensor data analytics in FDD and categorized the analytical approaches into three categories: (a) simple detection of exceptions; (b) signal processing, condition-based logic, and algorithmic estimation of imminent problems; and (c) model-based parameter estimation to determine inefficiencies. The authors also noted how wireless sensors are critical to enabling measurements that can provide diagnostic and prognostic functions using an energy management control system. Dai and Gao [8] explained that an FDD system is a data-processing system on the basis of information redundancy, in which sensor data and human understanding of the data are two fundamental elements. Human understanding may be an explicit input-output model representing the relationship among the system's variables. Therefore, FDD is executed through modeling, signal processing, and intelligence computation. Dai and Gao reviewed a variety of FDD techniques within the unified data-processing framework to give a full picture of FDD and achieve a new level of understanding. Zucker et al. [15] also reviewed sensor failure, selection of sensors, processing of sensor data, data analysis of operation data, and data sanitation in building energy system FDD. In addition, Yan et al. [16] presented a summary table to review feature selection (a subtopic of data science) from available sensor sets in chiller FDD. Yu et al. [17] reviewed typical faults in AHU sensors and controllers. They addressed how the range of confidence for error measurement can be analyzed by using accurate sensors or virtual calibration sensor techniques and virtual sensors. Signal processing can be analyzed and discussed in terms of data processing for analytical models. In this review, signal processing methods are included in data-driven approaches because the main FDD process is based on data processing by sensors.

Some papers review the topic of sensor layout, location, and availability for FDD. In the FDD tool review paper written by Bruton et al. [18], the authors addressed that the method of FDD applied to a system differs depending on the number and location of sensors. Bruton et al. [19] addressed how air handling unit (AHU) FDD tools should be applied effectively and comprehensively for different component and sensor layouts. Bruton et al. [20] also concluded that the primary objectives of the AHU FDD tool are to (a) have the flexibility to work with combinations of sensors and components found in typical AHUs to ensure cross-company compatibility, and (b) have the ability to use already available measurements (avoiding the need to install additional sensors) to limit associated installation costs.

Smart sensor networks are trending upward for future sensor networking in fault detection applications. Hannan et al. [21] presented a critical review of the potential of an Internet-of-Energy-based building energy management system to enhance the performance of future-generation building energy utilization. FDD is an important application field of Internet-of-Energy-based networks. However, data/sensor management, cost, and scalability are major limitations of FDD techniques. Mahapatro's 2013 survey [22] also integrated research efforts that have been produced in fault diagnostics, specifically for wireless sensor networks.

In summary, existing review papers related to sensor topics in FDD cover the topics of (a) sensor measurement constraints caused by incompatible sensor network architectures, (b) smart sensor networks, (c) FDD sensor layout, location, and availability, (d) configuration of sensor networks (sensor numbers and location), and (e) data science as applied to sensor data. Interestingly, most review papers focus on FDD

Table 2
Levels of FDD to be reviewed.

No.	Level of FDD	Section	Description
1	Building-level FDD	Section 4.1	Typically addresses the overall performance of a building and does not require building operation information.
2	System-level FDD	Section 4.2	Focuses on the HVAC (include lighting) faults at the system scale, such as variable air volume (VAV) systems, variable refrigerant flow (VRF) systems, rooftop unit (RTU) systems, etc.
3	Component-level (or equipment-level) FDD	Section 4.3	Focuses on the operation of individual HVAC components such as chiller, AHU, boiler, fan coil unit, VAV terminal, room/zone level system, etc.

Table 3
Sensor topics to be reviewed at each level of FDD.

No.	Sensor Topic	Description
1	Sensor fault	Detect sensor fault including bias, drift, precision degradation, and complete failure
2	Feature selection from available sensors	Apply machine learning or information science to extract, generate, and select features (inputs, or variables) from available sensor data for FDD models
3	Additional and built-in/existing sensors	Relate to whether FDD solutions require additional sensors or can perform well using built-in/existing sensors
4	Sensor data analysis/mining	Apply data-driven techniques to extract information from sensor data to improve FDD performance
5	Virtual sensor	Apply virtual sensor techniques that provide feasible and economical alternatives to costly or impractical physical sensors to improve FDD model or reduce cost
6	Sensor calibration	Actively adjust and tune sensor and remove structural sensor errors and faults, which is part of sensor maintenance and a follow-up step for sensor fault detection
7	Sensor layout/location	Discuss the impact of sensor layout and location on sensor accuracy and efficiency

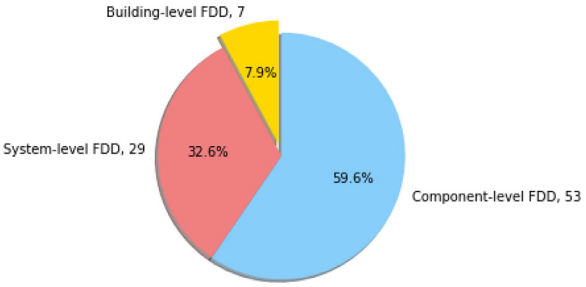

Fig. 1. Distribution of reviewed technical papers in terms of FDD levels.

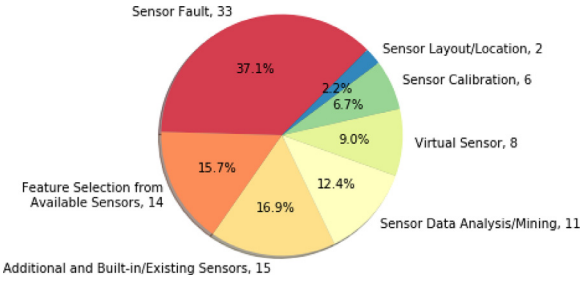

Fig. 2. Distribution of reviewed technical papers in terms of sensor topics.

more broadly and sensor topics are covered by only a fraction of papers; few papers focus primarily on sensor topics in FDD. Also, those papers focus on very specific topics (not more than a few sensor topics of interest are typically covered) as opposed to considering sensor topics in a comprehensive way. Finally, most review papers focus on very specific equipment and fault types. For example, Bruton et al. [18] and Yu et al. [17] focus solely on AHU applications. As a result, no comprehensive paper exists that systematically reviews sensor topics in FDD in a logical way (e.g., by FDD model types and fault types).

Next, we move from review papers to technical papers, and analyze them in terms of FDD levels (building, system, and component); major sensor topics are reviewed at each FDD level.

4. Review of technical papers at different FDD levels

We review sensor-related topics in building FDD in two dimensions. The first dimension is the level of FDD: building, system, or component [23], as summarized in Table 2.

Then, for each level of FDD, a variety of sensor topics are reviewed, as summarized in Table 3.

In total, 89 technical papers are reviewed in this section. The distribution of reviewed technical papers across FDD levels is shown in Fig. 1; the distribution of reviewed technical papers across sensor topics is shown in Fig. 2.

4.1. Review of sensor topics in building-level FDD

Building-level FDD typically addresses the overall performance of a building and does not require building operation information (which is the most common input for FDD in practice). The most common sensors/meters for building-level FDD are energy meters that record building total or end-use energy consumption/power. Table 4 lists technical papers addressing sensor topics in building-level FDD, which include: (a) sensor calibration, (b) sensor fault, and (c) sensor data analysis/mining. These papers are discussed in detail according to sensor topic in the following subsections.

4.1.1. Sensor fault, building-level FDD

Chen and Lan [7] proposed a method of FDD and data recovery for building heating/cooling billing systems. Sensor bias, drift, and complete failure are considered in building heating/cooling billing systems for detection and identification. They used a principal component analysis (PCA) approach to extract the correlation of measured variables in the heating/cooling billing system and reduce the dimension of measured data. The measured data of billing systems under normal operating conditions are used to build the PCA model. They developed a reconstruction algorithm to infer the correct measurement of a faulty sensor using correlations among system variables. Fan et al. [27] applied a framework for sensor data mining, which also includes fault detection of power consumption sensors. In terms of end-use sensors, Field

Table 4
Summary table of sensor topics in building-level FDD.

No.	Authors	Ref.	Sensor Topics	Details
1	Shao and Claridge	[24]	Sensor calibration	Verify building energy-use data
2	Masuda et al.	[25]	Sensor calibration	Verify building energy-use data
3	Field et al.	[26]	Sensor fault	Detect faulty building energy data by end-use submeters
4	Chen and Lan	[7]	Sensor fault, sensor data analysis/mining	Sensor fault detection, data recovery, and principal component analysis (PCA)
5	Sun et al.	[10]	Sensor data analysis/mining	Identify potential outlying observations in electricity consumption
6	Fan et al.	[27]	Sensor fault	Fault detection of power consumption sensors
7	Khan et al.	[28]	Sensor data analysis/mining	Detecting abnormal lighting energy consumption

et al. [26] utilized various energy end-use performance indices to assess building energy performance and detect faulty building energy data.

4.1.2. Sensor calibration, building-level FDD

Shao and Claridge proposed a quality control method using "Energy Balance Load" for verifying and diagnosing whole-building energy-use data [24]. The method is derived from the first law of thermodynamics and based on whole-building energy analysis, which has been theoretically proven to be an effective tool for verifying and calibrating whole-building energy use data. Masuda et al. [25] further included outside air enthalpy variables to the method and presented a possible enhancement of data screening capability for buildings operated in hot and humid climates.

4.1.3. Sensor data analysis/mining, building-level FDD

In order to eliminate the influence of outliers and improve the robustness of data-based models, Sun et al. [10] employed three methods (boxplot, local outlier factor, and PCOut) to identify potential outlying observations in a raw dataset. Khan et al. [26] described three different data mining techniques for detecting abnormal lighting energy consumption using hourly recorded energy consumption and peak demand data. Two outlier detection methods were applied to each class and cluster to detect abnormal consumption in the same dataset. This approach help building energy management systems reduce operating cost and time by alleviated the need to detect faults manually or diagnose false warnings.

The Performance and Continuous Recommissioning Analysis Tool (known as PACRAT), the Whole Building Diagnostician (known as WBD), and the Automated Building Commissioning Analysis Tool (known as ABCAT) are three well-recognized whole-building diagnostic tools [29]. These tools apply data analysis to identify a building with poor energy performance or faulty energy data when it is difficult to explain and identify the causes of poor performance [23].

4.2. Review of sensor topics in system-level FDD

More detailed detection and diagnostics methods extend the examination of energy performance and FDD from the building level to the system and component levels, and consequently enable more targeted FDD. System-level FDD focuses on HVAC faults at the system scale. A typical HVAC system can consist of an airside loop, a chilled-water loop, a refrigeration-equipment loop, and a heat-rejection loop, requiring more detailed sensors than building-level FDD; consequently, there are many more sensor topics in system-level FDD. Table 5 lists papers covering sensor topics for system-level FDD, including: (a) sensor fault, (b) feature selection from available sensors, (c) additional and built-in/existing sensors, (d) sensor data analysis/mining, and (e) virtual sensor. These papers are discussed in detail according to sensor topic in the following subsections.

4.2.1. Sensor fault, system-level FDD

Wang et al. [30] presented a strategy for FDD of HVAC systems that leverages sensor fault detection at the system level. Two schemes are involved in the system-level FDD strategy: (1) a system FDD scheme and (2) a sensor fault detection, diagnostics, and estimation scheme. A method based on PCA is used to detect and diagnose sensor bias and correct it prior to application of the system FDD scheme. The sensor FDD method works well in identifying and correcting sensor biases even when system faults coexist.

Papadopoulos et al. [39] presented a model-based methodology for diagnosing actuator and sensor faults affecting the temperature dynamics of a multi-zone HVAC system. For every subsystem, they designed a monitoring agent that combines local and transmitted information from its neighboring agents to decide the type, number, and location of faults.

Guo et al. [47] presented an enhanced sensor FDD method based on both the Satizky-Golay method and PCA method for a VRF system, together called the Satizky-Golay-PCA method. Raw data are first smoothed using the Satizky-Golay method, and then the smoothed data are used for PCA model training and FDD.

Verhelst et al. [50] investigated the economic fault impact of sensors and actuators via dynamic simulation using an emulator model of an office building in combination with four different control strategies. They developed a virtual test-bed consisting of two emulated office zones and one HVAC system, with persistent faults in temperature sensor and hydronic flow rate actuators. Both the fault-free and fault-present performances are investigated and compared through relevant, control-associated costs using an economic framework. This methodology determines the fault sensitivity of different supervisory control strategies and assists with the selection of the most economical, fault-robust controller for a given building type. Also, the most critical sensors and actuators are identified.

In the context of smart buildings, it is important not only to detect the occurrence of sensor faults but also to isolate the location of the fault as expediently as possible [34]. This topic is called sensor fault isolation. Reppa et al. [34] presented a design and analysis methodology for detecting and isolating multiple sensor faults in HVAC systems. Their proposed methodology is captured via a distributed framework, considering a multizone HVAC system as a set of interconnected nonlinear subsystems. A dedicated local sensor fault diagnostics agent is designed for each subsystem, although it may exchange information with other local sensor fault diagnostics agents. Distributed sensor fault detection is conducted using robust analytical redundancy relations of estimation-based residuals and adaptive thresholds. The distributed sensor fault isolation procedure is carried out by combining the decisions of the local sensor fault diagnostics agents and applying a reasoning-based decision logic.

Lee and Yik [45] presented the results of a study on the energy cost impacts of a range of common system faults in variable air volume (VAV) air-conditioning systems, which are widely adopted for their good part-load energy efficiency. The sensor-related faults studied include room air temperature sensor offset and supply air temperature sensor offset. The simulation results indicated that the two sensors' offset (or bias) significantly increases energy use in buildings.

4.2.2. Feature selection from available sensors, system-level FDD

Zhao et al. [57] evaluated fault detection performance using different feature selections. The selection criteria are: (1) they should be able to identify unique operating conditions and distinguish between faulty data and normal data, (2) they can provide informational redundancy

Table 5
Summary table of sensor topics in system-level FDD.

No.	Authors	Ref.	System Type	Sensor Topics	Details
1	Wang et al.	[30]	System of cooling tower, chiller, secondary chilled water pump, heat exchangers	Sensor fault, sensor data analysis/mining	PCA-based FDD on sensor bias
2	Dong et al.	[31]	Chiller-AHU-VAV system	Additional and built-in/existing sensor	Sensor schema and suggested built-in sensors for common FDD applications
3	Sun et al.	[32]	Cooling tower-chiller-AHU-room system	Sensor fault	Sensor fault detection, sensor noise problem
4	O'Neill et al.	[33]	Chiller-AHU-VAV system	Additional and built-in/existing sensor	Additional sensors including electrical power sub-metering, fluid flow meters, and temperature sensors
5	Reppa et al.	[34][35]	Chiller-chilled water tank-VAV system	Sensor fault	Distributed sensor fault isolation via dedicated local sensor fault diagnostics and reasoning-based decision logic
6	Guo et al.	[36]	A VRF system with five indoor units and one outdoor unit	Additional and built-in/existing sensor	Built-in/existing sensors without additional sensor
7	Frank et al.	[37]	Chiller-AHU-VAV system	Additional and built-in/existing sensor	FDD that requires fewer sensors and less configuration
8	Alsaleem et al.	[38]	AHU, furnace, and condensing unit	Additional and built-in/existing sensor	Use existing embedded sensors and monitoring modules
9	Papadopoulos et al.	[39]	Heat pump, condenser, storage tank, fan coil unit	Sensor fault	Sensor fault detection by a distributed fault diagnostics architecture
10	Wijayasekara et al.	[40]	Systems recorded in BAS, including any HVAC components	Additional and built-in/ existing sensor, sensor fault, sensor data analysis/mining	Use existing building energy management system sensors for FDD
11	Gao et al.	[41]	Complex primary–secondary chilled water system, AHU, plate heat exchangers	Additional and built-in/existing sensor	FDD that requires few measurement sensors
12	Verbert et al.	[42]	Boiler, AHU, and radiator	Virtual sensor	Conclude three steps in the design of virtual sensor
13	Li and Wang	[43]	Chiller-AHU-VAV system	Sensor calibration, feature selection from available sensors, sensor fault	Quantify the importance of sensors and determine a proper calibration frequency for sensors with high importance
14	Mohamed et al.	[11]	General HVAC system	Virtual sensor	Conclude two approaches of virtual sensing: analytical virtual sensing and empirical virtual sensing
15	Dibowski et al.	[44]	General building and home automation system	Additional and built-in/existing sensor, virtual sensor	Determine minimum sensor and necessity of adding more sensors
16	Lee and Yik	[45]	Chiller-AHU-VAV system	Sensor fault	Analyze impact of room and supply air temperature sensor offset
17	Guo et al.	[46]	VRF system	Feature selection from available sensors	Hybrid feature selection (correlation analysis method and association rule mining method) in VRF
18	Guo et al.	[47]	VRF system	Sensor fault, Sensor data analysis/mining	Sensor FDD method based on Satizky-Golay and PCA method for VRF
19	Shi et al.	[48]	VRF system	Sensor data analysis/mining	PCA is used to reduce the dimensionality of all feature variables to improve computational efficiency for VRF
20	Li et al.	[49]	VRF system	Virtual sensor	Virtual sensor-based fault indicators for VRF
21	Verhelst et al.	[50]	Cooling, heating, ventilation and water distribution system for office building	Sensor fault	Economic impact of persistent sensor and actuator faults
22	Yoon and Yu	[51]	ARS system	Sensor calibration	Virtual in-situ sensor calibration
23	Shi et al.	[52]	VRF system	Feature selection from available sensors	Employ the ReliefF algorithm for feature ranking for VRF FDD
24	Yu et al.	[53]	Rooftop unit system	Sensor calibration	Indirect virtual calibration method for supply air temperature in RTU
25	Kim	[54]	Air conditioner, chiller and heat pump systems	Virtual sensor	Review of virtual sensor, evaluation of sensors, development, and assessment of alternative virtual sensors in RTU
26	Katipamula et al.	[55]	Rooftop unit system	Additional sensor, sensor layout/location, sensor fault	Cost of additional sensors in RTU
27	Hjortland and Braun	[56]	Rooftop unit system	Virtual sensor	Virtual sensors for air-side diagnostics are developed and validated for RTU

to enhance robustness, and (3) number of sensors should be minimized to maintain sensitivity to faults at low severities and to reduce computational complexity.

Guo et al. [46] presented the optimized back propagation neural network method for fault diagnostics of an VRF air-conditioning system in heating mode. They proposed a feature variable set optimization approach of diagnostics models based on a data mining method. The correlation analysis method is first used to eliminate redundant variables and then the association rule mining method is used to optimize the feature set selection.

Shi et al. [52] developed a highly efficient fault diagnostics model, which employs the ReliefF algorithm for feature ranking/selection and applies the neural network for fault diagnostics. The results show that the model accuracy based on the 6 best features is sufficiently high in comparison to that for the model based on all 22 features.

Zhang et al. [58] developed a feature engineering framework for system-level FDD. Features are first extracted from raw sensor data via statistical feature extraction techniques with various window sizes and statistics. A hybrid feature selection algorithm that combines the filter and wrapper method then selects the optimal feature set. The framework considers diversity in the duration of fault behavior among fault types in system-level FDD and at the same time can deal with high dimensional extracted features.

4.2.3. Additional and built-in/existing sensor, system-level FDD

Katipamula et al. [55] studied additional sensors that are needed to deploy the refrigerant-side diagnostics. Accommodating additional sensors means either increasing the input/output capability of the RTU controller or adding another controller to handle the additional sensors, which increases the cost of deployment significantly. Besides, correctly locating the sensors is also challenging. The authors summarized three hurdles must be overcome to deploy refrigerant-side diagnostics and RTU controls: (1) the cost of additional sensors, (2) the cost of upgrading the RTU controller to handle additional sensors and, (3) solving the difficulties associated with installing sensors in the right location.

Teraoka et al. [59] explained that sensors that provide valuable information for uncovering building faults are often not installed. Researchers who use additional sensors focus on providing additional information to improve FDD performance with the most cost-effective set of additional sensors; researchers who use built-in sensors focus on maximizing FDD performance without introducing additional sensor cost.

Dong et al. [31] developed a building information modeling-enabled information infrastructure for FDD. They proposed a sensor schema for general FDD applications and recommended typical built-in sensors for common FDD applications.

O'Neill et al. [33] proposed an automated, model-based, real-time, whole-building performance monitoring and energy diagnostics system. The proposed system continuously acquires performance measurements of the HVAC system via an existing energy management control system augmented by additional sensors as required, with considerations for sensor noise and model uncertainties. Additional sensors include electrical power sub-metering, fluid flow meters, and temperature sensors to determine thermal energy flow rates. The problem of potential sensor bias is also addressed.

Dibowski et al. [44] explained that an analysis is needed to determine what additional types of sensors need to be installed for building FDD. Required but unavailable variables of FDD algorithms necessitate additional sensor installations or virtual sensors. The minimal set of additional sensors needed is driven by the FDD functionality to be added.

The papers mentioned so far in the section all discussed additional sensors used for FDD applications. The following papers address FDD applications based on built-in/existing sensors. Guo et al. [36] discussed FDD applications with built-in/existing sensors. They proposed a novel fault diagnostics approach based on deep belief network and investigated its application potential in the air-conditioning fault diagnostics field. All variables used in that study are collected by the sensors from the original equipment manufacturer and there are no additional sensors added.

Alsaleem et al. [38] presented a new monitoring and diagnostics model for residential HVAC systems. Using existing embedded sensors and monitoring modules for the indoor and outdoor HVAC units, various measurements are transmitted to a cloud server utilizing the homeowner's pre-existing Wi-Fi network and the model benefits from the advantage of cloud computing and offers continuous diagnostic capabilities.

Wijayasekara et al. [40] proposed a novel Fuzzy Anomaly Detection and Linguistic Description-based method for improving the understandability of building energy management system behavior for improved state-awareness. They used existing building energy management system sensors for FDD.

4.2.4. Virtual sensor, system-level FDD

Mohamed et al. [11] discussed how virtual sensors can provide low-cost sensing capabilities while for more accurate smart building energy diagnostics. They concluded that there are two approaches to virtual sensing: analytical virtual sensing and empirical virtual sensing. The analytical virtual sensing approach uses approximations of physical laws to estimate a quantity. The empirical virtual sensing approach uses current and previous sensor measurements to estimate a quantity.

Holub and Macek [60] explained that replacing unmeasured data with virtual sensors is a typical building maintenance workflow. Verbert et al. [42] concluded that the design of a virtual sensor essentially consists of three steps: (1) the choice for the quantity to be estimated (i.e., which variables are valuable features for diagnostics), (2) the selection of available sensor measurements that are relevant to estimate these quantities, and (3) the choice for the method to capture the relationship between the quantity of interest and the relevant sensor measurements (e.g., first principles or data-based approaches). The authors also demonstrated the use of virtual sensors to estimate missing variables.

Li et al. [49] proposed an improved decision tree-based fault diagnostics method for practical VRF systems. The proposed method is a three-stage method combining a decision-tree model with virtual sensor-based fault indicators. Kim [54] reviewed and studied the topics of virtual sensors, evaluation of sensors, and development and assessment of alternative virtual sensors for RTUs.

Hjortland and Braun [56] developed and validated virtual sensors for air-side diagnostics for rooftop air conditioners. The virtual air-side sensors require indoor fan differential pressure and speed measurements. Experimental data from laboratory measurements are used to evaluate the accuracy of the virtual sensors. The authors also develop and evaluate methodologies for improving the accuracy of air-side temperature sensors often used for outdoor-air economizer diagnostics. Outdoor air temperature correction correlations reduce single-point temperature inaccuracy caused by exhaust-air recirculation. The study also described and validated a model correcting a single-point mixed-air temperature measurement for inaccuracy caused by thermal stratification and non-uniform velocity distributions at the evaporator inlet. Finally, methods for estimating outdoor ventilation air fraction are presented and compared to measurements.

4.2.5. Sensor data analysis/mining, system-level FDD

Shi et al. [48] used PCA to reduce the dimension of all feature variables to improve computational efficiency while preserving the majority of feature information. With the inputs extracted from PCA, they adopted a dual neural network model for the refrigerant charge fault diagnostics strategy to improve diagnostic accuracy for the undercharge fault.

4.2.6. Sensor calibration, system-level FDD

Yoon and Yu [51] apply virtual in-situ sensor calibration (VIC) using Bayesian Markov chain Monte Carlo with system models to large-scale

building sensor networks in order to calibrate multiple working sensors, including virtual and physical sensors. Using the calibration strategies therein, VIC methods work to overcome various systematic errors (from simple to troublesome) that cannot otherwise be handled by a conventional calibration. The authors applied individual calibration strategies to a whole-building system, and their effectiveness and limitations in solving the VIC problem were evaluated for the calibration of each type of working sensor under the various error conditions that cause negative effects.

Li and Wang [43] proposed a preventive approach to determine sensor maintenance requirements. The approach aims to explicitly quantify the importance of sensors and determine a proper calibration frequency for sensors with high importance. The approach takes account of the sensor bias growth mechanism and relates sensor importance to a user-defined building performance index. Sensor importance is evaluated under a stochastic framework, which essentially is the way in which sensor bias grows. Desired calibration frequency is identified using a polynomial function which describes the degradation rate of the building performance index.

Yu et al. [53] developed an innovative indirect virtual calibration method for a manufacturer-installed supply air temperature sensor to address erratic measurement errors caused by non-uniform temperature distribution and intensive thermal radiation in a compact chamber. They demonstrated that a virtual calibrated manufacturer-installed supply air temperature sensor can provide accurate results when combined with a linear correlation for offset error that depends on heating stage and outside air damper signals. This virtual calibration method is generic for all RTUs with similar construction of gas furnaces and can be implemented for long-term use.

4.3. Review of sensor topics in component-level FDD

Component-level FDD targets the operation of individual HVAC components and equipment such as chillers, boilers, AHUs, fan coil units, VAV terminals, room/zone level systems, and so on. At the component level, the performance of key components within the HVAC system is examined in greater detail than at the component level. Sensor topics at the component level are the most varied across the three levels of FDD. Table 6 lists the papers covering sensor topics in component-level FDD, including (a) sensor fault, (b) feature selection from available sensors, (c) additional and built-in/existing sensors, (d) sensor data analysis/mining, (e) virtual sensor, (f) sensor calibration, and (g) sensor layout/location. These papers are discussed in detail according to sensor topic in the following subsections.

4.3.1. Sensor fault, component-level FDD

Neural networks are widely used for component-level sensor fault detection. Du et al. [61] explained that in real building and HVAC systems, FDD performance relies on the quantity and quality of sensor data. The authors developed combined neural networks to detect sensor faults in AHUs. They also applied adaptive subtractive clustering analysis to diagnose fault sources. Fan et al. [63] presented a self-adaptive sensor FDD strategy for a local system of AHUs. In the first stage of this strategy, a fault detection model built with back-propagation neural network models for the AHU control loop is developed. In the second stage, a fault diagnostics model is developed to combine the wavelet analysis method with an Elman neural network to identify sensor faults. Zhu et al. [69] introduced a new fault diagnostic method for sensors in an AHU based on a neural network pre-processed by wavelet and fractal analysis. Wavelet analysis is used to decompose the sensor data, and then fractal dimensions of each frequency band are extracted to extract the sensor failure characteristics. Du et al. [73] applied the dual neural network strategy to detect the sensor faults in the supply air temperature control loop of an AHU. Subbaraj and Kannapiran [78] presented the design and development of an artificial neural-network-based model for the fault detection of a pneumatic valve in a cooler water spray system utilized in the cement industry. The network is developed to detect a total of 19 faults including a pressure sensor fault and a rod displacement sensor fault. Kocyigit [79] applied fuzzy inference system and neural network to diagnose faults in a vapor compression refrigeration experimental setup. They developed a separate fuzzy inference system for detection of sensor errors.

Xiao et al. [67] presented a diagnostic Bayesian network for FDD of VAV terminals, including temperature sensor fault. Zhao et al. [71] developed four diagnostic Bayesian networks to diagnose faults in heating/cooling coils, sensors, and faults in secondary supply chilled water/heating water systems.

In the study from Yang et al. [75], a novel method using fractal correlation dimension was developed. Fractal correlation dimension deviation is applied to detect fixed and drift bias faults generated for an AHU supply air temperature sensor.

Shahnazari et al. [96] presented an integrated framework for fault detection and isolation and fault tolerant control of VAV boxes in HVAC systems. They first designed a statistical model-based fault detection and isolation framework as benchmarks for comparison. Next, they designed and implemented a novel linear causal model-based framework for fault detection and isolation of multiple actuator and multiple sensor faults.

Some researchers have developed FDD tools that account for sensor fault and noise. Pourarian et al. [104] developed and validated a software tool to simulate operational data generated from fan coil units that are operated dynamically under both faulty (including offset room temperature) and fault-free conditions. They developed a comprehensive process to validate the tool under both faulty and fault-free operating conditions in different seasons. Bonvini et al. [64] presented a computationally efficient and robust algorithm for both whole-building and component-level energy FDD. The algorithm can provide reliable estimation of multiple and simultaneous fault conditions in the presence of noisy and sometimes erroneous sensor data and provide uncertainty estimation.

4.3.2. Feature selection from available sensor set, component-level FDD

Han et al. [65] employed feature selection techniques, including a mutual information-based filter and genetic algorithm-based wrapper, to help search for important sensors in data-driven chiller FDD applications to improve FDD performance while reducing initial sensor costs.

Yan et al. [66] implemented the feature selection algorithm ReliefF to select the most significant features in chiller FDD modeling. For each feature, the ReliefF algorithm assigns a weight according to its importance in influencing the output. The most heavily weighted features are selected as model features. Mulumba et al. [68] also applied ReliefF in their model-based fault diagnostics method developed via support vector machine techniques. Yan et al. [82] proposed a novel hybrid method to detect faults for chiller subsystems without any faulty training data. A hybrid feature selection algorithm that combines ReliefF and adaptive genetic algorithm methods is applied to the chiller dataset collected by ASHRAE project 1043-RP to select the most significant feature variables.

Han et al. [81] investigated a hybrid model that combines a support vector machine with a genetic algorithm and parameter tuning technique for chiller FDD applications. Subsets of 6, 7, 8, 9, and 10 features were studied, respectively, and compared with the original 64-feature set in terms of overall model performance.

Yan et al. [16] proposed a cost-sensitive and sequential feature selection algorithm for chiller FDD to select the most important features using a back-tracing sequential forward feature selection algorithm. They used the ASHRAE dataset collected by project number 1043-RP. Also using data from project 1043-RP, Yuwono et al. [9] applied “ensemble rapid centroid estimation” to select important features from original measurements based on the relative entropy between the low- and high-frequency features. The work is based on ASHRAE-1312-RP datasets, containing a total of 49 days of data capturing various types of faults and corresponding severity. The effectiveness of the feature selection method is further investigated using two time-sequence classification al-

Table 6
Summary table of sensor topics in component-level FDD.

No.	Authors	Ref.	Component	Sensor Topics	Details
1	Du et al.	[61]	AHU	Sensor fault	Combined neural networks to detect sensor faults in AHU
2	Li and Wen	[62]	AHU	Sensor data analysis/mining	Apply wavelet-PCA on sensor data for fault detection
3	Zhao et al.	[57]	Chiller	Feature selection from available sensors	Mention three feature selection criteria for building sensors
4	Fan et al.	[63]	AHU	Sensor fault	Self-adaptive sensor FDD using back-propagation neural network and wavelet analysis method with Elman neural network
5	Bonvini et al.	[64]	Chiller	Sensor fault	FDD algorithm adaptive to sensor noise and sensor fault
6	Han et al.	[65]	Chiller	Feature selection from available sensors	Feature selection using mutual-information-based filter and genetic-algorithm-based wrapper
7	Yan et al.	[66]	Chiller	Feature selection from available sensors	Feature selection using ReliefF
8	Xiao et al.	[67]	VAV terminal	Sensor fault	Sensor FDD using diagnostic Bayesian network
9	Mulumba et al.	[68]	AHU	Feature selection from available sensors	Feature selection using ReliefF
10	Zhu et al.	[69]	AHU	Sensor fault	Sensor fault detection using neural network pre-processed by wavelet and fractal
11	Han et al.	[70]	Vapor-compression refrigeration systems	Sensor data analysis/mining	FDD tool combining PCA and support vector machine
12	Zhao et al.	[71]	AHU	Sensor fault	Sensor fault detection with diagnostic Bayesian network
13	Hu et al.	[72]	Chiller	Sensor data analysis/mining, sensor fault	Sensor fault detection using adaptive PCA
14	Du et al.	[73]	AHU	Sensor fault	Sensor fault detection with dual neural networks
15	Zhao et al.	[74]	AHU	Additional and built-in/existing sensor	Inadequacy of built-in/existing sensors
16	Yang et al.	[75]	AHU	Sensor fault	Sensor fault detection using fractal correlation dimension
17	Li and Wen	[76]	AHU	Additional and built-in/existing sensor	List typical sensors for FDD in AHU
18	Wang et al.	[77]	VAV terminal	Additional and built-in/existing sensor	FDD tool relies on sensors that are common in building management control systems
19	Subbaraj and Kannapiran	[78]	Cooler water spray system	Sensor fault	Sensor fault detection with neural network
20	Kocyigit	[79]	Vapor-compression refrigeration systems	Sensor fault	Sensor fault detection using fuzzy inference system
21	Cai et al.	[80]	Ground-source heat pump	Sensor data analysis/mining	Multi-source information fusion based FDD
22	Han et al.	[81]	Chiller	Feature selection from available sensors	Feature selection with hybrid method combining support vector machine with genetic algorithm
23	Yan et al.	[82]	Chiller	Feature selection from available sensors	Feature selection with hybrid method combining ReliefF and adaptive genetic algorithm
24	Hu et al.	[83]	Chiller	Sensor data analysis/mining, sensor fault	Statistical training data cleaning strategy for PCA-based chiller sensor FDD and data reconstruction
25	Zhao et al.	[84]	Chiller	Virtual sensor	Virtual fouling monitor sensor using low cost and common onboard chiller measurements for monitoring the fouling status of the condenser
26	Li et al.	[85]	Chiller	Sensor fault	Sensor FDD for screw chiller system using the support vector data description algorithm
27	Yan et al.	[86]	AHU	Sensor fault, sensor data analysis/mining	Use cluster analysis (PCA and Ordering Points to Identify the Clustering Structure) for AHU sensor fault detection

(*continued on next page*)

Table 6 (*continued*)

No.	Authors	Ref.	Component	Sensor Topics	Details
28	Wang et al.	[87]	VAV terminal	Sensor fault	Residual-based cumulative sum control charts are utilized to detect faults in VAV terminals
29	Yan et al.	[16]	Chiller	Feature selection from available sensors	Feature selection with back-tracing sequential forward feature selection
30	Sun et al.	[88]	Chiller	Sensor data analysis/mining, sensor fault	Data fusion techniques are applied
31	Hu et al.	[89]	Chiller	Sensor data analysis/mining, sensor fault	Sensitivity of chiller sensor fault detection based on PCA
32	Dey and Dong	[90]	AHU	Sensor fault	Bayesian belief network based sensor FDD
33	Yang et al.	[91]	AHU	Sensor fault	Fractal correlation dimension algorithm for AHU sensor FDD
34	Padilla and Choiniere	[92]	AHU	Sensor fault, sensor data analysis/mining	Passive/active AHU sensor FDD combining PCA and active functional testing
35	Kim et al.	[93]	Indoor air quality	Sensor fault validation, sensor data analysis/mining	Sensor validation method based on independent component analysis
36	Li et al.	[94]	AHU	Feature selection from available sensors	Information greedy feature filter as feature selection algorithm for FDD in AHU
37	Kim and Braun	[95]	Chiller	Virtual sensor	Three virtual refrigerant mass flow sensors that use mathematical models to estimate flow rate using low-cost measurements
38	Shahnazari et al.	[96]	VAV terminal	Sensor fault, Sensor data analysis/mining	Sensor-fault-tolerant control of VAV box
39	Wang et al.	[97]	Chiller	Feature selection from available sensors	Feature selection based on Bayesian network merged distance rejection
40	Li et al.	[98]	Outdoor unit of VRF	Additional and built-in/existing sensor, sensor data analysis/mining	Data mining using only built-in/existing sensor
41	Fernandez et al.	[99]	AHU	Sensor fault, virtual sensor	Self-correction capabilities for sensors, economizer dampers, and damper actuators in AHU
42	Karami and Wang	[100]	Chiller	Additional and built-in/existing sensor	The developed algorithm reduces the number of sensors needed in chiller plant FDD
43	Najafi	[101]	AHU	Additional and built-in/existing sensor	Sensor network architectures are not necessarily designed solely for diagnostic purposes
44	Dey et al.	[102]	HVAC terminal unit	Sensor layout/location	Note that the poor sensor location can result in faulty terminal unit behaviors
45	Kim and Braun	[103]	Chiller	Virtual sensor	Develop three virtual refrigerant mass flow sensors for FDD
46	Pourarian et al.	[104]	Fan coil unit	Sensor fault	FDD algorithm adaptive to sensor faults
47	Liu et al.	[105]	Indoor air quality	Sensor calibration, sensor fault, sensor data analysis/mining	PCA-based approach is used to detect, identify, and reconstruct sensor faults in monitoring indoor air quality
48	Sun et al.	[106]	Chiller	Sensor data analysis/mining, feature selection from available sensors	A hybrid refrigerant charge amount FDD combined support vector machine with wavelet de-noising and improved max-relevance and min-redundancy algorithm
49	Lee et al.	[107]	AHU	Sensor layout/location	Importance of proper sensor location and number of sensors
50	Yan et al.	[108]	AHU	Feature selection from available sensors	Cost-sensitive sequential forward feature selection algorithm
51	Wang and Haves	[109]	VAV terminal	Sensor fault	Monte Carlo analysis is employed considering sensor measurement uncertainty
52	Shi et al.	[110]	Zone level	Additional and built-in/existing sensor, sensor fault	Use available sensors installed in the experiment setup
53	Habib et al.	[111]	Chiller	Sensor data analysis/mining	Outlier detection via expectation maximization clustering algorithm
54	Yuwono et al.	[9]	Chiller	Feature selection from available sensors	Feature selection algorithm: Ensemble Rapid Centroid Estimation

gorithms (Nonlinear Auto-Regressive Neural Network with eXogenous inputs and distributed time delays and Hidden Markov Models).

4.3.3. Additional and built-in/existing sensor, component-level FDD

Zhao et al. [74] addressed the major challenge in AHU fault diagnostics is the incompleteness and inaccuracy of AHU measurements. AHU measurements are rich in data but often poor in information, and there is a limited number of sensors equipped in most AHUs due to cost considerations. Measurements are generally insufficient for fault detection, let alone fault diagnostics. Also, various levels of uncertainty exist in AHU measurements capturing fault symptoms. Braun [105] pointed out the need for adding low-cost sensors to make FDD solutions more appealing for HVAC systems compared to solutions for other industries such as nuclear power and air travel.

Most studies that capture the use of built-in or existing sensors do so at the component level. Li and Wen [76] listed typical sensors for AHU operation: outdoor air temperature, mixing box damper position, supply fan total power, mixed air temperature, heating coil valve position, return fan total power, supply air temperature, cooling coil valve position, supply fan speed, supply air duct static pressure, supply airflow rate, and return fan speed. In the study from Wang et al. [77], a rule-based fault classifier is utilized to find the sources of faults in VAV terminals. The fault diagnostic tool relies only on sensor data and control signals that are commonly available in building management control systems. Li et al. [98] proposed a data mining approach to identify and isolate fouling faults using only built-in sensors. The classification and regression tree-based classifier is used for fault detection. Shi et al. [110] implements a fault detection algorithm for thermal zones using Kalman Filter-based methods with a reduced order energy balance model, and tests its performance using both simulation and experimental data. The model estimates indoor air temperature change using available sensors installed in the experiment setup.

4.3.4. Virtual sensor, component-level FDD

Zhao et al. [84] presented a virtual condenser fouling sensor derived from low-cost and common onboard chiller measurements. Performance of the proposed virtual fouling sensor was evaluated by laboratory data collected over normal and faulty operating conditions. Moreover, the proposed virtual fouling sensor was evaluated on a chiller in the field. The test results show that the proposed method results in accurate and robust performance in chiller condenser FDD.

4.3.5. Sensor data analysis/mining, component-level FDD

PCA is a widely applied data analysis/mining technique to improve FDD performance. In Li and Wen's study [62], they explained that PCA is powerful as a data-driven model-based method for detecting AHU faults. They also mentioned that wavelet transform is a promising data preprocessing approach to remove the influence of weather conditions. The authors developed a combined Wavelet-PCA method and tested it using site data. They then demonstrated the feasibility of using the wavelet transform method for data pre-treatment. Compared to the conventional PCA method, the Wavelet-PCA method is more robust to changes in internal loads and weather conditions and generates no false alarms. Han et al. [70] proposed a novel FDD strategy for vapor-compression refrigeration systems, which combines PCA feature extraction and multiclass support vector machine classification algorithm. Hu et al. [72] presented a self-adaptive chiller sensor fault detection strategy based on the PCA method, namely the Self-Adaptive Principal Component Analysis method. Hu et al. [89] presented an algebraic solution of faulty sensors' undetectable boundary to evaluate the sensitivity of chiller sensor fault detection based on PCA. Bias sensor fault of a field screw chiller was studied for each sensor in the PCA model by introducing different fault severity levels. Hu et al. [83] presented a statistical training data cleaning strategy for a PCA-based chiller sensor FDD and data reconstruction method. The presented data-cleaning strategy can find and remove outliers from the training dataset, thus improving fault detection and data reconstruction.

Two papers are found to apply data fusion techniques for sensor topics in FDD. Sun et al. [88] developed a sensor FDD strategy based on data fusion technology to detect faults in the direct measurement of building cooling load. The confidence degree is generated by a data fusion algorithm, and it is used to indicate the existence of a fault. Cai et al. [80] proposed a multi-source information fusion-based fault diagnostics methodology using a Bayesian network. They demonstrated that the Bayesian network is well equipped to deal with the uncertainty problem inherent to fault diagnostics.

Habib et al. [111] discussed the steps involved in detecting data outliers in absorption chiller on/off state information. The authors developed two-layer K-Means clustering for detecting on/off as well as missing data state of the chiller. After automatic detection of the chiller's on/off cycle, the authors applied a method for outlier detection via Z-Score normalization and clustering outliers using expectation maximization clustering.

4.3.6. Sensor calibration, component-level FDD

Liu et al. [105] collected several key air pollutant data to effectively monitor and control indoor air quality in subway stations. The authors developed a PCA-based approach to detect, identify, and reconstruct sensor faults tied to monitoring indoor air quality. Four types of sensor failures, namely, bias, drift, complete failure, and precision degradation are considered. Test results for a real subway tele-monitoring system showed that the developed sensor validation technique can work well for all four kinds of sensor faults.

Kim et al. [93] proposed a new sensor validation method based on independent component analysis to detect, identify, and reconstruct sensor faults in a metro system. The independent component analysis method extracts essential information from non-Gaussian distributed indoor air quality data. To detect and identify sensor faults, squared prediction error and sensor validity index of the independent component analysis model were applied, respectively. Then, an iterative reconstruction algorithm was applied to the identified faulty sensor to eliminate the fault. The sensor faults of bias and drift were introduced to a particulate matter sensor in the metro system of Seoul, Korea, and the results demonstrated the effectiveness of the developed independent component analysis-based method.

4.3.7. Sensor layout/location, component-level FDD

We found very few papers related to this topic. Lee et al. [107] proposed proper location and number of sensors are important to conduct FDD in AHUs. Dey et al. [102] addressed potential issues that can result from faulty terminal units, including poor sensor location. Lack of knowledge of sensor location, weather data, and occupancy information make it difficult to detect and diagnose the cause of faults effectively, though the excellent accuracy of the proposed method points to the potential for real-world applicability of the findings.

4.4. Summary of technical papers

In Sections 4.1, 4.2, and 4.3, technical papers are reviewed according to FDD level. To facilitate a more comprehensive understanding of the state of sensor topics in FDD, we provide a table that summarizes sensor topics across each FDD level in terms of number of papers, subtopics, techniques applied, research potential, and whether current research is hardware or software focused. Research potential is defined by both the importance of the research topic and how well it has already been addressed. Besides the sensor topics mentioned in Table 3, we also include "Sensor cost-effectiveness" and "Sensor engineering as an integrated framework" because of their importance and research potential, although few papers are found addressing these two topics.

It can be concluded from Table 7 that:

Table 7
Summary of sensor topics across each FDD level.

No.	FDD Sensor Topics	# of Paper	Subtopics	Techniques Applied	Research Potential	Hardware or Software Focused
1	Sensor fault	33	Sensor FDD, sensor self-correction, sensor-fault-tolerant control, distributed sensor fault structure, economic impact of sensor faults, sensitivity of sensor FDD, passive/active sensor FDD, sensor fault reconstruction, sensor measurement uncertainty	Machine learning (neural network, Elman neural network, Bayesian network, support vector machine, Bayesian belief network, expectation maximization clustering, fractal correlation dimension algorithm), PCA, wavelet analysis, fuzzy inference system, Monte Carlo analysis, Satizky-Golay filter, Ordering Points, reasoning-based decision logic	Low	Software
2	Feature selection from available sensors	14	Feature selection criteria, cost-sensitive sensor selection	Ensemble Rapid Centroid Estimation, ReliefF, sequential forward feature selection, max-relevance and min-redundancy algorithm, information greedy feature filter, hybrid methods, correlation analysis method, association rule mining method, Bayesian network merged distance rejection, mutual-information-based filter method	Low	Software
3	Additional and built-in/existing sensors	15	FDD with additional sensors, FDD with built-in sensors, sensor schema, reduce number of sensors needed in FDD, cost of additional sensors, typical sensors, suggested built-in sensors, suggested additional sensors	Built-in-sensor-based data mining	Medium	Hardware
4	Sensor data analysis/mining	11	Data recovery, anomaly detection, outlier detection, data cleaning, data clustering, data fusion, data mining, noise cancelation	PCA, Satizky-Golay filter, wavelet analysis, multi-source information fusion, clustering techniques (such as expectation maximization clustering algorithm)	Medium	Software
5	Virtual sensor	8	Virtual sensor design, approaches of virtual sensing, virtual sensor assessment, virtual sensor validation, virtual sensing using low-cost sensors	Virtual fouling monitor sensor	High	Software
6	Sensor calibration	6	Energy meter verification, sensor calibration frequency, indirect virtual calibration, virtual in-situ sensor calibration	–	Medium	Hardware
7	Sensor layout/location	2	Importance of proper sensor location and number of sensors	–	High	Hardware
8	Sensor cost-effectiveness	0	–	–	High	Hardware
9	Sensor engineering as an integrated framework	0	–	–	High	Software/Hardware

- In terms of number of papers, sensor fault, feature selection from available sensors, additional and built-in/existing sensors, and sensor data analysis/mining are the most widely studied sensor-related topics in FDD. These topics include diversified subtopics and applied techniques. Relatively speaking, researchers have already explored these topics in detail, indicating both their importance and a reduced potential for future research.
- In terms of research potential, virtual sensor, sensor layout/location, sensor cost-effectiveness, and sensor engineering as an integrated framework are very promising topics. Sensor cost-effectiveness analysis is important to sensor design, but few FDD papers address this topic. Building and equipment design in the real world are increasingly cost-driven, and low-cost sensors with relatively high reliability are favored by engineers and designers. The trade-off between sensor reliability and sensor cost needs systematic quantification to help people make decisions on sensor selection. Sensor layout/location is also important to sensor design (significantly impacting sensor accuracy and efficiency) but only two papers cover this topic, and neither of them provides in-depth analysis. Although many sensor topics are found in the existing literature, a systematic framework or workflow that integrates sensor design, sensor data analysis, sensor selection, physics-based or data-driven algorithms, sensor fault detection, sensor calibration, and sensor maintenance is lacking and in great need, because most current sensor architectures in buildings are not designed with an emphasis on fault diagnostics. Such a framework is critical to enable building engineers and designers to streamline sensor engineering (from design stage to operation/maintenance stage) while ensuring the resulting sensor design and layout supports potential FDD applications.
- "Hardware or Software Focused" in the last column indicates whether the sensor topics relate to hardware research (focusing on sensing equipment, such as additional and built-in sensors, sensor calibration, and sensor layout) or to software research (focusing on the techniques and algorithms applied to the sensor data, such as sensor data analysis, virtual sensors, and feature selection on sensor data). There are 66 software-focused papers but only 23 hardware-focused papers. Software- and hardware-focused research are equally important: hardware is the foundation of the software that utilizes sophisticated algorithms and techniques to meet complicated research and engineering needs. Software-focused topics are much more studied and have more diverse subtopics than hardware-focused topics; we expect more hardware-focused research will strengthen the foundation of future FDD studies. We also predict integration of software- and hardware-focused research to optimize compatibility as a future trend.
- Machine learning techniques are increasingly being applied to sensor-related FDD work. The relevant machine learning algorithms include neural network, Elman neural network, Bayesian network, support vector machine, Bayesian belief network, expectation maximization clustering, fractal correlation dimension, etc. The concept of feature selection is a subtopic in machine learning but is borrowed by sensor-related FDD studies for sensor selection. Since machine learning techniques are easy to implement but lack interpretability, future work should focus on improving interpretability by integrating domain knowledge into the machine learning modeling process. Data mining and data fusion techniques are also widely applied, where the PCA family (including PCA, independent component analysis, and self-adaptive PCA) is the most widely used due to its ability to generalize information from high dimensional datasets representing a large number of sensors. It is worth mentioning that for hardware topics like sensor calibration and sensor layout/location, no machine learning or data-driven techniques are found to be applied. The integration of hardware topics with data-driven tools is important because data-driven tools can benefit design of hardware in a quantitative way; however, this topic is rarely discussed.

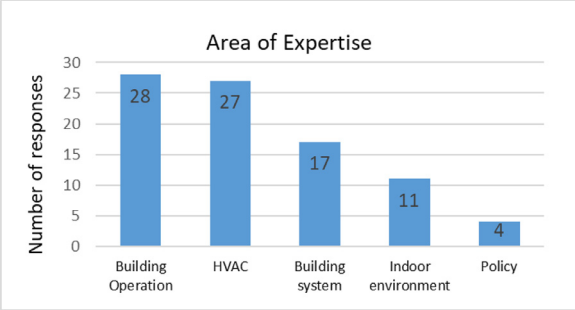

Fig. 3. Areas of expertise of interviewees.

5. Expert interviews

Expert interviews were designed and conducted to validate and compare with the findings of the literature review detailed in the previous sections. This section summarizes the interview results and findings. The interviews were performed to (1) investigate the current state and limitations of sensor configurations in FDD, and (2) identify the research gaps and potential for improvement in sensor configuration and deployment for FDD.

Thirty-one interviewees from industry, academia, and national labs participated in these interviews. We have invited 31 researchers from academia (6 individuals), industry (11 individuals), and national labs (14 individuals), who have expertise in building/HVAC sensors, system and building energy efficiency area. Most interviewees have at least 10 years of research and work experience in these fields. Fig. 3 shows the areas of expertise of the interviewees. It is worth mentioning that interviewees could choose multiple areas of expertise.

The significant factors identified by the interviews for selecting the sensor set are summarized in Fig. 4. Initial cost, reliability, and accuracy are considered much more important than other factors when selecting sensors for building FDD and control systems. 74% of interviewees identified "initial cost" as a key factor; we did not expect this because very few papers discuss the sensor cost topic in the literature.

The interviewees views on current issues in FDD sensor system design, deployment, and operation are shown in Fig. 5. The results indicate that reliability, initial cost, accuracy, and maintenance cost are the most significant issues for current sensor systems. 52% of interviewees think that current sensor systems are not reliable enough for FDD or control, which is in accordance with the findings of the literature review: many papers discuss sensor fault detection and calibration, in the context of improving sensor reliability.

The interviewees were also asked to select the sensor systems most important to building energy/thermal comfort performance and FDD. The results are summarized in Fig. 6. Thermal comfort sensors were identified as the most important sensor systems, followed by control sensors, indoor air quality sensors, and occupancy sensors. Occupancy-comfort-oriented sensors are noticeably less represented in literature than what the interviewees indicated.

Interviewees recommendations for improving sensor performance are shown in Fig. 7. The top 3 selections are (1) improve the current practice of sensor configuration/design, (2) install additional sensor sets, and (3) install advanced sensor system(s). The result is in accordance with the findings of the literature review.

In summary, we found that:

- Interviewees noted the importance of sensor reliability and sensor accuracy, which is in accordance with the findings of the literature review. Sensor fault detection and sensor calibration are widely studied topics because of the value placed on ensuring sensor reliability and accuracy.

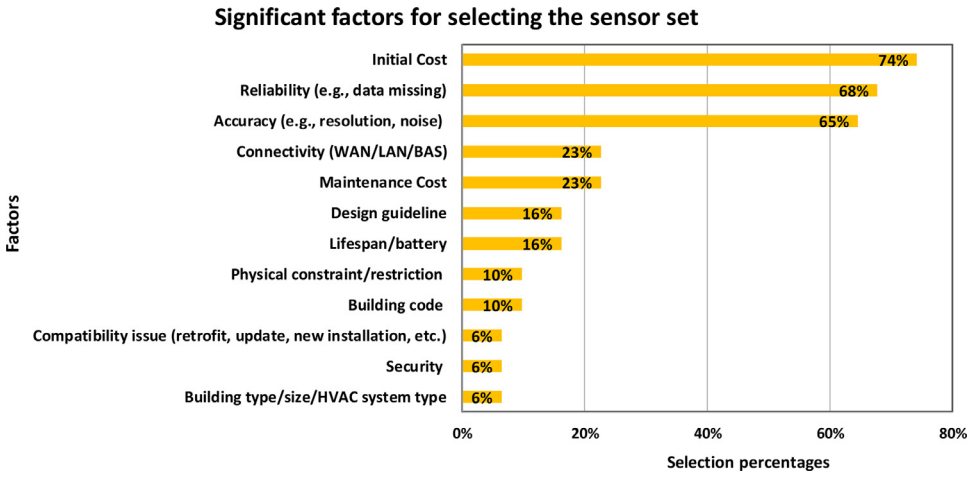

Fig. 4. Summary of significant factors for selecting the sensor set.

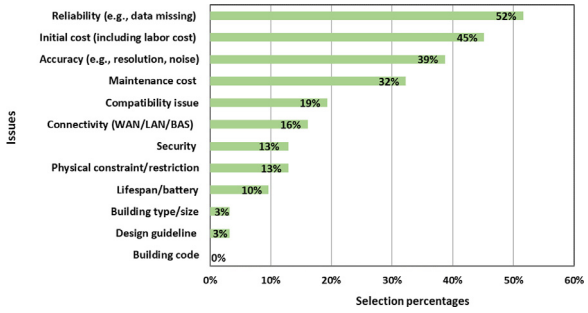

Fig. 5. Summary of current issues in sensor deployment.

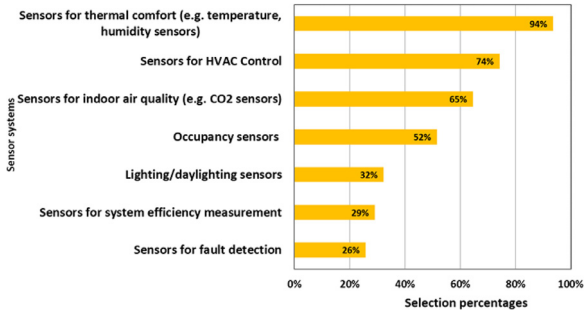

Fig. 6. Summary of important sensor systems with respect to building energy/thermal comfort performance and FDD.

- The importance of sensor cost (both initial and maintenance) was emphasized by the interviewees but is not well represented in the current literature. This indicates that sensor cost in FDD is a potential promising research topic.
- Interviewees care more about occupancy sensors and indoor air quality sensors than what the literature would indicate; occupancy-related sensors are not widely studied in the context of FDD. Future studies should focus more on the occupancy-related sensors.
- Interviewees and literature agree that sensor configuration, layout, and design in FDD are particularly important and should be improved for better FDD and building performance.
- The literature review identified many papers recommending that additional sensors can improve FDD performance; interviewees agree.

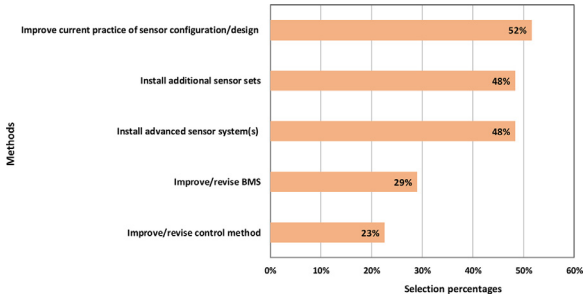

Fig. 7. Recommendations for improving sensor performance for building FDD and control.

6. Conclusions

This paper reviewed sensor-related topics in building FDD by categorizing FDD applications as building-level, system-level, or component-level (or equipment-level) applications and reviewing sensor related topics for each category. Key conclusions are as follows.

6.1. Major findings

Technical papers are reviewed according to FDD level.

Technical papers are reviewed according to three fault detection and diagnostics (FDD) levels: (a) building level, (b) system level, and (c) component level. Component-level FDD is the most covered; building-level FDD is the least covered. There are 7 papers (8%) at the building level, 29 (33%) at the system level, and 53 (59%) at the component level. For more detailed levels of FDD (with component level being the most detailed), sensor requirements increase, resulting in greater diversification of sensor topics.

Technical papers are reviewed by sensor topics.

Technical papers are also reviewed according to sensor topics: (a) sensor fault (33 papers, 37%), (b) feature selection from available sensors (14 papers, 16%), (c) additional and built-in/existing sensors (15 papers, 17%), (d) sensor data analysis/mining (11 papers, 12%), (e) virtual sensor (8 papers, 9%), (f) sensor calibration (6 papers, 16%), and (g) sensor layout/location (2 papers, 2%). Sensor fault and feature selection from available sensors are the most widely studied topics; sensor layout/location and sensor calibration are the least studied topics. A large number of papers study sensor faults, spanning all levels of FDD. Sensor faults have a significant impact on building energy efficiency and have been identified as an important fault type in existing FDD studies. Many papers discuss the feature selection problem in FDD modeling, particularly for component-level and system-level FDD. Feature selec-

tion studies typically focus on selecting the sensor set used for FDD from existing sensors to improve FDD performance rather than installing new sensors.

For building-level FDD, only (a) sensor calibration (b) sensor fault, and (c) sensor data analysis/mining are well studied. For system-level FDD, (a) sensor fault, (b) feature selection from available sensors, (c) additional and built-in/existing sensors, (d) sensor data analysis/mining, and (e) virtual sensor are mentioned or well-studied. For component-level FDD, all sensor topics are either mentioned or well-studied.

Current data-driven FDD research focuses more on FDD algorithms than sensors.

Data-driven (or history-based) FDD models account for 62% of FDD models from 197 research papers since 2004 [112]. The rapid development of machine learning techniques enables the development of data-driven FDD models with good performance and high reliability. Data-driven FDD models with sophisticated machine learning algorithms are hungrier for data. They require higher quantity and variety of data, and better support from a sensor design perspective is in great need. Many papers apply sophisticated machine learning algorithms but leverage only existing sensors common to building automation systems; they focus more on the algorithm than the sensors that provide data to the algorithm. There is a gap between fast-developing FDD algorithms and lack of support from a sensor design perspective.

Hardware research topics are carefully reviewed in this paper.

If sensor data analysis, virtual sensors, and feature selection on sensor data are the "software" research, then additional and built-in sensors, sensor calibration, and sensor layout are the "hardware" research. Hardware research is the foundation of software research: advanced data mining techniques and sophisticated FDD algorithm cannot work without a supporting sensor network with a well-designed sensor layout and accurate sensors. However, there are many more papers on the software side than on the hardware side: 61 papers (69%) on the software side compared to only 28 papers (31%) on the hardware side. Among the papers on the hardware side, there are 17 papers covering additional and built-in sensors, 7 papers covering sensor calibration, and 4 papers covering sensor layout/location. Despite this, hardware-related papers are carefully reviewed in this paper. The most widely studied hardware-related research topic is adding new sensors to current FDD applications. Researchers who employ additional sensors focus on identifying the most cost-effective sensors to provide additional information that can improve FDD performance. Despite the number of papers addressing this topic, the depth of discussion related to sensor calibration and sensor layout is lacking.

6.2. Potential research topics

Very few papers focus on sensor engineering as an integral aspect of FDD development.

Very few papers recognize sensor engineering as critical to FDD development. Most FDD research is based on existing sensor systems in buildings. Few papers are found to integrate sensor design with FDD in real applications, but some recent studies use simulation tools like EnergyPlus® and Modelica to simulate faults [113]. Because simulation tools have thousands of "virtual sensors," they can be used to decide which sensors are important for FDD and can inform sensor selection during design. We expect that tailoring sensor design and configuration to FDD algorithms can provide substantial improvement in FDD performance.

Some important sensor topics are not well studied.

Sensor noise is an important concern in FDD, but we only found only two papers that discuss it. Sensor cost-effectiveness is a key factor during sensor design, but few FDD papers address the topic. Sensor schema/layout/location is also important during sensor design (to improve sensor accuracy and efficiency), but only two papers are found to discuss this topic, and neither does so in depth.

A systematic sensor framework for FDD modeling is needed.

Although many sensor topics are covered in the existing literature, a systematic framework or workflow that integrates sensor design, sensor data analysis, sensor selection, physics-based or data-driven algorithms, sensor fault detection, sensor calibration, and sensor maintenance is lacking. A framework should (a) consider the cost-effectiveness of sensor design as it related to a particular FDD application, (b) maximize FDD performance based on an optimized sensor set determined via data analysis techniques, virtual sensors, and other data-driven techniques, and (c) enable sensor performance to be sustained via sensor fault detection and sensor calibration. Such a framework will enable sensor design to be appropriately captured during the development of FDD tools, and vice versa, resulting in better FDD performance.

Declaration of Competing Interest

None.

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