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Literature Review for Sensor Impact Evaluation and Verification Use Cases - Building Controls and Fault Detection and Diagnosis (FDD)

Piljae Im
Yeonjin Bae
Borui Cui
Seungjae Lee
Saptarshi Bhattacharya
Veronica Adetola
Draguna Vrabie
Liang Zhang
Matt Leach

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OAK RIDGE NATIONAL LABORATORY
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Energy and Transportation Science Division

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Prepared by
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Oak Ridge, TN 37831-6283
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TABLE OF CONTENTS

1. INTRODUCTION 1
2. LITERATURE REVIEW ON BUILDING CONTROL USE CASES 2
   - 2.1 THERMOSTATS 2
     - 2.1.1 Introduction 2
     - 2.1.2 Existing Technologies 2
     - 2.1.3 Impact and Benefit of Thermostat/Subzoning VAV Systems 3
     - 2.1.4 Future Research Opportunities 4
   - 2.2 OCCUPANCY SENSORS 4
     - 2.2.1 Occupancy Information in Building Control 4
     - 2.2.2 Existing Sensing and Estimation Technologies 5
     - 2.2.3 Control Strategies 6
     - 2.2.4 Future Research Opportunities 7
   - 2.3 ADVANCED BUILDING CONTROL 7
     - 2.3.1 Advanced Control 8
     - 2.3.2 Sensors for Advanced Building Control 9
     - 2.3.3 Impact of Sensing Accuracy on the Performance of Advanced Control Algorithms 11
     - 2.3.4 Concluding Remarks and Research Gaps 11
3. LITERATURE REVIEW ON FDD USE CASES 12
   - 3.1 INTRODUCTION 12
   - 3.2 SUMMARY OF REVIEW PAPERS 12
   - 3.3 REVIEW OF TECHNICAL PAPERS 14
     - 3.3.1 Review of Sensor Topics in Building-Level FDD 14
     - 3.3.2 Review of Sensor Topics in System-Level FDD 16
     - 3.3.3 Review of Sensor Topics in Component-Level FDD 21
   - 3.4 CONCLUSIONS OF SENSOR TOPICS IN FDD USE CASES 28

REFERENCES 30

1. INTRODUCTION

This report summarizes a comprehensive literature review for the selected sensor suites used in building controls and fault detection and diagnostics (FDD), which is a Q2 deliverable of the Sensor Impact Evaluation and Verification project. The project's overarching goal is to develop a framework for investigating the impact of sensor deployment and configuration for building energy optimization, fault detection and diagnosis (FDD), occupants' thermal comfort, and potential grid efficiency. The proposed project flow is shown in Figure 1. While the first phase of the literature review performed in Q1 reviewed the current methods of various sensor selection and placements and their impact, this report focuses on high impactful potential use cases for the selected sensor suites in building control and FDD. The use cases identified in this literature review will be further investigated and be included in the final sensor impact evaluation framework.

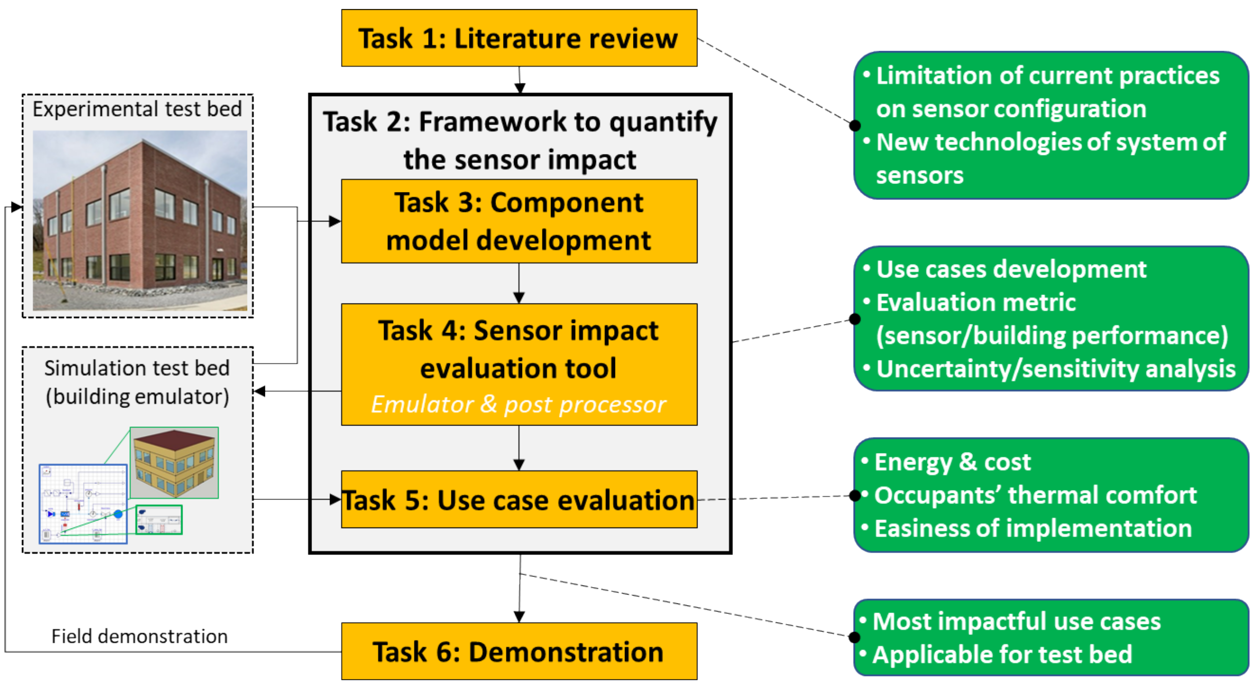

Figure 1. Schematic flow of the project.

For the review, the multi-laboratory team reviewed 241 research papers, technical reports, and books to identify existing technologies, the potential impact on energy savings and thermal comfort, and future research opportunities for the selected use cases in building controls and FDD. Along with the literature review, the team conducted a series of interviews with experts in sensors and controls area to identify the state-of-art sensor technologies, and the most impactful use cases in controls and FDD areas. The interview results will also be incorporated with the findings from the literature review in the next quarter, and the final use cases to be evaluated will be selected.

2. LITERATURE REVIEW ON BUILDING CONTROL USE CASES

In this chapter, three use cases for building controls are reviewed, which are thermostat, occupancy sensors, and advanced controls. These three use cases were selected based on the findings from the prior literature review in Q1 as they have high potential in energy savings and enhanced thermal comfort.

2.1 THERMOSTATS

2.1.1 Introduction

The commonly used parameter to control indoor thermal environment is the air temperature, which is controlled by a thermostat installed in each zone. The location of the thermostat is a significant factor that affects building energy usage and occupants' thermal comfort. However, existing standard code (i.e., ASRHAE standard 55 [1]) does not provide a practical solution for thermostat location, and the current practice of thermostat location is not necessarily optimal in terms of energy efficiency and thermal comfort.

In a typical building, a thermostat is installed in each zone and controls the room temperature, or a central thermostat controls the conditions of several zones based on average air temperature or representative zone air temperature [2]. Previous simulation and experimental studies [2–6] show that the temperature profile along the vertical direction at different locations is nonuniform and stratified in vertical direction, and is different under various conditions (e.g., supply airflow rate, geometry of zone, climate region, seasonal variation). Because of the temperature distribution profile, thermostat location will significantly impact energy efficiency and thermal comfort. One thermostat may not be sufficient for some cases and one thermostat for multiple zones can lead to significant occupant discomfort depending on zoning; therefore, subzonal strategies need to be investigated comprehensively.

Thermal comfort is a subjective concept to evaluate occupants' thermal satisfaction. Most existing standards (i.e., ASHRAE standard 55, ISO Standard 7730 [7], European standard EN 15251 [8]) adopted the predicted mean vote (PMV) model. ASHRAE Standard 55 provides acceptable operative temperature ranges predicted by the PMV model, acceptable floor surface temperature, and maximum allowable temperature difference between the head and ankle levels. European standard EN 15251 provides long-term evaluation criteria on limiting uncomfortable working hours every year [2,5]. The PMV model requires environmental parameters such as dry-bulb temperature, radiant temperature, humidity, air speed, and metabolic rate. Previous studies [2,4,5] show that occupants' thermal comfort varies significantly for different thermostat location because of the temperature distribution profile. Additionally, humidity or air speed is usually not measured in practice [9]; therefore, actual occupants' thermal comfort may differ from predictions based on the model.

2.1.2 Existing Technologies

2.1.2.1 Computational methods for thermostat location

Sensor locations and the number of sensors are generally selected based on engineering judgment or heuristic methods [10]. Previous research studies have provided multiple methods of optimal selections of thermostat location.

- Optimization method of algorithm

Yoganathan et al. [11] proposed a data-driven method, including clustering algorithm and Pareto principle, to select the optimal sensor measurement points in an office building. They found that the optimal spatial location of temperature and humidity sensors could vary with time. Aiming to reduce the number of required sensors, a method developing virtual sensors through combining the prior knowledge of temperature statistics and Bayesian model fusion to predict spatial temperature distribution by maximum-a-posteriori estimation was proposed [12]. GenOpt, which is an open-source program, was used as the optimization engine, and particle swarm optimization was selected as the optimization scheme to determine the thermostat location that leads to best thermal comfort [13].

- Simulation/design tools

Many studies used computational fluid dynamics (CFD) modeling or CFD/Modelica coupling. For maximizing indoor thermal comfort, an optimization platform using the coupled models of a grid fast fluid dynamics model for indoor airflow and Modelica models for the heating, ventilation, and air-conditioning (HVAC) system were proposed [13]. A reduced-order coupled CFD model was developed to simulate the dynamics of indoor environments and building envelopes [14]. An optimal location selection method was developed and applied to a large-scale room in Hong Kong [15]. The CFD-aided method in this research can help wireless temperature sensors find the optimal location to improve the accuracy of real-time generated temperature distributions. EnergyPlus was used to generate 50 testing samples of indoor temperature profiles in research from Chen and Li [12]. The sensor noise was modeled by a Gaussian distribution with a mean of zero and a standard deviation of 0.3°. Eventually, the measured temperature of a location with a sensor was assumed to be equal to the results generated by EnergyPlus and a randomly generated Gaussian noise. A simple coupling strategy—through a co-simulation method between the energy simulation of TRNSYS and thermal comfort analysis of CFD—for building energy was developed for a real HVAC system [4]. This strategy can assist the variable air volume (VAV) optimal control through simultaneously optimizing the energy consumption and thermal comfort.

HAMBase, a stand-alone software, was proposed to optimize the sensors' placement in large sport spaces [16]. A dedicated measurement performance index was calculated to determine the optimal sensors' location that provides the maximum accuracy with the minimum number of sensors to be deployed. The validation of the tool in a real indoor swimming pool showed that a maximum deviation of 4°C was found during the HVAC operation period.

2.1.2.2 Localized temperature sensing

Several previous studies [17–20] have investigated localized temperature sensing methodology. Multiple sensors such as wireless sensors have been used instead of one sensor, or existing sensor data has been used to control the indoor environment. By using a wireless sensor network (WSN), commercial building energy usage could be saved up to 40% [21]. State-of-the-art sensing technology such as an automated mobile sensing system using a sensor-rich navigation-capable robot [22] has been used to monitor indoor environment. However, despite the development of cost-effective sensors and simplification of deployment, simultaneous monitoring of numerous variables, data management, power consumption of wireless sensors, and maintenance issues still remain as challenges [22].

2.1.3 Impact and Benefit of Thermostat

The optimization of thermostat locations could reduce building energy consumption and peak demand. Liu et al. [23] suggested a method for optimizing sensor placement to reduce HVAC energy consumption. The space dimensions and sensor specifications, types, and locations were used as the inputs for optimization. Through integrating building energy simulation (BES) with CFD, the indoor temperature sensor placement in a real building in Shanghai was optimized while considering the energy consumption and PMV simultaneously [4]. The study also shows placing a temperature sensor for the VAV control loop at the return air inlet is not always the optimal solution. During the cooling season, the required airflow increases when the sensor is placed at the return air duct [24] since the temperature in the return duct is usually higher than the zone temperature, which can lead to overcooling.

Indoor environmental quality (IEQ) is a critical aspect of the built environment to ensure occupant health, comfort, well-being, and productivity. Existing IEQ monitoring approaches rely on sensor networks deployed at selected locations to collect environmental measurement. Optimal placement of thermostats could significantly improve occupants' comfort but could result in additional energy usage and initial cost.

Small- to moderate-sized commercial buildings commonly use rooftop units (RTUs) to provide indoor comfort. Such applications are often characterized by significant spatial variations in comfort due to poor thermostat placement and poor coordination of RTUs, leading to high energy and demand costs. A computationally efficient coupled indoor air and envelope modeling approach was proposed to assess the control algorithms used for such cases [14]. A reduced-order coupled CFD model was developed and applied to predict RTU return air temperature responses in comparison with measurements in a real restaurant.

An optimization platform can successfully seek the optimal placement of the thermostats in an office room [3] with displacement ventilation and a VAV terminal box. Either the best thermal comfort or the least energy consumption could be achieved by taking the particle swarm optimization algorithm as the optimization engine. The total time cost of the optimizations in the demonstration was about 6 h.

2.1.4 Future Research Opportunities

The literature review and future research opportunity on optimal thermostat location can be summarized as follows. First, model-based optimization needs to be performed using coupled simulation (BES and CFD) to find a good location for the thermostat. Without the spatial temperature distribution, optimizing the energy saving and thermal comfort comprehensively is difficult. Although tools such as CFD can capture spatial and temporal variations of flow and thermal properties for specified boundary conditions, they are not generally appropriate to use directly because of the required high computational demand of CFD [14]. Another drawback of CFD is that the models cannot immediately separate the (partial) differential equations that hold a volume from the boundary conditions. The creation of modular models is thus a complex task, in some cases unavoidably leading to quite cumbersome software implementation [16]. Although simplified models need less requirements compared with the CFD models, they are mostly developed for small rooms with specific domains of application, making them limited in large space cases [16]. Furthermore, by adding a WSN in the building, various temperature sampling information representing the different indoor positions can be used for spatial distribution of PMV and can enable more flexible and robust VAV control strategies. However, deployment of a WSN is a challenging task because there are many constraints that can influence the building performance. Finally, many research studies and applications of optimal thermostat location have been applied in the building and HVAC system successfully. However, a need exists for a practical and cost-effective tool/framework/guideline. The developed methodology can be used for new building design, monitoring, and commissioning purposes, and building retrofit design.

2.2 OCCUPANCY SENSORS

2.2.1 Occupancy Information in Building Control

Conventional building HVAC and lighting systems have been designed and operated based on conservative and fixed operating schedules assuming maximum occupancy in spaces. Because of the spatiotemporal mismatch between the conservative schedules and the actual building usage, the conventional building systems have wasted energy. Previous studies have claimed that a significant potential exists for the improvement of building energy efficiency without compromising occupants' comfort by adopting occupancy-based control (i.e., deploying energy where demand actually exists) [25–29].

In terms of lighting systems, because of their instantaneous system response, the development and implementation of occupancy-based control have been relatively straightforward. As a result, various building standards and green building rating programs have requested or recommended occupancy-based lighting control [30]. Literature has reported that the energy-saving potential of using occupancy information ranges from 20 to 75% [31–34]. However, limited performances of existing occupancy sensing technologies occasionally cause false on/off switches of lighting systems; consequently, occupants' dissatisfaction and energy-waste have been reported [34]. Additionally, control strategies for open-plan offices need further investigations [35].

Following the successful implementation and demonstration of occupancy-based lighting control, efforts have been made to use the occupancy information in HVAC control. However, because of the slow system response of HVAC systems, predictive strategies are often required to ensure occupants' comfort and minimize energy consumption [36], which makes the development of practical and scalable occupancy-based HVAC control somewhat obscure compared with occupancy-based lighting control. Moreover, the limited granularity of HVAC systems restricts the energy-savings potential of occupancy-based HVAC control. In previous literature, the energy-savings potentials vary from 5 to 60% [26,27,37,38].

2.2.2 Existing Sensing and Estimation Technologies

Supported by the high energy-savings potential of occupancy-based building control, occupancy sensing and estimation methods have drawn considerable attention in the building control domain. In previous studies, the methods have been categorized based on the level of information they can provide, such as presence (detection), the number of occupants, identity, and location (tracking) [30,39–44]. Occupant presence can be used to turn on/off lighting and HVAC systems. Also, setpoint temperatures can be adjusted by this information. The number of occupants can be used to adjust ventilation. Additionally, this information can be used to estimate/predict various building loads, which are necessary for the optimal control of HVAC systems [45]. Finally, occupant identity and location could be used to provide personalized/customized indoor environments to occupants to maximize their satisfaction while optimizing energy efficiency [46].

The occupancy sensing and estimation methods can also be categorized with sensors or measures used. Motion sensors—such as passive infrared (PIR), ultrasonic, and microwave sensors—have been widely employed because of their low cost and power consumption, small form factor, and the fact that they are nonintrusive and privacy-preserving [26,36,47–53]. Especially, PIR sensors are popular for real applications as they are robust to interference caused by environmental variances [54]. However, using motion sensors solely has major limitations [34,40,55]:

- Motion sensors can only provide the occupant presence/absence information (i.e., more detailed information such as the number of occupants, identity, and location is normally unavailable).

- Motion sensors require detectable movements (motion). If there is no movement, usually a 15–30-min delay is applied before switching over from the presence state (occupied) to the absence state (unoccupied). This delay can cause energy waste.

- Motion sensors can be triggered by other objects such as hot coffee/tea, appliances, or pets.

- PIR sensors require a direct line of sight between the sensor and occupants in a space.

Variation in ambient conditions (e.g., air temperature, humidity, CO2, acoustic, and light) can be used to infer occupancy information [28,47,48,50–52,56–59]. One advantage of methods based on the variation in ambient conditions over the motion sensors is that the number of occupants can be inferred. Since methods in this category rely on the fact that ambient conditions are likely to change with the number of occupants in the space (i.e., correlation), differential equations or statistical/optimization-based mapping methods (e.g., regression, machine learning algorithms) are exploited for the relationship. Therefore, additional costs could be required to adjust/tune the equations or methods for different spaces and buildings (i.e., transferability) [42]. Methods using the variation in CO2 concentration are most common in this category [53,60]. However, the slow gas mixture in buildings limits the estimation performance of a method that relies only on the CO2 concentration [48].

Vision-based methods have gained attention in recent years following the rapid development of sensing, computing, and computer vision technologies. In these methods, visual data from RGB/thermal imaging cameras or depth-map devices are used in conjunction with computer vision and machine learning algorithms [61–63], which can track multiple occupants. However, despite their high estimation performance and capability of providing high-dimensional information, their application is limited because of their definite drawbacks [64,65]:

- They are sensitive to ambient illumination.
- They require relatively expensive hardware for computation and communication due to high-dimensional data.
- They introduce privacy concerns.

Finally, occupants' interaction with furniture (e.g., chairs, doors) [39,57,66], appliances (e.g., computers) [40,67], or communication networks (Wi-Fi, Bluetooth) [58,68,69] or corresponding plug loads [70,71] can be used to estimate occupancy information. The collection of the above data requires no or minimal sensors or devices; estimation based on them could be promising for real-world applications. However, as in the case of methods based on the variation in ambient conditions, they require inference methods (e.g., rule-based, statistical modeling). Therefore, their transferability should be examined and improved to reduce the additional engineering cost, and consequently, improve their feasibility [42].

As briefly introduced, different sensors and estimation methods have their own characteristics, advantages, and disadvantages. Therefore, the use of multiple sensors and methods together, a.k.a., sensor fusion, have been investigated to take each method's advantages and compensate disadvantages [42]. Wang et al. [72] developed an estimation method with five different sensors/measures: CO2, humidity, PIR, RFID, and Wi-Fi, to improve the estimation performance. Tyndall et al. [49] used a PIR sensor and an IR camera together to reduce the electricity consumption of the sensing module.

2.2.3 Control Strategies

There are two different approaches in occupancy-based control: reactive and proactive/predictive. In the reactive approach, the controller operates building systems with real-time occupancy information. Since reactive control algorithms do not require heavy computation to provide control signals, they are preferred if reactive operations are sufficient to ensure system performance. In this context, most occupancy-based lighting systems adopt the reactive approach. However, in the case of occupancy-based HVAC control, the reactive approach cannot maximize the energy-savings potential because of the slow system response and limited granularity of HVAC systems. For example, activation of HVAC systems cannot be based on real-time occupancy information since it will cause occupants' thermal discomfort at the beginning of office hours [45]. Nevertheless, some studies have shown that even conservative reactive HVAC operations can save a notable amount of energy [25,73].

To maximize the energy-savings potential while ensuring occupants' comfort, proactive/predictive control algorithms have been investigated. In the proactive/predictive approach, the controller operates building systems with expected/predicted future occupancy states. More specifically, historical occupancy information (measured/estimated) is often used to develop an occupancy pattern heuristically or with automated methods (statistical/optimization-based); subsequently, the controller uses the pattern to improve the performance. Here, the goodness of the newly added step, pattern recognition, also significantly influences the overall control performance. For example, Erickson et al. [62] and Gunay et al. [74] saved HVAC energy consumption by 42% and 10–15%, respectively, using occupancy prediction models trained with motion sensor data. More recently, efforts have been made to use modern optimal control techniques (e.g., model predictive control [MPC]) to maximize performance. These efforts will be introduced and discussed in Section 2.3 in more detail.

As mentioned in Section 2.2.1, the energy-savings potential significantly varies in previous studies (20–75% for lighting systems, 5–60% for HVAC systems) because of the variation in the weather conditions, building characteristics, lighting/HVAC system configurations, occupancy patterns, and the way researchers define their baseline. In [30,45], the authors also discussed the difficulty in comparing the reported energy-savings potentials. Additionally, since occupancy-based control consists of multiple components (sensing/estimation, pattern recognition/learning, control logic/algorithm), how the superiority/imperfection of each component contributes to the overall performance is difficult to disentangle from the reported energy-saving potentials.

2.2.4 Future Research Opportunities

Toward effective and efficient occupancy-based building system control, previous literature has emphasized the necessity of good sensing and estimation methods. Continuous efforts are expected to improve sensing and estimation methods per this demand for them. To define the goodness, the level of information each method can provide, accuracy, cost efficiency, privacy efficiency and security, ease of maintenance, reliability, and the level of intrusiveness have been discussed [30,42,43,45,75]. However, among the available sensing and estimation methods, the optimal method and corresponding sensors for a specific building or space are not obvious. The reasons are (a) the expected performance of different control strategies change with various conditions (e.g., weather, building characteristics, and so on), and (b) different control strategies have different requirements for the sensing/estimation method. Additionally, the importance of different characteristics (e.g., accuracy, cost, privacy) vary by project, so the decision-making is even more difficult. Therefore, a methodology for optimal selection of a sensing/estimation method and a corresponding set of sensors (preferably with automated location optimization) would be required to promote occupancy-based building control.

2.3 ADVANCED BUILDING CONTROL

Control and automation are essential cogs in the wheel of smarter energy systems [76]. From buildings perspective, this entails a widespread use of monitoring, sensing, and instrumentation technologies. Sensing and control technologies within the buildings domain could have several market applications and potential R&D pathways [77]. A relatively recent study also validates this and provides a detailed insight into the state-of-the-art in building energy sensing and environmental monitoring, along with their socio-economic and legislative drivers [78]. The sensors are used to monitor essential parameters and variables, both inside and outside the building, that are key for operating buildings in an efficient manner. The purpose of building automation systems can include intra-building conditioning of comfort and energy usage, and enabling the buildings to actively participate as a resource under the smart grid framework.

This section describes the application of building sensing technologies for enabling (a) intra-building energy efficiency and thermal comfort, and (b) buildings to actively participate, as flexible energy resources within a smart grid framework. The literature review covers both traditional and emerging sensors for advanced building control. The impact of sensing accuracy on advanced control algorithms are discussed and future research opportunities are identified.

2.3.1 Advanced Control

Advanced control strategies have the potential to outperform classic feedback control such as PID (proportional-integral-derivative) control and rule-based or heuristic controls. For example, MPC has been shown in several simulation studies and real-world demonstrations to achieve significant improvement in thermal comfort while reducing building energy consumption by at least 15% [79–81]. The strength of the advanced control techniques lies in their prediction, optimization, and adaptation capabilities. These controllers systematically adjust the building operational setpoints (such as fresh air ventilation rate, cooling and heating setpoints) in a way that optimizes operational objectives (e.g., energy consumption, cost or peak demand reduction, thermal comfort). Adaptive, robust, and stochastic variants of advanced building controls also exist to address building uncertainties, including seasonal variations driven by weather, daily variation driven by occupancy, and equipment aging and degradation. Advancements in artificial intelligence are being used to enhance controller scalability and deploy-ability [82,83].

2.3.1.1 Optimization-based control for thermal comfort and energy efficiency

Several researchers have addressed the question of co-optimizing thermal comfort among occupants and energy consumption of building HVAC equipment through advanced control algorithms. For example, decentralized consensus-based algorithms (in which the occupant feedback is obtained through wearable sensors or interactive mobile applications) and singular perturbation methods (again, with active occupant feedback) have been proposed to attain this objective [84,85]. The importance of including humans in the automation process by their feedback was also highlighted in a study by Jung and Jazizadeh [30]. Model-based, predictive controllers [86,87] have also been proposed to solve the same problem of comfort-energy co-optimization. A key observation is that for achieving the aforementioned co-optimization objective, sensing and monitoring capabilities are important to understanding user comfort and energy usage in high spatiotemporal granularity [88]. In that context, researchers have stressed the need for a carefully selected subset of sensors to achieve accurate thermal modeling while economizing on infrastructure costs [89]. Recently, artificial intelligence–based techniques are being investigated as a potential means to reduce the need for dense and costly sensor infrastructure that may be needed for accurate prediction of thermal comfort [90]. Research from Kumar et al. [91] and Dong et al. [20] provide a more in-depth review of indoor air quality (IAQ) and energy sensing.

2.3.1.2 Controls for building-to-grid interaction

Control methods and algorithms for enabling building-based grid services have been studied from different perspectives. A relatively early investigation into the effectiveness of using buildings for demand response applications such as peak shaving can be found in research by Kiliccote et al. [92]. More recent efforts are exploiting building thermal flexibility in coordination with other distributed energy resources and energy storage to support grid-level objectives through advanced predictive control techniques [93,94]. The use of buildings as resources for high-quality fast ancillary services has also recently received significant attention. Hardware-in-the-loop algorithms and real building demonstrations have validated the capability of building ventilation systems to offer grid services at fast time scales [95–98]. Optimization-based building-to-grid frameworks have been proposed to optimize zone-level temperature setpoints and power generator setpoints to provide frequency regulation services while maintaining the quality of service bounds [99,100]. The use of a cohort of flexible devices, which includes responsive buildings, can also be leveraged to minimize grid voltage and frequency deviations and simultaneously alleviate harmonic distortions, as shown by Hong et al. [101]. The role of responsive buildings can also be of prime importance in defining new tariffs, energy-pricing structures, and contractual/transactive energy-usage schemes [102,103]. From a software perspective, intricate open-source platforms that use modern technologies such as cloud services have been devised to enable buildings to interact with the grid more effectively [104]. Research from Kosek et al. [105] and Kolokotsa [106] provide a more in-depth understanding of the role of responsive buildings in smart grids.

2.3.2 Sensors for Advanced Building Control

2.3.2.1 Environmental monitoring and occupancy sensors

Environmental monitoring sensors, used to monitor both internal and external conditions of the building, are valuable for advanced building controls. These sensors comprise temperature sensors, relative humidity sensors, pressure sensors, illuminance sensors, daylight sensors, and air quality sensors [78]. Such sensors are widely used in centralized or distributed predictive control schemes for building energy applications and demand response [46,84,86,87,92,107–109].

Occupancy sensors have proven energy and thermal comfort benefits in buildings [110]. These sensors are either used to detect the presence or quantify the number of occupants in a given space. More details on indoor occupancy sensing technologies are provided by Chen et al. [42]. In addition to providing real-time feedback for building management, historical occupancy sensor data can be used to develop accurate occupancy forecast models for advanced predictive control algorithms. Typically, occupancy sensors work in tandem with the temperature and airflow sensors in the HVAC system to control the cooling or heating energy delivered and amount of fresh air brought into the building based on the occupancy status. In research by Sandels et al. [111], occupancy sensor data was used to develop Hidden Markov Models that simulate end-user behavior, which was further used to devise demand response strategies.

Environmental monitoring and occupancy sensors remain the backbone of many state-of-the-art building energy management algorithms, which is validated by an extensive review of the field implementations of occupancy-based advanced building controls [110,112]. In a recent study, a 12-story residential building in Denmark was instrumented by more than 3,400 sensors to measure 19 different environmental parameters per apartment, including indoor conditions (temperature, humidity, and so on), domestic hot water usage, and district heating energy usage [113]. An important aspect of using extensive sensing infrastructures is the cost implications of the overall sensing and automation system [114]. The cost efficiency of sensing systems may be improved by using them for multiple building objectives. For example, occupancy sensors can be integrated into both HVAC energy management and lighting control systems [57,115–118].

2.3.2.2 HVAC sensors

Building HVAC systems range from packaged units to built-up systems, and they vary in designs. Some of the commonly used equipment or components are chillers, boilers, heat pumps, fans, pumps, valves, heat exchangers, filters, dampers, diffusers, ducts, and pipes. The equipment must be properly instrumented to maintain a stable and effective plant operation. Some HVAC equipment have built-in sensors and controls. Accessing the built-in monitoring points is cost-effective, when possible, to avoid the cost of installing redundant sensors for system-level control optimization. Sensors used in HVAC systems include temperature sensors (e.g., outside air temperature, chilled water temperature, supply air temperature), humidity sensors (indoor and outdoor), flow sensors (e.g., chilled water flow rate, supply airflow rate), pressure sensors (e.g., chiller water pressure, duct static pressure), and gas flow sensors (e.g., for absorption chillers or boilers). A detailed review of sensor types and required accuracy for typical chiller plant control can be found in Chilled water plant design guide [119]. HVAC equipment are often equipped with electrical meters but additional sensors such as BTU meters may be needed to establish baseline energy consumption and to verify the improved performance enabled by advanced control methods [120].

2.3.2.3 Emerging sensors

With the advent of information and communication technologies, researchers are now looking at the prospect of connected communities in which not only responsive assets are controlled in an asynchronous and decentralized manner within buildings, but buildings themselves can form collaborative, complex networks with city level objectives. A critical component for such paradigms is smart internet-of-things (IoT) sensors, which have widespread applications in advanced building controls of the future. A comprehensive primer for considerations, requirements, and architectures for the next generation of IoT based building energy management systems (BEMSs) can be found in research from Minoli et al. [121] and Khajenasiri et al. [122]. Such IoT-based building energy management sensors could find applications in demand-controlled ventilators, energy recovery ventilators, dedicated outdoor air systems, CO2 sensors, ultraviolet germicidal irradiation, displacement ventilation, and underfloor air distribution [121]. To add a layer of flexibility in operations by enabling mobile controllability, GPS service–based remote sensing capabilities would also be ubiquitous in future building energy control schemes [123]. IoT sensors are also being conjugated with advanced control methodologies for building energy management, whereby appreciable (30–40%) savings are projected, both in terms of cost of energy usage and peak demand power [124]. Specifically, in research from Tran et al. [124], IoT sensors are connected to lighting, plug loads, and HVAC systems to seamlessly transfer data to the cloud, which performs the scheduling optimization. Also, the question of optimal placement of sensors to have maximal sensing and observability using minimum infrastructure for building energy management in an IoT framework has recently been considered [125].

2.3.2.4 Power metering

Building-level power sensing for electricity is prevalent in commercial buildings. Sub-metering at the equipment or device level can provide better insight into the factors involved in energy consumption. Energy or power metering helps to identify energy efficiency opportunities and explore control methods for lowering energy demand or cost. Power measurement data is needed to learn or validate the power consumption model employed in predictive control strategies. Metering data are also used to provide direct feedback in advanced control. For example, model-free techniques (e.g., extremum seeking control) can systematically find control inputs that drive the building operation in a direction that minimizes a measured objective function, which is power consumption in this case [126,127].

Advancements in two-way communication and power metering (e.g., one-way automatic meter reading and bidirectional smart meters) are enabling an autonomous response of building automation systems and other connected devices to dynamic electricity prices and/or other grid signals. Power measurement feedback is also valuable for grid-responsive control strategies. These include frequency regulation [97,98] and ramping control [128] that need to track a given power consumption signal, dictated by a grid operator or distributed energy resource aggregator. This increasing use of automation, communications, and smart meters is also improving the precision of demand response dispatch and accuracy of measurement and verification.

2.3.2.5 Virtual sensors

As mentioned in Section 2.3.1.1, using a dense and intricate sensing infrastructure might prove to be costly and pose multiple challenges in terms of installation and maintenance. To circumvent these issues, virtual sensing through detection, estimation, and learning techniques become very important in advanced building control design [129]. In particular, MPC depends on a forecast model of the building thermal behavior. These models, which can be physics-based, data-driven, or hybrid, are calibrated with or learned from the real building sensor data. Estimation techniques are typically employed to deduce inputs and physical parameters that are otherwise difficult to sense directly (e.g., internal loads, wall temperature) [130]. Model-based virtual sensors are widely used in advanced controls. Examples include virtual occupancy sensors and virtual thermal energy metering as a function of mass air (or water) flow rate and inlet and discharge temperatures. Using existing sensor information to estimate unknown parameters or variables without additional physical installations also has applications in modern data-driven frameworks for building energy management [131]. Nonintrusive load monitoring processes for disaggregating a power signal (e.g., smart meter data) to building end-uses are also being researched as lower-cost alternatives to sub-metering [132].

2.3.3 Impact of Sensing Accuracy on the Performance of Advanced Control Algorithms

The temperatures of the air in rooms as well as air-conditioning ducts are measured in typical buildings, but these measurements may be inaccurate or noisy. Also, some sophisticated advanced control strategies require measurements or estimation of the slow dynamic states (e.g., temperatures of the walls, ceiling, and floor) and heat gains. Temperature sensing accuracy most likely impacts the performance of advanced HVAC control algorithms, but the effect has not yet been fully explored or quantified. Research from Maasoumy et al. [133] evaluated the impact of sensor noise on the performance of three control algorithms—on-off, linear MPC, and robust linear MPC—coupled with state estimation methods and provided a co-exploration framework for selecting the most cost-effective sensing platform and control algorithm that minimizes the building energy cost and occupants' discomfort. The sensing accuracy was inferred from the number and locations of temperature sensors, and Kalman filtering techniques were used to estimate the states of the building model from measurements. The evaluation of the performance of the estimator-controller combination, over a range of temperature measurement noise amplitude, showed that the advanced control methods outperformed the on-off controller in terms of energy cost and discomfort level even when affected by sensor noise. However, no clear superior was observed among the implemented advanced control variants (standard and robust MPC) because the results depended on the structure and trade-offs defined in their optimization objectives. The optimal solution also depends on the design requirements (e.g., acceptable discomfort levels) and the sensor monetary budget that drives the number of sensors and the accuracy of the sensor measurements. The impact of combined sensor error and inaccurate building models poses a great challenge to optimal performance of advanced control solutions [134,135]. A simple rule-based or classic controller could outperform advanced control if the model uncertainty exceeds a certain threshold [134].

2.3.4 Concluding Remarks and Research Gaps

The few available results on sensor impact analysis focus on sensor accuracy. The impact of communication reliability on the control algorithm must also be considered. For cost-effectiveness, the optimal sensing system (selection and configuration) will need to simultaneously optimize for multiple objectives. Example success metrics include building occupants' comfort, energy consumption, flexibility or cost, and fault detectability and diagnosis. A flexible framework and algorithms with prioritization capability will allow trade-offs between the sensing system total cost and the performance objectives. The methodology will account for modeling uncertainties, correlation between sensors, and higher-order interaction effects that may amplify or offset the importance of sensors.

3. LITERATURE REVIEW ON FDD USE CASES

3.1 INTRODUCTION

According to the inspection scope and examination details in a building, use cases of FDD can be categorized into three levels: building-level, system-level, and component-level [136]:

(a) Building-level FDD typically addresses the overall performance of a building and does not require the information of building operation.

(b) System-level FDD focuses on the faults of HVAC as a whole system, such as a VAV system, variable refrigerant flow (VRF) system, RTU system, and so on.

(c) Component-level (or equipment-level) FDD targets the operation of HVAC components such as chiller, air-handling unit (AHU), boiler, fan coil unit (FCU), VAV terminal, room/zone level system, and so on.

In this section, senor topics are reviewed at each level of use cases, and the sensor topics include

(a) Sensor faults: detect sensor fault including bias, drifting, precision degradation, and complete failure

(b) Feature selection from available sensors: apply machine learning or information science to extract, generate, and select features (inputs) from available sensor data for data-driven FDD models

(c) Additional and built-in/existing sensors: discuss whether the sensors used for FDD include additional sensors or only use built-in/existing sensors

(d) Sensor data analysis/mining: apply data-driven techniques to extract information from sensor data to improve FDD performance

(e) Virtual sensor: apply virtual sensor techniques that provide feasible and economical alternatives to costly or impractical physical sensors to improve FDD models or reduce cost

(f) Sensor calibration: actively adjust sensor and remove structural errors in the sensor outputs

(g) Sensor layout/location: discuss sensor layout/location to improve sensor accuracy/efficiency

A comprehensive literature review is conducted, and more than 100 FDD-sensor-related papers are reviewed in this section. First, the review papers on sensor topics in FDD use cases are summarized. Then, technical papers are categorized into three levels of FDD and summarized as tables with brief information. The papers with higher citations are introduced in detail. Conclusions are drawn in the last subsection.

3.2 SUMMARY OF REVIEW PAPERS

In this section, review papers related to sensor topics in FDD are introduced. In Najafi's PhD dissertation [137], the current status of sensors in FDD applications is summarized. One of challenges in building HVAC diagnostics is measurement constraints. In building HVAC systems, sensor network architectures are not necessarily designed solely on diagnostic purposes. Therefore, monitoring one or more components through only one sensor (or one set of sensors) is common. Measurement constraints can significantly expand the complexity of building HVAC diagnostic problems. To improve the diagnostic results, engineers and researchers either need to reduce the modeling/measurement errors or include other measurements—additional sensors—in the diagnostic process. A reliable solution to these constraints may reveal a new horizon in the diagnostics of building HVAC systems and could be used as a framework to analyze the effect of new measurements on diagnostic strength, thereby leading to better design or optimization of sensor network architecture from a diagnostic perspective.

In the same dissertation [137], Najafi aimed to develop an algorithm to quantify the impact of the measurement constraints on diagnostics capability. He developed model-based and non-model-based diagnostic algorithms with the capability of alleviating modeling and measurement constraints more effectively. He showed how the effect of measurement constraints can be traced to the information entropy of diagnostics assessments and how this can lead to a framework optimizing the architecture of sensor networks from the diagnostic perspective.

In the automated FDD (AFDD) tool review paper written by Bruton et al. [138], the authors addressed that the method of AFDD applied to a system differs depending on the number and location of sensors present. They also mentioned that testing the sensors for accuracy is an important step for some FDD tools. Bruton et al. [139] addressed that AHU intelligent fault optimization should be applied effectively and comprehensively for different component and sensor layouts. Bruton et al. [140] also concluded that one of the primary objectives of the AFDD tool of an AHU is to (a) have the flexibility to work with any combination of sensors and components found in typical AHUs to ensure cross company compatibility, and (b) have the ability to use already available measurements without the need to install additional sensors to limit associated installation costs.

Smart sensor network is a trend of future sensor networking in fault detection applications. A paper written by Hannan et al. [141] presented a critical review of the potential of an internet of energy (IoE)-based BEMS for enhancing the performance of future building energy use. FDD is one of the important application fields of an IoE-based network. However, data/sensor management, cost, and scalability are the major limitations of FDD techniques. One survey [142] also integrated research efforts that have been produced in fault diagnosis specifically for WSNs.

Fugate et al. [143] discussed the topic of sensor data analytics in FDD. Various approaches can be pursued to convert the sensor data into actionable information. The FDD analytical approaches fall 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 addressed that wireless sensors are considered a key enabling technology that can enable measurements that will provide diagnostic and prognostic functions using an energy management and control system (EMCS).

Molina-Solana et al. [144] reviews how data science has been applied to address the most difficult problems faced by practitioners in the field of energy management including FDD. Data science can also help in verifying the operational status and detecting faults of building infrastructures. By continuously monitoring the building, it is possible to detect when a fault has happened (typically an anomalous event) and how it affects other equipment (by means of correlation analysis). From a managerial perspective, it is particularly interesting to anticipate such faults by characterizing the situations that usually lead to them. In these regards, pattern recognition and regression techniques are very useful. They can help to implement countermeasures to increase building resilience and to prevent costly incidents. Zucker et al. [145] also reviewed the topics of sensor failure, selection of sensors, processing of sensor data, data analysis of operation data, and data sanitation in building energy system FDD.

Yu et al. [146] reviewed typical faults in AHU sensors and controllers. They addressed that 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 model. In that review, signal processing methods were included in data-driven approaches since the main process was based on data processing by sensors [146].

To summarize, review papers related to sensor topics in FDD use cases cover the topics of (a) sensor measurement constrains by incompatible sensor network architectures, (b) smart sensor network, (c) additional and built-in/existing sensors, (d) configuration of sensor networks (sensor numbers and location), and (e) data science on sensor data. The papers discussed here focused on very specific topics; a comprehensive paper that systematically reviews sensor topics in FDD is absent. In the next subsection, technical papers are review in terms of FDD levels (building-, system-, and component-level) in detail; senor topics listed in the last section are reviewed at each level of use cases.

3.3 REVIEW OF TECHNICAL PAPERS

In this section, technical papers are reviewed in terms of three FDD levels: building-, system-, and component-level FDD. Senor topics are reviewed at each level of use cases. This section reviews 89 technical papers. The distribution of reviewed technical papers on sensor topics of FDD is shown in Figure 2.

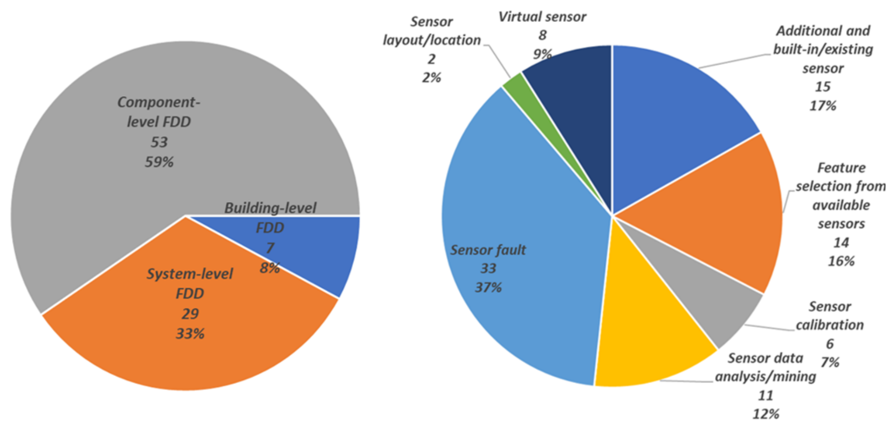

Figure 2. Distribution of reviewed technical papers on sensor topics of FDD in terms of (a) FDD level and (b) sensor topics.

3.3.1 Review of Sensor Topics in Building-Level FDD

Building-level FDD typically addresses the overall performance of a building and does not require information on building operations, which is the most common 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. **Error! Reference source not found.** lists the technical papers on sensor topics in building-level FDD. The sensor topics for building-level FDD include (a) sensor calibration, (b) sensor fault, and (c) sensor data analysis/mining.

Table 1. Summary of sensor topics in building-level FDD.

No.	Authors	Ref.	Sensor topics	Keywords
1	Shao and Claridge	[147]	Sensor calibration	Verification of building energy-use data
2	Masuda et al.	[148]	Sensor calibration	Verification of building energy-use data
3	Field et al.	[149]	Sensor fault	Detection of faulty building energy data by end-use submeters

4	Chen and Lan	[150]	Sensor fault, sensor data analysis/mining	Sensor fault detection, data recovery, principal component analysis
5	Sun et al.	[151]	Sensor data analysis/mining	Identification of the potential outlying observations in electricity consumption
6	Fan et al.	[152]	Sensor fault	Fault detection of power consumption sensors
7	Khan et al.	[153]	Sensor data analysis/mining	Detection of abnormal lighting energy consumption

3.3.1.1 Sensor calibration and verification

Shao and Claridge proposed a quality control method using an "energy balance load" for verifying whole-building energy-use data [147]. The method was derived from the first law of thermodynamics based on a whole-building energy analysis and has been theoretically proved to be an effective tool for verifying whole-building energy use data. Based on an energy balance load, Masuda et. al [148] further included outside air enthalpy variable to the method and presented a possible enhancement of data screening capabilities for buildings operated in locations with hot and humid climates.

3.3.1.2 Sensor faults

In a study from Chen and Lan [150], a method of FDD and data recovery was proposed for building a heating/cooling billing system. A principal component analysis (PCA) approach (a widely applied data analysis/mining technique to improve FDD performance) was used to extract the correlation of measured variables in a heating/cooling billing system and reduce the dimension of measured data. The measured data of the billing system under normal operating conditions were used to build a PCA model. Sensor faults of bias, drifting, and complete failure were introduced to the building heating/cooling billing system for detection and identification. Square prediction error statistics were used to detect sensor faults in the system. Then, sensor validity index was employed to identify faulty sensors. Finally, a reconstruction algorithm was presented to recover the correct data of faulty sensors in accordance with the correlations among system variables.

Fan et al. [152] applied a framework for sensor data mining that also included fault detection of power consumption sensors. In terms of end-use sensors, Field et al. [149] used various types of end-use energy performance indices to assess the building energy performance and detect faulty building energy data.

3.3.1.3 Sensor data analysis/mining

Analysis and application for real-time operational sensor data of buildings are important for energy management. However, original data inevitably contain a number of outliers that usually lead to a significant negative impact on the performance of data-based models [151]. To eliminate the influence of outliers and improve the robustness of data-based models, Sun et al. [151] employed three methods (Boxplot, local outlier factor, and PCOut) to identify the potential outlying observations in the original data set.

PACRAT (Performance and Continuous Recommissioning Analysis Tool), WBD (Whole Building Diagnostician), and ABCAT (Automated Building Commissioning Analysis Tool) are three well-recognized whole-building diagnosis tools [154]. These tools can help identify a building with poor energy performance or faulty energy data ; however, these tools experience difficulty in explaining performance and identifying the causes of poor performance [136].

Khan et al. [153] described three data mining techniques for detecting abnormal lighting energy consumption using hourly recorded energy consumption and peak demand (maximum power) data. Two outlier detection methods were applied to each class and cluster for detecting abnormal consumption in the same data set. In each class and cluster with anomalous consumption, the amount of variation from normal was determined using modified standard scores. The study is helpful for BEMSs to reduce operating cost and time by not having to detect faults manually or diagnose false warnings. Additionally, it is useful for developing an FDD model for whole-building energy consumption.

3.3.2 Review of Sensor Topics in System-Level FDD

Compared with building-level FDD, the more detailed diagnosis method extends the examination of energy performance and FDD from building level to system and component levels, and consequently can provide more useful information on specific and targeted FDD. System-level FDD focuses on the faults of HVAC as a whole system. A typical HVAC system consists of an airside loop, chilled-water loop, refrigeration-equipment loop, and heat-rejection loop, with more detailed sensors than building-level FDD, and consequently, system-level FDD includes many more sensor topics. Table 2 lists the papers on sensor topics in system-level FDD. The sensor topics for system-level FDD include (a) sensor faults, (b) feature selection from available sensors, (c) additional and built-in/existing sensors, (d) sensor data analysis/mining, and (e) virtual sensors.

Table 2. Summary of sensor topics in system-level FDD.

No.	Authors	Ref.	Sensor topics	Keywords
1	Wang et al.	[155]	Sensor fault, sensor data analysis/mining	Sensor fault detection
2	Dong et al.	[156]	Additional and built-in/existing sensor	Sensor schema
3	Sun et al.	[157]	Sensor fault	Sensor fault detection
4	O'Neil et al.	[158]	Additional and built-in/existing sensors, sensor noise	Additional sensors
5	Reppa et al.	[159,160]	Sensor fault	Sensor fault isolation
6	Yuwono et al.	[161]	Feature selection from available sensors	Ensemble of rapid centroid estimation
7	Guo et al.	[162]	Additional and built-in/existing sensors	Built-in/existing sensor
8	Stephen et al.	[163]	Additional and built-in/existing sensors	FDD that requires fewer sensors and less configuration
9	Alsaleem et al.	[164]	Additional and built-in/existing sensors	Built-in/existing sensor
10	Papadopoulos et al.	[165]	Sensor fault	Sensor fault detection, distributed fault diagnosis architecture
11	Dai and Gao	[166]	Sensor fault	Sensor fault detection
12	Wijayasekara et al.	[167]	Additional and built-in/existing sensors, sensor fault, sensor data analysis/mining	Built-in/existing sensors
13	Gao et al.	[168]	Additional and built-in/existing sensor	FDD that requires a small number of measurement sensors
14	Verbert et al.	[169]	Virtual sensor	Design of virtual sensor
15	Li and Wang	[170]	Sensor calibration, feature selection from available sensors, sensor fault	Determination of a proper calibration frequency
16	Mohamed et al.	[171]	Virtual sensor	Two approaches of virtual sensing
17	Dibowski et al.	[172]	Additional and built-in/existing sensors	Additional types of sensors to be installed

Table 2. Summary of sensor topics in system-level FDD (continued).

No.	Authors	Ref.	Sensor topics	Keywords
18	Lee and Yik	[173]	Sensor fault	Energy cost impacts of sensor faults
19	Guo et al.	[174]	Feature selection from available sensors	Hybrid feature selection, VRF
20	Guo et al.	[175]	Sensor fault, sensor data analysis/mining	Senor fault detection, VRF
21	Shi et al.	[176]	Sensor data analysis/mining	VRF
22	Li et al.	[177]	Virtual sensor	Virtual sensor-based fault indicators for a VRF
23	Verhelst et al.	[178]	Sensor fault	Economic impact of persistent sensor and actuator faults
24	Yoon and Yu	[179]	Sensor calibration	Virtual in-situ sensor calibration
25	Shi et al.	[180]	Feature selection from available sensors	VRF
26	Yu et al.	[181]	Sensor calibration	Indirect virtual calibration method for a supply air temperature in an RTU
27	Kim	[182]	Virtual sensor	Review of virtual sensor, evaluation of sensors, development and assessment of alternative virtual sensors in an RTU
28	Katipamula et al.	[183]	Additional senor, sensor layout/location, sensor fault	Cost of additional sensor in an RTU
29	Hjortland and Braun	[184]	Virtual sensor	RTU

3.3.2.1 Sensor faults

Sensor faults can be divided into four types: bias, drifting, precision degradation, and complete failure [150]. Wang et al. [155] presented a strategy for FDD of HVAC systems involving sensor faults at the system level. Two schemes were involved in the system-level FDD strategy: the system FDD scheme and the sensor FDD and estimation (FDD&E) scheme. A method based on PCA was used to detect and diagnose the sensor bias and to correct the sensor bias prior to the use of the system FDD scheme. The authors found that the sensor FDD&E method worked well in identifying biased sensors and recovering biases even if system faults coexisted, and the system FDD method was effective in diagnosing the system-level faults using processed measurements by the sensor FDD&E.

In a study from Sun et al. [157], a model-based and data-driven method is presented for robust system-level fault detection with the potential for large-scale implementation. It detects both sudden faults and gradual degradation, as well as device and sensor faults. Sensor noise was also addressed in the FDD process.

Papadopoulos et al. [165] presented a model-based methodology for diagnosing actuator and sensor faults affecting the temperature dynamics of a multizonal HVAC system. By considering the temperature dynamics of the HVAC system as a network of interconnected subsystems, a distributed fault diagnosis architecture is proposed. For every subsystem, the authors designed a monitoring agent that combined local and transmitted information from its neighboring agents to provide a decision on the type, number, and location of the faults.

Dai and Gao [166] mentioned in their paper that detecting sensor/actuator faults by parameter identification may be complicated since sensor/actuator faults may influence the input/output in the same way as the process (parameter) faults; for a system subjected to input noises and sensor noises, it is more challenging to estimate the sensor fault.

Guo et al. [175] presented an enhanced sensor FDD method based on the Satizky-Golay (SG) method and PCA method for the VRF system, namely the SG-PCA method. Because of the volatility of the original data set of the VRF system, the original data were smoothed using the SG method. Then, the smoothed data were used for PCA model training and FDD. To determine the parameters of the SG method, an optimization index was proposed, which was calculated by the signal to noise ratio, standard deviation, and self-detection efficiency.

In a study from Verhelst et al. [178], the economic fault impact was investigated by dynamic simulations using an emulator model of a concrete core activated office building in combination with four different control strategies. A virtual test-bed was developed, comprising two emulated office zones and a temperature-modulated concrete core activation HVAC system, augmented with persistent faults in temperature sensors and hydronic flow rate actuators. The fault-free performance and the fault-present performance were investigated and compared through the relevant, control-associated costs using an economic framework. This methodology determined the fault sensitivity of different supervisory control strategies and assisted with the selection of the most economical, fault-robust controller for a certain building type. Furthermore, the most critical sensors and actuators were identified.

In the context of smart buildings, detecting the occurrence of sensor faults and isolating the location of the fault as soon as possible are important [159]. This topic is termed as "sensor fault isolation." Reppa et al. [159] presented a design and analysis methodology for detecting and isolating multiple sensor faults in HVAC systems. The proposed methodology was developed in a distributed framework, considering a multizonal HVAC system as a set of interconnected nonlinear subsystems. A dedicated local sensor fault diagnosis (LSFD) agent was designed for each subsystem, although it may exchange information with other LSFD agents. Distributed sensor fault detection was conducted using robust analytical redundancy relations of estimation-based residuals and adaptive thresholds. The distributed sensor fault isolation procedure was carried out by combining the decisions of the LSFD agents and applying a reasoning-based decision logic.

3.3.2.2 Feature selection from available sensors

In an AFDD process, data from the components of the HVAC system are received. These data may, for example, include sensed data from various sensors within the system and feedback data from various components of the system. Additional data from external data sources can also be received, such as external weather data. Consequently, the dimensionality and volume of these data are enormous [161]. Selecting an optimal sensor set is a crucial step in the process of data-driven FDD. The benefits of selecting a minimal number of sensors while keeping the maximum information include correlation removal, computational complexity reduction, and optimization of the number of sensors to be installed.

Yuwono et al. [161] applied ensemble rapid centroid estimation (ERCE) to select important features from original measurements based on the relative entropy between the low- and high-frequency features. The materials used were the experimental HVAC fault data from the ASHRAE-1312-RP data sets containing a total of 49 days of various types of faults and corresponding severity. The effectiveness of the feature selection method was further investigated using two well-established time-sequence classification algorithms.

Guo et al. [174] presented the optimized back propagation neural network (BPNN) method for fault diagnosis of the VRF air-conditioning system in the heating mode. A feature variable set optimization approach of diagnosis models was proposed based on data mining method. First, the correlation analysis method was used to eliminate redundant variables. Then, the association rule mining method was used to optimize the feature set selection.

3.3.2.3 Additional and built-in/existing sensors

The topic of using additional sensors besides the existing building automation system or EMCS sensors or built-in sensors has been studied by several researchers. Although Katipamula et al. [183] have shown that integration of the refrigerant-side diagnostics onto the RTU controller is possible, numerous additional sensors are needed to deploy the refrigerant-side diagnostics. Both the air-side and the refrigerant-side algorithms assumed that the accuracy of the temperature sensor measurement was at least ±1°F. For refrigerant-side diagnostics, in addition to the cost for the additional sensors, locating the sensors in the correct location to measure the parameters was also a challenge. Because temperature sensors were being used as proxies for pressure measurements, mounting these sensors in the right location was critical; otherwise, the uncertainty in the measurement was high. Accommodating additional sensors also meant either increasing the input/output capability of the RTU controller or adding another controller to handle the additional sensors, which significantly increases the cost of deployment. The authors summarized that for deploying refrigerant-side diagnostics along with advanced RTU controls, three hurdles have to be overcome: (1) the cost of additional sensors, (2) the cost of upgrading the RTU controller to handle additional sensors, and 3) solving the installation difficulties of the sensors in the correct location.

Teraoka et al. [185] mentioned that the sensors that can provide valuable information to uncover building faults that are often not installed. Some researchers have used additional sensors to focus on providing additional information to improve FDD performance with the most cost-effective additional sensors. Furthermore, some researchers have used built-in sensors to focus on maximizing the FDD performance with the existing sensors without introducing additional sensors.

Dong et al. [156] developed a BIM-enabled information infrastructure for FDD. They proposed a sensor schema for general FDD applications and suggested the default built-in sensors for common FDD applications.

O'Neil et al. [156] proposed an automated, model-based, real-time whole-building performance monitoring and energy diagnostics system. The proposed system continuously acquired performance measurements of an HVAC system from the existing EMCS augmented by additional sensors as required, with considerations for sensor noise and model uncertainties. Additional sensors included electrical power sub-metering, fluid flow meters, and temperature sensors to determine thermal energy flow rates. Potential sensor bias was also addressed.

The mentioned studies discuss additional sensors used for FDD applications. The following study discussed the FDD applications with built-in/existing sensors. Guo et al. [162] proposed a novel fault diagnosis approach for building energy-savings based on a deep learning method, which was a deep belief network, and its application potential in the air-conditioning fault diagnosis field was investigated. All the variables used in that study were collected by the sensors from the original equipment manufacturer, and no additional sensors were added.

Stephen et al. [163] presented a hybrid, whole-building AFDD approach that combines energy modeling with data-driven analytics. Whole-building AFDD analyzes energy performance holistically, at the building scale, rather than for individual equipment; it therefore requires fewer sensors and less configuration than traditional rule-based methods. By reducing the engineering labor associated with AFDD setup and data integration, this hybrid approach has the potential to drive down implementation costs, enabling cost-effective FDD even for small buildings. Simulation-based trials with a small security building demonstrate the promise of the approach.

Alsaleem et al. [164] presented a new monitoring and diagnostics model for residential HVAC systems. This model provided a new diagnostics technology system that leveraged the latest technology advancements. The model benefited from cloud computing advantages and offered continuous diagnostic capabilities. Using existing embedded sensors and monitoring modules for the indoor and outdoor HVAC units, various measurements were transmitted to a cloud sever using the homeowner's preexisting Wi-Fi network.

Wijayasekara et al. [167] proposed a novel fuzzy anomaly detection and linguistic description–based method for improving the understandability of BEMS behavior for improved state awareness. The authors used existing BEMS sensors for FDD. Sensor fault was one of the fault types. Furthermore, an algorithm for normal behavior modeling and anomaly detection using online clustering and fuzzy logic rule extraction was presented.

Gao et al. [168] presented a system-level FDD method to detect and diagnose the low ΔT syndrome resulted from the performance degradation of an AHU system and plate heat exchanger system in a complex HVAC system. The proposed method was based on the system-level method, which is cost-effective and needs a small number of measurement sensors compared with the component-level method.

3.3.2.4 Virtual sensors

Holub and Macek [186] mentioned that replacing unmeasured data with virtual sensors is one of the typical building maintenance workflows. Verbert et al. [169] 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 diagnosis), (2) the selection of available sensor measurements that are relevant to estimate these quantities, (3) the choice for the method to capture the relation 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.

Mohamed et al. [171] mentioned that virtual sensors can provide low-cost sensing capabilities while expanding the data collection process for more accurate smart buildings energy diagnostics. Virtual sensors are logical sensors that provide economical alternatives to costly physical sensors. A virtual sensing system uses information available from other physical sensors to calculate an estimate of the quantity of interest. The authors concluded that there are two approaches of virtual sensing: analytical virtual sensing and empirical virtual sensing. The analytical virtual sensing approach is based on the calculation of the measurement estimate using approximations of the physical laws including those that involve the distances of the used physical devices. The empirical virtual sensing approach is based on the calculations of the measurement estimate using the available current and previous measurements.

Li et al. [177] proposed an improved decision tree–based fault diagnosis method for a practical VRF system. The proposed method was a three-stage method combining the decision tree model with virtual sensor-based fault indicators. Kim [182] reviewed and studied the topic of virtual sensors, evaluation of sensors, and development and assessment of alternative virtual sensors for RTUs.

3.3.2.5 Sensor data analysis/mining

In a study from Shi et al. [176], PCA was used to reduce the dimensions of all feature variables to improve the computational efficiency while preserving almost all feature information. To improve the FDA for the undercharge fault, a dual neural network model for the RCA fault diagnosis strategy was adopted.

3.3.2.6 Sensor calibration

In a study from Yoon and Yu [179], virtual in-situ sensor calibration (VIC) using Bayesian Markov Chain Monte Carlo methods with system models was applied to large-scale building sensor networks to calibrate multiple working sensors, including virtual and physical sensors. Using the calibration strategies mentioned here, VIC methods worked to overcome various systematic errors (from simple to troublesome) that could not otherwise be handled by a conventional calibration. The VIC strategies in a whole system were understood and evaluated with various error conditions to ensure reliable performance of VIC in the operational stage. 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 [170] proposed a preventive approach to determine sensor maintenance requirements, which aimed to explicitly quantify the importance of sensors and determine a proper calibration frequency for sensors with high importance. The approach considered the sensor bias growth mechanism and related the sensor importance to a user-defined building performance index. The sensor importance was evaluated under a stochastic framework, which is essentially the way in which sensor bias grows. The calibration frequency was identified using a polynomial function, which describes the degradation rate of the building performance index.

Yu et al. [181] proposed an innovative indirect virtual calibration method for a manufacturer-installed supply air temperature (MSAT) sensor to solve erratic measurement errors in a compact chamber. The method demonstrated that a virtual calibrated MSAT sensor could provide accurate results when combined with a linear correlation for offset error that depends on the heating stage and outside air damper signals. The linear correlation could be determined using the calculated temperature difference between the predicted theoretical true value of SAT and the direct MSAT measurement. This virtual calibration method was made to be generic for all RTUs with a similar construction of gas furnaces and to be implemented for long-term use.

3.3.3 Review of Sensor Topics in Component-Level FDD

Component-level FDD focuses on the operation of HVAC components such as the chiller, boiler, AHU, FCU, VAV terminal, room/zone level system, and so on. Compared with system-level FDD, the performances of main components of the HVAC system are further examined in detail at the component level. The sensor topics in the component-level are the most versatile among the three levels of FDD. Table 3 lists the papers on sensor topics in component-level FDD. The sensor topics for component-level FDD include (a) sensor faults, (b) feature selection from available sensors, (c) additional and built-in/existing sensors, (d) sensor data analysis/mining, (e) virtual sensors, (f) sensor calibration, and (g) sensor layout/location.

Table 3. Summary of sensor topics in component-level FDD.

No.	Authors	Ref.	Component	Sensor topics	Keywords
1	Du et al.	[187]	AHU	Sensor fault	Sensor fault detection, quality of sensor data
2	Li and Wen	[188]	AHU	Sensor data analysis/mining	Wavelet-PCA for fault detection
3	Zhao et al.	[189]	Chiller	Feature selection from available sensors	Feature selection criteria
4	Fan et al.	[190]	AHU	Sensor fault	Self-adaptive sensor fault detection
5	Bonvini et al.	[191]	Chiller	Sensor fault	FDD algorithm adaptive to sensor noise and sensor faults
6	Yu et al.	[192]	Chiller	Feature selection from available sensors	Feature selection with mutual information–based filters and genetic algorithm–based wrappers
7	Yan et al.	[193]	Chiller	Feature selection from available sensors	Feature selection with ReliefF
8	Xiao et al.	[194]	VAV terminal	Sensor fault	Sensor fault detection using diagnostic Bayesian network
9	Mulumba et al.	[195]	AHU	Feature selection from available sensors	Feature selection with ReliefF
10	Zhu et al.	[196]	AHU	Sensor fault	Sensor fault detection using neural network pre-processed by wavelet and fractal (NNPWF)
11	Han et al.	[197]	Vapor-compression refrigeration systems	Sensor data analysis/mining	FDD tool combining PCA
12	Zhao et al.	[198]	AHU	Sensor fault	Sensor fault detection with diagnostic Bayesian network
13	Hu et al.	[199]	Chiller	Sensor data analysis/mining, sensor fault	Sensor fault detection using adaptive PCA
14	Du et al.	[200]	AHU	Sensor fault	Sensor fault detection with dual neural networks
15	Zhao et al.	[201]	AHU	Additional and built-in/existing sensors	Limited built-in/existing sensors not adequate
16	Yang et al.	[202]	AHU	Sensor fault	Sensor fault detection using fractal correlation dimension
17	Li and Wen	[203]	AHU	Additional and built-in/existing sensors	Typical sensor
18	Wang et al.	[204]	VAV terminal	Sensor fault	Built-in/existing sensor
19	Subbaraj and Kannapiran	[205]	Cooler water spray system	Sensor fault	Sensor fault detection with neural network

Table 3. Summary of sensor topics in component-level FDD (continued).

No.	Authors	Ref.	Component	Sensor topics	Keywords
20	Kocyigit	[206]	Vapor-compression refrigeration systems	Sensor fault	Sensor fault detection using fuzzy inference system
21	Cai et al.	[207]	Ground-source heat pump	Additional and built-in/existing sensor	Information fusion
22	Han et al.	[208]	Chiller	Feature selection from available sensors	Feature selection with hybrid method
23	Yan et al.	[209]	Chiller	Feature selection from available sensors	Feature selection with hybrid method
24	Hu et al.	[210]	Chiller	Sensor data analysis/mining, sensor fault	Outlier detection, PCA
25	Zhao et al.	[211]	Chiller	Virtual sensor	Virtual fouling monitor sensors
26	Li et al.	[212]	Chiller	Sensor fault	NA
27	Yan et al.	[213]	AHU	Sensor fault	NA
28	Wang et al.	[214]	VAV terminal	Sensor fault	NA
29	Yan et al.	[215]	Chiller	Feature selection from available sensors	Feature selection with back-tracing sequential forward feature selection
30	Sun et al.	[216]	Chiller	Sensor data analysis/mining, sensor fault	Data fusion
31	Hu et al.	[217]	Chiller	Sensor data analysis/mining, sensor fault	Sensitivity of chiller sensor fault detection–based on PCA
32	Dey and Dong	[218]	AHU	Sensor fault	NA
33	Yang et al.	[219]	AHU	Sensor fault	NA
34	Padilla and Choiniere	[220]	AHU	Sensor fault	NA
35	Kim et al.	[221]	IAQ	Sensor fault validation, PCA on sensor	Sensor validation
36	Li et al.	[222]	AHU	Feature selection from available sensors	NA
37	Kim and Braun	[223]	Chiller	Virtual sensor	NA
38	Shahnazari et al.	[224]	VAV terminal	Sensor fault, sensor data analysis/mining	Sensor-fault-tolerant control
39	Wang et al.	[225]	Chiller	Feature selection from available sensors	NA
40	Li et al.	[226]	Outdoor unit of VRF	Additional and built-in/existing sensors, sensor data analysis/mining	Data mining using only built-in/existing sensors
41	Fernandez et al.	[227]	AHU	Sensor fault	NA
42	Karami and Wang	[228]	Chiller	Feature selection from available sensors, sensor fault	NA

Table 3. Summary of sensor topics in component-level FDD (continued).

No.	Authors	Ref.	Component	Sensor topics	Keywords
43	Najafi	[229]	AHU	Additional and built-in/existing sensor	Sensor network architectures not necessarily designed solely for diagnostic purposes
44	Dey et al.	[230]	HVAC terminal unit	Sensor layout/location	Impact of lacking sensor location
45	Kim and Braun	[231]	Chiller	Virtual sensor	NA
46	Pourarian et al.	[232]	FCU	Sensor fault	FDD algorithm adaptive to sensor fault
47	Liu et al.	[233]	IAQ	Sensor calibration, sensor fault, sensor data analysis/mining	Sensor validation
48	Sun et al.	[234]	Chiller	Sensor data analysis/mining	
49	Lee et al.	[235]	AHU	Sensor layout/location	Importance of proper location and number of sensors
50	Yan et al.	[236]	AHU	Feature selection from available sensors	NA
51	Wang and Haves	[237]	VAV terminal	Sensor fault	NA
52	Shi et al.	[238]	Zone level	Additional and built-in/existing sensors, sensor fault	Built-in/existing sensors
53	Habib et al.	[239]	Chiller	Sensor data analysis/mining	Outlier detection

3.3.3.1 Sensor faults

Neural networks are widely used for component-level sensor fault detection. Du et al. [187] developed combined neural networks to detect sensor faults in an AHU. Moreover, adaptive subtractive clustering analysis was presented to diagnose the fault sources. The authors also mentioned that in the real building and HVAC systems, the application of the proposed methodology relies on the quantity and quality of the operation sensor data.

Fan et al. [190] presented a self-adaptive sensor FDD strategy for local system of an AHU. This hybrid strategy consists of two stages. In the first stage, a fault detection model for the AHU control loop including two back-propagation neural network models is developed. In the second stage, a fault diagnosis model is developed which combines wavelet analysis method with Elman neural network. The Elman neural network is used to identify sensor faults.

Zhu et al. [196] presented a new fault diagnosis method for sensors in an air-handling unit based on neural network pre-processed by wavelet and fractal (NNPWF). Three-level wavelet analysis was applied to decompose the measurement data, and then fractal dimensions of each frequency band were extracted and used to depict the failure characteristics of the sensors.

In a study from Du et al. [200], a dual neural networks combined strategy was presented to detect the faults of sensors in the supply air temperature control loop of an AHU. Subbaraj and Kannapiran [205] 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 in the cement industry. The network is developed to detect a totally nineteen faults, which include pressure sensor fault and rod displacement sensor fault. In a study from Kocyigit [206], a fuzzy inference system (FIS) and an artificial neural network (ANN) were used to diagnose the faults of a vapor compression refrigeration experimental setup. A separate FIS was developed to detect sensor errors.

Xiao et al. [194] presented a diagnostic Bayesian network (DBN) for FDD of VAV terminals, including a temperature sensor fault. In a study from Zhao et al. [198], four DBNs are developed to diagnose faults in heating/cooling coils, sensors, and faults in secondary supply chilled water/heating water systems.

In a study from Yang et al. [202], a novel method using fractal correlation dimension (FCD) was developed, in which FCD deviation was adopted instead of direct residual. The method was validated by detecting fixed and drifting bias faults generated in a supply air temperature sensor of an AHU system.

Shahnazari et al. [224] presented an integrated framework for fault detection and isolation (FDI) and fault tolerant control (FTC) of VAV boxes, a common component of HVAC systems. First, a statistical model–based FDI framework was designed using existing techniques such as PCA and joint angle analysis as a benchmark for comparison. Then, a novel linear causal model–based framework for FDI of multiple actuator and multiple sensor faults was designed, implemented, and shown to possess superior FDI capabilities compared with the statistical model–based framework.

Pourarian et al. [232] aimed to develop and validate a software tool to simulate operational data generated from FCUs that are operated dynamically under both faulty (including offset room temperature and mixed air temperature) and fault-free conditions. A comprehensive and systematic validation process using data collected from real FCUs in a laboratory building was used to validate the tool under both faulty and fault-free operating conditions in different seasons.

Bonvini et al. [191] presented a robust and computationally efficient algorithm for both whole-building and component-level energy FDD. The algorithm provided reliable estimations of multiple and simultaneous fault conditions, even in the presence of noisy and sometimes erroneous sensor data, and provided uncertainty estimations.

3.3.3.2 Feature selection from available sensor sets

In a study from Zhao et al. [189], fault detection performance was evaluated using different variable selections. The selecting criteria were as follows: (a) they should be able to determine the unique operating conditions and make the fault data different from the normal data; (b) they can have proper information redundancy to enhance robustness; and (c) the number of sensors should be not very large to maintain sensitivities to faults at slight severity levels, and to reduce computational complexity. Yan et al. [215] created a summary table to review the feature selection from the available sensor set in chiller FDD.

Yu et al. [192] employed feature selection (FS) techniques such as mutual information–based filters and genetic algorithm (GA)–based wrappers to help search for the important sensors in data-driven chiller FDD applications to improve FDD performance and reduce initial sensor costs.

In another study, Yan et al. [193] implemented the feature selection algorithm ReliefF to select the most significant features in chiller FDD modeling. For each attribute A, the ReliefF algorithm assigns a weight $W(A)$ according to its importance in influencing the output. The most heavily weighted attributes are selected as model features. Mulumba et al. [195] also applied ReliefF in their model-based fault diagnosis method developed by support vector machine (SVM) techniques. In a study from Yan et al. [209], a novel hybrid method was proposed to detect faults for chiller subsystems without any faulty training data available (i.e., by training the normal data only). A hybrid feature selection algorithm that combined ReliefF and adaptive GA methods was applied to the chiller data set collected by ASHRAE project 1043-RP to select the most significant feature variables.

Han et al. [208] investigated a hybrid model that combined SVM, GA, and parameter-tuning techniques for chiller FDD applications. Subsets of 6, 7, 8, 9, and 10 features were studied and compared with the original 64-feature set in terms of overall performance (correct rate) and individual performance (hit rate and false alarm rate).

In a study from Yan et al. [215], a cost-sensitive and sequential feature selection algorithm for chiller FDD was proposed to select the most important features using a back-tracing sequential forward-feature selection algorithm. The ASHRAE data set collected by project number 1043-RP was used. SVM, which is one of the most effective FDD classification methods for chillers in existing works, was employed for accuracy measurements.

3.3.3.3 Additional and built-in/existing sensors

Li and Wen [203] listed typical sensors in AHU operations: outdoor air temperature, mixing box damper position signal, supply fan total power meter, mix air temperature, heating coil valve position signal, return fan total power meter, supply air temperature, cooling coil valve position signal, supply fan speed signal, supply air duct static pressure, supply airflow rate, and return fan speed signal. Zhao et al. [201] addressed a major challenge in AHU fault diagnosis: incompleteness and inaccuracy of the AHU measurements. First, AHU measurements are rich in data but often poor in information. A limited number of sensors is equipped in AHUs. Only the most essential sensors needed for control are installed because of cost considerations. Measurements are generally not sufficient for FDD. Furthermore, various levels of uncertainties exist in the AHU measurements and fault symptoms. Braun [240] observed the need for adding low-cost sensors to make the FDD solution more appealing for HVAC systems compared with other industries such as nuclear and aircraft.

In a study from Wang et al. [204], a rule-based fault classifier was designed and used to find the sources of faults in VAV terminals. The fault diagnosis tool relied only upon the sensor data and control signals that are commonly available in building management control systems.

Li et al. [226] proposed a data mining approach to identify and isolate fouling faults using only built-in sensors. Density-based spatial clustering of applications with noise was used for data preprocessing. A classification and regression tree–based classifier was employed for fault detection. Based on Pearson's correlation analysis, a multiple linear regression–based fault indicator was developed for fault isolation.

Shi et al. [238] implemented a fault detection algorithm for thermal zones using Kalman filter–based methods with a reduced-order energy balance model, and tested its performance using simulation and experimental data. The model estimated indoor air temperature change using available sensors installed in the experiment setup.

3.3.3.4 Virtual sensors

In a study from Zhao et al. [211], a method (virtual fouling monitor sensors) using low cost and commonly available onboard chiller measurements for monitoring the fouling status of the condenser was presented. The performance of the proposed virtual fouling monitor sensor was evaluated using laboratory data over a wide range of operating conditions in both normal and faulty conditions. Moreover, the proposed virtual fouling monitor sensor was also implemented and evaluated on a field chiller. The laboratory and field test results showed that the proposed method gave an effective and robust performance in terms of detecting the condenser fouling faults in chillers.

3.3.3.5 Sensor data analysis/mining

In a study from Sun et al. [216], an online sensor FDD strategy based on data fusion technology was developed to detect faults in the building cooling load direct measurement. The confidence degree, generated by a data fusion algorithm, was used to indicate the existence of the faults. The faults in the chilled water flow rate and supply temperature measurements were diagnosed according to the redundant information provided in building automation systems. The faults in the return water temperature measurements were diagnosed by reconstructing the confidence degree using the expected values of the chilled water flow rate and the supply temperature by considering the associated uncertainties.

Habib et al. [239] discussed the steps involved for detecting outliers in the data obtained from absorption chiller using their on/off state information. The authors also proposed a method for automatic detection of the on/off and/or missing data status of the chiller. The technique used two-layer k-means clustering for detecting the on/off and missing data state of the chiller. After automatic detection of the chiller on/off cycle, a method for outlier detection was proposed using z-score normalization based on the on/off cycle state of chillers and clustering outliers by the expectation maximization clustering algorithm.

Hu et al. [210] presented a statistical training data cleaning strategy for a PCA-based chiller sensor FDD and data reconstruction method. Finding and removing outliers from the original training data set, the training data quality was improved by the presented data-cleaning strategy. This improvement enhanced the efficiency of the fault detection and increased the accuracy of the data reconstruction. Outliers could not be easily found in the original data set used for training the PCA model. These outliers would severely affect the projection directions of the two PCA orthogonal subspaces (principal component subspace and residual subspace).

Cai et al. [207] proposed a multi-source information fusion–based fault diagnosis methodology by using a Bayesian network because it is considered to be one of the most useful models in the field of probabilistic knowledge representation and reasoning, and can handle the uncertainty problem of fault diagnosis well. The results show that the fault diagnosis model using evidence only from sensor data was accurate for a single fault, whereas it was not accurate enough for multiple simultaneous faults.

Li and Wen [188] addressed how PCA is powerful as a data-driven model–based method in detecting AHU faults. Wavelet transformation is a promising data preprocess approach to remove the influence of weather condition changes. A combined wavelet-PCA method was developed and tested using site data. The feasibility of using the wavelet transformation method for data pretreatment has been demonstrated. Compared with conventional PCA, wavelet-PCA was more robust to the internal load change and weather impacts and generated no false alarms. In a study from Han et al. [197], a novel AFDD strategy was proposed for vapor-compression refrigeration systems, which combined PCA feature extraction technology and the "one to others" (binary decision tree–based) multiclass SVM classification algorithm. Hu et al. [199] presented a self-adaptive chiller sensor fault detection strategy based on PCA, namely a self-adaptive PCA method. Hu et al. [217] presented an algebraic solution to an erroneous sensor's undetectable boundary to evaluate the sensitivity of chiller sensor fault detection based on PCA. A bias sensor fault of a fielded screw chiller was studied for each sensor in the PCA model by introducing different severity levels. Results showed that each sensor had different fault detection sensitivity using the same PCA model. The undetectable boundary can be a criterion used to easily evaluate the detection sensitivity of PCA-based methods.

3.3.3.6 Sensor calibration

In a study from Liu et al. [233], several key air pollutants data were collected every minute by an air sampler and telemonitoring system to effectively monitor and control IAQ in subway stations. The quality of the online measurement could decide the failure or success in environmental process assessments. Therefore, prompt detection of the occurrence of sensor faults and identification of those locations are of primary importance for efficient monitoring and control of IAQ. In the study from Liu et al., a principal components analysis–based approach was used to detect, identify, and reconstruct the sensor faults in monitoring IAQ. Four types of sensor failures—bias, drifting, complete failure, and precision degradation—were tested for monitoring IAQ. Several test results of a real subway telemonitoring system showed that the developed sensor validation technique could work well for the four kinds of sensor faults.

3.3.3.7 Sensor layout/location

Sensor layout/location is an important topic in the design of sensor layout/location to improve sensor accuracy, effectiveness, and efficiency. However, very few papers were found on this topic. Lee et al. [235] proposed a proper location and number of sensors that are important to conduct FDD in AHUs. Dey et al. [230] addressed that potential issues that can result in faulty terminal unit behaviors include poor sensor location. Because of the more realistic implementation (i.e., lack of knowledge of sensor location, weather data, and occupancy information), effectively detecting and diagnosing the cause of faults is difficult, although the excellent accuracy of the proposed method signifies the real-world effectiveness of the work.

3.4 CONCLUSIONS OF SENSOR TOPICS IN FDD USE CASES

- Technical papers are reviewed by FDD levels

Technical papers are reviewed in terms of three FDD levels: building-, system-, and component-level FDD. The papers in component-level FDD outnumber those in system-level FDD, which outnumber those in building-level FDD. As shown in Figure 2, 7 papers (8%) on building-level, 29 papers (33%) on system-level, and 53 papers (59%) on component-level were examined. With a more detailed level of FDD, the sensor requirement is higher and the studied sensor topics are more diversified. In other words, component-level FDD depends more on well-maintained and well-designed sensors than building-level FDD.

- Technical papers are reviewed by sensor topics

Technical papers are also reviewed in terms of 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. Numerous papers study sensor faults in building-, system-, and component-level FDD. Sensor faults have a great 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; feature selection from available sensors is a widely discussed topic in component-level and system-level FDD. Those feature selection studies focus on selecting the sensor set used for FDD from existing sensors to improve FDD performance rather than installing new sensors.

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

Data-driven (or history-based) AFDD models account for 62% of AFDD models from 197 research papers since 2004 [240]. The rapid development of machine learning techniques empowers data-driven AFDD models with good performance and high reliability. Data-driven AFDD models with sophisticated machine learning algorithms need more data. They require high data quantity, data quality, and data variety, as well as better support from a sensor perspective. Many papers apply highly sophisticated machine learning algorithms with existing sensors common to building automation systems. They focus more on the algorithm than the sensors. A gap exists between fast-developing AFDD algorithms and a lack of support from a sensor perspective.

- Hardware-perspective research topics are carefully reviewed

If sensor data analysis/mining, virtual sensor, and feature selection on sensor data are the software-perspective research, then additional and built-in/existing sensors, sensor calibration, and sensor layout/location are the hardware-perspective research. Hardware-perspective research is the foundation of software-perspective research: advanced data mining techniques and sophisticated FDD algorithm cannot work without systematic sensor networks, well-designed sensor layouts/positions, and accurate sensors. However, many more papers focus on the software perspective than on the hardware perspective. Even still, the hardware-perspective papers are carefully reviewed in this report. The most widely studied hardware-perspective research topic is adding new sensors for current FDD applications. Researchers who use additional sensor focus on providing information to improve FDD performance with the most cost-effective additional sensors. However, though many papers have been found in the literature review, the research topics such as sensor calibration and sensor layout/position lack in-depth discussion.

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

Very few papers address sensor engineering as part of FDD development. Most FDD research is based on existing sensor systems in buildings without considering the sensors. Few papers are found to integrate sensor design with FDD in real systems, but some studies use simulation tools such as EnergyPlus and Modelica to simulate faults [241]. Since simulation tools have thousands of virtual sensors, they can be used to determine which sensors are important for FDD, or can apply sensor selections before the sensors are physically installed. The authors of this report expect that tailoring sensor design and configuration to FDD algorithms can provide a substantial improvement in FDD performance.

- Some important sensor topics are not studied well

Sensor noise is an important concern in FDD, but only two papers were found to discuss sensor noise problems in FDD. Sensor cost-effectiveness analysis is important in sensor design in practice, but few FDD papers were found on this topic. Sensor schema/layout/location is also an important procedure in sensor design to improve sensor accuracy/efficiency, but only two papers were found to discuss this topic and neither of them provides in-depth analysis.

- A systematic framework of FDD sensors and models is needed

Although many sensor topics are found in the existing literature, a systematic framework or workflow that integrates sensor design/selection, sensor data analysis/mining techniques, feature selection techniques, physics-based or data-driven algorithms, sensor fault detection, sensor calibration, and sensor maintenance is greatly needed. The framework should (a) consider cost-effectiveness of sensor design to be compatible with specific FDD tools; (b) maximize the FDD performance after the sensors are designed using data analysis/mining techniques, virtual sensors, and other data-driven techniques; and (c) maintain the sensor performance with sensor fault detection and sensor calibration.

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