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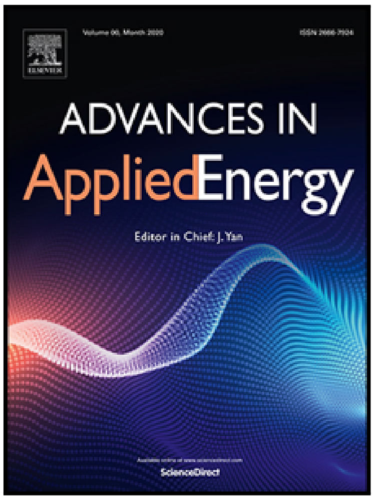

SENSOR IMPACTS ON BUILDING AND HVAC CONTROLS: A CRITICAL REVIEW

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SENSOR IMPACTS ON BUILDING AND HVAC CONTROLS: A CRITICAL REVIEW

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SENSOR IMPACTS ON BUILDING AND HVAC CONTROLS: A CRITICAL REVIEW

Title: Sensor Impacts on Building and HVAC Controls: A Critical Review for Building Energy Performance

Highlights

- Five major aspects of sensors impacts on building and HVAC controls
- Future research opportunities on sensor systems in building/HVAC systems
- Expert interviews to augment the literature review

Abstract

Building operations rely heavily on control systems and sensors. This paper provides a sophisticated literature review on sensor systems in building/HVAC systems, particularly in the context of controls, and their impacts on energy efficiency and thermal comfort. This study aims to understand the previous and current research and identify future research opportunities on this subject. The reviewed sensor systems were used for heuristic rule-based controls, local controls, and advanced optimal controls for existing and emerging technologies. Five major aspects of sensors are reviewed here: control loops for sensors, sensor types, sensor locations, sensor data, and a sensor impact evaluation framework. To augment the literature review, comprehensive standardized interviews were also conducted with relevant industry experts and practitioners. These interviews were designed and performed to (1) identify significant factors for selecting sensor sets and current undergoing issues, (2) identify potential improvements in sensor configuration/deployment, and (3) integrate expert (e.g., researcher, building operation practitioner) knowledge and experiences to develop structured use-case scenarios. Researchers collected and analyzed 31 interview responses for this paper.

Keywords: Sensors, sensor impacts, building control, building performance, energy performance, HVAC controls

1. INTRODUCTION

1.1 BACKGROUND

Commercial buildings consume more than 19% of the total energy usage in the United States, and HVAC systems account for 27% of this energy consumption [1]. The US Department of Energy's Building Technologies Office has ranked "advanced HVAC sensors" as the highest among 18 options in "Energy Savings Potential and Research, Development, and Demonstration Opportunities for Commercial Building Heating, Ventilation, and Air Conditioning Systems" [2]. However, buildings and HVAC operations have been developed and adapted for specific subsystems over many decades [3]. They focus on controlling each component in stable conditions, and the sensors are implemented without considering the whole building's performance; therefore, these conventional rules usually culminate in suboptimal operations in terms of energy efficiency, operational cost, and the occupants' comfort [4]. Optimally selecting and placing sensor systems are significant opportunities, and investigating optimal sensor deployment and configuration methods for different building and HVAC components enables bridging the gap between conventional and advanced strategies [5], steering the prevalent conventions toward the energy-efficient, cost-efficient and comfort-improvement strategies.

Recently, because of the rapid technology growth of the Internet of Things (IoT), new devices are introduced, tested, and permeated into building/HVAC applications (e.g., low-cost/versatile sensors [6], smart thermostat, occupancy sensors [7]). However, the performance of those new products regarding energy, cost, and the occupants' comfort is still anecdotal because of the lack of objectivity, quantitative evaluation, and comparative analysis. Also, investigations on the applicability and performance of integrated new devices into existing systems are limited even though the strong synergy between the two is evident. Therefore, evaluating the impact of new sensing technologies, as well as their integration with existing systems, is a significant research task that can provide crucial references and desirable guidelines to the building/HVAC industry.

However, evaluating sensor impact on building HVAC control is important because the impact varies significantly depending on the properties and characteristics of the building system (e.g., type, configuration, capacity, efficiency), as well as the control strategies used. For example, in a large office building that has an economizer, accurate measurements for outdoor air temperature and humidity are important for properly controlling the economizer. However, in a small office or residential building, the importance of that information is relatively low. Furthermore, advanced and sophisticated control strategies require more information compared with simple ones; the importance of sensors in their control performance is high.

The sensor system is the most essential component for collecting information for subsequent control systems in buildings, and it is significantly important for investigating sensor impacts. However, many challenges and questions are not well addressed in the literature, including the following

- Sensor and control systems: Buildings have local controls, rule-based controls and supervisory controls. What are the typical sensor/control use cases in buildings?
- Sensor types: Buildings have numerous sensor types, and new sensor types emerge continually. What are the sensor characteristics for different building controls?
- Sensor locations: Most commercial buildings are multi-zone buildings. There are many choices for deploying sensors across multiple zones. For residential buildings, it is usually one location picked for measuring indoor air temperature. Because different occupants have different behaviors, maintaining the zone temperature to satisfy all occupants is difficult. How can one find optimal sensor locations? How many sensors are

required? Also, the number of sensors directly affects building energy usage. One common scenario for multi-zone buildings is when occupants from zones with direct solar radiation decrease the temperature set points as a result of poor thermal comfort due to extra solar radiation, causing occupants in zones without direct solar radiation to experience colder indoor air temperature. This usually leads to extra energy consumption for HVAC systems.

- Sensor data: Once deployed in buildings and HVAC systems, some sensors might experience harsh conditions (e.g., extremely low outdoor air temperature in heating seasons, extremely high outdoor air temperature in cooling seasons, corrosion within local microenvironment, extra moisture). Sensor readings might become corrupt because of such unfavorable conditions, which is usually defined as a faulty sensor reading. What are the fault characteristics for different sensors? How do sensor faults affect building control performance? Furthermore, how can one properly deliver sensor data to control systems?
- Sensor impact evaluation and verification framework: Sensors are vital for buildings. However, limited efforts have been made to develop a unified framework for evaluating and verifying sensor impacts for the building domain through control systems. How can such a framework be developed?

1.2 STRUCTURE OF THE PAPER

To provide an understanding of the sensor systems in building/HVAC applications and the impact of sensor systems with respect to building performance, an extensive literature review and expert interviews were conducted, and the results are presented in Sections 2 and 3. The detailed structure of the paper is illustrated in Figure 1.

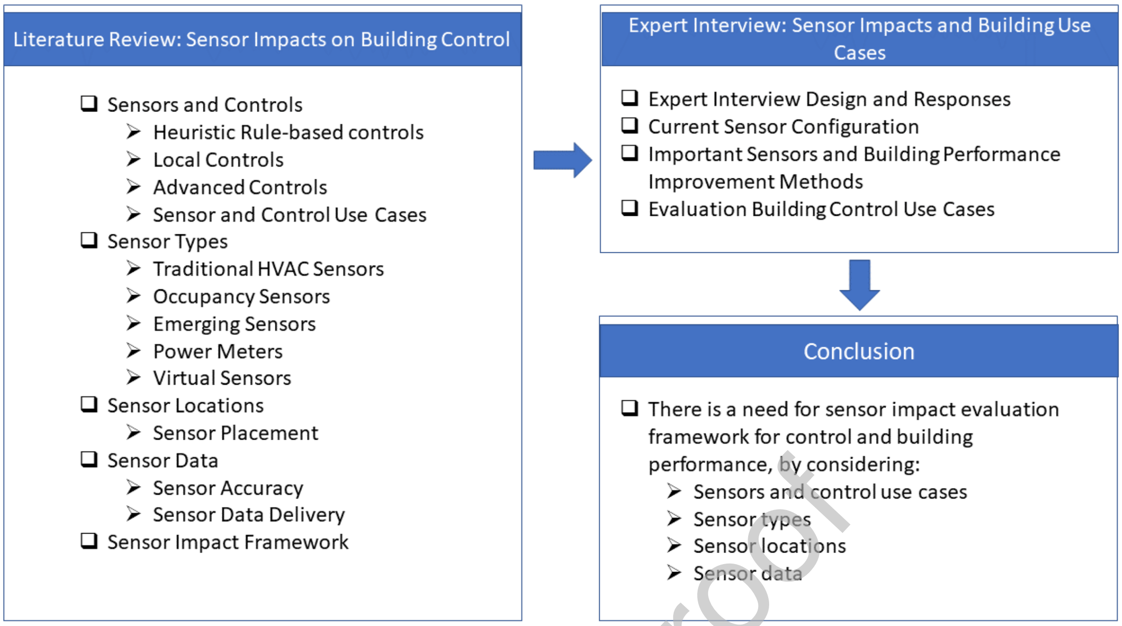

Figure 1. Structure of the paper.

Section 2 reviews 129 relevant papers related to sensor systems in building/HVAC applications for building controls and their impact on energy and thermal comfort. Because sensor impact varies significantly depending on building system and the control strategies deployed to the system, the sensor systems are reviewed from multiple perspectives including:

- sensors and controls,
- sensor types,
- sensor locations,
- sensor data, and
- sensor impact evaluation framework.

To augment the literature review, a series of comprehensive expert interviews was performed, and the interview results are analyzed in Section 3 to (1) investigate the current status and limitations of sensor configuration, (2) identify the research gaps and expectation for potential improvements in sensor configuration and deployment, and (3) integrate expert (e.g., researcher, building operation practitioner) knowledge and experiences to develop use-case scenarios.

2. LITERATURE REVIEW

Control and automation are essential to smart energy systems [8]. From a building 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 research and development pathways[4]. A recent study also validated these applications and pathways and provided a detailed insight into state-of-the-art building energy sensing and environmental monitoring, along with their socioeconomic and legislative drivers [9]. These sensors are used to monitor essential parameters and variables, inside and outside the building, that are crucial to efficiently operating buildings. The purpose of building automation systems can include intrabuilding conditioning for comfort and energy efficiency, thus enabling the buildings to actively participate as a resource under the smart grid framework.

In this section, three classes for building controls are presented: heuristic rule-based control, local control, and advanced control. As mentioned earlier, sensor impact varies significantly depending on control strategies used in the building system. Advanced controls usually require more information and often, the importance of sensing information within the overall control architecture is relatively higher than in heuristic controls.

2.1 SENSORS AND CONTROLS

This section describes the application of building sensing technologies for building control that enable energy efficiency and thermal comfort improvements. For any control loops, the information flow is as follows: data are collected from sensors, data are delivered to control algorithms, the control variable is estimated from control algorithms, and the control acts through actuators. If the data collection step suffers, then the subsequent steps will also be affected. The relationship between sensors and controls is shown in Figure 2.

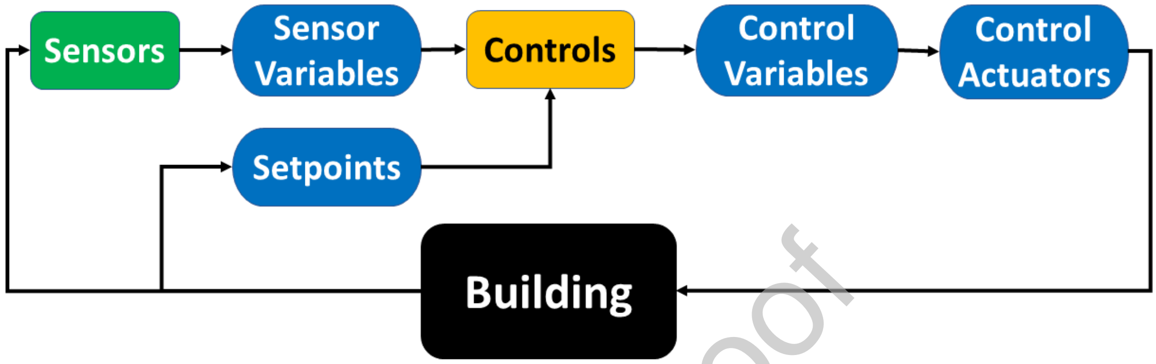

Figure 2. Sensor and control relationship.

2.1.1 Heuristic Rule-based Controls

Heuristic rule-based controls are common for HVAC systems. A typical building is operated with a set of standardized sequence of operations for HVAC systems, following some preset standards and codes. For example, the Sensor Characteristics Reference Guide [10] and ASHRAE Standards 90.1, 90.2, 55, and 62.1 are some of the standards that support multiple types of sensors (e.g., HVAC, room, and building sensors) used in building subsystems to facilitate energy efficiency and cost savings [11]. These codes provide sensor locations and configuration requirements for a wide range of application scenarios such as occupancy-based HVAC and lighting control, commissioning, indoor air quality control, ventilation, transactive energy, and renewable integration.

Some widely used rule-based control strategies are applied for variable air volume (VAV) and air-handling units, such as supply air temperature set point reset, static pressure set point reset, and VAV reheat controls. The information of zone state (e.g., heating, cooling, deadband, or occupied) or mode (e.g., occupied, setup, cooldown, warm-up, and setback) is needed in the control logics. The required input variables include cooling maximum/minimum airflow set points, heating maximum/minimum airflow set points, maximum/minimum supply air temperature set points, discharge air temperature set points, and highest/lowest values in the outdoor air temperature reset range [12]. Another study investigated sensor errors on demand control ventilation for single-duct VAV systems [13]. The study found that the annual energy consumptions deviation could range from 16.9% to 94.32% compared with the baseline case.

2.1.2 Local Controls

Local control loops are common in HVAC systems. According to a study of control loop performance assessment [14], the primary local control loops for HVAC are proportional control and proportional-integral control. Local control loops usually use one sensor. Sensor might also run under fault conditions. Sensor faults might lead to more or fewer normal control actions; thus, inaccurate sensor readings might directly affect local control loop performance. A few typical local control loop performances include rising time, over-shoot, and oscillations. To the best of the authors' knowledge, no studies have focused on how to quantify the sensor impacts on local control loop performance.

2.1.3 Advanced Controls

Advanced control strategies have the potential to outperform classic feedback control such as proportional-integral-derivative control and rule-based or heuristic controls. For example, model-predictive control (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% [15], [16]. The strength of the advanced control techniques lies in their prediction, optimization, and adaptation capabilities. These controllers systematically adjust the building operational set points (e.g., outdoor air ventilation rate, cooling, and heating set points) 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, activity variation driven by occupancy, and equipment aging and degradation. Advancements in artificial intelligence are being used to enhance controller scalability and deployment [17], [18].

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 [19], [20]. Studies have regularly highlighted the importance of including human feedback in the automation process [21], [22]. A simple coupling strategy—through a co-simulation method between the energy simulation of TRNSYS and the thermal comfort analysis of computational fluid dynamics—for building energy was developed for a real HVAC system [23]. This strategy assisted the VAV-optimal control through simultaneously optimizing the energy consumption and thermal comfort. Model-based predictive controllers [24], [25] have also been proposed to solve the same problem of comfort-energy co-optimization. To achieve the aforementioned co-optimization objective, sensing and monitoring capabilities are crucial in understanding user comfort and energy usage in high spatiotemporal granularity [26]. 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 [27]. Recently, artificial intelligence–based techniques have been investigated as a potential means to reduce the need for a dense and costly sensor infrastructure that could accurately predict thermal comfort [28]. Studies from Kumar et al. [29] and Dong et al. [30] provide an in-depth review of indoor air quality and energy sensing.

Sensing of building-level information and the corresponding usage in controls for enabling building-based grid services has been observed in literature. 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. [31]. 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 [32], [33]. Using 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 [34], [35]. Optimization-based building-to-grid frameworks have been proposed to improve zone-level temperature set points and power generation set points to provide frequency regulation services while maintaining the quality of service bounds [36], [37]. An ensemble of flexible devices, including responsive buildings, can also be used to minimize grid voltage and frequency deviations and simultaneously alleviate harmonic distortions as shown by Hong et al. [38]. The role of responsive buildings can also be critical in defining new tariffs, energy-pricing structures, and contractual/transactive energy-use schemes [39], [40]. 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 effectively [41]. Studies from Kosek et al. [42] and

Kolokotsa [43] provide an in-depth understanding of the role of responsive buildings in smart grids.

2.1.4 Sensor and Control Use Cases

Control loops are widely available for HVAC systems, and at least one sensor is associated with each control loop. How to quantify those sensors and control loops remains unknown. Different HVAC systems have different control loops. Chilled-water systems have a hierarchical layout, such as a primary system (e.g., chiller), secondary system (e.g., chilled water loops and condensing water loops), air-handler unit, and air terminals. Air systems have generally a supply system (e.g., rooftop unit), an air handler unit, and air terminals. Ground source heat pumps have even more complicated. Control loops for different HVAC systems must be investigated to provide a solid foundation for a sensor impacts study. A demonstration of sensor and control use cases is shown in Figure 3 and Table 1.

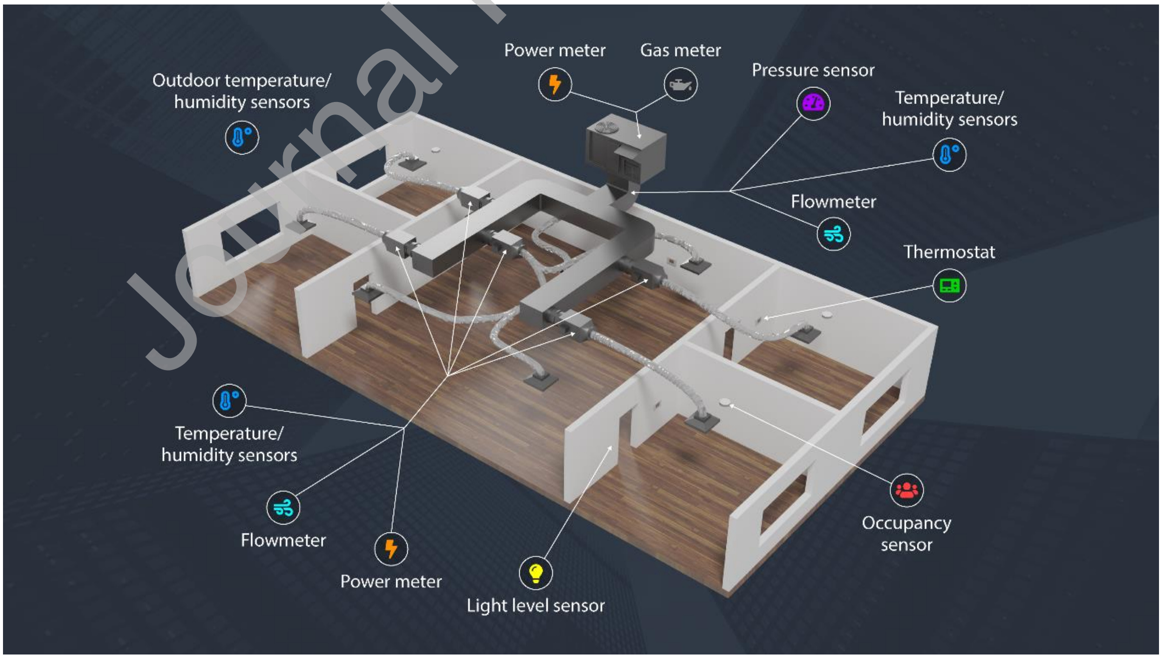

Figure 3. Typical sensors in building.

Control families	**Control logics**	**Example of sensors used for control**	**Note**
Rule-based controls	ASHRAE guideline 36 controls for single-duct VAV box and AHU [12]	Zone temperature sensor, zone humidity sensor, VAV box airflow rate sensor, VAV box supply air temperature sensor	Sensor might be different for other rule-based controls
Local controls	Generic controls	Chiller supply/return water flow rate sensor, fan flow rate sensor	Applicable to all HVAC control loops
Advanced controls	Model predictive control, reinforcement learning control	Zone temperature sensor, VAV-box airflow rate sensor, AHU supply air temperature sensor, AHU supply air flow rate sensor	Sensors might be different for other advanced controls
Advanced controls	Occupant control	Occupancy sensor	Different occupancy sensors can be used for detecting occupancy

Table 1. Sensor and control use cases demonstration.

2.2 SENSOR TYPES

With the development of HVAC and control fields, numerous sensor types exist. Sensors can be classified into multiple subgroups, and the details of each subgroup are discussed as follows.

2.2.1 Traditional HVAC Sensors

Building HVAC systems range from packaged units to built-up systems, and they vary in design. Commonly used equipment and components include chillers, boilers, heat pumps, fans, pumps, valves, heat exchangers, filters, dampers, diffusers, ducts, and pipes. The equipment must be properly instrumented to maintain stable and effective plant operation. Some HVAC equipment have built-in sensors and controls. When possible, accessing the built-in monitoring points is cost effective because it avoids the cost of installing redundant sensors for system-level control optimization. Sensors used in HVAC systems monitor temperature (e.g., outside air temperature, chilled water temperature, supply air temperature), humidity, flow (e.g., chilled water flow rate, supply airflow rate), pressure (e.g., chiller water pressure, duct static pressure), and gas flow for absorption chillers or boilers. These sensors are used in the control loop that is modulated to maintain the controlled variable (e.g., temperature or pressure point) at a set point. For example, the supply air temperature set point will be maintained in a VAV system by modulating chilled water and hot water flow, and the zone temperature set point will be maintained by modulating the VAV box damper position or turning on reheating. A more detailed review of sensor types and the accuracy required for typical chiller plant controls is provided in the *Chilled Water Plant Design Guide* [44]. Previous studies show that energy consumption in buildings could be reduced by 20%–40% via appropriate HVAC control strategies [45] and more advanced controllers by using neural network–based HVAC system control [46] and fuzzy logic–based HVAC system control [47] to minimize energy consumption and maximize the occupants' comfort metrics. HVAC equipment is often equipped with electrical meters, but additional sensors such as BTU meters may be needed to establish baseline energy consumption and verify the improved performance enabled by advanced control methods [48].

2.2.2 Occupancy Sensors

Conventional building HVAC and lighting systems have been designed and operated based on conservative and fixed operating schedules that assume maximum occupancy in spaces. Because of the spatiotemporal mismatch between the conservative schedules and the actual building use, conventional building systems often suffer from wasted energy. Previous studies have claimed that a significant potential exists to improve building energy efficiency without compromising the occupants' comfort by adopting occupancy-based control (i.e., deploying energy where demand actually exists) [49], [50].

Because of the instantaneous system response of lighting systems, developing and implementing occupancy-based control has been relatively straightforward. Therefore, various building standards and green building rating programs have requested or recommended occupancy-based lighting control [22]. Literature has reported that the energy-savings potential of using occupancy information ranges from 20% to 75% [51], [52]. However, limited performances of existing occupancy-sensing technologies occasionally cause false on/off switches of lighting systems; consequently, the occupants' dissatisfaction and energy-waste have also been reported [53]. Additionally, control strategies for open-plan offices need further investigations [54].

Following the successful implementation and demonstration of occupancy-based lighting control, efforts have been made to use the occupancy information in HVAC controls. However, because of the slow system response of HVAC systems, predictive strategies are often required to ensure the occupants' comfort and minimize energy consumption [55], which makes developing practical and scalable occupancy-based HVAC control somewhat difficult 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 varied from 5% to 60% [22], [56], [57].

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) [58], [59]. Information on the occupants' presence can be used to turn on/off lighting and HVAC systems, as well as adjust temperature set points. 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 [60]. Finally, occupant identity and location could be used to provide customized indoor environments to occupants to maximize their satisfaction while optimizing energy efficiency [25].

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 [61], [62]. PIR sensors are especially popular for real applications because they are robust to interference caused by environmental variances [63]. However, using only motion sensors has major limitations [53], [58], [64]. Motion sensors can only provide occupant presence/absence information (i.e., more detailed information such as the number of occupants, identity, and location is normally unavailable), and require detectable movements (motion). If no movement occurs, usually a 15 to 30 min delay is applied before switching from the present state (occupied) to the absent state (unoccupied). This delay can cause energy waste. Furthermore, motion sensors can be triggered by other objects such as hot beverages, appliances, or pets, and 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, CO_2, acoustics, light) can be used to infer occupancy information [65], [66]. One advantage of methods based on the variation in ambient conditions over the motion sensors is that the number of occupants can be inferred. Because 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) [59]. Methods using the variations in CO_2 concentration are most common in this category [67], [68]. However, the slow gas mixture in buildings limits the estimation performance of a method that relies only on the CO_2 concentration [69].

Vision-based methods have gained attention in recent years following the rapid development of sensing, computing, and computer vision technologies[70], [71] . The occupants' interaction with furniture (e.g., chairs, doors) [65], [72], [73], appliances (e.g., computers) [58], [74], communication networks (e.g., Wi-Fi, Bluetooth) [75], [76], and corresponding plug loads [77], [78] can be used to estimate occupancy information.

As mentioned, energy-savings potential significantly varied in previous studies (20%–75% for lighting systems, 5%–60% for HVAC systems) because of the variation in weather conditions, building characteristics, lighting/HVAC system configurations, occupancy patterns, and the way researchers defined their baseline. Jung and Jazizadeh [22], [60] also discussed the difficulty in comparing the reported energy-savings potentials. Additionally, because occupancy-based control consists of multiple components (sensing/estimation, pattern recognition/learning, control logic/algorithm), the way in which the superiority/imperfection of each component contributes to the overall performance is difficult to disentangle from the reported energy-savings potentials.

2.2.3 Emerging Sensors

With the advent of information and communication technologies, researchers are exploring the use of smart 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 can be found in research from Minoli et al. [79] and Khajenasiri et al. [80]. Such IoT-based building energy management sensors could find applications in demand-controlled ventilators, energy recovery ventilators, dedicated outdoor air systems, CO_2 sensors, ultraviolet germicidal irradiation, displacement ventilation, and underfloor air distribution [79]. 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 [81]. IoT sensors are also being linked with advanced control methodologies for building energy management, and appreciable (30%–40%) savings are projected in terms of cost of energy usage and peak demand power [82]. Specifically, in research from Tran et al. [82], IoT sensors were connected to lighting, plug loads, and HVAC systems to seamlessly transfer data to the cloud, which performs the scheduling optimization. Also, researchers have recently considered optimal sensor placement to provide maximal sensing and observability by using minimal infrastructure for building energy management into an IoT framework [83].

2.2.4 Power Meters

Building-level power sensing for electricity is prevalent in commercial buildings. Submetering at the equipment or device level can provide 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 are 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, such as power consumption [84], [85].

Advancements in two-way communication and power metering (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 strategies include frequency regulation [35], [86] and ramping controls [87] to track a given power consumption signal as directed by a grid operator or distributed energy resource aggregator. This increasing use of automation, communications, and smart meters also improves the precision of demand response dispatch and the accuracy of measurement and verification.

2.2.5 Virtual Sensors

Using a dense and intricate sensing infrastructure might be costly and pose multiple challenges for installation and maintenance. To circumvent these issues, virtual sensing through detection, estimation, and learning techniques has become very important in advanced building control design [88]. MPC particularly 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 real building sensor data. Estimation techniques are typically employed to deduce inputs and physical parameters that are difficult to sense directly (e.g., internal loads, wall temperature) [89]. 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 [90]. Nonintrusive load monitoring processes for disaggregating a power signal (e.g., smart meter data) to building end uses are also being researched as low-cost alternatives to submetering [91].

2.3 SENSOR LOCATIONS

Sensor location is another important factor in control loops. Commercial buildings have multiple thermal zones, and these thermal zones have different temperature profiles due to different occupant behaviors and solar radiation. Even within the same thermal zone, the temperature profile might be different for different parts of the zone. Most engineering designs and practices pick one location arbitrarily rather than installing multiple sensors because adding more sensors will increase the construction costs and maintenance costs.

Selecting and placing sensor systems requires considering significant factors that directly affect the building's performance. Additionally, investigating optimal sensor deployment and configuration methods for different building and HVAC components bridges the gap between conventional and advanced strategies [5]. Previous studies investigated how sensor locations affect building performance [5], [92], and the impact of different sensor types on HVAC system performance[93], [94]. Most of the sensors in the building space might require optimized locational deployments to considerably affect system-level energy consumption. Du et al. [23] observed that changing the sensor positions in one of the building's seven rooms resulted in an HVAC energy variation between −0.34% and 0.14%. Therefore, a sensor placement retrofit in a small subset of the building might not affect the overall HVAC energy consumption (air side and water side), and evaluating the impact of a set of sensors in buildings is desirable.

One commonly used parameter for controlling the indoor thermal environment is the zone air temperature, which is controlled by thermostats. In typical buildings, a thermostat is installed in each zone and controls the zone temperature, or a central thermostat controls the conditions of several zones based on the average air temperature or representative zone air temperature [95]. Previous simulation and experimental studies [96], [97] showed that the temperature profile along the vertical direction at different locations is nonuniform and stratified, and the temperature profile is also different under various conditions (e.g., supply airflow rate, geometry of the zone, climate region, seasonal variation). Because of the temperature distribution profile, thermostat locations significantly affect building energy usage [23], [93], [98] and occupants' thermal comfort [23], [95], [97].

Sensor locations and the number of sensors are generally selected based on engineering judgment or heuristic methods [99]. However, the existing standard code (i.e., ASHRAE

Standard 55 [100]) does not provide a practical solution for thermostat location, and the current practice of thermostat location selection is not necessarily optimal in terms of energy efficiency and thermal comfort. For example, one study showed that placing a temperature sensor for the VAV control loop at the return air inlet may not always be optimal [7]. During the cooling season, the required airflow increases when the sensor is placed at the return air duct because the temperature in the return duct is usually higher than the zone temperature, which can lead to overcooling.

Previous studies have provided multiple methods to optimally select thermostat locations. Data-driven optimization methods are especially popular. Yoganathan et al. [94] proposed a data-driven method, including a clustering algorithm and the Pareto principle, to select the optimal sensor measurement points in an office building. The study found that the optimal spatial location of temperature and humidity sensors could vary with time. Aiming to reduce the number of required sensors, Chen and Li [101] proposed a method of developing virtual sensors by combining the prior knowledge of temperature statistics and Bayesian model fusion to predict spatial temperature distribution by maximum-a-posteriori estimation. 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 optimal thermal comfort [5]. Tian et al. [96] proposed an optimization platform that successfully seeks the optimal placement of thermostats in an office room, with displacement ventilation and a VAV terminal box. Either the best thermal comfort or the least energy consumption could be achieved by using the particle swarm optimization algorithm as the optimization engine.

Several studies [55], [102] have investigated localized temperature-sensing methodology. Multiple sensors (e.g., wireless sensors) have been used instead of one sensor, or existing sensor data have been used to control the indoor environment. Up to 40% of commercial building energy use could be saved [103] by using a wireless sensor network. State-of-the-art sensing technology—such as an automated mobile sensing system that uses a sensor-rich, navigation-capable robot [104] —has been used to monitor indoor environments. However, despite developing cost-effective sensors and simplifying deployment, simultaneous monitoring of numerous variables, data management, power consumption of wireless sensors, and maintenance issues still remain as challenges [104].

Environmental monitoring sensors that monitor the internal and external conditions of the building are also valuable for advanced building control. These sensors monitor temperature, relative humidity, pressure, illuminance, daylight, and air quality [9]. Such sensors are widely used in centralized and distributed predictive control schemes for building energy applications and demand response [20], [24], [25].

Several studies have focused on low-cost sensors, especially minimum-cost sensor networks. Low-cost sensor networks are widely deployed in other domains, such as surveillance. A minimum-cost sensor placement algorithm was proposed for surveillance purposes for precious items [105]. In modern building automation systems, the wireless sensor/actuator network is widely used for lighting controls. A codesigned strategy was applied for building lighting controls [106], which achieved 45% energy savings with a 23% reduction in sensor costs. Another study used low-cost sensor networks for lighting glare controls [107]. Similarly, another study applied low-cost motion sensors and light sensors for LED light controls, resulting in 55% energy savings within a 6 month period, and 69% savings during spring months [108].

Studies on low-cost sensor networks for building monitoring and controls are limited. One study [61] applied the low-cost sensor network for an indoor monitoring system through experiments, which did not provide quantitative information for cost savings. Another effort made to reduce sensor costs for building monitoring with innovative sensor set hardware designs [109].

2.4 SENSOR DATA

Sensors have two tasks for control loops: collecting and delivering sensor data. Because control systems are more complicated, large sized commercial buildings have many sensors, and managing the sensor data remains a challenge. Two considerations for ensuring data quality are sensor accuracy and sensor data tagging.

2.4.1 Sensor Accuracy

Generally, sensors work as expected because they are calibrated by manufacturers. However, sensors might work with low fidelity. There are multiple reasons for sensor abnormality, such as harsh environments and manufacturing defects. In such scenarios, sensor reading accuracy might suffer, which is commonly considered a sensor fault. HVAC systems could have multiple faults [110]. There are nine types of sensor faults [111] and multiple approaches to sensor fault classification. Sensor faults can be classified as *precision* or *bias*. Precision is used to measure how precise the sensor reading is from the true reading because of measuring noise. Bias is used to measure how far the sensor reading is from the true reading because of the system bias. Figure 3 provides a typical diagram of precision and bias. Sensor faults could evolve and change with time, and these are usually called *incipient faults*. One typical characteristic of incipient faults is that the fault magnitude might change slowly with time, and effects on control performance might go unnoticed. Very few studies focus on incipient faults. One study [112] proposed a methodology to estimate the incipient fault magnitude for HVAC systems.

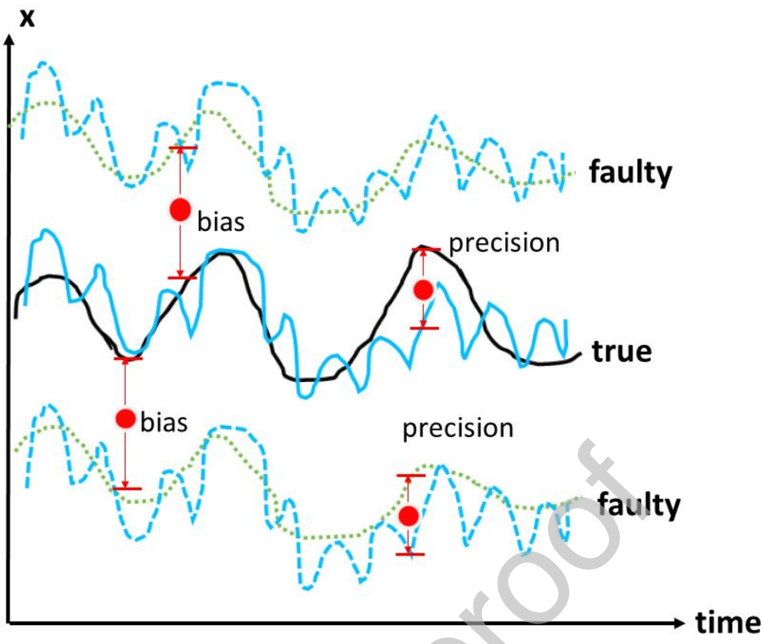

Figure 4. Sensor faults classification.

Multiple studies have investigated the sensor errors for sensor fault distributions. In a study that focused on a fault impact analysis framework [113], normal distributions were applied for sensor errors. Another study investigated sensor fault impacts on building energy consumption for demand control ventilation [13]. The normal distributions were applied for sensor errors. Different sensor types have different sensor errors, so the characteristics of each sensor error must be investigated.

A few studies have focused on sensor fault impacts on HVAC systems. Within the HVAC context, the air temperature of rooms and air conditioning ducts are measured. However, these measurements may be inaccurate or noisy. Also, some sophisticated advanced control strategies require measuring or estimating the slow dynamic states (e.g., temperatures of the walls, ceiling, and floor) and heat gains. Temperature-sensing accuracy likely affects the performance of advanced HVAC control algorithms, but the effect has not yet been fully explored or quantified.

Maasoumy et al. [106] 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. These results provided a co-exploration framework for selecting the most cost-effective sensing platform and control algorithm that minimizes the building energy cost and the 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 performance of the estimator-controller combination was evaluated over a range of temperature measurement noise amplitudes and showed that the advanced control methods outperformed the on-off controller for energy cost and discomfort level, even when affected by sensor noise. However, no clear superior system 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, which 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 [114], [115]. A simple rule-based or classic controller could outperform advanced control if the model uncertainty exceeds a certain threshold [114].

2.4.2 Sensor Data Delivery

Data delivery is another major task of sensors for controls. Large commercial buildings could have thousands of sensors, which make data transfer and management challenging. Thus, data delivery is extremely important. One approach is to add unique identifiers to sensors, which provides portability and accessibility. Data tagging is another solution. There are two emerging trends for data tagging schema: Project Haystack [116] and Brick [117]. Cybersecurity threats are increasing, and sensor data delivery could be hacked as a result. How hacked sensor data affects building control performance must be understood. A typical situation could include sensor data being modified by hackers and sent to the control loops, resulting in extreme control actions. To the best of the authors' knowledge, no such study has examined this challenge.

2.5 SENSOR IMPACT EVALUATION FRAMEWORK

Although many studies have focused on building controls and sensors, few frameworks can evaluate the sensor impacts on building controls and performance. Li and O'Neill [113] developed a comprehensive fault impact analysis framework for building and HVAC systems based on EnergyPlus. The faults in the study included sensor faults and HVAC-related faults. A control-oriented sensor impact evaluation framework is still desired, and such a framework must have the following characteristics:

- **Extensible and scalable**: There are at least 16 building types, including commercial and residential buildings, and there are numerous control systems and sensors. All the control systems and sensors must be integrated into a comprehensive framework to assess the effects of sensors for different control systems and building performance.
- **Definitive metrics**: Hierarchical building performance metrics lack control loop performance and building performance. Several typical metrics are available for control loop performance, such as rising time, overshoot, and oscillations. These metrics have been widely studied for the performance of local control loops and limited rule-based control loops [118], [119]. However, very few studies have examined advanced controls. For building performance, two typical metrics are available: thermal comfort (e.g.,

percentage of persons dissatisfied) and energy consumption. Other metrics should also be explored, such as indoor air quality and grid response impacts.

The proposed framework concept is demonstrated in Figure 4. This framework must integrate a currently available building simulation platform and potentially include more control loops.

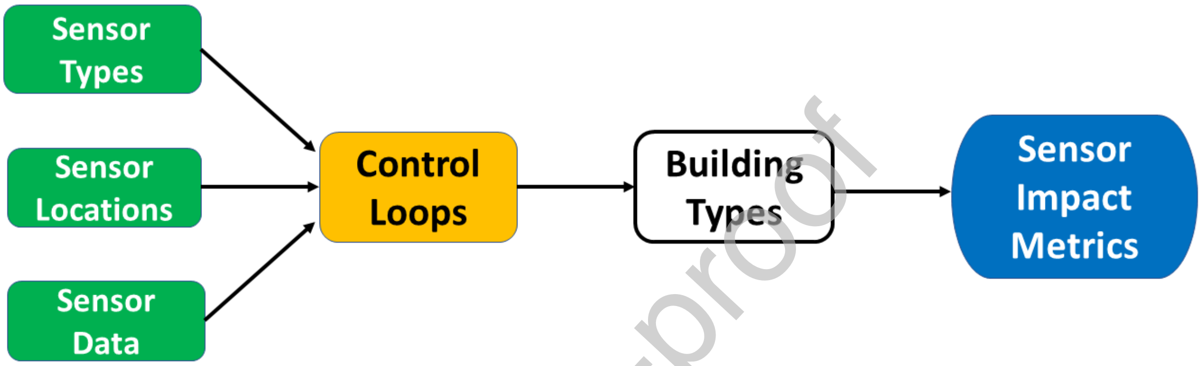

Figure 5. Sensor impact framework concept.

2.6 DISCUSSIONS

From the review presented in Sections 2.1–2.5, it is evident that sensor impacts for building controls have several interesting unexplored aspects that warrant systematic future investigation and research. At the outset, the authors established how sensors are critical for performing controls aimed at rendering buildings energy efficient while maintaining thermal comfort. These control sequences can often be simple rule-based controls, or more sophisticated optimization-based advanced controls. Through the literature review, the authors have also established that these sophisticated optimization-based algorithms often rely more heavily on accurate sensor measurements than simpler rule-based heuristic controls. Moreover, a wide variety of sensors is needed—including temperature sensors, pressure sensors, flow meters, occupancy sensors, power meters, and other virtual sensors—to implement building control schemes. The degree of control performance is often contingent upon the accuracy levels of these sensors; therefore, any possibility of error in sensing mechanisms must be understood carefully to extract maximal benefits from the advanced control algorithms rendered feasible through such sensing mechanisms. Furthermore, issues such as privacy concerns, cyber threats, deployment challenges, installation and maintenance costs, and sensor reliability are important to be considered when trying to assess the holistic capabilities offered by sensing infrastructures. To better understand the entire spectrum of salient points pertaining to sensor-based controls in buildings, the authors conducted an expert interview in which experts from industry and academia provided detailed feedback to a carefully constructed questionnaire related to multi-faceted sensor operations in buildings. Details related to this interview process are described in the following section.

The reviewed literature is summarized in Table 2. This section systematically investigates the major aspects of sensors, which directly affect control and building performance.

Table 2. Sensor impact literature review summary.

Control type	Sensor type	Sensor location	Sensor data	Building performance	Note
	Thermostat	Thermostat location		Zone temperature, Predicted Mean Vote	[5]
	Wireless	Hardware			[6]
Occupancy	Occupant			Energy saving	[7]
Demand control ventilation	Temperature, CO_2, airflow		Normal distribution of sensor errors	Energy saving	[13]
VAV	Temperature	Placement			[23]
	Temperature, airflow, power meter, lighting			Energy efficiency	[26]

	Temperature, humidity, sound, lighting, CO_2	Sensor cost			[27]
Advanced	Temperature, humidity, sound, lighting, CO_2	Sensor cost		Indoor air quality, Energy efficiency	[29]
	Temperature, lighting, airflow		Fixed sensor error		[31]
Predictive controls	Temperature		Normal distribution of sensor errors	Demand response	[32]
Advanced control	Temperature, humidity, airflow			Thermal comfort	[120]
Supervisory control	Temperature	Sensor cost		Energy consumption	[48]
Advanced control	Temperature, humidity			Energy consumption	[49]
Occupant control	Occupant	Sensor cost		Energy consumption	[51]
Light control	Occupant			Energy consumption	[52],[53],[54], [55],[73],[65], [76],[66],[78], [107],[108]
Advanced control	CO_2			Energy consumption	[56]
Demand control	Occupant			Energy consumption	[58]
	Occupant			Energy consumption	[59],[61],[69], [121],[122],[62], [123],[68],[75]
Model predictive control	Occupant			Energy consumption	[60]
Demand control ventilation	CO_2			Energy consumption	[67]
	Occupant			Power	[124],[70]
	Occupant		Sensor accuracy		[71]
	Generic	Placement		Energy consumption	[83],[92], [93],[125]
	Thermostat	Placement		Energy consumption	[95],[96]

	Temperature			Thermal comfort	[97]
	Contaminant	Placement	Normal distribution		[99]
	Temperature, flow rate	Placement		Thermal comfort, energy consumption	[102]
Advanced control	Temperature			Energy consumption	[126],[127]
		Optimal location		Energy consumption	[103]
			Incipient faults	Energy consumption	[128]
	Generic		Normal distribution of sensor errors	Energy consumption, thermal comfort	[113]
	Generic		Data-delivering schema		[116],[117]
	Generic	Sensor cost		Energy consumption	[109]

As shown in the Table 2, the sensor impact related literature can be summarized based on five key aspects: sensors and controls, sensor types, sensor locations, sensor data, and sensor impact framework. For sensors and controls, a few studies have investigated the advanced controls and rule-based controls. However, no study has investigated local controls. For sensor types, the majority of traditional HVAC sensors are covered, but emerging sensors are not. For sensor location, the literature is abundant; however, more studies focused on finding optimal locations for occupancy sensors. For sensor error characteristics and distribution, studies are very limited. Future work should explore and define the sensor error characteristics for all sensors. For building performance metrics, most studies used the energy consumption and thermal comfort. In the near future, the following research gaps should be investigated, including sensor and control quantifications, sensor for local controls, sensor locations, more sensor types, and sensor accuracy.

- A unified framework must be developed to investigate the sensor effects on building control loops. This framework can help facilitate sensor deployment and configurations for practical implementation.
- Within such a framework, various aspects of sensors must be included, such as different types of sensors, sensor locations in buildings, and sensor data accuracy or error. Furthermore, sensor cost needs to be considered because cost also impacts the adoption of sensor deployment and thus impacts control performance and building performance.
- The extensibility of the framework is also important. There are various commercial building types in which the HVAC systems are different, and different building types and HVAC systems likely need different sensors and sensor combinations.
- Control loops vary based on building type and HVAC system. They also determine different sensor sets. Sensors will likely be investigated based on the performance of control loops, such as local control, rule-based control, and supervisory controls.
- From the perspective of building energy savings, such a framework can help facilitate the sensor placement and configurations to reduce building energy consumption.
    - Investigating optimal sensor locations of multi-zone buildings can help reduce HVAC energy consumptions. A good example is deploying multiple sensors for multi-zone buildings, which can be used to make accurate control decisions.
    - Reducing or eliminating sensor errors will decrease HVAC energy consumption. Sensor error leads to a significant difference in target variables (e.g., zone air temperature), which causes the control loops to make incorrect decisions, leading to greater energy consumption.

- Studying different types of sensors for control loops can improve understanding sensors error characteristics. This is an essential step in establishing the database for sensor types and sensor error behaviors.

- Performing a stress test for HVAC system sensors is a robust approach for investigating the sensor data delivery (e.g., sensor data hacking). Sensor data hacking is becoming common as more IoT infrastructure is adopted.. This could lead to disastrous consequences for thermal comfort and normal building operations. The sensor impact framework can help improve understanding of the stress limits of various sensors and control loops.

3. EXPERT INTERVIEWS

Few studies have been performed on how sensors affect building performance. However, those studies did not cover all sensor aspects. One remaining question is, how sensors are currently used in building operation and affect building performance. A comprehensive expert interview [129] was conducted to answer this questions and better facilitate the understanding the sensor impacts on building performance. The goals of the interview were to (1) investigate the current status and limitations of sensor configuration, (2) identify the research gaps and expectations for potential improvement of sensor configuration/deployment, and (3) integrate expert (e.g., researcher, building operation practitioner) knowledge and experiences to develop use-case scenarios. The authors believe that this interview augments the findings from the detailed literature review presented. Detailed findings from this interview are summarized as follows.

3.1 EXPERT INTERVIEW DESIGN AND RESPONSES

The interview questionnaires contained items with multiple-choice and scale-rank questions. After the questions were designed, interviews were conducted with experts in the sensors and controls field, including those in academia, industry, and at various US national laboratories. The interviews consisted of six sections: (1) background of the study, (2) purpose of the interview, (3) area of expertise, (4) current sensor configuration practice, (5) how to improve building performance with sensor systems, and (6) use-case evaluation.

The most common type of question was multiple-choice, and the interviewees were asked to select one or more options from a list of predefined answers. An “other” option was provided for if an interviewee’s answer did not fit into the list of choices or the interviewee wanted to provide a custom response. Scale-rank questions were used to evaluate use cases identified from previous literature reviews. The experts were asked to evaluate each use case on a numeric scale from 1 to 5, with 1 meaning the lowest impact and 5 meaning the highest impact.

Thirty-one interview responses were collected: six from individuals in academia, 11 from individuals in industry, and 14 from individuals in US national laboratories. Interviewees could choose multiple areas of expertise, which included building operations, HVAC systems, building systems, indoor environment, and policy .

3.2 CURRENT SENSOR CONFIGURATION PRACTICE

To identify current sensor configuration practices, experts were asked the following questions: “What are the most significant factors for selecting the sensor set?” and “What are the current issues of sensor performance?” The interviewees selected one to three choices or each of these questions, and the selection percentages were calculated by dividing the sum of selections for each factor/issue by the total number of interviewees. As shown in Figure 5, three factors—initial cost, reliability, and accuracy—held a significant lead over the other factors, which means that most interviewees valued these elements in selecting an appropriate sensor set for their purpose of using a sensor system. The selection percentages were calculated by dividing the sum of the selections for each sensor system/manner by the total number of interviewees.

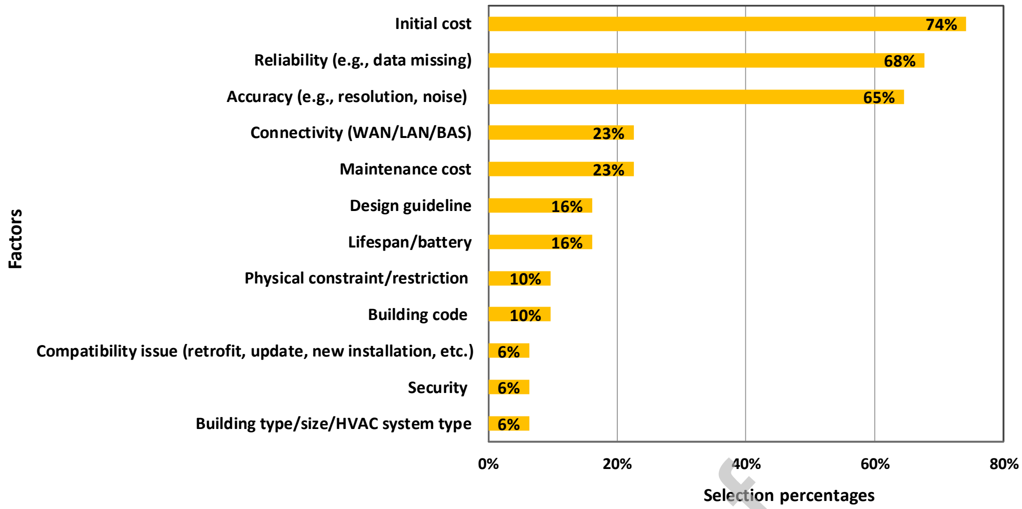

Figure 6. Summary of significant factors for selecting the sensor set.

Initial cost, including equipment and installation costs, was rated the most significant factor in sensor selection and sensor performance. Accuracy was chosen as a significant factor in selecting sensors by many experts; however, accuracy was not as highly regarded by other interviewees because they consider high accuracy to be required for only some of the applications for which they use sensors. Some interviewees noted that the significance of factors could differ according to the sensor type, which in turn depends on the application domain. For example, reliability and lifespan may be the most important factors for selecting lighting sensor systems, and for which accuracy is not a major concern. However, accuracy is a critical factor for air quality monitoring and is therefore a higher priority in considering choices for indoor air quality sensor systems. Also, interviewees pointed out that sometimes, using local sensors for ease of deployment may be economically and logistically viable. Besides the factors listed in the interviews, some interviewees mentioned that easy installation, less sensor drift over time, data handling, management, and accessibility were also key factors for selecting a sensor set.

Figure 6 shows the interview results for current issues in sensor system design, deployment, and operation. Interviewees chose reliability, initial cost, accuracy, and maintenance cost as the most common issues for current sensor systems. The same list of issues (a total of 12) was chosen as significant factors in selecting a sensor system (Figure 6).

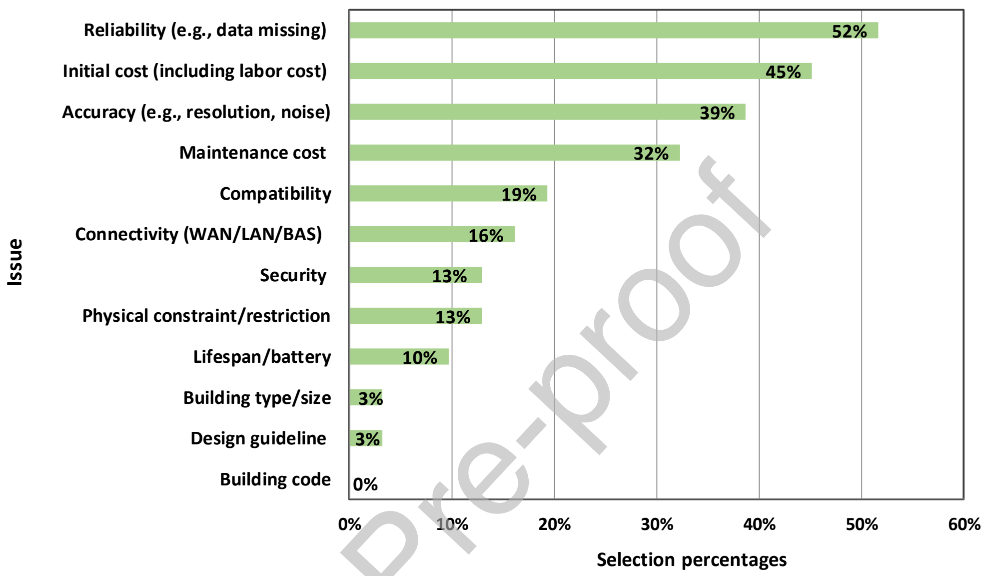

Figure 7. Summary of current issues of sensor deployment.

In addition to the issues presented in Figure 6, the following unlisted issues were reported from multiple interviewees: difficulties in deploying sensors, inaccuracy caused by sensor location, stability of sensor communication links, difficulties of autocalibration of sensors (especially CO_2 sensors and entropy sensors), long-term accuracy against sensor drift and bias, and inaccuracy because of indoor contaminants.

Another issue was related to increased demand for the use of sensors and the limitations of wireless sensors. In considering trade-offs between sensor cost and resulted benefits, one potential solution is to install wireless sensors. However, one interviewee suggested that a battery-operated system (i.e., wireless sensors) is not desirable for existing buildings because of the physical limitations of sensor location (e.g., ceiling height). Considering that most sensors are installed in ceilings and that the ceilings of existing buildings are difficult to access, wireless sensors are not desirable for calibration or maintenance work. Another interviewee stated that wireless sensors are limited in reliability and battery life, so choosing sensors with lower power consumption and longer lifespans is important.

3.3 IMPORTANT SENSORS AND BUILDING PERFORMANCE IMPROVEMENT METHODS

To identify the most influential sensor system and corresponding building performance improvement method, experts were asked two questions: “What are the most important sensor systems in terms of building energy/thermal comfort performance?” and “How would you improve on current sensor performance for new building or existing building design?” The selection percentages were calculated by dividing the number of interviewees who chose each sensor system/method of improvement by the total number of interviewees. The interviewees made at least one selection in each category (room layer and HVAC layer) for the first question. In the room-layer category, the choices were sensors for thermal comfort and indoor air quality, occupancy sensors, and lighting/daylighting sensors. Sensors for HVAC control and system efficiency were the choices for the HVAC-layer category.

Figure 7 shows that sensors for thermal comfort were identified as the most important sensor systems in terms of building energy/thermal comfort performance, followed by sensors for HVAC control, sensors for indoor air quality, and occupancy sensors.

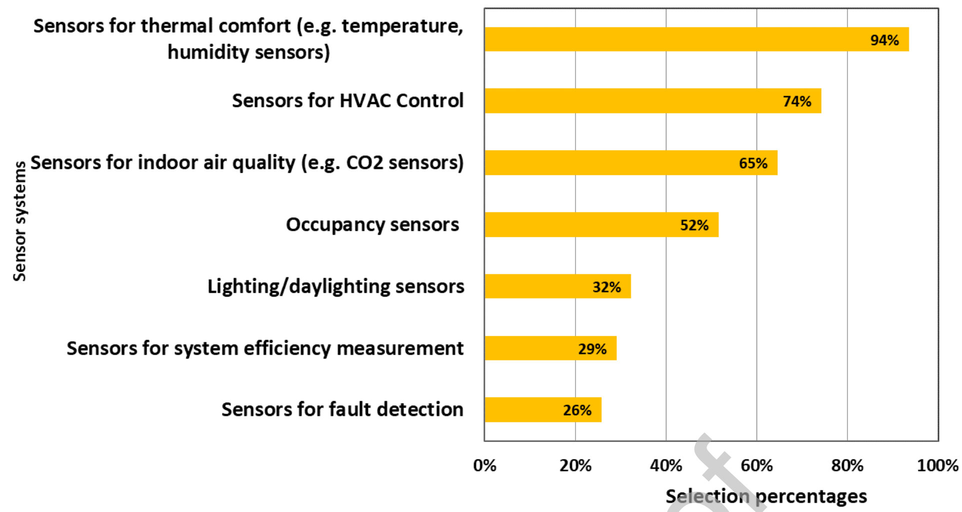

Figure 8. Summary of important sensor systems in terms of building energy/thermal comfort performance.

Besides the systems listed in Figure 7, other important sensor systems were proposed by multiple interviewees: mean–radiant-temperature sensors, energy meters, and refrigerant leakage sensors, which are important for fault detection but are quite expensive; and sensors for critical temperature and flow measurements, such as mixed air temperature.

Figure 8 shows the results for building performance improvement methods. Interviewees were asked to choose one of the proposed methods and to specify a detailed description of the method. The most common selections among all the proposed methods were to improve the current practice of sensor configuration/design, install additional sensor sets, and install advanced sensor system(s). Detailed descriptions of methods of improving current sensor performance suggested by interviewees are summarized in the following paragraphs.

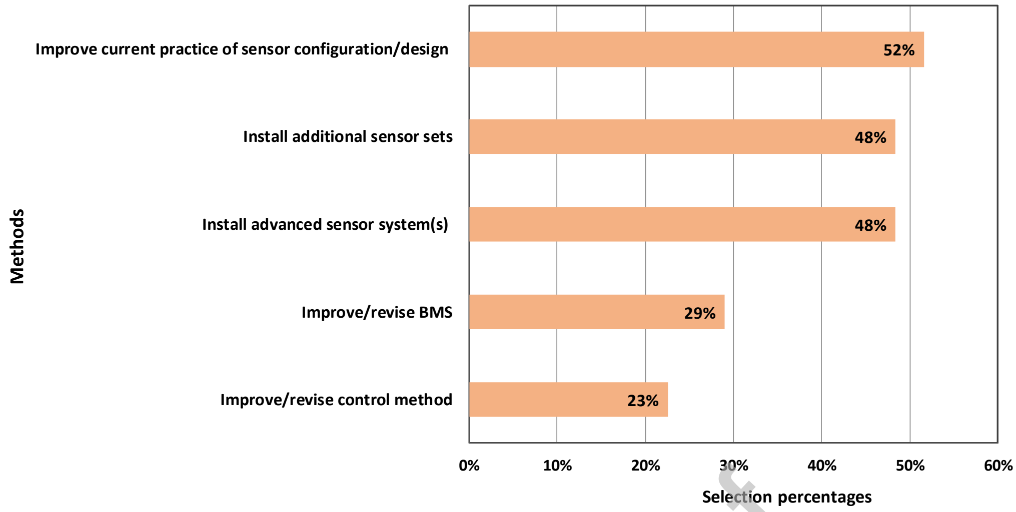

Figure 9. Summary of methods to improve sensor performance for building energy/thermal comfort performance.

Improve the current practice of sensor configuration/design: One interviewee suggested ensuring that sensors are labeled with the correct name and calibrated regularly. Another interviewee suggested adding redundant sensors to improve reliability and to perform self-calibration. Another mentioned that focusing on the end use by understanding how the sensor data can be used to cater to that end use before designing the sensor configuration may be ideal. Such approaches might render more simplistic and better configurations. Other suggestions included (1) including building automation system-integrated zone occupancy sensors for airflow/thermostat resets; (2) including more zone-level CO_2 sensors for flexible airflow control; (3) including more water flow and supply/return temperature monitoring systems to calculate and track energy output on each piece of equipment; and (4) ensuring better connectivity of sensors to the building automation system, especially zone-level information such as occupancy and lighting.

Install additional sensor sets: Installing more sensor sets was recommended to sufficiently cover the area. Wireless sensors were suggested because of the simplicity and cost-effectiveness;

hence, they can be installed without continuous monitoring of sensor data. One interviewee suggested that adding CO_2 and occupancy sensors, as well as adding more sensors to monitor various duct and pipe statuses, can be relevant. One interviewee also suggested including more self-commissioning and self-configuring sensor systems. A caveat to that recommendation is that adding sensors must be economically viable to attain those self-adaptive goals.

Install advanced sensors: Advanced sensors can have an open format and can be used by any kind of software for analysis. Improved new sensor technologies such as local thermal imaging and advanced imaging sensors were suggested. Enhanced sensor systems (e.g., lighting, occupancy, daylight, airflow meters, combined CO_2 for retrofits) are also recommended to install in office buildings. Electrical submetering of key equipment, natural gas interval metering, hot/chilled water flow submetering, room-level sensing (as opposed to only zone-level sensing), and direct airflow measurement (instead of estimations from indirect measurement) were also suggested. Some interviewees also proposed using advanced state-of-the-art sensors (such as IoT sensors, water flow rate sensors, or refrigerant leak sensors) as well, but these sensors might be cost-prohibitive. One interviewee also identified the use of advanced data-driven analytics to enhance sensor system performance by generating more actionable (rather than passive) data.

3.4 EVALUATION OF BUILDING CONTROL USE CASES

This section analyzes the evaluation of building control use cases from interviewees. Each interviewee was asked to evaluate each use case on a scale of 1 to 5 for least to highest impact. Based on a literature review conducted beforehand, the four most suitable building control use cases were selected. These use cases are worth investigating because of their significant impact on building operation performance. The selected use cases are shown in Table 3.

Table 3. Selected use cases for control.

Control use cases (additional information in Table A.1)	
1	Thermostat performance evaluation by thermostat locations, numbers, and different sensor characteristics for energy and thermal comfort (e.g., optimal thermostat locations)
2	Sub-zoning VAV system (e.g., one thermostat for multi-zones into individual thermostats in the zone)
3	Occupancy sensor impacts on energy usage and comfort
4	Sensor requirements for advanced control strategies (e.g., MPC, adaptive control)

Evaluation rationales for research potential and research limitations are also provided. Four selections were considered for research potential—energy savings, comfort, grid interactivity, and economic/cost potential. Five selections were examined for research limitations—already investigated in active academic research, already optimal, practically not feasible, no cost benefit, or code restriction. The rankings of the research potential and the research limitations of each use case are attached in Appendix A. The selection percentages shown in the figures were calculated by dividing the sum of selections for each research potential by the total number of interviewees who made the selections.

The weighted average values of the control use cases are shown in Figure 9. The weighted average score of each use case was calculated by dividing the sum of all the scales by the total number of interviewees who made selections (e.g., 25 interviewees made selections for control use-case occupancy sensor impacts on energy usage and comfort, and 24 interviewees made selections for control use-case sensor requirements for advanced control strategies). Figure 9 shows that three control use cases have similar weighted average scores (between 3.8 and 4.1), whereas the thermostat performance evaluation by the thermostat location, number, and sensor characteristics for energy and thermal comfort (the bottom bar) have a significantly lower score (3.1). The standard deviations are 1.19 for "CONTROL: Thermostat performance evaluation by thermostat locations, numbers, different sensor characteristics for energy and thermal comfort (e.g., optimal thermostat locations),", 1.15 for "CONTROL: Sub-zoning VAV system (e.g., one thermostat for multi-zones into individual thermostats in the zone)," 0.73 for "CONTROL: Occupancy sensor impacts on energy usage and comfort," and 0.98 for "CONTROL: Sensor requirements for advanced control strategies (e.g., MPC, adaptive control)."

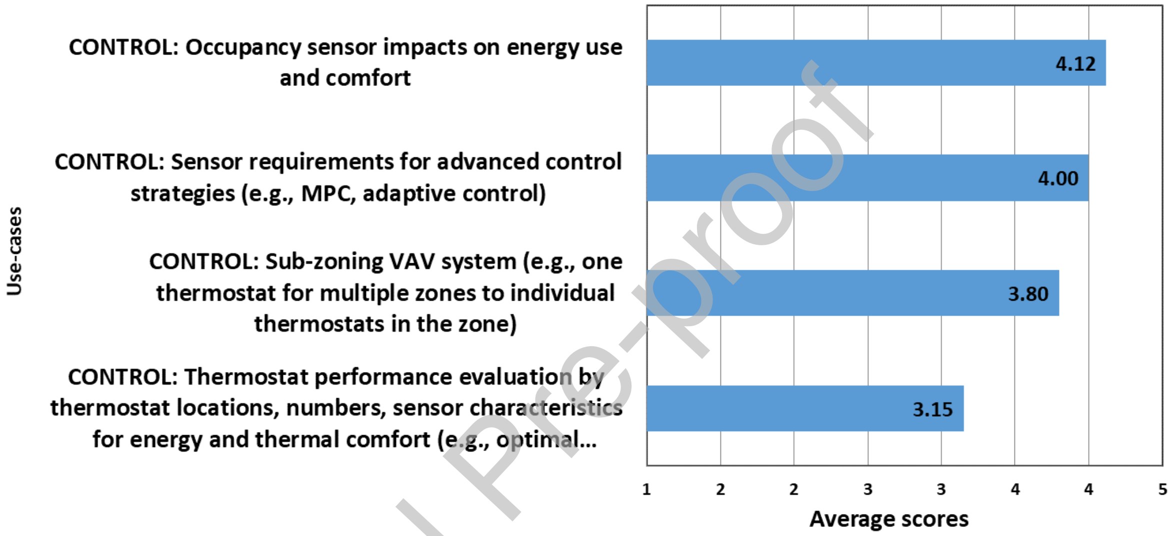

Figure 10. Comparisons of average values of control use cases.

The application suggestion for each control use case is summarized as follows:

Application suggestion for control use case—thermostat performance evaluation by thermostat locations, numbers, and different sensor characteristic for energy and thermal comfort: Because thermostats are the most commonly used type of sensor and they directly control HVAC systems, a proper design and improvement on this type of sensor can significantly affect the occupants' thermal comfort.

Application suggestion for control use case—sub-zoning VAV systems: One interviewee stated that a sub-zoned VAV system has significant potential for retrofitting. However, another interviewee stated that such a system can increase operating costs, and the effect is uncertain.

Therefore, a thorough investigation of this use case is needed to evaluate trade-offs between investment and building performance (i.e., energy efficiency and thermal comfort).

Application suggestion for control use case—occupancy sensor impacts on energy usage and comfort: Cost benefit and trade-offs of deploying occupancy sensors must be considered. The resulting benefits, in terms of energy savings and thermal comfort improvement, depend on the occupancy patterns in a building. One interviewee suggested optimization based on measured dynamic occupancy may be more realistic than optimization based on "static" existing building and engineering/HVAC design codes or local standards and permits. A significant portion of HVAC energy use is often wasted in an office building by conditioning the whole building while many zones are not occupied.

Application suggestion for control use case—sensor requirements for advanced control strategies: One significant challenge for applying advanced control strategies such as MPC is accurately predicting inputs, which significantly affects the control results. Additionally, developing an accurate model (e.g., a data-driven model) is critical for the advanced control. MPC algorithms developed in the previous research have been applied to buildings with simple layouts and configurations. Therefore, investigating the effects of MPC on full-scale buildings with more complicated setting and realistic sensor systems is necessary.

4. CONCLUSIONS

This paper provides a comprehensive literature review on how sensor impact building controls and performance. Expert interviews were performed to augment the findings of the literature review. Multiple aspects should be investigated further, including sensor control use cases, sensor locations, sensor types, sensor data, and a sensor impact evaluation framework.

The findings from this literature review and subsequent future research opportunities are summarized as follows.

- Sensors directly affect control loops. The review on sensors for controls included heuristic rule-based controls, local controls, and advanced building controls. Traditional HVAC sensors and occupancy sensors were studied through building energy management systems, which were validated by field implementations for heuristic rule-based control and occupancy-based advanced building controls. However, few studies focused on performing a sensor impact analysis, and practical and cost-effective tool, framework, and/or guideline is needed to quantify the sensor impact on building control.
- There are many sensor types. This study reviewed multiple sensors, including traditional HVAC sensors, occupancy sensors, emerging sensors, power meters, and virtual sensors. However, among the available sensing and estimation methods, the optimal method and corresponding sensors for a specific building or space are not obvious because the expected performance of different control strategies changes with various conditions (e.g., weather, building characteristics), and different control strategies have different requirements for the sensing and/or estimation. Additionally, the importance of different characteristics (e.g., accuracy, cost, privacy) varies by project, making decisions even more difficult. For 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, researchers have studied the level of information that each method can provide, accuracy, cost efficiency, privacy efficiency and security, ease of maintenance, reliability, and level of intrusiveness.

- Impacts of sensor location have been studied extensively. Multiple methods have been proposed to find the optimal sensor deployment locations. However, there is no consistent framework for systematically investigating sensor deployment locations on building performance. A methodology is desired for optimally selecting a sensing/estimation method, and a corresponding set of sensors—preferably with automated location optimization—would be required to promote occupancy-based building control. Sensor cost and placement are significant determining factors for sensor selection. For cost-effectiveness, the optimal sensing system (selection and configuration) must simultaneously optimize multiple objectives. Example success metrics include building occupant comfort, energy consumption, flexibility, and cost. A flexible framework and algorithms with prioritization capability will allow trade-offs between the sensing system total cost and performance objectives. The methodology will account for modeling uncertainties, correlation between sensors, and higher-order interaction effects that might amplify or offset importance of sensors.
- Sensor data are another important perspective regarding the sensor impacts, including sensor accuracy and sensor data delivering. Few studies are available regarding sensor impact analysis focusing on sensor accuracy or faults. How to quantify the sensor faults remains a research gap.
- To address the described issues for sensor impacts, a framework for control loops integrating these primary aspects is needed.

The interview results are summarized as follows.

- The most significant purposes of using sensor systems were observed to be largely consistent between interviewees; most interviewees identified sensor systems to address energy/power consumption, system efficiency, thermal comfort, and fault detection as being most relevant in the context of building operation and controls.

- Interviewees considered initial cost, reliability, and accuracy to be significant factors for selecting sensor sets. Similarly, the most pertinent current issues mentioned for sensor deployment were initial cost, reliability, accuracy, and maintenance cost.

- To improve sensor performance for new or existing buildings, the most common selections among the proposed methods were to (1) improve the current practices of sensor configuration/design, (2) install additional sensor sets, and (3) install advanced sensor system(s).

- The average score for control use cases ranged from 3.15 to 4.12, and interviewees verified that control use cases have research potential in the areas of energy savings and thermal comfort improvement. The interviewees also mentioned that the use cases in this questionnaire are already investigated or being investigated in academia. Therefore, better partnerships between academia and national laboratories are needed to identify future action plans consistent with the nationwide energy outlook. These partnerships will leverage the knowledge base built by academia toward the creation of a more standardized commercialization blueprint.

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Declaration of interests

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

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APPENDIX A

The rankings of the research potential and the research limitations of each building control use cases are listed in the following table.

Table A.1. Summary of control use case evaluations.

Control use case 1:	Thermostat performance evaluation by thermostat locations, numbers, and different sensor characteristics for energy and thermal comfort (e.g., optimal thermostat locations)	Weighted average scores: 3.15
Research potential/limitations		Selection percentage
Potentials	Comfort	85%
	Energy saving	65%
	Economic/cost potential	19%
	Grid interactive	15%
Limitations	No cost benefit	23%
	Already investigated	19%
	Practically not feasible	15%
	Code restriction	0%
	Already optimal	0%
Control use case 2:	Sub-zoning VAV system (e.g., one thermostat for multi-zones into individual thermostats in the zone)	Weighted average scores: 3.80
Research potential/limitations		Selection percentage
Potentials	Comfort	88%
	Energy saving	56%
	Grid interactive	32%
	Economic/cost potential	24%
Limitations	Already investigated	36%
	No cost benefit	12%
	Practically not feasible	8%
	Code restriction	4%
	Already optimal	0%
Control use case 3:	Occupancy sensor impacts on energy usage and comfort	Weighted average scores: 4.12
Research potential/limitations		Selection percentage
Potentials	Energy saving	92%
	Comfort	60%
	Economic/cost potential	44%
	Grid interactive	32%
Limitations	Already investigated	32%
	Already optimal	12%
	Code restriction	4%
	No cost benefit	4%
	Practically not feasible	4%
Control use case 4:	Sensor requirements for advanced control strategies (e.g., MPC, adaptive control)	Weighted average scores: 4.00
Research potential/limitations		Selection percentage
Potentials	Energy saving	92%
	Grid interactive	60%
	Economic/cost potential	44%
	Comfort	32%
Limitations	No cost benefit	25%
	Practically not feasible	17%
	Already optimal	4%
	Already investigated	4%

	Code restriction	0%

Declaration of interests

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

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: