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# A review of smart building sensing system for better indoor environment control

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ABSTRACT

This paper aims to provide a systemic review of how indoor sensors influence in managing optimal energy saving, thermal comfort, visual comfort, and indoor air quality in the built environment. The optimal management of energy saving and occupant comfort plays a vital role in the built environment because the occupant's productivity and health are highly influenced by indoor environmental quality. In order to do this, there must be a functional sensing system that connects the environment variables (e.g., temperature) with building environmental control systems such as the heating, ventilation, and air-conditioning system. This paper starts with an overview of the importance of energy saving and occupant comfort in the built environment. It then discusses sensors and their importance in the built environment and reviews the different types of sensors, which explains them in terms of how they influence the indoor built environment and occupant productivity. The paper further explores the application of sensors in the built environment and analyzes this in terms of energy saving, thermal comfort, visual comfort, and indoor air quality. Following this, the data analysis is discussed in terms of data, information, and knowledge accrued from the sensors. Lastly, the paper discusses the future challenges for the improvement of building indoor environmental quality and energy saving by the application of sensors.



## 1. Introduction

### 1.1. Motivation

According to a report from the U.S. Department of energy, buildings consumes 41% of the total energy in the U.S. [1,2]. The optimal control of building environmental variables such as temperature, humidity, light, etc. has significant impacts on indoor environmental quality and building energy efficiency. Such control is usually depending on a variety of sensors to connect the built environment with lighting and heating, ventilation, and air-conditioning (HVAC) systems.

On one hand, lighting and HVAC systems consumed 70% of the energy used in commercial office buildings [3–5]. In addition, the built environment consumes large energy from non-renewable energy sources, which are responsible to produce major global warming gases such as carbon dioxide, sulfur dioxide, and nitrogen dioxide [3,6]. Hence, it is important to reduce energy consumption in the built environment.

On the other hand, the energy consumption in the built environment is directly connected to the occupant behavior in the building. Therefore, knowing the fine-grained occupancy information in the building environment is an important parameter for efficient energy use. To understand the occupant behavior pattern in the built environment, different kinds of sensors have been used [7]. The sensor information helps to analyze the occupant behavior and presence patterns, and thermal and visual preferences, which facilitate the building automation system to create a better control of energy usage and indoor environment quality. In a typical day of a general office building, the occupant presence and absence vary. However, nowaday, the operation schedules of the light and HVAC systems usually do not change according to the actual occupancy schedule in most buildings. Therefore, a large amount of energy, up to 70% of HVAC and lighting, is wasted during this unoccupied period [8,9]. Hence, the extraction of fine-grained occupancy behavior pattern using occupancy sensors and implementing it to the building control system helps to pacify the energy consumption in the built environment [10].

Moreover, the occupant's productivity and health are highly influenced by the indoor environmental quality [11,12]. Maintaining the optimal comfort zone is critical to the built environment. For example, if the indoor environment is too cold, the occupant

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feels laziness and discomfort, and the coldness is responsible for some health issues, which affects the working mind of the occupant and the gradually decreases the productivity [13]. Hence, it is important to maintain a good thermal environment condition in the buildings. The lighting condition in the office building is also an important factor for the occupant's productivity [12]. According to the human physiology, daylight is more suitable for the better productivity of the occupant compared with artificial lights. Based on the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) 90.1 standard of occupant visual comfort, a 500 lx of illuminance intensity should be maintained for the work-space inside an office building [14].

Prior research studies show that it is important to understand the occupant presence and feedback of indoor environmental conditions based on individual thermal and visual comfort. In many prior research studies [15], the occupant presence is determined using various indoor sensors. Thermal comfort analysis in the indoor environment generally uses temperature, humidity, and air velocity sensors. In addition, to measure the individual thermal comfort preference, wearable sensors are used. Mobile pupilometer sensors and photo sensors are used to better sense individual visual comfort. To enable the better monitor and control of indoor air quality, volatile organic compound, particulate matter, and $CO_2$ sensors are implemented. A detailed summary of sensors used in previous research is described the section below.

### 1.2. Summary of previous research

To better understand the influence of sensing in built environment, we have reviewed a large number of papers with a focus on case studies. This covers energy saving, thermal comfort visual comfort, and indoor air quality as shown in Table 1. Table 1 shows the applicability of different sensors in the built environment in terms of the energy saving, thermal comfort, visual comfort, and indoor air quality.

Researchers investigated energy saving and visual comfort using different sensors, i.e., photo sensors were used for energy saving and mobile pupilometers were used for the analysis of visual comfort [11,12,16]. Some studies [15,17–19] focused only on the thermal comfort of the building occupant using the feedback obtained from the occupant through a sensor network. Some researchers focused on the combined analysis of energy saving and thermal comfort using different sensors, such as Passive Infrared (PIR) sensors, wearable sensors, ambient temperature sensors, smartphones, and thermofluidic sensors. These sensors can be used to controls of built environment in terms of energy efficiency occupant's thermal satisfaction [20,21]. Indoor air quality in the building is analyzed and an optimum range is achieved with the combined use of different sensors, such as the ambient temperature sensor, $CO_2$ sensor, humidity sensor, volatile organic compound sensor, and particulate matter sensor [22,23]. Recently, IEA EBC Annex 66 project has done a comprehensive review of occupant sensors [24]. In addition, a new chapter on occupant-centric sensing and controls is added to the ASHRAE 2019 HVAC Applications Handbook [25]. This paper focuses on the impact of occupancy and environmental sensors in the built environment for both efficient energy use and the better control of indoor environmental quality.

Virtual sensing could be an alternative for physical sensing. Virtual sensing has been used for smart building applications, in particular, for HVAC equipment monitoring and fault diagnostics [26–28]. Occupancy also can be determined through sensor fusion techniques using data collected from the built environment such as room air temperature, relative humidity, CO2, and indoor illuminance level, etc. Zhao et al. [29] presented a virtual occupancy sensor for real-time occupancy information in buildings using a Bayesian belief network to fuse data from chair sensor, keyboard, mouse, WIFI-connection, etc. Pedersen et al. [30] detected the occupancy presence using the trajectory of indoor climate sensor data. The challenges associated with virtual sensing technology is the uncertainty propagation associated with physical sensor errors. An extensive uncertainty analysis should be conducted to understand the robustness and accuracy of virtual sensing.

The structure of this paper is organized as follows. First of all, a review of the mechanism of a various sensing system for the built environment is conducted. In addition, major types of sensors used in the built environment are presented. Secondly, the application of those sensors is examined in the area of energy saving, better control of thermal comfort, and enabling improved visual comfort and indoor air quality. Common data analyzes methods for sensor data are reviewed which covers the basis of information extraction, data pre-processing and the knowledge discovered. Finally, the paper concludes with a summary of all previous research work, followed by future research challenges.

## 2. Sensing system for building operation

### 2.1. Overview of sensors in the built environment

Occupant health and productivity in the indoor environment depend on the indoor environmental quality (IEQ) [11,12,23,34,41]. There are many sensors used to understand the indoor environmental quality and the individual occupant satisfaction level. The fine-grained occupancy information in the built environment helps to improve energy saving, thermal comfort and indoor air quality [51,57,58]. In order to perceive the thermal environmental quality in the living space, thermostats, smart meters, $CO_2$sensors, and heart rate sensors are used [20,21,40,42,55]. A better understanding of occupants' perception on the indoor environment quality helps the occupants to become more productive and healthy. Simultaneously, analyzing the occupant behavior pattern using occupancy sensors helps to improve energy saving in the built environment [5,59]. Different types of sensors are being used in the built environment to understand the indoor environmental characteristics and occupant behavior. Table 2 categorizes the sensors for the smart building operations into three. The first category covers occupancy sensors in the built environment. Sensors listed in the second category are being used to find the indoor building environmental parameters. The last category represents sensors, which are being used to help understand the occupant behavior. In the rest of this section, we will discuss about the current state-of-the art occupancy sensing, then other built environmental sensing.

### 2.2. Current state-of-the-art occupancy sensing

#### 2.2.1. Image-based sensors

Image-based sensors work with the electromagnetic radiation technique and store the information in matrix form. The image-based sensors include infrared (IR) cameras, visible light cameras, and luminance cameras. Generally, the thermopile array is used for image detection in infrared (IR) cameras. The visible light camera uses a combination of image-based and multi-infrared sensors for occupancy detection. The sensor projects the dots of signals, which are used to analyze the background. The infrared sensors emit the rays which are propagated through the air and reflect them back once they hit an object. It helps to analyze the distance from the object. Again, the sensors project the cloud of dots to understand the object shape, which helps to differentiate the object from the background and analyze the occupancy presence, activity, and location [60].

Image-based sensing is a kind of implicit occupancy detection system. In general office buildings, cameras are installed for security purposes, and these can be used for the occupancy detection

**Table 1**
Summary of research on energy saving, thermal comfort, visual comfort, and indoor air quality.

| Year | Study | Sensor types | Energy saving | Thermal comfort | Visual comfort | Indoor air quality |
|---|---|---|---|---|---|---|
| 2005 | [31] | Motion sensor (PIR) | √ | | | |
| 2011 | [32] | Photo Sensor | √ | | √ | |
| 2012 | [33] | $CO_2$ sensor, Ambient Temperature sensor (Thermostat), Heart Rate sensor, Air Velocity sensor | | √ | | |
| 2012 | [34] | Motion sensor (PIR), $CO_2$ sensor, Pressure Mats, Sound sensor, HOBO sensor, Camera sensor | √ | √ | | |
| 2013 | [11] | Photo sensor | √ | √ | √ | |
| 2013 | [35] | Volatile organic compound sensor | | | | √ |
| 2013 | [36] | Ambient Temperature sensor (Thermostat), Air Temperature Sensor, Humidity Sensor | | √ | | |
| 2013 | [37] | Motion sensor (PIR), Photo Sensor | √ | | | |
| 2013 | [5] | Motion sensor (PIR), Camera sensor, Wireless sensor Network | √ | | | |
| 2013 | [38] | Photo Sensor | √ | | | |
| 2014 | [20] | Wearable sensor, Smart Phones, Ambient Temperature sensor (Thermostat) | √ | √ | | |
| 2014 | [39] | Wireless sensor Network | √ | | | |
| 2014 | [40] | Ambient Temperature sensor (Thermostat), Heart Rate sensor, Humidity Sensor, Skin Temperature Sensor | √ | √ | | |
| 2014 | [41] | Motion sensor (PIR) | √ | | | |
| 2015 | [7] | Ambient Temperature sensor (Thermostat), Humidity Sensor | √ | √ | | |
| 2015 | [42] | Humidity Sensor, Air Velocity sensor, $CO_2$ sensor, Ambient Temperature sensor (Thermostat), Heart Rate sensor | | √ | | |
| 2015 | [43] | Chair Sensor | √ | | | |
| 2015 | [44] | Wireless sensor Network, Camera sensor, Motion sensor (PIR) | √ | | | |
| 2015 | [16] | Mobile pupilometer | | | √ | |
| 2015 | [45] | Humidity Sensor, Ambient Temperature sensor (Thermostat), CO2 sensor, Motion sensor (PIR) | √ | | | |
| 2015 | [46] | Motion sensor (PIR), Photo Sensor | √ | | | |
| 2016 | [6] | Wearable sensor | √ | | | |
| 2016 | [47] | Wearable sensor | | √ | | |
| 2016 | [21] | Motion sensor (PIR), Wearable sensor, Smart Phones, Thermo-fluidic sensor | √ | √ | | |
| 2016 | [12] | Mobile pupilometer | | | √ | |
| 2016 | [48] | Wearable sensor, Fingerprint sensor | | √ | | |
| 2016 | [14] | Motion sensor (PIR), Photo Sensor | √ | | √ | |
| 2016 | [49] | Photo Sensor | √ | | √ | |
| 2016 | [14] | Motion sensor (PIR), Photo Sensor | √ | | √ | |
| 2016 | [50] | Photo Sensor | √ | | | |
| 2016 | [51] | Wearable sensor, Heart Rate sensor | | √ | | |
| 2016 | [52] | Motion sensor (PIR), Photo Sensor, $CO_2$ sensor, Camera sensor, Ambient Temperature sensor (Thermostat), Humidity Sensor | √ | | | |
| 2017 | [15] | Wearable sensor, $CO_2$ sensor, Heart Rate sensor, Air Temperature Sensor, Humidity Sensor, Air Velocity sensor, Skin Temperature sensor | | √ | | |
| 2017 | [53] | Wearable sensor, Wireless sensor network | | √ | | |
| 2017 | [54] | Air Velocity sensor, Humidity Sensor, $CO_2$ sensor, Ambient Temperature sensor (Thermostat), Air Temperature Sensor | | √ | | |
| 2017 | [53] | Wearable sensor | | √ | | |
| 2018 | [55] | Wearable sensor, Camera sensor, Smart Phones, Ambient Temperature sensor (Thermostat), Humidity Sensor | | √ | | |
| 2018 | [56] | Chair sensor | | √ | | |
| 2018 | [23] | Photo sensor, $CO_2$ sensor, Ambient Temperature sensor (Thermostat), Volatile organic compound sensor, | | √ | √ | √ |
| 2018 | [46] | Motion sensor (PIR), Photo Sensor, Pressure Mats | √ | | | |

**Table 2**
List of sensors related to intelligent building operation.

| Sensors for smart building operations | Sensor types |
|---|---|
| Occupancy sensors | Image based sensor, Passive infrared (PIR) sensor, radio-based sensor, Threshold and mechanical sensors, Chair sensors, Pressure Mats, Camera sensor, Photo sensor, Ultrasonic doppler, Microwave doppler, Ultrasonic ranging |
| Built environment measurements | $CO_2$ sensor, Air Temperature sensor, Humidity sensor, Thermo-fluidic sensor, Sound sensor, Light sensor, Volatile organic compound sensor, Particulate Matter (PM) sensor, Air velocity sensor |
| Other sensors | Wearable sensor, IoT based sensor, Smart Phones, Heart Rate sensor, Fingerprint sensor, Mobile pupilometer, Skin Temperature Sensor |

system in the built environment in order to save energy and maintain better indoor environment conditions [61,62]. Cameras are used to identify the occupant position, count, activity, and identity, and track the occupant [63]. For example, Dong et al. stated that occupancy detection is determined mostly using the visible light camera sensors and the luminance camera as compared to the IR camera, because of its reliability and accuracy [15]. The major disadvantages include: i) there is a need for a clear line of sight for the camera, ii) the placement is a major concern for the image detection, and iii) expensive hardware for the signal processing is required for occupant detection, count, identification and tracking [64]. The major concerns in using camera sensors are as follows: the higher cost, the limited coverage of sensors in a zone with respect to the number of sensors, the complexity of installing the system, the complexity of the algorithm to determine the occupancy presence, count, location and activity, and finally the privacy breach of the sensors [59].

#### 2.2.2. Motion sensors

Motion sensors are used to determine the occupancy presence. Passive infrared (PIR) sensors, ultrasonic Dopplers, photo sensors, microwave Dopplers, and ultrasonic ranging are the commonly used motion sensors in built environments [65–67]. Generally, The PIR sensor is able to only detect the occupant presence in an office building; however, it doesn't count the number of occupants in the zone [59]. The disadvantage is that when the occupant is not moving for a long time, the sensor notes it as a false signal [68]. Motion sensors are mostly used for occupancy detection for artificial light energy saving and HVAC control [69]. Therefore, false signal notification makes the system works imperfectly, which causes occupants discomfort. The photo sensor which is also used in the built environment to determine the occupancy presence/ absence and the distance, by using the light transmitter and receiver. Li et al. reported that the sensor can even be triggered by the heating of the HVAC system in the office space [59]. The ultrasonic and microwave Doppler sensors are used to measure the speed of the occupant movement toward or away from the sensor. It has a higher density than the PIR sensor, because of that it may overcount the occupancy presence for the small movements of objects in the indoor space. Ultrasonic sensors analyze the distance from the object, which is used to measure the occupancy passing through the doorway in a general office building [67].

#### 2.2.3. Radio-based sensors

This type of sensor uses a radio signal to detect the occupant presence in the built environment. Also, the sensor provides information on the occupant location, count, identity and movement [70]. The radio signal covers the electromagnetic waves in the range of 10 kHz to 300 GHz [71]. There are different radio-based technologies used for occupancy detection, such as radio frequency identification (RFID), WIFI or Bluetooth, global positioning system (GPS), and ultra-wideband (UWB).

Radio frequency identification (RFID) senses the people or objects using tags which have a unique code of identification [71]. It can identify active and passive RFID tags. Active RFID tags have a longer range of sensitivity, which helps in large office space to determine the occupancy presence. However, passive RFID tags have a limited range of sensitivity and work without batteries [72]. Also, the RFID tags reader is more expensive. The RFID sensors can be used for measuring the distance and the proximity of the occupant in the built environment.

WIFI or Bluetooth based devices have a short range of wireless sensitivity. The WIFI access points (APs) act as radar to detect the occupancy presence using the WIFI signal until it gets distorted [73]. It has an accuracy of 2–10 m based on the positioning method [74]. The Bluetooth low energy (BLE) profile is used as a low power solution for controls and monitoring applications [75]. The proximity BLE device is used for gathering the occupancy location and the distance information.

The ultra-wideband (UWB) is a wireless communication system which is used to transmit short signals, which help to measure the distance of the occupant presence. The accuracy of the occupant position is 10 to 50 cm [76]. The global positioning system (GPS) is used for the occupant detection and monitoring in the built environment. To determine the occupant position, the occupants need to carry GPS-enabled devices, either by smartphone or wearable devices. The accuracy of the GPS system is 1 cm to 10 m, depending on the type of technology used and the sky conditions [70].

#### 2.2.4. Threshold and mechanical sensors

Threshold and mechanical sensors detect the occupant presence in the building when they interact with the windows or doors [66,77]. There are a different threshold and mechanical sensors, such as reed contacts, door badges, piezoelectric mats, and IR beams. The reed contacts are used to detect when a door or window is open or closed. It is a low-cost sensor and consumes a low amount of energy.

Door badges are sensors which require occupants to swipe to access the building's interior, which helps to count the occupants; however, if more than one occupant passes through a single swipe the device doesn't count the number of occupants passes correctly since it counts only the number of swipes [78]. Moreover, the device is expensive.

Piezoelectric mats work when occupants pass or stand on the mats to produce an electrical signal. The device is less expensive. However, the occupants need to stand or walk on the mat long enough for it to detect them [79].

The IR beam functions by producing a signal, and when the signal beam is blocked by the occupant, it counts the occupant. If more than one occupant passes through the beam signal in one passage, the device will not count the multiple occupants correctly. Hence, it stores the wrong signal information [15].

### 2.3. Current state-of-the-art of environmental sensors

#### 2.3.1. Temperature and humidity sensor

Temperature and humidity sensor are used to measure the indoor environmental characteristics. Temperature and humidity sensors are widely available in the market with different quality, accuracy, and price range. For instance, the conventional temperature sensors can have the precision of less than +/− 0.5 K [80]. However, more precise (*e.g.*, +/− 0.1 K) temperature sensors [21] also available in the market. The sensor or instrument should be calibrated regularly to address the drift and ensure its stability.

Kim et al. [56] use a heating coil and a cooling fan attached to the chair to analyze the individual occupant thermal preference. The data collected from the temperature sensor and humidity sensor, which attached to the heating coil and cooling fan on the chair, helps to estimate the occupant comfort satisfaction and the energy use in the built environment. Cheng et al. [21] used a wireless sensor network of thermo-fluidic sensors to measure the temperature and humidity of the indoor environment. Jin et al. [23] use an automated mobile sensor to analyze the indoor environmental variables such as temperature and humidity. The study compared with the dense sensor network, based on the air change effectiveness (ASHRAE standard 129) [81]. The results showed that the automated mobile sensor accurately measures the environmental parameters with a low cost and fewer calibration efforts.

#### *2.3.2. Air velocity sensors*

Air velocity sensors are used to measure the airflow rate in the built environment. Sardini et al. [80] implemented a self-powered wireless sensor network to measure the air flow rate in the built environment. The sensor system consists of an electromechanical generator and the rotor frequency of the generator helps to analyze the air velocity in the built environment. The sensor network operates with a 433 MHz point to point communication system and records the data in very 2 s. The system can monitor indoor air velocity in real-time.

Synder et al. [82] developed a micro-electro-mechanical system (MEMS) to measure the air flow rate, it works based on the changes of gaseous particles and particulate matter (PM) present in the indoor environment. The rate of change of indoor environmental character based on the interaction between gaseous particles and particulate matter (PM) with the electrochemical cell or metal oxide semiconductor, which notified with the electrical pulses, and used to analyze the indoor air quality.

#### *2.3.3. Photometric sensor*

A light level sensor, photometric sensor, is used to control the luminaire intensity, based on the daylight availability in the built environment [11]. The optimal control of the lighting system with the photometric sensor, significantly reduce the electrical energy consumption, while maintaining the visual comfort. The major concern of this photometric sensor is on the placement in the built environment. If it is placed near to the window, which will dim the artificial light according to the daylight availability. However, if the occupant stayed a bit far from the window, he or she may feel unsatisfactory by the availability of natural light. The average illuminance value in the general office building is 500 lx in the occupied region and 300 lx in the unoccupied region based on the ASHRAE 90.1 [14]. Moreover, some more aspects must be considered for the control strategy using photometric sensors, such as the color temperature ratio, glare, vertical to horizontal illuminance ratio, and light spectrum [83,84].

#### *2.3.4. $CO_2$ sensor*

The $CO_2$ sensor is used for detecting the occupancy presence and people counting in the built environment. It finds the occupant presence and counts by analyzing the correlation between the presence and the concentration of $CO_2$, which exhaled by the occupants in the building [85,86]. It measures the concertation of $CO_2$ in the air by parts per million (PPM). It is a non-individualized and explicit sensor.

Haeusler and Meyer developed a low-cost $CO_2$ sensor, based on thick film technology, which was developed using semiconducting oxides [87]. The sensor works based on the variation in conductance of the metal oxides with the presence of $CO_2$ in the built environment. Park et al. [88] used a potentiometric $CO_2$ electro-chemical sensor, which was made of an electrochemical cell, to measure the $CO_2$ concentration in the indoor space. The arrangements consist of different electrolytes and reference materials, such as sodium-iron, $O_2$, $CO_2$, $Na_2O_3$, etc. It works based on the variation of oxygen pressure in the built environment.

#### *2.3.5. Volatile organic compounds (VOC) sensors*

A VOC sensor measures the concentrations of gaseous material found in the built environment, based on the reaction between the sensing material and the targeting gases concertation. Transducers are used to convert the environmental changes to an electrical signal, which is able to analyze the quality of the indoor space [89]. Brown et al. [90] stated that the VOC concentration in the established building is between 5 and 50 $\mu g/m^3$. However, the concentration of total volatile organic compound (TVOC) concertation will be much higher than that of VOC.

The other type of VOC sensor, solid-state sensor, works based on the changes of electrical properties in the semiconducting material [91]. Some other types of VOC sensing system are made by the micro-electro-mechanical system (MEMS). It is a transducer connected with a microprocessor and it works based on the indoor environmental changes. The transducer responded to environmental changes and generated electrical pulses, which were converted to the digital data using a microprocessor [82,92]. MEMS comes with different shapes, sizes, and it is made up of micro fabric or optical or nanomaterial based. Zampolli et al. [93] implemented a method to monitor the single volatile organic compounds in the built environment, the system works based on gas chromatography (GC). It is able to categories the volatile organic compounds and the metal oxides, thereby it can be used to detect the hazardous pollutants.

#### *2.3.6. Particulate matter (PM) sensor*

PM sensors are used to detect the concentration of particles in the indoor air below $2\mu$. The challenging part of any PM sensor is the detection of low concentration level of pollutants. Some of the PM sensors use a piezo-electrical crystal to measure the amount of particle in the indoor space. When the particles deposited on the system, the system vibrates, and the result shows the quality of air in the indoor space [82].

White et al. [89] used a microfabric piezoelectric film bulk acoustic resonator (FBAR) technique to analyze the PM concertation in the indoor space. When the particle deposits on the surface, the oscillation frequency changes from its normal frequency of 600 MHz, which is proportional to the particle mass deposition. There are sensors connected with smartphone applications to analyze the indoor environmental quality of the building. The microfabric technique is widely used in the indoor application due to its smaller size, lightweight, and low cost. Tapered element oscillating microbalance (TEOM) also works based on the rate of change of oscillation with respect to the particulate matter deposition.

### *2.4. Other sensors*

The following two type of sensors are selected to review as they are newly used in recent studies.

#### *2.4.1. Wearable sensors*

These sensors are used to collect individual occupancy data. The wearable devices can measure the skin temperature, the location, air temperature, relative humidity, heart rate and perspiration rate [47]. Customized wearable devices such as watches and bracelets are used to measure human skin temperature, motion [21] and sleep patterns [20], and the digital accelerometer helps to analyze sleep patterns. Yeom et al. [15] and Choi et al. [17] used a wearable sensor to measure the heart rate of an occupant.

*2.4.2. Internet of things (IoT) based sensors*

Smart devices with advanced communication technology are referred to as IoT [39]. This is a kind of an implicit and non-direct occupancy detection method: the use of existing devices in the built environment to determine the occupancy presence and comfort conditions. Smartphones can be used to gather information on the occupancy presence, location, identity, and tracking in the built environment. With the use of a special App in the smartphones, the occupancy feedback of the building environment based on the comfort level can be gathered, which can be used to save energy and provide better comfort for the building occupants, which directly affects the occupant productivity [20,40,44].

*2.5. Summary*

The following conclusions are drawn from the review of both occupancy sensing and another environmental sensing in the built environment. It is difficult to select one perfect sensor to identify the indoor environmental parameter, and the occupancy presence and satisfaction level. Each category of sensors has some limitations on it. Most of the researchers conducted the ground truth study for occupancy detection using camera sensors, however because of the higher cost and computation process, it is very less preferable for the study. The motion sensors, such as PIR, photo sensors, etc., are used to determine the occupancy presence or absence in the built environment. Even these motion sensors don't count the number of occupants in the given space, implementing them in the cubical space in the office building helps to regulate energy consumption. Radio-based sensors use RFIDs, Wi-Fi or Bluetooth, GPS, UWB, etc., are used to determine the occupancy presence and people counting in the built environment. Due to the small range of sensitivity and relatively low accuracy, these radio-based sensors are not widely applicable in the built environment. The mechanical sensors are used to determine the occupancy presence and the activity in the built environment. However, the accuracy of counting the occupant in the built environment using these mechanical sensors is very low as compared to other type sensors. Wearable devices and the IoT based sensors offer great opportunities in the built environment to identify the occupancy presence, count, activity, and environmental satisfaction level in the building. The implicit nature of wearable sensors helps them to reduce the cost of implementing the better control of the built environment and these sensors can be used to obtain real time feedback from an individual occupant in buildings.

## 3. Application of sensors in the built environment

Sensors are widely used for building energy and comfort management (BECM). The objective of BECM is to control, analyze, and optimize the building energy consumption and achieve better indoor environmental quality using different sensors. Many types of research pay significant attention to building energy saving and occupant comfort management using different sensors [17,20,47,55]. The major application of sensors in the built environment is to optimize energy consumption while achieving better thermal comfort, visual comfort, and indoor air quality.

*3.1. Sensors used for enabling energy saving*

*3.1.1. $CO_2$ sensor*

The $CO_2$ sensor is used for detecting the occupancy presence and people counting in the office space by correlating the presence and the concentration since CO2 is exhaled by the human being [85,86,94]. The $CO_2$ sensor measures the concentration of $CO_2$ gas in the air by parts per million (PPM). It is a non-individualized and explicit sensor, and has been widely used in the HVAC industry for $CO_2$-based demand control ventilation [43]. However, the sensor has a few drawbacks for occupancy detection. The opening and closing of the door in the office space, and varying air flow rates of the HVAC system, affect the mixing of air and $CO_2$ concentration, thus storing false data of occupancy counts [95]. One control strategy used for occupancy detection is through the evaluation of $CO_2$ concentration in the return duct of the HVAC system [85]. Both simulation based studies and actual field case studies show that $CO_2$ based demand controlled ventilation can offer up to a 60% energy savings compared with constant ventilation rate systems [96,97].

*3.1.2. Chair sensors*

The chair sensor is used to determine the occupancy presence in the built environment. If the occupant is absent, the light and HVAC system can be controlled, and energy can be saved. Li et al. [59] used 8 low-cost micro switches which have a thickness of about 5 mm each connected to the chair in parallel. The output is connected to a wireless transmitter, which is connected to the HVAC system. The HVAC system is only in operation when the occupant presence is noted. Thus, it can save energy when space is not occupied. Labeodan et al. [43] stated a few disadvantages of using pressure mats on chair sensor, such as i) if the occupant is standing it doesn't count the occupant in the zone, ii) the pressure must act on the exact point on the pressure pad otherwise the sensor notes a false signal, iii) a minimum weight is required to operate the sensor and iv) there is a sudden change in the signal when the occupant changes the seating position.

*3.1.3. PIR sensor*

The PIR sensor is used to determine the occupant presence in the built environment [34,44,45,98]. In the general office space, motion sensors (PIR) are used to detect the occupancy presence; if the occupant is not present, then the lights are turned off [94,32]. Through this, efficient energy usage can be achieved. Tetlow et al., used the text prompt as well as the PIR sensors to save light energy in the office building [41]. They used text and pictorial prompts to promote light energy saving in the meeting room when the occupant is not occupied. One of the prompts placed near to the lighting switches, which states "Please turn off the lights when you leave, thanks".

Choi et al. [50] used both PIR sensors and photo sensors in the cubical space of an office building. The paper discussed two methods for energy saving. For the first method, the authors reduced the timeout period from 20 min to 1 min in the PIR sensor, and the results showed that a 26% energy saving was achieved. For the second method, the authors integrated the LED light with the photo sensor, and the results showed that about a 35% energy saving was attained.

The major challenges in saving lighting energy using PIR sensors and photo sensors are the delay time and dimming time periods [5,37,50]. If the delay time is very short, then it will cause disturbances to the occupants, as when the occupant is not moving for a while in the office the light will turn off. However, if the delay time is longer, then during the unoccupied period more energy is wasted. Therefore, the optimal delay time setpoint is the critical factor while using a PIR sensor for occupancy detection.

*3.1.4. Photometric sensor*

A light level sensor, photoresistor sensor, has been used to control the luminaire intensity, based on the daylight availability in the built environment [11,14,23,31,37,49,50]. For example, Galasiu et al. [99] implemented three control strategies for light energy savings. Occupant sensors, light sensors, and individual dimming controls are used together for the control strategy and saved 42–47% light energy as compared to luminaries operating without any of these control methods. The occupant sensor alone saves 35% of energy, the light sensor saves 20% of energy and the individual dimming control saves 11% of energy. The individual dimming control provides better occupant satisfaction [100], during the combined use of three control strategies.

Gentile et al. [14] discussed three different methods of a light control system for energy saving and occupant satisfaction. The absence detector, presence detector, daylight harvesting, and desk lamp were used to analyze the energy saving. The absence detector and the general on/off system showed more preference from the occupants and performed more energy saving as compared to the presence detector, because the presence detector consumed more energy. Also, the author talked about the energy consumption of the lighting system in the standby mode but did not discuss how to reduce the energy consumption in the standby mode. Further research should be carried out to investigate how to reduce the standby energy of the luminaries. The daylight harvesting with the artificial light supplementation provided a 79% energy saving. However, the absence detector with the general on/off system showed a 75% energy saving, so only a 4% energy difference is achieved by the daylight integration. The occupant mostly prefers normal control rather than automatic control.

#### 3.1.5. Smartphones and IoT application

The data collected using the smart devices, along with the communication framework are referred to as the Internet of things (IoT) [39]. Those sensors include: i) smartphone, ii) wearable device, iii) IoT-based thermostat and light control units, iv) mobile application and other feedback services using wrist bands, v) smartphones with a GPS and the personal schedule, and vi) fusion of camera-based sensor and IoT network.

IoT-based thermostat and light control units are used to save energy in the built environment, which uses occupant information and resets the temperature and luminaire intensity based on human feedback. For example, Sheikhi et al. [6] used wearable devices which connected with the structural health monitoring (SHM) nodes, to get the occupant information such as the location, body temperature, heart rate, and humidity.

Cheng and Lee used smartphones, wearable devices, temperature and motion sensors for energy conservation and comfort management [20]. Using smartphones, the occupant position, the behavior pattern and occupant thermal preference can be obtained. Such sensor information feeds back to the smart HVAC control system to maintain the desired occupant temperature, which leads to better controls of energy and thermal comfort.

Smartphones with a GPS and the personal schedule of the occupant were used to obtain the occupant behavior pattern [44]. With the help of the occupant behavior pattern, the enclosed space can be cooled prior to the arrival of the occupant and maintain a good ambient condition in the office space and can save energy when the occupant is not in the enclosed space [51]. The wearable devices were also used to determine the occupant's sleep pattern. When the occupant falls into the deep sleep, the feedback from the wearable device was used to regulate the indoor temperature with the smart air conditioning system and saves energy up to 46.9% and maintains occupant health [20].

Akkaya et al. presented a methodology to determine occupancy presence using the existing resources in the built environment and without installing any apps in the smartphones of building occupants [44]. WIFI, camera, and sensor networks were used to detect the occupant in the built environment. A combination of WIFI signals, calendar schedules, and PC activity was used to monitor the occupant in the office space. Also, the sensors and camera-based sensor networks were fused with the IoT network to infer the occupant presence and track the occupant behavior pattern.

The mobile application and other feedback services using wrist bands were used to get the individual thermal comfort preference [40]. Personal comfort models in the built environment can benefit the occupants' satisfaction level as well as building industry, by providing the necessary data of individual comfort preference using the IoT device [48].

### 3.2. Sensors to enable human thermal comfort

Many research studies have been carried out to determine the occupant's thermal comfort preferences. The occupant's age, gender, and body mass index (BMI) are also considered as factors for determining the individual occupant's thermal comfort. To determine the individual occupant's thermal comfort preferences, experiments were conducted to determine the most sensitive part of the human body to validate the thermal comfort preference of the occupants. According to the variation of the ambient temperature in the built environment, the forehead, the wrist and the feet show the fastest response to environmental conditions, which can be used to analyze the individual thermal preference. One of the challenging factors is that the occupant thermal comfort range varies from person to person, and there is no stable point in which all occupants feel comfort [18,32,36,47].

#### 3.2.1. Temperature and humidity sensors

The thermo-fluidic sensor is used for measuring the temperature and the thermal comfort of the occupant [21]. They are now used as a wireless sensor network (WSN) to measure the indoor environmental parameters such as temperature, humidity, thermal radiation, and air velocity, which are then used to analyze the occupant thermal comfort.

Yun and Won introduce a microzone-centric concept to solve the problems of individual thermal comfort and energy saving in the built environment [19]. The authors used the chair as a personal comfort system (PCS) to validate the concept, which considered the individual chair as the microzone. The chair contains a heating strip and a fan, which are controlled by the Bluetooth from the occupant smartphone. Temperature and relative humidity sensors are attached to the control system in the chair. The cooperative control between the personalized micro-environment and the building control system helps to improve occupant comfort and reduce power consumption. Sardini et al. [80] used a wireless sensor network, to determine the ambient temperature. The sensor attached with the electromechanical generator, which is powered by the indoor air velocity. With the lower power consumption, the sensor can able to analyze the temperature in the built environment.

#### 3.2.2. Velocity sensor

For indoor air velocity sensing, the sensor must be a good response to real-time environmental changes and should perform efficiently. Xiang et al. [101] use a hybrid sensor network system to evaluate the airflow rate in the built environment. The hybrid system is the combined use of stationary and mobile sensing units. The result indicates that the hybrid system achieves an average of 40.8% error reduction in drift dependent and location dependent measurement errors.

Sardini et al. [80] use a wireless sensor network to measure both air velocity and temperature in the built environment. The sensor can work without any battery power, it works based on the air flow rate in the built environment. The sensor operates at the air flow rate of 3 m/s, which is enough to power the circuit. Then with the small power consumption the sensor capable to analyze both air velocity and the temperature in the built environment.

Choi and Moon discuss the impact of occupant's satisfaction level with air quality in the indoor environment [22]. The analysis conducted in terms of age, gender and location of the workstation in general office building. The result shows that the female occupants show more satisfaction with an air velocity of 0.2 m/s at 1.1 m height, and it is fit with ASHRAE standard 55 [102]. However, the male occupants feel dissatisfaction with the air velocity of 0.2 m/s and acknowledge that, they were satisfied at a lower air flow rate. Based on the age group of the occupants, most of the occupants prefer the air velocity higher than 0.1 m/s. However, the senior age group occupants feel negative statistician, if the air velocity increases above 0.1 m/s. Based on the workstation location, the occupants feel different satisfaction level. When the occupant work location is at the center, they are satisfied with a lower air velocity of 0.07 m/s. However, occupants work location to the perimeter shows less satisfaction with lower air velocity. Hence, the overall air velocity analysis, the occupants to the perimeter prefer to have an average of 0.2 m/s air velocity and occupants to the center prefer lower air velocity.

#### *3.2.3. Heart rate and skin temperature sensors*

To measure the human thermal comfort in the built environment, the human skin temperature from different parts of the body is used to evaluate the thermal sensation. Choi and Loftness used heart rate sensors, temperature sensors, humidity sensors, and air velocity sensors to evaluate the human thermal perception in the indoor environment [33]. The skin temperature from the forehead, posterior upper arm, wrist, head, chest, belly, thigh, anterior and posterior calf and foot are used to analyze the human thermal sensation of varying indoor environmental conditions. Their study found that the skin temperature from the wrist provides the best response of the occupant's thermal perception. Later, Choi and Yeom conducted an experiment conducted to obtain skin temperatures from different parts of the body [17]. Their study showed that the combined use of skin temperatures from the arms, back, and wrist helps to provide an overall thermal sensation of the occupant. The skin temperature is also used to develop a model of the local and whole-body sensation and comfort response of the occupant in the uniform and non-uniform, transient and steady-state environments [36,54,103].

Wearable devices are also used to measure heart rate and skin temperature. Abdallah et al. used [47] wearable devices and smartphones to determine those parameters. With these inputs, the thermal comfort of the occupant can be determined. Li et al. used [53] wearable sensor and mobile application to foster human-building interaction. The data collected from wearable devices and other wireless sensor networks are used to analyze individual thermal comfort and energy saving. The feedback from the smartphone application interacts with the smart air conditioning system to maintain the desired indoor temperature in the built environment. The results showed an accuracy of 80% for predicting the personal comfort model from the acquired environmental data and human behavior data.

### *3.3. Sensors used for enabling visual comfort*

Individual visual comfort is a major concern in the built environment because it directly affects the occupant's productivity and health. To determine the individual visual comfort, a few prior studies have been carried out based on photometric sensor and mobile pupilometer sensors. In addition, the proper position and the calibration of the light measurement are the important factors while using a daylight harvesting for energy saving [14]. Furthermore, occupant behavior often impacts both visual comfort and energy savings. Choi et al. showed that most of the occupants forgot to turn off the table lamp when the daylight availability was sufficient enough for the occupant [41,50], and energy was wasted. The detailed description of studies using different sensors for visual comfort is described as follows.

#### *3.3.1. Photometric sensor*

The average illuminance value in the general office building is 500 lx-based on ASHRAE 90.1 [14]. The major concern of the photometric sensor is the placement of a sensor in the built environment. Generally, the photometric sensor placed at the ceiling of the built environment. If the sensor is placed close to the window, which will dim the artificial light according to the daylight availability. However, if the occupant stayed away from the window, the daylight availability and artificial light intensity do not meet the occupant's satisfactory level. Hence occupant feels uncomfortable with the available intensity of light.

Miki et al. [104] suggested to place the wireless sensor at the desk of the occupant in the office space, thereby the occupant satisfaction level can be improved by implementing the wireless sensor module. However, there some practical problems which may encounter while using this method. If the sensor gets shadowed by the occupant or any object, it causes the sensor network fail to perform the operation and the disturbances in the wireless communication link, when the occupants moving in the indoor space, it breaks the connection of the wireless sensor [84]. Also, the author talks about distributed and centralized light control system architecture. The distributed control architecture, the light control is at the senor or luminaire itself. Whereas, in the centralized control architecture, the light controlled by the central system.

Choi and Moon [22] used a decision tree algorithm to reveal that age was a significant factor for evaluating the visual comfort of the occupant. Additionally, an illuminance intensity above 420 lx showed overall satisfaction in all gender groups; however, an illuminance intensity below 420 lx showed that the male occupants feel negative satisfaction as compared to female occupants.

#### *3.3.2. Mobile pupilometer sensors*

The human body's psychological characteristics can be used to investigate the visual sensation of the occupant in the indoor environment. Human pupil size responds to varying illuminance levels, and the lighting temperature level is used to analyze the individual's visual sensation. Pupilometers have been used for the investigation of the variation of pupil size with illuminance level. Choi's [12] study considered the occupant age, gender, eye color, and the glasses worn conditions. With the varying illuminance intensity, the large pupil size was a result due to the low intensity of light and the small pupil size was due to the higher intensity of light. The pupil size change pattern is similar in both lower and higher color temperature level. A seven-point scale visual comfort survey among the building occupants was conducted for varying illuminance intensity conditions and the occupant pupil change pattern was analyzed to measure the comfortable range of the illuminance intensity [16]. Hence suggesting that mobile pupilometer can be used as a tool to analyze the visual comfort of the occupant.

In summary, to maintain the occupant's productivity, better management of the lighting system is an important factor in the built environment. Generally, humans prefer to work in a daylight environment, which make them productive and refreshed. However, the better management of daylight harvesting is desirable to maintain better visual comfort. Otherwise, more energy has to be used to cool the office space in order to cool the warm environment due to excess daylight availability. Therefore, an optimal range of daylight harvesting has to achieve to maintain better visual comfort and efficient energy use.

### 3.4. Sensors used to enable better control of indoor air quality (IAQ)

Many prior research studies were conducted to investigate the air quality in the built environment, and it is found that one of the major parameters to consider is the air movement [22,23,35,105]. If the air is too still within the occupied zone, the quality of air will be considered poor. In addition, the particulate matter level in the indoor air is also an important variable. The major sources of indoor air pollution are: i) the cause of materials which used for the wall finishing, furniture, etc. react with the indoor temperature, humidity and velocity of air, produce volatile organic compounds (VOC), ii) machines (printing/copying) and equipment (air-condition system) generate pollutants and iii) ventilation and air distribution, mix the air improperly, generate air turbulence which causes to contaminated air [106,107]. The commonly found pollutants in the built environment are carbon monoxide (CO), Sulphur dioxide ($SO_2$), volatile organic compounds (VOC), and particulate matter (PM) [92,108].

The challenging task for any indoor air monitoring sensor is the detection of the low concentration level of pollutants. Most of the advanced indoor air monitoring sensors is battery operated, small in size, and mobile. The data transition from these sensors are via Bluetooth or Wi-Fi, which connected to cloud service or smartphone to view the real-time status [89]. The major indoor air quality sensors are gas sensors and particle sensors. It works based on the physical or chemical characteristics of the indoor environment and transducers are used to notify these changes and convert it to the electrical signal to analyze the quality of the indoor air. In order to analyze the gas and particle matters in the indoor environment, volatile organic compound (VOC) sensor and particulate matter (PM) sensor are commonly used which is described in details below.

#### 3.4.1. Volatile organic compound and particulate matter sensor

The indoor air quality analysis is one of the import aspects of the built environment. Air flow rate, temperature, humidity, and air quality are the parameters to measure the indoor environmental quality. To measure the personal pollution exposure, generally using a stationary sensor network or mobile sensor network. However, each of these sensor network systems has some advantage over the other. The stationary sensors network, which is very expensive as compared to the mobile sensor network. However, the accuracy of the stationary sensors network is high as compared to the mobile sensor network. Xiang et al. [101] introduce a hybrid sensor network architecture, to utilize both characteristics of mobile sensing and stationary sensing network. It used to predict the optimal indoor air concentration and its error estimation. The result shows that the hybrid sensor network system achieve 35.8% more accuracy as compared with a stationary sensor using alone and 23.9% more accurate when mobile sensing system using alone.

Jin et al. [23] use a mobile sensing unit to measure the air change effectiveness, temperature, humidity, volatile organic compound level, and illuminance level to analyze the indoor environmental quality. The data collected from the mobile sensing unit is compared with the dense sensor network, which considered as the ground truth. Using the extra tree method, the root means square error (RMSE) showed the reduction of mean error from 0.063 to 0.049. The results indicated that with minimal cost, an automated mobile sensing unit is capable of measuring accurate indoor environmental quality, which helps to monitor indoor air quality.

Because of the higher cost of a sensor to monitor the indoor environment quality, Boulic et al. [109] developed a low-cost indoor air quality measuring unit, which capable to measure the indoor temperature, relative humidity, particular matter, and carbon dioxide level. The sensor platform is called, SKOMOBO, which include a temperature sensor, humidity sensor, $CO_2$ sensor, particulate matter sensor, and PIR sensor. The design goal of the sensor platform mainly focusses on the low cost, the reliability of the data measured, maintenance and the privacy concerns. From the analysis of the new sensor with extensive experiment, found the limitation of using low-cost sensor. Hence, suggesting that, much research has to conduct to develop new low-cost sensor unit with improved system software and hardware.

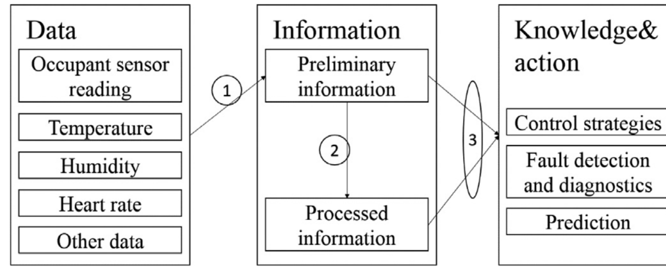


**Fig. 1.** Graphical representation of the typical sensor data analysis process.

### 3.5. Spatial and temporal resolution of sensing

Different applications of smart building sensing system require different spatial (i.e., the size of the space which the sensor covers-whole building, or a single room, or a zone) and temporal (i.e., how often the data is collected) resolution. For example, for real-time indoor environment monitoring for occupants' thermal and visual comfort, the selected sensors (e.g., temperature sensors, velocity sensors, acoustic sensors, etc.) were placed in the zone that occupants are residing in [21,22,110], and maybe wore by the occupant [53]. To implement the occupancy based control through adjusting required ventilation rates in commercial buildings following ASHRAE Standard 62.1, CO2 sensors in the zone were used to estimate the number of people in the ventilation zone [111]. Aggregated hourly mobile position data from smart phones were used to get the building level occupancy schedule for facilitating the building energy model calibration [112]. In most cases, sensors with relatively high temporal resolutions (e.g., minutes) are preferred for intelligent building operations for better indoor environment control due to a relatively large time constant of building envelope/enclosure (Tables 3–6).

## 4. Sensor data analysis

Sensor data acquisition is the first step along the way to harvest information from the built environment, and data analysis methods are needed to realize the end goals of using smart and advanced sensors in the built environment, reducing energy consumption and demand, creating thermally and visually comfortable environments, and improving indoor air quality. The process of turning sensor data into useful knowledge can be further split into two steps: data-to-information transformation, and information-to-knowledge/action transformation, as illustrated in Fig. 1.

It is evident that the three key concepts—data, information, and knowledge—are crucial for illustrating this data analysis process. However, these three concepts are interrelated, and they are used interchangeably in many situations. The meanings of these concepts in the context of the intelligent building operations are clarified as follows.

Data herein refers to the measured values directly acquired from sensors regardless of the sensors used. The information contains useful and relevant meaning, implication, or input for decisions and/or actions. It can be further subdivided to two types—

**Table 3**
Types of sensors used for energy saving.

| Study | Chair sensor | Motion sensor (PIR) | Photo sensor | Wearable sensor | CO2 sensor | Pressure mats | Sound sensor |
|---|---|---|---|---|---|---|---|
| [43] | √ | | | | | | |
| [37] | | √ | √ | | | | |
| [6] | | | | √ | | | |
| [34] | | √ | | | √ | √ | √ |
| [47] | | | | √ | | | |
| [18] | | | | | | | |
| [11] | | | √ | | | | |
| [5] | | √ | | | | | |
| [20] | | | | √ | | | |
| [21] | | √ | | √ | | | |
| [39] | | | | | | | |
| [44] | | √ | | | | | |
| [19] | | | | | | | |
| [40] | | | | | | | |
| [45] | | √ | | | √ | | |
| [46] | | √ | √ | | | | |
| [14] | | √ | √ | | | | |
| [14] | | √ | √ | | | √ | |
| [50] | | √ | √ | | | | |
| [49] | | | √ | | | | |
| [38] | | | √ | | | | |
| [31] | | | √ | | | | |
| [32] | | √ | | | | | |
| [41] | | | √ | | | | |
| [52] | | √ | | | | | |
| [98] | | √ | √ | | √ | | |

| Study | Camera sensor | Smart phones | Thermostat | Thermo-fluidic sensor | Heart rate sensor | Humidity sensor | Skin temperature sensor | Wireless sensor network |
|---|---|---|---|---|---|---|---|---|
| [34] | √ | | | | | | | |
| [47] | | √ | | | | | | |
| [11] | | | | | | | | |
| [5] | √ | | | | | | | √ |
| [20] | | √ | √ | | | | | |
| [21] | | √ | | √ | | | | |
| [39] | | | | | | | | √ |
| [44] | √ | | | | | | | √ |
| [19] | | | √ | | | √ | | |
| [40] | | | √ | | √ | √ | √ | |
| [45] | | | √ | | | √ | | |
| [98] | √ | | √ | | | √ | | |

**Table 4**
Types of sensors to enable Thermal comfort.

| Study | Wearable sensor | CO2 sensor | Thermo-fluidic sensor | Heart rate sensor | Fingerprint sensor | Air temperature Sensor | Humidity sensor | Thermostat | Air velocity sensor | Skin temperature sensor | Wireless sensor network |
|---|---|---|---|---|---|---|---|---|---|---|---|
| [21] | | | √ | | | | | | | | |
| [55] | | | | | | | √ | | | | |
| [56] | | | | | | | | | | | |
| [15] | | | | √ | | √ | √ | | √ | √ | |
| [17] | | | | | | | √ | | √ | √ | |
| [33] | | | | √ | | | | | √ | | |
| [23] | | | | | | | | | | | √ |
| [7] | | | | | | | | | | | |
| [19] | | | | √ | | | | | | | |
| [53] | | | | | | | √ | | | | |
| [110] | | | | | | | | | | | |
| [40] | | | | | | | | | | | |
| [48] | | | | √ | | | √ | | | √ | |
| [42] | | | | | √ | | | | | | |
| [54] | | | | √ | | | √ | | √ | | |
| [105] | | | | | | √ | √ | | √ | | |
| [103] | | | | | | | | | √ | | |
| [33] | | | | | | | | √ | | | |
| [53] | | | | | | √ | √ | | | | |
| [23] | | √ | √ | | | | | √ | | | |
| [7] | √ | | | | | | | | | | |
| [19] | | | √ | | | | | √ | | | |
| [53] | | | | | | | | | | | |
| [110] | √ | | | | | | | | | | |
| [40] | | | √ | | | | | √ | | | |
| [48] | √ | | | | | | | | | | |
| [42] | | √ | √ | | | | | √ | | | |
| [54] | | √ | √ | | | | | √ | | | |
| [105] | | | √ | | | | | √ | | | |
| [103] | | | √ | | | | | √ | | | |
| [34] | | √ | | | | | | | | | |
| [47] | √ | | | | | | | | | | |
| [18] | | | | | | | | | | | |
| [33] | | √ | | | | | | √ | | | |
| [53] | √ | | | | | | | | | | |
| [23] | | √ | | | | | | √ | | | |
| [20] | √ | | | | | | | √ | | | |
| [21] | √ | | | | | | | | | | |
| [7] | √ | | | | | | | | | | |
| [55] | √ | | | | | | | √ | | | |
| [56] | | | | | | | | | | | |
| [15] | √ | √ | | | | | | | | | |
| [17] | | √ | | | | | | √ | | | |

**Table 5**
Types of sensors to enable visual comfort.

| Study | Photometric sensor | Study | Photometric sensor | Mobile pupilometer sensor |
|---|---|---|---|---|
| [11] | √ | [41] | √ | |
| [12] | √ | [14] | √ | |
| [16] | √ | [22] | √ | |
| [23] | √ | [83] | √ | |
| [105] | | [12] | | √ |
| [14] | √ | [16] | | √ |
| [50] | √ | [11] | √ | |
| [49] | √ | [84] | √ | |

**Table 6**
Types of sensors to enable indoor air quality.

| Study | CO2 sensor | Sound sensor | Thermostat | Volatile organic compound sensor | Humidity sensor | Air velocity sensor | Particulate matter sensor (PM) | Wireless sensor network |
|---|---|---|---|---|---|---|---|---|
| [22] | √ | √ | √ | √ | √ | | √ | |
| [23] | √ | | √ | √ | | | | |
| [105] | | | √ | | | √ | | |
| [35] | √ | | | √ | | | | |
| [89] | | | | √ | | √ | | |
| [90] | | | | √ | | | | |
| [91] | | | | √ | | | | |
| [92] | | | | √ | | | | |
| [82] | | | | √ | | | √ | |
| [101] | | | | √ | | | √ | √ |

preliminary information and processed information. The former is the desired properties of the measured objects, such as the number of occupants, indoor air temperature, etc. It is very common that the preliminary information acquired from sensor needs to be fed into the data pre-processing process to improve its quality and ease-of-use, then transferred to processed information. Both preliminary and processed information will be inputs for the next step of knowledge and action, which usually include: (1) cognition of the built environment situation, such as indoor air quality and the energy performance, and/or the faults of HVAC systems (know-what), and (2) better control strategies or an action to repair the detected fault (know-how).

### *4.1. Information extraction*

Sensor data can be categorized into two separate classes. The first class of data gives the desired properties of the measured objects directly, which means it doesn't require much pre-processing and extraction methodology to analyze the data. For instance, thermometers will output the indoor air temperature directly. In the field of the built environment, the first data class includes temperature, humidity, luminance, heart rate, pupil size and other physiological states of occupants, $CO_2$ concentration, flow rate, pressure, energy consumption by power meters, etc. Choi et al. presented research to investigate the influencing factors on the occupants' heart rates [42]. In their research, heart rate information was collected by sensors and was then directly analyzed to get insights into the relationship between the occupant's heart rate and metabolic rates, thermal conditions, gender, and other factors.

For the second class of data, some pre-processing and extracting methods are required to obtain useful information from the raw data sets. As detailed in Section 3.2 there are a variety of occupancy sensors based on different detection mechanisms, and the pre-processing and extracting techniques used for different occupancy sensor systems are not always the same. The following section discuss about the sensor data extraction and analyzes of different sensors.

#### *4.1.1. Data extraction from CO2 sensor*

Occupants are considered to be the unique carbon dioxide ($CO_2$) source in most buildings, $CO_2$ sensors have been used to estimate the number of occupants for a long time [113,114]. Wang et al. [4] proposed a dynamic method to count the number of occupants in indoor spaces from the $CO_2$ concentration of the return air and the outdoor air. A simple formula based on the $CO_2$ derivative was proposed to calculate the number of occupants, and the $CO_2$ derivative can be further simplified using the $CO_2$ concentrations measured at the current and previous sampling instants. Similar studies were also presented by other researchers [114], and the information extraction methods used are mainly based on a deterministic relationship between $CO_2$ concentration and the number of occupants.

#### *4.1.2. Data extraction from PIR sensor*

Passive Infrared (PIR) sensors are another widely used technology for occupancy detection [115]. Dodier et al. developed and deployed a network of PIR occupancy sensors in two private offices, and an analysis tool based on the Bayesian probability theory was applied to determine occupancy. Because the PIR-only sensor is considerably less accurate to determine occupancy information, PIR sensors are often coupled with other sensors to improve the sensor system accuracy [116]. Dong et al. [115] proposed a large-scale wireless and wired environmental sensor network. This network collected data through PIR, $CO_2$, temperature, acoustic, and other sensors. Three machine-learning techniques, Support Vector Machines (SVM), artificial neural networks (ANN) and Hidden Markov Models (HMM) were then applied to extract occupant information from the proposed sensor network. The results showed that HMM outperformed the other two methods.

#### *4.1.3. Data extraction from radio -based sensor*

Some of the occupancy sensors mentioned in Section 3.2 can provide the number of occupants in indoor spaces, while they are unable to provide occupants' coordinates information, not to mention occupant's identities and activities. RFID based systems were proposed to bridge this gap [59,117]. Li et al. [117] used an

RFID based occupancy detection system to detect and track multiple stationary and mobile occupants in multiple spaces simultaneously. Passive tracking RF tags were attached to the measured objects, and the distances between tracking RF tags and the references tags were then calculated in a server. Based on these data, a proximity-based algorithm built on the K-nearest neighbor (KNN) technique was used to locate each object. In addition, a scattering analysis was used to determine the activities of occupants such as whether they were seated or mobile. This system turned out to detect the occupancy presence with a 100% accuracy and determined the number of occupants with an average accuracy of 75%. However, the idea of using the scattering analysis to determine occupants' activities needs to be further explored because although higher average distances always indicate more dynamic environments, the classification accuracy is just 60%, which is only slightly higher than a just random guess. Similar studies have been conducted by Zhen et al. [118]. In this research, a supporting vector machine (SVM) aided algorithm that followed a round-robin comparison rule was applied to locate the occupant. Besides, there are some other occupant detection systems which extract occupant information based on data from Wireless Sensor Networks (WSN), Camera images, GPS, and Bluetooth [113,119].

In summary, data analysis methods, especially machine learning methods, can successfully learn the number and location of occupants. Other occupant information extraction involves inferring activities and identifies of these occupants, which requires further research in both sensor technology and data analysis methods.

### 4.2. Data pre-processing

After the preliminary information extraction process, obtained the dataset for the analysis of occupant behavior and environmental parameters. However, discovering knowledge from these preliminary data presents many challenges, such as the low data quality problem, the curse of dimensionality, and exponentially growing amounts of data. To better understand and extract knowledge from these data, it is necessary to identify and tackle these challenges.

Poor-quality data might lead to ill-conceived strategies and inaccurate reporting. Two of the most important aspects for the data quality are accuracy and completeness, which determine if data is missing, duplicated, consistent, and adherent to a standard form. In general, data cleaning aims to clean the data and improve the quality of data [120]. There are usually two methods to deal with missing values: eliminating/removing the records, and estimating a replacement for the missing value. Moving average, imputation, and inference-based methods are three commonly used estimating methods for the missing values. "Noise," random errors in measured variables, is a major cause of inaccuracy. This might be due to environment disturbance, measurement uncertainty, operational uncertainty, and transferring of the data [121,122]. Binning and regression are two main data smoothing methods that can smooth out the noise. Duplication can be detected using distance analysis between records (e.g. Euclidean distance analysis). Inconsistency refers to the differences in the data scales or units, and unmatched records in different data sources [120].

The curse of dimensionality refers to various problems that arise when analysing and organizing data in high-dimensional spaces (often with hundreds or thousands of dimensions). This expression was coined by Bellman [123]. Fuelled by the advancement in sensor techniques, sensing systems become prevalent in modern building systems. Buildings generate massive time series data (e.g., a medium-sized commercial building will have over 10,000 sensor measurements over 500,000 time points on a minute base, per year). As a result, the dimensionality of sensor data is growing rapidly. In the study from Miller et al. [124], 120 power meters and 100 water meters were installed to monitor the energy and water usage of one building. Besides that, in order to improve the accuracy of data-driven models, one emerging technique, feature engineering, is now receiving a lot of attention from building science researchers [125]. As a result, many new features are engineered and the dimensions of the input information for knowledge discovery increases further. Feature selection and dimension reduction are two commonly used methods to reduce the dimensions. Feature selection methods include forward selection, backward elimination, decision tree induction, etc., while principle component analysis (PCA) and wavelet transformation are two widely used dimensionality reduction methods. Li et al. proposed a combined Wavelet-PCA method to reduce the dimensions of the dataset for a data-driven model which was then used to detect air handler faults [126].

The amount of sensor data generated by modern building systems is growing rapidly. However, data is just like crude oil. It is valuable, but if unrefined it cannot really be used. Automatic discovery of patterns from this large amount of data supports subsequent implementation of knowledge discovery. Miller et al. [123] proposed a data processing method that uses Symbolic Aggregate approximation (SAX), motif and discord extraction, and clustering methods to detect the underlying structure of building sensor data. The proposed process transformed quantitative raw data into qualitative subgroups based on daily performance similarity. The results can be used to support implementation of building commissioning, fault detection, and retrofit analysis techniques. Fan et al. [127] developed a framework to support the implementation of knowledge discovery. Similarly, they used a clustering analysis to identify the building's typical and non-typical operation patterns. They also suggested that some common data mining algorithms, such as decision tree and association rule mining, could be used in the knowledge discovery process. In the end, they illustrated the feasibility of applying an association rule mining method to diagnose faults existing in the systems. In addition, the feasibility of applying association rule mining methods to learn the underlying patterns of sensor data has been further confirmed in other studies [128–130].

In summary, preliminary datasets always involve three problems: the quality of data, the curse of dimensionality, and the growing amount of data. The knowledge discovery process becomes successful only when the challenges or issues are identified and coped with correctly.

### 4.3. Knowledge discovery

Knowledge discovery are usually context-aware computation tasks, the data obtained after pre-processing are used to analyze the occupancy behavior pattern and indoor environmental variables into a meaningful form for the effective control of energy use and also to maintain productive indoor built environment. In general, there are several application domains. Among different applications, the required database and applicable analytics methods also differ from each other. The knowledge discovery is categorized into three application domains: (1) prediction, (2) control strategy design, and (3) fault detection and diagnostics (FDD). There is also a huge crossover in applications and the use of data between domains. For instance, Bengea et al. [62] presented a fault-tolerant control technology for the HVAC system in a commercial building. Based on sensor data, probabilistic graphical models were used to detect in real time potential faults of the HVAC systems. Then by using model-based predictive control (MPC), the control strategies were adapted to the identified system faults to reach the largest energy consumption reduction levels. The proposed systems were demonstrated in a real building with about 30% energy saving.

Many studies on building energy demand prediction and occupancy prediction can be found in the existing literature. The data analysis methods used for building energy demand prediction include:(1) regression algorithms [131,132]; (2) support vector machines (SVM) [132–134]; (3) artificial neural networks (ANN) [135,136], etc.. And these studies range from short-term predictions to long-term predictions, and successful applications can be found in many practical cases [31,137]. In addition, occupancy predictions have also been widely studied. Leephakpreeda et al. implented a grey prediction methodology to predict the inactive period of occupant in a regular office room [138]. Besides, the Markov Chain Occupancy Model is a commonly used method in the occupancy prediction field. For instance, Erickson et al. [139] developed a Moving Window Markov Chain occupancy model to predict occupant information, and the data source was collected by a wireless sensor network.

The collected sensor data can also be used to design energy-saving and environment-friendly control strategies. Based on occupancy information, demand-based control can be designed and deployed. Kuutti et al. [140] compared several different visitor counting techniques, and then they proposed demand-controlled ventilation using the most promising sensors selected from their study. Other demand-based control strategies include maintaining higher temperatures in unoccupied areas [66] and maintaining lower ventilation rates in unoccupied areas [141]. Fisk et al. provided a detailed review on sensor-based demand-controlled ventilation [141]. In addition to these, control strategies based on the building automation system (BAS) data is also an extensively explored field. The underlying models used for control designs include physics-based, grey-box based, and black-box based models [142]. Wang et al. [143] provided a review of the state-of-art control strategies in the HVAC field. Li et al. [144] developed a data-driven state-space model and used it for an MPC controller to control the air handler's supply air temperature setpoints and room air temperature setpoints, which were implemented in a medium-sized office building with more than 20% electrical savings while improving occupants' thermal comfort in terms of room air temperatures.

Fault detection and diagnostics (FDD) is another extensively studied application using sensor data in the built environment. The methods applied range from quantitative model-based methods, to qualitative model-based methods, and to process history based methods, and each categories could be further divided [145]. Braun et al. [146] proposed a rule-based method, which is a typical method in the qualitative categories, for automated detection and diagnosis of faults in vapor compression air conditioners. Sensor data was used for comparisons with predicted states obtained from models for normal performance (residuals), and then the differences were used as indices for both fault detection and diagnosis. Bendapudi and Braun [147] also developed a dynamic centrifugal chiller model from first principles for FDD [147]. This FDD method is a good example for quantitative model-based methods. As for process history-based methods, some examples of the data analysis methods include: linear regression (LR) or multiple linear regression (MLR), artificial neural networks (ANNs), and fuzzy logic (FL). Recently, Kim and Katipamula did another great review for the data analysis methods for FDD, and more information can be found in their study [104]. Table 7 lists some commonly used data analysis methods used for building applications.

In summary, the knowledge discovery are the analyzes of pre-processed data from the sensors into a meaningful form, for making better decision in the building control system to maintain the occupant satisfaction level and efficiently managing energy consumption.

**Table 7**
Sensor data analysis methods.

| Application | Data analysis methods | Reference |
|---|---|---|
| Information extraction | Bayesian probability theory | [115] |
| | Support Vector Machine (SVM) | [116,118] |
| | Artificial Neural Network (ANN) | [116] |
| | Hidden Markov Model (HMM) | [116] |
| | K-Nearest Neighbor (KNN) | [59,117] |
| Data pre-processing | Binning method | [120] |
| | Regression | [120] |
| | Symbolic Aggregate approximation (SAX) | [124] |
| | Principle Component Analysis (PCA) | [126] |
| | Wavelet transform | [126] |
| | Association Rule Mining (ARM) | [127–130] |
| | Decision tree algorithm | [127] |
| | Clustering algorithms | [127,130] |
| Knowledge discovery | Regression | [131,132] |
| | Support Vector Machine (SVM) | [132–134] |
| | Artificial Neural Network (ANN) | [135,136] |
| | Grey prediction | [138] |
| | Markov chain | [139] |
| | Rule-based method | [146] |

## 5. Conclusions and future challenges

### 5.1. Summary

The paper conducted a comprehensive review of how the building sensors influence in managing optimal energy saving, thermal comfort, visual comfort, and indoor air quality in the built environment.

First, this paper talks about the working mechanism of commonly used sensors. There are many sensors used to understand the indoor environmental quality and occupancy sensing in the built environment. Understanding of the fine-grained occupancy information in the built environment helps to improve energy saving. From the literature review, sensors are categorized into three based on smart building operations. The first category covers occupancy sensors in the built environment. Sensors listed in the second category are being used to find the indoor building environmental parameters. The last category is other types of sensors that are being used to help understand the occupant behavior.

Secondly, this paper reviewed a large number of case studies that use the sensing technology to enable energy savings, better thermal and visual comfort, and indoor air quality. It is found that each type of sensor has its own advantages over the others in the built environment application. It is suggested that finding the best combination of sensing technology would help achieve an energy efficient and healthy built environment. Also, the reviewed studies showed that the occupancy-based sensor network can save up to 70% of the HVAC energy consumption. The control strategies using daylight harvesting, occupant sensing, load shifting, and delay time control activities also achieve up to 40% of light energy consumption in the built environment. To maintain the occupant's productivity, better management of thermal and virtual comfort is an important factor in the built environment. It is found that using skin temperature and heart rate sensors can better capture the thermal comfort of each individual with different ages for both genders. Photometric sensors are used to control the luminaire intensity, based on the daylight availability in the built environment. The optimal control of the light system with the photometric sensor can significantly reduce the energy consumption while maintaining the visual comfort. Finally, occupant productivity and the energy consumption in the built environment is directly related to air quality. The major component affecting the indoor air quality includes the gaseous components and the particle matters in the built environ-

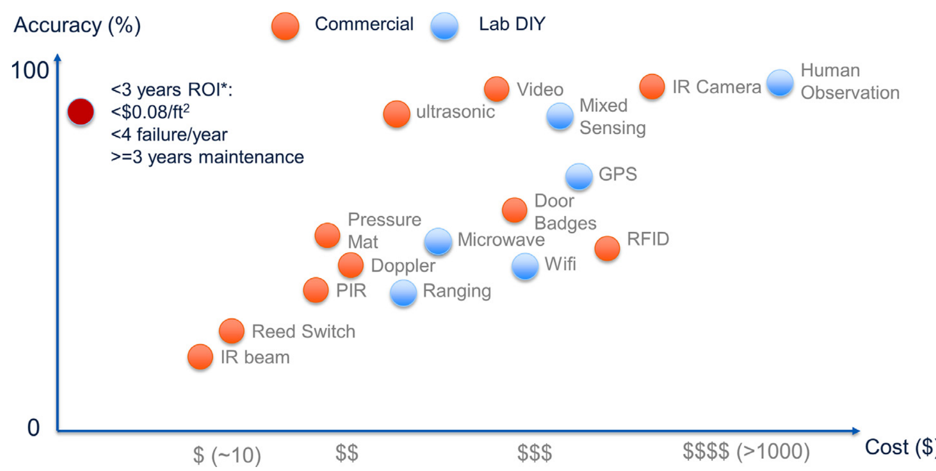


**Fig. 2.** Summary of current occupancy sensing technologies and ARPA-E SENSOR Goal.

ment, which are measured by a VOC sensor and PM sensor. The better control of air flow rate and the availability of fresh air in the door environment has to be analyzed, and occupant satisfaction level must be evaluated.

### *5.2. Future challenges*

#### *5.2.1. Cost-effective occupant sensors*

Fig. 2 summarizes most of current occupancy sensing technologies and compares with U.S. Department of Energy ARPA-E SENSOR program goal. As stated in the ARPA-E website: "The projects of ARPA-E's SENSOR (Saving Energy Nationwide in Structures with Occupancy Recognition) program will develop user-transparent sensor systems that accurately quantify human presence to dramatically reduce energy use in commercial and residential buildings." [143]. The future occupant sensing should be "peel and stick", self-configured with minimum maintenance as defined by U.S. Department of Energy roadmap. However, the challenges of such occupant sensing include (1) sensing element, (2) power consumption, (3) processing, and (4) communication. These review papers shows that currently the detection of the number of occupants is not accurate enough—even to detect if there is a human or not—for temperature setback or ventilation controls. There is thus a need for the development of advanced sensing elements that can capture occupants in a thermal zone accurately. In addition, most sensors depend on an external power source for a long-term function. This creates cost and wiring challenges for large-scale deployments, such as in a whole building. The power consumption mainly comes from three different sources on a sensor board: processing units, communication, and the sensing element itself. There is a need to research low-power consumption mechanisms so that an occupant sensor can be self-sticking and self-contained over a long time. Furthermore, the current data processing unit is either on-board or cloud-based. An onboard processing unit consumes power and a cloud-based requires high data security. The question remains how to intelligently collect and process on-board data in a way that sensors will consume the least power possible. For example, there is no need to collect data if there is no occupant in a space for a certain period. Finally, communication determines how frequent the data should be sent out for storage. Communication typically consumes the most power (>60%) of the whole sensor unit. The challenge is to determine how to perform communication as needed, and how to set up a communication network so that it minimizes the total data transmission power required.

#### *5.2.2. Individual differences in thermal and visual comfort*

People's thermal satisfaction level in the built environment varies from person to person. Therefore, finding the optimal range of indoor environmental temperature to satisfy all the occupant's thermal preference level is complex. Hence further research has to be conducted to obtain the optimum temperature to satisfy all the occupants with real-time scenarios.

*One potential research direction is to combine different sensors for better indoor environment control.* The combined effect of visual comfort and thermal comfort is not implemented widely, and this is the future research scope in the built environment. Also, indoor air quality is not investigated with thermal and visual comfort. The combined effect of visual comfort, thermal comfort and air quality in the built environment has to be researched further to optimize the energy usage by using minimum number of sensors and with the use of IoT devices.

*Other factors affecting occupant productivity* The acoustic comfort of the occupant is not considered in the built environment. This is one of the factors which effect the occupant productivity. It has to be further explored in term of indoor environmental quality.

#### *5.2.3. Privacy and security issues*

Nowadays, traditional building automation systems (BAS) are evolving to cyber-physical systems (CPS) that tightly integrate sensing, computation, communication, and control, leading to intelligent buildings that can sense the building environment and occupancy presence and adapt to them. However, most smart building sensing systems are designed for functionality, with litter consideration of privacy and cybersecurity. For example, in the era of the internet, private information such as occupancy from advanced sensing technology should be tracked under the supervision and protected. There is a need to integrate cyber-security and privacy research with the sensing system in future work.

## Declaration of Competing Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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## Supplementary materials

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## References

[1] R. Cantin, A. Kindinis, P. Michel, New approaches for overcoming the complexity of future buildings impacted by new energy constraints, Futures 44 (8) (2012) 735–745.
[2] U. Sbci, Buildings and Climate Change: Summary for Decision-Makers, Paris, 2009.
[3] P.G. Boonekamp, Price elasticities, policy measures and actual developments in household energy consumption – A bottom up analysis for the Netherlands, Energy Economics 29 (2) (2007) 133–157.
[4] L. Pérez-Lombard, J. Ortiz, C. Pout, A review on buildings energy consumption information, Energy and Buildings 40 (3) (2008) 394–398.
[5] T.A. Nguyen, M. Aiello, Energy intelligent buildings based on user activity: A survey, Energy and Buildings 56 (2013) 244–257.
[6] E.C. Sheikhi, Gian Paolo, Stephen P. Mahin, Adaptive energy consumption optimization using IoT-based wireless sensor networks and structural health monitoring systems, European Workshop on Structural Health Monitoring, EWSHM 8 (2016) 520–526.
[7] M. Andersen, G. Fierro, S. Kumar, J. Kim, E. Arens, H. Zhang, P. Raftery, D. Culler, Well-connected microzones for increased building efficiency and occupant comfort, in: the 2nd ACM International Conference, Pacific Grove, CA, 2015, pp. 21–26.
[8] F. Oldewurtel, D. Sturzenegger, M. Morari, Importance of occupancy information for building climate control, Applied Energy 101 (2013) 521–532.
[9] S.S. Kwok, E. W. Lee, A study of the importance of occupancy to building cooling load in prediction by intelligent approach, Energy Conversion and Management 52 (7) (2011) 2555–2564.
[10] L. Klein, J. Kwak, G. Kavulya, F. Jazizadeh, B. Becerik-Gerber, P. Varakantham, M. Tambe, Coordinating occupant behavior for building energy and comfort management using multi-agent systems, Automation in Construction (2012).
[11] S.G. Navada, C.S. Adiga, S.G. Kini, A Study on Daylight Integration with Thermal Comfort for Energy Conservation in a General Office, International Journal of Electrical Energy 1 (1) (2013) 18–22.
[12] J.-H. Choi, Investigation of human eye pupil sizes as a measure of visual sensation in the workplace environment with a high lighting colour temperature, Indoor and Built Environment 26 (4) (2016) 488–501.
[13] D.P. Wyon, The effects of indoor air quality on performance and productivity, Indoor Air 14 (7) (2004) 92–101.
[14] N. Gentile, T. Laike, M.-C. Dubois, Lighting control systems in individual offices rooms at high latitude: Measurements of electricity savings and occupants' satisfaction, Solar Energy 127 (2016) 113–123.
[15] D. Yeom, J.-H. Choi, Y. Zhu, Investigation of physiological differences between immersive virtual environment and indoor environment in a building, Indoor and Built Environment 28 (1) (2017) 46–62.
[16] J.-H. Choi, R. Zhu, Investigation of the potential use of human eye pupil sizes to estimate visual sensations in the workplace environment, Building and Environment 88 (2015) 73–81.
[17] J.-H. Choi, D. Yeom, Study of data-driven thermal sensation prediction model as a function of local body skin temperatures in a built environment, Building and Environment 121 (2017) 130–147.
[18] S.P. Corgnati, E. Fabrizio, M. Filippi, The impact of indoor thermal conditions, system controls and building types on the building energy demand, Energy and Buildings 40 (4) (2008) 627–636.
[19] J. Yun, K.H. Won, Building environment analysis based on temperature and humidity for smart energy systems, Sensors (Basel) 12 (10) (2012) 13458–13470.
[20] C.C. Cheng, D. Lee, Smart sensors enable smart air conditioning control, Sensors (Basel) 14 (6) (2014) 11179–11203.
[21] C.-C. Cheng, D. Lee, Enabling smart air conditioning by sensor development: A review, Sensors 16 (12) (2016) 2028.
[22] J.-H. Choi, J. Moon, Impacts of human and spatial factors on user satisfaction in office environments, Building and Environment 114 (2017) 23–35.
[23] M. Jin, S. Liu, S. Schiavon, C. Spanos, Automated mobile sensing: Towards high-granularity agile indoor environmental quality monitoring, Building and Environment 127 (2018) 268–276.
[24] D. Yan, T. Hong, B. Dong, A. Mahdavi, S. D'Oca, I. Gaetani, X. Feng, IEA EBC Annex 66: Definition and simulation of occupant behavior in buildings, Energy and Buildings 156 (2017) 258–270.
[25] T. Hong, B. Dong, J. Langevin, N. Luo, Occupant-centric sensing and control, in: ASHRAE HVAC Applications Handbook, 2019.
[26] H. Li, D. Yu, J.E. Braun, A review of virtual sensing technology and application in building systems, HVAC&R Research 17 (5) (2011) 619–645.
[27] V. Reppa, P. Papadopoulos, M.M. Polycarpou, C.G. Panayiotou, A distributed virtual sensor scheme for smart buildings based on adaptive approximation, in: 2014 International Joint Conference on Neural Networks (IJCNN), IEEE, 2014, pp. 99–106.
[28] H. Li, J.E. Braun, Decoupling features and virtual sensors for diagnosis of faults in vapor compression air conditioners, International Journal of Refrigeration 30 (3) (2007) 546–564.
[29] Y. Zhao, W. Zeiler, G. Boxem, T. Labeodan, Virtual occupancy sensors for real-time occupancy information in buildings, Building and Environment 93 (2015) 9–20.
[30] T.H. Pedersen, K.U. Nielsen, S. Petersen, Method for room occupancy detection based on trajectory of indoor climate sensor data, Building and Environment 115 (2017) 147–156.
[31] T. Leephakpreeda, Adaptive Occupancy-based Lighting Control via Grey Prediction, Building and Environment 40 (7) (2005) 881–886.
[32] F. Linhart, J.-L. Scartezzini, Evening office lighting – visual comfort vs. energy efficiency vs. performance? Building and Environment 46 (5) (2011) 981–989.
[33] J.-H. Choi, V. Loftness, Investigation of human body skin temperatures as a bio-signal to indicate overall thermal sensations, Building and Environment 58 (2012) 258–269.
[34] T. Ekwevugbe, N. Brown, D Fan, A design model for building occupancy detection using sensor fusion, in: 6th IEEE International Conference on Digital Ecosystems and Technologies (DEST), 2012.
[35] J. Kim, R. de Dear, C. Cândido, H. Zhang, E. Arens, Gender differences in office occupant perception of indoor environmental quality (IEQ), Building and Environment 70 (2013) 245–256.
[36] Y. Liu, L. Wang, J. Liu, Y. Di, A study of human skin and surface temperatures in stable and unstable thermal environments, Journal of Thermal Biology 38 (7) (2013) 440–448.
[37] A.A. Williams, Barbara, Karina Garbesi, Erik Page, Francis. Rubinstein, Lighting Controls in Commercial Buildings, LEUKOS: The Journal of the Illuminating Engineering Society of North America 8 (2013) 161–180.
[38] S.K.H. Chow, D.H.W. Li, E.W.M. Lee, J.C. Lam, Analysis and prediction of daylighting and energy performance in atrium spaces using daylight-linked lighting controls, Applied Energy 112 (2013) 1016–1024.
[39] F. Viani, A. Polo, F. Robol, G. Oliveri, P. Rocca, A. Massa, Crowd detection and occupancy estimation through indirect environmental measurements, in: Antennas and Propagation (EuCAP), 2014 8th European Conference on, IEEE, 2014, pp. 2127–2130.
[40] S.Y. Sim, M.J. Koh, K.M. Joo, S. Noh, S. Park, Y.H. Kim, K.S. Park, Estimation of Thermal Sensation Based on Wrist Skin Temperatures, Sensors (Basel) 16 (4) (2016) 420.
[41] R.M. Tetlow, C.P. Beaman, A.A. Elmualim, K. Couling, Simple prompts reduce inadvertent energy consumption from lighting in office buildings, Building and Environment 81 (2014) 234–242.
[42] S. Goyal, P. Barooah, T. Middelkoop, Experimental study of occupancy-based control of HVAC zones, Applied Energy 140 (2015) 75–84.
[43] T. Labeodan, W. Zeiler, G. Boxem, Y. Zhao, Occupancy measurement in commercial office buildings for demand-driven control applications—A survey and detection system evaluation, Energy and Buildings 93 (2015) 303–314.
[44] K. Akkaya, I. Guvenc, R. Aygun, N. Pala, A. Kadri, IoT-based occupancy monitoring techniques for energy-efficient smart buildings, in: Wireless Communications and Networking Conference Workshops (WCNCW), 2015 IEEE, IEEE, 2015, pp. 58–63.
[45] Z. Nagy, F.Y. Yong, M. Frei, A. Schlueter, Occupant centered lighting control for comfort and energy efficient building operation, Energy and Buildings 94 (2015) 100–108.
[46] E.E. Dikel, G.R. Newsham, H. Xue, J.J. Valdés, Potential energy savings from high-resolution sensor controls for LED lighting, Energy and Buildings 158 (2018) 43–53.
[47] M. Abdallah, C. Clevenger, T. Vu, A. Nguyen, Sensing occupant comfort using wearable technologies, in: Construction Research Congress 2016, 2016, pp. 940–950.
[48] J.-H. Choi, V. Loftness, D.-W. Lee, Investigation of the possibility of the use of heart rate as a human factor for thermal sensation models, Building and Environment 50 (2012) 165–175.
[49] J.F. De Paz, J. Bajo, S. Rodríguez, G. Villarrubia, J.M. Corchado, Intelligent system for lighting control in smart cities, Information Sciences 372 (2016) 241–255.
[50] H. Choi, S. Hong, A. Choi, M. Sung, Toward the accuracy of prediction for energy savings potential and system performance using the daylight responsive dimming system, Energy and Buildings 133 (2016) 271–280.
[51] B. Dong, D. Yan, Z. Li, Y. Jin, X. Feng, H. Fontenot, Modeling occupancy and behavior for better building design and operation—A critical review, Building Simulation 11 (5) (2018) 899–921.
[52] S.H. Ryu, H.J. Moon, Development of an occupancy prediction model using indoor environmental data based on machine learning techniques, Building and Environment 107 (2016) 1–9.
[53] C. Dai, H. Zhang, E. Arens, Z. Lian, Machine learning approaches to predict thermal demands using skin temperatures: Steady-state conditions, Building and Environment 114 (2017) 1–10.
[54] J.-H. Choi, D. Yeom, Investigation of the relationships between thermal sensations of local body areas and the whole body in an indoor built environment, Energy and Buildings 149 (2017) 204–215.
[55] J. Kim, S. Schiavon, G. Brager, Personal comfort models – A new paradigm in thermal comfort for occupant-centric environmental control, Building and Environment 132 (2018) 114–124.

[56] J. Kim, Y. Zhou, S. Schiavon, P. Raftery, G. Brager, Personal comfort models: Predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning, Building and Environment 129 (2018) 96–106.
[57] C. Spataru, S. Gauthier, How to monitor people 'smartly' to help reducing energy consumption in buildings? Architectural Engineering and Design Management 10 (1-2) (2013) 60–78.
[58] K. Christensen, R. Melfi, B. Nordman, B. Rosenblum, R. Viera, Using existing network infrastructure to estimate building occupancy and control plugged-in devices in user workspaces, International Journal of Communication Networks and Distributed Systems 12 (1) (2014) 4.
[59] N. Li, G. Calis, B. Becerik-Gerber, Measuring and monitoring occupancy with an RFID based system for demand-driven HVAC operations, Automation in Construction 24 (2012) 89–99.
[60] S. Seer, N. Brändle, C Ratti, Kinects and human kinetics: A new approach for studying pedestrian behavior, Transportation Research Part C: Emerging 48 (2014) 212–228.
[61] D. Liu, X. Guan, Y. Du, Q Zhao, Measuring indoor occupancy in intelligent buildings using the fusion of vision sensors, Measurement Science and Technology 24 (7) (2013) 074023.
[62] Y. Benezeth, H. Laurent, B. Emile, C Rosenberger, Towards a sensor for detecting human presence and characterizing activity, Energy and Buildings 43 (2-3) (2011) 305–314.
[63] V.L. Erickson, S. Achleitner, A.E. Cerpa, POEM: Power-efficient occupancy-based energy management system, in: 2013 ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN), Philadelphia, PA, 2013, pp. 203–216.
[64] L.V. Thanayankizil, S. K. Ghai, D. Chakraborty, D. P. Seetharam, Softgreen: Towards energy management of green office buildings with soft sensors, in: 2012 Fourth International Conference on Communication Systems and Networks (COMSNETS 2012), 2012.
[65] Y. Agarwal, B. Balaji, S. Dutta, R.K. Gupta, T. Weng, Duty-cycling buildings aggressively: The next frontier in HVAC control, Information Processing in Sensor Networks (IPSN), in: 2011 10th International Conference on, IEEE, 2011, pp. 246–257.
[66] Y. Agarwal, B. Balaji, R. Gupta, J. Lyles, M. Wei, T. Weng, Occupancy-driven energy management for smart building automation, in: Proceedings of the 2nd ACM workshop on embedded sensing systems for energy-efficiency in building, ACM, 2010, pp. 1–6.
[67] T.W. Hnat, E. Griffiths, R. Dawson, K. Whitehouse, Doorjamb: unobtrusive room-level tracking of people in homes using doorway sensors, in: Proceedings of the 10th ACM Conference on Embedded Network Sensor Systems, ACM, 2012, pp. 309–322.
[68] T. Teixeira, G. Dublon, A. Savvides, A survey of human-sensing: Methods for detecting presence, count, location, track, and identity, ACM Computing Surveys 5 (1) (2010) 59–69.
[69] X. Guo, D. Tiller, G. Henze, C. Waters, The performance of occupancy-based lighting control systems: A review, Lighting Research & Technology 42 (4) (2010) 415–431.
[70] P. Misra, P. Enge, Global Positioning System: signals, measurements and performance, second edition, Ganga-Jamuna Press, Massachusetts, 2006.
[71] M. Chiesa, R. Genz, F. Heubler, K. Mingo, C. Noessel, N. Sopieva, D. Slocombe, J. Tester, RFID: a week long survey on the technology and its potential, Harnessing Technology Project-Interaction Design Institute Ivrea, 2002.
[72] G. Deak, K. Curran, J. Condell, A survey of active and passive indoor localisation systems, Computer Communications 35 (16) (2012) 1939–1954.
[73] I. Sabek, M. Youssef, A.V. Vasilakos, ACE: An accurate and efficient multi-entity device-free WLAN localization system, IEEE transactions on mobile computing 14 (2) (2014) 261–273.
[74] A. LaMarca, E. De Lara, Location systems, An introduction to the technology behind location awareness, Synthesis Lectures on Mobile and Pervasive Computing 3 (1) (2008) 1–122.
[75] C. Gomez, J. Oller, J. Paradells, Overview and evaluation of bluetooth low energy: An emerging low-power wireless technology, Sensors 12 (9) (2012) 11734–11753.
[76] H.M. Khoury, V.R. Kamat, Evaluation of position tracking technologies for user localization in indoor construction environments, Automation in Construction 18 (4) (2009) 444–457.
[77] A. Caucheteux, A.E. Sabar, V. Boucher, Occupancy measurement in building: A litterature review, application on an energy efficiency research demonstrated building, International Journal of Metrology and Quality Engineering 4 (2) (2013) 135–144.
[78] S. Hay, A. Rice, The case for apportionment, in: Proceedings of the First ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings – BuildSys 09, 2009.
[79] J. Ranjan, Y. Yao, K. Whitehouse, An RF doormat for tracking people's room locations, in: Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing, ACM, 2013, pp. 797–800.
[80] E. Sardini, M. Serpelloni, Self-Powered Wireless Sensor for Air Temperature and Velocity Measurements With Energy Harvesting Capability, IEEE Transactions on Instrumentation and Measurement 60 (5) (2011) 1838–1844.
[81] J.-H. Choi, V. Loftness, A. Aziz, Post-occupancy evaluation of 20 office buildings as basis for future IEQ standards and guidelines, Energy and buildings 46 (2012) 167–175.
[82] E.G. Snyder, T.H. Watkins, P.A. Solomon, E.D. Thoma, R.W. Williams, G.S. Hagler, D. Shelow, D.A. Hindin, V.J. Kilaru, P.W. Preuss, The changing paradigm of air pollution monitoring, ACS Publications, 2013.
[83] J.A. Veitch, G.R.J.I.J.O.L.R. Newsham, Technology, Preferred luminous conditions in open-plan offices: Research and practice recommendations, 32 (4) (2000) 199–212.
[84] A. Pandharipande, D. Caicedo, Smart indoor lighting systems with luminaire-based sensing: A review of lighting control approaches, Energy and Buildings 104 (2015) 369–377.
[85] N. Nassif, A robust CO2-based demand-controlled ventilation control strategy for multi-zone HVAC systems, Energy and buildings 45 (2012) 72–81.
[86] S.A. Mumma, Transient occupancy ventilation by monitoring CO2, ASHRAE IAQ Applications 5 (1) (2004) 21–23.
[87] A. Haeusler, J.-U. Meyer, A novel thick film conductive type CO2 sensor, Sensors and Actuators B: chemical 34 (1-3) (1996) 388–395.
[88] C.-O. Park, C. Lee, S. Akbar, J. Hwang, The origin of oxygen dependence in a potentiometric CO2 sensor with Li-ion conducting electrolytes, Sensors and Actuators B: Chemical 88 (1) (2003) 53–59.
[89] R. White, I. Paprotny, F. Doering, W. Cascio, P. Solomon, L. Gundel, Sensors and 'apps' for community-based atmospheric monitoring, EM: Air and Waste Management Association's Magazine for Environmental Managers 5 (2012) 36–40.
[90] S. Brown, M.R. Sim, M.J. Abramson, C.N. Gray, Concentrations of volatile organic compounds in indoor air–a review, Indoor air 4 (2) (1994) 123–134.
[91] G.W. Ho, Gas sensor with nanostructured oxide semiconductor materials, Science of Advanced Materials 3 (2) (2011) 150–168.
[92] P. Kumar, C. Martani, L. Morawska, L. Norford, R. Choudhary, M. Bell, M. Leach, Indoor air quality and energy management through real-time sensing in commercial buildings, Energy and Buildings 111 (2016) 145–153.
[93] S. Zampolli, I. Elmi, J. Stürmann, S. Nicoletti, L. Dori, G. Cardinali, Selectivity enhancement of metal oxide gas sensors using a micromachined gas chromatographic column, Sensors and Actuators B: Chemical 105 (2) (2005) 400–406.
[94] S.J. Emmerich, A.K. Persily, State-of-the-art review of CO2 demand controlled ventilation technology and application, Citeseer (2001).
[95] S. Meyn, A. Surana, Y. Lin, S.M. Oggianu, S. Narayanan, T.A. Frewen, A sensor-utility-network method for estimation of occupancy in buildings, in: Decision and Control, 2009 held jointly with the 2009 28th Chinese Control Conference. CDC/CCC 2009. Proceedings of the 48th IEEE Conference on, IEEE, 2009, pp. 1494–1500.
[96] M. Mysen, S. Berntsen, P. Nafstad, P.G.J.E. Schild, Buildings, Occupancy density and benefits of demand-controlled ventilation in Norwegian primary schools, 37 (12) (2005) 1234-1240.
[97] X. Lin, J. Lau, Demand controlled ventilation for multiple zone HVAC systems: CO2-based dynamic reset (RP 1547), HVAC&R Research 20 (8) (2014) 875–888.
[98] M.M. Manning, M.C. Swinton, F. Szadkowski, J. Gusdorf, K. Ruest, The effects of thermostat set-back and set-up on seasonal energy consumption, surface temperatures and recovery times at the CCHT Twin House Facility, ASHRAE Transactions 113 (1) (2007) 630–642.
[99] A.R.N. Galasiu, Guy, Cristian Suvagau, M. Sander Daniel, Energy saving lighting control systems for open-plan offices: A field study, LEUKOS – Journal of Illuminating Engineering Society of North America 4 (2013).
[100] T. Moore, D.J. Carter, A. Slater, A comparative study of user opinion in offices with and without individually controlled lighting, in: Proceedings of the 9th European Lighting Conference (Lux Europa), Reykjavik, Iceland, 2001, pp. 234–241.
[101] Y. Xiang, R. Piedrahita, R.P. Dick, M. Hannigan, Q. Lv, L. Shang, A Hybrid Sensor System for Indoor Air Quality Monitoring, in: 2013 IEEE International Conference on Distributed Computing in Sensor Systems, 2013, pp. 96–104.
[102] ASHRAE129, Standard Method of Measuring Air Change Effectiveness, American Society of Heating, Air-Conditioning, and Refrigerating Engineerings, Inc., Atlanta, 1997.
[103] H. Zhang, E. Arens, C. Huizenga, T. Han, Thermal sensation and comfort models for non-uniform and transient environments: Part I: Local sensation of individual body parts, Building and Environment 45 (2) (2010) 380–388.
[104] M. Miki, A. Amamiya, T. Hiroyasu, Distributed optimal control of lighting based on stochastic hill climbing method with variable neighborhood, Systems, in: Man and Cybernetics, 2007. ISIC. IEEE International Conference on, IEEE, 2007, pp. 1676–1680.
[105] R. Li, S.C. Sekhar, A.K. Melikov, Thermal comfort and IAQ assessment of under-floor air distribution system integrated with personalized ventilation in hot and humid climate, Building and Environment 45 (9) (2010) 1906–1913.
[106] K.W. Tham, Indoor air quality and its effects on humans—A review of challenges and developments in the last 30 years, Energy and Buildings 130 (2016) 637–650.
[107] P. Wolkoff, Indoor air pollutants in office environments: assessment of comfort, health, and performance, International Journal of Hygiene and Environmental Health 216 (4) (2013) 371–394.
[108] D. Rickerby, A. Skouloudis, Application of nanocrystalline metal oxide gas sensors for air quality monitoring, International Journal of Nanotechnology 11 (5-678) (2014) 583–593.
[109] R. Weyers, J. Jang-Jaccard, A. Moses, Y. Wang, M. Boulic, C. Chitty, R. Phipps, C. Cunningham, Low-cost Indoor Air Quality (IAQ) Platform for Healthier Classrooms in New Zealand: Engineering Issues, in: 2017 4th Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE), IEEE, 2017, pp. 208–215.

[110] K. Venneti, M. Lenin, D.A. Thilagavathy, Ban Technology Based Wearable Wireless Sensors for Real-Time Environments, Applied Mechanics and Materials 573 (2014) 381–387.
[111] Z.D. O'Neill, Y. Li, H.C. Cheng, X. Zhou, S.T. Taylor, Energy Savings and Ventilation Performance from CO2-based Demand Controlled Ventilation: Simulation Results from ASHRAE RP-1747 (ASHRAE RP-1747), Science and Technology for the Built Environment (just-accepted) (2019) 1–20.
[112] Z. Pang, P. Xu, Z. O'Neill, J. Gu, S. Qiu, X. Lu, X. Li, Application of mobile positioning occupancy data for building energy simulation: An engineering case study, Building and Environment 141 (2018) 1–15.
[113] E. Hailemariam, R. Goldstein, R. Attar, A. Khan, Real-time occupancy detection using decision trees with multiple sensor types, in: Proceedings of the 2011 Symposium on Simulation for Architecture and Urban Design, Society for Computer Simulation International, 2011, pp. 141–148.
[114] R.H. Dodier, G.P. Henze, D.K. Tiller, X. Guo, Building occupancy detection through sensor belief networks, Energy and Buildings 38 (9) (2006) 1033–1043.
[115] B. Dong, B. Andrews, K.P. Lam, M. Höynck, R. Zhang, Y.-S. Chiou, D. Benitez, An information technology enabled sustainability test-bed (ITEST) for occupancy detection through an environmental sensing network, Energy and Buildings 42 (7) (2010) 1038–1046.
[116] L.M. Ni, Y. Liu, Y.C. Lau, A.P. Patil, LANDMARC: indoor location sensing using active RFID, in: Pervasive Computing and Communications, 2003.(PerCom 2003). Proceedings of the First IEEE International Conference on, IEEE, 2003, pp. 407–415.
[117] Z.-N. Zhen, Q.-S. Jia, C. Song, X. Guan, An indoor localization algorithm for lighting control using RFID, in: Energy 2030 Conference, 2008. ENERGY 2008. IEEE, IEEE, 2008, pp. 1–6.
[118] J. Hallberg, M. Nilsson, K. Synnes, Positioning with bluetooth, in: Telecommunications, 2003. Ict 2003. 10th International Conference on, IEEE, 2003, pp. 954–958.
[119] H. Liu, H. Darabi, P. Banerjee, J. Liu, Survey of wireless indoor positioning techniques and systems, IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 37 (6) (2007) 1067–1080.
[120] Y. Liao, Uncertainty analysis for chiller sequencing control, Energy and Buildings 85 (2014) 187–198.
[121] A.S. Morris, Measurement and instrumentation principles, IOP Publishing, 2001.
[122] R. Bellman, Dynamic programming, Courier Corporation, 2013.
[123] C. Miller, Z. Nagy, A. Schlueter, Automated daily pattern filtering of measured building performance data, Automation in Construction 49 (2015) 1–17.
[124] A. Ng, Machine Learning and AI via Brain simulations, Andrew Ng (2013).
[125] S. Li, J.J.E. Wen, Buildings, A model-based fault detection and diagnostic methodology based on PCA method and wavelet transform, 68 (2014) 63-71.
[126] C. Fan, F. Xiao, C. Yan, A framework for knowledge discovery in massive building automation data and its application in building diagnostics, Automation in Construction 50 (2015) 81–90.
[127] Z.J. Yu, F. Haghighat, B.C. Fung, L. Zhou, A novel methodology for knowledge discovery through mining associations between building operational data, Energy and Buildings 47 (2012) 430–440.
[128] F. Feng, Z. Li, A Methodology to Identify Multiple Equipment Coordinated Control with Power Metering System, Energy Procedia 105 (2017) 2499–2505.
[129] S. D'Oca, T. Hong, Occupancy schedules learning process through a data mining framework, Energy and Buildings 88 (2015) 395–408.
[130] S.C. Bengea, P. Li, S. Sarkar, S. Vichik, V. Adetola, K. Kang, T. Lovett, F. Leonardi, A.D. Kelman, Fault-tolerant optimal control of a building HVAC system, Science and Technology for the Built Environment 21 (6) (2015) 734–751.
[131] M. Bauer, J.-L. Scartezzini, A simplified correlation method accounting for heating and cooling loads in energy-efficient buildings, Energy and Buildings 27 (2) (1998) 147–154.
[132] W.-C. Hong, Electric load forecasting by support vector model, Applied Mathematical Modelling 33 (5) (2009) 2444–2454.
[133] D. Niu, Y. Wang, D.D. Wu, Power load forecasting using support vector machine and ant colony optimization, Expert Systems with Applications 37 (3) (2010) 2531–2539.
[134] A. Kusiak, M. Li, Z. Zhang, A data-driven approach for steam load prediction in buildings, Applied Energy 87 (3) (2010) 925–933.
[135] S. Kalogirou, C. Neocleous, C. Schizas, Building heating load estimation using artificial neural networks, in: Proceedings of the 17th international conference on Parallel architectures and compilation techniques, 1997, p. 14.
[136] A. Dhar, T.A. Reddy, D. Claridge, A Fourier series model to predict hourly heating and cooling energy use in commercial buildings with outdoor temperature as the only weather variable, Journal of solar energy engineering 121 (1) (1999) 47–53.
[137] J.K. Kissock, A methodology to measure retrofit energy savings in commercial buildings, 2008.
[138] V.L. Erickson, A.E. Cerpa, Occupancy based demand response HVAC control strategy, in: Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building, ACM, 2010, pp. 7–12.
[139] V. Pavlovas, Demand controlled ventilation: A case study for existing Swedish multifamily buildings, Energy and Buildings 36 (10) (2004) 1029–1034.
[140] J. Kuutti, K. Blomqvist, R. Sepponen, Evaluation of visitor counting technologies and their energy saving potential through demand-controlled ventilation, Energies 7 (3) (2014) 1685–1705.
[141] W.J. Fisk, A.T. De Almeida, Sensor-based demand-controlled ventilation: a review, Energy and Buildings 29 (1) (1998) 35–45.
[142] P. Li, D. Vrabie, D. Li, S.C. Bengea, S. Mijanovic, Z.D. O'Neill, Simulation and experimental demonstration of model predictive control in a building HVAC system, Science and Technology for the Built Environment 21 (6) (2015) 721–732.
[143] S. Wang, Z. Ma, Supervisory and optimal control of building HVAC systems: A review, HVAC&R Research 14 (1) (2008) 3–32.
[144] S. Katipamula, M.R. Brambley, Methods for fault detection, diagnostics, and prognostics for building systems—a review, part I, Hvac & R Research 11 (1) (2005) 3–25.
[145] T.M. Rossi, J.E. Braun, A statistical, rule-based fault detection and diagnostic method for vapor compression air conditioners, Hvac & R Research 3 (1) (1997) 19–37.
[146] S. Bendapudi, J.E. Braun, A review of literature on dynamic models of vapor compression equipment, 2002.
[147] W. Kim, S. Katipamula, A review of fault detection and diagnostics methods for building systems, Science and Technology for the Built Environment 24 (1) (2018) 3–21.