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*Review*

# Indoor Occupancy Sensing via Networked Nodes (2012–2022): A Review

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**Abstract:** In the past decade, different sensing mechanisms and algorithms have been developed to detect or estimate indoor occupancy. One of the most recent advancements is using networked sensor nodes to create a more comprehensive occupancy detection system where multiple sensors can identify human presence within more expansive areas while delivering enhanced accuracy compared to a system that relies on stand-alone sensor nodes. The present work reviews the studies from 2012 to 2022 that use networked sensor nodes to detect indoor occupancy, focusing on PIR-based sensors. Methods are compared based on pivotal ADPs that play a significant role in selecting an occupancy detection system for applications such as Health and Safety or occupant comfort. These parameters include accuracy, information requirement, maximum sensor failure and minimum observation rate, and feasible detection area. We briefly describe the overview of occupancy detection criteria used by each study and introduce a metric called "sensor node deployment density" through our analysis. This metric captures the strength of network-level data filtering and fusion algorithms found in the literature. It is hinged on the fact that a robust occupancy estimation algorithm requires a minimal number of nodes to estimate occupancy. This review only focuses on the occupancy estimation models for networked sensor nodes. It thus provides a standardized insight into networked nodes' occupancy sensing pipelines, which employ data fusion strategies, network-level machine learning algorithms, and occupancy estimation algorithms. This review thus helps determine the suitability of the reviewed methods to a standard set of application areas by analyzing their gaps.

**Keywords:** smart devices; occupancy detection; networked sensors; data fusion

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## 1. Introduction

In the last decade, there has been a considerable shift from high-performance and energy-efficient buildings towards co-optimizing occupant comfort and building energy demand [1,2]. However, multiple studies show that a significant proportion of occupants in U.S. office buildings (up to 75%) are dissatisfied with their thermal environment [3,4]. The primary motivation behind this review article is to assess the suitability of networked node occupancy detection methods for a standard set of application areas. Our focus on networked nodes-based occupancy sensing methods derives from existing stand-alone occupancy sensors providing limited performance that can cause false negatives (switching off heating and lights during occupancy), resulting in occupant dissatisfaction [2]. Stand-alone occupancy sensor-based methods struggle to achieve the same level of improvement in occupant comfort level compared to networked occupancy sensor nodes while deployed under the same configuration [5]. Among recent review articles [2,6–9], an overwhelming majority focus on the methods that are based on stand-alone occupancy sensors. As such, no review exists that is dedicated to an algorithmic aspect of multi-node occupancy sensing [10]. Thus, in the past decade, a marked shift in the trend is observed where a growing number of methods propose more thorough and accurate occupancy detection models for applications such as HVAC Control and Occupant Comfort [11], involving an interconnected network of occupancy sensors. These models are aware of the room connectivity, time-sensitive occupancy behavior, and expected use of each space under observation.

The use of multiple sensing nodes is a common technique for improving detection performance. A few examples of how this can be achieved include extracting ML network-level features from a multivariate raw-sensor data [12] or determining occupancy via a PF [5] that fuses the node-level ML inference to estimate an occupancy belief.

We also observed that among all the reviewed articles, a basic premise is missing, i.e., the actual occupancy behavior depends upon the building design, sensor node positioning, room connectivity, purpose of each space in a residential or office unit, and occupant priorities, which tend to be highly time sensitive. Thus, any review study that lists out the subjective accuracy measures comparisons in a non-standardized form leaves a certain margin of uncertainty for the intended audience. While there are review studies that use evaluation metrics from the cost [9] of the proposed solution, to the accuracy and the failure rate [13] of the solution, our review study aims to evaluate the occupancy sensing methods for networked sensor nodes from an application's perspective while using suggested standard parameters that help in the evaluation process. Methods are assessed based on the ADPs, i.e., accuracy requirement, information requirement, maximum sensor failure, minimum observation rate, and feasible detection area. While we value the importance of underlying sensor technologies toward greater occupancy detection accuracy, it is not the focus of our review study. We instead focus and comment on the employed occupancy detection measure by the methods, network-level data filtering and fusion techniques, NDD, and the spatial and temporal resolution of occupancy detection. The presented review is novel in assessing the impact, the gaps, and the enhanced accuracy networked-node occupancy detection systems offered.

In Section 2, gaps in closely related review articles from the literature are highlighted. Section 3 outlines the methodology for conducting this review. Section 4 identifies occupancy sensing gaps, application areas, and their ADPs based on the searched literature. Section 5 presents various networked node sensor-based occupancy detection solutions and their suitability to the already presented application areas. In Section 6, an accuracy and suitability analysis are performed for each identified solution, determining the extent to which each solution satisfies the ADPs put forward by each application area. Section 7 notes several emerging trends in the networked sensor nodes-based occupancy estimation domain. Finally, Section 8 presents a conclusion to this review article.

## 2. Comparison with Contemporary Review Articles

It may be helpful to elaborate here on the contributions of this review. This review offers the following unique advantages.

a. The review's primary objective is to guide a method selection process for occupancy sensing via a decision-making process that relies on quantifiable parameters called ADPs. A flowchart that illustrates the method selection process based on ADPs is presented in Figure 1.
b. The review limits its focus by only considering methods employing networked sensor nodes and making it mandatory to use PIR technology in combination with other underlying sensing technologies. PIR was explicitly chosen to judge the algorithmic performance of occupancy sensing methods; these need to perform on a standard modality. PIR is the most frequently used occupancy sensing modality [14].
c. The review comments on the conformity of reviewed articles to the claimed application areas based on the conformance criteria attached to ADPs which is detailed in Section 4.

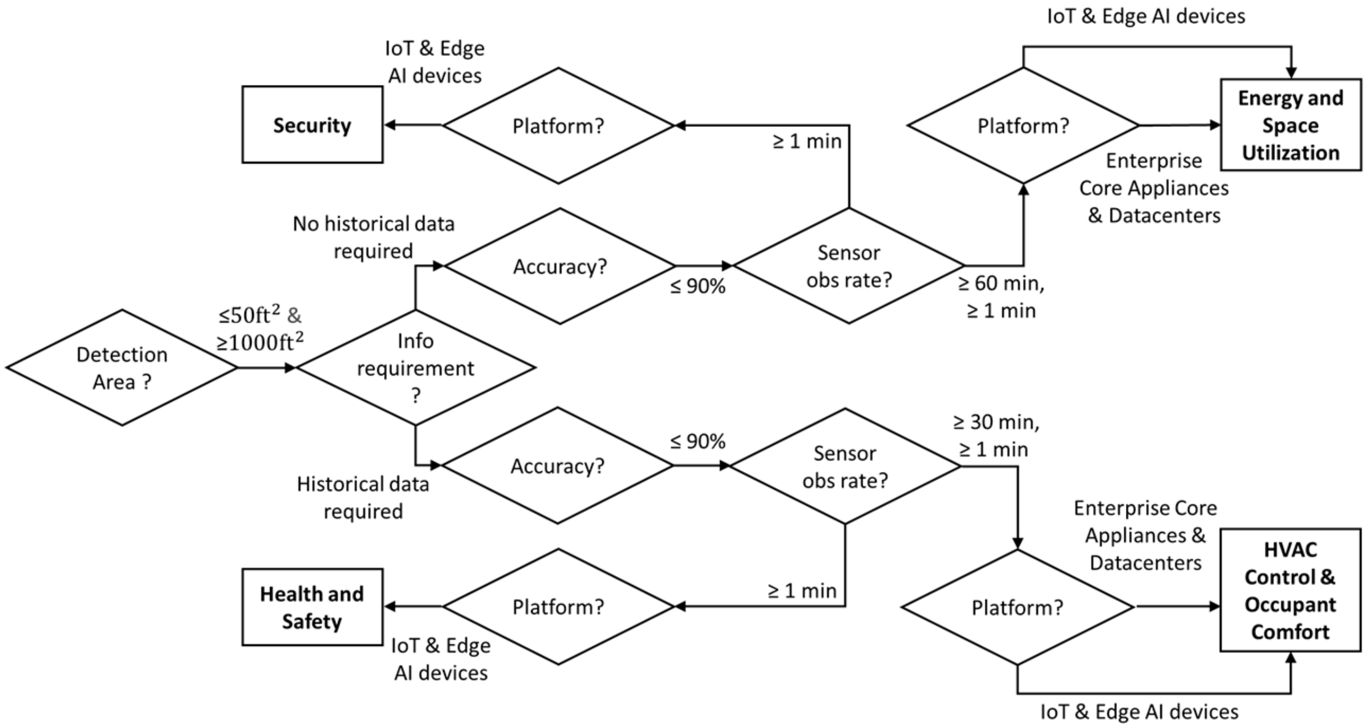


**Figure 1.** A decision tree that illustrates the expected use of ADPs (in diamond shaped boxes) to determine the suitable application area for the reviewed method. The same illustration is used to perform suitability analysis in Section 6. Sensor failure rate ADP is not used in the decision-making process as some reviewed methods did not specify the sensor details.

Moreover, to further establish the novelty of this review, the contributions of contemporary review studies related to occupancy sensing, along with their corresponding gaps are listed in Table 1.

**Table 1.** Contribution and gaps for contemporary occupancy sensing review studies involving networked sensor nodes.

| Reference | Review Study Title | Study Gaps |
|---|---|---|
| [15] | Review on occupancy detection and prediction in building simulation | a. Although occupancy models from the literature are compared under three broad categories. the models' accuracies are not standardized and thus no meaningful comparison is made.<br>b. Details about the presence and deployment of networked sensor nodes are not provided.<br>c. Suitability of methods to applications is not made using any quantifiable parameters. |
| [10] | A comprehensive review of approaches to building occupancy detection | a. The study compares the performance, the occupancy resolution, the type of sensors used, the type of buildings, and the energy-saving potential of occupancy sensing algorithms, yet it does not focus on algorithms specifically designed for networked sensor nodes.<br>b. The performance comparison lists the accuracy without considering the spatial complexity of the observed environment. Temporal resolution information is missing from the analysis.<br>c. Application suitability for the algorithms is not discussed. |

**Table 1.** *Cont.*

| Reference | Review Study Title | Study Gaps |
|---|---|---|
| [16] | Deep and transfer learning for building occupancy detection | a. Although the study compares occupancy sensing algorithms for networked nodes, it does not differentiate between single node and multiple sensor node algorithms. The node quantity, spatial resolution and temporal resolution are missing from the accuracy analysis.<br>b. No application suitability analysis is performed for the reviewed algorithms. |
| [17] | Occupancy detection systems for indoor environments: A survey of approaches and methods | a. The study presents a novel taxonomy that helps classify the occupancy sensing methods, yet it primarily relies on sensor features rather than occupancy prediction and detection algorithms for classification purposes.<br>b. There is no algorithmic analysis that signifies accuracy improvement due to networked nodes.<br>c. No application suitability analysis is conducted except that suitable target environment categories such as Office, Residential, Others, are associated with each reviewed algorithm. |
| [18] | Occupancy detection in non-residential buildings: A survey and novel privacy preserved occupancy monitoring solution | a. The study provides the area of overall observed space and the temporal resolution for each of the occupancy sensing algorithms, yet it does not mention the number of deployed nodes and thus, spatial resolution information is missing.<br>b. There is no discussion about the fusion techniques or fusion framework execution platform.<br>c. No application suitability analysis is presented. |
| [19] | Occupancy detection and localization strategies for demand modulated appliance control in Internet of Things (IoT) enabled home energy management system | a. The study evaluates the occupancy detection and localization schemes based on various factors that decide their suitability for home energy management systems. These factors do not include spatial or temporal resolution of the occupancy sensing system.<br>b. No discrimination was made among multi-node and single node systems. Accuracy comparison was performed using non-standardized measures. |
| [2] | Sensor impacts on building and HVAC controls: A critical review for building energy performance | a. Five major factors were used for evaluating occupancy sensing algorithms, i.e., control loops for sensors, sensor types, sensor locations, sensor data, and a sensor impact evaluation framework.<br>b. Spatial and temporal resolution for occupancy sensing algorithms was completely ignored during the comparison phase. |
| [8] | Indoor human occupancy detection using Machine Learningclassification algorithms and their comparison | a. The study evaluates methods that determine occupancy with the help of datasets whose data was collected from different sensors and using different ML algorithms.<br>b. While the study evaluates models with datasets comprising of multivariate time-series, spatial and temporal resolution details are missing from the comparison.<br>c. No application suitability analysis is presented. |
| [20] | Fit-for-purpose: Measuring occupancy to support commercial buildingoperations: A review | a. First, the data requirements and characteristics for the applications are established. Then, certain occupancy sensing technologies are recommended for each application.<br>b. Sensor features and spatial sensing resolution are considered during the sensing technology to application suitability analysis.<br>c. Temporal resolution and multi-node occupancy sensing algorithm analysis is missing. |

## 3. Methodology

This review considers research articles that outline the occupancy estimation methods and algorithms involving two or more networked occupancy sensor nodes. It tabulates the studies highlighting gaps in using networked sensor nodes for occupancy sensing. These occupancy sensing gaps exist in several application areas. Each application area demands a specific set of parameters from the networked sensor nodes and the occupancy estimation methods to address application area challenges. These parameters are termed as ADPs. These ADPs are identified from the reviewed studies and are tabulated and associated with these studies. This phase is referred to as Occupancy Sensing Gap and ADP Identification phase. Articles in the literature that address the identified gaps are then evaluated. Comments are added to each article on whether the proposed solutions in the articles contain the ADPs demanded by a particular application area. This phase is termed the Solution to Application Mapping phase. The review is concluded by comparing the accuracy delivered by each solution. A discussion is added at the end of this chapter about the occupancy estimation methods used by each solution, and the reasons behind the reported accuracies are highlighted. Explanations are also listed as to why specific proposed solutions are not suitable to some application areas despite the contrary claims of the authors. This phase is termed the Accuracy and Suitability Analysis phase. The review thus presents a complete picture to the reader, from identifying sensing gaps, to the suitability of each available solution in the literature, to the gaps and application areas. It must be mentioned here that although the review's primary focus lies on networked sensor nodes-based occupancy estimation solutions, the underlying sensor modalities for each solution are listed. The reviewed estimation methods may not be agnostic to the underlying sensing technology. An illustration summarizing the review methodology is shown in Figure 2.

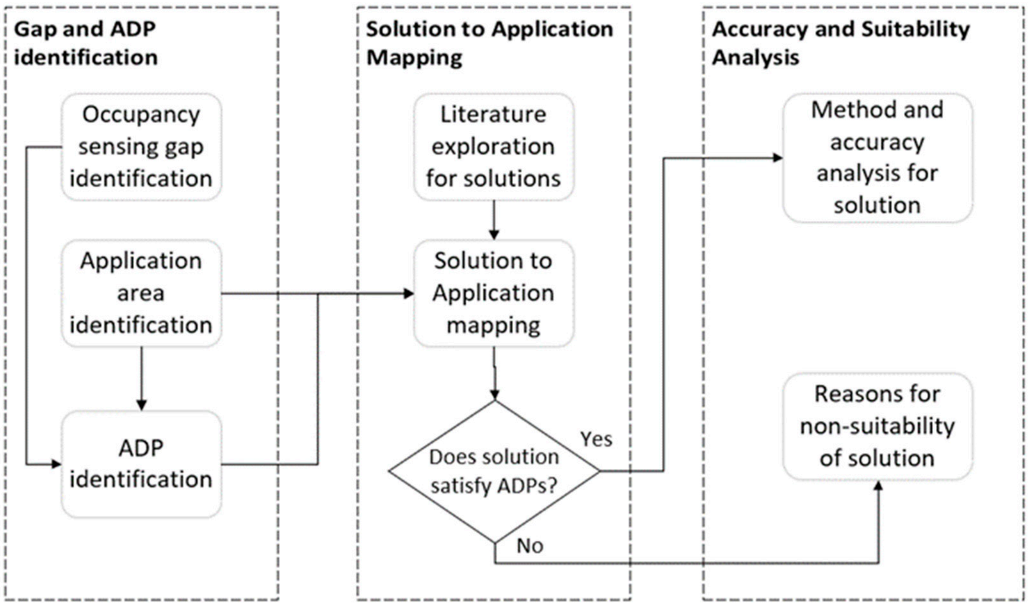


**Figure 2.** A phased methodology chart outlines the review strategy. First, occupancy sensing gaps that require networked occupancy sensors and corresponding estimation techniques are identified. ADPs for the application area are identified. Solutions from the literature are explored and an analysis is performed to see whether the solutions are suited to the claimed application area.

## 4. Occupancy Sensing Gaps and ADP Identification

We first focus on identifying the occupancy detection gaps found in the literature for networked sensor node methods. Table 2 provides a non-exhaustive, but representative list of the most common gaps and the corresponding occupancy detection application area found within a set of representative studies. The gaps identified in Table 2 point towards a specific set of incapabilities that are present either within the underlying sensing technologies, the occupancy estimation method, or the communication and integration framework that enables the networking between these sensor nodes. As mentioned, this review only focuses on the shortcomings of the occupancy estimation methods. The impact of underlying sensing technologies and wireless sensor networks' communication reliability are separate topics with dedicated studies [8,21] in the literature dealing with these topics. The shortcomings present within occupancy estimation methods for any given application area can be overcome through a set of parameters to which the estimation method must conform. We term these parameters ADPs. Table 3 transforms the identified gaps into ADPs with specific application values. Standard documents from various associations and agencies, such as the ASHRAE [22], CEC [23], IBC [24], NFPA [25], and IECC [26], are used in the table. The table lists IoT and Edge AI devices among the potential execution platforms.

**Table 2.** Occupancy sensing gaps for Networked Sensor Nodes-Based Estimation Methods.

| References | Application Area | Gaps |
|---|---|---|
| [5,12,20–25] | HVAC Control and Occupant Comfort | a. Stationary human detection<br>b. Real-time occupancy detection<br>c. Privacy concerns<br>d. Infrastructure overhead<br>e. False Negatives<br>f. Historical and expected occupancy data required.<br>g. Reliability and fault tolerance required |
| [12,20–22,25–31] | Health and Safety | a. Stationary human detection<br>b. Real-time occupancy detection<br>c. Privacy concerns<br>d. Infrastructure overhead<br>e. False positives<br>f. Zone-level detection<br>g. Historical and expected occupancy data required.<br>h. High accuracy required<br>i. Reliability and fault tolerance required |
| [23,25,26,32–34] | Energy and Space Utilization | a. Stationary human detection<br>b. Occupant count required<br>c. Zone level detection<br>d. Infrastructure overhead |
| [35–40] | Security | a. Stationary human detection<br>b. Infrastructure overhead<br>c. Realtime occupant tracking required.<br>d. False negatives<br>e. High accuracy required<br>f. Zone-level detection<br>g. Infrastructure overhead<br>h. Reliability and fault tolerance required |

**Table 3.** ADPs for each Application Area.

| Application Area | ADPs |
| --- | --- |
| HVAC Control and Occupant Comfort | **Accuracy requirement (ASHRAE):** ≥90%<br>**Info requirement:** Historical/expected occupancy info<br>**Execution platforms:** Enterprise core appliances, Datacenters, IoT and Edge AI devices<br>**Min sensor obs rate (ASHRAE):** ≤30 min<br>**Max sensor failure rate:** No quantification found. Still a research gap [2]<br>**Feasible Detection Area (ASHRAE):** Office (≤250 $ft^2$), storage (≥50 $ft^2$ and ≤1000 $ft^2$)<br>**Feasible Detection Area (CEC):** Office (≤250 $ft^2$), multipurpose rooms (≤1000 $ft^2$), indoor spaces (≤300 $ft^2$)<br>**Feasible Detection Area (IECC):** Indoor spaces (≤300 $ft^2$) |
| Health and Safety | **Accuracy requirement (IBC, NFPA):** ≥95%<br>**Info requirement:** Historical/expected occupancy info<br>**Execution platforms:** IoT, Edge AI devices<br>**Min sensor obs rate:** ≤1 min (dictated by sensor limitations)<br>**Max sensor failure rate (IBC, NFPA):** 0.01%<br>**Feasible Detection Area (CEC):** Lightening control not permitted for shutoff control in healthcare facilities or Egress lightening where power consumption ≤0.1 $W/ft^2$ |
| Energy and Space Utilization | **Accuracy requirement (ASHRAE, IECC):** ≥90%<br>**Info requirement:** Contiguous indoor spaces need to be monitored to enable tracking applications. No historical or expected occupancy data needed.<br>**Execution platforms:** Enterprise core appliances, Datacenters, IoT, Edge AI devices<br>**Min sensor obs rate:**Hourly<br>**Max sensor failure rate:** No quantification found. Still a research gap [2]<br>**Feasible Detection Area (CEC):** Indoor spaces (≤300 $ft^2$), storage rooms (≥50 $ft^2$ and ≤1000 $ft^2$), office space (≤250 $ft^2$). |
| Security | **Accuracy requirement (IBC):** ≥95%<br>**Info requirement:** Moderate NDD to enable tracking applications.<br>**Execution Platforms:** IoT, Edge AI devices<br>**Min sensor obs rate:** ≤1 min (dictated by sensor limitations)<br>**Max sensor failure rate (IBC):** 0.01%<br>**Feasible Detection Area (CEC):** Indoor spaces (≤300 $ft^2$), storage rooms (≥50 $ft^2$ and ≤1000 $ft^2$), office space (≤250 $ft^2$). |

The ADPs listed in Table 3 serve as the suitability criteria when selecting a particular occupancy estimation solution for a specific application. These ADPs also bring to light certain exciting insights. For example, the accuracy requirement for occupancy sensors used for HVAC controls varies depending on the specific application and building type. However, the occupancy sensor accuracy should generally be high enough to correctly detect the presence or absence of occupants in a particular area. The accuracy requirement becomes more stringent in the case of both safety and security applications. This is because these applications include critical services, such as emergency evacuation, fire detection and suppression, and security depending on the occupancy sensor's ability to accurately detect the presence or absence of people in a building. Another important insight is that the response time of the occupancy detection method becomes essential for safety and security applications, as it should be fast enough to detect the presence of people and activate the safety system accordingly. We thus see that the potential execution platform for such applications excludes time-consuming cloud-based processing options, such as Enterprise core appliances and Datacenters.

It is additionally worth noting that CEC standards recommend using occupancy sensors in smaller indoor spaces with high traffic that have an area less than 300 $ft^2$, while at the same time, these standards recommend using occupancy sensors in storage rooms or multi-purpose spaces as large as 1000 ft$^2$. It must be mentioned here that these standards do not make recommendations for emergency facilities such as healthcare facilities or fire stations since critical operations may be affected due to automated control.

We observe that security applications demand high sensor NDD since it is crucial to achieving reliable tracking of occupants indoors. In addition, security applications such as intrusion detection are required to detect the path or trajectory (entering or leaving) that the occupant is pursuing.

## 5. Solutions to Application Mapping

This review aims to establish the suitability of state-of-the-art networked sensor nodes-based occupancy estimation solutions to occupancy detection application areas. It is critical to mention that the sensor nodes can be exposed to phenomena that interfere with sensor measurements. The phenomena can include pronounced variations of temperature, pressure, radiation, IR shielding [27], EM shielding [28], IR noise [5], and EM noise [29]. In short, sensor measurements are error prone. Data fusion techniques have been widely employed in the literature to overcome such errors. Data fusion is "the use of techniques that combine data from multiple sources and gather this information to achieve inferences" [30]. The inferences are expected to be more accurate and robust than if these were achieved via simple aggregation techniques, such as average, maximum, minimum, or a union of outputs of multiple sensor nodes. Moreover, strong inferences can be achieved through networked sensor nodes whenever a node-level communication breakdown occurs as these may observe common observation zones. In practice, networked sensor nodes commonly suffer from communication breakdowns. The literature contains data fusion methods that can be centralized or distributed systems. In centralized systems, raw sensor data is sent to a central hub or sink node, and the data fusion method processing is performed at the central node. In distributed systems, the distributed components of the fusion method would execute on distributed nodes in the design, with each node utilizing its local data.

It is well known that data fusion caters to the spatial and temporal coverage blind spots of sensor nodes [5]. For occupancy sensors, the spatial coverage of a sensor usually means the sensor's FoV or its effective volumetric detection range. Their temporal coverage usually depends on the sensor's sampling rate, node's duty cycle, and communication delays [30]. Table 4 lists the reviewed methods along with the employed occupancy detection measure, network-level data filtering and fusion techniques, NDD, and the spatial and temporal resolution of the occupancy detection.

**Table 4.** Reviewed solution details and claimed application area.

| Solution | Data Filtering and Fusion Techniques | Input Data Streams | Detection Measure | NDD | Spatial/Temporal Resolution and Average Accuracy | Author Claimed Application Areas |
|---|---|---|---|---|---|---|
| [31] | Bayesian Occupancy Model | PIR sensor nodes | Bayesian Inference based on Prior Probability computed over historical data and Sensor Model output | 403 ft$^2$/node | Multiple Zones, 60 s, 71% | Energy and Space Utilization |
| [32] | SVM, LDA, QDA, RF-based ML algorithms | PIR, Light, Temperature, Sound, $CO_2$ | ML Inference | 49 ft$^2$/node | Single Zone, 30 s, 98.4% | Health and Safety, Security, HVAC Control and Occupant Comfort |

**Table 4.** *Cont.*

| Solution | Data Filtering and Fusion Techniques | Input Data Streams | Detection Measure | NDD | Spatial/Temporal Resolution and Average Accuracy | Author Claimed Application Areas |
|---|---|---|---|---|---|---|
| [33] | Decision Tree | PIR, Sound, Power use, $CO_2$ | ML Inference | 28 $ft^2$/node | Single Zone, 60 s, 97.9% | Health and Safety, Security, HVAC Control and Occupant Comfort |
| [35] | RBF-based Neural Network | PIR, Humidity, Light, Sound, Temperature, $CO_2$ | ML Inference | 430 $ft^2$/node | Multiple Zones, 60 s, 87.62% | Energy and Space Utilization |
| [34] | Statistical Feature-based FFNN | PIR, Temperature, Sound, $CO_2$ | ML Inference | 27 sensor nodes in an open-plan office space with max 8 occupants | Multiple Zones, 5 min, 75% | Energy and Space Utilization |
| [5] | Particle Filter-based Estimator | SLEEPIR, PIR, Temperature | Threshold placed on presence probability | 364 $ft^2$/node | Zone-level, 60 s, 96.2% | HVAC Control and Occupant Comfort, Energy and Space Utilization |
| [36] | AR HMM | PIR, Temperature, Reed switches, Airspeed, $CO_2$ | Expectation Maximization algorithm applied to find the local optimal solution for AR HMM | 19 sensor nodes in a lab with max 10 occupants | Multiple Zones, 20 s, 84% | Energy and Space Utilization |
| [41] | Multinomial Logistic Regression | PIR, Power usage, Temperature, Humidity, Light, Door sensors, $CO_2$ | Predicted probability of the occupants being active, inactive or away | 14 $ft^2$/node | Multiple Zones, 60 s, 94.9% | HVAC Control and Occupant Comfort |
| [37] | RF, Decision Tree, KNN, SVM | PIR, Temperature | ML Inference | 140 $ft^2$/node | Multiple Zones variable time, 99% | Energy and Space Utilization |
| [7] | FFNN | PIR, Humidity, Light, Pressure, Temperature, $CO_2$, TVOC, Sound, Door and Window sensor | ML Inference | 296 $ft^2$/node | Multiple Zones, 60 s, 94.3% | HVAC Control and Occupant Comfort, Energy and Space Utilization |
| [38] | Trajectory Analysis of Indoor Climate Sensor data | PIR, Temp, $CO_2$, VOC, RH, AWT, Sound | 2-min and 5-min trends of sensor data are analyzed to determine occupancy probability | 54 $ft^2$/node | Single Zone, 5 min, 77.8% | HVAC Control and Occupant Comfort |

**Table 4.** *Cont.*

| Solution | Data Filtering and Fusion Techniques | Input Data Streams | Detection Measure | NDD | Spatial/Temporal Resolution and Average Accuracy | Author Claimed Application Areas |
|---|---|---|---|---|---|---|
| [39] | Gaussian Distribution Model | PIR | Gaussian distribution used to fit the occupancy profiles. An accumulative function of Gaussian distributions for all sensors is used to predict occupancy | 731 $ft^2$/node | Multiple Zones, 60 min, 85% | Energy and Space Utilization |
| [40] | Multi-sensor Aggregation | PIR | Aggregation of PIR triggers over 5 min duration | 122 $ft^2$/node | Multiple Zones, 5 min, 87.5% | HVAC Control and Occupant Comfort, Energy and Space Utilization |
| [42] | Inhomogeneous HMM | PIR | Posterior probability evaluated via Maximum a posteriori and Viterbi Algorithm | 18 $ft^2$/node | Single Zone, 60 s, 99% | HVAC Control and Occupant Comfort, Energy and Space Utilization |

Some specific observations can be made about the data presented in Table 4.

a. A solution can only be used in Energy and Space Utilization applications if and only if these are scalable, i.e., NDD is low. Energy and Space utilization is usually measured across an entire commercial or residential unit. Any solution with a relatively high NDD is essentially non-scalable due to additional infrastructure costs.
b. Health and Safety and Security applications require high occupant tracking and detection accuracy. The solutions usually achieve this at the expense of high NDD. Even though such solutions have high accuracy ($\geq$95%), these cannot be employed for HVAC Control, and Occupant Comfort and Energy and Space Utilization applications as scalability is infeasible.
c. Although NN-based classification and regression techniques achieve relatively high accuracy, the network training input size is fixed. Thus, any missing sensor time-series data would need to be imputed for the model to be able to produce an inference. Moreover, the pre-requisite of collecting a dataset must be satisfied to deploy any NN.
d. Sensors such as $CO_2$ and VOC require almost 30 min to respond reliably to occupancy. Likes of PIR, temperature and light sensors can register occupancy several times a second. This disparity and the resulting advantage of high frequency sensors should be kept in mind while comparing the accuracies for various presented solutions.
e. Sensors such as $CO_2$ and VOC are sometimes placed at the ventilation ducts in some of the methods listed in Table 4. Under such scenarios, NDD tends to be very low for these sensors, thus presenting an advantage for using these sensors.

## 6. Accuracy and Suitability Analysis

There are broad fusion implementation categories mentioned in [10], namely: (1) analytical methods, (2) knowledge-based methods, and (3) data-driven methods. Each of these categories has its own set of shortcomings that either emanate from node-level detection errors or are an artifact of the network-level occupancy detection method.

The analytical methods study the physical behavior of occupants and its impact on the indoor environment. These methods exploit the relationship between environmental variables and human presence to derive occupancy decisions. For example, Ref. [22] presents an occupancy detection method based on various indoor climate sensor data trajectories. Data from $CO_2$ and VOC sensors were used to evaluate vacancy, while data from PIR sensors were used to judge occupancy. No prior information about the testbed or dataset prerequisites is required by this method. Despite relying on three different sensor modalities, this method reported as much as 43.5% false negatives and 11.8% false positives for a dormitory occupancy scenario.

The knowledge-based methods, also known as expert systems, use specialized knowledge represented by rules to solve complex problems. A good example is a Finite State Machine-based State Switch algorithm [43] that utilizes SLEEPIR [44] nodes capable of detecting stationary occupants. Yet, it is not able to robustly handle the node-level detection errors, and a transition to the wrong state would be produced in case a false occupancy determination was made at the node level. Similarly, any network-level aggregation algorithm, e.g., the union of outputs of stand-alone sensor nodes, will fail to handle a false positive detection determination made at the node level.

The data-driven methods include the following sub-categories of methods.

1. Statistical and deep learning ML methods
2. Bayesian inference methods
3. HMM-based methods

ML-based network-level occupancy detection methods that process statistical features extracted from raw sensor-node observations can handle uncertainty, but have limited application due to the pre-requisite of acquiring labeled training dataset [37]. Not only automated occupancy labeling itself is resource intensive for such datasets, but also achieving a class balance between "occupied" and "unoccupied" label classes is an equally challenging task [37]. It has also been shown that typical ML algorithms only accept training data with fixed sizes; thus, a networked node occupancy detection problem which can have a variable number of sensor nodes (due to occasional communication or hardware failure), would need to reformat the data into a fixed format, which often requires data fusion to happen prior to ML training phase [37,45]. Furthermore, deep learning ML models require large datasets to train. Thus, it is infeasible to re-collect a large amount of data to retrain to handle any novelty in the occupancy patterns [46]. In the Bayesian inference methods sub-category, node-level occupancy estimation is usually performed via ML algorithms or knowledge-based methods. In contrast, the network-level occupancy estimation is performed by fusing the node-level assessment through a Bayesian inference-based framework [45]. Although this approach has produced accuracies up to 93% [21] in uncontrolled experiments, generating ML inference for each node, on-device, is resource intensive.

Based on the above discussion on categorizing occupancy sensing methods for networked nodes, a taxonomy chart is presented in Figure 3.

In the past, many review articles attempted to vaguely attribute the categories of occupancy sensing methods to specific application areas. As such, no one-to-one or one-to-many correspondence exists between the method categories shown in Figure 3 and the application areas mentioned in Table 2. The problem of suitability of applications to methods is much more nuanced and requires specific criteria to be met before suitability can be established. To achieve this end, Table 5 details the breakdown of how the ADPs for each application area map to each of the reviewed solutions in Table 4.

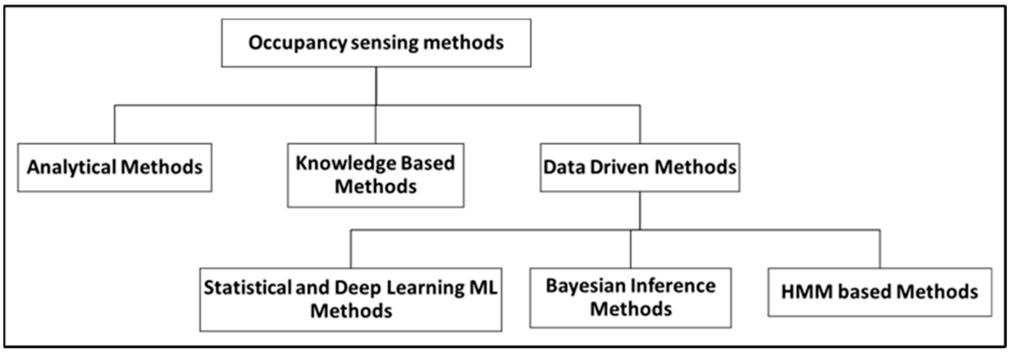


**Figure 3.** Taxonomy of occupancy sensing methods.

**Table 5.** ADPs conformance for each application area.

| Solution | ADPs |
| --- | --- |
| [31] | **Accuracy:** 71.0%<br>**Information requirement:** Prior probabilities for Bayesian model were calculated using four weeks of historical data.<br>**Execution Platforms:** Samsung SmartThings Hub<br>**Sensor observation rate:** 60 s<br>**Sensor Failure rate:** High MTBF as per datasheet for ZMOTION® ZEPIR0AA PIR sensor<br>**Detection Area:** 403 $ft^2$/node |
| [32] | **Accuracy:** 98.4%<br>**Information requirement:** Labeled dataset for ML<br>**Execution Platforms:** ARM based Beaglebone SoC<br>**Sensor observation rate:** 30 s<br>**Sensor Failure rate:** Unspecified PIR sensor<br>**Detection Area:** 49 $ft^2$/node |
| [33] | **Accuracy:** 97.9%<br>**Information requirement:** Labeled dataset for ML<br>**Execution Platforms:** PC/Server<br>**Sensor observation rate:** 60 s<br>**Sensor Failure rate:** PIR Sensor MTBF unknown (Phidgets 1111 IR Motion Sensor)<br>**Detection Area:** 28 $ft^2$/node |
| [35] | **Accuracy:** 87.6%<br>**Information requirement:** Labeled dataset for ML<br>**Execution Platforms:** Arduino Black Widow single-board MCU, MATLAB on PC/Server<br>**Sensor observation rate:** 60 s<br>**Sensor Failure rate:** Unspecified PIR sensor<br>**Detection Area:** 430 $ft^2$/node |
| [34] | **Accuracy:** 75.0%<br>**Information requirement:** Labeled dataset for ML<br>**Execution Platforms:** HOBO U series event loggers, MATLAB and WEKA on PC/Server<br>**Sensor observation rate:** 5 min<br>**Failure rate:** Unspecified PIR sensor<br>**Detection Area:** <50 $ft^2$/node |
| [5] | **Accuracy:** 96.2%<br>**Information requirement:** Sensor data for correlation evaluation, Labeled dataset for ML<br>**Execution Platforms:** Onboard SoC (EFR32BG13, Silicon Labs) onboard nodes, Edge AI (Raspberry Pi 4)<br>**Sensor observation rate:** 60 s<br>**Sensor Failure rate:** >10,000 h (Panasonic® EKMB1391111K)<br>**Detection Area:** 364 $ft^2$/node |

**Table 5.** *Cont.*

| Solution | ADPs |
|---|---|
| [36] | **Accuracy:** 84.0%<br>**Information requirement:** time-series data correlations need to be evaluated pre-deployment.<br>**Execution Platforms:** wireless measurement nodes, PC/Server<br>**Sensor observation rate:** 20 s<br>**Failure rate:** Unspecified PIR sensor<br>**Detection Area:** <50 $ft^2$/node |
| [41] | **Accuracy:** 94.9%<br>**Information requirement:** Labeled dataset for ML<br>**Execution Platforms:** BACnet ™ for sensor connectivity, R on Workstation<br>**Sensor observation rate:** 60 s<br>**Failure rate:** Unspecified PIR sensor<br>**Detection Area:** 14 $ft^2$/node |
| [37] | **Accuracy:** 99.0%<br>**Information requirement:** Domain knowledge, Labeled dataset for ML<br>**Execution Platforms:** NI Compact DAQ, scikit-learn on ARM based Beaglebone Black SoC<br>**Sensor observation rate:** Variable<br>**Failure rate:** Unspecified PIR sensor<br>**Detection Area:** 140 $ft^2$/node |
| [7] | **Accuracy:** 94.3%<br>**Information requirement:** Labeled dataset for ML<br>**Execution Platforms:** Arduino Uno, ARM based Kerlink® IoT Wirnet 868 Station<br>**Sensor observation rate:** 60 s<br>**Failure rate:** >10000 h (Panasonic® PaPIRs EKMB)<br>**Detection Area:** 296 $ft^2$/node |
| [38] | **Accuracy:** 77.8%<br>**Information requirement:** Some method parameters and thresholds are set empirically for each sensor node.<br>**Execution Platforms:** Arduino Mega, PC/Server<br>**Sensor observation rate:** 5 min<br>**Failure rate:** High MTBF as per datasheet (RE 200 B)<br>**Detection Area:** 54 $ft^2$/node |
| [39] | **Accuracy:** 85%<br>**Information requirement:** Historical sensor data required for past twenty-four days.<br>**Execution Platforms:** PC/Server<br>**Sensor observation rate:** 60 min<br>**Failure rate:** High MTBF as per datasheet (HPC005 infrared people counter)<br>**Detection Area:** 731 $ft^2$/node |
| [40] | **Accuracy:** 87.5%<br>**Information requirement:** No historical data required.<br>**Execution Platforms:** SmartThings cloud platform, IoT devices<br>**Sensor observation rate:** 5 min<br>**Failure rate:** High MTBF as per datasheet (T3L-SS014, IM6001-MTP01, STS-IRM-25)<br>**Detection Area:** 122 $ft^2$/node |
| [42] | **Accuracy:** 99%<br>**Information requirement:** Prior ground-truth and historical sensor data required for parameter training.<br>**Execution Platforms:** MATLAB 2016a, Pycharm<br>**Sensor observation rate:** 60 s<br>**Failure rate:** High MTBF as per datasheet (AMG8853)<br>**Detection Area:** 18 $ft^2$/node |

*Comments on Solution Conformance to the Claimed Application Areas*

Ref. [31]: Not feasible for the author-claimed *Energy and Space Utilization* application as the solution accuracy does not meet ADP accuracy criteria, i.e., 71% < 90%. It is a data-driven method, thus has a pre-requisite of historical data collection before its deployment.

Ref. [32]: Suitable for the author claimed *HVAC Control and Occupant Comfort* application on a smaller scale. The solution cannot scale up well as the spatial NDD is high, i.e., 49 $ft^2$/node. It is a data-driven method.

Ref. [33]: Not feasible for the author-claimed *HVAC Control and Occupant Comfort* application even on a smaller scale. This is because the execution platform for the algorithm is a PC or Server, and the implementation is not optimized for an IoT or Edge AI device. In addition, the solution cannot scale up well as the spatial NDD is high, i.e., 28 $ft^2$/node. It is a data-driven method and has a dataset pre-requisite. Alternatively, the method is suitable for *Energy and Space Utilization* applications.

Ref. [35]: Not feasible for the author-claimed *HVAC Control and Occupant Comfort* application. Although the sensor node data is logged via MCU, the ML algorithm execution platform for the algorithm is a PC/Server. Moreover, solution accuracy does not meet ADP accuracy criteria, i.e., 87.6% < 90%. It is a data-driven method and has a dataset pre-requisite.

Ref. [34]: Not feasible for the author-claimed *HVAC Control and Occupant Comfort* application. Sensor data is logged via third party loggers, the ML algorithm execution platform for the algorithm is MATLAB/WEKA on a PC or Server. Moreover, solution accuracy does not meet ADP accuracy criteria, i.e., 75% < 90%. It is a data-driven method and has a dataset pre-requisite.

Ref. [5]: Suitable for the author-claimed *HVAC Control and Occupant Comfort* and *Energy and Space Utilization* applications. The solution can scale up as the spatial NDD is low, i.e., 364 $ft^2$/node. It is a data-driven method and thus requires a labeled dataset to be collected. The method also needs historical sensor data for correlation evaluation. The solution is optimized in terms of node power consumption, local processing at nodes via an IoT device. The ML pre-processing inference is made on an IoT device, which is mentioned to be a CPE. The solution is also alternatively suitable for *Health and Safety applications* as it meets the desired ADP guidelines for this application area and can track occupancy at room level. For reference, a system level diagram for the solution is illustrated in Figure 4.

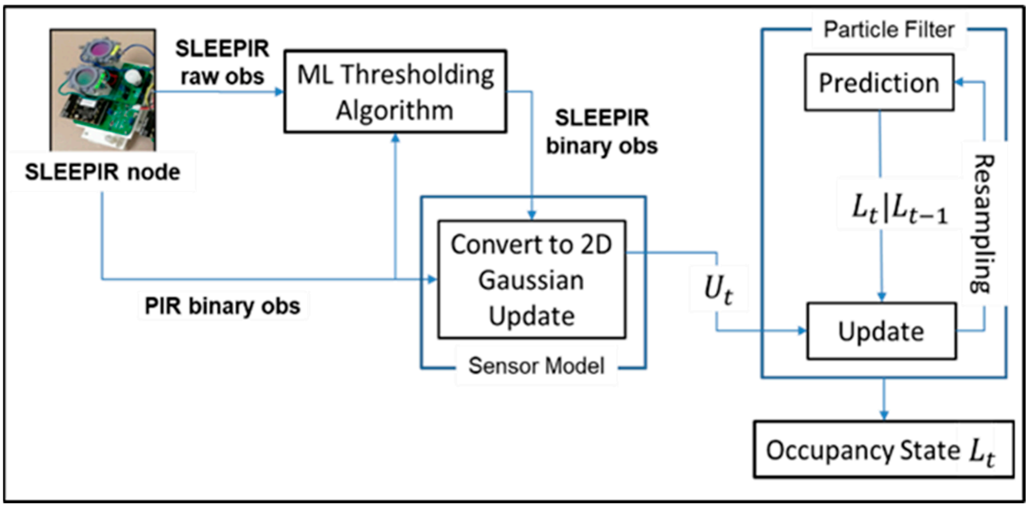


**Figure 4.** PF-based human occupancy detection method flow chart. Networked sensor nodes (SLEEPIR) generate voltage, ambient temperature, and PIR data. The voltage is converted to binary occupancy observations via an ML-based thresholding algorithm. The node-level occupancy observations then update a system-level occupancy estimate via a PF.

Ref. [36]: Not feasible for the author-claimed *HVAC Control and Occupant Comfort* application. Algorithm execution platform for the algorithm is a PC or Server. Moreover, solution accuracy does not meet ADP accuracy criteria, i.e., 84.0% < 90%. It is a data-driven method and requires historical sensor data for time-series data correlation evaluation.

Ref. [41]: Not feasible for the author-claimed *HVAC Control and Occupant Comfort* application. The solution cannot scale up well with the spatial NDD of 14 $ft^2$/node. It is a data-driven method and thus, requires a labeled dataset. Although the method uses a standard protocol by ASHRAE for sensor communication, the regression algorithm execution is not optimized for IoT execution which makes the feasibility of the algorithm questionable to be used as a solution for occupancy detection.

Ref. [37]: Suitable for the author-claimed *HVAC Control and Occupant Comfort* application. The solution can scale up well as the spatial NDD is sufficient to cover an average-sized room, i.e., 140 $ft^2$/node. It is a data-driven method; thus, it requires a dataset to be collected pre-deployment. Moreover, a human activities layer is incorporated in the learning model which requires domain knowledge about the occupancy patterns. The solution has matured to the point that it has been implemented over an IoT device.

Ref. [7]: Suitable for the author-claimed *HVAC Control and Occupant Comfort* and *Energy and Space Utilization* applications. The solution can scale up as the spatial NDD is low, i.e., 296 $ft^2$/node. It is a data-driven method and thus, requires a labeled dataset to be collected. The solution is optimized in terms of node power consumption and local processing at nodes via an IoT device. The ML pre-processing, training and inference, however, is made at a back-end machine. Since a two FFNN is relatively simple to implement over an IoT-compatible ML framework, such as TensorFlow Lite, a case can be made that the solution is suitable for an IoT-based implementation. The solution is also alternatively suitable for *Health and Safety applications* as it meets the desired ADP guidelines for this application area.

Ref. [38]: Not feasible for the author-claimed *HVAC Control and Occupant Comfort* application. The solution can also not scale up well with the spatial NDD of 54 $ft^2$/node. It is an analytical method; thus, it may only require domain knowledge, yet certain thresholds and parameters for Zero Lag Exponential Moving Average algorithm require empirical tuning. The algorithm can be easily ported to IoT for execution which makes the method suitable for IoT execution, but the accuracy needs to meet ADP accuracy criteria, i.e., 77.8% < 90%. Ref. [39]: Not feasible for the author-claimed *Energy and Space Utilization* application. The solution accuracy does not meet ADP accuracy criteria, i.e., 85% < 90%. It is a data-driven method and requires historical sensor data for developing Gaussian distribution models for diverse occupancy patterns for all monitored spaces. It is achieved via averaging the fitting results for the past twenty-four days.

Ref. [40]: Not feasible for the author-claimed *Energy and Space Utilization* and *HVAC Control and Occupant Comfort* applications. The solution accuracy does not meet ADP accuracy criteria, i.e., 87.5% < 90%. Although the execution platforms are mature (IoT and cloud-based), the fusion algorithm is a simple aggregation algorithm that does not work well with motion sensors. The motion sensors are placed at a distance no less than 30 cm from under the desk of subjects, yet the occupancy sensing algorithm assumes that subjects not completely stationary while sitting at their desks and while not present at their desks, the office space is vacant.

Ref. [42]: Suitable for the author-claimed *HVAC Control and Occupant Comfort* and *Energy and Space Utilization* applications. The solution is not expected to scale up as the spatial NDD is very high, i.e., 18 $ft^2$/node. The method requires ground-truth data to label and train IHMM parameters via supervised learning. New sensor data is also needed to update the historical dataset to periodically tweak the model parameters, for accurate long-term applications, such as space usage analysis and occupancy modeling. The solution is not optimized in terms of node power consumption and IoT/Edge AI execution. The solution system level diagram is shown in Figure 5 for reference.

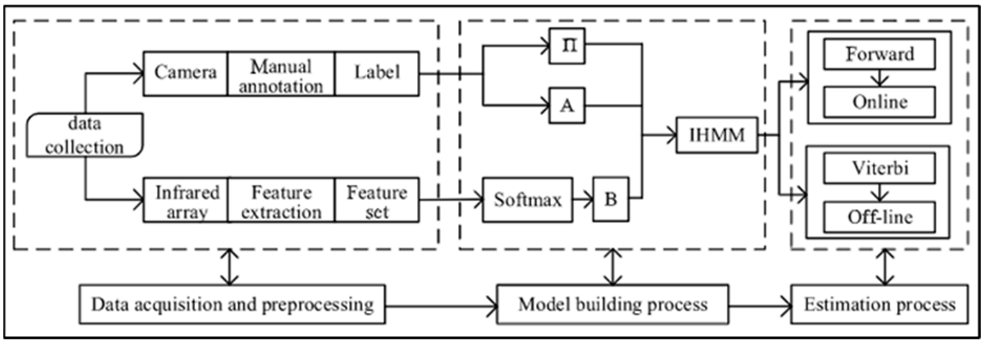


**Figure 5.** Raw data is obtained through infrared array sensors along with a camera to build occupancy transition probability matrix A. The parameter learning process of the IHMM model is introduced and the emission probability matrix B is calculated by Softmax Regression Model. Finally, according to the constructed IHMM, the Forward Algorithm and the Viterbi Algorithm are used to realize the online estimation and offline estimation of the indoor occupancy of a building.

## 7. Discussion and Future Trends

One of the important ADP indicators used in the suitability analysis is NDD. It is interesting to note here that this density is a simple indicator that is evaluated by dividing the total area of the monitored indoor space by the number of sensor nodes employed by the method. This indicator has no direct relationship with the sensor FoV or range, which is usually significantly smaller than the NDD. There is a list of factors that contributes to determining the NDD. The most impactful ones include the node positioning strategy, estimation method accuracy, network/communication reliability, environment-contributed sensor noise, and the floor plan of the monitored area. Among these factors, the node positioning strategy, estimation method accuracy, and network reliability are the factors that can be optimized to decrease NDD. In effect, NDD can be considered a proposed optimization measure by a method for the node positioning strategy, estimation method accuracy, and network reliability. However, dedicated studies exist for the node-positioning strategy [47] and network reliability [21], but none of the reviewed articles devised their positioning strategy.

During the review effort, it was noticed that most studies focused on *HVAC Control and Occupant Comfort* and *Energy and Space Utilization* applications rather than applications such as *Health and Safety* and *Security.* This is because the latter have ADPs that require high reliability and accuracy, which is difficult to achieve given the challenging task of occupancy detection and tracking in dynamic environments. Most of the reviewed works attempted to tackle the challenge of highly noise-prone and dynamic environments by adding to the suite of sensor modalities. However, a small minority of methods [7,38] presented the sensor data responsible for false positives or negatives and proposed consequent solutions to resolve the errors.

Among the researched literature, one of the significant gaps for data-driven occupancy detection methods was the need for periodic collection of training sets to incorporate novel occupancy scenarios. The dataset also includes ground-truth occupancy data. This is a problem because the collection and labeling of new training datasets are far from ideal tasks for an end user or, in some cases, infeasible. To address this issue, certain studies [48–50] have suggested unsupervised methods, as these algorithms do not need to label the dataset. Yet, such methods have limited applicability since error-prone prior expert knowledge is used to initialize classes. This knowledge may be based on assumptions or sensor data distribution that may only be valid once the occupancy patterns evolve.

The future for tracking such a complex issue lies in employing more capable IoT devices, such as Edge AI devices [51], so that on-device ML training and inference can be produced incorporating newer occupancy scenarios. The dedicated field of ODLL [46,52,53] offers benefits, such as a local learning approach where occupancy patterns are learned on the fly, thus making such methods suitable for practice. Moreover, privacy-preserving automated labeling techniques are the flip side of the coin when an OODL approach is used, as the collected dataset also needs to be labeled. The literature needs reliable privacy-preserving techniques, but video or image-based automated yet privacy-compromising ground-truth collection techniques [54,55] can be found.

## 8. Conclusions

This review presents a matching strategy for mapping occupancy estimation methods involving networked sensor nodes to the most suitable application areas. During the course of the evaluation, multiple application areas were investigated to identify a set of ADPs that can help guide the suitability determination process. The ADPs represent the most demanding requirements presented by each application area, as suggested by the literature. The ADPs can be used to derive design specifications for developing a new occupancy-sensing solution or can equally be used to assess an already designed solution. ADPs are determined based on occupancy standards documentation published by various regulatory and research bodies, performance constraints dictated by the sensing technologies and computing equipment, and application area considerations. As a result of stringent application area requirements placed by standardization agencies, sensor limitations, and challenging environmental constraints, only a limited number of reviewed methods conform to the ADPs criteria proposed by this review study.

In future work, more ADPs can be extracted for each application area. In addition, conformance criteria can be fine-tuned for each ADP based on industrial demands, published building and sensing technology codes, as well as market trends.

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## Abbreviations

| | |
|---|---|
| AI | Artificial Intelligence |
| ADP | Application-desired Parameters |
| AR | Autoregressive |
| ARM | Advanced RISC Machine |
| ASHRAE | American Society of Heating, Refrigerating and Air-Conditioning Engineers |
| AWT | Absolute Water Content |
| CEC | California Energy Commission |
| CPE | Customer Premise Equipment |
| EM | Electromagnetic |
| FFNN | Feed-Forward NN |
| FoV | Field-of-View |
| HMM | Hidden Markov Model |
| HVAC | Heating Ventilation and Air-Conditioning |
| IHMM | Inhomogeneous HMM |
| IBC | International Building Code |
| IECC | International Energy Conservation Code |
| IR | Infrared |
| IoT | Internet of things |
| KNN | K-Nearest Neighbor |
| LDA | Linear Discriminant Analysis |
| MCU | Microcontroller Unit |
| ML | Machine Learning |
| MTBF | Mean Time Before Failure |
| NDD | Node Deployment Density |
| NEMA | National Electrical and Manufacturers Association |
| NN | Neural Networks |
| NFPA | National Fire Protection Association |
| ODLL | On-device Lifelong Learning |
| PF | Particle Filter |
| PIR | Passive Infrared |
| QDA | Quadratic Discriminant Analysis |
| RF | Radiofrequency |
| RH | Relative Humidity |
| SLEEPIR | Synchronized Low Energy Electronically chopped PIR |
| SoC | System-on-a-Chip |
| SVM | Support Vector Machine |
| TVOC | Total VOC |
| VOC | Volatile Organic Compounds |
| WEKA | Waikato Environment for Knowledge Analysis |

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