**Optimal Sensor Deployment in Smart Buildings**

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**ABSTRACT**

Smart buildings are considered to be the new age buildings. They are expected to evolve continuously and provide intelligent solutions such as thermal comfort to the occupants, safe evacuation during an emergency, alert users about a possible fire in the building, and minimize and optimize the energy usage. Such types of buildings require sensing of different factors, which necessitate the deployment of sensors. All the existing approaches to sense the required factors overlook the problem associated with the deployment of a large number of sensors in the buildings. The most critical issue being the abundant generation of e-waste. Towards this problem, the paper presents a novel and holistic optimal sensor deployment method for sensing different factors to make buildings smarter. It describes how intelligently using the existing information can lead to a reduction in sensors. The results show how the factors such as power consumption, ON appliances, occupancy and temperature are sensed using a minimum number of sensors. The effectiveness of this approach is demonstrated on a real-world problem to demonstrate the impressive reduction in sensors.

**Key words:** Smart Buildings; Sensor Deployment; Optimization Model; Sensor Reduction; Soft Sensors.

**INTRODUCTION**

Internet of Things (IoT) and Cyber-Physical Systems (CPS) are the two very commonly heard terms nowadays. Due to the advent of these technologies, buildings have evolved from being intelligent to becoming smarter. A smart building is expected to fulfill tasks like monitoring the health of appliances, provide thermal comfort to the users(Reena *et. al.* 2018), maintain desired air quality, track occupants in the building, and optimize and reduce the wastage of energy (Karmakar *et. al.* 2018). But fulfilling these tasks requires sensing of factors such as energy consumption, occupancy, air quality and type of appliances that are switched ON. Therefore, it is important to deploy sensors in the building to sense the factors of interest (Agarwal *et. al.* 2016a). There exist techniques which discuss placement of sensors in the buildings to sense different factors. But these techniques do not consider the issues related to the deployment of a large number of sensors, such as increased user inconvenience and capital cost of procuring, installing, maintaining and up-grading the sensors, disturbing the aesthetics of the building, incremental investment on storage and communication facilities for the sensors(Hnat *et. al.* 2011, Stankovic *et. al.* 2014), and threat to privacy. The most worrying drawback being the increased generation of e-waste.

In 2016, the CEO of SoftBank Group Corporation estimated that there will be at least a trillion connected devices around the world in the next 20 years (Higginbotham, S., 2018). According to the International Telecommunication Union (ITU), the global quantity of e-waste generation in 2016 was around 44.7 million metric tons (Mt), or 6.1 kg per inhabitant. The amount of e-waste is expected to grow to 52.2 Mt in 2021, with an annual growth rate of 3 to 4%(Baldé *et. al.* 2017, Lemonbeat *et. al.* 2018). The existing techniques fail to provide effective solutions with sensor minimization as an important parameter.

In fact, rapid research in data mining, algorithms and machine/deep learning approaches has led to efficient techniques for processing large amounts of sensor data. This encourages the approach of throwing sensors at the problem so that large amounts of data are generated and can be processed to provide smart applications and experience.

**Objective and Contribution**

The objective of this paper is to propose an approach that reduces the number of sensors to be deployed so that the issues related to the deployment of a large number of sensors, like installation of sensors and generation of e-waste, can be tackled effectively.

The major contribution of this paper is a novel and holistic approach of optimal sensor deployment in buildings which deploys a minimum number of sensors while making the building smarter by sensing the factors of interest. It uses soft sensing, which implies inferring a factor from other set of factors, as the primary tool to reduce the deployment of sensors; it defines how existing information can be intelligently used to infer the factors of interest, and thus reduce the number of sensors to be deployed. For instance, Ciftler *et. al.* (2018) demonstrate how occupancy can be inferred in the buildings using the Wi-Fi signal information. The effectiveness of this approach is tested on a real-world problem of sensor deployment in buildings to make them smarter, and demonstrates impressive reduction in sensors.

**PROPOSED METHODOLOGY: OPTIMIZATION FRAMEWORK**

In this paper, a novel solution to optimal sensor deployment approach is provided, by developing an optimization model. This optimization model outputs the optimal number, type and location of sensors such that required factors are sensed in the smart buildings. Figure 1 represents the flowchart summarizing the proposed approach.

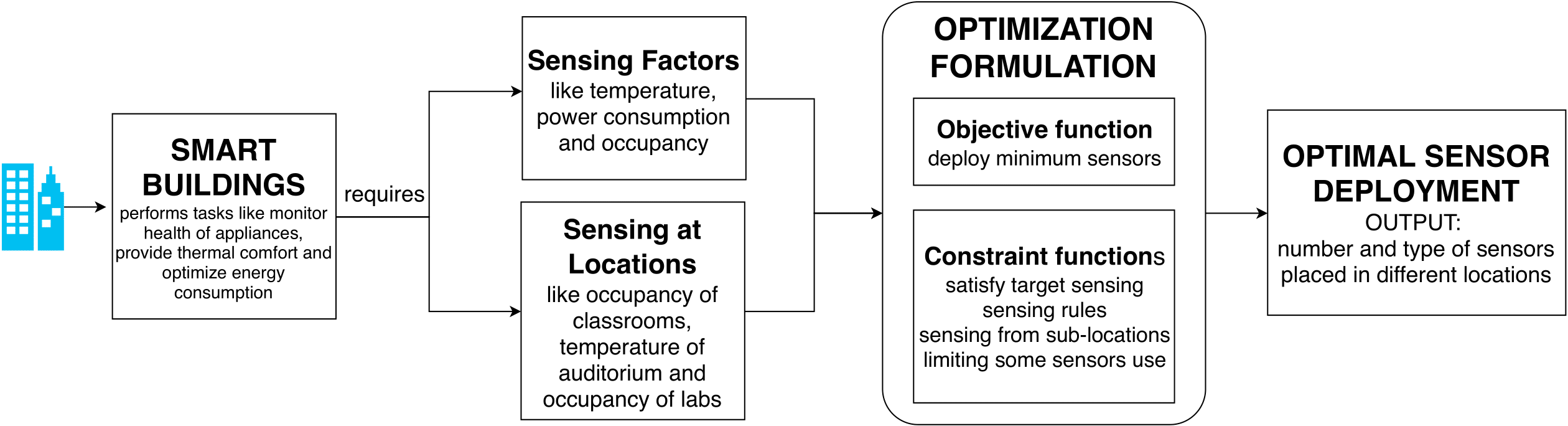


Fig. 1. Flowchart summarizing the proposed approach for optimal sensor allocation

The various components that constitute the optimization model are described as follows.

**Inputs**

* **Locations:** It represents the set of different locations that are present in the building, and where different factors should be sensed; like labs, server rooms, data centers, floors, meeting rooms, office space and wings of the building. It is denoted by .
* **Factors:** It represents the type of factors to be sensed to analyze the state and behavior of the building. For example, the temperature should be sensed in buildings to determine whether thermal comfort is provided to the occupants, and power consumption of appliances should be sensed to monitor their health. It is denoted by .
* **Sensors:** These are used for sensing factors and are categorized into:
  1. Hard sensors: represent the physical sensors, like smart meter and temperature sensor. Hard sensors that sense factor *k* are denoted by . Note that in this paper, a sensor will always refer to a hard sensor unless stated otherwise.
  2. Soft sensors: represent virtual sensors that infer a factor from another set of factors . Thus, if factors are already being sensed in a location, then no additional hard sensor is required to sense factor since it is being inferred from the soft sensor. Therefore, it helps in the reduction of hard sensors. Soft sensors use techniques like deep/machine learning, logic and formulaic based approaches to infer facets(Salimi, *et. al.* 2019). Examples of soft sensors are: using an artificial neural network to infer power consumption from temperature and time as input(Agarwal, *et. al.* 2016b) and inferring occupancy status from analyzing Wi-Fi signals (Ciftler, *et. al.* 2018). The soft sensors serve as the primary tool for reducing the number of hard sensors.
* **Maximum number of sensors:** It represents the maximum limit on the sensors of a particular type that can be used. This is an optional input. It is denoted as where denotes sensor that senses factor *k*.
* **Target sensing:** It represents the target sensing that should be achieved by the optimal sensor deployment approach. Suppose it is required to sense the temperature of room *R* to determine whether the desired temperature is maintained in the room. This requirement is specified as which implies that temperature in room *R* should be sensed. By default, each element of matrix is initialized with 0.

**Optimization Model for the optimal deployment of sensors**

The aim of this model is to determine the minimum number of sensors that should be deployed in the building to sense various factors for making the building smarter. The various symbols used for this model are as indicated in Table 1.

Table 1. Description of different symbols used in the paper

|  |  |
| --- | --- |
| **Input Variables** | **Description** |
|  | set of locations where factors are required to be sensed; like rooms, floors and wings of the building. |
|  | set of factors to be sensed in the building; like occupancy and temperature. |
|  | set of hard sensors to sense factors, where denotes sensor that senses factor *k.* For example, passive infrared sensors (PIR) and camera are used to sense the factor occupancy. |
|  | limit on the number of sensors of type that can be deployed for sensing factor *k.* For example, implies that a maximum of *2* PIR sensors can be deployed to sense occupancy. |
|  | a matrix containing binary numbers, which denote whether factor *k* should be sensed at location *l*. The value is 1 if factor *k* should be sensed at location *l*; 0 otherwise. For example, implies that occupancy should not be sensed in location *HVAC room*. |
| **Decision/output Variables** | **Description** |
|  | if sensor is used at location *l* to sense factor *k;*  otherwise |
|  | if factor *k* is sensed at location *l;*  otherwise |

**Objective function:** It is used to specify the aim of deploying minimum number of sensors in the building to sense factors.

|  |  |
| --- | --- |
|  | (1) |

**Constraint functions:**

**A.** Satisfy the required target of sensing: this constraint ensures that the final optimal sensor allocation satisfies the target sensing required for the smart building.

|  |  |
| --- | --- |
|  | (2) |

**B.** Sensing Rules: for sensing a factor *k* at a location *l*, the following *sensing rules* apply.

Rule 1: If a sensor is deployed in location *l*, then the factor *k* is sensable in location *l.*

Rule 2: If a soft sensor, that infers factor *k* from factors, is deployed in location *l*

and factors are sensible in location *l*, then the factor *k* is sensable in location *l.*

This constraint is represented as:

|  |  |
| --- | --- |
|  | (3) |

**C.** Sensing from sub-locations: A location may be composed of sub-locations or relatively small locations (Figure 2). Let the sub-locations of a location *l* be represented by . Thus, this constraint states that if a factor *k* that is sensable in all the sub-locations of a location *l,* then the factor *k* is also sensable in this location *l.* For example, consider a room that consists of two zones. Now to sense the temperature of room, temperature values of its sub-locations, i.e., zones are sensed using hard sensors. These values are then aggregated using a function like average to represent the temperature of the room.

|  |  |
| --- | --- |
|  | (4) |

**D.** Limiting the use of certain sensors: if , which represents the maximum number of sensor sensing factor *k* that can be deployed, is provided as input, then this constraint ensures that the total number of sensors of type deployed in the optimal sensor allocation does not exceed the provided limit.

|  |  |
| --- | --- |
|  | (5) |

**Application area:** The novel methodology proposed in this paper was used for optimal sensor allocation in a set of rooms of KReSIT building of Computer Science and Engineering Department, IIT Mumbai (India). The building consists of floors, small and big rooms, and zones of rooms as shown in Figure 2. A separate location for HVAC room is denoted since it provides common cooling to all the rooms of the building and consumes a very high amount of power.

Fig. 2. Representation of the application area building

**RESULTS AND DISCUSSION**

A smart building provides thermal comfort at optimum power consumption based on the occupancy. It can be achieved by occupant detection and appliance automation. To fulfill these tasks, four primary factors need to be sensed: power consumption, number and type of ON appliances, occupancy and temperature of the rooms.

**Inputs used for optimal sensor allocation**

* Set of locations: as represented in Figure 2.
* Factors to sense: power consumption, number and type of ON appliances, occupancy and temperature.
* List of different types of sensors used to sense the factors is shown in Table 2.

Table 2. List of different types of sensors for sensing factors

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Sensor type** | **Power** | **ON Appliances (#ONapp)** | **Occupancy** | **Temperature** |
| *Hard Sensor* | smart meter | smart switch | PIR (passive infrared), camera | temperature sensor |
| *Soft Sensor*  *(infer from factors)* | **#**ONapp | Occupancy and temperature | - | - |

* Target sensing: sense all the factors in all the locations, except *HVAC room .*

For location *HVAC room ,* only power consumption should be sensed since the room is never occupied, and sensing other factors is not meaningful.

Sensing temperature, occupancy and ON appliances in rooms and zones leads to the sensing of these factors in the building since the state of these factors of the building is represented by the rooms and zones.

**Output**

The optimization model has been implemented in PuLP (Mitchell *et. al.* 2011). Providing the inputs discussed above, the optimization model implements the objective function Eq. (1) and constraint functions Eq. (2) – (5). Following are the output matrices of the optimization model.

1. *sensed matrix:* determines the factors that are sensable in different locations. From the following output, it can be observed that input of *target sensing,* which specified that all factors should be sensed in all the locations except HVAC room where only power consumption should be sensed, is satisfied by the optimization model (Constraint A, Eq. (2)). The matrix is shown as follows.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Locations** | **Power** | **ON appliances** | **Occupancy** | **Temperature** |
| Building |  |  |  |  |
| Floor 1 |  |  |  |  |
| Floor 2 |  |  |  |  |
| HVAC room |  |  |  |  |
| Small Room 1 |  |  |  |  |
| Big Room 1 |  |  |  |  |
| Zone 1 |  |  |  |  |
| Zone 2 |  |  |  |  |
| Small Room 2 |  |  |  |  |
| Big Room 2 |  |  |  |  |
| Zone 1 |  |  |  |  |
| Zone 2 |  |  |  |  |

1. *used matrix:* determines the type of sensors placed in different locations for sensing the factors.It indicates the optimal sensor deployment strategy that should be followed to sense factors in the smart building. Value of 1 denotes the sensor type which should be deployed at the location. The matrix is shown as follows.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Locations** | **Power** | **ON appliances** | **Occupancy** | | **Temperature** |
| **Smart meter** | **Smart switch** | **PIR** | **Camera** | **Temperature sensor** |
| Building |  |  |  |  |  |
| Floor 1 |  |  |  |  |  |
| Floor 2 |  |  |  |  |  |
| HVAC room |  |  |  |  |  |
| Small Room 1 |  |  |  |  |  |
| Big Room 1 |  |  |  |  |  |
| Zone 1 |  |  |  |  |  |
| Zone 2 |  |  |  |  |  |
| Small Room 2 |  |  |  |  |  |
| Big Room 2 |  |  |  |  |  |
| Zone 1 |  |  |  |  |  |
| Zone 2 |  |  |  |  |  |

The details of the optimization model output, which represent the optimal sensor allocation, are explained as follows.

1. Since no soft sensor is available to sense temperature (Table 2), temperature sensors are used to sense the temperature in small rooms and four zones (two each) of big rooms. In big rooms, the temperature is sensable since temperature of the zones is sensed (Constraint C, Eq. (4)). Similarly, the temperature of floors and the building become sensable. Thus, a total of six temperature sensors are deployed.
2. Occupancy is sensed either by placing Passive infrared (PIR) sensor or a camera to sense occupancy in small rooms and zones of big rooms. No soft sensor is used since occupancy cannot be inferred from the other factors in these rooms. Using Constraint C Eq. (4), occupancy of big rooms, floors and the building becomes sensable. A total of six PIR + camera sensors are deployed.
3. Information of ON appliances can be inferred from occupancy and temperature using a soft sensor (Table 2). Since all the locations already sense temperature and occupancy, the number and type of ON appliances is sensed using the soft sensor (Constraint B, Eq. (3)). Therefore, no hard sensor is deployed to sense this factor.
4. In the HVAC room, only one smart meter is placed to sense power consumption since no other factor is sensed in this location. In all the remaining locations, power consumption is inferred from number and type of ON appliances information using a soft sensor (Constraint B, Eq. (3)).

Therefore, to sense the factors in all the locations of the building, only 13 sensors are required as tabulated in Table 3.

Table 3. Optimal sensor allocation for sensing the factors in all the locations of the building

|  |  |  |
| --- | --- | --- |
| **Hard Sensors** | **Locations of hard sensors** | **Number of sensors placed** |
| *Temperature sensor* |  | 6 |
| *PIR or Camera* |  | 6 |
| *Smart Switch* | - | - |
| *Smart meter* | *HVAC room* | 1 |
| ***Total*** | **13** | |

Other scenarios where optimal sensor allocation changes when the goal to be satisfied is changed and *limit* of sensors as input (Constraint D, Eq. 5) is provided, are detailed in Table 4.

Table 4. Optimal sensor allocation for satisfying different goals of sensing in building

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Goal:** | **Optimal number of sensors** | **Smart meter to sense power** | **Smart switch to sense ON appliances** | **PIR, camera to sense occupancy** | **Temperature sensor** | **Description** |
| **Sense all the factors using minimum sensors** | 13 | 1 in HVAC room | 0 | 6 in(two) small rooms and (four)zones of big rooms | 6 in small rooms and zones of big rooms | ON appliances inferred from occupancy and temperature using a soft sensor; power consumption inferred from ON appliances (except in HVAC room) |
| **Same as above** | - | - | - | - | - | For no feasible solution is obtained since power in HVAC room can be sensed only using a smart meter |
| **Sense *power* using minimum sensors** | 7 | 7 in HVAC room, small rooms and zones of big rooms | OR 7 in HVAC room, small rooms and zones of big rooms | - | - | Either smart meter or switch status is placed in HVAC room, small rooms and zones of big rooms. Power in other locations are sensed since their sub-locations sense power |
| **Sense *power* using minimum smart meters** | 7 | 1 in HVAC room | 6 in small rooms and zones of big rooms | - | - | Power in small rooms and zones of big rooms is inferred from ON appliances using the soft sensor. |
| **Sense *ON appliances* using minimum sensors** | 6 | - | 6 in small rooms and zones of big rooms | - | - | ON appliances in in other locations are sensed since their sub-locations sense ON appliances |
| **Sense *ON appliances* using minimum smart switches** | 6 | - | 6 in small rooms and zones of big rooms | - | - | No change in optimal sensor allocation since inferring ON appliances in one location entails deployment of two sensors for occupancy and temperature; thus, only one smart switch is deployed. |

**Performance comparison**

To evaluate the effectiveness of the proposed approach, sensor deployment using the baseline and the proposed optimal sensor allocation approach is presented in Figure 3. The baseline approach consists of deploying appropriate sensors for all the factors in all the locations where they should be sensed. For example, to sense power, ON appliances, occupancy and temperature in all the location of the building (Figure 2), four sensors (one for each factor) is deployed in all the locations, leading to the deployment of 48 sensors. In comparison, the novel approach deploys only 13 sensors while sensing all the factors in all the locations of the building. Thus, using the proposed technique, a reduction of 35 sensors is obtained. To demonstrate this approach on a large number of buildings, Figure 3 shows the number of sensors to be deployed by the baseline and optimal sensor allocation technique to sense all the factors in all the locations of the building. Note that the x-axis represents the number of buildings with a structure similar to Figure 2. It can be observed that for 100 thousand of buildings, the optimal sensor allocation approach reduces the number of sensors to be deployed by 72.92% (3500k), and thus the e-waste generation is decreased by a significant amount when developing smart cities and buildings. This impressive reduction demonstrates how practical the proposed technique is and should be used as a primary tool for sensing factors when developing smart cities and buildings.

Fig. 3. Comparison of number of sensors deployed using the baseline and the proposed optimal sensor deployment approach.

**LITERATURE REVIEW**

Homes and buildings are becoming smarter. Internet of Things (IoT) technologies are being used extensively in developing smart cities as highlighted by Zanella et. al. (2014) and El-Shafie *et. al.* 2018. One of the biggest challenges in smart buildings is the storage and analysis of real time sensor data (Bashir *et. al.* 2016). It proposes a technique for integration of big data analytics and IoT for effectively dealing with real time building sensor data. Biljana *et. al.* (2017) discuss a holistic framework for integrating smart home objects into a cloud centric framework. The solution discusses the communication protocols and their interoperability. A review paper by Minoli *et. al.* (2017) discusses the practical challenges faced by the Internet of Things in the smart home domain. Smart homes also provide location services. A novel approach regarding the same is discussed in Lin *et. al.* (2016), which analyzes the pedestrians past locations and tries to produce accurate results in smart buildings. Pan *et al.* (2015) proposes an IoT framework which uses smartphone and cloud platforms for saving energy and improving the home network intelligence. Hernández-Ramos *et. al.* (2015) propose an ARM compliant security framework using IoT. The applications are discussed with respect to smart buildings. The approach integrates the contextual data to control the building management and security behaviour. Ghayvat *et. al.* (2015) discuss how wellness of the home residents are monitored to determine if they are fine; the approach is extended to smart building environment. But none of these techniques discuss about the issue of sensor placement in buildings.

For optimizing the energy consumption of smart buildings, it is important to have detailed information and status of different loads, like HVACs and plug loads, operating in the building. Authors of Weng et. al. (2012) provide this information and discuss how this information is used to optimally plug level loads and HVACs for saving energy of the building. Light-emitting diodes (LEDs) are becoming popular in buildings since they are considered to be energy efficient. But it entails issues such as high costs, installation issues, and difficulty of maintenance. Therefore, to solve these issues, authors Magno et. al. (2015) propose a low cost, wireless, easy to install, adaptable, and smart LED lighting system to automatically adjust the intensity of light for saving energy. It has been shown that if lighting systems are augmented with sensors and actuator systems, more energy savings can be obtained. In this regard, Basu et. al. (2014) discusses a sensor-based intelligent lighting system for future grid-integrated buildings. The system is expected to participate in energy markets using sparse sensing of indoor light distribution. Technique for optimizing the energy usage and improving the thermal comfort of residents in smart buildings is discussed by Schumann et. al. (2014). The authors try to address the problem of identifying Energy Management System (EMS) input amongst thousands of sensors deployed in the building. They propose a solution for semi-automating this challenging task. In order to facilitate smart services to the residents of the building, different factors of the building, like occupancy and energy consumption, should be sensed. There exist numerous techniques for sensing different factors in a building and satisfying certain requirements of the building. Authors of Yang et. al. (2014) have proposed an approach for learning interaction between the residents and Nest learning thermostats in the building to improve energy savings and user comfort. Data driven system to estimate personal energy footprint in real time is discussed in Wei et. al. (2018). It estimates the footprint even in environments that do not have access to energy or population data. Shwehdi et. al. (2015) present case studies on how HVACs affect the building energy consumption. Factors such as power supply and others which are important for user comfort are discussed in Au-Yong et. al. (2019). Gul et. al. (2015) present a work that studies the relationship between occupancy and energy behaviour of the building. The authors claim that the current BMS provides minimum access to the building residents, and extra information about the building residents pattern can help in the better performance of the building. A novel approach of using environmental and room sensors to control the installed HVACs is presented in Hafeez et. al. (2017). It augments the HVACs with a simple ON/OFF control based mechanisms and show savings in energy consumption and issues in scalability of the approach. Using the resident’s feedback to maintain a comfortable temperature inside the room is discussed in Shin et. al. (2017). The authors propose a new methodology of using the users feedback such that fairness is ensured. Estimating occupancy information and using to control commercial office buildings is presented in a review paper by Shen et. al. (2017). All of these issues lack the holistic approach of sensing all the factors of interest in a building using optimal number and placement of sensors.

There exist multiple works which discuss inferring a factor from other set of factors (Agarwal *et. al.* 2016c). Using virtual sensors to abstract hard sensors for programmatically specifying high level requirements is discussed in Kabadayi *et. al.* (2006). Using Wi-Fi signals to infer the occupancy status and information is discussed in Çiftler et. al. (2018) and Thanayankizil et. al. (2012). Using Wi-Fi infrastructure, along with smart phones with Wi-Fi connectivity, to provide fine grained HVAC control based on occupant comfort is discussed by Balaji et. al. (2013). Occupancy prediction using CO2 based physical and statistical modelling is presented by Zuraimi et. al. (2013). Authors of Salimi et. al. (2019) propose an adaptive probabilistic occupancy prediction model. Since occupancy information is useful for efficient functioning of buildings with respect to parameters like energy efficiency and thermal comfort through HVACs, authors Ekwevugbe et. al. (2013) discuss a low cost and non-intrusive method for sensor network deployment. It combines information such as sound level, case temperature, CO2 and motion; it is augmented with infrared cameras to validate the ground truth information. Learning about occupants and their sleep patterns to optimally operate HVACs is the topic of discussion in Lu et. al. (2010). The authors call it smart thermostat. But all of these existing approaches focus on only particular factors of the building. The proposed approach of this paper, on the other hand, presents a generalized and holistic approach of sensing the factors to make the buildings smarter.

**CONCLUSION**

The baseline technique, which is generally used in the buildings, uses 48 sensors for sensing the important factors in all the locations of a building. However, the proposed methodology uses only 13 sensors for sensing all these parameters. Thus, a reduction of 35 sensors was observed which is a very impressive achievement.

Scaling this technique to 100 thousand of buildings, when compared with the baseline technique, a reduction of 3500 thousand sensors or 72.92% can be achieved, making it an impressive proposition and leading to a large reduction in e-waste generation.

Therefore, it can be concluded that if the existing information is used intelligently, it will lead to a reduction in sensors. Factors such as power consumption, ON appliances, occupancy and temperature can be sensed using a minimum number of sensors. The effectiveness of this approach is demonstrated on a real-world problem and proved to be very effective.

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Abstract in Arabic:

تعتبر المباني الذكية المباني الحديثة. من المتوقع أن يتطوروا باستمرار ويقدموا حلولًا ذكية مثل الراحة الحرارية للركاب والإخلاء الآمن أثناء الطوارئ وتنبيه المستخدمين عن حريق محتمل في المبنى وتقليل استخدام الطاقة إلى الحد الأدنى وتحسينه. تتطلب هذه الأنواع من المباني استشعار العوامل المختلفة ، مما يستلزم نشر أجهزة الاستشعار. جميع النهج الحالية لاستشعار العوامل المطلوبة تغفل المشكلة المرتبطة بنشر عدد كبير من أجهزة الاستشعار في المباني. القضية الأكثر أهمية هي وجود وفرة من النفايات الإلكترونية. لحل هذه المشكلة ، تقدم الورقة طريقة نشر مثالية وجديدة ومستشعرة لاستشعار العوامل المختلفة لجعل المباني أكثر ذكاءً. وهو يصف كيف يمكن أن يؤدي استخدام المعلومات الموجودة بذكاء إلى انخفاض في أجهزة الاستشعار. توضح النتائج كيف يتم استشعار العوامل مثل استهلاك الطاقة وأجهزة التشغيل والشغل ودرجة الحرارة باستخدام الحد الأدنى لعدد أجهزة الاستشعار. يتم توضيح فعالية هذا النهج في مشكلة العالم الحقيقي لإظهار الانخفاض المذهل في أجهزة الاستشعار.