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A novel optimization framework for 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. This is achieved by sensing the different factors of the building. The existing approaches overlook the problems associated with the deployment of a large number of sensors. However, this article presents a novel and holistic optimal sensor deployment method – an optimization framework for sensing different factors to make buildings smarter. It describes how intelligently using the existing information can lead to a reduction in sensors. The optimization framework is compared with the baseline approach, which deploys sensors at all the locations where they should be sensed, for an existing building. The results indicate that the newly developed optimization framework requires 72.92% less sensors as compared to the baseline approach. This feature makes it an impressive proposition and results in lesser in e-waste generation.

Keywords Smart Buildings · Sensor Deployment · Optimization Framework · Baseline Approach · Sensor Reduction

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1 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), track occupants in the building, and optimize and reduce the wastage of energy (Karmakar et al., 2018). However, fulfilling these tasks requires sensing of factors such as energy consumption, occupancy and type of appliances that are switched ON. Therefore, it is important to deploy sensors in the building to sense these factors of interest (Agarwal et al., 2016a). There exist various techniques for placement of sensors in the buildings to sense different factors (Bellala et al., 2012; Meyn et al., 2009). However, 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 upgrading the sensors, disturbing the aesthetics of the building, incremental investment on storage and communication facilities for the sensors and threat to privacy (Hnat et al., 2011; Stankovic, 2014). The most worrying drawback of these techniques is the increased generation of e-waste. In 2016, the CEO of SoftBank Group Corporation estimated that there would be at least a trillion connected devices around the world in the next 20 years (The Internet of Trash: IoT Has a Looming E-Waste Problem, 2018). Therefore, 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.

The objective of this article is to provide an approach that reduces the number of sensors that should be deployed to overcome the various issues related to the deployment of a large number of sensors in a smart building. The major contribution of this article is a novel and holistic approach to optimal sensor deployment in buildings to make it smarter by sensing the factors of interest. It uses soft sensing which implies inferring a factor from other set of factors; for instance, Ciftler et al. (2018) demonstrated how occupancy can be inferred in the buildings using the Wi-Fi signal information. Soft sensing defines how existing information can be intelligently used to infer the factors of interest, and thus used as a primary tool to reduce the number of sensors to be deployed. The effectiveness of this approach is tested on a real-world problem of sensor deployment in an existent building to make it smarter and demonstrate an impressive reduction in sensors.

2 Literature Review

This article presents (a) a holistic optimization framework for making buildings smarter (b) seamless deployment of hard and soft sensors and (c) utilizing a minimum number of sensors and deploying them at the right places in a building. A survey of the work done in these and related areas is presented in this section.

Integration of Internet of Things (IoT) with buildings has led to buildings becoming smarter. One of the challenges in smart buildings is the storage and analysis of real-time sensor data (Zanella et al., 2014; El-Shafie and Fakeih, 2018). Bashir and Gill (2016) proposed a technique for the integration of big data analytics and IoT for effectively dealing with real-time building sensor data. Stojkoska and Trivodaliev (2017) described a holistic framework for integrating smart home objects into a cloud-centric framework. Minoli et al. (2017) discussed the various practical challenges faced by IoT in smart buildings. Pan et al. (2015) proposed an IoT framework that used smartphone and cloud platforms for saving energy and improving the home network intelligence. Hernández-Ramos et al. (2015) proposed an ARM compliant security framework using IoT. Ghayvat et al. (2015) discussed how wellness of the home residents is monitored to determine if they are fine and extended this approach to the smart building environment.

Buildings play an important role in efficient functioning of electric grids. It is important for building to not impose higher loads on the electric grids, since they have other factors that bring in uncertainties like renewable energy sources, dispatchable resources and storage devices (Tao et al., 2019). Gross and Finlay (2000) have proposed a novel framework for the analysis of bids in competitive electricity market. Supplying electricity to remote areas requires optimal sizing of hybrid renewable energy systems (HRES) such that load requirements are satisfied with high reliability and low cost (Eltamaly et al., 2017). To minimize the total energy and operating cost of the microgrid, an efficient algorithm based on particle swarm optimization is proposed by Radosavljević et al. (2016).

There exist multiple works that discuss inferring a factor from other sets of factors (Agarwal et al., 2016b; Balaji et al., 2013). Using virtual sensors to abstract hard sensors for programmatically specifying high-level requirements has been described by Kabadayi et al. (2006). Using Wi-Fi signals to infer the occupancy status and information has been demonstrated by Ciftler et al. (2018); Thanayankizil et al. (2012). Occupancy prediction using CO_2 based physical and statistical modeling has been investigated by Zuraimi et al. (2017). Salimi et al. (2019) proposed an adaptive probabilistic occupancy prediction model. Ekwevugbe et al. (2012) discussed a low cost and non-intrusive method for sensor network deployment to combine information such as sound level, appliance case temperature, CO_2 and motion. Using inference models like support vector regression and ensemble models to manage building power is discussed by Bellala et al. (2017). A network of sensors and cloud infrastructure can be used to monitor different behaviour inside homes as discussed by Mora et al. (2018). The work uses different soft sensing approaches to infer different behavioural patterns. Barker et al. (2019) have proposed a virtual power meter, an example of a soft sensor, for online load tracking. Iyengar et al. (2017) have proposed a soft sensor model called as SolarCast for predicting solar power for smart homes. Ujager and Mahmood (2019) have discussed a type of soft sensor context-aware accurate wellness determination

(CAAWD) for estimating the wellness of elderly people in homes. A review article is presented by Li et al. (2019) to discuss modeling of occupancy behaviour and its effect on building performance. Learning about occupants and their sleep patterns to optimally operate HVACs has been described by Lu et al. (2010). These work utilize various soft sensing approaches to infer different behavioural patterns. But these soft sensing approaches are not holistic since they aim to sense only one kind of factor. To understand the behaviour of the buildings, the factors such as energy consumption, occupancy, appliance information and air quality are sensed individually in the existing literature. The optimization framework proposed in this article emphasizes that factors should be monitored in conjunction with each other to reduce the number of sensors to be deployed and obtain a better perspective about the building functioning.

Chang et al. (2011) proposes a solution for achieving observability by optimally deploying sensors in nodes by formulating it as an optimization problem. Even though it reduces the number of sensors to be allocated, it does not present a holistic approach for sensing multiple factors at different granules of a building, unlike the optimization framework proposed in this article. Bellala et al. (2012); Meyn et al. (2009) sense factors using only physical sensors and ignore the problems associated with deployment of large number of sensors. Agarwal et al. (2016b) proposed a technique for reducing the number of sensors for sensing building factors. But the solution, unlike the proposed approach of this article, does not provide solutions with optimal allocation of sensors. Pre-deployment strategies with respect to sensors are discussed by Krause et al. (2006). But it demands a prerequisite knowledge about the outdoor area statistics beforehand. Prakash et al. (2015) proposed a a smartmeter allocation method to sense power consumption of building. But it considers only smartmeter sensors, and thus fail to provide a generic minimum sensor allocation strategy.

A popular approach to represent building metadata has been proposed by Balaji et al. (2016). It discusses an improved technique for preparing a uniform schema to represent building metadata. But this approach contains a drawback; it assumes that sensors are already deployed in an intelligent way, and thus, does not propose any efficient technique for allocating the sensors. Therefore, the optimization framework proposed in this article can be added as a layer of optimal sensor deployment technique in this framework, enhancing it to be more holistic and pragmatic .

The problem of sensing building factors with reduced sensors is similar to observing the electric grid using minimum number of Phasor Measurement Unit (PMU) sensors. PMUs sensors help to estimate the state of electric grid by measuring line parameters like voltage and current phasors (Phadke, 1993), which leads to observability of the grid. The electric grid is represented as a graph, where the set of nodes represent buses (power generation centers or electric substations) of electric grids, and the edges of the graph correspond to the transmission lines between the the buses. It is not desirable to install PMUs on all the nodes to observe state of the grid since they are expensive sensors (Ree et al., 2010). Therefore, the goal is to deploy reduced number of PMU sensors in the electric grid. Numerous work has been done on developing solutions for placing minimum PMUs in the grid to achieve observability (Noureen et al., 2017; Manousakis et al., 2012). Optimal PMU placement for observing the grid is NP-Complete as proven by Gyllstrom et al. (2012). Formulating optimal PMU placement as an optimization problem is discussed by Dua et al. (2008); Abur and Magnago (1999); Xu and Abur (2004). Comparing this problem with the goal tackled in this article, the optimal PMU placement problem considers only a single type of sensor (PMU). In addition, it primarily focuses on sensing only one factor, that is voltage, since current value is obtained using Ohm's Law and Kirchhoff's laws. Thus, this is a relatively simple problem where only one sensor and one factor is considered. On the other hand, the proposed optimization framework of this article provides a holistic solution which deals with sensing multiple factors using a set of heterogeneous type of sensors, while ensuring that a minimum number of sensors are deployed in the building.

3 Methodology

In this article, a new optimization framework has been developed for optimal sensor deployment. This optimization framework outputs the optimal number, type, and location of sensors such that required factors are sensed in the smart buildings.

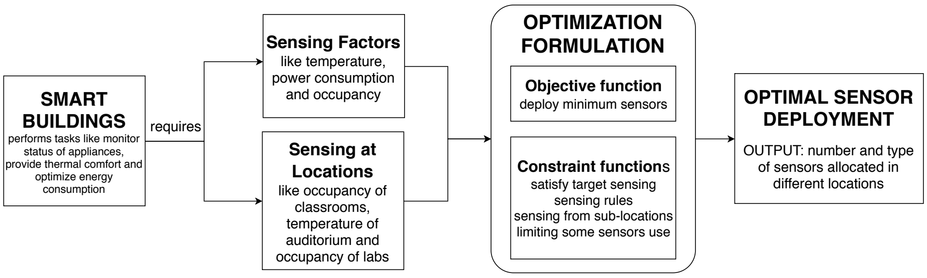

Fig. 1 Block diagram summarizing the proposed approach

A block diagram to summarize the proposed optimization framework has been demonstrated in Figure 1. Details of the various inputs and symbols given to the framework and the output produced by it are described in Table 1.

Table 1 Description of different symbols used in the optimization framework

Input	**Description**
$\{L\}$	set of locations where factors are required to be sensed like rooms, levels and wings of the building
$\{K\}$	set of factors to be sensed in the building like occupancy and temperature
$\{s^k\}$	set of hard sensors to sense factors, where s_i^k denotes sensor s_i that senses factor k. For example, passive infrared sensors (PIR) and camera are used to sense occupancy
$limit(s_i^k)$	denotes the limit on the number of sensors of type s_i^k that can be deployed for sensing factor k. For example, *limit(smartmeter) = 2* implies that a maximum of 2 smartmeters can be deployed to sense power
$tosense(l,k)$	outputs a value 1 if factor k should be sensed at location l; 0 otherwise
Output	**Description**
$used(l,k,s_i^k)$	outputs a value 1 if sensor s_i^k is allocated in location l to sense factor k; 0 otherwise
$sensed(l,k)$	outputs a value 1 if factor k is sensed in location l; 0 otherwise

3.1 Application Area

For the application of optimization framework, a classroom building, in the Computer Science and Engineering Department, IIT Bombay (India) was selected. The building consists of one HVAC room and two levels. Each level consists of one small and one big room as shown in Figure 2. Each big room was divided into two zones to sense different factors. A separate location for the HVAC room is denoted since it provides common cooling to all the rooms of the building and consumes a very high amount of energy.

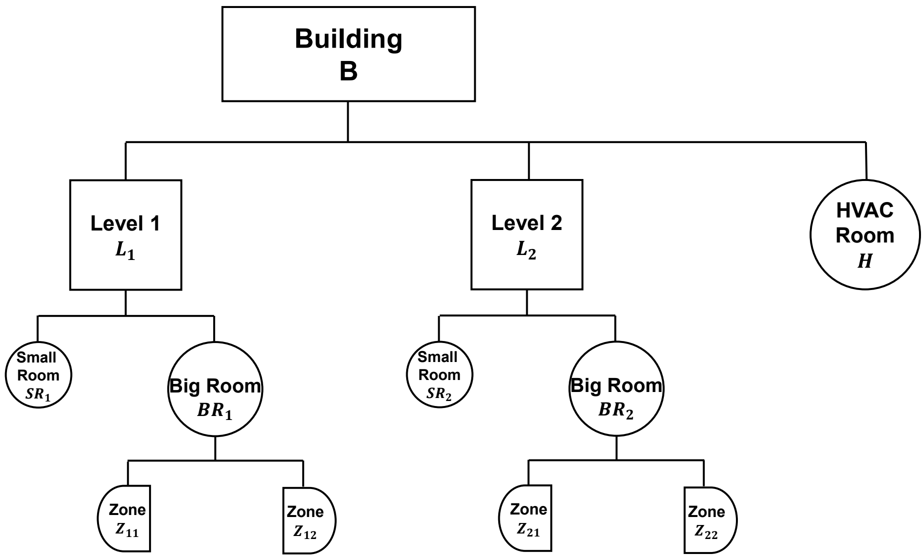

Fig. 2 Hierarchical representation of the application area building

3.2 Optimization Framework

It consists of an objective function and set of constraint functions which are described as follows.

3.2.1 Objective Function

Equation (1) is used to specify the aim of deploying minimum number of sensors in the building to sense factors.

$$minimize \sum_{l \in \{L\}} \sum_{k \in \{K\}} \sum_{s \in \{s^k\}} used(l, k, s) \tag{1}$$

3.2.2 Constriant Functions

$\diamond$ Sensing Requirement: It denotes the set of factors that should be sensed in different locations of the smart building. This requirement is specified by *tosense(l,k)* matrix. The constraint specified by Equation (2) ensures that the set of factors sensed (denoted by *sensed matrix*) due to the final optimal sensor allocation is in agreement with the sensing requirements of the smart building.

$$\forall l \in \{L\} \ \ \forall k \in \{K\} \quad sensed(l, k) = tosense(l, k) \tag{2}$$

$\diamond$ Sensing Rules: A hard sensor denotes a physical sensor like smartmeter and temperature sensor. A soft sensor is defined as a model that infers a factor from the set of other available factors. An example of a soft sensor is inferring power consumption from temperature and time of the day (Agarwal et al., 2016b). Soft sensors can be used to reduce the number of hard sensors given the type of information available in a location. The following set of rules specify if the factors are sensable for a given allocation of sensors:

Rule 1: If a hard sensor s_i^k is allocated in location l, then the factor k is sensable in location l. This rule is denoted by Equation (3).

$$\forall l \in \{L\} \ \ \forall k \in \{K\} \quad sensed(l, k) = \sum_{s \in \{s^k\}} used(l, k, s) \tag{3}$$

Rule 2: If a soft sensor, that infers factor k from others factors $\{k_i\}$, is allocated in location l and factors $\{k_i\}$ are sensable in location l, then the factor k is sensable in location l. This rule is denoted by Equation (4).

$$\forall l \in \{L\} \;\; \forall k \in \{K\} \quad sensed(l,k) = \prod_{j \in \{k_i\}} sensed(l,j) \tag{4}$$

Combining Equations (3) and (4), the constraint specifying the sensing rules is denoted by Equation (5) as follows:

$$\begin{aligned} \forall l \in \{L\} \;\; \forall k \in \{K\} \quad sensed(l,k) = \max \Bigg(& \sum_{s \in \{s^k\}} used(l,k,s), \\ & \prod_{j \in \{k_i\}} sensed(l,j) \Bigg) \end{aligned} \tag{5}$$

◇ Sensing from sub-locations: A location may be composed of sub-locations or relatively small locations (Figure 2). Let the set of sub-locations of a location l be represented by $\{subl^l\}$. 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 at location l. For example, consider a room that consists of two zones. If the power consumption of these zones is sensed, then aggregating these values will produce the total power of the room. This constraint is represented by Equation (6) as follows:

$$\begin{aligned} \forall l \in \{L\} \;\; \forall k \in \{K\} \quad sensed(l,k) = \max \Bigg(& \sum_{s \in \{s^k\}} used(l,k,s), \\ & \prod_{sub \in \{subl_l\}} sensed(sub,k) \Bigg) \end{aligned} \tag{6}$$

◇ Limiting the sensors: $limit(s_i^k)$ represents the maximum number of sensors of type s_i sensing factor k that can be deployed in the building. The constraint denoted by Equation (7) ensures that the total number of sensors s_i^k deployed in the optimal sensor allocation does not exceed the provided limit.

$$\forall k \in \{K\} \;\; \forall s \in \{s^k\} \quad \left(\sum_{l \in \{L\}} used(l,k,s) \right) \leq limit(s) \tag{7}$$

4 Results and Discussion

A smart building provides thermal comfort at optimum power consumption based on the occupancy in different building locations using minimum number of sensors. It can be achieved by detecting occupancy, monitoring power and temperature, and accordingly automating the appliances. 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.

4.1 Inputs used for optimal sensor allocation

- Set of Locations $\{L\}$: as represented in Figure 2.
- Factors to Sense: power consumption, number and type of ON appliances, occupancy and temperature.
- Type of Sensors: used to sense the above factors as shown in Table 2.

Table 2 List of sensors for sensing different factors

Sensor Type	**Power Consumption**	**Number and Type of ON Appliances**	**Occupancy**	**Temperature**
Hard Sensor	Smartmeter	Smart Switch	PIR (passive infrared), Camera	Temperature sensor
Soft Sensor (infer from factors)	Number of ON appliances	Occupancy and Temperature	-	-

- Sensing Requirement: All the factors in all the locations, except HVAC room (H), should be sensed. This requirement is specified using Equation (8) as follows:

$$\forall l \in \{L \setminus H\} \;\; \forall k \in \{K\} \quad tosense(l,k) = 1 \tag{8}$$

In HVAC room H, only power consumption should be sensed since the room is never occupied, and sensing other factors is not meaningful. It is specified by Equation (9) as follows:

$$\begin{aligned} tosense(H, power) &= 1, \\ \forall k \in \{K \setminus power\} \quad tosense(L^H, k) &= 0 \end{aligned} \tag{9}$$

4.2 Output

The optimization framework has been implemented in python library PuLP (Mitchell et al., 2011) which is used for solving linear programs. After the inputs are provided to the optimization framework, it implements the objective function Equation (1) and constraint functions (Equation (2) – (7)) to output the optimal sensor allocation for the application area, whose details are summarized in Table 3 and Table 4.

Table 3 *sensed* matrix denoting the factors that are sensable in different locations

Locations	Power	ON Appliances	Occupancy	Temperature
Building B	1	1	1	1
Level L_1	1	1	1	1
Level L_2	1	1	1	1
HVAC room H	1	0	0	0
Small Room SR_1	1	1	1	1
Big Room BR_1	1	1	1	1
Zone Z_{11}	1	1	1	1
Zone Z_{12}	1	1	1	1
Small Room SR_2	1	1	1	1
Big Room BR_2	1	1	1	1
Zone Z_{21}	1	1	1	1
Zone Z_{22}	1	1	1	1

Observing the *sensed* matrix (Table 3), it can be concluded that the sensing requirement of sensing all the factors in all the locations, except HVAC room, is satisfied by the optimization framework. In HVAC room, only power consumption is observed. The details of optimal sensor allocation for satisfying the sensing requirements is denoted by *used* matrix (Table 4) and are explained as follows.

Table 4 *used* matrix denoting the details of sensor allocation

Locations	**Power**	**ON Appliances**	**Occupancy**		**Temperature**
	Smartmeter	**Smart Switch**	**PIR**	**Camera**	**Temperature Sensor**
Building B	0	0	0	0	0
Level L_1	0	0	0	0	0
Level L_2	0	0	0	0	0
HVAC room H	1	0	0	0	0
Small Room SR_1	0	0	1	0	1
Big Room BR_1	0	0	0	0	0
Zone Z_{11}	0	0	1	0	1
Zone Z_{12}	0	0	1	0	1
Small Room SR_2	0	0	1	0	1
Big Room BR_2	0	0	0	0	0
Zone Z_{21}	0	0	1	0	1
Zone Z_{22}	0	0	1	0	1

- Since no soft sensor is available to sense temperature (Table 2), two hard sensors are used to sense the temperature in two small rooms (one for each room) and four sensors for big rooms (one for each zone). In big rooms, the temperature is sensable since temperature of the zones is sensed (Equation (6)). Similarly, the temperature of levels and the building becomes sensable. Thus, a total of six temperature sensors are deployed.
- Occupancy is sensed either by placing a Passive infrared (PIR) sensor or a camera in two small rooms (one for each room) and two big rooms (one for each zone). No soft sensor is used since occupancy cannot be inferred from the other factors in these locations. Using Equation (6), occupancy of big rooms, levels and the building becomes sensable. Therefore, a total of six PIR + camera sensors are deployed.
- 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 (Equation (5)). Therefore, no hard sensor is deployed to sense this factor.

– In the HVAC room, only one smartmeter is allocated to sense power consumption since no other factor is sensed at this location. In all the remaining locations, power consumption is inferred from number and type of ON appliances information using a soft sensor (Equation (5)).

Therefore, to sense the factors in all the locations of the building, only 13 sensors are required as tabulated in Table 5.

Table 5 Sensor allocation for sensing the factors using the optimization framework

Type of Hard Sensor	**Location**	**Number of Sensors Allocated**
Temperature Sensor	$SR_1, Z_{11}, Z_{12}, SR_2, Z_{21}, Z_{22}$	6
PIR or Camera	$SR_1, Z_{11}, Z_{12}, SR_2, Z_{21}, Z_{22}$	6
Smart Switch	–	–
Smartmeter	HVAC Room (H)	1
Total		**13**

However, the effectiveness of the proposed optimization framework is compared with baseline approach for sensor deployment at the same application area. 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 at 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 as shown in Table 6.

Therefore, it can be concluded that the newly developed optimization framework is highly effective as compared to the baseline approach. This is because, to satisfy the same sensing requirements, the baseline approach needs 48 sensors while the newly developed optimization framework requires only 13 sensors, which is about 72.9% savings in the number of sensors to be deployed.

Table 6 Sensor allocation for sensing the factors using the baseline approach

Type of Hard Sensor	Location	Number of Sensors Allocated
Temperature Sensor	$B, L_1, SR_1, BR_1, Z_{11}, Z_{12}, L_2, SR_2, BR_2, Z_{21}, Z_{22}, H$	12
PIR or Camera	$B, L_1, SR_1, BR_1, Z_{11}, Z_{12}, L_2, SR_2, BR_2, Z_{21}, Z_{22}, H$	12
Smart Switch	$B, L_1, SR_1, BR_1, Z_{11}, Z_{12}, L_2, SR_2, BR_2, Z_{21}, Z_{22}, H$	12
Smartmeter	$B, L_1, SR_1, BR_1, Z_{11}, Z_{12}, L_2, SR_2, BR_2, Z_{21}, Z_{22}, H$	12
Total		**48**

Table 7 Sensor allocation for satisfying different sensing requirements

Sensing Requirement	Baseline Approach		Optimization Framework	
	Number of Sensors	Description	Number of Sensors	Description
Sense power consumption (using smartmeters)	12 (smart-meters)	Smartmeters are allocated on all the nodes	7 (smart-meters)	Smartmeters allocated only on leaf nodes
Sense power consumption(temperature and occupancy information is already available)	12 (smart-meters)	Smartmeters are allocated on all the nodes	1 (smart-meter)	1 smartmeter allocated in HVAC room and power inferred from temperature and occupancy in other locations
Sense number of ON appliances using smart switches	12 (smart switch sensors)	Smart switches are allocated on all the nodes	7 (smart switch sensors)	Smart switches allocated only on leaf nodes
Sense number of ON appliances (temperature and occupancy information is already available)	12 (smart switch sensors)	Smart switches are allocated on all the nodes	0	ON appliances inferred from temperature and occupancy in all the locations

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. For example, if this methodology is used for a smart city consisting of one thousand smart buildings of the same size and design (as described in the application area), it will require only thirteen thousand sensors while the baseline approach will require forty-eight thousand sensors, resulting into a net savings of thirty-five thousand sensors. However, in the semi-smart buildings, sometimes it is required to sense only one or two parameters. For example, it may be required to sense only the number of ON appliances at any one time or total power consumption of the building. Under all such scenarios, Table 7 summarizes that the developed optimization framework is very effective as compared to the baseline approach.

It is depicted from Table 7 that for sensing the number of ON appliances, twelve smart switch sensors are required by using the baseline approach. However, using the newly developed optimization framework, only seven smart switch sensors are required. If the information about temperature and occupancy is available, then the optimization framework allocates only one smart switch sensor. Similarly to measure the power consumption, twelve and seven smartmeters are required using the baseline approach and optimization framework, respectively. In presence of temperature and occupancy information, the optimization framework does not deploy any smart switch sensors. Therefore, the newly developed optimization framework is an effective tool to reduce the number of sensors required to make buildings smarter.

5 Conclusion

Various factors such as power consumption, number and type of ON appliances, occupancy and temperature can be sensed using a minimum number of sensors. This can be achieved by using the newly developed optimization framework which is an effective tool to reduce the number of sensors required to sense various factors in a smart building. This optimization framework has been compared with the baseline approach and results are found to be very encouraging. When this technique is applied to an existing building, it requires 72.92% less sensors as compared to the baseline approach. This feature makes it an impressive proposition and leads to a large reduction in e-waste generation. However, if this approach is extended to a smart city, it will not only result in huge savings of sensors, but also lead to huge 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.

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