Wireless Energy Efficient Occupancy-Monitoring System for Smart Buildings

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Abstract

Rationalizing energy consumption in smart buildings is considered in this paper, and a wireless monitoring system based on Passive Infrared sensors (PIRs) is proposed. The proposed system is pervasive and can be integrated in existing buildings without any complicated wiring or setting. Realistic constraints are considered for this purpose such as sensing-hole, battery limitation, user comfort, etc. To ensure maximum coverage in presence of holes, the optimal placement of PIRs is formulated as a mixed integer linear programming optimization problem (MILP). Experimentations have been carried out to quantify the effects of the holes on the detection accuracy and to demonstrate the impact of the optimal PIRs placement on energy consumption. To facilitate installation and integration without complicated settings, notably in existing buildings, the system is designed to be battery operated. Therefore, energy efficiency will not be limited to optimize energy consumption in buildings, but also to optimize consumption in the components of the system (sensors and actuators). Duty cycling is inevitable to extend the network lifetime of such components, but the setting of this cycle yields a trade-off in optimizing the energy consumption i) at the building level, vs., ii) that consumed by sensors and actuators. Reducing energy consumption (duty cycle) of sensors/actuators will delay non-occupancy detections and thus will increase the building energy wastage, and vice-versa. Duty cycling the radios is dealt with and modeled as a cooperative game, which allows to derive a Nash Bargaining as the optimal balancing cycle. The proposed approach is analytically investigated using realistic parameters of the existing hardware and users' comfort. The results demonstrate that the system can survive for more than 6 years without battery replacement.

1. Introduction

Energy consumption in residential and commercial buildings has increased dramatically worldwide in the last decade as an inevitable consequence of the proliferation of electronic and consumer appliances, as well as the constant economic and population growth notably in urban areas. The later cover 2% of the earth's surface but are responsible of 78% world's energy consumption and 60% of CO_2 emission [1]. Buildings are the cause of 40% of the total energy consumption in the US and the EU [2]. Similar figures are reported worldwide, which makes the building sector the main source of energy consumption and expected to remain as such in the next decades [3]. Moreover, it has been estimated that as much as 30-to-50% of the building's energy is wasted due to misuse and non-optimal management [4]. This motivates research efforts towards improving and modernizing Building Energy Management Systems (BEMS) in the last few years. Such systems should have attributes from all facets of building to control and manage functions such as Heating, Ventilation and Air-Conditioning (HVAC), lighting, fire alarm system, etc. An efficient design of BEMS allows to achieve smooth buildings' operations and maximize energy saving while preserving users' comfort. Recent advances in ubiquitous wireless communications and sensing technologies have promoted the deployment of Wireless Sensor Networks (WSNs) in many application areas, including BEMS. Battery operated WSNs add flexibility to BEMS and allow deployment without hard or intrusive installations. This is particularly motivating in old buildings that does not incorporate any intelligent BEMS system. In such buildings, the installation of a BEMS system maybe impossible and very expensive due the lack of the basic standards in the building structure to support such a sophisticated installation and where the modification of the existing structures is usually undesirable. Further, the solution can also be used in modern buildings to reduce cost and facilitate maintenance compared to existing wired BEMS. For instance, when modifying space partitions to make new or extend the size of the offices, additional wiring is required to connect to the existing BEMS. By using our solution, both the installation cost and times are minimized. However, factors such as the use of low cost components (e.g., infra-red sensor for occupancy detection) and supplying the system with batteries raise some design challenges on the system accuracy, reliability and sustainability. Detecting user occupancy in buildings is a fundamental step for reducing wastage of energy and improving users' comfort. In fact, most BEMS in old buildings use a set of predefined actuation schedules for managing electrical appliances, such as HVAC and lights. These schedules have a coarse-grained time dependability that is generally related to static issues such seasons, days of the week, etc. However, by dynamically detecting vacant places, more optimized context-aware schedules can be implemented to shorten the actuation durations without compromising the user's convenience. Many of the solutions proposed for tracking the presence of occupants in buildings are based on the use of passive infrared (PIR) sensors [5], [6], [7], [8], [9]. These sensors are made from inexpensive pyroelectric materials that react to the change of infrared emissions in the environment, which helps in capturing the presence of humans in a specific space. The low cost and low energy consumption of such sensors enable their large use in battery-operated wireless systems. Further, they do not affect the privacy of people, contrary to other sensors such as cameras and microphones. This privacy preservation make such sensors appropriate for monitoring private spaces such as offices, meeting rooms, homes, etc.

However, a major drawback of PIR sensors is the false negatives (non-detection) in some situations. The first reason behind this shortcoming is that these sensors are only capable of detecting motion, but not static bodies. Whilst this does not represent any problem in many premises of buildings where people are moving, such as corridors and near to the doors, it prevents accurate monitoring in places such as offices where workers tend to stay immobile for relatively long periods. To tackle this problem, some solutions have been proposed in the literature that complement the PIRs with information provided by additional sensors. For example, the occupancy detection system proposed by Agarwal et al. [5] is enhanced with a magnetic reed switch sensor that tracks the open/close events of an office door. This information is matched with the output of the PIRs. ThermoSense [8] uses, in addition to a PIR sensor, a thermal sensor array that is able to measure temperatures of a $2.5\ m \times 2.5\ m$ area discretized as a 8×8 grid. Alternatively, some other solutions use other sensing techniques, such as [10]. The second problem is that the sensing area of a typical PIR module is not a contiguous volume, but it includes spaces where changes of infrared emissions are not captured by the sensor. We refer to these uncovered spaces by, *sensing-holes*. The dimensions of these sensing-holes become larger as the distance separating the sensor to the detection zone increases. For instance, with state-of-the-art PIRs, it reaches the scale of a human body movements at a distance of $2\ m$ to $3\ m$, which represents typical hight of ceiling at offices where PIRs are usually installed. Consequently, a PIR cannot detect a person within the sensing-hole even when he performs small movements (e.g., in the office scenario, moving his arms, his head, rotating the chair when sitting, etc.). While it seems infeasible to detect static body only with PIRs (the first problem), it is possible to tackle the second one by investigating the sensing-holes and their impact, and using optimal deployment of PIRs to eliminate/minimize such holes.

In addition to the false negatives, lifetime of battery operated sensor has always been an issue in real deployments. Frequently replacing the batteries after installation is impractical and makes the solution unattractive. The trend in many applications is to use energy harvesting technologies to supply sensor motes. Solar energy is currently the most effective source given its high efficiency as compared to other technologies such as wireless charging. However, this cannot be used for indoor deployment, which features the application considered in this work. A possible alternative in the future will be wireless recharging, but it does not seem possible in the short or mid-term horizon to achieve reasonable charging efficiency with this technology. This makes optimal energy management of batteries the only remaining option. Given that the radio consumes the largest amount of a node's battery [11], the only way to extend the lifetime is to duty-cycle the radio component and repeatedly switching it between active and sleep modes. In active mode, a node can receive and transmit packets, while in the sleep mode, it completely turns off its radio to save energy. Using low cycles with high period of sleep mode trivially allows to extend the battery lifetime but may delay reporting of detections to the control system and/or the appropriate actuator (also called switch-mote in simplified settings), which have undesired effect on the user comfort and/or the BEMS. Whereas high cycles reduces this problem but at the cost of reducing the batteries' lifetime.

In this paper, we tackle all the above mentioned problems and propose an efficient yet low cost occupancy detection system for energy saving in buildings. For occupancy monitoring, the system uses only PIR sensors. This facilitates installation in existing buildings and even in buildings that does not use any BEMS (e.g., in developing countries). The main contribution of this paper are summarized in the following.

- We propose a solution to the occupancy detection accuracy using low cost PIR sensors and formulate the problem of placing minimal number of PIR that maximizes the coverage of the monitoring area with mixed integer linear programming. Realistic features such as sensing holes are considered in the model. A short version of the solution has been already published in [12].
- We consider maximizing system lifetime by duty-cycling different components of the system with the use of PIRs to trigger their wakeup and ensuring user comfort. Without loss of generality, we consider a simple setting in offices with PIRs/light sensors that monitor the occupancy and day light, respectively, and switch actuator that react upon detections. We determine the optimal duty-cycle period that tradeoff the PIR sensor motes lifetime with the switch by defining a cooperative bargaining game model between the two motes. This model allows to derive the Nash Bargaining point as the optimal balancing cycle.
- Analytical and experimental results are provided to validate the proposed approach and empirically demonstrate the efficiency of the solution in saving electrical energy while ensuring user comfort.

The remaining of the paper is organized as follows. Sec. 2 states some existing electrical energy management systems and sensor based solutions. Sec. 3 presents the proposed solutions for the occupancy monitoring system, starting with a general overview of the proposed system in Sec. 3.1, followed by the occupancy detection in Sec. 3.2, and then the duty-cycling solution, in Sec. 3.4, which has been proposed for extending the system lifetime. The proposed game theory-based model of duty-cycle balancing with the different experiments results are presented in Sec. 4. Finally, Sec. 5 draws the conclusions.

2. Related Work

Energy saving in smart buildings is emerging as a hot research topic. The study in [13] has examined the possible energy saving opportunities in modern buildings. The authors have estimated potential energy saving in a large university campus to be 80% for lighting, 60% for computing, 50% for server rooms, and 20% for mechanical loads. Reena et al. [14] have showed that there is an increasing need to deploy wireless based building automation system when (i) wiring is time-consuming and too expensive, (ii) scalability and flexibility are necessary, and (iii) redeployment or alteration is needed without affecting the aesthetics of existing buildings. Various wireless energy control systems have been developed in the last few years [7, 5, 15, 16, 17]. Most of these system try to adapt automation to individual behavior patterns and accordingly mimic the energy saving policy. The first step is to have an efficient occupancy detection. Several occupancy detection systems have been proposed; using camera [18], PIR sensors [5], [15], [12], ultrasonic [19], carbon-dioxide (CO2) sensors [20], RFID [21], WiFi [22], etc. PIR-based occupancy detection is a low power, low cost approach, and it preserves people privacy. This make it suitable for building applications. The authors in [5] have developed a PIR-based wireless presence sensor platform to report the occupancy state in an existing building. An additional magnetic reed door switch sensor has been used to improve accuracy. The authors have estimated the battery lifetime of the occupancy detection module alone to be over five years. This estimation is reasonable as the system is not interacting with a remote actuator and stays most of the time in power save mode, and it only wakes upon occupancy detection. However, this estimation is not accurate when the system interacts with actuation and control units (HVAC control or lighting), where battery depletion would be much faster. In [7], reactive and predictive strategies have been examined to control an HVAC system within residential buildings using PIR-sensors. Based on a Hidden Markov Model, the predictive strategy is determined and probabilities of different possible home states are estimated. By testing the system in 8 homes, the authors demonstrated that the system can achieve a 28% energy saving on average. In [17], a PIR based wireless lighting control system has been developed. It allows the users to manually configure the time out, i.e. the continuous period of non-movement before claiming non-occupancy of the monitored space. Optimal setting of this parameter is important to avoid reporting false negatives, i.e. claiming unoccupied state while the space is occupied by a static user (users with small or less movement), who cannot be captured by the PIR motion sensor. However, this manual configuration overwhelms the user and does not allow to get optimal values. For more details about occupancy detection systems, we refer the reader to a recent survey given in [23].

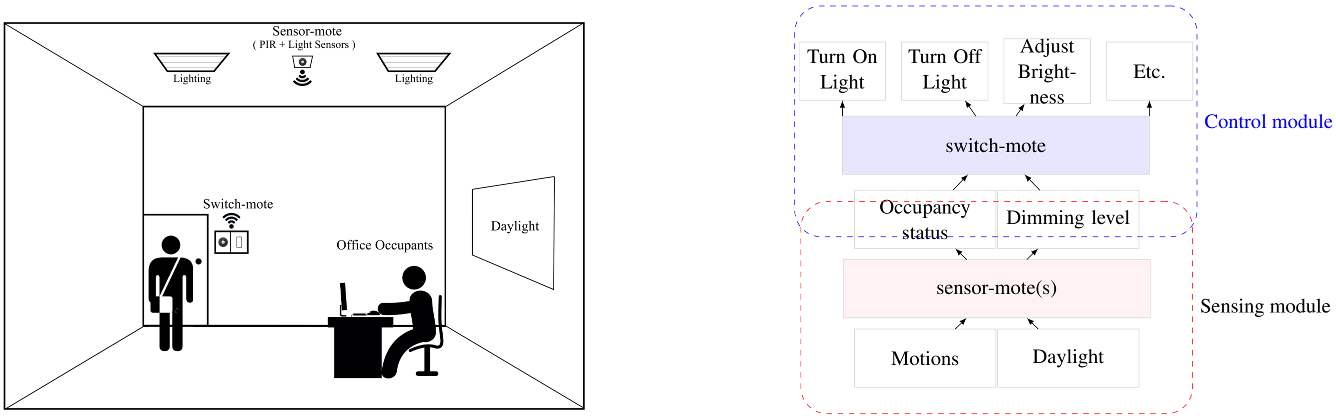
While most works on building power management have been focusing on electrical energy saving or users' comfort, few works have considered the lifetime of the deployed system. Guinard et al. [24, 25] have presented a WSN design tool for optimal sensor node placement within the monitored building by maximizing a utility function that captures both building energy efficiency and wireless network performances. However, the latter focuses only on the communication and sensing performances without considering the network lifetime. Aftab et al. [26] proposed an online algorithm to balance the lifetime of wireless sensors and the effective temperature control. The problem is formulated as an optimization problem that maintains thermal comfort within the building, while maximizing the battery lifetime of sensor devices. The wireless sensor decides, according to the fluctuation in ambient temperature, to update transmission frequency of new values in such a way that the amount of the communicated information is minimized. Mady et al. [27] have developed a building lighting control system and proposed an analytical model for the network design by considering the cost and the Quality of Control (QoC) metrics. The cost of each node includes CPU, buffer and battery usage. Although the battery usage in communication is modeled based on a given MAC protocol, the authors have not considered the radio duty-cycle parameter optimization that has been assumed to be fixed. For instance, the LPL (Low Power Listening) protocol, also known as BoX-MAC and considered as the canonical energy efficient MAC implemented in TinyOS stack protocols[1], sets the radio duty-cycle parameter to 2% (i.e. carrier sensing is performed 4ms each 2 seconds) regardless of the devices' packet exchange rate. This leaves room for further improvement by appropriately setting this parameter.

The only notable efforts to extended the WSN lifetime have been mainly devoted to address energy efficiency by optimizing MAC protocols following pure experimental approaches or protocol modeling, such as using Markov models [28, 29]. Other solutions have considered MAC parameters optimization under some performance metrics such as reliability and latency [30, 31]. However, in these works, the optimization parameters have been designed independently of the different application objectives such as electrical energy saving and users' comfort. Game theoretical models are appealing approaches in multi-objective optimization, and they are widely applied in economics and in network resource allocation to address tradeoff between conflicting application objectives [32, 33]. In this work, we consider the tradeoff between the building's energy, the occupancy accuracy and the system lifetime and we try to jointly optimize these parameters by applying a Bargaining cooperative game in building energy management to balance performance objectives of the system.

[1] http://tinyos.stanford.edu/tinyos-wiki/index.php/CC2420_Asynchronous_Low_Power_Listening_Implementation

3. The Proposed Power Management System

3.1. Overview



(a) (b)

Figure 1: Building energy control system: (a) An office equipped with a sensor-mote and switch-mote to control the light. (b) Logical view of the different modules of the system.

We consider a typical electrical energy control system that mainly consists of occupancy detection sensors, electrical power actuators, and a central control unit. The occupancy sensors are responsible of reporting the occupancy state of the area/room where are deployed, to the central control unit. Once received by the control unit, the occupancy states are translated to an action that is transmitted to actuators to turning On/Off appliances or adjusting the heating or the cooling temperature of an HVAC system. Without loss of generality and for the purpose of illustrating the proposed methods in real application, we consider an automatic lighting control system. However, the proposed solutions can be applied to any control system that is occupancy-based. This choice is motivated by the ubiquity of the light control systems, as well as the high ratio of energy consumed for lighting, estimated at 39% of annual electricity use in buildings [3], which justifies the usefulness of the proposed application. We consider the scenario of an office as depicted in Fig.1(a). The goal is to eliminate energy wastage by switching off the light, often forgotten On, when employees leave their offices. The system should turns on the light once offices become occupied. To meet the user comfort, this action should take place *immediately* or at a very low latency (at a sub-second scale) after the occupant enters. In this system, the occupancy detection module (that we call the sensor-mote) is equipped with a passive infrared (PIR) sensor. It is placed on the ceiling of the office to monitor people movements and activities. Whenever a new occupancy state is detected by the sensor, the sensor-mote reports the new state using wireless communication to the controller (switch-mote) that commands the light switch. We also embed the sensor-mote with a light sensor that measures ambient light in the office. The light sensor allow to tune the control system by turning On/Off the

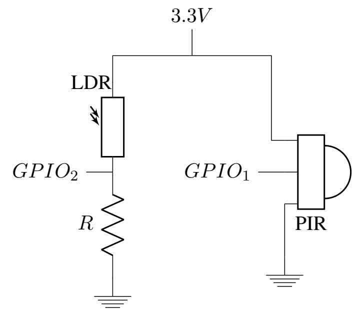


Figure 2: Sensing module circuit

light with respect to the available ambient light. Dimming in accordance with the ambient light is also possible but is not considered in our study. The switch-mote can be located anywhere in the office or incorporated with the light switcher, which is generally placed on the wall at the office entrance. Fig. 1(b) illustrates the logical view of the system and shows the different modules and their corresponding input and output.

In addition to the objectives related to electrical energy saving and users' comfort, providing a cost-effective occupancy detection and ensuring long lifetime to the sensing/actuating system are other objectives that elevate the complexity of the problem, but essential to make the solution reliable. The objectives are conflicting; deploying few number of low-cost sensors reduces the system cost but will have a negative impact on the accuracy of the occupancy detection, and therefore it will reduce the amount of energy saving and adversely affect the users' comfort level. Further, using a low duty-cycle (inactive radio for long period) will significantly increases the system lifetime but might delay reports on occupancy detection and thus the relevant actuation, which impacts the user comfort. Our aim is to propose solutions that balance these conflicting objectives. A low-cost electronic system has been developed for each module, which is described hereafter.

3.1.1. Sensing Module

The circuit of the sensing module integrates a PIR sensor and a Light Dependent Resistor (LDR) sensor, which allow the detection of moving people and ambient light, respectively. The used sensors are small in size, consume very low-power, and inexpensive. The resistive value of the LDR sensor depends on its illumination. The LDR connects to a Potential Divider (PD) as shown in Figure 2. This circuit outputs a high voltage when the LDR is exposed to the light, and a low voltage when the LDR is in dark conditions. The output voltage of the potential divider was converted into a digital value by the ADC of the sensor-mote.

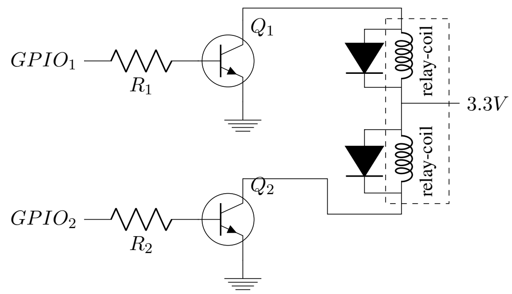


Figure 3: Control module circuit

3.1.2. Control Module

The control module is equipped with a latching (stay) relay that can maintains its state indefinitely without power. The latching relay is the most suitable for our energy-saving application as it consumes very low power. The Panasonic DS1E-SL2-DC3V relay has been chosen, which allows activation by pulse, and has zero power consumption after activation. The pulses (ON) and (Off) are generated by the two transistors, Q_1 and O_2 that are controlled through $GPIO_1$ and $GPIO_2$ of the switch-mote, as shown in Figure 3.

3.2. Occupancy Detection

3.2.1. Background and Problem Statement

PIRs are low-power PIR sensors that use pyroelectric transducers that convert infrared radiations into electrical signals. To increase the PIR sensitivity, a Fresnel lens is used. It concentrates infrared radiations onto the detector. This results in a field-of-view (FoV) that is more like a discrete set of beams or cones with many *sensing-holes*. To be detected, the movements of the person should take place within the FoV. Fig. 4(a) illustrates the different types of motion made by a human and the corresponding maximum sensing-hole size for which the motion can be detected by a PIR [34]. The sensing-holes should not exceed $0.6\ m$ to ensure an efficient detection of a sitting person's hand motions. The size and distribution of the holes impact the granularity of the PIR detections. Fig. 4(b) illustrates the projection of the actual FoV of a Panasonic EKMB PIR sensor on a two dimensional plane [35]. The PIR is placed at the ceiling of an office and the projection is performed on the plane parallel to the ground and elevated at a typical height of desks, where most of persons' low movement activities take place (e.g. arm and hand movement when sitting). The figure shows the presence of several sensing-holes that represent more than 87% of the total monitored office area, and their sizes vary from one region to another within the PIR's FoV. They may exceed $1\ m$ in some places. These large sensing-holes may affect PIR-based occupancy detection systems and cause incorrect decisions, such as turning off a light or HVAC in the presence of a person, which limit the credibility of the system.

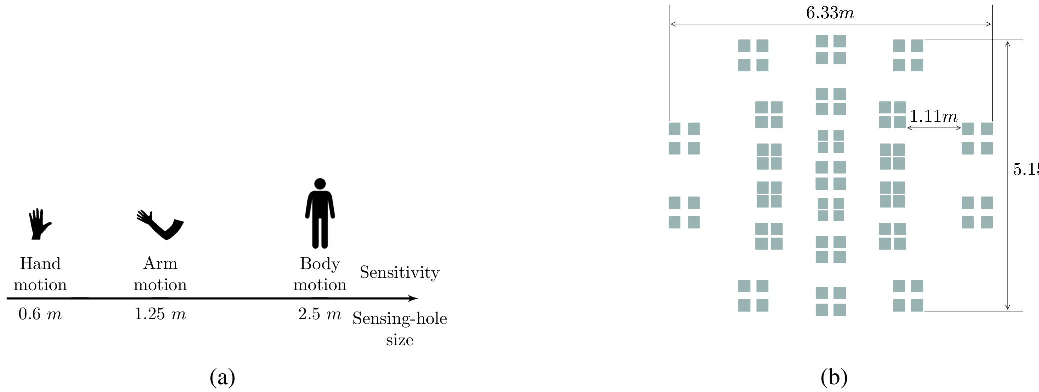


Figure 4: (a) The relation between the size of sensing-holes and motion sensitivity. (b) 2D view of a PIR Field-of-View. Solid rectangles represent detection zones.

3.2.2. Problem Formulation

In the following, we define the *Maximal PIR Coverage* (MPC) problem that finds the optimal positions of the PIRs for maximum coverage in the area of interest while considering the sensing-hole. To simplify the formulation, we consider the projection of the covered area on a two dimensional plane as explained before. Despite such simplification, the computation of the detection zones for a given set of PIRs is difficult to formulate mathematically. The monitored area is discretized and considered as a set of points, where a point will be considered covered iff it is within the coverage zone of at least one PIR.

Let D denotes the two dimensional space to be monitored by a set, S, of PIRs. For the sake of simplicity, we assume that D has a rectangular shape of width W and length L. The problem is discretized by dividing D using a step l, which results in a grid of points $\tilde{D} = \{(il + \frac{l}{2}, jl + \frac{l}{2}) \mid 0 \leq i \leq \lfloor \frac{W}{l} \rfloor \wedge 0 \leq j \leq \lfloor \frac{L}{l} \rfloor\}$. In general, the density of persons in the space $\tilde{D}$ is not homogeneously distributed and obstacles (e.g., bookshelf, desks, table, etc.) are present. Therefore, we introduce a weighting matrix $\Phi_{(x,y)\in\tilde{D}}$ that enriches the geometric deployment space with a semantic dimension indicating the places where people are more likely to be detected. This is by given, i) a high weight to areas where people are likely to stay and exhibit low movement activity once there (e.g., area of a desk chair, meeting table chairs), ii) a zero weight at obstacles (e.g., bookshelf, table, etc.), and iii) a regular weight elsewhere where people are likely to move. We assume that PIRs are placed on the ceil of the deployment area without any rotation. Consequently, the detection zones of any PIR, $s \in S$, will have a rectangular shape and can be modeled by a set $Z_s \subseteq \mathbb{R}^4$, where a tuple, $(x_0^i, x_1^i, y_0^i, y_1^i) \in Z_s$, denotes the boundaries of a single detection zone, z_i, on the X and Y, when s is placed at the origin $(0,0)$. The consequence of a change in the PIR coordinate from the origin, say to the position (X_s, Y_s), is a simple translation of the zone, z_i, on the abscissa and ordinate axes, by, X_s, and Y_s, respectively. The MPC problem is then formalized as a mixed integer linear problem (MILP) as follows. We define the decision variables X_s and Y_s for denoting the coordinates of a PIR $s \in S$, and the binary decision variables $C_{(x,y)}$ that indicate wether the point $(x, y) \in \tilde{D}$ is covered by at least one PIR or not. The problem is formulated with the following mixed linear problem:

$$\max \sum_{(x,y)\in\tilde{D}} \Phi_{(x,y)} C_{(x,y)}, \tag{1}$$

s.t.

$$\begin{aligned} &\forall(x,y) \in \tilde{D}: \quad C_{(x,y)} = 0 \vee \\ &\exists s \in S, \exists(x_0^i, x_1^i, y_0^i, y_1^i) \in Z_s: \\ &\quad (X_s + x_0^i \leq x \leq X_s + x_1^i) \wedge \ (Y_s + y_0^i \leq x \leq Y_s + y_1^i) \end{aligned} \tag{2}$$

$$\forall s \in S: \quad (0 \leq X_s \leq W) \wedge (0 \leq Y_s \leq L) \tag{3}$$

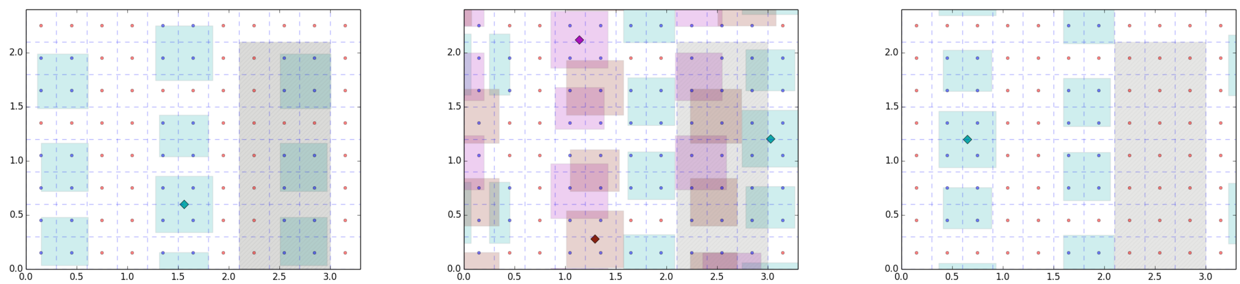
The first constraint formalizes that $C_{(x,y)} = 1$ iff there is at least one detection zone of a sensor, s, that covers the point (x, y), while the second restricts the coordinates of the sensors within the deployment area.

To eliminate the operators $\exists$ and $\vee$ in Eq. (2) and transform the MILP into a standard form that can be handled by solvers, we use the big-M method [36]. Artificial binary variables $W_{x,y,s,z}$ are introduced for each constraint in Eq. (2), and a sufficiently large number M is associated with $W_{x,y,s,z}$. On application of the Big-M method, the previous optimization problem transformed into,

$$\begin{aligned} &\forall(x,y) \in \tilde{D} : \forall s \in S : \forall(x_0^i, x_1^i, y_0^i, y_1^i) \in Z_s : \\ &\quad (C_{(x,y)}\ x) - X_s - x_1^i \leq (1 - W_{x,y,s,z})\ M \wedge \\ &\quad (C_{(x,y)}\ y) - Y_s - y_1^i \leq (1 - W_{x,y,s,z})\ M \wedge \\ &\quad X_s + x_0^i - \big(x + (1 - C_{(x,y)})\ M\big) \leq (1 - W_{x,y,s,z})\ M \wedge \\ &\quad Y_s + y_0^i - \big(y + (1 - C_{(x,y)})\ M\big) \leq (1 - W_{x,y,s,z})\ M, \end{aligned} \tag{4}$$

$$\forall(x,y) \in \tilde{D}: \sum_{(s,z)\in S*Z} W_{x,y,s,z} \geq 1, \tag{5}$$

$$\forall s \in S: \quad (0 \leq X_s \leq W) \wedge (0 \leq Y_s \leq L). \tag{6}$$



(a) (b) (c)

Figure 5: Three deployments scenarios considered during the experimentation. Circle points represent the discrete grid of the deployment area and diamond points represent the PIRs. The gray zone delimits the place of the office's desk, which has been given a greater weight in Φ. (a) Optimal deployment with one PIR. (b) Optimal deployment with three PIRs ensuring full coverage of the desk's area. (c) Hole-unaware deployment where the desk area is completely uncovered.

3.3. Experiments

We have deployed an experimental PIR-based occupancy detection system to monitor an office and quantify the impact of the sensing-holes on the performances of the system. The experiments were performed using the EKMB PIR sensors from Panasonic, integrated to an nRF51-based mote by Nordic Semiconductors, which features a low-power SoC that embeds an ARM Cortex-M0 MCU, and a $2.4GHz$ wireless transceiver. The considered deployment area is a single-occupant office of $3.3 \times 2.4\ m^2$. Most activities are concentrated over the office desk that received greater weights in the matrix Φ. The discretization step[2] l was fixed to $0.3\ m$ resulting in a grid of 11×8 points. While the all the office space fall within the sensing range, the real covered space is not the continuous space over this range but includes gaps (sensing-holes), and it might be represented as a set of discontinued squares (Sec. 3.2). Three deployments scenarios have been evaluated. The first one corresponds to the optimal solution of the MPC problem when using one PIR. As shown in Fig. 5(a), this deployment covers nearly 63% of the desk's area. Optimal full coverage of this space is ensured with 3 PIRs, which corresponds to our second deployment scenario depicted in Fig. 5(b). In the third scenario, a single PIR was placed in a way to put the largest holes at the desk area as shown in Fig. 5(c). It shows the real impact of sensing-holes on the performances of the detection system. It is worth noting that existing solutions consider the deployment represented by the third scenario as optimal since they ignore the presence of the sensing-holes and consider the PIR covers the whole space within its sensing range (all the office).

The deployed motes actively monitor the state of the PIR and notify a central base station about any detection event. The latter maintains a database for logging the incoming sensory data along with ground truth presence/absence

[2]The discretization here is made only to decrease the complexity of searching the optimal solution.

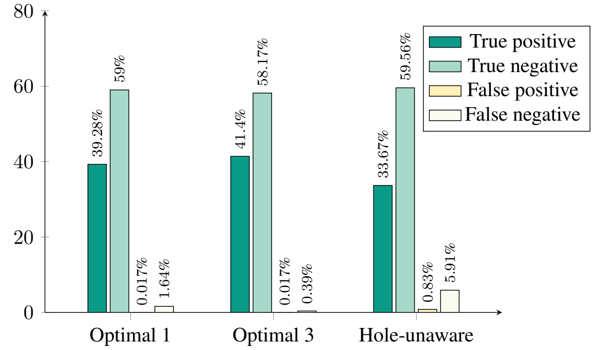


Figure 6: Experimental results for the three scenarios: Time proportion for the different cases of detection based on raw data.

Predicated	Actual: Presence	Actual: Absence	Total
Presence	TP = 39.28%	FP = 0.017%	39.29%
Absence	FN = 1.64%	TN = 59%	60.64%
Total	40.92%	59.017%	

(a) Optimal 1

Predicated	Actual: Presence	Actual: Absence	Total
Presence	TP = 41.4%	FP = 0.017%	41.41%
Absence	FN = 0.39%	TN = 58.17%	58.56%
Total	41.79%	58.187%	

(b) Optimal 3

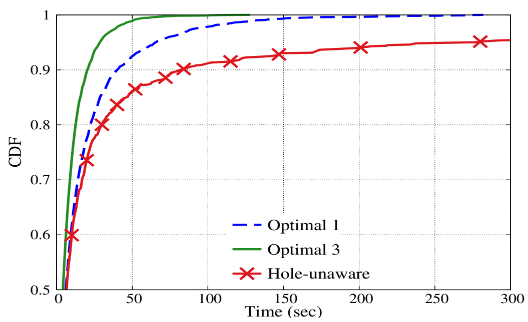
Predicated	Actual: Presence	Actual: Absence	Total
Presence	TP = 33.67%	FP = 0.83%	34.5%
Absence	FN = 5.91%	TN = 59.56%	65.47%
Total	39.58%	60.39%	

(c) Hole-unaware

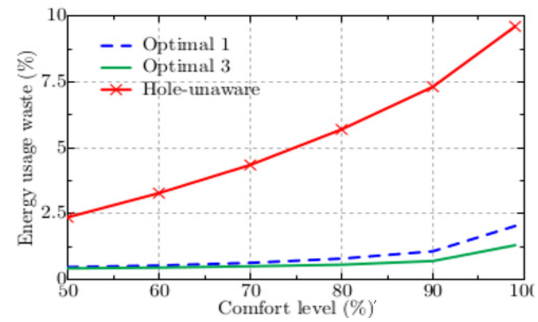
Figure 7: Confusion matrix for the three scenarios: Time proportion for the different cases of detection based on raw data.

intervals, which are provided manually by occupants. To accurately capture the real occupancy state of the office (ground truth), two push buttons wired to the base station are made available at the entrance of the office. For practicality, one button is labeled ”ENTER” with green color, and the other ”EXIT” with red color. When a person enter (resp. exit) the office, he must push the green (resp. red) button to increment (resp. decrements) the number of office occupants. The experiments were performed over a period of three months. The obtained results are depicted in Fig. 6 and the confusion matrices (Fig. 7) that summarizes, for the three deployment scenarios, the ratios of the reported detections: true presence (TP), true absence (TA), false presence (FP), and false absence (FA). The results confirm that taking into consideration the presence of sensing-holes helps in reducing the FA, i.e. the system is able to capture more occupant movements. However, these results represent the distribution of the *raw data* collected from PIRs and cannot be used as a reliable indication of absence. As the PIR signal fluctuates significantly when occupants are moving, detection systems generally implement a filtering mechanism to smooth the collected raw data. The filter is based on a timeout mechanism that is launched when no motion is detected, which delays the decision about absence detection to overcome FA.

To evaluate the performance of the system in the different deployment scenarios and under different timeout values, we have measured two metrics, (i) the *comfort level*, and (ii) the *waste in energy usage*. The first metric quantifies the ability of the system to preserve the convenience of users, that is, the ability not to disturb the occupants by keeping office energy supply on when they are present in the target area (i.e. ability to overcome FA). The second metric reflects the proportion of time the system fails to effectively detect (or react to) the absence of occupants, which



(a)



(b)

Figure 8: (a) The Cumulative Distribution Function (CDF) of correct absence decisions in function of times. (b) The variation of the energy waste for different levels of users' comfort using a timeout smoothing.

implies a missed opportunity to reduce the energy consumption. Before presenting the results related to these metrics, we First plot the Cumulative Distribution Function (CDF) of correct absence decisions as a function of the required time (time out) to take that decision (Fig. 8(a)). The results in Fig. 8(a) shows fast convergence of the proposed solution vs. hole-unaware deployment, and they help in selecting the corresponding timeout to achieve a particular TA probability (percentage). For instance, to realize 90% of TA, according to Fig. 8(a), the timeout should be set to $20sec$, $35sec$ and $80sec$ for optimal3, optimal1, and hole-unaware deployment scenarios, respectively.

Formally, the comfort level $\mathcal{C}$ and the energy usage waste $\mathcal{W}$ are computed as follows:

$$\mathcal{C} = \frac{\mathbb{T}_P}{\mathbb{T}_P + \mathbb{F}_A}, \mathcal{W} = \frac{\mathbb{F}_P}{\mathbb{F}_P + \mathbb{T}_A},$$

where $\mathbb{T}_P$ (respectively $\mathbb{F}_P$) denotes the total durations of TP (respectively FP), and $\mathbb{T}_A$ (respectively $\mathbb{F}_A$) denotes the total durations of TA (respectively FA).

For every deployment scenario, the value of the absence timeout has been varied, and $\mathcal{C}$, $\mathcal{W}$ have been measured for every case. Fig. 8(b) shows the variation of the observed usage waste for different levels of comfort. The results clearly show that the energy waste for the hole-unaware deployment is remarkably higher than for the proposed solution, and it considerably grows with comfort level (in case of hole-anware). In fact, to ensure a high level of comfort in the presence of sensing-holes, absence decisions need to be delayed for long periods (high timeout). This is explained by the fact that these zones hamper the proper capture of small movements, which increases the time required to catch such events. The consequence of high values of the timeout is that occupants leaving the office are not timely detected (reported), which causes energy waste.

We can also notice from Fig. 8(b) that the performances of the optimal solution using only one PIR are very close to the optimal full coverage solution using three PIRs. This is as the fact the first deployment covers an important proportion of the chair-side of the office desk. This result demonstrates that it is important to properly construct the Φ matrix in order to focus the optimization problem on the most relevant spaces which helps reducing the number of required sensors.

3.4. Extending System Lifetime

As the proposed control system rely on battery-operated sensor motes, it is important to optimize the battery power usage. Each mote should switch to power-save mode during inactivity periods. Table 1 reports the power consumption of the different components of a Nordic Beacon platform [37], used in the experiments. By comparing the energy consumptions presented in this table, we conclude that the radio is the most energy hungry component. Therefore, the medium access control (MAC) protocol plays a key role in extending the system lifetime, by controlling the radio states and by employing low duty-cycles. In our occupancy detection scenario, the sensor-mote requires to report its new PIR or ambient light readings to the switch-mote to *instantly* turn on the light when the space becomes occupied or when the ambient light level becomes undesired. Instantaneous reporting is required to meet the expected users' comfort. Because the moment when the occupancy state changes is unknown, the radio transceiver of the switch-mote should be always in standby (receive mode). This causes waste of an important amount of energy given that consumption in the reception mode is significant (see table 1). The trivial solution to this problem is by implementing a low duty-cycle MAC protocol, where energy saving is achieved by repeatedly switching the radio between active and sleep modes (duty-cycling). In active mode, a node can receive and transmit packets, while in the sleep mode, it completely turns off its radio to save energy.

Many energy efficient duty-cycled MAC have been proposed and implemented in current sensor operating systems such as LPL [38] and ContikiMAC [39]. Considering the use of a typical LPL MAC in our solution. In this case, a switch-mote turns off its RF module most of time during T (the wakeup period) to maximize the lifetime as shown in Fig. 9.(a). To enable sensor-motes to communicate with the Switch (actuator), it is required to 'capture' the active time when a switch-mote wakes-up to sense the channel during T_{cs} (see Fig.9.(a). The sensor-mote does not have any knowledge on the receiver active time, and thus to send the detected presence or the absence state it has to turn on its radio and waits actively by transmitting a preamble (a packetized preamble used in LPL [38]) until meeting the switch-mote active period. A long wakeup period allows the switch-mote to save a considerable amount of energy but certainly impact the users' comfort parameter as it delays the light turning on. The wakeup period T should be carefully selected in order to maintain an acceptable users' comfort level. To enable the switch-mote to turn on the

Table 1: CPU, PIR, and Radio Power Consumption for NORDIC BEACON platform [37]

	CPU	**PIR Sensor**	**Light Sensor**	**Radio**
Specification	ARM Cortex-M0 MCU	Panasonic EKMB PIR	PDV-P8001 LDR	nRF51 2.4 GHz
Power Consumption	2.3 μA Power save 3.1 μA Oscillator on	1 μA Inactive 100 μA Active	430 μA ADC read	10.5 mA TX 13 mA RX

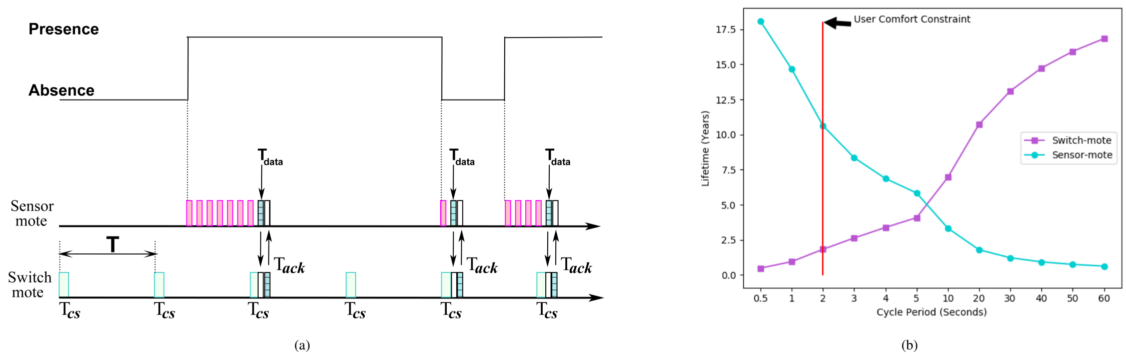


Figure 9: (a) The communication scheme using duty-cycled MAC based solution, (b) The sensor-mote and the switch-mote lifetime for different values of the wakeup cycle T.

light within an acceptable time, say ϵ time units after the space becomes occupied, the T period must not exceed ϵ.

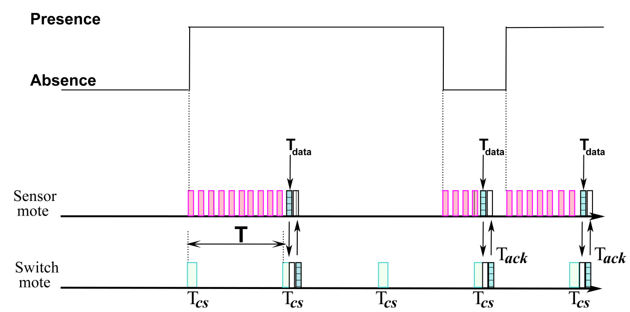
To assess the system lifetime when using existing duty-cycled MAC solutions (LPL used for illustration), we calculated the average energy consumption of the system according to the communication scheme depicted in Fig. 9.(a). According to the absence/presence profile recorded by our installed light control prototype during one month, the sensor-mote turns on its transceiver and sends the new occupancy state to the switch-mote (once detecting that the space becomes occupied or when a new ambient light reading becomes available). To ensure that this new state will be received by the switch-mote, the sensor-mote repeatedly retransmits this message along the period of the T till receiving the acknowledgement from the Switch. The same thing happen when the space becomes unoccupied.

We plotted the lifetime of the sensor-mote and the switch-mote as a function of the wakeup period T in Fig. 9.(b). The users' comfort latency constraint (ϵ) has been set to $2sec$. The results show that the switch-mote lifetime increases as the wakeup period become longer. However, due to comfort constraint, the switch-mote lifetime cannot exceed 1 year and few months. This highly limits the suitability of existing duty-cycled MAC solution to our light control system.

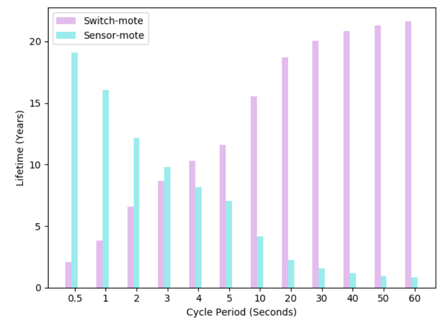
In order to ensure the users' comfort required by the automatic light control system and extend its lifetime, we propose to embed the switch-mote with a low cost PIR sensor. The later will be responsible of triggering the switch-mote once a movement is detected. By placing the switch-mote within the light-switch, next to the space entry, the new PIR sensor will be able to capture any entry and thus, enable the system to *instantly* turn on the light when the space becomes occupied. In this case, the switch-mote's transceiver can be turned off without affecting the users' comfort requirement. However, because the FoV of the new PIR sensor used by the switch-mote is mainly directed towards the space entrance, the latter cannot autonomously determine if the space is actually unoccupied (i.e. cannot rely on its PIR for that). This information can be only provided by the sensor-motes that have an appropriate coverage of the monitored space. As depicted in Fig. 10.(a), both the sensor-mote and switch-mote are in power save mode with the radio turned off when the office is unoccupied. When a person enter the office, the new PIR sensor will trigger the switch-mote to immediately turn on the light and start duty-cycling the radio to receive occupancy state or ambient light reading from the sensor-mote. Whenever the later detects the activity in the office or read a new light value, it will activate its radio and start sending the new information to the switch-mote using the packetized preamble model similarly to the LPL scheme. The switch-mote keeps duty-cycling its radio until receiving an absence state. The sensor-mote returns to sleep mode after sending the new state. When an absence is detected, the sensor-mote reactivates its radio and reports the switch-mote in order to turn off the light and enable it go to sleep mode to save energy. The duty cycle period of the switch-mote (T) has a conversely effect on the two motes' lifetime as depicted in Fig. 10.(a). In addition to the instantaneous turning on of the light upon occupancy (as explained above), the figure shows that the proposed solution allows to prolong the lifetime of both motes. For instance setting T to $2sec$ enables to reach a lifetime of more than 6 years for the switch-mote, and more than 12 years for the sensor-mote (vs. less than 2 years and 11 years, respectively, when using LPL as depicted in Fig. 9.(b)). But the figure shows a clear trade-off due to the conversely effect of the period T, i.e. sensor-mote's lifetime decreases with T because of the rise of the number of packetized preamble transmissions, while the switch-mote's lifetime increases proportionally with T because of the reduction of time spent in idle listening. Optimal balancing these two performance metrics (sensor-mote lifetime vs. switch-mote life time) will dealt with in the next section.

4. Parameter Optimization

To calculate the optimal value of the wake-up period (T) that enables making a balance between the sensor-mote lifetime and that of the switch-mote, we formulate the problem using game theory modeling. We use the Bargaining model to define our two-player game. Instead of defining the individual nodes as players– which is common in the literature [32, 33]– The game players in our model are the systems objectives (sensor-mote and switch-mote lifetime). This limits the number of players and makes it independent from the problem size, which is scalable. The utility



(a)



(b)

Figure 10: (a) The communication scheme using duty-cycled MAC based solution, (b) The sensor-mote and the switch-mote lifetime for different values of the wakeup cycle T.

function of each player is used by the model to determine the optimal wakeup period parameter, T^*. Each player threats the other with using his best optimal point obtained from a non-cooperative game in which the player finds his best optimal operating value, i.e. player sensor-mote obtains its longest lifetime at the cost of decreasing the switch mote and vis versa. A bargaining game is then defined in order to find an agreement operational point that satisfies both players. The different components of the game are introduced in the following.

4.1. Utility Function

The utility function represents the lifetime that each player tends to maximize. For the sake of simplicity, we consider the cost function of each player instead of its utility in order to obtain a convex form of the optimization problem. The two functions are just reversely dependent. The cost function is expressed by the energy consumption of the mote that can be represented by the effective duty cycle, i.e. the fraction of time the component is switched on during a period of time. This period has been set to one working day in in our experiments that will be presented later.

Given the current draws in each operating mode, the mote's lifetime can be easily expressed as a function of the duty-cycle. Let Q be the battery capacity measured in mAh, DC_k, the duty-cycle of the mote in an operating mode k, and I_k, the current draws in each operating mode. Then the device lifetime would be,

$$\text{Lifetime} = \frac{Q}{\sum_k \Big(DC_k \times I_k \Big)}. \tag{7}$$

The energy consumption is expressed in the following as the cost function of each player:

Table 2: Symbols used in sensor-mote & switch-mote cost functions

Symbol	Description	Values	Symbol	Description	Values
T_{lig}	Time to read from Ambient light sensor [s]	0.001	I_{sens}	Current draws in light sensor reading [μA]	430 + I_{ps}
T_{occ}	Occupancy event processing duration [s]	0.01	I_{evt}	Current draws in event processing [μA]	100 + I_{ps}
T_{sw}	Time to perform light switching [s]	1.0	I_{sw}	Current draws in light switching [μA]	120 + I_{ps}
T_{up}	Radio wakeup time [ms]	0.130	I_{up}	Current draws in radio startup [mA]	8.7 + I_{ps}
T_{data}	Data packet transmission time [s]	128/250 [Bytes]/[kbits/s]	I_{tx}	Current draws in transmission [mA]	10.5 + I_{ps}
T_{ack}	Ack transmission time [s]	14/250 [Bytes]/[kbits]	I_{rx}	Current draws in reception [mA]	13 + I_{ps}
T_{ifs}	Inter frame space duration [ms]	0.640	I_{ps}	Current draws in power save mode [μA]	4.1
T_{pre}	Preamble transmission time [s]	T_{data}			
T_{lis}	Time to listen to early Ack [s]	T_{ifs} + T_{ack}			
T_{cs}	Channel sensing time [s]	$T_{up}+3/2*(T_{pre}+T_{lis})$			

4.1.1. Sensor-mote Energy

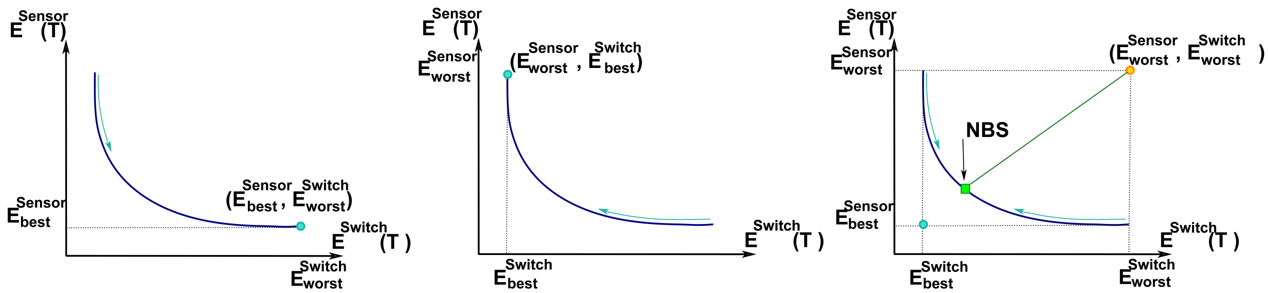
The sensor-mote spends its energy in, i) processing for the occupancy event detection, T_{occ}, ii) processing for ambient light reading, T_{lig}, iii) transmission when a new occupancy is detected, T_{tx}, iv) receiving acknowledgment T_{rx}, c) and in power save mode, T_{ps}. Given the wakeup period, T, and the number of retransmissions, N_{rtx}, the time to transmit a data packet using LPL MAC may be expressed by, [40],

$$T_{tx} = N_{rtx} \times \lceil \frac{T}{T_{pre} + T_{lis}} \rceil \times T_{\text{data}}, \tag{8}$$

where T_{pre} is the time for preamble transmission and, T_{lis} is the listen time to the early acknowledgment. Explanation of each term appearing in equations is provided in Table 2. The sensor-mote cost function is thus expressed by,

$$\begin{aligned} E_{Sensor} = {} & N_{occ}\, T_{occ}\, I_{evt} + N_{lig}\, T_{lig}\, I_{sens} + N_{tx}\, T_{tx}\, I_{tx} + \\ & N_{rx}\, T_{rx}\, I_{rx} + T_{ps}\, I_{ps} \end{aligned} \tag{9}$$

where N_{occ}, N_{lig}, N_{tx}, and N_{rx} denote the numbers of, occupancy detections, light readings, packets transmissions, and packet receptions, respectively.



(a) (P1) (b) (P2) (c) (NBS)

Figure 11: (a) Sensor-mote cost minimization, (b) Switch-mote cost minimization, and (c) NBS trade-off solution. and NBS solution.

4.1.2. Switch-mote Energy

Similarly, the energy consumption of the switch-mote is the energy spent in, i) processing the triggered event detection, T_{occ}, ii) periodic channel sensing for eventual sensor-motes packets reception, T_{cs}, iii) acknowledgment transmission T_{ack}, iv) performing light switching command, T_{sw}, and, v) power save mode T_{ps}. To cover detecting the sensor-mote transmission, the channel polling period must span for the preamble transmission time plus the time of listening to the early acknowledgment [38]. Therefore, the switch-mote cost function is given by,

$$\begin{aligned} E_{Switch} = {} & N_{occ}\, T_{occ}\, I_{evt} + N_{cs}\, T_{cs}\, I_{rx} + N_{tx}\, T_{ack}\, I_{tx} + \\ & N_{sw}\, T_{sw}\, I_{sw} + T_{ps}\, I_{ps} \end{aligned} \tag{10}$$

where N_{cs}, N_{tx}, N_{sw} respectively denote the number of, channel sensing, ACK transmissions, switching commands. To determine these numbers, the occupancy profile of an area/office must be first extracted from the log file recorded by the installed light control system prototype, and the total time spent in the given mode is then calculated as a function of the occupancy intervals, T_{occup_Intv}, and the wakeup period parameter, T.

Given the energy functions, the following optimization problem is defined for a sensor-mote

$$\begin{aligned} \text{(P1)} \quad & \min \quad E_{Sensor}(T) \\ & \text{var.} \quad T. \end{aligned}$$

On the other hand, the following optimization problem is defined for switch-mote's cost minimization:

$$\begin{aligned} \text{(P2)} \quad & \min \quad E_{switch}(T) \\ & \text{var.} \quad T \end{aligned}$$

The optimal solution of problem $(\boldsymbol{P1})$, T^*_{Sensor}, will result in the pair$(E^{\text{Sensor}}_{\text{best}}, E^{\text{switch}}_{\text{worst}})$ as depicted in Fig 11.(a).

Whereas, the optimal solution of problem $(\boldsymbol{P2})$, T^*_{switch}, will result in the pair $(E^{\text{switch}}_{\text{best}}, E^{\text{Sensor}}_{\text{worst}})$ as depicted in Fig. 11.(b).

4.2. Nash Bargaining Solution

To find the optimal trade-off solution for the objectives presented above (minimizing E_{Sensor}, vs. minimizing E_{switch}), we define a bargaining problem where each objective is represented by a player. The Bargaining model is a powerful tool that helps understanding how several agents should cooperate when selfish behavior of players leads to Pareto-inefficient results. Nash Bargaining Solution (NBS) [41] is a possible solution to this problem that defines a set of axioms[3] to characterize the equilibrium point. Note that a bargaining game with two players selects one of the possible player's outcomes of a joint collaboration [41] [42]. Let A$\subset$R^2 be the set of alternatives the players face, S={s=(u_1(a),u_2(a)) | a$\in$A} the set of feasible utility payoffs, and $v = (v_1, v_2)$ ($v \in S$ the threat point. Given the latter, the NBS chooses a feasible agreement, Φ:$(S, v) \to S$, that results from the negotiation, and it assumes that S is convex, compact, and $\exists s \in S$, such that $s > v$ for both players. The NBS solution can be calculated by solving the following optimization problem [41]:

$$
\begin{array}{lll}
\text{(NBS)} & \max & (s_1 - v_1)(s_2 - v_2) \\
 & \text{s.t.} & s \in S, (s_1, s_2) \geq (v_1, v_2) \\
 & \text{var.} & s.
\end{array}
$$

We define the intervals A^{Sensor}=$[E^{Sensor}_{\text{worst}}, E^{Sensor}_{\text{best}}]$ and A^{switch} =$[E^{switch}_{\text{worst}}, E^{switch}_{\text{best}}]$ to be the set of strategies that respectively the sensor-mote and the switch-mote may take, and $s^{Sensor} \in A^{Sensor}$, $s^{switch} \in A^{switch}$ the strategies effectively chosen by the players. Fig 11.(c) shows how the NBS optimal point can be achieved where each player can choose a strategy that reduces its threat value looking for a feasible point that satisfies both players. Thus, the general Bargaining problem when considering the sensor-mote and switch-mote as players is expressed as,

$$
\begin{array}{lll}
\text{(P3)} & \max & (E^{Sensor}_{\text{worst}} - E^{Sensor}(T))(E^{switch}_{\text{worst}} - E^{switch}(T)) \\
 & \text{s.t.} & (E^{Sensor}_{\text{worst}}, E^{switch}_{\text{worst}}) \geq (E^{Sensor}(T), E^{switch}(T)) \\
 & & (E^{Sensor}(T), E^{switch}(T)) \in S \\
 & \text{var.} & T.
\end{array}
$$

[3]The NBS axioms are: (i *Pareto Optimality*, (ii *Symmetry*, (iii *Invariant to affine transformations*, and (iv *Independence of Irrelevant Alternatives [41].*

The solution of the optimization problem $(\boldsymbol{P3})$ will be the optimal cost for both players under the agreement and will satisfy: E^*_{Sensor}=$E^{Sensor}(T^*)$ and E^*_{switch}= $E^{switch}(T^*)$.

4.3. Numerical Results

We have applied the Nash Bargaining model to find the optimal wake-up period parameter in a case study, where we used the occupancy profile of a single person office as an input for the defined Bargaining game.

The profile was extracted from a log file recorded by our light control system prototype installed in the office. The record contains the occupancy states of the office during a period of 1 month. The profile was built upon averaging the office occupancy states of 22 working days of the month. It has been used by the cost function along with the wakeup period parameter to calculate the time spent by each player (sensor-mote and switch-mote) in each operating mode. The current draws of each operating mode is taken from the device's datasheet and validated through the energy measurement taken on the prototype during experiments. Table 2 summarizes different symbols used in sensor-mote and switch-mote cost functions with typical values. Alkaline Energizer industrial AAA batteries have been modeled with 1200mAh of capacity and Shelf Life factor of 10 years at $21°C$ [43].

4.3.1. Tradeoff Solution

We first searched for the equilibrium point without any constraints on the objectives, i.e. no preference or differentiation between the objectives. Then, to prioritize and force the system to extend the sensor-mote lifetime, a constraint that set the minimum desired lifetime has been added, i.e. $(P3)$: $E^{Sensor}(T) \leqslant E^{Sensor}_{\max}$. This prioritization can be argued by the fact that the battery replacement of a sensor-mote, which is placed at the ceiling of offices/rooms, is more constrained than the battery of a switch-mote. The results are depicted in Fig.12, for Nash Bargaining solution with and without the minimum sensor-mote lifetime constraint. The square in Fig. 12 shows that the obtained optimal point for the unconstrained problem is 6.4 years for the motes, which represents the trade-off solution of the system that ensures a fair equilibrium. The circle in Fig. 12 shows that solving the constrained variant of the problem by setting sensor-mote lifetime to 9 (as a constraint) yields 4.3 years lifetime for the switch-mote. The figure also shows the resulted optimal values for the duty-cycle parameter, T^*, which are $5.65sec$ and $3.45sec$ for unconstrained and constrained optimization problem, respectively.

4.3.2. Weighted Optimization

In this section, we consider a weighted model, where a weight (α) is given to ensure a minimum sensor-mote lifetime with respect to the switch-mote life time, i.e. it is α times more important than the switch-mote lifetime

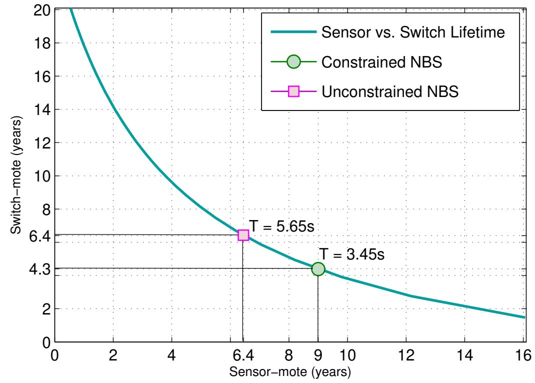


Figure 12: The NBS solution with constrained and unconstrained optimization between sensor-mote and switch-mote lifetime

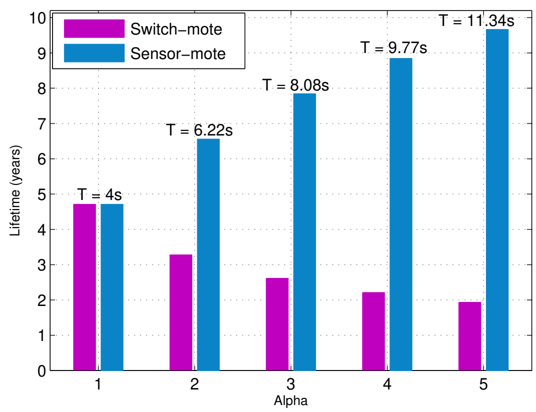


Figure 13: sensor-mote and switch-mote lifetime for different values of the weight α

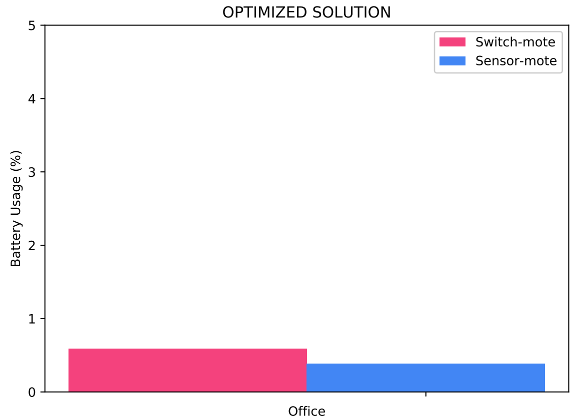
($\alpha \geq 1$). Thus, the following constraint is added to the formulation:

$$E^{Sensor}(T) \leqslant \alpha E^{switch}(T).$$

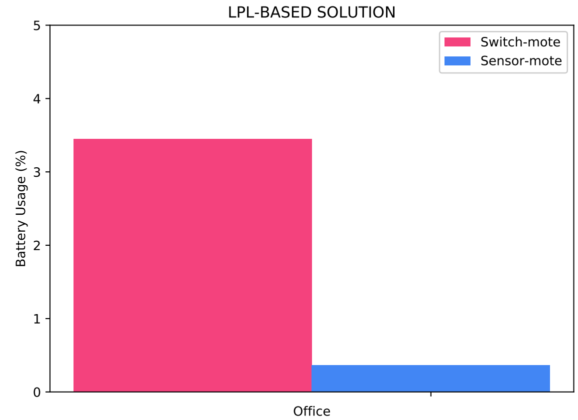
Fig.13 depicts the obtained results (lifetime and duty-cycle parameter) for values of α from 1 to 5. The figure shows that sensor-mote lifetime can reach more than 9 years, and about 2 years for the switch-mote. Note that 2 years is a tolerable frequency of battery replacement, for the switch-mote, given its ease accessibility.

4.3.3. Power Consumption Evaluation

To assess the performance of the proposed solution, we have measured the power consumption of the automatic light control prototype system deployed in our campus. The energy consumption was measured for the different



(a)



(b)

Figure 14: Sensor-mote and switch-mote Battery Usage for (a) the optimized solution and (b) LPL-based solution.

modules of the system over a period of 1 month and compared to the LPL-based solution. The LPL-based solution consists in using the default MAC layer protocol to manage the radio interface of the system components, which is widely used for low-power sensor devices and implemented in the TinyOS operating system protocol stack[4].

This experiment consists in running the automatic light control system using: (a) the proposed solution with optimized parameters and (b) the LPL-based solution, In both cases, we used the occupancy dataset recorded by our deployed prototype in a single office during two months.

We considered in all experiments that the system components are equipped with an Energizer CR2032 battery with 1200mAh capacity. The results of energy consumption is depicted in Fig.14.(a) and Fig.14.(b) for the optimized and the LPL-based solutions, respectively. In the proposed system, the battery usage over 1 month of running was 0.58% for the Switch-mote and 0.38% for the PIR-mote. Whereas, in the LPL-based solution the Switch-mote and the PIR-mote consume 3.4% and 0.36% , respectively. For both solutions, the power usage of the PIR-mote is approximately the same. However, for the Switch-mote, the energy consumption in LPL-based solution is much more important compared to that of our proposed solution (≈ 5.8 times). This can be explained by the fact that the LPL protocol is scheduled to set the wakeup period of checking the channel activity to 2 seconds all the time which does not fit the data packets exchange generated by the office occupancy profile. On the other hand, the proposed solution has been configured to run with the optimized wakeup parameter according to the user occupancy profile as seen in Section 4.

[4] http://tinyos.stanford.edu/tinyos-wiki/index.php/CC2420_Low_Power_Communications_Design_Considerations

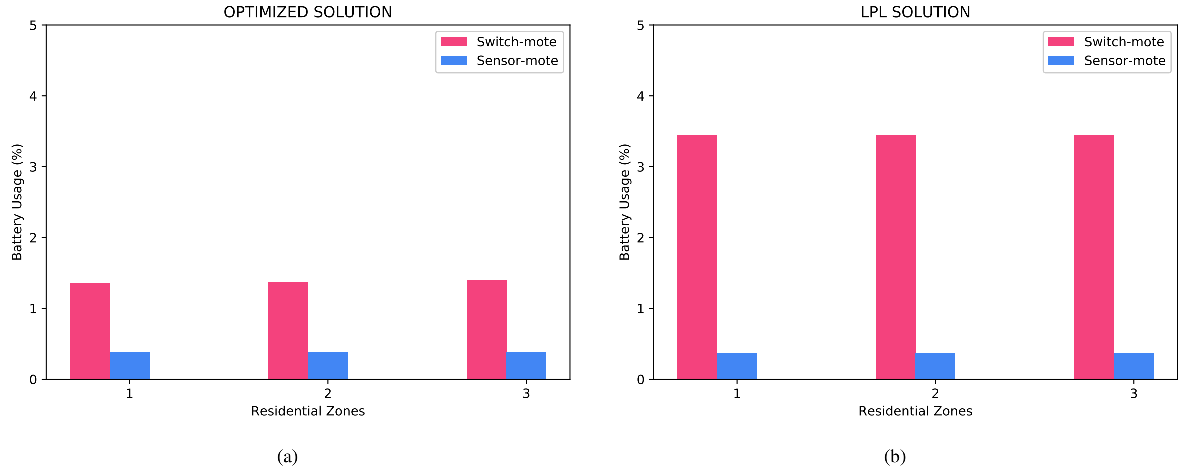


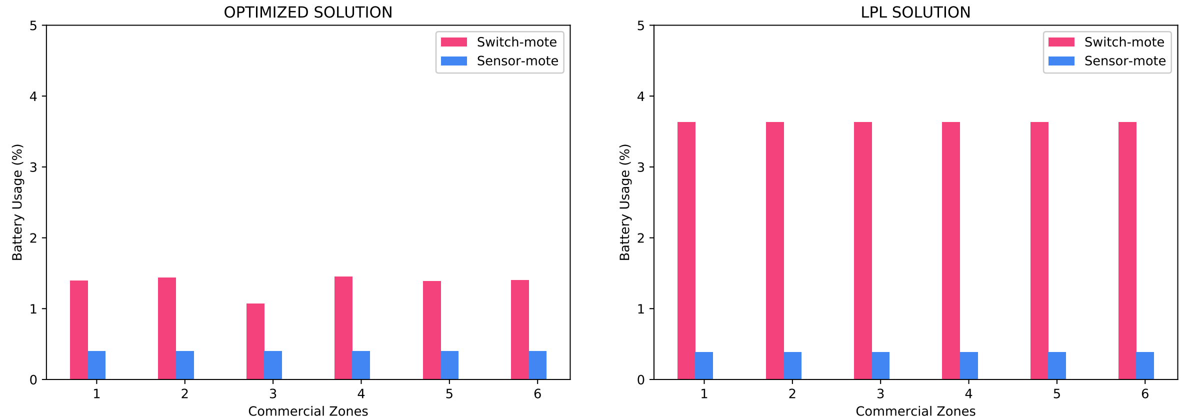
Figure 15: Sensor-mote and switch-mote Battery Usage for (a) the optimized solution and (b) LPL-based solution applied to 3 rooms in a residential building.

4.3.4. Multiple Offices Deployment

Our system has been deployed and tested using a single office within our campus. However, the system can be easily deployed in a large-scale environment, i.e. in a large residential or commercial building. It is notabely suitable for old buildings where the *easy-to-install-and-maintain* feature is required. To confirm this, we have evaluated the proposed solution using real occupancy datasets recorded from residential and commercial multi-offices buildings. We have used two open-source occupancy datasets from OpenIE [5]. The first dataset includes information about occupancy status (occupied vs. unoccupied) of three zones in a residential building. These zones are the container house with a living room, master bedroom, and kitchen. The second dataset, contains occupancy data of six offices in a commercial building. The residential and commercial occupancy datasets cover one month with at least fifteen minutes measurement time interval.

We have measured the energy consumption when running the automatic light control system using our solution (with optimized parameters) and the LPL-based solution. The obtained results when considering both the residential and commercial occupancy datasets are depicted in Fig.15 and Fig.16, respectively. The consumed energy in the residential building (in the three zones), using our solution (Fig.15.(a)) is between 1.35% and 1.40% for the switch-motes and around 3.44% in case of LPL-based solution (Fig.15.(b)). For the PIR-motes, the energy consumption in both solutions is around 0.38%. The same pattern is also observed in case of the commercial building, where the energy consumption is much better in our solution (Fig.16.(a)) for the switch-mote compared to the LPL-based

[5] https://openei.org/datasets/dataset/long-term-occupancy-data-for-residential-and-commercial-building



(a)

(b)

Figure 16: Sensor-mote and switch-mote Battery Usage for (a) the optimized solution and (b) LPL-based solution applied to 6 offices in commercial building.

solution (Fig.16.(b)). For the PIR-motes, the results are very similar with a little advantage for the LPL-based solution. This clearly demonstrate the advantage of using the Nash Bargaining method in our solution to find the optimal parameters that can considerably reduce the battery usage by approximately a factor of 2.5. This is due to considering users' occupancy profile and finding the best tradeoff that ensure an equilibrium in battery usage between the different system components.

5. Conclusion

We have jointly considered the problems of optimal occupancy monitoring for building energy management, and maximizing the battery lifetime of the wireless devices used for the monitoring. Without loss of generality, the study has been focusing on a simple setting for optimal light control in offices, but while considering realistic constraints, e.g., i) the intrinsic property of sensing holes and its impact on the accuracy of detection, ii) the preservation of the users' comfort when maximizing the battery lifetime, iii) balancing the lifetime of the different wireless devices used in the framework (sensor-mote vs. switch-mote). For optimal deployment, the problem has been formulated with mixed integer linear programming (MILP), where the positions of a set of PIRs are sought out in a way to maximize the *real* covered area. For extending the lifetime of the battery powered motes without compromising the user comfort, we used a duty-cycling mechanism with an adapted architecture. We realized that by duty-cycling the motes, maximizing the lifetime of the sensor-mote and the switch-mote becomes a conflicting objective problem. A cooperative game has been developed using Nash Bargaining Model for a fair tradeoff solution of the system. The proposed approaches have been evaluated analytically using occupancy data collected from real experimentations.

Results of occupancy detection demonstrate clear improvements in terms of detection when using the proposed hole-aware placement, and a reduction in the waste of energy usage from 9.61% (in case of hole-unaware placement) to 1.3%. The numerical results evaluating the game theory model show that the system lifetime can reach as long as 6 years for both sensor-motes and switch-mote. Given the placement constraints, it might be more flexible to replace the switch-mote batteries (usually placed on the wall) than the Sensor-mote batteries (usually placed on the ceilings), and thus the lifetime of the latter becomes more crucial. We considered this and defined a weighted variant of the proposed game that enables to capture this feature. The results show that it is possible to have a 10-year lifetime in the sensor-mote and a 2-year in the switch-mote. As the occupancy monitoring is a central part for energy management system in buildings, the proposed solution does not limit to light control, but it can easily bee extended to other applications such as HVAC systems, appliances control in smart homes, etc., which represent one of the perspectives of this work. The user preferences have been limited to the instantaneous switching of the light upon entrance. Other preferences might be considered such as customized dimming, temperature, operation modes of devices, etc. In addition to the physical information from the sensors (used in this work), it is possible to enrich the system with information from other sources (crowd-sensing, social networks, etc.). Such information might feed machine learning and data-mining tools to dynamically determine the user preferences. All these issues are in our agenda.

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