Smart occupancy sensors to reduce energy consumption

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Received 20 April 1999; accepted 23 July 1999

Abstract

Occupancy sensors have long been used for control of various devices (like artificial light, HVAC devices, etc.). Past research has shown that use of occupancy sensors for control of lighting can save up to 30% electrical energy used for lighting. However, most of the sensors, which are currently being put to use, have a preset (sometimes user adjustable) time delay (TD) (the time after which the lights or any other load will be switched “off” after the last motion detected by the sensor). If this TD is too long, it will have less energy savings, as the load will remain “on” during unoccupied period also. At the same time, if the TD is kept short then it may result in unwanted switching “off” (false off) of the lights when no motion is detected during periods of occupancy. It has been observed in our research that the activity level of a user changes over the time of the day. Also, it is seen that activity level of different users is different. Hence, single TD for all the users and for all times of the day is not desirable. The commonly used sensors do not adapt to changing activity levels. In this paper, we present design of smart occupancy sensors which can adapt to changing activity levels. A model is also proposed for “human movement” of a person working at a computer. Smart occupancy sensor can learn the variation in activity level of the occupants with respect to time of the day. With this information, it can change the TD with time of the day. Experiments conducted have shown that about 5% more energy can be saved by using smart occupancy sensor as compared to non-adapting fixed TD sensors.

Keywords: Occupancy sensors; Energy; Time delay

1. Introduction

Occupancy sensors have a potential to significantly reduce energy use by switching off electric loads when a normally occupied area is vacant. While occupancy sensors can be used to control a variety of load types, their most popular use has been to control lighting in commercial buildings. Although occupancy sensors have been used in many commercial facilities over the last decade, published third party performance data is surprisingly sparse. Both the Electric Power Research Institute (EPRI) and American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) estimate an average 30% savings from this technology in generic assessments for commercial buildings [2,6]. With occupancy sensor controls for lighting equipment in one or two person offices, the estimates of energy savings vary from 25% to 50% [5]. These data are supported by a utility evaluation by Consolidated Edison who found a 30% reduction in average lighting demand for its projects that installed occupancy sensors [5]. Measured data from case studies suggest that good performance from occupancy sensor installations can be realized. A retrofit of an office building with passive infrared occupancy sensor controls in South Australia yielded a 40% reduction in lighting energy use with a simple payback of 2 years [4]. Energy saving potential is highly dependent on baseline assumptions and operations but values of 35%–45% are typical [1]. Also, several case studies of occupancy sensor installations show savings of 25%–75% in variety of spaces [7]. These savings are dependent on average or peak occupancy rates. Stannard et al. [15] in their work provide a brief discussion of the impact of occupancy profiles on the reduction in peak demand and energy use due to lighting controls. The result of a survey by Lighting Research Center discusses the importance of considering occupancy use patterns in predicting potential savings [10]. A detailed study of occupancy sensors used in a US national laboratory found a
31% average lighting energy reduction [14] with savings strongly affected both by type of space and time delay (TD; the time after which the lights will be switched “off” by the sensor after the last motion is detected) setting. Savings were highest for mixed ownership spaces (e.g., lunchrooms, copy rooms, restrooms, etc.) and lowest for administrative areas. Savings were more than doubled by reducing TDs from the manufacturer recommended settings of 10 to 20 to 2.5 min. Researchers at Rensselaer Polytechnic Institute performed field survey at an elementary school and junior high school to determine classroom occupancy patterns and to estimate wasted energy using a methodology described by Rae and Jaekel [13]. In the elementary school, the wasted lighting energy averaged 25%, while in junior school, the figure was 15%. There are also reports that the electricity consumption actually increased with the installation of occupancy sensors [8]. This increase has been attributed to poor sensor installation, setup and user operation of the devices. The results of a study done by Prig et al. [12], showed that people in offices with occupancy sensors were less likely to turn off the lights when they left the room. Instead, they relied on the occupancy sensors to control the lights for them. This tendency reduced the savings from the occupancy sensors by about 30%.

Turning “off” the lights when the space is unoccupied can bring saving in two ways. First, as the lights are turned “off”, the electricity consumption is reduced and there are obvious energy savings; secondly, the calendar life of the lamp is increased, thereby reducing lamp replacement and maintenance costs. It has also been shown that turning off fluorescent lights save energy, extend overall lamp life, and reduce replacement costs [9]. Use of occupancy sensors is increasing for automatic switching (“on/off”) of the light where the space is unoccupied. Most of the commercially available occupancy sensors have variable TD (ranging from 3 s to 30 min), so the user can set the TD according to his requirements. The cost of these sensors varies from $40 to $150 [11]. However, if the TD is very small, the sensor may cause abnormal turning “off” of the lights even when the occupancy is there which can be annoying. And if the TD is large then there maybe wastage of energy, as the lights may remain on even when there is no occupancy.

Experiments conducted by us show that activity level of a person varies throughout the day therefore the TD should also vary accordingly. We have developed sensors that can adjust themselves to the new environment and can change TDs suitably.

It is shown that if the sensor can learn this variation in activity level and adjust accordingly the TD, then more energy savings are possible with lesser number of “false switching” of lights. The sensor can learn the time of the day when the user leaves the room and reduce the TD for that time to facilitate faster switching off thus saving energy. To find TD at a given time of the day two methods are proposed. The first method uses the maximum inactivity period for last few days at the given time as TD for that time. The second method uses a statistical model of inactivity period to set the TD.

2. Methodology

We assume that the activity level of a person changes with the time of the day and shows a particular trend, specific to that person. We further assume that similar type of trend is exhibited on all the days. These assumptions were verified by the experiments. Therefore, TD for optimal switching should depend on time of the day. Hence, important issue is the method used for fixing the TD for a given time of the day.

Our first method is a simple heuristic, which measures the maximum inactivity period during a small interval of time, at a given time of the day, over several days, and uses it as the TD for that time of the day. The drawback of this method being that it requires a long time for learning. Secondly, the probability of False Offs (not detecting occupancy when person is actually there and switching off the load) cannot be controlled by this method.

The second method uses a statistical model for inactivity period (time difference between two consecutive

![Fig. 1. Unoccupied and occupied periods on a typical day.](image-url)
Fig. 2. “TD,” with time of the day, as learned by the occupancy sensor in 5 days training.

detection of motion during occupancy) derived from the observed data and modeling inactivity period as a random variable. We took observations of inactivity period over several days and derived an the empirical distribution to model probability density function of inactivity period. Based on this model we can set the TD to achieve a given False Off probability. If the activity level changes throughout the day and shows distinct patterns, different parameter values can be used in the probability density functions for different parts of the day.

3. Experimental setup

The occupancy sensor used in our experiments was a commercially available passive infrared sensor. We placed the sensor near the monitor of a PC, facing the user, so that it can detect small motion while typing. The sensor’s output signal was fed to the computer that was used for building automation system. The signal from the occupancy sensor was transmitted to the data acquisition unit through radio frequency (RF) based cordless transmitter. Observations were made every millisecond to detect the occupancy, though the signal persisted for few hundred milliseconds once the motion was detected. The high sampling rate was taken to pick the starting of the signal so that a resolution of 1 s between two signals could be achieved. The time period between two signals was measured. Based on this time period and the TD for that time of the day, action was taken and 4 × 40 W, T8 fluorescent lamps and 2 × 55 W, compact fluorescent lamps (CFLs) were switched and dimmed, respectively. The CFLs were dimmed when no motion was detected indicating the user the shutting off of the lights after few seconds. If the user responded by moving, the TD was increased and the lighting restored to the original level. The CFLs were used for task lighting and were constantly dimmed in response to the available daylight. In calculating the savings in lighting energy we have used only the load of fluorescent lamps. Load of CFLs has been omitted to exclude energy savings due to daylighting.

4. Logic for occupancy sensor

4.1. Method 1

Whole day was divided into 144 parts of 10 min each. For every part, there was a value of TD, \( i = 1–144 \). At the beginning of the training, the TD, for all the parts of

<table>
<thead>
<tr>
<th>Time</th>
<th>Duration (s)</th>
<th>TD for smart sensor I (s)</th>
<th>TD for ordinary sensor (s)</th>
<th>Energy saving by smart sensor (kWh/day)</th>
<th>Energy saving by ordinary sensor (kWh/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0:30</td>
<td>900</td>
<td>70</td>
<td>300</td>
<td>0.055</td>
<td>0.04</td>
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<tr>
<td>1:17</td>
<td>1020</td>
<td>54</td>
<td>300</td>
<td>0.064</td>
<td>0.048</td>
</tr>
<tr>
<td>1:30</td>
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<td>38</td>
<td>300</td>
<td>0.269</td>
<td>0.252</td>
</tr>
<tr>
<td>1:51</td>
<td>1140</td>
<td>54</td>
<td>300</td>
<td>0.072</td>
<td>0.036</td>
</tr>
<tr>
<td>2:49</td>
<td>180</td>
<td>39</td>
<td>300</td>
<td>0.009</td>
<td>0</td>
</tr>
<tr>
<td>2:52</td>
<td>1020</td>
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<td>300</td>
<td>0.066</td>
<td>0.048</td>
</tr>
<tr>
<td>2:30</td>
<td>300</td>
<td>17</td>
<td>300</td>
<td>0.019</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td>0.581</td>
<td>0.456</td>
</tr>
</tbody>
</table>

Table 1
Comparison of energy savings by a smart sensor and an ordinary sensor.
the day was set to 10 s. Whenever there was no movement over the duration of TD, (for respective part of the day), the sensor sounded a "beep" for 15 s and reduced the CFL light output, which announced the shutdown of the lights in few seconds. If the user moved (i.e., the area was still occupied) in that period, the sensor increased the TD, by the delay in movement plus 15 s. If the user does not move (i.e., the area was unoccupied) the lights were switched "off" after 15 s. This process continued. Likewise, the sensor learned the activity level of the user for various parts of the day. For exceptionally long TDs (greater than 10 min), there was a provision of reducing the TD. If the sensor recorded no motions and switched off the lights after TD, + 15 s, it deduced that the user was not present in the duration of TD, signifying longer TD, than required; it recorded this observation. If this happened more than three times for the same TD, then that TD, was reduced by 25%.

4.1.1. Observations

The sensor was trained in a laboratory environment. The sensor was placed near a computer. The occupant was working for most of the time on the computer. The training was done for 5 days. Fig. 1 shows the general occupancy trend in the laboratory. Fig. 2 shows the learned TDs with respect to time of the day. The total working time was

![Graph](image)

Fig. 3. (a) Number of observations vs. inactivity period in seconds. (b) Detailed view. (c) Log-log graph of G.

*Note: The figure contains graphs showing the frequency of inactivity periods and the relationship between inactivity periods and the number of observations.*
4.1.2. Explanation of graphs

1. 2. ... indicate the points on the graph.

(1) As the day begins, TD is low, which indicates faster movements and high activity level. TD steadily increases for a short duration.

(2) TD falls at this point, as the user usually leaves the room. Therefore, the lights can be dimmed/switched off after a shorter duration.

(3) TD again rises slowly to this point. This shows low activity levels. Primarily the user was working on computer in this duration. The TD is longer thus avoiding annoying shut downs (False OFFs) when the room is occupied.

(4) This point denotes the starting of unoccupied period during the lunch period. The sensor has learned that and can shut down after a small interval.

(5) The activity level again reduces to this point. This is the time when there is least movement as the user is usually busy in reading, writing activity.

(6) TD again reduces as the user leaves around this time. As this time is not fixed and the user does not leave everyday at the same time so there is no sharp fall in TD, but some reduction in its value.

(7) This point again represents a regular unoccupancy.

(8) The activity level again reduces. The user usually works at the computer during this period.

(9) This point detects the end of day. The user leaves at this time almost everyday, so the TD reduces significantly.

4.1.3. Energy savings

Table 1 shows the energy savings. The first column shows the time when the room is unoccupied and the second column gives the duration of unoccupancy. Both these data are taken from Fig. 1. The third column has TD, for the smart sensor taken from Fig. 2. It is evident from the table, that the smart sensor shuts down the lights with a smaller TD, during periods of known unoccupancy. This does not happen in case of an ordinary sensor wherein the TD is either fixed or is adjustable by the user, which in most cases is set at very high values (typically 15 min), thus, diluting the purpose of installing an occupancy sensor.

This table shows observed energy savings (columns 5 and 6) at various moments of the day (column 1) when the room was unoccupied for different durations (column 2). Columns 3 and 4 give TD for both the sensors. TD for smart sensor varies with the time of the day.

In calculating the savings, we have taken lighting load of four fluorescent lamps $4 \times (40 + 20) = 240$ W. The base case was taken as full lights on from 0900 to 1830 h. Taking base case energy consumption of 2.28 kWh/day, ordinary occupancy sensor saved 20% energy and smart occupancy sensor saved 25%.

4.2. Method 2

In this method, the way of observation remains the same as in the method 1 and it has been applied to the same data as obtained in method 1. Here instead of taking the maximum inactivity period as the $T_D$, a model of human inactivity period is used for determining the $T_D$. The frequency distribution of inactivity period is plotted as shown in Fig. 3. The graph shows that small inactivity periods are more frequent. We modeled this frequency distribution using Pareto distribution, which is given by equation:

$$Y = c \cdot x^{-k}$$

We observed the data for 5 days and found the following values of c and k

$$c = 28317, \quad k = 2.17$$

The correlation between the actual data and the fitted curve being 98%.

$$R^2 = 88.17\%$$

Let $TD(p)$ be the pth percentile of the distribution. $TD(p)$ and $p$ are related by

$$\int_1^{TD(p)} \frac{k-1}{x^k} \, dx = p$$

$$1 - \frac{1}{(TD(p))^{k-1}} = p$$

$$TD(p) = \frac{1}{(1-p)^{1/k}}$$
So for a given probability of 99.5% occupancy and value of \( k = 2.17 \), we get

\[
TD = \frac{1}{1.17 / \sqrt{1 - 0.995}}
\]

TD = 93 s

In our experiments, we have used same parameters of the model for the whole day. It might be useful to take multiple models for different parts of the day to account for changing occupancy behavior throughout the day.

If we increase \( p \) then the TD increases and the probability of False Offs decreases and vice-versa. User can make a choice of \( p \) based on his criteria of energy savings and number of false offs. Fig. 4 shows the variation of TD with \( p \).

4.2.1. Energy savings

Table 2 gives the energy savings by smart sensor 2 and ordinary sensor. It shows observed energy savings (columns 5 and 6) at various moments of the day (column 1) when the room was unoccupied for different durations (column 2). Columns 3 and 4 give TD, for both the sensors. TD, for smart sensor and ordinary sensor both remain constant for the full day as compared to method 1 where TD, of smart sensor varied with the time of the day. The concept of different TD for different times of the day can also be applied in the method 2 by having different parameters of the model for different parts of the day.

These investigations are still under progress.

In calculating the savings, we have taken lighting load of four fluorescent lamps = 240 W. The base case was taken as full lights on from 0900 to 1830 h. Taking base case energy consumption of 2.28 kW h/day, ordinary occupancy sensor saved 20% energy and smart occupancy sensor saved 24.6%. The energy savings using this type of logic are dependent on \( p \). If we increase \( p \) the savings will also increase. The benefit of this method is that it learns faster then sensor 1 and reduces False Off in the learning phase.

4.3. Validity of model for different user

To see the effect of placement of occupancy sensor and change of user, we did the same experiment with a new user and different placement of sensor. In this previous experiment, the occupancy sensor was placed near a keyboard so it detected small motions of typing also. In the case of the new user, it was put in a room of a professor who worked on study table and used computer on another table. The sensor was about 1 m from the study table and 2 m from the computer table. It did not detect small motions. Only large motions like movement of hand were detected.

For this case also, we got the same model but with different parameters:

\[ C = 2605, \ K = 1.57 \]

Correlation \((R) = -0.966\)

\[ R^2 = 93.47\% \]

For the same probability of 99.5% occupancy (as in case 1) and value of \( k = 1.57 \), we get

\[ TD = 10886 \text{ s} \]

<table>
<thead>
<tr>
<th>Time</th>
<th>Duration (s)</th>
<th>TD, for smart sensor 2 (s)</th>
<th>TD for ordinary sensor (s)</th>
<th>Energy saving by smart sensor 2 (kW h/day)</th>
<th>Energy saving by ordinary sensor (kW h/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0930</td>
<td>900</td>
<td>93</td>
<td>300</td>
<td>0.054</td>
<td>0.04</td>
</tr>
<tr>
<td>1054</td>
<td>480</td>
<td>93</td>
<td>360</td>
<td>0.026</td>
<td>0.012</td>
</tr>
<tr>
<td>1117</td>
<td>1020</td>
<td>93</td>
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</tr>
<tr>
<td>1501</td>
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<tr>
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<td>93</td>
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<tr>
<td>1723</td>
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<td>93</td>
<td>300</td>
<td>0.062</td>
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</tr>
<tr>
<td>1830</td>
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<td>93</td>
<td>300</td>
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<td></td>
<td></td>
<td></td>
<td>0.56</td>
<td>0.456</td>
</tr>
</tbody>
</table>

Table 2: Comparison of energy savings by a smart sensor 2 and an ordinary sensor.
This value is very high. So if we take probability of 95% we get
TD = 192 s

For this location of sensor, the ordinary sensor will usually be set for TD = 7 min. So the economic analysis should be done with TD = 420 s for ordinary sensor and TD = 192 s for smart sensor. The lower value of percentage (namely 95% as compared to 99.5%) does not necessarily imply more False Offs.

This gives an idea as to how the sensor location, sensitivity of sensor effects the parameters of occupancy model. This in turn varies the TD and the effective energy savings.

5. Conclusion

The experiments have shown that intelligent occupancy sensors can save more energy than ordinary sensors. It is expected that intelligent sensor can save about 5% more energy than an ordinary sensor. Further, if the sensor uses human inactivity model then it can learn faster and reduce False Offs. There is a possibility of giving the "chance of False Off" as a setting to the occupancy sensor. Different parameters of the model can be used for different times of the day, thereby changing TD with time, resulting in improved performance of the model based occupancy sensor. This is achieved by using different TD for different time of the day with the change in occupancy behavior. The model based approach needs more computations and memory as compared to non-model based approach, therefore, in large building automation systems, it will be desirable to make the calculations at a central computer instead of at each occupancy sensor. This will only reduce the cost of providing memory and microprocessor to each sensor but also facilitate complex algorithms used by the model-based approach. Different TDs can be kept for different appliances. For the appliances which cause immediate discomfort on their switching off, like lights, should have longer TD as compared to appliances which do not cause immediate discomfort like a room heater.

References