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Smart Building Automation Using Device Free Localization Technology

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Abstract

This paper proposes the implementation of wireless sensor network for campus monitoring using Device Free Localization technology. Such an approach improves occupancy detection systems, manages power consumption intelligently and low installation cost. The method is based on fact that human body contains 70% water which resonates with radio signals by causing shadowing effects. Significant attenuation in the signal strength pattern indicates possibility of presence of a human. Without application of a complex set of sensors for human detection, the proposed approach achieves the human detection by analyzing radio signal strength variations incorporated in messages exchanged between radio transceivers operating at 2. 4 GHz.

Key words: Occupancy Detection System, Low Cost, Device Free Localization, Energy Saving, Zigbee Protocol, Wireless Sensor Network

Introduction

Buildings are one of the major consumers of electricity. Due to lack of implementation of effective energy efficiency factors such as building insulation, dynamic window shading, centralized ventilation etc, buildings give rise to significant energy wastage [1]. Various researchers are focusing on making buildings more energy efficient and smart. The energy usage in a building can typically be divided among several subsystems, such as IT loads, lighting and mechanical equipments used for climate control. Mechanical equipments include the combined heating, ventilation and air-conditioning (HVAC) loads and constitute a significant amount of energy consumption. An important factor of energy wastage is careless usage of electricity [2]. Various researchers have measured wasted energy in HVAC, lighting and IT loads even when there are no occupants [3][4][5][6][7][8]. For energy efficient and smart buildings, mainly appliances are governed by dynamic controlled algorithms implemented using sensor networks sensing environmental conditions (light, temperature etc.) and actuators to affect the environment such as dimmers, fans and chillers.

In this paper, it is presented that incorporating fine grained occupancy information as additional input can increase energy efficiency. Various models have been developed to control electrical energy in buildings using occupancy detection as an essential driving input. It has been shown that the presence of human and their activities in buildings have large impact on HVAC demand, energy consumption of lighting systems and building controls. Energy-unaware behavior can add one-third to a building's designed energy performance. Therefore presence of human can be considered as a key element and used for controlling of various devices such as lights and HVAC systems [9]. Various efforts have been done to optimize the occupancy detection techniques, so as to improve the accuracy of estimating the occupancy. Elder Naghiyen et. al have reviewed occupancy measurement techniques. In this review, Passive Infrared (PIR) sensor, Carbon Dioxide (CO_2) sensor and Device-free Localization (DFL) have been compared. It has been found that $CO_2$and PIR sensors based occupancy systems have many limitations. CO_2 based occupancy detection is based on the fact that human naturally exhales CO_2 on constant basis. The concentration of carbon dioxide can be used as an indicator of occupancy assuming human as a major source of CO_2 in the buildings. But due to varying ventilation rates (such as ventilation is achieved by opening windows) inaccurate detection is possible. Due to slow and coarse-grained detection of occupancy, CO_2 based method cannot be used frequently in buildings and offices. DFL has great potential but requires further research. [10] [11] [12]. PIR technology is mostly used for human presence. PIR sensors exploit the fact that heated objects emit infra-red light. They detect moving objects of one temperature on a background of another temperature. In buildings, PIR sensors are usually adjusted as closely as possible to the average human body temperature to identify occupancy more effectively. Heat currents from HVAC systems can also trigger a PIR sensor creating false positive, as mentioned by Teixeira et al. [13]. PIR sensors also suffer from false negative outputs if occupant remains still for a long time. Many models have been proposed to overcome false negatives of PIR based occupancy systems. Usually additional sensors are used to reduce false negatives. Yuvraj et. al have proposed a PIR based occupancy system for detecting the occupancy to control HVAC [14]. Reed switch was used additionally to reduce false negatives. Even then, the system fails to achieve accurate occupancy detection since the occupancy detection by reed switch depends on closing or opening of the door. Few researchers have used Passive Infra-Red (PIR) and microphone for occupancy detection [15] [16]. Such occupancy detection systems are fairly coarse-grained and inaccurate since system can work efficiently only if frequent conversation is possible. It is not applicable for individual cabins of staff or faculty or officers working calmly for a long period. Usually PIR based appliances controlled systems run on time delay algorithm for high accuracy which causes energy savings as well as energy wastage [17].

DFL technique is most recent human detection technique which has been under research. It works on the fact that the presence of a human subject within the wireless network range results in significant signal strength variations at the receiver input, whereas the degree of variations is correlated with the level of human motion. As such systems require the radio channel as the only source of information, people being monitored need not to carry or wear any electronic device (e. g. mobile phone, RFID tag, low-power transceiver) to take part in occupancy detection [18]. DFL works particularly well at the 2. 4 GHz frequency, as this corresponds to the resonant frequency of a water molecule and as the human body is mainly made of water. The IEEE802. 15. 4 standard on the other hand, is more appropriate as it is designed for low data rates, low power and high reliability. Wil-son and Patwari demonstrated a successful human tracking system using DFL technology[19][20].

Few researchers have been proposed energy management systems based on DFL technology.

Bojan Mrazovac et. al have proposed residential smart energy management systems using DFL based occupancy systems [21]. Their system has been implemented in residential environment. Compared to existing works, the proposed work focuses on occupancy detection based on DFL technology for a wide campus. The aim of proposed occupancy based appliances control system is that it should be of low cost and not only controls lighting systems but also other appliances like fans and HVAC systems to increase power savings during working hours. Integration of enhanced occupancy detection algorithm (based on third order moment) reduced error significantly for fast, accurate detection and to make the system robust as described in the result section. The proposed occupancy detection system has been implemented in rooms of Sharda University, Greater Noida, India with above mentioned goals in mind and it has been evaluated in terms of energy savings. Section 2 describes the design and development of low-cost wireless sensor node for accurate occupancy detection and environmental conditions detection. Section 3 describes working of occupancy detection system and wireless network infrastructure used to collect occupancy information. Section 4 explains the results of the system in terms of accuracy of occupancy detection and energy-efficiency. The system is also evaluated using Energy Plus to show that the proposed sensing platform can be used to reduce building energy use by 18% to 20%.

2. Proposed design

The energy break down of Sharda University is illustrated in fig. 1. Fan consumes 21%, lighting loads consume about 16% and HVAC loads consume 38% of electrical energy per annum of the baseline electrical usage. The state government defines the baseline electric usage of commercial buildings. The system has been implemented on one of the floor of Electronics and Communication Engineering (ECE) department of Sharda University. The proposed design aims at controlling HVAC systems along with lights and fans based on occupancy detection to achieve potential power savings per annum.

The Electronics and Communication Engineering (ECE) block of Sharda University can be divided into different regions namely, ECE teaching department consisting of cabins of faculties and researchers, classrooms, laboratories and Head of the Department's (HoD) cabin.

The proposed Wireless Sensor Network (WSN) for energy savings named Ecosystem for Sharda University (ES-SU).

2. 1 Hardware development

The hardware of ES-SU comprises of mainly two parts:

a. Monitoring point
b. Transmitter

a. Monitoring point of ES-SU

The design of monitoring point was based on accurate occupancy detection, low cost and easily deployable within entire campus. The cost was significantly reduced as compared with commercially available wireless motes [22] using commercially available Integrated Circuits (ICs). To develop an experimental test bed and to make the node of low cost, discrete and easily available sensors/components were used to cost only $10. The hardware design of the monitoring point was divided into three modules. The first module was aimed at detection of human subject using Device Free Localization technology. This technology uses Received Signal Strength Indication (RSSI) by measuring variation of signal strength. The system was equipped to monitor the changes in the RSSI values as a result of human detection within the line of sight between transmitter and receiver.

The second module was used to monitor environmental conditions. Digital temperature and humidity sensor was mounted for sensing the environmental conditions. A Real Time Clock (RTC) was used in the monitoring point to define time schedule of sensing area for different working and non-working days.

The third module was applied for analysing the received data from sensors and controlling appliances. Low power microcontrollers (PIC16F877A) was used for analysing data from environmental sensors and provided proper control to appliances. To facilitate few selected occupants to change the time schedule and threshold parameters as per requirement, a keyboard matrix is interfaced with microcontroller. Zigbee protocol is used for a reliable, low power and robust communication between the node and the transmitter. The block diagram of monitoring point of ES-SU is shown in the fig. 2.

b. **Transmitter**

A Zigbee module, connected via a Universal Serial Bus to a processor running the software acts as the transmitter.

3. Working of ES-SU:

The working may be divided into three sections:

a) Occupancy Detection and Algorithm

b) Detection of Ambient conditions and Controlling appliances

c) Deployment of nodes and wireless network

a) Occupancy Detection and Algorithm

Occupancy detection can be successfully achieved using DFL technology. The detection pattern was obtained by measuring the range of detection as a function of angular variation. Fig. 3a-3b shows the top view and side view of the detection pattern of DFL. DFL works in the Line of Sight (LOS). Hence, sensitivity decreases as the obstacle (human) moves away from the LOS. For an individual cabin, the transmitters and receivers were placed diagonally to get the maximum coverage area. The deployment scheme has been shown in fig. 4.

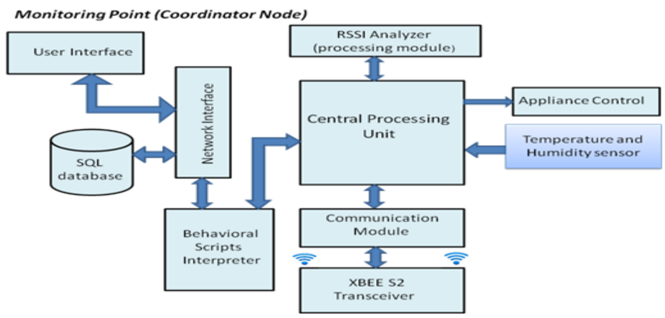

Fig. 2. Block diagram of monitoring point of ES-SU

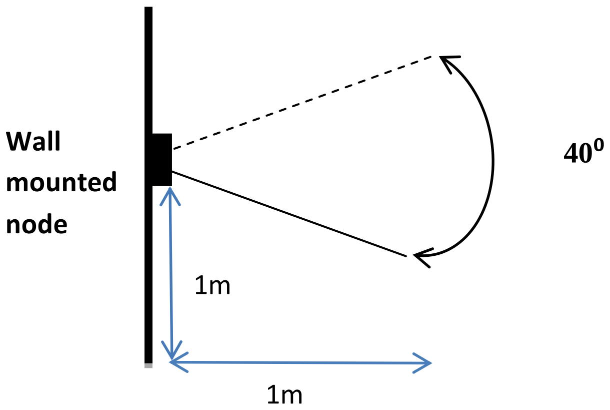

Fig. 3a. Top view of detection pattern of DFL

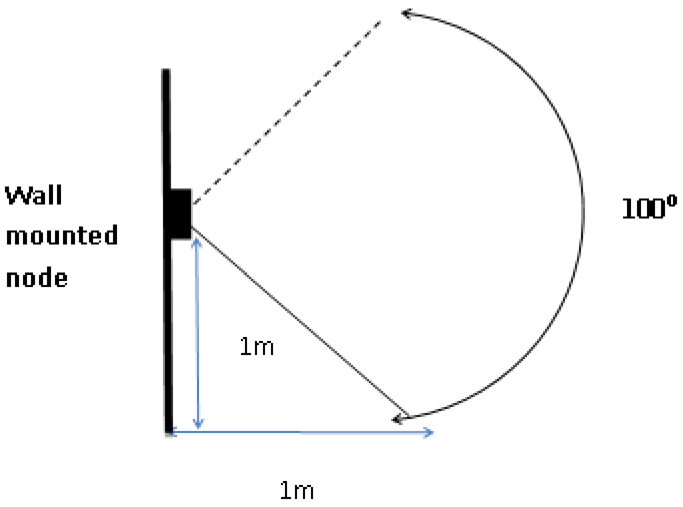

Fig. 3b. Side view of detection pattern of DFL

The system could generate a functional status, dependent on people entering or leaving the room by analyzing RSSI variations at monitoring point. RSSI was often found to fluctuate with smaller or higher variations around its mean in different environments. It showed significant increase in variation in RSSI due to the presence of a human. When nobody was present in a room, the initial RSSI variations were analyzed for each communication link. In such case RSSI variation was only due to environmental conditions (such as temperature, humidity, setup of furniture, quality of curtains etc.). It was named as Non-shadowed Signal Strength Mapping (NSSM). In case of presence of human, the signal strength mapping was named Shadowed Signal Strength Mapping (SSSM). The RSSI variations were used to define the maximum and minimum thresholds in each case. These thresholds were defined using a set of RSSI samples taken within a predefined time interval. There was a significant difference in the RSSI variations for NSSM and SSSM. For example, for NSSM, the RSSI was-48dBm whereas for SSSM the value was-64dBm for a particular monitoring point.

The Received Signal Strength(RSS) can be discussed with most appropriate shadowing model [23].

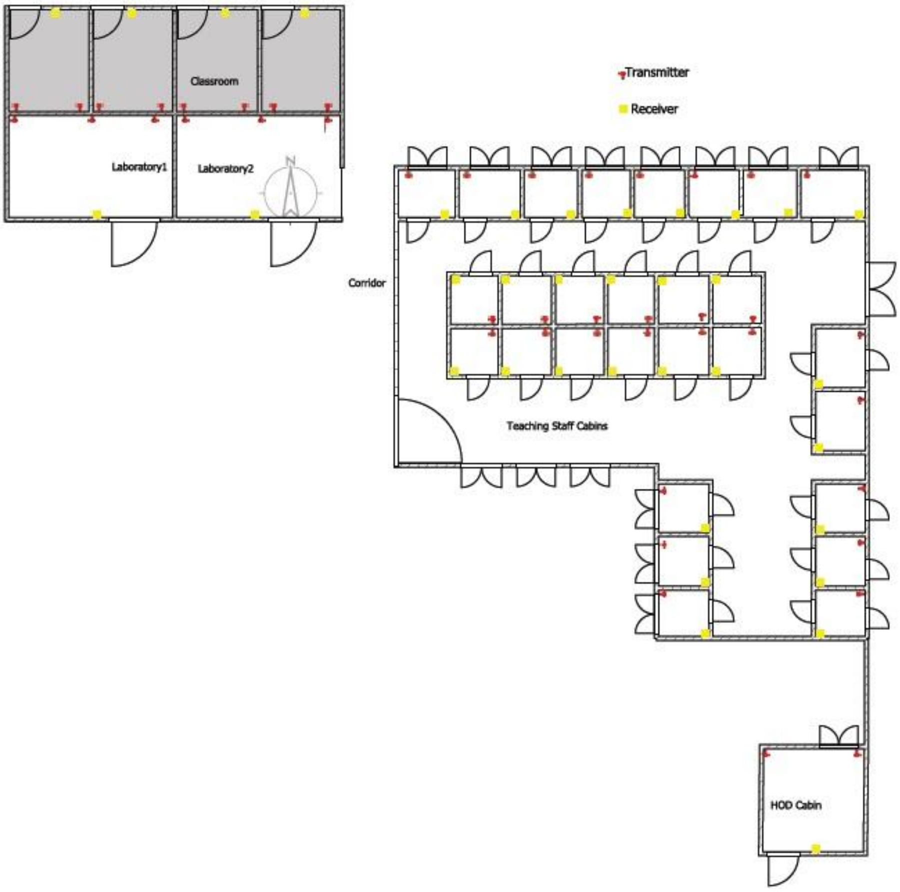

Fig. 4. Deployment Scheme in one of floor of ECE block

With the shadowing model, RSS measurements $Rt(i, e)$ of link i with the frequency f and transmission power level of e at time t is defined by

$$Rt(i, f, e) = Gt(i, f, e) + Pt(i, f, e) - Lt(i, f, e) - 10\beta t(f) \log 10\, di$$

$$- St(i, f, e) + vt(i, f, e), \quad (1)$$

where $Gt(i, f, e)$ is the receiver gain (dB), $Pt(i, f, e)$ is the transmission power (dBm), $Lt(i, f, e)$ is the signal attenuation power (dB) at the distance of 1m, $\beta t(f)$ is the path loss exponent, and di represents the Euclidean distance between the pair of nodes in meters. Generally, the above parameters are always steady and time-invariant. $St(i, f, e)$ is the shadowing loss due to the target that attenuates the signal, and $vt(i, f, e)$ represents the measurement noise. In this proposed design, link frequency was constant and transmitter power level was also assumed to be constant.
The equation reduces to

$$Rt(i) = Gt(i) + Pt(i) - Lt(i) - 10\beta t(f) \log 10\, di - St(i) + vt(i) \quad (2)$$

After time t, the change of the RSS measurement

$\Delta Rt(i)$ is defined by

$$\Delta Rt(i) = Rt(i) - R0(i)$$

$$\approx -St(i) + vt(i) - v0(i) \qquad (3)$$

where $R0(i)$ is the reference RSS measurement which can be learned from the link measurements when the deployment area is vacant i. e. NSSM. Since measurement noise are negligible compared with the shadowing loss. Hence, $\Delta Rt(i)$ is primarily determined by the shadowing loss of time t [24]. By analyzing RSSI variations of the messages exchanged between nodes, the system can generate a functional status, dependent on people entering or leaving the room. In proposed system, two thresholds Th_1 and Th_2 of ΔRSSI are defined to generate presence and no presence status of human during initial signal strength mapping.

During the start-up phase, the high and low thresholds were determined as:

$$Th_1 = Th_{max} \text{ in SSM-}Th_{min} \text{ in NSSM,} \qquad (4)$$

$$Th_2 = Th_{min} \text{ in SSM-}Th_{min} \text{ in NSSM,}$$

Where Th_{min} and Th_{max} denoted minimum and maximum values of thresholds for human occupancy detection from the set of samples in NSSM and SSM.

$$\Delta RSSI = \textit{presence}, \text{ if } Th_1 > \Delta RSSI < Th_2 \qquad (5)$$

$$\textit{no presence}, \text{ if } Th_1 < \Delta RSSI$$

Where RSSI was always negative and is expressed in dBm (decibel-milliwatts units). But one of the main drawbacks of the DFL technique is that the RSS signal is too sensitive, and a slight variation of the environment will cause the variation of RSS measurements, which causes the wrong judgment of shadowed links and degradation of localization performance. To solve this problem, updated thresholds were recalculated periodically compared with the last sample. In previous approaches, standard deviation of RSSI was calculated over a set of one minute sliding window of RSSI samples to update thresholds. In proposed work, third moment was used to recalculate the thresholds. Compared with standard deviation method, less error was achieved as discussed in result section.

$$y = \frac{1}{n}\sum_{i=1}^{n}((rssi_i - rssi\ mean)/sd(rssi))^3$$

Where
y= Third Moment

n= No. of samples
sd = Standard Deviation

b) Detection of Ambient conditions and Controlling appliances
The lights were turned ON, as soon as human presence was detected. The active hours of the zones were defined by the collection of occupancy patterns on hallway of the concerned zone. If human detection was not within defined active hours for the zone, security was alarmed. Secondly, if human detection was within defined active hours only then sensor circuits would be active to sense ambient environmental conditions. Microcontroller processed the data getting from sensor and switch ON/OFF the appliances according to algorithm as discussed in fig. 5. Thresholds of temperature depend upon the seasons and weathers. For example, if temperature was more than 27^0C, air conditioners were ON and if it was less than 10^0C, room heaters were ON.

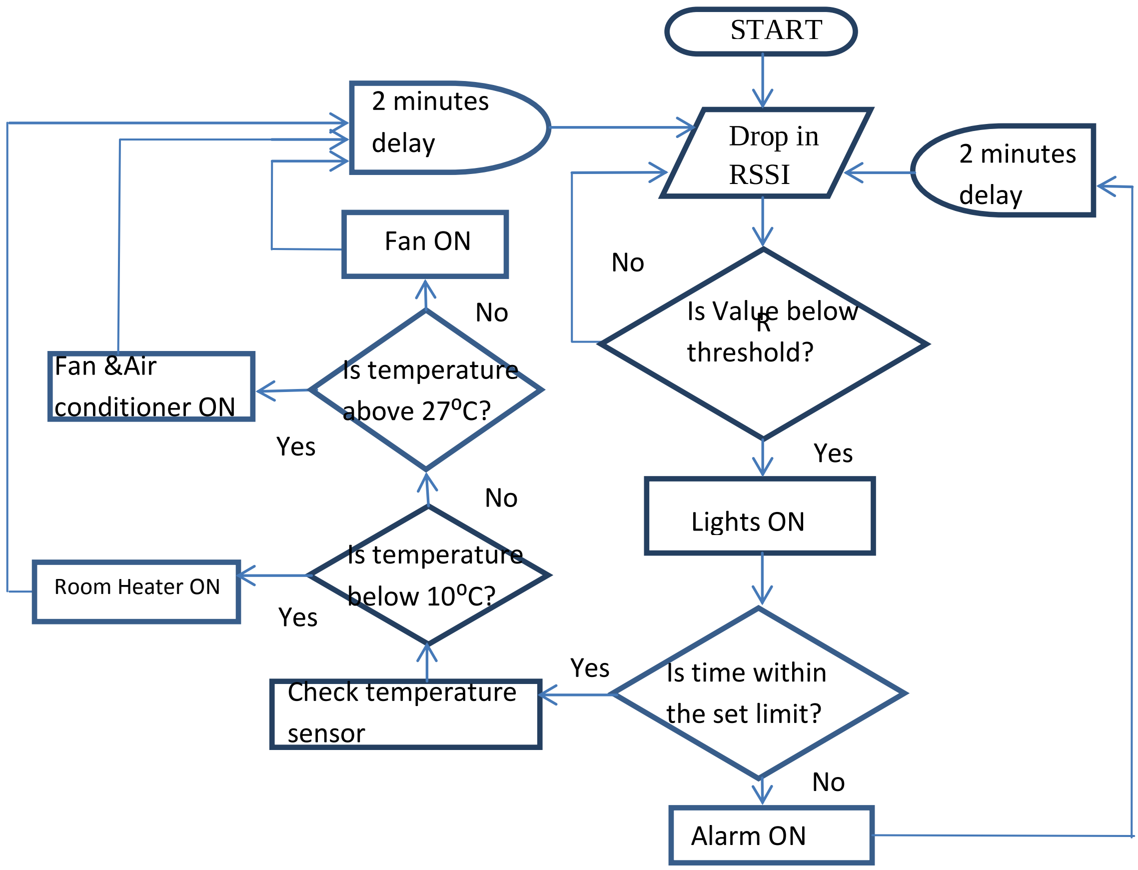

Fig. 5. Algorithm of working of ES-SU

The zones, under observation in this work, were Head of the Department (HoD) cabin, faculty cabins and laboratories. These data were collected over a period of one month during teaching period and examination period respectively for eight working hours per day. The total period was of 200 hours, the number of working days being 25 in that month. Fig. 6a and 6b show the occupancy patterns for different areas for 200 working hours which corresponds to working hours of one month during teaching period and examination period respectively. There was a significant change in occupancy pattern for faculty cabins and laboratories during teaching period and examination period because nature of work was different. Mostly laboratories remained empty during examination time. Similarly most of the faculties were busy during examination time so their cabins remained empty. But occupancy of HoD cabin remained unchanged in both observations.

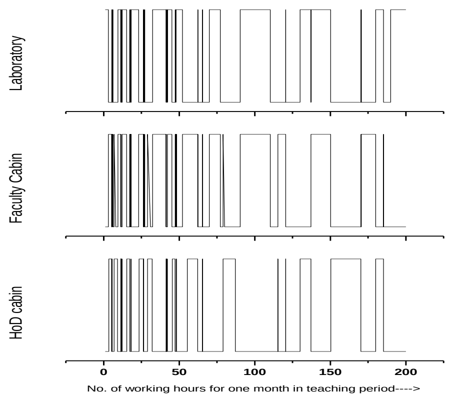

Fig. 6a. Occupancy patter of three zones during teaching period

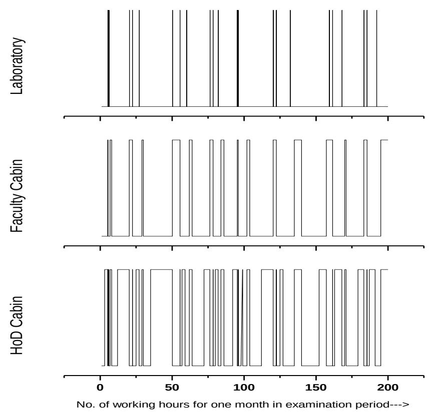

Fig. 6b. Occupancy patter of three zones during examination period

4. Experimental Results:

4. 1 Performance Evaluation in Terms of Occupancy Detection:

In order to test the accuracy of the system, the situations of entering and leaving the area were simulated same as occupants would behave normally. Initially, single pair of transmitter and receiver was taken into account. Fig. 7 illustrates the significant change in RSS when a person enters the room and shadowed effect remained as long as the person remained in the detection region between transmitter and receiver.

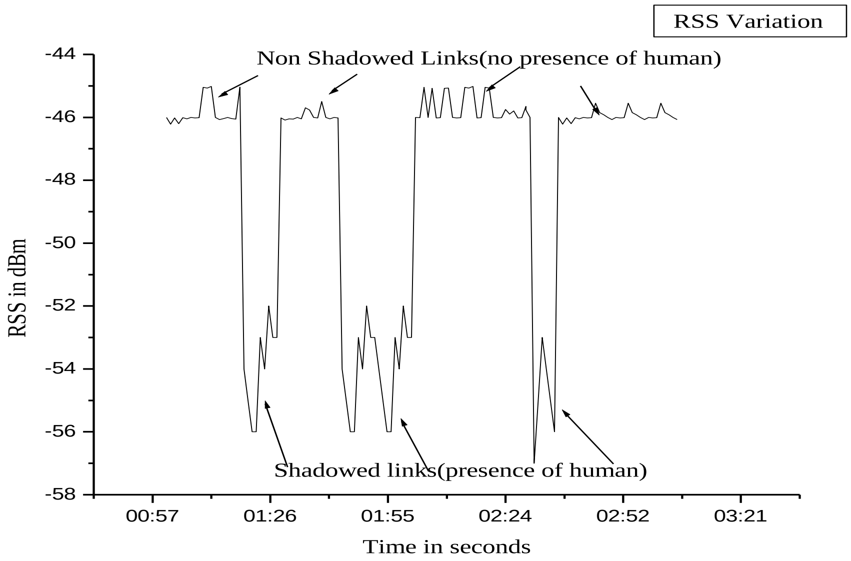

Fig. 7. RSS variation for Shadowed and Non Shadowed Links

In this work, the third moment was proposed as an additional parameter to monitor the dynamic of the signal strength deviation over a period of time. With the help of third moment, based on the last sampling time, thresholds were automatically recalculated. Further, error percentage due to third moment was much less than the error percentage due to standard deviation which as shown in table. 1.

Table. 1. Error Percentage

	Error due to standard deviation	Error due to third moment
5m(Non Shadowed)	2. 467%	0. 808%
5m(Shadowed)	3. 33%	0. 811%
2m(Non Shadowed)	1. 101%	0. 588%
2m(Shadowed)	3. 1%	0. 315%

Fig. 8a and 8b demonstrate the occupancy test by ES-SU in laboratory and faculty cabin. Accuracy of occupancy test ranges from 98 to 99%. False positive and false negative were also reduced significantly.

4. 2 Performance Evaluation in Terms of Energy Savings:

In order to evaluate energy efficiency, first of all, electrical energy consumption were recorded in each observed area without deployment of nodes. Energy meters were connected to measure consumption of electrical energy in each area under observation.

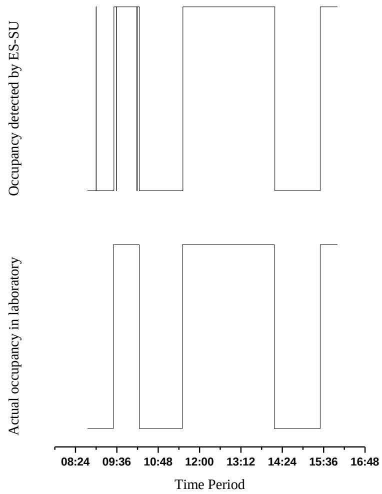

Fig. 8a. Comparison of Occupancy detection in laboratory of ES-SU vs. Actual occupancy

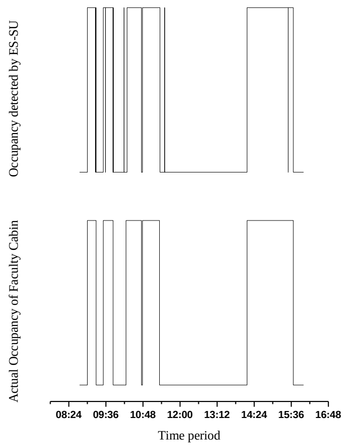

Fig. 8b. Comparison of Occupancy detection in faculty cabin of ES-SU vs. Actual occupancy

The power consumption would depend on seasons (summer, winter, spring and rainy season), daily weather, construction of sensed area (sun facings, number of windows, material type of flooring, etc.), number of occupants in cabins, laboratories etc. To achieve a clear view of power savings, two consecutive months of almost same environmental conditions and nature of working conditions. For example, March and April both months have almost same weather conditions (spring season) and same working conditions (teaching sessions). Similarly, December and January are months of winter seasons and examination periods, July and August are months of rainy seasons with teaching sessions, May and June are months of summer seasons with examination duration. Power consumption was measured without application of ES-SU for one month and the same was measured with ES-SU in next month of same electrical load as explained earlier. Figs. 9-12 show the power consumption as function of time with and without ES-SU in the case of one month of each (summer, winter, spring and rainy) season. It is evident that the rate of consumption of power is much lower when the ES-SU was activated. Fig. 9 shows power consumption rate decrements in winters with the application of ES-SU. The average power savings was ~ 15% while on daily basis percentage power saving ranges from10% to 20% in winter. While in summer the power saving on daily basis varies from 15% to 36%m with the use of ES-SU. The average power savings is 21%. The effect of ES-SU on power consumption in spring and rainy seasons respectively. In spring season average power saving was ~26% and daily power savings ranges from 15 to 35%. In rainy season average power saving was ~ 32% while daily power savings ranges from 10 to 40%. Therefore, it was revealed that with the implementation of ES-SU a power savings of 26 to 32% was achieved in a year

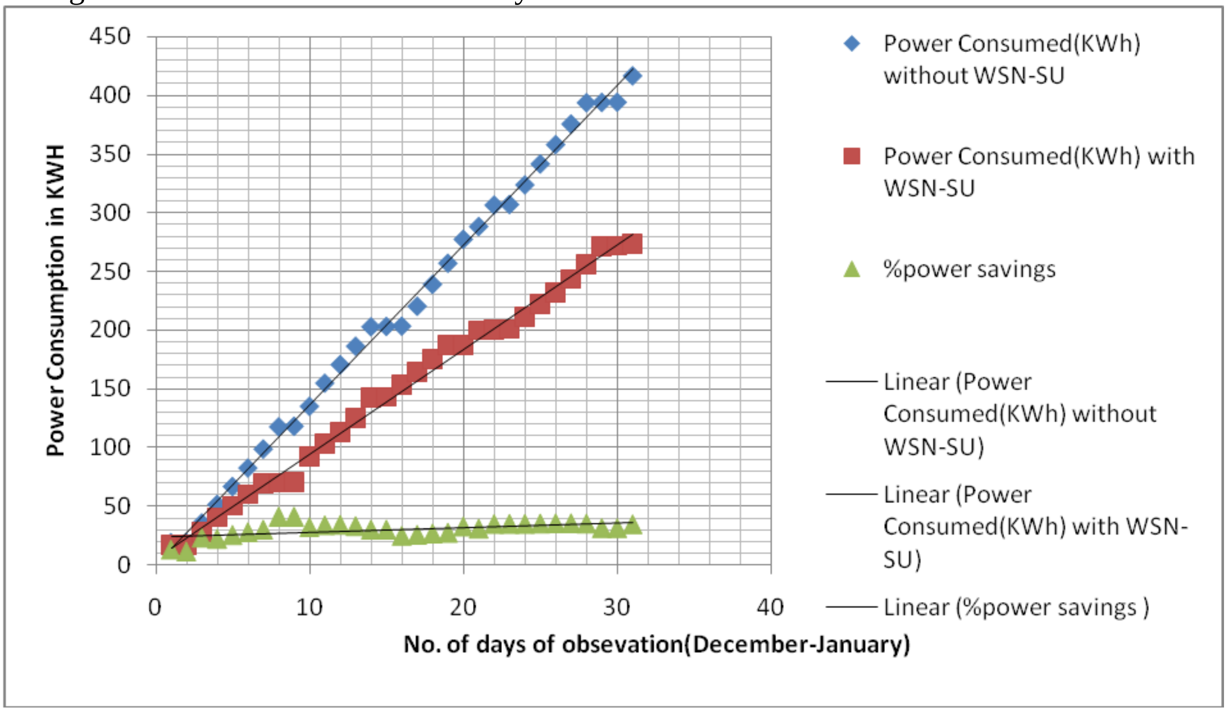

Fig. 9. Power Consumed with and without ES-SU in December-January

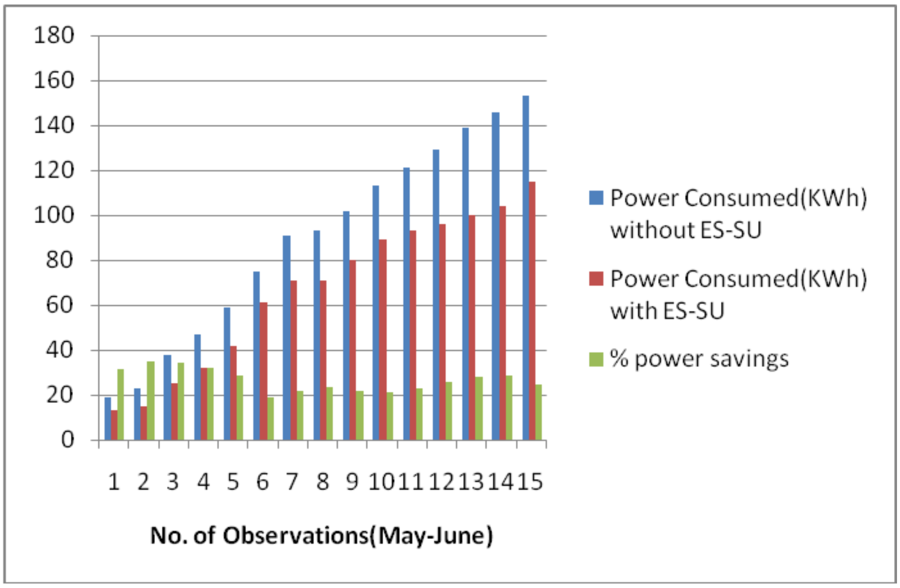

Fig. 10. Power Consumed with and without ES-SU in May-June

4. 3 Simulation

The effect of ES-SU on energy cost was studied using energy plus building energy simulation program [25] developed by US department of energy. The building model was simulated for one year including two modes: i) Appliances were turned ON during entire working hours and ii) with ES-SU which turns ON appliances only when there was occupancy and according to algorithm as discussed section 3a and 3b. Fig. 13 shows that the monthly power savings using our occupancy systems is between 18 to 19%.

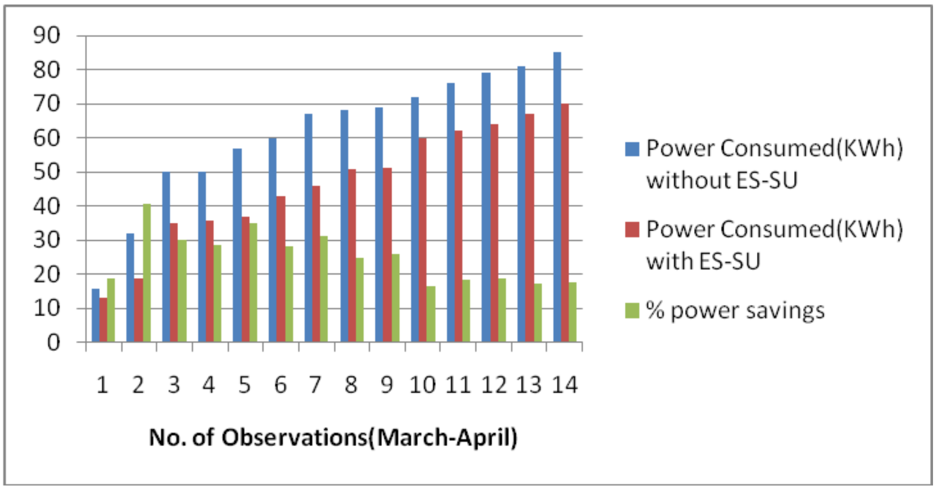

Fig. 11. Power Consumed with and without ES-SU in March-April

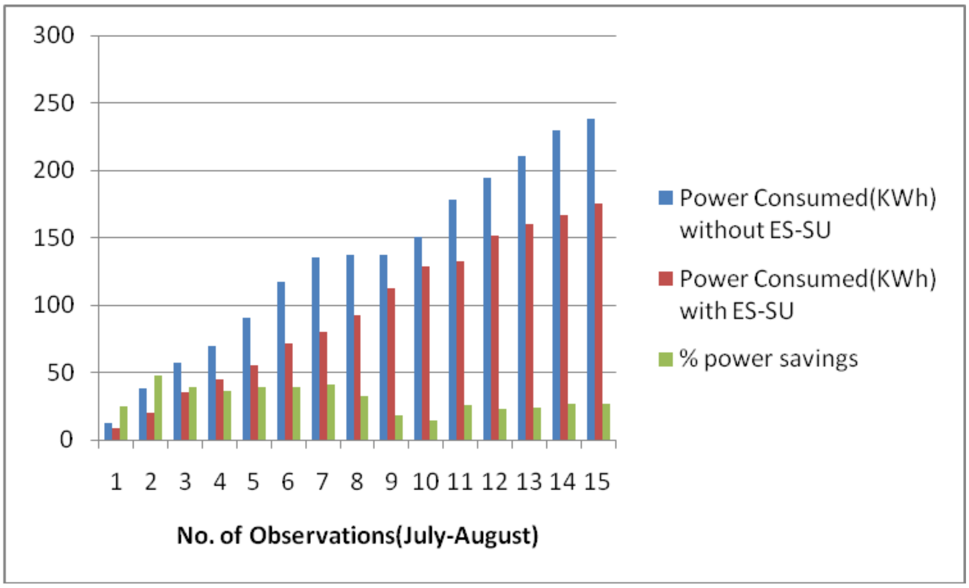

Fig. 12. Power Consumed with and without ES-SU in July-August

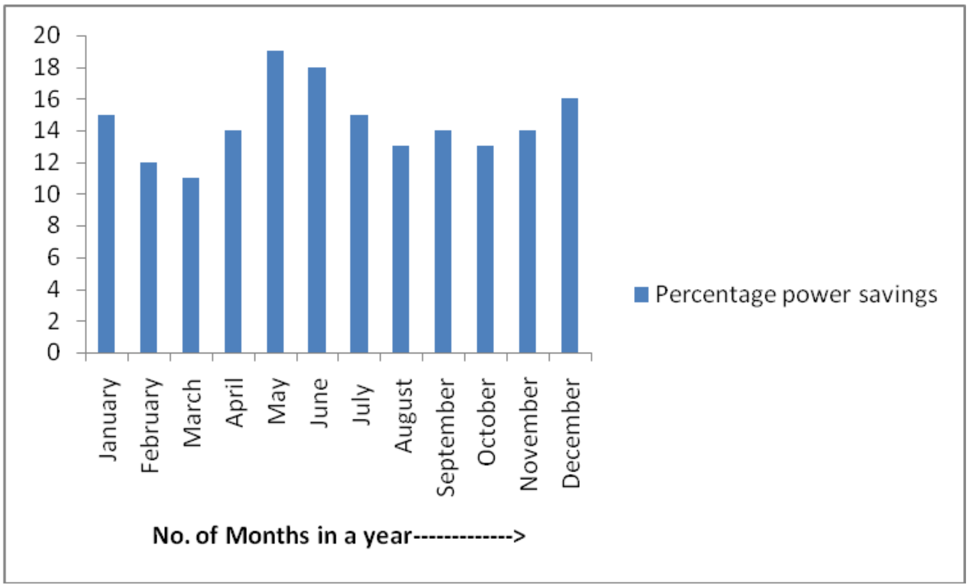

Fig. 13. Percentageof power savings per month

Conclusion

The use of third order moments in the algorithm resulted in the reduction of error in detection. The system has 98 to 99 percent accuracy in occupancy detection without applications of sensors because it works on detection of variation in RSSI due to interference of human body in radio frequency links at 2.4 GHz. Due to reduction of sensors, cost and size of nodes reduces significantly. A power savings 18 to 19% was achieved by the system along with the saving of workforce.

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