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A Novel Smart Home Energy Management System for Residential Buildings

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Abstract: Development of smart environments is one of the hot researching fields of this digital era. Integration of data mining techniques with building energy management mechanisms improve the accuracy of energy management strategies. The goal of such mechanisms is to reduce the electricity consumption while maintaining maximum user comfort. Introduction of Time of Use (TOU) tariff reduces the energy consumption charges. Hence, appropriate demand shifting mechanisms can reduce the electricity cost by scheduling some of the peak load to less costive hours. The behavior profiling of the residents of a smart home equipped with ambient sensing is expected to give vital inputs to intelligent appliance scheduling algorithms designed with an objective to minimize residential energy consumption. Simulation results show that 16-17% of energy is saved by integrating TOU based scheduling with occupancy detection system without reducing user comfort.

Key words: Novel, smart, home, energy, system

INTRODUCTION

The global demand for electricity is increasing continuously. The mismatch between demand and supply, lack of automation and monitoring tools have already caused major blackouts worldwide. The basic idea of smart grid is to add monitoring, analysis, control and communication capabilities to the national grid in order to improve reliability, maximize throughput, increase energy efficiency, provide consumer participation and allow diverse generation and storage options (Pathak *et al*., 2012). The milestone in the process of transition from the traditional grid to the smart grid is the integration of Information and Communication Technologies (ICT) to the power grid. The advances in ICT can be employed to increase automation, integrate distributed renewable resources, secure the grid infrastructure, adopt Electric Vehicles (EVs) and enable efficient Demand-Side Energy Management (DSM). DSM consists of a series of activities employed by utilities or government agencies in order to achieve better load management, energy efficiency and energy saving with the help of energy usage information collected through advanced energy monitoring devices like smart meters (Pathak *et al*., 2012). Within the concept of demand-side energy management, residential energy management is recently attracting increasing interest from the research community. Therefore, the advent of smart grid framework paves way for novel residential energy management techniques that involve communications and interaction between consumers, devices and the grid with an overall objective of optimizing the energy generation, distribution and consumption fronts.

The main objectives of residential energy management techniques found in the literature are to match the generation/supply of electricity according to the predicted energy demand scenario and to reduce peak our power consumption. In the smart grid implementation, smart meters are in wide spread usage in majority of consumer premises and Time of Use (TOU) tariffs are already in place in many developed countries in UK and US. The same is expected to be adopted shortly by many other countries. TOU metering involves dividing the time of the day into different tariff slots with higher rates at peak load periods and low tariff rates at off-peak load periods Experts believe that in developing nations people are expected to be willing to modify their lifestyle if thy can save on electricity charges [Dr.RagulThongia, advisor to the Smart Grid Task Force, Governemnt of India , The Hindu, 5th August 2015. Recently, residential energy management has become an active topic and several appliance scheduling schemes have been proposed (Dong and Andrews, 2009; Heierman *et al*., 2004; Infield *et al*., 2007; Mohsenian-Rad *et al*., 2010; Molderink *et al*., 2010; Pedrasa *et al*., 2010; Erol-Kantarci *et al*., 2011a, b) focusing on reducing the peak-to-average electricity usage ratio through optimal scheduling of home appliances. Mohsenian *et al*. (2010)

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proposedan automatic controller design to schedule appliances that achieves an optimum electricity cost. Molderink *et al.* (2010) used neural network-based prediction approach to optimize the scheduling of microCHP devices. Pedrasa *et al.* (2010) used the particle optimization method to schedule demands in an automated way.

Ambient intelligence refers to an artificial intelligence technology that makes our environments responsive and supportive to our needs through automatic and nonobtrusive way. They personalize themselves in response to the presence and behavior of the users. In the context of residential energy management, ambient intelligence is expected to play a key role as an enabling technology that is used to model the activity profile of the occupants through environmental sensor network. When this occupancy information is integrated as a part of the home appliance scheduler, more accurate and dynamic energy management strategies could be devised. Ambient intelligence is still in its early stage and several open issues need to be addressed before it can be considered as a fool proof enabling technology in realizing smart home environments.

Several researchers have carried out investigations on the various techniques used to model the occupant presence and their interactions with the environment. Fritsch *et al.* (1990) proposed markov chains model to model the movements of occupants. Degelman (1999) developed a Monte Carlo modeling approach for space occupancy prediction. Reinhart *et al.* (2004) used stochastic model of arrival and departure to determine the occupant presence for controlling the lighting devices. Wang *et al.* (2005) applied Poisson distributions to generate daily occupancy profile in a single-occupied office. Mahdavi studied the correlations between the user control behavior and the environmental parameters such as illuminance and irradiance. Bourgeois *et al.* (2006) integrated an occupancy model based on Reinhart's algorithm into ESP-r to investigate lighting use. However, most of the previous occupancy presence models were either tested on a single person office or presented a specific application such as lighting control. However, Page *et al.* (2008) targeted individual occupancy behavior by developing a generalized stochastic model for the simulation of occupant presence with derived probability distributions based on Markov chains. Dong *et al.* (2009) demonstrated the energy saving potential of using a data-driven model of occupant behavior for energy management.

Most of the previous works on occupancy detection are based on supervised approaches, which require ground truth occupancy information. In addition, the latest models are all based only on motion sensors, which often fail to detect occupants that are sitting or standing still and thus have been shown in some cases to provide insufficient accuracy for occupancy detection (Lam *et al.*, 2008). None of the previous works have attempted to integrate the occupancy information and the behavior profile in the appliance scheduling algorithm.

The reported piece of research work aims at developing an intelligent appliance scheduler based house-hold energy management scheme through occupancy detection and behavior profiling system. The proposed integrated framework focuses on reducing the energy bill of the residents whilst not compromising on their comfort level by reducing the peak hour energy consumption by optimally scheduling the appliances to less expensive hours according to the TOU tariffs preparing devise operation schedules as per the behavior profile learned through historic ambient sensing data and dynamically adjusting operation schedules according to the current occupancy information. For example, by analyzing the historic environmental sensor data, routine activities repeated at regular intervals could be determined e.g dining and study activities are likely to happen regularly at specified time periods. Hence, HVAC and the illumination systems could be scheduled to turn on during preset intervals. But when there is no motion detected during the specific interval for a given observation window, the HVAC system and the illumination systems would be automatically turned off. Similarly, depending on the current occupancy level learned through the ambient sensing network, the intensity of the lighting system/ cooling level of the HVAC system can be automatically adjusted without causing too much disruption to the occupants. In the current work, we restrict our investigation to the control of illumination devices and ventilating devices

The proposed system has two key parts: occupancy behavioral pattern detection and appliance scheduling. The Occupancy Pattern Detector (OPD) analyzes the historical sensor data and generate user interesting episode models. The appliance scheduler minimizes the energy expenses and reduce peak hour load by scheduling appliances to less expensive hours according to (a) TOU tariff and (b) .

Chapter 2 presents a detailed explanation of the model. Chapter 3 shows the results of comparison between the proposed system with the naïve approach. Chapter 4 concludes the study and outlines possible future directions.

The integrated approach

Scheduling with occupancy detection-An integrated approach: In this reported research, the appliance scheduling algorithm is integrated with resident activity pattern detection technique with an objective of reducing the peak hour power consumption while preserving the residents' comfort level. The entire system is divided into three modules: historic sensor data analysis for behavior profiling, smart device scheduling and real time ambient sensing for occupancy detection.

The architecture: The core parts of the system are occupancy pattern detection and appliance scheduling. Occupancy pattern detector identifies significant energy related episodes of the occupants based on the historic data gathered through ambient sensor network. Interesting energy related episodes are mined from the observed data and thus a behavior profiling is done as explained in the following section.

Sensor data analysis: The presence of occupancy and their activity level are detected through various sensors installed in residential buildings. The various environmental parameters used to monitor the occupancy level and activity profiling include acoustics, illumination, motion, CO_2, temperature and relative humidity. The system continuously monitors ambient parameters through environmental sensor network and generate energy related behavior episodes. A richer sensor environment shall deliver better accuracy in predicting occupant presence.

Acoustic sensors are capable of sensing spatial acoustic level. Based on the acoustic sensor inputs, two types of events are detected. Acoustic level between 15% to 20% with a minimum increase of 5% is defined as ventilation noise. Acoustics level above 20% with a minimum increase of 10% is defined as human activity [base] (conversations, handling objects etc). Light sensors help to detect the intensity level of luminance level of the ambience. Motion sensors detect the presence and absence of motion in the environment. To avoid capturing high frequency fluctuations, a 10 min time window is used to smooth the signal. CO_2 sensors can predict human presence, because the level of CO_2 increase of 50 ppm in 10 min has a high correlation with human presence. Temperature and relative humidity sensors can analyze human presence by measuring the rate of change in humidity and temperature.

The environment data gathered through the above set of sensors are then analyzed to detect significant energy events and thus occupant behavior profiling is done. This is then used as a vital input for appliance scheduler in addition to the user requests generated for devise operations.

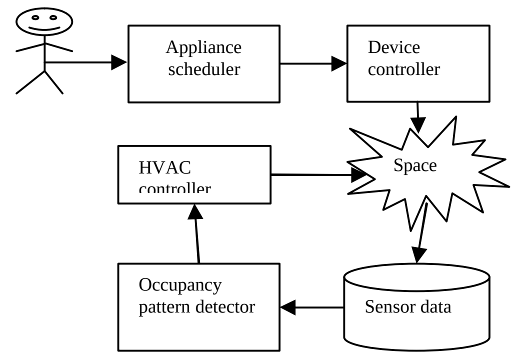

Fig. 1: The architecture of intergrated energy management framework

Table 1: TOU slots

Category	Time slot
Peak hours	6AM-10 AM 6PM-10PM
Mid peak hours	10 PM-6AM
Off peak hours	10 AM-6 PM

Dynamic appliance scheduler: The appliance scheduler is capable of shifting the working schedules of the smart appliances under consideration for the purpose of this study to lesser expensive hours. Appliance scheduler also takes into consideration the real time occupancy information gathered from the occupancy pattern detector and perform corresponding HVAC and ventilation actions. Occupant presence and behavior in building have been observed to have large impacts on space heating, cooling and ventilation demand, energy consumption of lighting and space appliances and building controls (Page *et al*., 2008). The block schematic diagram of the proposed model is shown in Fig. 1.

The appliance scheduler gets operation requests from smart appliances in various points of time. Smart appliances are scheduled to work during less costly hours based on the time of unit tariff. TOU time slots are shown in Table 1.

In working out the devise operation schedules, the scheduler not only considers the ToU tariff, but also reads the ambience through the occupancy pattern detector and accordingly it decides which of the appliances need to be switched on / off. For example, if there is no occupant presence is detected through the use of sensing elements, then the lighting and ventilating devices can be scheduled to work in sleep mode until some occupant presence (an episode) is again discovered.

MATERIALS AND METHODS

Smart appliance scheduling: Scheduling of smart appliances is designed with the motive of lessening the

Table 2: Definition of events from sensors

Sensor	State/ state transition	Notation	Sensor	State transition	Notation
Acoustics	Low acoustic	A_l	CO_2	Increasing	C_a
	Loud acoustic	A_h		Decreasing	C_b
Illumination	Off-On	I_a	Temperature	Increasing	T_a
	On-Off	I_b		Decreasing	T_b
Motion	Off-On	M_a	Relative Humidity	Increasing	H_a
	On-Off	M_b		Decreasing	H_b

Table 3: Repetition of dining episode

Time (day)	Expected frequency
{1, 20:12- 20:33}	Daily
{2, 20:08- 20:30}	Daily
{3, 20:04-20:28}	Daily
{4, 20:03-20:24}	Daily
{5, 20:05-20:31}	Daily
{6, 20:02-20:28}	Daily
{7, 20:06-20:26}	Daily

peak hour electricity load and thereby reducing the electricity bill of the users. When a smart appliance is turned on, a REQ (request) packet will be sent to the scheduler with the device id, a timestamp indicating the time the device is turned on, the users' tolerance on time delay and the duration of operation of the appliance. If the appliance is schedulable and if it is turned on during peak hours, the scheduler checks for lesser expensive slots and estimates the delay in starting the device operation. Since appliances are scheduled to less costly hours, an operational delay is incurred which in turn reduces users' comfort. In order to overcome this problem, two delays namely user defined delay and a maximum allowable delay are defined. If the waiting time of the appliance is less than the user defined delay, the scheduler then sends a REP (reply) packet back to the device controller with the estimated waiting time. Based on the estimated delay, user sends his permission to start delayed. Otherwise, the appliance is scheduled to operate immediately. The scheduler gathers all such requests from several smart appliances and then prepares an optimal operation schedule and forwards it to the device controller which operates the appliances based on the working schedule prepared.

Occupancy pattern detection: Occupancy pattern detection is based on various sensor events. The sensor events are denoted using particular notations for the ease of use. Sensor events and the notations are described in Table 2.

Dynamic energy episode discovery: Energy episode discovery is a process of identifying interesting energy related event patterns by generating candidate sequences, then pruning these sequences to generate important sequences (base 2). Continuous event sequences are generated by applying a sliding time window to the historic sensor event sequences. All possible subsets of episodes are generated for a given time period and subsequently relevant patterns are filtered. The sequences that repeat in a same interval are considered as most relevant events.

For instance, let us consider the sequence "$I_aA_lM_aM_bA_hC_aT_aH_aA_hM_aM_bI_b$" which represents a sample episode generated in dining room during the time of dinner. Illumination sensor senses the presence of light when the lighting device is turning on. Acoustics and motion sensors are triggered when the occupants are inside the room. The presences of occupants are validated by the increase of CO_2, relative humidity and the temperature in the room. This episode is repeated for about 15-30 min every day in between 8PM and 8:30PM. The pattern detection algorithm marks this as a relevant episode. Dining event measured in a random week of February is shown in Table 3.

A brief algorithm for the integrated model is discussed in the preceding sections is given below. The device controller reads episode e_i from pattern detector, the appliance starting time and device id from the device controller. Device scheduler schedules the appliance and perform possible HVAC actions. Occupancy pattern detector reads the sensor data and match with the candidate episode. To smooth the sensor data a one minute sliding window is used.

Alogrithm

Alogrithm: Pseudo code for the Integrated approach:

Define Sd_i:Data from sensor with id i
Define D_i:Device id
Define St_i:Starting time of device i
Define d_u: Desired delay (of user)
Read input D_i,St_i
Energy Event Detector( )
Device scheduler(D,St, d_u)
ei=Energy event detector ()
Device controller(Dsc, x,e_i)

Energy Event Detector():
Read ambient data from sensor array
S_i for i=1,2,.. N
Let candidate episodes E={e_1,e_2……e_n}
For every e_i ? E
Check whether S_i matches e_i
return (e_i)

Device scheduler(D,St, d_u)
Define d_i:Delay of appliance i
Define D_{max}:Maximum allowable Delay

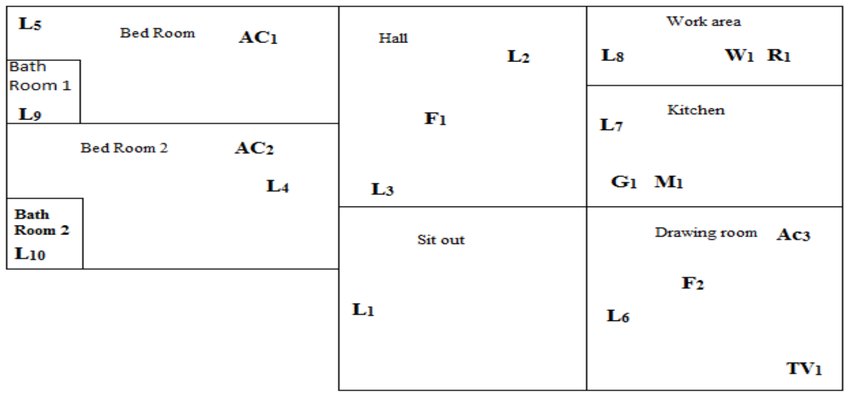

Fig. 2: Blue print of the test bed

```
Define x: devise schedule status
    x:{0 – start immediately
        1 – start delayed}
For all devices i=1 to N turned on during a given time window
{
    di= next offpeak hour- Sti
  if(Sti is in peak) then
if(dui<di<Dmax)then
      x=startdelayed( )
  shiftToMidPeak()
     else if(di<dui<Dmax)then
    {
x=startdelayed( )
shiftToOffPeak()
}
  else if(di>Dmax)then
xi=StartImmedietly()
endif
if(Sti is in mid peak) then
     Dmax=Dmax/2
if(dui<di<Dmax)then

xi=StartImmedietly()
:elseif(di<dui<Dmax)then
xi=StartDelayed( )
 shiftToOffPeak()
else
xi=StartImmedietly()
end if
end if
prepare devise operation schedule Dsc for all i=1to N[Di, Sti-sc] where
Di=device id
Sti-sc-scheduled starting time
```

Device Controller (Dsc,e i):
1:Check the type of event e_i
2:Perform the corresponding lighting on/off action and/or HVAC increase/decrease action
3:Check the device schedule status x
4:If(xi=1) then
5:Start the appliance after the scheduled delay Sti-sc
6: Else issue command to start the device

RESULTS AND DISCUSSION

The testing environment: The model is tested in a two bed room apartment in which the sensors are deployed in appropriate locations to continuously monitor the he environment for occupancy behavior detection. The blue print of the test bed is shown in Fig. 2.

The apartment has 8 lights having power rating of 20W and two lights with 40W. Two 60W fans are installed. Three air conditioners have 1050W power rate. Washer, mixer, grinder, Television and refrigerator have power rate of 240, 450, 500, 50 and 150 W respectively.

The values of electricity consumption are measured continuously for a period of one month. Electricity cost is calculated based on the TOU tariff. Electricity consumption using the proposed integrated model is compared with the normal power consumption and with the naïve appliance scheduling model.

The aim of the reported piece of research work is to demonstrate through empirical study the energy saving potential of the proposed integrated framework for residential buildings. The monthly average of normal energy usage of the residential apartment is calculated without scheduler. These values are compared with the device scheduler alone and the proposed integrated approach viz. device scheduler with occupancy pattern detection. The gathered results are indeed encouraging and serves as a proof of concept to develop such systems for the smart buildings that are envisioned to create a huge impact on the energy management strategies.

The proposed framework is tested for two climate conditions (summer and winter). The electricity cost is calculated based on the TOU tariff shown in Fig. 3-5.

Power consumption in summer: During the summer season, the device scheduler shows 2.7% of peak hour power reduction while the integrated approach shows 15% of electricity reduction.

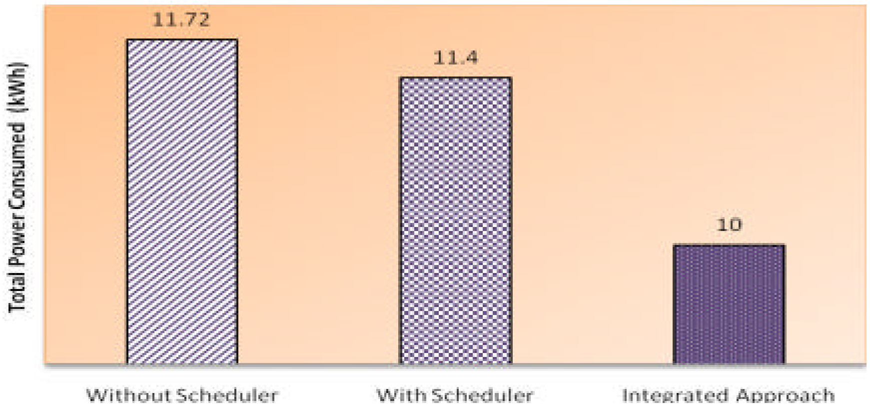

Fig. 3 Average Peak hour power consumption in winter

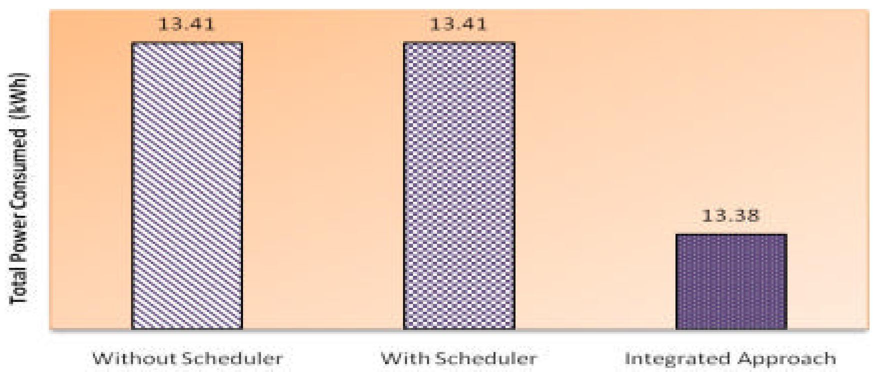

Fig. 4: Average Mid Peak hour power consumption in summer

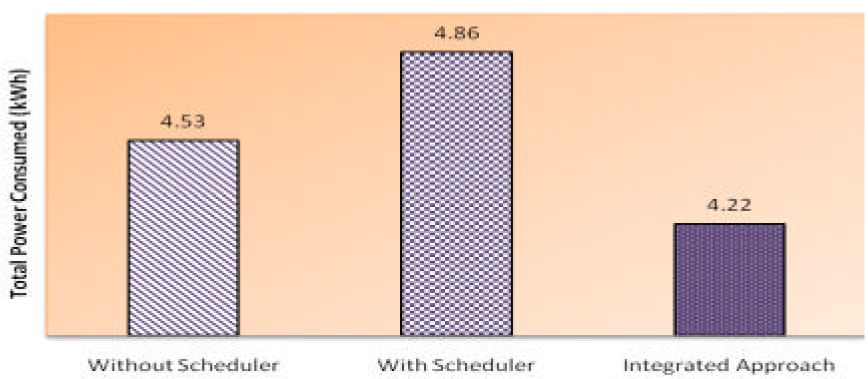

Fig. 5: Average Off peak hour power consumption in summer

Since no scheduling is happening during the mid peak hours scheduler application shows no change when compared to the normal reading. The proposed system shows 2% of power reduction during the mid peak hours.

The smart device scheduler schedules the smart appliances to off peak hours. So the energy consumption during the off peak hour is increased by 7% while the proposed system shows 7% of power reduction during the off peak hours.

Power consumption in winter: In India power consumption in winter season is less as compared with the summer season. In winter season the device scheduler

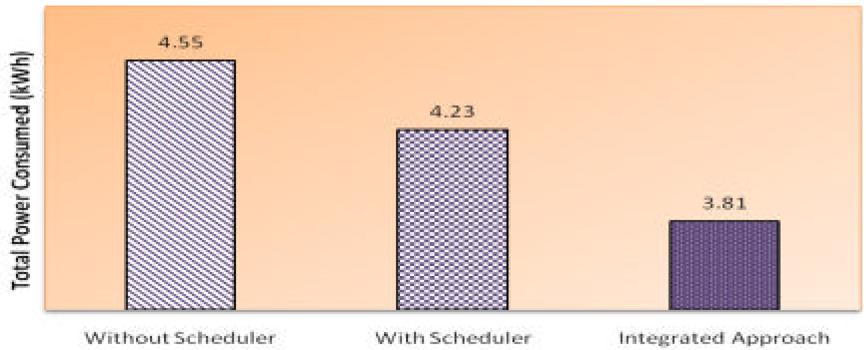

Fig. 6: Average Peak hour power consumption in winter

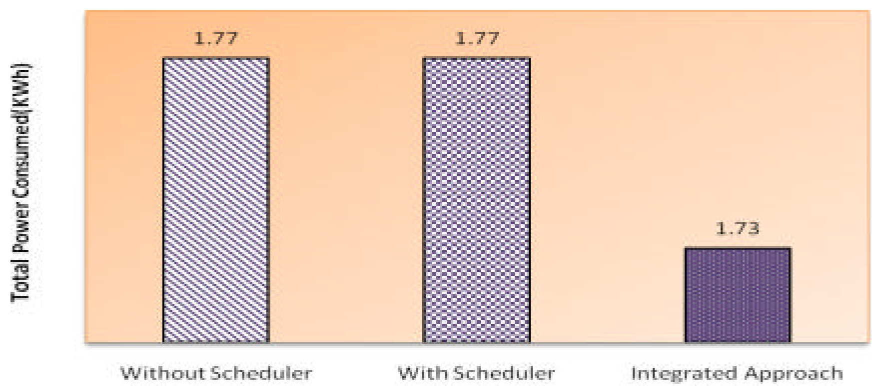

Fig. 7: Average Mid peak hour power consumption in winter

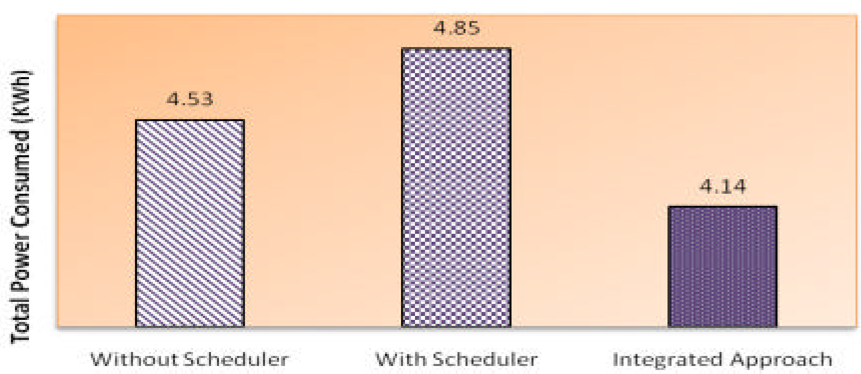

Fig. 8: Average off peak hour power consumption in summer

shows 7% of peak hour power consumption reduction by applying the device scheduler and 17% with integrated approach.

Due to the absence of scheduling during the mid peak hours device scheduler shows no power reduction but integrated approach shows 3% of power reduction. Since the device scheduler schedule the working of appliances to off peak hours off peak hour power consumption is increased by 7% by applying the scheduler and the proposed system shows a 9% of reduction in power consumption shown in 7-8.

CONCLUSION

The study proposes a cost and energy reduction mechanism that can be applied to residential buildings.

The system integrates two mechanisms, sensor based occupancy behavioral pattern recognition (Erol *et al*., 2010a, b; Erol and Mouftah, 2011) and device scheduling mechanism (Dong and Andrews, 2009). The model has been tested in two climate conditions, during the winter and summer. The system shows 15% of reduction of peak hour power consumption during the summer and shows 17% of reduction of peak hour energy consumption during winter.

Useful episode selection is most challenging in this work. Efficiency of occupancy based pattern detection can be improved by trying more efficient algorithms. Since the energy consumption and number of appliances are high in commercial building, the method can be applied to commercial building.

Ambient sensing data such as lighting, acoustics, CO2, temperature and relative humidity are incorporated into an event-based pattern detection algorithm used for occupant behavior toward HVAC system control.

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