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The Contribution Of Occupancy Behavior To Energy Consumption In Low Income Residential Buildings

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ABSTRACT

Energy consumption in residential buildings consumes 22% of the total US energy each year and is highly impacted by the occupant behavior. In order to model domestic demand profiles more accurately, it is important to understand occupancy behavior profile. Four low income houses in Texas are used as the test beds. The occupancy sensors are installed in every room. The real-life occupancy data from the occupancy sensors were compared with the American Time Use Survey (ATUS) data. The study period is from July 1 to August 31. The preliminary result shows that there is a similarity between ATUS data and actual occupancy profile. In addition, simulations in EnergyPlus were conducted to test how much energy consumption can be saved based on the thermostat control of real-life occupancy behavior patterns. The results show that such control can save cooling energy by 7%.

1. INTRODUCTION

The US residential sector is currently responsible for an estimated 22% of the country's primary energy consumption (EIA, 2010). Although the energy efficient technologies are developing fast, from 1990 to 2009, energy consumption in residential buildings still increased by 24% (DOE, 2010). As energy costs rise, so does the burden of these costs upon American households. Low income households are shown to be the most vulnerable to these rising costs. Even with programs such as the Low Income Home Energy Assistance Program (LIHEAP) in place, many American families must make the difficult choice of either heating or eating (AEP, 2013). In addition, the low-income housing constitutes an important but often overlooked part for energy use with in the US residential sector. The US department of housing and urban development (HUD), which provides operating subsidies to affordable rental homes for the low-income public reveals the data indicating overall utility costs in HUD-assisted housing increased by 4.9 percent since 2009. Total expenditures on utilities in public and assisted housing are estimated at $7.1 billion in FY 2011, which with HUD's share of the total estimated at $ 6.4 billion (HUD, 2012). And a 2010 report by the National Consumer Law Center estimates that a 20% reduction in energy consumption in low income housing would save at least $1 billion annually (Harak, 2010).

Among various factors contributing to the energy consumption in residential houses, occupant behavior is a determinant part, and occupant behavior is also one of the most significant sources of uncertainty in the prediction of building energy use by simulation programs (Hong and Lin, 2012). Occupant behavior here may include occupant's presence, activities, how they operate appliances and other human related subjects. Previous studies have shown that occupant behavior might play an important role in the estimation of energy consumption (Jeeninga et al., 2001, Richardson et al., 2008). Most recently, Santin (2011) carried out correlation tests between the occupant behavior and the energy use and identified the behavioral patterns to be used in energy calculation. However, how to identify an occupancy profile for energy simulation is still a challenging topic. Richardson et al. (2008) presents a model to estimate occupancy time-series data at a ten minute resolution using a Markov-Chain technique to generate further data with statistical characteristics that match the original. Wahl (2012) proposes a method to estimate the occupancy in commercial building using distributed strategically placed PIR sensors and algorithms that can process the distributed sensor information. Most of above studies focus on the impact of occupant behavior for commercial buildings energy consumption, while few focus on the low-incoming group, where the case can be totally different. Only recently, Langevin et al. (2013) developed an interview guide and response-scoring framework, with the methods for developing, scoring, and analyzing these interviews both quantitatively and qualitatively. His study demonstrated the use of a semi-structured interview approach to explore the energy behaviors of low-income public housing residents in Phalidaphia. In this paper, we will develop simulation models to evaluate the energy impact of occupant behavior especially the occupant presence based on real-time measurement. To achieve this, first we will collect the occupancy data from our test-bed. Then the real-life occupancy data is compared with the ATUS data. Finally the real-life data is integrated into a validated EnergyPlus house model and energy saving potential for cooling in low income residential house is evaluated.

2. Technical Approaches

2.1 Analysis of American Time Use Survey Data

The American Time Use Survey (ATUS) provides nationally representative estimates of how, where, and with whom Americans spend their time, and is the only federal survey providing data on the full range of nonmarket activities, from childcare to volunteering. The data files include information collected from over 136,000 interviews conducted from 2003 to 2012 (ATUS, 2012). Due to the lack of information about occupant behavior, analyzing ATUS data almost become the only standard way for occupancy related research. In this study, the occupancy behavior from ATUS will be processed for obtaining the occupants' presence. There is already a lot of work done on this kind of time-use survey. Richardson (2008) provided a model for generating realistic occupancy data for UK households based on UK time use survey data. Aerts (2013) performed hierarchical cluster analysis on the ATUS data to discover groups of the population showing different behaviors and a set of occupancy profiles were also presented in his paper based on the deterministic approach, which is suitable for building energy simulations.
In our case, we focus on the low income households. ATUS data is sorted and analyzed according to their work status. 23,000 activities in 2012 from 2,000 families are processed to reveal the occupancy patterns for both employed and unemployed. The activity data contains information about how respondents spent their diary day and related information such as activity codes, activity start and stop times, and locations.

Occupant Presence: Since ATUS is a national survey, in order to dig information about the low income households. Activities are categorized by individual's work status (employed or unemployed) in our case. In this way, we can get the occupants' presence probability by combining those activities happened at home. Figure 1 shows unemployed occupants have a higher probability at home at any time during a day, while employed residents are more likely to be absent. Significant difference can be observed from 8am to 7pm. In our four houses test-beds, we may have both employed and unemployed occupants.

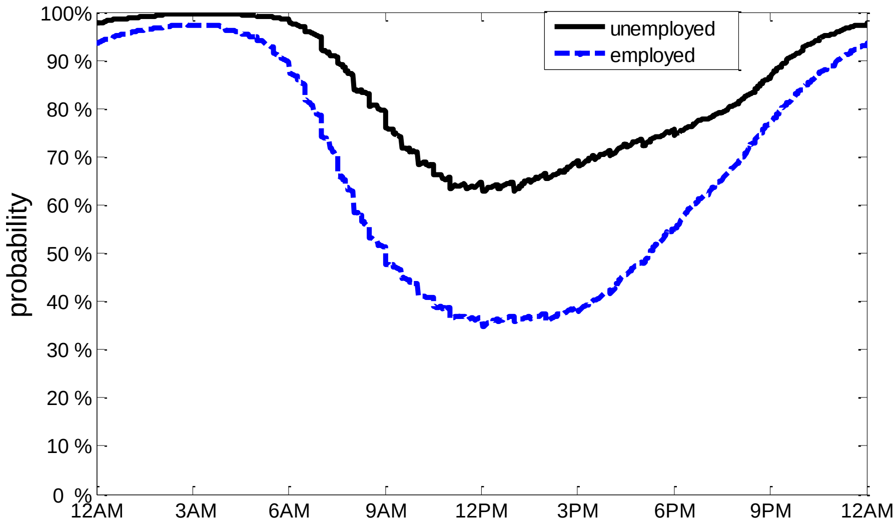

Figure 1: The probability of being at home for an individual from ATUS data

2.2 Analysis of Real-time Measured Occupancy Data

Description of Test-beds: Four low income houses in San Antonio, Texas were used as the test beds, shown in Figure 2. Those four houses are one floor, three bedrooms and 1,100 ft^2 each. They were initially built for testing purpose so each house is built in one kind of material. In our study, UX90 Occupancy/Light loggers provided by HOBO are installed in each house and every room for detecting occupants' presence, as shown in Figure 3. Those Passive Infrared (PIR) sensors measures infrared (IR) light radiating from objects in its field of view and a time stamped event are generated and stored into its data logger once motion is detected. An occupied to unoccupied event occurs only when there has been no motion for a time interval that averaged 15 min. In additions, four sets of power monitor system provided by Powerhouse Dynamic are installed. Each monitor system has more than 15 channels to monitor the energy use on every circuit and the real time data is uploaded online every one minute giving us the visibility into where energy is being used. In this paper, we will use the third house which is single occupied (container house) as an example to elaborate our findings.

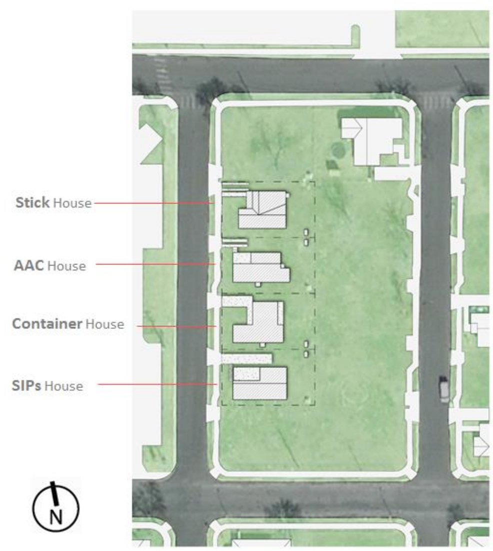

Figure 2: Four low income residential houses

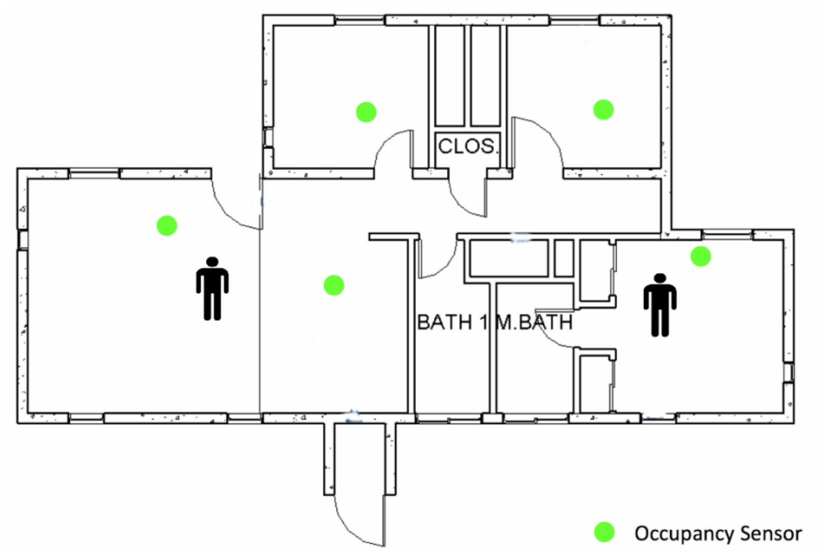

Figure 3: Occupancy sensors deployed in each room

Analysis of Occupancy Patterns: Preliminary results from sensor showed bedroom and living room are major zones with lot of activities while the rest are lightly occupied. The curves in Figure 4 and Figure 5 shows several expected features including: a)high level of presence probability throughout the night for the bedroom from 10pm to 8am lower value for living room since people are always sleeping during that period and, b)peaks corresponding to the lunch and dinner around 12pm and 7pm in the living room, c) highest probability value for the living room is around 60% due to the aggregated uncertainty of occupant activities in daytime, for example at 12am people are always sleeping while at 12pm people either can be eating or outside of house.

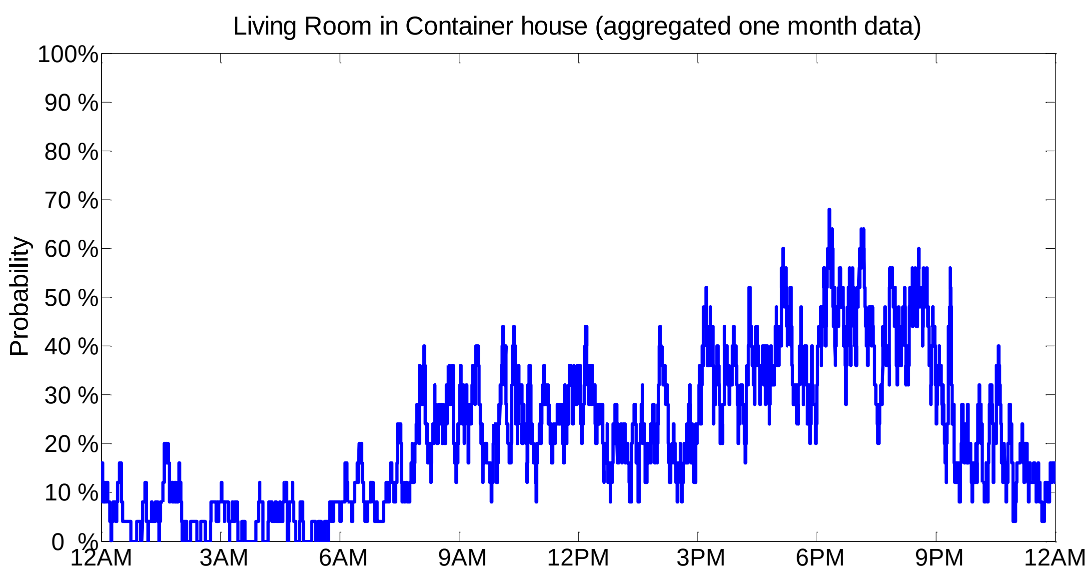

Figure 4: The probability of being occupied in Living Room along one day

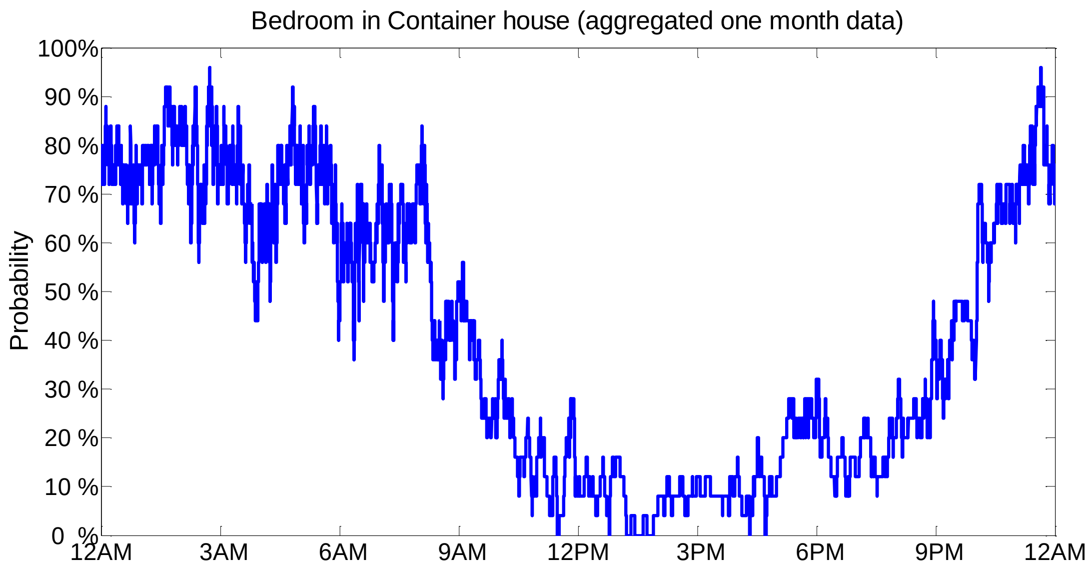

Figure 5: The probability of being occupied in Bedroom along one day

Total occupancy presence probability for house could be determined in the similar way as for zones. The difference is to integrate individual component zones together and the house will be considered as unoccupied in our 15 min interval if no motion in was detected, otherwise it is occupied, Figure 6.

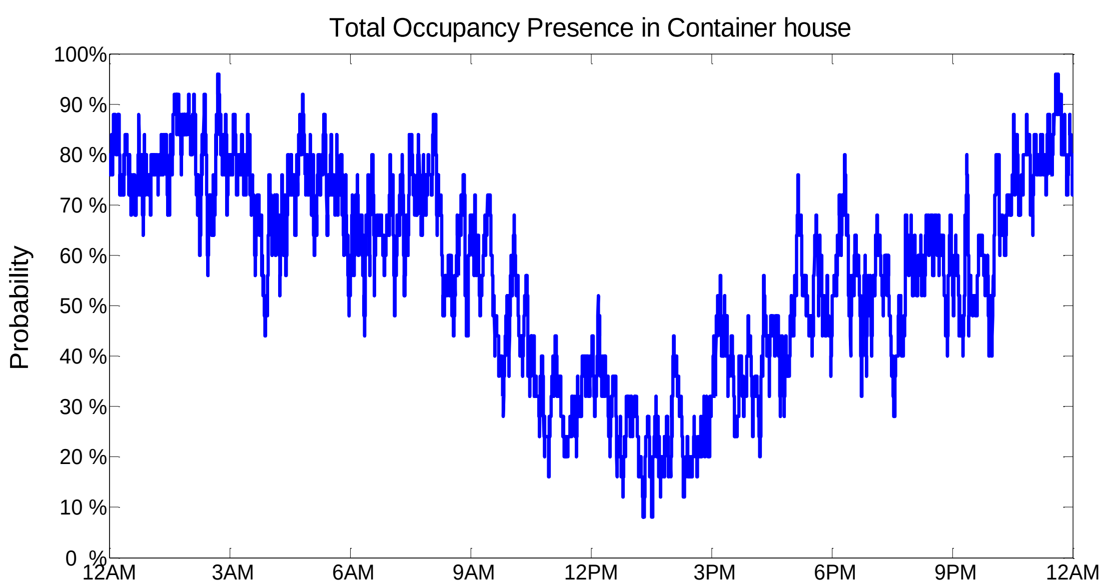

Figure 6: The probability of house being occupied along one day

2.3 Energy Impact Analysis

Baseline energy models: DesignBuilder and EnergyPlus were used to build up the baseline energy consumption models. During the modeling, we used measured appliance energy information as inputs into the simulation model. Meanwhile, we also get the thermostat schedules from houses. Residential thermostats control a substantial portion of both fuel and electrical energy- 9% of the total energy consumption in the U.S. Consumers install programmable thermostats to save energy, yet numerous recent studies found that homes with programmable thermostats can use more energy than those controlled manually depending on how or if they are used (Peffer et al., 2011). All four houses from our test-beds are equipped with programmable thermostats provide by TRANE. Figure 7 shows the existing thermostat schedules. Compared with the ASHRAE standard thermostat setting in baseline modeling which is 78F, we found two households use them very well while the rest set either too high or too low. In this study, in order to establish the baseline energy models, we use the actual thermostat setting from our measurement.

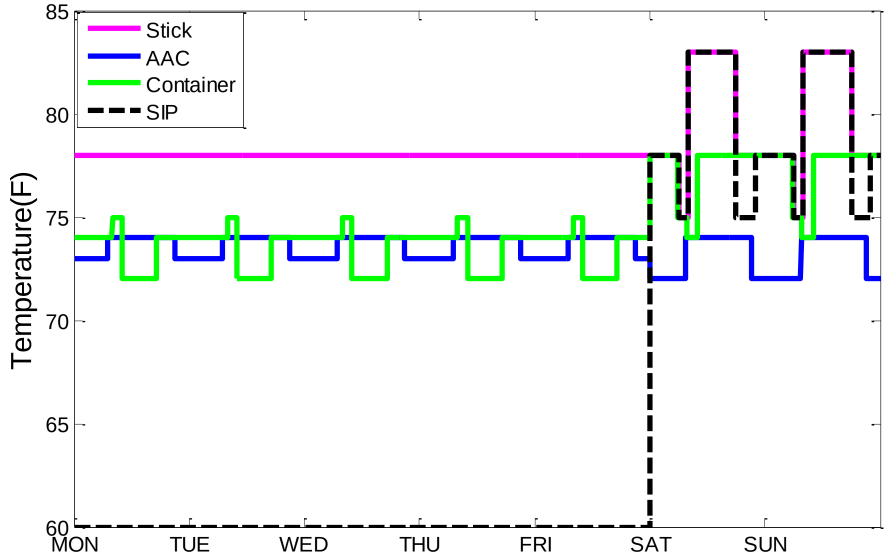

Figure 7: All four houses thermostat schedule

Integration with Occupancy Behavior Patterns: Figure 8 shows the overall energy analysis based on real-time measured occupancy behavior. Ideally we will use BCVTB for implementing complex control strategy. The BCVTB allows simulating a building in EnergyPlus and the thermostat control in Matlab, while exchanging data between the software as they simulate. Then the calculated result will be compared with the measured data in order to get the accurate energy saving. But for this study, since only two zones-living room and bedroom are occupied alternately, we just integrate the occupancy information into the EneryManagementSystem (EMS) module in EnergyPlus and set up a baseline to estimate the total saving.

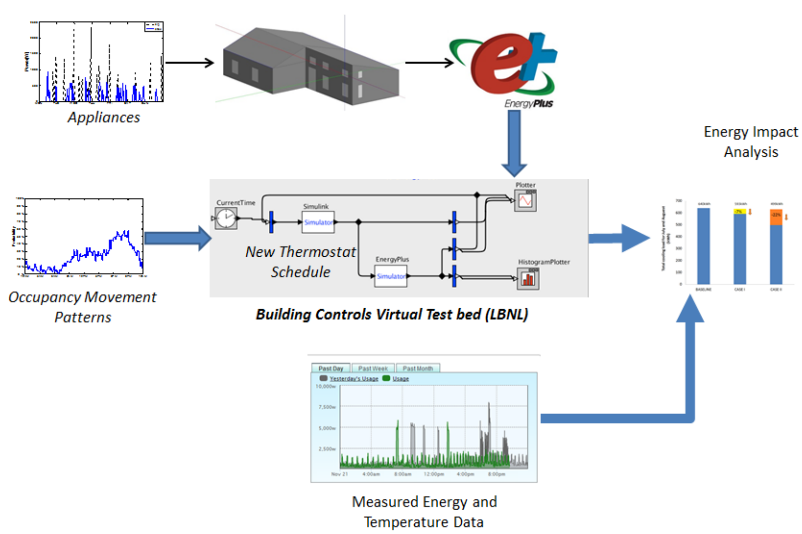

Figure 8: Occupancy data integrated with energy model

3. RESULTS AND DISCUSSIONS

3.1 Comparison between ATUS data and test-bed data

It is interesting to note that occupancy profile from test-bed has a striking similarity to the ATUS employed profile instead of the unemployed as in Figure 9, even though the single occupant is unemployed. And the notable difference during night from 12am to 6am is caused by the sensors' incapability of detecting over static object like sleeping people. Overall, ATUS data shows its capability of revealing occupancy information.

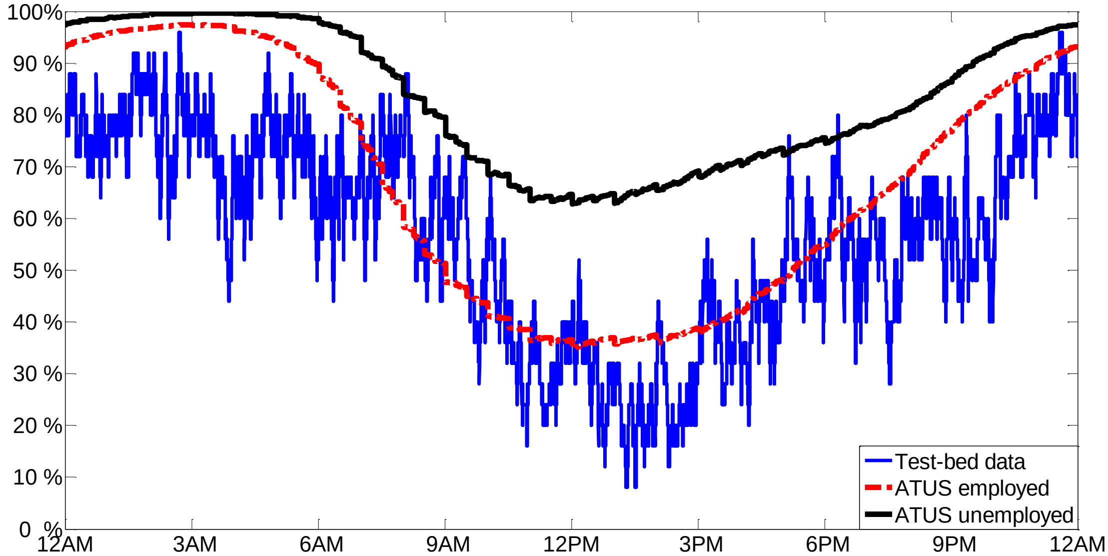

Figure 9: Comparison between ATUS data and test-bed data

3.2 Energy Simulation Analysis

In an attempt to test the how much energy consumption can be saved using the result of this study, three simulations were conducted.
In this section, a virtual test residential building was set up in EnergyPlus according to one of our test-beds, Container house. By maintaining the temperature of current occupied zone in a comfort level without considering too much for the rest unoccupied zones, we expect less energy consumption.
Baseline: was a simulation of the container house using the default setting, which is our benchmark. The temperature set-point is from the real-time measurement, and the only thermostat is located in the living room representing the common case in residential buildings. In that way, it controls the A/C systems according to the temperature in living room.
Case I: two thermostats were placed both in living room and bedroom, respectively. One of them will be in charge of the air-conditioning system alternately to fit the occupancy patterns. The pattern shows the higher probability of presence in bedroom before 8am and after 10pm. During that time the thermostat in bedroom will override the one in living room to control the whole air conditioning system on or off. During 8am to 10pm, the living room thermostat will dominate, and the living room will be controlled to satisfy the setting point. In that way the system will focus on the current occupied zone properly along a day.
Case II: Although during 8am to 10pm the living room is mainly occupied, the probability of occupants' present is still under 60%, even under 40% in most time. In that case, we may assume the whole dwelling is lightly occupied or not occupied. From that point in case II, the temperature set-point of the living room was increased by 1.8 ˚F during its operation time from 8am to 10pm, while the bedroom thermostat and its setting point is same as in case I .
We implement our strategy into the EnergyPlus model and results are shown in Figure 10.

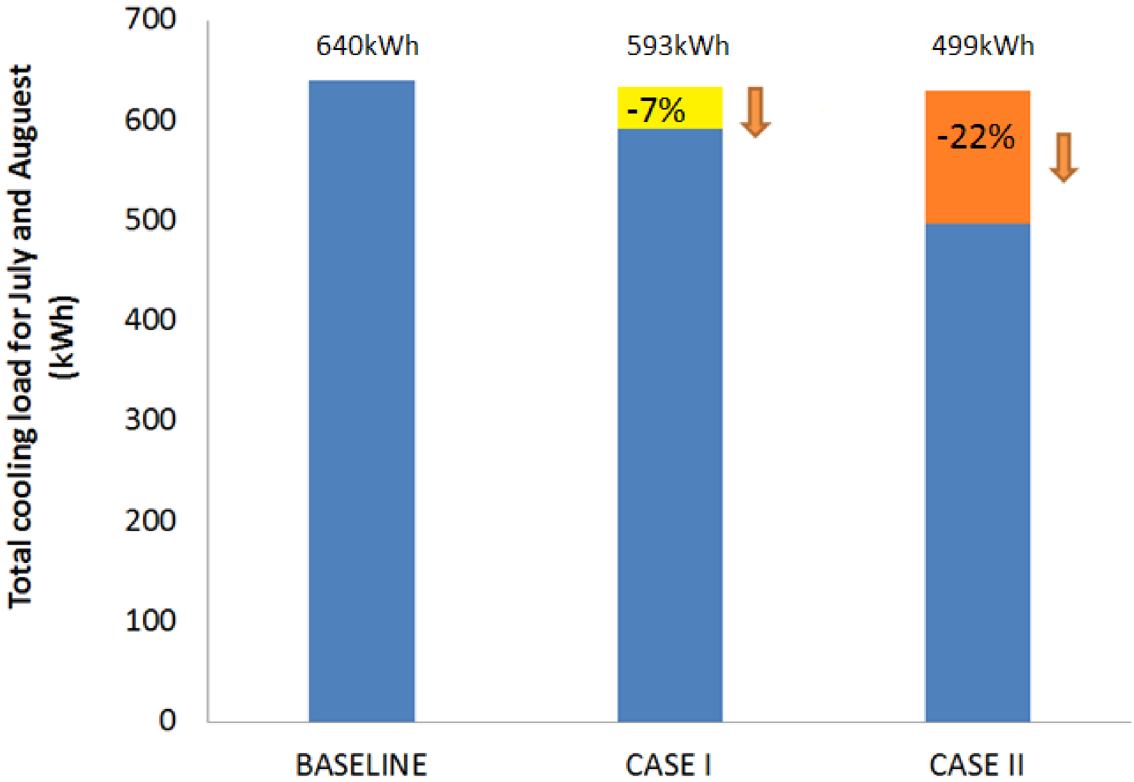

Figure 10: Simulation results for each case

Comparing to the baseline case, case I shows a 7.3% reduction in energy consumption for cooling. If we increase the air conditioning thermostat by 1.8 ˚F during the light occupied period as described in case II , more savings could be achieved. Case II consume 15.8% less energy compared with case I, and overall 22% compared with baseline case.

4. CONCLUSION

This study firstly showed the occupancy pattern from ATUS survey, and then compared it with our own test-bed data. The similarity indicates the capability of conducting occupancy research through ATUS data.
Simulation found using the occupancy pattern to determine which room to be controlled instead of monitoring single zone all the time can reduce the energy consumption for cooling by 7%. In addition, by increasing air condition setting point by 1.8 ˚F during living room unoccupied/light occupied period, another 15.8% and total 22% reduction should be expected. This considerable result indicates the large energy saving potential could be achieved by integrating detailed occupant behavior into control system. This new strategies to conserve energy will have significant savings for the low income household not only on air conditioning system, in the future lighting, heating and other appliance related with occupancy profile could be rescheduled to optimize the energy use without lowering the comfort level.
Unfortunately due to the limit of our current sensor technology, obtaining the accurate number of occupants in each room is still a challenging topic, which prevents us from implementing more delicate control strategy such as demand ventilation control. This paper is the first step in a detailed research based on field measurements for the role of the occupant behavior in energy consumption. For future research, we will engage more households to establish a complete occupancy profile based on different household characteristics. Detailed occupancy behavior including the occupant number and appliance usage could be integrated into system.

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REFERENCES

Aerts, D., Minnen, J., Glorieux, I., Wouters, I. and Descamps, F., 2013, Discrete Occupancy Profiles from Time-use Data for User Behavior Modelling in Homes, *13th Conference of International Building Performance Simulation Association, pp: 2421-2427*

American Electric Power, 2013, Issues in Electricity-Affects of Rising Energy Costs on Low-income Households, available at: http://www.aep.com/about/IssuesAndPositions/Financial/docs/risingcostLow-Income.pdf

Energy Information Administration (EIA), 2010, Annual Energy Review, available at: http://www.eia.gov/totalenergy/data/annual/pdf/aer.pdf

DOE, 2010, Buildings Energy Data Book, available from: http://buildingsdatabook.eren.doe.gov/TableView.aspx?table=1.1.1

Harak, C., 2010, Up the chimney: How HUD's Inaction Costs Tax Payers Millions and Drive Up Utility Bills for Low-income Families, https://www.nclc.org/images/pdf/pr-reports/up_the_chimney_082610.pdf

Hong, T., Lin, H., 2012, Occupant Behavior: Impact on Energy Use of Private Offices, *Asim IBSPA Asia Conference 2012*

HUD, 2012, Progress Report and Energy Action Plan, available at: http://portal.hud.gov/hudportal/documents/huddoc?id=oshcenergyreport2012.pdf

Jeeninga, H., Uyterlimde, M., Uitzinger, J., Energy Use of Energy Efficient Residences, 2001, Report ECN& IVAM

Langevin, J., Gurian, P., Wen, J., 2013, Reducing Energy Consumption in Low Income Public Housing: Interviewing Residents about Energy Behaviors, Appl. *Energy, vol. 102, pp. 1358-1370*

Peffer, T., Pritoni, M., Meier, A. K., Aragon, C. and Perry, D., 2011, How People Use Thermostats: A Review, *Building and Environment, 46(12), 2529-2541*

Richardson, I., Thomson, M., and Infield, D., 2008, A High-resolution Domestic Building Occupancy Model for Energy Demand Simulations, *Energy and Buildings, vol. 40, no8, pp. 1560-1566*

Santin, OG., 2011, Behavioural patterns and user profiles related to energy consumption for heating, *Energy and Buildings 43: 2662-2672*

U.S. Department of Labor, 2012, Basic ATUS Data Files, available at: http://www.bls.gov/tus/datafiles_2012.htm

U.S. Department of Health and Human Services, 2013, available at: http://www.acf.hhs.gov/programs/ocs/programs/liheap

Wahl, F., Milenkovic and M., Amft, O., 2012, A Distributed PIR-based Approach for Estimating People Count in Office Environment, *2012 IEEE 15th international conference, pp. 640-647*