Behavior Oriented Metrics for Plug Load Energy Savings in Office Environment

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ABSTRACT

Plug load energy consumption represents up to 40% of the total energy consumption in efficient buildings. Occupant behavior has a huge impact on plug load energy consumption. Studies have shown that up to 40% plug load energy savings can be achieved through users' engagement in sustainable behaviors.

To save energy from plug loads, either a company can replace their appliances with more efficient ones, or an occupant can change his/her behavior to control them more efficiently. Existing metrics such as Energy Use Intensity (EUI) cannot sufficiently evaluate behavioral impacts on energy use. To address this issue, a set of Metrics of Sustainability is developed for an Intelligent Dashboard for Occupant (ID-O) to integrate both company policy and individual behavior towards sustainable practices in office spaces. Through the ID-O, occupants can control their appliances and monitor energy consumption. The Metrics include (1) appliance selection, (2) effectiveness of occupant behavior, and (3) intensity of useful energy consumption. Occupancy status is one important input factor for the effectiveness determination. An occupancy detection method is proposed by mining the office appliance energy consumption data.

The Metrics of Sustainability and method for occupancy detection are tested at two office buildings in Pittsburgh, PA. The results suggest that, (1) the Metrics are novel, practical and unbiased to evaluate occupants' behavioral impact on plug load energy; (2) 23% of energy savings were achieved by integrating the Metrics of Sustainability with the ID-O during the study period; and (3) the occupancy detection method is feasible for use in office spaces.

Introduction

Commercial buildings consumed about 35% of the end use electricity produced in the United State in 2012 (EIA, 2012), while plug load accounts for 15% to 50% of this consumption depending on building types and attributes (NBI, 2013). Compared to lighting and HVAC energy saving strategies, the technical aspect of reducing plug load is straightforward, energy saving is achieved simply by turning off the appliances when they are not in use. However, appliance usage is highly dependent on occupant behavior, which is difficult to learn and control under current practice. Understanding occupant behavior and users' collaboration is essential to reduce plug load.

Numerous studies have demonstrated feasible solutions to learn occupancy status and occupant behavior in buildings. The methods mainly can be categorized as "direct detection" and "indirect detection" (Zhang et al., 2012). Direct detection methods include using computer vision, WiFi fingerprint, Bluetooth, and ultrasound together with mobile devices (Dong et al., 2011, Peters et al., 2011, Bauereiß, 2013, Google, 2013, Hughes, 2013, Zhao et al., 2013). Indirect methods include using data mining algorithms to learn from environmental sensor networks and electricity meter data (Glicksman et al., 1997, Tanimoto et al., 2008, Agarwal et al., 2010, Dong et al., 2010, Wang et al., 2011, Zhao, Yun et al., 2013). Those methods are demonstrated to be effective, however from a cost and privacy standpoint, electricity meter data mining might be a more viable solution for office buildings (Zhao, Yun et al., 2013).

Several studies have shown that up to 40% of plug load energy savings could be achieved in the workplace by changing user behavior and improving control of appliances (Lucid-Design, 2010, Carrico et al., 2011, Yun et al., 2013, Yun et al., 2013). However, few have focused on integrated strategies to understand and measure both individual user behavior and sustainable company policy in office appliance energy consumption simultaneously. It is essential to consider both the individual user behavior and company policy, because unlike the home environment, office workers often lack incentives to save energy since they do not pay the office utility bills (Lehrer et al., 2011, Foster et al., 2012).

To save plug load energy and promote sustainability in the workplace, a set of Metrics of Sustainability and an occupancy detection method are developed for an online dashboard – called the Intelligent Dashboard for Occupants (ID-O), an image of which is shown in Figure 1 (Yun, Lasternas et al., 2013). The paper first introduces the function and system architecture of ID-O. Then the occupancy detection method and the Metrics of Sustainability are developed. The methods are implemented and experimental results are presented and discussed.

Intelligent Dashboard for Occupants

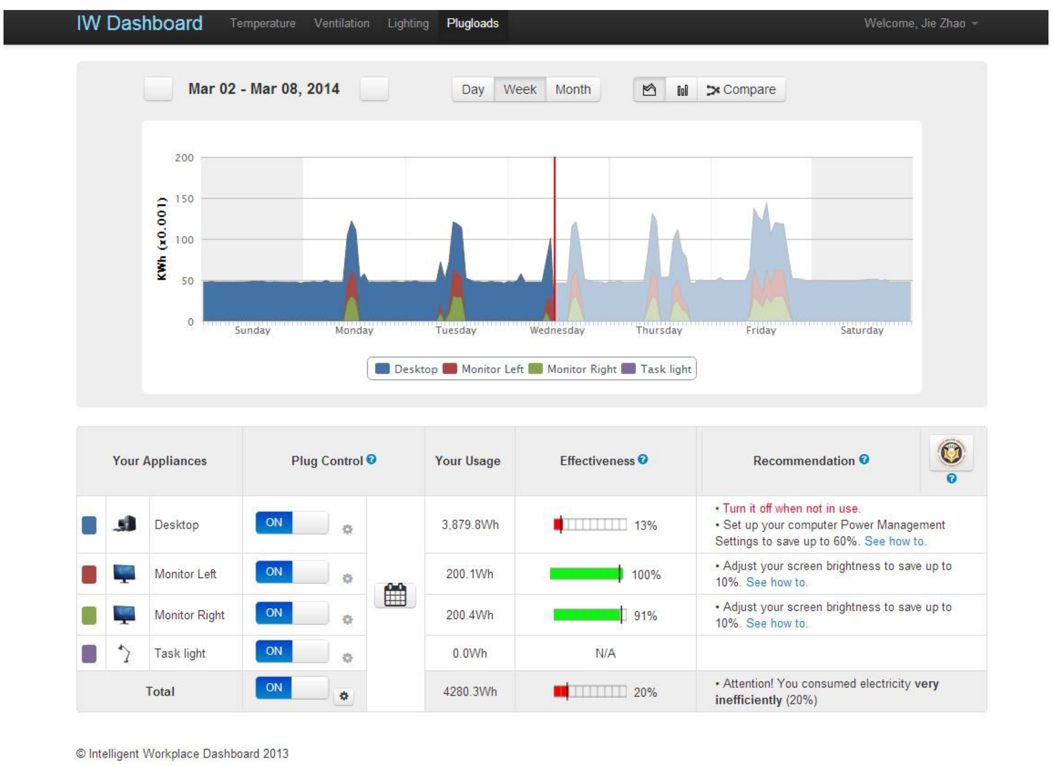


Figure 1. Intelligent Dashboard for Occupant (ID-O).

Individual appliance electricity consumption is measured by Plugwise® wireless smart meters. Besides energy metering and display, Plugwise® also allows remote control via its on-off breaker in the device and a wireless network system. Occupants can log on to the ID-O using a

PC or mobile device to see their appliances' energy consumption (laptops, monitors, task lights, and phones). Occupants can also turn on/off their appliances and set automated control schedules with the ID-O, as shown in the lower left-hand corner of Figure 1. Detailed information about the ID-O can be found in (Yun, Lasternas et al., 2013).

Figure 2 shows the dashboard system architecture. The energy consumption data collected by all the meters is sent to a main server where it is processed and analyzed.

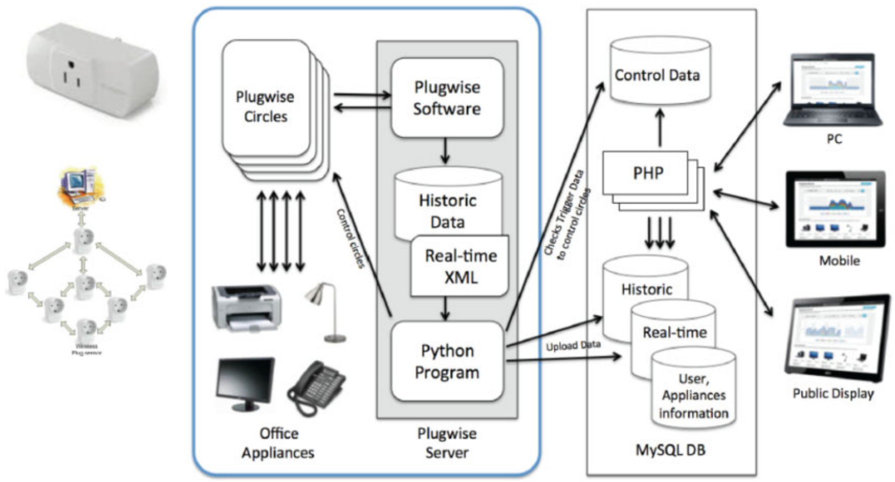


Figure 2. Plug Load meter data collection and control system architecture.

Occupancy Detection Method

Occupancy status is critical to evaluate occupant behavior in energy awareness and to effectively control his/her appliances. Occupancy status "ground truth" data is collected with Fitbit® Flex™ pedometer with its Bluetooth Dongle and a computer idle-time logging program installed in the occupant's computer.

Occupancy status "ground truth" data is classified into 4 categories, (1) "Occupied computer-based work" indicates the occupant is working with the computer actively at his/her bay. (2) "Occupied non-computer-based work" indicates the occupant is at his/her bay, but does not use the computer. The possible activities include paper-based tasks, discussions with colleagues, having lunch, having phone calls and so on. (3) "Unoccupied" means the occupant is not in his/her office bay and is not working with the computer. (4) "Other" means the computer is actively running in the office, but the occupant is not in the office. Possible scenarios yielding this outcome include the occupant remotely accessing the computer, forgetting to wear or charging the Fitbit® while working in the office, or no battery life in the Fitbit® sensor.

Electricity meter data of office appliances are used to predict occupancy status. The metered office appliances include laptop computers, task lights, computer monitors, personal fans, chargers, and printers. Plugwise® wireless smart meters are used to collect individual office appliance electricity data for each occupant in 5-minute time intervals. The data collection system is shown in Figure 3. Both "ground truth" and electricity meter data are collected with Python (Python, 2012) programs and stored in an online MySQL database.

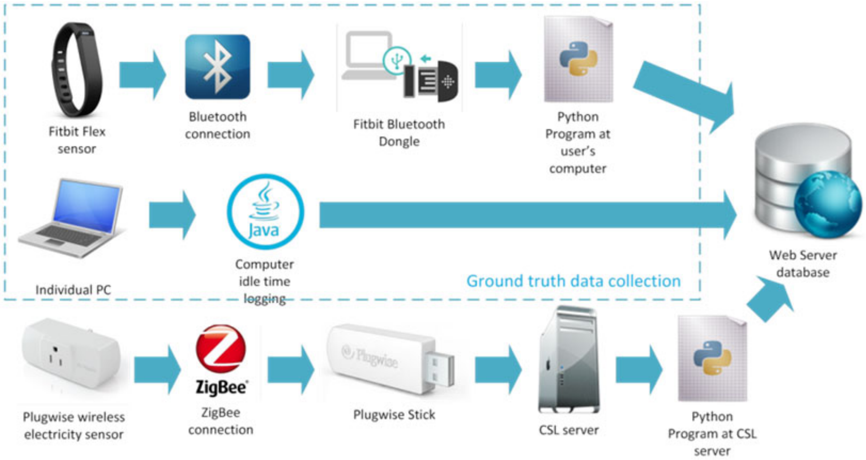


Figure 3. Plug Load meter data and ground truth data collection architecture.

Metrics of Sustainability

Office occupants can reduce the energy consumption by changing their use pattern and/or by managing their appliances better such as enabling energy savings mode. However, their ability to save energy is limited by the type of appliances given by the company. Therefore, straight energy saving comparisons between occupants will not be fair without considering different appliances' efficiency. In order to integrate both the user behavior and appliance efficiency parameters, we developed the following Metrics of Sustainability. Three metrics are introduced: (1) appliance selection, (2) occupant behavioral effectiveness, and (3) intensity of useful energy consumption.

The Metrics of Sustainability are tested in a corporate office with a total of 80 voluntary participants. The experimental study is designed as two phases, where baseline energy consumption is collected during the first phase for eight weeks, and then the dashboard with Metrics of Sustainability is implemented in the second phase for eight weeks.

Appliance Selection

The appliance selection is a metric to evaluate the level of sustainability reached by the company for its selection of energy efficient appliances. It ranks each appliance from inefficient to very efficient compared to equivalent devices in the Energy Star database (EPA, 2014). . For example, one of the office buildings we used for the experiment only uses laptop computers for all its employees. On average, the typical power consumption of the laptop in the tested building is about 17 – 25W, compared to 50 – 80W of the typical power of an Energy Star rated desktop. So it is safe to say this office has very good computer selection policy, in terms of energy usage.

Occupant Behavioral Effectiveness

Occupant behavioral effectiveness (OBE) is a metric to evaluate only individual occupant use patterns of his/her appliances. It is calculated with Equation (1),

$$\mathrm{OBE} = \frac{P_{rated} \times n_{occ}}{E_{total}} \tag{1}$$

where:

P_{rated} is the average power drawn (in Watts) by the appliances the occupant utilized in active mode in the baseline data collection period[1],

n_{occ} is the number of occupied working hours, calculated based on the result of occupancy detection,

E_{total} is the total energy consumption (in Wh) measured over the total number of hours in the measured period.

An OBE of 100% represents the perfect use of the appliance during the period of time (n_{total}). In other words, the appliance is only "on" during occupied working hours and always "off" during non-occupied hours. An OBE of 50% represents a potential energy saving of 50% can be achieved just by behavior change. By introducing OBE, we have not only quantified energy savings, but also eliminated the bias of appliance efficiency differences and thus focused only on behavioral impact.

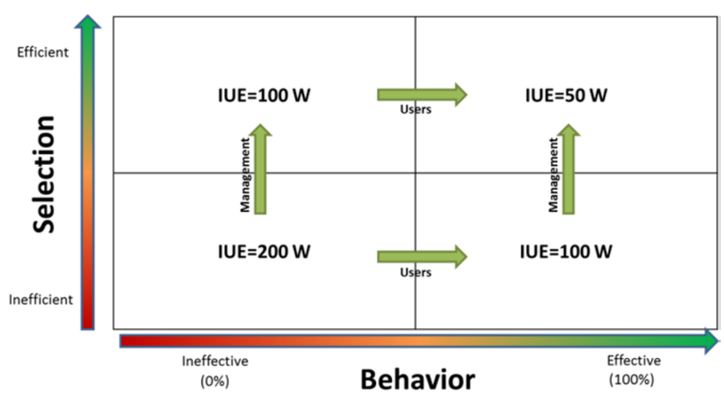
Intensity of Useful Energy Consumption

The intensity of useful energy consumption (IUE) combines the appliance selection and the OBE into one metric to evaluate both company policy in equipment selection and individual occupant behavior in sustainability, as shown in Equation (2),

$$IUE = P_{rated} \times OBE \tag{2}$$

where IUE is measured with (W).

Figure 4 shows an example of IUE in the chart of Metrics of Sustainability. The x-axis represents individual behavior towards appliance use. The y-axis represents the efficiency difference of appliance selection due to company policy. An IUE in the upper-right quadrant suggests the company has chosen efficient appliances for the occupant, and the occupant manages use of his/her appliances in an energy-saving manner. This chart can explicitly inform both the company and its employees about the company's overall sustainability of appliance selection and usage and where improvements can be made.



[1] Refer to "Metrics of Sustainability Testing Results and Discussions" section for detailed information about the baseline data collection.

Figure 4. An example of the Metrics of Sustainability.

Experimental Results and Discussions

Occupancy Detection Results and Discussions

The objective of occupancy detection is to identify the occupancy status at each 5-minute time step by learning the office appliance electricity power consumption data.

11,141 valid data instances of 10 valid participants are collected over 49 workdays out of 84 total days of the measurement, as shown in Figure 5.

Each participant has at least one laptop and one task light. Some have personal fans, printers, computer screens, and chargers, which are categorized as “other” in this study for generalization and privacy purposes. The appliance electricity data of each participant is trained with Locally Weighted Learning (LWL), Support Vector Machine (SVM), and C4.5 decision tree algorithms, tested using 10-fold cross validation, and compared with paired-T test (p=0.05) (Dong et al., 2005, Ian H. Witten, 2011, Zhao et al., 2012).

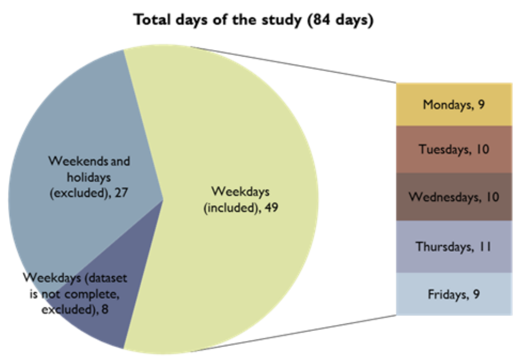


Figure 5. Total days of the study.

The three columns in the middle of **Error! Reference source not found.** illustrate the percentage of correctly classified instances of the three algorithms for each occupant. C4.5 has statistically significantly better accuracy in 9 out of 10 cases compared to LWL, and 8 out of 10 cases compared to SVM.

Table 1. Algorithm and individual occupant behavior data mining result comparison

	LWL	SVM	C4.5	
	Correctly Classified (%)	Correctly Classified (%)	Correctly Classified (%)	Kappa statistic
User A	94.16*	95.00	95.00	0.88
User B	91.64*	91.84*	92.93	0.83
User C	91.36	88.64*	91.36	0.77
User D	78.87*	79.48*	82.53	0.29
User E	88.17*	92.35*	93.52	0.84
User F	89.50*	89.58*	90.05	0.77
User G	89.07*	89.38*	89.86	0.60
User H	84.15*	84.31*	85.81	0.60
User I	94.30*	94.32*	94.51	0.74
User J	87.15*	87.19	87.37	0.55
Mean value:			90.29	0.69

*statistically significant lower value compared to C4.5 (p = 0.05)

Furthermore, the average computation time of training and testing C4.5 models is 0.030 seconds. It has clear advantage over the SVM's 0.058 seconds and LWL's 6.959 seconds. Therefore, C4.5 is selected to build the occupancy detection model for all the occupants.

In order to reduce the possibility of over-fitting, the minimum instances per leaf of the C4.5 decision tree algorithm is set to be 10, which suggest that when testing the trained model, there should be at least 10 cases for each behavior category.

Kappa statistic is used to measure the agreement of categorization by two or more raters (class values), taking into consideration the agreement occurring by chance. It is defined by Equation (3)

$$\kappa = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \qquad (3)$$

where,
$\Pr(a)$ is the relative observed agreement among raters,
$\Pr(e)$ is the hypothetical probability of chance agreement of all the raters.

If $\kappa = 1$, it means the model's classification result is in complete agreement with the ground truth. If $\kappa = 0$, it means the model's classification result is completely different from the ground truth.

The fifth column in **Error! Reference source not found.** shows the Kappa statistics of different occupants. The mean value of all the occupant behavior predictions is $\bar{\kappa} = 0.69$, the median value is $\tilde{\kappa} = 0.77$, the highest value is $\kappa_{max} = 0.88$, and the lowest value is $\kappa_{min} = 0.29$. These results indicate that on average, if the algorithm is applied to a new set of data, the accuracy of the prediction would be trustworthy (over 0.6).

User C and User F have the same Kappa statistic value as the median value $\tilde{\kappa} = 0.77$. For generalization purpose, a detailed comparative analysis is presented for those two users. As shown in Figure 6, User C only has a laptop computer and a desk lamp, and no clear pattern can be found from the plot; while User F has another appliance beside the computer and the lamp. In most cases, the lamp is turned off, and the third appliance is in active mode.

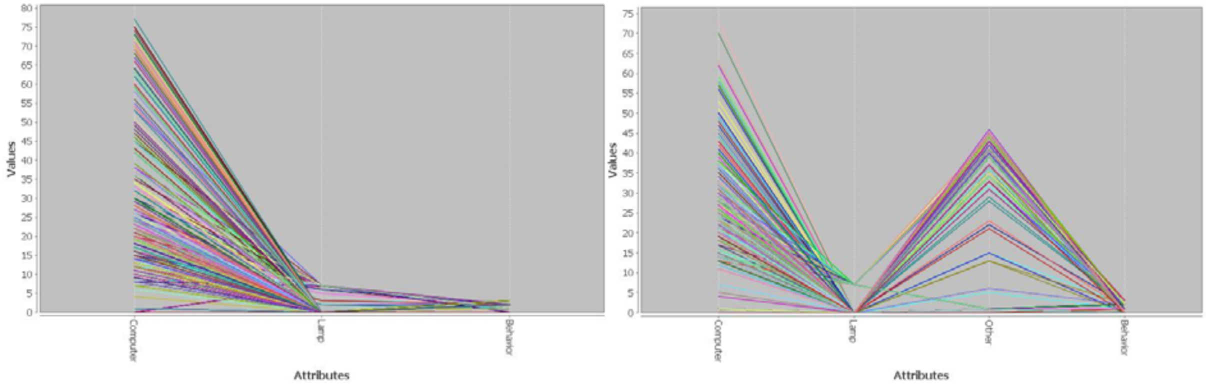


Figure 6. Attributes and class value parallel coordination plots of User C and User F.

The C4.5 decision tree models shown in Figure 7 also suggest different use patterns for the two users. User C has a very clear and consistent use pattern for his/her computer. If the computer power is more than 12W, for more than 90% of time, it is safe to draw the conclusion that the person is actively working in the office, vice versa. However, the model is not able to recognize non-computer-based work and the use of the lamp is not related to his/her occupancy status for this model.

User F has more complex use patterns and the occupancy status depends on far more tree nodes, therefore it is not evident to classify. Computer and the third appliance are influential factors to classify his/her behavior. Figure 10 shows the ground truth value and C4.5 predicted value for a typical workday. Two types of errors occurred. (1) “Occupied non-computer-based work” is incorrectly categorized as “computer-based work”, when the time duration of non-computer-based work is less than 10 minutes. (2) “Occupied non-computer-based work” is incorrectly categorized as “not occupied” when the time duration of non-computer-based work is longer than 30 minutes. Another noticeable pattern is that when status changes, there usually is a 5-minute time delay between the ground truth value and the predicted value. This is because the power consumption data is collected at the end of every 5 minutes. However, this delay has minimum impact on detecting overall occupancy status.

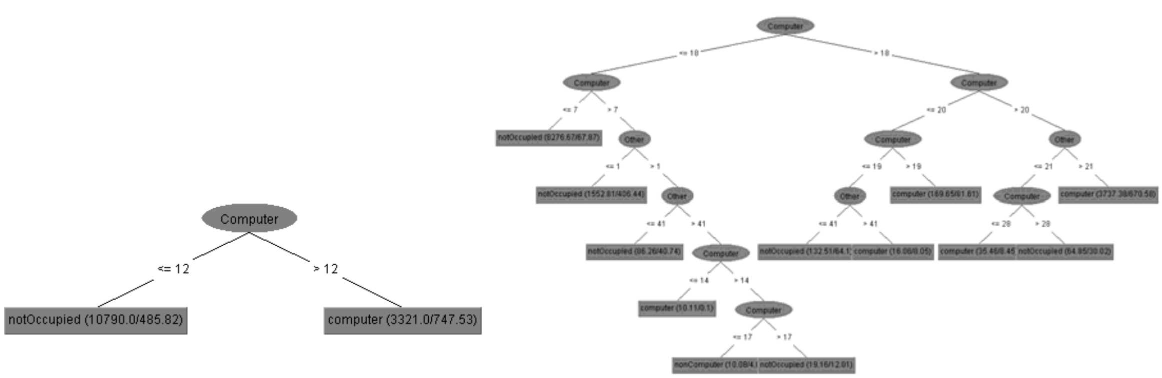


Figure 7. C4.5 decision tree models of User C and User F.

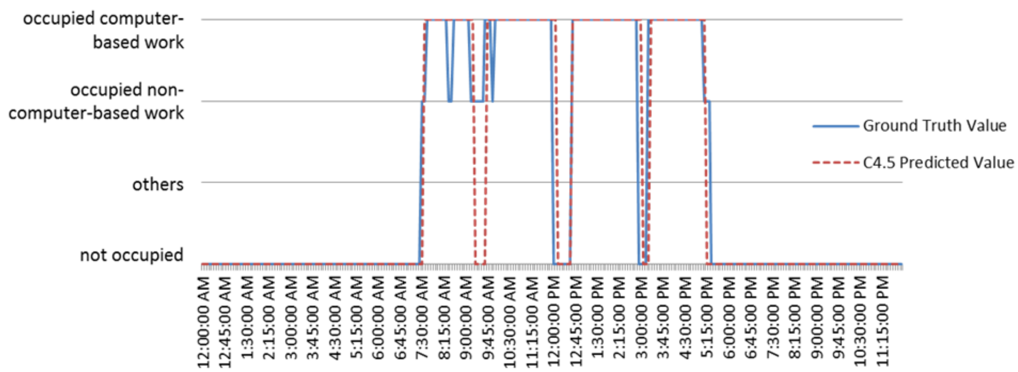


Figure 8. Comparison of ground truth and model predicted value.

Metrics of Sustainability Testing Results and Discussions

As shown in the highlighted area (Effectiveness) in Figure 9, the OBE is calculated and displayed in real time in the second phase of the experiment. The following color code is used to differentiate effectiveness levels:

- Red color: $OBE < 33\%$;
- Yellow color: $33\% \leq OBE < 66\%$;
- Green color: $OBE \geq 66\%$.

A vertical black-color bar is added on top of the effectiveness color-coded display. This vertical bar represents the user's OBE during the baseline data collection and allows the user to quickly compare his/her behavior change after the Metrics of Sustainability is implemented.

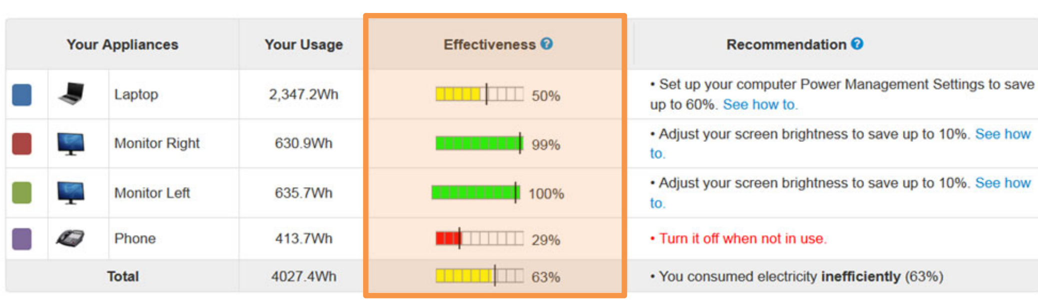


Figure 9. Implementation of the metrics of sustainability in the dashboard.

Based on the OBE value for each appliance, specific recommendations are given, as shown in the right-hand side column in Figure 9.

Figure 10 represents the IUE values of ten randomly selected occupants before and after the implementation of the Metrics of Sustainability. In the first phase baseline experiment, the average OBE of the ten participants is 55%. Furthermore, all the occupants' IUE values fall into the upper half part of the chart (in the first and second quadrants). It suggests that the company is using high efficiency appliances, therefore reduce the maximum energy saving potential

Five out of ten participants' IUE values fall into the second quadrant of Figure **10**. In the second phase of the experiment, the average OBE reaches 70%, only one participant's IUE value falls into the second quadrant.

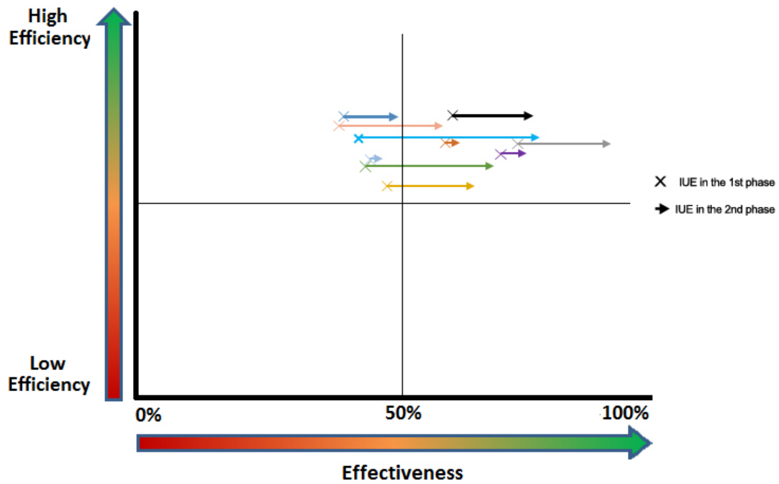


Figure 10. Behavior level before (cross) and after (arrowhead) the deployment of the Metrics of Sustainability.

Figure 11 shows the average weekly energy consumption of the ten participants before and after the Metrics system is implemented. A total of 23% of energy savings are achieved. Most of the energy savings are from a better control of the appliances during unoccupied nighttime and weekends. 50% of energy is saved during weekends, 24% of energy is saved during unoccupied nighttime, and 13% of energy is saved during workday daytime.

However, we find that some laptops in the office are required to stay on during nighttime, because the policy of IT department requires those laptops to stay active 24/7 to receive unnoticed updates. Discussions are ongoing with the company executive team to find alternative solutions to update those laptops without wasting energy, which would yield further energy savings from laptop nighttime operation.

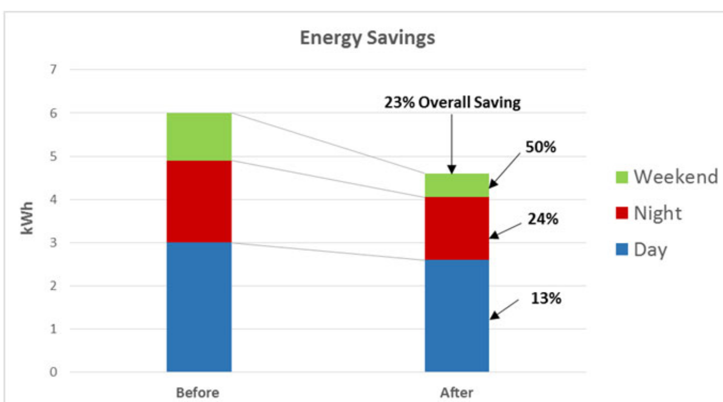


Figure 11. Energy savings before and after the deployment of the Metrics of Sustainability.

Conclusions

This study investigates the development of a set of novel metrics – Metrics of Sustainability to quantify and engage office workers and company policies toward sustainability. An Intelligent Dashboard for Occupants (ID-O) to monitor and control plug load appliances is developed and deployed in an office building. An occupancy detection method is developed and tested in an office building using the exiting wireless plug load smart meters. On average, occupancy status is correctly detected more than 90% of the time.

The baseline energy consumption data is collected using the baseline ID-O in the first phase of the experiment. Then the Metrics of Sustainability is integrated in the ID-O to actively influence occupant behavior in the second phase of the experiment. Compared to the baseline energy consumption, a 23% energy reduction is achieved through user behavior change during the study period.

The Metrics of Sustainability can be used by companies as a tool to highlight energy saving potentials through appliance updates, company level policy change regarding appliance purchasing, and worker engagement. The concept can also be applied to other building systems, such as lighting and HVAC systems, to evaluate the impact of occupant behavior on system energy consumption.

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