Implementing Occupant Behaviour in the Simulation of Building Energy Performance and Energy Flexibility: Development of Co-Simulation Framework and Case Study

Rongling Li[1*], Feng Wei[2], Yang Zhao[3], Wim Zeiler[2]
* liron@byg.dtu.dk
[1]Department of Civil Engineering, Technical University of Denmark, Lyngby, Denmark
[2]Department of Built Environment, Eindhoven University of Technology, Eindhoven, the Netherlands
[3]Institute of Refrigeration and Cryogenics, Zhenjiang University, Hangzhou, China

Abstract

Occupant behaviour has a substantial impact on the prediction of building energy performance. To capture this impact, co-simulation is considered an effective approach. It is still a new method in need of more development. In this study, a co-simulation framework is established to couple EnergyPlus with Java via Functional Mock-up Interface (FMI) using the EnergyPlusToFMU software package. This method is applied to a case study of a single occupant office with control of lighting, plug load and thermostat. Two control scenarios are studied. These are occupancy and occupant behaviour based control (OC), and sensor based control (SBC) triggered by dynamic electricity price under demand side management (DSM) program. The building energy performance in the OC scenario is then used as reference to evaluate the building energy (cost) saving and energy flexibility. This is an improvement of current studies on DSM and building energy flexibility, in which predefined user schedules are commonly used.

Introduction

Occupant behavior is one of the main factors that influence energy consumption in office buildings. Conventionally, building simulation tools use static occupant behavior inputs to model occupancy. This method is simple yet fails to capture the stochastic and dynamic character of occupant behavior. Inaccurate inputs of occupant behavior lead to discrepancies between predicted and actual energy consumption, making these simulations fail to yield accurate numbers on energy consumption. Over the past decades, researchers such as Bourgeois (2006), Page (2008) and Gunay (2016) have studied the patterns of occupant behavior and developed stochastic occupant behavior models, which are available to be integrated with building models for whole building simulation.

Co-simulation is able to model the stochastic character of occupant behavior since behavior models are established in a different simulation tool with specific functions, according to Yan (2015) and Gunay (2015). Building model and occupant behavior models are processed in different simulation tools. During time integration, data is exchanged between the building model and the occupant behaivor model. In the research of Nouidui (2014), Feng (2015) and Hong (2016), occupant behavior models were developed as Functional Mockup Units (FMU) for co-simulation with EnergyPlus using XML and FMI standard. These studies demonstrated the capability of using FMU for co-simulation with EnergyPlus.

With co-simulation, building energy profile can be predicted more precisely taking user behavior into consideration. Therefore, this building energy profile can serve as a better reference to calculate demand flexibility potential of the building. This is an improvement of current studies on demand side management (DSM) and building energy flexibility, in which predefined user schedules are commonly used. Energy flexibility in buildings has become a research topic in recent years. To date, there is no standardized definition of building energy flexibility. De Coninck (2016) defined the flexibility of building as the ability to deviate from its reference electic load profile. To research this topic in a collaborative manner, an international working group (Annex 67 Energy Flexible Buildings) was formed by the International Energy Agency.

Related to Annex 67 research activities, this study aims to develop a method that is capable of modeling dynamic and stochastic occupant behaviors in EnergyPlus. Occupant-related parameters such as occupancy level, lighting control, notebook computer (PC) usage and thermostat settings are determined based on behavior models and environmental parameters at each time step during simulation. The stochastic character of occupants and their response to a changing environment can be accounted for in this method. This method is used in a case study to simulate building energy consumption and potential energy flexibility under a DSM scheme.

Methodology: Development of co-simulation framework

We employ Java and EnergyPlus co-simulation to implement stochastic behavior models in EnergyPlus. This co-simulation is based on the FMI standard (2014), an open standard designed to enable links between disparate simulation programs. Java is used to model occupancy behaviors and serves as co-simulation manager, while EnergyPlus is used to build building models. Unlike Nouidui (2014), Feng (2015) and Hong (2016), in our approach, the building model is exported as an FMU file using the EnergyPlusToFMU package developed by Lawrence Berkeley National Laboratory (2016). This software allows users to export the EnergyPlus file as a FMU for co-simulation according to the FMI standard. Figure 1 shows an example of setting the interface for lighting control inputs. 'LigntZone1' is the FMU variable name. This variable name represents the simulation input Lighting. The value of inputs is determined in Java.

Field	Units	Obj1
Schedule Name		Lighting
Schedule Type Limits Names		on/off
FMU Variable Name		LightZone1
Initial Value		0

Figure 1: Example of creating external interface in EnergyPlus

This FMU can be imported to simulation programs that support the import of FMU. Figure 2 shows the data flow of the co-simulation framework. We use JFMI, a Java wrapper of FMI to communicate with FMU (UC Berkeley, 2013; Nouidui, 2014). It initializes the FMU through the FMI function: fmiinstantlateSlave and fmiintilaizeSlave. Through these two functions, Java manages the simulation passing data between Java and EnergyPlus. In Java, we created an occupancy model and occupant behavior model for lighting control, plug load control, and thermostat settings. At each time step, Java gets variables such as illuminance from EnergyPlus and updates the EnergyPlus variables for occupancy, lighting control, PC usage and thermostat set points. At the end of each time step, Java checks if it is the end of the simulation through the fmiDoStep function.

Applications

Case study

Occupancy influences building energy consumption by directly contributing heat gains and indirectly affecting occupant behavior such as lighting control and electronic device usage. A broadly used occupancy model developed by Wang (2005) is selected for this study and reproduced in Java. This model is a non-homogeneous Poisson model. It uses two exponential distributions of vacancy intervals and occupancy intervals to represent occupancy in single office rooms. Occupancy and vacancy interval are generated alternately. Arrival, departure and lunch time follows a normal distribution. In this model, eight input parameters are used: arrival time, departure time, lunch break time, the variation of arrival time, the variation of departure time, the variation of lunch break time, average occupant interval and average vacant interval.

To demonstrate the capability of this co-simulation method, the utilization of lighting, PC and air-conditioner in a single occupant office is simulated. This simulation is based on a small-scale office building with building surfaces are set according to the standard of ASHRAE 189.1-2009 for climate zone 5. The office room is 16 m^2, at the southwest corner of the building with windows on the south and west façade. For the control of the lighting, PC and air-conditioner, we designed two scenarios: 1) occupant control (OC) using occupancy and occupant behavior models; 2) sensor-based control (SBC), in which the energy systems are controlled using occupancy sensors, smart plugs, smart thermostats and a smart meter with dynamic electricity price. The OC scenario serves as a baseline of building energy consumption. Annual electricity prices are obtained from European Electricity Index (2016). It need to be clarified that this data is electricity spot market price not the consumer price. It is used as a signal to trigger DSM.

Lighting control

The behavior of switching on/off lights is mainly dependent on three parameters: occupancy, absent interval and indoor illuminance. The act of switching on/off light usually occurs when the occupant enters or leaves the room. Mahdavi (2009) reported that the probability of switching on light is highly related to office illuminance. According to Pigg (1996), the possibility of switching off lights is dependent on the absent interval. These models can be seen in Figure 3. The left figure shows that with the room illuminance decreasing from 150 lux, the probability to turn on lights increases dramatically. The right figure illustrates that the longer

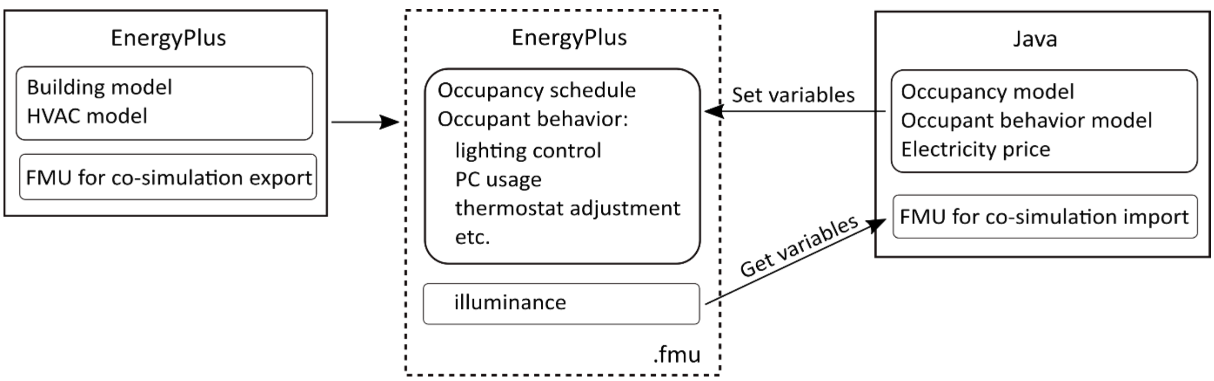

Figure 2: Dataflow of Java and EnergyPlus co-simulation framework

time occupant leave the room the larger probability he/she switches off the lights. In this study, the lighting switch-on model developed by Mahdavi and the switch-off model developed by Pigg are used.

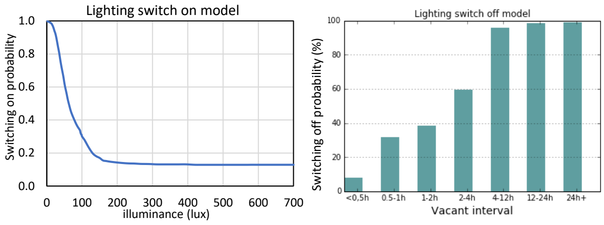

Figure 3 left: Light switch on model from Mahdavi (2009), right: Light switch off model from Pigg (1996)

For sensor based lighting control, an occupancy sensor, photo sensor and smart meter are used to control the system. Lights are switched on when the office is occupied and switched off when it is vacant. In this case study, dimmable lights are considered. The office illuminance level is designed to maintain 500 lux when electricity price is below 3.7 cent/kWh and maintain 400 lux when electricity price is higher. During the presence of the occupant, the power of the lighting is adjusted to ensure sufficient indoor illuminance and when Illuminance exceeds designed level, the light is turned off. The threshold of 3.7 cent/kWh is defined using the arbitrary method below. The spot market price is firstly divided into two groups: (a) lower than annual average price and (b) higher than annual average price. Then the threshold is defined as the mean value of group (b).

Plug load control

Plug loads in offices influence both the internal heat gains and electricity use. Commercial Buildings Energy Consumption US Energy Information Administration (2003) reported that plug loads account for 12% of energy end-use in commercial office buildings. To the best of our knowledge, there are no plug-load models available for prediction during short time absence. Gunay (2016) developed a plug-load model corresponding to the duration of absence. However, this model does not have short time resolution and is only suitable for long absence time. The result of several tests on power readings of notebooks and desktops was published on the website of University of Pennsylvania (2013). Based on these published data, in this study we assume that the power of the laptop is 50 W at moderate use, 1 W during standby and 70 W when charging the battery and the run time of the battery is 5 hour.

Thermostat control

Heating, cooling and ventilation systems account for half of the electric load of office buildings in developed countries (Perez-Lombard, 2008). However, there is no model available for thermostat control. According to the ISO 7730 (2005) standard, we assume that in the OC scenario, the occupant keeps the thermostat set points at 22±2°C in winter and 23±2°C in summer when the office is occupied. During lunch break, the room temperature can be lower in winter and higher in summer. In SBC scenario, a smart thermostat and a smart meter is used. These sensors automatically adjust the heating or cooling setpoints according to room occupancy and real-time electricity price. The detailed settings of both the OC and SBC case can be seen in Table 1.

Table 1: Control settings

Devices	**Occupant control (Reference)**	**Sensor-based control (DSM)**
Lighting	turn on upon arrival, turn off upon departure; turn-on/off probability is according to room illuminance and absent interval	Turn on when occupied, off during absence by using occupancy sensor; lighting power reduces when room illuminance or electricity price is high
Plug load (PC)	50 W (present), 20 W (short time absent), 1W (standby)	Discharging battery when electricity price is high, charging battery when electricity price is low
Thermostat	From occupant arrival to departure Heating: 22±2°C, 20.5°C lunch break Cooling: 23±2°C, 24.5°C lunch break	Heating: 22°C (present and short time absence), 20.5°C (high electricity price or lunch break), 18°C (lunch break with high electricity price), Cooling: 23°C (present and short time absence), 24.5°C (high electricity price or lunch break), 27°C (lunch break with high electricity price)

Results

Simulations for OC and SBC were run over a whole year with a time step of 15 minutes. The occupancy status is generated at each time step based on the probability indicated by the occupancy model. To explain and illustrate results in details, three winter days (January 11-13) are arbitrarily chosen. As can be seen in Figure 4, the generated daily occupancy profile is stochastic and varies from day to day. The results of occupancy, lighting control, plug load control and thermostat control are presented in the following sections.

Lighting

During the working hours of these three days, the daylight illuminance is mostly above 500 lux which is the threshold for turning on/off room lights. Therefore, as can be seen in Figure 4, the result of SBC shows that the lighting is mostly off except the arriving on the morning

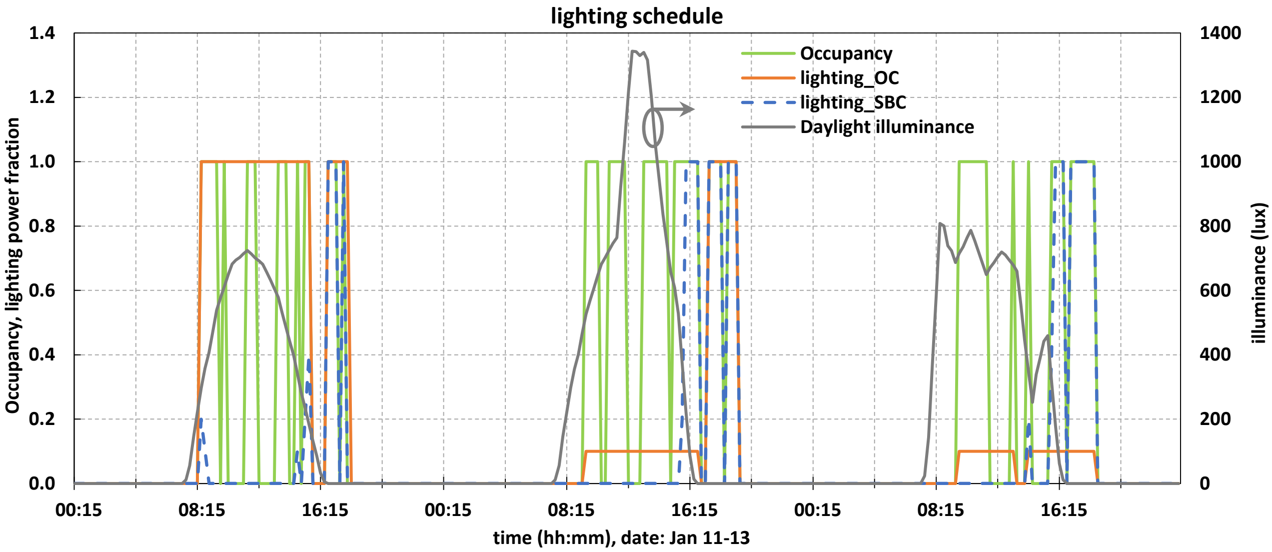

Figure 4: Occupancy, lighting control schedule and daylight illuminance on three winter days. The curve marked with the arrow symbol is plotted on the right axis.

of the first day and a few moments in the late afternoon when the daylight illuminance is below 500 lux. The figure shows how the lighting schedule of OC strongly relates to the room daylight illuminance, which is the determinant of probability for switching on lights and of the lighting power fraction when entering the room. The value the fraction is in the range of 0 to 1, in which 0 means that lights are off and 1 means that lights are turned on with full power. On the first day, when the occupant arrives in the morning, the room illuminance is low and thus the lighting power fraction is high (1.0 for the first morning). Conversely, in the morning of the last two days, the room illuminance is high and thus the lighting power fraction is small (0.1 for these two days). In the late afternoon of the first two days, when the occupant returns to the room from a break, he/she noticed that the room illuminance is low and the lights are switched on with a higher lighting power fraction (1.0 in these two late afternoons). On the last day, the lighting setting was constant on 0.1 except when the lights were turned off during a break. When the occupant entered the room after the break, the daylight illuminance was above 400 lux and he/she turned on the lights with a small power and kept it till the occupant finished working of the day. The length of absence is the determinant of probability for switching lights off when leaving the room. As can be seen in Figure 4, the occupant switched off the lights during breaks once per day.

The energy use per 15 minutes of lighting for both OC and SBC is illustrated in Figure 5. The filled area (gap) is the deviation of energy consumption between SBC and OC. It can be seen that the electricity usage of SBC is zero during midday because of high daylight illuminance, but higher than OC in the late afternoon on the last two days. These results indicate that, in comparison with occupant control, a sensor-based lighting system can significantly decrease the lighting energy usage when the room has sufficient daylight, but can use more power when daylight is lower than the threshold in the control method.

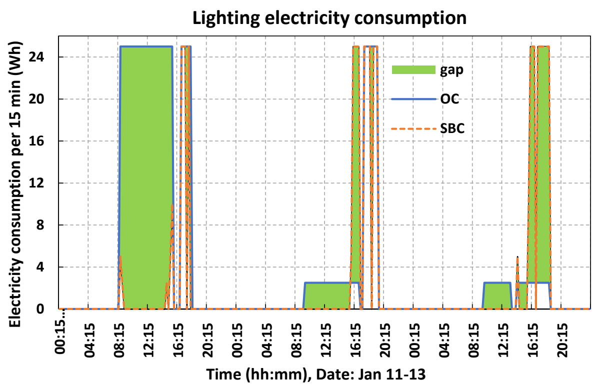

Figure 5: lighting electricity consumption on three winter days

PC

The three-day simulation result of a notebook usage is shown in Figure 6. The orange curve shows the plug load under occupant control (OC) scenario. As the PC usage is modeled based on occupancy, it is obvious that the use of the PC is synchronized with occupancy. The blue dashed curve represents the PC under sensor-based control (SBC) scenario. Plug loads of SBC are influenced by both occupancy and electricity price. It can be observed from the first day that the plug loads is zero when electricity price is higher than 3.7 cent/kWh and one (which means the battery is charging) when the price is below the threshold. On the last two days, as the price is below the threshold most time during the working hours, the plug load is similar to the one under occupant control and occasionally charging when the price is lower. In this way

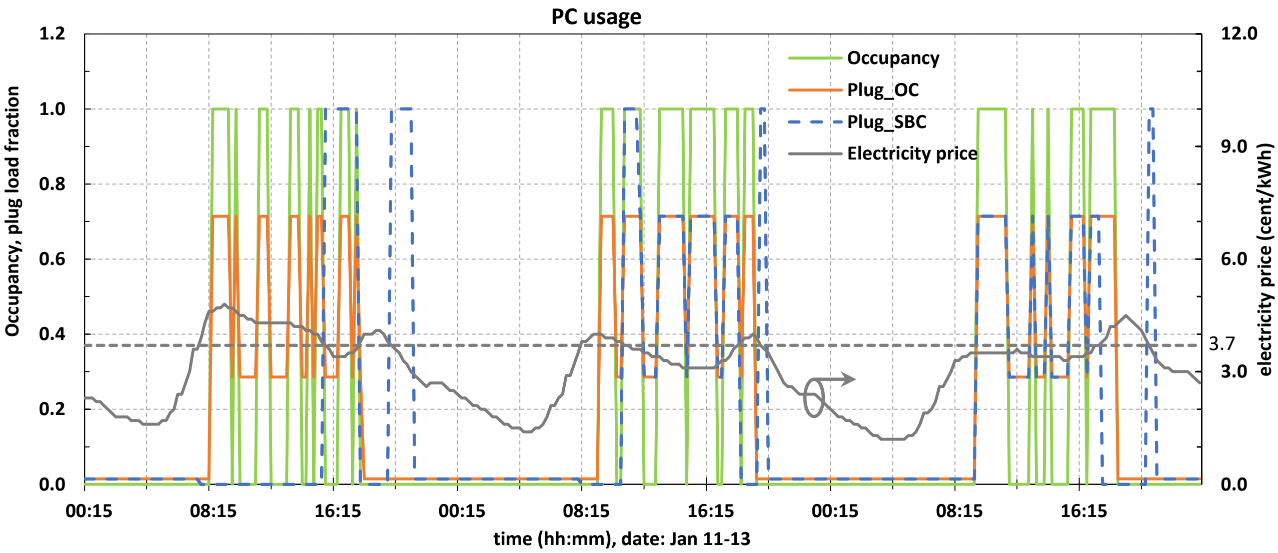

Figure 6: Occupancy, electricity price, plug load control on three winter days. The curve marked with the arrow symbol is plotted on the right axis.

the electricity load is shifted to the time when electricity price is low.

The electricity consumption per 15 minutes is shown in Figure 7. The gap in the figure illustrates the difference in energy usage between two scenarios. It can be seen that in comparison with OC, the plug load in SBC is effectively shifted to the time when the electricity price is low.

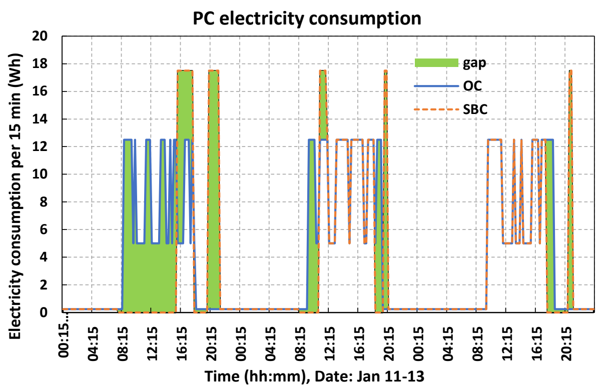

Figure 7: PC electricity consumption on three winter days

Air-conditioner

Figure 8 shows the 3-day simulation result of thermostat control. In OC, thermostat set-points are generated according to the working hours of the day. The value is constant except during lunch break when the set point is slightly lower. In the SBC scenario, real-time electricity price is considered. If the price is higher than the threshold, the room temperature setting is lower. If the

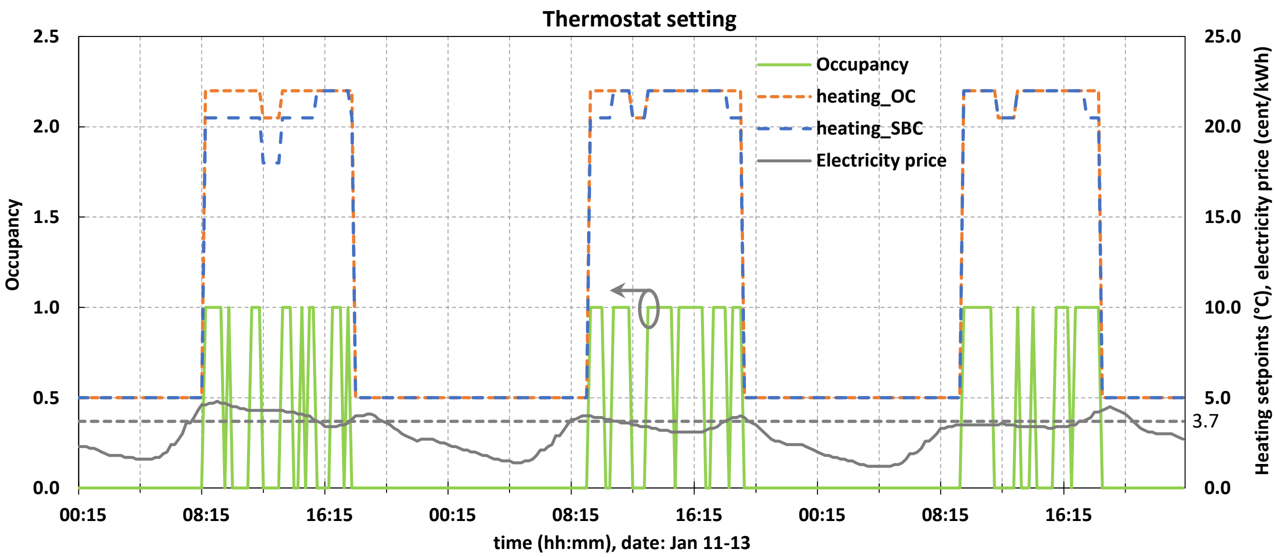

Figure 8: Heating thermostat set points on three winter days. The curve marked with the arrow symbol is plotted on the left axis.

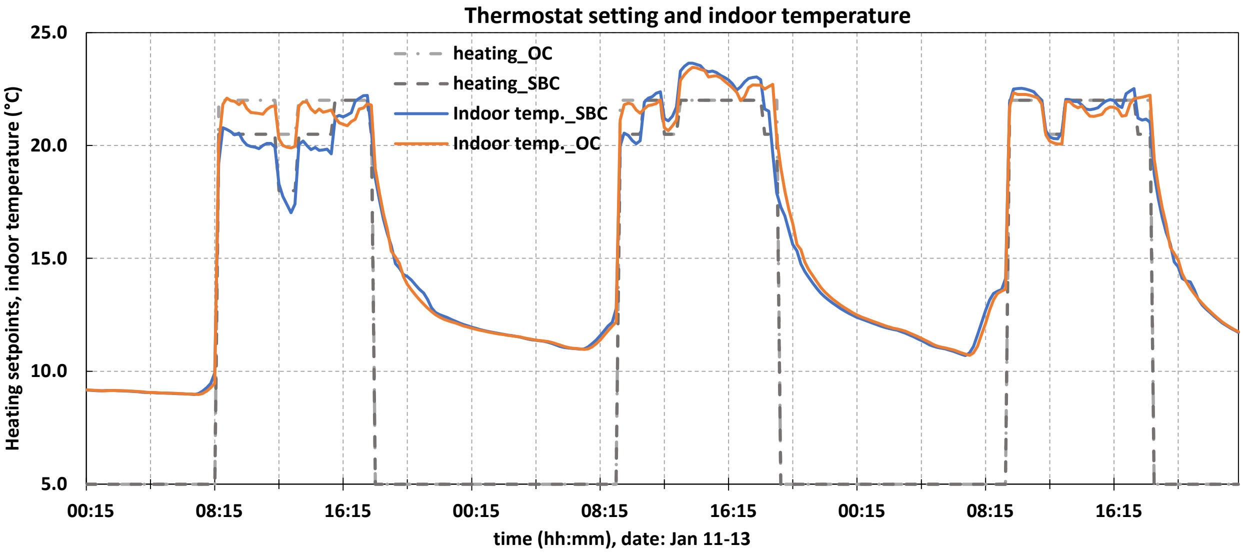

Figure 9: Indoor temperature on three winter days

high price happened to be at lunch break, the room temperature is set even lower (18˚C). It can be seen in Figure 8 that on the first day, the heating temperature setting is obviously different between SBC and OC. This is because of the high electricity price on that day. Accordingly, the indoor temperature is different in these two scenarios, as shown in Figure 9. The room temperature under SBC is slightly lower when the electricity price is high. However, the temperature is still within the comfort boundary of ISO 7730 (2005).

Figure 10 shows the electricity consumption of the two heating control. The peak load at the starting time of heating is reduced considerably on the first two days in SBC. In general, the energy use during high price period is lower in SBC in comparison with OC. However, the energy consumption surpasses OC just after the price decreased in the late afternoon of the first day. This is because the temperature setting has a two-degree increase at that moment.

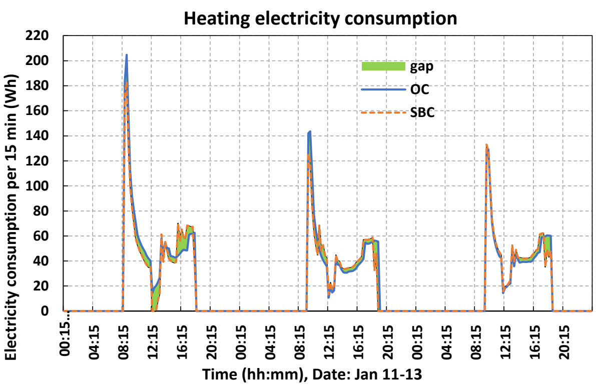

Figure 10: Heating electricity consumption on three winter days

Total energy consumption of three days, annual energy consumption and energy flexibility

The total energy consumption during the three days in two control scenarios is shown in Figure 11. It can be seen that on the first day with high electricity price, energy consumption in SBC scenario is much lower than that in OC scenario. This is due to the lower temperature setting, more strict lighting control and the load shifting of PC during the high electricity price period. However, in the late afternoon and evening of these three days, the energy consumption of SBC is slightly higher than in the case of OC. This is because of higher lighting power fraction and the charging of battery in SBC scenario.

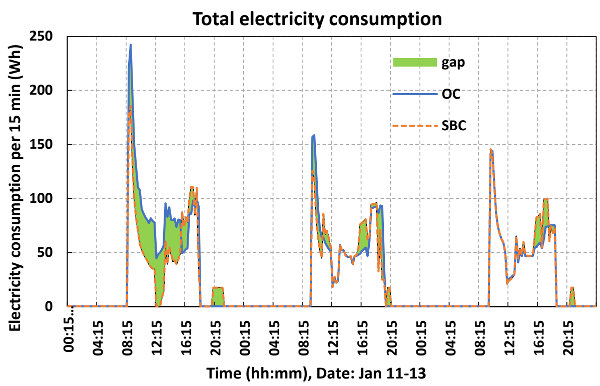

Figure 11: Total electricity consumption on three winter days

In compassion with OC, annual energy saving of SBC is 5.3% and annual energy cost saving is 9.0%. De Coninck (2016) defined the flexibility of a building as the ability to deviate from its reference electric load profile. Following this definition and using OC as a reference, the deviation of energy consumption from OC is considered energy flexibility of the office in SBC scenario. Positive value of the deviation shows the potential for the reduction of energy demand and is called positive flexibility. While, negative value is named negative flexibility and means the potential for increasing energy demand. In this study, annually positive energy flexibility is 55.0 kWh and negative flexibility is 33.8 kWh.

In addition, to evaluate the effect of load shift, the flexibility factor defined by Le Dréau (2016) as shown in equation (1) is calculated.

$$flexibility\ factor = \frac{\int_{low\ price\ time} load \cdot dt - \int_{high\ price\ time} load \cdot dt}{\int_{low\ price\ time} load \cdot dt + \int_{high\ price\ time} load \cdot dt} \quad (1)$$

This factor shows the ability to shift energy consumption to low price period from high price period. The value of this factor is in the range of -1 to 1, in which 1 means that no energy is used during high price periods, 0 means that the energy use is similar in low and high price periods, and -1 means that no energy is used in low price periods. In this study of SBC, the flexibility factor of the office is 0.69, which reveals a fairly high ratio of load shift.

Conclusions and limitations

The major contribution of this study is an approach using Java and EnergyPlus co-simulation, for simulating the effect of occupancy, dynamic occupant behaviors, and DSM on building energy consumption and energy costs. The Java and EnergyPlus co-simulation method is based on the FMI standard. Java is used to model occupancy and occupant behavior and serves as a co-simulation manager, while EnergyPlus is used to establish building models and serves as a co-simulation slave. Dynamic occupant behavior inputs such as lighting, plug loads and thermostat control are generated according to occupancy, illuminance and electricity price at each time step and send to EnergyPlus for co-simulation.

The method is applied, considering three type of occupant behavior: lighting control, plug load control and thermostat control in relation to occupancy, illuminance and electricity price. The stochastic nature of the energy usage behavior and occupancy is captured and demonstrated successfully by using this method. In the sensor-based control, a total of 5.3% in energy consumption and 9.0% of electricity cost is reduced compared with the reference case (OC). The annual energy flexibility potential is found to be 55.0 kWh (positive) and 33.8 kWh (negative). Energy consumption is shifted from high electricity price period to low price period with a flexibility factor of 0.69.

This paper presented a study on three aspects of occupant behavior. However, many other aspects also impact energy consumption, such as window operation and shading control. Future work can be extended to these behaviors. In addition, other environmental parameters such as CO_2 concentration, humidity can also be considered as influential factors of occupant behavior for future studies.

In this study, the occupant control of plug loads and thermostat are modeled based on serval assumptions. Future work can focus on more accurate modeling of such behavior. Another limit of this study is that it only models one private office room. Future studies should apply the model to whole buildings.

Acknowledgement

The authors thank Dr. Thierry Nouidui of Lawrence Berkeley National Laboratory for answering our questions. This work is related to the research activities of EnergyLab Nordhavn, CITIES and the International Energy Agency Energy in Buildings and Communities Program Annex 67, Energy Flexible Buildings.

References

Yan, D. (2015). Occupant behavior modeling for building performance simulation: Current state and future challenges. *Energy and Buildings 107*, 264-278.

Bourgeois, D. (2006). Adding advanced behavioral models in whole building energy simulation: a study on the total energy impact of manual and automated lighting control. *Energy and Buildings 38*, 814-823.

Page, J. (2008). A generalized stochastic model for the simulation of occupant presence. *Energy and Buildings 40*, 83–98

Gunay, HB. (2016). Modeling plug-in equipment load patterns in private office spaces. *Energy and Buildings 121*, 234-249

Gunay, HB. (2015). Implementation and comparison of existing occupant behavior models in EnergyPlus. *Journal of Building Performance Simulation 9*, 567-588

Nouidui, T. (2014). Functional mock-up unit for co-simulation import in EnergyPlus. *Journal of Building Performance Simulation 7*(3), 192-202.

Feng, X. (2015). Simulation of occupancy in buildings. *Energy and Buildings 87*, 348-359.

Hong, T. (2016). An occupant behavior modeling tool for co-simulation. *Energy and Buildings 117*, 272-281.

FMI (2014). https://www.fmi-standard.org/

Wang D. (2005). Modeling occupancy in single person offices. *Energy and Buildings 37*, 121-126

ISO 7730 (2005). Ergonomics of the thermal environment – Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria.

EnergyPlusToFMU (2016). Lawrence Berkeley National Laboratory.http://simulationresearch.lbl.gov/fmu/EnergyPlus/export/

Mahdavi, A. (2009). Toward empirically-based models of people's presence and actions in buildings.

Proceedings of the eleventh International IBSPS Conference, Glasgow, 537-544

Pigg, S. (1996). Behavioral Aspects of Lighting and Occupancy Sensors in Privates Offices: A case study of a University Office Building. *Proceedings of the 1996 ACEEE Summer Study on Energy Efficiency in Buildings 8*, 161-171

US Energy Information Administration (2003). Commercial Buildings Energy Consumption Survey http://www.eia.gov/consumption/commercial/

University of Pennsylvania (2013). Computer Power Usage. https://secure.www.upenn.edu/computing/resources/category/hardware/article/computer-power-usage

European Electricity Index (2016). http://www.epexspot.com/en/market-data/elix/index-table/2016-11-07/EU

Perez-Lombard, L. (2008). A review on buildings energy consumption information. *Energy and Buildings 40*, 394-398

De Coninck, R. (2016). Quantification of flexibility in buildings by cost curves-Methodology and application. *Applied Energy 162*, 653-665

Le Dréau, J. (2016). Energy flexibility of residential buildings using short term heat storage in the thermal mass. *Energy 111*, 991-1002

UC Berkeley, (2013). JFMI - A Java Wrapper for the Functional Mock-up Interface. http://ptolemy.eecs.berkeley.edu/java/jfmi/

Nouidui TS. (2014). Tool coupling for the design and operation of building energy and control systems based on the Functional Mock-up Interface standard. *Proceedings of the 10th International Modelica Conference*, Lund, Sweden