A Comparison of Cooling Energy Use of Residential Buildings According to Air Conditioner On/Off Behavior Using Co-Simulation

S H Mun¹, Y H Kwak², I K Kwak¹ and J H Huh¹

¹Department of Architectural Engineering, University of Seoul, Seoul, Republic of Korea,
²School of Architecture, Kyonggi University, Gyeonggi-do, Republic of Korea.
huhj0715@uos.ac.kr

Abstract. This study quantitatively analyzed the impact of resident AC (Air Conditioner) use behaviors on the cooling energy use of residential buildings. Behavior models extracted from different households were applied to a building of identical performance to compare cooling energy use according to behaviors. The behavior model used in this study is an AC on/off state prediction model using random forest algorithm; three models extracted from respective households were used. To apply the AC on/off state predicted through random forest, BCVTB was utilized for a co-simulation of a data analysis tool (R) and an energy analysis tool (EnergyPlus). The results showed that despite the identical physical and system performance of the building, the cooling energy use differed by as much as 2.5 times at set temperature 24°C.

This study confirmed the possibility of integrating various prediction algorithms with energy analysis tools in future studies and quantitatively reaffirmed the need for behavior studies in the cooling energy use analysis for residential buildings.

1. Introduction

The reason for studying building occupant behavior is that such behaviors are the final determining factor for a building’s energy use. Because of this, behavior models on window operation, AC (Air Conditioner) and heating use, lighting use, and blind use have been developed.

The ultimate utilization of the developed behavior model requires that behaviors be applied when analyzing a building’s performance. Here, the resident behavior and factors that determine the behaviors are often interlinked with one another. That is, indoor thermal environment determined by resident behavior once again influences occupation or behavior, making a one-way simulation inadequate. In the case of EnergyPlus, widely used for building performance analysis, it is possible to realize the logit behavior model through EMS (Energy Management System) Class. However, when predicting resident behavior through methods rather than a regression model, it becomes difficult to apply behaviors to the building performance analysis tool.

To realize a behavior model based on rote learning when conducting building performance analysis, this study co-simulated R and EnergyPlus on BCVTB (Building Controls Virtual Test Bed). The AC on/off behavior prediction model presented in a previous study was reflected in the co-simulation environment that had been constructed and analyzed the influence of resident behavior on cooling energy use.
2. Air conditioner On/Off status prediction

Mun (2018) conducted a study on the apartment resident AC use during summer. She attempted to explain the resident behavior of each household according to physical factors, thereby collecting and analyzing AC use behavior while controlling social, contextual, and biological elements. Based on the collected data (indoor temperature and humidity, outdoor temperature and humidity, solar radiation), Logit, Random Forest (RF), and Support Vector Machine (SVM) performance on AC on/off state were comparatively tested. The results showed that compared to logit and SVM, random forest had better performance. Table 1 shows the parameter and prediction performance of RF models of each household for a previous study.

Table 1. Outline of AC on/off prediction model and results of cross-validation

| Model parameter | RF1     | RF2     | RF3     |
|-----------------|---------|---------|---------|
| Model parameter | Ntree   | 400     | 521     | 953     |
|                 | Mtry    | 4       | 2       | 5       |
| Model performance | OOB error | 1.39% | 0.28% | 1.01% |
| Cross validation results | F-measure | 0.71 | 0.91 | 0.90 |
|                  | Cohen’s Kappa | 0.51 | 0.86 | 0.83 |

3. Simulation

3.1. Co-simulation between R and EnergyPlus

R was used for AC on/off state prediction through data analysis, and EnergyPlus (v. 8.5) was used for building performance analysis. The two were integrated on BCVTB (1.6.0), as can be seen in Figure 1.

Figure 1. Integration concept diagram of R and EnergyPlus on BCVTB

That is, the variables extracted from EnergyPlus (indoor temperature and humidity, solar radiation) become the input to predict the AC on/off state and the AC on/off state predicted through R is input into EnergyPlus again as the AC schedule. Two elements were considered for co-simulation. First,
while R predicts the on/off state using the variables from the final timestep in the simulation of EnergyPlus, EnergyPlus requires the cumulative AC schedule from the beginning of the simulation to the corresponding timestep. This was taken into account by having the output file of each program be accumulated by timestep, and R was coded to utilize only the information from the final timestep. Next, the execution file of R script, not that of R, had to be used for the integration.

3.2. Outline of the simulation

To study the influence of the occupant AC on/off behavior in a residential building, a standard residential household in Korea was selected as the study subject. Figure 2 and Table 2 is the floor plan and the outline of the target unit. In Korea, the living room and the kitchen form a conditioned space. Hence, the separately identified area in Figure 2 shows the conditioned space, accounting for 58.27m² (68% of the total floor area). Window operation, which can affect the AC use, was assumed to always be at a closed state, and the occupancy duration was set at 8 AM to 2 AM the following day. The standard weather data of the Seoul area was used as the weather data for the study. The simulation timeframe for cooling energy use analysis was four days, from August 4 to August 7.

The main factors that determine the energy use of ACs are the AC operation state and the set temperature. This study only considered the prediction model for AC operation state, and the case analyses were conducted for set temperatures of 24°C, 26°C, 28°C in each model.

Figure 2. Target unit plan

Table 2. Outline of Target Unit

| item                        | value                               |
|-----------------------------|-------------------------------------|
| Typical floor area          | 84.99 m²                             |
| Floor(Ceiling) height       | 2.8 m (2.3 m)                       |
| Orientation                 | South                               |
| U-value, area of wall       | 0.35 W/m² K, 76.72 m²                |
| U-value, area of window     | 1.8 W/m² K, 25.68 m²                 |
| Shading coefficient         | 0.8                                 |
| Air leakage                 | 3.0 ACH@50                           |
4. Results

4.1. Air Conditioner operation
Table 3 outlines the duration of AC use and the number of on/off operations during the simulation based on the simulation results extracted by applying AC on/off state prediction model. Despite the same set temperature, the duration of the AC operation showed large differences according to the behavior model. It had been predicted that the higher the set temperature, the longer the duration of AC operation. The results were on the contrary, with longer overall duration of the operation. Also, no particular propensities were discovered in the number of on/off operations.

| Set-point temp.(℃) | RF1 | RF2 | RF3 |
|--------------------|-----|-----|-----|
| Operation duration(min.) |     |     |     |
| 24                 | 720 | 1,470 | 645 |
| 26                 | 1,410 | 1,485 | 1,260 |
| 28                 | 1,590 | 1,545 | 1,065 |
| On/off frequency(times) |     |     |     |
| 24                 | 36 | 6 | 11 |
| 26                 | 13 | 8 | 10 |
| 28                 | 6 | 19 | 16 |

4.2. Cooling energy consumption
Figure 3 shows the cooling energy used at each set temperature according to the AC on/off state prediction based on each behavior model. Overall, cooling energy use appeared to be reduced with the rise of set temperature. Interestingly, despite that equipment system identical to the physical performance of target unit were applied, cooling energy use differed by as much as 2.5 times (at set temperature 24℃). As can be seen from the figure, the lower the set temperature, the larger the differences in absolute energy use.

![Figure 3. Cooling energy consumption according to the AC behavior model for each set temperature](image)

5. Discussion and conclusion
To reflect the AC on/off state prediction model extracted through measurements in the field on building energy analysis, R and EnergyPlus were integrated on BCVTB. The cooling energy based on
the AC on/off prediction model were compared for a standard residential household in the co-simulated environment.

The simulation results showed that overall cooling energy decreased as the set temperature increased. However, there were no specific propensities in the duration of AC operation and number of on/off operation according to set temperature. Also, despite identical physical and system performance, cooling energy use showed 2.5 times difference according to occupant behavior at the set temperature of 24°C.

The on/off state prediction model used in this study was verified for prediction performance (accuracy and consistency) through cross-validation, but the application results of the simulation were not verified. The validation will need to be conducted through cooling energy use monitoring in future studies. Also, to improve the performance of the developed behavior model, not only statistical validation, but the frequency of behaviors that may affect energy use will be required simultaneously. That is, the discrepancies that exist with actual behavior caused by the inability to reflect the frequency or duration will need to be covered in the future.

References
[1] Habara H, Yasue R, and Shimoda Y. 2013. Survey on the occupant behavior relating to window and air conditioner operation in the residential buildings, Proceedings of BS 2013: 13th Conference of the International Building Performance Simulation Association, pp 2007-2013.
[2] Jun T. and Aya H. 2005. State transition probability for the Markov Model dealing with on/off cooling schedule in dwellings, Energy and Buildings, Vol 37, Issue 3, pp 181-187.
[3] Kaiyu S. and Tianzhen H. 2017. A framework for quantifying the impact of occupant behavior on energy savings of energy conservation measures, Energy Build. Vol 146, pp 383-396.
[4] Mun S. H. 2018. An Analysis of Air Conditioner Use Behavior of Apartment Residents and Operating Status Prediction for Building Energy Simulation Reflecting Behavior, Ph.D. Thesis, University of Seoul(Republic of Korea).
[5] Sheikh A Z, Aya H, Ryosuke F, and Nur F. 2017. Development of a model for generating air-conditioner operation schedules in Malaysia, Building and Environment. Vol 122, pp 354-362.
[6] Xiaoxin R, Da Y, and Chuang W. 2014. Air-conditioning usage conditional probability model for residential buildings, Building and Environment, Vol 81, pp 172-182.
[7] Xin Z, Da Y, Xiaohang F, Guangwei D, Yiwen J, and Yi J. 2016. Influence of household air-conditioning use modes on the energy performance of residential district cooling system, Building Simulation, Vol 9, pp 429-441.

Acknowledgments
This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (No. NRF-2017R1A2A2A05001443)