OCCUPANT BEHAVIOR MODEL FOR HOUSEHOLDS TO ESTIMATE HIGH-TEMPORAL RESOLUTION RESIDENTIAL ELECTRICITY DEMAND PROFILE

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ABSTRACT
This paper presents a preliminary study on occupant behavior modeling for estimating high-resolution electricity demand profile of residential buildings. First, the existing occupant behavior models are considered. We then introduce an occupant behavior model developed on the basis of the approach employed in an existing model and an energy demand model that uses the output of the occupant behavior model to produce a high-temporal resolution electricity demand profile. The results of the models were analyzed to address the key challenges in modeling high-temporal resolution electricity demand. We finally suggest a research plan to overcome these key challenges.

INTRODUCTION

Background
This paper introduces a preliminary study on modeling high-temporal resolution electricity demand profiles of residential buildings. The electricity demand profiles of houses, districts, and regions have been attracting interest because the performance of a number of emerging technologies and local energy systems depends on these profiles. For example, the operation and optimum capacity of combined heat and power depends on the electricity demand (Wright et al., 2007). Another example is the application of an electric storage battery that absorbs the fluctuation in the electricity generated by photovoltaic cells that exceeds electricity demand (Fujimoto et al., 2011). The management of electricity demand profiles is also a major issue. After the 2011 Tōhoku earthquake and tsunami in Japan, shortage of electricity supply emerged in the Kanto region. Therefore, there is an urgent need to understand the composition of electricity demand and its management method.

Several models have been developed for modeling the high-temporal resolution electricity demand of households. They principally model the stochastic behavior of occupants in households. The behavior determined by the models is defined by the following factors:

- the daily activities of the occupants, including sleeping, cooking, and working.

To convert behavior to energy consumption, the relationship between the living activities and the operation of home appliances and equipment (e.g., air-conditioning) is defined in energy demand models. For example, if one or more family members are watching television in the evening in the living room, the television and lighting of the living room are determined as operating, and the heating/cooling demand is estimated through a dynamic thermal simulation.

Relationship between the energy demand and occupant behavior
The behavior of occupants is one of the most significant sources of household energy consumption. Santin et al. (2009) analyzed the factors determining the energy consumption for space and water heating in Dutch residential homes. They found that the household characteristics and occupant behavior significantly affect the total energy consumption. Firth et al. (2007) measured the electricity consumption of 72 households in the UK over a two-year monitoring period. They observed that the large variation in the annual energy consumption probably resulted from variations in the number of occupants, the number and type of appliances, and the behavior patterns of the occupants. The electricity consumption was measured at 5-min intervals, and they observed that it significantly fluctuated according to changes in the behavior of occupants.

Existing occupant behavior models
Usually, in a household energy demand model, the occupant behavior is given by a pattern that represents an average occupant’s behavior (e.g., Yao et al. 2005). Although this approach is easy to set up and useful to estimate the total energy consumption of households or the average pattern of energy consumption, it does not provide useful inputs to replicate a high-resolution electricity demand profile. To replicate this profile, stochastic occupant behavior must be directly simulated.

Our examination of the existing occupant behavior models revealed three models proposed by Richardson et al. (2010), Widén et al. (2010), and Tanimoto et al. (2008). These models employ time
use data (TUD), which show how people spend their time. The data is usually developed on the basis of one-day diaries recorded by several thousands of people. If the raw data of a diary are available, information on the number of respondents who performed an activity \( k \) (\( M_k \)) and who changed their behavior from behavior \( i \) to \( j \) (\( N_{ij} \)) are also available. However, sometimes only statistically treated data are available, for example

- Average ongoing minutes (AOM) of the activity that occurs in a day,
- Standard deviation of AOM (SDOM), and
- Percentage of respondents who adopt the behavior (PB) at a specific time of a day.

The approaches proposed by Richardson and Widén model the behavior of occupants as a Markov chain process, which is a stochastic process in which transitions of the state (i.e., change of behavior in the occupant behavior model) only depend on the state at the previous time step. In Widén’s model, there are nine states (or behaviors) that occupants can undertake. Behaviors of all the examined household members are individually simulated. The probability of the transition of state for each time step at the corresponding time in TUD is given by \( N_{ij} \).

In Richardson’s model, the Markov chain process is used to determine the number of “active occupants” who are in the house and are not sleeping. The states that can be undertaken are each number of occupants up to the household size (the number of family members). The approaches use the results of the UK time use survey organized for each household size from one to six persons. The transition probability is directly developed by counting the number of people who undergo the following four transition states using \( N_{ij} \): from active to active, from active to inactive, from inactive to active, and from inactive to inactive. After the number of active occupants is determined, the operation of home appliances by them is determined. First, the results of the time use survey are grouped on the basis of the number of active occupants in order to determine the proportion of households that undertake a particular behavior for all the time steps in a day. The probability of a household undertaking a behavior is given by the proportion corresponding to the time and the number of active occupants. If the proportion adjusted by a scalar is larger than a random number between zero and one, it is determined that the examined household undertakes the activity.

Both the models accurately show the stochastic behavior of occupants. However, they require raw data of the time use survey, and in many countries, only statistical data are publicly available. Tanimoto’s model overcomes this limitation. His approach uses only AOM, SDOM, and PB from the time use survey. First, the time period of all considered behaviors is determined while assuming a logarithmic Gauss distribution defined by AOM and SDOM. The list of discrete behaviors with a determined time period is located on a day by considering PB in the following manner. First, a time step is randomly selected. One behavior is selected using PB at the time step. After the first behavior is located, the behavior beginning from the time at which the first behavior ends is selected using PB at that instant. This process is repeated until all discrete behaviors in a day are placed.

**Purpose of this paper**

The purpose of this paper is to introduce a preliminary study on an occupant behavior model used to simulate a high-temporal resolution electricity demand profile of a household. We discuss the following two points:

1. Development of time use data for a household.
2. Replication of stochastic behavioral change.

The authors developed a stochastic occupant behavior model by the approach proposed by Tanimoto et al. (2008), but with a few modifications. As mentioned earlier, this approach does not require the raw data of the time use survey to develop transition probabilities for reproducing the transition of behavior. Instead, AOM, SDOM, and PB are used. These statistical data are derived from several thousands of time-use diaries. Hence, when the developed model is applied to a specific house, the distribution of time at which behaviors such as sleeping occur routinely might be too large. Thus, TUD must be customized for the target household. In this paper, we propose a method to develop TUD by extracting behavior information from the measured electricity data and the time use survey.

Furthermore, in Tanimoto’s model, the frequency at which transitions of behavior occur might be lower than in the other two approaches. This is because the time period of discrete behavior is determined first and the number of transitions depends on the number of discrete behaviors. It is vital to examine whether the model accurately reproduces the actual stochastic behavior of a household.

In this paper, we first introduce the developed simulation model and analyze the results to understand the two abovementioned drawbacks. We then introduce a research plan to develop a method for extracting TUD from both the measured electricity data and the time-use diary. Then, we compare the simulation result of electricity demand calculated for a single male household with the actual electricity demand measured in five single male households. Based on the results, we discuss the efficiency of the model for replicating the stochastic behavior of occupants.
A STOCHASTIC OCCUPANT BEHAVIOR MODEL

Overview of the model

Figure 1 shows the simulation procedure of the model. The input of the model is the same as that of Tanimoto’s model and AOM, SDOM, and PB are used. These data are obtained from TUD developed by the Broadcasting Culture Research Institute of Japan (2001) on the basis of their survey on the time use of 12,600 Japanese residents. 27 types of activities such as sleep, work, and watching TV on weekdays, Saturdays and holidays are defined for 24 h. The data are classified into 24 categories consisting of three categories of days (weekday, Saturday, and holiday) and eight classifications based on the attributes of family members (working male and female, housewife, senior male and female, and primary, junior high, and high school students). PB is calculated with a 15-min time interval. For the model, the time interval was shortened to 5 min by interpolation under the assumption of a linear relationship between the adjacent 15-min time steps.

First, the time period of each considered behavior is determined by assuming that it follows the Gauss distribution defined by AOM and SDOM. Then, five behaviors are placed on a day prior to the rest of behaviors. These five behaviors are sleeping, commuting to and from work/school, eating, and bathing. These behaviors are undertaken routinely by occupants. The method to place the behavior is the same as in Tanimoto’s model. A random number is generated to determine a time step. If another random number is larger than the PB of the behavior at the selected time and the time step has not been occupied by a behavior, the time step is allocated to the selected behavior. Then, the time at which the occupant starts the behavior is determined using PB. PB before and after the selected time is used to measure the difference between the starting time and the selected time and between the selected time and the time at which the occupant stops the behavior. If a behavior has been allocated to time steps, the probability is assumed to be zero. If the time period of a behavior is larger than the time steps selected for the behavior, the behavior is allocated to the selected time steps and the period of the behavior is shortened by the selected amount so that the remaining amount can be selected at other time steps.

Next, the remaining behaviors are placed on the day. An unoccupied time step is randomly selected. Then, a random number is assigned to PB at the time step to select a behavior. The selected behavior is allocated to the selected time step. The times at which the occupant starts and stops the behavior are determined using the method mentioned above. This process is repeated until all time steps are occupied by a behavior. The initially determined time period for each behavior can be divided according to this process, resulting in more frequent changes in behavior.

The five behaviors dining, conversations and personal relationships, watching television, listening to the radio, and reading the newspaper, two behaviors can be allocated to one time step.

Simulation result

Figure 2 shows the estimated average time period in which each behavior was undertaken and its standard deviation. The estimated results are compared with AOM and SDOM in TUD for the working male category. Figure 3 compares PB estimated by the model and that obtained from TUD. The results are in good agreement with the values obtained from TUD.

Figure 4 shows the simulation result of occupant behavior for a four-member family on May 11 (Wed) and 12 (Thu). Each colored box indicates a behavior and its duration. As shown in the figure, each occupant has different behavior characteristics. For example, the mother stayed longer in the house because she was a stay-at-home wife and her behavior varied more frequently than the other occupants.
Several problems were observed in the produced behavior data:

- Family members who are at home probably share breakfast and dinner; however, the family members have breakfast and dinner at different times.
- Daily behaviors that are routinely repeated on weekdays cannot be observed. For example, many people wake up and go to school or work at fixed times. However, the observed times of awakening and going out are different on these two days.

These problems are caused by the TUD averaged over thousands of samples. Thus, for a simulation, it is necessary to establish a method to develop TUD for the household under examination. We will discuss this problem later.

Figure 2: Comparison of AOM and SDOM between those given by TUD and the model.

Figure 3: Comparison of PB between the TUD and the model.

Figure 4: Occupants' behavior for a four-member family on May 11 and 12.
ENERGY DEMAND MODEL FOR A RESIDENTIAL BUILDING

Conversion from behavior to electricity

Figure 5 shows the simulation procedure of the residential energy end-use model (Shimoda Y., 2007). A variety of sub-models and databases were used to estimate the energy demand, as shown in the figure. First, the occupant behavior is inputted from the occupant behavior model. Each behavior is linked to the use of home appliances and equipment, the end-use demand for water heating, and the location of the occupants. For example, if one or more family members are watching television in the evening in the living room, the television and the lighting are estimated as operating and the heating/cooling demand is calculated via a dynamic thermal simulation.

It is assumed that all occupied rooms and corridors are illuminated at night except when any occupant is asleep. In the daytime, occupied rooms are classified into rooms that are always illuminated, rooms that are never illuminated, and rooms in which the lighting depends on the brightness of daylight. The ratio of these categories is determined on the basis of the results of a questionnaire survey conducted by the authors. The brightness of daylight is calculated from meteorological ground observation data.

The energy demand for water heating is calculated using the amount of utilized hot water, the hot water temperature, and the city water temperature. The city water temperature is given by a function of the outdoor air temperature. For the heating and cooling model, dynamic heat load simulations are conducted using both building data and meteorological data. Ventilation and heat conduction between rooms is considered using a thermal circuit network method. The internal heat gain is calculated on the basis of the energy consumption of home appliances and the occupants’ behavior.

All calculations are performed with 5-min time intervals in order to estimate an electricity demand profile with a time step corresponding to the occupant behavior model.

Simulation result for the four-member family

Figure 6 shows the simulation results of the electricity demand for each end-use for a four-member family on May 11 and 12. The results correspond to the behavior shown in Figure 4. The energy consumption of the refrigerator and the standby electricity of the television and other appliances can be observed throughout the day. The electricity demand for television, appliances, lighting, and cooking occurs when occupants’ behaviors correspond to the use of these appliances. As shown in the figure, the estimated electricity demand varies significantly.

Electricity demand of three family compositions

Figure 7 shows the simulation result of the electricity demand profile on May 11 and 12 of a household with three family compositions. Figure 8 shows the frequency distribution of the electricity demands. For calculating the energy demand, the same occupant behavior model determining the behavior and place at which occupants present is used.

ON/OFF operation of home appliance Rooms used by occupants

Penetration rate of appliances
Power consumption of appliances

Conversion from behavior to ON/OFF operation
Dynamic heat load simulation (Thermal network model)
Efficiency & operation characteristics
Room layout
Specification of lighting devices
Amount of hot water use
Efficiency & operation characteristics

Database for demand estimation
Database for consumption calculation

Simulation procedure & database

Electricity consumption of home appliances
Air-conditioning system model
Electricity consumption of lighting devices
Water heating system model (boiler, HP, CHP)
Energy consumption for other end use

Electricity, city gas and kerosene demand at 5-min time interval

Figure 6 Electricity demand for each end-use and electricity generation for a four-member family

Figure 5 Database and sub-models of the residential energy end-use model
behavior data were used for a working male, a wife, and children among the family compositions. The electricity demand is different owing to the difference in family compositions; a larger household has a larger demand. However, the increase in energy demand is not linear to the number of occupants because 1) there are a number of appliances and equipment that are shared among family members and 2) the behavior pattern is different, for example, elderly people stay indoors for longer periods.

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**Figure 7 Electricity demands of three family compositions on a weekday (May 12)**

**Figure 8 Cumulated frequency of electricity demand calculated for three family compositions**

**COMPARISON BETWEEN ESTIMATED AND MEASURED CONSUMPTION**

We have already mentioned the two problems of the occupant behavior model. These problems are caused by the TUD averaged over thousands of samples. We have not examined whether the characteristics of behavior changes of occupants are accurately reproduced by the behavior model. To this end, we applied an energy end-use model to a single working male household and compared it with the actual electricity demand of five single-male households (all are full-time students) from April 24 to May 9. We assumed that the frequency of variations in electricity consumption represents the frequency at which changes in behavior occur. The actual electricity demands were measured using current transformers attached to each electric circuit of the distribution board in order to determine the total electricity consumption. The time interval of measurement was 1 min and the result was converted to 5-min time intervals for comparison with the simulation result.

Figure 9 shows the electricity consumption on May 5, which is a national holiday. As shown in the figure, the electricity consumption estimated by the model is higher than the actual consumption at midnight. The consumption is the sum of that of the refrigerator and the stand-by power. This can be improved using the actual electricity consumption of the refrigerator and the stand-by power. There are two patterns of the actual consumptions of the refrigerator and stand-by power at night; Those of No. 3 and No. 5 are almost constant, whereas those of No. 1, 2, and 4 periodically repeat a pattern with a trapezium shape. This consumption pattern was also observed during the day when the occupants are probably absent. Here, we assumed that the occupant is inactive (outside the house or sleeping) and the same consumption pattern as that at midnight is observed. During the remaining time period, we assume that the resident is active (in the house and not sleeping).

We also assumed that a change in electricity consumption when the resident is active is only given by a change in behavior. Based on these assumptions, we calculated the following indicator by using the electricity consumption over the measurement period from April 24 to May 9:

\[
BCF = \frac{NOC}{TAM}
\]

where BCF is the frequency at which the change in behavior occurs, TAM is the total minutes during which the occupant is active, and NOC is the number of changes in electricity consumption defined by the deviation of adjacent electricity consumption. Note that this number is counted when the deviation is larger than the peak value observed while the resident is inactive in order to eliminate changes due to the cyclic change observed in the consumptions of the refrigerator and stand-by power.

Table 1 shows the indicators estimated for the five single-male households. It also includes those calculated from the result of the occupant behavior model. During the time period, the modeled single
DRAWDACKS OF OCCUPANT BEHAVIOR MODELING

The results of the previous section imply that changes in behavior occur more frequently than that estimated by the occupant behavior model. This is probably because of the method used to determine the occupant behavior. The model must be improved in this regard for application to a household. In the section on the behavior model, we pointed out two problems caused by TUD averaged over thousands of samples. Thus, it is necessary to establish a method to develop TUD for the household examined for simulation as well as a method to improve the replication accuracy of the stochastic behavior of occupants. To solve these problems, the authors are conducting measurements of electricity consumption of home appliances at 30-min intervals as well as that at each line of the distribution board at 1-min intervals. The time resolution of the two types of measurement is restricted by the device used for measurement. The measured data is used to develop TUD and validate the simulation result. By combining the electricity consumption measured at both the appliance and the circuit, the nature of electricity demand and its relationship with occupant behavior would be clearly understood.

Method to develop TUD for a household

We propose a method to develop TUD for a household, although it still needs to be validated.

A member of a household records a diary of daily routine activities including sleeping, leaving for/arriving from work/school, eating, and bathing, if he/she is routinely performing these activities. Based on this, the TUD of daily routine activities can be developed. To count the number of active occupants who are in the house and are not sleeping, the leaving and arriving time for outings other than going to work/school is also recorded. The record of these behaviors is important to develop TUD for all family members because appliances and equipment can be shared among occupants. It is difficult to detect the number of occupants by using the measured electricity consumption. We attempted to detect the waking time of occupants on the basis of the measured consumption by detecting the first electricity increase alteration over the consumption for the refrigerator and stand-by appliances. Although it can be assumed that a household member has woken up, it is impossible to identify which one.

After the number of active occupants is provided, Richardson’s approach, mentioned in the introduction, is useful to determine the operation of appliances and equipment. First, based on the measurement of electricity consumption, appliances and equipment that are operated for each time period can be detected. These data are grouped on the basis of the number of active occupants. Then, the probability showing the relationship between the active appliances/equipment and the number of occupants can be obtained. If there are appliances that are operated by only one member, e.g., those for cooking by the wife, the probability of the relationship between the appliance operation and the state of the occupant can be developed.

CONCLUSION

This paper presented a preliminary study on occupant behavior modeling for estimating high-resolution electricity demand profiles of residential buildings. Although previous researchers have established excellent algorithms to reproduce the stochastic behavior of occupants, they have drawbacks when applied to a household. First, the time use data of the household occupants must be developed. Second, a modeling method to reproduce the stochastic characteristics of the change of behaviors is necessary. To overcome these problems, we proposed a research plan to develop TUD for a household and obtain data for validating occupant behavior models. The plan includes 1) collection of diaries from the members of the household and 2) measurement of electricity consumption of individual home appliances and equipment as well as the total electricity consumption at the electric circuit of the distribution board.

The application of this method and improvement of the occupant behavior model are our future work.

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