COMPARISON OF OCCUPANT BEHAVIOR MODELS APPLIED TO A HOUSEHOLD

Yohei Yamaguchi, Marcos Tanaka, Yoshiyuki Shimoda
Graduate School of Engineering Osaka University, S4 Building, 2-1 Yamadaoka,
Suita, Osaka, 565-0871, JAPAN. Yohei@see.eng.osaka-u.ac.jp

ABSTRACT

This paper presents a preliminary study on occupant behavior modeling for estimating high-resolution energy demand profile of residential buildings. The authors developed two occupant behavior models based on the existing modeling approaches. We then applied the models to a four-member household living in Osaka, Japan, to evaluate the capability of the behavior models. Time use diary for nine days was collected for each household member to develop time use data as the input of the models. Several indicators showing the duration and transition of behaviors were calculated for the actual time use and simulation results were calculated and compared. Based on the comparison, the authors discussed the strength and weakness of the modeling approaches and proposed methods to improve the modeling approaches.

INTRODUCTION

Usually, in a household energy demand model, the occupant behavior is given by a pattern that represents an average occupant's behavior. 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-temporal resolution energy demand. To replicate such 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 *i* and who changed their behavior from behavior *i* to *j* (N_{ij}) can be generated.

The approaches proposed by Richardson and Widén model such behavior transitions as a Markov Chain (MC) 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 MC 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 transition probability is developed considering 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.

One of the limitations of the modeling approach is that it requires raw data of the time use survey, while only statistical data are publicly available in many countries. Tanimoto's model overcomes this limitation. His approach only uses the following statistic information:

- 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.

First, the duration time 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 the discrete behaviors in a day are placed.

Although the duration of behaviors can be modeled by using AOM, SDOM, and PB, in the Tanimoto's approach, the transition of behaviors are unnecessarily well replicated. This is because the number of transitions depends on the number of discrete behaviors. This might be the vital weakness to well replicate the actual stochastic behavior of the energy demand of a household, while the MC model well replicates it.

In order to evaluate the strength and weakness of the two modeling approaches, the authors developed two occupant behavior models based on the MC approach and Tanimoto's approach and applied the models to a residential household. By comparing the actual time use data of the household members and the simulated time use, the authors evaluate the performance of the modeling approaches.

In the remaining parts of the paper, we first introduce the household to which the models were applied. The method used to develop TUD is also described. Then, we explain the occupant behavior models. The simulation result is then compared with the actual time use. We finally discuss the strength and weakness of the modeling approaches to model high-temporal resolution energy demand for households.

COLLECTION OF TIME USE OF A HOUSEHOLD and TUD

The household to be modeled is a four member family living in Osaka, Japan, consisting of a working male, a working female, a high school student, and a junior high school student. The authors handed a format of time use diary shown in Figure 1 to collect time use of each household member. The time use was classified into 11 categories in addition to two lists for free description. The diary was filled by all the family members for two weeks. Then 9 weekdays of time-use diary was collected. Based on the time use diary, TUD necessary to perform behavior models (AOM, SDOM, and PB) was developed by following the definition from 9 days data.

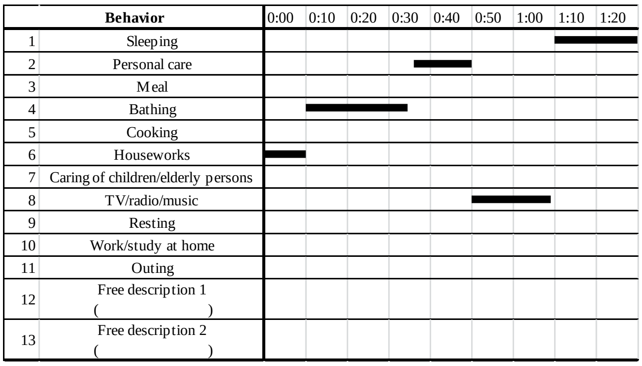

***Figure 1**. The format of the time use diary (the respondents were asked to draw a line on the cell of corresponding time and behavior listed on the left side).*

OCCUPANT BEHAVIOR MODELS

Two behavior models were developed based on the abovementioned approaches. As previously mentioned, the Markov Chain model is based on a stochastic process in which transitions of the state only depend on the state of the previous time step. For this model, a 2 dimension matrix (13x13) was generated for each time step (B_{ijt}) indicating the probability of transition from behavior i, into behavior j, at time step t. On the start of each simulation, the behavior of the first time step is determined by using PB at time step 0:00 and a random number. For the next time step, another random number is generated and by the probabilities inputted on the transition matrix B_{ijt}, the behavior is determined. All time steps are filled with behaviors 1 to 13 following the above mentioned process using transition matrix B_{ijt}.

Figure 2 shows the simulation procedure developed based on the Tanimoto's approach mentioned above. Several modifications were added. We call this model the Roulette Selection (RS) model in this paper. The model was originally developed to model occupant behavior by using the TUD developed by the Broadcasting Culture Research Institute of Japan (2001). 27 types of behaviors such as sleep, work, and watching TV are defined.

First, the duration of considered behavior per day is determined by assuming that it follows the Gauss distribution defined by AOM and SDOM. Then, discrete behaviors made for the following five behaviors, sleeping, outing for work or school, eating, and bathing, are placed on a day prior to the rest of behaviors. We call these five behaviors "routine behaviors" since these behaviors are undertaken routinely by occupants. The method to place the discrete behaviors is same as in the Tanimoto's model. A random number is generated to determine a time step from those with positive PB. Then, the time at which the occupant begins the behavior is determined by using PB as the duration time before and after the selected time step is determined by PB before and after the selected time step. If a behavior has been occupied to the time steps, the probability is assumed to be zero. If the duration of the behaviors is larger than the time steps selected for the behavior, the behavior is allocated to the selected time steps and the duration of the behavior is shortened so that the remaining amount can be selected at other time steps.

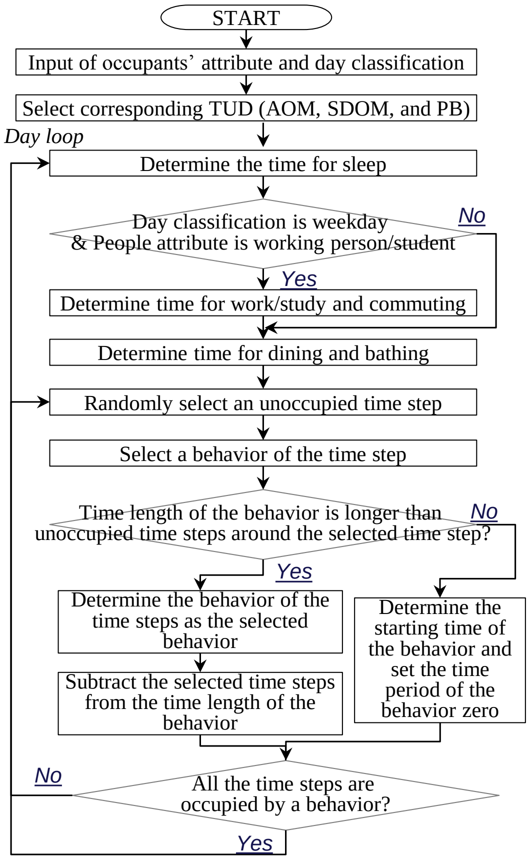

Figure 2. *Flowchart of the occupant behavior model.*

Next, the remaining non-routine 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 in this process, resulting in more frequent changes in behavior.

RESULT AND DISCUSSION

The simulation result was evaluated by using the following indicators:

- Duration time for the behaviors per day,
- Time at which the routine behaviors start and end,
- Number of behavior transitions per day,
- Probability distribution showing percentage of behaviors at each time step, and
- Number of different pattern of occupant behavior transition in 500 simulations

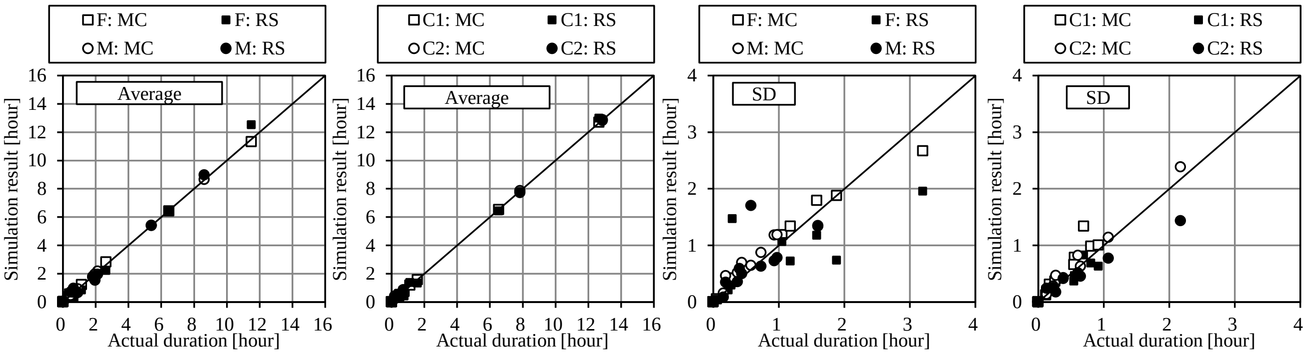

Figure 3. *Average and standard deviation (SD) of the duration time for the behaviors.*

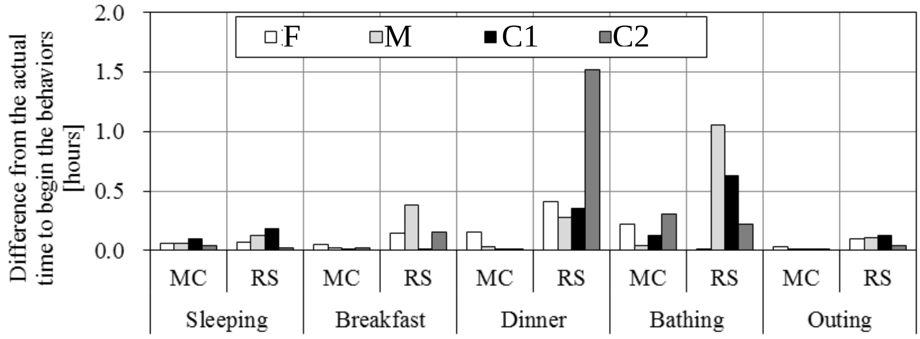

Figure 4. *The difference between the averages of the simulated time and the actual time at which the occupants began the behaviors.*

Figure 3 shows the duration time of 11 behaviors. The two figures on the left side show the average and the ones on the right side show the standard deviation of the duration time of each behavior shown by the plots. The F, M, C1, and C2 shown in the graph legends indicate the household members, the working male, working female, high school student, and junior high school student.

For the result of the average duration time, most of the results well agree with the actual duration time. The result of the outing calculated for the working male by the RS model. For standard deviation, the results of the MC model agree well with the actual duration time. The RS model showed relatively large discrepancy is the standard deviation.

Figure 4 shows the time difference between the simulated time and the actual time at which the occupants began the routine behaviors listed on the horizontal axis. As shown in the figure, the beginning time of the routine behaviors for the MC model well agree with the TUD. However a larger discrepancy was observed in the beginning time of bathing and dinner of the RS model. Figure 5 shows the probability distribution calculated for the working male. The result on the top is the actual probability distribution. The following two figures show the results estimated by the MC model and RS model. The figure well illustrates the characteristics of the modeling approaches. There is no difference between the actual probability distribution and the result of the MC model. However, the sharp steps that were observed in the actual probability distribution should not be replicated since the sharp steps were created due to the number of sample is too small (9 weekdays). Additionally, visual check was done to evaluate simulations coherency. While many of the MC simulations had a coherent behavior output, some of the simulations show abnormal behavior such as having dinner or bathing more than once a day.

On the other hand, RS simulations do not show this abnormal pattern since the program only allows dinner and bathing behaviors to occur once a day. The result of the RS model shows a smooth change in the probability distribution. However, there is a large difference with the actual probability distribution. For example, the probability of meal (dinner) around 19:00 is significantly smaller than the actual probability. This is because the Gaussian distribution was assumed to determine discrete behaviors and the discrete behaviors for routine behaviors were placed without splitting. As the result, the behaviors whose probability distribution does not follow the normal distribution had a large error. This is the cause of the errors shown in Figure 3 and Figure 4.

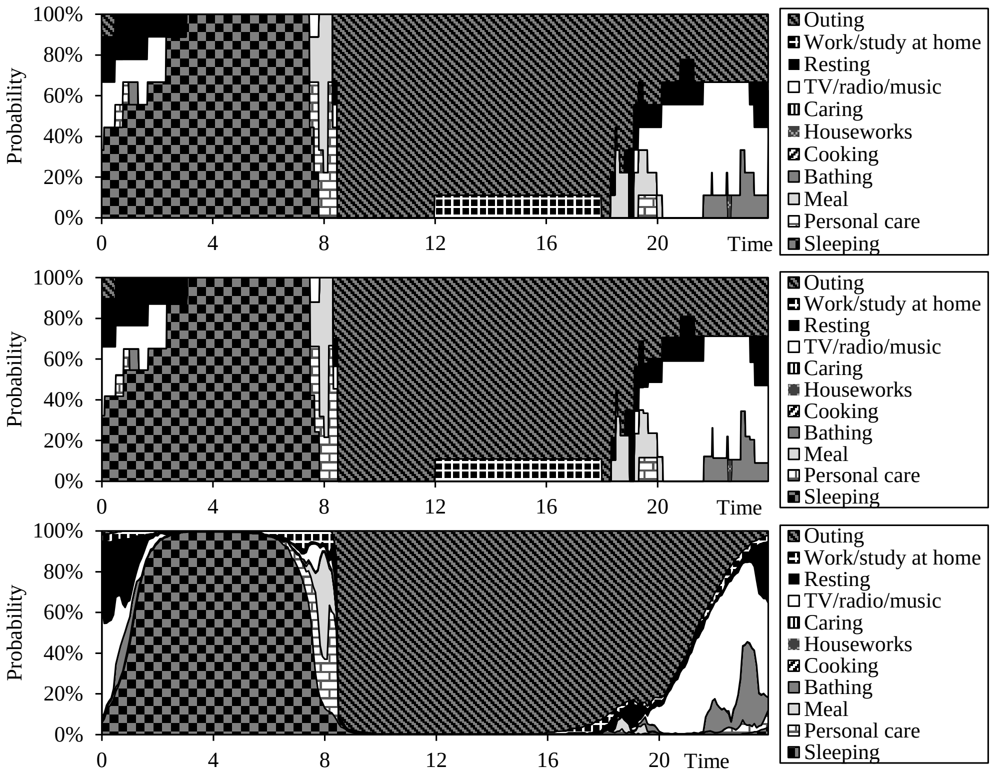

Figure 5. *Probability distribution (actual probability distribution, the result by the MC model, and the result by the RS model from the top).*

Figure 6 shows the average (left) and standard deviation (right) of the number of behavior transitions per day. The results of the MC model well agree with the actual value. On the contrary, the RS model overestimates the number of behavior transitions. The reason of the larger behavior transition is that the discrete behaviors of the non-routine behaviors were divided into several discrete behaviors as placed in a day as explained earlier.

It should be noted that the variety in the behaviors produced by the MC model are smaller than those produced by the RS model. Table 1 lists the number of different daily behavior transition patterns counted from the result of 500 simulation runs. While the RS model produced different patterns every simulation run, a limited number of patterns were produced by the MC model for Child 1 and Child 2. This is because the transition patterns gained by the sample of time use data were very limited for Child 1 and Child 2.

The MC model showed a good capability of replicating the duration and transition of behaviors. However, the result of behavior transitions was restricted by the sample TUD. If the number of sample is very small, only a limited number of behavior transition patterns can be generated. To increase the variety in the simulation result, it would be effective to adjust the transition matrix or increase the sample. Moreover, the MC model shows no memory logic to avoid repeated behaviors that would be incoherent, like having dinner or bathing twice. This is because the MC model does not include any kind of memory logic.

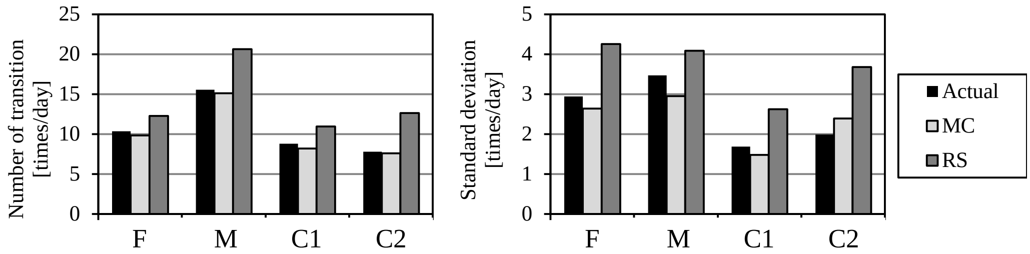

Figure 6. *Number of behavior transitions per day (left: average; right standard deviation).*

Table 1. *Number of different behavior patterns generated from 500 runs*

Margin	MC	RS
F: Working male	496	500
M: Working female	500	500
C1: Child 1	360	500
C2: Child 2	270	500

The RS model showed a good capability of replicating the duration of behaviors. The model produced a variety in the behavior transition compared to the MC model. However, the model showed a weakness in modeling the routine behaviors that do not fit to the Gaussian distribution. In addition, the model overestimated the number of transitions of non-routine behaviors. The following improvements to the model would be beneficial to improve the modeling approach:

- In the current model, fixed behavior kinds (27 kinds) are used. This behavior classification must be changeable according to the actual time use data. For example, if outing of working male is divided into outing for work and others, a long duration after 20 o'clock in Figure 6 can be generated by combining an outing for work routinely repeated every weekday and an outing after work occurring a limited number of days in a week.

- Statistical information on duration of non-routine behaviors must be taken into account to avoid an overestimation of the frequency of the behavior transition, as the non-routine behaviors can be divided without any restriction in the current model.

CONCLUSION

This paper applied two different modeling approaches of occupant behavior, the Markov Chain model and the Roulette Selection model, to a household that time use data for nine days was available. The Markov Chain modeling approach is capable of replicating the duration and transition of behaviors. However, the variety of behavior patterns is limited, if the amount of samples on time use is small. On the other hand, the Roulette Selection model showed weakness in replicating the duration and transition of behaviors compared to the Markov Chain model. However, the model has strength to generate a variety of behavior patterns even when the sample of time use data is limited. Finally, the authors also discussed methods to improve the modeling approaches.

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