Behavior Model of Occupants in Home based on Japanese National Time Use Survey

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ABSTRACT
This paper proposes a new approach for modelling time allocation of occupants in home. In this model, behaviors are divided into routine and non-routine behaviors. Routine behaviors are those undertaken routinely every day like sleeping and working. First, the duration of routine behaviors is determined based on a statistical information on the duration. Then these discrete behaviors are placed on timeline of day by using probability distribution of time allocation. Then, gaps between routine behaviors are filled by non-routine behaviors. For the filling process, two kinds of data are used. The first data is transition probability from a behavior to another behaviors. After a routine behavior is ended, a random number is given to the transition probability to determine the behavior after the routine behavior. Then, by using the second data, statistical data of the duration of non-routine behaviors, the duration of the selected non-routine behavior is determined. This process is repeated until all the gaps are fulfilled. This paper presents the procedure of the model and the method to prepare input data. We evaluate the proposed approach by applying it to generate behavior results of 2000 weekdays for working male and housewife by comparing simulation result with original time use data that are used to generate input data of the model.

KEYWORDS
Time use, Residential building, Stochastic modelling

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 with a realistic variety. To replicate such profile, stochastic occupant behavior must be directly simulated.

Our examination of the existing occupant behavior models revealed three

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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 potential weaknesses of the modeling approach is that Transition probability is defined for each time step, duration of each behavior is not necessarily reproduced, as duration is determined as a result of behavior transition in Markov Chain. Another practical weakness 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 the practical weakness. His approach only uses the following statistic information:

- Mean and standard deviation of duration of activities in a day
- 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 the mean and standard deviation. The list of duration for each activity is referred to discrete behaviors. Discrete behaviors are placed on the timeline of a day by considering PB in the following manner. First, the total length of duration is adjusted to 24 hours. Then, a time step is randomly selected. One behavior is selected using PB at the time step. After the first behavior is placed, 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 of the discrete behaviors in a day are placed. For following days, the selection of the first time step is replaced with the time step at which the behavior placed lastly ends.

Although the duration of behaviors can be modeled by using limited statistical information 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.

This paper proposes a new approach for modelling occupants' time allocation in home. The approach combines the abovementioned two modelling approaches to overcome their weaknesses. This paper presents the procedure of the model and the method to prepare input data. In the remaining parts of the paper, we first introduce the modelling approach and data preparation. We then evaluate the capability of the modelling approach of replicating statistical characteristics of TUD.

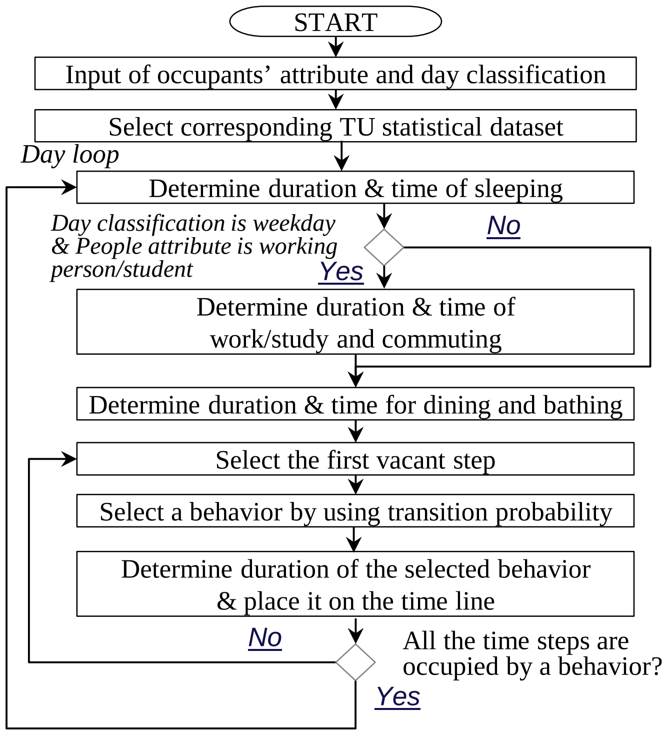

Figure 1. *Procedure of the simulation model*

PROPOSED BEHAVIOR MODEL

Simulation algorithm

Figure 1 shows the modelling procedure to generate occupants' behavior in home. In this model, the behaviors are divided into routine and non-routine behaviors. Routine behaviors are those undertaken routinely every day, which are sleeping, outing for work or school, eating, and bathing. These routine behaviors are placed on a day prior to the rest of behaviors, non-routine behaviors. The method to place the discrete behaviors is similar to Tanimoto's model. First, the duration of routine behaviors is determined based on a statistical information on the duration. Then these discrete behaviors are placed on timeline of day by using probability distribution of time allocation. For sleeping, probability distribution is given for ending time, while it is given for beginning time. This is because we observed that standard deviation of awaking time is smaller than sleep beginning time. Order of placement is sleeping, working/study, breakfast, lunch, dinner, and bathing.

After placing all the discrete routine behaviors, the gaps between the routine behaviors are filled by non-routine behaviors. For this process, two kinds of data are used. The first data is selection probability of behaviors, $SP_{t,n}$ at time t for behavior n. After a routine behavior is ended, a random number is given to the selection probability to determine the behavior after the routine behavior. Then, by using the second data, statistical data on the duration of non-routine behaviors, the duration of the selected non-routine behavior is determined. The statistical data is arranged as a cumulative frequency, $Dr_{tr,n,du}$, where n is behavior and du is duration. This process is repeated until all the gaps are fulfilled. The cumulative frequency of duration is prepared for time regions, tr, distinguishing 24-hours of timeline. Weekdays are divided into two time regions, for people going work or school, the time region from awaking time and outing time for work or school and the time region from arriving time from work or school to sleeping time. For holidays and other attributes like housewives, the timeline is divided into four time regions by using sleeping and three meals, breakfast, lunch, and dinner. The reason why we distinguished timeline is that the selection probability considerably differs among the regions.

To develop the selection probability for non-routine behaviors, $SP_{t,n}$ for behavior n, we use the percentage of people who adopt the behavior n, $PB_{t,n}$ at time step t, which is developed based on raw data of time-use diary. Then, this probability is adjusted by the cumulative frequency, $Dr_{tr,n,du}$, as shown in Equation (1).

$$APB_{t,n} = \frac{\sum_{du}^{VS} PB_{t+du,n} \cdot Dr_{tr,n,du}}{VS} \qquad (1)$$

The reason why $APB_{t,n}$ is adjusted is that the appropriateness of behaviors differs according to the number of available vacant steps (VS) created by routine behaviors and the non-routine behavior lastly placed. Each behavior has a certain characteristic in duration defined by $Dr_{tr,n,du}$. If the number of vacant step is few, probability of selection for a behavior with relatively long duration should be small. To take into account this point, we defined $APB_{t,n}$ as in Equation (1). By using $APB_{t,n}$, we define $SP_{t,n}$ is defined as in Equation (2).

$$SP_{t,n} = APB_{t,n} \Big/ \sum_{i}^{N} APB_{t,i} \qquad (2)$$

Data preparation

This model has five input data listed in Table 1. All of the data are developed based on the result of the national time-use survey conducted by the Statistics Japan in 2006 (2014). This data collected time use diary from approximately 80 thousands households living in the whole country. All persons aged 10 and over in the sample households are asked to respond to the survey. The number of sample diary totals around 200 thousands. To develop the data listed in Table 1, we first distinguished samples into seven classifications by demographic attributes considering gender, age, and occupation as shown in Table 2, which can be done by using information on attributes given for each respondent. The categories has several categories listed in Table 2, which totals 25 sub-categories.

***Table 1**. Input data of the proposed model*

Input data	Diary data
Probability distribution of duration of routine behaviors	Diary A
Probability distribution of beginning or ending time for routine behaviors	Diary A
Percentage of people who adopt the behavior at time t (*PB*)	Diary B
Probability distribution of duration for non-routine behaviors (*CF*)	Diary B

***Table 2**. Classification of occupant attributes*

Classification	Description
Working male	Male with a job aged from 20 to 65 with three sub-categories by working time: 1) full time worker with morning and afternoon working time, 2) long working time worker with longer working time than 1), 3) worker with afternoon and night working time.
Working female	Female with a job aged from 20 to 65 with five sub-categories: three categories as working male 1) to 3), 4) morning and 5) afternoon part time worker
Housewife	Female without a job aged from 20 to 65 with five sub-categories by age and parental care: 1) those without children younger than 45, 2) 45 and older, 3) those with children whose youngest is preschool, 4) primary to high school student, and 5) aged 18 and older
Student male	Primary, junior high, high school, university and collage male student
Student female	Female student with four sub-categories same as student male
Elderly male	Male older than 65 with two categories for those who live alone and with family
Elderly female	Female older than 65 with two sub-categories same as elderly male

There are two kinds of time-use diary developed under the survey, namely Diary A and B. Diary A has 20 classifications of time-use. The number of sample is very large. For example, the number of sample collected from working male and female on weekdays is 27.7 and 16.0 thousands. Problem of Diary A in application to the occupant behavior model is the classification of time-use is too rough, though all the routine behaviors are covered in Diary A. On the contrary, Survey B classifies time-use into 85 kinds that is sufficiently detail to model energy consuming behavior in home. For example, household maintenance activities are divided into 14 kinds. However, the number of sample is relatively small, as it is 1.5 thousands for working male and 1.3 thousands for working female on weekdays.

Based on the feature of Diary A and B, Diary A is used to develop the input data for the routine behaviors. Diary B is used to develop those for non-routine behaviors.

RESULTS

In this section, we evaluate the simulation result for the full-time working male whose working hour is morning and afternoon and housewives who have primary school children to validate the model. As mentioned earlier, the Markov Chain model unnecessarily replicates duration of each behavior and the Tanimoto's roulette selection model does not replicate behavior transitions. Based on this understanding, we evaluated the simulation result by using the following indicators:

- Duration time of routine and non-routine behaviors,
- Time at which the routine behaviors start and end, and
- Probability distribution on each time of day showing percentage of simulated days on which each behavior is undertaken.

Time at which the routine behaviors start and end

Figure 2 shows the cumulative frequency of sleeping beginning time and ending time of the other routine behaviors of the working male. The bold lines show those of simulation results and thin dash lines show those of original TUD. The figure shows that the simulation result agreed well with the original TUD. It should be noted that the beginning time of dinner and bathing have small discrepancy. This is due to the order of placement of the discrete behaviors. When discrete behaviors like working that is placed earlier than others had occupied time steps with certain probability of occurrence of other behaviors placed lately, like dinner and bathing, these routine behaviors cannot be placed on the time steps. This is why simulation result of dinner beginning time is slightly delayed than the original.

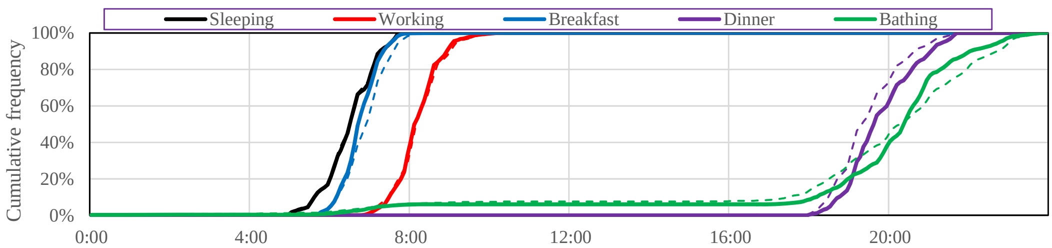

Figure 2. *Cumulative frequency of sleeping ending time and beginning time of the other routine behaviors*

Figure 3 shows mean durations of non-routine behaviors observed for working male and housewife. Although the behaviors are not specified, the result shows that the simulation result was underestimated for most of behaviors compared to the original TUD. This can be attributed to the same reason as the discrepancy observed in the beginning time of dinner and bathing. As designed in the algorithm, the routine behaviors are first placed and vacant steps between routine behaviors are filled by non-routine behaviors. Thus, cumulative frequency distribution that is used for determining duration of non-routine behaviors is not fully applied, as duration larger than vacant steps is ignored.

Figure 4 shows the probability distribution calculated for the working male and housewife. The result agreed well with the original TUD.

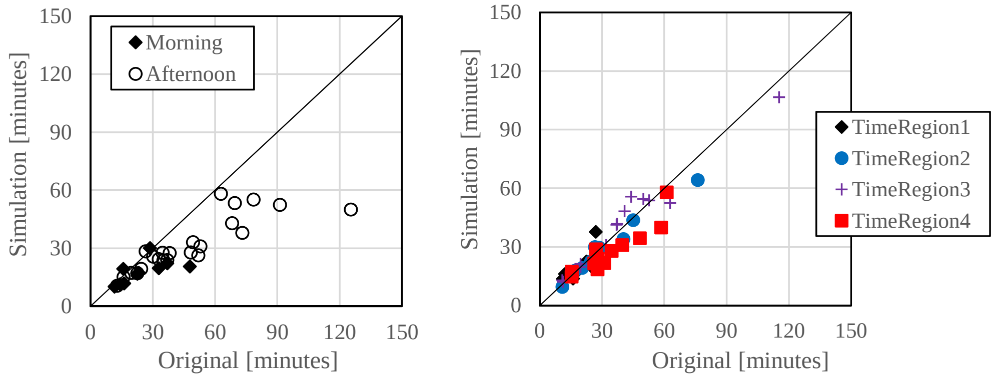

Figure 3. *Mean duration of non-routine behaviors*

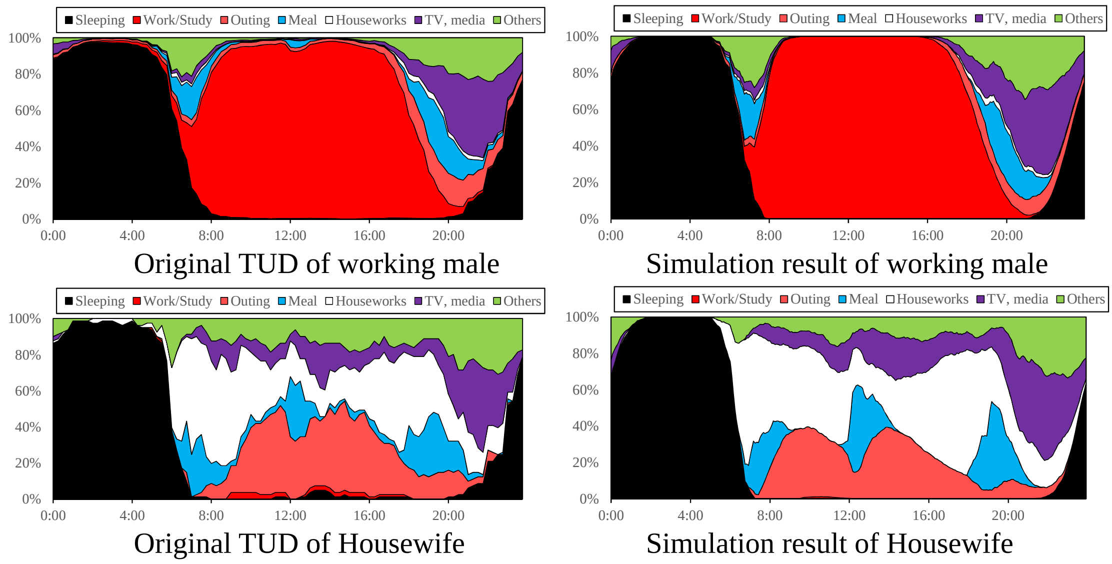

Figure 4. *Percentage of days on which each behavior is conducted at times of day*

CONCLUSION AND IMPLICATIONS

This paper proposes a new approach for modelling occupants' time allocation in home. In the modelling approach, routine and non-routine behaviors are distinguished. Routine behaviors are first placed on timeline and then gaps between routine behaviors are filled by non-routine behaviors. For the filling gap process, behavior after the end of previous behavior is selected while considering behavioral sequence and percentage of behaviors at time of day observed in sample time use data. The result of the case study showed that the modelling approach accurately generates routine behaviors but underestimates duration of non-routine behaviors. As our future work, we will compare the proposed approach with the existing approaches.

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