# Development of Household Members' Behavior Model in Urban Scale Using Dynamic Time Warping and Particle Swarm Optimization Algorithms Based on National Time Use Survey

Hengxuan Wang
Graduates School of Human-Environment Studies
Kyushu University
Fukuoka, Japan
e-mail: whx7174615@gmail.com

Daisuke Sumiyoshi
Faculty of Human-Environment Studies
Kyushu University
Fukuoka, Japan
e-mail: sumiyoshi@arch.kyushu-u.ac.jp

***Abstract*—For the target of energy demand estimation of residential buildings in urban scale, occupants' behavior model has been paid much attention. In this paper, a new model for simulating occupants' behavior schedules in urban scale has been proposed using only public stochastic data (national lifetime survey) combined with Dynamic Time Warping and Particle Swarm Optimization algorithms. We use this proposed model to generate the 5 type occupant behavior schedules with 5-minutes interval in working and resting day. The generated results - percentages of occupants adopt the given behavior at specific moments are calculated and compared with public stochastic data to verify the accuracy. Also, based on the mutual influence of household members, the generated schedules are filtered and combined into a group of behavior schedules, which is suitable for a household. By the proposed model in this paper, behavior schedule combinations of family members are generated and prepared for residential energy demand calculations in urban scale.**

***Keywords—occupants' behavior model; household members; public stochastic data; particle swarm optimization; dynamic time warping.***

## I. INTRODUCTION

This paper is an extended research considering family member based on the publication on Energy 2023 [1]. To get the target of decarbonized society in 2050 [2], the Japanese government is promoting the introduction of decentralized renewable energy devices in urban area to reduce carbon emissions. However, without a suitable introduction plan the surplus electricity generated at times by various devices would disturb the balance between the supply and demand of power system. There is also a prospect of failing to reach the decarbonization target because of insufficient devices. Thus, it is essential to develop a decentralized energy introduction plan based on the energy demands of buildings in urban areas The renewable energy is limited to natural condition (e.g., solar energy) and outpower changes dramatically over time. Therefore, the energy demand of buildings should be estimated with high temporal resolution. Non-residential buildings (e.g., office) have temporal characteristics of energy demand because of fixed schedule of users. However, the energy demand of residential building is decided by appliances' operation, which is influenced by the behavior of the occupants with significantly personal characteristics. In previous studies about energy demand estimation for residential buildings, the behavior schedules of occupants had been set to several cases. This assumption would significantly affect the accuracy of results. The reason is that even the same type occupants in urban scale would have numerous kind behaviors at the same time, but there are only a few cases in these few schedules that would overlay the peak or trough energy demand amount. Thereby, the demand results and the amount of renewable energy devices need to be introduced would be a departure from reality. Thus, a method to simulate the occupants' behavior schedules in urban scale is very essential for the plan of introduction of decentralized renewable energy in urban scale.

In this paper, a new occupants' behavior model generating behavior schedules of occupants in one household with only public stochastic data has been proposed. Compared with existing models in previous research, this model has the following characteristics of innovation:

- No need to analysis of raw Time Use Data (*TUD*)
- Without classification of behaviors.
- Without prior assumptions about the number of occurrences of behavior.
- Consider the mutual influence of household members and generate behavior schedule combinations of household members.

Section II introduces the related work of this study. Section III introduces the detailed procedures of the proposed model. Section IV corrects the simulation processes based on the simulation results. In Section V, the final generated results of each type occupant in working and resting day are shown. In Section VI, a model has been proposed to combine generated behavior schedules considering the interactions among household members. In Section VII, the conclusions about features and weaknesses of proposed model are introduced. Based on that, the directions of improving model in future are also introduced.

## II. RELATED RESEARCH

There is much previous research about the occupants' behavior model in urban scale [3]. The models could be divided into two types based on whether to use *TUD*, which describes occupants' behavior by time.

For the first type without *TUD*, Tanimoto et al. [4] developed a model using only public stochastic data of *TUD* include mean and standard deviation of behaviors' duration time in a day and percentages of occupants adopt the behavior at special moments by 15-minutes interval of a day. They firstly selected the behaviors according to probabilities and arranged their total duration time into 24 hours. Next, they placed the first behavior into the slot in timeline according to random number and placed the next behavior into the end of previous behavior one by one. As one merit, this method could generate the occupants' behavior schedules with only public stochastic data. But the accuracy of the simulation results was greatly influenced by the randomly decided slot for the first behavior, which was inserted. Additionally, the results had not been validated.

For the type of models using *TUD*, Richardson et al. [5] developed a model using the Markov Chain, which is a stochastic model to determine the transition of behavior from another only depend on the condition at the previous time step. They collected the *TUD* from a great number of households and analysis the transition probability between behaviors. But the behavior items were limited in at room or not.

Widén et al. [6] proposed a Markov Chain model and expanded analysis of the number of behavior items. They simulated the household's members independently. These Markov Chain models considered and simulated the transitions probability between the behaviors precisely, but the accuracy of behavior duration time was dependent on the timing and number of behavior transitions. This could be a weakness for simulating the occupants' behavior schedules. Yamaguchi et al. [7] developed a occupants' behavior model dealing with above problems. They divided behaviors into routine and non-routine and considered them separately. The behaviors' duration time and transition probabilities between them were acquired by analyzing the *TUD* from the national time-use survey conducted by Statistics Japan in 2006 and been utilized for placing the behaviors into the timeline. They firstly placed the routine behaviors (including sleeping, commuting to work & school, dining and bathing) into timeline, then selected the non-routine behaviors according to the probabilities and placed them in the gap between the routine behaviors until all gaps had been filled. They improved the model in [8] considering the interaction among household members (e.g., household members always have dining together at one time and bathing one by one) and time-dependent characteristics of the specific behaviors (e.g., for a single person, bathing often happens immediately after waking up or breakfast, but it's not shown in *TUD* because it was originated from a wide range of people.). In [9], they explored several machine learning methods to pre-process the *TUD* to improve the accuracy of behavior model. Although the duration time and transition probabilities of behaviors were detailed considered in their model, predetermining the number of behavior occurrences with a subjective assumption was made. For example, three meals over a day, one sleeping at night with long period were considered in their model. But according to the public stochastic data, there are also sleeping at the daytime for many type people), this might be a weakness of their model for ignoring these specific cases. On the other hand, raw *TUD* are required to make this kind of model while only public stochastic data are available in many countries.

As mentioned above, until now there are many developed occupants' behavior models in urban scale with own strengths and weaknesses. But there is still no precise occupants' behavior model that considering the interaction among household members, without prior analysis of large amount of raw *TUD*, pre-classification of behaviors according to routinely or not and predetermined number of occurrences with subjective assumption.

## III. PROPOSED BEHAVIOR MODEL

In Section III, we will discuss the processes model.

### *A. Parameters of purposed occupants' behavior model*

The proposed model simulates the occupants' behavior schedules with 5-min interval based on the public stochastic data called National Lifetime Survey in 2020 from Japan Broadcast Institution (*NHK*) [10]. It should be noted that target of simulating behavior schedules is to estimate energy demand of residential building, so the behaviors that have no relationship with energy demand in residential building (e.g., working outside, commuting to work, school) have not been simulated in this paper. This assumption, which is one of the differences between the previous studies, can greatly simplify the model. Table I shows the classification result of behaviors on public stochastic data. These behaviors have been simplified into 24 types and divided into interior and exterior. According to whether using appliances, the interior behaviors are further divided into two categories.

TABLE I. CLASSIFICATION OF BEHAVIORS

| **Interior Behavior** (lighting & HVAC used) | | **Exterior Behavior** |
|---|---|---|
| ***Appliance used*** | ***Non-appliance used*** | |
| eating | children care | shopping |
| bath | leisure | conversation personal relationships |
| sleeping | newspaper | work |
| hobbies, entertainment and culture (with Internet) | magazines comics | leisure and exercise |
| hobbies, entertainment and culture (without Internet) | | class and lecture |
| cooking, cleaning, laundry | | commuting |
| radio | | sporting |
| household chores | | |

To make the model, the public stochastic data would be utilized include:

- ***PM***: probabilities of adopting given behavior by 15-minutes interval (the data has been processed into 5-minutes interval by liner interpolation).
- ***PA***: probabilities of adopting given behavior over a day.
- ***MTB***: average duration time of adopting given behavior.
- ***SDTB***: standard deviation of duration time of given behavior.

Some samples of public stochastic data are shown in Table II.

During the process of simulation, a blank timeline with 288 time slots (time of a day with 5-minutes interval) is generated firstly and prepares for filling up with behaviors separately. The given behavior's occurrences will span corresponding time slots in the timeline depend on its duration time length. The detail steps are explained as:

*1)* Iterates over all given behaviors in order of the ***PA***'s values and determines whether to adopt based on its ***PA***.

*2)* Once the given behavior has been adopted, the duration time (***DT***) is determined according to the Gaussian Distribution defined by ***MTB*** and ***SDTB***.

*3)* To insert these given behaviors into the timeline, it is critical to decide several parameters' solution of the given behavior including:

*a)* ***n***: number of behavior occurrences. (***n*** =1~4 randomly)

*b)* *sm*: start moment of each behavior occurrence.

***SMN***: $\left[sm_1, sm_2, \cdots sm_n\right]$

*c)* *pn****:*** probability of each number of behavior occurrences.

(e.g., $pn_2$ : probability of behavior occurring twice)

***PNN***: $\left[pn_1, pn_2, \cdots pn_n\right]$

*d)* *pt*: each occurrence's duration time as percentage of ***DT*** in a large number of schedules.

***PTN:*** $\left[pt_1, pt_2, \cdots, pt_n\right]$

(e.g., Fig. 1 shows the difference between ***PTN₁***: $[\frac{1}{3}, \frac{1}{3}, \frac{1}{3}]$ and ***PTN₂***: $[\frac{1}{6}, \frac{1}{3}, \frac{1}{2}]$)

### *B. Start moments of behavior occurances*

It is necessary to decide ***SMN*** 's solution to determine the positions of timeline where the behavior occurrences are going to be inserted.

Fig. 2 shows the process of deciding the start moment of each behavior occurrence by the cumulative distribution of ***PM***. In detail, one day is divided into ***n*** time regions which have the same sum of ***PM***. The start moment of splitting time region is generated randomly (e.g., 6:30). It is assumed that object behavior occurs once in each time region. Based on that assumption, the cumulative distribution function of ***PM*** in each time region has been calculated to determine the start moment of each occurrence.

TABLE II. SAMPLE OF PUBILC STOCHASTIC DATA OF WORK-MALE IN SUNDAY AND TARGET BEHAVIOR - SLEEPING

| **Behavior** | ***PA*** | ***MTB*** | ***SDTB*** | ***Time*** | ***PM*** |
|---|---|---|---|---|---|
| sleeping | 99.20% | 8:25 | 2:07 | 0:00 | 70.20% |
| eating | 97.60% | 1:38 | 0:52 | 0:05 | 71.27% |
| bath | 96.00% | 1:04 | 0:34 | 0:10 | 72.33% |

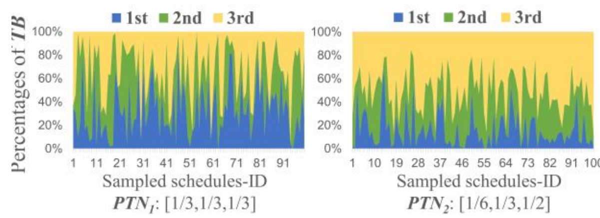


Figure. 1 Percentages of each occurrence's duration time in sampled schedule

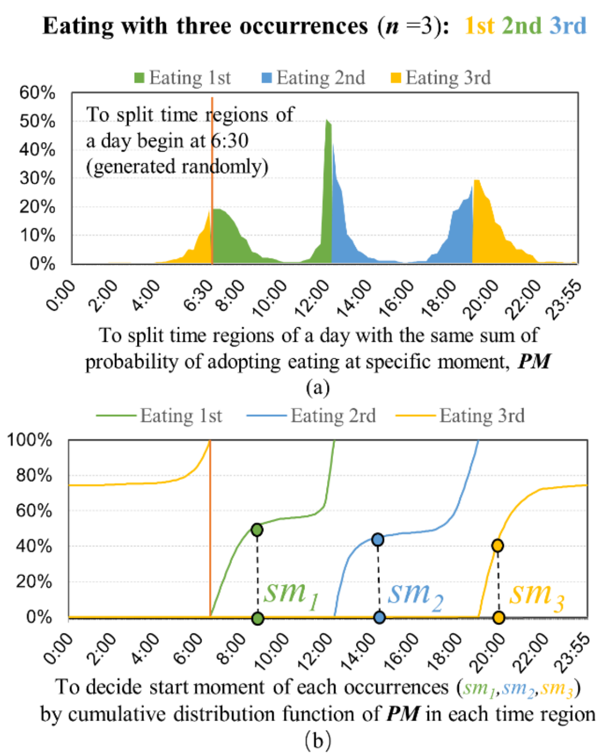


Figure 2. Processes of determining start moment of each occurrence of eating

### C. Process of proposed model

Fig. 3 shows the proposed model's all processes for generating the behavior schedules. The process of searching the optimal solution is as follows.

### D. Dynamic Time Warping

Different from ***SMN***, it is impossible to get ***PNN***&***PTN*** solution based on the existing public stochastic data merely. Therefore, it is necessary to introduce parameter optimization method to obtain the optimal ***PNN***&***PTN*** solution.

To verify the fitness of ***PNN***&***PTN*** candidate solution, we introduce the objective function to compare ***PM*** and probability of adopting given behavior at 5-min interval, which is calculated by schedules generated using ***PNN***&***PTN*** candidate solution (***PM'***). For ***PM*** and ***PM'*** are both time series data, Dynamic Time Warping (*DTW*) introduced in [10] is used as objective function to measure their similarity. *DTW* of ***PM*** and ***PM'*** is calculated by (1):

$$DTW(\boldsymbol{PM}, \boldsymbol{PM'}) = \min \sqrt{\sum (x_i - y_j)^2} \quad (i,j) \in L \tag{1}$$

$$\boldsymbol{PM} = [x_1, x_2, \cdots, x_{287}],\ \boldsymbol{PM'} = [y_1, y_2, \cdots, y_{287}]$$

The list of index pairs $L = [l_0, l_1, \cdots, l_{287}]$ shows the matching pairs of the elements of ***PM*** and ***PM'*** (e.g., $l_k = (i_k, j_k)$ shows the $x_{i_k}$ and $y_{j_k}$ would be matched) that satisfies the following properties are shown in (2) (3) (4):

$$0 \le i_k, j_k \le 287 \tag{2}$$

$$l_0 = (0,0),\ l_{287} = (287, 287) \tag{3}$$

$$l = (i_k - 1, j_k)\ or\ (i_k, j_k - 1)\ or\ (i_k - 1, j_k - 1) \tag{4}$$

Different from the traditional matching method which would match PM and PM' at the same index pairs ($(x_1, y_1)$, $(x_2, y_2)$ ,…, $(x_{287}, y_{287})$ ). In DTW, based on the above properties, there is a large number (T) of possible matching solutions as candidates, which is shown in (5):

$$T[l_0, l_1, \cdots, l_{287}] = \begin{bmatrix} (x_0, y_0) & (x_1, y_0) & (x_1, y_1) & \cdots & (x_{287}, y_{287}) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ (x_0, y_0) & (x_0, y_1) & (x_0, y_2) & \cdots & (x_{287}, y_{287}) \end{bmatrix} \tag{5}$$

all matching solutions' distances between ***PM*** and ***PM'*** would be compared and the smallest one would be called *DTW*. By calculating the *DTW* obtained from different ***PNN***&***PTN*** candidate solutions, the most suitable solution would be decided with the minimal *DTW*.

### E. Patricle Swarm Optimization

As mentioned above, the best ***PNN***&***PTN*** solution can be found by finding the minimal *DTW*. In this paper, we use

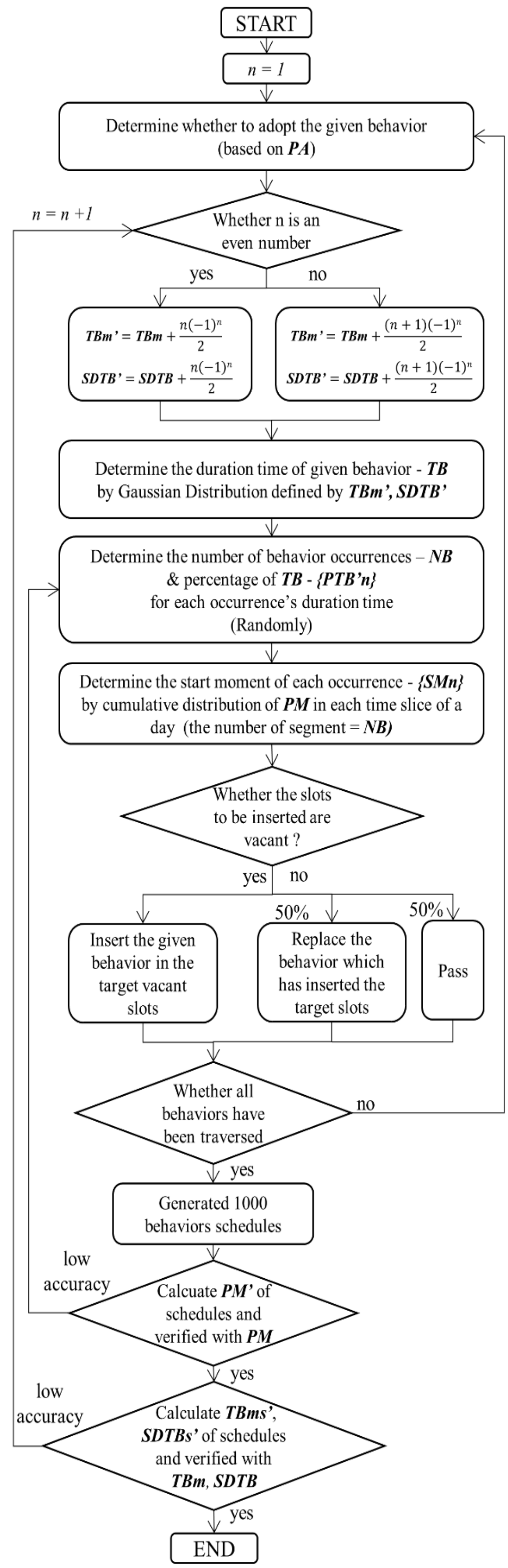


Figure 3. Simulation processes of proposed model

Particle Swarm Optimization (*PSO*) algorithm to find the minimal *DTW*. *PSO* is an evolutionary algorithm introduced in [12] that could optimize a problem by iteratively trying to improve a candidate parameters' solution to get the better position in a D-dimensional space (D is the number of parameters).

In the process of the *PSO* algorithm, firstly, a large number of particles have been generated and each particle is a candidate solution of ***PNN&PTN*** with different *DTW* result. At 1st iteration, particle' initial position ($p_1$) and velocity ($v_1$) are randomly generated. $p_1$ means ***PNN&PTN*** solution and $v_1$ means the distance between $p_1$ and $p_2$ (position at 2nd iteration) as showed in (6). These particles make up a cloud that covers the entire space, then the *DTW* of all particles are calculated to decide their fitness. Based on fitness values, the globally best particle position ($pg_1$) and locally best particle position ($pl_1$) are determined. As showed in (7), according to $pg_1$, $pl_1$ and $p_1$, $v_1$ would be updated to $v_2$, which would continue to update $p_2$ to $p_3$.

$$p_{k+1} = p_k + v_k \qquad (6)$$

$$v_{k+1} = wv_k + \varphi_1(pg_k - p_k) + \varphi_2(pl_k + p_k) \qquad (7)$$

| | | | |
|---|---|---|---|
| $k$ : | $k^{th}$ iteration | $pl_k$ : | locally best particle's position at $k^{th}$ iteration |
| $w$: | inertia weight | $\varphi_1, \varphi_2$ : | $\varphi_1 = c_1 r_1$ , $\varphi_2 = c_2 r_2$ |
| $v_k$ : | particle's velocity at $k^{th}$ iteration | $r_1, r_2$ : | random numbers in the range [0,1] |
| $p_k$ : | particle's position at $k^{th}$ iteration | $c_1, c_2$ : | $c_1 = c_2 = 2$ |
| $pg_k$ : | globally best particle's position at $k^{th}$ iteration | | |

With the iteration advancing, the cloud contracts gradually and performs the exploration for best ***PNN&PTN*** solution with minimal *DTW*.

## IV. CORRECTION OF SIMULATION PROCESS

According to the schedule results, there are two significant errors include:

1) Fig. 4 shows the results of sleeping are inaccurate thoroughly.
2) Fig. 5 shows the delaying of start moments of ***PM'*** compared with ***PM***.

The above errors would be dealt with as follows:

### A. Correction of sleep simulation process

The error 1) can be attributed to the inaccurate determination of start moments of sleeping. Different from other behaviors, people always have a long period sleeping in the evening and add a short period sleeping during the daytime. For this type of behavior with a clear temporal characteristic, the method deciding behavior start moments based on sum of ***PM*** is not suitable any longer. To solve this problem, we revise the model to simulate sleeping behavior in the following process:

*a)* The number of sleeping occurrence (***n***) is set to 1~2. If sleeping occurs once, it occurs at night; if sleep occurs twice, the first and longer sleeping occurs in the evening and second one occurs at daytime.

*b)* For sleeping in the evening, people wake up at a more concentrated time than when they fall asleep. Therefore, we use the moments of waking up (ending of sleeping) to decide the position of sleeping in timeline where being inserted into.

*c)* The range of end moments of first sleeping in the evening is set as 0:00-12:00, the range of start

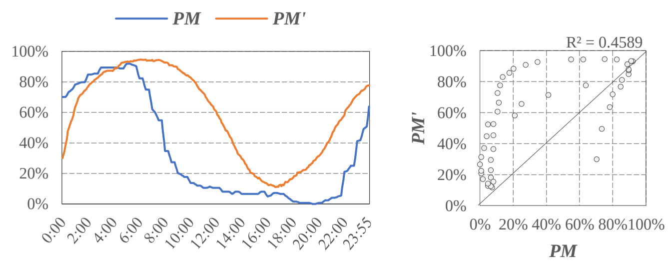


Figure 4. Comparation of simulated stochastic data -***PM'*** and public stochastic data -***PM*** (sleeping)

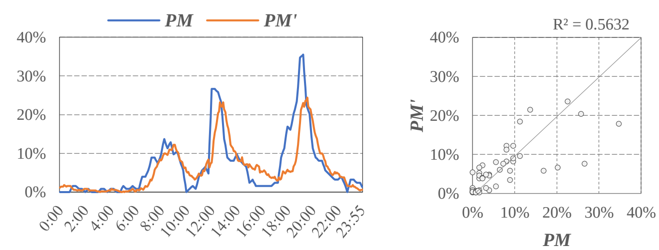


Figure 5. Comparation of simulated stochastic data-***PM'*** and public stochastic data -***PM*** (eating)

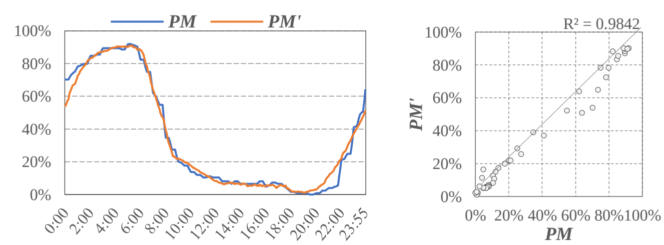


Figure 6. Comparation of simulated stochastic data -***PM'*** after corrected and public stochastic data -***PM*** (sleeping)

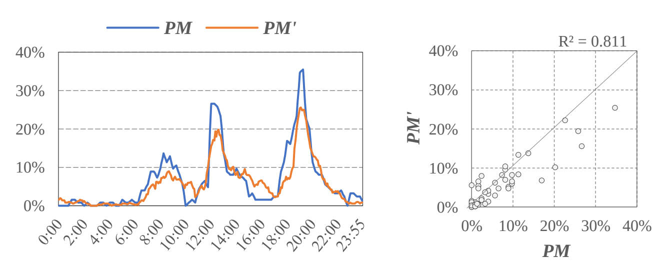


Figure 7. Comparation of simulated stochastic data -***PM'*** after corrected and public stochastic data -***PM*** (eating)

moments of second sleep is set as 12:00-18:00. The specific moments in the range are searched by *PSO* method too.

To sum up, the parameters of sleeping for *PSO* method are reset showed as (8):

$$\boldsymbol{SMN} = [sm_1, sm_2] \ \boldsymbol{PNN} = [pn_1, pn_2] \ \boldsymbol{PTN} = [pt_1, pt_2] \quad (8)$$

After the calculation by *PSO*, Fig. 6 shows the results of sleeping's ***PM*** and ***PM'*** by this revised process, which is better than original one.

*B. Correction of start moment*

For the error 2), the reason being considered is that the decision of start moment based on cumulative distribution function of ***PM*** always drop behind actual situation. To solve this issue, the new parameter *ad* is introduced to adjust the $\boldsymbol{SMN}: [sm_1 + ad, sm_2 + ad, \cdots, sm_n + ad]$. The decision of *ad* is also calculated by *PSO* method. Therefore, the solution of ***PNN&PTN,*** *ad* would be decided together by minimal *DTW*. Fig. 7 shows the simulation results of ***PM*** and ***PM'*** after the adjustment of behavior start moments and it demonstrates higher accuracy than before.

## V. Simulation Results

In Figs. 8-12, comparation of simulated stochastic data - ***PM'*** and public stochastic data-***PM*** of 5 type occupants include working-male, housewife, child, teenager and elder are shown, each color block shows the probability that a behavior is undertaken at corresponding period of day. The result shows that ***PM'*** agreed well with ***PM*** and it confirms our model's accuracy.

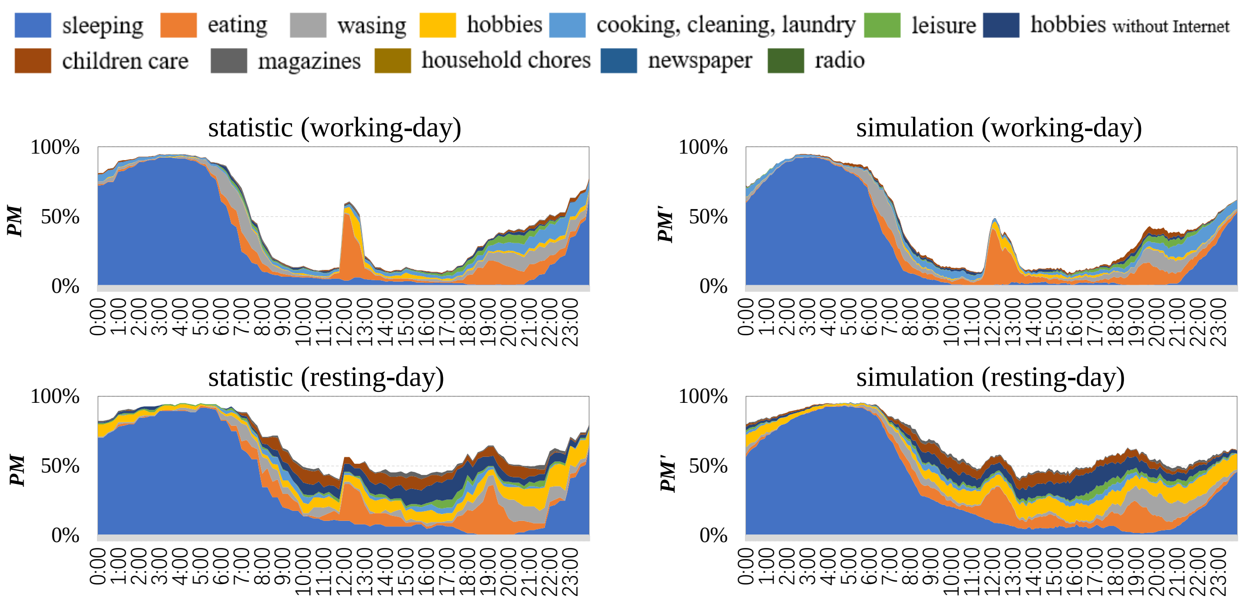


Figure 8. Comparation of simulated stochastic data - PM' and public stochastic data-PM (working-male)

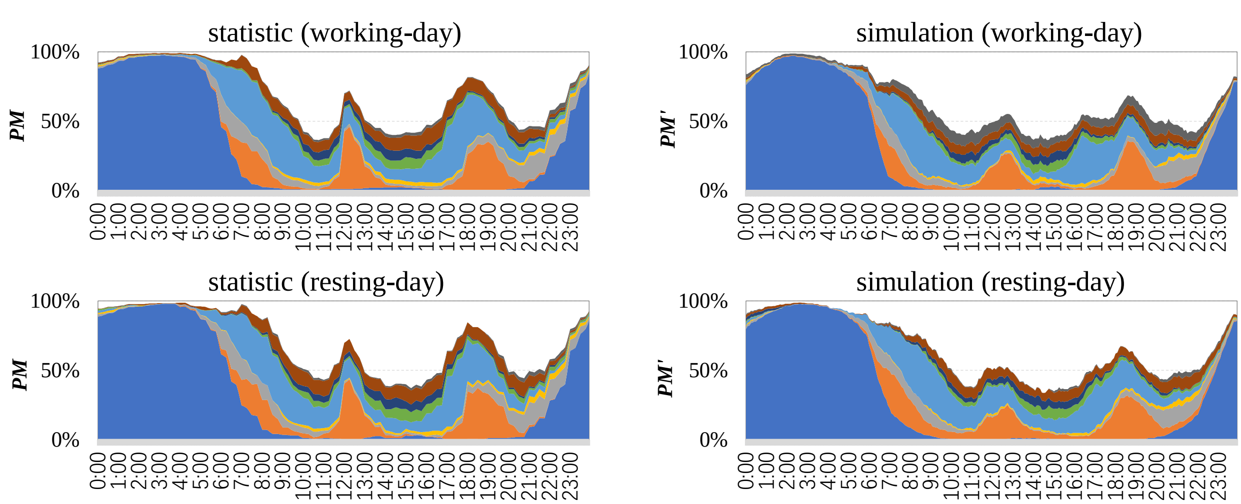


Figure 9. Comparation of simulated stochastic data - ***PM'*** and public stochastic data-***PM*** (housewife)

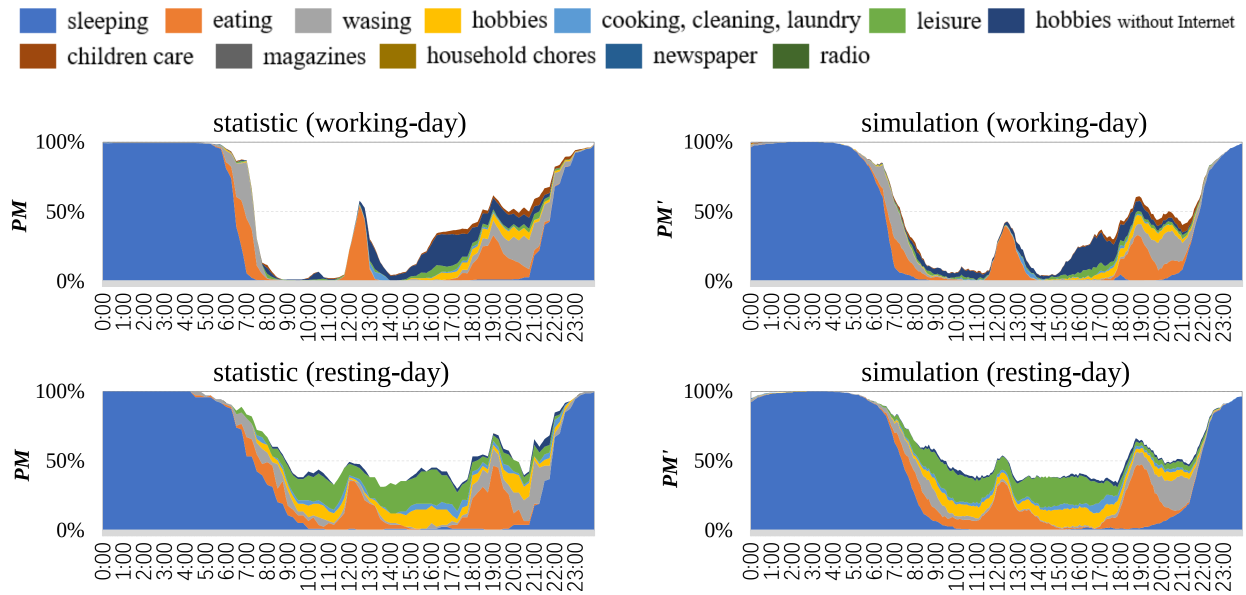


Figure 10. Comparation of simulated stochastic data - ***PM'*** and public stochastic data-***PM*** (child)

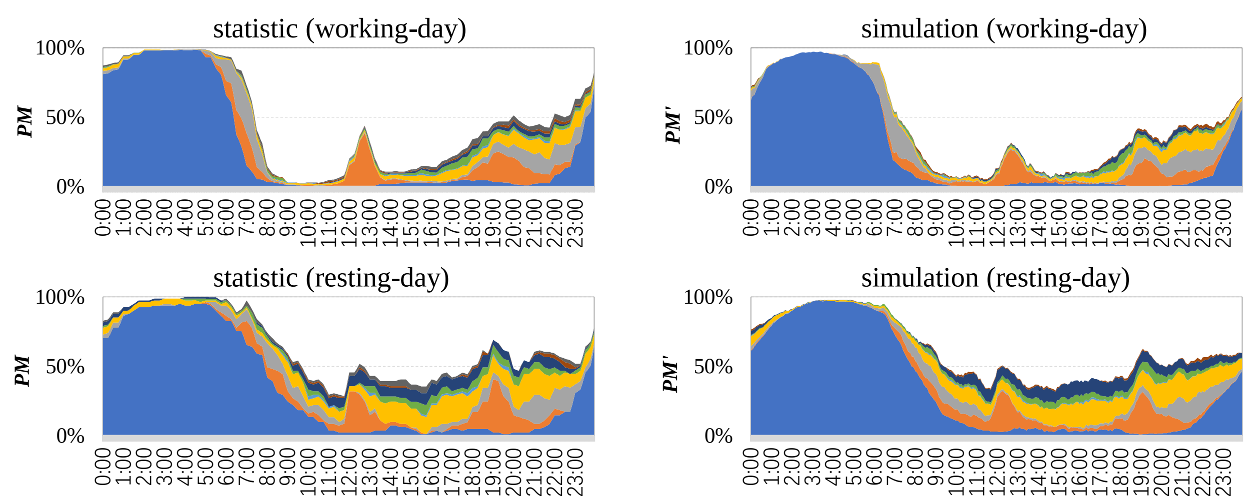


Figure 11. Comparation of simulated stochastic data - ***PM'*** and public stochastic data-***PM*** (teenager)

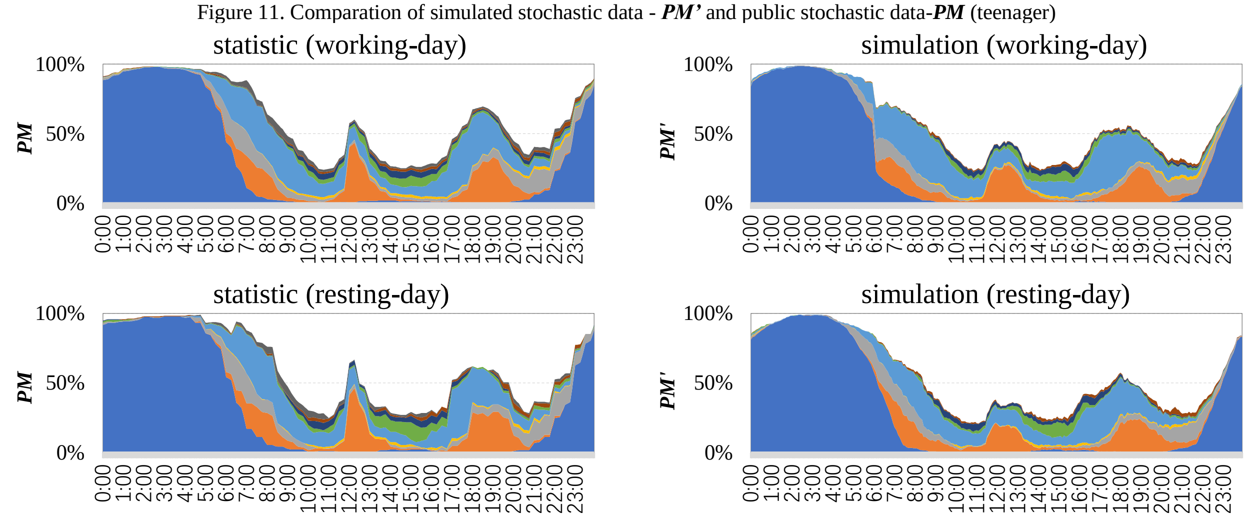


Figure 12. Comparation of simulated stochastic data - ***PM'*** and public stochastic data-***PM*** (elder)

## VI. SIMULATION RESULTS OF HOUSEHOLD

Considering the energy demand simulation of residential building, the behavior schedules of household members are necessary. Although the model could simulate each type occupant behavior schedules properly, there is no connections among these results, which could not be used directly because behaviors of household members are always related. Therefore, a model for filtering and matching generated results is proposed.

According to [8], the Japanese household members tend to eat together and take a bath one by one. Based on this assumption, among the above generated results of each type occupants with a large number, the schedules of eating at the same time and bathing at different time would be filtered and matched into behavior schedules of a household. It should be pointed out that the start moment, duration time of eating, bathing by each household member is not the same or different exactly.

The detail process of the proposed model is explained as follow:

The target is to select suitable behavior schedules from above 1000 simulation results of each occupants to form the behavior schedule combination of a household. Therefore, *PSO* algorithm is used again to search the suitable solutions. The candidate solution of behavior schedules-ID of each member is set as $[x_1, x_2, ..., x_n]$ ( $1 \le x_1, x_2, ..., x_n \le 1000$ , n=household member number) and the objective function is set as (8)

$$y = T_{bath} - T_{eating} \tag{8}$$

$T_{bath}$ : Duration time that more than two members are bathing at the same time by candidate solution.

$T_{eating}$ : Duration time that more than two members are eating at the same time by candidate solution.

According to (8), among each member, less overlap of bathing behaviors and more overlap of eating behaviors at the same time means the better fitness of candidate solution. It should be pointed out that this process is not to search the best solution but to find a group of appropriate solutions with certain number.

As two examples, the behavior schedules of three members (working-male, housewife and one child) and five members (two elders, working-male, housewife and one child) of two households in working day and resting day are Figs. 13-16 show 5 behavior schedule combinations of

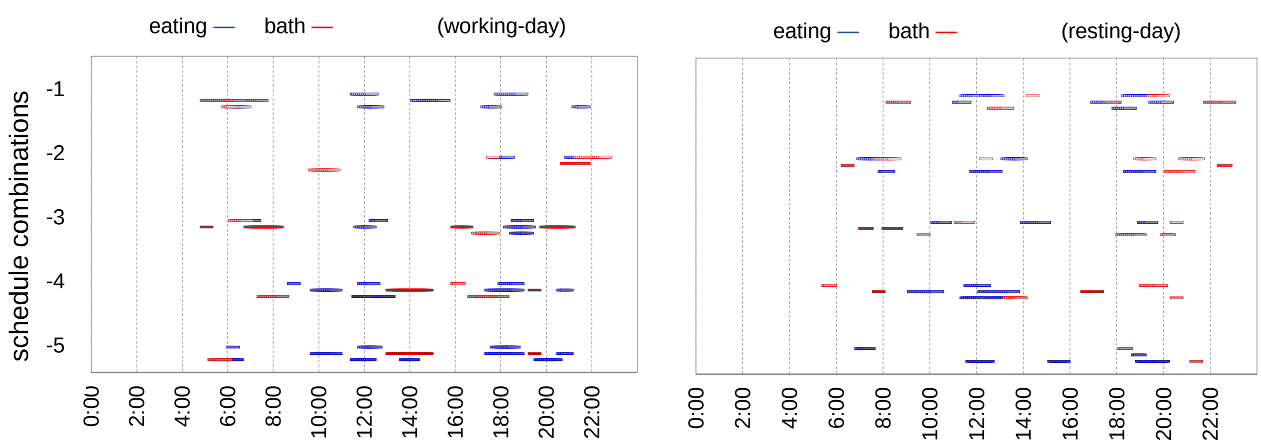


Figure 13. Behavior (eating and bath) schedule combination of a household (working-male, housewife, one child) (selected randomly)

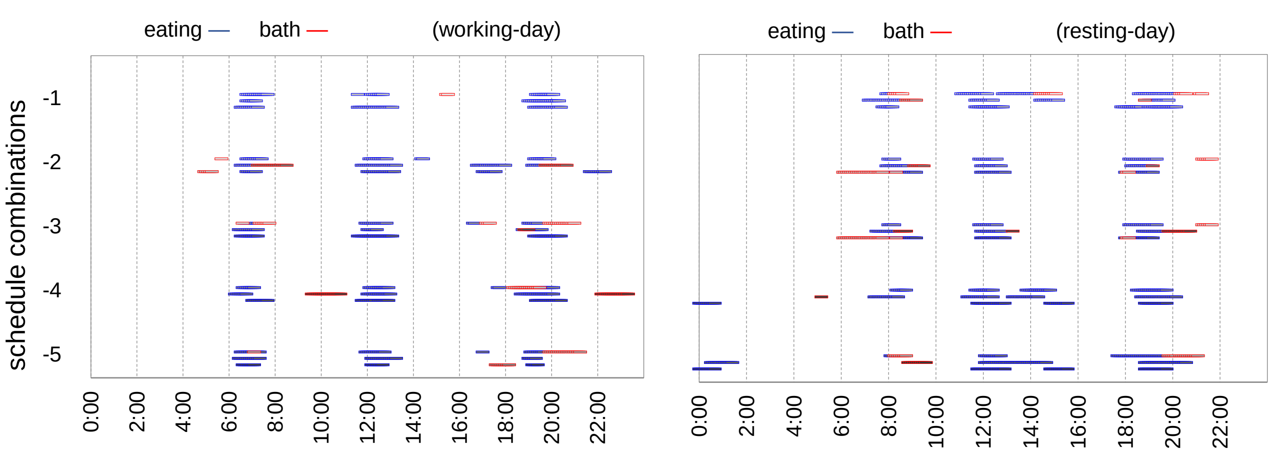


Figure 14. Behavior (eating and bath) schedule combination of a household (working-male, housewife, one child) (selected by *PSO* algorithm)

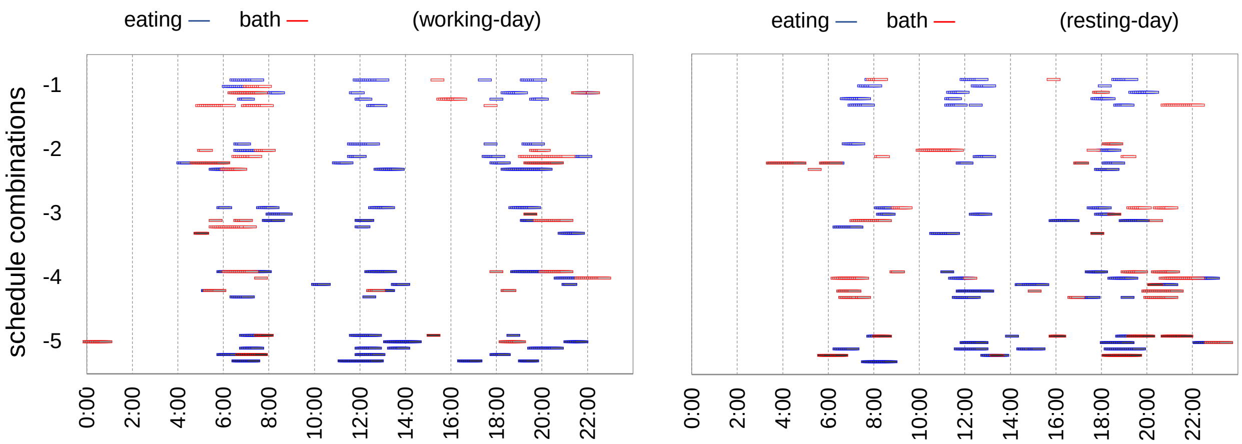


Figure 15. Behavior (eating and bath) schedule combination of a household (two elders, working-male, housewife, one child) (selected randomly)

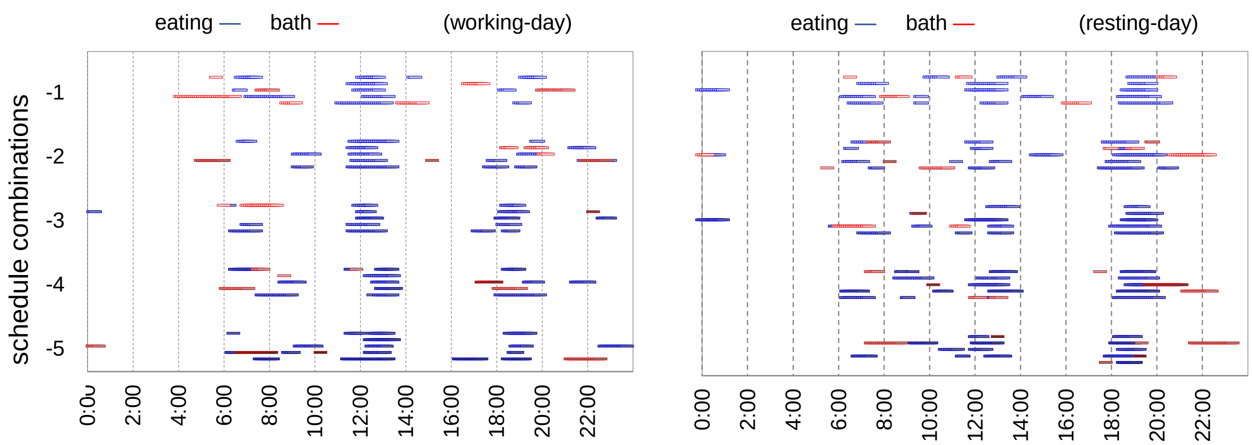


Figure 16. Behavior (eating and bath) schedule combination of a household (two elders, working-male, housewife, one child) (selected by *PSO* algorithm)

selected randomly and with assistant of *PSO* algorithm. each situation. To compare the results precisely, average $R_{eating}$ and $R_{bath}$ (ratios of time by more than two members performing the same behavior to the sum time of this behavior) of 5 schedule combinations are calculated and shown in Table III. It could be concluded that compared with random selection, by *PSO* algorithm, eating behaviors of each member are gathered at the same periods with larger $R_{eating}$, while the bathing behaviors are scattered at different periods with smaller $R_{bath}$. This is consistent with the basic characteristics of household members' lives and proved our model's merit in generating household member behavior schedules.

TABLE III. $R_{EATING}$ AND $R_{BATH}$ OF EACH RASULTS BY RANDOM OR *PSO* IN WORKING DAY AND RESTING DAY

| Household | Day-type | Method | $R_{eating}$ | $R_{bath}$ |
|---|---|---|---|---|
| household-3 people | working-day | random | 0.13 | 0.06 |
| | | *PSO* | 0.24 | 0.005 |
| | resting-day | random | 0.17 | 0.07 |
| | | *PSO* | 0.31 | 0.02 |
| household-5 people | working-day | random | 0.17 | 0.11 |
| | | *PSO* | 0.22 | 0.002 |
| | resting-day | random | 0.19 | 0.06 |
| | | *PSO* | 0.22 | 0.001 |

## VII. CONCLUSION AND FUTURE WORK

This paper proposes a model based on public stochastic data to generate occupants' behavior schedules and form behavior schedules of household members. This model could be used in energy demand estimation of residential buildings in urban scale. Compared with existing behavior model's research, the proposed model has the following features:

- Generating occupants' behavior schedules based on
- public stochastic data only. Without statistical analysis of large amounts of raw *Time Use Data* (*TUD*), which is not available in many countries, making the behavior model simpler and more efficient.
- No classifying the behaviors or setting the specific number and duration time of behavior occurrences. This feature could exclude the errors from subjective assumptions.
- Utilizing the *Dynamic Time Warping* (*DTW*) and *Particle Swarm Optimization* (*PSO*) algorithms to search the suitable number of behavior occurrences and percentages of occurrences' duration time. It would make the simulation results match the public stochastic data as closely as possible.

- Deciding the start moments of behavior based on cumulative distribution of public stochastic data. As the simulation results do not agree with the public stochastic data, the start moments calculated by the above method have been corrected using *PSO* algorithm.
- Considering the behaviors connection among the household members. By *PSO* algorithm, the suitable combination of generated behavior schedules from each occupant would be searched as the household members' behavior schedules.

For single occupant, 5 type occupant's behavior schedules in two type days have been generated with the proposed model. The result shows that our model has a good accuracy. But there are also several drawbacks:

*a)* In public stochastic data, during some periods (12:00~12:30 and 22:00~22:30, probabilities of adopting eating, sleeping by 5-minutes interval increase rapidly, but the simulation results fail to reflect such phenomenon.

*b)* No consideration of interaction between behaviors (e.g., people are likely to wash themselves when they wake up, but behavior transition between sleeping and bath can't be simulated in a single schedule).

For household, an example household with three members has been searched with suitable behavior schedule combination. The result shows that the behavior schedules of each member tend to eat together and wash at different period and this is the purpose of the model. However, some limitations are still need to be solved:

*c)* Only behaviors include eating and bath are considered in our model, other behaviors like watching TV are still need to be considered. As the number of considered behaviors increases, the difficulty of matching the suitable behavior schedules is also increasing.

*d)* As shown in results, household members tend to have lunch together in working day, which is inconsistent with reality. The reason is that the records of public data about behavior eating do not distinguish between being at home and going out. Therefore, this problem needs to be considered in the energy simulation of residential buildings.

There are also some details need to be explained. Firstly, by *PSO* algorithm merely, the start moment of each behavior occurrence (***SMN***) could be determined without using cumulative distribution of probabilities of adopting given behavior by 15-minutes interval (***PM***). But with the assistance of cumulative distribution, the *PSO* algorithm could narrow the search range and get solution quickly. Secondly, more than just simulation for behavior schedules based on past public stochastic data, it might be useful for assuming the future people behavior change by altering the inputting public stochastic data (e.g., the working time at home increased because of covid-19). Finally, compared with similar studies with *TUD* in other country such as UK [5] and US [13], the simulation results show the uniqueness of Japanese occupant behaviors.

In future, we are going to deal with mentioned drawbacks to improve the model. About drawback *a)*, more in depth analysis of public stochastic data especially in specific period will be done so that different weights will be given during these time intervals in simulation process. For *b)*, which had been raised in much previous research, analysis the raw *TUD* to get the results of behavior transition probabilities is a feasible option. About last *c)*, more behaviors and more efficient algorithms will be considered. For last *d)*, the classification of indoor behaviors needs to be more detailed based on the types of occupant and target days. Also, it should be noted that the behavior schedules could not be used directly in the energy demand estimation model without appliance operation possibilities based on behaviors. More work about the relationship between behavior and appliance operation is also necessary in future.

## References

[1] H.Wang and D.Sumiyoshi, "Development of Occupants' Behavior Model in Urban Scale Using Dynamic Time Warping and Particle Swarm Optimization Algorithms Based on National Lifetime Survey," ENERGY 2023, The Thirteenth International Conference on Smart Grids, Green Communications and IT Energy-aware Technologies, pp. 17-22, Mar. 2023.

[2] Ministry of the Environment, Japan, Outlines of Japan's Long-term Strategy under the Paris Agreement, 2019.

[3] G. Happle, J. A. Fonseca, and A. Schlueter, "A review on occupant behavior in urban building energy models," Energy & Buildings, vol. 174, pp. 276-292, Sept. 2018, doi: 10.1016/j.enbuild.2018.06.030.

[4] J. Tanimoto, A. Hagishima, and H. Sagara, "Validation of methodology for utility demand prediction considering actual variations in inhabitant behavior schedules," Journal of Building Performance Simulation, vol. 1, no. 1, pp. 31-42, Mar. 2008, doi:10.1080/19401490701868471.

[5] I. Richardson, M. Thomson, and D. Infield, "A high-resolution domestic building occupancy model for energy demand simulations," Energy and Building, vol. 40, no. 8, pp. 1560-1566, Feb. 2018, doi:10.1016/j.enbuild.2008.02.006.

[6] J. Widén, M. Lundh, I. Vassileva, E. Dahlquist, K. Ellegård, and E.Wäckelgård, "Constructing Load Profiles for Household Electricity and Hot Water from Time-Use Data – Modelling Approach and Validation," Energy and Building, vol. 41, no. 7, pp. 753-768, Mar. 2009, doi:10.1016/j.enbuild.2009.02.013.

[7] Y. Yamaguchi and Y. Shimoda, "Evaluation of behavior model of occupants in home based on Japanese national time use survey," Proceedings of Building Simulation 2015: 14th Conference of IBPSA, Dec. 2015, pp. 2897-2904, doi: 10.26868/25222708.2015.2520.

[8] Y. Yamaguchi and Y. Shimoda, "A stochastic model to predict occupants' activities at home for community-/urban-scale energy demand modelling," Journal of Building Performance Simulation, vol. 10, no. 5-6, pp. 565-581, Jun. 2017, doi: 10.1080/19401493.2017.1336255.

[9] Y. Li, Y. Yamaguchi, and Y. Shimoda, "Impact of the pre-simulation process of occupant behavior modelling for residential energy demand simulations," Journal of Building Performance Simulation, vol. 15, no. 3, pp. 287-306, Mar. 2021, doi:10.1080/19401493.2021.2022759.

[10] Japan Broadcast Institution (*NHK*), National Lifetime Survey in 2020, Japan.
[11] H. Sakoe and S. Chiba, "Dynamic programming algorithm optimization for spoken word recognition," IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 26, no. 1, pp. 43-49, Feb. 1978, doi:10.1109/TASSP.1978.1163055.
[12] J. Kennedy and R. Eberhart, "Particle swarm optimization," Proceedings of ICNN'95 – International Conference on Neural Networks, Nov. 1995, pp. 1942-1948, doi: 10.1109/ICNN.1995.488968.
[13] L. Diao, Y. Sun, Z. Chen, and J. Chen, "Modeling energy consumption in residential buildings: A bottom-up analysis based on occupant behavior pattern clustering and stochastic simulation," Energy and Building, vol. 147, pp. 47-66, July 2017, doi:org/10.1016/j.enbuild.2017.04.072