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ANALYSIS OF FACTORS CREATING VARIETY IN RESIDENTIAL ENERGY DEMAND BASED ON MEASURED ELECTRICITY CONSUMPTION

Yuya Itagaki, Yohei Yamaguchi, Yoshiyuki Shimoda

Division of Sustainable Energy and Environmental Engineering,
Graduate School of Engineering, Osaka University
2-1, Yamadaoka, Suita, Osaka, 565-0871, Japan

ABSTRACT

This paper analyzed electricity consumption measured from 226 households in order to understand factors creating the variety in electricity consumption among households. We found that approximately 5 % of households have one or more extreme conditions in their behavior, appliance ownership and usage that accompany a considerably high energy consumption. Second, there is an interrelationship between these factors directly determining energy consumption. Based on the result, we discuss sampling methodology of input data for residential energy demand simulation so that simulated households have a sufficient variety in estimated energy demand among households for community/urban scale modelling of residential energy demand.

INTRODUCTION

Energy demand of residential buildings has been recognized as one of the most important components in a variety of energy related social issues, for example, global warming mitigation and peak electricity demand reduction for electric utility companies. The residential sector has also been recognized to be capable of providing flexibility in electricity demand to improve the overall performance of electric systems in the development of modern smart grids.

In this context, it is important to model energy demand accurately in terms of time-varying characteristic and variety among households. Time variation in energy demand is mainly driven by people's behavior in residential buildings, including time allocation for behaviors (like sleeping and watching TV) and operation of home appliance and equipment that accompany when behaviors are conducted. To model the time-varying characteristic, stochastic modelling approach are often adopted to model people's behavior. In addition to people's behavior, climate conditions, family structure, ownership and specification of home appliances significantly alter energy demand and carbon dioxide emission of a household. By assuming these conditions appropriately, realistic energy demand can be generated. However, our observation revealed that the variety among households cannot be replicated by simply collecting data on these conditions and giving conditions randomly to households based on developed databases. We applied an energy demand model for residential buildings to a multi-family building consisting of 226 households for which measured electricity consumption was available. Figure 1 shows the distribution of annual electricity demand among the simulated households. In this application, we only knew the specification of buildings, while all the other factors mentioned above were given from databases randomly. The detail is given in Appendix A.

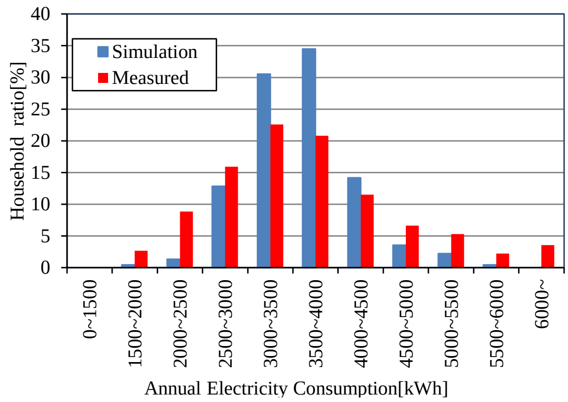

Figure 1. Distribution of annual electricity demand of households (N=226)

As shown in Figure 1 the variety among households was significantly underestimated. The mean value of the annual electricity consumption was 3639 kWh in the measured data, 3584 kWh in the simulated data. The estimated standard deviation was 578 kWh, while it was 1426 kWh in the measured data. The underestimation might be due to the following three causes involved in the data preparation for input data of the model:

1. A number of common parameters were used in the input data for all the simulated households;
2. The input data ignores households with extreme conditions that creates households with extremely high and low energy demand;
3. Interrelationship among input data is ignored;

The first cause cannot be avoided if there is no available data on the distribution in input data. Thus, we especially focused on the last two causes in this paper. Regarding the second cause, we ignored households with extreme conditions as we assumed that occupants behave rationally in their daily practice. For example, we assumed that occupants switch off their air-conditioner when they leave room, while there are a small percentage of households in which occupants do not operate air-conditioner in such way. Regarding the third cause, we ignored interrelationship among input parameters, as we randomly sampled data independently among input parameters. However, there might be interrelationships that increase or decrease energy consumption of households.

Based on this background, we analyzed the abovementioned electricity consumption data measured from 226 households to confirm the hypotheses. If these hypotheses are true, the existence of extreme households and the interrelationship among input parameters must be taken into account in the sampling process of input parameters prepared for simulations, so that the simulation model can generate energy consumption with a sufficient variety among households.

The analysis in this paper can be divided into two parts. First, we analyze households with an extremely high electricity consumption. Second, we analyze the remaining non-extreme households to evaluate the interrelationship among determinants of electricity consumption. Finally, this paper discuss the methodology of sampling to generate input data that can generate a sufficient variety among households in simulation result.

ANALYSIS METHODOLOGY

Measured data

In the analysis, we used electricity consumption measured at each circuit of distribution boards installed in the 226 houses in a multi-family building located in Osaka, Japan. The time resolution of the measurement is 1 minute. The electric distribution board has a dedicated circuit for air-conditioner, refrigerator, cloth washer, microwave and dish washer. The other circuits are to deliver electricity to lighting and plug load in a room or a group of rooms. Table 1 lists the circuits that were measured. In the table, L, D, K, and PR indicate living room, dining room, kitchen, and private room respectively. For the households, no information was available on family composition, ownership and specification of appliances.

Table 1. Measured circuit

AC (LDK)	Lighting & plug (Washroom)
AC (PR 1)	Lighting & plug Toilet & hall)
AC (PR 2)	Lighting & plug (PR 1 & PR 2)
AC (PR 3)	Lighting & plug (PR 3 & PR 4)
AC (PR 4)	Lighting (LD)
Lighting & Plug (Kitchen)	Plug (LD)
Microwave	Laundry
Dish Washing Machine	Warm Water Bidet
Refrigerator	

Indicators used for the analysis

In order to analyze the characteristics of energy consumption, we developed the indicators listed in Table 2. These indicators were designed to capture the magnitude of consumption and the operation characteristic of room and appliances to understand the cause generating the variety among households in electricity consumption. Based on the analyzed data, all the indicators were calculated for each household.

To quantify the indicators, the operation status of living room, dining room, kitchen (LDK) and private rooms (PR) were judged based on the measured electricity consumption. The operation status has two status, namely active and inactive. To judge the operation status, a threshold value was defined that contains stand-by power of all appliances connected to the circuit and consumptions by appliances that is always operated like refrigerator. If electricity consumption of a circuit is larger than the threshold value, the circuited is judged to be active. For living room, dining room, and kitchen (LDK), while the circuits connected to lighting and plug of LDK was active, LDK was judged to be active. The same judgement was made for two private rooms (PRs), PR1 and PR2.

The first two indicators are the average active hours per day of LDK and PR. The third indicator shows how often household members share LDK. Its value increases when two or more occupants share LDK instead of using private rooms separately. The third and fourth indicators are those related to the use of air-conditioner (AC). The remaining indicators are the electric intensity of lighting and plug of living and dining rooms (LD) and PRs. It is defined as the mean of electricity consumption while the rooms are being active. The intensities represent the magnitude of electricity consumption by appliances used in the room.

Analysis of households with extreme electricity consumption

In order to analyze households with extreme electricity consumption, households whose annual electricity consumption is larger than 6,000 kWh were selected (see Figure 1).

There are 10 households satisfying the condition. The indicators listed in Table 2 were quantified to understand why these households have an extremely high electricity consumption.

Analysis on interrelationship among determinants of energy consumption

By using the indicators listed in Table 2, the authors conducted the Ward's method in cluster analysis to classify the non-extreme households (N=216). By analyzing the result, the existence of the interrelationship among the indicators can be evaluated. It is further discussed how the result can be interpreted as the variety in direct determinants of energy consumption.

Table 2. Factors great impact on electricity demand

Indicator	**Definition**
Active hour of LDK [hours/day]	Mean active hour per day of living room, dining room and kitchen (LDK)
Active hour of PR [hours/day]	The sum of the mean active hour per day of private rooms (PR1 and PR2)
Use ratio of LDK [%]	Ratio of the active hour of LDK over the sum of the active hour of LDK and private room
AC operation during non-use [hours/day]	Operation hours of air-conditioners during August while all occupants were inactive during the period from 7 am to 9 pm
Operation ratio of AC [%]	Ratio of the total operation hours of air-conditioner over the sum of the active hour of LDK and PRs
Electricity intensity of lighting (LD) [W]	Average electricity consumption of lighting in LD while LD was operated
Electricity intensity of plug (LD) [W]	Average electricity consumption of plug load in LD while LD was operated
Electricity intensity of PR [W]	Average electricity consumption of lighting and plug load in private rooms while private rooms were operated

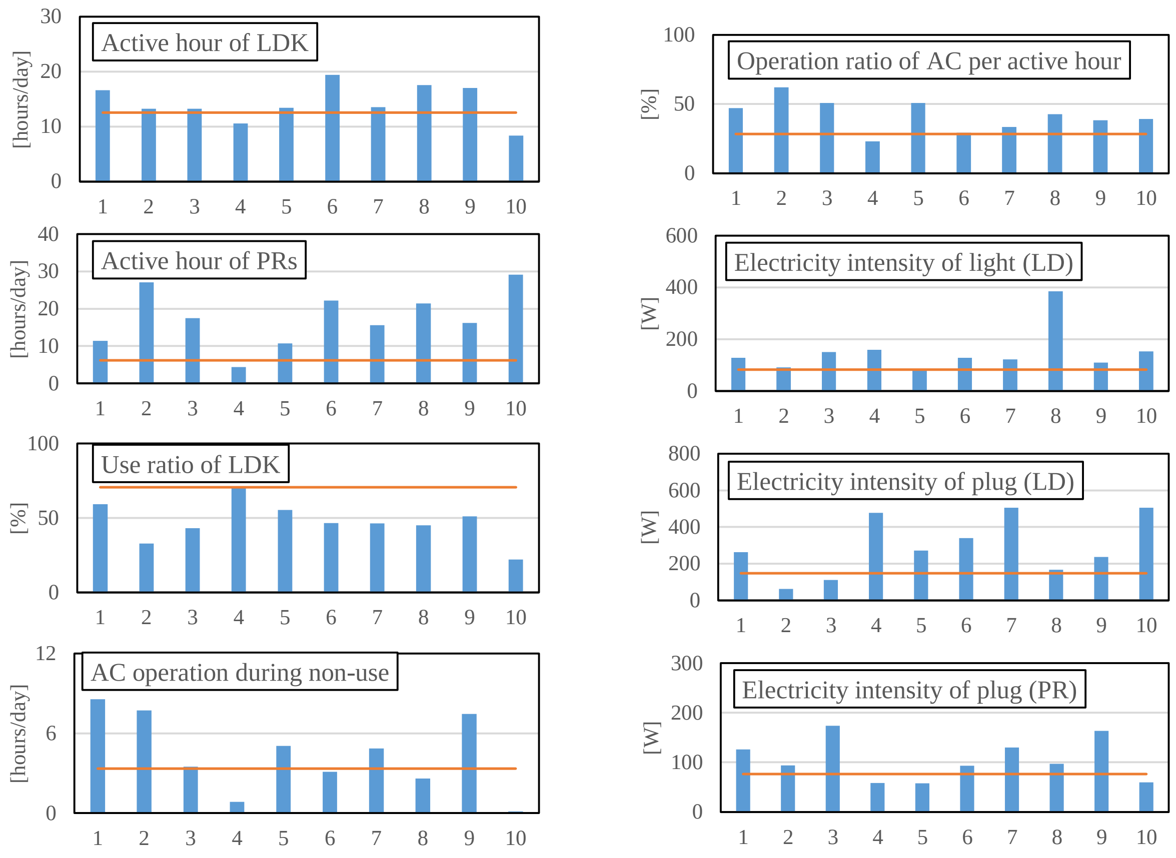

Figure 2. Indicators of the extreme households

ANALYSIS ON HOUSEHOLDS WITH EXTREME ELECTRICITY CONSUMPTION

Figure 2 shows the indicators calculated for each extreme household. The lines on the bar graphs indicates the mean of the non-extreme households. Figure 3 shows annual electricity consumption of households with an extreme electricity consumption. The figure also shows the mean of the non-extreme households, labelled “others”. The figure shows that all of the compositions have a larger value than the mean of the non-extreme households. In addition to it, the extreme households have one or more composition that is considerably larger than those of the non-extreme households. As electricity consumption of a room is determined by the electricity intensity and the operation hour, the active hour of PR and electricity intensity of lighting and plug of LD have a significant impact on the electricity of LD, which is shown in Figure 3. However, compare between Figure 2 and Figure 3 implies that the intensity has a larger impact than the operation hour on the electricity consumption of LD. For private rooms, in addition to the electricity intensity of PR, the active hour of PR is significantly larger than the mean of the non-extreme households except the household ID 4. This result implies that occupants use private rooms more frequently than the non-extreme households. Correspondingly, the use ratio of LDK is smaller than the mean. The two indicators related to air-conditioners also larger than the mean except the household ID 4 that has a commensurate electricity consumption for AC with the mean.

In sum, the result indicates that the households with an extremely large electricity consumption have certain behavior, appliance ownership and usage that accompany a considerably large energy consumption.

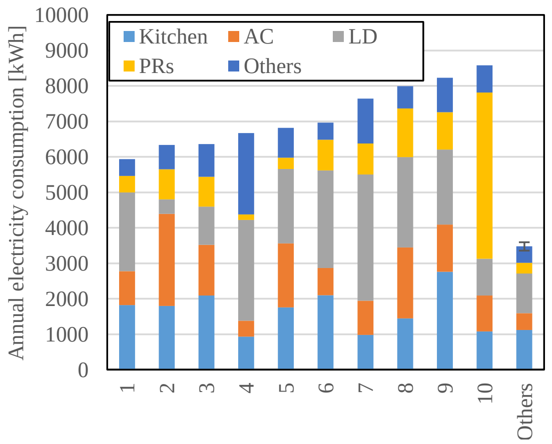

Figure 3. Annual electricity consumption of the extreme households

ANALYSIS ON INTERRELATIONSHIP AMONG DETERMINANTS OF ENERGY CONSUMPTION

As a result of the cluster analysis, the non-extreme households were divided into five groups. Table 3 shows the number of households involved in each group. Figure 4 shows Annual electricity consumption of each group. The electricity consumption of the groups showed differences among the groups as the error bars indicates the 95 % confident intervals of the means. This result implies that the indicators well represent determinants of electricity demand. Figure 5shows the mean value of the indicators within the groups. CL3 and CL4 have a larger electricity consumption in LD as shown in Figure 4. This can be attributed to the larger electricity intensity in lighting and plug than the other groups as active hour of LDK is comparable for all the groups. CL2 and CL5 have a larger electricity consumption in private rooms. This can be attributed to both of the longer active hour of PR and higher electricity intensity of PR. More importantly, the active hour of PR correlates to the electricity intensity of plug in private rooms for CL1, CL2 and CL3. This result implies that there is an interrelationship between occupants' behavior using private rooms and ownership and/or operation of appliances in private rooms. It is natural that occupants who spend longer hours in PRs own or use more appliances in private rooms.

Table 3. Number of households of each cluster

CL1	112
CL2	39
CL3	51
CL4	7
CL5	6

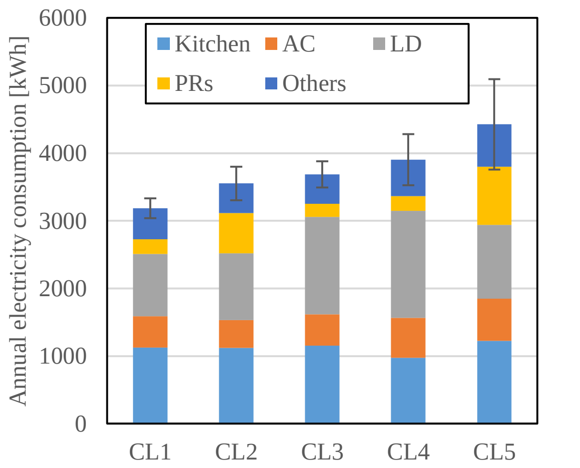

Figure 4. Annual electricity consumption and 95 % confident intervals shown by error bars

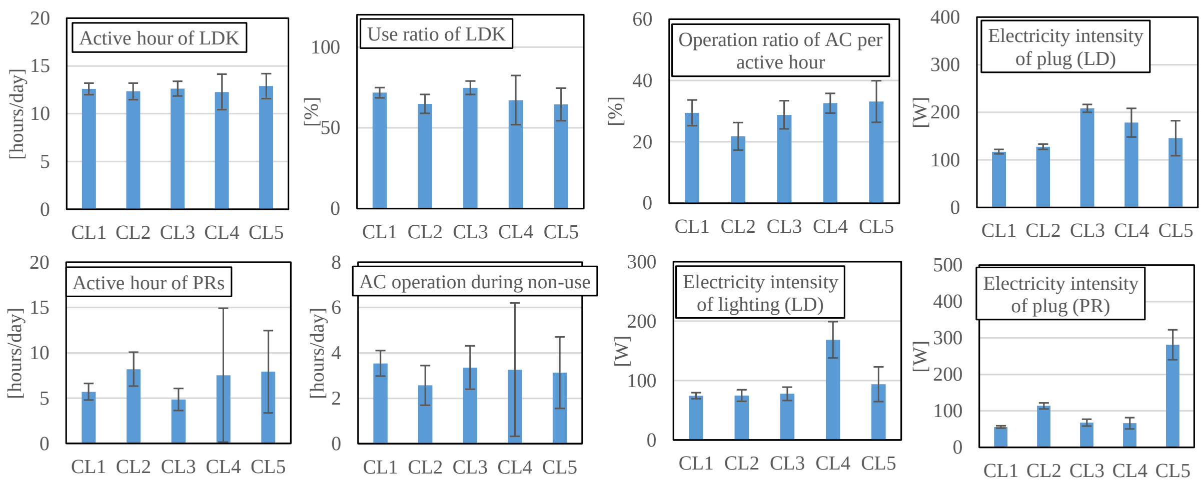

Figure 5. Indicators of the groups and 95 % confident intervals

DISCUSSION

Consideration of extreme households

As shown in Figure 3, the mean electricity consumption of the households with an extremely large electricity consumption is larger by 4000 kWh/year than the mean of the non-extreme households. The difference increased the standard deviation of annual electricity consumption by approximately 200 kWh. Thus, it is important to take into account such extreme households in the sampling process in energy demand modelling. The analysis described above showed that the households with an extremely high electricity consumption have one or more causes that make electricity consumption considerably high, such as high electricity intensity of lighting and plug load in living room, dining room and private rooms. Thus, these extreme households might have practices in daily behavior and appliance usage and in practice of appliance purchase that accompany a considerably high electricity consumption compared to the non-extreme households.

Interrelation among determinants of energy consumption

The analysis using the non-extreme households showed that the electricity intensity in living room, dining room and private rooms is the most important factor explaining the difference in electricity consumption among the non-extreme households. The difference in electricity consumption of living room (LD) can be explained by the intensity of plug and lighting, as the active hour of the rooms was comparable. In addition to this, there is an interrelationship between the active hour of private rooms and the electricity intensity of private rooms. This implies that occupants who use private rooms for longer hours have a higher electricity intensity in private rooms. The longer operation hour might be due to family composition with a number of children. If children own and use home appliances for entertainment, access to media like TV and PC, they might spend more time in their private room and electricity intensity of plug becomes higher. It is often dependent on parents' policy on childcare in Japan.

Sampling method taking into account the analysis results

First, in the modelling of residential energy consumption, households with an extremely high electricity consumption must be distinguished. Based on the analysis, such extreme households occupy approximately 5 %. For these extreme households, extreme conditions should be given on their behavior, appliance ownership and/or usage.

For remaining non-extreme households, more understanding is needed on how the analyzed indicators were determined in households since the analyzed indicators, the active hour of room and the electricity intensity of room, are alternative indicators of direct determinants of residential energy consumption.

Figure 6 shows the structure we assumed for the analysis presented in the previous sections. On the left, there are a list of the direct determinants of energy consumption. On the right, electricity consumption is placed. In between, two of the analyzed indicators are placed. Based on the structure determining energy consumption, we assumed that the direct determinants determining the active hour of a room is the first three, family composition, time-use and room-use of occupants. Similarly, electricity intensity of a room is determined by the remaining elements, use, ownership and specification of appliances.

The result of the previous section showed that the variation in electricity consumption of living and dining rooms is generated by the difference in the electricity intensity. As specification of appliances are mainly determined by appliance manufacturers, the influence can be due to those of appliance ownership and use. It can be also implied that a number of households corresponding to the ratio of CL3 and CL4 can be randomly generated to give them appliance ownership and lighting intensity, since any interrelation was not observed with the other factors. Based on this understanding, we will conduct a survey on the ownership and usage of appliances and lighting in living and dining rooms as our future work.

CL2 has the smallest operation ratio of AC per active hour among the groups. However, this difference is not statistically significant. Thus, the analysis in the previous section could not detect a difference in the usage of air-conditioners among the groups. However, there are some researches that have shown some attitudes in the usage of air-conditioners. This implies that we can assume that the preference on the usage of air-conditioners distributes randomly among the groups. Thus, the preference of the usage of air-conditioners can be independently given to simulated households in the preparation of input data. To develop database on the use of air-conditioners, we will analyze the relationship between the usage of air-conditioner and outdoor air-conditions in our future work.

For private rooms, the relationship between the analyzed indicators and the direct determinants is more complicated as there is a large freedom in the direct determinants creating the indicators. Regarding the active hour of private rooms, family composition and time use of occupants can be given in the preparation of input data by using databases developed based on population census and time use survey. Thus, we will conduct a survey on how people choose rooms in their daily practice in our future work. In the survey, we will also investigate ownership and usage of appliances in private rooms. This is because we observed the interrelationship between the active hour and the electricity intensity in private rooms. The sampling method should reflect the interrelationship.

Figure 7 shows the scale factor of electricity intensity of the rooms for the groups calculated as the ratio between the observed mean intensity of the groups and the global mean of the analyzed households. This difference should be generated in sampling methodology to give input data for households.

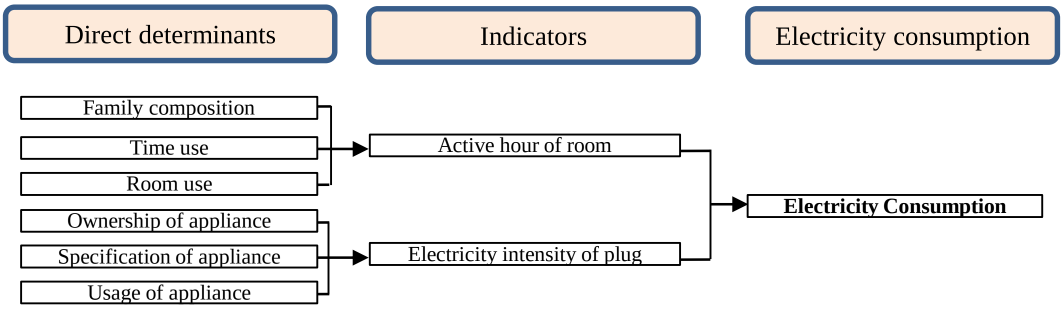

Figure 6. Relation with direct determinants and indicators

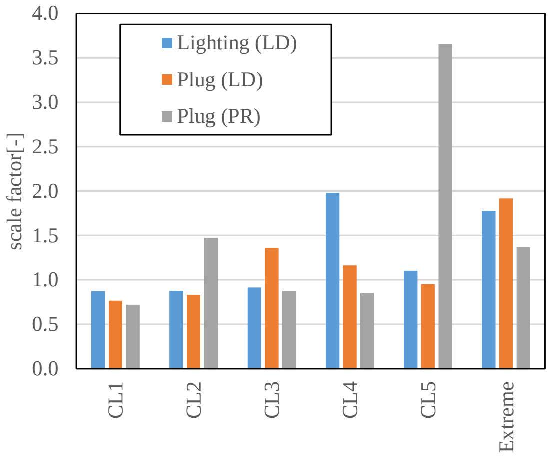

Figure 7. Scale factor of electricity intensity

CONCLUSION

In the introduction, we pointed out that energy demand model whose input data is randomly sampled underestimates the variety among households in estimated energy demand. Our hypotheses on the cause were, first, the ignorance of households with conditions that make energy demand considerably high or low and, second, the ignorance of interrelationship among input data. This paper confirmed these hypotheses by analyzing measured electricity consumption from 226 households. There exist 5 % in households with an extremely high electricity consumption due to one or more extreme conditions in their behavior, appliance ownership and usage that accompany a considerably high energy consumption. For non-extreme households, the electricity intensity of lighting and appliance in living and dining rooms and private rooms is important factor creating differences in annual electricity consumption. In addition to it, there is an interrelationship between usage of private rooms and ownership and usage of appliances. We finally discussed sampling methodology to reflect the findings.

APPENDIX A: RESIDENTIAL ENERGY DEMAND MODEL

Preparation of input data

Figure 8 shows the procedure of the simulation model. The first step of simulation is to define specification of house and family members of simulated households. The model contains databases on house specification and family composition. The family composition is defined by a combination of family members with attributes distinguished by age, gender and occupation. There are 6 and 9 house specifications for detached and apartment houses classified by the size of house. For each house specification, a house archetype is prepared. The archetypes have specific conditions in size, shape, floor plan, and other physical conditions of house like insulation performance, which is necessary to conduct a thermal simulation to estimate energy consumption for space heating and cooling.

Second, the ownership and specification of home appliances are given to simulated house. For this process, we use probability distributions on these data. The frequency distributions were developed based on a questionnaire survey that collected information from approximately 800 households. By giving a random number to a frequency distribution, a condition for each appliance is randomly determined. For example, by giving a random number, a number of TV used in a house is selected. Then, the size of TV is selected by giving a random number to the corresponding frequency distribution. Finally, specification of electricity consumption of selected TV is determined using a frequency distribution on electricity consumption of TV stock with a variety of TV size.

After selecting appliances used in a house, a room is selected in which each appliance is placed. If two TV is owned in a simulated household, one TV is placed in the living room and the other TV is placed in a private room of a children.

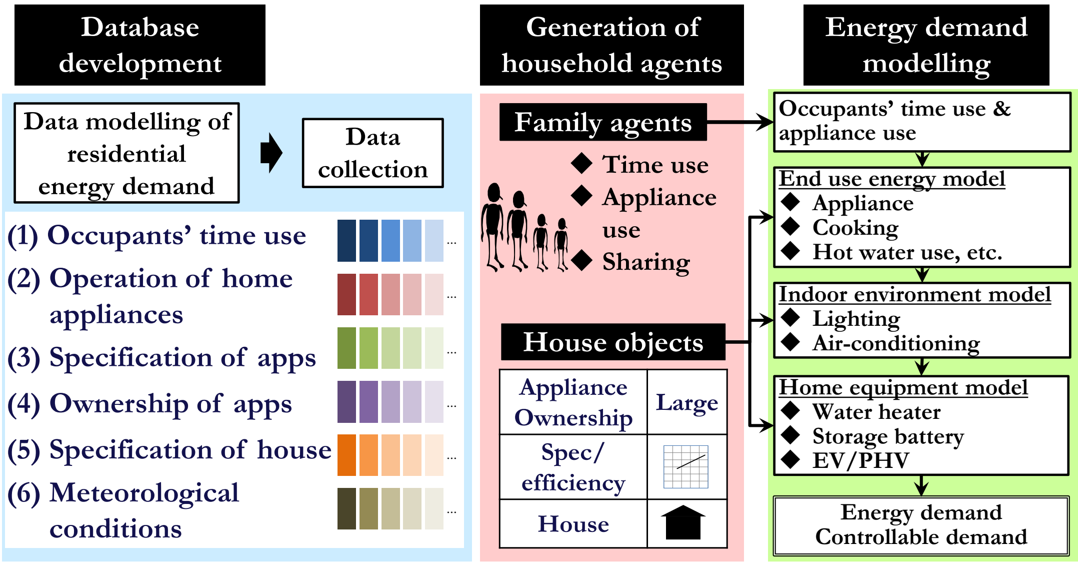

Figure 8. Procedure of energy demand simulation

Estimation of energy demand

In the previous step, attributes of household members were defined. According to the attributes, time use data, the input data to generate time use of household members, is prepared. Time use data contains statistical information on time use for 85 kinds of behaviors on weekdays and holidays. By using time use data, time use on the simulated days is stochastically generated. A detail explanation is given elsewhere (Yamaguchi et al. 2015). Then generated time use is converted into presence and action of occupants in home. This time use data is then converted to the operation of home appliances (Yamaguchi et al. 2014). For this conversion, a probability showing how frequently considered appliances and equipment is operated when a behavior is undertaken is given as an input data. By using this probability, the operation of appliances is randomly determined. Finally, energy consumption of each appliance is determined by considering specification of the appliances.

Based on the simulation result of time use, the room in which occupants spend time is determined based on an input file defining the relationship between behavior and room. This room use information is used to determine the operation of space lighting, heating and cooling. For rooms in which occupants spend time, the necessity of operation is judged based on the result of indoor condition. For lighting, illuminance at a reference point in rooms is simulated and compared with a reference value. If the natural illuminance is higher than the reference value, the lighting is judged to be off. For space heating and cooling, similar judgment is conducted. Thermal load and natural room air temperature is first calculated by a thermal circuit model utilizing house archetype data as well as internal heat gain and meteorological data. Internal heat gain is calculated by using energy consumption of home appliances and lighting. If natural room air temperature exceeds pre-defined comfort range in room air temperature, it is assumed that air-conditioner or heating devices are operated. To calculate energy consumption of air-conditioner, a regression model of coefficient of performance (COP) is used that takes into account the influence of part load ratio and indoor and outdoor conditions.

Estimation of residential energy demand

We have already shown the distribution in the annual electricity demand in Figure 1. Figure 9 shows the mean electricity demand of a representative weekday, May 14. On these days, most households do not use air-conditioner. The red line shows simulation result while the black line shows measured demand that is the sum of electricity consumptions measured at all of the electric circuits. As shown in the figure, the mean value agreed well with the measured consumption. However, the variety among households was significantly underestimated. Figure 9 also shows the upper and lower quartile points among households. Pink range shows those of simulation result, while ash range shows those of the measured demand. As shown in the figure, the distribution among households in the simulated electricity demand is smaller than the measured demand.

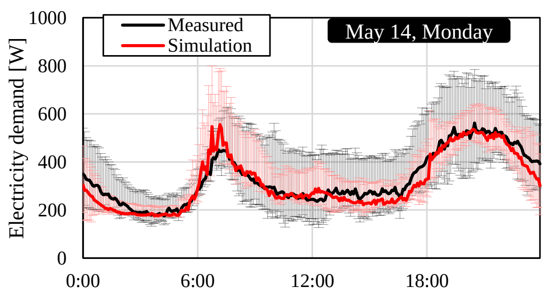

Figure 9. Simulation result of electricity demand on May 14

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