Estimating Macroscopic Occupant Behavior with an End-use Simulation Model and Smart Meter Data

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Abstract

This study focuses on city-scale human behavior, using smart meter data and a bottom-up energy end-use simulation model to analyze macro-scale behavior such as going out on holidays and changing behavior due to weather conditions. With national time-use survey data as input, the end-use energy model simulates household occupant time-use schedules and energy-use behavior using attributes such as age and occupation, and estimates energy consumption for an appliance operation schedule based on these factors. By comparing the model's estimated energy consumption with the actual smart meter data under specific conditions, such as bad weather and holidays, discrepancies likely attributable to differences between the responses given by those answering the survey and their actual behavior can be identified. For example, it was found that the level of electricity consumption indicated in the smart meter data was larger than the consumption estimated by the simulation model, both at midnight and on rainy days. This suggests that the bedtime of household residents is later than is indicated in their responses to the survey, and that the out-of-the-house rate decreases on rainy days. However, there are exceptions on special event days, such as Christmas Eve. Utilizing the bottom-up model makes it possible to examine city-level human behavior from a macro perspective using smart meter data that only provides energy use information. Understanding the characteristics of human behavior in various regions is important for efficient city-level energy management. By estimating human behavior at the macro level and revising the model using the results it produces, further improvements in the accuracy of the proposed city-level simulation model can be expected.

Introduction

In Japan, electric power companies have been encouraging the use of residential smart meters to promote energy efficiency. At the same time, the electricity consumption data obtained from smart meters is being used in a variety of ways. For example, as a means for saving energy, the data can be shared with a Home Energy Management System (HEMS) that controls home appliances and equipment for more efficient operation. It can also be used to visualize electricity consumption to promote energy-saving, and to give advice according to energy consumption trends. It is also possible to generate useful information by analyzing household smart meter data in regional units. For instance, on a household-by-household basis, it is possible to estimate micro-household characteristics such as the residents' at-home status and lifestyle habits. Using smart meter data for larger units, such as an entire city or geographic region, can provide useful insights at the macro level into such features as the electricity consumption characteristics of the selected unit. The purpose of this study is to determine macroscopic human behavior based on the lifestyles of people by using smart meter data collected in city units in combination with the Total Residential End-use Energy Simulation (TREES) model developed by Shimoda et al. (2017). The TREES model is a bottom-up simulation model that reproduces the energy consumption of home appliances such as water heaters and air conditioners based on the behavior of household residents. The model can adjust various parameters related to human behavior and equipment operation.

The method can be summarized as follows: First, the smart meter data are averaged by the number of households of each household type. The electricity consumption estimated by the TREES model is similarly divided. The smart meter data and the TREES estimates are then compared in various time series, such as at midnight, on holidays, and on rainy days, and any differences between the smart meter data and the estimated values that can attributed to human behavior are noted. The human behaviors reflected in the smart meter data are estimated by adjusting parameters of the TREES model that are related to human behavior. (A concrete method to optimize the bottom-up simulation model based on the results is introduced later.)

By utilizing the features of the bottom-up model, where parameters such as appliance characteristics can be changed systematically, it is possible to determine the macro living behavior of residents living in a targeted area solely from the data provided by smart meters. Importantly, by optimizing the parameters of the TREES model, it should be possible to effectively estimate the energy consumption of an entire city.

Methodology

Smart Meter Data Overview

The smart meter values used in this study are 30-minute timestep averages of household energy consumption for each of seven household types, as randomly sampled from households in the Kansai Electric Power Company service area. Table 1 shows the household types and the number of households of each type included in the sample. The measurement period is from April 1, 2017, to March 31, 2018.

Table 1: Smart meter data by household type with corresponding sample size

Household Type	Sample
1 person	4840
2 people ＆Detached	1800
2 people & Apertment	2600
3-4 people ＆Detached	2470
3-4 people & Apertment	2140
5 people ＆Detached	480
5 people & Apertment	200

Simulation Model

The TREES model is used to estimate the electricity consumption of households of the same type as those in the smart meter data. The model calculates energy consumption based on household member behavior, which affects equipment usage and operating status. The TREES model can accommodate 25 types of behaviors, such as sleeping, eating, and going out, for various types of household members, including workers, housewives, and elderly residents, based on the national time-use survey conducted by Statistics Bureau Japan (2006). It is also possible to modify the schedule of each action. Occupant behavior and equipment operation, as well as energy consumption, can all be estimated in 5-minute time steps. Using these characteristics, it is possible to estimate occupant behavior by integrating the TREES model results with the smart meter data and adjusting the behavior schedule. Figure 1 shows the TREES model estimation flow. First, 0.03% of about 9.3 million households in the Kansai region were chosen as a representative household sample. Based on the household/housing information estimation model developed by Kambayashi et al. (2018), household attributes of a representative household, such as family size, and the age, gender, and employment/school status of each family member, together with household income, building type, and building construction period, were randomly assigned. The household/housing information estimation model was developed with the distribution described in the Population Census conducted by Statistics Bureau Japan (2015), and Housing and Land Survey conducted by Statistics Bureau Japan (2013) as input data. Next, based on the household attributes and building information, the input data for the energy end-use model, which includes the household members' behavior schedule, the home's thermal performance, the efficiency and number of household appliances such as TVs, refrigerators, air conditioners, the hot water supply/heating equipment type, and hot water filling frequency for each season in each household, are determined by the data preparation models. The behavior schedule of each household member is generated in a 5-minute time step using the occupant behavior schedule model developed by Yamaguchi et al. (2017) based on the national time-use survey. Behavior schedules are created according to occupant attributes such as age, gender, length of working hours, and presence of children in the household. The type and performance of home appliances and equipment, as well as the frequency of hot water use, are determined by logit models with household attributes as explanatory variables.

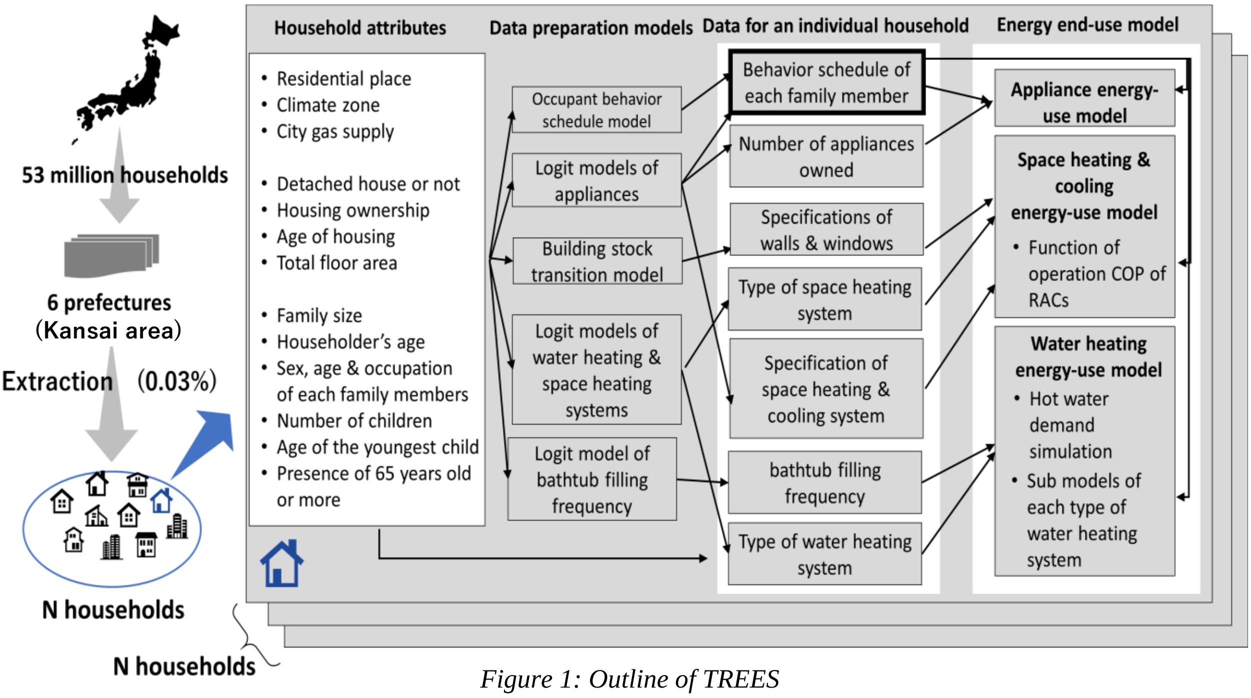

Figure 1: Outline of TREES

Based on the behavior schedule and the device operation probability by time, the appliance operation schedule is stochastically determined. The energy consumption of the appliance is then determined based on the appliance operation schedule and the energy efficiency of the appliance.

Total energy consumption in the target prefecture was estimated by extrapolating the simulation results of the sampled households to all households in the prefecture. Finally, the estimated households were classified into seven household types, as shown in Table 1, and the hourly average value of electricity consumption was calculated.

Screening of estimated values

The TREES model estimates average values for the Kansai area; the smart meter data are made up of the average values for customers served by the Kansai Electric Power Company. These values differ due to deregulation. Therefore, some households were removed from the representative households of the TREES model in order to match both values.

That there were no differences in the standard deviations of the results of the screened TREES estimates and the smart meter data suggests that this screened load curve value replicated the distribution of actual households. Therefore, these estimated values were used for comparisons with the smart meter data.

Results

A comparison of the electricity consumption in the smart meter data and the TREES estimates shows a large difference late at night, on holidays, and on rainy days.

Occupant behavior at midnight

Figure 2 shows the average value of the smart meter data and the TREES estimates by time on weekdays during May and June (hereinafter, the intermediate period) , when the air conditioner usage rate is low. The household type shown here is a detached house with 3-4 residents. "SM" indicates smart meter data.

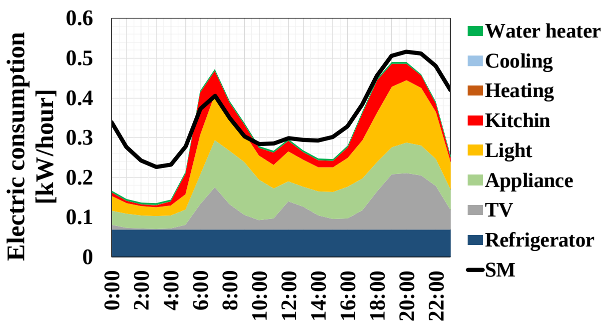

Figure 2: Average electricity consumption versus time of day

As shown, the SM values exceeded the model estimates from 22:00 to 5:00, with a difference of approximately 0.12 [kW/h/household]. One of the reasons for this is that the behavior schedule, which is the input data of TREES, is different from the residents' actual behavior. TREES reproduces an individual's behavior schedule based on the national time-use survey. Thus, it was assumed that there is a difference between the responses given in the survey and the actual bedtime of Kansai area households.

Accordingly, we re-did the TREES calculation using a behavior schedule that delayed the bedtime of all household members by two hours. The results of the re-estimation are shown in Figure 3 as an average value by time, and in Figure 4 as monthly electricity consumption.

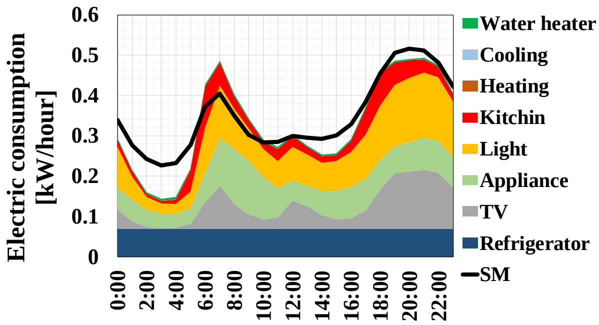

Figure 3: Average electricity consumption versus time of day after delaying bedtime by two hours

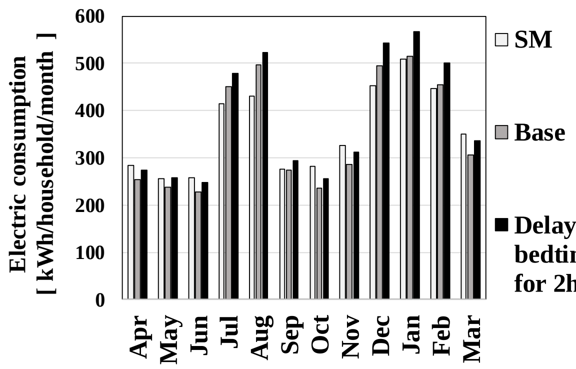

Figure 4: Monthly electricity consumption per household

As shown in Figure 3, the error from 22:00 to 0:00 is reduced by delaying bedtime by two hours. Figure 4 shows that the error in the intermediate period is reduced from approximately 10% to 2%. However, there is still error from 0:00 to 5:00, due primarily to factors not considered by TREES, such as smartphone or tablet charging, or the use of Wi-Fi devices. Failure to turn off lights or leaving appliances on are also possible reasons for this error. Notably, during the cooling period from July to August and the heating period from December to February, the error became larger when bedtime was delayed, indicating the need to improve the accuracy of the model's air conditioner usage estimates.

Occupant behavior on holidays

Figure 5 shows the average electricity consumption for the same class of households (3-4 residents in a detached home) on weekdays and holidays during the intermediate period. Figure 6 shows the error in electricity consumption by time for both the intermediate period (May and June) and the summer period_ (July and August).

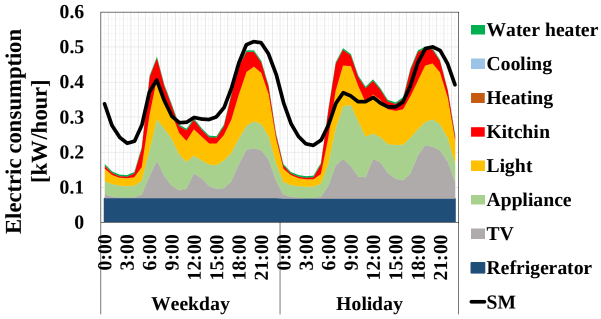

Figure 5: Comparison of average electricity consumption versus time of day between weekdays and holidays

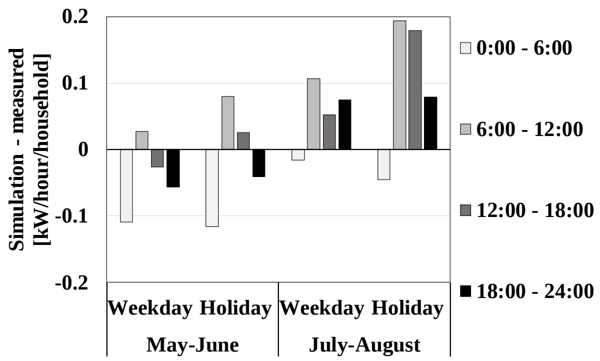

Figure 6: Comparison of electricity consumption error between weekdays and holidays, and between the intermediate period and the summer period

As indicated, the error on holidays increases by about 0.05 [kW/h/household] from 6:00 to 12:00 during the intermediate period. During the summer period, the error increases by approximately 0.08 [kW/h/household] from 6:00 to 12:00 and by approximately 0.12 [kW/h/household] from 12:00 to 18:00. Moreover, from 6:00 to 12:00 on holidays, when the model estimates are compared to the smart meter data, the error of the TREES estimates was nearly 26% during the intermediate period and nearly 36% during the summer period. This suggests that the values used to represent the probability of residents being out of the house at various times on holidays are understated in the TREES input data.

In response, the rate at which people leave the house in the morning on holidays was re-estimated and corrected by increasing the rate for all household members by the amounts shown in Table 2 between 6:00 to 12:00. The rate is changed in 5% increments to prevent the number of people who are outside their home from increasing unnaturally within a 15 minute period.

Table 2: Increase in rate at which residents leave house

	6:15	6:30	6:45	7:00~11:00	11:15	11:30	11:45	12:00
Increase(%)	5	10	15	20	15	10	5	0

Figure 7 shows the results of the re-estimation after changing the behavior schedule as described. During the intermediate period, the error for the 6:00 to 12:00 interval is roughly 17%, which is an improvement of approximately 9%. For the 11:00 to 12:00 interval, the results of the re-estimation is higher than electricity consumption before modification likely due to the fact that the behavior schedule and appliance operation were determined stochastically and averaged for all types of households, and applied only to the particular subgroup involved here (3-4 residents in detached homes). In this case, it can be considered that many households originally had a low rate of leaving the house or had a low rate of increase. During the summer period, the error was approximately 22% (a 14% improvement). However, the error is still larger than in the intermediate period. The main reason for this is that the electricity consumption of the air conditioners is overestimated and the TREES estimate of the level of activity in various private rooms, which affects air conditioner activity, differs from reality.

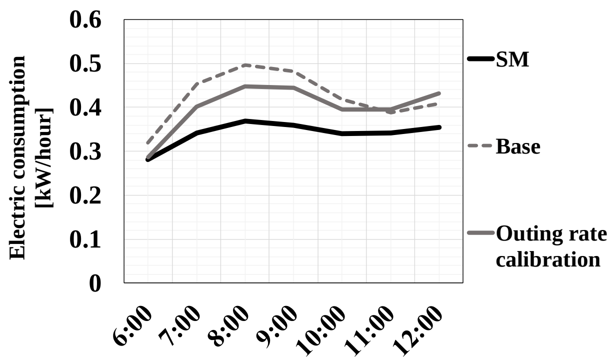

Figure 7: Average electricity consumption for each case

Resident behavior on rainy days

Based on a comparison of TREES estimates and smart meter data on rainy days and non-rainy days, it appears that the error in electricity consumption was larger on non-rainy days, especially on non-rainy holidays. Figure 8 shows a scatter diagram in which the vertical axis represents the difference between the TREES estimated values and the smart meter data (TREES estimate minus smart meter data). The horizontal axis shows the amount of precipitation for each day. The blue dot indicates the average error (i.e., the average difference between the TREES estimate of electricity consumption and the SM data) on days without rain during the cooling season. The red dashed line indicates the average value during the heating season. The black dashed line indicates days where an air conditioner is unlikely to be used. As shown in the figure, 9/16 (Sat) is non-air-conditioning days and rainy days, but the errors are smaller than the black dot. On rainy days, the stay-at-home rate increases, and electricity consumption is higher than on non-rainy days. However, TREES does not consider the effect of weather on human behavior. Therefore, the error in electricity consumption is higher on rainy days than on non-rainy days. If the plot is below the black dashed line, the rainy day has a smaller out-of-the-house rate than a non-rainy day, while a plot above the line indicates the opposite. The red dashed line indicates the difference in electricity consumption during the winter period (December to March), which is 1.16 [kWh/day] on non-rainy days. As shown, this is larger than the electricity consumption difference during the intermediate period. The difference in the summer period is as large as that in the winter, at 2.38 [kWh/day]. However, these differences are considered to be due to the overestimation of air conditioning energy consumption in the TREES model.

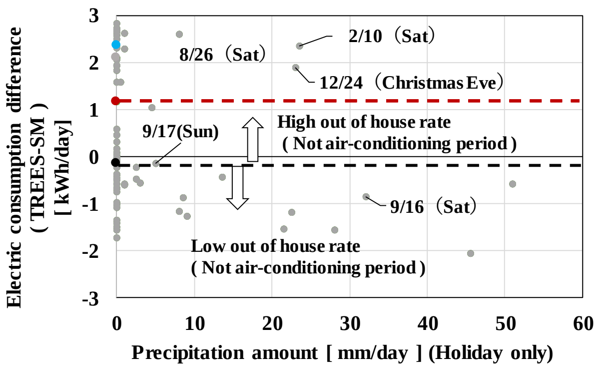

Figure 8: Relationship between electricity consumption error and weather for 3-4 person detached homes.

From Figure 8, it can be seen that the out-of-the-house rate is generally lower on rainy days. For holidays, the error increases during rainy days to about 2% of the annual electricity consumption (for households with 3-4 residents living in a detached home). However, even on rainy days, there are days when electricity consumption is greater than on the non-rainy days and the out-of-the-house rate does not decrease. According to Figure 8, February 10, which is the first day of three consecutive holidays, and December 24, which is Christmas Eve, are days with a high out-of-the-house rate even though they were rainy days. Figure 9 shows a scatter plot of the subject households. As described in the graph, the out-of-the-house rate is high on the 16th and 17th of September, two consecutive days of a three-day holiday. It would appear that on special event days and on consecutive holidays, there is a tendency for the out-of-the-house rate to be high even in rainy weather.

To understand the relationship between the number of people leaving the house and household electricity consumption, we estimated the electricity consumption in the following two cases for a four-person household in a detached home (specifically, a couple with two elementary school children). In Case 1, all four people are out of the house from 9:00 to 18:00; in Case 2 all four people are in the house during these hours. The electricity consumption difference between representative days in the intermediate period in the two cases (9:00 to 6:00) is approximately 3.45 [kWh]. Assuming that household residents leave the house at the same time, the effect on electricity consumption is estimated to be 0.86 [kWh] per person. However, since the electricity consumption per person is relatively small in a household with a large number of members, the relationship may not be linear.

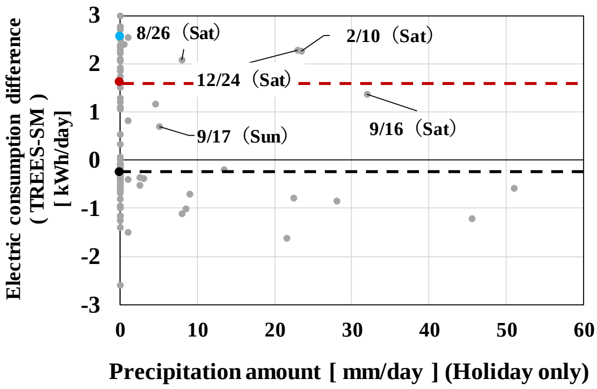

Figure 9: Relationship between electricity consumption error and weather for 3-4 person apartment suites

Discussion

In this study, by comparing smart meter data with the load curve of the TREES bottom-up model, the behavior of people living in the city, from a macro perspective, was predicted. For such a bottom-up model to be effective, it is important to accurately reproduce behavior patterns based on the lifestyles of city residents so that more reliable energy consumption estimates can be made, especially for the estimation of the load curve. The model in this research uses a detailed survey of human behavior as input data. However, the information in the survey is limited, making it difficult to fully understand individual behaviors that change daily due to a variety of factors. In response, comparisons of city-scale smart meter data and the electricity consumption estimates produced by the TREES model were used to identify changes in the model that would improve its performance by including behaviors that were not originally considered and adjusting the model's parameters accordingly.

Based on study results, the behavior and lifestyle adjustments that would need to be made include

1. later bedtimes
2. a higher out-of-the-house rate during the day on holidays
3. a lower out-of-the-house rate on rainy days
4. forgetting to turn off the electricity or leaving lights and appliances on at midnight

These behaviors and lifestyles are not yet included in the TREES model but are considered to be the trends of people living in cities.

Optimizing the bottom-up model will not only provide more accurate estimates of energy demand, but it will also enable us to quantitatively evaluate the effects of city resident behavior characteristics, such as later bedtimes and lower out-of-the-house rates on rainy days, on energy consumption and load curves.

Conclusion

In this paper, we compared smart meter data and the electricity consumption estimated by the TREES model. For any discrepancies that could be attributed to human behavior, the TREES model parameters related to that behavior were adjusted to estimate behavior in the real world.

Our findings can be summarized as follows:

1. At midnight, the TREES model result was too low by approximately 0.12 [kW/h/household]. When bedtimes in the TREES model were delayed by two hours, the error for the intermediate period was reduced from 10% to 2%. The implication is that actual bedtimes are later and the activity rates at midnight are higher than is indicated in the responses to the time-use survey used as input for the TREES model.
2. From 6:00 to 12:00 on holidays during the intermediate period, the TREES model result was too high by approximately 26%. When the out-of-the-house rate during this time was increased by 20%, the error was reduced to 17%. It appears, then, that on holidays, the rate of going out is higher than is indicated in the survey statistics. Further, the error for this time interval during the period in which the use of air conditioning is extensive was large, indicating that the occupancy rate in private rooms also deviated from reality.
3. On rainy days, electric consumption was higher than on non-rainy days, and the stay-at-home rate increased. However, some rainy days showed low electricity consumption and a high out-of-the-house rate. These days were special event days, such as Christmas Eve or consecutive holidays.
4. For more accurate estimates of urban energy consumption and to better reflect the behavioral characteristics of people living in the city, the TREES model needs to be optimized. Based on the error factors identified in this study, the parameters associated with bedtimes, the out-of-the-house rate, and the nighttime waking rate are appropriate first targets for the optimization effort that will be required.

References

Statistics Bureau, Ministry of Internal Affairs and Communications, Japan. (2006). Survey on Time Use and Leisure Activities.Population Census.

Statistics Bureau, Ministry of Internal Affairs and Communications, Japan. (2013). Housing and Land Survey.

Statistics Bureau, Ministry of Internal Affairs and Communications, Japan. (2015). Population Census.

Y. Kambayashi, Y. Yamaguchi, A. Taniguchi-Matsuoka, Y. Shimoda. (2018). Census and Time-use Data based Community-scale modelling of Residential Energy Demand. Proceedings of the 4th Asia Conference of International Building Performance Simulation Association, Hong Kong, ID:426.

Y. Shimoda, T. Asahi, A. Taniguchi and M. Mizuno. (2007). Evaluation of city-scale impact of residential energy conservation measures using the detailed end-use simulation model. Energy, 32-9, pp.1617-1633.

Y. Yamaguchi and Y. Shimoda. (2017). A stochastic model to predict occupants' activities at home for community-/urban-scale energy demand modelling, Journal of Building Performance Simulation, 10 -5-6, pp.565–581.