PREDICTION OF THE ENERGY DEMAND IN THE JAPANESE RESIDENTIAL SECTOR IN 2030 BY RESIDENTIAL ENERGY END-USE MODEL

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ABSTRACT

In this paper, residential sector electricity demand for 2030 is predicted on a regional scale via the use of the Residential Energy End-use Model, which developed by the authors. The model is a bottom-up simulation type which replicates energy demand via a procedure that is commonly used by actual cities while also considering numerous factors which affect the energy demand. Therefore, the model can predict future electricity demand simply by changing input conditions. Herein, we will use the model to predict the annual electricity consumption and electricity load curve for 2030, while also clarifying the factors contributing to electricity demand changes between 2012 and 2030.

INTRODUCTION

Since the Great East Japan Earthquake and Fukushima Daiichi Nuclear Power Plant accident of March 2011, the Japanese government has been pursuing a variety of new energy policies, including a comprehensive appraisal of present and future power source compositions. One of the most important information types needed to determine these policies are accurate energy demand forecasts. Therefore, it is clear that a method of accurately predicting future energy demand will be extremely valuable when considering decisions that influence the future, such as energy sources and the electric power plant capacities.

However, a simple regression equation formed on the basis of measured value trends is insufficient for predicting future residential energy demand because it is affected by numerous intricately related factors, many of which could change with the passage of time. Therefore, development of a simulation model which can clarify and reproduce residential sector energy demand occurrence mechanisms in order to predict the future demand is necessary.

The Residential Energy End-use Model developed by the authors is a bottom-up simulation type model which replicates city-scale or larger energy use (Shimoda et al., 2007, 2010). This model simulates energy use based on occupant behaviour in each household and estimates total electricity demand in a target region by summing up the results of each household. More precisely, this model simulates electricity demand using a procedure that is similar to that used by actual cities.

Another characteristic of this model is that it is capable of considering numerous factors in detail. These can include family composition, residence floor area, building insulation levels, number and type of appliances, and appliance specifications. Furthermore, by changing these input conditions, even the energy demands of a virtual city, such as future society, can be estimated. Hereafter, we will focus on the estimation of future electricity demand.

The purpose of this paper is to predict residential sector electricity demand of the residential sector in 2030. More specifically, the simulation is performed for both 2012 (deemed the current situation) and for 2030, after which the electricity demand change is evaluated.

The sensitivity of several electricity demand factors are analysed by the model. Later, a case study on dissemination of heat pump (HP) water heaters, fuel cell (FC) cogeneration systems, and photovoltaic (PV) power generation systems is performed, because it has been noted that such systems significantly change the electricity load curve.

The Residential Energy End-use Model can perform this analysis and case study because the model replicates energy demand via a procedure that is commonly used by actual cities.

SIMULATION MODEL

Outline of the Residential Energy End-use Model

Figure 1 shows the flowchart of the Residential Energy End-use Model. First, the occupant behaviour schedule model creates a behaviour schedule for every occupant in each household. Next, the appliance energy use model determines the operation of appliances related to each occupant behaviour. Based on the specifications of the each household appliance, the model then estimates electricity consumption. Heating and cooling energy consumption is estimated via a dynamic heat load calculation based on the occupant presence, building insulation levels, and weather conditions. The model simulates energy use for every 5 minutes. Regional energy consumption is then estimated by aggregating the simulation results of each household.

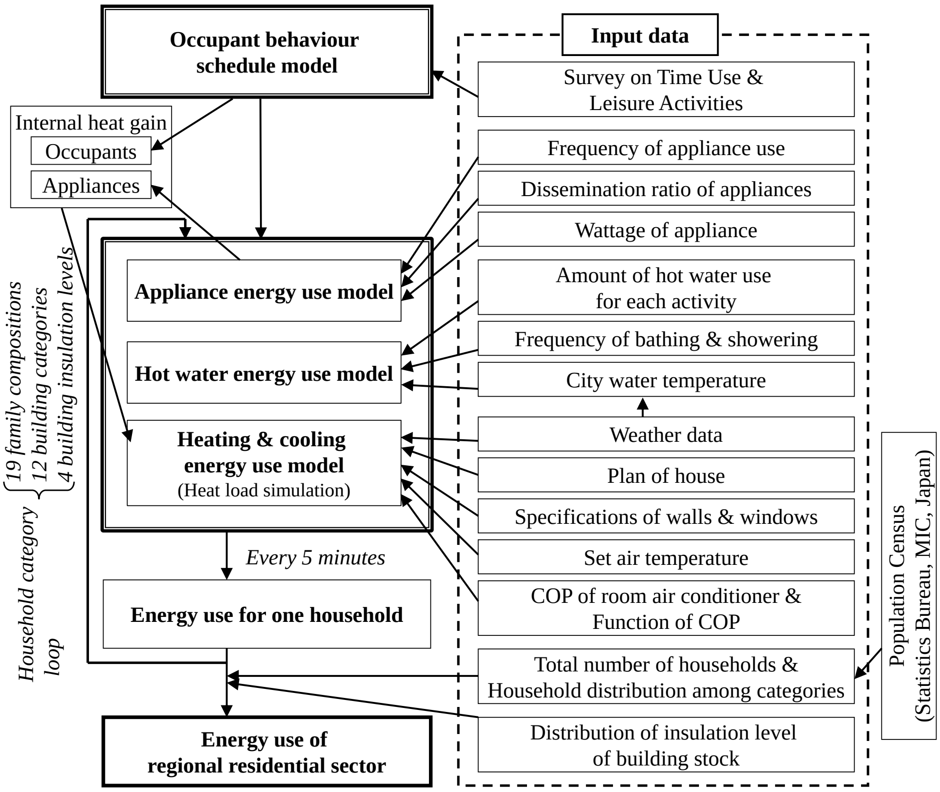

Figure 1 Flowchart of the Residential Energy End-use Model

Occupant behaviour schedule model

Based on a national time-use survey conducted by the Statistics Bureau of Japan's Ministry of Internal Affairs and Communication (MIC), a stochastic model which simulates behaviour schedules using the attributes of each occupant was developed (Yamaguchi et al., 2014). In this model, occupants are classified not only according to age and gender, but also by length of working hours and whether they have children. The behaviour schedule created by the occupant behaviour schedule model is then used as input data of the Residential Energy End-use Model.

Appliance energy use model

Next, appliances which have operation possibilities in relation to certain behaviour are listed. The relationships among occupant behaviours, rooms, and appliances are shown in Table 1. Appliance operations levels are determined stochastically. When the appliance is operated, electricity consumption is calculated based on the wattage of the appliance possessed by the household. When the appliance is not being operated, standby power consumption continues to accrue. Additionally, daily refrigerator electricity consumption is simulated by a function that considers outdoor air temperature and normalized annual power consumption as shown in Equation (1):

$$E_d = E_{normal} \times \frac{1000}{365} \times (a \cdot t_d^2 + b \cdot t_d + c) \quad (1)$$

$$a = 2.9 \times 10^{-4}, b = 5.3 \times 10^{-3}, c = 8.14 \times 10^{-1}$$

where d is a day, E_d [Wh/day] is the daily power consumption, E_{normal} [kWh/year] is the normalized annual power consumption, t_d [°C] is the average daily outdoor air temperature.

The operation probabilities of kitchen appliances, such as rice cookers, microwave ovens, toasters, and dishwashers, are set for breakfast, lunch, and dinner.

Heating and cooling energy use model

The heating and cooling energy use simulation is based on the heat load calculation, operation state decisions, and energy performance of the room air conditioners (RACs) in the residence. A thermal circuit network method (Shimoda et al., 2007) is used to calculate heat loads using weather data, house plans, and wall/window specifications. This model, which considers internal heat gain from human occupancy and appliance usage, is linked with the occupant behaviour schedules and appliance operation schedules. Therefore, it can factor in appliance efficiency improvements that decrease internal heat gain and thereby modify the heating or cooling load.

The operation state of heating appliances or RACs is determined using state transition probabilities (Habara et al., 2004). In situations where there are any occupants awake in a room, heating equipment or RAC operation states are determined by the state transition probability corresponding to the simulated natural room air temperature.

Table 1 Relationship between occupant behaviours, rooms, and appliances

Occupant behaviour	Room	Appliances			
Sleeping	Bedroom	—			
Meal	Living room	TV			
Bathing	Bathroom	—			
Face-washing	Washroom	—			
Dressing	Bedroom	—			
Drying hair	Washroom	Hair dryer			
Cooking	Kitchen	Rice cooker	Microwave	Toaster	Fan
Dishwashing	Kitchen	Dishwasher			
Cleaning	Living room	Vacuum cleaner			
Washing	Washroom	Washing machine	Clothes dryer		
Ironing	Living room	Iron			
TV	Living room	TV	Kotatsu [a]	Electric carpet	
	Bedroom	TV			
VCR	Living room	TV	VCR	Kotatsu [a]	Electric carpet
Radio/Music	Living room	Stereo component	Kotatsu [a]	Electric carpet	
	Bedroom	Stereo component			
PC	Living room	PC	PC accessories		
	Bedroom	PC	PC accessories		
Study/Reading	Bedroom	Desk lamp			
Resting	Living room	Kotatsu [a]	Electric carpet		
	Bedroom	—			

[a] A Kotatsu is a Japanese type of foot-wamer.

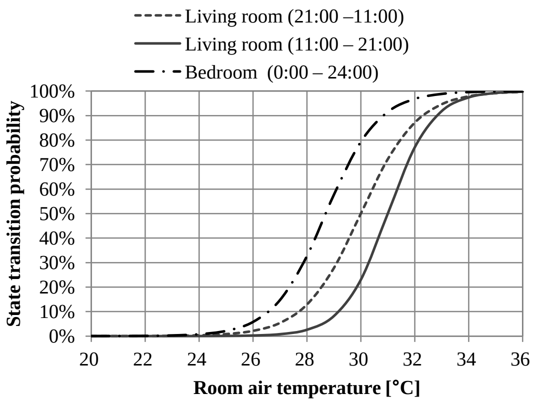

Figure 2 Cooling State transition probability

The transition probability for cooling is shown in Figure 2. Here it can be seen that the state transition probabilities are different between the living room and a bedroom, and that the living room probabilities between the hours of 11:00 and 21:00 are different from other hours. This is because operation state decisions will differ depending on the occupant conditions such as getting out of bed, going to bed, and being active.

The coefficient of performance (COP) of an RAC depends on outdoor air temperature and heat load. In this model, the operation COP is estimated based on outdoor air temperature, heat load, and the rated COP (Institute for Building Environment and Energy Conservation, 2009).

Regional scale energy use estimation

This model considers total of 912 household categories made up of 19 family compositions, 12 building categories (6 apartment house and 6 detached house categories are set depending on floor area), and 4 building insulation levels.

In this paper, we simulate electricity consumption in the Kansai region (population, 20.9 million; number of households, 8.6 million; area, 27,000 km^2). Currently, a single power company supplies electricity to the entire region. The households in the region are classified into 912 categories based on the Population Census (Statistics Bureau, 2011) and the insulation level percentages for residential building stocks estimated by the authors (Taniguchi et al., 2008). Maintaining this distribution, a total of 5,000 households were set to represent the region. Energy use for the entire Kansai region is then estimated by expanding proportionally the simulated energy use of those 5,000 households into 8.6 million households.

DATA PREPARATION

Parameters changed from current condition

The parameters that were modified from the current condition (2012) in order to predict the energy demand in 2030 are as follows:

- Number of households
- Household distribution among categories
- Building insulation level
- Appliance efficiency
- Dissemination of appliances
- Share of heating equipment
- Share of hot water equipment

The simulation setup conditions for 2012 and 2030 are shown in Table 2, where the number of households is set based on the population projections issued by the National Institute of Population and

Social Security Research. In addition to number of households and population, household distribution among family compositions and building categories is estimated. Family composition and the ratio of elderly people could be ascertained from the population projection. The house size distribution is estimated by a regression equation obtained from past data (Statistics Bureau, 2011).

The authors estimated insulation level percentages for residential building stocks (Taniguchi et al., 2008) by considering residential building replacements based on the predicted number of newly built houses (which is determined by changes in the number of households), the insulation level percentages of newly built houses, and a function for estimating building lifetimes (Shima et al., 2003).

The average energy efficiency for appliance stock is estimated using the same method as used for residential building stock insulation levels. It was assumed that the energy efficiency of RACs, televisions (TVs), videocassette recorders (VCRs), refrigerators, and personal computers (PCs) would change by 2030, and energy efficiency was estimated by considering the replacement of appliance stock using the number of shipments and energy efficiency distribution of each manufacturing year, and the appliance service life distributions.

Energy efficiency of appliances that will be shipped after 2012 is needed to estimate energy efficiency for appliance stock. It is assumed that the energy efficiency of RACs, refrigerators, and PCs will not be improved from 2010 and that of TVs and VCRs will be improved based on a logarithmic trendline obtained from past data.

Since the dissemination ratio of appliances is also expected to change, appliances considered in the model were classified into the following three categories, from which the dissemination ratio was predicted:

- Saturated appliances
- Appliances that have become commonplace
- Appliances that currently have a low dissemination ratio and for which higher future diffusion can be expected

In the model, the heating load is processed using four kinds of heating equipment: RACs, electric space heaters, gas heaters, and kerosene heaters. The heating equipment share is estimated by a regression equation formulated using past data. For cooling, RACs are most commonly used in Japan.

Table 2 Simulation setup conditions

		2012	2030
Population	Total	20,903,173[a]	19,042,205
	≥ 65 years old	4743323[a]	5,965,808
Households	Total	8,603,561[a]	7,926,938
Average number of family members		2.43	2.40
Average total floor area per household [m^2]		85.94	89.81
Insulation levels of building stock	No insulation	28%	10%
	1980 standard	43%	29%
	1992 standard	25%	31%
	1999 standard	5%	30%
Rated COP of RACs (cooling mode)	2.2 kW	4.75	5.08
	2.5 kW	4.70	5.03
	2.8 kW	4.61	4.74
	3.6 kW	3.76	3.78
	4.0 kW	3.66	3.80
Appliance power consumption (operation mode) [W]	TV	134.8	81.3
	VCR	35.2	24.3
	PC	56.6	25.9
Refrigerator power consumption [kWh/year]	≤ 250 l	583	429
	300 – 350 l	655	431
	350 – 400 l	642	433
	400 – 450 l	650	334
	450 – 500 l	723	280
	> 500 l	923	367
Heating equipment share	Room air conditioner	34%	46%
	Electric space heater	12%	11%
	Gas heater	27%	23%
	Kerosene heater	27%	20%
Hot water equipment share	Conventional gas water heater	92%	0%
	Condensing gas water heater	2%	93%
	Electric resistance water heater	2%	0%
	HP water heater	2%	4%
	Kerosene water heater	3%	3%
	FC cogeneration system	0%	0%

[a] The data of the 2010 Population Census are used as the input data of 2012.

With respect to the hot water equipment, the model considers six hot water heater types: conventional gas, condensing gas, electric resistance, HP, kerosene, and FC cogeneration systems. Because the service lives of hot water units in Japan are generally 10 – 15 years, it can be assumed that most existing hot water equipment will be replaced prior to 2030. In this paper, it is assumed that all of electric resistance water heaters will be replaced by HPs in 2030.

2030 ENERGY DEMAND PREDICTION

Estimation of electricity demand in 2012

The comparison of simulated annual secondary energy consumption with statistical data compiled by the Agency for Natural Resources and Energy of the Ministry of Economy, Trade, and Industry (METI) is shown in Figure 3. As can be seen in the figure, annual electricity consumption is lower and natural gas and kerosene consumption is higher than indicated in the statistical data.

With respect to the heating and hot water equipment shares, it is felt that a potential reason for this discrepancy is that actual RAC shares might be higher and that gas and kerosene heater shares might be lower than the values set in the simulation conditions. Additionally, the actual HP water heater share may be higher and the gas water heater share may be lower than the setup condition values. Furthermore, because miscellaneous appliances, such as mobile phone chargers and devices for network communication, were not considered in the model, electricity consumption might have been underestimated.

The electricity load curve for the summer of 2012 as simulated by the model is shown in Figure 4. It is important to examine summer electricity demand, since peak electricity demand occurs in daytime of the summer in the Kansai region. The simulated electricity load curve shows good agreement with the actual data measured by the smart meters attached to more than 1,200 households (Taniguchi et al., 2015). Electricity demand for hot water production peaks from 3:00 to 6:00 because this low-demand period is the time electric resistance and HP water heaters can complete boiling of the hot water in their storage tanks with the lowest tariff.

Prediction of electricity demand in 2030

Figure 5 shows the change to the annual electricity consumption simulated by the model. As can be seen in the figure, the simulation result is 35.8 TWh in 2012 and 28.8 TWh in 2030, respectively. The decrease in annual electricity consumption by 2030 results from decline in population and improvements to appliance energy efficiency. The reduction from 2012 is 19.6%, whereas the population reduction is 8.9%.

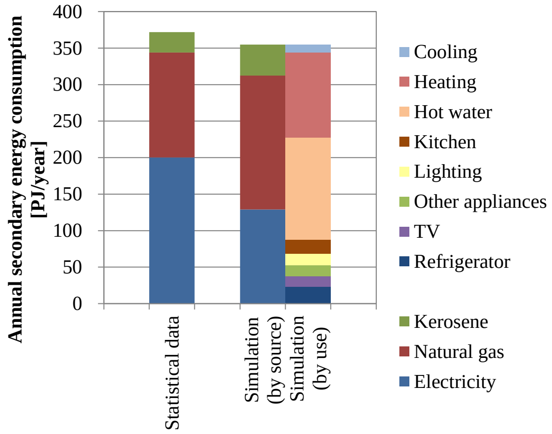

Figure 3 2012 annual secondary energy consumption

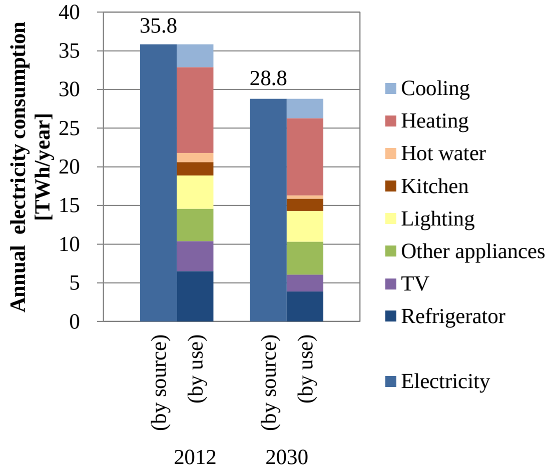

Figure 5 Annual electricity consumption change between 2012 and 2030

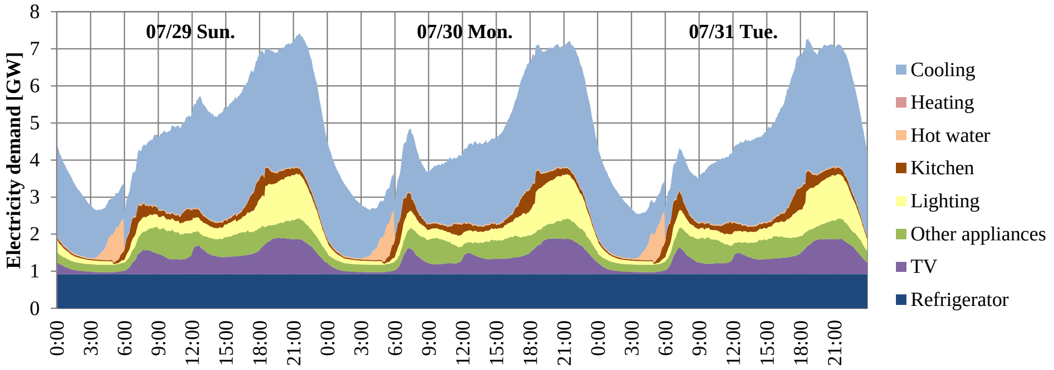

Figure 4 Simulated electricity load curve in 2012

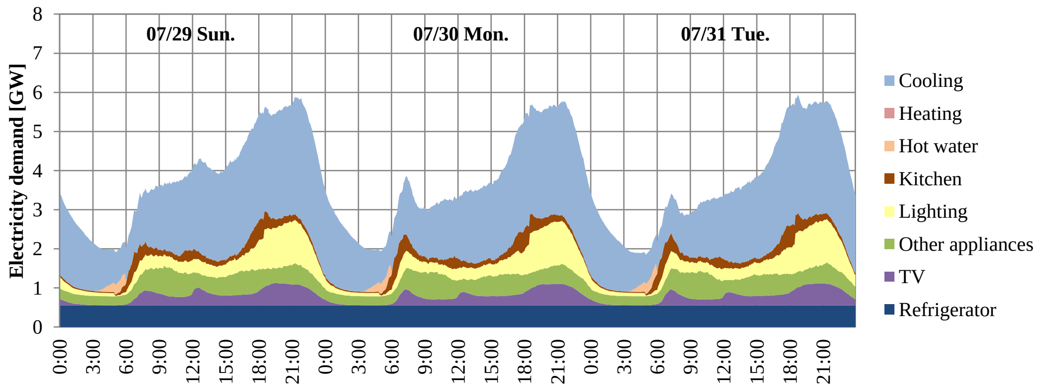

Figure 6 Predicted electricity load curve in 2030

The electricity load curve result for 2030 is shown in Figure 6. Here, to facilitate comparison, the simulation was conducted for the same day of the week and weather data conditions used in 2012. In comparison to the 2012 electricity load curve (Figure 4), it can be seen that the peak demand around 21:00 decreases by more than 1 GW. This is because population declines and appliance energy efficiency improvements have the same effect as reductions to annual electricity consumption. The replacement of electric resistance water heaters to HP water heaters decreases the electricity demand by hot water in the early morning.

Analysis of factors contributing to electricity demand

In this section, the factors contributing to the change in electricity demand are analysed by changing each factor independently from the 2012 condition to that of 2030. Figure 7 shows the factors contributing to the change in annual electricity consumption in the Kansai region, where the total electricity consumption decreased by 19.1 TWh. The dominant factors resulting in the decrease are population decline and appliance efficiency improvements. The contributions are 8.6 TWh and 13.2 TWh, respectively.

On the other hand, household distribution shows an increasing factor (0.6 TWh), while small-member family increases show corresponding per-person energy consumption increases.

Figure 8 shows the factors contributing to the change in the electricity load curve. Interestingly, the contribution of each factor is different depending on the hours. For example, the contribution of appliance efficiency improvements is 0.4 GW at 5:00, but reaches 0.9 GW between 20:00 and 21:00. This factor affects electricity demand more strongly in the evening because it is the period when appliance use is most frequent. The contribution of building insulation level improvements is most notable in the daytime because such improvements are effective in reducing electricity demand for cooling in situations when outdoor air temperatures are higher than indoor air temperatures. On the other hand, the household distribution change factor results in an increase in daytime electricity demands because the number of elderly people (who normally stay at home during the daytime) increases significantly.

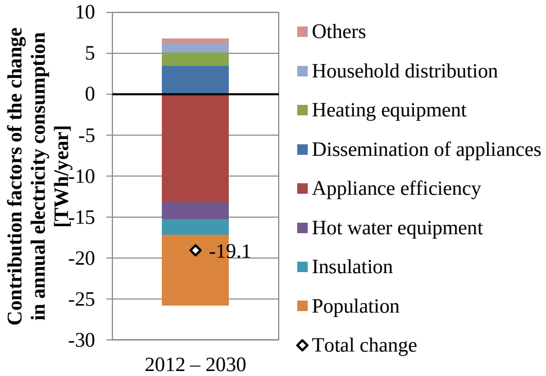

Figure 7 Factors contributing to annual electricity consumption change

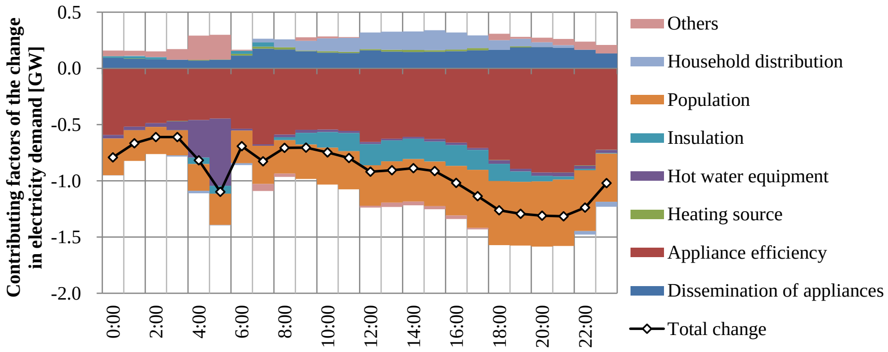

Figure 8 Factors contributing to electricity load curve change (weekday, August)

Case study

Deployment of new residential water heaters and increased future usage of PV systems are the most uncertain and influential conditions impacting our model, whereas the predictions and analysis mentioned above did not consider drastic changes resulting from improvements to hot water heater shares and PV system diffusion. Since systems such as HP, FC cogeneration, and PV systems can significantly affect energy demand (and thus the electricity load curve), this section discusses electricity demand changes that might potentially result from their widespread increased use. The model estimates the electricity demand in HP, FC, and PV cases, and then compares them with a business-as-usual (BAU) case.

In this case study, it is assumed that 1.0 million of the 7.9 million total Kansai region households in 2030 will adopt HP or FC or PV systems. The households assumed to adopt these systems are restricted to those living in detached houses with two or more family members, and which did not use an HP system for hot water supply in the BAU case.

There are approximately 2.6 million households that satisfy these conditions in the Kansai region. From these households, 1.0 million households were randomly assumed to have adopted each system case.

Figure 9 shows the simulated annual electricity consumption and power generation for each case.

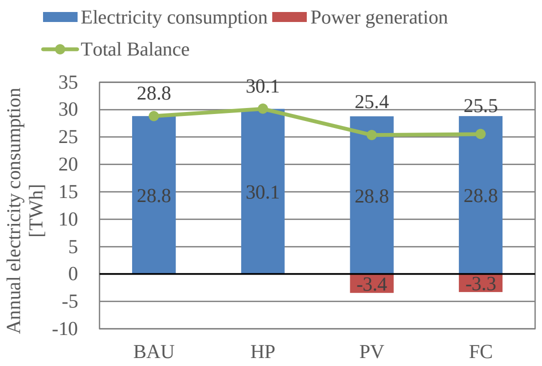

Figure 9 Annual electricity consumption and power generation in each case

Electricity consumption in the PV case and FC cases are almost same as the BAU case. In the HP case, electricity consumption increases and becomes 30.1 TWh because gas water heaters were replaced with HP water heaters.

The power generation in the PV case is 3.4 TWh and that in the FC case is 3.3 TWh. Total balances in the PV case and the FC case are 25.3 TWh and 25.5 TWh, respectively. These values are very close to each other.

The simulated electricity load curve in each case is shown in Figure 10. In the HP case, water boiling is conducted from 3:00 to 6:00. This raises the demand bottom by a maximum of 1 GW. In the PV case, electricity demand declines significantly, especially around noon, with a more than 1.5 GW reduction effect from the BAU case.

It should be noted that even though the annual electricity balance values in the PV and FC cases are very close to each other (Figure 9), the electricity load curve is quite different. In the FC case, a constant reduction of electricity demand of approximately 0.5 GW results, except during the hours from midnight to early morning.

CONCLUSION

Electricity demand in 2030 was predicted via the use of the Residential Energy End-use Model developed by the authors, which simulates the residential energy use via a procedure that is nearly the same as that used in actual city. Additionally, because the model considers a multiplicity of factors, predictions could be produced simply by changing some of the input conditions.

The contribution of each factor to the overall change in electricity demand was analysed by changing each factor independently from the 2012 condition to that of 2030. Factors found to be particularly important to the prediction of future electricity demand were population and appliance efficiency. Furthermore, our case study suggests that the deployment of new residential water heaters and PV systems can change the electricity load curve remarkably.

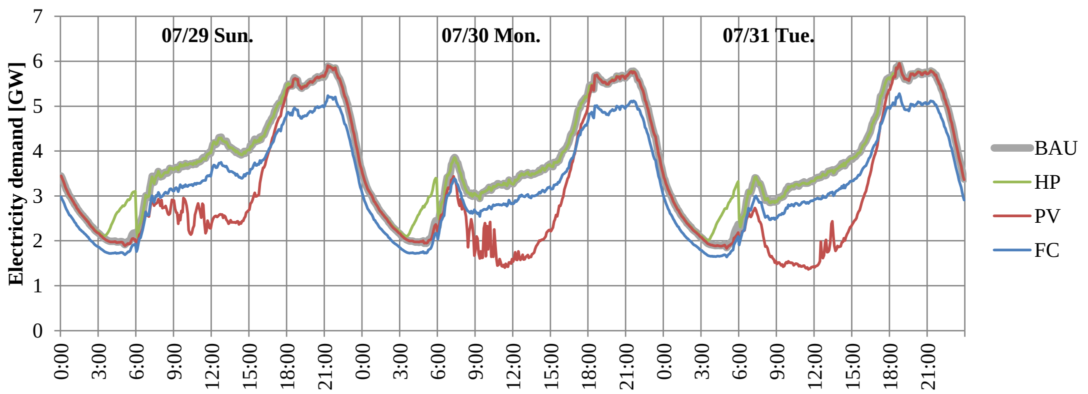

Figure 10 Electricity load curve in each case

Future issues related to our research include improving simulation accuracy for the total annual energy consumption of each energy source. This will enable us to more accurately estimate not only electricity demand but also primary energy consumption and carbon dioxide emissions. It will also be important to conduct multilateral evaluations into situations where energy sources change, such as those occurring due to the widespread adoptions of FC cogeneration systems.

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