URBAN-SCALE ENERGY MODELING OF FOOD SUPERMARKET CONSIDERING UNCERTAINTY

Yohei Yamaguchi[1], Yusuke Suzuki[1], Ruchi Choudhary[2], Adam Booth[2], Yoshiyuki Shimoda[1]

[1] Graduate School of Engineering, Osaka University
2-1 Yamada-oka, Suita, Osaka 565-0871, Japan, yohei@see.eng.osaka-u.ac.jp
[2] Department of Engineering, University of Cambridge
Trumpington Street, Cambridge CB2 1PZ, UK

ABSTRACT

This paper proposes a methodology to develop an urban scale model of energy use of buildings. This methodology addresses the diversity in energy use through two approaches: classification of the building stock and archetype modelling; supported by Bayesian calibration. The Bayesian approach allows quantification of uncertainties in model input parameters. We designed a hierarchical calibration so that uncertain input model parameters are calibrated for different time resolutions of analysis. We validated the calibration process by applying it to a food supermarket building stock in a region as a case study. The results generally showed that the proposed approach enables urban scale models to take into account not only the overall characteristics of the building stock represented by annual energy consumption but also the influence of meteorological conditions shown in the variation of weekly energy consumption.

INTRODUCTION

There are a number of urban-scale models developed in recent years for estimating the energy use of building stocks. The most commonly used methodology for urban scale modelling are archetype engineering models, discussed in Swan et al. (2010). The procedure of model development is as follows: 1) the building stock is divided into several stock categories according to the building characteristics and internal activities; 2) An archetype model, representative of a particular building category, is developed; 3) The unit energy consumption (EUI) for each category is quantified by performing building performance simulation using the archetypes as input; and 4) The total energy consumption is quantified by multiplying the unit energy consumption by the number of units in each stock category. The archetype simulation process thus enables the identification of key factors determining the energy use in each stock category.

The main shortcomings of the archetype approach can be illustrated through the following example: Figure 1 shows the cumulative frequency of total floor area and energy use intensity (EUI) of Japanese retail facilities (Yamaguchi et al. 2012). It can be seen that the EUI and total floor area are widely distributed (a logarithmic scale is used in Figure 1). No single archetype model can reasonably represent this wide distribution. Indeed, further sub-classifications of buildings become necessary as they can considerably reduce the large spreads in energy use. For a particular sub-category of building, a probabilistic energy model can be used to effectively incorporate the remaining variability in the EUI.

This paper focuses on addressing how to incorporate within energy analysis this variability of EUI within a building stock category in urban scale energy modelling, while Matsuoka et al. (2013) addresses the sub-classification of Japanese retail facilities.

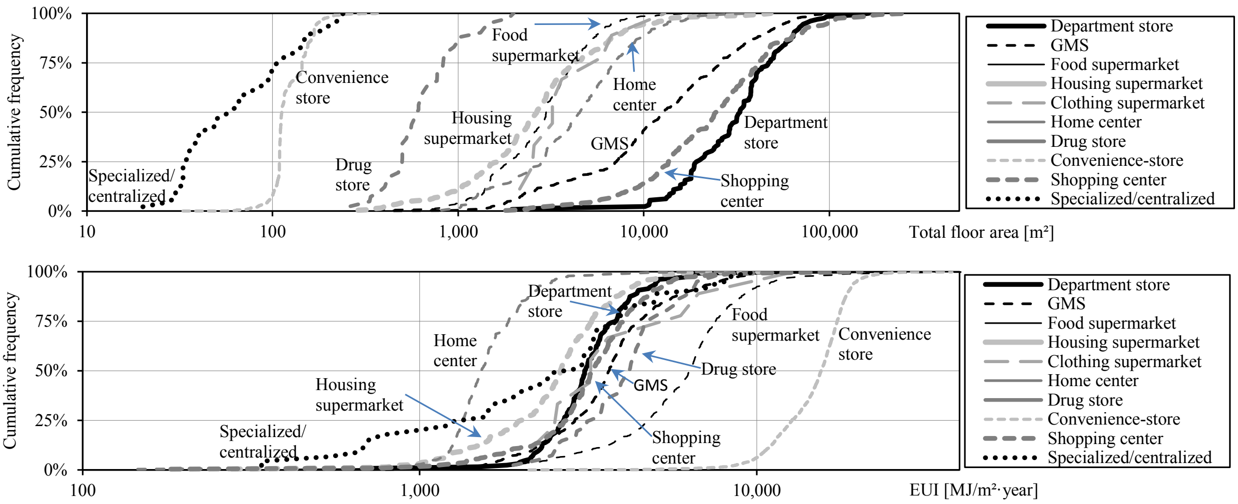


Figure 1 Distribution of total floor area and EUI of the sample

The variability in EUI is due to a number of factors. A probabilistic approach, which gives input parameters as statistical distributions and which generates a large number of simulation outputs by sampling from these statistical distributions, is useful to take into account the variety in EUI. However, distributions of input parameters are usually unknown. Heo et al. (2012) and Booth et al. (2012) presented a Bayesian calibration methodology that develops calibrated distributions for uncertain input parameters so that the distribution of simulation outputs reflects the actual energy consumption for a given sample of buildings. This calibration process combines 1) sensitivity analysis to select those model parameters whose uncertainty has a significant influence on simulation outputs and 2) a Bayesian calibration method to quantify uncertainties for selected important uncertain parameters. Sensitivity analysis is important to select a limited number of the most important uncertain parameters, since the Bayesian calibration process can be computationally expensive.

These previous applications of a probabilistic approach showed the usefulness of the methodology to address the uncertainty in simulation output. However, they are only limited to calibrating the model parameters against a single resolution of simulation output: monthly energy consumption. However, usually a number of simulation outputs are analysed in building performance simulation, for example weekly energy consumption to consider seasonal variation and hourly energy consumption to model the time-series characteristics of energy use. Furthermore, the effect of uncertainty in input parameters may be different at different time resolutions. For example, if the operational time is simply moved a few hours earlier, simulation results of hourly energy consumption considerably vary from the original, but annual energy consumption might only be modestly different. Similarly, whilst building insulation performance might have a large impact on seasonal variation, represented by weekly energy consumption, its influence on annual energy consumption might be modest in mild climate zones due to the balancing of energy consumption for heating and cooling.

The consideration of this time-resolution brings forward issues related to data availability. and the calibration process requires comparing simulation outputs with actual energy consumption under different known scenarios. For the calibration process to reasonably capture the variability within a sub-category of building, energy consumption data from a large sample of buildings must be available. However, whilst annual energy consumption for a large number of samples is often available, higher time resolution data is not.

METHODOLOGY

Based on this background, we propose a hierarchical calibration process for urban scale modelling, shown in Figure 1. In this paper, we develop an urban scale energy model of food supermarkets in Hyogo prefecture, Japan, as a case study. We selected annual and weekly energy consumption as simulation outputs, against which uncertain parameters are calibrated . However, input parameters can be calibrated for other simulation outputs also, e.g. hourly energy consumption.

In the first step, parameter screening is carried out to identify important uncertain input parameters explain annual total energy consumption and weekly energy consumption. We call selected parameters annual total variation parameter and weekly variation parameter in this paper. In the second step,

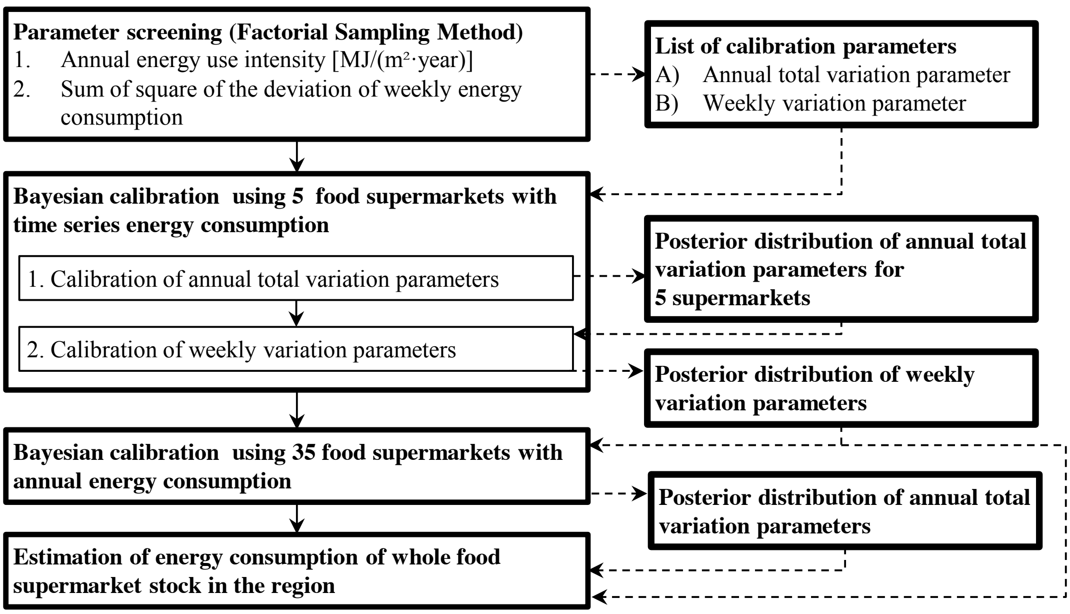


Figure 2. Proposed calibration process

probability distributions for the weekly variation parameters are estimated using two Bayesian calibrations. In this step, we applied the calibration to five food supermarkets for which detailed energy consumption data was available, with 10 min time resolution, as well as information on building, operation schedule and equipment configuration (e.g. refrigeration cabinets). The first calibration was used to develop a probability distribution for the annual variation parameters and the generated distributions are only applicable to the five food supermarkets. This step is necessary for assigning the most plausible values for the annual variation parameters in the calibration of weekly variation parameters. The Bayesian calibration framework used in this work is based on Kennedy & O'Hagan (2001). It is described fully in the context of building simulation by Heo et al (2011) and Booth et al (2012)

In the third stage, uncertainty surrounding the collective macro-scale parameters that affect annual energy consumption was addressed. This was to develop a scheme to aggregate the energy consumption for the target building stock. For this process, we used available data for the annual energy consumption of 35 food supermarkets, as well as information on building size and business hour. In this calibration, the posterior distributions developed in the previous step were assumed for the weekly variation parameters.

We finally carried out a Monte Carlo simulation to estimate the total energy consumption of the whole building stock of food supermarket located in Hyogo prefecture. Based on the application, the authors discuss the methodology to address uncertainty in urban-scale energy models.

FOOD SUPERMARKET MODEL

This section introduces the archetype of food supermarkets and the process to quantify energy consumption. Suzuki et al. (2011) conducted measurements and field surveys on two food supermarkets to develop a simulation model. The model combines a whole building energy demand model and a refrigeration cabinet energy demand model. The building model calculates end-use energy demand and corresponding energy consumption for heating, cooling, ventilation, lighting, water heating and others (Yamaguchi et al. 2010). The refrigeration cabinet energy demand model first calculates refrigeration load for the cabinet display and energy consumption to generate cooled air corresponding to the calculated refrigeration load.

Archetype of food supermarket

Figure 3 shows the floor plan applied to the simulated food supermarkets. The total floor area was given from those of simulated food supermarkets. The ratio between sales floor area and total floor area was assumed to be 65%. The business hour was assumed to be from 10 am to 10 pm. It was assumed that air source heat pump system is used for heating and cooling. The north sarface was assigned as the building frontage. Refrigeration cabinets were assumed to be placed everywhere along the walls of the sales area except the north surface. The total length of cabinets was derived from a regression model based on statistical data from a sample set of supermarkets (Yamaguchi et at., 2012).

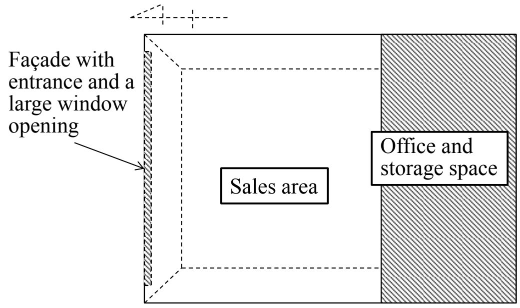


Figure 3 Floor plan of the archetype

Refrigeration cabinet energy demand model

In this model, 17 kinds of cabinet type were identified according to the shape of cabinet and set point temperature corresponding to displayed items. First, the total length of the cabinet is given. The composition was then determined based on the data listed in Table 1. Table 1 also lists the capacity of refrigeration equipment and air volume used in the simulation model. The capacity of equipment for a refrigerated display cabinet including fan, defogger heater, lighting and defrost heater, was set on the basis of manufacturer specifications. The defogger heater is controlled by the humidity sensor; its heat gain decreases when the air is drier on the winter months of January, February and December.

We divided operation time into four groups as shown in Table 2 for assuming the operation of each component of cabinet into business hour, preparation hour, closing hour and defrost operation. This schedule was set for each display cabinet. In this condition, the thermal load caused by internal heat gain and air leakage is calculated.

The heat load of the refrigeration cabinet can generally be divided into two categories: heat gain and infiltration load.

The heat gain of the cabinet Q_{HG} [kW] is given by Equation (2) where Cap [kW] is the capacity of cabinet-related equipment including cabinet lighting, fan, defogger and defroster and UR is the usage rate [%] corresponding to the operation conditions. .

$$Q_{HG} = Cap \cdot UR \tag{2}$$

Whilst a constant volume of air is circulated in a cabinet, the infiltration load is caused by leakage of circulated air to the outside of cabinet. A portion of leaked air is defined by air filtration ratio RI [-], which is a constant dependent on the type and operation model of cabinets. In addition, the volume of leaked air surrounding the cabinet is inhaled at the air inlet of cabinet. Thus, the sensible infiltration load

Q_{IS} [kW] is calculated by Equation (3) where V is the volume of air circulation of cabinet [m³/s].

$$Q_{IS} = C_a \cdot RI \cdot V \cdot (T_{floor} - T_{case}) \quad (3)$$

where C_a is the specific heat of air [kJ/K·m³], T_{floor} [ºC] is indoor air temperature and T_{case} is the set point temperature of the cabinet. The latent heat load Q_{IL} [kW] is then given by Equation (4), where C_V [kJ/m³·ºC] is the vapour water specific heat capacity and γ [kJ/ m³] is the latent heat of water evaporation.

$$Q_{IL} = (C_V \cdot \Delta T_2 + \gamma) \cdot (H_{floor} - H_{case}) \cdot RI \cdot V \quad (4)$$

Thus, the infiltration load Q_I [kW] is given by Equation (5)

$$Q_I = Q_{IL} + Q_{IS} \quad (5)$$

The power consumption of the refrigeration cabinet is calculated by Equation (6).

$$E' = (Q_{HG} + Q_I) / COP \quad (6)$$

The coefficient of performance (COP) is modeled by a regression curve, developed based on measured power consumption considering load factor and outdoor temperature.

SELECTION OF UNCERTAIN PARAMETERS

Methodology for parameter screening

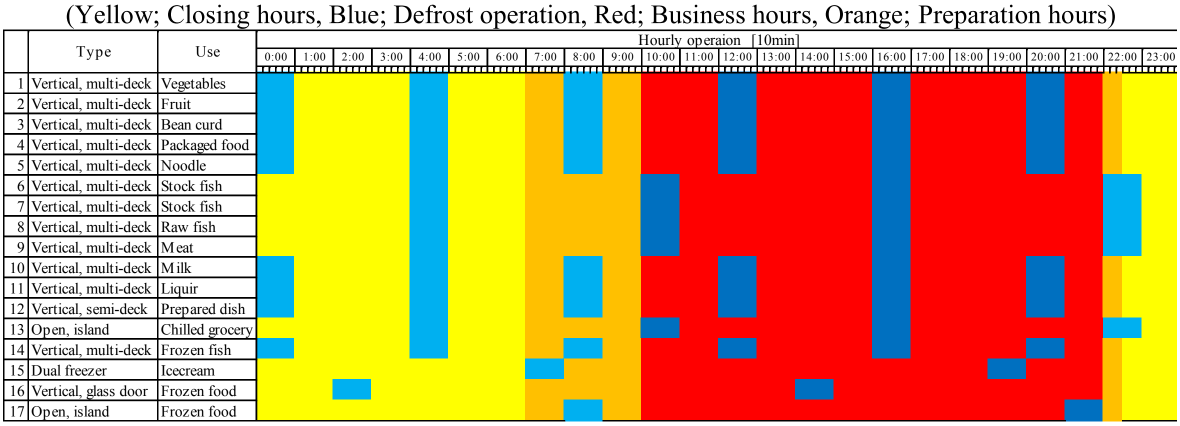
In this study, we examined the uncertainty involved in the 13 parameters listed in Table 3. The influence of the parameters on simulation output (i.e. energy consumption) was quantified by using the Factorial Sampling Method (FMS).

FSM is a useful technique for finding parameters that have a significant influence on the outputs of a simulation model with a large number of input parameters. In this study, we used the FSM procedure as suggested by Wit (1997). In this procedure, we only used the two extreme values of each parameter range, which were collected through a reference survey and interview of experts. These values are labeled as 'OFF' and 'ON'. Initially, all parameters are set to 'OFF'. Then one parameter is randomly selected and its value is changed to 'ON'. This parameter's elementary effect can be observed

Table 1Settings of thermal load inside refrigerated cabinets

	Type	Item	Set point temperature [ºC]	Heat gain [W/m]								
				Fan	Defogger heater				Canopy lighting	Cabinet lighting	Defrost heater
					Summer (Daytime)	Summer (Night)	Winter (Daytime)	Winter (Night)			
1	Vertical, multi-deck	Vegetables	6	24.5	12.3	12.3	12.3	12.3	17.7	70.6	0.0
2	Vertical, multi-deck	Fruit	6	15.7	9.7	9.7	9.7	9.7	10.1	111.9	0.0
3	Vertical, multi-deck	Bean curd	6	14.1	8.2	8.2	8.2	8.2	17.6	87.9	0.0
4	Vertical, multi-deck	Packaged food	6	13.8	8.2	8.2	8.2	8.2	17.7	88.5	0.0
5	Vertical, multi-deck	Noodle	6	18.4	12.8	12.8	12.8	12.8	0.0	166.6	0.0
6	Vertical, multi-deck	Stock fish	0	30.6	11.6	11.6	11.6	11.6	17.5	87.0	0.0
7	Vertical, multi-deck	Stock fish	0	23.0	12.5	12.5	12.5	12.5	17.7	88.5	0.0
8	Vertical, multi-deck	Raw fish	0	7.9	15.2	15.2	15.2	15.2	17.7	17.7	196.7
9	Vertical, multi-deck	Meat	0	22.2	12.5	12.5	12.5	12.5	17.7	88.5	0.0
10	Vertical, multi-deck	Milk	6	22.6	12.5	12.5	12.5	12.5	17.7	80.9	0.0
11	Vertical, multi-deck	Liquir	6	23.9	16.4	16.4	16.4	16.4	14.0	104.4	0.0
12	Vertical, semi-deck	Prepared dish	6	15.0	7.3	7.3	7.3	7.3	10.9	49.0	0.0
13	Open, island	Chilled grocery	−18	14.0	39.7	31.8	7.9	6.4	0.0	0.0	459.0
14	Vertical	Frozen fish	−18	36.2	229.3	183.4	45.9	36.7	13.9	69.7	804.9
15	Dual freezer	Icecream	−18	34.5	334.6	267.7	66.9	53.5	26.9	63.9	1236.1
16	Vertical, glass door	Frozen food	−18	44.3	510.8	408.6	102.2	81.7	0.0	88.5	486.9
17	Open, island	Frozen food	−18	22.9	98.7	78.9	19.7	15.8	0.0	0.0	937.1

Table2 Settings of hourly refrigerated display cabinet operation
(Yellow; Closing hours, Blue; Defrost operation, Red; Business hours, Orange; Preparation hours)



by comparing the simulation outputs with the two sets of input parameters. This process is repeated until the values of all considered parameters have been changed to 'ON'. Repeating this observation 100 times in this study, the mean value and standard deviation of the elementary effect are determined. We selected parameters for the Bayesian calibration if the sum of the mean and standard deviation of elementary effect exceeded 10% of the mean elementary effect.

In the Bayesian calibration process, we use weekly and annual energy consumption. Thus, parameters significantly affecting weekly and annual energy consumption must be selected. For this purpose, we used two kinds of energy consumption for parameter screening. The first one is annual total energy consumption. The second one is weekly variation of energy consumption defined by the annual sum of weekly variance given by Equation (7) where Ew_{week} is the total weekly energy consumption and Ew_{min} is the minimum value of weekly energy consumption.

$$Ewv_{week} = Ew_{week} - Ew_{\min} \quad (7)$$

For weekly energy consumption, the effect of each parameter is calculated by the difference in weekly energy consumption from the previous step of FMS.
Result of parameter screening

Figure 4 and Figure 5 show the effect of the examined parameters. Based on the result, we chose five parameters for weekly energy consumption and four parameters for annual energy consumption (listed in Table 4). Four parameters are included in both annual and weekly energy analysis, and the cabinet air infiltration ratio is evaluated for the weekly energy consumption only. Based on this result, the procedure shown in Figure 1 can be simplified. It was unnecessary to calibrate annual variation parameters before carrying out calibration for weekly uncertain parameters. Thus, only two calibrations were performed as explained below.

BAYESIAN CALIBRATION FOR WEEKLY ENERGY CONSUMPTION

The Bayesian calibration method (Kennedy and O'Hagan, 2001) was applied to the model of five food supermarkets located in Hyogo prefecture. Table 5 lists the general information of the food supermarkets. For these supermarkets, 30 min resolution energy consumption data was available. The values of the calibrated parameters were randomly selected using Latin Hypercube Sampling method (MacDonald 2009) so that these calibrated parameters covered their value range. Prior distributions for all the calibrated parameters were assumed to follow a triangular distribution with lower and upper limits that were assumed to be the parameters' lower and upper bounds, whilst the vertex was to be the centre of the bounds.

Figure 6 shows calculated weekly energy consumption based on the prior distributions using Latin Hypercube Sampling, whilst the horizontal axis shows mean outside air temperature during the corresponding week. The figure also shows the actual weekly energy consumption which is the mean of the 5 supermarkets. The data shown in the figure were inputted to the calibration.

Table 3 Examined uncertain parameters

Category	no	Parameter	Unit
Building and HVAC	1	Lighting intensity	W/m²
	2	Appliance intensity	W/m²
	3	Occupants intensity	Person/m²
	4	Air change ratio	Times/hour
	5	Rated COP of air-conditioner	-
Refrigera-tion system	6	Length of cabinet	m
	7	Rated COP of refrigerators	-
	8	Defrost heater capacity	W/m
	9	Circulation fan capacity	W/m
	10	Anti-sweat heater capacity	W/m
	11	Cabinet lighting capacity	W/m
	12	Air infiltration ratio	-
	13	Air velocity of air-curtain	v/s

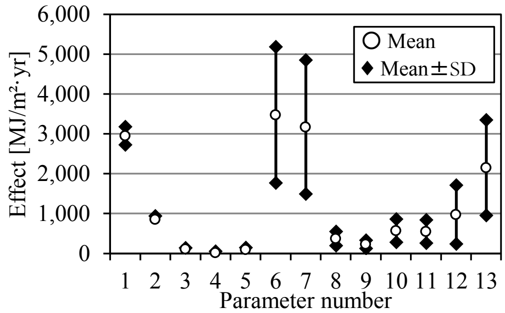


Figure 4 Effect of uncertain parameters on annual energy consumption

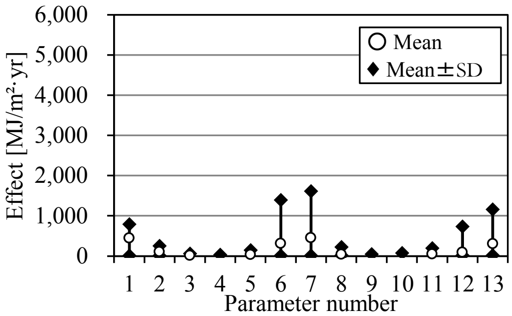


Figure 5 Effect on weekly energy consumption

Table 4 Parameters selected by FSM

Energy	Parameter	Effect†
Annual	Refrigerator Rated COP	41%
	Length of cabinet	33%
	Lighting intensity	20%
	Air velocity of air-curtain	16%
Weekly	Refrigerator Rated COP	50%
	Length of cabinet	32%
	Air velocity of air-curtain	19%
	Lighting intensity	17%
	Cabinet air infiltration ratio	17%

† The effect is shown in a relative value compared to those calculated under base conditions

The purpose of this calibration is to learn about the air-infiltration ratio of refrigeration cabinets, since all the other parameters will be updated by the second calibration, using the annual energy consumption data. Figure 7 shows the prior and posterior distributions of the calibrated parameters. As shown in the figure, the posterior distribution did not significantly vary with prior distributions for the length of refrigeration cabinet [1], air-velocity of cabinet air-curtain and lighting intensity. For rated COP of refrigerators equipped with refrigeration cabinet, there are three frequent zones. These zones could represent actual COP of the five supermarkets. The posterior distribution of cabinet air- infiltration ratio slightly shifted to left on the horizontal axis.

Figure 8 shows weekly energy consumption calculated based on the posterior distributions shown in Figure 7. As shown in the figure, the calibrated result agrees well with the actual energy consumption. By changing the distributions of the calibrated parameters from the prior to posterior, root mean square error (RMSE) improved from 22.6 to 18.5 MJ/(m²·week).

Table 5 General information of 5 food supermarkets

No	Total floor area [m²]	Sales area [m²]	Cabinet length [m]	Business hour
1	2,972	1,932	168	10-22
2	2,803	1,822	167	10-22
3	2,807	1,825	167	10-22
4	2,924	1,901	168	10-22
5	1,975	1,284	146	10-22

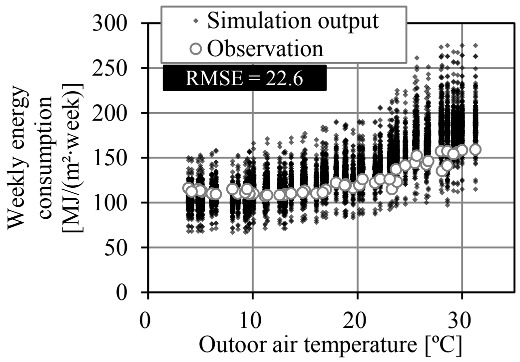


Figure 6 Simulation result of weekly energy consumption calculated based on prior distributions

BAYESIAN CALIBRATION FOR ANNUAL ENERGY CONSUMPTION

The Bayesian calibration method was applied to a food supermarket model estimating the annual energy consumption of 35 food supermarkets located in Hyogo prefecture. Here, the four calibrated parameters listed in Table 4 were examined. Values of the calibrated parameters were randomly generated using Latin Hypercube Sampling whilst using the prior distributions for all the calibrated parameters. Only for the cabinet air-infiltration ratio was the posterior distribution used, as shown in Figure 7.

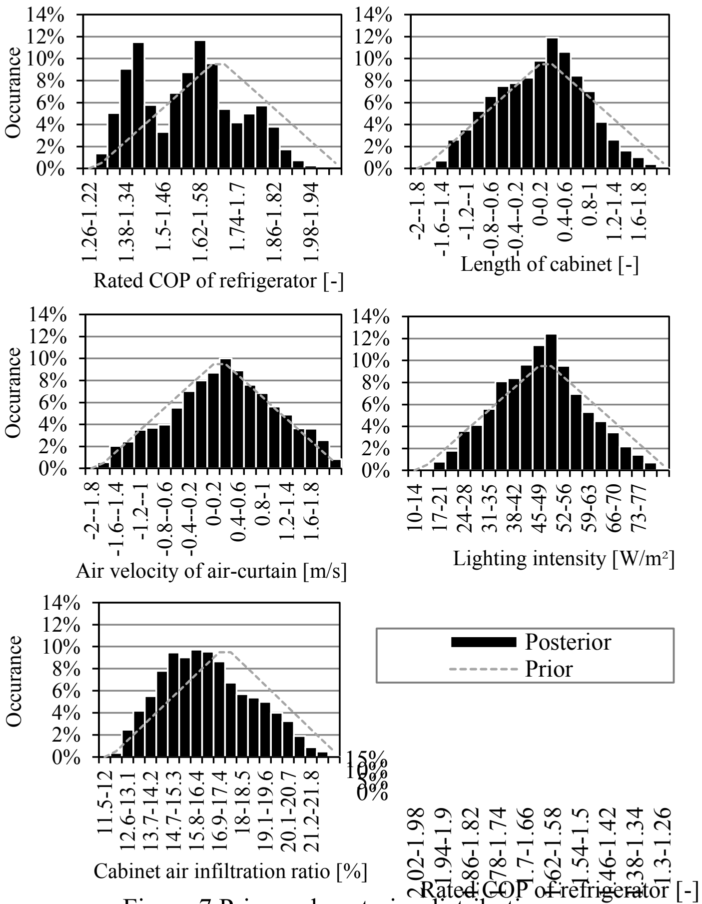


Figure 7 Prior and posterior distributions

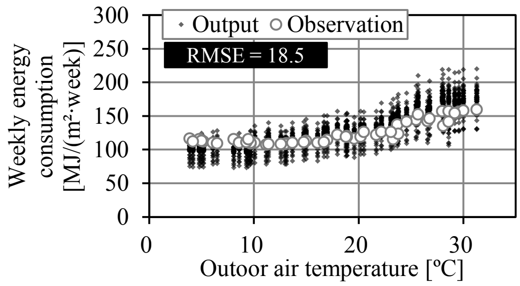


Figure 8 Simulation result calculated based on posterior distributions

The purpose of this calibration is to understand the variation of the uncertain parameters over the food supermarket stock in the region. Figure 9 shows the simulation outputs and observations of annual energy use intensity of the 35 food supermarkets. The horizontal axis shows the total floor area of the food

[1] It should be noted that the length of the refrigeration cabinets was modelled as the sum of mean length of cabinets and deviation that was given as the uncertain parameter. The value in Figure 7 can be converted to the length by multiplying the standard deviation of the variation of cabinet length.

supermarkets. These data were inputted to the Bayesian calibration. Figure 10 shows the prior and posterior distributions of the four calibrated parameters. Figure 11 shows the simulation outputs estimated by using the posterior distributions for the calibrated parameters. The calibration improved the root mean square error from 1,950 to 1,260 MJ/(m²·yr).

Based on the result shown in Figure 10, we can infer the following: (a) the posterior distribution of the rated COP of refrigerators is towards the upper bound. In physical terms, this means that the COP of refrigeration cabinets is higher than expected in the prior distribution. (b) The length of refrigeration cabinets was estimated to be longer than assumed in the prior distribution. In addition, the length is more concentrated in the range from 0 to 1. (c) Lighting intensity was estimated to be more intensive than assumed in the prior distribution. (d) The posterior distribution of the velocity of air curtain of refrigeration cabinets does not vary significantly from the prior estimates.

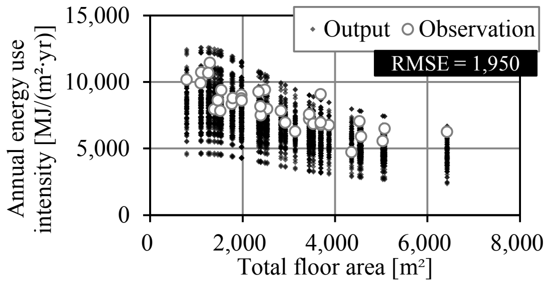


Figure 9 simulation result of weekly energy consumption calculated based on prior distributions

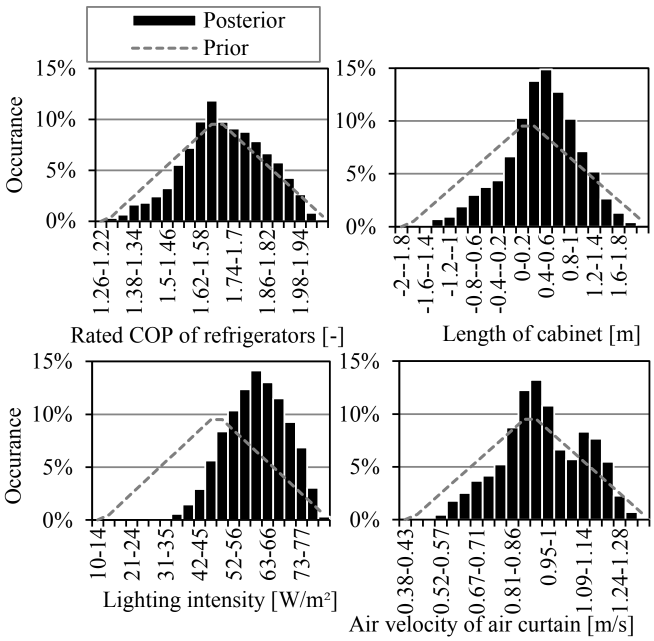


Figure 10 Prior and posterior distributions

Figure 12 shows monthly energy consumption of the 35 food supermarkets estimated using the prior and posterior distributions. The figure also shows the mean of actual monthly consumption of the 35 food supermarkets. As shown in the figure, the simulation outputs using the posterior distributions well cover the actual monthly energy consumption except the plot of January and the range in which simulation outputs distribute became narrower compared to those estimated based on the prior distributions. This result implies that the proposed hierarchical calibration improved the model to take into account not only the overall characteristic of the food supermarket stock but also the influence of meteorological conditions shown in the seasonal variation of energy consumption.

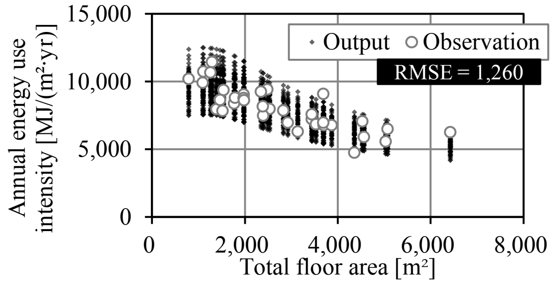


Figure 11 Simulation result calculated based on posterior distributions

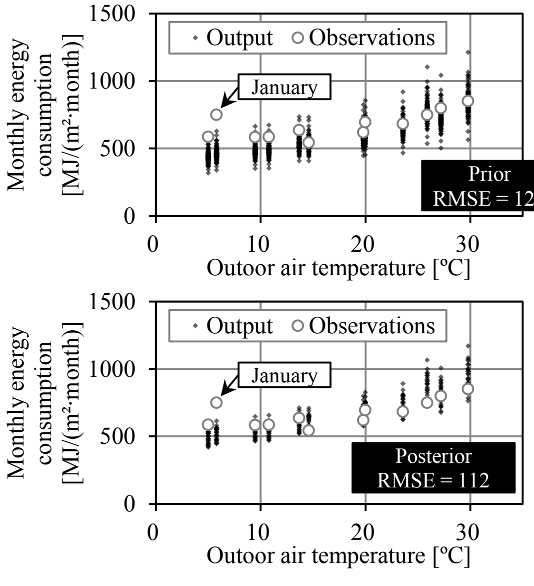


Figure 12 Mean monthly energy consumption of the 35 food supermarkets estimated using the prior and posterior distributions

ESTIMATION OF TOTAL ENERGY CONSUMPTION OF THE WHOLE FOOD SUPERMARKET BUILDING STOCK

The total energy consumption of the whole food supermarket stock was estimated by using the posterior distributions gained for the four calibration parameters. Figure 13 shows the estimated mean energy use intensity and its composition. It was estimated to be 8,000 MJ/(m²·yr) and more than 50% is occupied by energy consumption for refrigeration. Figure 14 shows the distribution of estimated primary energy use intensity among the food supermarket stock in Hyogo prefecture. Based on this result, the total energy consumption in the prefecture was estimated to be 9.1±0.1 PJ/year for the food supermarket stock with total floor area of 1,154 thousand m².

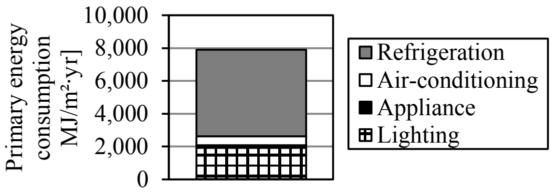


Figure 13 Calculated mean EUI of food supermarkets

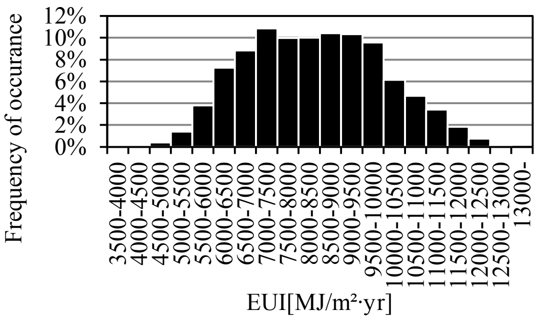


Figure 14 Estimated total energy consumption

CONCLUSION

This paper proposed a methodology to develop an urban scale model of energy use of buildings. This methodology addresses the diversity in energy use through two different approaches: classification of the building stock and archetype modelling; and Bayesian calibration, producing a probability distribution for the uncertain input model parameters for each building stock category. We especially focused on the calibration process and proposed a hierarchical calibration in order to develop probability distributions applicable to a number of simulation outputs with different time resolutions.

The proposed methodology was applied to a food supermarket building stock in Hyogo prefecture in Japan. The results generally showed that the methodology significantly reduce uncertainty in the simulation output of the urban scale food supermarket model. The root mean square error calculated for 35 existing food supermarkets was improved from 1,950, which was calculated based on prior knowledge, to 1,260 MJ/(m²•yr).

However, we have not validated that the probability distributions given by the parameter calibration reflect the actual condition. This validation will be done as part of a future study.

ACKNOWLEDGEMENT

This work is supported by Grants-in-Aid for Scientific Research, Japan Society for the Promotion of Science No. 23760550 and 22360237.

REFERENCES

Booth A.T., Choudhary R., Spiegelhalter D.J.. 2012. Handling uncertainty in housing stock models. Building and Environment, vol. 48, pp. 35-47.

Heo Y., Choudhary R., Augenbroe G.A. 2012. Calibration of building energy models for retrofit analysis under uncertainty. Energy and Buildings, vol 47, pp. 550-560.

Kennedy M.C., O'Hagan A. 2001. Bayesian calibration of computer models. Journal of Royal Statistical Society B. vol. 63, pp.425-464.

Macdonald, I. 2009. Comparison of sampling techniques on the performance of Monte-Carlo based sensitivity analysis. In 11th International IBPSA Conference, pp. 992–999, Glasgow.

Matsuoka, A., Yamaguchi, Y. Suzuki, Y., Shimoda, Y. 2013. Urban-scale Modelling of Energy Demand of Retail Facilities. The Proceedings of the Building Simulation 2013.

Morris M.D. 1991. Factorial Sampling Plans for Preliminary Computational Experiments. Technometrics. vol.33, pp.161-174.

Suzuki, Y., Yamaguchi, Y. Shiraishi, K., Narumi, D., Shimoda, Y. 2011. Analysis and modeling of energy demand of retail stores. The Proceedings of the Building Simulation 2011, pp. 1824-1831.

Swan LG., Ugursal V.I. 2009. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. Renewable and Sustainable Energy Reviews, vol 13,pp. 1819-1835.

Yamaguchi Y., Shimoda Y. 2010. District-scale Simulation for Multi-purpose Evaluation of Urban Energy Systems. Journal of Building Performance Simulation. vol. 3, pp. 289-305.

Yamaguchi Y. et al. 2012. Classification of Japanese Retail Facilities to Establish Benchmark Energy Consumption, Proceedings of ACEEE Summer Study 2012. San Francisco.

Wit De M. S. 1997. Identification of the important parameters in thermal building simulation models, Journal of statistical computation and simulation, Vol. 57, pp. 305-320