Review of the methodology and challenge in the modelling of home appliance operation

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ABSTRACT
This paper presents a review of the methodology for modelling the operation of home appliances as an important component of models of residential electricity demand. There have been a number of bottom-up models in which electricity consumption of home appliances is stochastically simulated. The review especially focused on the occurrence of switch-on event developed in these bottom-up models. The authors recognized four types of modelling methodology. One develops a model based on empirical data of appliance operation, whereas the other three use time use data. The authors briefly explain the features of the methodologies and address six issues that have a significant impact on the accuracy of models. Empirical evidence showed that more research is needed to address these issues.

KEYWORDS
Occupant behavior, appliance operation, residential building, stochastic modelling

INTRODUCTION
There have been a number of models that estimate residential electricity load curve at a variety of time resolution from a few hours to 1-min. Fischer, Härtl and Wille-Haussmann (2015) divided models of the residential electricity demand into two groups: statistical model and bottom-up model. Statistical models are basically data-driven in which the behavior of electricity demand observed in the measured data is reproduced by using statistical techniques. The drawback of the statistical models is that the system determining energy demand is dealt with as black box. This issue can be overcome by the bottom-up approach. In the bottom-up approach, the total electricity demand is modelled as sum of the consumption of individual appliances. To replicate dynamic behavior of electricity demand, stochastic models have been employed for the behavior of household members including the presence and activity at home as well as the appliance operation.

The existing stochastic models considering the occupant behavior generally have the structure shown in Figure 1. First, the occurrence of switch-on event is stochastically determined by using the probability of the occurrence of switch-on event, $p_{switch\text{-}on}$. Then, the operation mode of appliance after the occurrence of switch-on event is determined. The most typical operation modes are ON mode,

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standby mode and OFF mode. More complicated conversion schemes have been proposed to address the characteristics of home appliances (Widén at el. 2009, Caprino et al. 2014, Gruber et al. 2014). Finally, the electricity consumption of considered appliances is determined based on a given specification of appliance corresponding to the operation modes.

There are three variations in the input of the switch on probability, $p_{switch\text{-}on}$. They are the time of day, the number of active household members who are being at home and wake, and the activity of individual household members.

This paper focuses on the modelling of the switch-on probability. The purpose of this paper is to present the methodologies that have been developed in published articles and to describe issues in the appliance operation modelling. After presenting the methodologies in Chapter 2, we raise 6 issues in Chapter 3. Chapter 4 evaluates the importance of the issues by using empirical data related to the operation of clothes washer collected in Japan. Chapter 5 concludes this paper.

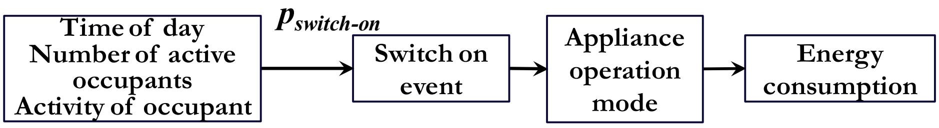

Figure 1. *Structure of models of energy consumption of appliances*

MODELLING OF APPLIANCE OPERATION

Grandjean, Adnot and Binet (2012) presented a review of published residential electric load curve models and classified models into the five types. In their classification, the probabilistic empirical model and the time of use (TOU) based model employ the structure shown in Figure 1. In the probabilistic empirical model, the switch-on probability is given for each time of day developed based on measured data. First, the number of switch-on event occurring on the simulated day is determined. Then, the time at which the switch-on events occur is determined by using the switch-on probability. The previous studies have developed methodologies to reflect the difference in the switch-on probability due to the day of week, household socio-economic and demographic conditions (Paatero and Lund 2005, Ortiz et al. 2014, Gruber et al. 2014). We refer to this model as the empirical operation data based time-dependent switch-on probability model.

Fischer, Härtl and Wille-Haussmann (2015) developed a method to calculate the switch-on probability at each time of day based on time use data. Based on time use data, the probability at which household members undertake each activity can be developed for each time of day. This probability is used in the same manner as the previous model. Socio-economic and demographic conditions can be considered by classifying time use data by conditions to be considered. We refer to this model as the time use data based time-dependent switch-on probability model.

These two models do not stochastically generate occupant behavior at each time of day. In contrast, the other two models first generate occupant behavior explicitly to be converted to appliance operation (Torriti 2014). Richardson, Thomson and Infield (2008) proposed a discrete time Markov chain model dealing with the number of active household members as transition states. “Active” means that the person is being at home and wake. The transition probability is developed based on time use data collected from households with the corresponding number of household members. Then, the probability of occurrence of activities corresponding to considered appliance, such as cooking for microwave, is first quantified at each time of day based on the number of active household members (Richardson et al. 2010). This probability is then multiplied by so called the calibration scaler. If the calibration scaler is one, the occurrence of switch-on event is examined by the occurrence probability of examined activities. The calibration scaler is used to adjust the total number of switch-on event per year to replicate the annual total electricity consumption of examined home appliance. This approach has a number of applications (Baetens et al. 2012, Santiago et al. 2013 and Palacios-Garcia et al. 2015, Good et al. 2015, McKenna Krawczynski and Thomson 2015). We refer to this model as the family behavior based switch-on probability model.

Widén at el. (2009) proposed another discrete-time Markov chain model in which a number of activities are defined as transition states and the activity of household members are independently simulated. Then the activity is converted to the use of appliances at home (Widén and Wäckelgård 2010, Widén, Molin and Ellegård 2012, Muratori et al. 2013). Wilke et al. (2013) proposed a discrete-event model based on the survival analysis. In this model, the activity of household members is independently simulated by repeating the following two processes: the selection of an activity starting at the first vacant slot and the selection of the duration of the selected activity. Wilke (2013) developed a linear regression model of appliance switch-on probability at each time of day using logit form in which the occurrence probability of each activity is used as explanatory variable. We refer to this model as the individual agent based switch-on probability model.

In summary, the existing modelling approach of appliance operation can be divided into four types. The empirical operation data based and time use data based time-dependent switch-on probability models develop the switch-on probability depending on the time of day. The former uses measured switch-on event data, while the other uses time use data to develop switch-on probability. Whereas these two model does not simulate the presence or activity of household members, the other two models stochastically simulate them. In the family behavior based switch-on probability model, the number of active household members is used as input variable, while the activity of each household member is used in the individual agent based switch-on probability model.

ISSUES IN THE APPLIANCE OPERATION MODELLING

Based on the published articles related to appliance operation, we found 6 issues that might have a significant impact on the accuracy of the simulation model as listed below.

1) Consideration of individual specificity

Torriti (2014) raised the lack of individual specificity as an important issue in the residential energy demand models using time use data. The three models using time use data suffer from this issue. Time use data is usually collected from a large number of people and a limited number of days. Thus, it is difficult to replicate intra-household variation in the occurrence time of activities. In contrast, the empirical operation data based model is able to replicate household specific characteristics in appliance operation if the switch-on probability is developed based on data collected from a specific household.

2) Consideration of the influence of socio-economic and demographic conditions

It is well known that the socio-economic and demographic conditions significantly differentiate the time use of household members. It is also true for the interaction among household members. The interaction among household members involves the sharing of space, time and appliances, as well as the coordination among household members to use a limited household resources, such as bathroom. The empirical operation data based switch-on probability model naturally involves the influence. The models using time use data are capable of considering the influence by using time use data classified by the condition to be considered (e.g. Fischer's model and Richardson's model) or developing regression models considering the condition (e.g. Wilke 2013). In the individual agent based switch-on probability model, Collin et al. (2014) proposed a probabilistic approach to consider sharing among household members by using "with whom" information collected in time use survey.

3) Time resolution of the model

Borg and Kelly (2011) presented an empirical operation data based model that quantifies electricity consumption at 1-min resolution. The model first calculates 1-hour resolution profile of considered appliance. This data is then converted to 1-min resolution data by calculating the duration of appliance operation while considering the power level of appliance at the ON mode. The beginning time of operation is randomly selected within the hour in which appliance is operated. This method to increase the temporal resolution is beneficial to replicate realistic behavior of electricity consumption of appliances.

4) Applicability to a variety of context

The development of the empirical operation data based model needs empirical data of appliance operation. It makes developed models difficult to be applied to entire housing stock in a region or nation, if the empirical data was not collected from sample representing the population. In contrast, the time use data based models are able to represent the time use of entire population because time use survey is usually designed so that time use data represent the entire population in a region or nation.

5) Quantification of the conversion factor from activity to appliance switch-on event occurrence

The last two issues are related to data availability in the development of the models using time use data. The models need the conversion probability from the occurrence of activity to the appliance switch-on event or the probability of occurrence of activity to it. We refer to this as conversion factor. As in the Richardson's model, some models use a constant value over time for the conversion factor. However, this approach ignores the variation in the conversion factor over the time of day. If hourly electricity consumption is available, the conversion factor can be estimated for each time of day. However, it is rare that coherent data are available both on people's activity and appliance operation.

6) Resolution of time use data

The last issue is related to the resolution of time use data. Each time use survey uses different definition of activities. For example, the Japanese national time use survey uses two survey formats (Statistics Bureau of Japan 2006). One classifies activities into 20 kinds, while the other classifies activities into approximately 100 kinds. In the latter format, the household maintenance, which is one of the 20 activities of the former format, is classified into 14 kinds. Thus, activities that link more directly to appliance operation can be assumed in the model. This is beneficial because the conversion factor from activity to appliance operation can be kept high and constant over the time of day.

EVALUATION OF THE IMPACT OF THE ISSUES

This chapter evaluates the importance of the first, forth, fifth and sixth issues by using empirical data related to the operation of clothes washer.

Analysis of inter/intra-household variation

By using measured electricity consumption of clothes washer from 557 households living in a multi-family building in Osaka, the statistical distribution of the beginning time of the operation of clothes washer was developed for each household. The measurement was conducted through the entire year in 2013 at the 1-min resolution. In order to evaluate the degree of concentration of the beginning time, entropy defined in Equation 1 was calculated (Kwac, Flora, and Rajagopal 2014), where *p(t)* is the ratio of the occurrence of switch-on event at each time of day, *t*, summarized using 1-hour interval.

$$Entropy = \sum_{t=0}^{23} p(t) \log p(t) \tag{1}$$

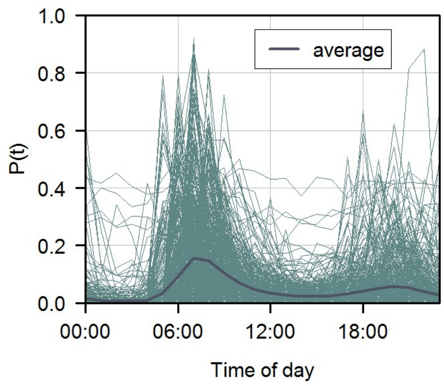

Figure 2. Distributions of the operation beginning time of 557 households

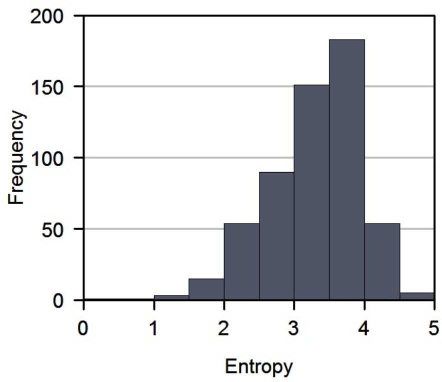

Figure 3. Distribution of the entropy

Figure 2 shows the distribution of the beginning time of operation. Each line shows the result of a household. The figure also shows the average at each time of day by the black bold line. The average represents the inter-household variation of the operation beginning time. The entropy of the average is 4.5. Figure 3 shows the distributions of the entropy of all households. The entropy of the households distributes in smaller region than that of the average. This means that the intra-household variation is smaller than inter-household variation. In order to replicate household specific characteristics in appliance operation, a methodology must be established to distinguish intra/inter household variations, in the model is applied to a context in which individual specificity is important.

Applicability to a variety of context

The models using time use data need the conversion factor from activity related information to appliance operation, as mentioned above. This section evaluates how the applicability of conversion factor is problematic. Two data are used for the evaluation. One is the average of the switch-on probability of clothes washer shown in Figure 2. The other is the time use for laundry observed in the time use data collected in the Japanese national time use survey (Statistics Bureau of Japan 2006).

Figure 4 shows three data. The blue and red lines show the probability of the occurrence of laundry activity observed in the time use of full-time housewife (N=609) and working female (N=1911). The black line shows the switch-on probability at each time of day observed in the measured data. Here we assumed that the conversion factor is proportional to the ratio of the two data, the switch-on probability divided by the laundry time use. However, the time use data of full-time housewife and working female show different time variation with the switch-on probability. Thus, the measured data seems to be inconsistent with the time use data.

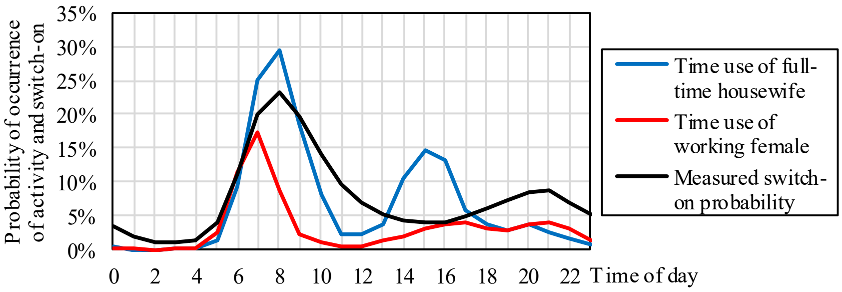

Figure 4. Estimated conversion factor consumption

Time variation in the conversion factor and resolution of time use data

This section evaluates the time variation in the conversion factor and a method to address the time variation. The authors carried out a questionnaire survey in 2012 in which the respondents were asked to report their time allocation for activities related to laundry on typical weekdays. Figure 5 shows the composition of the laundry related activities collected from 167 women who conduct laundry in their daily life. The result showed that clothes washers are more often operated in the morning than in the afternoon. After the operation of clothes washer, most respondents reported to do hanging clothes outside. They reported that ironing and folding of clothes are done in the late afternoon or evening. Figure 6 shows the conversion factor from the laundry activity to the operation of clothes washer calculated based on the result shown in Figure 5. This result implies that it is important to consider the time variation of the conversion factor.

However, it is not easy to detect an appropriate conversion factor based on available data as shown in Figure 4. One possible solution is to disaggregate an activity into several subcategories so that activities can be directly converted to appliance operation. As shown in Figure 6, the ratio is high in the morning and decreases in the afternoon until 6 pm. This is because an activity for laundry does not always accompanies the operation of clothes washer especially in the afternoon. Thus, it is useful to distinguish subcategories of activity, though additional survey is needed.

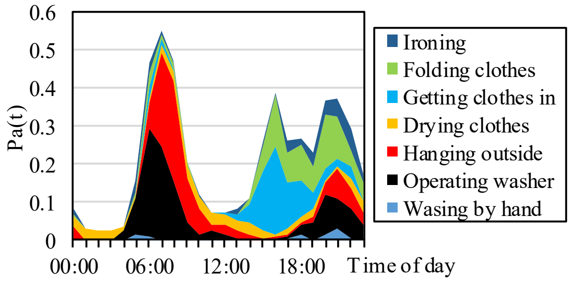

Figure 5. Composition of laundry activity

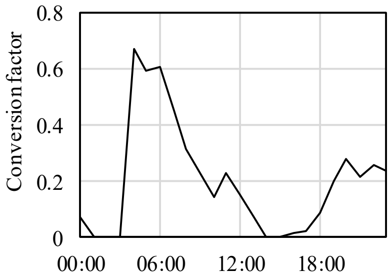

Figure 6. Estimated conversion factor

CONCLUSION AND IMPLICATIONS

This paper presented a review on the existing models of appliance operation. Based on the review, the authors raised 6 issues that potentially have a significant impact on the accuracy of the model. The first issue, the consideration of individual specificity, has been ignored in the models using time use data. This issue should be considered especially in community scale energy demand modelling where household specific time-dependent characteristics in electricity demand is meaningful. Regarding the second and third issues, the consideration of the influence of socio-economic and demographic conditions and the time resolution of the model, a number of methods have been established. The empirical data based modelling has difficulty in addressing the forth issue, the applicability of the model to a variety of context, as the empirical analysis showed that measured electricity consumption of clothes washer was not consistent with the Japanese time use data. The fifth and sixth issues are related to the development of the conversion factor from the occurrence of activity to the switch-on event. The empirical data showed that there is a time variation in the conversion factor. Ignorance of its time variation results in an error in the time variation of electricity demand. However, it is not easy to develop it consistent with time use data used to develop models. One possible solution is to increase the resolution of time use data by distinguishing subcategories of activity so that activities can be directly converted to appliance operation. More research is needed in the six issues to establish the modelling methodology for appliance operation.

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