A cross-analysis of existing methods for modelling household appliance use

This paper presents a cross-analysis of the existing methods for modelling the use of household appliances and aims to provide insights into modelling approaches for researchers and designers. Five factors regarding appliance use modelling that have a significant impact on the modelling performance are defined: consideration of the intra/inter-household variation, consideration of the influence of socio-demographic conditions, time resolution of the data, quantification of model calibration parameters and applicability to a variety of modelling contexts. Four existing modelling methods commonly used in literature for modelling appliance use are studied to address these factors. Monitored data of 333 multi-family buildings in Japan and a Japanese time use survey are used in the cross-analysis to simulate the switch-on time profiles for the case of washing machines. The design of future research studies (including monitoring strategies, modelling and sample sizes) are discussed to further improve the ability to model home appliance use.

Keywords: Occupant behaviour; activity modelling; appliance use; residential building; stochastic modelling

1. Introduction

Modelling residential electricity demand has received significant interest from researchers worldwide for use in building simulations. Researchers have published their methods developed to predict the temporal evolution of the electricity demand with different time and space scale considerations (Grandjean et al., 2012). Several examples of residential electricity demand models are used for the studies of i) better prediction of the time variations of the demand and the peak power demand to analyse the impact of energy efficiency schemes or demand response (Paatero and Lund, 2010; Gottwalt et al., 2011; Fujimoto et al., 2017); ii) planning and performance of local energy systems and emerging technologies (Yao and Steemers, 2005); iii) building performance for low-carbon buildings due to heat gains from the appliances (Hoes et al., 2009) and (iv) the impacts of Electric Vehicle charging and discharging on residential demand profiles at specific times (Grahn et al., 2013).

Household electrical appliances can be classified into three groups according to their use by occupants (Firth et al., 2008). Appliances in the first group operate for all day without any intervention by occupants such as refrigerators and network routers. The second group involves appliances that are operated by the occupants when they perform certain activities. These appliances deliver a function or service necessary for activities. Examples include washing machines for laundry activity, microwave and oven for cooking, and TV for entertainment. The third group involves, heating, air-conditioning and lighting that are operated to control the indoor environment depending on the presence of household members. Using electrical appliances impacts on the timing and magnitude of a household's overall electricity consumption. Electricity consumption of individual appliances depends on the different operation modes such as ON, OFF and stand-by, and the electricity consumed during each mode. Wet appliances such as washing machines and dishwashers have cycles with several high peaks during different stages of the cycle. Air-conditioners have time-varying electricity consumption as they have a function to control delivered service depending on the indoor environment.

The structure in which residential electricity demand can be modelled hierarchically consists of the following four levels of inputs: 1) the whole household electricity demand; 2) electricity consumption of each appliance; 3) the mode and power demand of appliances; and 4) the activity and presence of household members. Data-driven models are used to model the electricity consumption of the residential sector when the input is the whole household electricity consumption or that of each appliance in which the behaviour of electricity demand observed in the measured data is reproduced by using statistical techniques (Swan and Ugursal, 2008; Fischer et al., 2015). Several studies model the electricity consumption of the residential sector in a more detailed bottom-up approach using the latter two inputs. These models use numerous engineering and stochastic methods to account for the electricity consumption of individual appliances and model the activity and/or presence/absence of household members to determine which and when appliances are used (Grandjean et al. 2012).

A considerable variation is found in the methodology of modelling the occurrence of appliance switch-on events. Each model is unique in terms of statistical representation, input data necessary for modelling and resultant model performance. However, these models have not been evaluated under the same application conditions (Gaetani et al. 2016). The purpose of this paper is to compare the existing methods which us the detailed bottom-up approach that has been developed and to describe issues and challenges in appliance use modelling considering the second group of appliance types mentioned above. The washing machine is chosen as an example from the second group appliances. Cross-analysis using washing machines is useful because their appliance use can be accurately extracted from measured data, the relationship between appliance use and activity driving the use is relatively clear, and the washing machine itself has been recognised as an important appliance with great potential for demand response and energy management (e.g. Kobus et al. 2015, D'hulst et al. 2015). When doing cross-analysis, it is important to test the different methods using the same underlying data. In this case for cross-analysis, the models are calibrated using two datasets which are monitored data of 333 multi-family buildings in Minamisenrioka and the Japanese time use survey. Switch-on time profiles are simulated and results from the simulations are analysed and compared to evaluate the strengths and limitations of the presented models and provide insights into the future development of appliance use modelling. The existing methods for modelling appliance use are described in Section 2; issues for modelling appliance use are raised and evidence from literature is given in Section 3; datasets used to develop the models, model performance indicators and methods used to evaluate the modelling performance are presented in detail in Section 4; Section 5 presents the evaluation of these issues using the existing methods and by using our own dataset; Section 6 provides discussion and Section 7 concludes the paper.

2. Modelling approaches for appliance use

In this paper, appliance use modelling methods used in the literature are categorised based on how the switch-on of appliances in households is modelled. It is divided into four categories, as illustrated in Figure 1, which are 1) the empirical data based time-dependent switch-on probability model; 2) the TUD (time use data) based time-dependent switch-on probability model; 3) the household occupancy based switch-on probability model and 4) the individual agent activity based appliance use model. Model types 1 and 2 use switch-on probability depending on the time of day to which a uniform random number is generated to determine the occurrence of an appliance switch-on event. However, they use different types of datasets to quantify switch-on probability, namely; empirical data (recorded power demand) and TUD. In model types 3 and 4, the presence or activity of occupants are explicitly simulated. In model type 3, the number of active occupants, who are at home and awake, is randomly generated, and is then used to quantify appliance switch-on probability. In model type 4, switch-on probability is not quantified. Instead, activity of household members is first stochastically generated. Then, the activity is converted to the occurrence of a switch-on event.

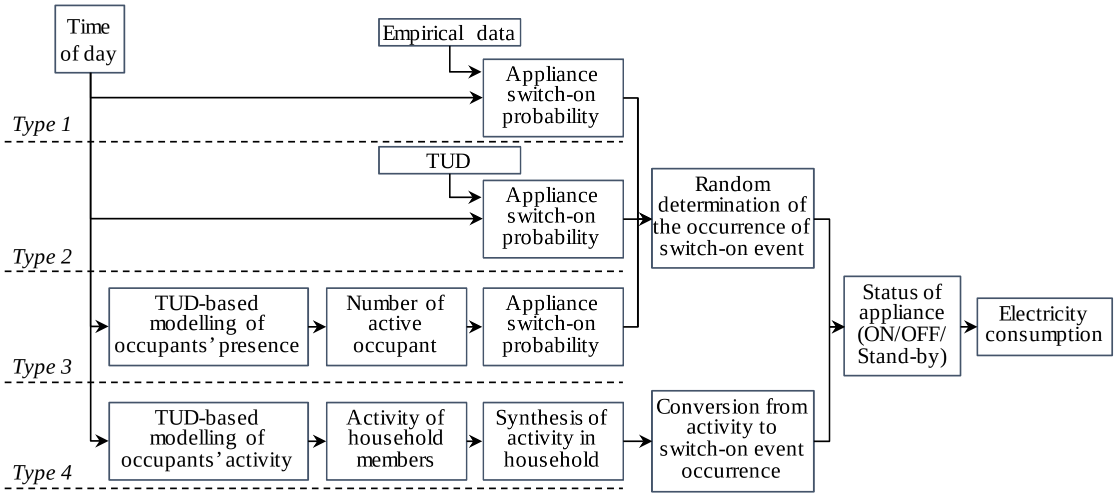


Figure 1. Procedure for modelling appliance use according to model types

Examples of studies in literature for each model type and their methodology are presented in detail below:

Model type 1: The empirical data based time-dependent switch-on probability model

In the probabilistic empirical model, a switch-on event is defined as the start of the use of an appliance and is considered as a time-dependent quantity. The switch-on times are identified from power demand measurements of appliances. For each time step the switch-on probability would be the sum of measured "switches on" observed divided by the total number of days. Example studies using this approach are Paatero and Lund (2006), Page (2007), Gruber et al. (2014) and Yilmaz et. al. (2017). The method of Yilmaz et al. (2017) constructs a cdf (cumulative distribution function) for the number of switch-on events for every household. Then the number of switch-on events is assigned individually for every day using this cdf. This improves the accuracy of modelling in terms of the daily number of switch-on events and also includes the variation of the number of switch-on events during different days within the same household.

Model type 2: The TUD based time-dependent switch-on probability model

Fischer et al. (2015) developed a method to calculate the switch-on probability based on TUD that determines how frequently an appliance is operated at each time of day. This probability is used in the same manner as the model type 1. López-Rodríguez et al. (2013) also developed a similar model.

Model type 3: The household occupancy based switch-on probability model

Richardson et al. (2010) proposed a discrete time Markov chain that generates the number of active people for a day. The switch-on probability is assumed to be proportional to the probability of occurrence of activity corresponding to the considered appliance (e.g. cooking for microwave) and the so-called calibration scalar. The probability of activity occurrence is quantified for each time of day based on TUD corresponding to the number of active people in the household. The calibration scalar is used to adjust the total number of switch-on events per year to replicate the annual total electricity consumption of the appliance. This approach has a number of applications (Baetens et al. 2016, Cao and Sirén 2015, Evins, Orehounig, and Dorer 2015, Good et al. 2015, McKenna, Krawczynski and Thomson 2015). One of the weaknesses of Richardson's model is that the variation in the number of switch-on events per day cannot be replicated because switch-on events occur as a result of random trials made at each time step. Flett and Kelly (2017) overcome this weakness by first determining the number of switch-on events on the simulated day based on empirical data. The switch-on events are then allocated to the timeline by considering occupancy.

Model type 4: The individual agent activity based appliance use model

This model type explicitly simulates the activity of household members. The activity is then converted to the occurrence of switch-on events. There are two studies which can be considered for this model type. First, Widén at el. (2010, 2012) proposed a discrete-time Markov chain model in which a number of activities are defined as transition states. Secondly, Wilke et al. (2013) proposed a discrete event model in which the activity of household members is simulated by repeating the following two processes: the selection of an activity starting from the examined time of day and the selection of the duration of the selected activity. For the selection of activity, the starting probability, at which each considered activity starts, is calculated by multinomial logit models developed for each time of day. Yamaguchi et al. (2017) and Tanimoto et al. (2010) developed a similar discrete event model. The occurrence of an appliance switch-on event is examined in relation to the stochastically determined activity. We consider the activity-based switch-on probability that indicates how frequently a switch-on event occurs when an activity is undertaken. This has not been discussed in the previous papers. For example, Widén et al. (2010, 2012) assumed the probability to be 1 as the washing machines are switched-on when the activity finishes. In addition to such discrete-event modelling, the probability can be defined for discrete-time trials in which the occurrence of a switch-on event is examined at each time step while the activity is being undertaken.

3. Application context and factors in appliance use modelling

This section classifies the application context of appliance use models and related factors that could have a significant impact on the model performance. Table 1 lists the papers based on their application context. In order to classify the application context, we studied papers using one of the four model types. Application contexts of the appliance use models were classified by (A) availability of empirical data by which models were developed. Empirical data is available in terms of time series, hourly mean and annual total. The second classification is (B) application target to which developed models were applied. The application target was classified as internal or external. For internal application, target households were those from which empirical data was collected. For external application, some papers normalized influences of factors that significantly affect appliance use (e.g. socio-demographic conditions), so that the effect of influencing factors can be taken into account in simulation results when models were applied to an external context. Thus, the availability of influencing factors of households from which empirical data is collected (C), and those to which developed models are applied was recognized as an important aspect of application. The final point is the importance of specificity of individual households (D). In community/urban-scale modelling, the models might be applied to model the group behaviour of appliances used in a number of households without specifying individual households (Taniguchi et al. 2016). On the other hand, individual specificity might be important when models are applied to a specific household.

Based on this understanding of application context, we derived five factors which are i) consideration of the intra/inter-household variation; ii) consideration of the influence of socio-demographic conditions; iii) time resolution of the data; iv) quantification of calibration scalar or activity-based switch-on probability and v) applicability to a variety of contexts. The first factor dealing with intra/inter-household variation is related to (D) importance of household specificity (i.e. characteristics of an individual household). The second factor focuses on households' socio-demographic conditions as one of the most important influencing factors (C). The third and fourth factors are related availability of empirical data (A). The fifth factor considers external application (B). This section presents these five factors in detail and provides evidence from the literature.

Table 1. Classification of the models by their application context

Reference study	**Model type***	**(A) Availability of empirical data**	**(B) Application target**	**(C) Availability of influencing factor**	**(D) Importance of household specificity****
Paatero and Lund 2006	Type 1	Hourly mean	External	Season and various socio-demographics	No
Page 2007	Type 1	Hourly mean	Internal	Individual specificity	Yes
Gruber et al. 2014	Type 1	Time series	External	Appliance ownership	No
Yilmaz et al. 2017	Type 1	Time series	Internal	Individual specificity	Yes
Armstrong et al. 2009	Type 1	Mean hourly	External	Appliance ownership	No
Ortiz et al. 2014	Type 1	Time series	Internal	Region	No
Fisher et al. 2015	Type 2	Not used	External	Household size, household composition, age, housing time and working pattern	No
López-Rodríguez et al. 2013	Type 2	Not used	External	Household size	No
Richardson et a. 2010	Type 3	Annual total	External	Household size	No
Cao et al. 2015	Type 3	Annual total	External	Household size	No
McKenna et al. 2016	Type 3	Annual total	External	Household size	No
Evins et al. 2016	Type 3	Annual total	External	Household size	Yes
Good et al. 2015	Type 3	Annual total	External	Household size	No
Baetens et al. 2015	Type 3	Annual total	External	Household size and occupancy pattern	Yes
Flett and Kelly 2017	Type 3	Time series	External	Various socio-demographic	Yes
Widén et al. 2010	Type 4	Not used	External	Household size and housing type	No
Wilke 2013	Type 4	Time series	External	Various socio-demographic	Yes
Taniguchi et al. 2016	Type 4	Not used	External	Various socio-demographic	Yes

* Model types are explained in Section 2.

** No: not important; Yes: important

3.1 Intra/inter-household variation

Here we define intra-household variation is the difference in occupant behaviour within the household whereas inter-household variation as the difference in daily occupant behaviour among households. The difference between intra- and inter-household variation is often ignored in modelling of energy demand (O'Brien et al., 2016). This might be because individual specificity has not been considered as an important aspect of modelling as shown in Table 1. However, consideration of intra-household variation is important in some applications, such as the planning of micro-generations (Cao and Siren, 2015), because time dependent characteristics of energy demand unique for individual households are created due to intra-household variation.

It is difficult to replicate intra-household variation in the occurrence time of activities in modelling types using TUD (Torriti, 2014). TUD is usually collected from a large number of people and for a limited number of days (Table 2). Therefore, TUD based models fail to capture intra-household variation (Yamaguchi and Shimoda, 2017). In contrast to that, TUD based models are capable of producing inter-household variation generated by socio-demographic conditions. However, Flett and Kelly (2017) revealed that the inter-household variation that can be generated considering socio-demographic conditions is smaller than the variation observed in empirical data.

In contrast, the empirical data based time-dependent switch-on probability model analyses the measured data for an extended period to obtain the frequency and time of occurrence of a switch-on event. This model type is able to capture the intra/inter-household variation as the household has been observed for an extended period and therefore is able to replicate household specific characteristics in appliance use. Table 3 gives several examples of monitored datasets collected using electrical power sensors to develop residential energy demand models.

Table 2. Examples of TUD used to develop residential energy demand models.

Study	Dataset used and year collected	Number of participants	Collection details (resolution)
Yun-hang Chiou et al. (2009)	American Time-Use Survey (2008)	13,000 individuals	One weekday and weekend. (10-minute)
Richardson et al., (2010)	UK Time Use Survey (2000)	10,000 individuals	One weekday and weekend. (10-minute)
Widén et al., (2012)	Statistics Sweden (SCB) (1996)	463 individuals in 179 households	One weekday and weekend. (5-minute)
Wilké et al., (2013)	French Time Use Survey (1999)	15,441 individuals from 7949 households	One weekday and weekend. (10-minute)
Neu et al., (2013)	National Time-Use Survey of Ireland (2005)	1089 individuals from 567 households	One weekday and weekend. (15-minute)

Table 3. Examples of empirical datasets used to develop residential energy demand models.

Study	Collected data	Monitored households and appliances	Monitoring period
Paatero and Lund (2006)	Finnish Load Research Project	702 households	365 days
		1,082 households	143 days
Page (2007)	Own dataset	8 households	8 weeks
Brog et.al. (2011)	REMODECE,	60 households, 778 appliances	2 weeks
Yilmaz et al. (2017)	Household Electricity Survey	225 households, 1,076 appliances	1 month

This section also shows empirical evidence of the existence of intra/inter-household variation. Figure 2 (a) shows the distribution of households for the mean number of switch-on events of washing machines per day on weekdays over the entropy values of switch-on time that were observed in 333 households living in a multi-family building located in Osaka, Japan throughout a year (see Appendix A for the detailed explanation).

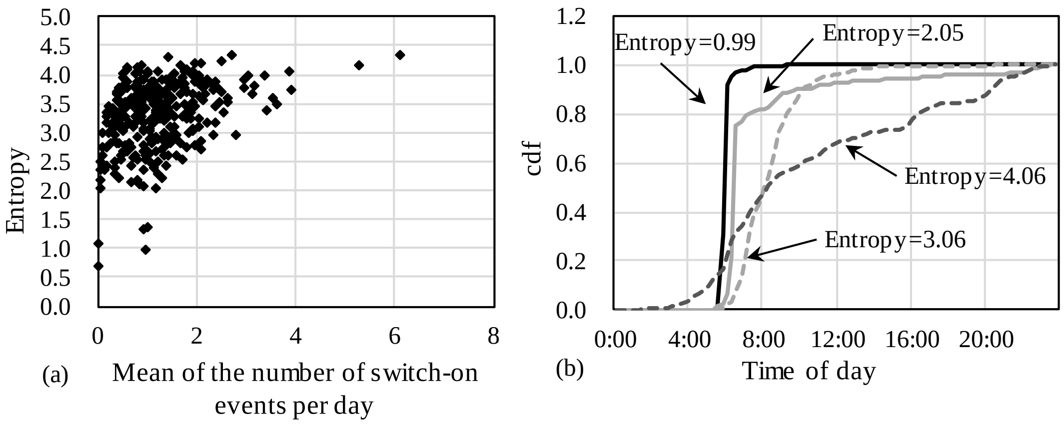


Figure 2 (a) Distribution of mean of the number of switch-on events per day over the entropy of switch-on time of washing machine observed in Minamisenrioka Electricity Use (N = 333, see Appendix A); (b) cdfs of switch-on probability of four representative households with different entropy value of switch-on time

Kwac et al. (2014) used entropy to represent intra-household variation. The definition is given by Equation (1) where *p(t)* is the pdf (probability distribution function) of switch-on probability at each time of day, *t*, summarised using 15-minute interval.

$$Entropy = -\sum_{t=1}^{96} p(t) \log p(t) \tag{1}$$

Entropy is highest if all the cluster centres are equally likely in the dataset and lowest if the household follows a single cluster centre. The lower the entropy, the higher the concentration of switch-on time within limited times of day. It can be seen from Figure 2(a) that there is a significant variation in the number of switch-on events per day and in the concentration of switch-on time among households as represented by the entropy value. Figure 2(b) shows switch-on time cdf of four representative households with an entropy value ranging from approximately 1 to 4. Such intra/inter-household variation cannot be reproduced by TUD based models. In contrast, empirical data based models are capable of replicating both intra/inter-household variations.

3.2 Consideration of the influence of socio-demographic conditions

Several studies show that the socio-demographic conditions give rise to significant differences in time use of household members (López-Rodríguez et al. 2013; Santiago et al. 2014; Jones et al., 2015; Fisher et al. 2015; Sekar et al., 2016; Matsumoto 2016). Thus, the normalisation of developed models by the socio-demographic conditions improves the model performance when models are applied to an external context. The models using TUD are capable of considering the influence by using TUD classified by the condition to be considered. Richardson et al. (2010) classified households by household size. Fischer et al. (2015) and Baetens and Salenes (2016) classified households by household size and occupancy pattern (Aerts, 2014; Widén et al. (2010) considered the housing type (detached house or apartment). Wilke et al. (2013) considered various socio-demographic conditions as predictor variables of their regression models. For empirical data based models, the previous studies simply divided their data points into groups to reflect the difference in the switch-on probability due to the day of week, household socio-demographic condition (Paatero and Lund, 2006; Ortiz et al., 2014). However, due to the high cost of monitoring, the sample sizes of these studies are too small to perform meaningful statistical comparisons. Therefore, it is difficult for the empirical data based models to capture behavioural diversity among different socio-demographic groups.

3.3 Time resolution of data

The data time resolution is important in order to accurately represent peak demands and cycling of individual appliances (Wright and Firth, 2007). There is a considerable loss of detail at lower time resolutions such as 5 and 15-minutes (Richardson, 2010). For example, kettles and microwaves have high demands for a short time period, while for a washing machine the power demand is not constant throughout the cycle. The cycle shows a high peak at the start (up to 2000W) and an increase at the end of the cycle while spinning (Bilton et al., 2014). It is important to determine the precise appliance switch-on times to allocate the peaks and cycles accurately in the high-resolution electricity models. The models which use TUD cannot identify the switch-on times precisely as users write down their daily activities every 10 or 15 minutes. In addition, the laundry activity in TUD could consist of different sub-activities such as sorting out the clothes, loading the machine and so on. Therefore, it is not possible to derive the exact switch-on time of the washing machine, which could hinder the model accuracy. Widén and Wäckelgård (2010) assume that the washing machine switches on at the end of the laundry activity, which may not be the case in reality.

3.4 Quantification of calibration scalar and activity-based switch-on probability

The calibration scalar of the household occupancy based switch-on probability model shows the ratio between the occurrence of a switch-on event over the probability at which an activity is being undertaken under simulated occupancy conditions. The activity-based switch-on probability of the individual agent activity based appliance use model indicates the frequency of use when an activity is undertaken. Both are quantified by using empirical data of appliance switch-on.

Although both factors are important for modelling appliance use accurately, less attention has been paid to them. This might be due to unavailability of time series data as shown in Table 1. Studies such as Widén et al. (2010) assume that every time an activity is performed, the appliance related to that activity is switched-on (activity-based switch-on probability =1) as mentioned above. Richardson et al. (2010) takes an approach where a constant calibration scalar for each appliance is allocated which is used to calibrate the switch-on probability to ensure that each appliance is used a particular number of times per year to meet its contribution level to the overall annual total number of uses and electricity consumption. However, this may not be the case.

Yamaguchi et al. (2016) carried out a questionnaire survey in which the respondents were asked to report their time allocation for laundry related activities on typical weekdays. Figure 3 shows the survey format and the composition of laundry related activities collected from 167 women. In the format, laundry related activities are listed in the first column and the timeline of a day is indicated horizontally with 1-hour intervals. As can be seen from the composition, an activity for laundry does not always imply the use of a washing machine especially in the afternoon. The results show that washing machines are more often operated in the morning than in the afternoon. After the use of the washing machine, most respondents reported hanging clothes outside and laundry activity more associated with folding and ironing the washed clothes in the evenings. This indicates that the constant factor suggested by Widén (2010) and Richardson et al. (2010) can be improved so as to have more accurate factors representing activities throughout the day to match the switch-on probabilities with the daily profile.

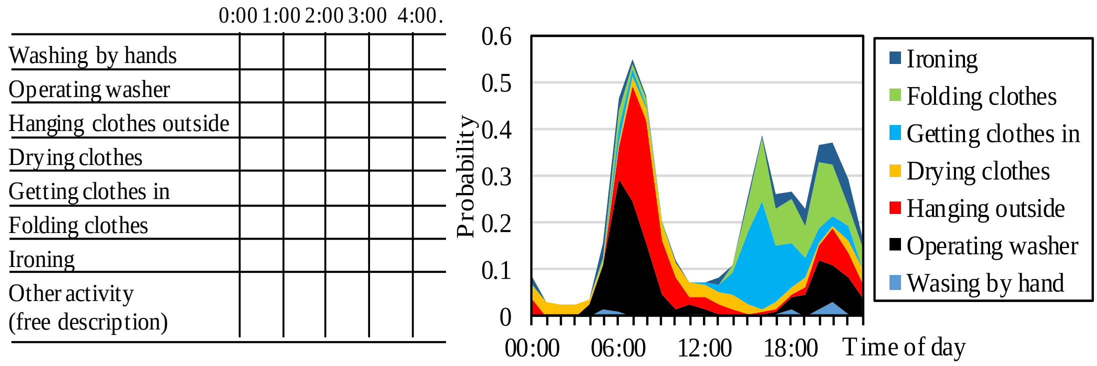


Figure 3. Survey format (left) and composition of laundry activity (right) (Yamaguchi et al. 2016)

3.5 Applicability to a variety of contexts

This last factor is an issue of external application of developed models. As listed in Table 1, most models in the table are applied externally. As mentioned in Section 3.1, the empirical data based models are capable of replicating intra/inter-household variation in appliance use. However, empirical data cannot be simply extended because the number of households from which empirical data is provided is usually limited (Table 3). On the other hand, TUD based models might be applicable to various contexts as TUD is usually collected so that it represents the entire population in a region or nation. This is a useful advantage in community/urban-scale energy demand modelling. However, TUD based models require households to be simulated. The TUD, households, and calibration scalar or activity-based switch-on probability should all be consistent to replicate appliance use accurately.

4. Method

4.1 Datasets

Table 4 gives a detailed description of the three datasets that were used as input for the modelling approaches presented. A detailed explanation of the Minamisenrioka Electricity Use data is provided in Appendix A.

Table 4. Description of datasets

Dataset name	Dataset variables	Description
Minamisenrioka Electricity Use (2014)	Power demand of washing machines and of total house	5-minute resolution 333 households monitored between January 2012 to December 2014 (3 years) All home-owners and families.
Japanese TUD (2006)	Diaries of activities Demographic condition of respondents	Time use survey conducted in 2005. 18,291 diaries collected from people aged 10 or older in 3,866 households. Survey participants were asked to describe their main activity at 15-min intervals over two sequential days Activity described in diary was converted to activity code
Japanese Census (2010 and 2015)	see Table 5.	Data collected in National Census conducted in Year 2010 and 2015 was used.

Japanese TUD was used to apply the TUD based models. For TUD based models, it was necessary to assume socio-demographic conditions of simulated households. The data listed in Table 5 collected by the Japanese Census is used for this study. The first three data items are available for Minamisenrioka, while the others are for Settsu city and Osaka prefecture in which Minamisenrioka is located. Based on this data, 877 households were randomly sampled to represent the households living in Minamisenrioka. The methodology to define the households is given in Appendix C.

Table 5. Data items developed from on the Japanese Census used for assuming socio-demographic conditions of households in Minamisenrioka.

Item		**Contents**	**Area**
1	$Page_{m,y}$ $Page_{f,y}$	Pdf of number of male (*m*) and female (*f*) within age groups (*y*).	Minamisenrioka
2	Phs_n	Pdf of households larger than 3 classified by the household size (*n*)	
3	*Phc*	Number of households classified by the household composition	
4	*Pca*	Pdf of households with the combination of children classified by age	Settsu city
5	$Pflf_{k,ac}$	Labour force participation ratio of female with children classified by the number of children (*k*) and the age of youngest child (*ac*).	
6	$Ppa_{k,am,af}$	Two dimension pdf considering the age of couple (*am* and *af*) when their youngest child was born classified by *k*	Osaka prefecture
7	$Plf_{st,am}$ $Plf_{st,af}$	Labour force status (*st*: fulltime, part time, and unemployed) distinguished by *am* and *af*.	
8	Pad_d	Pdf of the age difference between married couple.	

4.2 Model performance indicators

In this section, indicators to evaluate the model performance are summarised. The performance is evaluated by comparing the switch-on probabilities, which indicates the ratio of households that start using a washing machine to the total number of households at each time of day, and the number of switch-on events per day. The model can serve different purposes therefore some indicators had to be defined to evaluate the model performance as summarised in Section 4.3.

4.2.1 Indicator 1: Mean relative population share deviation

The value of this indicator lies in showing how well/adequately the model performs regarding total predictions of the population average. A similar approach to Wilke et al. (2013) is taken to calculate the indicator. The indicator in Equation 2 shows the magnitude of the differences between the result estimated by the models (X_{sim}) and reference value (X_{ref}).

$$D = \frac{1}{M}\sum_{m=1}^{M}\left|X_{sim,m} - X_{ref,m}\right| \qquad (2)$$

When switch-on probabilities are compared, switch-on probability quantified with 15-min intervals is used as X_{sim} and X_{ref} where m = 1 to 96. This "deviation" (*D)* is referred to as the "deviation in probability" (*DP)*. When the number of switch-on events is compared, the cdf of households developed from the mean number of switch-on events per day is used as X_{sim} and X_{ref}.. This "deviation" (*D)* is referred as the "deviation in switch-on events" (*DS)*. The cdf is quantified with an interval of 0.1 times per day. X_{sim} and X_{ref} of three times per day or more is summarized (m = 1 to 30). The possible range of the value set of deviations (both "DP" and "DS") is bounded between zero and one. The value of D is a measure of the performance of the model (the higher the value, the greater the deviation from the measured value).

4.2.2 Indicator 2: Entropy

Entropy defined by Kwac et al. (2014) shown by Equation (1) in Section 3.1 is used as an indicator to show how well the model performs regarding the representation of the intra-household variation in the measured dataset. A histogram is formed from the entropies calculated for the simulated households.

4.3 Method to evaluate the model performance

Firstly, the performance of the models is evaluated by comparing the switch-on probabilities and the number of switch-on events per day of the simulation to those monitored in 333 households in Minamisenrioka. Mean relative population share deviations defined in Section 4.2, *DP* and *DS*, are used as performance indicators.

The second part evaluates the model performance on the five factors presented in Section 3. Table 6 shows the linking of the modelling methods, datasets used, and indicators for each factor. Model type 2 is not chosen as its methodology is the same as model type 1 (see Section 2). For model type 3, Flett and Kelly's (2017) model was not developed for this study because empirical data with detailed household information was not available. The hourly defined calibration scalar used for Richardson et al. (2010) and hourly defined activity-based switch-on probability used for Widén et al. (2010) and Wilke et al. (2009) are explained in Section 3.4. For Wilke's model, modifications are explained in Appendix B. Switch-on probabilities are calculated directly from the readings of power demand. Calibration scalar is quantified by using household mean of switch-on times per day and hourly switch-on probability. Activity-based switch-on probability is quantified in the same manner as for model type 3.

Table 6. Linking the factors to existing modelling methods, datasets used, indicators as well as modifications done to the models.

Factors	**Methods compared**	**Modifications done to model**	**Dataset used**	**Indicators**
Consideration of intra/inter-household variation	Empirical model : Yilmaz et al. 2017 (Type 1)	-	Minamisenrioka Electricity Use	Entropy and *DS*
	TUD based models: Richardson et al. 2010 (Type 3);	Hourly defined calibration scalar	Japanese TUD, Japanese Census	
	Widén et al. 2010 (Type 4); Wilke et al. 2013 (Type 4)	Hourly defined activity-based switch-on probability		
Consideration of the influence of socio-demographic condition	Wilke et al., 2013 (Type 4)	Hourly defined activity-based switch-on probability	Japanese TUD, Japanese Census	*DS*
Time resolution of data	Empirical model: Yilmaz et al. 2017 (Type 1)	-	Minamisenrioka Electricity Use	*DP*
Quantification of calibration scalar or activity-based switch-on probability	Activity based model: Richardson et al.'s 2010 (Type 3)	Hourly defined calibration scalar	Japanese TUD, Japanese Census	*DP*
Applicability to a variety of contexts	Wilke et al., 2013 (Type 4)	Hourly defined activity-based switch-on probability	Japanese TUD, Japanese Census	*DS*

4.3.1 Intra/inter-household variation

The entropy of the switch-on probabilities simulated by these modelling methods is calculated using Equation 1 to represent the intra-household variation provided by these models. *DS* is used to represent the inter-household variation.

4.3.2 Consideration of the influence of socio-demographic conditions

Minamisenrioka Electricity Use does not contain any socio-demographic condition of households. Thus, the change of appliance use due to demographic conditions cannot be considered for the empirical data based model. In contrast, the TUD based models can take into account the influence of socio-demographic conditions. Wilke's regression model is most adaptable as it considers 16 predictor variables related to socio-demographic conditions as explained in Appendix B. Contrary to this, Richardson's model only considers the household size and Widén's considers the housing type. To evaluate the influence of socio-demographic conditions, Wilke's regression model is developed only considering household size as predictor variable[1] and the result is compared with the model fully considering all demographic conditions. *DS* is used as an indicator.

4.3.3 Time resolution of the data

Two ways of switching on the appliance are modelled with Model Type 1 using empirical data of Minamisenrioka Electricity Use. First, the switch-on time is determined using the empirical data (5-minute interval). Second it is resampled to a 15-minute interval by assigning the activities to the end of each period. For example, if the switch-on time of a washing machine occurs at 09:05, we assigned a switch-on time of 9:15. This is done in order to treat the empirical data as TUD data with a resolution of 15 minutes and the effect of the data time resolution on the accuracy of the model can be shown. Power demand profiles of washing machines at a 5-minute resolution were calculated using the method of Yilmaz et al. (2017).

4.3.4 Quantification of calibration scalar and activity-based switch-on probability

The TUD based models use the calibration scaler or the activity-based switch-on probability. To quantify them, Minamisenrioka Electricity Use is used. Two cases are assumed to evaluate the influence of the availability of empirical data. The annual data

[1] Dummy variables indicating 1-, 2- and 4-member households and 5 or more-member household were used as predictors so as to model the difference in activity starting probability from 3-member household.

case assumes that only the mean number of switch-on events per day is available. The hourly data case assumes that the hourly mean number of switch-on events is available.

4.3.5 Applicability to a variety of contexts

The models are assumed to model appliance use in a city or larger scale area. All models were applied to 34,579 households living in Komae city, Tokyo, Japan, generated based on Japanese census by the method explained in Appendix C. The empirical data based model cannot consider the influence of the difference in household composition between Minamisenrioka and Komae city. The switch-on probability observed in each of 333 households is extended by the scaling factor of 11, the ratio of the number of households in Minamisenrioka and Komae city. Figure 4 shows the proportion of the size of households assumed for Komae city and those assumed for households from which Minamisenrioka Electricity Use was collected. The most significant difference is in the percentage of single households and households with pre-school child (see Appendix C). The empirical data based model developed on Minamisenrioka Electricity Use data might overestimate the switch-on probability for single households. To address this issue, the model of Wilke et al. (2013) is used. *DS* is used as the indicator. X_{ref} in Equation 2 is given by the model result for Komae city while X_{sim} is as estimated for Minamisenrioka.

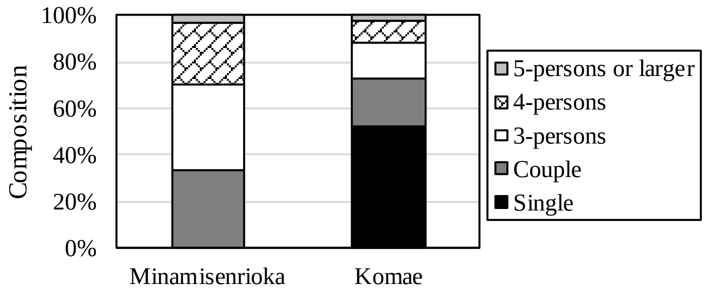


Figure 4. Composition of households in Minamisenrioka and Komae city.

5. Result

5.1 Comparison of the switch-on time profiles and the number of switch-on events

The hourly probability of switching on of washing machines for the 877 households estimated by Yilmaz et al. (2017), Richardson et al. (2010), Widén et al. (2010) and Wilke et al. (2009) on 10,000 weekdays are compared with empirical data is shown in Figure 5. All models agreed well with the empirical data. Table 7 lists the *DP* of the models. Yilmaz et al. (2017) has the smallest *DP* followed by Richardson et al. (2010), Widén et al. (2010) and Wilke et al. (2013). The difference between Richardson et al. (2010) and the remaining two TUD based models is in the flexibility of the calibration scalar that can be greater than 1 for Richardson et al. (2010) but is not allowed for the activity-based switch-on probability of Widén et al. (2010) and Wilke et al. (2013). The range is from 0:00 to 4:00. This point is further discussed later for the evaluation of quantification of calibration scalar and activity-based switch-on probability.

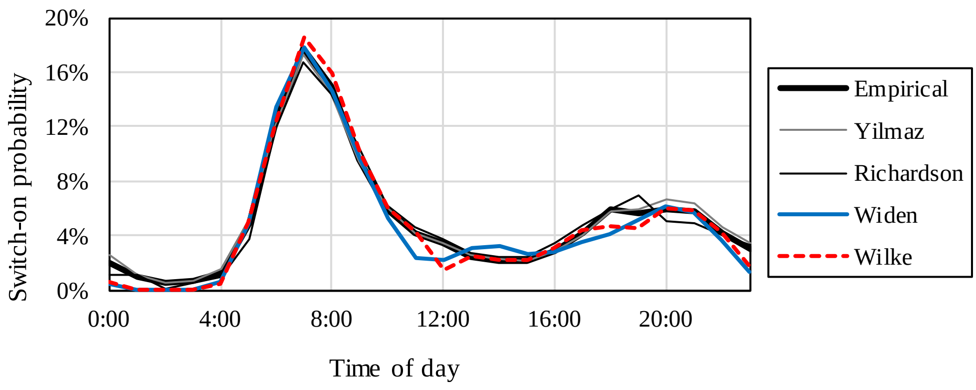


Figure 5. Comparison of measured (denoted by Empirical) and simulated (with the four models) switch-on probability (TUD based models using hourly calibration scalar and activity-based switch-on probability).

Table 7. DP and DS of the four models.

Model	**DP**	**DS**
Yilmaz	0.0009	0.031
Richardson	0.0018	0.158
Widén	0.0033	0.107
Wilke	0.0037	0.118

Figure 6 shows the cdf of households with the number of switch-on events per day shown on the horizontal axis. Yilmaz et al. (2017) agreed well with empirical data. The three TUD based models have a large discrepancy. Empirical data shows that the number of switch-on events changes from 1 to 7 times during the monitored days with some days showing no appliance use (0 switch-on events). Such intra-household variation cannot be replicated by TUD based models.

The most notable difference among the TUD based models is that Richardson et al. (2010) and Widén et al. (2010) have a few jumps in cdf corresponding to the household size. Contrary to their cdf, Wilke et al. (2013) showed wider distribution in the switch-on times per day resulting from the consideration of socio-demographic conditions. The differences among the models are represented by the *DS* of the models listed in Table 7. Yilmaz et al. (2017) agreed well with empirical data having the lowest *DS*.

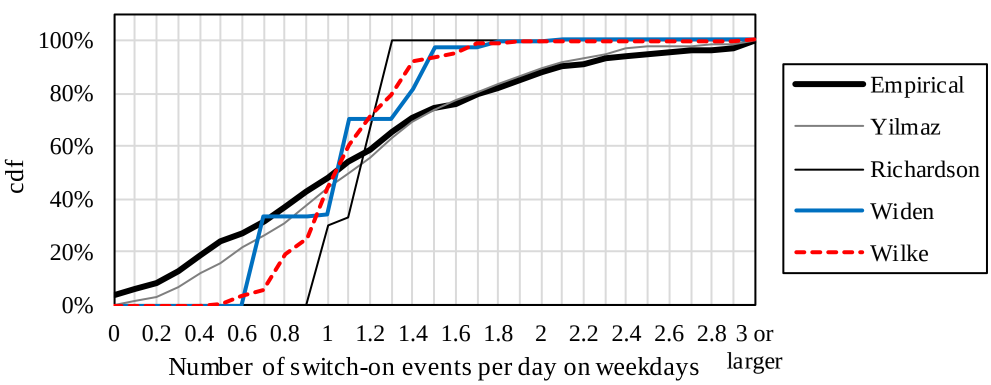


Figure 6. Comparison of cdf of the number of switch-on events per day on weekdays.

5.2 Evaluation of the modelling performance of the existing methods for five factors

5.2.1 Intra/inter-household variation

Figure 7 shows the entropy calculated for simulations by the four models under consideration. The results show that the distribution of Yilmaz et al. (2017) well replicates empirical data distribution while the TUD based models cannot replicate it.

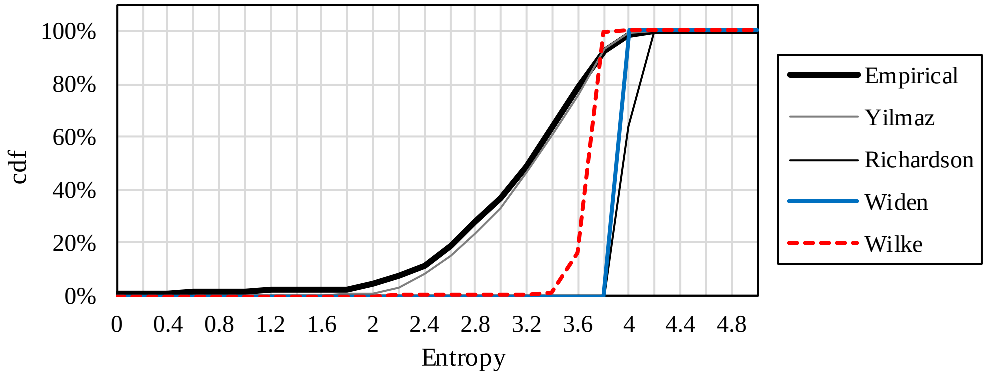


Figure 7. Comparison of cdf with the number of switch-on events per day on weekdays

Based on the result shown in Figure 6 and Figure 7, it is implied that empirical data based models are capable of replicating both intra/inter-household variations as the method of Yilmaz et al. (2017) individually assigns the number of switch-on events for every day by ensuring to integrate the variation of the number of switch-on events during different days. The most notable difference between the empirical data and the TUD based models can be found in the region with small entropy values. This result implies that the TUD based models cannot reproduce intra-household variation. This is because the TUD based models only reproduce population means. Flett and Kelly (2017) demonstrated that TUD based models can be improved in the replication of the number of switch-on events per day by adopting the above-mentioned approach of Yilmaz et al. (2017).

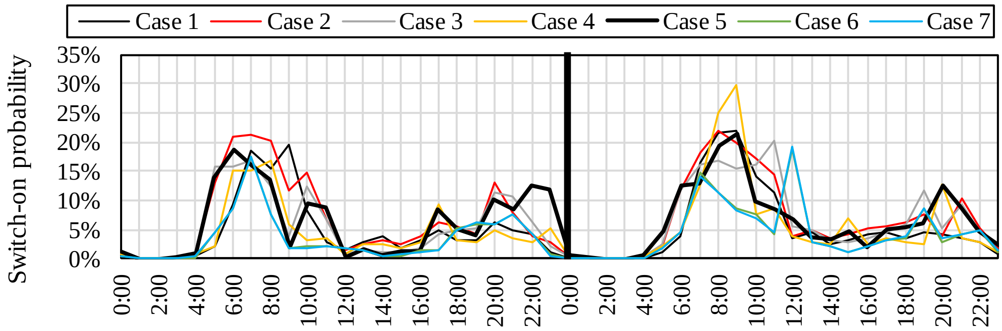
5.2.2 Consideration of the influence of socio-demographic conditions

Figure 8 shows switch-on probability estimated for the representative households using Wilke’s model with distinct household socio-demographic conditions listed in Table 8. Figure 8(a) shows the results estimated by the model considering all the 16 predictors, while Figure 8(b) shows those estimated by the model only considering household size. As shown in the figures, the socio-demographic conditions, especially occupation and existence of children, have a significant influence on switch-on event occurrence.

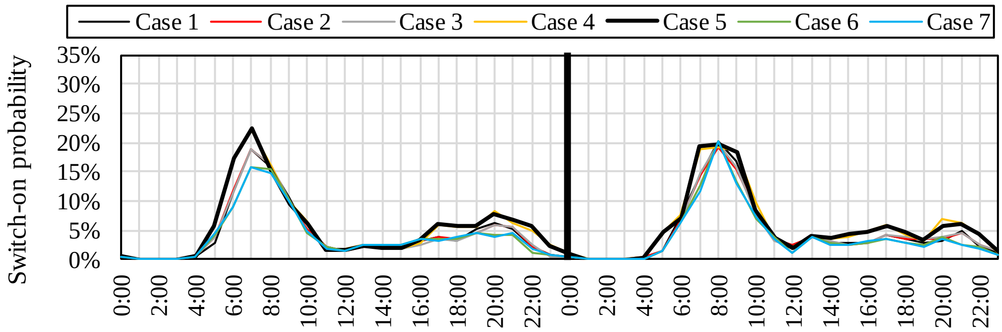
Figure 9 shows the pdfs of the number of switch-on events per day estimated by Wilke’s model. The result of the model considering only household size has only five variations in the number of switch-on events per day corresponding to the household size. Contrary to this, the model considering all the predictors showed a wider distribution among households due to the difference in household socio-demographic conditions. *DS* increased from 0.09 of the model with all predictors to 0.13 of the model with household size.

Table 8. Composition of seven representative households with different conditions on occupation, age and the composition and number of children.

Case	Couple		age	Children	
	Full time working male	Female employment status		preschool child	school child
Case 1	yes	Unemployed	30-44	yes	no
Case 2	yes	Part-time	30-44	yes	no
Case 3	yes	Full time	30-44	yes	no
Case 4	yes	Unemployed	30-44	yes	yes
Case 5	yes	Full time	30-44	yes	Yes
Case 6	yes	Full time	30-44	Yes	no
Case 7	yes	Full time	45-65	no	no



(a) Full predictor Weekdays Holidays



(b) Household size Weekdays Holidays

Figure 8. Estimated switch-on probability of the seven representative households listed in Table 8. The result over the first 24 hours shows those for weekdays, while the remaining result shows those for holidays.

This result implies that Richardson's and Widén's models are less sensitive to the socio-demographic conditions compared to Wilke's model because the household size is only considered in Richardson's and Widén's models. It also implies that a) the influence of socio-demographic conditions should be taken into account in appliance use modelling, and b) the consideration of socio-demographic conditions is not enough to reproduce the variety among households as shown in the difference between the Wilke's model and empirical data in Figure 6.

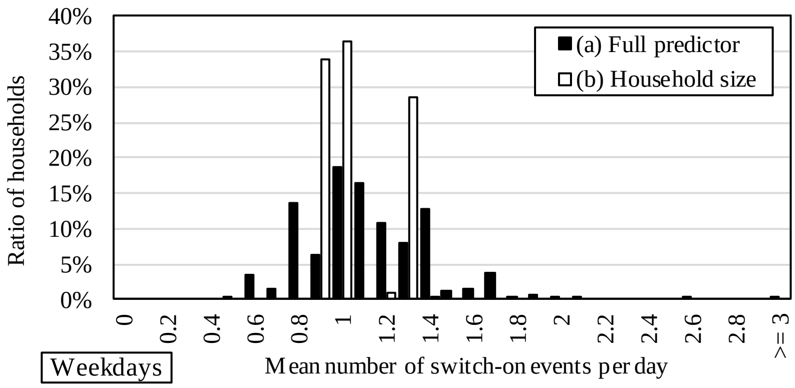


Figure 9. Distribution of the number of switch-on events per day on weekdays estimated for households living in Minamisenrioka

5.2.3 Time resolution of the data

Figure 10 shows the comparison of the simulated mean power demand of households depending on switch-on times determined from 5-minute empirical data and 15-minute resampled data (see Section 4.3.3). *DP* calculated for the methods using 5-minute and 15-minute resolution data are 0.0078 and 0.54 respectively. Spikes are seen at quarter hour intervals in power demand. This is because the high peaks at the beginning of the washing machine cycle always occur at the end of 15-minute time slots, which was not the case in the 5-minute data. This has important implications for models which use 15-minute TUD to develop high-resolution electricity demand models (i.e. at 1-minute resolution). The higher resolution data which precisely determines the switch-on time improves the accuracy of the electricity demand model.

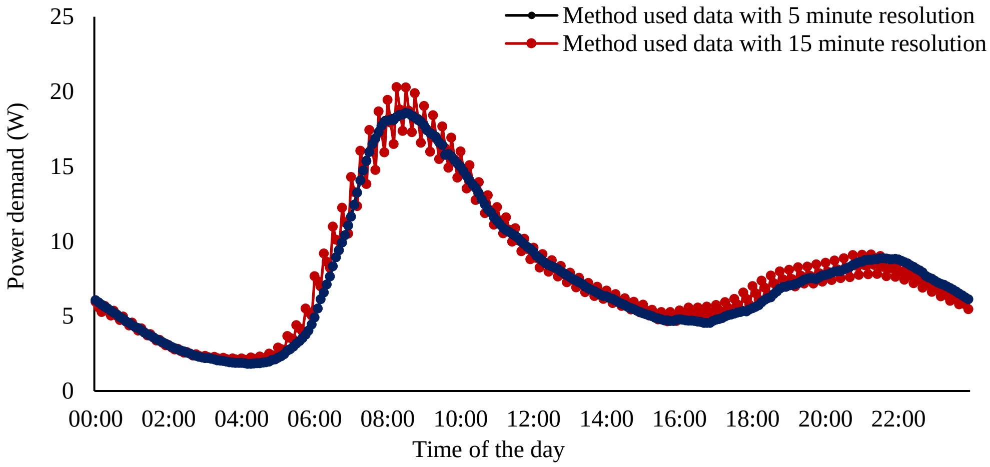


Figure 10. Comparison of the power demand profiles of simulations depending on switch-on times determined from 5-minute and 15-minute intervals.

5.2.4 Quantification of calibration scalar and activity-based switch-on probability

Figure 11 compares the switch-on probability of the washing machines simulated by Richardson et al. (2010) using a constant and hourly defined calibration scalar quantified by using Minamisenrioka Electricity Use data. The modelling approach which uses an hourly defined calibration scalar shows an improvement in matching the switch-on probability profile as opposed to the modelling method which uses the constant calibration scalar. *DP* calculated for the simulation using the hourly calibration scalar and the constant calibration scalar are 0.0018 and 0.0069 respectively. It is important to note that Richardson's method with constant or hourly defined calibration scalars predicts the number of daily switch-on events close to the measured value. For future studies, as more smart meter data emerges from individual appliances, modellers can be encouraged to use the hourly defined calibration scalar and activity-based switch-on probability.

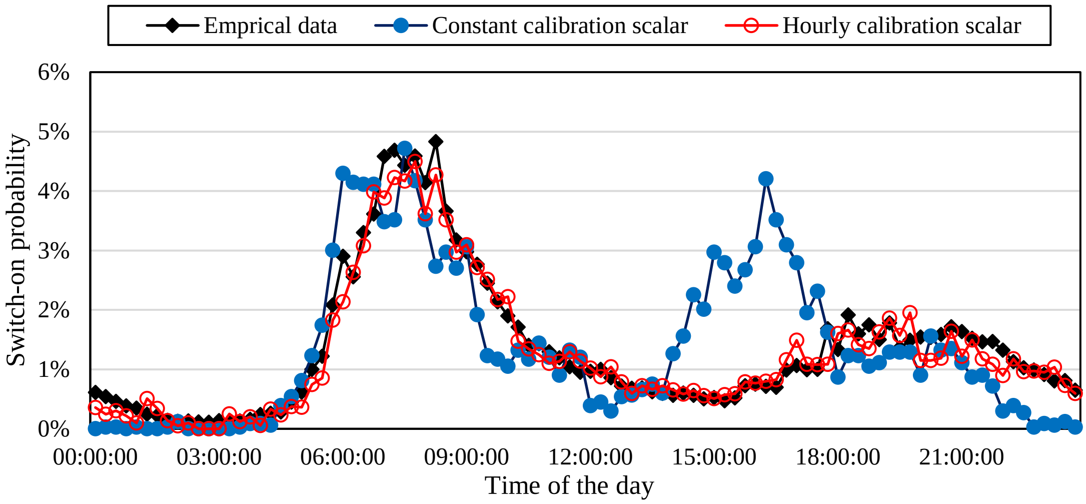


Figure 11. Comparison of the switch-on probability in weekdays (simulated by using the method of Richardson et al. (2010) with constant and hourly defined calibration scalars) with the empirical data.

As shown in Section 5.1 and this section, all the TUD based models well replicate the mean of the quarter hourly switch-on probability if hourly calibration scalar and activity-based switch-on probability are used. It should be noted that the meaning of these factors is different and well highlights the difference in models. Figure 12 shows the estimated calibration scalar and activity-based switch-on probability of the models. Richardson's calibration scalar is larger than the activity-based switch-on probability of the other two except for a few hours in the morning and afternoon. The reason for the large calibration scalar compared to activity-based switch-on probability is attributed to the difference in the underlying estimation approach for activity occurrence probability. The calibration scalar considers activity occurrence probability as the ratio of time steps involved in the target activity to the total number of time steps in an hour, when the hourly calibration scalar is quantified. Richardson et al. (2010) referred to the probability as activity probability. In contrast to that, activity based switch-on probability evaluates activity occurrence probability as the ratio of the number of households that conduct the target activity within an hour to the total number of households, which is referred to as activity starting probability in Wilke et al. (2013). Thus, activity probability is smaller than activity starting probability, which makes the calibration scalar larger than the activity-based switch-on probability.

In addition to this, Richardson’s calibration scalar can be greater than 1 (between 20:00 and 4:00) to calibrate the occurrence of a switch-on event corresponding to empirical data while Widén’s and Wilke’s activity-based switch-on probability cannot be greater than 1 given its definition. The difference between Widén’s and Wilke’s probability is moderate compared to that with Richardson’s calibration scalar, although the difference can be attributed to the difference in modelling methodology.

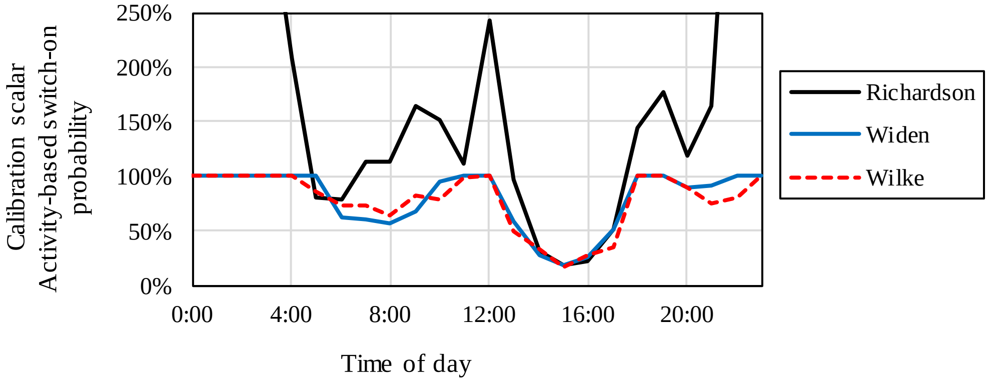


Figure 12. Estimated calibration scalar and activity-based switch-on probability of the TUD based models.

5.2.5 Applicability to a variety of contexts

Figure 13 shows the cdf of households with the number of switch-on events per day shown by the horizontal axis estimated for households in Minamisenrioka and Komae city by Wilke’s model. The difference between the results can be attributed to the difference in the composition of households in the simulated areas. *DS* between the two cdf values was estimated to be 0.10. The result implies that local conditions have significant influence on appliance switch-on. This further implies that empirical data based models (Type 1) developed from data collected from a specific local context cannot be applied to another area. Applicability of empirical data based models should be confirmed.

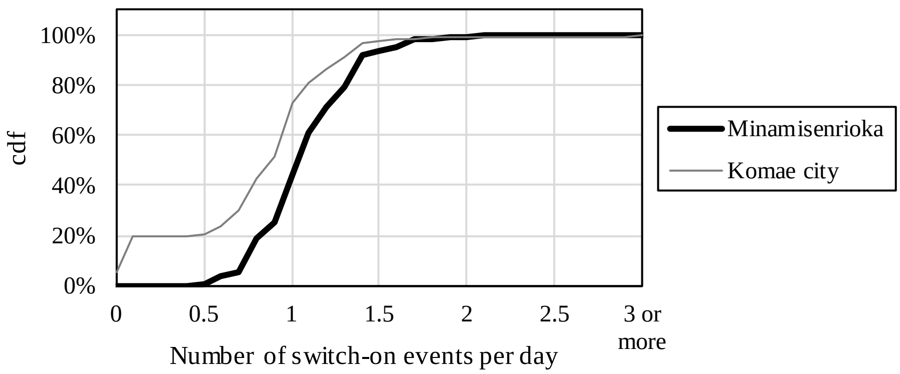


Figure 13. Distribution of the number of switch-on events per day on weekdays estimated for Minamisenrioka and Komae city.

6. Discussion

This study has contributed to an improved understanding of the limitations of the existing methods in modelling of household appliance use and issues that potentially have a significant impact on the accuracy of the model. A cross-analysis has been conducted to discuss the modelling performance of the existing methods. For this, switch-on probabilities were simulated by the existing methods in literature using the same dataset to provide more objective comparison of the methods. This section brings together findings from the results presented in Section 5 and jointly discusses their implications, addressing the issues. Several recommendations are also made.

- Figure 5 and Figure 6 showed that the empirical data based model (Type 1) well replicates both how frequently and at what time switch-on events occur. Although the TUD based models (Types 2 to 4) well replicate the behaviour of the mean switch-on probability at each time of day, they have limitations in replicating the intra- and inter-household variations as shown in Figure 6 and Figure 7. This is because TUD is collected for a limited number of days. To replicate the intra/inter-household variation in TUD based models, factors determining intra/inter-household variation should be taken into account. TUD based models could be improved by using longitudinal time use data or taking into account occupants' weekly schedules such as the distribution of the number of uses of an appliance throughout the week (Flett and Kelly, 2017).

- Figure 8 and Figure 9 showed that socio-demographic conditions have a significant influence on frequency and time of occurrence of switch-on events for home appliances. Appliance use models should take into account the socio-demographic conditions. However, it is not always easy to collect empirical data combined with socio-demographic conditions to develop empirical data based models in order to cover households with various conditions sufficiently. TUD based models have an advantage as TUD usually has wide population coverage. However, the variety among households is much larger than the variety that can be produced by considering socio-demographic conditions as discussed above.
- Figure 10 showed that modelling the power demand profiles by using 15-minute resolution of TUD could have a significant impact on the accuracy of the model. The high-power level at the start of the washing machine cycle causes spikes in the power demand profiles. Therefore, for appliances with varied power levels during use such as dishwashers, tumble dryers and washing machines, a higher resolution is recommended for time use surveys to determine the precise switch-on time of the appliance.

- Figure 11 and Figure 12 showed that there is a time variation in the calibration scalar and activity-based switch-on probability. Ignoring it results in an error in the time variation of electricity demand. Thus, the calibration scalar and activity-based switch-on probability should be quantified at a higher time resolution if electricity consumption is available with hourly or shorter intervals. Another solution is to disaggregate an activity into several subcategories so that activities can be linked more directly to appliance use, even though additional surveys might be needed. More research is needed to develop a representative dataset with simultaneous recordings of occupancy and activities, as well as appliance use. Such a survey would be complex due to the nature of the two different kinds of survey.
- Calibration scalar and activity-based switch-on probability of TUD based models highlight the difference among the modelling methods (Figure 12). The difference in modelling methodology was found in (A) the difference between discrete-time and discrete-event modelling (the former is larger than the latter especially for appliances accompanied by activities with shorter duration) and (B) the nature of the calibration scalar and the activity-based switch-on probability (the former can be greater than 1 while it is not allowed for the latter, which is important when available TUD and empirical data are inconsistent). The difference in the modelling of activity between Widén’s and Wilke’s models was not significant for the modelling of the use of washing machines. This difference might be significant if more activities are simultaneously considered.
- TUD based models can be applied to any simulation context when socio-demographic conditions used as model input are prepared. Figure 14

demonstrates the advantage of the TUD based models in illustrating applicability. On the contrary, the applicability of empirical data based models should be confirmed if socio-demographic conditions are not sufficiently considered during model development.

- The cross-analysis has provided key implications for the usability of appliance use models for different application contexts. First, the availability of empirical data is critically important for model performance. It is recommended to use larger samples with higher temporal resolution, if available. As most developed models are applied to external contexts, it is recommended to normalise developed models by influencing factors, especially households' socio-demographic conditions so that their influence can be reflected. When time series empirical data is unavailable, the TUD based models are a good alternative. Wilke's regression-based activity model showed the highest applicability to various contexts when households' socio-demographic conditions can be defined. It is also possible to include the function to take into account the influence of socio-demographic conditions in the other TUD based models. However, it is difficult to replicate intra/inter-household variations as they are in reality. The most difficult aspects to replicate by TUD based models are inter-household variation in the number of switch-on times per day, its intra-household variation, and intra-household variation in switch-on time. The variations cannot be accounted for by socio-demographic conditions. Thus, further research is needed to understand which factors generate these variations and to develop methodologies to replicate them in TUD based models. It is also recommended to consider these aspects in empirical data based models to take advantage of utilizing rich empirical data. The TUD based models are also a good alternative when available empirical data is not representative of households in the application context. In such cases, available data can be used to quantify limited key parameters to improve the TUD based models, such as time dependent calibration scalar and activity-based switch-on probability.

- This paper only deals with washing machine for the case study. The findings related to TUD based models can only be applied to modelling of appliances that are operated when only one activity is undertaken. There are appliances whose use relates to a number of activities (e.g. TV) and are modelled through interaction with other household members. Further research is needed for those appliances.
- Data cleaning of the empirical data is quite important. The challenging part of the empirical data is the identification of the actual use of the appliance. A robust methodology should be developed to identify incorrect readings.

7. Conclusion

This paper presented the issues and challenges in the modelling of use of home appliances based on a cross-analysis of the existing methods that are commonly used in literature to evaluate factors related to modelling performance. The conclusions arising from this study are:

- The case study demonstrated that Yilmaz et al. (2017), used as an example of the empirical data based time-dependent switch-on probability models, is capable of replicating the household specific characteristics in appliance use (intra-variation) due to the inclusion of day-to-day variability derived from the extended period of monitoring.

- The case study showed that socio-demographic conditions have significant influences on appliance use in households and consideration of their significance will improve the model performance, though it is not enough to replicate the intra/inter-household variations. However, the capability of TUD based models in reflecting socio-demographic conditions enables models to be applied to various areas where these conditions are available. In contrast, it is difficult to address cross-area variation in empirical data based models as empirical data lacks socio-demographic information. Thus, the applicability of empirical data based models should be evaluated when developed models are extended to external contexts.
- Time resolution of the data has a significant impact on the accuracy of the model.
- The calibration scalar and activity-based switch-on probability of TUD based models have time dependency. Consideration of their time dependency improves model performance. TUD based models require a consistent dataset of socio-demographic conditions of households, TUD and empirical data to quantify calibration scalar and activity-based switch-on probabilities. The difference between calibration scalar and activity-based switch-on probabilities arising from the difference between discrete-time and discrete-event modelling, and the nature of the calibration scalar that can be greater than 1 whereas activity-based switch-on probability is not allowed to be so.

Modelling the operation of home appliances is a challenging task, given the variability in occupant behaviour. It is clear that some of the approaches have advantages over others in certain circumstances. In future work, a methodology will be developed to incorporate the advantages of empirical data and TUD based models.

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9. Appendices

9.1 Appendix A. Minamisenrioka Electricity Use

Minamisenrioka Electricity Use contains electricity consumption data collected from 333 households in a multi-family building located in Minamisenrioka in Settsu city, Osaka, Japan. All of the dwellings are owner-occupied but socio-demographic conditions are unknown for each household. For electricity measurements, each dwelling is equipped with current sensors attached to each circuit of an electrical distribution board which was also connected to a washing machine. The current sensor was produced by Panasonic and the time resolution of measurement was 1-minute. Switch-on data was extracted from the measured data and converted to 15-min resolution data for this study. The minimum value that can be measured was 20 W. The monitoring period was from January 2012 to December 2014 (3 years).

9.2 Appendix B. Application of Wilke et al. (2013)

Wilke et al. (2013) applied the multinomial logit model (MNL) to model the selection of activity starting at each time of day with one-hour intervals. The probability is called the starting probability. When the starting probability of an activity is modelled only for laundry activity, the starting probability can be modelled as the binomial logit form shown in Equation (3):

$$\log \frac{p_t}{1-p_t} = \beta_{t,0} + \sum_{m=1}^{M} \beta_{t,m} x_m \quad (3)$$

where p_t is the starting probability at time t (t = 1 to 96 for this study), x_m is the m^{th} predictor variable, $\beta_{t,0}$ and $\beta_{t,m}$ are the regression coefficients. Table 9 lists the predictor variables considered in this study (M = 16). Although more predictors can be prepared by using data available with TUD, the predictors that can be prepared based on the national census were only selected because the model is applied to a specific district in this study.

It should be noted that the following three arrangements were added to Wilke et al. (2013).

- Four sets of regression models were developed for segments formed by gender and the distinction between weekdays and holidays, while they are dealt with as predictor variables in Wilke et al. (2013).
- In the regression analysis, the predictor variables were selected so that Akaike's Information Criterion could be minimized, while crude models were used in Wilke et al. (2013).
- Duration of the operation of washing machines was assumed to be 45 minutes for all households based on Minamisenrioka Electricity Use.

To validate the model, the goodness-of-fit of the developed models was evaluated based on the Hosmer-Lemeshow goodness-of-fit test (Helbe 2006). Figure 14 shows the estimated *p* values. As all of the *p* values are larger than 10%, the developed models fit well with the occurrence of laundry activity observed in TUD.

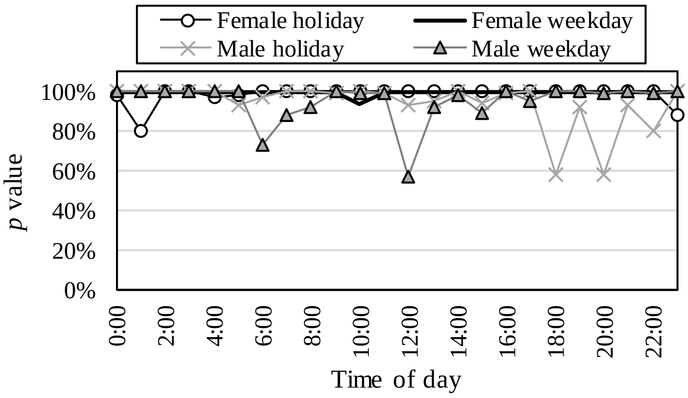

Figure 14. Result of goodness-of-fit test.

Table 9. Predictor variables considered in this study. Except for household size, all variables are modelled as a dummy variable. The coefficient of the predictors shows how starting probability is high compared with the reference case given by the third column.

Variable	Demographic condition	Reference case
Age	Person aged 10–19, 20–29, 30–44, > 65	Person aged 45 to 64
FullWorker	Person with a fulltime job	Unemployed person
PartWorker	Person with a part-time job	
HouseOwner	Person is living in owner-occupied house	Person living in rent
TwoIncomes	Person in household with two or more incomes	Person in a household with single income
WithParent	Person living with parents	couple of household
GrParents	Person in the highest generation of a three generation household	
Wipreschc	Person living with one or more preschool child	Person without both of preschool and school children.
Wichild	Person living with one or more school children	
WithPs&Sc	Person living with preschool child and school child. Wipreschc and Wichild become zero if there are both preschool and school child.	
Singles	Person living alone	Person living in a household whose size is three or larger
Couple	Person living a couple household	
Hsize	Household size	-

5.3 Appendix C. Random sampling of households based on the national census

The application of TUD based models needs the socio-demographic conditions of households. Probabilistic distributions of the household size and composition as well as the age, sex, employment/school status of each household member were developed by using the data listed in Table 5. Households are randomly sampled by evaluating the probabilistic distributions with uniform random numbers. The probability distributions using the data for Minamisenrioka were updated at every sampling to conduct sampling without replacement.

Figure 15 shows the actual and sampled number of male and female in the Minamisenrioka area. As shown in the figure, the largest age groups are children younger than 10 and their parents aged 30 to 49. This occurs given that two large multi-family buildings were constructed recently. The figure shows that the sampling result well reflects the actual distribution of male and female. It should be noted that we did not consider single households and couple households consisting only of people aged 65 or older for the households in the multi-family building from which Minamisenrioka Electricity Use data was collected. This is because the multi-family building is for families and there is a condominium solely for elderly people in Minamisenrioka. We assumed that households consisting of people aged 65 or older were in the condominium.

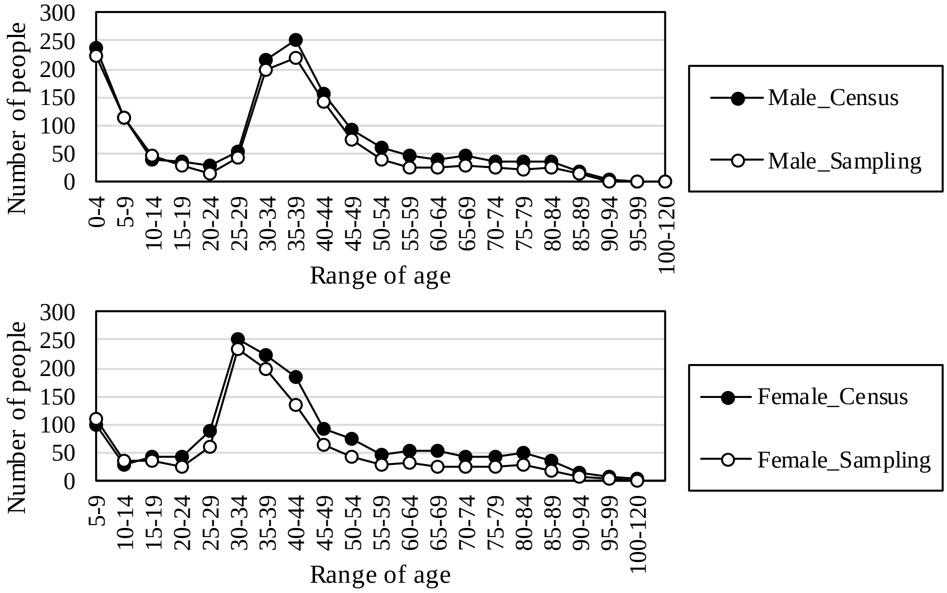

Figure 15. Distribution of male and female by age. The sampling result was compared with the actual data described in the census.