Household Power Consumption Simulator with Compact Representation of Occupant Behaviors

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***Abstract*—We propose a household power consumption simulator with a compact representation of household occupant behaviors. The proposed simulator models a working cycle of occupant behavior using start time intervals and duration. Such easily interpreted and compact parameter representation simplifies the operation processes of the simulator in trials involving energy management services. Based on a numerical experiment and theoretical analysis, we reveal that the proposed simulator can simulate power consumption more accurately in terms of a temporal drift compared to conventional simulators, in spite of the limitation of model complexity.**

I. Introduction

A household power consumption simulator is required for saving time and money with regard to trials involving energy management services, such as consulting for electrical equipment installation and configuration, coordinate control of a photovoltaics (PV) and storage battery, and demand response programs. There are three types of household power consumption simulator[1]: type-1: directly modeling interactions between input data and power consumption[3], type-2: explicitly modeling both the household occupant behaviors (daily activities, such as cooking and washing (clothes), that define appliance usage patterns) and appliance power characteristics, then simulating power consumption by combining both the household occupant behavior model and appliance power characteristic model[4]-[7], type-3: modeling the energy efficiency characteristics, such as heat propagation, of target buildings[8]. Our aim was to develop the type-2 simulator. This simulator simulates not only power consumption, but also household occupant behaviors. This feature extends the application range of the simulator compared to other types[6]. For instance, trials involving electrical equipment consultation services require power consumption when particular appliances in a target household are to be replaced. The type-2 simulator can satisfy this requirement by changing the parameters of the replaced appliances to new parameters. Trials involving demand response programs require an increase-decrease degree of power consumption which caused by changing the household occupants behavior, for decision of electricity price. The type-2 simulator can also satisfy this requirement by coordinating the model parameters of occupants behaviors.

One of the major challenges of the type-2 simulator is using an easily interpreted and compact parameter representation. The representation simplifies the process for service trials. We address this issue in this paper.

A. Contribution

Our simulator parameterizes household occupant behaviors using both start time differentials and duration in a probabilistic manner. This design scheme provides the following advantages.

- Easy interpretation: It enables trials to be conducted based on an understanding in which the parameters represent perturbation of start time cycles and duration of each behavior
- Compact parameter representation: It requires less parameters that should be handled by operators compared to conventional simulators

The concept of the behavior design scheme was proposed in the author's previous paper[2]. The new development in this paper is as follows.

- Development of the power consumption simulator with the proposed behavior design
- Revealing simulation characteristics of the proposed simulator based on a numerical experiment and theoretical analysis

B. Related Work

Behaviors are defined as daily activities that define appliance usage patterns[1]. For instance, ovens and dishwashers are assigned the behavior "cooking". Conventional simulators construct a behavior model using probabilities of each behavior occurrence. There are two types of simulators: (a) designing conditional probabilities given by current time step [4],[5] and (b) designing conditional probabilities given by both the current time step and behavior that occur at the previous time step[6],[7]. The order of the number of parameters is $O(N_h K)$ and $O(N_h K^2)$ (N_h: number of samples in one day, K: number of behaviors). For instance, if 5 behaviors and 10[min] time resolution are employed for a simulation condition, then the number of parameters should be handled by the operator will be 720 and 3600 for one household, respectively. These parameters are understood as behavior perturbations at a given time step, for instance, the probability that cooking will be done at 6:00, and the probability that washing will be done at 7:00 after cooking. However, these simulators cannot provide a direct interpretation in terms of behavior occurrence time perturbations, for instance, cooking started between 6:00 and 7:00 lasting 1 to 2 hours. Human beings commonly use the latter interpretation to plan daily activities. Based on the

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above discussion, there is an advantage and disadvantage with these conventional simulators over the proposed simulator. The advantage is that these simulators have the potential to achieve highly accurate simulation because of a large number of parameters. The disadvantage is that parameter coordination in trials is difficult because of the large number of parameters and non-intuitive representation.

For the power-decomposition task, which decomposes the total power into that of each appliance, a decomposition method that uses the start cycle and duration of appliances was proposed[9]. The decomposition method is applied only to convector, and does not model behaviors. Our research is therefore regarded as an extension of the applicable scope (behaviors and types of appliances) and deployment on the simulation task of the decomposition method.

II. Problem Setting

This section gives an overview of the type-2 simulator. Suppose $\mathbf{X}$ denotes behavior sequences, $\mathbf{Y}$ denotes appliance power consumption sequences, $\boldsymbol{\theta}$ denotes a set of parameters that represents the occupant behaviors, and $\boldsymbol{\xi}$ denotes a set of parameters that represents appliance power characteristics, then the type-2 simulator is defined as

$$\mathbf{X} = f(\boldsymbol{\theta}), \quad (1)$$

$$\mathbf{Y} = h(\mathbf{X}, \boldsymbol{\xi}). \quad (2)$$

This architecture allows detailed simulation by coordinating any $f(\boldsymbol{\theta})$, and $h(\mathbf{X}, \boldsymbol{\xi})$. For instance, power consumption fluctuation caused by behavior changes can be simulated by the coordination of $f(\boldsymbol{\theta})$. Also, power consumption fluctuation caused by replacement of particular appliances can be simulated by the coordination of $h(\mathbf{X}, \boldsymbol{\xi})$.

III. Compact Representation of Occupant Behaviors

A. Definition of Occupant Behavior

The definition of occupant behavior with our simulator is the same as with conventional ones, which is defined as daily activities that define appliance usage patterns. For instance, ovens and dishwashers are assigned the behavior "cooking" and laundry machines are assigned the behavior "washing".

B. Assumption of Behavior Dynamics

With the proposed simulator, it is assumed that behaviors are driven on a queuing system framework. A behavior queuing system has the following characteristics.

- Start the system at a certain time (awake time)
- Then, execute tasks (the behaviors) in order of priority (e.g. perform cooking after completing washing)
- Each task has a duration (e.g. cooking requires 1 hour to complete), and upper and lower limit of a start time
- Each task will be started after the previous task, which can not be performed in parallel with the current task, is completed (e.g. washing will be delayed 30 minutes if the completion of cooking is delayed 30 minutes)
- If the previous task completion is late for the upper limit, then the target task will not be performed
- If the previous task completion is early for the lower limit, then the target task performed after the lower limit

The above characteristics are also attached to the following two conditions. The priority and completion time of each behavior are different between weekday and weekend, and among households. All tasks are allowed to be executed more than once.

This queuing system-based design easily and intuitively constructs interpreted parameters that represent the perturbation of the start and duration of behaviors.

C. Design Framework

The state space of the behavior for parameterizing the above assumption is constructed as follows. Suppose K denotes the number of behaviors, and N_h denotes the number of samplings in one day. The behavior subsequences $\mathbf{x}_d$, which is the d-th partition of the behavior sequences $\mathbf{X}$ w.r.t. one day, is defined as

$$\mathbf{x}_d = (\mathbf{x}_{1d}, \ldots, \mathbf{x}_{Kd})^{\mathrm{T}}, \mathbf{x}_{id} \in \{0, 1\}^{N_h},$$

where 0 and 1 mean the deactivated and activated state of the behavior, respectively. The proposed simulator represents the behavior subsequence $\mathbf{x}_{id}$ (i : target behavior d : target day) using the start time t_{dij} and duration m_{dij}. The state spaces of a behavior i throughout the day d is given by

$$\begin{aligned} Time &: t_{dij} \in \mathcal{T}, \mathcal{T} = [t_0, t_\infty), \\ State &: m_{dij} \in \mathcal{M}, \mathcal{M} = (0, t_\infty - t_0), \end{aligned}$$

where t_0 denotes the start (awake) of d, and t_∞ denotes the end of d. The behavior subsequence $\mathbf{x}_{id}$ is defined on the state space $\mathcal{S} = \mathcal{T} \times \mathcal{M}$ such that

$$\mathbf{s}_{di} = (t_{i1}, \ldots, t_{in_d}, m_{i1}, \ldots, m_{in_d}),$$

where n_d denotes the number of starts of i throughout d. The relationship between $\mathbf{x}_{id}$ and $\mathbf{s}_{di} \in \mathcal{S}$ is illustrated in Fig. 1. For simplification, the subscript d is omitted for the remainder of this paper. Unless otherwise noted, the variables introduced above implicitly have the subscript d.

We developed a behavior model based on the defined state space. The behavior subsequences $\mathbf{s} = (\mathbf{s}_1, \ldots, \mathbf{s}_K)$ are distributed under

$$p(\mathbf{s}) = \prod_{i=1}^{K} \mu_0(t_{i1}) \prod_{j=2}^{n} \mu_1(t_{ij}, t_{ij-1}) \prod_{j=1}^{n} \eta(m_{ij}), \quad (3)$$

where

$$\mu_0(t) = G(t - t_0; \lambda_i^{(0)}, \kappa_i^{(0)}), \quad (4)$$

$$\mu_1(t_a, t_b) = G(t_a - t_b; \lambda_i^{(1)}, \kappa_i^{(1)}), \quad (5)$$

$$\eta(m) = G(m; \nu_i, \iota_i). \quad (6)$$

In the above equations, G means the gamma distribution. The parameters of the proposed simulator are $\boldsymbol{\theta} = (t_0, \{\lambda_i^{(0)}\}_{i=1}^K, \{\kappa_i^{(0)}\}_{i=1}^K, \{\lambda_i^{(1)}\}_{i=1}^K, \{\kappa_i^{(1)}\}_{i=1}^K \{\nu_i\}_{i=1}^K, \{\iota_i\}_{i=1}^K)$. These parameters are prepared for both weekday and weekend. The order of the number of parameters of the proposed simulator

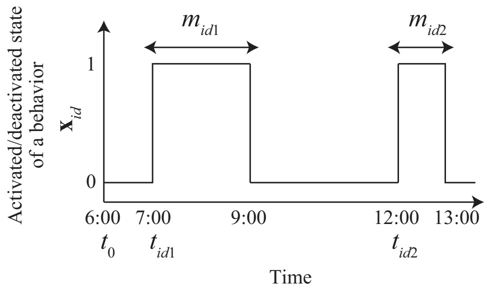

Fig. 1: State space of occupant behaviors

is $O(6K + 1)$. This order is small compared to those of the conventional simulators, $O(N_h K)$ and $O(N_h K^2)$ under the $N_h \gg 6$ assumption. Also, the weekend and weekday factor is omitted in the above discussion for simplification.

The derivation concept of (3) is described as follows. The modeling features are summarized in three parts: (a) the start time is represented by the differential form $t_{ij} - t_{ij-1}$ ($t_{i0} = t_0$), (b) two types of differentials, between the awake and start time of the first execution and between the start time of the second or later execution, are developed, and (c) the duration is represented as independent and identically distributed (i.i.d.) w.r.t. each behavior. These design strategies are developed for model simplification. Part (a) makes explicit modeling of start time dependency, $t_0 < t_{i1} < \cdots < t_{in} < t_\infty$, unnecessary. Parts (b) and (c) result in compact parameter representation. The gamma distribution is assigned to both the differential of the start time and duration. The assumptions and approximations for the use of the gamma distribution are as follows. Behavior i is constructed by ι_i subtasks (e.g. washing, rinsing, and drying for the behavior "washing"). Each subtask duration of i is distributed under the exponential distribution. The duration of all subtasks of i is i.i.d.. The gamma distribution for the duration is then induced by summation of the subtask duration time, which is i.i.d. exponential. There are some behaviors during the time interval of the start time of i. The behaviors in the interval include those undefined in the model and do not include those performed in parallel to i. The duration of these behaviors is also distributed under the gamma distribution. The duration of all the prevenient behaviors is i.i.d.. The gamma distribution for the differential of the stat time is then induced by the summation of the duration of the prevenient behaviors that are i.i.d. gamma. The upper and the lower limit of start time are also ignored for simplicity.

The parameters of our simulator are also interpreted as follows.

- t_0 denotes awake time
- $\lambda_i^{(0)} \times \kappa_i^{(0)}$ and $\lambda_i^{(0)} \times (\kappa_i^{(0)})^2$ denote the mean and variance of the first start time of i, respectively
- $\lambda_i^{(1)} \times \kappa_i^{(1)}$ and $\lambda_i^{(1)} \times (\kappa_i^{(1)})^2$ denote the mean and variance of the differential between the start time of the second or later execution of i, respectively
- $\nu_i \times \iota_i$ and $\nu_i \times \iota_i^2$ denote the mean and variance of the duration of i, respectively

IV. Behavior to Power Conversion

We explain a power consumption model under a condition in which the behaviors are given. The consumption model has the following process: (a) the occupant selects appliances that will be used during the execution of each behavior, and (b) the selected appliance uses constant power when running. Suppose C denotes the number of appliances, $\mathbf{x} = (\mathbf{x}_1, \ldots, \mathbf{x}_K)^{\mathrm{T}}$ denotes the behaviors throughout d, and $\mathbf{w} = (\mathbf{w}_1, \ldots, \mathbf{w}_K)^{\mathrm{T}} \in \{0, 1\}^{C \times N_h}$ denotes the activated/deactivated state of the appliances throughout d. The power consumption throughout d, $\mathbf{y} = (\mathbf{y}_1, \ldots, \mathbf{y}_C)^{\mathrm{T}} \in \mathbb{R}^{C \times N_h}$, is distributed under

$$p(\mathbf{y}|\mathbf{x}, \boldsymbol{\xi}) = \sum_{\mathbf{w}} p(\mathbf{y}|\mathbf{w}, \boldsymbol{\xi}) p(\mathbf{w}|\mathbf{x}), \tag{7}$$

where $p(\mathbf{w}|\mathbf{x})$ and $p(\mathbf{y}|\mathbf{w}, \boldsymbol{\xi})$ denote an appliance selection distribution and appliance power consumption distribution, respectively. The formulation of these distributions are given by

$$p(\mathbf{w}|\mathbf{x}) = \begin{cases} \prod_{c=1}^{C} \prod_{i=1}^{N_h} q_{ci}{}^{w_{ki}} (1 - q_{ci})^{1 - w_{ki}} & (x_{ki} = 1, k \in \mathcal{K}_c) \\ 0, & (otherwise) \end{cases} \tag{8}$$

$$p(\mathbf{y}|\mathbf{w}, \boldsymbol{\xi}) = \begin{cases} \prod_{c=1}^{C} \prod_{i=1}^{N_h} \mathrm{tN}(y_{ci}; \mu_{c1}, \sigma_{c1}) & (w_{ci} = 1) \\ \prod_{c=1}^{C} \prod_{i=1}^{N_h} \mathrm{tN}(y_{ci}; \mu_{c0}, \sigma_{c0}), & (otherwise) \end{cases} \tag{9}$$

where q_{ci} denotes the selection probability of an appliance c per unit time during execution of i, $\mathcal{K}_c$ denotes a set of behaviors to which c corresponds, $\mathrm{tN}(\cdot)$ denotes the truncated Gaussian distribution, which restricts the support by $[0, \infty)$, μ_{c0} and σ_{c0}^2 denotes the mean and variance of the standby power of c, and μ_{c1} and σ_{c1}^2 denote the mean and variance of the driving power of c, respectively.

Equation (8) means the occupant decides appliance usage by an independent process per unit of time. Equation (9) means all appliances have the standby mode and one driving mode, and the power consumption of both modes is a nonnegative constant. This is one of the most naive designs for representing the behavior to power conversion. Widén describes a more accurate design[6].

V. Evaluations

The aim with the evaluations was to (a) determine the validity of the proposed simulator in term of behaviors and (b) reveal the differences in the simulation characteristics between the proposed and conventional simulators.

A. Environment

The power consumption data set used for the evaluations were measured from 3 Feb. 2013 to 31 Oct. 2013 in three households. The time and power resolution of the data set were 10[min] and 10[Wh]. The measured appliances in each household are listed in Table I. The definition of the behaviors are given in Table II. This data set only included the behaviors "relaxation", "washing", and "cooking", because of the limitations of the metering system and target households used for the evaluations. The true values of the behavior sequences were estimated before each evaluation. The true value was "1" if any appliance assigned with a target behavior ran during the current 10[min]; otherwise, the true value was "0". A threshold for estimating the running/standby mode of the appliance is power consumption of the 2nd saddle point on a curve, which plots power consumption of the appliance in ascending order. With this strategy, it was assumed that power consumption lines up in the order of the standby mode, mixture of standby and running modes, and running mode, on the curve. This assumption is illustrated in Fig. 2.

B. Validity of Proposed Simulator

The validity of the proposed simulator was evaluated using a goodness of fit (GoF) test. The test was applied to the distributions given in (4)-(6) for each weekday/weekend, behavior, and household. We tested 48 distributions. The one-sample kolmogorov-smirnov test, which is standard tool of GoF test for non-Gaussian and nonparametric distributions, was used as the test with significance level 0.05 and sample size 30 (uniformly selected from the data set). The sample size setting makes power of the test to 1, when differences in the mean and standard deviation between the target gamma distributions are greater than 1 hour with the used significance level. The acceptable differential value was derived from the assumption of the requirement of the coordinate control service of the PV and storage battery. The sample size was calculated by computer simulation. The awake time parameter was set to 42 (7:00).

The test results show that the null hypotheses of 35 out of the 48 distributions were not rejected. This means the 35 distributions were distributed with the proposed simulator. Base on these results, the simulator well approximated behaviors under the limitations of the environment and assumed requirements.

C. Simulation Characteristics

We validated the simulation characteristics by numerical and theoretical comparative analysis. The two types of behavior representation simulators: (a) designing the conditional probabilities given by each time step[4],[5] and (b) designing the conditional probabilities given by both the current time step and behavior that occurred at the previous time step[6],[7] were compared with the proposed simulator. The simulator proposed by Capasso et al. (Capasso simulator)[4] was used for (a) and that proposed by Widén et al. (Widén simulator)[6] was used for (b). Both the simulators are represented by

$$\text{Capasso} \quad : \quad p(\mathbf{x}) = \prod_{i=1}^{K} \prod_{j=1}^{N} q_{ij}^{x_{ij}} (1 - q_{ij})^{(1-x_{ij})} \tag{10}$$

$$\text{Widén} \quad : \quad p(\mathbf{x}) = \prod_{i=1}^{K} \pi_1(x_{i1}) \prod_{j=2}^{N} \pi_j(x_{ij}, \mathbf{x}_{j-1}^{*}) \tag{11}$$

where q_{ij} denotes the probability that x_{ij} becomes 1, $\mathbf{x}_{j-1}^{*}$ denotes the behavior vector at time $j-1$ (the $j-1$-th row vector of the matrix $\mathbf{x}$), $\pi_j(x_{ij}, \mathbf{x}_{j-1}^{*})$ denotes the transition probability in which i is activated at time j when $\mathbf{x}_{j-1}^{*}$ is given. The term $\pi(\cdot)$ is given by a normalized frequency. These simulators were prepared for both weekday and weekend. The various heuristic techniques[4],[6] used in the Widén and Capasso simulators were omitted because the heuristic techniques insignificant in the evaluations. The appliance model, which was integrated into each behavior model, was the model introduced in Section 4. The first half of the data set was used for the parameter estimation of each simulator, the other half of the data set was used for validation. The awake time parameter was set to 42, and the appliance selection probabilities whose appliance-behavior correspondence not listed in Table II were set to 0.

The evaluation measures are defined as follows. Suppose N denotes the number of time samples in the entire period of the validation data, and $\hat{N}^{(ui)}$ and $N^{(ui)}$ denote the number of simulated and true samples in the state space of i in household u. The behavior simulation error of i in u is measured by

$$\sum_{n=1}^{N} \frac{|\hat{x}_{in}^{(u)} - x_{in}^{(u)}|}{N}, \tag{12}$$

$$\frac{\sum_{j=1}^{\hat{N}_t^{(ui)}} \min_k |\hat{t}_{ij}^{(u)} - t_{ik}^{(u)}| + \sum_{k=1}^{N_t^{(ui)}} \min_j |t_{ik}^{(u)} - \hat{t}_{ij}^{(u)}|}{\hat{N}^{(ui)} + N^{(ui)}}, \tag{13}$$

where $\hat{x}$ and $\hat{t}$ denote the simulated values of the behaviors, and x and t denote the true values of behaviors. Equation (12) measures the error of the activated/deactivated state of the behaviors at each time step and (13) measures the error of the start time of the behaviors. The power consumption simulation error of c is also measured by

$$\sum_{n=1}^{N} \frac{|\hat{y}_{cn}^{(u)} - y_{cn}^{(u)}|}{N}, \tag{14}$$

$$\frac{1}{|\hat{\mathbf{O}}|} \sum_{l=1}^{|\hat{\mathbf{O}}|} |\hat{o}_l - \hat{p}_l|, \tag{15}$$

where

$$\{\hat{\mathbf{O}}, \hat{\mathbf{P}}\} = \underset{o_1,\ldots,o_L,p_1,\ldots,p_L}{\operatorname{argmax}} \sum_{l=1}^{L} d(y_{o_l}, \hat{y}_{p_l}). \tag{16}$$

Here y and $\hat{y}$ denote the simulated and true values of power consumption, and $d(\cdot,\cdot)$ denotes the distance metric. Equation (16) is called dynamic time warping[10], which matches

TABLE I: Measured appliances

household ID	measured appliances
1	TV, laundry machine, dishwasher, oven, microwave, rice cooker
2	laundry machine, dishwasher, oven, microwave
3	TV, laundry machine, kitchen unit, oven, toaster

TABLE II: Behavior definition

behaviors	appliances
relaxation	TV
washing	laundry machine
cooking	dishwasher, oven, toaster, microwave, rice cooker, kitchen unit

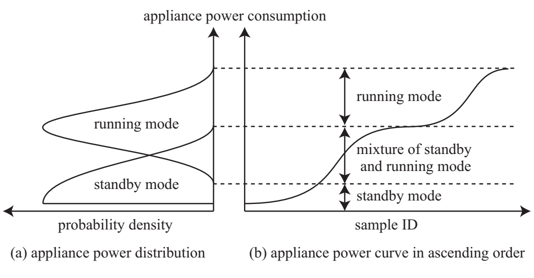

Fig. 2: Appliance running and standby mode characteristics

two given sequences by nonlinear deformations of the time scale. Equation (14) measures the error of power consumption at each time step, and (15) measures the error in terms of time drifting[11] of power consumption. These measures were based on an assumption of an energy management service scenario. For instance, the coordinate control service of the PV and battery should estimate the requirements of supply power at each time step and should secure resources for the requirements. The service trials, therefore, should include validations of both the satisfaction degree of the requirements and resource use efficiency. Equations (12)-(15) are used to estimate both validation errors if each simulator will be used. Equations (12) and (14) are used to estimate the former validation error, and (13) and (15) are used to estimate the latter validation error. In the rest of this paper, Equations (12 and 14) are described as "quantitative-error", and (13) and (15) are described as "phase-error".

The simulation results are listed in Tables III-VI. The smallest errors among the three simulators are in bold. These results show that the proposed simulator had the largest quantitative error, followed in order by the Capasso simulator and Widén simulator, the smallest behavior phase-error, followed in order by the Widén simulator and Capasso simulator, and the smallest power consumption phase-error, followed in order by the Capasso simulator and Widén simulator.

For analyzing both the quantitative-error and phase-error characteristics, the conditional intensity function (CIF)[12]

$$r(t_l|H_{t_l}), \tag{17}$$

is introduced, where H_{t_l} denotes the history of behavior activations. Equation (17) means the conditional probability of the behavior occurance at t_l given by the history of behavior activations H_{t_l}. The three simulators can be represented using CIF. The Capasso simulator is represented as $r(t_l|H_{t_l}) = r(t_l)$ because the behavior occurrences are independent between each time step and dependent on the current time step. The Widén simulator is represented as $r(t_l|H_{t_l}) = r(t_l|x_{t_{l-1}})$ (where $x_{t_{l-1}}$ denotes the activated behavior on previous time step) because the behavior occurrences are dependent on both the history (the behavior at the previous time step) and current time step. The proposed simulator is represented as

$$r(t_l|H_{t_l}) = \frac{G(t_l - t_j; \lambda, \kappa)}{1 - \int_0^{t_i - t_j} G(u; \lambda, \kappa)du} + \int_0^{t_i - t_j} G(u; \nu, \iota)du \tag{18}$$

where λ and κ denote $\lambda_i^{(1)}$ and $\kappa_i^{(1)}$, ν and ι denote ν_i and ι_i, which are used in (5) and (6), t_j denotes the previous start time, respectively. The distribution introduced by (4) is omitted for simplification of analysis. Equation (18) means the behavior occurrences are only dependent on the history (the previous start time). The left term of (18) means that the behavior occurred as the start time, and the right term of (18) means that the behavior occurred as the duration. If a condition $\kappa > 1$ is satisfied, the left term is a monotonically increasing function w.r.t. $t_l - t_j$.

For analysis of the phase-error, the characteristics of the phase-error measure are explained. Equation (13) has two types of terms: the left term of the numerator ($E1$) measures the distances from each simulated sample (on the state space $\mathcal{S}$, which means the start time of the behavior sequence) to the closest true sample, and the right term of the numerator ($E2$) measures the distances from each true sample to the closest simulated sample. This means (13) imposes penalties on both the start time differential and deficiency and excess of the number of simulated samples. Equation (15) also imposes penalties on the duration differential in addition to the penalties which imposed by (13).

Base on the above discussion, we first analyzed the quantitative-error characteristics. The behavior activation history is stochastic variable, and includes a simulation error. The current time step is deterministic variable and do not includes a simulation error. Samples on the Capasso simulator are only depend on each current time step, and samlples on the Widén simulator are depends on not only the behavior activation history, but also each current time step. On the other hand, samples on the proposed simulator are only depend on the behavior activation history. Therefore, we believe that the proposed simulator has the largest quantitative error because of the simulation error propagation caused by the behavior activation history. We then analyzed the phase-error characteristics. The ratios of the number of simulated samples to the number of true samples $\hat{N}^{(ui)}/N^{(ui)}$ are listed in Table VII. The proposed simulator had Table VII shows that the proposed simulator had the ratio closest to 1 (bold face), followed in order by the Widén simulator and Capasso simulator (greater than 1). CIF representations also suggest that the Widén and proposed simulators can obtain the parameters that can represent the behavior that has not been started for a while after the behavior was started once. These parameters are learned explicitly in the proposed simulator with the condition $\kappa > 1$. Also, κ of all behavior distributions became greater than 1 via the learning in the experiment. Therefore, we can consider that the proposed simulator has the smallest phase error despite the error propagation effect because it can simulate the behaviors in just proportion of the number of sample ratio.

VI. Conclusion

We proposed a household power consumption simulator, which has easily interpreted and compact parameter representation, for simplifying the process for energy-management-service trials. The proposed simulator represents occupant behaviors based on the start time interval and duration. The simulation characteristics of the proposed simulator exhibited high accuracy in terms of the phase-error and low accuracy in terms of the quantitative-error, compared to the conventional simulators. We revealed the phase-error advantage with the proposed simulator is derived from the start time differential based temporal dependency with the gamma distribution and the quantitative disadvantage from the error propagation on the dependency cycle.

We are interested in three topics for future work: (a) explaining the reason that the proposed simulator produces the bigger phase-errors in some cases, (b) revealing the effect on the simulation value by the right term (duration) of the proposed simulator CIF, (c) revealing the limitation of the proposed simulator based on an exhaustive experiment w.r.t appliances (especially in terms of thermal equipments), households, and period of time.

References

[1] L. G. Swan and V. I. Ugursal, "Modeling of end-use energy consumption in the residential sector: A review of modeling techniques," *Renewable and Sustainable Energy Reviews* vol. 13 no. 8, pp. 1819-1835, Oct. 2009.

TABLE III: Quantitative-error of behaviors

-	household 1			household 2			household 3		
simulators	relaxation	washing	cooking	relaxation	washing	cooking	relaxation	washing	cooking
Capasso	**0.2527**	0.1712	0.3819	N/A	**0.1551**	0.3607	**0.2466**	0.0996	0.2228
Widén	0.2927	**0.1582**	**0.3222**	N/A	0.1540	**0.3031**	0.2761	**0.0874**	**0.2014**
proposed	0.3630	0.2011	0.3413	N/A	0.1557	0.3396	0.3546	0.1156	0.2336

TABLE IV: Phase-error of behaviors

-	household 1			household 2			household 3		
simulators	relaxation	washing	cooking	relaxation	washing	cooking	relaxation	washing	cooking
Capasso	11.4688	36.8542	17.1479	N/A	39.1848	4.0146	21.0877	28.0205	23.4434
Widén	**10.5805**	32.5318	15.9884	N/A	38.0056	4.0869	20.6407	**27.3515**	**19.3193**
proposed	12.3414	**30.5676**	**15.3959**	N/A	**37.1402**	**4.0023**	**20.0221**	31.0824	21.9471

TABLE V: Quantitative-error of power consumption

household ID	simulators	TV	laundry machine	dishwasher	kitchen unit	oven	toaster	microwave	rice cooker
1	Capasso	**0.0052**	0.0091	0.0159	N/A	0.0007	N/A	0.0012	0.0097
	Widén	0.0055	**0.0081**	**0.0126**	N/A	**0.0005**	N/A	**0.0010**	**0.0089**
	proposed	0.0065	0.0102	0.0135	N/A	**0.0005**	N/A	**0.0010**	0.0091
2	Capasso	N/A	**0.0071**	0.0144	N/A	0.0012	N/A	0.0032	N/A
	Widén	N/A	**0.0071**	**0.0125**	N/A	**0.0010**	N/A	**0.0025**	N/A
	proposed	N/A	**0.0071**	0.0134	N/A	0.0012	N/A	0.0029	N/A
3	Capasso	**0.0169**	0.0023	N/A	0.0085	0.0024	0.0033	N/A	N/A
	Widén	0.0177	**0.0018**	N/A	**0.0066**	**0.0019**	**0.0027**	N/A	N/A
	proposed	0.0198	0.0027	N/A	0.0086	0.0024	0.0033	N/A	N/A

TABLE VI: Phase-error of power consumption

household ID	simulators	TV	laundry machine	dishwasher	kitchen unit	oven	toaster	microwave	rice cooker
1	Capasso	**14.1410**	34.3052	30.4706	N/A	61.8101	N/A	27.2532	**27.2605**
	Widén	16.6112	32.6368	31.2964	N/A	62.7662	N/A	**27.0663**	28.0136
	proposed	19.6490	**31.7604**	**28.7177**	N/A	**60.6307**	N/A	28.4385	30.7547
2	Capasso	N/A	**11.0994**	13.1894	N/A	**30.0590**	N/A	4.2429	N/A
	Widén	N/A	12.7486	13.7869	N/A	30.1064	N/A	**3.3951**	N/A
	proposed	N/A	11.1817	**10.5265**	N/A	30.5526	N/A	3.5727	N/A
3	Capasso	**25.7903**	36.9248	N/A	46.6748	28.2318	30.9439	N/A	N/A
	Widén	30.2204	34.1694	N/A	46.4653	30.8889	31.1230	N/A	N/A
	proposed	32.6554	**30.2448**	N/A	**45.5142**	**28.0954**	**29.1113**	N/A	N/A

TABLE VII: Ratio of number of simulated samples to number of true samples

-	household 1			household 2			household 3		
simulators	relaxation	washing	cooking	relaxation	washing	cooking	relaxation	washing	cooking
Capasso	3.9880	4.7496	3.0702	N/A	4.9410	1.9401	6.7975	2.0678	1.6171
Widén	3.5444	2.9793	1.1494	N/A	3.5978	**1.4480**	6.0521	**1.1356**	1.0479
proposed	**3.0702**	**1.9457**	**1.1202**	N/A	**1.4207**	1.6400	**1.2239**	0.7377	**0.9932**

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