

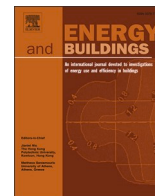


Title	Aggregated smart meter data driven occupant behavior analysis based on inverse problem optimization
Author(s)	Uchida, Hideaki; Kishimoto, Kazumasa; Nishizawa, Kazuki et al.
Citation	Energy and Buildings. 2025, 345, p. 116074
Version Type	VoR
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Aggregated smart meter data driven occupant behavior analysis based on inverse problem optimization

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ARTICLE INFO

Keywords:

Energy modeling
Smart meters
Residential sector
Occupant behavior
Parameter calibration
Energy demand estimation
Data-driven analysis
Sustainability
Climate goals
Data integration

ABSTRACT

This research offers an innovative advancement in bottom-up building energy end-use modeling, vital for residential energy system analysis and planning. Conventional models rely on extensive demographic, behavioral, and equipment data from various sources, but these methods often compromise accuracy. To address this, our study introduces a novel methodology for parameter calibration using half-hourly smart meter data, despite its lower resolution due to capacity, management, and privacy constraints. Incorporating these data enhances the precision of energy demand estimations and accurately reproduces occupant behavior (OB). This method refines model accuracy and identifies OB across various household types, providing valuable insights for planning targeted energy conservation measures crucial for achieving climate goals. Moreover, it enables the tracking of behavioral changes over time, which traditional statistical methods cannot achieve, amplifying its utility. However, this study recognizes the need for further enhancement through the integration of additional data sources, such as movement data from smartphone applications and sensor-based household measurements. These improvements have the potential to revolutionize energy system analysis, contributing to a more sustainable, carbon-free society.

1. Introduction

Bottom-up building energy end-use models are powerful tools for energy system analysis, allowing examination of current energy use, prediction of future energy use under various energy-efficiency scenarios, and evaluation of power generation and distribution system stability using electricity load curves. To achieve climate goals and create a carbon-free society, energy consumption across all sectors, including residential, industrial, and transportation sectors, must be reduced. A bottom-up model called TREES [1–3] (Total Residential End-use Energy Simulation) was developed to estimate the final energy demand in the residential sector. However, the accuracy of this model may be compromised due to the requirement of extensive questionnaire- and literature-survey-driven information on household demographics, occupant behavior (OB), and equipment in each region. Therefore, potential deviations from reality can be encountered in the generated annual schedule of residents' activities.

In recent years, smart meters have gained popularity worldwide

because they provide detailed data on electricity consumption. Despite the low data resolution resulting from capacity, management, and privacy concerns, bottom-up modeling systems can be significantly improved through inverse problem optimization of the OB model. This approach allows for more reproducible OB estimations by calibrating the parameters of OB. In response to the Japanese government's plan to reduce greenhouse gas emissions by 46 % from the fiscal 2013 level by fiscal 2030, this study proposes an efficient parameter calibration method using the mean and standard deviation of half-hourly smart meter data for electricity consumption by household type. This calibration enhanced the accuracy of the model and offered detailed estimates of trends in OB, which were previously unattainable through statistical approaches. Additionally, by interpreting the calibration results, trends in the behavior of residents in each household category were estimated, providing valuable information for planning targeted countermeasures. Overall, this study presents a promising low-rate energy data utilization method that enables more effective planning of energy-reduction measures.

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<https://doi.org/10.1016/j.enbuild.2025.116074>

Received 16 October 2023; Received in revised form 16 May 2025; Accepted 26 June 2025

Available online 27 June 2025

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2. Literature review

This section provides an overview of the related studies that used smart meter data in building simulation research. Amasyali et al. [4] reviewed several studies forecasting data-driven energy demand estimates, with 12 of the 63 studies focusing on the residential sector and approximately half of them (36 studies) using hourly time granularity. Most studies have applied machine learning methods such as artificial neural network (ANN) and support vector machine (SVM). Wang et al. [5] provided a comprehensive review of research trends in smart meter data utilization, excluding non-intrusive load monitoring (NILM), which is the primary method. Most smart meter data considered 15-min to hourly electricity consumption data, and most load forecasting studies used machine learning methods along with individual smart meter data as the subject of analysis. Multiple regression analyses have been performed when individual data were unavailable. Chalmers et al. [6] focused on utilizing smart meter load disaggregation to detect activities of daily living (ADLs) and routine behaviors in dementia patients living alone. This study aimed to improve the monitoring and support of patients with dementia, enabling them to live independently for longer periods. By applying NILM techniques to smart meter data, the authors disaggregated the total energy consumption into individual appliance usage patterns. These patterns were then used to identify ADLs and routine behaviors in them. This study highlighted the potential of using smart meter data for unobtrusive and cost-effective monitoring of patients with dementia, ultimately providing valuable insights for healthcare providers, caregivers, and families. Zhao et al. [7] proposed a machineless learning method that decomposes the hourly smart meter data of each household into power consumption data for each individual device considered in the survey. By inferring equipment's operation from changes in the smart meter data with the base component removed, the accuracy of their method was compared with that of other supervised learning methods. Liu et al. [8] constructed a model to predict the operating state of cooling systems based on the measured electricity consumption of air conditioners and room environmental data, such as room temperature, relative humidity, and CO₂ concentration. They used ANN and gradient boosting decision tree (GBDT) to obtain a certain level of accuracy while reducing the number of input parameters. However, obtaining input data such as CO₂ concentration remains a challenge because indoor measurement data are difficult to acquire.

As the present study is designed to use statistically processed smart meter data and does not assume the existence of individual data, it is not possible to detect the operation of devices in individual households from changes in the data, as in Zhao et al. and Liu et al. Analyzing OB based on very low-rate data with coarse temporal resolution is generally challenging, and only a small number of studies have attempted this, including decomposition by NILM. Therefore, an inverse problem analysis using a bottom-up energy demand estimation model was employed to estimate the average appliance operation for the entire region. In this study, the standard deviation in the smart meter data, which has not been considered in existing studies, and the Wasserstein distance between the measured and estimated electricity consumption distributions as an error measure to achieve high-dimensional optimization based on the optimal transport theory were utilized. For optimization, Bayesian optimization was applied, which is suitable for objective functions with high evaluation costs, such as bottom-up models.

Furthermore, the concept of OB was reviewed in the context of building simulation research. The energy use of a building can be viewed as originating from a combination of physical and social conditions. The influence of building occupants, a primary component of social conditions, can be categorized into their presence (or occupancy) and the impact of their actions, as described by Yu et al. [9]. These social conditions interact with physical conditions and shape energy demand [10]. They are closely associated with heating, ventilation, air-conditioning,

lighting, and household appliances [11]. Divergence between measured and simulated energy use has been reported [12]. Subsequent studies confirmed that occupant-behaviour mismatches are a dominant source of error [13]. A broader review came to the same conclusion [14]. Various studies have concluded that in models incorporating OB, probabilistic approaches consistently surpass traditional deterministic methods [15]. They also outperform agent-based simulations in replicating day-to-day variability [16]. This confirms the recommendation of utilizing a probabilistic model in building simulation research for OB and calibrating its parameters using a data-driven method.

From existing reviews on OB models, it is evident that these models are predominantly analyzed at the individual building level. However, several studies pioneered frameworks for considering OB at the community scale [17–20]. While regional-scale OB data might be sourced from diverse channels encompassing individual users and institutions operating within the built environment, the absence of a structured data collection approach often results in the acquisition of sparse and inconsistent data. Such conditions complicate the task of modeling residents' behavior at the community level.

Recent advances in this field have led to novel methodologies for parameter estimation and model calibration. Lim et al. [21] employed a combined stochastic and deterministic approach to identify unknown parameters in urban building energy modeling while addressing uncertainties. Tardioli et al. [22] presented a method for calibrating building energy models at the district level using clustering algorithms and surrogate models. Both studies share common ground with the present research in that they utilized an inverse problem approach to calibrate the parameters. However, they are different from the present research in two key aspects: they did not handle time-series data, and they did not directly address OB. The present study aimed to incorporate time-series data analysis and integrate an OB model, further enhancing the accuracy and applicability of building energy simulations in policy evaluation, energy efficiency, and urban planning.

Bayesian inverse calibration has recently emerged as a robust means of reducing parameter uncertainty in bottom-up demand models. Kristensen et al. demonstrated that assimilating half-hourly and hourly smart-meter data via Bayesian updating consistently improved predictive accuracy, with finer temporal aggregation yielding tighter posteriors [23]. Building on this idea, the MARTINI framework proposed by Nweye et al. estimates HVAC start-up and set-back schedules directly from aggregated meter traces, eliminating the need for intrusive sensors [24]. At the community scale, Yu et al. implemented a multi-agent occupant model that synthesizes realistic schedules for hundreds of dwellings and markedly enhances district-level load forecasts [25]. Quantifying goodness-of-fit remains critical: Shin et al. introduced an auto-encoder residual metric based on the Wasserstein distance, showing superior sensitivity to distributional shape compared with KLD and CVRMSE, and motivating the present study's use of that metric [26]. Complementarily, Jeong et al. applied bias-corrected Bayesian inference to daytime load discrepancies, achieving a 15 % RMSE reduction after accounting for systematic bias [27]. Ensemble machine-learning benchmarks by Ramnath et al. further reveal that fusing survey variables with smart-meter features yields up to 12 % MAE gains over single-source models [28]. Recent representation-learning work by Zhang et al. shows that embedding optimized occupant-behavior vectors into prediction pipelines improves hourly forecasts across multiple horizons, reinforcing the value of calibrated behavior modules [29]. A comprehensive 2024 review by Guyixin et al. highlights the paucity of probabilistic, data-calibrated frameworks at urban scale and explicitly calls for community-level validation—precisely the gap addressed by our TREES extension [30]. Earlier evidence from Liisberg et al. confirms that Hidden-Markov inference can recover latent occupancy states even from 30-minute data, validating behavior detection at coarse resolutions [31].

In summary, conventional OB calibration studies lack coherent integration with urban-scale bottom-up frameworks. No study to date

combines probabilistic OB calibration with the urban building energy model while explicitly quantifying distributional fit via distance function defined between probability distributions.

3. Methodology

This section provides an overview of the household sector energy end-use model and the detailed specifications of the OB model. In this study, the household energy consumption was estimated using TREES model. Household energy consumption is determined by various factors, including the number of residents, their attributes, differences in behavioral habits, housing specifications, and types of appliances owned. Therefore, when assessing household energy conservation, estimating the energy demands of diverse households by considering these factors is necessary. Therefore, a model was developed that can estimate household energy demand by reproducing the variation among households considering all the influential factors.

3.1. Overview of the residential energy end-use model

An overview of the household energy end-use model is shown in Fig. 1. Prior to executing the calculations of this model, data related to household attributes, such as family composition, house type, and specifications of home appliances and water heaters, were determined. Furthermore, OB was considered to have patterns based on the attributes of household members, such as their gender and occupation. Ultimately, the energy end-use model projected the energy consumption for appliances, air conditioning, and water heating supplies based on this behavior.

Fig. 1 provides a more detailed and systematic explanation of the study procedure. Initially, in the “Household Attributes” section, attributes such as household personnel, residence location, house type, family size, and household income were sampled and established based on statistical data. Within the “Data Preparation Models” section, the status of appliance ownership and temporal changes in the housing stock were considered based on the sampled individual household attributes, and an OB schedule was established. The results of these processes were then input into “Data for an Individual Household.” In addition to information on room occupancy, the model can project occupant equipment usage by linking the contents of their activities to equipment

usage. The “Energy Demand Model by Final Demand” estimated the energy demand of each sampled representative household. The model calculated the energy demand for appliances, lighting, kitchens, hot water, etc. in five-minute increments throughout the year based on the on-and-off status of appliances. The heating and cooling energy consumptions were calculated through heat load calculations, considering the internal heat generated by the operation of the equipment besides weather conditions. Finally, the total energy consumption was computed by summing the estimated results for all sampled, representative households.

3.2. Occupant behavior model

The TREES model computes the energy consumption of operating equipment based on the behavior of household members and simulates actual equipment usage. On the other hand, the OB model, a component of the “Data Preparation Models,” generates a one-year lifestyle behavior at five-minute time intervals according to the occupant attributes. The OB model represents the behavior of household members using the results of the survey on time use and leisure activities as input data for 26 types of behavior, including sleeping, eating, cleaning, bathing, commuting, and explicitly encodes differences attributable to employment status and age category. A comprehensive description of the activity taxonomy and demographic segmentation is provided in [3].

In the OB model, the cumulative frequency distributions for each attribute were established using information acquired from the survey on time use and leisure activities, specifically for the commencement (or termination) and duration of each major routine activity. Based on these cumulative frequency distributions, the action schedule for each household member was determined. For other nonroutine activities, the occurrence probability was defined, and these activities were probabilistically scheduled during time slots when nonroutine activities were not planned. The smallest unit of action was a five-minute time interval.

For home appliances, such as televisions (TVs) and refrigerators, power consumption was determined by the size and year of device manufacturing. For lighting, the power consumption was determined by the room size, and for other home appliances, the average power consumption was established based on energy-saving performance catalogs. All these appliances operate based on OB, which allows power consumption to be estimated in five-minute time steps.

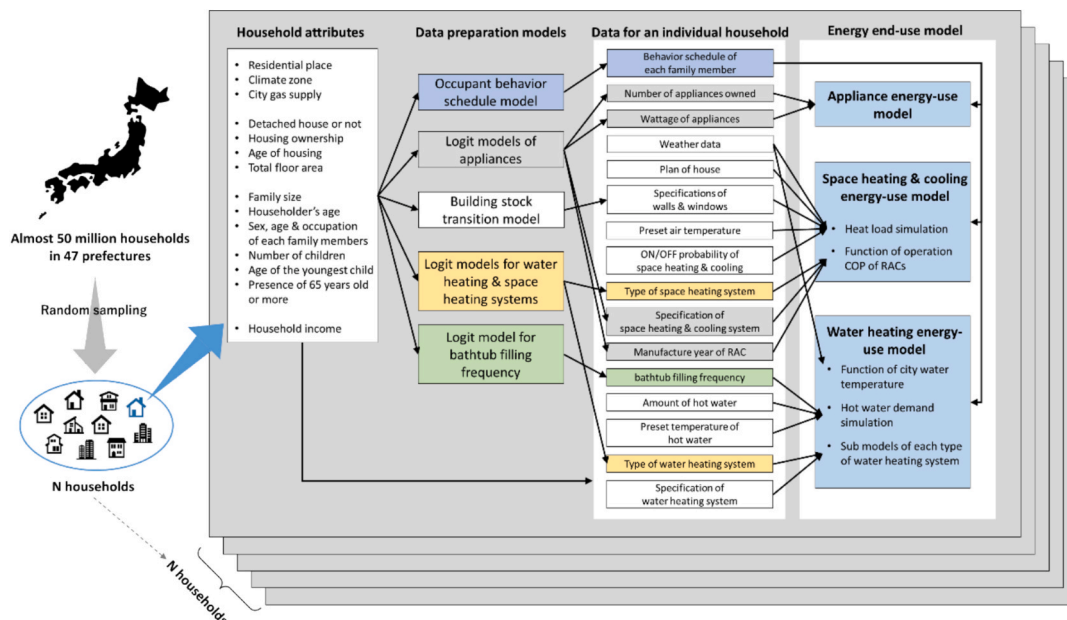


Fig. 1. TREES Model flowchart.

3.3. Dataset outline

The smart meter dataset used in this study was a sample of approximately 2,600 randomly selected two-person households living in apartment complexes supplied with electricity by the Kansai Electric Power Company (KEPCO). The samples were classified by household category and aggregated into averages and standard deviations every half hour for each category. The measurement period was from April 1, 2017 to April 30, 2019, and all-electrified houses were excluded.

3.4. Energy consumption distribution

In this study, optimization was performed using the mean value of the smart meter data and standard deviation information. In this process, assuming an appropriate frequency distribution of the electricity consumption of households in the smart meter data based on the mean and standard deviation enabled high-quality optimization. Since electricity consumption is non-negative and uniquely determined from the mean and standard deviation, a gamma distribution, which is also applied to the income distribution, was assumed. The probability density function of the gamma distribution can be expressed using the shape parameter k and scale parameter θ as in Equation (1). The shape and scale parameters are expressed in Equation (2) using mean and variance.

$$f(x) = \frac{1}{\Gamma(k)\theta^k} x^{k-1} e^{-(x/\theta)} (x > 0) \quad (1)$$

$$k = \frac{E(X)^2}{V(X)}, \theta = \frac{V(X)}{E(X)} \quad (2)$$

where $\Gamma(k)$ is Gamma function; $E(X)$ is mean electricity consumption of all households; and $V(X)$ is variance in electricity consumption for all households.

To examine the validity of the gamma distribution assumptions, it was evaluated whether the distribution of monthly electricity consumption in this dataset follows a gamma distribution, using maximum likelihood estimation. Fig. 2 presents the result of comparing the maximum-likelihood fits for two-person households living in apartment complexes using the gamma distribution and the normal distribution. At every time step the gamma distribution achieved lower Akaike information criteria (AIC) values, indicating a superior fit; the same tendency was observed for all other household categories. Because the empirical energy consumption distributions are typically skewed toward lower consumption, the gamma specification provides a more realistic representation than the normal distribution.

3.5. Inverse problem formulation

(1) Parameters for Optimization

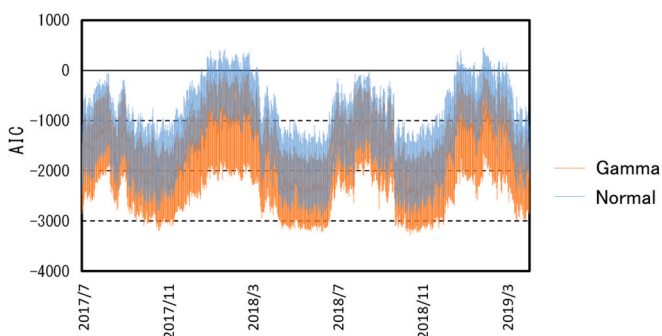


Fig. 2. AIC comparison of maximum likelihood estimation results for two-person households.

The parameters of the major behaviors that predominantly influenced household energy consumption patterns were calibrated. For routine activities, the median and variance of the cumulative frequency distribution were targeted. By varying the variance besides the median, it is possible to consider not only the start times and duration lengths but also the diversity of daily activities. For nonroutine activities, normal probability was targeted.

(2) Optimization Method

We employed the Bayesian optimization method. It is a technique that sequentially searches for the maximum or minimum value of a probability distribution when the evaluation function is unknown. Generally, Bayesian optimization is applied to problems with high execution costs and where high-frequency evaluations are unrealistic, making it suitable for calibrating bottom-up models such as TREES. In this study, the optimization was conducted using the Tree-structured Parzen Estimator (TPE), which is a representative Bayesian optimization method.

(3) Objective Functions

In this study, optimization was performed by considering not only the mean but also the standard deviation. The Wasserstein distance is a measure of the distance between probability distributions in a distance space; it defines the minimum transport cost between the probability distributions. The optimization problem is expressed in Equation (3). The Wasserstein distance is particularly useful in scenarios where other distance measures, such as the Kullback–Leibler divergence or total variation distance, may not capture the true dissimilarity between the two distributions. This is because the Wasserstein distance considers not only the mass of the distributions but also the geometric distance between individual points.

$$\operatorname{argmin}_p \sum_{t=1}^T W(E^p(t), O(t)) \quad (3)$$

where $E^p(t)$ is the distribution of TREES estimates at time t for parameter set p ; $O(t)$ is the distribution of smart meter observations at time t ; and $W(A, B)$ is the Wasserstein distance between distributions A and B .

In this study, the optimization targeted both “routine activities” that occur regularly in daily life and “non-routine activities.” Therefore, the optimization target parameters include four parameters for “routine activities”: the median and variance of the end time and the median and variance of the duration. For “non-routine activities,” two coefficients were used for the first-order affine transformation of the occurrence probability. The target period was set to intermediate seasons, when the influence of air conditioning was considered sufficiently small and limited to weekdays and non-rainy days. This is because, by ignoring the power consumption caused by air conditioning and further limiting it to weekdays and non-rainy days, the impact of schedules and weather can be eliminated, making it easier to verify the accuracy of optimization. The number of optimization iterations was set to 100.

4. Numerical experiment

The inverse problem analysis method, processing of smart meter data, and error indices have been discussed. In this section, the proposed inverse problem analysis method was used to optimize a two-person household and identify their actual OB. As the operation of air-conditioning equipment was dominant in the household load curves, the intermediate period was targeted to eliminate its influence. The results are validated and discussed based on the following surveys:

4.1. Determination of target activities to be optimized based on current state analysis

Among the TREES model's input parameters, those with deviations from initial settings (actual conditions) were considered targeted for optimization. Fig. 3 shows a comparison of the estimates from the TREES model (BAU; its breakdown is as shown in the stacked surface graph) and the time-averaged values of the smart meter data (SM2017) in the interim period.

From Fig. 3, TREES estimates were found to be underestimated during the nighttime hours (20:00 to 05:00). The TREES estimates showed a decrease in electricity consumption starting at approximately 20:00, while the smart meter data showed a decrease starting approximately 22:00. These findings indicate that the occupants represented in TREES follow unrealistically regular routines. In particular, the model predicts that television usage falls to nearly zero at midnight, a pattern not supported by empirical data. Accordingly, the model must be recalibrated to temper the excessive reduction in television power demand and to account for the gradual decline in activity rates during sleeping hours. Furthermore, adjustments for irregular going out, such as walking, which excludes commuting to work and school, were also considered important in the TREES model. The TREES estimates were overestimated for the morning hours between 06:00 and 10:00 because of significant electricity consumption by home appliances; vacuum cleaners, although used only for short durations, draw exceptionally high power and therefore contribute a disproportionately large share of the load and adjustments for cleaning activities must also be considered. The presence or absence of work has a significant impact on electricity consumption during the daytime. As teleworking has become more common among workers in recent years, it should be considered to reflect the actual situation.

In summary, it was decided that the optimization of the interim period should include the calibration of sleeping hours, work availability, TV viewing, going out, and cleaning activities.

4.2. Modeling of behavior calibration

In this section, the calibration method for OB modeling is described. The OB model can be classified into two categories: routine activities, which are the main activities habitually performed daily; and nonroutine activities, which include all other activities. Among the targeted behaviors determined in the previous section, sleeping and working were classified as routine behaviors, whereas watching TV, going out, and cleaning were classified as non-routine behaviors.

(1) Calibration of Routine Activities

For routine activities, the occurrence time and duration were modeled using ordinal logistic regression. The distribution generated for each attribute was fitted to a sigmoid function, and the parameters were manipulated by adjusting them. The sigmoid function is shown in Equation (4), where a is the parameter corresponding to the variance and θ is the mean. Based on the results of the preliminary experiments, only sleep and work duration were considered in this study.

$$f(x) = \frac{1}{1 + e^{-a(x-\theta)}} \quad (a > 0) \quad (4)$$

(2) Calibration of Non-Routine Activities

For nonroutine activities, such as watching TV, going out, and cleaning, the behavior was calibrated by applying a one-dimensional affine transformation that remains common at all times, as in Equation (5), and has a time-specific activity implementation probability p_t and parameters b_1 and b_2 .

$$p'_t = b_1 \times p_t + b_2 \quad (5)$$

4.3. Result

This section presents the optimization results for the intermediate period in a two-person aggregate household. The parameters calibrated by optimization are listed in Table 1 under "BEST," and the probabilities of action implementation and load curves are shown in Figs. 4 and 5, respectively. In Figs. 4 and 5, BAU represents the estimations obtained from the original TREES settings. As shown in the error column of Table 1, the Wasserstein distance has been substantially reduced. Although RMSE was not explicitly minimized, it also exhibits an improvement.

Table 1 and Fig. 4 show that the difference between BAU and optimized scenarios for sleep duration is 100 min, and the probability of occurrence of the work activities is negligible; furthermore, TV viewing activity increased, going out activity decreased, and cleaning activity did not change significantly. Fig. 5 shows that the accuracy of the time-series electricity consumption estimation improved, with very good accuracy in the late-night period (00:00–05:00). The timing of the decline in electricity consumption from approximately 22:00 was slightly slower, resulting in a smooth load curve similar to that of the smart meter data. This was because of the effects of increased electricity consumption after 20:00, decreased sleeping hours, and increased TV

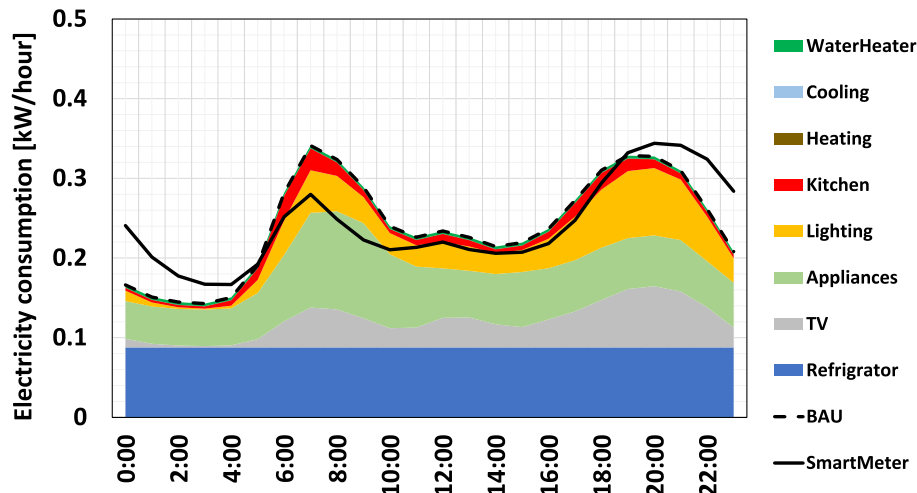
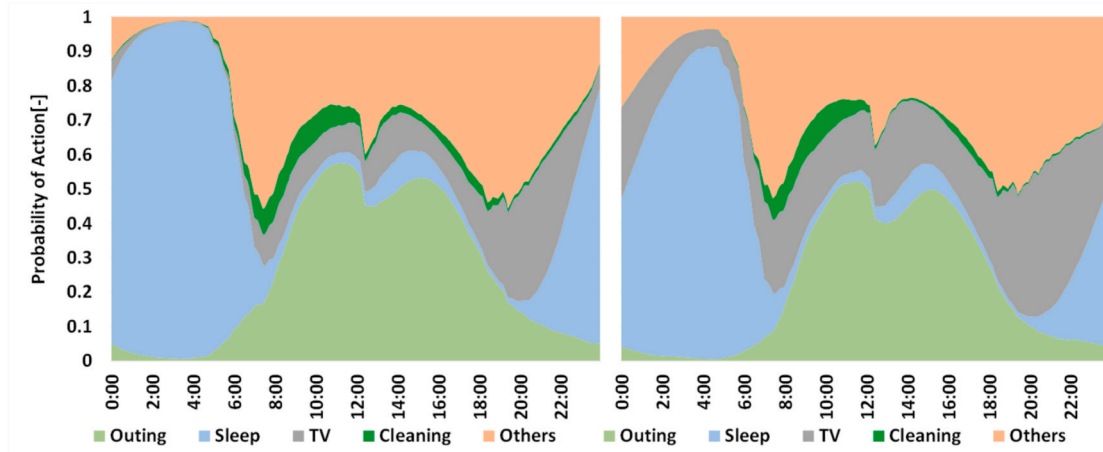
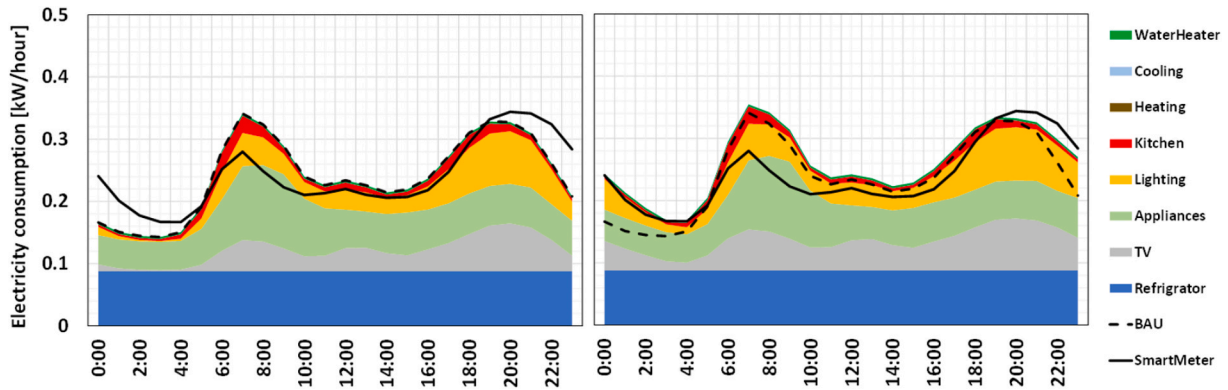


Fig. 3. Comparison of electricity load curves for the interim period.

Table 1

Calibration results of behavioral parameters.

	Sleep duration		TV viewing		Going out		Cleaning		Error
	a	θ [min]	b_1	b_2	b_1	b_2	b_1	b_2	
BAU	1.00	460	1.00	1.00	1.00	1.00	1.00	1.00	70.6
BEST	0.58	360	1.84	0.08	1.60	-0.20	1.82	-0.06	57.1

**Fig. 4.** Calibration results of action implementation probability for (a) BAU and (b) Optimization.**Fig. 5.** Calibration results for electricity load curves for (a) BAU and (b) Optimization.

viewing activities. Although the load curves agreed well with the smart meter data for some time periods, they remain overestimated in the morning at approximately 06:00–10:00, exhibiting a slight difference from the BAU case. This may be because TV viewing and cleaning activities have relatively large impacts in the morning.

Fig. 6 shows the change in the distribution of electricity consumption at each time point on May 10, 2017, owing to the optimization of sleep using the Wasserstein distance. In the optimized case, compared to the BAU case, the distribution of TREES electricity consumption at 00:00 and 03:00 can be observed to be closer to the distribution of electricity consumption estimated from the statistics of smart meter data.

4.4. Validation

In the following section, the validity of the calibrated parameters is discussed. Among the target behaviors of this optimization, the validity of sleep and TV viewing behaviors was examined, for which statistical and measured data exist.

For sleep behavior, the average sleep duration θ in the BAU was found to be 460, while the optimized average sleep duration was 360

min. TREES determined these default values for the OB model based on the results of survey on time use and leisure activities conducted by the Ministry of Internal Affairs and Communications (MIC) in 2006. A similar, more recent survey is the 2015 national time use survey conducted by NHK, the only national broadcaster in Japan. a 2018 survey conducted by C2 Corporation, a provider of smartphone apps for measuring sleep time, included 19,451 users, and 2019 survey by Brain Sleep Corporation, a seller of wearable devices for measuring sleep time, encompassed 10,343 users. These surveys differ from the statistical survey based on the aforementioned questionnaire in that they involve actual measurements. Table 2 shows the average sleep duration for each gender and age group based on different statistical surveys. In the questionnaire-based surveys, the average sleep duration was 430–465 min. These survey results suggest the validity of the BAU case; however, as previously indicated, questionnaires may reflect biases based on individual subjectivity and not necessarily reality. Questionnaires may reflect respondents' ideal life patterns and the trends of the past few days, which may not be suitable for annual estimates. In contrast, smartphone apps and wearable devices' sleep statistics showed a significantly different trend because they were based on actual

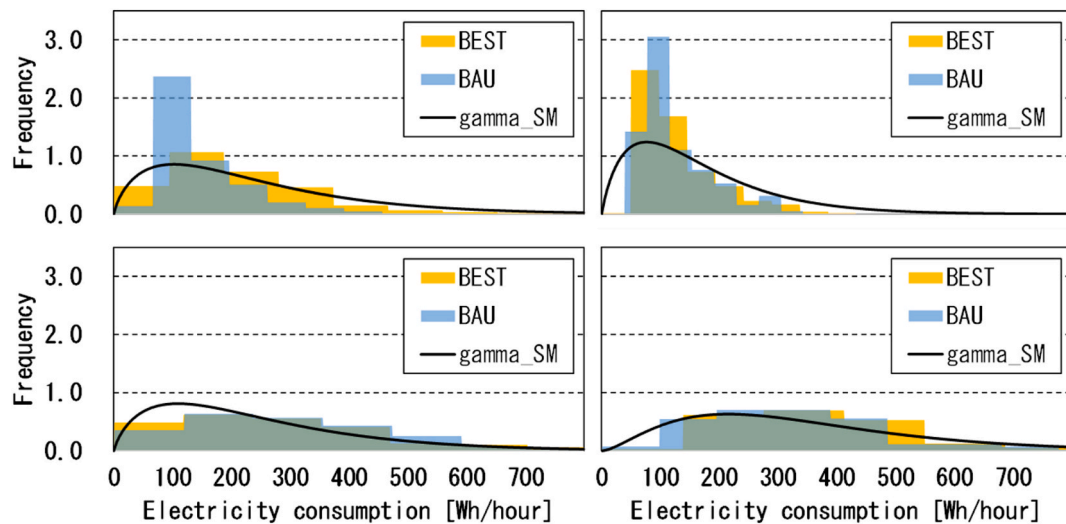


Fig. 6. Changes in the electricity consumption distribution on a representative day at (a) 0:00, (b) 3:00, (c) 6:00, and (d) 21:00.

Table 2

Average sleep duration according to different statistical survey.

[min]	2006 MIC		2015 NHK		2018 Apps		2019 Devices
	Male	Female	Male	Female	Male	Female	
All	465	455	442	430	364	365	387
20's	472	473	450	439	344	360	–
40's	439	424	413	402	352	358	–
60's	461	437	442	426	380	374	–

measurements taken by these devices, which were accurate and reliable in capturing real sleep behavior. The average sleep time for all generations was 364–387 min, which aligned well with the calibrated parameters, suggesting that this result was valid.

The validity of TV viewing behavior was examined using the people meter (PM) audience ratings survey results. The PM system simultaneously surveys both household and individual audience ratings. Fig. 7 shows a comparison between the household using television (HUT) obtained through PM and the household TV viewing rate calibrated by optimization. HUT represents the ratio of real-time television viewing. Compared with the BAU case, the optimized household TV viewing rate closely agreed with HUT, except for a slight overestimation in the 00:00–03:00 period. This overestimation in the early morning hours may be attributed to power consumption by devices like computers and others not considered in the model. Possibly, the power consumption

during sleep, such as smartphone and tablet charging, was inadvertently represented as TV power consumption in the TREES model.

5. Conclusions

This study contributes to improving the estimation accuracy of bottom-up models through the estimation of macroscopic OB. In this study, the TREES model, a bottom-up model for estimating energy consumption in the residential sector, was improved by calibrating the input parameters through an inverse problem analysis. The bottom-up model has many input parameters, the accuracy of which significantly affects the estimation accuracy. Therefore, the input parameters must accurately reflect the actual situation; however, reproducing the actual situation is difficult using only information from the literature, leading to uncertainty in the input parameters. The higher the level of detail in the input parameters, the greater the uncertainty. Therefore, this study improved the accuracy of the time series of electricity consumption estimation by calibrating the input parameters of the TREES model through inverse problem analysis. The TREES model provided more accurate estimations with higher precision. Furthermore, by estimating the macro OB for each year, it became possible to accurately monitor changes in OB over time, a capability not attainable through statistical surveys alone, and to track the impact of changes in lifestyle or behaviors on energy consumption over time. The Wasserstein distance was used as an error indicator to calculate the differences between the frequency distributions of household electricity consumption. However, the frequency of household electricity consumption was assumed to follow a gamma distribution. Although the optimization converged well for two-person households in the housing complexes targeted in this study, the behavior of other types of households should be thoroughly examined. An appropriate design of error indices would further improve the accuracy of the optimization, allowing higher-dimensional optimization. The validity of the parameters calibrated by inverse problem analysis was evaluated using various statistical surveys on sleep duration and TV viewership data, but not for other activities, such as going out or cleaning behaviors. Validating estimates with measured data, not self-reported surveys such as questionnaires, is important. However, capturing in-home human behavior is challenging due to data limitations. To address this, consider using smartphone applications' movement data or household-installed sensors for insights on going out and work-related activities.

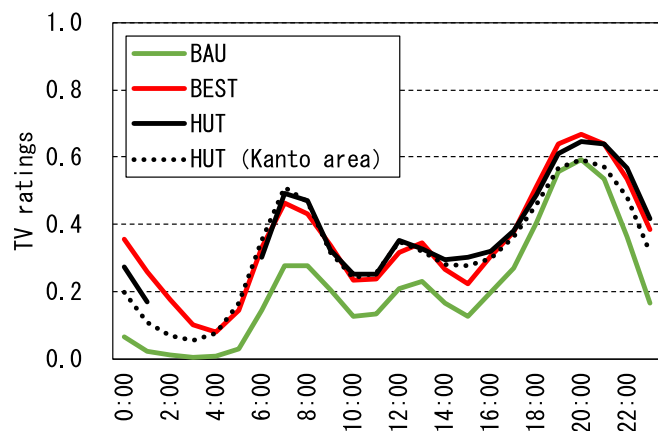


Fig. 7. Comparison between Household Using Television (HUT) and television ratings.

CRediT authorship contribution statement

Hideaki Uchida: Conceptualization, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing, Investigation. **Kazumasa Kishimoto:** Data curation, Formal analysis, Validation, Visualization. **Kazuki Nishizawa:** Data curation, Formal analysis, Validation, Visualization. **Yoshiyuki Shimoda:** Funding acquisition, Project administration, Resources, Supervision. **Yohei Yamaguchi:** Supervision. **Kazuya Togawa:** Data curation, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Hideaki Uchida reports financial support was provided by the Environmental Restoration and Conservation Agency of Japan.

Acknowledgement

This research work was financially supported by the Environment Research and Technology Development Fund (Grant No.: JPMEERF20212005) of the Environmental Restoration and Conservation Agency, Japan.

Data availability

The data that has been used is confidential.

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