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# Recognizing Home Activity from Coarse Branch Circuit Energy Usage Data

Fukuharu TANAKA [a,1], Teruhiro MIZUMOTO [b] and Hirozumi YAMAGUCHI [a]
[a] *Osaka University*
[b] *Chiba Institute of Technology*
ORCiD ID: Fukuharu Tanaka https://orcid.org/0000-0002-8324-9455, Teruhiro Mizumoto https://orcid.org/0000-0003-0281-1205, Hirozumi Yamaguchi https://orcid.org/0000-0003-2273-4876

**Abstract.** This study proposes a method for home activity recognition solely from the cumulative power consumption data of individual circuits obtained from HEMS distribution boards, recorded every 30 minutes. The proposed method targets seven activities: waking up, going to bed, cooking, laundry, dishwashing, bathing, and personal hygiene, aiming to estimate which activity occurred in each 30-minute time slot. Initially, it identifies the circuits most closely related to each activity. For activities identifiable by the ON/OFF status of appliances, it uses the presence or absence of power consumption in the corresponding circuit to recognize them. For other activities, it constructs models to estimate their presence using machine learning based on specially designed features. Furthermore, it adapts to inter-household differences using transfer learning. We conducted experiments using one year's HEMS data from 17 households through collaboration with a cooperative company. As a result, we confirmed that it could recognize each of the seven activities with an average F1 score of 0.86. Furthermore, we confirmed that the recognition accuracy of each activity could be improved by performing transfer learning.

**Keywords.** home activity recognition, machine learning, HEMS (Home Energy Management System), power consumption

## 1. Introduction

In recent years, Home Energy Management Systems (HEMS) have been increasingly deployed to monitor and control household electricity and gas usage. With the Japanese government aiming to install HEMS in all households by 2030, greater adoption and utilization of HEMS are anticipated. Activity recognition based on consumption data offers advantages such as avoiding privacy infringement and low acceptability associated with intrusive sensors like cameras or microphones [1–5], as well as eliminating the need for environmental sensors or wearable devices [6–8]. If the activities of residents can be identified from HEMS data, various non-intrusive and cost-effective applications can be expected. These include providing feedback on energy usage, improving accuracy in energy demand forecasting, consumer profiling, targeted marketing, and remote healthcare

[1]Corresponding Author: Fukuharu Tanaka, f-tanaka@ist.osaka-u.ac.jp

services such as monitoring elderly individuals [9, 10]. Although various activity recognitions based on electricity consumption have been studied, prior research has mainly focused on relatively high temporal resolution power consumption data [9, 11–15]. While recent HEMS distribution boards have emerged with systems capable of measuring at high temporal resolutions, most existing HEMS distribution boards are not configured to output such high-resolution data for other service purposes due to hardware costs and cost-effectiveness considerations. However, given the ability to aggregate power consumption by branch circuits (after this referred to as "branches"), it is highly feasible to grasp the use of household appliances associated with activities such as cooking, dishwashing, and laundry. Additionally, even with low temporal resolution, detecting activities involving long periods of activity, such as bathing or using high-power-consuming appliances like dryers, is possible.

This study proposes a method for activity recognition from 30-minute cumulative power consumption data for each branch obtained from HEMS distribution boards. The proposed method targets seven activities: waking up, going to bed, cooking, laundry, dishwashing, bathing, and personal hygiene. First, it identifies the branches assumed to be most relevant to each activity. For activities that can be clearly identified by the ON/OFF status of household appliances, recognition is based on whether the respective branch's power consumption is being utilized. For other activities, it constructs models to estimate the presence or absence of each activity using features we design, employing machine learning techniques. Additionally, it proposes a method to adapt to differences between households through transfer learning.

We conducted experiments using HEMS data for one year from 17 households obtained through collaboration with partner companies. We labeled the data with multiple people for two months in summer and winter, resulting in over 530,000 data entries. As a result, we confirmed that each of the seven activities could be recognized with an average F1 score of 0.86. Furthermore, we confirmed that the recognition accuracy of each activity improved through transfer learning.

*Contributions of This Paper*

In this study, we aim to recognize activity based on the branch power consumption data to provide detailed energy usage feedback and monitor the elderly.

Utilizing electricity data offers non-intrusive and cost-effective alternatives compared to cameras, microphones, environmental sensors, or wearable sensors. Existing studies often utilize high-resolution consumption data at a granularity of seconds, providing a detailed perspective. However, these datasets require dedicated measurement devices, incurring installation costs. In this study, we use branch-level power consumption data obtained from existing HEMS at a granularity of 30 minutes. While this limits detailed features, it excels in installation cost, leveraging existing infrastructure.

The contributions of this study are as follows: We propose a method for activity recognition from branch-wise power consumption data with such low granularity that activity recognition would be difficult with other methods. We improve estimation accuracy by adapting transfer learning to address differences in household patterns. We design features that can estimate activities even at 30-minute granularity based on observations of real-world data collected from 17 households over one year, as well as heuristics such as trends in appliance usage and lifestyle patterns in Japanese households.

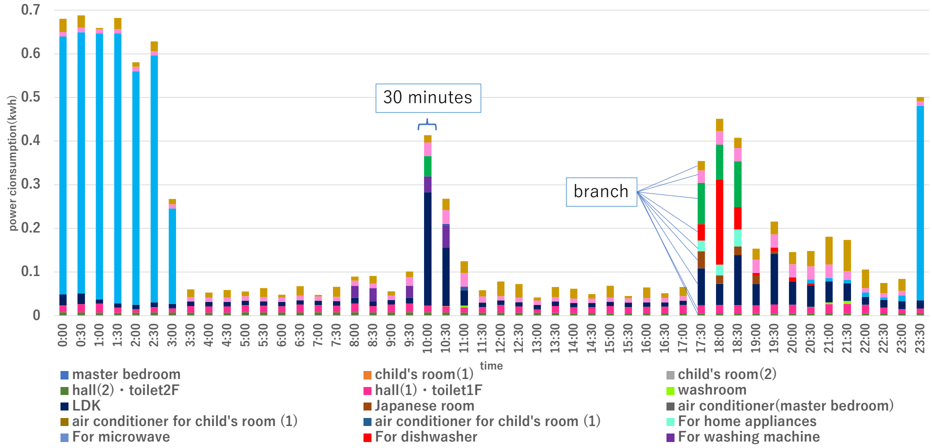


**Figure 1.** Example of low-grain branch circuit power consumption data.

## 2. Proposed Method

### 2.1. HEMS Data

In order to achieve activity recognition from the power consumption data obtained from the HEMS distribution board, we obtained a total of 10 million data points observed over one year from 17 HEMS in collaboration with cooperative companies. The provided data are all from the same construction company, using cooking appliances such as IH instead of gas for cooking and also equipped with dishwashers and washing machines. Figure 1 shows a daily data sample from one household. As shown in Figure 1, in the HEMS currently prevalent in Japan, power consumption is separately aggregated for each room or specific appliances such as air conditioners to visualize power consumption effectively. However, currently prevalent HEMS can only measure cumulative power consumption every 30 minutes due to specifications, resulting in a very low temporal granularity. Due to the cumulative aggregation, it is impossible to separate multiple activities or appliances operating. The same value may be obtained when the lighting is used for 30 minutes and when the dryer, which consumes 30 times as much power as the lighting, is used for 1 minute. Therefore, it is difficult to use conventional methods to identify the types of appliances in operation and estimate the activities associated with specific appliances.

However, as seen in Figure 1, branch names are assigned for visualization in each branch. Data analysis revealed two types of circuits: dedicated circuits and general-purpose circuits. Dedicated circuits are branches dedicated to specific appliances, while general-purpose circuits aggregate the total power consumption of all lighting and appliances in a room. With dedicated circuits, it is possible to estimate the operation of specific appliances, and activities directly corresponding to those appliances are recognizable. On the other hand, in general-purpose circuits, the number and types of connected appliances are not specified, and due to the coarse aggregation time granularity, it is difficult to identify the presence and type of appliances. However, there is a high correlation between room types and the types of appliances used, and in many cases, it

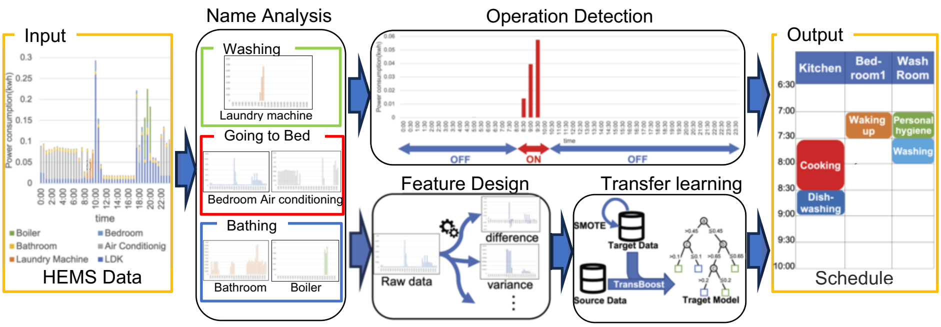


**Figure 2.** Overview of the proposed method.

is possible to narrow down the types of appliances from the room names. Additionally, suppose a room does not typically show high power consumption. In that case, the operation of appliances with significantly high power consumption can be confirmed, making activities such as using dryers or hair irons recognizable, especially in bathrooms. Furthermore, activities characterized by prolonged distinctive power usage trends before and after events, such as waking up, going to bed, and bathing, can also be recognizable. Based on the above reasons, we considered activities with changes in activity over a long period (waking up, going to bed, bathing), high power consumption activities (personal hygiene), and activities leaving traces of appliance usage on dedicated circuits (cooking, laundry, dishwashing) as recognizable. In addition to the above reasons, considering the generality of branches corresponding to data from many households, this study defines seven activities as recognition targets: waking up, going to bed, bathing, personal hygiene, cooking, laundry, and dishwashing.

## 2.2. *Method Overview*

The proposed method takes cumulative power consumption values for each 30-minute interval (slots) from HEMS residential distribution panels, branch by branch, as input. The daily life activities to be estimated include waking up, going to bed, cooking, laundry, dishwashing, bathing, and personal hygiene, totaling seven activities. The proposed method outputs the presence or absence of each activity for each slot.

Figure 2 illustrates an overview of the proposed method. Firstly, it analyzes the names assigned to each branch to classify the branches into dedicated circuits and general-purpose circuits. At this time, the appliance names and room names are identified, and relevant activities are assigned. Next, for dedicated circuits, as the types of appliances connected to each branch are known, it performs operation recognition by peak detection, allowing for the recognition of activities using the operated appliances. For general-purpose circuits, we define features for each activity, and it employs machine learning for activity recognition. Additionally, since lifestyle habits and power consumption tendencies generally vary significantly from household to household, it applies transfer learning to adapt models created using data from multiple households to each household.

### 2.3. Name Analysis

As illustrated in Figure 1, the branch names exhibit various patterns, ranging from only room or appliance names to those followed by floor numbers or identifiers. However, analysis revealed that the patterns are finite and follow a context-free grammar. Therefore, we first parse the context-free grammar to extract information such as room names, appliance names, and associated numbers or floor levels from the branch names. Then, we map the activities to the branches based on the following rules:

- Circuits for bedrooms, such as “Master bedroom” or “Children’s room” and their corresponding air conditioning circuits are mapped to waking up and going to bed.
- Circuits for washrooms, such as “Washroom” or “Dressing room,” are mapped to personal hygiene.
- A Dedicated circuit for the dishwasher is mapped to dishwashing.
- Dedicated circuits for cooking appliances, such as IH cookers or microwaves, as well as circuits labeled “kitchen appliances,” are associated with cooking.
- The general-purpose circuit for the bathroom and the dedicated circuit for the water heater are mapped to bathing.
- The dedicated circuit for the washing machine is mapped to laundry.

### 2.4. Operation Detection

The dedicated circuits are connected to a single appliance, so there is no operation outside the activity time, and power consumption is zero when not in use. Therefore, the activity time is detected using a simple rule based on whether the power value is zero. However, in circuits labeled “kitchen appliances” associated with cooking activities, there may be appliances connected that are not directly related to cooking. Examples of appliances unrelated to direct cooking time include ventilation fans, lighting, electric kettles, coffee makers, and rice cookers. The power consumption indicated by these appliances is distinctive; for example, ventilation fans and lighting show waveforms with slight variation. Additionally, electric kettles and coffee makers boil water and then maintain warmth, while rice cookers keep rice warm after cooking, resulting in a characteristic pattern of initially high power consumption followed by sustained low power consumption. In this study, these characteristics are captured using rule-based methods, and branches exhibiting these characteristics are excluded from being utilized for activity recognition.

### 2.5. Feature Design

The branches used for detecting activities such as bathing aggregate the power consumption of lighting and general outlets, which fluctuates even when there is no activity, making it difficult to detect with simple rules. Therefore, we employs machine learning(XGBoost) for activities such as bathing, waking up, going to bed, and personal hygiene. The following sections will explain the features and their importance. Table1 gives the symbolic definitions that represent the features used in each activity.

#### 2.5.1. Feature Design for Recognition of Getting Up and Going to Bed

First, we list the features used for waking up and going to bed. Since the characteristics for recognition are similar, we use the same features. Specifically, we use the following features.

**Table 1.** Symbolic definitions for features.

| Feature Name | Feature Description |
|---|---|
| $(T^n_{cos}, T^n_{sin})$ | time of sample $n$ (trigonometric representation) |
| $S^n$ | Season of sample $n$ (summer or winter) |
| $L^n_x$ | Power consumption of branch $x$ of sample $n$ ($x$ is bedroom (BED), air conditioning (AC), bathroom (BATH), boiler (BOILER) or washroom (WASH)) |
| $Ldiff^n_x$ | Power consumption difference of branch $x$ of sample $n$ to sample $n-1$. |
| $Lratio \uparrow^n_x$ | Power consumption ratio of branch $x$ of sample $n+1$ to sample $n$ |
| $Lratio \downarrow^n_x$ | Power consumption ratio of branch $x$ of sample $n-1$ to sample $n$ |
| $Lvar^{[n+a,n+b]}_x$ | Variance of power consumption of branch $x$ from sample $n+a$ to $n+b$ ($a \leq b$) |
| $\Delta\overline{L}^n_x$ | Difference between the power consumption of branch x of sample $n$ and the average of the power consumption of branch x of the previous 24 samples |

1. Time $(T^n_{sin}, T^n_{cos})$. Due to high dependence on the time of day.
2. Season $S^n$. Due to the seasonal dependence on electric power.
3. Power consumption of bedrooms and air conditioning $L^{n-1}_{BED}$, $L^n_{BED}$, $L^{n+1}_{BED}$, $L^{n-1}_{AC}$, $L^n_{AC}$, $L^{n+1}_{AC}$.
4. Difference from the previous slot's power consumption of bedroom and air conditioning $Ldiff^n_{BED}$, $Ldiff^{n+1}_{BED}$, $Ldiff^n_{AC}$, $Ldiff^{n+1}_{AC}$. To capture the temporal variations in electricity consumption due to appliance operation.
5. Change in power consumption from before and after samples (slots) in bedrooms and air conditioning $Lratio \uparrow^n_{BED}$, $Lratio \downarrow^n_{BED}$, $Lratio \uparrow^n_{AC}$, $Lratio \downarrow^n_{AC}$. This is introduced to capture the sudden rise and fall in power observed by turning off appliances when going to bed and turning on appliances when waking up.
6. Variance of power consumption in bedroom and air conditioning $Lvar^{[n-6,n-1]}_{BED}$, $Lvar^{[n+1,n+6]}_{BED}$, $Lvar^{[n-6,n-1]}_{AC}$, $Lvar^{[n+1,n+6]}_{AC}$. To capture the differences in power consumption due to the explicit operation of appliances during awake and asleep states, we introduced this feature.

The formulas for calculating each feature are shown below. In this study, we used a trigonometric function applied to 48 slots, which correspond to one day, as the features in order to give them periodicity. $n$ is the sequential number (sample number) given to each slot from the beginning of the HEMS data. $\varepsilon$ is a very small value that prevents the denominator from becoming zero.

$$T^n_{sin} = \sin\frac{(n \mod 48)\pi}{48}, \quad T^n_{cos} = \cos\frac{(n \mod 48)\pi}{48} \tag{1}$$

$$Ldiff^n_x = L^n_x - L^{n-1}_x \tag{2}$$

$$Lratio \uparrow^n_x = \frac{L^{n+1}_x}{L^n_x + \varepsilon}, \quad Lratio \downarrow^n_x = \frac{L^{n-1}_x}{L^n_x + \varepsilon} \tag{3}$$

$$Lvar^{[n+a,n+b]}_x = \frac{1}{b-a+1}\sum_{k=a}^{b}(L^k_n - \frac{1}{b-a+1}\sum_{l=n+a}^{n+b} L^l_x)^2 \tag{4}$$

Considering that waking up and going to bed occur only once a day, and assuming that at least one of them occurs if the resident is not outside, we examine the likelihood and select the maximum positive slot among those exceeding a certain threshold; if no positive slot exists within a day. Conversely, all except the maximum one are masked if there are multiple positive slots. Furthermore, we consider the timing relationship between waking up and going to bed and operating appliances such as IH cookers, which individuals manually operate.

### 2.5.2. Feature Design for Recognition of Bathing

We then show the features of bathing as follows.

1. Time $(T^n_{sin}, T^n_{cos})$. This is because bathing is time-regular and highly dependent on the time of day.
2. Season $S^n$. This is used because of the seasonal dependence on electric power.
3. Power consumption of bathroom $L^{n-2}_{BATH}$, $L^{n-1}_{BATH}$, $L^n_{BATH}$, $L^{n+1}_{BATH}$, $L^{n+2}_{BATH}$. This is because turning on the room lighting and the ventilation fan while bathing causes an increase in power consumption.
4. Difference from the previous slot's power consumption of bathroom and boiler $Ldiff^n_{BATH}, Ldiff^{n+1}_{BATH}, Ldiff^n_{BOILER}, Ldiff^{n+1}_{BOILER}$. To capture the temporal variations in electricity consumption due to appliance operation.
5. Difference from the average of the last 24 samples of bathroom power consumption. $\overline{L}^{n-2}_{BATH}$, $\overline{L}^{n-1}_{BATH}$, $\overline{L}^n_{BATH}$, $\overline{L}^{n+1}_{BATH}$, $\overline{L}^{n+2}_{BATH}$. The moving average and the difference between each slot are used to reduce the effect of differences in power consumption during inactivity between houses.
6. Power consumption of boiler $L^{n-3}_{BOILER}$, $L^{n-2}_{BOILER}$, $L^{n-1}_{BOILER}$, $L^n_{BOILER}$. The water heater's power consumption increases before bathing to fill the bathtub with hot water. Therefore, we use the power consumption of the water heater over the past several slots.

We show the formulas for the features not defined in equation (1)∼(4).

$$\Delta\overline{L}^n_x = L^n_x - \frac{1}{24}\sum_{k=n-24}^{n-1} L^k_x \tag{5}$$

### 2.5.3. Feature Design for Recognition of Personal Hygiene

We then show the features of personal hygiene as follows.

1. Time $(T^n_{sin}, T^n_{cos})$. This is because personal hygiene is time-regular and highly dependent on the time of day.
2. Power consumption of washroom $L^{n-2}_{WASH}$, $L^{n-1}_{WASH}$, $L^n_{WASH}$, $L^{n+1}_{WASH}$, $L^{n+2}_{WASH}$. This is because turning on the dryer or hair iron causes an increase in power consumption.
3. Difference from the previous slot's power consumption of wathroom $Ldiff^{n-1}_{WATH}$, $Ldiff^n_{WATH}$, To capture the temporal variations in electricity consumption due to appliance operation.
4. Difference from the average of the last 24 samples of washroom power consumption. $\overline{L}^{n-2}_{WASH}$, $\overline{L}^{n-1}_{WASH}$, $\overline{L}^n_{WASH}$, $\overline{L}^{n+1}_{WASH}$, $\overline{L}^{n+2}_{WASH}$. The moving average and the difference between each slot are used to reduce the effect of differences in power consumption during inactivity between houses.

#### 2.5.4. Transfer Learning

In each household, while the characteristics of power consumption due to activities are similar, differences in appliance performance and activity duration result in varying scales and the timing of activities. Training with all possible patterns of data is theoretically feasible but not practical. Obtaining a large amount of labeled data for target households is challenging due to the granularity of 30-minute data, resulting in only 48 data points per day. Therefore, our approach focuses on the similarity of recognition tasks across households and overcomes inter-household differences by leveraging transfer learning to build models from relatively small amounts of data from target households. In this study, we employed TransBoost [16], which extends XGBoost. In TransBoost, two GBDT (Gradient Boosting Decision Tree) models are prepared: one trained on the target data and the other trained on the source data. The loss function for the GBDT trained on the target data is defined as the weighted sum of the loss functions of the two GBDT models, allowing the utilization of source information while learning target-specific features.

Additionally, the proportion of each behavior within a day is very low, with only one positive data point obtained per day, especially for waking up and going to bed. Using a small and imbalanced dataset for transfer learning may lead to overfitting. Therefore, in this study, we addressed the imbalance issue by using the Synthetic Minority Over-sampling Technique (SMOTE) [17], which increases the proportion of positive data points.

## 3. Evaluation

### 3.1. Evaluation Metrics and Dataset

To evaluate whether the proposed method can recognize the seven activities, we obtained power consumption data from the HEMS of 17 households through collaboration with our partner companies. For this evaluation, we labeled one month of data for both summer and winter, based on rules derived from our previous study [18], where household appliance usage is typically higher. We conduct cross-validation to evaluate the generalization performance, and 10 days of data from each household are reserved for transfer learning. Considering each of the seven activities as a binary classification problem, we compared the estimated results of each time slot with the ground truth. We then counted the number of matches and discrepancies to calculate true positives, false positives, false negatives, and true negatives.

### 3.2. Recognition Accuracy of Activities through Operation Recognition

**Table 2.** Recognition accuracy of each activity by operation recognition.

| Activity | Precision | Recall | F1-Score |
|---|---|---|---|
| Cooking | 0.996 | 0.964 | 0.980 |
| Washing | 0.951 | 0.996 | 0.973 |
| Dish-Washing | 0.981 | 0.966 | 0.974 |

First, we evaluate the accuracy of activity recognition through the recognition of appliance operation. Table 2 shows the recognition accuracy of each activity. The proposed method achieved high accuracy for the three activities: cooking, laundry, and dishwashing. However, the recall for cooking is slightly lower, which is attributed to the fact that different appliances are connected during summer and winter. Therefore, it is necessary to confirm which appliances are connected for cooking periodically.

### *3.3. Recognition Accuracy of Activity through Machine Learning*

**Table 3.** Recognition accuracy for each activity with/without transfer learning.

| | XGBoost | | | TransBoost | | |
|---|---|---|---|---|---|---|
| Activity | Precision | Recall | F1-Score | Precision | Recall | F1-Score |
| Waking up | 0.781 | 0.633 | 0.699 | 0.822 | 0.764 | 0.792 |
| Going to Bed | 0.778 | 0.631 | 0.697 | 0.818 | 0.707 | 0.759 |
| Bathing | 0.824 | 0.830 | 0.827 | 0.872 | 0.882 | 0.877 |
| Personal Hygiene | 0.847 | 0.897 | 0.871 | 0.859 | 0.931 | 0.893 |

Next, we evaluated the recognition accuracy of activities when machine learning was applied. Table 3 shows the recognition accuracy for each activity. The accuracy improved for all activities with transfer learning. The improvement is attributed to the complementary role played by the loss function of the source data model during training, sharing knowledge while mitigating overfitting, leveraging the similarity of tasks across households, where a small amount of target household data alone would lead to overfitting. Particularly, the accuracy for waking up and going to bed was lower without transfer learning but improved significantly with transfer learning. This improvement can be attributed to variations in how households use bedrooms and the types of appliances found in bedrooms. On the other hand, the recognition accuracy for personal hygiene was already high, and there was minimal improvement. This is likely because personal hygiene is characterized by significant power consumption and relatively uniform household patterns.

## 4. Conclusion

This paper proposed a method for activity recognition from low-granularity branch power consumption data obtained from HEMS. The performance evaluation results confirmed that each of the seven activities could be recognized with an average F1 score of 0.86. Furthermore, it was confirmed that recognition accuracy improved by performing transfer learning.

The presence or absence of residents in a room can be estimated based on the magnitude of fluctuations in power consumption, similar to the recognition of wake-up and going to bed. If the presence or absence of residents in a room can be recognized, it is conceivable to estimate whether all occupants are out of the house in conjunction with the other activities. Finally, we are considering conducting a verification experiment to introduce our proposed method into HEMS.

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