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Finding Load Profile Primitives by using Independent Component Analysis

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Abstract

In this paper, we describe our work on finding load profile primitives. Analyzing home electricity consumption is an important issue for designing, managing, and analyzing a future smart grid. Load profile data have additive property because of the same property of electric current. It will enable us to decompose observed data into a small number of elemental components, named load profile primitives. We measured several sets of home load profiles and applied independent component analysis (ICA) to extract load profile primitives. We investigate the possibility of finding load profile primitives by analyzing the measured data set with independent component scores. We evaluate its performance by comparing with originally observed data, qualitatively. We also adopted ICA to load profiles of one hundred houses measured in Higashiomi city and shows that the method can extract the seasonal changes in load profiles of local grid.

1 Introduction

1.1 Decentralized local smart grid

Decentralized electricity networks have recently been attracting attention. People believe a decentralized electricity network is appropriate to power generators using various renewable energies, e.g., photovoltaic generators (PV) and wind power generators. Many kinds of micro grids have been studied for a long time. Recently, researchers, mainly in Europe, studied Virtual Power Plant (VPP), which is an aggregated electricity resource managed integrally and efficiently [1–3]. However, in such studies, distributed resources tend to be controlled in a centralized way. In contrast, many researchers have started trying to manage distributed electricity resources in a decentralized way [4].

We have proposed and studied a model for a future smart grid named the inter intelligent renewable energy network (i-Rene) [5,6]. In the i-Rene, most houses are equipped with a PV and a battery. However, electric energy produced by a PV cannot be consumed by the single house. Therefore, the surplus electricity should be put into circulation in the decentralized local power grid by charging and discharging their batteries. For this, each house uses a smart meter (or a power router) with artifcial intelligence, which would be based on a machine learning system, to trade electricity in the networks adaptively and automatically. To circulate surplus electric power efficiently within the smart grid, not only an averaged load profile of the entire network but also individual load profiles must be predicted for each house. Thus, microscopic analysis of load profile data becomes more and more important.

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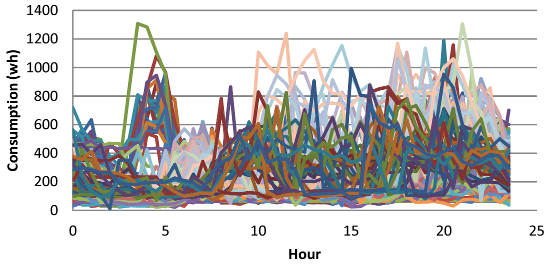


Figure 1. Randomly sampled measured load profiles

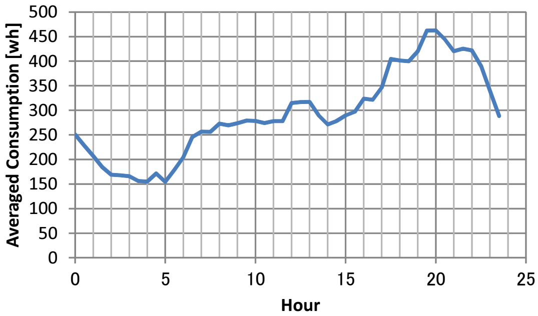


Figure 2. Averaged power consumption by a household sector

1.2 Load profile primitives

The averaged load profile of the household sector is often dipicted as shown in Fig. 2. These kind of measured data are widely known[1]. However, individual load profiles are very different from the averaged one. Figure 1 shows load profiles randomly sampled from home electric consumption data we measured. This shows that daily home electric power consumptions are diverse and noisy. Empirically, a home load profile seems to have a certain kind of consistent pattern, but fluctuates stochastically depending on the day of the week and schedules of people living in the house. Therefore, it is difficult for us to understand characteristics of individual load profiles from only looking at measured data for each house.

On the other hand, load profile data have additive property because of the same property of electric currents. This additive property, i.e., linear property, will enable us to decompose observed load profiles into a small number of elemental load profiles. We call these *load profile primitives*. Decomposition of load profiles has been studied to distinguish elemental pattern representing usage of electric appliances from the profiles in the context of machine learning and data mining [7–9]. On the other hand, Yanagida et al. tried to find an underlying structure in annual electric load data using independent component analysis [10].

In this paper, we measure several sets of home load profile data and try to extract load profile primitives by applying independent component analysis (ICA). By qualitatively investigating the measured load profiles and results of ICA, we study the possibility of finding load profile primitives and using them to predict and/or model individual load profiles.

2 Method for finding load profile primitives

An independent component analysis (ICA) is a statistical technique to extract key low-dimensional representations from a set of given time series data. There are various algorithms to perform ICA. The fastICA [11,12] is proposed to use for analyzing the target data set in this paper. fastICA is one of the most popular ICA algorithm having high computational efficiency. ICA tries to decompose

[1]This figure shows the averaged load profile that was averaged using seven homesf electric consumption data measured in our research during summer 2010.

Figure 3. SHOENE NAVI: an electric power meter [13]

a target signal data by assuming that source signals are independent.

$$X = SA \quad (1)$$

$$XKW = \hat{S} \quad (2)$$

$$\hat{A} = (KW)^+ = ((KW)^T(KW))^{-1}(KW)^T \equiv B \quad (3)$$

where $X = \{x_{tk}\}$, $S = \{s_{tk}\}$, $A = \{a_{dk}\}$ and $B = \{b_{dk}\}$ are matrices. ICA assumes that the observed signal X is generated by mixing independent signals S by using a mixing matrix A. To evaluate independence of signal sources, fastICA uses negentropy representing non-Gaussianity. The abstract procedure is as follows.

1. Centering and whitening X by calculating K using PCA
2. Finding an orthogonal matrix W that maximizes approximate value of negentropy

By estimating K and W, we can estimate source signal $\hat{S}$ (Eq. 2). We can also estimate mixing matrix A via calculating a pseudo-inverse matrix of KW (Eq. 3). By calculating $\hat{A}$, we can estimate each independent component score for each piece of the load profile data. Therefore, we also estimate A.

In this study, we assume X contains load profiles. $t \in \{1, \cdots, T_{max}\}$ represents an index of time slot during which electric load is summed up. d is the index of independent components. k is the number of samples of load profiles. The fastICA can extract load profile primitives in an unsupervised way.

3 Experiment 1: individual homes

3.1 Materials

Electric load profiles of seven houses were measured by using the electric power meter produced by Chugoku Electrical Instruments Co., Ltd. [13] (Fig. 3). This can easily record electric load profiles every 15, 30, or 60 minutes. In our experiment, load profile data of the seven houses were recorded every 30 minutes during July and August 2010.

Six of the seven target houses are occupied by six independent families, and the other is occupied by two university students. The family structures and other properties are shown in Table 1.

We used the daily individual load profiles as an input data X. $T_{max} = 48$ and $K = 434 = 7[homes] \times 72[days]$. In this study, we set the number of independent components to five.

Table 1. Target families

Home no.	House type	The number of residents	family structure
Home 1	Apartment 1LDK	4	Parents and two infants
Home 2	Apartment 3DK	3	Parents and an infant
Home 3	House	2	Married couple
Home 4	House	5	Parents and three children
Home 5	House	5	Parents and three children
Home 6	House	4	Parents and two children
Home 7	Apartment 1LDK	2	Two students

3.2 Results

3.2.1 Overview

Fig.5 shows the five extracted independent components, i.e., load profile primitives. Fig. 4 shows the averaged mixing coefficients of independent components for each house. If a coefficient is big, the family living in the home consumes electric power on the basis of a load profile pattern containing the corresponding independent components in large amounts. We consider each independent component (IC) as a load profile primitive.

For example, Home 1 is affected by IC3 negatively. Home 3 is characteristically affected by IC2. Homes 3 and 5 have similar ratios of ICs. These results show that family structure is a poor explanatory variable to explain load profiles. We also averaged mixing coefficients over days of the week for each home. In the next subsection, we look at results for all seven homes.

3.2.2 Home 1

Fig. 6 shows that IC1 was relatively active on Wednesday. Fig. 7 shows Home 1's load profiles on Wednesdays. IC1 increases electricity consumption from 9 a.m. to 7 p.m. This tendency can be found in the graphs shown in Fig. 7.

3.2.3 Home 2

Fig. 8 shows that IC1 and IC3 negatively affect Home 2. They are both especially active on Friday. Negative IC1 and IC3 drag down daytime consumption (Fig. 9). Negative IC1 also increases nighttime consumption. The two ICs mainly characterized load profiles of Home 2.

3.2.4 Home 3

Fig. 10 shows that most ICs negatively affect Home 3's load profiles. Fig. 11 shows load profiles of Home 3 on Fridays. This family's load profiles are relatively similar to averaged data in Fig. 2.

3.2.5 Home 4

Fig. 12 shows that IC3 and IC5 negatively affect Home 4's load profiles. Fig. 11 shows load profiles of Home 4 on Saturdays. On Saturday, IC1 increases daytime electricity consumption. This means that people living in Home 4 tend to stay at home on Saturday.

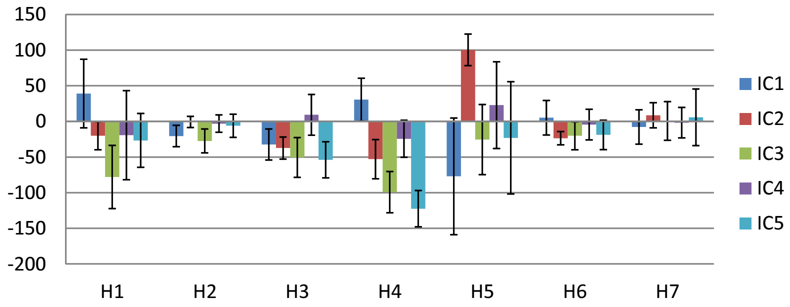


Figure 4. Averaged mixing coefficients of independent components for each house

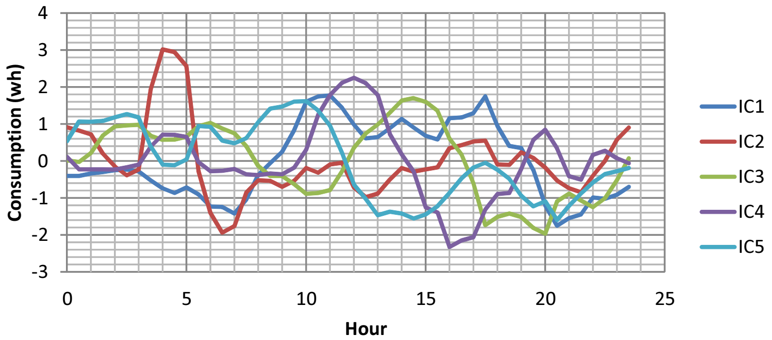


Figure 5. Extracted independent components

3.2.6 Home 5

Fig. 14 shows that the fifth house typically used IC2 positively and IC1 negatively. Comparing Figs. 5 and 14, we found that IC2 clearly represents Home 5's specific profile from 2 a.m. to 6 a.m. (Fig. 15). This family has a contract with an electric power company that allows them to buy nighttime electricity cheaply. Therefore, they regularly buy electricity during that period and heat water automatically. Independent component analysis could extract this feature automatically[2].

3.2.7 Home 6

Fig. 16 shows that IC1 gives a relatively larger contribution on Saturday and Sunday. Comparing weekday load profiles and weekend load profiles, we found that growth of consumption at 6 p.m. was very different between weekdays and weekends. We also found that averaged electricity consumption during the daytime on weekends was larger than that on weekday. ICA could find such difference automatically.

3.2.8 Home 7

Fig. 18 shows no IC had significant soceres. Fig. 19 shows load profiles of Home 7. Two students studying at different universities live in Home 7. They live irregular lifestyles. They come back home at different times, some days they do not come back home, and wake up late in the morning. From these kind of load profiles, ICA obviously could not find regular load profile primitives.

[2]However, no meaning of IC2 can be inferred, of course.

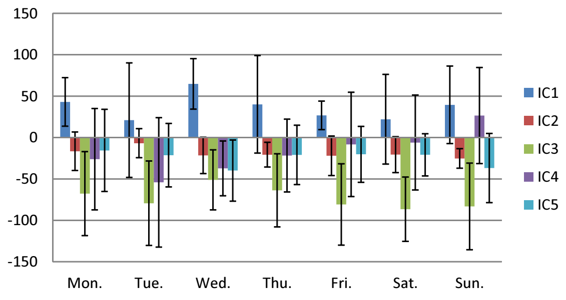


Figure 6. Mixing coefficient for days of the week of home 1

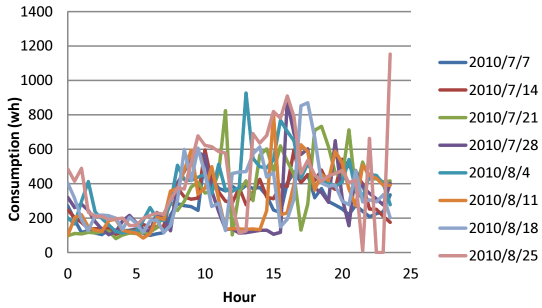


Figure 7. Load profiles of Home 1 on Wednesdays during July and August

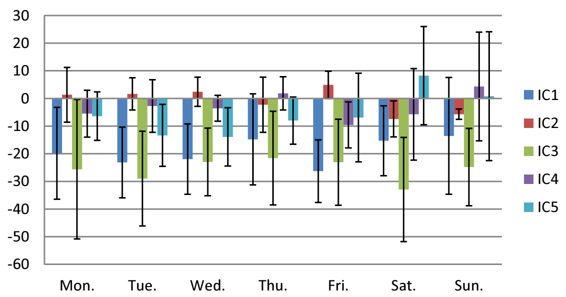


Figure 8. Mixing coefficient for days of the week of home 2

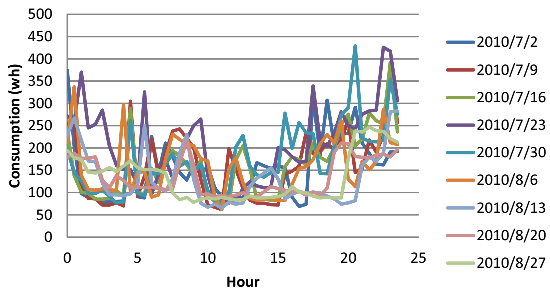


Figure 9. Load profiles of Home 2 on Fridays during July and August

3.3 Discussion

In this experiment, it was shown that the fastICA could extract a small number of independent components which characterize daily electricity consumption of each individual home. Each home had very different load profiles although the very famous shape of the averaged load profile shown in Fig. 2 is almost consistent all over the nation. ICA also extracted weekly trend in the very complicated load profile data as clearly shown in the home 6.

There exists a classical technique extracting low dimensional representation, a principal component analysis (PCA). PCA also assumes that an input data has an additive property, i.e., linear assumption. However, PCA also assumes Gaussianity to the input data. If the target data has Gaussianity, finding axis that has maximal variation in sequence means finding independent components. However, natural consumption data does not have this kind of property. Figure 20 shows the scatter chart of consumption data at different time. This clearly shows that the load profiles do not have Gaussianity. Figure 21 shows the extracted load profile primitives using PCA. For example, PC2, PC4 and PC5 share information about morning peak load of Home 5 in contrast that IC2 clearly has the information in ICA (Figure 5).

This experiment showed that mixing scores of independent components of load profiles could describe differences in load profiles among homes and days. However, this experiment did not show that this technique could extract seasonal trend by finding load profile primitives. In the next section, we apply data measured during a longer period and in a wider area, Higashiohmi city,

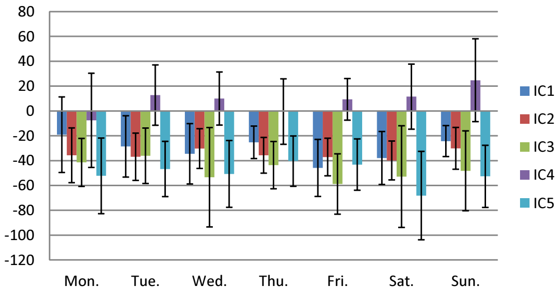


Figure 10. Mixing coefficient for days of the week of home 3

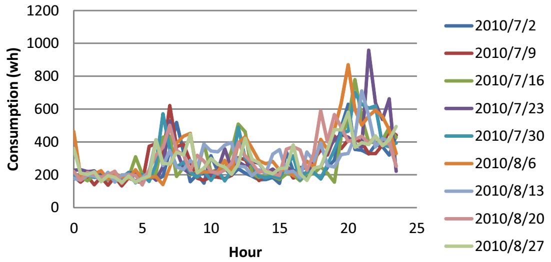


Figure 11. Load profiles of Home 3 on Fridays during July and August

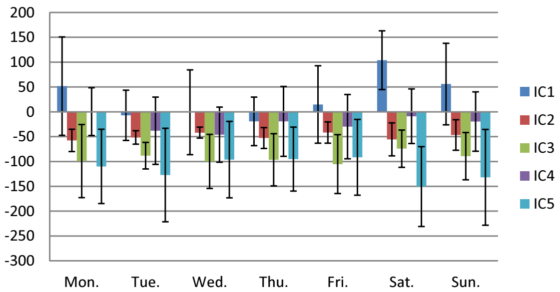


Figure 12. Mixing coefficient for days of the week of home 4

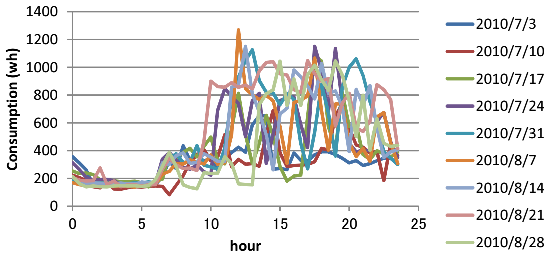


Figure 13. Load profiles of Home 4 on Saturdays during July and August

through natinal project.

4 Experiment 2: Higashiomi city

In the previous section, we treated individual load profiles. Each independent component score changed depending on two independent variables, i.e., days and homes. In the next experiment we treat regionally aggregated load profiles at Higashiomi city in Japan. To reach our final goal, clarifying daily fluctuations of regionally aggregated load profiles as a whole is also an important topic. We can make use of the information about the regionally aggregated demand for planning electric power generation, trading electrisity and demand-side management. We estimate hidden load profile primitives from the regionally aggregated load profiles.

4.1 Materials

For the last few years, Japanese Ministry of Internal Affairs and Communications has promoted the project called "green decentralization reforms" which aims to retain sustainable and decentralized development throughout the regions of Japan [14]. Higashiomi City (figure 22 [3]) participates in this project and challenges to progress energy independence by developing smart grid technologies [15]. This project aims to investigate the capacity of solar photovoltaic (PV) power generation

[3]The figure is referred from Wikipedia - http://en.wikipedia.org/wiki/Higashi%C5%8Dmi,_Shiga

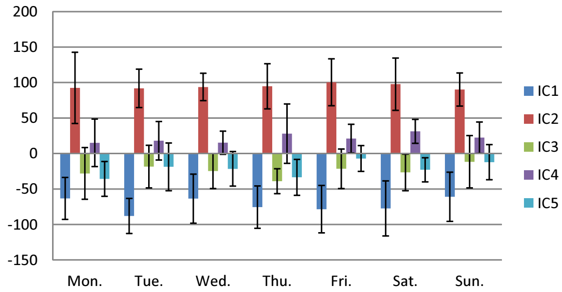


Figure 14. Mixing coefficient for days of the week of home 5

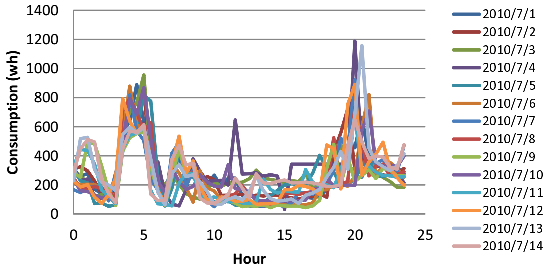


Figure 15. Load profiles of Home 5 over two weeks

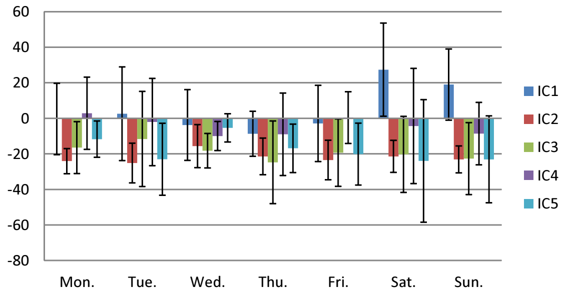


Figure 16. Mixing coefficient for days of the week of home 6

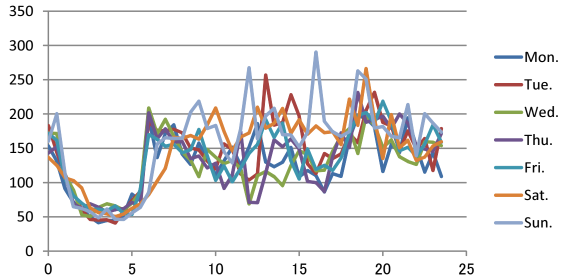


Figure 17. Averaged load profiles of Home 6 for each day of the week

at Higashiomi City.

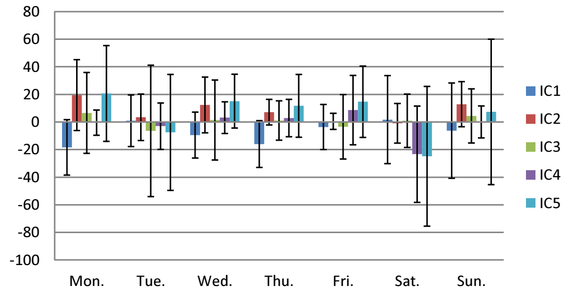
Electric load profiles of over 200 houses were measured by using an electric power meter "CK-5" produced by Chugoku Electrical Instruments Co., Ltd. [13, 15] which was also used in the experiment 1. In the investigation, load profile data were recorded every 30 minutes during a 6-month period in 2010 (from July 2010 to December 2010). The number of households whose load profiles can be recorded in sufficient quality for our analysis was 103. More specific experimental conditions are obtainable in Higashiomi's Report [15].

We used daily aggregated load profiles as an input data X. $T_{max} = 48$ and $K = 172$. In this study, we set the number of independent components to four.

4.2 Results

Fig. 23 shows the four extracted independent components, i.e., load profile primitives. Fig. 24 shows the time course of mixing coefficients of independent components for each day. This result clearly shows that ICA can extract seasonal and daily trends of regionally aggregated load profiles.

As an example, we focus on IC2. We can find the load profile primitive has clear peak around 6 a.m. in the morning. This component's coefficient increases gradually through the measurement period. It is easy to be inferred that this peak represents the heater usage in the morning which is demanded highly in the winter season. In contrast, IC4 decreases clearly and has negative value in the summer season. Decrease of IC4 corresponds to the increase of electricity demands in afternoon and decrease of it in midnight. This will also represent usage of air-conditioners.



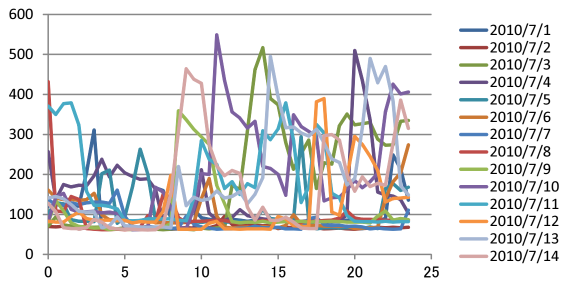
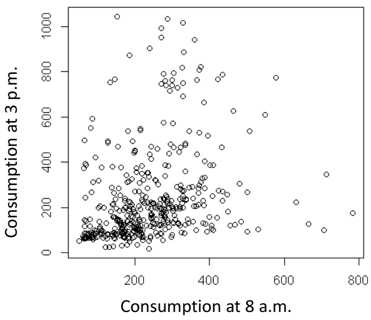


Figure 18. Mixing coefficient for days of the week of home 7

Figure 19. Load profiles of Home 7 for two weeks



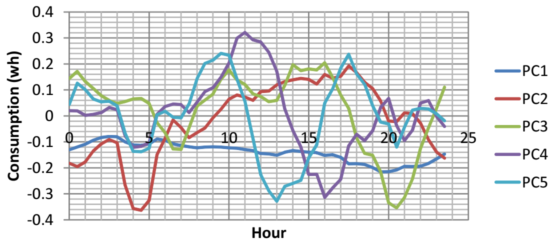


Figure 20. Distribution of consumption data at 8 a.m. and 3 p.m.

Figure 21. Extracted principal components

Fig. 25 shows the averaged value of mixing coefficients for each month. This shows that the load profile gradually changes according to the season.

As a result, ICA extracted four-dimensional space for representing daily load profiles. Although the extracted IC scores fluctuated day by day, seasonal changes in load profiles were expressed by mixing the four extracted independent components.

5 Conclusion and future works

This is our first work on finding load profile primitives. Analyzing home electricity consumption patterns is important for designing, managing, and analyzing a future decentralized local grid that will be automatically managed by some artificially intelligent agents. Load profile data have additive property because of the same property of electric current. We applied ICA to electricity consumption data measured at seven different datahomes and tried to find load profile primitives. We observed the results and investigated the possibility of finding load profile primitives by qualitative analyses on the measured home load profiles and extracted primitives. The qualitative investigation gave us some comprehension of the ICA capability for extracting load profile primitives.

In addition, we also adopted tahe method to the load profile data of one hundred houses measured in Higashiomi city. We showed that the method could extract the seasonal changes in load profiles

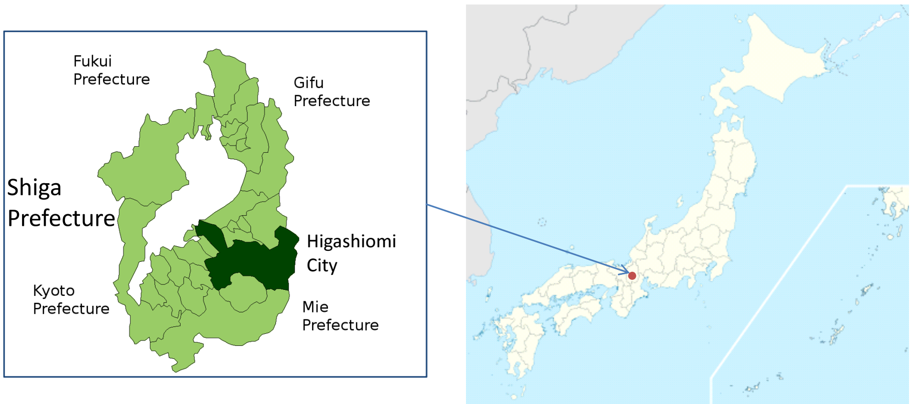


Figure 22. Figure shows the observation site of this study: Higashiomi city in Shiga prefecture, Japan. Green area shows Higashiomi city.

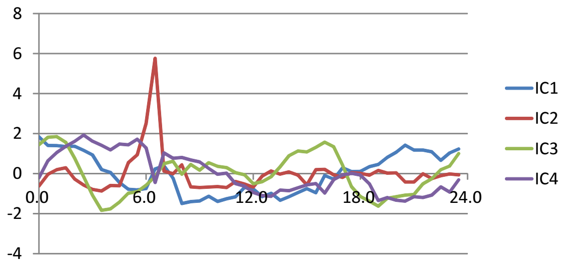


Figure 23. Extracted independent components

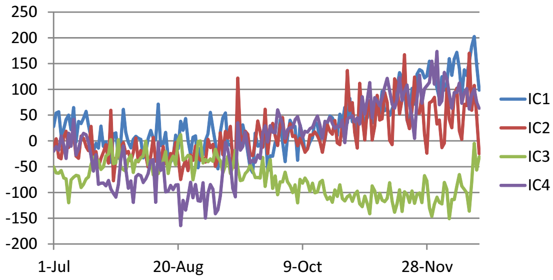


Figure 24. Mixing coefficients of independent components for each day

of local grid.

5.1 Visualization

Our future work is to develop adequate visualization technique by extending this method. As we observed in this paper, the individual load profiles are very diverse and noisy. Direct visualization of consumption data is not effective for consumers to understand their load profiles and change their daily consumption. The ICA or other alternative techniques are able to extract such differences automatically. Our future work is to develop visualization technique which enables consumers to understand the way to change their load profiles and their lifestyle effectively.

5.2 Composition of load profile primitives

Quantitative evaluation about the effectiveness of smart grid concepts is required. Some kinds of such evaluations would be done in a simulation method. Simulating smart grid requires load profiles of many families. However, usually such a big number of load profiles is not available for researchers. Therefore, generating virtual load profiles is an important topic for simulation studies of a smart grid. Found load profile primitives can be used for base functions for generating virtual load profiles directly. However, ICA has a problem in generating virtual data. Composed

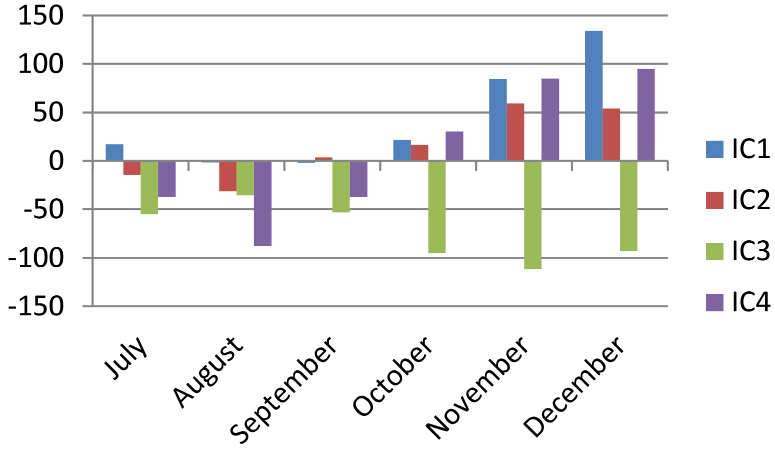


Figure 25. Monthly changes in mixing coefficients of independent components

virtual load profiles could have negative values because ICs take negative values in many cases (see Fig. 5). To avoid this problem, use of non-negative matrix factorizations (NMFs) or non-negative ICA should be considered.

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