Incremental Electricity Consumer Behavior Learning Using Smart Meter Data

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ABSTRACT
Electricity consumption behavior features can be represented by the load patterns extracted from daily load data clustering. Such representative load patterns should be updated because consumer behaviors may be changed over time. We propose a novel incremental clustering algorithm with probability strategy, known as ICluster-PS, to update load patterns without overall daily load curve clustering. Given the existed load patterns and new daily load data, the method first extracts new load patterns from new data, and then intergrades the existed load patterns with the new ones. Finally, an addition modification is performed on the intergraded sets to obtain the optimal updated load patterns. Several essential parameters are updated after this procedure so that the algorithm can be performed continuously. Extensive experiments are implemented on real-world dataset. The results are evaluated by both accuracy measures and clustering validity indices, which indicate that our method can provide an efficient response for electricity consumption patterns analysis to end consumers via smart meters or other facilities with resource constraints.

CCS Concepts
• **Theory of computation→Theory and algorithms for application domains**; ***Machine learning theory*****; Unsupervised learning and clustering.**

Keywords
Incremental clustering; time-series mining; load pattern; smart meter data.

1. INTRODUCTION
In smart grid, smart meter data can be used for various studies and applications, such as load forecasting, load profiling, anomaly detection and consumer categorization. One significant characteristics of these data is that they present the electricity consumption behaviors of consumers, which can be represented by the load patterns extracted from daily load curve clustering. As load patterns are essential for consumer segmentation and even demand response, various machine learning algorithms with or without feature extraction or feature construction are proposed for load curve clustering in load profiling. However, they generally focus on the clustering of static load data in a certain period, ignoring new coming load data. One solution to deal with the new load data is conducting another clustering on overall load data including the new ones, while this may result in extra computation and storage, especially in batch-oriented data processing. Another solution is incremental learning that refers to learning from streaming data that arrive over time [1]. As incremental learning can make full use of the historical information, reduce the training scale and save training time [2, 3], it is necessary to conduct an incremental clustering using smart meter data streams, especially for end consumers with limited resource.

The electricity consumption behaviors in the real world industry are complex. It is uncertain that all coming load patterns are new, we cannot simply add every load patterns extracted from the new coming data or assign them to any existed load patterns. How to update load patterns accurately is the main challenge of our incremental clustering problem. Therefore, we propose an incremental clustering algorithm with probability strategy, ICluster-PS, to deal with smart meter data streams for updating the load patterns efficiently for every end consumer through facilities with time and space limitations. Its incremental clustering algorithm contains three phases which are load pattern extraction, load pattern intergradation and load pattern modification. The main contributions of this work are summarized as follows:

- An incremental clustering algorithm is proposed for continuously updating load patterns based on smart meter data. To the best of our knowledge, this is the first work on incremental consumer behavior learning problem in smart grid.
- Probability strategy is proposed for distance measure to optimize the incremental clustering performance. Parameter updating is considered for performing the incremental clustering continuously with ceaseless coming new data.
- Both accuracy and clustering validity of the proposed algorithm are validated on real-world dataset containing 1,168 electricity consumers with diverse types in various districts.

The rest of this paper is organized as follows. Section 2 briefly reviews the related works. Section 3 introduces the proposed incremental electricity consumer learning method. Section 4 presents the experimental evaluation. Finally, we conclude this work in Section 5.

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2. RELATED WORK

Load Pattern Extraction. Load pattern extraction is an unsupervised classification problem, also called clustering problem. Clustering techniques for load clustering are classified into two categories, direct clustering and indirect clustering [4]. In direct clustering, load data are directly adopted in clustering without any dimension reduction or other processing methods. The frequently used clustering techniques include *K*-means, fuzzy *K*-means, self-organizing map (SOM), support vector clustering (SCV) and other clustering algorithms [5–7]. As for indirect clustering, most of works mainly focus on the methods of dimension reduction, feature extraction and feature construction. In [8], the authors constructed three new types of features and proved that the clustering performance of constructed features outperforms the one of default features. In [9], two variations of *K*-means algorithm with four proposed dimension reduction methods are adopted for enhancing the clustering process in load profiling. Another algorithm called FCCWT, which is a fused load curve clustering algorithm based on wavelet transform, is proposed in [10].

Incremental Learning Algorithms. In recent years, incremental and online learning gain more attentions especially in big data and data stream areas [11]. There are many incremental learning algorithms based on *v*-support vector regression, support vector machines (SVM), random forest (RF), neural networks, etc. [3, 12–14] Based on incremental support vector machine (ISVM)[15], an ISVM with Markov resampling (MR-ISVM) is introduced in [3] to study how dependent sampling methods influence the learning ability of ISVM. Nevertheless, most of incremental learning algorithms focus on supervised classification without considering any new classes. Although an incremental learning based on RF is studied to incrementally learn new classes for large-scale image [14], this method adds new classes into the trees without judging whether or not the coming classes are new. In [16], the authors provided an incremental version of the clustering algorithm based on fast finding and searching of density peaks (CFS) for clustering large data in industrial Internet of Things. However, CFS does not present well performance on relatively high dimensional data, and many clusters may be missed because only global structure of data are considered [17].

In summary, the works on load pattern extraction do not consider the incremental learning problem in their clustering algorithm while the existing incremental learning algorithms are not designed for load clustering. Therefore, it is useful to provide an incremental clustering method for our load clustering problem.

3. INCREMENRAL LEARNING MODEL

3.1 Incremental Clustering Algorithm

For an electricity consumer, her/his electricity load data X_0 contains N_0 daily load data, which are also called daily load curves. We can extract the load patterns A_0 from these data by conducting daily load curve clustering. Then a new set of daily load curves X_1 comes due to the continuous electricity power consumption. We aim to obtain a set of updated load patterns A_1 based on the existed load patterns A_0 and the new daily load curves X_1. This means that we conduct an incremental clustering with X_1 and A_0 rather than an overall clustering with $[X_0, X_1]$.

The main challenge of this problem is how to determine whether or not creating a new load pattern. Since consumer behaviors are complex, it is uncertain that there are any different load patterns in X_1 comparing with A_0. We cannot conduct a simple clustering by regarding all load patterns $\mu_{0i} \in A_0$ as the cluster centers. Therefore, we propose a seriatim incremental clustering algorithm to intergrade the load patterns of X_1 into A_0. This algorithm can determine whether integrating a load pattern into a μ_{0i} or keeping it as a new load patterns. It contains three phases: load pattern extraction, load pattern intergradation and load pattern modification. Given a set of exiting load patterns $A_0 = \{\mu_{01}, \mu_{02}, \dots, \mu_{0K_0}\}$ and a set of new daily load curves $X_1 = \{x_{11}, x_{12}, \dots, x_{1N_1}\}$, we describe these phases in detail:

Load pattern extraction: The new daily load curves X_1 are processed before the load pattern intergradation. We apply a fused load curve clustering algorithm FCCWT [10], which is designed specially for daily load curve clustering, to X_1 and obtain the set of its load patterns a_1. FCCWT first applies a multi-level wavelet transform to daily load curves for dimension reduction, and then fuses the *K*-means clustering results of both normalized approximation signals and detail signals, which are two outputs of wavelet transform, to gain an optimized clustering result. The corresponding probability of a_1 is P_{a_1}, and each $p_{a_1 i} \in P_{a_1}$ denotes the percentage of daily load curves represented by load pattern $\mu_{a_1 i}$ in the while daily load curve dataset X_1, and $1 \le i \le K_{a_1}$.

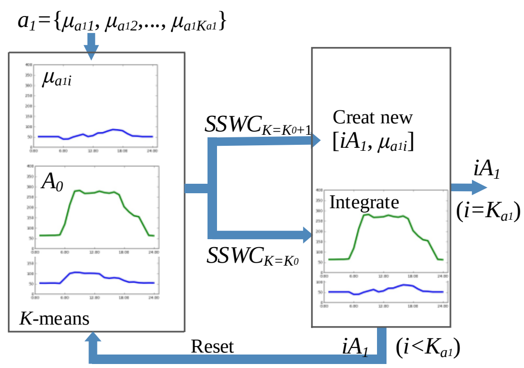


Figure 1. Diagram of load pattern intergradation

Load pattern intergradation: In this phases, each load pattern in a_1 is integrated with the existed load patterns A_0, respectively. Figure 1 illustrates the diagram of load pattern intergradation.

Let iA_1 denotes the result of load pattern intergradation, and then we initialize $iA_1 = A_0$. The ith load pattern $\mu_{a_1 i} \in a_1$ is combined with all load patterns in iA_1, which is denoted as $[iA_1, \mu_{a_1 i}]$. We perform two *K*-means clustering on $[iA_1, \mu_{a_1 i}]$ with $K = K_0$ and $K = K_0 + 1$, respectively. Two clustering results are evaluated by the Simplified Silhouette Width Criterion (SSWC), which is one variant of the well-known index Silhouette Width Criterion (SWC) for evaluating clustering performance [10]. Given $[iA_1, \mu_{a_1 i}] = \{\mu_1, \mu_2, \dots, \mu_{K_0}, \mu_{K_0+1}\}$ and its clustering result $C = \{c_1, c_2, \dots, c_K\}$ with the set of corresponding cluster centers $\bar{A} = \{\bar{\mu}_1, \bar{\mu}_2, \dots, \bar{\mu}_K\}$, the SSWC is calculated as the average of the Simplified Silhouette of the individual load pattern μ_j over $j = 1, 2, \dots, K_0 + 1$.

$$\mathrm{SSWC} = \frac{1}{K_0+1} \sum_{j=1}^{K_0+1} \frac{b_{c_r,\mu_j} - a_{c_r,\mu_j}}{\max\left\{a_{c_r,\mu_j}, b_{c_r,\mu_j}\right\}}, \tag{1}$$

where a_{c_r,μ_j} and b_{c_r,μ_j} are distances calculated as follows:

$$a_{c_r,\mu_j} = \mathrm{dist}\left(\mu_j, \bar{\mu}_r\right),\ b_{c_r,\mu_j} = \min\left\{\mathrm{dist}\left(\mu_j, \bar{\mu}_w\right)\right\}, \tag{2}$$

where $1 \le r, w \le K$ and $r \ne w$.

Then two obtained SSWCs are denoted as $\mathrm{SSWC}_{K=K_0}$ and $\mathrm{SSWC}_{K=K_0+1}$, respectively. When $\mathrm{SSWC}_{K=K_0} \geq \mathrm{SSWC}_{K=K_0+1}$, the ith load pattern $\mu_{a_1 i}$ is not kept as a new load pattern, and the integrating result of $[iA_1, \mu_{a_1 i}]$ is the set of cluster centers when $K = K_0$. When $\mathrm{SSWC}_{K=K_0} > \mathrm{SSWC}_{K=K_0+1}$, the ith load pattern $\mu_{a_1 i}$ is kept as a new load pattern, and the integrating result of $[iA_1, \mu_{a_1 i}]$ is the set of cluster centers when $K = K_0 + 1$.

The set iA_1 is reset with the integrating result of $[iA_1, \mu_{a_1 i}]$ after the above judgement. We gradually integrate each $\mu_{a_1 i}$ over $i = 1,2, \ldots, K_{a_1}$ with iA_1 according to this procedure, and obtain the final intergraded set iA_1 with K_{iA_1} load patterns.

Load pattern modification: An addition modification is performed on the intergraded set iA_1 in order to obtain the optimal incremental clustering result. Considering the number of load patterns usually is within the range $K \in [2,10]$ [8, 10], we apply multiple K-means clustering to iA_1 with $K \in [2, \min\{K_{iA_1}, 10\}]$. The SSWCs of $\min\{K_{iA_1}, 10\} - 1$ times clustering are calculated and compared with each other. The K with the largest SSWC is then selected as the optimal one, and the set of cluster centers with the optimal K is the target set of updated load patterns A_1.

3.2 Optimization via Probability Strategy

The load patterns usually have different probabilities so that they should not be treated equally in the incremental clustering. Therefore, we propose an optimized distance measure with probability strategy for the incremental clustering algorithm, in which Euclidean distance measure is replaced with this measure when performing both K-means clustering and SSWC calculation.

Given a set of load patterns $A = \{\mu_1, \mu_2, \ldots, \mu_K\}$ with the set of corresponding probability $P = \{p_1, p_2, \ldots, p_K\}$, where $p_i = n_i / N$ and N is the number of daily load curves that A refers to, the optimized distance with probability strategy between μ_i and μ_j is:

$$\mathrm{dist}_p\left(\mu_i, \mu_j\right) = p_i N p_j N \left\| \mu_i - \mu_j \right\|_2 = n_i n_j \left\| \mu_i - \mu_j \right\|_2, \qquad (3)$$

where n_i and n_j denote the numbers of daily load curves that μ_i and μ_j represent, respectively. As the cluster center $\bar{\mu}_r$ in K-means clustering with Euclidean distance is calculated as the mean of the objects that contained in the cluster, we simply set the probability of $\bar{\mu}_r$ with $p_{\bar{\mu}_r} = 1/N$ when performing K-means clustering with the optimized distance. Therefore, the calculation of cluster center based on optimized distance with probability strategy is:

$$\bar{\mu}_r = \frac{1}{\sum_{\mu \in C_r} p_r N} \sum_{\mu \in C_r} p_r N \mu_r = \frac{1}{\sum_{\mu \in C_r} n_r} \sum_{\mu \in C_r} n_r \mu_r, \qquad (4)$$

where n_r denotes the number of daily load curves that the load pattern μ_r refers to, and $\sum_{\mu \in C_r} n_r$ denotes the total number of daily load curves that all $\mu \in C_r$ refer to.

3.3 Parameters Updating

New daily load data continuously come with the electricity power consumption of consumers. As a result, several essential parameters should be updated after one incremental clustering in order to prepare for the next one. Let $P_1 = \{p_{11}, p_{12}, \ldots, p_{1K_1}\}$ be the set of corresponding probabilities of A_1, the probability of $\mu_{1r} \in A_1$ for the rth cluster C_{1r} is updated as:

$$p_{1r} = \frac{n_{1r}}{N_0 + N_1}, \quad n_{1r} = \sum_{\mu_0 \in C_{1r}} n_{0r} + \sum_{\mu_{a_1} \in C_{1r}} n_{a_1 r}, \qquad (5)$$

where n_{1r} is the number of daily load curves that the load pattern μ_{1r} represents, $\sum_{\mu_0 \in C_{1r}} n_{0r}$ denotes the total number of daily load curves that all $\mu_{0r} \in A_0$ belonging to C_{1r} represent, and $\sum_{\mu_{a_1} \in C_{1r}} n_{a_1 r}$ denotes the one that all $\mu_{a_1 r} \in a_1$ belonging to C_{1r} represent. After the updating of P_1, A_1 is ready to be conducted in another incremental clustering with the next coming data set X_2.

Moreover, given the existed load patterns A_0 and new daily load curves $X = \{X_1, X_2, \ldots, X_t\}$, the parameters are updated as follows:

$$p_{sr} = \frac{n_{sr}}{\sum_{i=0}^{s} N_i}, \quad n_{sr} = \sum_{\mu_{s-1} \in C_{sr}} n_{s-1,r} + \sum_{\mu_{a_s} \in C_{sr}} n_{a_s r}, \qquad (6)$$

where N_i. is the number of daily load curves that X_i contains, and μ_{s-1} and μ_{a_s} are the load patterns that belong to A_{s-1} and a_s, respectively. Then the incremental clustering is continuously performed with the coming of $X_s \in X$, where $1 \leq s \leq t$.

4. EXPERMENTS

4.1 Experimental Settings

4.1.1 Datasets

The dataset used in the experiment refers to 1,168 non-residential electricity consumers in various locations of United States. It contains 24-value daily load data over one year and records the electricity power consumption at every 1 hour from 1:00 to 24:00 per day. For the data of one electricity consumer, we select 3 months, 6 months and 9 months daily load data as the initial set X_0, respectively. The remaining data are divided by month and then regarded as $X_1, X_2, \ldots, X_t$. For example, when t=3, daily load data from January to September are selected as X_0, and the data of left three months are regarded as X_1, X_2 and X_3, respectively.

4.1.2 Evaluation Criterion

As we aim to obtain $A_s = \{\mu_{s1}, \mu_{s2}, \ldots, \mu_{sK_s}\}$ that equals or approximates to $A'_s = \{\mu'_{s1}, \mu'_{s2}, \ldots, \mu'_{sK'_s}\}$, which is the load patterns extracted directly from $[X_1, X_2, \ldots, X_s]$, we employ the accuracy measures for time-series forecasting to evaluate the load patterns in A_s comparing with those in A'_s, including Normalized Root Mean Square Error (NRMSE), Mean Absolute Error (MAE) and Symmetric Mean Absolute Percentage Error (sMAPE) [18, 19].

$$\mathrm{NRMSE}\left(\mu'_{si}, \mu_{sj}\right) = \sqrt{\frac{1}{d} \sum_{l=1}^{d} \left(\frac{\mu'_{si,l} - \mu_{sj,l}}{\mu'_{si,l}} \right)^2}, \qquad (7)$$

$$\mathrm{MAE}\left(\mu'_{si}, \mu_{sj}\right) = \frac{1}{d} \sum_{l=1}^{d} \left| \mu'_{si,l} - \mu_{sj,l} \right|, \qquad (8)$$

$$\mathrm{sMAPE}\left(\mu'_{si}, \mu_{sj}\right) = \frac{1}{d} \sum_{l=1}^{d} \frac{2 \cdot \left| \mu'_{si,l} - \mu_{sj,l} \right|}{\left| \mu'_{si,l} \right| + \left| \mu_{sj,l} \right|}, \qquad (9)$$

where d is the dimensions of load patterns.

Moreover, The clustering performance of the proposed method is also evaluated by diverse clustering validity indices including Davies-Bouldin index (DB), Dunn validity index (DVI), and SWC [10]. Let $C_s = \{C_{s1}, C_{s2}, \cdots, C_{sK_s}\}$ be the corresponding clustering results of A_s, then

$$\mathrm{DB}(C_s)=\frac{1}{K_s}\sum_{r=1}^{K_s}\max_{w\neq r}(\frac{\bar{C}_{sr}+\bar{C}_{sw}}{\|\mu_{sr}-\mu_{sw}\|}), \tag{10}$$

$$\mathrm{DVI}(C_s)=\frac{\min\limits_{0<r\neq w<K_s}\left\{\min\limits_{\forall x_i\in C_{sr},\forall x_j\in C_{sw}}\left\{\|x_i-x_j\|\right\}\right\}}{\max\limits_{0<r\le K_s}\max\limits_{\forall x_i,x_j\in C_{sr}}\left\{\|x_i-x_j\|\right\}}, \tag{11}$$

$$\mathrm{SWC}(C_s)=\frac{1}{N}\sum_{j=1}^{N}\frac{b_{C_{sr},x_j}-a_{C_{sr},x_j}}{\max\{a_{C_{sr},x_j},b_{C_{sr},x_j}\}}, \tag{12}$$

where $\bar{C}_{sr}$ and $\bar{C}_{sw}$ are the average within-group distance for C_{sr} and C_{sw}, respectively; x_i and x_j denote two daily load curves contained in $[X_1, X_2, \cdots, X_s]$; $N=\sum_{i=0}^{s} N_i$; a_{C_{sr},x_j} denotes the mean distance of x_j to all other daily load curves in C_{sr}, and b_{C_{sr},x_j} denotes the minimum mean distance of x_j to all daily load curves in C_{sw}, $w\neq r$.

4.1.3 Comparison Methods

- *FCCWT*: The non-incremental clustering algorithm designed specially for daily load curve clustering [10].
- *ICluster-PS*: The proposed method, which is incremental clustering algorithm with probability strategy (PS), designed for daily load curve clustering.
- *ICluster*: The proposed method without PS.
- *K-means-PS*: The method that adopts *K*-means with probability strategy in the incremental procedures.
- *K-means*: The method that adopts *K*-means without probability strategy in the incremental procedures.

4.2 Experimental Results

4.2.1 Incremental Clustering Performance

We conduct the experiments with *t*=9, *t*=6 and *t*=3, which means that nine, six and three incremental clustering algorithms are performed in one experiment, respectively.

Table 1 shows the mean error comparison of the methods on the dataset of 1,168 consumers. As the minimum error indicates the highest accuracy, our proposed algorithm ICluster-PS shows the optimal performance. The smaller errors of methods with probability strategy comparing with those without the strategy proves the optimization of the strategy. Moreover, the incremental clustering algorithm, especially the load pattern intergradation and modification, improves the accuracy of *K*-means based on the comparisons between ICluster and *K*-means with or without probability strategy. As for the three groups of errors with different *t*, it is noticed that the mean errors decrease with the reduction of *t*, which means that the errors may increasingly rise over the continuous incremental clustering.

Table 2 shows the mean clustering performance comparison of the methods on the same data. According to the definitions of three clustering validity indices, ICluster-PS outperforms other three methods excluding FCCWT, which is non-incremental clustering used as the target. The comparisons of four methods indicate similar results as mean error comparisons shown in Table 1.

In summary, the proposed incremental clustering algorithm, ICluster-PS, can achieve an acceptable accuracy with mean error less than 10% and an improved clustering validity via its designed algorithm and probability strategy. This result indicates that we can provide an efficient response when consumers require consumption analysis via smart meter or other facilities with limited resource. Although our experiments set X_s as the data of one month, it can be set optionally in practical application.

4.2.2 Consumer Behavior Case Analysis

A random electricity consumer is selected to be analyzed in details for a further discussion of the proposed method and electricity consumer behaviors. The selected consumer is a full service restaurant, which have three typical load patterns based on the overall daily load curves. Figure 2 illustrates the load patterns obtained by ICluster-SP and FCCWT in the experiment when *t*=6. Each subfigure presents both the incremental and non-incremental cluster centers of the data $[X_1, X_2, \dots, X_s]$, where $1 \le s \le t$. The load patterns in solid line style denote the incremental cluster centers of ICluster-SP while those in dashed line style denote the non-incremental cluster centers of FCCWT.

According to the experimental settings and the mean clustering performance comparison of the methods, the load patterns of FCCWT are regarded as the accurate results. It can be noticed that these accurate load patterns are relatively stable and there is not distinct electricity consumption behavior shift happened to this consumer from July to December. The three typical load patterns of this consumer are distinct in terms of power degrees, the starting time of the increase in the morning and the ending time at

Table 1. Mean Error Comparison of the Methods

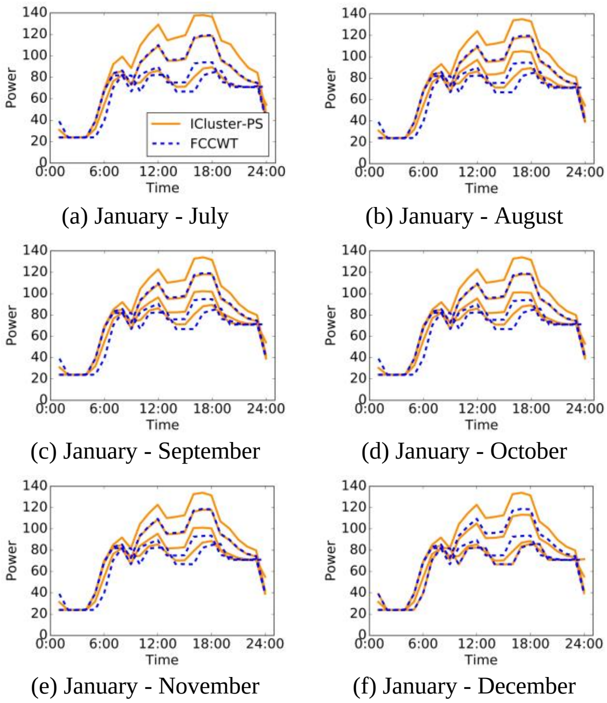
Methods	$t=3$			$t=6$			$t=9$		
	NRMSE	MAE	sMAPE	NRMSE	MAE	sMAPE	NRMSE	MAE	sMAPE
ICluster-PS	**0.1025**	**25.7071**	**0.0735**	**0.0839**	**19.5880**	**0.0606**	**0.0359**	**9.4525**	**0.0257**
ICluster	0.1317	32.7690	0.0947	0.1202	29.7604	0.0873	0.0935	25.3145	0.0674
I*K*-means-PS	0.1359	33.2000	0.0975	0.1251	0.1480	0.0927	0.0662	16.9731	0.0481
I*K*-means	0.1568	38.1873	0.1128	0.1480	36.2019	0.1088	0.0907	23.8862	0.0653

The best results are highlighted in bold.

Table 2. Mean Clustering Performance Comparison of the Methods

Methods	$t=3$			$t=6$			$t=9$		
	DB⁻	DVI⁺	SWC⁺	DB⁻	DVI⁺	SWC⁺	DB⁻	DVI⁺	SWC⁺
FCCWT*	0.7838	0.3394	0.6312	0.8069	0.2691	0.6121	0.8035	0.2538	0.6101
ICluster-PS	**1.1118**	**0.1457**	**0.4444**	**1.1924**	**0.1020**	**0.4070**	**1.2861**	**0.0827**	**0.3649**
ICluster	1.1336	1.1442	0.4228	1.2000	0.1001	0.3919	1.2874	0.0798	0.3558
I*K*-means-PS	1.4562	0.1279	0.3557	1.6818	0.0993	0.2794	1.9713	0.0679	0.1047
I*K*-means	1.5132	0.1325	0.3434	1.6597	0.1000	0.2798	1.9424	0.0680	0.1163

*: the baseline method; ⁻: the minimum is the best; ⁺: the maximum is the best.



(a) January - July (b) January - August
(c) January - September (d) January - October
(e) January - November (f) January - December

Figure 2. Load pattern comparison between ICluster-PS and FCCWT of one electricity consumer when *t*=6.

night. The possible reasons for these distinctions are daylight saving time and seasonal influence. As for the incremental clustering results, their load patterns shift once on August shown in Figure 2(b). Therefore, we can find out three typical load patterns in Figure 2(a) and four typical load patterns in other subfigures. These updated load patterns show similar patterns as the accurate ones if the power degrees of them are not taken into account. However, the distinct starting time of the increase in the morning shown by the accurate ones are not revealed by those of ICluster-PS until December, shown in Figure 2(f).

5. CONCLUSION

In order to achieve efficient demand response and consumer segmentation for both electricity end consumers and suppliers, we propose an incremental clustering algorithm ICluster-PS to update the load patterns from smart meter data streams. ICluster-PS is able to be performed continuously based on parameter update. Moreover, the accuracy and validity of its incremental clustering model, especially load pattern intergradation, modification, and probability strategy are proven by the experimental results of real-world dataset. Although it cannot provide load patterns as the same as those extracted directly from overall load data, it achieves acceptable updated results when saving time, reducing the clustering scale and making full use of the historical information.

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