A Novel Load Profile Analysis Method to Improve Electricity Consumption Pattern (ECP) Using Image Processing

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Abstract- An in-depth understanding of consumer energy consumption patterns is essential for accurate forecasting and efficient management. In this paper, a novel load profile analysis methodology is proposed using an image processing technology that simplifies the understanding and improvement of electricity consumption patterns. Theelectricityconsumptionpatternsovertimearerepresentedasloadimageprofiles in two dimensions. These profiles are modified by image processing using filtering and thresholding techniques to suppress excessive sensitivity. Subsequently, the clustering algorithms are performed to classify the load image profiles, and representative class load image profiles are obtained. The resulting clusters are compared to the results of conventional load profile analysis. The proposed methodology shows enhanced performance over the conventional approach from the view point of evaluation among the different load image profile classes.

Keywords:Class Load Image Profile, Clustering, Data Processing, Image Processing, Load Image Profile, Load Profile.

1. INTRODUCTION

The paradigm within the electric power industry is changing due to the spread of smart meters and distributed resources. The spread of smart meters makes it possible to obtain improved metering data on energy consumption, of which the patterns are becoming more diverse with the spread of distributed resources [1], [2]. Electricity consumption data are used to create electricity load profiles (LPs) and provide electricity usage information over time. These data enable the development of detailed strategies for planning and managing electricity supply. Understanding the stability of daily electricity usage patterns over time provides deeper insights into how households use electricity. This information can help operators improve load forecasting and planning, design tariffs, and efficiently operate and manage demand side response and distributed energy resources. Consumers have the potential to cut their electricity bills and sell surplus electricity by reducing unnecessary electricity usage [3], [4]. In particular, various energy consumption patterns are emerging due to the gradual expansion of solar panel installations and electric vehicles. For utilities and operators, an adaptive approach is needed for efficient planning and management of distributed resources in order to accommodate changes in such a smart grid environment.

Load profiles show electricity usage patterns over time and are fundamental to systematic management. Load profiles depict daily consumption patterns by averages calculated for specific time periods during the day. The load curve created provides operators with visual information about electricity consumption. This information includes the timing and magnitude of electricity use; it also describes the lifestyle of electricity consumers, including peak loads [5]–[7].

These widely used load profiles can exhibit inherent loss of information due to the averaging effect over the time period of interest. The load curve may provide incorrect information if the electricity usage patterns are irregular, and the resulting analysis may lead to unexpected errors, which in turn could lead to operational instability and economic loss. In order to provide more accurate information, an intuitive approach is needed for deriving intrinsic information so as to obtain a deeper understanding of electricity usage patterns.

Existing studies related to load profiling use approaches based on engineering, statistics, and data mining and artificial intelligence[2],[8].The engineering approach generally uses bottom-up and top-down techniques for load modelling [3]. The load profile is generated and analyzed based on the load modelling using parameters such as the types of household appliances. In [9], the physical model was designed and the load shape was estimated using physical factors that affect the individual use of various household appliances. In [10], the load profile of house hold appliances was predicted using a thermal dynamic model with physical and behavioural factors. A methodology for the development of static load models and load characteristic profiles was presented and a seasonal load characteristic profile has been developed with high-resolution loadat1ssamplingrate[11].Various engineering approaches were also proposed in [3].

Statistical approaches typically characterize electricity use based on probability, statistics, and regression analysis. These analyses involve factors that affect energy consumption, such as electric appliances, dwelling information, lifestyle, and activity patterns. Statistical approaches are mainly used for customer segmentation and settlement [4], [12]–[15].

Most of the aforementioned approaches have described electrical consumption characteristics based on magnitude over time (i.e., the load curve or load shape). a novel load profile analysis methodology is proposed using an image processing technology that simplifies the understanding and improvement of electricity consumption patterns [16]-[18]. This study proposes and analyses a new load profile, called load image profile (LIP) that simplifies the understanding of the variation of electricity consumption by hour and day, thus providing deeper insights into consumer behaviour. Methods for creating three types of LIPs are described and followed by a clustering method for creating class load image profiles (CLIPs) from the LIPs. Next, the characteristics of the generated LIPs and CLIPs are discussed and shown to be efficient. In particular, it is shown that the proposed load profiling methodology enables efficient operation and management in a complicated smart grid environment by presenting more information than a conventional load profile.

2. METHODOLOGY

This section describes a methodology for creating LIPs and CLIPs, asshowninFig.1. The first stage of this methodology creates three types of LIP sand these Cond stage creates CLIPs from the LIPs.Theone-dimensionaltimeseriesdatacollected from a smart meter are processed into a two-dimensional array to create a Type-1 LIP. Next, an image processing method (the filtering method) is applied to the Type-1 LIP to generate a Type-2 LIP. Another image processing method (the threshold method) is applied to the Type-2 LIP to create a Type-3 LIP. Finally, the three LIPs created in the first stage aregroupedusingaclusteringmethodtogeneratethreetypes of representative CLIPs. The following subsections describe each step of the methodology in detail.

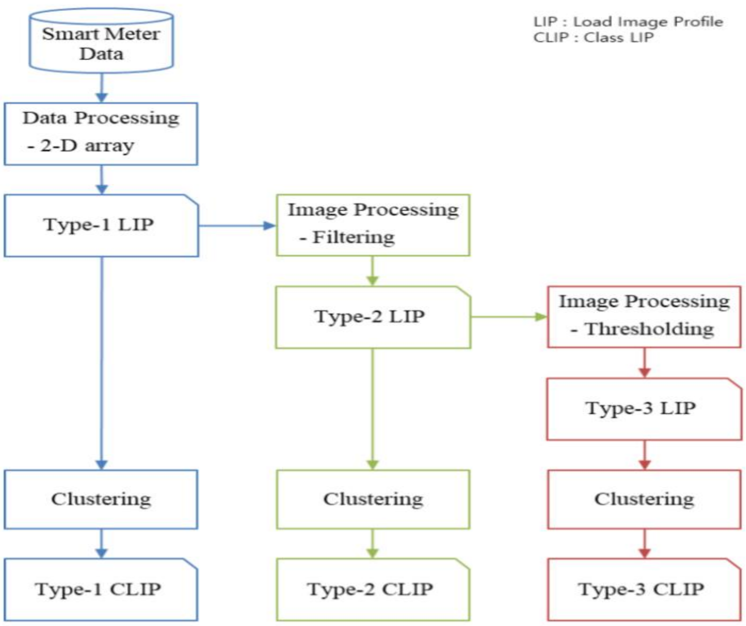

Fig 1. Methodology for creating LIPs and CLIPs.

A) Creation of Load Image Profile

The load profile (Fig. 2(a)) is a one-dimensional time series data set representing the electricity consumed by a consumer over time. This profile can be expressed in a vector formimage.

B) Image Processing

The Type-1 LIP, derived from the raw smart meter data, can be improved by image processing to produce a clearer loadThe Type-2 LIP created by the smoothing filter depicts certain areas with similar electricity consumption in the day and hour domains. Thresholding improves the visual clarity of the image and the identity of areas with similar electricity consumption by applying the class thresholds; this process produces the Type-3 LIP.

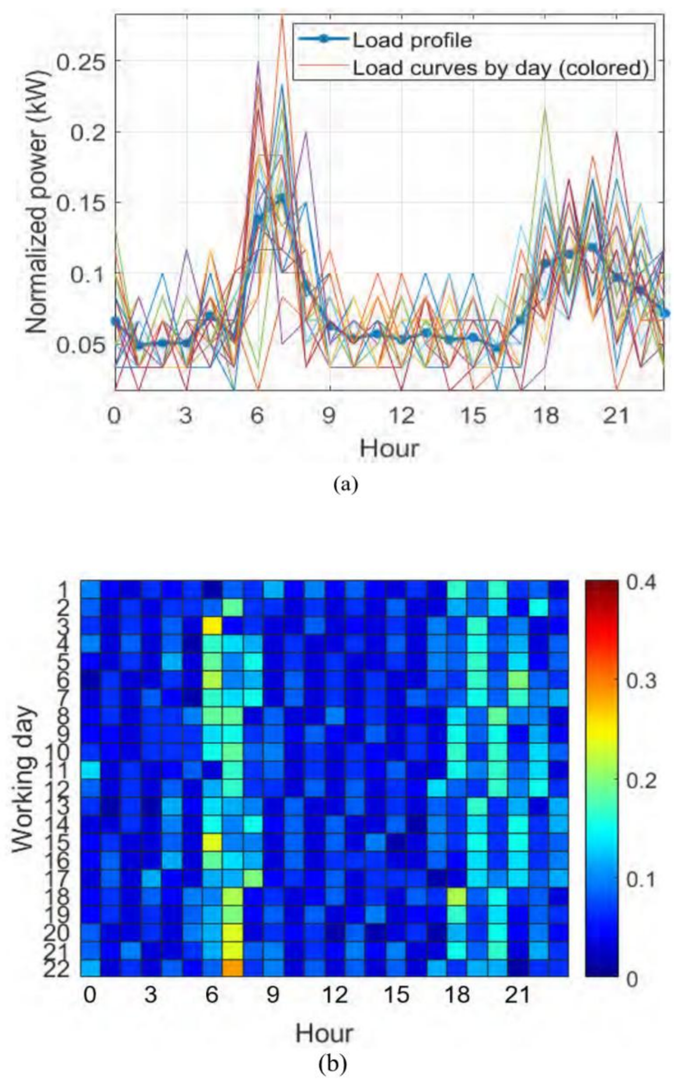

Fig. 2. Illustration of LPs and corresponding LIP. (a) Load profiles (hour 0 corresponds to midnight). (b) Load image profile (hour 0 corresponds to midnight).

3. PROPOSED WORK

A) Modules

This system model consists and implements the following modules.

Admin Module

- In this module, admin login to the system.
- Here, once he login to the system he can view the users and authorize them, view upload data, view load profile of users, view load profiles in chart, view clustered load profile and view the results.
- He can analyse the user's electricity consumption based on their loads.

User Module

- In this module, the users of the system must be register and login to the system to create a load image profile.
- He can create the load profile and add the data to the profile.
- He can also view the load consumption information of their electricity Usage.

Create LIP

- The load profile is a one-dimensional time series data set representing the electricity consumed by a consumer over time. This profile can be expressed in a vector form and it can be converted in two-dimensional vector to represent one-month usage of electricity.

$$LIP_m^j = \begin{bmatrix} (LP_1^j)^T \\ (LP_2^j)^T \\ \vdots \\ (LP_d^j)^T \end{bmatrix} = \begin{bmatrix} p_{1,0}^j & p_{1,1}^j & \cdots & p_{1,h}^j \\ p_{2,0}^j & p_{2,1}^j & \cdots & p_{2,h}^j \\ \vdots & \vdots & \ddots & \vdots \\ p_{d,0}^j & p_{d,1}^j & \cdots & p_{d,h}^j \end{bmatrix},$$

Clustering

- The objective is to group together customers with similar electricity consumption patterns using clustering methods.
- The most widely studied clustering algorithms are partition-based and hierarchical-based clustering algorithms.
- These algorithms have been used in a wide range of real applications due to their simplicity and less computational complexity.

- Partition-based clustering algorithms identify groups within the data by optimizing a specified objective function and iteratively improving the quality of the partitions.

B) Implementation Methods

- In this proposed method the first stage of this methodology creates three types of LIPs and the second stage creates CLIPs from the LIPs.
- The one-dimensional time series data collected from a smart meter are processed into a two-dimensional array to create a Type-1 LIP.
- Next, an image processing method (the filtering method) is applied to the Type-1 LIP to generate a Type-2 LIP. Another image processing method (the threshold method) is applied to the Type-2 LIP to create a Type-3 LIP.

Finally, the three LIPs created in the first stage are grouped using a clustering method to generate three types of representative CLIPs.

B) Algorithms

K- Means Clustering Algorithm

- The K-means clustering algorithm is the most widely used partition-based clustering algorithm.
- To perform this algorithm, the input vector is constructed by transforming a two-dimensional array (in this case, the LIP) into a one-dimensional vector; the length of this vector is 24 (hours per day) multiplied by the number of days in the month.
- The algorithm starts by selecting K initial representative vectors. Each vector is then assigned to the closest centroid based on a particular proximity measure (the Euclidean distance).
- Once the clusters are formed, the centroids for each cluster are updated. And then the algorithm iteratively repeats these two steps until the centroids do not change or some predefined convergence criterion is met.

FCM Clustering Algorithm

- Fuzzy C-means (FCM) clustering algorithm, another partition-based clustering algorithm, performs clustering using a degree of membership that each input vector belongs to one or more clusters. FCM algorithm partitions input vectors into fuzzy groups. Each input vector is assigned groups with a membership degree between 0 and 1. The centroids for each cluster and membership degrees are updated until the objective function is minimized and converged.

EM Algorithm

- The ExpectationMaximization (EM) algorithm, which is a distribution-based clustering algorithm, is an iterative method of generating an optimal model by adjusting the probability that each input vector belongs to a Gaussian mixture model.
- The EM algorithm consists of an expectation step and a maximization step. In the Expectation step, the expected values for the given data and model parameters are calculated.
- In the Maximization step, the model parameters are estimated by the maximum likelihood estimation using the expected value obtained in the Expectation step.
- The estimated parameters repeat the Expectation and Maximization steps again and repeat these two steps until convergence.

4. EXPERIMENTAL RESULTS & DISCUSION

In this section, we evaluate the performance of our proposed scheme in experiments.

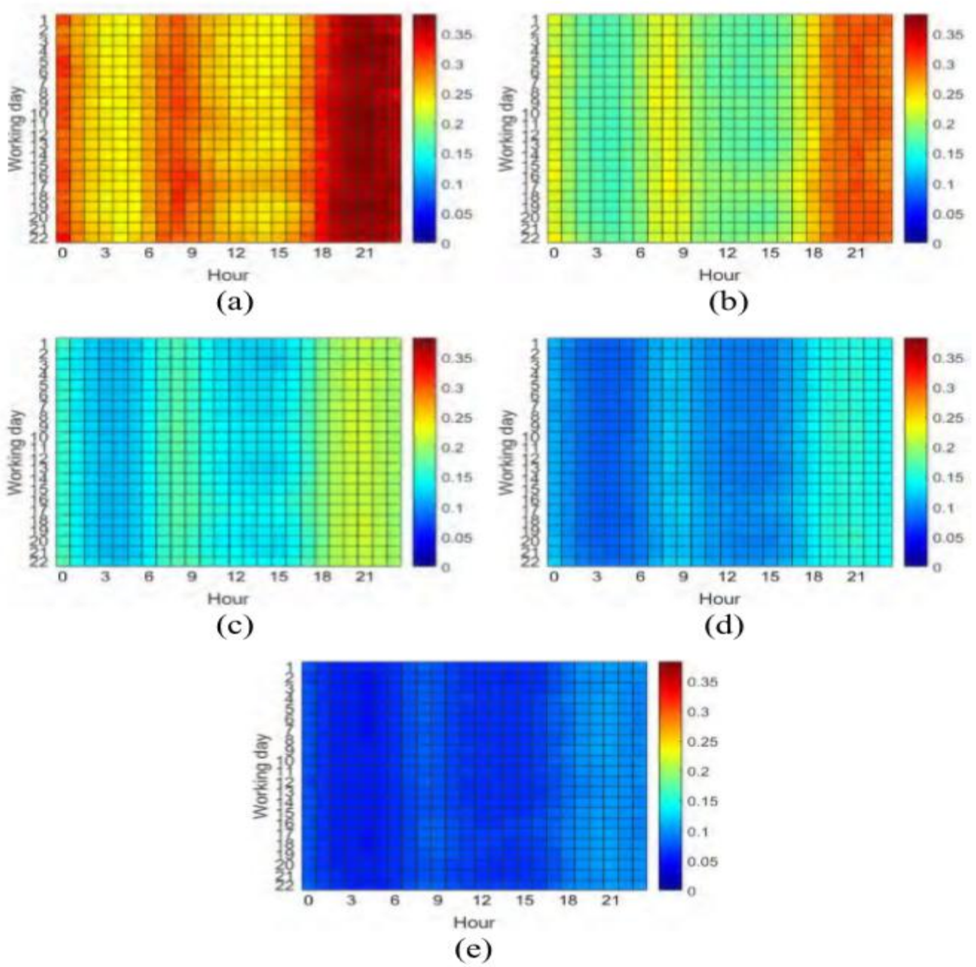

Fig3. CLIPs for August 2019. (a) Class 1. (b) Class 2. (c) Class 3. (d) Class 4. (e) Class 5.

Fig. 3 shows the CLIPs grouped into five classes for August 2019. The Class 1 CLIP has the highest electricity consumption. This level of electricity consumption is maintainedforapproximately18workingdaysfromthebeginning of the month.

Furthermore, electricity is consumed in all time except for the early morning hours with the peak time occurring during hours 20−23. The Class 2 CLIP has high electricity consumption from hours 20 to 23 during the first 15daysfromthebeginningofAugust.

TheClass3CLIPhas high electricity consumption around hour 20 in the middle of the month. The Class 4 CLIP shows a similar electricity consumption pattern as that of Class 3 but with less overall electricityconsumptionthanClass3.TheClass5CLIPhasa similar electricity consumption pattern as that of Class 2, but with very little electricity consumption.

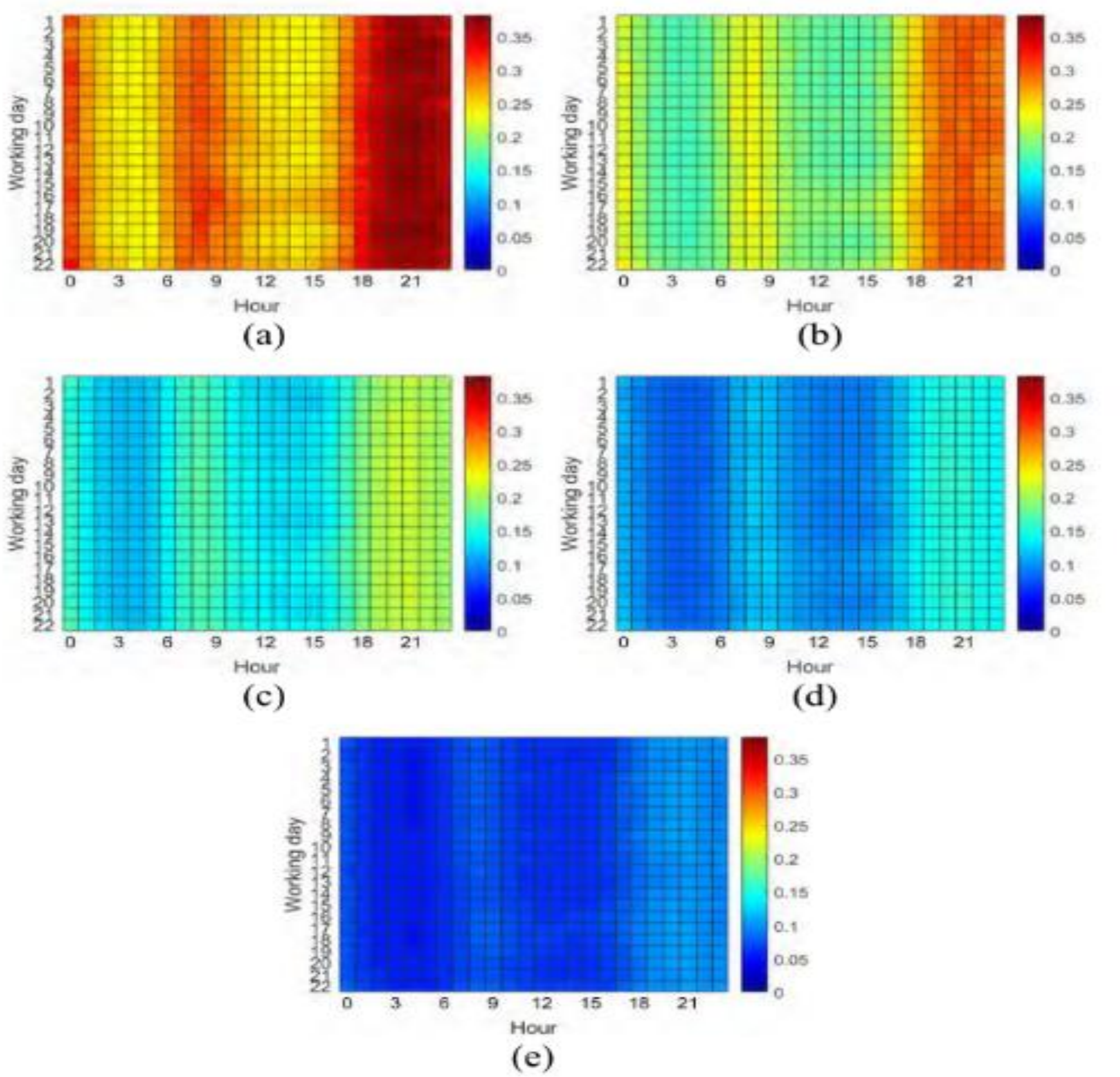

Fig4. CLIPs for December 2019. (a) Class 1. (b) Class 2. (c) Class 3. (d) Class 4. (e) Class 5.

Fig. 4 shows the Type-3 CLIPs grouped into five classes for December 2019. The electricity consumption patterns for all the classes are nearly similar. The patterns areroughly constant by day, and the peak hour occurs during hours 19−23.

Fig. 5 shows the dissimilarity of the three types of LIPs examined in this study. Figs. 5(a) and 5(b) show the comparisonofthedissimilaritiesfortheworkingdaysofAugustand December 2019, respectively. The LI of the three LIPs showed worse dissimilarity than the LP. After converting the LIPstoLCs,theLCsfortheType-2andType-3LIPsshowed good dissimilarity.

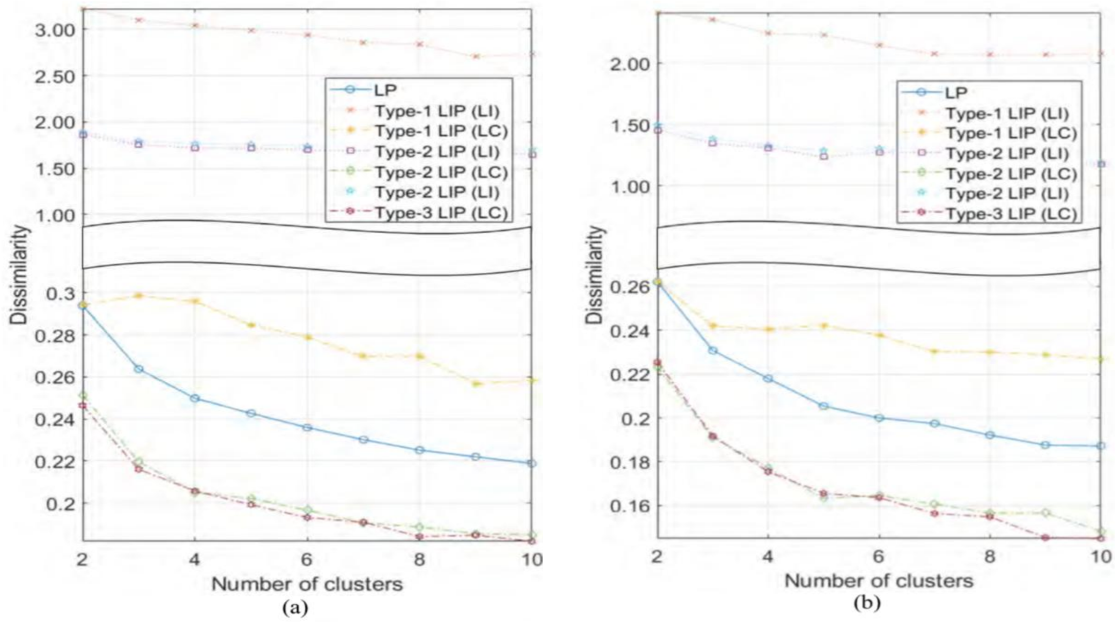

Fig5. Comparison of dissimilarity between CLIPs and CLPs. (a) August. (b) December.

The reason for the worse dissimilarity of the LIs is that their vector dimension is a product of hour andday,whichishigherthanthevectordimensionoftheLP. The LC for the Type-1 LIP has a low degree of dissimilarity due to the variation of the electricity consumption patterns by day and hour. The reason why the dissimilarities of LCs for the Type-2 and Type-3 LIPs are better than that of the LPis because the filtering and thresholding techniques reduced the variation in the electricity consumption patterns by day and hour. This meant that the class groupings of the LCs for the Type-2 and Type-3 LIPs were better than that of the LP. Therefore, the LCs for the Type-2 and Type-3 LIPs formed a better class grouping than the LP.

5. CONCLUSION

In this paper, we have presented three new types of LIPs that can provide insights into the electricity consumption behaviorsofcustomersmoreeffectivelyandvisually.Existingload curvescandistortinformationaboutelectricityconsumption. In particular, the load curve is difficult to grasp the behavior of the consumer's power consumption at the same time on a different day or on the day of going out, but the proposed method can easily grasp the variability of these behaviors. The methodology for creating these LIPs was developed by using data processing and image processing techniques. One-dimensionaltimeseriessmartmeterdatawereconverted to two-dimensional arrays as images in data processing, and filteringandthresholdingmethodswereusedtoprocessthese images in image processing. The same analysis was performed for other months from January to December, and similar results were obtained.

Further study remains to address these problems. The current literature indicates that a variety of methodologies, algorithms, and corresponding parameters can be applied in creating and utilizing the LIPs. Furthermore, the results of this study indicate that the proposedLIPscanprovidemoreinformationaboutconsumer behaviors than the existing LPs. This information can be customized for the operation, planning, and management of smartgridsystems,includingsuchtasksasloadclassification and forecasting, settlement and tariff design, and distributed energy resource and transaction management.

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