Classification Method for Power Load Data of New Energy Grid based on Improved OTSU Algorithm

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***Abstract*—The classification method for power load data of new energy grid based on improved OTSU algorithm is studied to improve the classification accuracy of power load data. According to the idea of two-dimensional visualization of time series, GAF (Geographical Adaptive Fidelity) method is used to transform the current data of power load in new energy grid into two-dimensional image of power load in new energy grid. The intra class dispersion is introduced, and the improved OTSU algorithm is used to segment the foreground and background of the two-dimensional image according to the pixel gray value of the two-dimensional image and the one-dimensional inter class variance corresponding to the pixel neighborhood gray value. The two-dimensional foreground image of power load is taken as the input sample of convolution neural network. The convolution neural network extracts the features of the two-dimensional foreground image of power load through convolution layer. According to the extracted features, the classification results of power load data of new energy grid are output through three steps: nonlinear processing, pooling processing and full connection layer classification. The experimental results show that this method can accurately classify the power load data of new energy grid, and the classification accuracy is higher than 97%.**

Keywords*—*Improved OTSU algorithm; new energy grid; power load; classification method

I. Introduction

The classification of power load data of new energy grid helps power selling companies accurately grasp the power consumption characteristics of users, introduce a reasonable demand response mechanism and formulate scientific marketing strategies, which is of great significance for peak shaving and valley filling, optimizing power consumption curve, improving power quality and so on [1]. Improving terminal efficiency and guiding users to use electricity reasonably is one of the important contents of power demand side management. To realize this demand side management, it is necessary to timely understand the power consumption of household users and realize the interaction between supply and use. DSM (Demand Side Management) is a means to guide power consumers to adopt a reasonable way of using electricity [2] and achieve energy conservation and emission reduction. Smart grid utilizes advanced technology to dispatch demand side resources and improve the participation rate of power consumers, so as to realize the two-way interaction between information and power. Power consumers can respond to DSM strategy only when they understand their own power consumption mode [3]. For household power users, only electricity meters provide information for both suppliers and users, while the current smart electricity meters only have the function of time-sharing pricing, which provides limited information. Therefore, in order to enhance the demand response of power users and optimize the power consumption mode [4], it is necessary to effectively monitor the household load and then measure it by classification. The current smart meter has neither time-sharing measurement nor load classification measurement [5], and can not provide power consumption details to power management departments and users, so it is very necessary to classify the power load data of new energy grid.

Image segmentation is an important step in the process of image analysis. Its goal is to divide the regions of interest in the image. Among many image segmentation methods, threshold segmentation technology is a widely used method in image segmentation [6]. Its basic principle is to calculate the segmentation threshold based on the image gray histogram, and then segment the image according to the threshold. OTSU algorithm is a commonly used algorithm in threshold segmentation. It selects the threshold by maximizing the variance between classes [7]. This method has the characteristics of easy to understand principle, considerable segmentation effect and stable algorithm. However, one-dimensional OTSU algorithm can not deal with more complex images. When segmenting images with too small gray difference between the background and the pixels in the target area, false segmentation will occur. Since the OTSU algorithm was proposed, it has attracted widespread attention of researchers. OTSU algorithm mainly lies in its simple principle, efficient calculation, wide application range and good segmentation effect [8]. OTSU algorithm is an image segmentation method without real-time supervision, without parameter regulation and automatic optimization. Based on the one-dimensional histogram, the threshold is selected by maximizing the variance between classes. Although OTSU algorithm has a good segmentation effect, it is prone to false segmentation when the gray value of the image background and the pixel points in the target area are not much different [9]. The segmentation result of one-dimensional OTSU algorithm is not accurate, but it has been reasonably improved in two-dimensional OTSU algorithm. The expression form of two-dimensional OTSU algorithm is good anti-interference ability, but its calculation process is too complex and requires a lot of running time to process it.

A. Related Work

At present, many researchers have studied power load. J. J. Hu et al. applied data mining algorithm to power load forecasting [10], and verified that this method can effectively predict power load through simulation tests; H. Bakhtiari et al.

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uUsed Markov chain Monte Carlo simulation method [11] to simulate the uncertain random load in the operation of independent microgrid of renewable energy. Although the above two methods can realize the function of power load and uncertain random load prediction, they do not specifically classify the power load of users, so their applicability is poor.

In view of the problems of the above two methods, to further improve the classification accuracy of power load data, the classification method of power load data of new energy grid based on improved OTSU algorithm is studied, and the OTSU algorithm is used to segment the two-dimensional visual image of power load data transformation of new energy grid, so as to obtain the classification results of power load data of new energy grid. The experiment shows that the contribution of this method is that it can accurately classify the power load data of new energy grid, and has high applicability. The specific process schematic diagram of the method used in this paper is shown in Fig. 1.

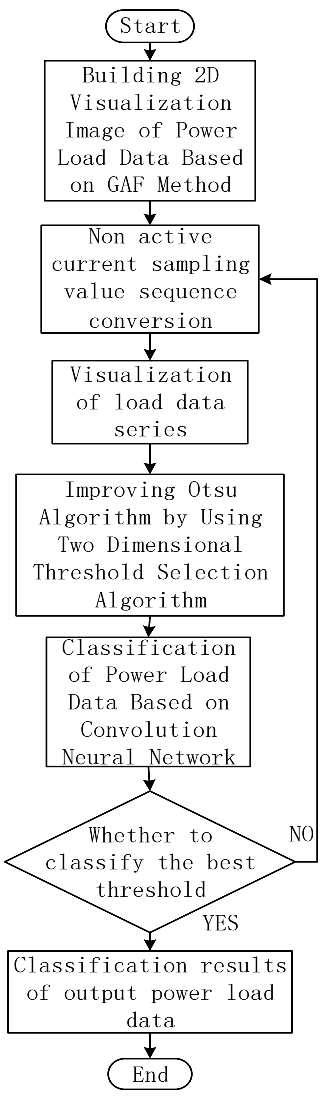

Fig. 1. The Specific Process Schematic Diagram of the Method used in this Paper.

II. Materials and Methods

A. *Sequence Visualization of Power Load Data of New Energy Grid*

The power load data of new energy grid can be visually displayed through the current monitoring data, and the current can be regarded as a one-dimensional sequence related to time in essence. According to the idea of two-dimensional visualization of time series [12], GAF method is introduced into the power consumption field of new energy grid to build a two-dimensional visualization image for the power load data of new energy grid. Assuming that $X = \{x_1, x_2, \cdots, x_n\}$ is a sequence containing n sampling values of non-active components of current, the steps to convert it into a two-dimensional visual GAF diagram of power load of new energy grid are as follows:

1) The elements in X is normalized to the interval [-1, 1], that is:

$$\tilde{x}_i = \frac{(x_i - \max X) + (x_i - \min X)}{\max X - \min X} \tag{1}$$

2) The current sequence after standardization is encoded in polar coordinates, namely:

$$\begin{cases} \Psi_i = \arccos \tilde{x}_i \quad \tilde{x}_i \in [-1,1] \\ \quad r = t_i, \quad t_i - i - 1 \end{cases} \tag{2}$$

Where: $\tilde{x}_i$ is the non-active component of the load current of x_i in new energy grid after standardization; Ψ_i is the arccosine of the encoded sample value; r is the radius after timestamp coding; t_i is the sampling timestamp corresponding to x_i.

Since $\tilde{x}_i \in [-1,1]$ after standardization, the definition domain of the inverse cosine function is [-1,1], so $\Psi_i \in [0, \pi]$.

When the current sequence of the power load of the new energy grid is given, each sampling point has and only has a unique mapping result in the polar coordinate system [13], that is, the bijection relationship.

3) After completing the polar coordinate transformation of the current sequence of the standardized new energy grid power load, the GAF method is used to convert the current sequence of the one-dimensional new energy grid power load into an n-order matrix, and the values of the elements in the matrix are mapped to the blue-red color range, making the matrix a two-dimensional image with color and texture distribution [14].

GAF method has two definition methods, namely, Gramian Angular Summation Field (GASF) and Gramian Angular

Difference Field (GADF), and the corresponding matrices A_s and A_D are respectively:

$$A_s=\begin{bmatrix}\cos(2\Psi_1) & \cos(\Psi_1+\Psi_2) & \cdots & \cos(\Psi_1+\Psi_n)\\ \cos(\Psi_2+\Psi_1) & \cos(2\Psi_2) & \cdots & \cos(\Psi_2+\Psi_n)\\ \vdots & \vdots & \ddots & \vdots\\ \cos(\Psi_n+\Psi_1) & \cos(\Psi_n+\Psi_2) & \cdots & \cos(2\Psi_n)\end{bmatrix} \quad (3)$$

$$A_D=\begin{bmatrix}0 & \sin(\Psi_1-\Psi_2) & \cdots & \sin(\Psi_1-\Psi_n)\\ \sin(\Psi_2-\Psi_1) & 0 & \cdots & \sin(\Psi_2-\Psi_n)\\ \vdots & \vdots & \ddots & \vdots\\ \sin(\Psi_n-\Psi_1) & \sin(\Psi_n-\Psi_2) & \cdots & 0\end{bmatrix} \quad (4)$$

GAF method is evolved from Gram matrix. Polar coordinate system is used to represent time series instead of Cartesian rectangular coordinate system. Trigonometric function is used to refine the implicit current difference information between each two sampling points in the sequence to expand the amount of data, so as to improve the dimension of the sequence. Compared with the one-dimensional sequence of the current of the power load in the new energy grid, the two-dimensional image of the current sequence of the power load in the new energy grid significantly improves the identification of the power load. Polar coordinate coding of current sequence has the following advantages: polar coordinate transformation meets the double shooting condition, and the sampling point of current sequence of each new energy grid load has and only has a unique mapping result in the polar coordinate system, ensuring the uniqueness of the coding process; After the polar coordinate transformation, the time from the upper left corner to the lower right corner of the matrix element increases continuously; Compared with the rectangular coordinate system, the polar coordinate system retains the current magnitude relationship and time information of the new energy grid load between the sampling points. Through the above process, the power load data of new energy grid is transformed into a two-dimensional image of time series.

B. Two-dimensional Image Segmentation of Power Load in New Energy Grid based on Improved OTSU Algorithm

1) Image segmentation method based on OTSU: The gray level $G=1,2,\cdots,L$ of the two-dimensional image of the power load in the new energy grid is set, and f_i is used to represent the total number of pixels contained in the gray level i. The total number of pixels in the two-dimensional image of the power load of the new energy grid is N, $N=f_1+f_2+\cdots+f_t=\sum_{i=1}^{l} f_i$. P_i is used to indicate the occurrence frequency of i, a gray-scale pixel, $p_i=f_i/N$, then $p_i>0$, $\sum_{i=1}^{l} p_i=1$. A threshold t is selected to divide all pixels of the two-dimensional image of the power load in the new energy grid into two parts, C_0 and C_1, $C_0=\{1,2,\cdots,t\}$, $C_1=\{t+1,t+2,\cdots,L\}$. The probability distributions of these two types are as follows:

$$\omega_0=P_r(C_0)=\sum_{i=1}^{t} P_i=\omega(t) \quad (5)$$

$$\omega_1=P_r(C_1)=\sum_{i=t+1}^{t} P_i=1-\omega(t) \quad (6)$$

The two types of gray mean values in the two-dimensional image of the power load in the new energy grid are respectively:

$$u_0=\sum_{i=1}^{t} i\times P_r(i/C_0)=\sum_{i=1}^{t}\frac{iP_i}{\omega_0} \quad (7)$$

$$u_1=\sum_{i=t+1}^{t} i\times P_r(i/C_1)=\frac{u_r-u(t)}{1-\omega(t)} \quad (8)$$

Then $u_r=u(L)=\sum_{i=1}^{l} ip_i$, $u(t)=\sum_{i=1}^{t} ip_i$, $\omega(t)=\sum_{i=1}^{t} p_i$.

For any t, the following formula is satisfied:

$$\omega_0+\omega_1=1 \quad (9)$$

$$\omega_0 u_0+\omega_1 u_1=u_r \quad (10)$$

The evaluation function is introduced to judge the advantages and disadvantages of the threshold in OTSU algorithm:

$\lambda=\frac{\sigma_B^2}{\sigma_w^2}$, $k=\frac{\sigma_r^2}{\sigma_w^2}$, $\eta=\frac{\sigma_B^2}{\sigma_r^2}$. σ_B^2, σ_w^2 and σ_r^2 are inter class variance, intra class variance and overall variance respectively. The three decision functions are maximized, and the objective function becomes the selection of the optimal threshold t.

Since $\sigma_r^2=\sigma_B^2+\sigma_w^2$, the following relationship is satisfied:

$$k=\frac{1}{1-\eta} \quad (11)$$

$$\eta=\frac{\lambda}{\lambda+1} \quad (12)$$

It can be seen from the above formula that the monotonicity of the three decision functions is the same [15]. Since σ_r^2 is a known constant and has nothing to do with the value of t, η is the simplest of the three functions, $\eta(t)=\frac{\sigma_B^2(t)}{\sigma_r^2}$, so σ_B^2 can be used as a judgment function for the performance of two-dimensional image segmentation of power load in new energy grid:

$$\sigma_B^2(t)=\frac{\left[u_r\omega(t)-u(t)\omega(t)\right]^2}{\omega(t)\left[1-\omega(t)\right]} \tag{13}$$

Where, $u_r=u(L)=\sum_{i=1}^{l}ip_i$, $u(t)=\omega(t)=\sum_{i=1}^{t}ip_i$

The optimal threshold t^* of two-dimensional image segmentation of power load in new energy grid is:

$$\sigma_B^2(t^*)=\max_{1\le t\le l}\left\{\sigma_B^2(t)\right\} \tag{14}$$

2) Two-dimensional OTSU algorithm with improved threshold selection algorithm: Aiming at the high computational complexity of two-dimensional OTSU algorithm, an improved OTSU algorithm is proposed. This algorithm divides the traditional two-dimensional algorithm into two one-dimensional OTSU algorithms: a threshold is obtained from the one-dimensional histogram based on the gray value of the two-dimensional image of the new energy grid's power load, and its purpose is to extract the target; A threshold value [16] is obtained from the one-dimensional histogram based on the neighborhood average gray value of the two-dimensional image of the new energy grid's power load, and its purpose is to filter out noise. The two thresholds obtained by these two one-dimensional OTSU algorithms are used to replace the thresholds of the original two-dimensional OTSU algorithm. This improved algorithm not only considers the gray information of the two-dimensional image of the new energy grid's power load itself, but also considers the information of its neighborhood pixels, so that the algorithm has good denoising ability. From the frequency f_{ij} of (i,j) in the two-dimensional image histogram of the new energy grid's power load, the frequency $q_i=\sum_{j=0}^{L-1}f_{ij}$ of the pixel gray value i in the two-dimensional image of the power load of the new energy grid and the frequency $r_j=\sum_{i=0}^{L-1}P_{ij}$ of the neighborhood gray value j are derived. By analogy, the probability distribution P_{ij} can be used to obtain the one-dimensional histogram distribution of the pixel gray value i and the neighborhood gray value j of the two-dimensional image of the new energy grid's power load, and their probabilities are $U_i=\sum_{j=0}^{L-1}P_{ij}$, $V_i=\sum_{i=0}^{L-1}P_{ij}$ respectively,.

In two-dimensional OTSU algorithm, edge points and noise points account for a small number [17], that is, the probability corresponding to the noise and edge part can be approximately 0, that is, $\sum_{i=s+1}^{L-1}\sum_{j=0}^{t}P_{ij}=0$, $\sum_{i=0}^{s}\sum_{j=t+1}^{L-1}P_{ij}=0$. It can get the expression of the proportion ω_0 and ω_b of the target and background in the one-dimensional histogram corresponding to the pixel gray value i of the two-dimensional image of the new energy grid's power load as follows:

$$\omega_0=\sum_{i=0}^{s}\sum_{j=0}^{s}P_{ij}+\sum_{i=0}^{s}\sum_{j=t+1}^{L-1}P_{ij}=\sum_{i=0}^{s}U_i \tag{15}$$

$$\omega_b=\sum_{i=s+1}^{L-1}U_i \tag{16}$$

The mean vectors corresponding to the two categories are:

$$\mu_{oi}=\sum_{i=0}^{s}iU_i/\omega_0 \tag{17}$$

$$\mu_{bi}=\sum_{i=s+1}^{L-1}iU_i/\omega_b \tag{18}$$

The overall mean vector of the improved OTSU algorithm is:

$$\mu_i=\sum_{i=0}^{L-1}\sum_{j=0}^{L-1}iP_{ij}=\sum_{i=0}^{L-1}iU_i \tag{19}$$

From the above formulas, it can be deduced that the one-dimensional interclass variance corresponding to the pixel gray value i of the two-dimensional image of the new energy grid's power load is:

$$\sigma_{B_i}(s)=(\omega_0+\omega_b)(\mu_{oi}-\mu_i)^2+(\mu_{bi}-\mu_i)^2 \tag{20}$$

Similarly, it can be obtained that the one-dimensional interclass variance corresponding to the neighborhood gray value v of the two-dimensional image of the new energy grid's power load is:

$$\sigma_{B_j}(t)=(\omega_0+\omega_b)(\mu_{oj}-\mu_j)^2+(\mu_{bj}-\mu_j)^2 \tag{21}$$

Where: ω_0 and ω_b represent the proportion of target and background respectively, and μ_{oj}, μ_{bj} and μ_j represent the average vector and overall mean vector of the two categories respectively.

According to the principle of one-dimensional Otsu algorithm, the optimal threshold s^*, t^* should meet:

$$\sigma_{B_i}\left(s^*\right)=\max_{0\le s\le L-1}\left\{\sigma_{Bi}\left(s\right),\sigma_{Bj}\left(t^*\right)\right\}=\max_{0\le t\le L-1}\left\{\sigma_{Bj}\left(t\right)\right\} \tag{22}$$

Although the threshold segmentation method for the traditional OTSU algorithm considers the variance between the foreground class and the background class [18], it does not consider the discreteness within the class, so it can not more comprehensively reflect the quality of classification and achieve more accurate segmentation. By introducing the intra class dispersion, the segmentation result of the two-dimensional image of the new energy grid's power load not only achieves the maximum variance between classes, but also better realizes the intra class consistency. The classification discrete measure corresponding to the pixel gray value of the two-dimensional image of the new energy grid's power load is defined as:

$$\tau_{di}=\left(\omega_0+\omega_b\right)\sum_{i=0}^{s}\left|\mu_{oi}-iU_i/\omega_0\right|+\sum_{i=s+1}^{L-1}\left|\mu_{bi}-iU_i/\omega_b\right| \tag{23}$$

Based on the above formula, a new threshold recognition function expression is constructed as follows:

$$\xi_i=\omega_0\left(1-\omega_0\right)\times\sigma_{Bi}/\tau_{di} \tag{24}$$

Similarly, the threshold recognition function ξ_j is also constructed for the one-dimensional histogram composed of the average value of neighborhood gray.

In order to optimize the segmentation effect of two-dimensional image of power load in new energy grid and minimize the dispersion within the class, it is necessary to calculate the maximum value of ξ_i and ξ_j, that is, to calculate the minimum value of τ_{di} and τ_{dj}. In order to quickly and effectively determine the two-dimensional image segmentation threshold of the power load of the new energy grid, the solution of ξ_i and ξ_j is taken as the fitness function, and the genetic algorithm is used to automatically obtain the appropriate threshold vector, so as to realize the two-dimensional threshold segmentation for the two-dimensional image of the power load of the new energy grid.

C. Classification of Power Load Data of New Energy Grid based on Convolutional Neural Network

Compared with the traditional neural network, convolutional neural network has a special structure. The weight structure can reduce the complexity of the classification model and reduce the amount of calculation of the algorithm. Convolutional neural network is often used in image classification. Images can be directly used as the input of classification model. The extracted three-dimensional feature signals make the classification accuracy of convolutional neural network higher. Convolution neural network is used to classify the load data of new energy grid. Convolution neural network is divided into four parts: convolution, nonlinear processing, pooling and full connection layer classification.

1) Convolution layer: In convolution neural network, the main purpose of the first step convolution is to extract its feature matrix from an input image, and extract image features through the graphic signal of the input data, so as to maintain the spatial relationship between pixels. The convolution kernel size $G(s,t)$ used for convolution is $A\times B$, and the weight of convolution kernel function directly affects the effect of the final recognition result. The larger the weight is, the stronger the force is. $C(i,j)$ is the characteristic matrix, which is the convolution matrix obtained by convoluting the two-dimensional image of the power load of the original new energy grid with the convolution kernel G. The operation expression is as follows:

$$\begin{aligned}C(i,j)&=f(x,y)\times G(s,t)\\&=\sum_{x=1}^{a}\sum_{y=1}^{b}G(s,t)\times f(i+x-1,t+y-1)\end{aligned} \tag{25}$$

Where, the value range of s and t is $1\le i\le M-A+1$, $1\le j\le N-B+1$.

It is obvious from formula (25) that the convolution neural network algorithm is to use the convolution kernel matrix to filter the original signal image, extract the features of the corresponding positions, and finally obtain a new feature image. One of the most important features of convolution neural network operation is the operation through convolution layer. Multiple convolution checks are used to extract features from the two-dimensional image of power load of new energy grid [19], forming multiple new feature matrices.

It is very important to extract characteristic signals and establish convolution kernel function of characteristic matrix in the convolution process of two-dimensional image of power load in new energy grid. The number of convolution kernels is an important parameter. The extracted number corresponds to the convolution kernel function used in the convolution operation. Different convolution kernel functions are used to convolute the two-dimensional image of the power load of the new energy grid to map different features. The number of convolution kernels corresponds to the number of types of features selected for convolution. The magnitude of the convolution kernel matrix sliding in the image is also an important parameter. When the step is 1, we only move one pixel at a time. When the step is 2, the sliding filter processes two pixels at a time. The larger the step is, the longer the sliding span is, and the smaller the characteristic matrix is generated at the same time. The value of convolution kernel matrix is also an important parameter. Different convolution kernels map different characteristic matrices. The value in the convolution kernel matrix is needed to control, that is, control the output range of the characteristic matrix.

2) Nonlinear processing: After convolution processing of convolution neural network, the second step of nonlinear transformation is required. Its purpose is to process the target in the two-dimensional image of power load of new energy grid by using nonlinear function. The sigmoid function is used for nonlinear processing of the two-dimensional image of the new energy grid's power load, and the expression is as follows:

$$f\left(x\right)=\frac{1}{1+e^{-x}} \tag{26}$$

Nonlinear processing can further purify and sample the data, optimize the data type, and facilitate the subsequent sampling calculation. Nonlinear processing further processes the signal and replaces all negative pixel values to zero during feature mapping. The purpose of nonlinear processing is that most real-world data are not smooth and ideal. It is hoped that through further processing of signal data, convolutional neural network can recognize signals more accurately and reliably.

3) Pooling processing: Pooling can also be called subsampling or subsampling. Its purpose is to reduce the dimension of each feature map and retain the most important information. Pool processing can be: maximum value, average value, adjacent and so on. In the process of pooling, a feature window $a\times b$ is defined, and the secondary feature extraction of the first step feature matrix is carried out through the pooling window. Through pooling, we can gradually reduce the size of the input space, make the input dimension smaller and easier to calculate, and retain the important characteristics of the network, so that the small transformation, distortion and translation in the two-dimensional foreground image of the segmented power load of the new energy grid remain unchanged.

4) Full connection layer classification: Each pixel of the characteristic matrix in the two-dimensional image of all new energy grid power loads after pooled sampling is arranged in turn to form a feature vector. The feature vector forms a full connection with the output layer as a full connection layer. The full connection layer is the last step of the convolutional neural network, which is used for the output of the whole neural network. In the full connection layer, a classifier is usually trained for the convolutional neural network [20]. Generally speaking, the full connection layer adopts the traditional multi-layer classifier, such as softmax or support vector machine. The purpose of full connection layer is to use the characteristics of data to achieve the classification purpose of input and output through training. The full connection layer is located in the classification link of convolutional neural network structure.

In the process of convolution neural network classifying the power load data of new energy grid, the first step is to select the test set and sample set, and select the foreground image of the two-dimensional image of new energy grid's power load obtained after segmentation as the input sample of convolution neural network. After determining the test sample and training sample, the classification process is as follows:

1) Initialize the weight matrix and bias parameters of convolutional neural network.

2) Select a sample from the training samples, input the selected samples into the network, and obtain the corresponding actual output value.

3) Calculate the error between actual data input and ideal output.

4) Carry out back propagation and adjust the parameters.

5) Input the remaining training samples into the network in turn until all training samples are input, and complete an iteration.

6) Input the test samples into the trained sample model, and use the classifier to obtain the accuracy of classification.

The convolution neural network is used to classify the segmented two-dimensional image of the power load of the new energy grid, and the classification results of the power load data of the new energy grid are output.

III. Results

In order to verify the classification effectiveness of the classification method for power load data of new energy grid based on the improved OTSU algorithm, the method in this paper is applied to the new energy grid's power consumption management of a power enterprise. The power enterprise uses current sensors to collect the current changes of different smart meters, as shown in Table I.

According to the current changes of smart meters in the new energy grid collected by the current sensor in Table 1, the GAF method is used to build a two-dimensional visual image of the time series of power load data in the new energy grid, as shown in Fig. 2.

According to the experimental results in Fig. 2, the current data related to load data in the new energy grid can be effectively converted into two-dimensional visual images by using the method in this paper, and the two-dimensional visual images can be used to visually display the load changes in the new energy grid. In this paper, the improved OTSU algorithm is used to segment the two-dimensional visual image of time series. The segmentation results of the two-dimensional visual image of the new energy grid's power load data are shown in Fig. 3.

According to the segmentation results of the new energy grid's electricity load image in Fig. 3, the accurate segmentation of the two-dimensional visual image of the new energy grid's electricity load can be achieved by using the method in this paper, and the two-dimensional visual image can be divided into the target foreground area and the background area by image segmentation. The experimental results in Fig. 3 show that the method in this paper has a high image segmentation effect, and the edge of the segmented image is clear, which can effectively display the target information contained in the image.

TABLE I. CURRENT CHANGE ACQUISITION RESULTS

Electric meter account number	58156 /A	84516 /A	89145 /A	68421 /A	68115 /A
10s	1.85	2.16	3.25	1.79	1.94
20s	2.16	2.85	3.46	1.86	1.58
30s	3.28	3.16	2.85	2.35	1.68
40s	2.84	2.75	1.64	1.64	2.34
50s	2.69	3.16	3.69	1.85	2.49
60s	2.75	2.84	2.46	1.54	1.85
70s	3.16	3.64	1.85	1.35	1.95
80s	1.05	3.85	1.62	1.65	2.47
90s	0.95	1.26	1.57	1.05	2.05
100s	3.25	2.64	1.69	2.06	2.13

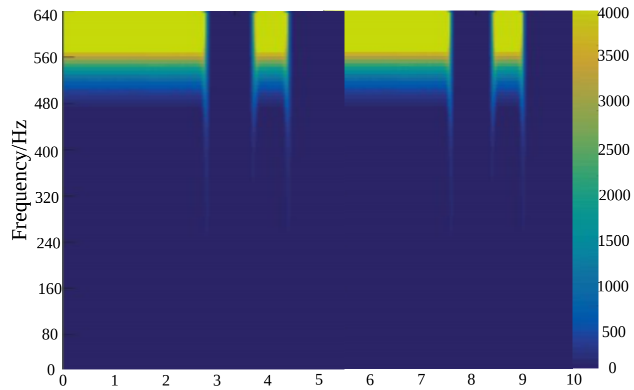

Fig. 2. 2D Visualization of Time Series.

Fig. 3. Image Segmentation Results.

The method in this paper is used to classify the load data managed by a smart meter in the new energy grid to verify the effectiveness of this method. According to the segmented electricity load image of new energy grid, the classification results of electricity load data of new energy grid using this method are shown in Table II.

According to the experimental results in Table II, the improved OTSU algorithm can be used to classify the power load data of new energy grid with high classification accuracy. The experimental results in Table II verify that the method in this paper has high classification effectiveness of power load data of new energy grid. This method can accurately classify the power load data of the new energy grid, which is helpful for the dispatching management decision-makers of the new energy grid to make the dispatching and management decisions of the new energy grid according to the classification results of the power load data of the new energy grid.

The method in this paper is used to classify the power load data in the new energy grid. The operating power changes of each power load are shown in Table III.

According to the experimental results in Table III, there are obvious differences in the power of different power loads in the new energy grid. The method in this paper can effectively classify the load data of the new energy grid, and accurately analyze the load data of the new energy grid through the power changes of different load types.

Statistics adopts the method in this paper to classify the power load data of new energy grid. For the classification accuracy of different types of load data, the classification performance of this method is verified by the classification accuracy of load data. The statistical results are shown in Fig. 4.

TABLE II. CLASSIFICATION RESULTS OF ELECTRICITY LOAD DATA OF NEW ENERGY GRID

Time	Classification result	Is the classification correct
8:05	Turn on the rice cooker	Yes
8:13	Turn off the rice cooker	Yes
8:25	Turn on the TV	Yes
18:16	Turn on the refrigerator	Yes
18:32	Turn off the tv	Yes
19:25	Turn on the rice cooker	Yes
19:35	Turn off the rice cooker	Yes
19:51	Turn off the refrigerator	Yes
20:18	Turn on energy-saving lamps	Yes
20:23	Turn off the hair dryer	Yes

TABLE III. CHANGES IN OPERATING POWER OF ELECTRICAL LOAD

Electric load type	Max power/W	Minimum power/W	Average power/W
refrigerator	185.6	134.4	148.5
TV set	285.4	234.5	257.6
electric fan	135.5	126.5	129.4
hair dryer	1820.4	1685.4	1710.5
kettle	1864.5	1812.5	1835.7
air conditioner	1358.6	1205.7	1285.4
washing machine	280.6	250.4	265.8
Micro-wave oven	750.4	658.6	716.5
induction cooker	4050.4	3895.8	3925.4
computer	330.5	290.4	315.6

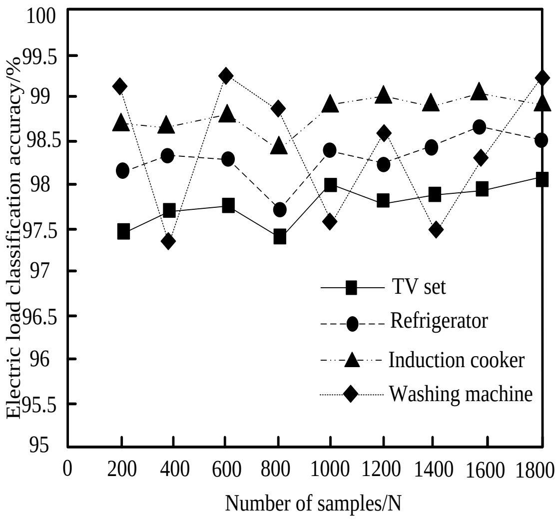

Fig. 4. Load Data Classification Accuracy.

According to the experimental results in Fig. 4, the classification accuracy of different types of power load data using the method in this paper is higher than 97%. The experimental results verify that this method has high classification effectiveness of power load data of new energy grid. For different types of load data, this method can achieve accurate classification. It is verified that the method in this paper has high efficiency of load data classification, and can be applied to the practical application of power load data classification in new energy grid.

The classification calculation time of this method is counted for different types of load data. The statistical results are shown in Fig. 5.

As shown in Fig. 5, the classification time of the present method is less than 50ms, indicating that the method has high load data classification efficiency and is suitable for the practical application of power grid load data classification.

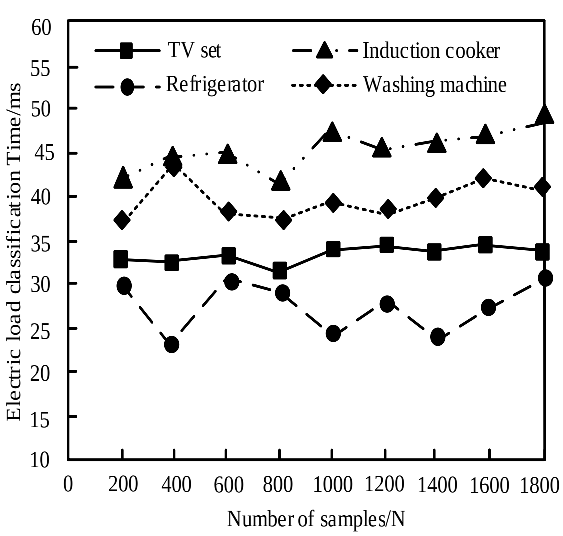

Fig. 5. Classification Time.

IV. Discussion

This paper studies the classification method for power load data of new energy grid based on improved OTSU algorithm, and verifies that this method can accurately classify the data of new energy grid through experiments. The energy problem has always been a problem perplexed by mankind. With the development of the times, the energy crisis and greenhouse effect have become increasingly serious. How to effectively improve energy efficiency and reduce polluting gas emissions has become a high concern and attention of all sectors of society. The new energy grid has become the main trend of the development of the power field. The working state and energy consumption of each power load in the new energy grid can be obtained by classifying the power load data of the new energy grid. According to the comprehensive information such as energy consumption information, time-of-use electricity price and electric energy measurement, effective energy-saving measures can be obtained, reasonable energy-saving plans can be formulated, and targeted power loads can be purchased.

The significance of power load data classification of new energy grid is specifically shown in:

1) In the planning of power system, medium and long-term load forecasting is the basis of power system development planning and fuel planning, while short-term load forecasting is the premise of making daily power generation plan and determining the operation mode of power system. The classification of power load data of new energy grid only through the installation of monitoring equipment at the user's power entrance to understand the power consumption, operation status and operation time of the load, and in-depth understanding of the energy consumption and detailed power consumption information of each load. The fine-grained power consumption information is helpful to obtain the characteristics and power consumption modes of different load types, and more accurately predict the spatial density distribution map of load at various spatial scales and time scales, to improve the accuracy and reliability of load forecasting which greatly improves the scientificity of power system planning and the real-time, safe and economic operation of the power grid.

2) The classification method for power load data of new energy grid can obtain the specific power consumption information of each power load, carefully consider the time-varying characteristics of load operation, provide the possibility for load modeling and dynamic management of load model parameters, improve the operation accuracy of load model in the process of power system simulation, and reduce the economic loss of error caused by load model.

3) The classification of power load data of new energy grid can enable power companies to obtain detailed power consumption information such as the type, working state, power consumption time and energy consumption of different loads, and can help power companies formulate electricity prices and power demand side management more scientifically and provide corresponding incentive policies. At the same time, the working state information of power load can help power companies verify whether users make timely and accurate response to grid demand according to the relevant demand of power demand side management, such as load shedding during peak hours of grid operation. At the same time, the power supply company can carry out user expansion business according to the power consumption information. For example, the power supply company can formulate a detailed power consumption plan for users and obtain corresponding remuneration.

4) The classification of power load data of new energy grid to obtain the detailed power consumption information of users can greatly improve the visualization of power system, especially for the fault state and abnormal operation state of power grid load, which is conducive to the detection, quasi positioning, self-healing reconstruction and rapid restoration of power supply and other functions of power system distribution network's outage fault.

5) The classification of power load data of new energy grid can obtain the working state, power consumption time and energy consumption of each power load in real time, such as whether the electric kettle is in the heating state, whether the LCD TV is in the working state, and whether the refrigerator is in the fault state.

6) Residential users adjust and optimize their power consumption behavior according to the detailed power consumption information of the power load, so as to achieve the purpose of saving electricity and reducing electricity expenses, such as changing the use time of the power load, avoiding the peak electricity price, or adjusting the operating parameters of the power load, so as to reduce unnecessary power waste.

7) According to the detailed power consumption information, users can quickly and accurately obtain whether the power load is in fault and which equipment is high-efficiency equipment, and use energy-saving power loads as much as possible. For example, if the refrigerator is monitored to be in the operation state of maximum power all the time, rather than the intermittent operation state, the refrigerator is in the fault state; Or if it is judged that the air conditioner consumes too much power, it can be considered to replace the energy-saving air conditioner, which is conducive to saving electricity expenses. At the same time, the detailed electricity consumption information of residents' various loads provides a regulation basis for smart home and household electricity automation.

8) In the research, the challenge encountered in this paper is to use the image segmentation for classification data, which is prone to noise interference and affects the classification accuracy. Therefore, this paper uses the one-dimensional classification threshold to filter out the noise and obtain accurate results.

9) The importance of all quantities in the relationship lies in that this paper uses the average vector and the overall average value corresponding to the gray value of the neighborhood of the new energy grid load two-dimensional image to calculate the one-dimensional inter class variance, find the best gray threshold, and perform more accurate segmentation. By introducing intra class dispersion, the load two-dimensional image segmentation results reach the maximum variance within the class, and the classification results are optimized; The convolution kernel matrix is used to filter the original signal image, extract image features, and nonlinear process the load two-dimensional image, which improves the accuracy and efficiency of classification.

V. Conclusion

With the growing maturity of smart grid and the gradual enhancement of users' awareness of energy conservation, the demand for household electricity transparency on the power demand side is also more urgent. Therefore, in this paper, the classification method for power load data of new energy grid based on the improved OTSU algorithm is studied, to display the collected power load data of new energy grid in the form of two-dimensional images, segment the two-dimensional image of power load data of new energy grid using the improved OTSU algorithm, and use the segmented two-dimensional image to realize the effective classification of new energy grid's power load data. The classification of power load data of new energy grid can optimize the power consumption mode of users and improve the participation of power consumers in demand side management. Due to the limited conditions, the present method has some shortcomings and only study the data classification, and future studies can optimize the user power consumption pattern using the classification results.

VI. Fund

This study did not receive any funding in any form.

VII. Conflicts of Interest

The authors declare that they have no competing interests

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