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Novel Power System Load Forecasting Method Based on Multi-indicator Clustering Optimization and Sensors

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As the new generation of power load management systems is gradually being implemented, there is an increasing demand for accuracy in power load forecasting. To meet this demand, a new load forecasting method of the power system based on multi-index clustering optimization is proposed in this paper. Firstly, the sensor technology is fully utilized to realize the data acquisition of the power system and the real-time monitoring of key parameters, providing more accurate and timely data for the load forecasting model. Secondly, the real-time data collected by the sensor is combined with the *K*-means clustering algorithm, which is improved, and the optimal number of clusters is selected by evaluating the clustering effect of multiple indicators. Then, an improved Particle Swarm Optimization-Back Propagation (PSO-BP) neural network prediction model is built by combining the ability of the BP neural network to solve complex nonlinear function approximation and the global optimization ability of the PSO algorithm. The model's parameters are adjusted flexibly to improve the prediction accuracy and response speed. Finally, the model is compared with the BP neural network to verify the optimization effect. The experimental results of the simulation test show that the proposed method can effectively ensure the reliability of data transmission, realize the effective classification and aggregation of heterogeneous data, provide accurate load prediction results quickly, and improve robustness.

1. Introduction

In recent years, the transformation of the power system has made electricity load diversity and flexibility the main characteristics of the power system.[(1)] Load forecasting, a core task of estimating future electricity demand, involves the statistical analysis of large amounts of historical load data considering multiple factors such as weather, production, and lifestyle habits,

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and using mathematical methods to accurately predict future electricity demand and load curves.[2] In the new power system, short-term load forecasting relies on the real-time sensing of the state and parameter changes of various nodes in the grid using sensors and monitoring devices, thereby monitoring the overall operation of the power system in real time.[3–5] Subsequently, short-term load forecasting is conducted through data analysis and intelligent algorithms to ensure the stable operation of the grid and supply-demand balance. Currently, deep learning methods have demonstrated outstanding capabilities in power load forecasting. However, the challenge lies in selecting appropriate deep learning architectures to shorten development cycles, accelerate convergence, and enhance the practicality of algorithms and has become a pressing issue for current scholars. In the constantly evolving power environment, choosing suitable deep learning architectures for load forecasting tasks is crucial. This not only improves prediction accuracy but also adapts to the continuously changing electricity demands.[6] Therefore, in-depth research and innovation in deep learning methods to better serve load forecasting tasks are urgent needs in both academia and industry. With the continuous evolution of the power system and the introduction of new technologies, there still exists significant research and innovation space for improving the accuracy and flexibility of load forecasting to cope with increasingly complex electricity demands and changes.

Fukushima and others proposed the neocognitron model in the 1970s and 1980s, which led researchers to conduct extensive studies on convolutional neural networks.[7] With the emergence of deep learning theory, convolutional neural networks experienced rapid development in the field of computer vision.[8] Ren *et al.* addressed the necessity of diversity in ensemble learning and proposed a quantification method based on an improved K-means clustering algorithm.[9] Ni *et al.* introduced a hybrid model for power load forecasting that leverages a deep neural network. This model was enhanced through a multi-objective optimization algorithm and a sophisticated data preprocessing strategy. Integrating the deep neural network into power load time series forecasting has proven highly successful, delivering outstanding prediction accuracy and stability.[10] Although these data aggregation and analysis techniques have matured over several years, there are still difficulties in handling large amounts of heterogeneous secure data, necessitating innovative development in conjunction with load forecasting methods. In terms of traditional load forecasting methods, Apolinario *et al.* proposed a method based on the fusion of LSTM and discrete wavelet transform (DWT) for power peak load forecasting and achieved reasonable energy distribution and power grid operation planning.[11] Xia and Ji proposed an exponential smoothing method with the characteristic of “thick near and thin far,” solving the challenges of long time spans and wide distribution in medium and long-term load forecasting.[12] While these traditional prediction methods can quickly yield results, they suffer from disadvantages such as low accuracy and precision, requiring optimization and improvement based on actual conditions. In the field of machine learning prediction methods, Hou *et al.* proposed a rolling prediction method based on the phase space reconstruction of chaos theory and stacking ensemble learning. Constructing a stacking ensemble learning model for load forecasting and combining the advantages of various machine learning algorithms provides a new idea for the field of power load forecasting.[13] Although the results predicted by these methods are highly accurate, there is still room for improvement in data mining. In terms of deep learning prediction methods, Chen *et al.* addressed the challenge of accurately predicting short-term power load using Back Propagation (BP) neural networks as the foundation and introducing genetic algorithms to optimize the learning connection weights and thresholds of the network structure, thereby enhancing the reliability and accuracy of short-term load prediction.(14) Utilizing the advanced data mining prowess of deep learning, Shen *et al.* developed a cutting-edge multiscale neural network. This network amalgamates long-term memory, gated cycle units, and temporal convolution to form its core. Enhanced by the random weight average differential evolution method, it is applicable to single and multiple models, substantially boosting the accuracy of short-term load forecasting.(15)

Although extensive research has been conducted on electricity load forecasting and data protection security, the existing literature does not adequately cover the new power system, especially in terms of sensor applications and the explosive growth of data from smart metering systems, as well as the complexity of data quality and security issues. Additionally, current research, despite its advantages in long-term memory dependence, still faces challenges such as low training speed, high training difficulty, and unsatisfactory short-term forecasting results.

In addressing the above-mentioned issues, we first utilize sensors to collect key parameters in the new power system. Subsequently, the data is analyzed using the *K*-means clustering method with multi-indicator evaluation, optimizing the calculation process for higher clustering accuracy and improved computational efficiency. Next, the adaptive mechanism of the Particle Swarm Optimization-Back Propagation (PSO-BP) prediction algorithm is employed to enhance training efficiency, enabling rapid convergence while improving prediction accuracy. The optimization algorithm is then compared with a single BP neural network to validate the performance of the model. This demonstrates that the short-term load proposed in this paper meets the requirements of the new power system in terms of accuracy and speed, thereby ensuring the normal operation of the power system.

2. Wireless Sensor-based Power Information Monitoring

Ensuring the accuracy and real-time nature of data is essential in achieving load forecasting for new power systems. Therefore, we deploy wireless sensor nodes in the power system to monitor parameters such as current, voltage, active energy, and reactive energy in real time, ensuring data accuracy for load forecasting

2.1 Measurement of current and voltage

The measurement method for current involves taking the average of several instantaneous samples within half a cycle of the power frequency. Then, using the relationship between the effective and average values, the corresponding effective value of the current is determined. The relationship between the instantaneous and effective values of the current is represented as

$$i=\sqrt{2}I\sin\omega t,\ \ \bar{i}=\frac{1}{\pi}\int_0^{\pi}\sqrt{2}I\sin\omega t d(\omega t)=\frac{2\sqrt{2}}{\pi}I,\ \ I=\frac{\pi}{2\sqrt{2}}\bar{i}. \tag{1}$$

The measurement method for voltage is similar to that for current. The relationship between the instantaneous and effective values of the voltage is represented as

$$U = \frac{\pi}{2\sqrt{2}}\bar{u}. \tag{2}$$

2.2 Measurement of active energy and reactive energy

The expressions for the calculation of three-phase instantaneous power are given by

$$p = p_A + p_B + p_C = u_{AN} i_A + u_{BN} i_B + u_{CN} i_C, \tag{3}$$

$$i_A + i_B + i_C = 0,\ i_B = -i_A - i_C. \tag{4}$$

Substituting Eq. (4) into Eq. (3), we obtain

$$p = (u_{AN} - u_{BN}) i_A + (u_{CN} - u_{BN}) i_C = u_{AB} i_A + u_{CB} i_C = p_1 + p_2. \tag{5}$$

The expressions for three-phase active power and three-phase active energy are respectively represented as

$$P = \frac{1}{T}\int_0^T (p_1 + p_2)dt = p_1 + p_2 = U_{AB} I_A \cos(30° + \varphi_A) + U_{CB} I_C \cos(30° - \varphi_C), \tag{6}$$

$$W_P = \int_0^T Pdt = \int_0^T (P_1 + P_2)dt. \tag{7}$$

When measuring three-phase reactive energy, the expression for three-phase instantaneous power is given by

$$q = u_{BC} i_A + u_{AB} i_C = q_1 + q_2. \tag{8}$$

The formula for calculating three-phase reactive power is given by

$$Q = Q_1 + Q_2 = \frac{1}{T}\int_0^T (q_1 + q_2)dt = U_{BC} I_A \cos(90° - \varphi_A) + U_{AB} I_C \cos(90° - \varphi_C). \tag{9}$$

The expression for three-phase reactive energy is given by

$$W_q = \int_0^T Qdt = \int_0^T (Q_1 + Q_2)dt. \tag{10}$$

From the results of the above analysis, it is evident that both measurements can utilize current signals taken from i_A and i_C, and voltage signals taken from u_{AB} and u_{CB}. The only difference is that for measuring reactive energy, u_{BC} (the inverse of u_{CB}) is used.

3. Aggregation Model for Load Data Based on *K*-means Clustering

3.1 Load data preprocessing

The provided data consists of load values for a specific region over two months, including terminal three-phase voltage, three-phase current, active power, reactive power, and power factor, obtained at 15 min intervals. Firstly, regarding the different situations of terminal three-phase currents, the unbalance degree of the three-phase current is commonly used as an indicator to measure the distribution of system current. The detailed formulas are as follows.

$$I_{ub} = \frac{\max\{I_A, I_B, I_C\} - \min\{I_A, I_B, I_C\}}{\max\{I_A, I_B, I_C\}} \times 100\% \tag{11}$$

$$E = P_{useful} \times 0.25 \tag{12}$$

1) Import the original load data into SPSS software for data preprocessing. Firstly, use the median absolute deviation (*MAD*) method for outlier identification and replace the detected outliers with the mean. *MAD* is defined as

$$MAD = \text{median}(|Y_i - \text{median}(Y)|). \tag{13}$$

Assuming the data follow a normal distribution, the outliers should fall outside the 50% probability range, while the normal values fall within the middle 50% region. This is expressed as

$$P(|Y - \mu| \le MAD) = P\left(\frac{|Y-\mu|}{\sigma} \le \frac{MAD}{\sigma}\right) = P\left(Z \le \frac{MAD}{\sigma}\right) = 0.5. \tag{14}$$

To transform it into a standard normal distribution, it is expressed as

$$P\left(Z \le \frac{MAD}{\sigma}\right) = \phi\left(\frac{MAD}{\sigma}\right) - \phi\left(-\frac{MAD}{\sigma}\right) = 0.5. \tag{15}$$

Furthermore, owing to the properties of the standard normal distribution, $\phi(-y) = 1 - \phi(y)$, we can deduce that $\phi(MAD/\sigma) = 0.75$. This implies that $MAD/\sigma = \phi^{-1}(0.75)$. By consulting a standard normal distribution table, we obtain $MAD/\sigma = 0.6749$.

In a normal distribution, the area under the curve for ±0.6749 covers 50% of the total area. Since 1/0.6749 ≈ 1.4826, we have

$$MAD_c = 1.483 \cdot MAD. \tag{16}$$

2) To mitigate the impact of varying data units on the analysis of the results, normalization is performed using the min–max method. This process scales the data values to a dimensionless range within (0,1). The specific formula is expressed as

$$y_{i,j}^{*} = \frac{y_{i,j} - y_j^{min}}{y_j^{max} - y_j^{min}}, \tag{17}$$

where y_j^{max} and y_j^{min} respectively represent the maximum and minimum values of the column in which y_i is located.

3.2 Load data aggregation analysis based on *K*-means clustering

Cluster analysis, a crucial part of data mining, relies on the authenticity and correctness of the data. Given that the data collected are, in most cases, incomplete or inaccurate, preprocessing is necessary to enhance the accuracy and effectiveness of the model. We conduct cluster analysis on preprocessed electricity load data using an improved *K*-means algorithm.

3.2.1 Cluster analysis of load profiles based on *K*-means clustering

The *K*-means algorithm is the most representative method for cluster analysis and is known for its speed and simplicity in implementation. It is a dynamic clustering method where the input consists of a dataset D containing n data points, the number of cluster centroids (k), the clustering stopping condition ε, and the maximum number of iterations (*mStep*). The output is a clustering partition $C = \{C_1, C_2, ..., C_k\}$ that satisfies the termination condition. In the *K*-means algorithm, let $D = \{X_i \mid X_i \in R^m, i = 1, 2, ..., n\}$ represent the dataset to be clustered, and let m and n denote the dimensionality and the number of data points, respectively. The calculation of data similarity is typically based on the Euclidean distance:

$$DIST(X_i, X_j) = \sqrt{\left(X_i - X_j\right)^T \left(X_i - X_j\right)}. \tag{18}$$

The standard measure function often used is the sum of squared errors within clusters (SSE), calculated as

$$E = \sum_{i=1}^{k} \sum_{x \in C_i} \left\| x - \mu_i \right\|_2^2, \tag{19}$$

where k represents the number of cluster centers and μ_i denotes the center of cluster C_i, which is the mean value, expressed as

$$\mu_i = \frac{1}{|C_i|}\sum_{x\in C_i} x. \tag{20}$$

According to the following equation, compute the average vector of different user load curve vectors in each class and use the calculated vector as the load curve vector corresponding to the cluster center of that class. The coordinates of the vector are shown as

$$c_i = \frac{1}{m}\sum_{i=1}^{m} u_{(i,j)},\ i = 1,2,3,\ldots,n. \tag{21}$$

In this equation, i represents the c_i cluster center vectors of user load curves, where the jth load curve is denoted by $u_{(i,j)}$, and the total number of load curves is m.

3.2.2 Assessment of clustering effectiveness using multiple indicators

The performance metrics for cluster analysis, also known as evaluation metrics, can be used to assess the quality of clustering algorithms and parameter selection. In this study, four internal metrics are employed to evaluate the effectiveness of different numbers of cluster centers.

The formula for the silhouette coefficient is

$$S_i = \frac{b(i) - a(i)}{\max[a(i), b(i)]},\ i = 1,2,3,\ldots,n. \tag{22}$$

Here, $a(i)$ and $b(i)$ respectively represent the average distance from a sample point to other sample points in the same cluster and the minimum average distance from the sample point to centers of other clusters. The silhouette coefficient has a range of [−1, 1], where a higher silhouette score indicates better clustering effectiveness.

The formula for calculating the CH index is given by

$$CH_i = \frac{SSB}{SSW} \times \frac{(N-k)}{(k-1)},\ i = 1,2,3,\ldots,n, \tag{23}$$

where SSB and SSW respectively represent the total between-cluster variance and the total within-cluster variance, k denotes the number of cluster centers, and N is the number of observations.

The specific formula is expressed as

$$DBI = \frac{1}{k}\sum_{i=1}^{k} \max\left[\frac{\tilde{d}_i + \tilde{d}_j}{D(c_i, c_j)}\right], \tag{23}$$

where k is the number of clusters, $\tilde{d}_i$ and $\tilde{d}_j$ represent the norm of the distance vectors from elements in the ith and jth clusters to their respective cluster centroids, and h is the norm of the distance vector from the ith to the jth cluster centroid.

The gap value (GAP) is shown as

$$GAP = E_n^*\{\lg(W_k)\} - \lg(W_k)\cdot \tag{25}$$

Here, n represents the sample size and k represents the number of clusters under the gap value evaluation.

By comprehensively evaluating the clustering effect using multiple indicators, one can fully consider the characteristics of the dataset and the quality of the clustering results, thereby avoiding the one-sidedness caused by a single indicator and determining a more appropriate number of cluster centers. The introduction of multiple objective indicators enhances the robustness of the clustering algorithm, making it suitable for different types of data. By taking into account multiple indicators, subjectivity and randomness are reduced, making the clustering results more reliable.

4. PSO-BP Prediction Algorithm and Its Improvement

The PSO-BP algorithm involves the BP neural network and PSO algorithm. In the initial stage of PSO-BP, accurate input is very important for adjusting the weight and deviation. The multi-index clustering algorithm improves the accuracy of the initial clustering center and provides more reliable input for PSO-BP. Therefore, this study combines a multi-index clustering algorithm with the PSO-BP algorithm, which can greatly improve the search probability of a globally optimal solution. Below is a more detailed introduction.

4.1 Backpropagation neural network

The BP neural network, widely applied as a model, undergoes training via the BP algorithm, adjusting the network's node weights and biases to optimize the model. Figure 1 illustrates a simple neural network diagram.

While the BP neural network has achieved significant success in simulating animal nervous systems, its complex structure leads to relatively low learning speeds, susceptibility to local minima, and challenges in stability.

In neural networks, the output H_j of the hidden layer is expressed as

$$H_j = g\left(\sum_{i=1}^{n} \omega_{ij} x_i + a_j\right), \tag{26}$$

where n is the number of nodes in the input layer, ω_{ij} represents the weights from the input layer to the hidden layer, and a_j represents the biases from the input layer to the hidden layer.

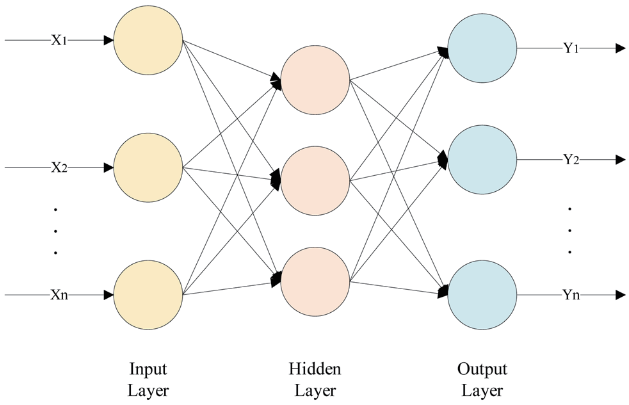


Fig. 1. (Color online) Neural network diagram.

The output O_k of the output layer is represented by

$$O_k = \sum_{j=1}^{l} H_j \omega_{jk} + b_k, \tag{27}$$

where l represents the number of nodes in the hidden layer, ω_{jk} denotes the weights from the hidden layer to the output layer, and b_k represents the bias from the hidden layer to the output layer.

The error formula is given by

$$E = \frac{1}{2}\sum_{k=1}^{m}(Y_k - O_k)^2, \tag{28}$$

where m represents the number of output layer nodes and Y_k represents the desired output.

The weight update formula is expressed as

$$\begin{cases} \omega_{ij} = \omega_{ij} + \eta H_j (1 - H_j) x_i \sum_{k=1}^{m} \omega_{jk} (Y_k - O_k), \\ \omega_{jk} = \omega_{jk} + \eta H_j (Y_k - O_k), \end{cases} \tag{29}$$

where η represents the learning rate.

4.2 PSO algorithm

Another widely used machine learning algorithm is the PSO algorithm, which employs swarm intelligence for learning and exhibits good global optimization capabilities. In each iteration of the PSO algorithm, each particle updates its position based on its individual best solution and the current global best solution. The velocity and position update formulas are respectively given by

$$v_i = v_i + c_1 \cdot rand() \cdot (pbest_i - x_i) + c_2 \cdot rand() \cdot (gbest_i - x_i), \tag{30}$$

$$x_i = x_i + v_i, \tag{31}$$

where c_1 and c_2 represent the individual and social cognitive factors, respectively. Typically, when c_1 is large and c_2 is small, the algorithm exhibits poor global search capabilities; conversely, when c_1 is small and c_2 is large, the algorithm demonstrates improved global search capabilities.

On this basis, researchers introduced the inertia weight w and proposed dynamic adjustment to balance the convergence's globality and convergence speed. This algorithm is known as the standard PSO algorithm:

$$v_i = \omega \cdot v_i + c_1 \cdot rand() \cdot (pbest_i - x_i) + c_2 \cdot rand() \cdot (gbest_i - x_i), \tag{32}$$

where v_i represents the particle's velocity and v_{max} denotes the maximum velocity (greater than 0), which determine the precision of the region between the current position and the best position. x_i is the particle's current position and *rand*() is a random number between (0, 1). The inertia factor ω, with a nonnegative value, indicates the effect of the particle's velocity from the previous generation on the current velocity.

Dynamic inertia factors can yield better optimization results than fixed values. Currently, the linearly decreasing weight strategy represented by Eq. (33) is widely adopted:

$$\omega = \omega_{max} - (\omega_{max} - \omega_{min}) \cdot \frac{run}{run_{max}}. \tag{33}$$

In this equation, ω_{max} represents the maximum inertia weight, ω_{min} represents the minimum inertia weight, *run* denotes the current numbers of iteration, and run_{max} represents the total number of iterations in the algorithm.

4.3 PSO-BP algorithm

The PSO-BP algorithm combines the global search and weight optimization properties of PSO with the learning and model fitting properties of BP neural networks. This integrated approach accelerates the training process of the neural network and helps to solve problems such as weight initialization and local minima, thus improving the efficiency and performance of training. The core idea of the PSO-BP algorithm is to combine global search (PSO) with neural network weight optimization (BP) to train neural networks more efficiently and to improve their convergence speed, performance, and accuracy in various tasks. The flowchart of this process is shown in Fig. 2.

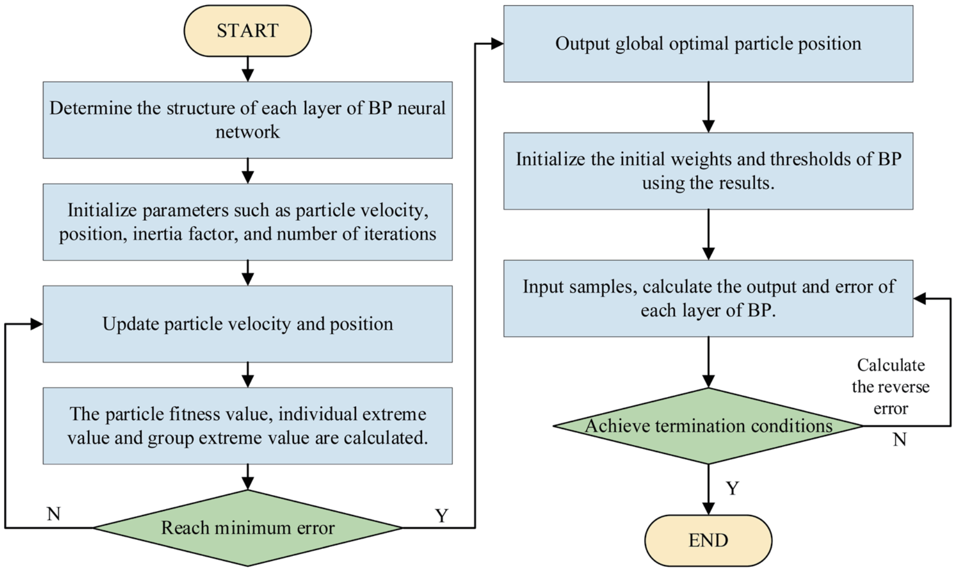


Fig. 2. (Color online) Flowchart of PSO-BP algorithm.

The PSO-BP algorithm has the property of global search, which helps to avoid the problem of falling into local optimal solutions, thus ensuring that better combinations of weights and bias values are found in the entire parameter space.

In addition, through the global search and optimization process of the PSO-BP algorithm, the model is more likely to capture potential patterns in the dataset, thus improving the generalization ability of the load forecasting model and enabling it to have a better prediction ability for future load changes.

4.4 Improved PSO-BP prediction algorithm

This part mainly introduces the specific operation of the multi-index clustering algorithm based on PSO-BP, as shown in Fig. 3.

The above figure is a simple flowchart. The detailed steps of each operation are as follows.

1) Data Acquisition: Deploy sensors in the new power system, use sensor technology to collect key parameters, and realize the real-time monitoring of the power system. These parameters include current, voltage, active power, and reactive power, which ensure the accuracy and real-time performance of the data and provide basic data for the load forecasting model.
2) Data Preprocessing: The original load data is imported into SPSS software for preprocessing. First, the MAD method is used to identify outliers in the data and replace them with mean values. Then, to reduce the effect of different data units on the result of the analysis, the min–max method is used to standardize the data, and the data value is scaled to the unidimensional range of (0, 1).
3) Multiple Attribute Clustering: A multi-index clustering model is constructed to select the optimal number of clustering centers by evaluating multiple indicators. The improved *K*-means algorithm is used to cluster the preprocessed data.

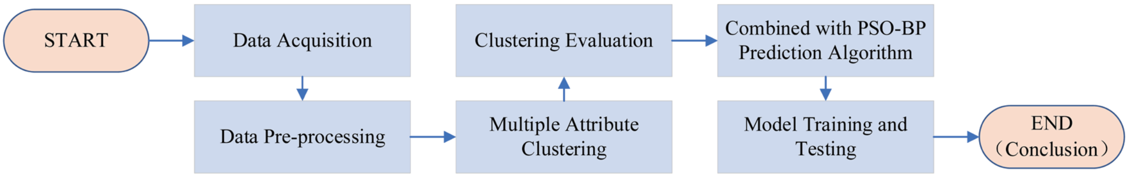


Fig. 3. (Color online) Total flowchart of algorithm.

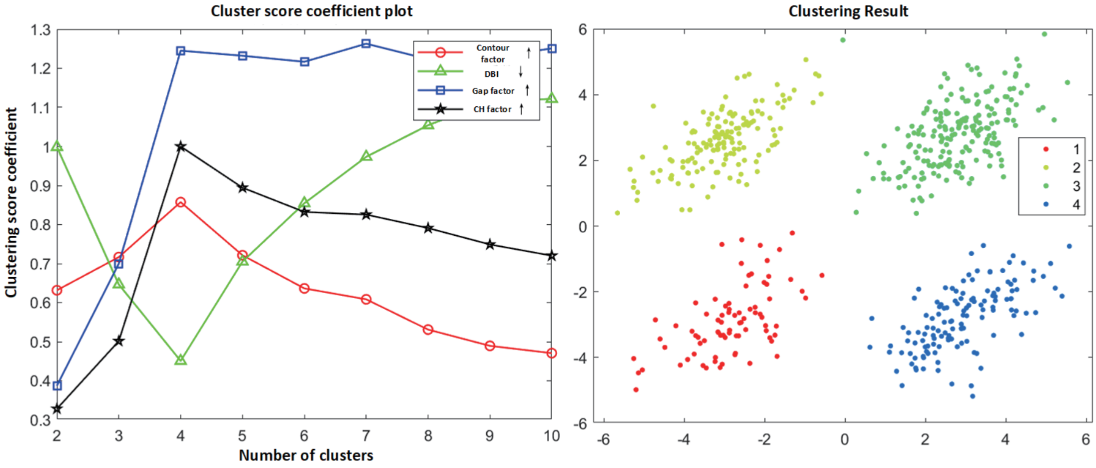
4) Clustering Evaluation: Multiple internal indicators are used to evaluate the clustering effect of different numbers of clustering centers. These indicators comprehensively consider the characteristics of the dataset and the quality of the clustering results, avoiding the one-sidedness that a single indicator may cause, thereby determining a more appropriate number of clustering centers.
5) Combined PSO-BP Prediction Algorithm: For the combination of the PSO algorithm and BP neural network, the PSO algorithm uses swarm intelligence to learn and optimize, and has good global optimization ability, while the BP neural network optimizes the model by adjusting the weight and bias of network nodes to improve training efficiency and prediction accuracy.
6) Model Training and Testing: The training dataset is used to train the neural network model, and the prediction effect of the model is verified using the test set data. In the process of model training, the training state and performance of the model are evaluated by observing the gradient change of the loss function and optimizing the fitness curve.
7) Conclusion: Analyze the prediction results, compare the predicted values with the actual values, obtain the accuracy and response speed of the model in load forecasting, and emphasize the practical application value of the method.

5. Experimental Results and Analysis

5.1 Analysis of the effect of multi-indicator clustering

We conducted simulation experiments using MATLAB R2023b on a Windows 10 system. The experimental data used were obtained from the Yunnan region of the Southern Power Grid in China, covering the period from March 20 to November 20, 2022, with a sampling interval of 15 min. The data included voltage, current, power, total active power, total reactive power, power factor, and other parameters from the ABC three-node system. First, the above dataset is preprocessed to eliminate outliers and null values. Then, 80% of the dataset is selected as the training set, and the remaining 20% is used as the test set. After the above preparation work is completed, the optimal number of clusters corresponding to each indicator is computed using the multi-index calculation formula. The results are shown in Fig. 4(a).

In Fig. 4(a), it can be observed that compared with the traditional K-means clustering algorithm, which only determines the number of clusters based on the silhouette coefficient, selecting the optimal number of clusters using multiple indicators is more reasonable. In this case, the optimal k value is shown in Fig. 4(b). After clustering, the data are processed to be



(a) (b)

Fig. 4. (Color online) (a) Multi-indicator score coefficient and (b) cluster effectiveness visualization.

dimensionless, resulting in four distinct user types based on their features, as shown in Fig. 4(b). It is evident that the improved *K*-means algorithm yields evenly distributed sample sizes across the different clusters, indicating the absence of clusters with significantly fewer samples.

5.2 Analysis of PSO-BP training and testing results

MATLAB R2023b is used to implement the process. The processed data is divided into the source domain (A) and the target domain (B). The effectiveness of the adversarial domain adaptation data aggregation model is validated through feature visualization and convergence verification. 60% of the samples from the target domain are used as the training set, 20% as the validation set, and the remaining as the test set. Firstly, the neural network model is trained using the training set data, as depicted in Fig. 5. Here, the gradient represents the gradient of the loss function, Mu denotes the damping factor, and the loss function gives the difference between the predicted value and the known value. A smaller gradient indicates that the function is closer to a certain minimum value.

In Fig. 5(a), it can be observed that the gradient parameters reach a favorable state after the 5th iteration. The data in Fig. 5(b) further confirm that the optimal performance position in the 5th iteration is close to the target position, indicating that the performance meets the requirements. Figure 5(c) depicts the optimization curve of fitness. A smaller fitness value indicates better performance, and thus, the aim of the iterative process is to minimize the fitness value. The results indicate that the optimal fitness decreases as the number of iterations increases, and it stabilizes after the fourth iteration. Using the trained parameters, load prediction was conducted with the test set as input, and the results were compared with the actual values, as shown in Fig. 5(d). The experimental results demonstrate that compared with using only the BP neural network, the proposed PSO-BP method converges more rapidly to the optimal solution, with smaller errors relative to the actual values. This indicates that the proposed algorithm not

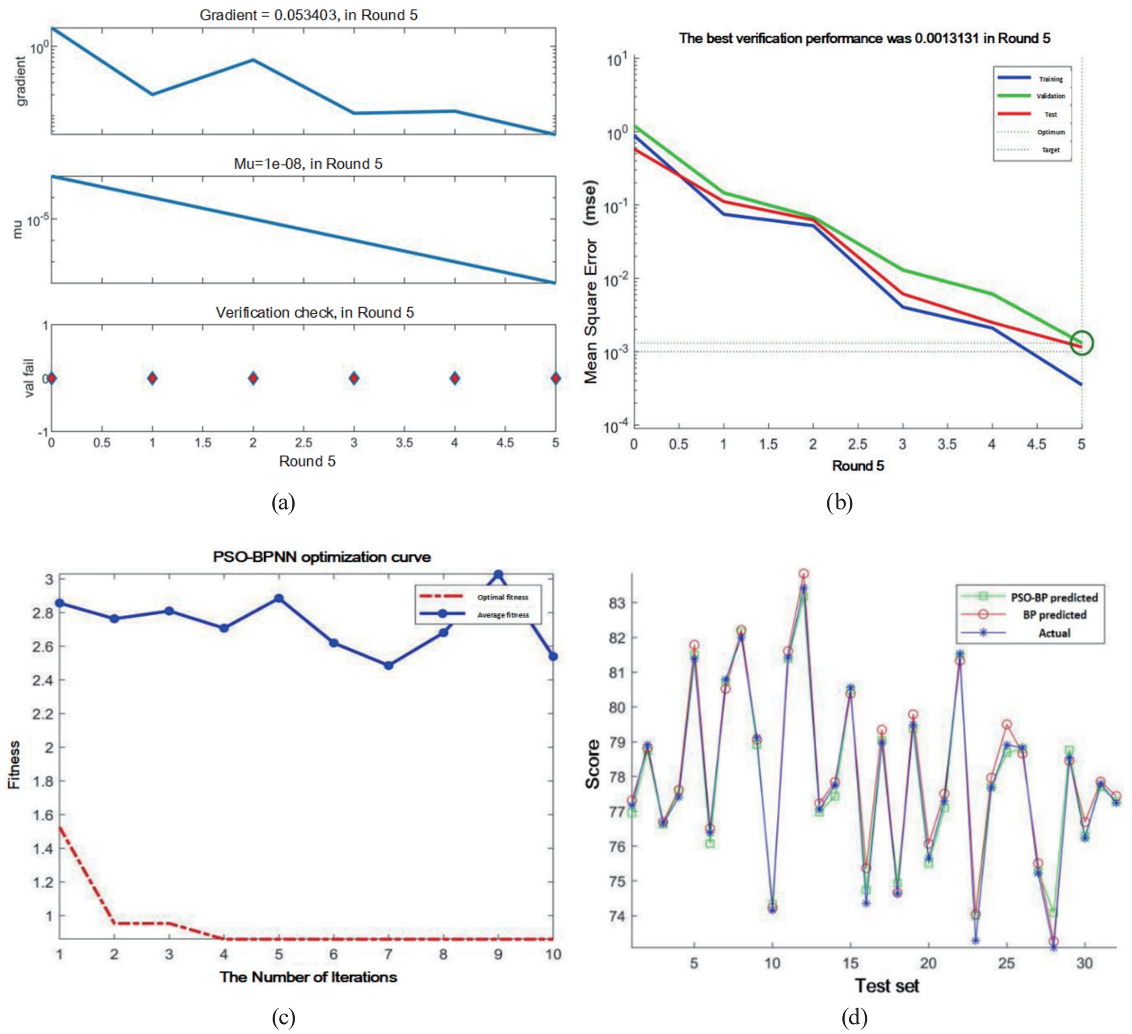


Fig. 5. (Color online) (a) Neural network training state diagram, (b) training performance visualization, (c) optimization fitness curve graph, and (d) graph of estimated performance.

only enhances prediction speed but also significantly improves the prediction accuracy, thereby greatly enhancing the predictive performance of the model. Therefore, it is sufficiently validated that the load prediction method based on multi-index clustering and PSO-BP proposed in this paper can achieve high-speed and high-precision short-term load prediction in new power systems, demonstrating its significant practical value and application potential.

6. Conclusions

In this research, we introduced an innovative approach to short-term load forecasting for power systems. This method leverages a combination of multi-index clustering and the PSO-BP algorithm to enhance the aggregation and predictive capabilities of power load data. Our findings indicate that this technique not only boosts the precision and swiftness of predictive outcomes but also holds significant practical value and potential for application in the field.

By deploying sensors in the new power system, collecting key parameters, and performing data preprocessing, dimension inconsistency and outlier interference are eliminated, which provides high-quality input data for subsequent algorithms. At the same time, a multi-index clustering model is constructed, which effectively solves the problem of selecting the number of clustering centers in traditional clustering methods, achieves accurate data aggregation and good convergence, and provides high-precision input for subsequent algorithms. The PSO-BP prediction algorithm is used to improve the accuracy and response speed of short-term load forecasting. Compared with the single BP neural network, the PSO-BP optimization algorithm based on multi-index clustering achieved higher prediction accuracy and significantly higher iteration speed in this study.

Experimental results demonstrated that the proposed novel prediction method effectively improves the accuracy and response speed of short-term load forecasting in new power systems, providing accurate load prediction results rapidly to meet the daily operation and scheduling needs of power systems. It helps the system to respond in a more timely fashion to emergencies and load fluctuations, enhances the security level of new power systems, and has important practical value and impact on the operation and management of new power systems.

In future work, the application of this method in different regions and scale power systems can be further explored, and the incorporation of more influencing factors into the model can be considered to achieve more comprehensive load forecasting.

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References

1 E. Berg: J. Enterprise and Business Intelligence **1** (2021) 186. https://doi.org/10.53759/5181/JEBI202101022
2 L. Dong, H. N. Zhu, J. Y. Wu, F. S. Li, J. J. Zhang, and H. Z. Sun: Proc. 2021 IEEE 5th Conf. Energy Internet and Energy System Integration (IEEE, 2021) 3004–3010.
3 J. L. Chen, L. Sun, and B. Wu: J. Phys.: Conf. Ser. **2625** (2023) 012061. https://doi.org/10.1088/1742-6596/2625/1/012061
4 N. N. Bon and L. V. Dai: Int. J. Eng. Technol. Innov. **12** (2022) 91. https://doi.org/10.46604/ijeti.2022.7571
5 T. T. Ngoc, L. V. Dai, and L. B. Minh: Adv. Technol. Innov. **7** (2022) 258. https://doi.org/10.46604/aiti.2022.9227
6 X. S. Han, Y. Shi, R. J. Tong, S. T. Wang, and Y. Zhang: Energy Rep. **9** (2023) 238. https://doi.org/10.1016/j.egyr.2023.05.162
7 K. Fukushima: Biol. Cybern. **36** (1980) 193. https://doi.org/10.1007/bf00344251
8 Y. Zhou, S. C. Chen, Y. M. Wang, and W. M. Huan: Proc. 2020 IEEE 5th Information Technology and Mechatronics Engineering Conf. (IEEE, 2020) 1713–1720.
9 C. Ren, Z. Sun, X. Li, G. Fan, C. Huo, and L. Cheng: Proc. 2020 Asia Energy and Electrical Engineering Symp. (IEEE, 2020) 652–657.
10 K. L. Ni, J. Z. Wang, G. Y. Tang, and D. X. Wei: Energies **12** (2019) 2467. https://doi.org/10.3390/en12132467
11 G. F. D. Apolinario, Y. Y. Hong, Y. D. Lee, J. L. Jiang, and S. S. Wang: Proc. 2021 IEEE 4th Int. Conf. Power and Energy Applications (IEEE, 2021) 88–92.
12 J. S. Xia and P. R. Ji: J. Electric Power **34** (2019) 23. https://doi.org/10.13357/j.cnki.jep.002770 (in Chinese).

13 H. Hou, C. Liu, Q. Wang, Z. Bo, L. Q. Zhang, X. X. Wu, and C. J. Xie: IEEE Trans. Ind. Appl. **59** (2023) 2296. https://doi.org/10.1109/TIA.2022.3225516
14 L. Chen, X. Zhang, and M. Yao: Proc. 2023 4th Int. Conf. Power Engineering (IEEE, 2023) 323–328.
15 Q. Shen, L. Mo, G. Liu, J. Zhou, Y. Zhang, and P. Ren: IEEE Access **11** (2023) 111963. https://doi.org/10.1109/ACCESS.2023.3322167

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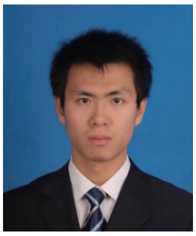

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