IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 5 August 2024, accepted 23 August 2024, date of publication 26 August 2024, date of current version 3 September 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3450273

RESEARCH ARTICLE

Research on Low-Frequency Oscillation Situational Awareness and Prediction of Power System Based on L2R-DLR-LGDMM Method

MIAO YU, ZIHAO LIN, YANG DI, AND TIANYI WANG
School of Mechanical-electronic and Vehicle Engineering, Beijing University of Civil Engineering and Architecture, Beijing 100044, China
Beijing Engineering Research Center for Building Safety Inspection, Beijing 100044, China

Corresponding author: Miao Yu (olivermiaoer@163.com)

This work was supported in part by Beijing Natural Science Foundation under Grant 4242035; in part by Shandong University Key Laboratory of Power System Intelligent Dispatch and Control, Ministry of Education; in part by the Cultivation Project Funds for Beijing University of Civil Engineering and Architecture (BUCEA) under Grant X23050; in part by the National Natural Science Foundation of China under Grant 51407201; and in part by the BUCEA Post Graduate Innovation Project under Grant PG2024147.

ABSTRACT With the development of power grid technology, low-frequency oscillation has become a key issue affecting the stable operation of the power system. In view of the difficulty of accurate prediction of low-frequency oscillation situational awareness of power grid and the difficulty of considering less environmental factors, the L2R-DLR-LGDMM method is proposed to predict the situation awareness of the comprehensive indicators of power grid, which combines with Topsis normalization, L2 regularization (L2R), dynamic learning rate (DLR) and Logistic gradient descent with momentum factor (LGDMM). Firstly, the original data collected by the phasor measurement unit (PMU) is analyzed and processed. A variety of indicators are fused into a comprehensive indicator, the attribution degree is calculated by substituting the safety prediction indicator, and the fuzzy evaluation matrix is established to construct a comprehensive indicator dataset. Secondly, the comprehensive indicator dataset is substituted into the L2R-DLR-LGDMM prediction method, the model parameter gradient is calculated according to the comprehensive indicator dataset, and the learning rate and momentum factor size are adaptively adjusted during the training process. After the difference between the two gradient changes is less than the set minimum value, the proposed method stops the iteration process and best parameters are obtained. This proposed method can use comprehensive indicators to achieve the situational awareness prediction of low-frequency oscillation. Finally, the proposed method has a better prediction effect on the low-frequency oscillation of the New England 10-machine and 39-node system and the Western Electricity Coordinating Council (WECC) 146-machine and 243-node system. The prediction accuracy of the comprehensive indicator is higher than that of other methods, and the prediction accuracy can reach 86.74% and 95%, respectively. Therefore, the proposed method provides a reference for the stable operation of power systems.

INDEX TERMS Situational awareness, logistic momentum gradient descent method, comprehensive indicator forecasting, L2 regularization, dynamic learning rate.

I. INTRODUCTION

With the rapid development of smart grid technology in China, the scale of the power grid is increasing day by day. After the new energy is connected, the operation mode and structure of the power grid are becoming more and more complex, which greatly increases the difficulty of security and stability control of the power system. When generators operate in parallel through transmission lines and are disturbed, if the relative swing between the generator rotors cannot be effectively suppressed by the system damping, the low-frequency oscillation will occur. Low-frequency oscillation has become an important problem affecting the stable operation of the power system. In order to ensure the safe and

The associate editor coordinating the review of this manuscript and approving it for publication was Rossano Musca.

stable operation of the power grid and avoid the occurrence of low-frequency oscillation, it is urgent to study the problem of low-frequency oscillation prediction of the power system, predict the possible low-frequency oscillation in advance, and take timely measures to prevent and control it, which is of great significance to improve the stability of the power system. It will also improve the monitoring ability of the power grid, ensure the safe operation of the power grid, and optimize the dispatching and management of the power grid. Therefore, in order to avoid the harm caused by low-frequency oscillation of the power system, situational awareness prediction of low-frequency oscillation of power grid is an urgent problem to be solved.

At present, many scholars conducted in-depth research on the field of low-frequency oscillation situational awareness and prediction of power systems. Erten et al. [1] used a regression model to predict solar power generation, and the prediction results showed that logistic regression could accurately predict solar power generation and predict the probability of event, but it was sensitive to outliers. Sengupta et al. [2] proposed a distributed model prediction controller for eliminating low-frequency oscillations in power systems. The advantages of the method were that the response speed and stability were higher than those of the traditional PSS, and the flexibility and adaptability were better. The practical application value of the multi-machine system was improved, while the disadvantage was that the calculation was more complex, and its robustness needed to be further studied and verified to ensure that the method could maintain its performance under different conditions. Cui et al. [3] proposed a Logistic regression algorithm for transmission line trip prediction under icing conditions, which had the advantages of high prediction accuracy and improved data quality and availability, but the disadvantages were that the data dependence was high and the generalization ability of the model needed to be verified. Zhang et al. [4] used situational awareness and prediction technology to realize the real-time monitoring ability of various security risks, and greatly improved the ability of reasoning judgment and knowledge control of the network security situation, but the disadvantage was that it was still in the initial stage, and many problems had not been solved. Feng et al. [5] used clustering and logistic iterative regression models to predict saturation load, which had the advantage of high prediction accuracy and good prediction of saturation load, while the disadvantage was that the considerations and dataset size were small. Hassani et al. [6] used a graph regularization algorithm to accurately locate smart grid faults, which had the advantage of determining the exact location of grid faults, but they did not study the applicability of this method under the optimal arrangement of recording equipment. Oyekanlu et al. [7] used random forests to achieve situational awareness prediction of grid impedance. The method used only four features to achieve the purpose of optimizing the impedance prediction of the power grid, but it did not carry out the impedance situational awareness prediction of the narrowband PLC. Feng et al. [8] proposed a DFIG grid-connected low-frequency oscillation analysis method based on the wind speed interval prediction and eigenvalue trajectory, which had the advantages of simple method and fast operation speed, and the regression method was used to improve the computational efficiency and establish a quantitative relationship between wind speed and eigenvalue. But the disadvantage was that only the wind speed was considered. Yu et al. [9] proposed a three-level random forest method based on the fuzzy matrix to realize the early warning classification of low-frequency oscillation, which had the advantage of reducing the amount of data and the overall accuracy and efficiency. But the disadvantage was that the simulation data set was small and could not verify the generalization ability of the method. Zhang et al. [10] proposed an improved low-frequency oscillation control method for power systems based on the Prony prediction compensation, which improved the prediction accuracy and suppressed the low-frequency oscillation with the introduction of fixed and variable delays, but the delay jitter would affect the prediction accuracy by affecting the accuracy of angular velocity data. Yu et al. [11] used Vinnicombe distance to solve the problem of low-frequency oscillation in the power system, which could effectively detect the presence or absence of low-frequency oscillation, and the error was small. But the unsolved node distance close to the value of 0 would cause misjudgment and failed to predict the situational awareness of the comprehensive indicator. Subsequently, Yu et al. [12] continued to propose a low-frequency oscillation comprehensive indicator algorithm based on the kernel matrix analytic hierarchy process of fuzzy comprehensive evaluation method, proposed the corresponding comprehensive indicator, and used the comprehensive indicator to effectively predict the situation awareness of the types of low-frequency oscillation of the power grid, but the disadvantage was that the method obtained too few comprehensive indicators, and could not achieve the purpose of using the comprehensive indicator to effectively predict the situation awareness of the low-frequency oscillation. Yu et al. [13] proposed a method based on the state feedback decoupling control to improve the damping ratio of the power system with DFIG and suppress the low-frequency oscillation. The advantage of this method was that it could effectively improve the system damping ratio and suppress the voltage amplitude variation at the PCC node, thereby suppressing the low-frequency oscillation. However, the disadvantage was that the influence of the parameter variation of DFIG was not considered. Carvalho et al. [14] proposed a switched robust model-based method for predicting and suppressing the low-frequency oscillation in power system. The advantage of this method was that it could successfully suppress the low-frequency oscillation of power system and limit all the poles of the system within the unit circle. However, the disadvantage was that it had not been compared with other control strategies, so the advantage of the proposed strategy could not be fully demonstrated and the stability analysis of the discretized model was not sufficient. Satheesh et al. [15] proposed a power system oscillation mode recognition method based on the deep learning. This method could accurately estimate the instantaneous parameters of low-frequency oscillation, but the disadvantage was that this method only considered the generator speed signal and did not consider the interference of other factors such as noise about the results.

By studying the above representative references, this paper mainly solves the problem of situation awareness and prediction of low-frequency oscillation in power grid oriented to the fusion of multi-oscillation characteristic indicators. According to the comprehensive indicator proposed in Reference [12], multiple influencing factors can be synthesized. So this paper uses the comprehensive indicator proposed in Reference [12] to predict the situational awareness of low-frequency oscillation of power system. From references [1], [3], [16], [17], [18], it can be seen that logistic regression has the characteristics of fast, stable, effective, widely used and high prediction accuracy in power grid prediction, transmission line trip prediction under icing conditions, short-term power prediction and low-frequency oscillation mode identification of wind power system. But the power outage prediction, trip prediction and power prediction are caused by multiple factors, and the weather and other data required for prediction are nonlinear data. This is similar to the causes and predictions of low-frequency oscillations in power grid. Therefore, this paper uses the Logistic regression method to predict the situation awareness of low-frequency oscillations of the power grid, but the Logistic regression algorithm has the problem of falling into the local optimum. Therefore, this paper chooses to use the Logistic Gradient Descent Method combined with Momentum factor (LGDMM), Topsis normalization, L2 Regularization (L2R) and Dynamic Learning Rate (DLR) to predict low-frequency oscillations in power systems.

The rest of this paper is as follows. Section II outlines the fuzzy comprehensive evaluation method. Section III unfolds the research on low-frequency oscillation prediction of power system based on L2R-DLR-LGDMM in this paper. Section IV shows some case studies, and gives the introduction of a 10-machine and 39-node system of new England for simulation verifications. Section V concludes this paper. The contributions of this paper are: 1. Combining with Topsis normalization and L2 regularization to predict the processed comprehensive indicator dataset; 2. Replace the fixed learning rate of the original model with a dynamic learning rate to improve the prediction accuracy of the model; 3. Add the momentum factor to the cost function to achieve the purpose of preventing overfitting of the model.

II. FUNDAMENTAL THEORIES

A. FUZZY COMPREHENSIVE EVALUATION METHOD

References [9] and [12] use the fuzzy comprehensive evaluation method combined with the comprehensive indicator to achieve good results in the early warning of low-frequency oscillation of power system, so this paper uses the fuzzy comprehensive evaluation method to process the dataset. According to Reference [12], we can obtain the membership functions of amplitude, frequency, and peak-to-peak values as shown from Fig. 1 to Fig. 3.

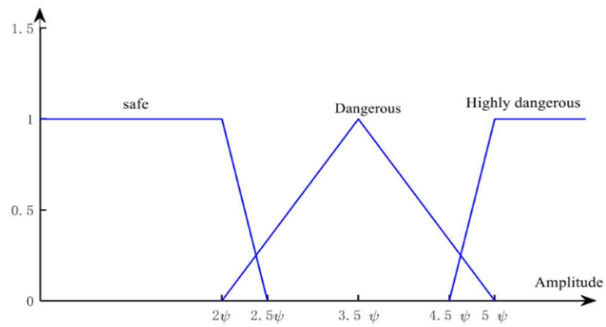


FIGURE 1. Amplitude affiliation function.

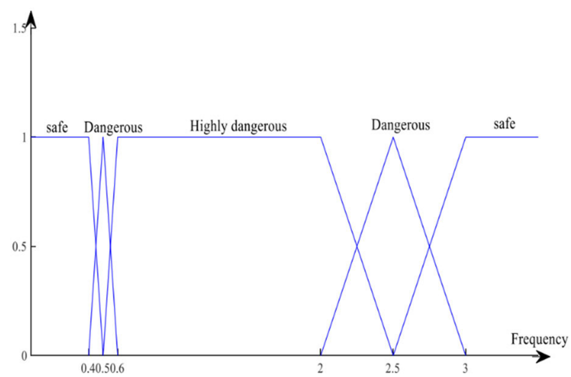


FIGURE 2. Frequency affiliation function.

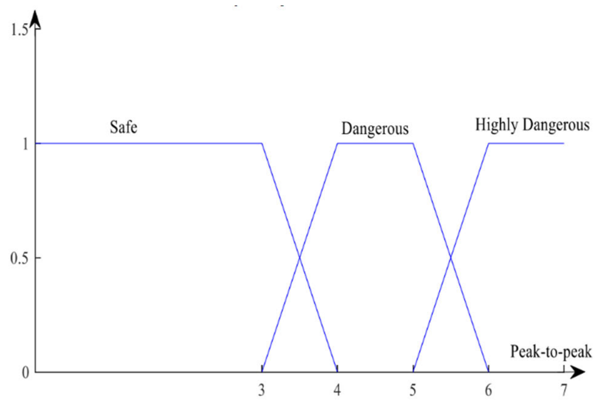


FIGURE 3. Peak-to-peak affiliation function.

Then, substituting the security prediction indicator calculated by online identification into the attribution function, the attribution degree of each indicator can be obtained, and the fuzzy evaluation matrix R is established, as shown in Eq. (1).

$$R = \begin{bmatrix} \varphi_{11} & \varphi_{12} & \cdots & \varphi_{1n} \\ \varphi_{21} & \varphi_{22} & \cdots & \varphi_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \varphi_{m1} & \varphi_{m2} & \cdots & \varphi_{mn} \end{bmatrix} \quad (1)$$

Suppose set $X = \{x_i \mid i \in N\}$ is a set of indicators, x_i is the evaluation indicator of low-frequency oscillation warning. Synthesizing the expert evaluation information, where E is the number of experts, and the complementary judgment matrix of the trapezoidal fuzzy number of the mth expert is $\tilde{U}\left(\tilde{u}_{ij}^m\right)_{n\times n}$, where $\tilde{u}_{ij}^m = \left(a_{ij}^m, b_{ij}^m, c_{ij}^m, d_{ij}^m\right), m \in \{1, 2, \ldots, E\}$, $i, j \in N$. $\tilde{u}_{ij} = (a_{ij}, b_{ij}, c_{ij}, d_{ij})$ indicates the importance of the evaluation indicator of low-frequency oscillation in power system; $a_{ij} \le b_{ij} \le c_{ij} \le d, \forall i, j \in N(i \ne j)$, $a_{ij}, b_{ij}, c_{ij}, d_{ij}$ are ambiguous numbers,whcih meet the following criteria.

(1) $a_{ii} = b_{ii} = c_{ii} = d_{ii} = 0.5, \forall i \in N$;

(2) $a_{ij} + d_{ij} = 1, b_{ij} + c_{ij} = 1, d_{ij} + a_{ij} = 1$

Then, we can get:

$$\begin{aligned}\tilde{u} &= (a_{ij}, b_{ij}, c_{ij}, d_{ij}) \\ &= \left(\frac{1}{E}\sum_{m=1}^{Y} a_{ij}^m, \frac{1}{E}\sum_{k=1}^{Y} b_{ij}^k, \frac{1}{E}\sum_{m=1}^{Y} c_{ij}^m, \frac{1}{E}\sum_{m=1}^{Y} d_{ij}^m\right)\end{aligned} \tag{2}$$

It is calculated from Eq. (2) to obtain $\tilde{U} = (\tilde{u})_{n\times n}$. Let the evaluation indicator be z, and then the weight and the fuzzy evaluation value of each indicator z_i can be obtained:

$$\begin{aligned}\tilde{f}_i(a_i, b_i, c_i, d_i) = (&\frac{\sum_{j=1}^n a_{ij}}{\sum_{i=1}^n \sum_{j=1}^n d_{ij}}, \frac{\sum_{j=1}^n b_{ij}}{\sum_{i=1}^n \sum_{j=1}^n c_{ij}}, \\ &\frac{\sum_{j=1}^n c_{ij}}{\sum_{i=1}^n \sum_{j=1}^n b_{ij}}, \frac{\sum_{j=1}^n d_{ij}}{\sum_{i=1}^n \sum_{j=1}^n a_{ij}}\end{aligned} \tag{3}$$

The fuzzy evaluation expectations for indicator z_i can be expressed as:

$$I\left(\tilde{f}_i\right) = \frac{1}{4}(a_i + b_i + c_i + d_i) \tag{4}$$

Normalize $I\left(\tilde{f}_i\right)$ to get the relative weights:

$$w_i = \frac{1}{\sum_{i=1}^n I\left(\tilde{f}_i\right)} I\left(\tilde{f}_i\right), \quad i \in N \tag{5}$$

By establishing the weight vector W and the fuzzy evaluation matrix R, the membership degree C of each indicator can be calculated under three levels. Among them, b_1, b_2, and b_3 are different subordination degrees under safety, danger, and high hazard levels, respectively.

$$C = W \otimes R = (b_1, b_2, b_3) \tag{6}$$

In Eq. (6), $\otimes$ is a fuzzy operator symbol. Commonly used operator symbols include weighted average operator and Zadeh operator, etc. The fuzzy comprehensive evaluation model will vary depending on operators.

In summary, we set three safety level scores as 5,3,1 shown in Fig. 4, and use the exponentially weighted algorithm to construct a comprehensive indicator of low-frequency oscillation in power system.

$$S = e^{5\times b_1 + 3\times b_2 + 1\times b_1} \tag{7}$$

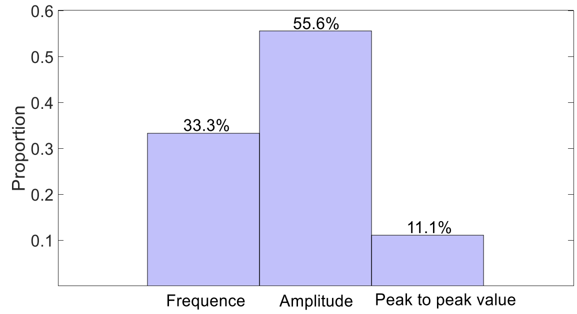


FIGURE 4. Score chart of fuzzy comprehensive evaluation of PMU data.

B. TOPSIS NORMALIZATION METHOD

From Reference [19], we can see that Topsis normalization can reduce the influence of differences between data weight features and speed up the search for optimal solutions for models. Therefore, this paper chooses to use Topsis to normalize the data to achieve the purpose of speeding up the Logistic regression model to find the optimal solution.

For positive indicators, the following normalization method is used: x_{min} is the minimum value in the data, x_{max} is the maximum value in the data, x_{best} is the optimal value, and $\{x_i\}$ is a set of intermediate indicator series, so that $M = \{|x_i - x_{best}|\}$.

$$x_{Forward\ direction} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{8}$$

For negative indicators, the Topsis normalization method is generally used:

$$x_{Negative\ direction} = 1 - \frac{x - x_{min}}{x_{max} - x_{min}} \tag{9}$$

For intermediate indicators, the Topsis normalization method generally uses:

$$\tilde{x}_i = 1 - \frac{|x_i - x_{best}|}{M} \tag{10}$$

The normalized matrix for each element is Z, and each element in Z is z_{ij}, and x_{ij} is the element in the column.

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^n x_{ij}^2}} \tag{11}$$

The normalization matrix is:

$$Z = \begin{bmatrix} z_{11} & z_{12} & z_{13} & \cdots & z_{1j} \\ z_{21} & z_{22} & z_{23} & \cdots & z_{2j} \\ z_{31} & z_{32} & z_{33} & \cdots & z_{3j} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ z_{i1} & z_{i2} & z_{i3} & \cdots & z_{ij} \end{bmatrix} \tag{12}$$

C. L2 REGULARIZATION METHOD

The results of Reference [6] show that the graph regularization can be used to accurately locate power system faults and avoid the problem of model overfitting, so this paper uses the L2 regularization method to process the data to avoid the problem of model overfitting. The L2 regularization formula is as follows:

$$L(W,b) = J(\theta) + \frac{\lambda}{2m}\sum_{j=1}^{n_x} ||W||_2^2 \tag{13}$$

where $J(\theta)$ is the loss function, W is the network weight, b is the bias value, m is the number of samples, n_x is the number of network layers, and λ is the hyperparameter.

III. LOW-FREQUENCY OSCILLATION PREDICTION OF POWER SYSTEM BASED ON L2R-DLR-LGDMM AND FUZZY COMPREHENSIVE INDICATOR

It can be seen from references [1], [3], [15], [19], [20] that logistic regression has the characteristics of fast, stable, effective, widely used and high prediction accuracy in the field of grid prediction, transmission line trip prediction under icing conditions, short-term power prediction of wind power generation system and low-frequency oscillation mode recognition, as well as in the field of grid prediction. Therefore, this paper chooses to use the logistic method to predict the low-frequency oscillation of the power grid. Due to many problems of the traditional Logistic gradient descent method, the main reason is that the algorithm calculation efficiency is low, and the methods of improving the prediction accuracy of Logistic gradient descent mainly include the selection feature tool, regularization, learning rate adjustment, and batch normalization. According to the references [6], [13], [14], we select four improved methods, namely Topsis normalization, momentum factor, dynamic learning rate, and L2 regularization, and use Topsis normalization to comprehensively consider the weights and scores of multiple indicators, provide decision support, and enhance the interpretability of the model, so as to improve the performance and accuracy of the model. The gradient descent method combined with momentum factor is used to accelerate the convergence speed and convergence accuracy of the gradient descent method, and the oscillation of the gradient descent method is reduced to make the descent algorithm more stable and prevent the local optimal phenomenon. Taking advantage of the dynamic learning rate and improving the prediction accuracy of the model by changing the learning rate, L2 regularization is used to avoid the problem of overfitting the model and improve the generalization ability by adding regularization terms to the loss function.

A. DYNAMIC LEARNING RATE

In order to improve the Logistic regression model, the learning rate can be adaptively adjusted according to the number of iterations, so as to avoid falling into local optimization and improve the prediction accuracy of the model.

$$\eta(t) = \frac{\alpha}{1+\beta t} \tag{14}$$

In Eq. (14), the initial learning rate is α, the number of iterations is *t,* and β is a normal number to control the rate of decline in the learning rate. This formula also indicates that the learning rate gradually decreases as the number of iterations increases, and the rate of decline is controlled by β. By adjusting the β value, we can flexibly control the trend of learning rate and improve the training effect of the model.

The formulas for the gradient descent are:

$$\theta_j := \theta_j - \alpha\frac{\partial J(\theta)}{\partial\theta_j} \tag{15}$$

$$\frac{\partial J(\theta)}{\partial\theta_j} = \frac{1}{m}\sum_{i=1}^{m}((h_\theta(x^{(i)}) - y^{(i)})x_j^{(i)}) \tag{16}$$

Bringing Eq. (15) into Eq. (16) yields:

$$\theta_j := \theta_j - \alpha\frac{1}{m}\sum_{i=1}^{m}\left(\left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right)x_j^{(i)}\right) \tag{17}$$

In Eq. (17), the initial learning rate is α; the parameter gradient is θ_j; m is the number of samples; $h_\theta(x^{(i)})$ is the predicted value; $y^{(i)}$ is the true label of the i-th sample; $x_0^{(i)}$ is the j-th feature of the i-th sample; ": =" is the meaning of the assignment. Using the dynamic learning rate instead of the learning rate in the gradient descent method, we get:

$$\theta_j := \theta_j - \frac{\alpha}{(1+\beta t)m}\sum_{i=1}^{m}\left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right)\cdot x_j^{(i)} \quad for\ j = 0, 1, 2, \ldots n \tag{18}$$

B. LOGISTIC GRADIENT DESCENT METHOD COMBINED WITH MOMENTUM FACTOR

In order to improve the logistic regression model, improve the convergence speed and convergence accuracy, make it more stable in the iterative process, and prevent the occurrence of local optimal phenomenon, we choose to add a momentum factor to the gradient descent formula to achieve the above purposes. Eq. (19) is the gradient descent formula with the momentum factor added.

$$\theta_j := \theta_j - \alpha\frac{\partial J(\theta)}{\partial\theta_j} - w\frac{\partial J(\theta)}{\partial\theta_j} \tag{19}$$

where w is the normal number. The remaining variables all have the same meaning as Eq. (17). Combining Eq. (18) of dynamic learning rate and Eq. (19) with the momentum factor, we can get the final gradient descent formula:

$$\theta_j := \theta_j - \frac{\alpha\partial J(\theta)}{(1+\beta t)\partial\theta_j} - w\frac{\partial J(\theta)}{\partial\theta_j} \tag{20}$$

Bringing Eq. (16) into Eq. (20), we can get Eq. (21):

$$\theta_j := \theta_j - \frac{\alpha}{(1+\beta t)m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})\cdot x_j^{(i)} - \frac{w}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})\cdot x_j^{(i)} \quad for\ j = 0, 1, 2, \ldots n \tag{21}$$

Add L2 regularization terms from Eq. (13) to Eq. (21) to get the final cost function, we have:

$$\theta_j := \theta_j - \frac{\alpha}{(1+\beta t)\,m}\sum_{i=1}^{m}\left(h_\theta\left(x^{(i)}\right)-y^{(i)}\right)\cdot x_j^{(i)} - \frac{w}{m}\sum_{i=1}^{m}\left(h_\theta\left(x^{(i)}\right)-y^{(i)}\right)\cdot x_j^{(i)} + \frac{\lambda}{2m}\sum_{j=1}^{n_x}||W||_2^2 \quad for\ j=0,1,2,\ldots n \tag{22}$$

C. L2R-DLR-LGDMM

Based on the above basic theories and theorems, this paper proposes a situational awareness prediction method for comprehensive indicators based on the L2R-DLR-LGDMM method. Firstly, according to the method in Reference [12], the original data collected by the Phasor Measurement Unit (PMU) is processed using the Fuzzy Comprehensive Evaluation Method. The evaluation indicator set, evaluation result set, weight, membership function and metric weight set are introduced. By substituting the safety prediction indicator to calculate the degree of belonging, the fuzzy evaluation matrix and comprehensive indicator are established, and the comprehensive indicator data set is constructed according to the comprehensive indicator. Then, the comprehensive indicator data set is substituted into the L2R-DLR-LGDMM method. This method first performs Topsis normalization about the comprehensive indicator data set, and then calculates the data to obtain the gradient of the L2 regularization term, the gradient of the loss function with respect to the model parameters, the learning rate and the magnitude of the momentum factor. Secondly, model parameters are updated according to the gradient direction and the learning rate, and the momentum update amount is calculated. At the same time, the magnitudes of the learning rate and the momentum factor are adaptively adjusted during the data iteration process. The model prediction accuracy is improved by changing the learning rate, and the convergence speed and convergence accuracy are improved by using the momentum factor, making the iteration process more stable and preventing the local optimum phenomenon. Subsequently, the L2 regularization is used to process the data to improve the generalization ability and prevent the model from overfitting. When the difference between the gradients of the previous and the next iterations is less than the set minimum value, this method will stop the iteration. Then, this method uses the trained parameters to predict the comprehensive indicator data, and finally obtains the situational awareness result of whether the comprehensive indicator is normal in the future.

Fig. 5 shows the flow chart of the situational awareness prediction algorithm based on L2R-LDR-LGDMM method. Specific implementation steps of the proposed algorithm are as follows:

Step 1: The PMU data is processed according to the method in Reference [12] to obtain two different sets of PMU datasets.

Step 2: The obtained PMU datasets are substituted into the fuzzy comprehensive evaluation method respectively to obtain comprehensive indicator 1 and comprehensive indicator 2.

Step 3: Construct labels based on comprehensive indicator 1 and comprehensive indicator 2 to form a comprehensive indicator dataset.

Step 4: Normalize the comprehensive metric dataset to prevent certain features from having too much impact on model training.

Step 5: L2 regularization is carried out on the comprehensive indicator dataset, and the gradient of the L2 regularization term is added to the loss function gradient to improve the generalization ability, control the size of model parameters and avoid the overfitting problem of the model, so as to make the model more stable.

Step 6: According to the establishment of a comprehensive indicator dataset, we iterate on the data and calculate the gradient of the loss function with respect to the model parameters, and update the model parameters and calculate the momentum update amount according to the gradient direction and learning rate, so as to optimize the model.

Step 7: At the same time, the learning rate is adaptively adjusted in terms of the performance of the model training process to improve the model convergence speed and prediction accuracy.

Step 8: The loss function and gradient of the comprehensive indicator dataset are calculated by the Logistic gradient descent model, and the data is visualized. The comprehensive indicator dataset is divided into two categories, namely the data test set and the data prediction set.

Step 9: The method processes the test set data in the prediction process, predicts and constructs labels on the two sets of features of the prediction set data according to the results of the test set data processing, so as to achieve the purpose of predicting the prediction set. If the sample point label is 0, the future comprehensive indicator will be normal, and if the sample point label is 1, the comprehensive indicator will be abnormal. Finally, the situational awareness results of the comprehensive indicator test set are calculated and compared with the real value results.

IV. DATA SOURCES AND SIMULATION RESULTS

A. SIMULATION ENVIRONMENT AND DATA SOURCES

In order to verify the feasibility and effectiveness of the method mentioned in this paper, the authors use system simulation configuration with Intel(R) Core (TM) i7, 16G memory, 512G SSD+2TB HHD, Windows 11 64 bit, and all programs are running in Matlab R2022b.

Firstly, the measured PMU data of the New England 10-machine and 39-node system shown in Fig. 6 is calculated to obtain the power indicators, and then according to the Reference [12], the calculated amplitude indicator, frequency indicator and peak-to-peak indicator are substituted into the fuzzy comprehensive evaluation method for processing.

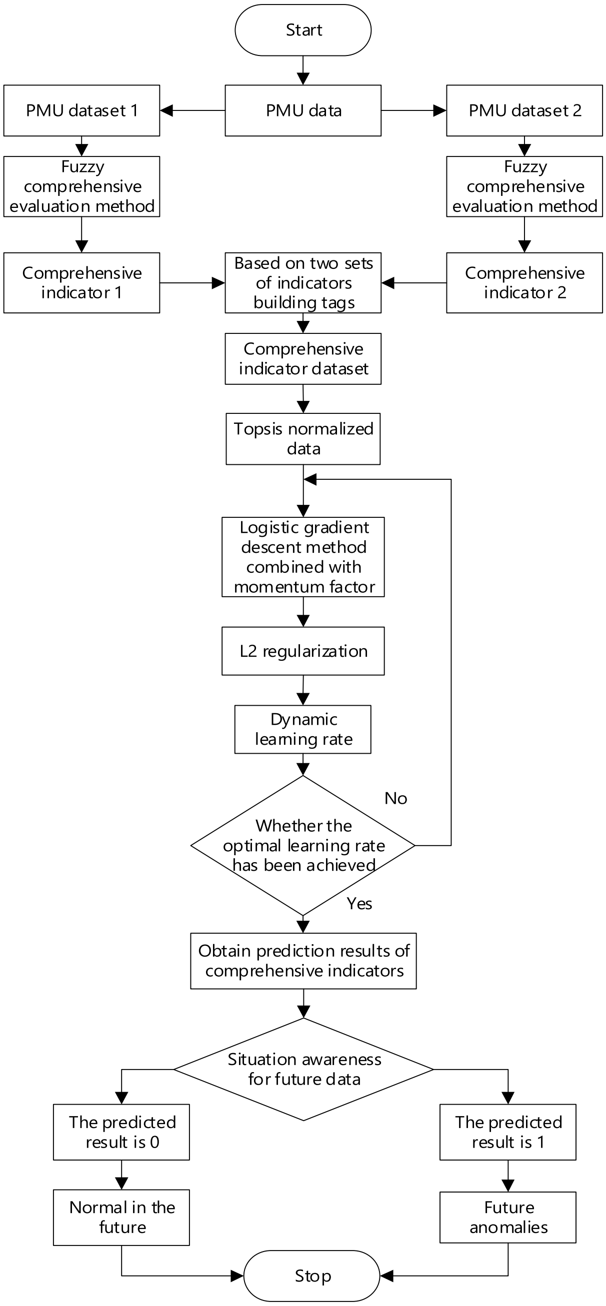


FIGURE 5. Flow chart of the proposed situational awareness prediction algorithm.

Finally, the comprehensive indicator data is obtained, because the PMU data selected in this paper is from 0 seconds to 180 seconds, and each seconds corresponds to a large amount of data. In order to simplify the calculation and label the data, we select two sets of continuous data per seconds from the PMU data, The former group is called comprehensive indicator 1, the latter group is called comprehensive indicator 2, and the labels are constructed using these two sets of comprehensive indicator data, where the labels are based on the control selected data and the corresponding indicators before the selected data are synthesized. Using the central limit theoretical standard confidence interval probability method in Reference [12], we can obtain the safety thresholds of the comprehensive indicator data, which is less than 5.08 for safety, greater than 5.08 and less than 5.38 for danger, and greater than 5.38 for high risk. Table 1 shows the scores of the comprehensive indicators. When the score of the comprehensive indicator is less than or equal to 5.08, the label is 0, and when the score of the comprehensive indicator is greater than or equal to 5.38, the label is 1. The comprehensive indicator dataset can be obtained by constructing labels for the selected data according to the above method, and then the comprehensive indicator dataset is divided into two parts. The first 120 sets of data is the test set, and the last 60 sets of data is the prediction set.

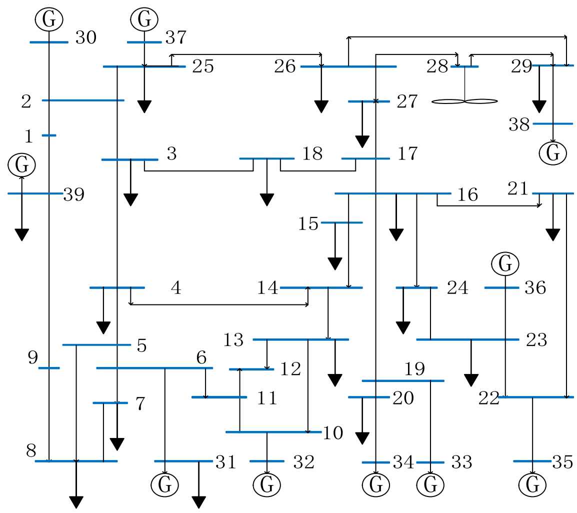


FIGURE 6. New England 10-machine and 39-node system.

TABLE 1. Comprehensive indicator score level.

Safety level	★ (Safe)	★★ (Dangerous)	★★★ (Highly dangerous)
S Score	<5.08	5.08~5.38	>5.38

B. L2R-DLR-LGDMM PREDICT RESULTS

The authors calculate the PMU data according to the data processing methods mentioned in Section IV-A, and we can obtain a comprehensive indicator data set. By using the comprehensive indicator dataset, the purpose of situational awareness prediction of the comprehensive indicators can be achieved. Fig. 7 shows the dataset image in time series.

The visualization results from the dataset in Fig. 7 show that the PMU data has obvious low-frequency oscillation between 60 seconds and 130 seconds. Fig. 8 shows the cost convergence curves of the loss function at different iterations.

In Fig. 8, the abscissa represents the number of iterations, and the curve in Fig. 8 represents the curve of cost as the number of iterations increases. From Fig. 8, we can know the direction and amplitude of the gradient descent vector

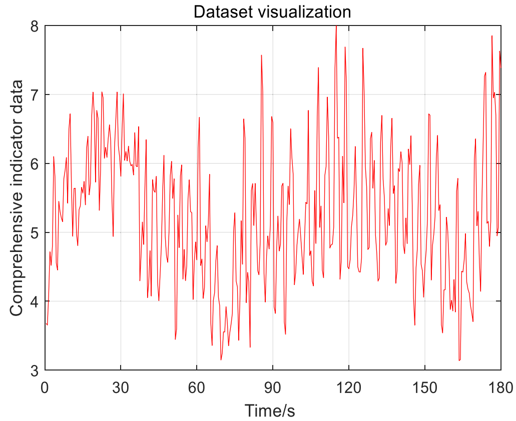


FIGURE 7. PMU data image in time series.

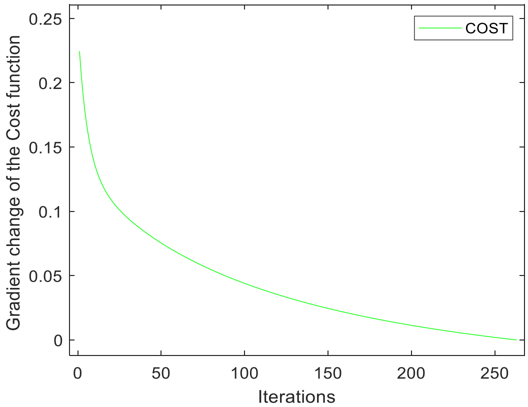


FIGURE 8. Loss function cost convergence.

gradient. According to the gradient variation, we know that the loss function converges very quickly, which indicates that the model converges very quickly. The cost of the loss function fluctuates less in the late iteration, which indicates that the learning rate is appropriately selected, the feature scaling is sufficient, and the logistic gradient descent method can be used to solve the model parameters and models. There is no underfitting or overfitting phenomenon. Fig. 9 shows the forecast results of the comprehensive indicators.

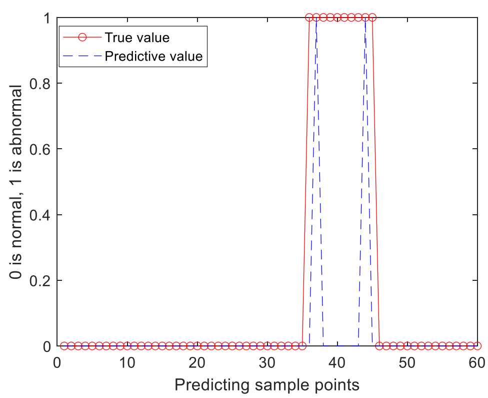


FIGURE 9. Comprehensive indicator prediction.

As can be seen from the prediction results in Fig. 9, we use the Sigmoid function during the calculation process, and the calculated data is processed by binary classification. For this reason, we can add a label to each set of data in the dataset, rate the comprehensive indicators according to Table 1. Then mark the normal data group in the training set as 0, and mark the abnormal data group in the training set as 1. If the ordinate of the sample point is 0, it means that the prediction result of the sample point is normal; If the ordinate of the sample point is 1, it means that the prediction result of the sample point is abnormal. It can be seen from the results in Fig. 9 that after using the method in this paper to predict 60 sets of data and comparing them with the real value results, the prediction accuracy of 60 groups of prediction sample points reaches 86.67%, which shows that the prediction accuracy of the proposed method is high. Fig. 10 shows the forecast results of the comprehensive indicator after the reverse normalization. The blue line with "*" is the true value result, and the orange line with "△" is the prediction result of the method in this paper.

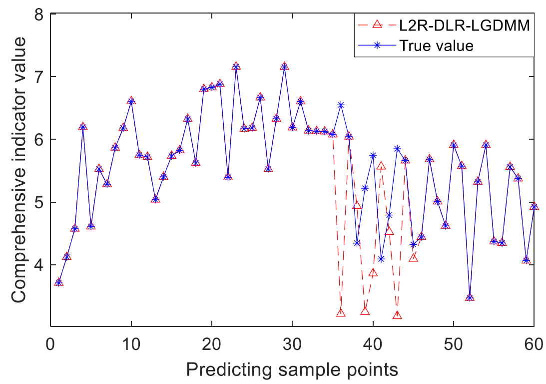


FIGURE 10. Prediction of the reverse normalization comprehensive indicator.

V. COMPARISION RESULTS WITH DIFFERENT METHODS

The random forest method is widely used in many aspects, and the BP neural network has strong self-organization and self-learning ability in predicting data. Therefore, the proposed method is compared with random forest and BP neural network. At the same time, the proposed method will compared with the Logistic gradient descent method to prove the correctness and effectiveness.

A. COMPARED WITH THE RANDOM FOREST METHOD

The comprehensive indicator dataset obtained in Section IV-A is substituted into the random forest method, and then comprehensive indicators are predicted. Fig. 11 is the prediction result of the random forest method. From Fig. 11, it can be seen that the prediction accuracy of the random forest method for the comprehensive indicator dataset is 75.93%, and the random forest method has many prediction errors during the process of predicting the comprehensive indicator dataset, which shows that the random forest method has poor prediction accuracy for the comprehensive indicator data. In Fig. 11, the orange line with "*" is the true value result, while the blue line with "△" is the random forest model prediction.

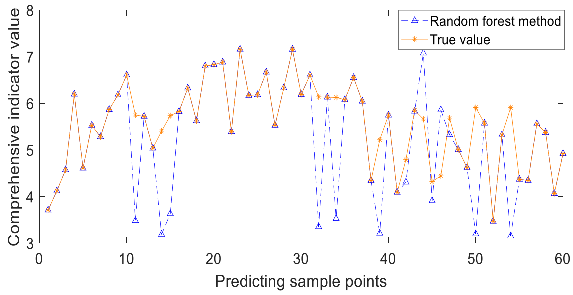


FIGURE 11. **Prediction of random forest method.**

B. COMPARED WITH THE LOGISTIC GRADIENT DESCENT METHOD

The comprehensive indicator dataset is substituted into the Logistic gradient descent method, and the prediction results of the Logistic gradient descent method in Fig. 12 are obtained. Among them, the prediction accuracy of 60 groups of prediction sample points reaches 61.67%, which shows that the addition of dynamic learning rate and the momentum factor will improve the accuracy. In Fig. 12 the blue line with "△" is the prediction result, and the red line with "◯" is the true value result.

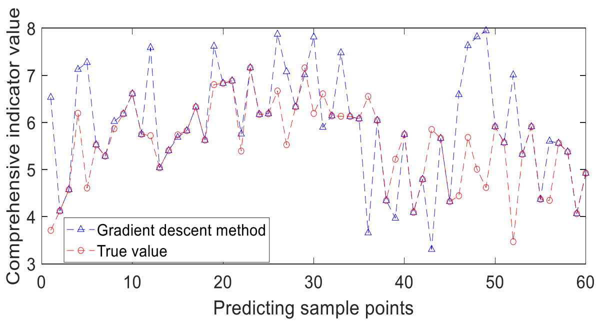


FIGURE 12. **Prediction of Logistic gradient descent method.**

C. COMPARED WITH BP NEURAL NETWORK

The comprehensive indicator dataset is substituted into the BP neural network method, and the comprehensive indicator is predicted, and the prediction result graph of the BP neural network in Fig. 13 is obtained.

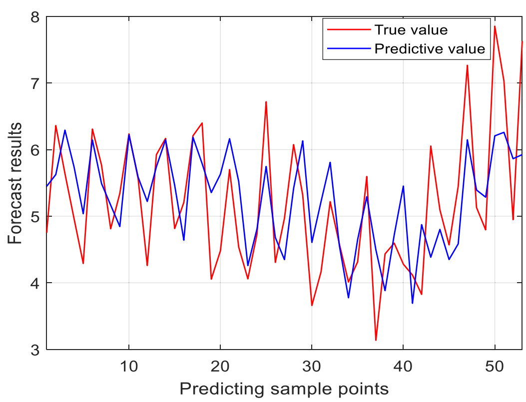


FIGURE 13. **Prediction of BP neural network method.**

Through Fig. 13, it can be seen that the blue straight line is the predicted value, the red straight line is the real value, and the BP neural network fits poorly with the real value data of the comprehensive indicator, and the root mean square error is 8.1023, indicating that the prediction value deviates greatly from the real value and the prediction accuracy is low. All of the above predictions are combined to get Fig. 14, which shows a comparison of different forecasting methods.

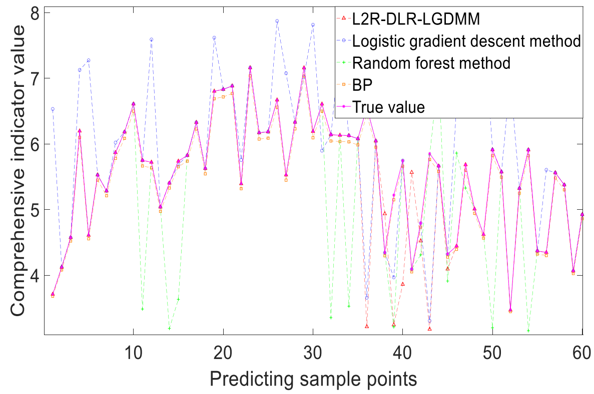


FIGURE 14. **Comparison of different forecasting methods.**

From Fig. 14, we can see that the pink line with "*" is the true value result, the red line with "△" is the prediction result of the method in this paper, the blue line with "◯" is the prediction result of the Logistic gradient descent method, the green line with "+" is the prediction result of the random forest method, and the orange line with "□" is the prediction result of the BP neural network method. From the prediction results, it can be clearly seen that the prediction accuracy of the L2R-LDR-LGDMM method is higher than that of the random forest method and the BP neural network method. After running the proposed method, gradient descent method, random forest method and BP neural network method for many times, we can obtain the comparison of prediction accuracy of different prediction methods, as shown in Table 2.

TABLE 2. **Comparisons of prediction accuracy using different prediction methods.**

Different methods	MSE	MAE	Prediction accuracy	Average accuracy of multiple predictions
Proposed method	1.0304	0.0044	86.67%	86%
Random forest method [7]	1.0438	0.075	75.93%	70%
BP Neural network method [15]	1.4251	0.12	55.0%	60%
Logistic gradient descent method	1.0585	0.0297	61.67%	75%

After using the machine learning model to predict the comprehensive indicator dataset many times, it is found that the prediction accuracy of the BP neural network method is basically about 55% when it predicts the comprehensive indicator dataset for multiple times. When the random forest method predicts the comprehensive indicator dataset for many times, its accuracy rate will be basically about 70%. When the logistic gradient descent method predicts the comprehensive indicator dataset for multiple times, its accuracy will be basically about 75%. However, when the L2R-LDR-LGDMM method predicts the comprehensive indicator for multiple times, the accuracy of the prediction results will change little and the prediction accuracy is basically about 86%. From Table 2, we can also see that the proposed method is better than the other three comparison methods in terms of MSE, MAE and prediction accuracy. It can be seen that the L2R-DLR-LGDMM proposed in this paper has two advantages in predicting the comprehensive indicator dataset compared with the BP neural network method, random forest method and gradient descent method.

To further verify the effectiveness of the method in this paper, PMU data from the WECC 146-machine and 243-node test system [21] is selected for the prediction. This system has 243 nodes, 146 generating units (including 109 synchronous motors and 37 renewable generators) in 56 power plants, 329 transmission lines, 122 transformers, 7 switched shunts, and 139 loads. The data used is the data that appears due to the low-frequency oscillation caused by the increase of motor loads. Fig. 15 shows prediction results of the comprehensive indicator after the de-normalization progress. The results in Fig. 15 show that the prediction accuracy of the method in this paper is relatively high, with an accuracy of 95%. The red line with "◯" is the real value result, and the blue line with "△" is the prediction result of the method in this paper. By bringing the WECC data into the random forest, BP neural network and Logistic gradient descent method, we can obtain Fig. 16. Fig. 16 shows the comparison results of different prediction methods using WECC data.

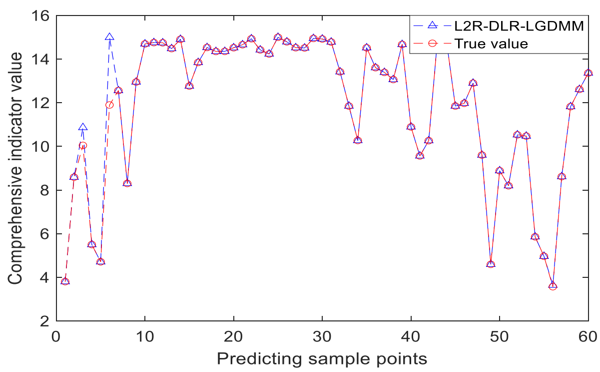


FIGURE 15. The comprehensive indicator prediction chart of WECC data de-normalization.

From Fig. 16, it can be concluded that the prediction accuracy of the method in this paper is 95%, the prediction accuracy of the Logistic gradient descent method is 88%, the prediction accuracy of the random forest method is 78%, and the prediction accuracy of the BP neural network is 67%. The pink line with "*" is the real value result, the red line with "△" is the prediction result of the method in this paper, the blue line with "◯" is the prediction result of the Logistic gradient descent method, the green line with "+" is the prediction result of the random forest method, and the orange line with "□" is the prediction result of the BP neural network method. Through the prediction results, it is obvious that the prediction accuracy of the L2R-DLR-LGDMM method proposed in this paper for the comprehensive index is higher than that of the random forest method and the BP neural network method for the comprehensive indicator.

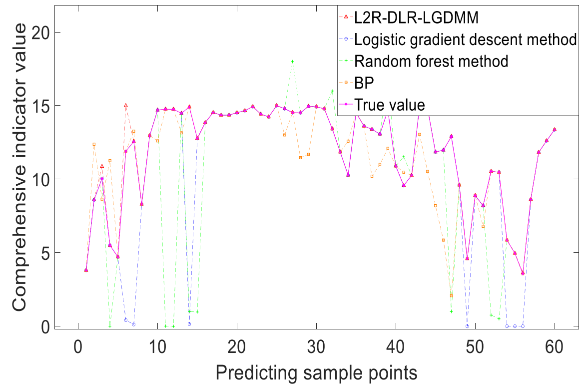


FIGURE 16. Comparisons of different prediction methods using WECC data.

In summary, the method in this paper has good prediction accuracy for PMU data in different test environments, and has certain reference significance for the analysis of the stability of the low-frequency oscillation of the power system.

VI. CONCLUSION

In order to solve the problem of lack of effective machine learning algorithms for situational awareness prediction of comprehensive indicators in the current low-frequency oscillation of power system, this paper proposes a L2R-DLR-LGDMM method to predict the situational awareness of comprehensive indicators, and gives the implementation steps of the whole method. After processing PMU data, a prediction system based on Logistic gradient descent method is formed, which can intuitively and accurately predict the situational awareness of comprehensive indicators. By comparing and analyzing with the random forest method, the Logistic gradient descent method and the BP neural network method, prediction results show that the prediction accuracy of the proposed method is 86.74%, the random forest method is 75.9%, the BP neural network is 55%, and the gradient descent method is 61.67%. In this paper, the average accuracy of multiple predictions is 86%, while the random forest method is 70%, BP neural network method is 55%, and Logistic gradient descent method is 75%. In addition, this paper also uses the data of the WECC 146-machine 243-node test system to predict the low-frequency oscillation. The prediction results show that the prediction accuracy of the method in this paper is 95%, which is higher than the random forest method with a prediction accuracy of 78%, the BP neural network with a prediction accuracy of 67% and the Logistic gradient descent method with a prediction accuracy of 88%. In a word, the prediction accuracy and stability of the method proposed in this paper are better compared to other methods. Therefore, the proposed method in this paper can effectively solve the problem of situational awareness and prediction of comprehensive indicators, and has a strong reference role in the prediction of low-frequency oscillation of new power system. At the same time, there is still a problem that the method in this paper cannot determine which type of oscillation causes low-frequency oscillation in power system, and further study is needed to study in the future.

REFERENCES

[1] M. Y. Erten and H. Aydilek, ''Solar power prediction using regression models,'' *Int. J. Eng. Res. Develop.*, vol. 14, no. 3, pp. 333–342, 2022.

[2] A. Sengupta and D. K. Das, ''Design of decentralized model predictive controller to eliminate low frequency oscillation in power system,'' in *Proc. IEEE Appl. Signal Process. Conf. (ASPCON)*, Kolkata, India, Oct. 2020, pp. 227–231.

[3] C. Wei, H. Jingshan, L. Zheng, W. Cong, and W. Jiahao, ''Research on transmission line trip prediction based on logistic regression algorithm under icing condition,'' in *Proc. IEEE 4th Adv. Inf. Manage., Communicates, Electron. Autom. Control Conf. (IMCEC)*, vol. 4, Chong Qing, China, Jun. 2021, pp. 565–569.

[4] Z. Liang, Q. Gang, L. Huixing, and J. I. N. Haochun, ''Research and application of key technologies of network security situation awareness for smart grid power control systems,'' *J. Shanghai Jiao Tong Univ.*, vol. 55, no. 2, pp. 103–109, 2021.

[5] R. Feng, Y. Xue, W. Wang, and M. Xiao, ''Saturated load forecasting based on clustering and logistic iterative regression,'' *Electr. Power Syst. Res.*, vol. 202, Jan. 2022, Art. no. 107604.

[6] H. Hassani, R. Razavi-Far, M. Saif, and G.-A. Capolino, ''Regression models with graph-regularization learning algorithms for accurate fault location in smart grids,'' *IEEE Syst. J.*, vol. 15, no. 2, pp. 2012–2023, Jun. 2021.

[7] E. Oyekanlu and J. Uddin, ''Random forest-based ensemble machine learning data-optimization approach for smart grid impedance prediction in the powerline narrowband frequency band,'' in *Deterministic Artificial Intelligence*. London, U.K.: IntechOpen, 2020.

[8] P. Feng, G. Jiang, J. Xu, J. Ye, and S. Li, ''Low-frequency oscillation analysis of power system containing DFIG wind farm based on wind speed interval prediction and eigenvalue trajectory,'' in *Proc. Power Electron. Power Syst. Conf. (PEPSC)*, Hang Zhou, China, vol. 26, Nov. 2023, pp. 97–102.

[9] M. Yu, S. Yang, F. Shi, S. Gong, D. Yang, and Z. Lin, ''A three-stage random forest integrating fuzzy matrix method in low frequency oscillation classification of power system,'' *Natural Hist.*, vol. 124, no. 10, pp. 2–19, 2023.

[10] S. Chang, C. Peng, Y. Hu, and Y. Mou, ''An improved Prony prediction compensation-based wide-area damping control approach for power system low-frequency oscillation suppression,'' *J. Sensors*, vol. 2021, no. 1, pp. 1–10, Jan. 2021.

[11] M. Yu and W. Du, ''Research on the accuracy of low-frequency oscillation warning in power system based on Vinnicombe distance,'' *Control Eng. China*, vol. 29, no. 2, pp. 340–347, 2022.

[12] M. Yu, W. Du, J. Li, S. Zhang, and J. Hu, ''Study on a comprehensive indicator and online classification of early warning of low frequency oscillation in power system,'' *Eng. Appl. Artif. Intell.*, vol. 124, Sep. 2023, Art. no. 106592.

[13] M. Yu and J. Li, ''Research on low frequency oscillation suppression of power system with DFIG based on state feedback decoupling control,'' *Renew. Energy Resour.*, vol. 40, no. 2, pp. 214–221, 2022.

[14] L. Carvalho, J. M. De S. Filho, R. R. T. Alves, M. V. S. Costa, V. P. B. Aguiar, and E. V. Fortes, ''Switched robust model predictive control applied for damping low-frequency electromechanical oscillations in power systems,'' in *Proc. 15th IEEE Int. Conf. Ind. Appl. (INDUSCON)*, São Bernardo do Campo, Brazil, Nov. 2023, pp. 109–116.

[15] R. Satheesh, N. Chakkungal, S. Rajan, M. Madhavan, and H. H. Alhelou, ''Identification of oscillatory modes in power system using deep learning approach,'' *IEEE Access*, vol. 10, pp. 16556–16565, 2022.

[16] Y. Zhang, P. Li, H. Li, W. Zu, and H. Zhang, ''Short-term power prediction of wind power generation system based on logistic chaos atom search optimization BP neural network,'' *Int. Trans. Electr. Energy Syst.*, vol. 2023, pp. 1–11, Mar. 2023.

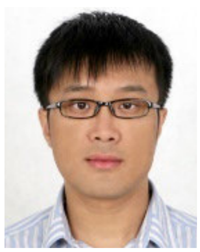
[17] Y. Fu, L. Chen, Z. Yu, Y. Wang, and D. Shi, ''Data-driven low frequency oscillation mode identification and preventive control strategy based on gradient descent,'' *Electric Power Syst. Res.*, vol. 189, Dec. 2020, Art. no. 106544.

[18] V. Sharma, T. Hong, V. Cecchi, A. Hofmann, and J. Y. Lee, ''Forecasting weather-related power outages using weighted logistic regression,'' *IET Smart Grid*, vol. 6, no. 5, pp. 470–479, Oct. 2023.

[19] Y. Li and Z. Chen, ''Study on regional electric energy substitution potential evaluation based on TOPSIS method of optimized connection degree,'' *Power Syst. Technol.*, vol. 43, no. 2, pp. 687–693, 2019.

[20] C. Bai, Q. Li, X. Zheng, X. Yin, and Y. Tan, ''Dynamic weighted-gradient descent method with smoothing momentum for distributed energy management of multi-microgirds systems,'' *IEEE Trans. Smart Grid*, vol. 14, no. 6, pp. 4152–4168, Nov. 2023.

[21] H. Yuan, R. S. Biswas, J. Tan, and Y. Zhang, ''Developing a reduced 240-bus WECC dynamic model for frequency response study of high renewable integration,'' in *Proc. IEEE/PES Transmiss. Distrib. Conf. Expo.*, Oct. 2020, pp. 1–5.



MIAO YU was born in China. He received the Ph.D. degree in control science and engineering from Beijing Institute of Technology, Beijing, China, in 2010. He is currently working as an Associate Professor with Beijing University of Civil Engineering and Architecture. His research interests include power system dynamical analysis and PMU data processing.

ZIHAO LIN was born in China. He is currently pursuing the bachelor's degree with Beijing University of Civil Engineering and Architecture, Beijing, China. His research interest includes low-frequency oscillation prediction in power systems.

YANG DI was born in Sichuan, China. He is currently pursuing the bachelor's degree with Beijing University of Civil Engineering and Architecture, Beijing, China. His research interest includes dynamic estimation of the operating state of synchronous generators.

TIANYI WANG was born in China. He is currently pursuing the bachelor's degree with Beijing University of Civil Engineering and Architecture, Beijing, China. His research interests include transformer fault diagnosis and prediction.