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Research on transformer operation state prediction based on comprehensive weights and BO-CNN-GRU

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Aiming at the problem that it is difficult to predict the future operating state of the transformer, this paper proposes a method for predicting the operating state of transformers based on comprehensive weight and BO-CNN-GRU (Bayes Optimization -Convolutional Neural Network- Gated Recurrent Unit). Firstly, 11 kinds of monitoring data in three categories including oil chromatography gas content, temperature, and electrical quantity are selected as feature parameters; Then, the game theory method is used to integrate the weight values of the three methods of G1 method, entropy weight method and CRITIC method to get the comprehensive weight value of each feature parameter, and the transformer operation state index is constructed based on the comprehensive weight; Finally, the BO-CNN-GRU combination prediction model is built, which solves the problem of difficulty in determining the hyperparameters of the model. After the example analysis, it can be seen that the five evaluation indexes of this paper's model present the optimal results, effectively showing that this paper's method has better predictability for the transformer operation state.

KEYWORDS

transformer, bayes optimization, CNN, GRU, state prediction

1 Introduction

The power transformer is one of the core equipment of the power system, which is the carrier of power supply from the grid to the user. Whether the transformer can operate stably plays a decisive role in the stability of the power supply. Once the transformer fails, it will cause regional power outages, casualties, and a series of problems, resulting in serious safety issues and economic losses (Cheng et al., 2022; Cheng et al., 2020a; Cheng et al., 2020b). The photograph of the scene where the transformer failure caused the explosion is shown in Figure 1.

Prediction of transformer operation state can provide a data basis for transformer maintenance and overhaul, which in turn improves the stability of power system operation and has an important role in promoting the intelligent development of the power grid (Zhou et al., 2014; Arshad et al., 2014; Bakar and Abu-Siada, 2016; Li et al., 2021).

FIGURE 1
Transformer explosion scene diagram.

In recent years, with the rapid development of artificial intelligence technology, intelligent detection technology, and data-driven methods (Cao et al., 2024; Bai et al., 2024; Liu et al., 2024; Li et al., 2024; Li et al., 2023), scholars at home and abroad have made better research results in the fields of transformer fault diagnosis, transformer operation state prediction, and transformer life prediction. In Lei et al. (2024), Lei et al. proposed a zero-sample fault diagnosis technique for transformers based on a variable-weight attribute matrix for the problem of missing information on fault samples caused by the long-tail effect. In Du et al. (2023), Du et al. proposed a power transformer fault detection method based on multiple eigenvalues of vibration signals for the problem of poor generalization of diagnostic algorithms. In Zhou et al. (2024), Zhou et al. used a cloud model and a weighted implicit semi-Markov model to predict transformer operating conditions. In Ge et al. (2021), Ge et al. proposed a transformer fault data enhancement method based on an Improved Autoencoder (IAE) to address the problem of insufficient data in machine-learning transformer fault diagnosis methods. In Li et al. (2022), Li et al. proposed a transformer state analysis method that combines autonomous discretization of signs and autonomous dimensionality reduction preference of signs and single event multi-model fusion analysis of data distribution, to overcome the problem that existing studies have neglected the diagnosis of a single sample. In Wang et al. (2022), Wang et al. proposed a transformer fault diagnosis model combining a multi-strategy improved sparrow algorithm (MISSA) with a bidirectional long and short-term memory network (BiLSTM) for the problem of low fault diagnosis accuracy of transformers. In Pan et al. (2022), Pan et al. addressed the problem of winding vibration under the unbalanced operation mode of the transformer, carried out the vibration signal decomposition and reconstruction based on wavelet packet transform, investigated the energy distribution law of different frequency domain scales, and proposed a vibration feature identification method based on the scale-energy occupancy ratio.

Analyzing the above research content, it can be seen that most of the existing research revolves around the analysis of transformer fault data, typical transformer fault diagnosis, and traditional condition assessment algorithms. This has played a role in promoting the development of this research field, but the research on the use of transformer multi-feature parameters, the construction of transformer condition assessment indexes, and high-performance prediction models is still inadequate. Therefore, based on the multi-dimensional transformer feature parameter information, this paper carries out in-depth research on the construction of transformer operating state index and prediction model.

With the continuous development of technology, more and more online monitoring data can be collected on the transformer, how to make good use of a variety of online inspection data is of great significance to the transformer condition assessment (Guo et al., 2025). Traditional neural network-based prediction methods have the problems of long model training time, gradient vanishing problem, and complex hyperparameter selection (Cheng and Yu, 2019). As an improved model of LSTM, the gated recurrent unit (GRU) can effectively alleviate the problem of gradient disappearance in the recurrent neural network, and at the same time, it has a faster training speed under the premise of guaranteeing the prediction accuracy (Ma et al., 2023). However, GRU neural networks cannot solve the problem of complex selection of hyperparameters of neural networks and need to be combined with other optimization algorithms.

Based on the insufficiency of existing research and the difficulty of confirming the hyperparameters of the prediction model, this paper proposes a transformer operation state prediction method based on BO-CNN-GRU. Taking 11 kinds of transformer feature parameters as the data basis, the G1 method, entropy weight method, and CRITIC method are used to calculate the corresponding feature parameter weights, and the comprehensive transformer weights are constructed through game theory, to construct a more accurate transformer state index. The BO-CNN-GRU combination prediction model is adopted to complete the optimization of model parameters, which improves the accuracy of the prediction model and provides a new method for transformer state prediction.

2 Basic principle

The overall flow of the transformer operation state prediction method based on comprehensive weights and BO-CNN-GRU is shown in Figure 2. The main model algorithms include the G1 method, entropy weight method, CRITIC method, Game theory, Bayes optimization, CNN, and GRU.

2.1 Calculation of the comprehensive weights of the feature parameter

The results of the calculation of the weights of the feature parameters will directly affect the accuracy of the construction of the transformer condition index results, so the calculation of the weights of the feature parameters is one of the key steps in the assessment of the transformer condition. However, the weight allocation results obtained by the existing weight calculation methods have a large error with the actual situation, which leads to a large error in the actual operation status obtained by calculation, and such problems have been widely concerned in the fields of nondestructive testing of equipment and materials (Versaci et al., 2020; Versaci, 2016). Therefore, this paper adopts the comprehensive weight

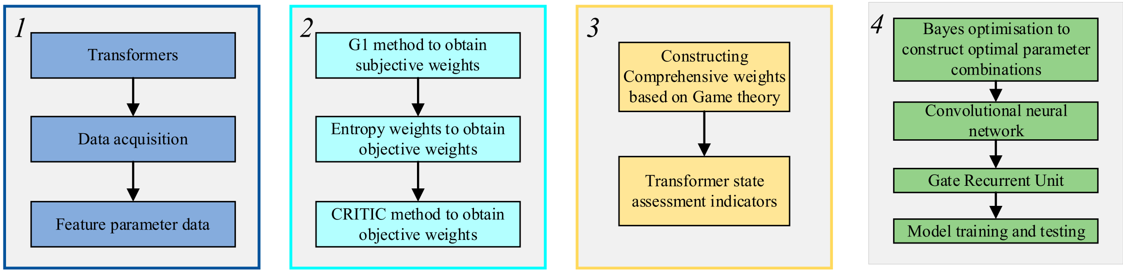

FIGURE 2
The overall flow of the transformer operation state prediction method.

TABLE 1 Transformer state classification results table.

Health Grade	Range of values	Condition Description
Excellent	[0,0.1)	Equipment performance is good, and safe operation
Good	[0.1–0.3)	The equipment is in general running condition, and still can run stably, but needs strengthened monitoring
Average	[0.3–0.7)	The equipment is abnormal and needs regular maintenance
Deteriorated	[0.7–0.9)	The equipment has been faulty and should be repaired as soon as possible
Severe	[0.9–1.0]	The equipment has been unable to run and should be shut down for inspection and overhauling

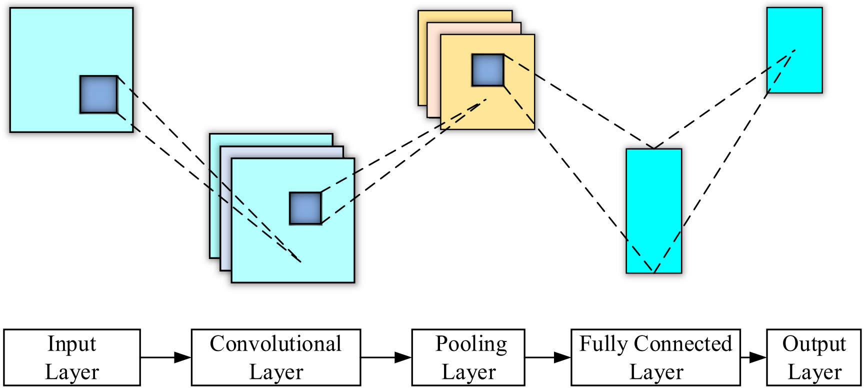

FIGURE 3
Structure diagram of CNN.

calculation method to construct a more reasonable transformer feature parameter weight.

2.1.1 G1 method for determining subjective weights

The G1 method avoids the shortcomings of the hierarchical analysis method and has strong operability for practical engineering applications. The specific calculation process is as follows:

(1) Each of the feature parameters is ranked in order of importance according to the experience of the experts.

(2) Determine the value of the ratio r_k of the degree of importance of the neighboring feature parameters x_k and x_{k-1}.

(3) If the ratio of the degree of importance is r_k, then the weight w_m of the mth feature parameter is calculated by Equation 1:

$$w_m = \left(1 + \sum_{k=2}^{m} \prod_{i=k}^{m} r_k\right)^{-1} \quad (1)$$

(4) The weights of the other feature parameters are calculated by the weight w_m of the mth feature parameter, and the calculation process is shown in Equation 2.

TABLE 2 Table of formulae for convolutional structures.

Convolutional structure	Calculation formula
Convolutional layer	$y_j^l = f\left(\sum_{i \in M_j} x_i^{l-1} \omega_{ij}^l + b_i^j\right)$
Pooling layer	$(S_K)_{\max-pooling} = \max\left(a^{l(i,t)}\right)$
Fully connected layer	$h(x^i) = f\left(\omega x^{l-1} + b\right)$

$$w_{k-1} = r_k w_k, k = m, m-1, \cdots 3, 2 \tag{2}$$

where w_{k-1} is the weight of the *k-1*th feature parameter, r_k is the ratio of the degree of importance of two neighboring feature parameters, and w_k is the weight of the *w*th feature parameter.

2.1.2 Entropy weighting method for objective weight calculation

Entropy weighting is a method that can determine the weights by the amount of information contained in the data, the smaller the entropy value of the feature parameter, the more information it contains and the higher the corresponding weight (Xu and Fang, 2022).

Let x_{ij} (i = 1, 2, ⋯, n; j = 1, 2, ⋯m) be the *j*th data under the *i*th feature parameter, then the entropy weight e_j of the *j*th feature parameter is calculated by Equation 3:

$$e_j = -k \sum_{i=1}^{m} p_{ij} \ln p_{ij} \tag{3}$$

where e_j is the entropy weight of the *j*th feature parameter, p_{ij} is the weight of x_{ij} in all data, and *k* is a constant.

Finally, the weight u_j of the *j*th feature parameter is calculated by Equation 4:

$$u_j = 1 - e_j / n - \sum_{j=1}^{n} e_j \tag{4}$$

2.1.3 CRITIC method for determining objective weights

The CRITIC method calculates objective weights by comparing intensity and conflictiveness between feature parameters. The specific calculation process is as follows:

(1) Calculate the standard deviation s_j of the *j*th feature parameter by Equation 5.

$$s_j = \sqrt{\frac{\sum_{i=1}^{n}\left(x_{ij} - \bar{x}_j\right)^2}{n-1}} \tag{5}$$

where s_j is the standard deviation of the *j*th feature parameter, x_{ij} is the *i*th data of the *j*th feature parameter, and x_j is the mean of the *j*th feature parameter data.

(2) Calculate the conductivity of the feature parameter with other variables R_j by Equation 6.

$$R_j = \sum_{i=1}^{p}\left(1 - r_{ij}\right) \tag{6}$$

where r_{ij} is the correlation coefficient between the feature parameters *i* and *j*.

(3) Calculate the informativeness of the feature parameters c_j by Equation 7.

$$c_j = s_j R_j \tag{7}$$

(4) The objective weights of the *j*th feature parameter were as follows by Equation 8.

$$\theta_j = \frac{c_j}{\sum_{j=1}^{m} c_j} j = 1, 1, \cdots m \tag{8}$$

2.1.4 Game theory comprehensive weighting calculation

Game theory is a theory for studying things with a competitive nature. Game theory can analyze the problem of rational behavior and its decision-making equilibrium when the behavior of multiple decision-making subjects interacts with each other. In game theory, it can be assumed that each option is the result of rational decision-making, which is made by decision-makers to maximize their benefits or minimize their losses. This competitive outcome is not controlled by one decision-maker but is achieved by all decision-makers. The purpose of the game theory portfolio assignment is to optimize the combination of weights calculated by various methods to obtain the optimal weight values.

For a basic set of weight vectors, *n* vectors are arbitrarily linearly combined into one possible combination of weights, and the calculation process is shown in Equation 9.

$$U = \sum_{k=1}^{n} \alpha_k \boldsymbol{u}_k^T \left(\alpha_k > 0\right) \tag{9}$$

where *U* denotes the possible optimal weights, α_k is the weight coefficient and $\boldsymbol{u}_k$ is the weight vector.

The objective of game theoretic optimization is to minimize the deviation between the combination of weights and the individual weights, and the calculation process is shown in Equation 10.

$$min \left\| \sum_{j=1}^{n} \alpha_k \times \boldsymbol{u}_k^T - \boldsymbol{u}_k^T \right\|_2 (i = 1, 2, L, n) \tag{10}$$

The optimal first-order derivative condition obtained from the differential properties of the matrix is calculated by Equation 11.

$$\sum_{j=1}^{n} \alpha_k \times \boldsymbol{u}_k \times \boldsymbol{u}_k^T = \boldsymbol{u}_k \times \boldsymbol{u}_k^T (i = 1, 2, Ln) \tag{11}$$

The resulting game-theoretic model is shown in Equation 12.

$$\begin{bmatrix} u_1 u_1^T & u_1 u_2^T & \cdots & u_1 u_n^T \\ u_2 u_1^T & u_2 u_2^T & \cdots & u_2 u_n^T \\ \vdots & \vdots & \vdots & \vdots \\ u_n u_1^T & u_n u_2^T & \cdots & u_n u_n^T \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} u_1 u_1^T \\ u_2 u_2^T \\ \vdots \\ u_n u_n^T \end{bmatrix} \tag{12}$$

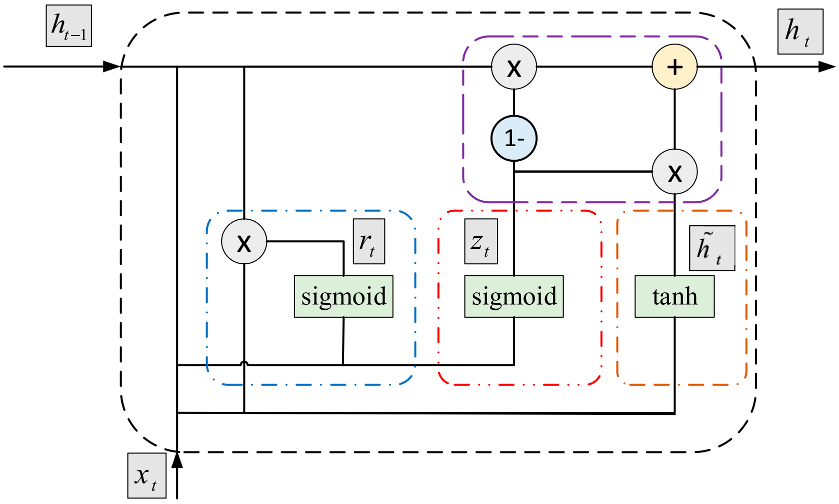

FIGURE 4
Internal structure diagram of GRU.

TABLE 3 Table of formulae for GRU.

GRU structure	Calculation formula
Reset Gate r_t	$r_t = \sigma(x_t W_{xr} + h_{t-1} W_{hr} + b_r)$
Update Door z_t	$z_t = \sigma(x_t W_{xz} + h_{t-1} W_{hz} + b_z)$
Candidate hidden state h_t	$h_t = tanh(x_t W_{xh} + (r_t \odot h_{t-1}) W_{hh} + b_h)$
Hidden State h_t	$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot h_t$

In the above table, W_{xr}, W_{xz}, W_{hr}, W_{hz}, W_{xh}, W_{hh} are weighting parameters, b_r, b_z, b_h are deviation parameters, and x_t is the current time step input.

TABLE 4 Transformer feature parameter table.

Primary feature parameter	Secondary feature parameters
Oil Chromatography	H_2 content
	CH_4 content
	C_2H_2 content
	C_2H_4 content
	C_2H_6 content
	CO content
	CO_2 content
	Total hydrocarbon content
Temperature	Oil temperature
	Winding temperature
Electrical quantities	Core grounding current

Based on the weighting coefficients, the combination coefficients for each weight are calculated by Equation 13.

$$\alpha_k^* = \frac{\alpha_k}{\sum_{k=1}^{n} \alpha_k} \tag{13}$$

The final comprehensive weights were calculated by Equation 14.

$$u^* = \sum_{k=1}^{k} \alpha_k^* \boldsymbol{u}_{\boldsymbol{k}}^{\boldsymbol{T}} \tag{14}$$

2.2 Condition classification of transformers

Concerning the regulatory requirements of the National Grid and the historical summary of experience, the transformer is divided into five state levels, and the relationship between each state level and the state of the transformer is shown in Table 1.

2.3 BO-CNN-GRU transformer state prediction model

2.3.1 Bayes optimization principle

Bayes optimization is an approximation idea that has the advantage of better hyperparameter confirmation in the case of more complex computations and a higher number of iterations. The hyperparameter combination selection process of the model is shown in Equation 15.

$$x^* = \operatorname{argmin} f(x) \tag{15}$$

where $f(x)$ is the minimized objective function, which is used to assess the optimal performance of the objective function, and $x^*$is the optimal hyperparameter combination obtained at the end.

TABLE 5 Weights of the transformer feature parameter.

Primary feature parameter	Secondary feature parameters	G1 method	Entropy weight method	CRITIC method	Comprehensive weighting
Oil Chromatography	H_2 content	0.1541	0.0571	0.1108	0.1107
	CH_4 content	0.0954	0.0600	0.1056	0.0853
	C_2H_2 content	0.1285	0.0628	0.0748	0.0938
	C_2H_4 content	0.1071	0.1200	0.1687	0.125
	C_2H_6 content	0.0973	0.1643	0.0880	0.119
	CO content	0.0811	0.1714	0.963	0.1154
	CO_2 content	0.0795	0.0757	0.1051	0.0832
	Total hydrocarbon content	0.0722	0.1028	0.0642	0.0812
Temperature	Oil temperature	0.0339	0.0545	0.0525	0.0452
	Winding temperature	0.0678	0.0472	0.0497	0.0565
Electrical quantities	Core grounding current	0.0847	0.0847	0.0847	0.0847

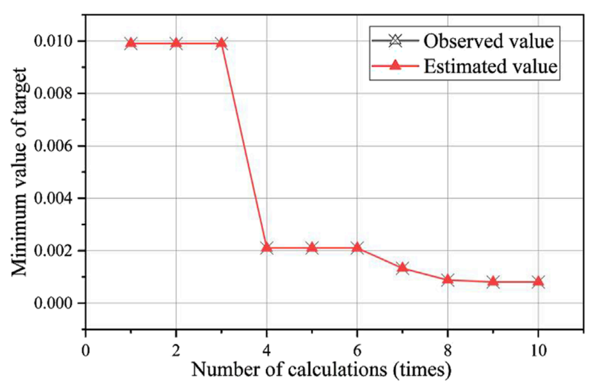

FIGURE 5
Bayes optimization process parameter variation.

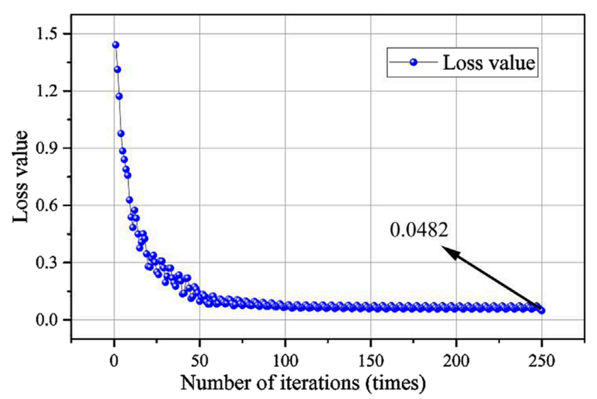

FIGURE 6
Loss value changes during model training.

Bayes optimization stems from Bayes' theorem and uses the BO formula to establish a probability distribution for the optimization process. The calculation process is shown in Equation 16.

$$P(E|D) \propto P(D|E)P(E) \tag{16}$$

where P(E) is a Gaussian distribution, and P ($E|D$) is a Gaussian regression process.

2.3.2 CNN convolutional neural network

CNN is a feed-forward neural network, which is mainly composed of the input layer, convolutional layer, pooling layer, fully connected layer, and output layer, and the input feature vector can be a multi-dimensional vector set, which adopts local perception and weight sharing. The convolutional layer extracts the feature volume of the original data and deeply mines the intrinsic connection of the data, the pooling layer can reduce the complexity of the network and reduce the training parameters, and the fully connected layer merges the processed data and calculates the classification and regression results (Ye et al., 2024).

The main components of the convolutional neural network are shown in Figure 3.

The convolutional neural network computation process is shown in Table 2.

Where y_j^l is the jth feature mapping in the lth layer of the current layer, f is the activation function, M_j is the input feature mapping x_i^{l-1} is the ith feature mapping of the previous layer, w_{ij}^l is the convolution

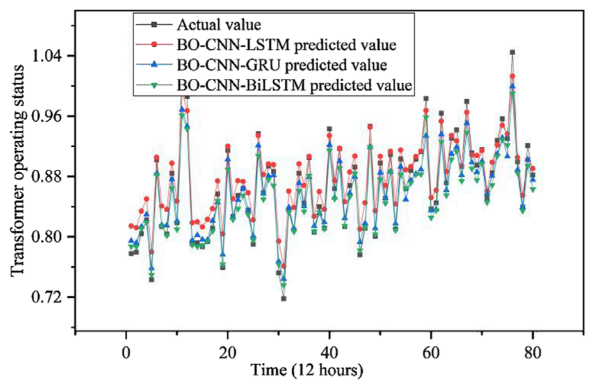

FIGURE 7
Multiple method prediction results comparison plot.

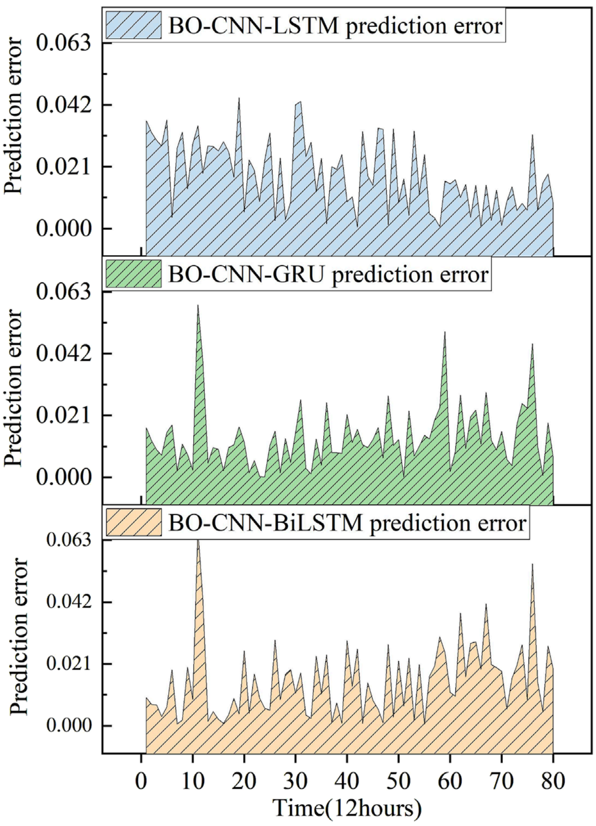

FIGURE 8
Multiple method prediction error comparison plot.

kernel of the ith and jth layers, b_i^j is the bias, $(S_K)_{\text{max-pooling}}$ is the value of the corresponding neuron after pooling, $a^{l(I,t)}$ is the output of the tth neuron of the ith mapping in layer l, $h\ (x^i)$ is the fully connected output of layer l, f is the activation function, ω is the weight of the neuron node, x^{l-1} is the fully connected input of layer l and b is the bias.

2.3.3 GRU recurrent neural network

GRU modifies the calculation of hidden states in recurrent neural networks by simplifying the input, forgetting, and output gates to update and reset gates based on LSTM. The internal structure of the GRU is shown in Figure 4.

The formula for GRU is shown in Table 3.

3 Transformer feature parameter selection and comprehensive weight construction

3.1 Selection of the feature parameters

In this paper, a 500 KV oil-immersed transformer is used as an experimental object. To accurately assess the operating state of the transformer, the feature parameters that have a great influence on the operating condition of the transformer should be selected. Feature parameters related to transformer state can be divided into two categories: those that can be monitored online and those that cannot be monitored online. This paper mainly adopts the feature parameters that can be monitored online in real time to predict the future operating state of the transformer. Three types of features, including oil chromatography, temperature, and electrical quantity, are selected. The specific feature parameters are shown in Table 4:

3.2 Comprehensive weighting calculation

Based on the feature parameter data, G1 method, entropy weight method, and CRITIC method are used to calculate the corresponding weights of each feature parameter of the transformer, and the calculation results are 0.4332 for the G1 method, 0.3505 for the entropy weight method, and 0.2173 for the CRITIC method. The feature parameter weight data and the comprehensive weights calculated by the three methods mentioned above are shown in Table 5.

The operating state index data of the transformer is obtained by using the data of each feature parameter of the transformer and the comprehensive weights. The use of comprehensive weights makes the operating state index data more similar to the actual operating state and can reflect the overall degradation of the transformer more comprehensively. Based on the transformer operating state index data, the future operating state of the transformer is predicted.

4 Transformer operating state prediction analysis

4.1 Comparative analysis of multiple prediction methods

400 sets of data for 200 days from February to October 2021 of the transformer are selected for example analysis. Multi-feature input matrix is constructed based on temperature, humidity, and condition indicator data to realize future transformer condition prediction. The data through the first 160 days is used as a training set and the data of the next 40 days is used as a test set.

TABLE 6 Table of indicators for the evaluation of prediction models.

Prediction model	RMSE	MAE	MAPE	Computing time	Running memory
BO-CNN-LSTM	0.0022	0.0018	0.0190	482s	9576 MB
BO-CNN-GRU	0.0017	0.0014	0.0152	407s	9521 MB
BO-CNN-BiLSTM	0.0020	0.0015	0.0167	514s	9632 MB

TABLE 7 Evaluation index table for the optimized prediction model.

Prediction model	RMSE	MAE	MAPE
SSA-CNN-GRU	0.0018	0.0014	0.0155
GA-CNN-GRU	0.0021	0.0019	0.0171
WOA-CNN-GRU	0.0019	0.0016	0.0173
BO-CNN-GRU	0.0017	0.0014	0.0152

TABLE 8 Table of indicators for evaluating single-input prediction models.

Prediction model	RMSE	MAE	MAPE
BO-CNN-LSTM	0.0027	0.0021	0.0213
BO-CNN-GRU	0.0019	0.0015	0.0161
BO-CNN-BiLSTM	0.0023	0.0017	0.0172

The Bayes parameter optimization process of this paper's method is shown in Figure 5. The variation of loss values during model training is shown in Figure 6. The prediction results of different methods are shown in Figure 7. The error result graph is shown in Figure 8.

Analysis of Figure 5 shows that when the number of iterations of the Bayes optimization process reaches 8 times, the minimum target observation value and the estimated value tend to be stable and basically the same, and at this time, the optimal hyperparameter combination is determined. Analysis of Figure 6 shows that in the model training process, when the number of iterations reaches about 100 times, the loss value is unchanged, indicating that the model training is completed at this time.

Analyzing Figures 7, 8, it can be seen that the trends of future transformer operating state changes predicted by the three prediction models, BO-CNN-GRU, BO-CNN-LSTM, and BO-CNN-BiLSTM, are all closer to the actual transformer state changes, which are shifted from the Excellent state to the Good state. However, the prediction results of the BO-CNN-GRU are more accurate.

To better illustrate the advantages of the method in this paper, four evaluation indexes, namely, RMSE, MAE, MAPE, Computing time, and Running memory, are calculated to evaluate the model performance. The calculation results are shown in Table 6.

Analyzing Table 6 shows that the RMSE, MAE, and MAPE, of the BO-CNN-GRU, prediction model are the smallest, which indicates that BO-CNN-GRU, can better reflect the trend and fluctuation of the data compared to the BO-CNN-LSTM, and BO-CNN-LSTM, prediction models. Meanwhile, the BO-CNN-GRU, prediction model has the shortest computation time and occupies less memory, indicating lower computational cost.

4.2 Comparative analysis of multiple optimization algorithms

To better analyze the superiority of the BO Optimization Algorithm, the Sparrow Search Optimization Algorithm (SSA), Genetic Optimization Algorithm (GA), and Whale Optimization Algorithm (WOA) were used to optimize the CNN-GRU prediction model, respectively, and the evaluation indexes of the CNN-GRU model after optimization of each optimization algorithm are shown in Table 7.

Analysis of Table 7 shows that compared with SSA, GA, and WOA Optimization Algorithms, the BO Optimization algorithm has the lowest values of RMSE, MAE, and MAPE, which indicates that the BO optimization algorithm has a better optimization ability to improve the performance of CNN-GRU prediction model, and can better complete the prediction of transformer's future state when used in combination with CNN-GRU.

4.3 Comparison of multi-input and single-input results

To further verify the necessity of constructing a multi-feature input matrix based on temperature, humidity, and state indicator data, the prediction process is completed only through the state indicator data, and the prediction result evaluation indexes are shown in Table 8.

Analyzing the evaluation index data in Tables 6, 8, it can be seen that compared with the single feature input, the multivariate input matrix constructed using temperature, humidity, and state index data has a better prediction effect, and the RMSE, MAE, and MAPE of the prediction results are lower than that of the prediction effect using the single feature input, which further verifies the superiority of this paper's method.

5 Conclusion

In this paper, a transformer future operating state prediction method based on comprehensive weights and BO-CNN-GRU is proposed, a 500 KV oil-immersed transformer is taken as an experimental object, and the following conclusions are obtained based on the example analysis:

(1) Based on 11 kinds of transformer feature parameters, the game theory method is used to integrate the G1 method, entropy weight method, and CRITIC method to construct the comprehensive weights of feature parameters, and more accurate data of the transformer's operation status indicators are obtained.
(2) The BO-CNN-GRU transformer future operating state prediction model is constructed, which solves the problem of difficulty in confirming the hyperparameters of the prediction model. After comparative analysis, it can be seen that compared with other state prediction models, the method of this paper has lower RMSE, MAE, MAPE, and higher computational efficiency. This shows that this paper can better complete the transformer operation state prediction.
(3) In future research, the weight allocation scheme of transformer feature parameters will be further explored. The applicability of the paper's methodology in multiple types of transformers and the impact of extreme influences on the model performance will also be further verified.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

YL: Writing–original draft, Writing–review and editing, Conceptualization, Methodology, Validation. WC: Conceptualization, Data curation, Investigation, Writing–original draft, Writing–review and editing. XZ: Conceptualization, Formal Analysis, Funding acquisition, Resources, Visualization, Writing–review and editing. YS: Formal Analysis, Funding acquisition, Methodology, Project administration, Supervision, Validation, Writing–review and editing. XS: Data curation, Formal Analysis, Funding acquisition, Project administration, Resources, Software, Writing–review and editing.

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Conflict of interest

Authors YL, WC, XZ, YS, and XS were employed by State Grid Chaoyang Electric Power Supply Company.

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