Calculation of Fundamental Frequency Amplitude of Transformer Surface Vibration Based on ABC-ELM

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Abstract. The fundamental frequency amplitude of transformer surface vibration is an important indicator for analyzing and diagnosing transformer faults. This article proposed a model for calculating the fundamental frequency amplitude of transformer surface vibration (ABC-ELM) based on Artificial Bee Colony (ABC) optimized Extreme Learning Machine (ELM). Considering the influence factors of transformer vibration, the ELM model was constructed by using the operating voltage, load current and oil temperature as input vectors, and the fundamental frequency amplitude of the transformer surface vibration as output vectors. The data measured by transformer was used for experiments, and the weights and hidden layer biases of the ELM input layer were optimized using ABC. Experimental results showed that ABC-ELM had higher calculation accuracy and smaller error fluctuations than ELM and BP neural networks, which proves the effectiveness of ABC-ELM model in calculating the fundamental frequency amplitude of transformer surface vibration.

1. Introduction
Transformer is the core equipment used for voltage level conversion and power distribution, and its operating status is of great significance to the reliability of the electric power system. According to the statistics of historical data, Iron core and winding are the places where transformer faults occur frequently[1]. The vibration signal on the surface of the transformer contains a lot of information that can reflect the health status of the core and the winding, and the amplitude of the fundamental frequency of the vibration signal is an important indicator for analyzing the health status of the core and the winding[2-5]. The fundamental frequency amplitude of the transformer surface vibration refers to the amplitude of the frequency component of the transformer surface vibration signal at 100 Hz, which is mainly affected by the operating voltage, load current, and oil temperature [6].

Core and winding vibrations are not linearly superimposed during transmission. However, in the traditional transformer box vibration model, the relationship between the fundamental frequency amplitude of the transformer surface vibration and the operating voltage and load current is roughly regarded as a superposition of positive correlations, which has limitations. [7-9]. The neural network has a strong nonlinear fitting ability. It can rely on data to adjust the internal parameters of the model, and then obtain the relationship between the variable and the dependent variable. It is less affected by the user and has a wider range of application. Compared with the traditional neural network method, the extreme learning machine (ELM) has the advantages of good generalization performance, fast learning speed, high prediction accuracy, and not easy to fall into the local optimum[10-11]. Since ELM...
randomly generates input layer weights and hidden layer biases during training and does not require iterative adjustment, the training speed is faster, but at the same time it is easy to cause large fluctuations in the model output[12]. Artificial Bee Colony (ABC) is a swarm intelligence optimization algorithm proposed by Karaboga. It has the advantages of high search accuracy, strong robustness and simple operation[13-14]. Compared with traditional optimization algorithms such as genetic algorithm, particle swarm optimization, and differential evolution algorithm, the best solution obtained by artificial bee colony algorithm has high quality [15].

To solve the above problems, this article establishes a fundamental frequency amplitude of transformer surface vibration calculation model based on artificial bee colony algorithm (ABC) optimization extreme learning machine (ELM). ABC is used to optimize the input layer weights and hidden layer biases of ELM, improve the calculation accuracy and stability of ELM by improving its random parameter generation process, and verify its feasibility and effectiveness on the measured data of the transformer.

2. Principle of Extreme Learning Machine

Extreme learning machine (ELM) is a single hidden layer feedforward neural network algorithm model. The model structure is composed of input layer, hidden layer and output layer. The connection mode between each layer is fully connected. The mathematical model of ELM is:

$$\sum_{i=1}^{L} \beta g(w_i x_j + b_j) = y_j, j=1,2,...,N$$

In formula (1), $L$ is the number of hidden layer neurons, $\omega_i$ is the input layer weight, $b_j$ is the hidden layer offset, $\beta$ is the output layer weight, $g(\cdot)$ is the activation function of the hidden layer neuron, $x_j$ is the input value, $y_j$ is the output value, $N$ is the number of training samples.

Formula (1) can also be abbreviated as matrix form:

$$H \beta = Y$$

$H$ is the hidden layer output matrix, the specific form is:

$$H = \begin{bmatrix} g(w_1 x_1 + b_1) & \ldots & g(w_L x_1 + b_L) \\ g(w_1 x_2 + b_1) & \ldots & g(w_L x_2 + b_L) \\ \vdots & \ldots & \vdots \\ g(w_1 x_N + b_1) & \ldots & g(w_L x_N + b_L) \end{bmatrix}_{NL \times N}$$

In the ELM, the input weights and the hidden layer biases are randomly generated and remain unchanged during the training process, so $H$ is a certain matrix. The training of the feedforward neural network is transformed into a problem of solving the least squares solution of the output weight matrix, which can be obtained by solving the following formula:

$$\hat{\beta} = H^+ Y$$

$H^+$ is the generalized inverse matrix of $H$.

3. Artificial bee colony algorithm

The bee colony is divided into three types: employed bee, onlooker bee and scout bee. Among them, the employed bee and the onlooker bee each account for half of the number of bee colonies and are equal to the number of food sources. When solving the optimized problem, the position of the food source represents a set of feasible solutions of the problem to be optimized, and the amount of nectar represents the fitness value of the feasible solution.

Let the dimension of the solution problem be $D$, then each solution is a $D$-dimensional vector. The position of the food source $i$ at the $t$-th iteration in the solution space is $X^*_t = \{x_{1i}, x_{2i}, \ldots, x_{di}\}$, $x_{di} \in (L_d, U_d)$, where $t$ is the number of iterations, and $U_d$ and $L_d$ are the upper and lower limits...
of the search space, \( d \in \{1,2,\ldots,D\} \), \( i \in \{1,2,\ldots,S_n\} \). The food source is randomly generated in the search space using formula (5):

\[
x_{id} = L_d + \text{rand}(0,1)(U_d - L_d)
\]

The employed bee mines the food source \( x_{id} \) and is disturbed by the neighborhood of the food source. The candidate food source position is generated by formula (6):

\[
v_{id} = x_{id} + \phi (x_{id} - x_{jd}) \\
\phi \in \{1,2,\ldots,S_N\}, j \neq i \tag{6}
\]

In formula (6), \( x_i \) represents the initial solution; \( x_j \) represents the candidate solution; \( d \) is a random integer in \([1, D]\); \( \phi \) is a random number in the range of \([-1, 1]\). When the adaptability of the new food source \( \phi \) is better than that of the old food source, \( t \) is selected by greedy selection, otherwise \( t \) is retained. After employed bee to complete the formula (6), return to the hive to share the food source information.

The onlooker bees use roulette to select food sources. The probability formula of following bees to select each food source is:

\[
P_i = \frac{\text{fit}_i}{\sum_{i=1}^{NS} \text{fit}_i} \tag{7}
\]

Where \( \text{fit}_i \) is the fitness of the \( i \)-th food source. The onlooker bees to search for new food sources according to formula (6) in the selected food source field, and retain the better food sources in the same way as the employed bees.

During the search process, If the food source \( X_i \) reaches the threshold(limit) after \( t \) cycles, its position information is still not updated, the corresponding bee gives up the food source and becomes a scout bee, and starts searching for the food source again. The scout bee uses formula (8) to randomly generate a new honey source in the search space instead of \( X_i \):

\[
X_{t+1} = L_d + \text{rand}(0,1)(U_d - L_d) \tag{8}
\]

4. Establishment of ABC-ELM model

Step1: Randomly generate \( S_n \) food sources, initialize the maximum cycle number of the food source(limit), the maximum number of iterations(MAX), the bee colony size and the upper limit(\( U_d \)) and the lower limit(\( L_d \)) of the search space, each food source position is the input weight and hidden layer neuron biases of a set of extreme learning machines, food source dimension \( D = n \times L + L \), where \( n \) is the number of input layer neurons of the extreme learning machine, and \( L \) is the number of hidden layer neurons.

Step2: This article uses the root mean square error as the fitness function, as shown in formula (9). Calculate the fitness of the top \( S_n \) food sources in the training set:

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \tag{9}
\]

In formula (9), \( y_i \) is the expected output value; \( \hat{y}_i \) is the actual output value, and \( N \) is the number of samples in the training set;

Step3: The employed bee search for a new food source \( v_{id} \) according to formula (6) in the neighborhood of food source \( x_{id} \), calculate and compare the fitness value of the new and old food sources.
sources, select the larger one, and perform the transboundary processing according to formula (10) at the same time:

\[ x_{id} = \max(L_d, x_{id}) = \min(U_d, x_{id}) \]  

(10)

In formula (10), \( L_d \) and \( U_d \) are the lower limit and upper limit of the search space of the first element of the food source, respectively;

Step4: After all employed bees have selected the food source, return to the hive and share the food source information with the onlooker bees. The onlooker bees select the search target according to formula (7) and then search for new food sources in the same way as the employed bees and retain the larger.

Step5: A food source has not been updated after the limit-th iteration. The bees corresponding to the food source search for new food sources according to formula (8).

Step6: Determine whether MAX is reached. If it is reached, the search ends; otherwise, return to Step3 to continue execution until the number of iterations reaches MAX.

Step7: Use the parameters corresponding to the food source with the highest fitness value in the cycle as the ELM optimal input layer weights and hidden layer biases to establish the ABC-ELM model.

5. Experiment and Analysis

5.1 data collection

This article collects the working condition data and surface vibration data of a certain transformer during normal operation. A total of 6 vibration measurement points are selected, which are located in the transformer high voltage A, B, C phase and low voltage a, b, Phase c, at a height of 1/3 from the bottom of the mailbox, the sensor collects every 5 minutes, each sampling time is 1 second, the sampling frequency is 10kHz.

238 sets of data arranged in chronological order of the transformer low-voltage phase a are selected as the sample set, including the operating voltage, load current, oil temperature and surface vibration data collected by low-voltage phase a through FFT to obtain the vibration fundamental frequency amplitude. The first 50% of the selected sample data is used as the training set, the last 50% of the data is used as the test set, and the three-dimensional data of the transformer operating voltage, load current, and oil temperature at the same time are used as the model input, and the fundamental frequency amplitude of the transformer surface vibration is used as the model Output. Before the experiment, the sample set needs to be normalized. This article uses the Premm function to normalize the input data of the model and denormalize the output data.

5.2 Experimental process and result analysis

In this article, we set the colony size to 20, the maximum number of iterations(MAX) to 150, the maximum cycle number of the food source(limit) to 100, the search space range to [-1,1], the number of hidden layer neurons(L) to 10, and the activation function to sigmoid. In order to verify the effectiveness of the ABC-ELM model in improving the calculation accuracy of fundamental frequency amplitude of the transformer surface vibration, an ELM model and a BP model were established for comparison.
Fig. 1 ABC-ELM training process and comparison of calculation results

The fitness curve obtained by training the established ABC-ELM model is shown in Fig. 1(a), and it converges to the optimal value after 83 iterations. Fig. 1(b) and Fig. 1(c) are the final calculation results and absolute percentage error of ABC-ELM, ELM and BP, respectively. Combined with Fig. 1(b) and Fig. 1(c), it can be seen that ABC-ELM has higher calculation accuracy and smaller error fluctuations than ELM and BP, and can more accurately predict the change trend of the transformer vibration fundamental frequency amplitude.

In order to better analyze and compare the performance of the three models, three error evaluation indicators are introduced, which are the maximum absolute percentage error (MAXAPE), the average absolute percentage error (MAPE), and the root mean square error (RMSE). Obviously, the smaller the values of MAXAPE, MAPE, and RMSE, the closer the output value of the model is to the actual value, and the higher the calculation accuracy of the model. The results of comparing the performance of the three models of ABC-ELM, ELM and BP are shown in Table 1:

| Model  | MAXAPE% | MAPE% | RMSE% | TIME   |
|--------|----------|-------|-------|--------|
| BP     | 21.922   | 7.941 | 0.118 | 5.526s |
| ELM    | 17.102   | 5.657 | 0.084 | 0.396s |
| ABC-ELM| 11.432   | 4.310 | 0.065 | 2.898s |

As shown in Table 1, the three indicators of MAXAPE, MAPE, and RMSE of the ABC-ELM model are lower than those of the other two models. Among them, the MAXAPE plays a very important role in the abnormal vibration detection and fault diagnosis of the transformer. The MAXAPE of the ABC-ELM model is much lower than the ELM model and BP model, indicating that the ABC-ELM calculation error is smaller and the credibility is higher. Since ABC-ELM requires multiple iterations in the optimization process, the training time is longer than ELM, but still shorter than BP.

6. Conclusion

Aiming at the characteristics of the nonlinear superposition of the vibration signals of the internal iron core and the winding during the transmission process, this article proposed an ABC-ELM model for calculating the fundamental frequency amplitude of the transformer surface vibration. The model uses the ABC algorithm to optimize the ELM input layer weights and hidden layer biases, overcoming the shortcomings of the traditional ELM output results with large fluctuations. According to the measured data of a transformer, the operating voltage, load current, and oil temperature are used as the model input, and the fundamental frequency amplitude of the transformer surface vibration is used as the model output to start the experiment, and the following conclusions are drawn:

1. Compared with ELM and BP, ABC-ELM has higher calculation accuracy and smaller error fluctuation, and the stability is stronger;
2. In practical applications, the ABC-ELM model can be established to calculate the fundamental frequency amplitude of the transformer surface vibration. Based on the difference between the calculated
value and the measured value, it provides a basis for transformer fault diagnosis and guarantees the safe and stable operation of the transformer.

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