Optimization of Transformer Fault Diagnosis Using Least Squares Support Vector Machine Based on Improved Bald Eagle Search

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Abstract: To solve the problem of low accuracy in fault diagnosis of oil immersed transformers, a transformer fault diagnosis method based on improved bald eagle search algorithm optimized least squares support vector machine is proposed. Aiming at the problem of difficulty in selecting the optimal values of the penalty factor γ and kernel function parameter σ based on manual experience and low fault diagnosis accuracy in least squares support vector machines, an improved Bald Eagle Search (IBES) algorithm is proposed to optimize its parameters. The results indicate that the proposed method has the characteristics of high diagnostic accuracy, simple model, and strong generalization ability.

Keywords: Bald Eagle Search Algorithm; Transformer; Fault Diagnosis; Least Squares Support Vector Machine

1. Introduction

Transformers are key equipment for ensuring the safe transmission of electrical energy in power systems. With the continuous expansion of voltage levels and power grid scale, the number of transformer applications is increasing, resulting in a geometric increase in the probability of transformer failures, which seriously threatens the normal operation of the power system. Therefore, efficient and accurate diagnosis of transformer faults is of great significance for ensuring the safety of the power system.

At present, partial discharge detection technology and Dissolved Gas Analysis (DGA) technology have been widely used as preventive monitoring technologies for power equipment in transformer fault monitoring and diagnosis. With the continuous development of AI technology, most transformer fault diagnosis is improved by combining DGA with intelligent diagnosis. Common intelligent diagnosis methods include neural networks, artificial bee colony algorithm, support vector machine, etc. Neural network methods have disadvantages such as relatively complex systems, slow convergence speed, and overfitting [1-4]. The artificial bee colony algorithm effectively improves the diagnostic accuracy by optimizing the kernel parameters of the kernel principal component analysis method. However, the ABC local search ability is weak, which can easily lead to low search efficiency [5]. Compared with neural networks and ABC algorithms, support vector machines can better handle local minima and have strong learning generalization ability. However, the kernel parameters and penalty factors limit the classification performance of SVM, and improper values can cause significant errors in diagnostic results [6-8].

Bald Eagle Search (BES) is a new type of swarm intelligence metaheuristic optimization algorithm with strong global search ability and fast convergence speed. It has shown good performance in many optimization problems, but still has the drawbacks of easily falling into local optima and low convergence accuracy [9-13].

This paper proposes an IBES optimized LSSVM method for transformer fault diagnosis. By introducing tent chaotic mapping, adaptive t-distribution, and dynamic selection to improve and optimize BES. Firstly, the first generation population is uniformly distributed in the search space through tent chaotic mapping initialization, and the bald eagle position update random number r is optimized using tent chaotic mapping to enhance the global search capability in the initial stage of the algorithm. Secondly, an adaptive t-distribution and dynamic selection strategy are adopted to balance the proportion of global and local search, in order to enhance the algorithm's global search and local development capabilities and accelerate the convergence speed of the algorithm. Using IBES to optimize the penalty factor γ and kernel function parameter σ of LSSVM, and applying the IBES-LSSVM model to transformer fault diagnosis. The feasibility and reliability of the proposed IBES-LSSVM transformer fault diagnosis model were verified through comparative experiments with FA-LSSVM and CS-LSSVM models.

2. Bald Eagle Search Algorithm

BES is a novel heuristic algorithm with strong global search capability [14]. BES simulated three stages of bald eagle hunting fish behavior, namely randomly selecting a search space, then searching for spatial prey, and finally diving to capture prey. The main process of the algorithm is as follows.

1) Randomly select the search space and update the optimal search position based on the number of prey. The position update formula is as follows:

$$P_{i,new} = P_{best} + ar \times (P_{mean} - P_i) \quad (1)$$

Where, $P_{i,new}$ and new represent the updated position of the i-th bald eagle, P_{best} is the current optimal search position, a is the position change control parameter with a value range of (1.5,2), r is a random number within (0,1), and P_{mean} is the average distribution position, P_i is the position of the i-th bald eagle before the update.

2) Within the selected search space, spiral flight and search for the optimal diving capture position for prey. The update formula for spiral flight position is as follows:

$$\theta(i) = \pi\delta r \quad (2)$$

$$\gamma(i) = \theta(i) + rR \quad (3)$$

$$x(i) = \frac{\gamma(i)\sin(\theta(i))}{\max\left|\gamma(i)\sin(\theta(i))\right|} \quad (4)$$

$$y(i) = \frac{\gamma(i)\cos(\theta(i))}{\max\left|\gamma(i)\cos(\theta(i))\right|} \quad (5)$$

Where, $\theta(i)$ and $\gamma(i)$ are the polar angle and polar diameter of the spiral flight equation, respectively. δ and R are the control parameters for the spiral trajectory, with δ ranging from (0,5) and R ranging from (0.5,2). $x(i)$ and $y(i)$ are the polar coordinates of the bald eagle, both ranging from (-1,1). The update formula for the optimal diving capture position is as follows:

$$\begin{aligned} P_{i,new} &= P_i + x(i) \times (P_i - P_{mean}) \\ &+ y(i) \times (P_i - P_{i+1}) \end{aligned} \quad (6)$$

Where, P_{i+1} represents the next updated position of the i-th bald eagle.

3) Quickly dive from the optimal capture position towards the target prey, while other individuals in the population simultaneously move towards the optimal position and launch an attack. The equation of motion state for this stage is as follows:

$$x_1(i) = \frac{\theta(i)\sinh(\theta(i))}{\max\left|\theta(i)\sinh(\theta(i))\right|} \quad (7)$$

$$y_1(i) = \frac{\theta(i)\cosh(\theta(i))}{\max\left|\theta(i)\cosh(\theta(i))\right|} \quad (8)$$

The position update formula for the subduction process is as follows:

$$\begin{aligned} P_{i,new} &= rP_{best} + x_1(i) \times (P_i - c_1 P_{mean}) \\ &+ y_1(i) \times (P_i - c_2 P_{best}) \end{aligned} \quad (9)$$

Where, c_1 and c_2 represent the intensity of the bald eagle's movement towards the center position, with values ranging from (1, 2).

In the first stage of BES, the randomness of the initial position of bald eagles may lead to uneven distribution of their individual positions, thereby reducing population diversity and optimization speed. Therefore, this article proposes an improved bald eagle search optimization algorithm.

3. IBES

3.1 Tent Chaotic Mapping

Considering the significant advantages of tent chaotic mapping in terms of traversal, uniformity, regularity, and iteration speed, the tent chaotic mapping is first used to improve the initialization process of the bald eagle population. The expression for tent chaotic mapping is:

$$x_{k+1}^i = \begin{cases} 2x_k^i & 0 < x_k^i \le 0.5 \\ 2(1 - x_k^i) & 0.5 < x_k^i \le 1 \end{cases} \quad (10)$$

Where, x_{k+1}^i and x_k^i are chaotic sequences, $i = 1,2,\cdots,N$ is the population size, and

$k=1,2,\cdots,d$ is the spatial dimension. By selecting d initial values and following equation (10), d chaotic sequences can be obtained. Then, x_k^i is inverse mapped to the search space to obtain the initialized population.

$$y_k^i = b_{1i} + (b_{ui} - b_{1i})x_k^i \tag{11}$$

Where, b_{ui} and b_{1i} are the upper and lower bounds of x_k^i search, respectively. Then, the tent chaotic mapping is used to improve the position update equation (1) to reduce the impact of random number r on the global search ability of bald eagles. The updated position formula after improvement is as follows:

$$P_{i,new} = P_{best} + a x_{k+1}^i \times (P_{mean} - P_i) \tag{12}$$

3.2 Adaptive T-distribution and Ynamic Selection Strategy

The probability density function of the adaptive t-distribution is as follows:

$$p(x) = \frac{\Gamma(\frac{n+1}{2})}{\sqrt{n\pi}\Gamma(\frac{n}{2})} \times (1+\frac{x^2}{n})^{\frac{n+1}{2}}, \quad -\infty < x < +\infty \tag{13}$$

When the degree of freedom parameter $n=1$, it satisfies $t(n=1)=C(0,1)$ and follows a Cauchy distribution. As n increases, it tends to follow a normal distribution. When $n=\infty$, $t(n\to\infty)\to N(0,1)$ is an approximate Gaussian distribution. The adaptive t-distribution and its mutation operator λ are used to mutate the optimal diving capture position of the second stage bald eagle, in order to improve the global search ability of the algorithm. Taking n as the number of iterations T, the value of T is relatively large in the later stage of iteration, and $t(T)$ is approximately a Gaussian distribution mutation. At this time, the effect of the mutation term is reduced, which is beneficial for the algorithm to perform local search and can improve the convergence speed of the algorithm. But if all individuals introduce the mutation operator λ during each iteration, it will inevitably increase the algorithm's computation time, so dynamic selection probability ρ is used for adjustment.

$$\rho = \omega_1 - \omega_2 \times (T_{max} - T) / T_{max} \tag{14}$$

Where, T_{max} is the maximum number of iterations, ω_1 is the upper limit of dynamic selection probability, $\omega_1 = 0.5$, ω_2 is the magnitude of change in dynamic selection probability, $\omega_2 = 0.1$. The improved position update formula is as follows:

$$P_{i,new}^{'} = P_{i,new} + \lambda t(T) P_{i,new}, \rho < r \tag{15}$$

Where, $P_{i,new}^{'}$ is the position of the i-th bald eagle individual after mutation, $P_{i,new}$ is the position of the i-th bald eagle individual before mutation, λ is the mutation operator, and $\lambda = 1 - T/(T_{max} - 1)$, $\lambda \in [0,1]$. As the number of iterations T increases, λ gradually decreases, and the control of mutation intensity becomes weaker.

4. Least Squares Support Vector Machine

Least Squares Support Vector Machine (LSSVM) is an improved Support Vector Machine (SVM) based on statistical theory. Compared with traditional SVM, LSSVM with kernel function has the advantages of fast computation speed and low computational complexity when processing large-scale data. In this paper, LSSVM is selected for fault type classification [15-17]. LSSVM principle: In the total number of data n and training data $(x_i, y_i), i=1,2,\cdots,n$, x_i and y_i represent the input vector and output data. A nonlinear function is used to map the input space to the feature space. At this time, the classification function is follows:

$$f(x) = \omega\phi(x) + b \tag{16}$$

Where, ω represents the weight vector, and b represents the deviation. For LSSVM, the optimization problem can be transformed into the following equation.

$$\min J(\omega,\xi) = \frac{1}{2}\omega^T\omega + \frac{1}{2}\gamma\sum_{i=1}^{n}\xi_i^2 \tag{17}$$

$$s.t. y_i[\omega^T\phi(x_i) + b] - 1 + \xi_i = 0 \tag{18}$$

Where, ξ_i and γ are the error term and penalty factor, respectively. Introduce Lagrange function to solve optimization problems.

$$L(\omega,b,\xi,a) = J(\omega,\xi) - \sum_{i=1}^{n} a_i[\omega\phi(x) + b + \xi_i - y_i] \tag{19}$$

a_i is a Lagrange multiplier, and according to the KKT condition, the partial derivative of ω, b, ξ, a is calculated.

$$\begin{cases} \dfrac{\partial L}{\partial \omega} = 0 \Rightarrow \omega = \sum_{i=1}^{n} a_i y_i \phi(x_i) \\ \dfrac{\partial L}{\partial b} = 0 \Rightarrow \sum_{i=1}^{n} a_i y_i = 0 \\ \dfrac{\partial L}{\partial \xi_i} = 0 \Rightarrow a_i = C\xi_i \\ \dfrac{\partial L}{\partial a_i} = 0 \Rightarrow y_i[\omega\phi(x)+b]-1+\xi_i \end{cases} \tag{20}$$

Simplify equation (20) by eliminating ω and ξ, and obtain the following formula.

$$\begin{bmatrix} 0 & Y^T \\ Y & \Omega_{i,j}+C^{-1}I \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ I_n \end{bmatrix} \tag{21}$$

Where, $Y^T = [Y_1, Y_2, \cdots, Y_n]$, $a = [a_1, a_2, \cdots, a_n]$, $I_n = [1,2,\cdots,n]^T$, $\Omega_{i,j} = Y_i Y_j \phi(x_i)^T \phi(x_j)$. According to Mercer's condition, the kernel function and mapping function have the following relationship.

$$K(x_i, x_j) = (x_i)^T \phi(x_j) \tag{22}$$

The radial basis function (RBF) is chosen as the kernel function here.

$$K(x_i, x_j) = \exp(-\frac{\|x_i - x_j\|}{2\sigma^2}) \tag{23}$$

Where, σ is the kernel function. By substituting the results of the above two equations into $f(x) = \omega\phi(x) + b$, the classification function is obtained as follows:

$$f(x) = a_i Y_i K(x_i, x_j) + b = 0 \tag{24}$$

However, the key parameters γ and σ of this method have a significant impact on the fault diagnosis results. Therefore, this paper adopts the proposed IBES method to optimize the two key parameters. The main process is as follows:

Step 1: Extract data and divide it into a training set and a testing set.

Step 2: Set the population size of bald eagles, the optimization range of key parameters γ and σ, the maximum number of iterations, the objective function dimension, and the initial value boundary conditions, and initialize the population using chaotic mapping according to equation (11).

Step 3: Update the values of parameters γ and σ, calculate the fitness of bald eagle individuals, and rank their fitness values to determine the current optimal fitness and corresponding position.

Step 4: Optimize the random number r using tent chaotic mapping and update the position of the bald eagle according to equation (12).

Step 5: If $\rho \geq r$, update the spiral movement position of the bald eagle according to equation (6); If $\rho < r$, introduce the adaptive t-distribution and its mutation operator λ, and update the position of the bald eagle spiral movement according to equations (6) and (15).

Step 6: Determine if the maximum number of iterations has been reached. If not, return to the Step 3 loop; If achieved, output the optimal parameters γ and σ, and obtain the optimal IBES-LSSVM model.

Step 7: Apply the optimal IBES-LSSVM model to diagnose and classify transformer faults.

5. Experimental Verification

According to references [18-20], 422 sets of transformer fault data were selected, and Table 1 shows the specific distribution of data samples:

In Table 1, there are 295 training sets and 127 testing sets, with six types of faults: medium low temperature overheating fault, high temperature overheating fault, partial discharge fault, low-energy discharge fault, high-energy discharge fault, and normal state. These faults are sorted by encoding from 1 to 6.

422 sets of data were used for fault diagnosis using the IBES optimized LSSVM method proposed in this paper, and the experimental results are shown in Figure 1.

The diagnostic accuracy of the IBES optimized LSSVM diagnostic model in Figure 1 is 94.49%. The proposed diagnostic method is more sensitive to medium and low temperature overheating, normal state, and partial discharge faults, and has a relatively low diagnostic effect on high temperature overheating. However, the comprehensive diagnostic accuracy is above 94%. To verify the effectiveness of the method proposed in this paper, it was compared with the FA-LSSVM method and CS-LSSVM method, and the results are shown in Figure 2 and Figure 3, respectively.

From Figures 2 and 3, it can be seen that the accuracy of the FA optimized LSSVM diagnostic model is 81.1%, while the comprehensive accuracy of the CS optimized LSSVM method is 88.98%, which is significantly lower than the method proposed in this paper, verifying the effectiveness of the proposed method.

Table 1. Data Sample Distribution

	Type	Sample size	Training set	Test set
1	Normal	67	47	20
2	partial discharge	69	48	21
3	Low energy discharge	72	50	22
4	High-energy discharge	71	50	21
5	Medium low temperature overheating	72	50	22
6	High temperature overheating	71	50	21

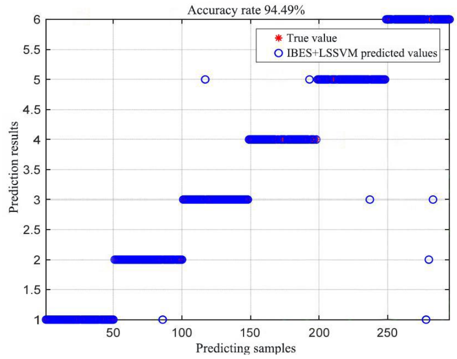

Figure 1. Fault Diagnosis Results of IBES Optimized LSSVM Method

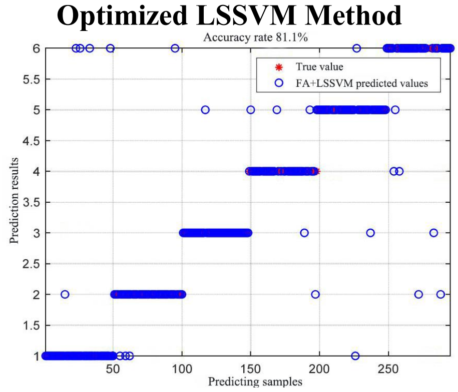

Figure 2. Fault Diagnosis Results of FA Optimized LSSVM Method

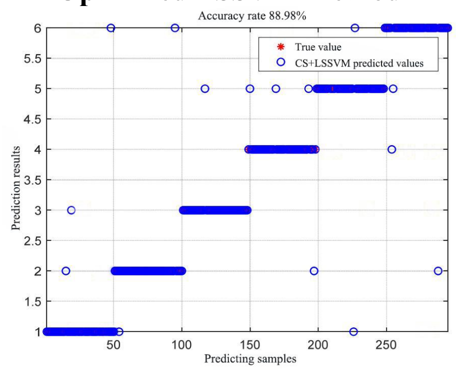

Figure 3. Fault Diagnosis Results of CS Optimized LSSVM Method

6. Conclusion

To solve the problem of low accuracy in transformer fault diagnosis, a transformer fault diagnosis method based on IBES optimized LSSVM is proposed. By introducing tent chaotic mapping and adaptive t-distribution to improve BES, the algorithm's optimization ability is enhanced. Using IBES to optimize LSSVM parameters, the generalization ability and classification accuracy of LSSVM are improved. And the proposed IBES-LSSVM method was compared with FA-LSSVM and CS-LSSVM to verify its effectiveness.

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