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Fault diagnosis of power transformer based on improved particle swarm optimization OS-ELM

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Abstract: A transformer is an important part of power transmission and transformation equipment. Once a fault occurs, it may cause a large-scale power outage. The safety of the transformer is related to the safe and stable operation of the power system. Aiming at the problem that the diagnosis result of transformer fault diagnosis method is not ideal and the model is unstable, a transformer fault diagnosis model based on improved particle swarm optimization online sequence extreme learning machine (IPSO-OS-ELM) algorithm is proposed. The improved particle swarm optimization algorithm is applied to the transformer fault diagnosis model based on the OS-ELM, and the problems of randomly selecting parameters in the hidden layer of the OS-ELM and its network output not stable enough, are solved by optimization. Finally, the effectiveness of the improved fault diagnosis model in improving the accuracy is verified by simulation experiments.

Key words: power transformer, fault diagnosis, improved particle swarm optimization, OS-ELM, parameter optimization

1. Introduction

A transformer is an important part of the power transmission and transformation equipment, and the normal operation of the transformer ensures the safety of the power system. Once the transformer is damaged, it will not only cause long-term interruption of the power supply, but also greatly affect the industrial and agricultural production. In addition, the transformer is an expensive device with a complicated structure. Once the damage is caused, the repair is extremely difficult and inevitably causes serious economic losses. Therefore, accurately identifying the potential failure of the transformer can effectively maintain and repair the transformer. In order to ensure the smooth operation of the transformer, effective detection is required to prevent various faults. Among them, monitoring methods for transformers include: insulation monitoring, temperature monitoring, on load tap changer (OLTC) monitoring of core and insulation leakage current monitoring, monitoring of winding and monitoring of working conditions.

In the case of partial discharge and overheating, oil and insulation paper in the transformer will be decomposed, and produce CO, CO_2 and various hydrocarbon gases. Therefore, there is a close relationship between the composition and concentration of the gas in the oil and the type of transformer fault. Almost all the large transformers use transformer oil for insulation and heating. During the operation of the transformer, the solid insulation material in the transformer oil will be aging and decomposition under the mixed effect of the combination of various factors such as discharge, high temperature and oxidation will occur. Some gases will be produced, such as low molecular hydrocarbons like CH_4, C_2H_6, C_2H_4 and C_2H_2, as well as gases of CO, CO_2 and H_2. When partial discharge or overheating occurs in the transformer, the gas will be produced in large quantities, so the analysis of the gas content in the oil to diagnose the transformer fault is a trend in recent years [1]. In addition, the dissolved gases analysis (DGA) in oil will not be affected by external electric fields and magnetic fields, and it can detect the latent faults existing inside the transformer and can become an effective method for the fault diagnosis of oil-immersed transformers [2].

By analyzing the gas composition and concentration in the oil of the transformer, the type of transformer fault can be judged. In recent years, researchers have proposed a variety of transformer fault diagnosis methods, such as a characteristic gas method and three-ratio method. The advantage of these methods is that the principle is simple and easy to implement, but because the ratio boundary is too absolute, it is difficult to provide an explanation for all possible ratio combinations. Besides, transformers of different voltage levels are difficult to make reasonable adjustments when applying the ratio, so most of these traditional diagnosis methods only make a vague judgment on the type of fault, and may even cause misjudgment of the fault type. Due to the diagnosis results of the traditional diagnosis methods are not ideal, the transformer diagnosis methods based on artificial intelligence algorithms such as neural networks [3–11], genetic algorithms [12], fuzzy theory [13] and expert systems [14] have developed rapidly.

Yan Luo *et al*. proposed an algorithm based on the quantum immune optimization of a back-propagation (BP) neural network for transformer fault diagnosis. Compared with the traditional back-propagation neural network (BPNN), it can improve the accuracy of fault diagnosis and reach the effective identification of transformer faults [7]. Wenxiong Mo *et al*. combined a particle swarm optimization (PSO) algorithm with support vector machine to optimize the key parameters to enhance the fault diagnosis capability [8]. Jie Dai *et al*. proposed a transformer fault diagnosis method based on deep belief networks (DBN) to improve diagnosis accuracy, their DBN model adopts multi-layer and multi-dimension mapping to extract more detailed differences of fault types [9]. Xingquan Ji *et al*. established a fault diagnosis model based on stacked auto-encoders and softmax regression, and the method can solve the problems such as availability of data extraction, a better local optimum and a gradient to dissipate more efficiently [10]. The performance of an artificial intelligence method mainly depends on its parameters, but the current selection of various artificial intelligence algorithms is difficult. Therefore, how to use an intelligent optimization algorithm to find suitable model parameters has become the research focus of an artificial intelligence method for transformer fault diagnosis. In order to improve the shortcomings of the artificial intelligence algorithms, some transformer fault diagnosis algorithms based on improved artificial intelligence algorithms have been proposed [15–17].

In this paper, the online sequence extreme learning machine (OS-ELM) algorithm is studied. And we found that the OS-ELM algorithm randomly selects the input weight and the hidden layer deviation, which causes some hidden layer nodes to be invalid. Therefore, the sample generalization is insufficient and the network output is not stable enough. In response to this problem, the paper proposes an improved particle swarm optimization (IPSO) algorithm to optimize the OS-ELM. The main contributions of the paper are as follows: first, the PSO algorithm is improved and applied to optimize the parameter selection of the OS-ELM algorithm, the algorithm is named IPSO-OS-ELM, which overcomes the instability of the OS-ELM algorithm. Secondly, the transformer fault diagnosis model is established based on the IPSO-OS-ELM algorithm, which improves the accuracy of transformer fault diagnosis. Finally, the experimental results show that the proposed model has a good effect on transformer fault diagnosis.

2. Improved particle swarm optimization

2.1. Particle swarm optimization

Particle swarm optimization (PSO) is an evolutionary computation that finds the optimal solution in a given search space based on the probability law. Its characteristics are as follows:

1. The PSO can get more accurate results without complicated operations.
2. Because the PSO is a probabilistic application, it is more flexible and effective.
3. It can overcome premature convergence and improve search ability.
4. PSO optimization takes less time.
5. In online mode, the PSO will get a better solution.

The PSO algorithm is a matrix-based stochastic optimization technique proposed by Kennedy and Eberhart in 1995. The algorithm compares the search process to the process of birds searching for food in a given search space. There is a specific spatial area, although the birds do not know the specific location of the food, they know the distance of the food, each time the bird searches for food, it will be closer to the food. In this process, each bird is likened to a particle. Each particle has two properties: speed and position and each particle has a memory function. The particle can remember the best position it searched. Each time the particles search, they will follow the current optimal particle until the optimal solution is found [18].

In the particle swarm optimization process, each particle is a solution, and each iteration is a process of finding the optimal solution, which is better to move closer to the search space. The calculation formula is as shown in (1):

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 \left[y_i(t) - x_i(t)\right] + c_2 r_2 \left[g_i(t) - x_i(t)\right]. \tag{1}$$

In the above formula, ω is the inertia weight, $y_i(t)$ is the optimal position of the particle individual in the iterative process, $g_i(t)$ is the optimal position of the whole in the iterative process. The optimal position of the single particle is represented by p_{best}, that is the best position of the particle is in the search process at time t, g_{best} represents the best position of the overall position found by the entire particle swarm after searching the global. The fitness is calculated by the objective function. The current position of the calculated particle is represents by $x_i(t)$, c_1 and c_2 both represent the acceleration of the particle, r_1 and r_2 indicating the direction of motion, and the number is randomly selected from the uniform distribution, and the speed has a limit value, and the general limited range is $(V_{\min}, V_{\max})$.

After one iteration, the particle will update its position, as shown in (2):

$$x_i(t+1) = x_i(t) + v_i(t+1). \tag{2}$$

2.2. Improved particle swarm optimization

In order to improve the optimization ability of particle swarm optimization (PSO) algorithm, many scholars have studied the improvement of particle swarm optimization algorithm. For example, the literature [19] proposed a particle swarm optimization algorithm based on fuzzy control, generating an optimized fuzzy function to the improved PSO. In [20], a new chaotic optimization particle swarm optimization algorithm is proposed. The algorithm integrates chaotic thought into the particle swarm search process and builds a chaotic particle swarm model. It overcomes the defect of the traditional particle swarm optimization algorithm, due to which it is easy to fall into precocity, and it gets local extremum points in the initial stage of the optimization, which further improves the global optimization ability. In this paper, a new particle swarm optimization algorithm is proposed. The principle of the algorithm is to use the trigonometric function to improve the dynamic mode of inertia weight (ω) with time, so that ω remains a larger value at the beginning of the algorithm. As the algorithm runs down, keeps ω smaller, the particle swarm global search ability is effectively improved, and the convergence performance is effectively improved.

During the search of the IPSO algorithm, the inertia weight ω is continuously adjusted, that is, in the initial stage of the algorithm, a larger value is taken, and as the algorithm continues to decrement the value of ω, it is possible to find the better seed in the global scope. In the later stage of the algorithm, if ω is small, it can ensure that the particle is searched in the vicinity of the extreme point. The accuracy of the convergence of this algorithm is greatly improved [21].

Based on the above analysis, according to the characteristics of the sum, the inertia weight ω is adjusted so that the change formula of ω is shown in (3):

$$\omega_1(t+1) = [0.65 + 0.25 \times \cos(\pi \times t/t_{\max})] \times [a \times \sin(2\pi \times t/t_{\max}) + 1], \tag{3}$$

where, $\omega_1(t+1)$ represents the $t+1^{\text{th}}$ inertia weight value obtained by t iterations, a is the adjustment factor, the value range is $a > 0$, after a number of data experiments to determine $a = 0.02$ in this paper.

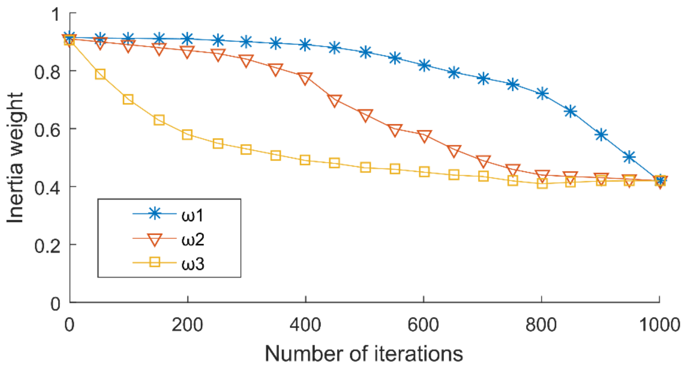
Therefore, the particle swarm speed is updated as (4):

$$v_i^{t+1} = \omega_3(t+1) \cdot v_i^t + c_1 r_1 (p_{\text{best}}^t - X_i^t) + c_2 r_2 (g_{\text{best}}^t - X_i^t). \tag{4}$$

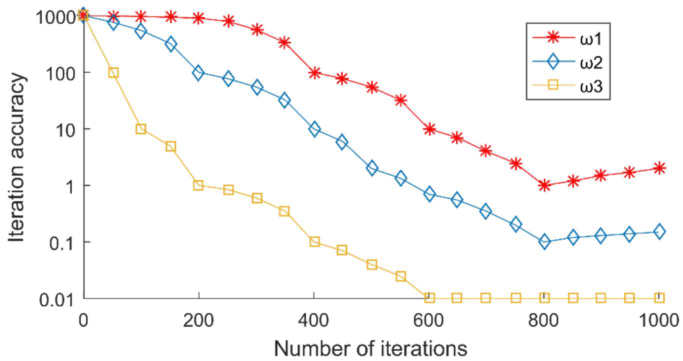
In order to ensure that the position change of the particles is in the proper range, the speed of the particles is adjusted according to (5), so that it is controlled within the maximum speed:

$$v_i^{t+1} = \min\left(V_{\max},\ \max(-V_{\max},\ v_i^{t+1})\right). \tag{5}$$

In this paper, the optimization performance of the IPSO algorithm is tested. This experiment uses the classical Griewank test function to test the optimization of the algorithm $\omega_1 - \text{PSO}$, $\omega_2 - \text{PSO}$ and $\omega_3 - \text{PSO}$. Where the global minimum value of the function is 0, the particle number of the algorithm is 40, and $c_1 = c_2 = 40$, when the iteration accuracy reaches 10^{-10} or the number of iterations exceeds 1 000, the optimization process ends. The process is shown in Fig. 1(b).



(a)



(b)

Fig. 1. Inertia weight dynamic trend (a), Griewank function test for optimization performance of different algorithms (b)

3. Transformer fault diagnosis model based on IPSO-OS-ELM

The OS-ELM has the advantages of fast learning speed, good generalization performance and high classification accuracy, but its classification performance is affected by random parameters of the network, input weights and the thresholds, so the network output is unstable. The IPSO algorithm has the advantage of using simple and easy operations to get the best value. Therefore, the paper uses the IPSO algorithm to select the input weight and deviation of the hidden layer, and uses the generalized matrix analysis to calculate the output weight. In the improved particle swarm optimization algorithm, the inertia coefficient changes linearly with time, and the fitness of each particle is obtained by the average error.

The specific optimization process is as follows:

1. Initialize the particle swarm to randomly define the initial position and speed of each particle.
2. Determine the fitness; calculate the fitness of each particle.

3. Compare the position of the optimal fitness of each particle, and update its position.
4. Compare the position of the optimal fitness of each particle, and update its position.
5. Adjust the speed and position of the particles.
6. If the termination condition is reached, the process ends; otherwise, step 2 is continued.

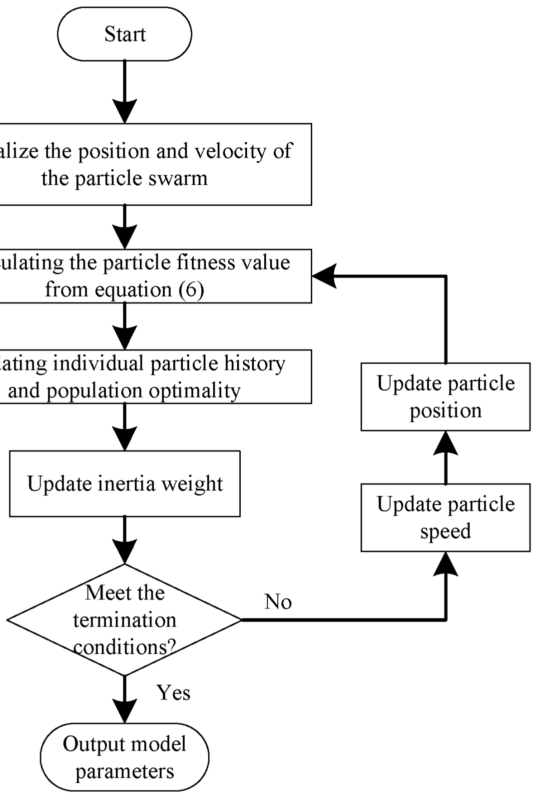
The core idea of the improved particle swarm optimization algorithm for optimizing the OS-ELM algorithm is to optimize the parameters in the OS-ELM.

The fitness function of the particle swarm is obtained by (6):

$$F_{RMSE} = \sqrt{\frac{\sum_{j=1}^{N} \left\| \sum_{j=1}^{L} \beta_i g(\omega_i \cdot x_j + b_i) - t_i \right\|_2^2}{mN}}. \tag{6}$$

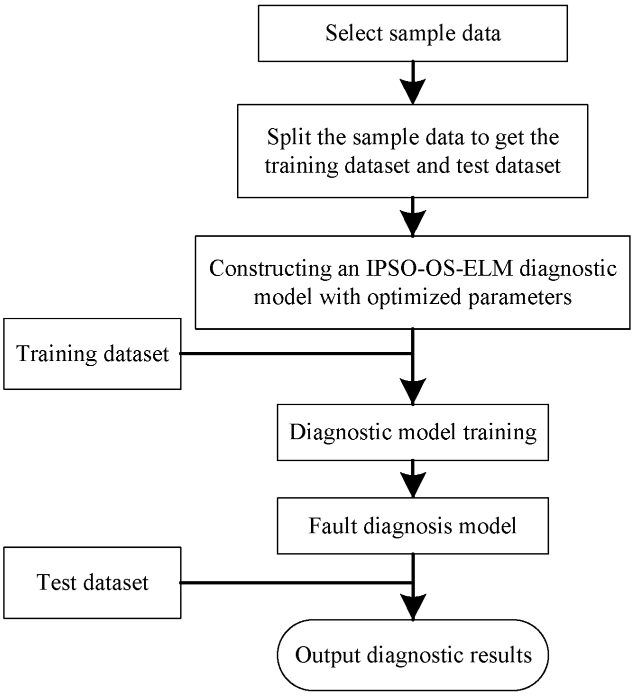
The specific flow chart of the improved particle swarm optimization algorithm for optimizing the OS-ELM algorithm is shown in Fig. 2(a).

After optimization by the IPSO algorithm, we obtain the parameters of the optimized OS-ELM model, and then we use these parameters to construct the transformer fault diagnosis model based on the IPSO-OS-ELM algorithm. The diagnosis model is shown in Fig. 2(b).



(a)

Fig. 2.



(b)

Fig. 2. Improved particle swarm optimization algorithm optimizing the parameters of OS-ELM algorithm (a); fault diagnosis model based on IPSO-OS-ELM (b)

4. Experiment and result analysis

The experiment was run on Windows 7 64-bits and on Matlab R2016a. In the experiment, the 4182 data collected from the grid company was used and divided into training data and test data according to a ratio of 3:1. Divide the transformer status into nine categories, such as, low temperature overheating (less than 150°C), low temperature overheating (150~300°C), medium temperature overheating (300~700°C), high temperature overheating (above 700°C), partial discharge, low energy discharge, low energy discharge and overheating, arc discharge, arc discharge and overheating. The output of the OS-ELM model is used as a classification vector. The dimension of the classification vector is the number of state categories in the sample. The state code of each class is shown in Table 1.

Since the OS-ELM algorithm randomly selects parameters of the hidden layer, the network output is not stable enough. For this problem, the improved particle swarm optimization algorithm is proposed to optimize the input weight and threshold of the OS-ELM. In the test, the hidden layer node of the OS-ELM was set to 20 according to experience, and the control parameters were all set to 2.0, in which the initial inertia was 0.9 and the end inertia was 0.4. The population size of the particle swarm algorithm is set to 20, and the maximum number of iterations is set to 500, so

Table 1. Transformer status code table

Status category	State vector
Low temperature overheating (less than 150°C)	(0, 0, 0, 0, 0, 0, 0, 0, 1)
Low temperature overheating (150~300°C)	(0, 0, 0, 0, 0, 0, 0, 1, 0)
Medium temperature overheating (300~700°C)	(0, 0, 0, 0, 0, 0, 1, 0, 0)
High temperature overheating (above 700°)	(0, 0, 0, 0, 0, 1, 0, 0, 0)
Partial discharge	(0, 0, 0, 0, 1, 0, 0, 0, 0)
Low energy discharge	(0, 0, 0, 1, 0, 0, 0, 0, 0)
Low energy discharge and overheating	(0, 0, 1, 0, 0, 0, 0, 0, 0)
Arc discharge	(0, 1, 0, 0, 0, 0, 0, 0, 0)
Arc discharge and overheating	(1, 0, 0, 0, 0, 0, 0, 0, 0)

that the particles will have enough time to complete the information exchange, the initialization range of all components in the particle is selected between $[-1, 1]$. The evolution curve is shown in Fig. 3.

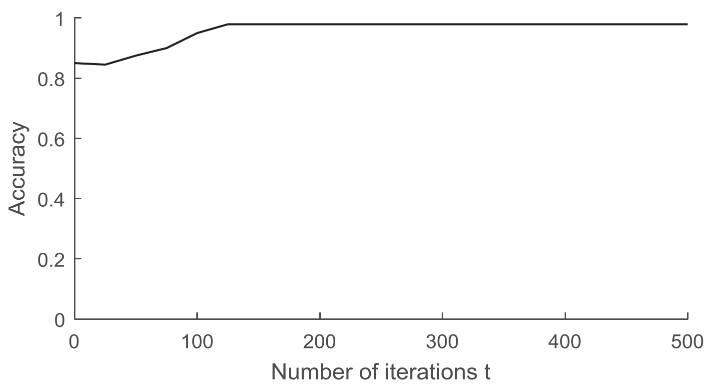
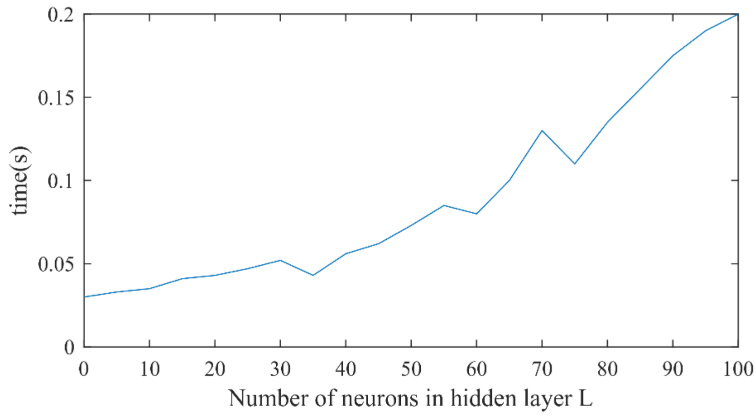


Fig. 3. IPSO optimizes OS-ELM parameters

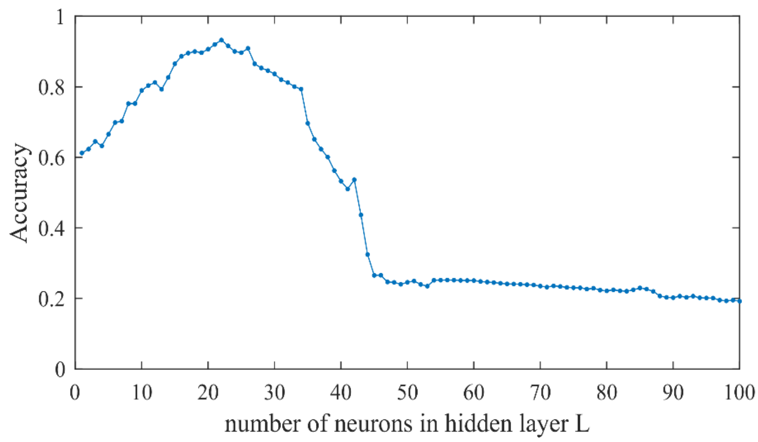
It can be seen that when the IPSO algorithm optimizes the OS-ELM, the optimal classification accuracy rate is 97.9% in the 125th generation, and the classification accuracy rate reaches a high level, which has a good effect. Therefore, the parameters adopted in the IPSO-OS-ELM fault diagnosis model of this paper are the parameters generated after 125 iterations optimization.

The parameters selected by the optimized OS-ELM algorithm are as follows: the number of neurons in hidden layer L, set the size of the dataset $N_0 = 100$ during training, and the size of the data block BLOCK = 10 during the learning process.

The training time of the IPSO-OS-ELM diagnostic model varies with the number of neurons in the hidden layer as shown in Fig. 4(a):



(a)



(b)

Fig. 4. Training time of IPSO-OS-ELM fault diagnosis model (a), accuracy rate of IPSO-OS-ELM fault diagnosis model (b)

It can be seen from the experimental results that the training time of the IPSO-OS-ELM fault diagnosis model increases with the number of hidden layer neurons.

The classification accuracy of the IPSO-OS-ELM diagnosis model varies with the number of hidden neurons L as shown in Fig. 4(b).

It can be seen from the experimental results that the classification accuracy of this model is closely related to the selection of the number of hidden layer neurons, and the accuracy rate reaches 93.25% when the number of the hidden layer neurons is 22.

It can be seen from the experimental results that when we choose the number of hidden layer neurons, we need to consider the two factors, that is, we need to achieve the unity of correct rate and training efficiency.

Next, in the same experimental environment and experimental data, the fault diagnosis model based on the ELM and OS-ELM algorithm is compared with the IPSO-OS-ELM model proposed in this paper.

The training time and classification accuracy of the three models are shown in Fig. 5(a) and Fig. 5(b), respectively.

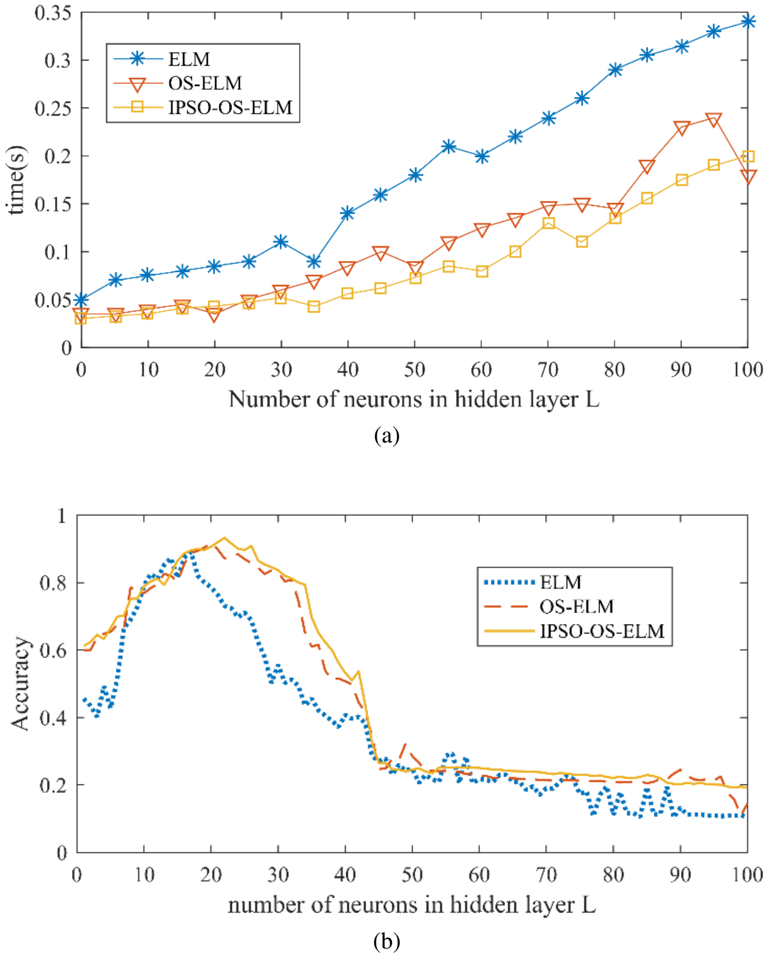


Fig. 5. Comparison of the training time of the three fault diagnosis models (a), comparison of the accuracy rate of the three fault diagnosis models (b)

It can be seen from the experimental results that the training time of the transformer fault diagnosis model based on the IPSO-OS-ELM algorithm is less than that required by the ELM and OS-ELM, as well as the achieved accuracy (highest accuracy is 93.25%) is better than the ELM (the highest accuracy is 89.09%) and OS-ELM (highest accuracy rate of 91.77%), that is, the model proposed in this paper has better performance in transformer fault diagnosis.

5. Conclusions

In this paper, the particle swarm optimization algorithm is improved and applied to the transformer fault diagnosis model based on the OS-ELM. The problem of randomly selecting parameters in the hidden layer and the network output is not stable enough in the OS-ELM was solved by optimization, which improves the diagnosis accuracy and stability of the transformer fault diagnosis model. The experimental results verify the good performance of the transformer fault diagnosis model based on the IPSO-OS-ELM algorithm in fault diagnosis.

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