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Method for Troubleshooting Construction Machinery Based on Particle Swarm Optimization and Wavelet Theory

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Abstract: The research of fault diagnosis and prediction technology of construction machinery can not only improve the working efficiency of the staff, but also shorten the fault time. Therefore, the use of appropriate engineering machinery fault diagnosis and prediction methods, early prediction of the fault, failure, can quickly and accurately determine the nature and location of the fault, timely troubleshooting, to avoid economic losses caused by the fault. In this paper, a fault diagnosis model based on particle swarm optimization wavelet neural network is proposed. In order to effectively enhance the optimization ability of particle swarm optimization algorithm and solve the problem of slow convergence speed of particle swarm optimization, the optimization ability of improved particle swarm optimization algorithm is greatly improved through the improvement of inertia weight factor, learning factor and position iteration formula. Experimental results show that the proposed optimization algorithm can obtain higher classification accuracy, which verifies the effectiveness of PSO-WNN in identifying fault degree.

1. Introduction

Accurate fault diagnosis and prediction technology of construction machinery can reduce the offline time caused by the fault of the system, so as to reduce the economic loss caused by the fault, and avoid the problem of people's life safety caused by the offline. Traditional fault diagnosis and prediction technology need maintenance personnel to site inspection, and some live remote, equipment failure occurs, the staff can not arrive in time, at this time, the fault diagnosis technology, it has played a large role, reduce the time of fault diagnosis, quick to judge, and was relieved from the waste of human resources [1-2]. In the same way, some small chips, it is difficult to quickly judge the fault point by manual, so to improve the ability of fault diagnosis, is one of the important issues in the development of construction machinery. Secondly, effective fault diagnosis and prediction technology of construction machinery can save the system status of each fault, and in the event of the same fault again, an effective emergency mechanism can be quickly formed to achieve fast, accurate and stable recovery operation [3-4]. In the traditional fault diagnosis, due to the data preservation and update is not timely, it still needs to waste a lot of manpower and material resources to identify the fault when the fault occurs, and also wastes a lot of rescue time. Accurate fault diagnosis can be performed by comparing real-time data with historical data to develop effective fault prediction. When the same fault occurs again and is diagnosed, the system can immediately run the historical fault handling method to repair the system [5-6]. Finally, the fault prediction technology of construction machinery can nip the fault in the bud before it happens. Accurate fault prediction technology will greatly reduce the probability of failure and reduce the risk caused by failure.

The development of foreign fault stage technology can be divided into two periods: the first stage started in the early 1960s, when the United States started the research on fault diagnosis and established the National Machinery Research Institute, which greatly reduced the failure rate of equipment, saved a lot of manpower and material resources, and produced great economic benefits [7]. Research on fault diagnosis was carried out in the UK in the early 1970s, and the UK Mechanical Health Center is a pioneer in the field of fault diagnosis in the UK [8]. Although compared with the United States and the United Kingdom, Japan carried out the research on fault diagnosis technology later, but the development speed was fast, and it only took 6 years to apply the fault diagnosis technology into practice [9]. The second stage is in the late 1980s. With the development of modern science and technology, a large number of high and new technologies are combined with fault diagnosis technology, and fault diagnosis technology tends to be mature [10]. With the development of computer technology, computer has become an indispensable tool in the field of fault diagnosis, and many institutions have developed computer diagnosis systems and applied them in practice [11]. For example, the "test equipment Monitoring" and "steam turbine monitoring equipment" developed by the United States can realize the real-time acquisition, monitoring, calculation, drawing and other functions of equipment signals. When a device fails, the monitoring device can be used to automatically diagnose and analyze the fault, and at the same time, the computer will save a lot of data about the operation of the device [12].

The fault prediction technology can nip the fault in the bud before it happens. Accurate fault prediction technology will greatly reduce the probability of failure and reduce the risk caused by failure.

2. Fusion of Particle Swarm Optimization Algorithm and Wavelet Theory Troubleshooting Algorithm

2.1. Particle Swarm Optimization Algorithm

(1) Basic particle swarm optimization algorithm

Particle Swarm Optimization (PSO) algorithm, according to the simulation of birds in the process of searching for food through mutual cooperation of migration, clustering, communication and other behaviors thus proposed a population intelligent Optimization algorithm, in the computer we can build a mathematical model for it, Similar to many of the particles are placed in a search for solution of search space, space of all the particle position with the objective function to evaluate, and each particle according to their own place in the history of the individual best position and best position for the history of all the particles within the search space, with random disturbance to the space move on to the next step, the optimal solution The final particle will be in the position of the optimal solution of the objective function [13-14]. PSO algorithm is also an iterative form of optimization algorithm. Every iteration will bring the particle closer to the optimal solution until it reaches the global optimum and the iteration ends [15]. The mathematical model of PSO is described as follows: In a D-dimensional search space, a group composed of N particles flies at a certain speed. When each particle makes the next flight, it will give priority to the historical best position in its search process and the global best position in the group, and choose the best one to change its position. The so-called position is also the solution of the objective function [16-17].

(2) Improved particle swarm optimization algorithm

Inertia weight factor. The factor mainly affects the weight of the particle velocity performance in this system. Relevant studies point out that the parameter in the range of [0.3,0.7] has the best performance and better global optimization ability. Therefore, a nonlinear decreasing change strategy is designed to make as many parameters as possible within the numerical interval of the optimal parameter. The formula is modified as follows:

$$\omega' = \frac{3\omega'' - \omega'''}{2} - (\omega'' - \omega''') * (\frac{2t}{t'} + 0.5\cos(\frac{\pi t}{t'})) \tag{1}$$

Where, ω"and ω ' ' ' respectively represent the maximum and minimum value of inertia weight factor parameter, t represents the current iteration number, and t 'is the maximum iteration number.

The learning factor. The learning factors C1 and C2 represent the weight parameters of particle motion approaching the individual optimum and the global optimum respectively, and their main functions are to adjust the global search level of system particles and the later convergence speed [18]. Generally speaking, C1 decreases and C2 increases. Such parameter setting method is very beneficial to the improvement of algorithm's optimization ability. Therefore, C1 is set to decrease from 2.5 to 0.5, and C2 is set to increase from 0.5 to 2.5.

Particle velocity and position update formula. After modifying the inertia weight factor and learning factor, the new particle velocity update formula is:

$$V_i^{kg+1} = \omega' V_i^{kg} + c_1' r_1 (p_i^{kg} - X_i^{kg}) + c_2' r_2 (BestS_i^{kg} - X_i^{kg}) \tag{2}$$

2.2. Wavelet Neural Network Particle Swarm Optimization Improved Algorithm

Since wavelet theory has better localization performance, it has been widely used in various fields since it was proposed. On the basis of artificial neural network and wavelet analysis, researchers have gradually developed a new kind of artificial neural network with layered and multi-resolution, called wavelet neural network. In the process of network training, wavelet neural network is established on the basis of theory and the whole network structure, which can significantly improve the learning and generalization ability of wavelet neural network.

The PSO first needs to initialize a bunch of random particles. The neighbor of a particle is represented by substituting part of the particle for the whole population, and the local extreme value is the extreme value in the neighbor. Pbesti and GBESTI are abbreviated as individual extremum of particle and global extremum of particle respectively. Suppose in S = a1, b1 x... In the search space of the D-dimensional hypercube represented by ×aD and bD, the individual and global extremum of particle search are updated in each iteration according to the following formula.

R1 and r2 are independent random numbers in the interval [0,1]. C1 and C2 are acceleration constants during particle search. Pbesti and Gbesti represent particle I's own experience and group experience, respectively. The fitness value of the whole particle is evaluated by the optimized function F (x), and the size of individual extreme points pbesti and Minf (x) is determined according to the size of F (pbesti). The best point of individual extreme points in the whole population is regarded as the global extreme point. When Vmax is set large, the global search ability of PSO is strong. When Vmax is small, the optimization algorithm of particle swarm optimization has strong local ability. In the process of particle search, if the number of iterations reaches the maximum while the minimum error accuracy does not reach the requirements, or the error accuracy value reaches the requirements, the iteration of particle search will be terminated.

The specific implementation process can be expressed as:

Initialize, the population X (t) represents x1,x2... Xm has a total of m particles, which are randomly selected in the space Rn. V(t) is determined according to the change of the initial displacement of particles. The initial evolution algebra t is 1, the acceleration factor is set as C1, C2, and the maximum allowable iteration step MaxIter. The velocity of the particle V.

Each parameter in the wavelet neural network is randomly initialized, that is, each connection weight, threshold and other parameters in the neural network are randomly selected.

Randomly generate a particle swarm matrix with the number of particles m, velocity V and position X.

Evaluate the fitness value of the function corresponding to each particle.

Through the iteration of particle direction and step size in the search process, if the number of iterations reaches the maximum while the minimum error accuracy does not meet the requirements, or the error accuracy value reaches the requirements, the iteration of particle search will be terminated.

The corresponding values of Pgd were substituted into the stretching factor A, translation factor B and each weight and threshold of the wavelet neural network to calculate the network output.

3. Fault Diagnosis Experiment

The fault degree identification process of simulation model based on PSO-WNN recognition system is shown as follows:

Obtain fault data in simulation model;

Fault feature sets were extracted, and RMI and SMI were used to screen fault features.

Transfer learning is carried out on the selected features, and a new feature matrix is mapped.

According to the classification performance, PSO is used to optimize the important parameters of WNN.

The important parameters obtained by optimization are imported into PSO-WNN for the final fault degree classification.

The feature samples of transfer learning based on the characteristics of simulation data under different working conditions are used as the training input of 1000 sets of features mapped by transfer learning at 45Nm, and the training sample is set to 40%. 120 sets of features mapped by transfer learning at 85Nm are randomly selected as the test samples. The system is run for 10 times and then the average value is taken.

4. Analysis of Experimental Results

4.1. Fault Degree Classification of Simulation Model

Table 1. Classification accuracy of different models

	40	80	120	160
Model1	83.24%	86.17%	87.90%	92.47%
Model2	80.32%	83.68%	88.74%	94.98%
PSO-WNN	85.06%	89.51%	92.03%	95.76%

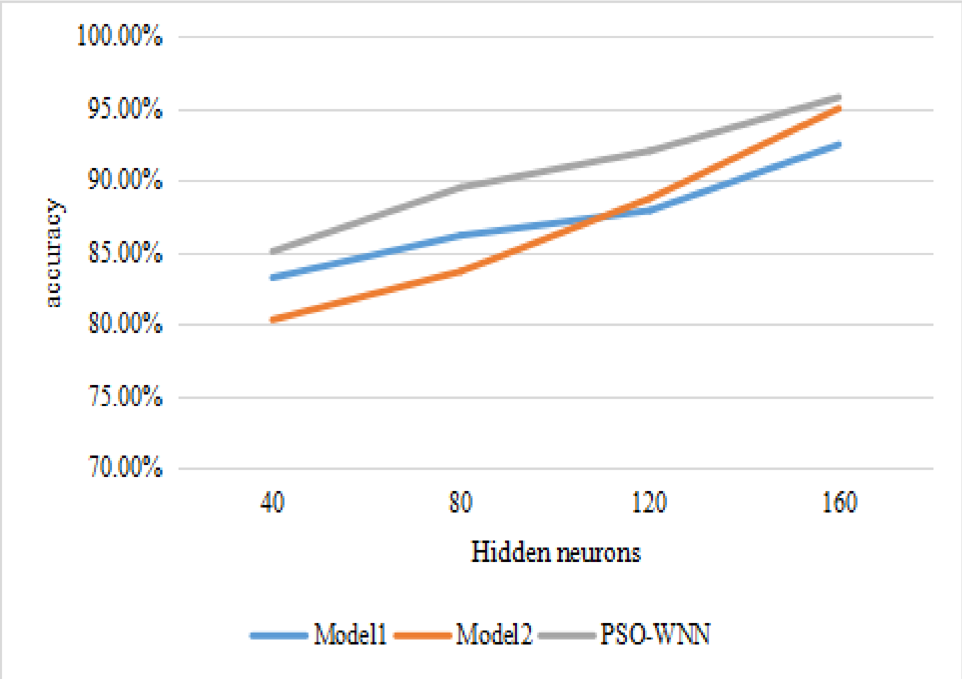

Figure 1. Statistics of classification accuracy of three models

As shown in Table 1 and Figure 1, at first, the classification accuracy of PSO-WNN was 85.06%, while the classification accuracy of Model1 and Model2 were 83.24% and 80.32%, respectively. With the increase of the number of neurons, the classification accuracy gradually improved. When the number of neurons in the hidden layer was between 40 and 80, the accuracy of WK-ELM was significantly higher than that of the other three classifiers. Finally, the classification accuracy of WK-ELM reached 95.76%.

4.2. Fault Degree Classification of Measured Sample Feature Mapping

Table 2. Classification accuracy of measured sample feature mapping

	40	80	120	160
Model1	86.85%	89.53%	92.36%	93.07%
Model2	82.59%	86.08%	86.34%	89.51%
PSO-WNN	86.17%	90.58%	93.72%	97.28%

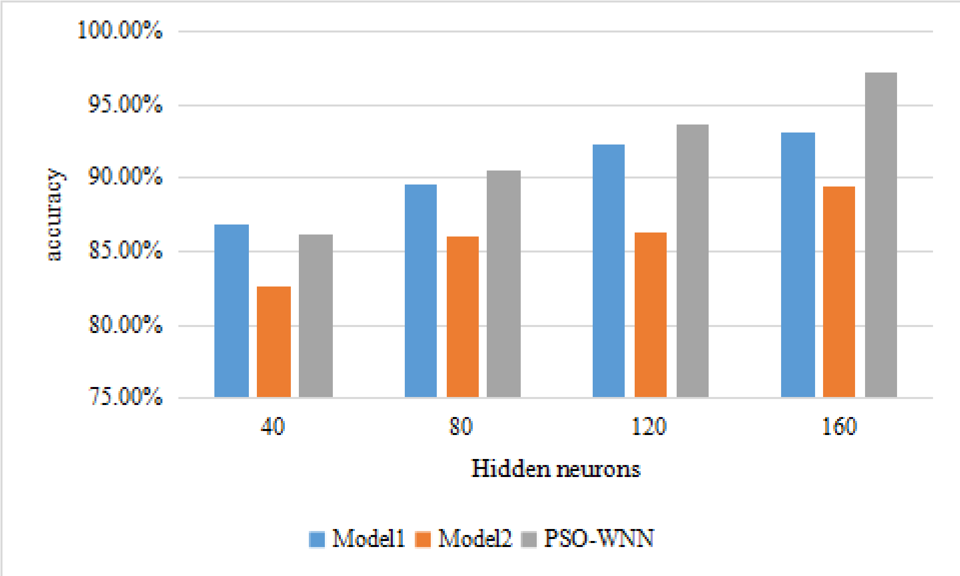

Figure 2. Classification accuracy of different models for feature mapping of measured samples

As shown in Table 2 and Figure 2, at first, the classification accuracy of PSO-WNN was only 86.17%, while that of Model and Mode2 were 86.85% and 82.59%, respectively. As the number of neurons in the hidden layer increases, the classification accuracy gradually improves. It can be noted from the figure that when the number of neurons is 120 to 180, the classification effect of PSO-WNN is better than the other three. Finally, the classification accuracy of PSO-WNN will reach 97.28%, which is higher than the accuracy of the other two classification algorithms.

4.3. Verification of Classification Accuracy

Table 3. Fault level grading performance

Method	Classification Accuracy
Sensitivity Analysis	96.14%
Specificity Analysis	97.67%
Average	97.02%

Through calculation, as shown in Table 3, the classification accuracy of PSO-WNN is 96.14% through sensitivity analysis, and 97.67% through specificity analysis, which proves that the proposed method has a good classification accuracy.

5. Conclusion

This paper focuses on the fault diagnosis research under different working conditions. Model simulation and practical experiments are combined, and feature sets sensitive to fault degree are obtained by screening feature sets and transfer learning, and these feature sets are applied to the proposed fault diagnosis system. In this paper, wavelet transform and neural network are organically and closely combined to form wavelet neural network, so that it not only has the advantages of wavelet transform, but also contains the artificial neural network generally have the unique characteristics of self-adaptation, self-learning and strong fault tolerance. Then the principle and algorithm flow of wavelet neural network are described. The characteristic parameters of the fault diagnosis experiment are used for fault diagnosis by wavelet neural network.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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