

Research Article

Intelligent Malfunction Identification Method in Mechanical Manufacturing Process Based on Multisensor Data

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Received 8 April 2022; Accepted 4 May 2022; Published 23 May 2022

Academic Editor: Zaoli Yang

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Current technology trends have been gradually integrated into the production of all walks of life, which play an indispensable part in promoting the intelligent development of enterprises, and have brought a greater impact on production and reformation. With the rapid development of the economy and technology, the manufacturing industry has played a very important role. For this reason, the introduction of artificial intelligence into machinery manufacturing can not only improve production efficiency but also save labor and reduce labor costs. The application of artificial intelligence in machinery manufacturing has a critical good role in promoting industrial upgrading and transformation. This time, through the application of smart algorithms in machinery manufacturing and its automation, we expect that such a technological revolution can provide a new development prospect for the development of manufacturing intelligence and automation. Taking the malfunction identification of string striking machinery as an example, this paper studies the smart identification method of mechanical malfunction based on multisensor. In the process of malfunction identification of keyboard stroke machinery, the accuracy of malfunction identification results is low due to the influence of the identification model. Moreover, a malfunction identification and analysis method for keyboard stroke machinery based on BP optimized by GA is proposed. The mechanical data of keyboard chords are acquired by sound-sensitive sensors, and the data features are extracted by wavelet packet decomposition. Based on the optimized BP, a mechanical malfunction judgment model is constructed, and various parameters in the model are calculated. The results show that the intelligent identification method proposed has exhibited strong adaptability and superiority compared with the traditional method.

1. Introduction

The manufacturing industry has played a very important role in pushing for technological innovation. It can be said that the level of manufacturing development will have an important impact on technological innovation. Intelligence and automation have become very lively topics in today's society. Researchers [1–3] will integrate artificial intelligence into machine manufacturing to drive the development of the entire industry. This promotes the continuous upgrading and transformation of machinery manufacturing. In addition, this can also highlight its own competitive advantages in optimization and enhance core competitiveness [4–6]. At present, artificial intelligence has covered all walks of life, and its application scope is becoming wider and wider, but the links involved in machinery manufacturing are very complex and

changeable. The integration of new technologies still requires constant running-in. How to make full use of artificial intelligence to upgrade the improvement of manufacturing level and quality has become the focus of the current industry. By analyzing the application advantages of artificial intelligence in machinery manufacturing and its automation, the application situation at different levels is expounded, and then, the positive impact of artificial intelligence on the development of the manufacturing industry is revealed.

To meet the spiritual needs of people and the needs of the country, the application of musical instruments, such as the piano, is more extensive. Among them, due to the complex structure of the piano, there are many failures. The most common one is the mechanical failure of the keyboard [7–9]. Due to the prolonged use of the keyboard mechanism, the mechanism may be deformed or damaged, thus affecting the

normal operation of the piano. Therefore, it must be implemented immediately to conduct regular inspections of the keyboard action mechanism. In the research process of conventional mechanical malfunction identification method, there are always shortcomings. At present, the traditional feature extraction method mainly includes wavelet analysis [10–12], Empirical Mode Decomposition [13, 14], Ensemble Empirical Mode Decomposition [15, 16], wavelet packet analysis [17, 18], and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise decomposition [19, 20]. Traditional feature extraction and malfunction classification method rely heavily on manual engineering and expert knowledge. In particular, with the advent of the era of industrial big data and the development of sensor technology, traditional feature extraction and malfunction classification method have been unable to meet the diagnostic needs under massive data. In this context, the development and promotion of intelligent malfunction identification have begun. Intelligent malfunction identification refers to the application of machine learning theories such as artificial neural networks, support vector machines, and deep neural networks to machine malfunction identification. However, the traditional recognition method is given to the traditional algorithm such as artificial neural network or support vector machine to realize the calculation process. Due to the shallow network structure, their ability to extract complex malfunction features is limited. In recent years, deep neural networks such as deep autoencoders and deep convolutional neural networks have been widely used to build end-to-end intelligent identification models, reducing the dependence on manual labor and expert knowledge, and greatly promoting the development of intelligent malfunction identification. Based on a convolutional neural network, Zhao et al. [21] extracted features from mechanical vibration data and used long-term and short-term memory networks to judge malfunction conditions. The diagnostic accuracy of this method has been improved, but the scope of application is small. Senger and Karim [22] used the improved random forest method to obtain useable mechanical malfunction feature vectors through the mechanical principal features, thereby constructing a malfunction identification model. Through research, it can be seen that this method has a strong anti-interference ability, but the calculation process is complicated and takes more time.

Aiming at the shortcomings of the above identification method, the mechanical malfunction identification method is designed based on the BP optimized by GA and based on the principle of wavelet packet analysis through the extraction of mechanical features, the construction of network models, and the design of model parameters. In addition, high-precision identification and identification results of mechanical malfunctions in piano keyboard strokes are obtained. Before elaborating on the main text, for the convenience of readers, we intend to use the following abbreviations to replace the cumbersome words in the text. The main contents include replacing BP neural network with BP and replacing the genetic algorithm with GA. This substitution is only for the convenience of reading the article and does not involve grammatical issues of the overall terminology.

2. Design of Mechanical Malfunction Identification and Analyze Method

In the process of mechanical malfunction identification, all diagnostic analysis behaviors need to be based on mechanical characteristic signals. Through the extraction of feature vectors, basic data are provided for subsequent malfunction identification. Firstly, the acoustic wave sensor is used to collect the corresponding keyboard vibration signal, and the interference information in the signal is removed by soft threshold denoising, including high-frequency noise signal and ultra-low-frequency signal trend item. Then, the preprocessed signal is decomposed by multilayer wavelet packet analysis, which is an upgraded algorithm of the wavelet transform. The influence of the number of decomposed layers and the selected wavelet basis function on the decomposition result is obvious. In the process of mechanical signal analysis, the wavelet basis function needs to meet the requirements of orthogonality, regularity, and compactness. According to the previous research [23–25], this paper selects “db10” to decompose the collected acoustic signal with 5 layers of wavelet packets, which is used to explore the distribution of mechanical signals in the frequency domain. Next, the decomposed results are processed by the normalization method, and the eigenvectors of the frequency channel and the overall eigenvectors are obtained, respectively. The detailed process of wavelet packet decomposition is shown in Figure 1.

In the figure, $D_{j,k}$ represents the original signal and f represents the signal frequency. It can be seen that the original signal is decomposed into 3 layers.

According to the feature extraction results, to ensure that the processing speed of the neural network is improved, the network input nodes are minimized so that the network speed can be improved. In this way, the purpose of selecting the feature quantity in the mechanical data can be achieved.

2.1. BP Optimized Based on GA. As one of the data-driven method, BP does not require complex mathematical calculations but only relies on the computing power of computers. By correcting the weights and thresholds of the learning samples in BP, we can improve the nonlinear fitting effect. Because the information synthesis ability of BP is extremely powerful, this intelligent prediction method can be applied to other scientific research fields and has wide adaptability. However, the recognition system also has certain problems. It mainly includes the selection of the initial threshold and weight of the neural network, the construction of the overall framework of the neural network, and the problem of how to correctly and reasonably select the prediction output function.

GA is a parallel random search optimization method that simulates the natural genetic mechanism and biological evolution theory. Based on the biological evolution principle of nature, it is introduced into the coding tandem group formed by the optimized parameters. Individuals are screened according to a chosen fitness function and by the selection, crossover, and mutation in genetics. Individuals with good fitness values are retained, and individuals with

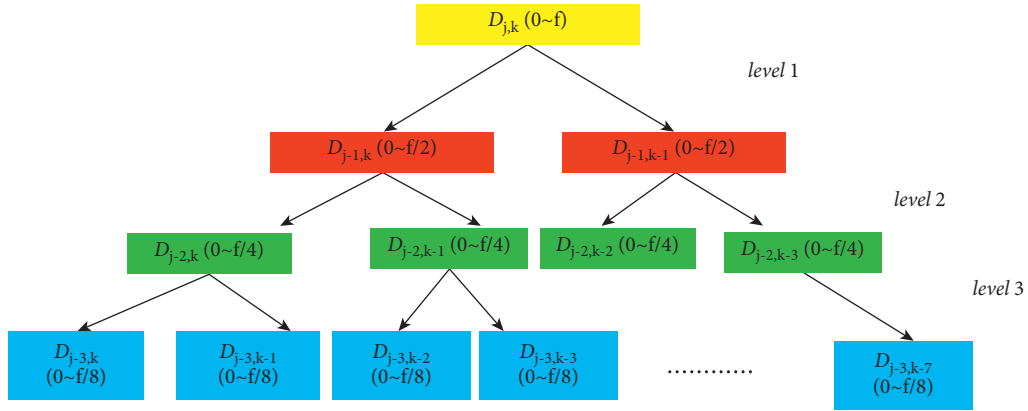


FIGURE 1: Schematic diagram of wavelet packet decomposition.

poor fitness values are eliminated. The advantages of genetic algorithms are mainly manifested in three main aspects. Moreover, its applicability has been recognized by domestic and foreign scholars and institutions.

GA optimization-based BP includes three parts: neural network structure determination, GA optimization, and BP prediction. Among them, GA is used to optimize the initial weights and thresholds of BP so that the optimized BP can better predict the output. GA finds the optimal initial weights and thresholds for BP neural network through selection, crossover, and mutation operations.

Aiming at the analysis of the malfunction identification, the problem of the hammering machinery belongs to the field of nonlinear pattern recognition and is suitable for the recognition problem of BP. Therefore, in the process of malfunction identification, it is necessary to optimize the overall identification system by setting the relevant GA factors based on the BP, building a network model, and expressing the output part of the model to the malfunction identification result file. The input part of the network model is the malfunction identification of the hammering machinery, and the BP model optimized by the GA is used to complete the real-time judgment of the mechanical malfunctions of the keyboard hammering. The application of the BP recognition system based on GA optimization is shown in Figure 2.

Typically, the operation of a BP model consists of two parts. On the one hand, there is the working link, in which the connection weights of different nodes need to be fixed. The calculation of the network model starts from the input layer, and through various levels of calculation, the output value of each node is obtained. On the other hand, there is the learning link, in which the output is guaranteed to be a fixed value, and each connection weight is calculated in reverse from the output layer, to modify each connection weight in the reverse calculation process of the neural network model. Figure 3 exhibits the operation procedure of the simplest neural network.

In the figure, X_1 and X_2 represent neurons corresponding to the input layer. h represents the computational error of the hidden layer and the output layer. w is the calculation weight. A_1 and A_2 represent the correlation coefficients of the output layer.

The BP network belongs to a multilayer feedforward neural network, which transmits the signal forward and transmits the error backward. The results of each training prediction are different, which is due to the randomness of the parameter selection of the BP network, and the initial value of each time is different. And the BP network is easy to fall into the local optimum in the process of evolutionary learning, the proficiency speed is slow, and the global optimum cannot be found. GA includes population initialization, fitness function, selection operation, crossover operation, and mutation operation. It is a global search algorithm. Combining the local search ability of the BP with the global search ability of the GA makes up for the random defect in the parameter selection of the BP, and the prediction results are more accurate.

In the actual operation process, the initial weights and thresholds of the BP can be obtained according to the individual, and the BP is trained with the training data to predict the system output, and the absolute value of the error between the predicted output and the expected output and E is used as the individual fitness. The formula for calculating the value F is as follows:

$$F = k \left(\sum_{i=1}^N \text{asb}(y_i - o_i) \right), \quad (1)$$

where N is the number of network output nodes, y_i is the expected export of the i th node of the BP, o_i is the actual output of the i th node, and k is the coefficient related to the built-in laws of the algorithm.

GA selection operation has many methods such as the roulette method and the tournament method. When we choose the roulette method, that is, the selection strategy based on the fitness ratio, the selection probability p_i of the individual can be expressed as follows:

$$\begin{cases} f_i = \frac{J_i}{F_i}, \\ p_i = \frac{J_i}{\sum_{j=1}^m f_j}, \end{cases} \quad (2)$$

where F_i is the value of the fitness function of the individual, J_i is the relevance reduction factor, and m is all databases involved in overall intelligent computing.

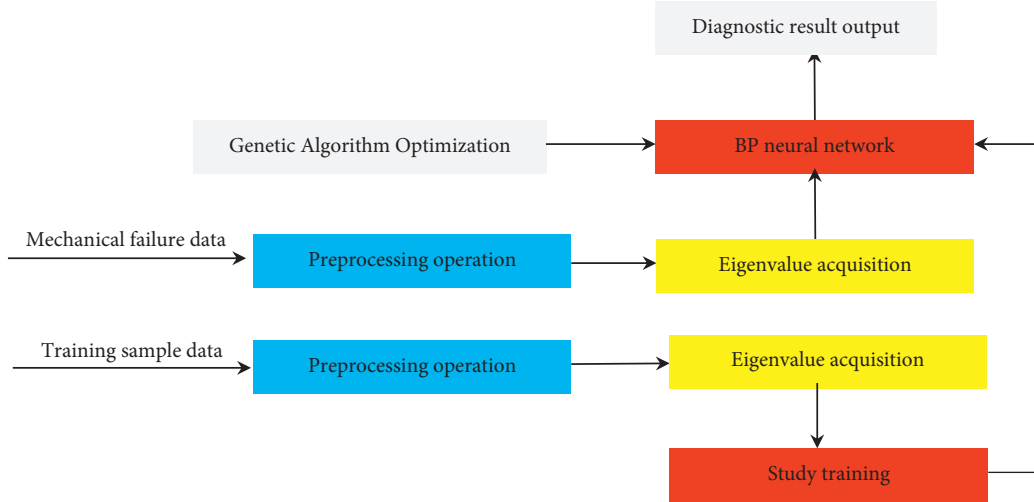


FIGURE 2: Design of identify structure based on GA-optimized neural network pattern recognition function.

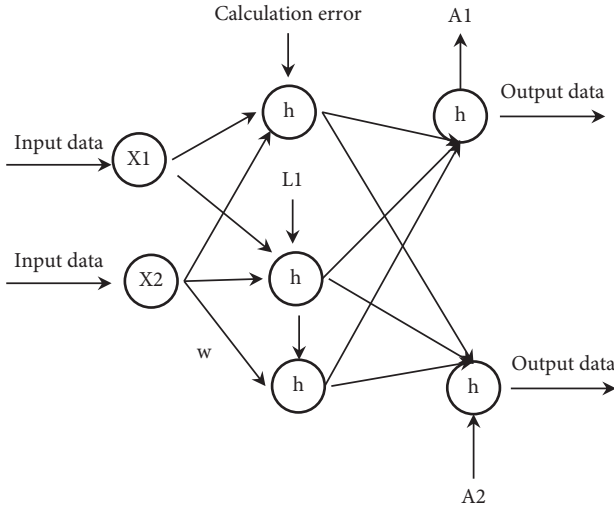


FIGURE 3: The operation flow of BP.

The crossover operation method of the k th chromosome and the l th chromosome at j is as follows:

$$\begin{cases} a_{kj} = a_{kj}(1-b) + a_{lj}b, \\ a_{lj} = a_{lj}(1-b) + a_{kj}b, \end{cases} \quad (3)$$

where b is an artificially set Gaussian random number. Its value range can be preprocessed by normalization.

We can select the j th gene of the i th individual to perform the mutation operation to complete the overall process of the GA.

Based on the idea of biological evolution, the GA performs genetic operations on the solution domain to find the optimal value and the corresponding optimal fitness value. GA optimization BP is divided into three parts, namely, BP structure determination, GA optimization, and BP prediction. The main content of the first part is to determine the BP structure according to the number of input and output parameters and then determine the individual

length of the GA. The main content of the second part is to use the GA to optimize the parameter value. Each individual in the population contains a network ownership value and threshold value, and the minimum value of the fitness function is found through selection, crossover, and mutation operations. Finally, the BP prediction uses the network initial weights and thresholds corresponding to the optimal individual to assign values, and the function output is predicted after training. The basic process of genetic algorithm optimization of the neural network is shown in Figure 4.

2.2. Calculation Parameters of Malfunction Identification Model. In the model calculation process, to ensure good communication between the input layer and the output layer, it is necessary to enable the concealed layer to receive and extract the output layer information and transmit the processed information to the output layer. The research on the number of concealed layers shows that it has a non-negligible impact on the computing power of the prediction system. As the number of layers increases, the computing power will increase accordingly. However, it also increases the computation time of the prediction system. Neural network structures all contain a concealed layer. Taking into account the computational accuracy of the network, the appropriate number of neurons is determined by increasing the quantity value of concealed layer nodes. In the process of determining the number of neurons in the concealed layer, it is indispensable to analyze the input and output of the prediction system.

$$m = \sqrt{n+l} + a, \quad (4)$$

where n , l , and m represent the number of nodes in the input layer, the concealed layer, and the output layer, respectively. a represents the linear coefficient in the calculation process.

Simultaneously, two transfer functions are needed in the BP structure to safeguard the accuracy and real-time performance of data transmission. The sigmoid activation function is used to complete the information transfer at different levels. Because the range of output values involved

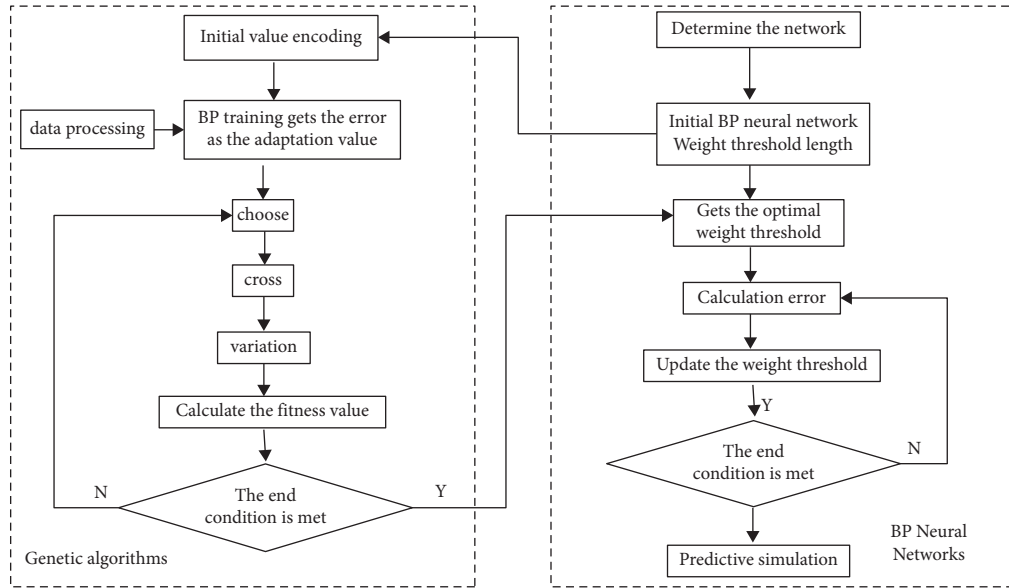


FIGURE 4: GA optimization-based BP.

in malfunction identification is small, the sigmoid function can be selected for both transfer functions.

$$f(n) = \frac{1}{1 + \exp(-n)}, \quad (5)$$

where n represents the number of layers of decomposition.

In the process of model application, it is also necessary to determine the learning efficiency. On the one hand, based on the experience, the learning rate of network training is selected, and then, the value of numerical experimental error is used to analyze whether the network learning rate meets the requirements. On the other hand, when the network is trained for a long time and cannot produce a large degree of error reduction, it proves that the selected learning efficiency cannot meet the requirements. Through the continuous trial calculation and back-calculation process, we can obtain the computational network model required for error prediction. Figure 5 exhibits the variation law of numerical experimental error with respect to training time.

As shown in Figure 5, when the number of training times reaches the optimal value, the experimental error of the network will reach the minimum value. Beyond this range, there will be a state of overtraining, increasing the range of training errors. For each network trial calculation, the optimal training times of the model can be determined through a mapping relationship curve similar to that shown in Figure 6.

To sum up, the operation of the mechanical malfunction identification system based on the GA optimization neural network proposed in this paper can be completed in Figure 6.

3. Brief Description of Experimental Monitoring and Experimental Results

3.1. Case Verification and Analysis. To ensure that the designed malfunction identification method can exert good performance in practical application, an experimental test is

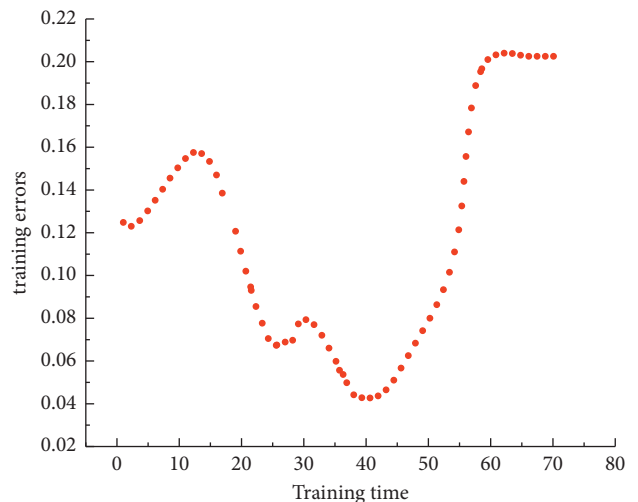


FIGURE 5: Training times and training errors of BP.

carried out. The mechanical transition data set of keyboard stringing is used, which contains 300 fundamental wave data, including multiple sets of single-string and multistring malfunction data. Since the ratio between the two is set to 10:2, the purified signal data extracted from multiple sets of experiments are used to verify the correctness, rationality, and adaptability of the proposed method. Due to the designed diagnostic method, it is based on the BP optimized by GA.

Among them, the typical signal collected is shown in Figure 7.

According to the calculation principle of GA and BP, the GA optimization BP algorithm is realized in MALTAB. The graph of adaptation degree with increasing computation time is shown in Figure 8.

According to the above calculation results, the optimal parameter values, namely, weights and thresholds, are obtained. Then, we can assign optimal initial weights and

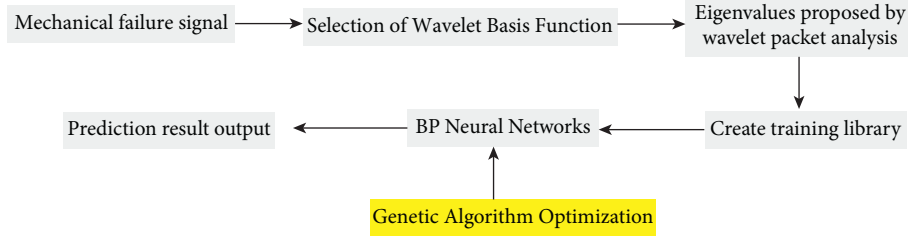


FIGURE 6: Mechanical malfunction identification system based on GA optimized neural network.

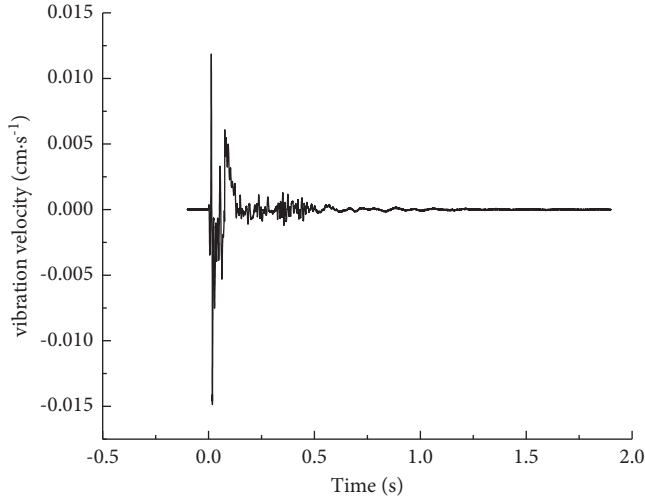


FIGURE 7: Typical time history curve of signal.

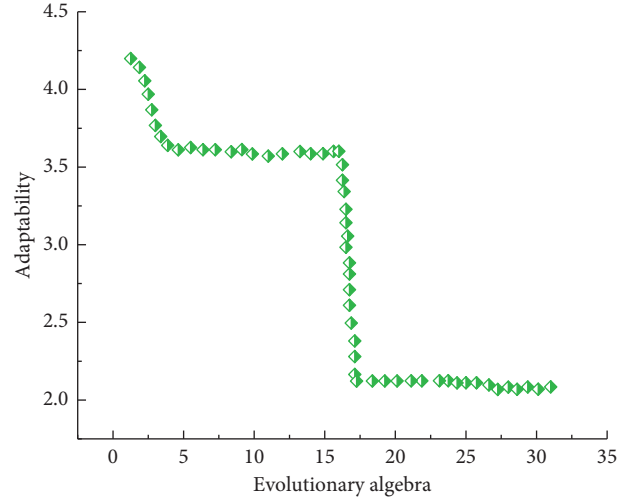


FIGURE 8: The change of the fitness function with the number of calculation steps.

thresholds to the neural network. Finally, it is output after training 1000 times with the training data.

At the beginning of the experiment, the number of neurons must be decided, and the number of input neurons for the identification subnet is set to $n = 10$. The number of output neurons is represented by L , and here, we set $L = 7$. The value range of the number of hidden layer nodes is set between 6 and 16. Table 1 summarizes the analysis data of the preprocessing results of the numerical experiments.

According to Table 1, when the number of concealed nodes is 9, 10, 11, and 12, the training error will change. It can be clearly found that when the numerical value of the total number of nodes is 12, the number of training steps of the neural network is the smallest, only 168 steps. Figure 9 is the training error curve of the overall system. Figure 10 shows the relationship between the training error and the number of concealed nodes.

Since the network converges in step 168, the number of nodes in the concealed layer of the BP network is set to 11. The above parameters are used for mechanical malfunction Identity, and two conventional malfunction identification methods are selected for testing under the same conditions. Through the comparison of experimental results, the performance of different malfunction identification methods is analyzed.

To show the accuracy of the prediction method, the optimized BP is compared with the traditional neural network. The comparison errors of the 100 groups of training

TABLE 1: Relevant training results of BP.

The number of concealed layer nodes	Training error	Training step
6	$4.37e-4$	532
7	$1.64e-4$	346
8	$1.22e-4$	235
9	$1.02e-4$	219
10	$9.87e-5$	200
11	$9.62e-5$	168
12	$1.01e-4$	212
13	$1.35e-4$	378
14	$1.38e-4$	352
15	$1.25e-4$	333
16	$1.23e-4$	311

data obtained in the experiment are shown in Figure 11. It can be seen from Figure 10 that the prediction error of the BP is relatively large compared with the measured relative variables of mechanical failure, and the maximum has reached -0.4 . The error of the network optimized by the GA is basically kept up and down the horizontal axis, the error is small, and the maximum error is less than 0.1. The above analysis results show that it can basically reflect the changing trend of mechanical failure variables in the spatial dimension.

In order to further verify the reliability of the experimental results, as shown in Figure 12, the root mean square

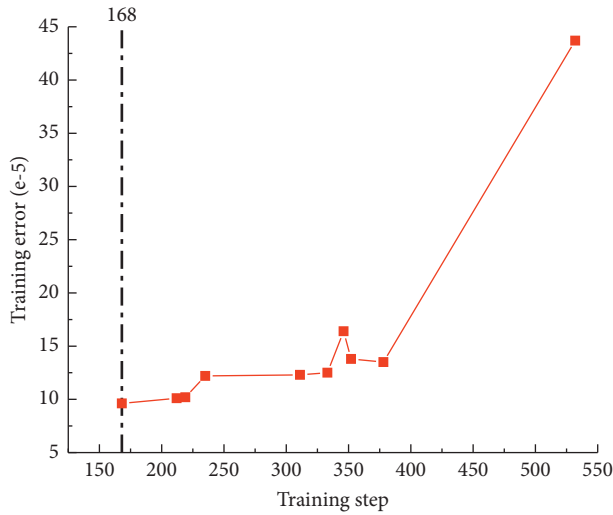


FIGURE 9: Mathematical relationship curve of two key variables of neural network steps.

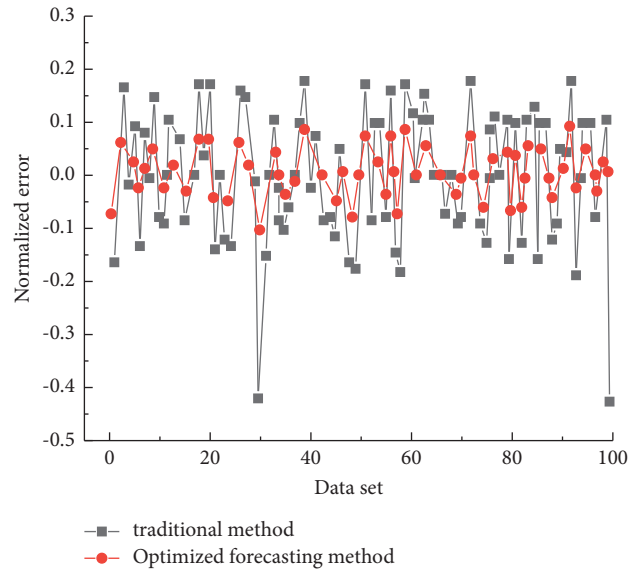


FIGURE 11: Comparison of training errors of the two methods.

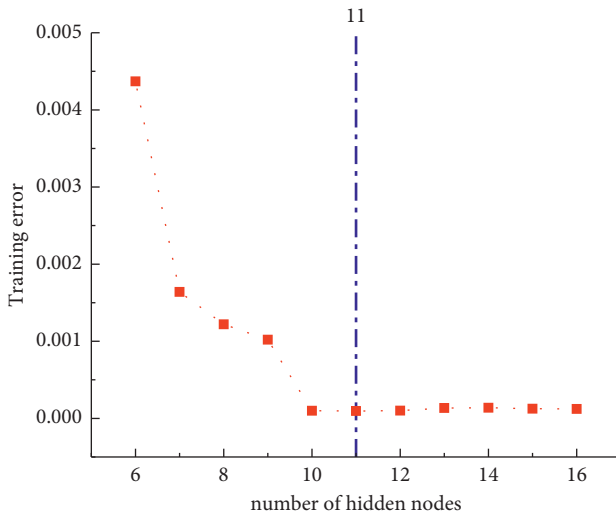


FIGURE 10: Correlation mathematical fitting curve between the number of nodes and the experimental normalization error nodes.

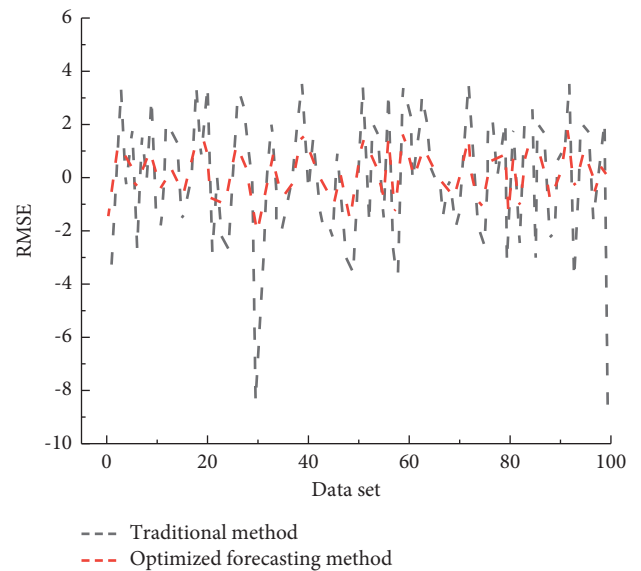


FIGURE 12: Comparison of root mean squared difference of the two methods.

difference of the two methods is compared. The comparison results are consistent with the results obtained by experimental error.

Figure 13 is an overall model data display effect diagram. We can clearly draw the following viewpoints that when training rounds reach 225, the training losses of the three methods gradually stabilize. However, the analysis shows that the stability of the designed diagnostic method is better, and the overall loss is significantly reduced compared with the other two conventional traditional prediction methods. This also proves the advanced nature and adaptability of the aforementioned method.

3.2. Comparison of Experimental Results of Single-String Malfunction Identification. For single-string mechanical malfunctions, it is divided into 3 test sets for malfunction

identification testing, and the single-string malfunction identification results are recorded. In addition, we calculated the diagnostic accuracy of different malfunction identification methods through the previously formulated calculation program. The specific experimental results are shown in Table 2.

From the accuracy comparison relationship in Table 2, it can be found that the identification result of the aforementioned method optimized by GA is obviously better than the two conventional methods. The diagnostic accuracy of the method in this paper is higher than 90%, and the average accuracy is 92.51%. The average diagnostic accuracy of the two conventional methods was 86.94% and 87.85%, respectively. Through multiple network model training, the number of

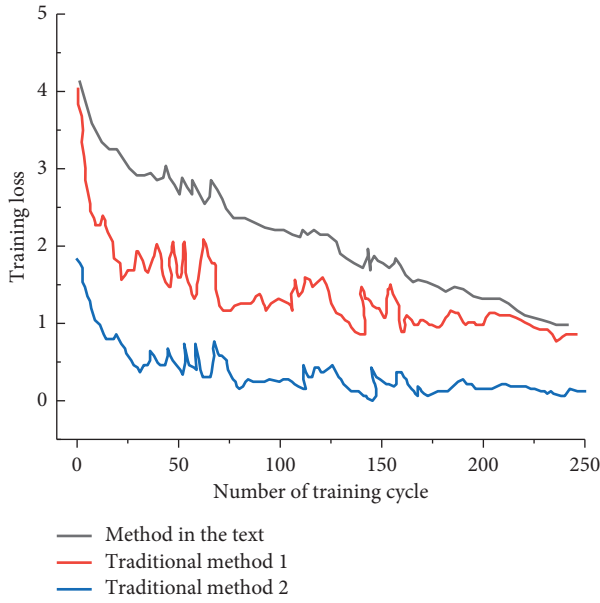


FIGURE 13: Comparison of training losses for the three methods.

TABLE 2: Comparison of single-string malfunction identification accuracy.

Method	Accuracy of test identification			Average accuracy
	U1 (%)	U2 (%)	U3 (%)	
Proposed method	90.53	93.27	93.75	92.51
Traditional method 1	84.34	88.79	90.68	86.94
Traditional method 2	87.16	88.79	87.51	87.85

TABLE 3: Comparison of multistring malfunction identification accuracy.

Method	Accuracy of test identification			Average accuracy
	U1 (%)	U2 (%)	U3 (%)	
Proposed method	91.27	90.18	89.68	90.38
Traditional method 1	85.71	83.57	84.54	86.41
Traditional method 2	83.93	84.03	81.46	83.32

layers of the BP is increased, various intelligent parameters in the BP network are optimized, and the malfunction identification accuracy is effectively optimized. Compared with the two conventional traditional methods, the diagnostic accuracy was increased by 2.57% and 5.66%, respectively.

3.3. Comparison of Experimental Results of Multistring Malfunction Identification. Similarly, for multistring mechanical malfunctions, it is divided into 3 test sets for

malfunction identification testing, and the single-string malfunction identification results are recorded. We can calculate the diagnostic accuracy of different malfunction identification methods through a preset program. The specific experimental results are shown in Table 3.

From the accuracy comparison relationship in Table 3, it can be found that the identification result of t the aforementioned method optimized by GA is obviously better than the two conventional methods. The diagnostic accuracy of the method in this paper is higher than 89%, and the average accuracy is 90.38%. The average diagnostic accuracy of the two conventional methods was 86.41% and 83.32%, respectively. Through multiple network model training, the number of layers of the network is increased, the various intelligent parameters in the BP network are optimized, and the malfunction identification accuracy is effectively improved. Compared with the traditional method, the diagnostic accuracy is increased by 5.76% and 7.15%, respectively.

To sum up, the identification design method of the aforementioned method optimized by GA has better malfunction identification performance for mechanical malfunctions. The introduction of this method based on coding calculation provides a new innovative idea for solving similar engineering cases.

4. Conclusion

- (1) From a global and local perspective, the experimental operator can optimize the parameters of BP through GA and organically combine the global search ability of GA with the local search ability of BP. In this way, the defects caused by the randomness of weights and thresholds in the actual algorithm can be compensated to the greatest extent. The identification method proposed here has more accurate prediction results and better innovation than traditional prediction ideas.
- (2) In view of the shortcomings of the traditional malfunction identification method, a learning model is constructed through BP, and reasonable malfunction identification model parameters are set by using its learning mechanism and nonlinear mapping level. The results show that the designed malfunction method improves the performance of mechanical malfunction identification, which makes the field of mechanical malfunction detection have a better development prospect. The research results have achieved the expected goal, and more in-depth research will be conducted on mechanical malfunction identified in the future.
- (3) It has certain engineering significance in the processing of mechanical construction. According to the current practical application situation, the practical direction of artificial intelligence in mechanical design and manufacturing and its automation mainly includes mechanical design, information processing, and malfunction identification which brought an important impetus that cannot be ignored.

Data Availability

The data set can be accessed upon request.

Conflicts of Interest

The author declares no conflicts of interest.

Acknowledgments

This work was supported by Hebei University Science and technology research project “Intelligent maintenance of production line based on digital twin and deep learning”(QN2022201).

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