Research on adaptive diagnosis algorithm for fuel injection failure system of construction machinery diesel engine

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Abstract: Shipping is the main transportation mode of international bulk trade at present. Diesel engine is the main power source of shipping ships. The stable and reliable operation of diesel engine injection system affects the safe navigation of ships. In order to find the fault of diesel fuel injection system in time, an adaptive diagnosis algorithm of fault system based on adaptive genetic algorithm and Elman neural network is constructed. The simulation results show that the output membership of the improved GA Elman neural network adaptive fault detection model is maintained within the range of [0.81, 0.95], the membership accuracy is high and the absolute error is small. The fault diagnosis accuracy of the improved GA Elman neural network adaptive fault detection model is 95.67%, which can effectively carry out adaptive diagnosis of fault problems and predict the occurrence of fault problems in advance. It provides judgment basis for maintenance personnel, improves maintenance efficiency, ensures the normal operation of diesel engine, and provides a new research idea for fault adaptive diagnosis of construction machinery.

Keywords: fuel injection system; fault diagnosis; Elman neural network; genetic algorithm.

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1 Introduction

The cost of maritime transportation is low. At present, international bulk trade mainly depends on maritime transportation. Maritime transportation has always been one of the important transportation modes of China's domestic and foreign trade. Ensuring the normal operation of diesel engine is the necessary premise and guarantee to ensure the safe operation of ships (Bejger and Drzewieniecki, 2019; Lan et al., 2021). Complex sea conditions and long operation cycle during maritime shipping will increase the incidence of diesel engine failure. It is difficult to repair and maintain diesel engine during maritime shipping. Mechanical failure may cause the diesel engine to stop the supply of ship power and even the unit to be scrapped (Kamaltdinov et al., 2019; Huo et al., 2020). Therefore, the running state detection and fault diagnosis classification of marine diesel engine have become the focus of attention from all walks of life. Many researchers have proposed a diesel engine fault diagnosis model based on machine learning algorithm, and constructed a fault classification and recognition system by using BP neural network, support vector machine and other algorithms, However, there are few special fault diagnosis studies on diesel engine fuel injection system (Vijay et al., 2019; Li et al., 2021a). Therefore, the research combines adaptive genetic algorithm and Elman neural network to diagnose the fault of diesel engine fuel injection system. It is expected to monitor and diagnose the working state of diesel engine fuel injection system in real time and warn possible abnormal operation in advance, which can reduce the judgment time of maintenance personnel, quickly find the point of fault and avoid misjudgement, and ensure the navigation safety of the ship.

2 Literature review

In recent years, more and more attention has been paid to the safety and stability of marine diesel engine. Many researchers take the fault diagnosis and identification of diesel engine as the starting point. He et al. (2021) used BP neural network for fault diagnosis of diesel engine and optimised and improved it combined with genetic algorithm, which effectively improved the efficiency and accuracy of system fault diagnosis and reduced the training time of BP neural network . Tharanga et al. (2020) diagnosed and analysed the fault of the diesel engine from the vibration signal, and diagnose the working state of the engine by analysing the change of pulse characteristics in the vibration signal of the diesel engine, so as to diagnose whether the rotating parts of the diesel engine are unbalanced.

Shao et al. (2020) used manifold learning algorithm to extract the vibration signal characteristics of diesel engine, and use limit learning engine model to diagnose and analyse the operation state of marine diesel engine. It is found that this method has high fault classification accuracy and can effectively realise real-time fault diagnosis of diesel engine (Shao et al., 2020). Bi et al. (2020) used variational mode decomposition and kernel fuzzy c-means clustering algorithm to build the fault diagnosis model of diesel engine, and carry out simulation experiments for various faults of diesel engine. The results show that the classification accuracy of the diagnosis model is high, the operation is simple, and the application prospect is good (Bi et al., 2020). Hou et al. (2020) proposed to build a diesel engine fault classification and recognition model based on support vector machine algorithm, and optimise it by using the improved particle swarm optimisation algorithm. The fault data samples are processed by principal component analysis and sample size optimisation strategy to improve the classification performance of the fault recognition model. The results show that the diagnosis accuracy of the fault recognition model is high (Hou et al., 2020).

It can be seen from the above research that some achievements have been made in the research of diesel engine fault diagnosis and identification, but there are few studies on the fault diagnosis of diesel engine fuel injection system. Therefore, a fault adaptive diagnosis model based on adaptive genetic algorithm and Elman neural network is proposed to diagnose and classify the faults of diesel engine fuel injection system. It is expected to further improve the accuracy of diesel engine fault diagnosis and ensure the safe and stable operation of diesel engine.

3 Adaptive diagnosis algorithm based on Elman neural network and genetic algorithm

3.1 Improved Elman neural network technology

Elman neural network introduces a negative feedback system on BP neural network, adds a receiving layer, and carries out negative feedback on the hidden layer by adjusting the output weight and threshold, which has better stability and data classification ability (Wang et al., 2019; Li et al., 2021b). The operation process of Elman neural network is shown in Figure 1. On the basis of the input, hidden and output layers of BP neural network, a receiving layer is added to give delayed feedback to the output of the hidden layer, so that the model has memory ability. The input layer is used to receive external information input, and the hidden layer makes a global response. The receiving layer is a special hidden layer in the hidden layer part. By adjusting the weight and threshold of the previous hidden layer output vector, the model is negatively fed back, and finally the output result of the hidden layer enters the output layer for linear weighting. Elman neural network maps the dynamic working characteristics of the fuel system by storing the internal state, adapts to the process of time-varying input, enhances the global stability, and is more suitable for fault adaptive diagnosis (Chen et al., 2020; Ryblov et al., 2021).

Elman neural network uses the error function to calculate the error of the output result, and back propagates the error to the hidden layer to adjust the weight and threshold of the neural network (Lv et al., 2021). The error function of Elman neural network is expressed as follows:

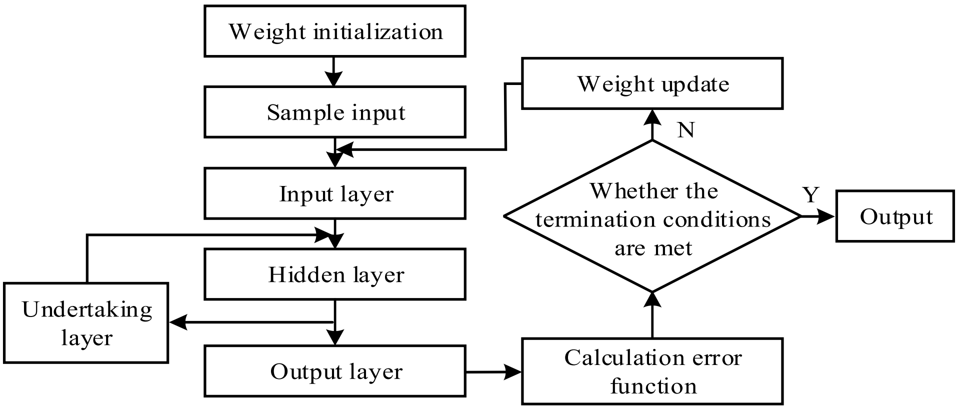
$$E = \frac{1}{2}\left(y_j(k) - y(k)\right)^2 \tag{1}$$

In formula (1), $y_j(k)$ represents the output of the output layer at the node j, $y(k)$ represents the expected output. The gradient descent method is used to learn the weight. The learning algorithm is shown as follows:

$$\begin{cases} \triangle w_{hj} = -\eta \xi_j x_h(k) \\ \triangle v_{ih} = -\eta \xi_h u_q(k-1) \\ \triangle r_{lh} = -\eta \sum_{j=1}^{d} \left(\xi_j r_{lh}\right) x(k-1) + r_{lh} \dfrac{\partial x(k-1)}{\partial r_{lh}} \end{cases} \tag{2}$$

In formula (2), r_{lh} represents the connection weight of l and h. Elman model is a dynamic recursive algorithm based on time series, which is suitable for fault detection and modeling of dynamic working state of diesel engine.

Figure 1 Elman neural network flow chart



The learning algorithm, network structure and excitation function are improved and optimised to further improve the convergence speed and algorithm effect. An improved adaptive gradient descent method is introduced to learn the weights of neural networks, and an adaptive parameter $\lambda = 0.85$ is introduced. The improved Elman model adopts a double hidden layer structure, increases the negative feedback of the output layer, increases the number of nodes in the receiving layer and improves the operation speed and dynamic information processing ability. In terms of excitation function, trigonometric function is used as a new excitation function, and the function is expressed as follows:

$$f(x) = A\cos(\omega x + \phi) + B \tag{3}$$

In formula (3), $A = 0.5$, $B = 0.5$, which keeps the value of the function in the range of [0, 1], the longitudinal expansion of the function is controlled by ω, and the transverse expansion of the function is controlled by ϕ, so as to enhance the convergence effect and approximation ability of the function.

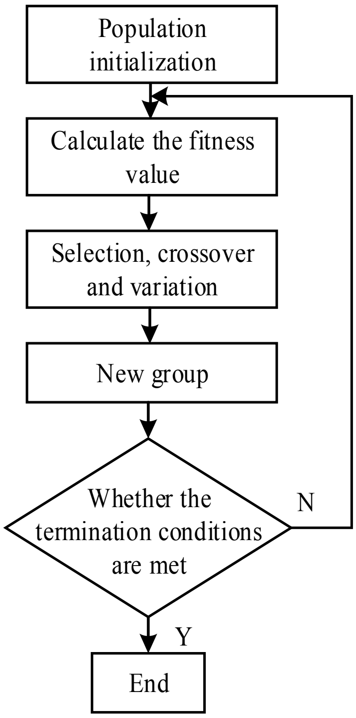
3.2 Elman neural network optimisation based on adaptive genetic algorithm

The Elman model is further optimised by adaptive GA to obtain the optimal weight and threshold. The running process of GA is shown in Figure 2. An initial population is established, the fitness function is introduced to screen chromosomes and a new population is obtained through the selection, crossover and mutation of operators until the optimal solution of the algorithm is obtained.

The selection operator is improved. Assuming that the number of individuals in the population as *m*, the number of iterations as n, $F(t) = \{F(n,1), F(n,2), ..., F(n,m)\}$, and the selection operator p_i is improved in the early stage of the algorithm as:

$$P(F(n,m)) = \begin{cases} \dfrac{f(F(1,i))}{\sum_i^m f(F(1,i))} - \dfrac{n}{k_1 \cdot N} \cdot \dfrac{f(F(1,i))}{f_{ave}} > 1 \\ \dfrac{f(F(1,i))}{\sum_i^m f(F(1,i))} - \dfrac{n}{k_2 \cdot N} \cdot \dfrac{f(F(1,i))}{f_{ave}} \le 1 \end{cases} \tag{4}$$

Figure 2 Genetic algorithm flow chart



In the later stage of the algorithm, the selection operator p_i is improved as follows:

$$P(F(n,m)) = \begin{cases} \dfrac{f(F(1,i))}{\sum_i^m f(F(1,i))} - \dfrac{n}{k_1 \cdot N} \cdot \dfrac{f(F(1,i))}{f_{ave}} \le 1 \\ \dfrac{f(F(1,i))}{\sum_i^m f(F(1,i))} - \dfrac{n}{k_2 \cdot N} \cdot \dfrac{f(F(1,i))}{f_{ave}} > 1 \end{cases} \tag{5}$$

In formula (5), *N* represents the total number of iterations, k_1 is the coefficient of [12, 15], k_2 is the coefficient of [10, 12], $\dfrac{f(F(1,i))}{\sum_i^m f(F(1,i))}$ represents the selection operator in the random sampling method, and f_{ave} represents the average fitness value. The crossover operator of genetic algorithm is improved, and the improved function is expressed as follows:

$$p_c = \begin{cases} P_1 - k_3\left(\dfrac{f_{\max}^2 - f^{2\,'}}{f_{\max}^2 - f_{avg}^2}\right)^{\frac{1}{2}}, f' \geq f_{avg} \\ P_1, f' < f_{avg} \end{cases} \tag{6}$$

In formula (6), P_1 and k_3 are constants in the range of [0, 1], $f_{\max}$ represents the maximum fitness value, f' represents an individual with a larger fitness value, and P_1represents the crossover probability in the early stage of the algorithm.

The mutation operator p_m of genetic algorithm is improved, and the improved function is expressed as follows:

$$p_m = \begin{cases} P_2 - k_4\left(\dfrac{f_{\max}^2 - f^{2\,'}}{f_{\max}^2 - f_{avg}^2}\right)^{\frac{1}{2}}, f_m \geq f_{avg} \\ P_2, f_m < f_{avg} \end{cases} \tag{7}$$

In formula (7), P_2 and k_4 are constants in the range of [0, 0.05], and f_m represents the fitness value of the variable individual. In the later stage of the algorithm, the mutation probability of individuals with high fitness value is reduced, and the mutation probability of individuals with low fitness value remains unchanged, which effectively avoids the failure of convergence in the later stage of the algorithm and optimises the convergence effect of the algorithm.

The adaptive genetic algorithm is used to assign the weights and thresholds of Elman neural network. The weights and thresholds are taken as an individual, and the genetic algorithm is used to solve them. The obtained optimal solution is used as the initial weights and thresholds to speed up the operation speed of the neural network and improve the generalisation ability of the network. Firstly, the topology of the neural network is determined, the initial weight and threshold of the adaptive genetic algorithm are randomly selected and encoded to obtain the initial population of the genetic algorithm, the weight and threshold are obtained by algorithm decoding, and the Elman neural network is assigned. The Elman neural network is trained with the training sample set, and the test set is used to complete the network test, calculate the network error and fitness value, and then update the selection, crossover and mutation operators to complete the selection, crossover and mutation operations. If the update conditions are not met, skip the update steps and directly enter the selection, crossover and mutation operations. After completing the above operations, a new group will be obtained. Repeat the operation until the maximum number of iterations is reached, and finally decode to obtain the optimal weight and threshold of Elman neural network.

To improve the adaptive fault detection model of GA Elman neural network, firstly, it is necessary to collect relevant data and parameters, use the parameters to determine the training sample set and test sample set of neural network and normalise the original data. The normalisation function is expressed as follows:

$$y = \frac{(y_{\max} - y_{\min}) * (x - x_{\min})}{(x_{\max} - x_{\min}) + y_{\min}} \tag{8}$$

In formula (8), y represents the normalised value of matrix elements, and the normalised interval is $[y_{\max} - y_{\min}]$. Generally, $y_{\min} = -1$, $y_{\max} = 1$, $x_{\min}$ and $x_{\max}$ represent the maximum and minimum values of each row of elements in the matrix. The improved GA Elman neural network adaptive fault detection model uses adaptive genetic algorithm to assign the weight and threshold in Elman neural network, and calculates the error norm of each generation. The calculation function is expressed as follows:

$$f = \left(\sum_{j=1}^{M}\sum_{i=1}^{N}\left(P_{ji}^2 - Z_{ji}^2\right)\right)^{\frac{1}{2}} \tag{9}$$

In formula (9), f represents the fitness value function, M represents the number of samples, N represents the number of nodes, and P_{ji} and Z_{ji} represent the expected output result and actual output result of the j neuron under the i node, respectively. The obtained error norm is taken as the fitness, and the individuals with higher fitness value are obtained through the crossover and mutation operation of operators. Finally, the optimal solution is obtained, the weight and threshold are assigned, and the Elman neural network is optimised for fault diagnosis of diesel engine fuel injection system.

4 Model performance verification results

In order to verify the feasibility and effectiveness of the constructed adaptive diagnosis algorithm, the fault simulation experiment of marine diesel engine fuel injection system is carried out by using Ubuntu 17.04 simulation environment. The CPU is Intel Core i5-3470 and the memory size is 8GB. It is developed by Python 3.5 programming language, and the data is read by pandas. The speed, power, maximum burst pressure, high-pressure oil pipe pressure, exhaust pressure and exhaust temperature of the diesel fuel injection system are taken as the input vector of the simulation experiment, and the output vector is 4. The model adopts the structure of double hidden layer and double receiving layer, the weight of both hidden layer and receiving layer is 36, the weight of output layer is 36 and the threshold of output layer is 4. The traditional genetic algorithm and the improved adaptive genetic algorithm are used for simulation experiments, respectively. The error norms of the two GA are shown in Figure 3.

It can be seen from Figure 3 that the curve of traditional genetic algorithm decreases rapidly in the first 10 iterations, and the error norm decreases faster, but it converges prematurely after 15 generations, falling into the problem of local optimisation. The improved genetic algorithm surpasses the traditional genetic algorithm after the 20th iteration, and the error norm is smaller. BP neural network model, BP neural network model optimised by genetic algorithm, support vector machine model optimised by particle swarm optimisation algorithm and GA Elman model optimised by adaptive genetic algorithm are used for fault diagnosis of diesel engine fuel injection system, respectively. The membership and absolute error of the four fault diagnosis models are shown in Figure 4.

Figure 3 Error comparison between adaptive GA and traditional GA

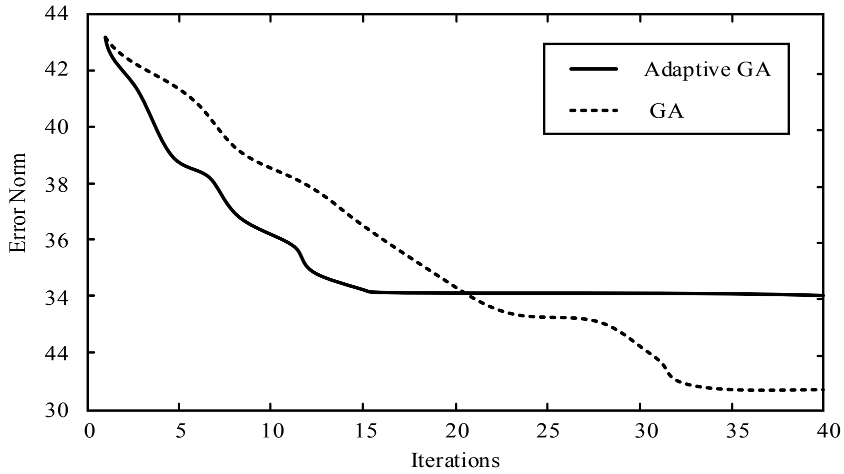
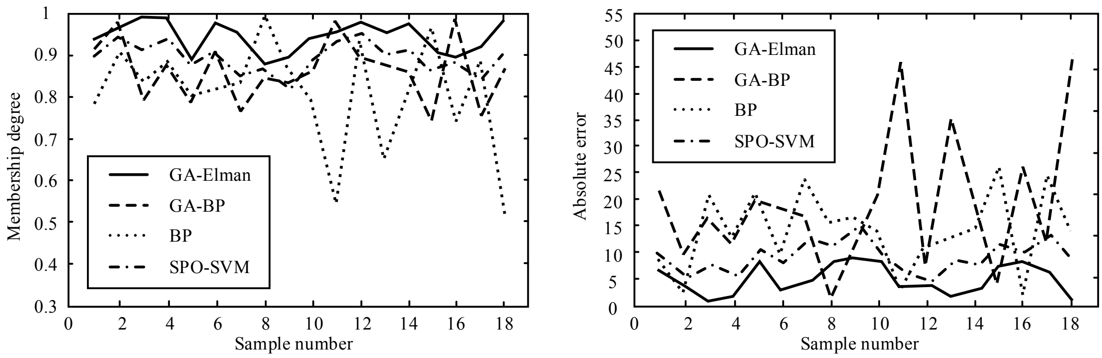


Figure 4 Membership degree and absolute error of four fault diagnosis models



(a) Comparison of Membership degree

(b) Absolute error percentage comparison

As can be seen from Figure 4, the membership degree of BP neural network is the lowest. It falls into the local minimum in the diagnosis of group 11 sample data and group 18 sample data, so it cannot better diagnose the type of fault, and the absolute error value of BP neural network is the largest and the ability to accurately diagnose the fault is the lowest. Compared with BP neural network, the membership degree of BP neural network optimised by genetic algorithm is improved to a certain extent and the absolute error is relatively small. The fault diagnosis performance of the support vector machine model optimised by particle swarm optimisation has been further improved. The membership range is [0.81, 0.95], and the fault diagnosis accuracy of the model is 90.84%. The improved GA Elman neural network adaptive fault detection model has the best fault adaptive diagnosis ability. The output membership degree of GA Elman neural network is maintained in the range of [0.89, 1], the accuracy of membership degree is the highest and the absolute error is relatively minimum. The fault diagnosis accuracy of GA Elman neural network is 95.67%, which is better than the other three diagnosis models. It can effectively diagnose and identify the faults of diesel fuel injection system.

5 Conclusion

The stable operation of the diesel fuel injection system supports the safe navigation of the ship. The working environment of the marine diesel engine is complex and needs to operate at sea for a long time, with a high failure rate. In order to find the fault of diesel fuel injection system in time, an adaptive diagnosis algorithm of fault system based on adaptive genetic algorithm and Elman neural network is explored. The simulation results show that the traditional genetic algorithm converges prematurely in the 15th generation, and the error of the adaptive genetic algorithm is lower than that of the traditional genetic algorithm after the 20th iteration. The adaptive genetic algorithm can effectively avoid the problem that the traditional genetic algorithm is easy to fall into the local optimal solution. The output membership of the improved GA Elman neural network adaptive fault detection model is maintained in the range of [0.81, 0.95], with high accuracy and small absolute error. The fault diagnosis accuracy of the improved GA Elman neural network adaptive fault detection model is 95.67%, which can effectively carry out adaptive diagnosis of fault problems. During the actual navigation of the ship, the real-time sea conditions and the working time of the diesel engine will affect the parameters of the injection system. In the future, we can further refer to the actual parameters of the diesel engine injection system under different conditions to optimise the algorithm model and enhance the adaptability of the diagnosis algorithm.

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