Afault Diagnosis Model of Marine Diesel Engine Lubrication System Based on Improved extreme Learning Machine

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Abstract. The lubrication system provides lubrication oil to various moving parts in the marine diesel engine. Once faults occurred in lubrication system, it can result in dramatically damage to the diesel engine. Development of fast and accurate fault diagnosis method of lubrication system is therefore highly urged. In this paper, we present a novel intelligent fault diagnosis method based on improved extreme learning machine (ELM). Firstly, we use chaotic mapping to enhance capability of the particle swarm optimization (PSO) algorithm; Then, an enhanced PSO algorithm is used to determine initial input weights (connecting input layer nodes and hidden layer nodes) and thresholds of ELM. Finally, we carry out fault diagnosis experiment on the marine diesel engine lubrication system. The experiments demonstrated that the proposed model could achieve more ideal performance.

1. Introduction
A ship is like a floating city that carries cargo and passengers from one port to another. As the vital part of the ship, marine diesel engine provides adequate power to keep the ship sailing [1]. In case of overheat and poor lubrication, the lubrication system is used to supply lubrication oil to the diesel engine and other moving parts. Due to the importance of the lubrication system, a fast and accurate fault diagnosis for the lubrication system is highly urged to guarantee the safety of the whole ship.

The fault diagnosis technology was firstly developed by Naval Research Institute and NASA in 1967, and then many fault diagnosis methods have been proposed. The primary diagnosis methods were mainly based on machine mechanism and human experience. With the development of computer technology, the fault diagnosis methods based on sensor and computer had been developed rapidly. In this period, the accuracy of fault diagnosis had been greatly improved since the sensors can provide accurate parameters. The intelligent diagnosis methods were proposed to deal with complex equipment. Some representative methods has been formed after decades of development, as a consequence, most famous intelligent diagnosis methods include Case based reasoning method [2, 3], Fuzzy theory reasoning method [4, 5], Fault tree analysis method [6, 7] and Neural network diagnosis method [8, 9]. They all obtained outstanding achievements and greatly promoted the development of fault diagnosis technology. However, all of these intelligent methods has disadvantages according to No Free Lunch Theorem [10]. In order to solve this problem, we proposed a combinational method that combines PSO algorithm, ELM and chaotic mapping to improve the capability of fault diagnosis.
The remainder of this paper is organized as follows. The ELM and PSO algorithm are briefly described in Section 2. In Section 3, we develop the fault diagnosis model using improved ELM. In Section 4, the fault diagnosis experiments are carried out and the results are analyzed. Finally, conclusions are given in Section 5.

2. A Brief Review of ELM and PSO Algorithm

2.1. Extreme learning machine

ELM, a novel learning algorithm, was initially proposed by Huang et. al. in 2004 [11], aiming to reach the lowest training error and norm of the output weights. ELM randomly generates the input weights and hidden biases. Fig.1 depicts the structure of ELM. Like SLFN, ELM consists of input layer, hidden layer and output layer. In an ELM, the output of the network is calculated by Eq. (1). Thus, the solution of the output weights can be found by Eq. (4).

\[ T = H\beta \] (1)

\[ H = \{h_{ij}\} \quad (i=1,2, \ldots, N \text{ and } j=1,2, \ldots, K) \] (2)

\[ h_{ij} = g(W_j \cdot X_i + b_j) \] (3)

Where \( H \) denotes the hidden layer output; \( h_{ij} \) is the output of the hidden neuron; \( X_i \) is an input matrix; \( b_j \) is the bias term; \( \beta \) denotes the weights linking hidden layer to output layer (output weights); \( g(x) \) is the activation function.

\[ \hat{\beta} = H^\dagger T \] (4)

Where \( H^\dagger \) denotes the Moore-Penrose generalized inverse of matrix \( H \).

![Figure 1. Structure of an ELM](image)

The activation function \( g(x) \) should be infinitely differentiable. Activation function has various types, such as the typical sigmoid function, Gaussian function, Hardlimit function, multi-quadratic function,
Fourier function and so on. In Eq. (4), the Moore-Penrose generalized inverse $\mathbf{H}^\dagger$ can be calculated by orthogonal projection, iterative methods, singular value decomposition and orthogonalization.

2.2. The PSO algorithm

In 1995, Kennedy and Eberhart developed a basic PSO to optimize continuous nonlinear function [12]. The PSO algorithm simulates the behavior of bird block to search for the optimal solution in the solution space. With time, PSO and its variants have been widely used in many fields due to its easy implementation and powerful optimization capability.

In the swarm, each particle adjusts its behavior according to its own experience and that of its companions. The initial population consists of $m$ particles, and each particle has a position and velocity. The velocity and position of a particle are updated by tracking two target values: the best local solution and the best global solution. At iteration $k+1$, the $i$th particle updates its velocity and position according to the following formulas:

$$
\mathbf{v}_{i}^{k+1} = w \mathbf{v}_{i}^{k} + c_1 \xi (\mathbf{p}_{i}^{k} - \mathbf{x}_{i}^{k}) + c_2 \eta (\mathbf{p}_{g}^{k} - \mathbf{x}_{i}^{k})
$$

$$
\mathbf{x}_{i}^{k+1} = \mathbf{x}_{i}^{k} + \mathbf{v}_{i}^{k+1}
$$

Where $\mathbf{v}_{i}^{k}$ denotes the velocity of the $i$th particle in the $k$th iteration, and $\mathbf{x}_{i}^{k}$ denotes the position of the $i$th particle in the $k$th iteration. $\mathbf{p}_{i}^{k}$ represents the best local solution of the $i$th particle in the $k$th iteration, and $\mathbf{p}_{g}^{k}$ denotes the best global solution of the whole population in the $k$th iteration. $w$ is the inertia weight, $c_1$ and $c_2$ are the learning factors. $\xi$ and $\eta$ are the uniformly distributed random variables in the range of 0 to 1.

The PSO algorithm is very simple to implement and has fast convergence speed. The specific steps of basic PSO are shown as follows:

Step 1. Initialize a population $X$ with random positions and velocities, and set initial parameters: $c_1$, $c_2$;
Step 2. Calculate fitness value of each particle, and find the global best solution whose fitness value is the highest in all particle solutions;
Step 3. Update the velocities and positions using Eq. (5) and (6);
Step 4. Calculate new particle’s fitness value and compare the fitness value with the local best solution. Choose the higher one as the new local best solution;
Step 5. Compare each particle’s local best solution with the global best solution. Choose the higher one as the new local best solution the new global best solution;
Step 6. Loop to step (3) until a stopping criterion is met.

3. Fault Diagnosis Using Improved Elm Model

In this section, a fault diagnosis model of marine diesel engine lubrication system is presented in Fig.2.
Determine the network topology

Initial population

Calculate the fitness function

Meet end condition?

Y

N

Update velocity and position

Determine and output the optimal solution

Optimal weights and thresholds

Test ELM with test data

Faults diagnosis

Figure 2. The flowchart of the fault diagnosis model based on improved ELM

3.1. Normal Faults in Marine diesel Engine Lubrication System

In marine diesel engine, the lubrication system supplies lubricating oil to engine bearings, and cooling oil to pistons. The lubricating oil pump pumps oil from lubricating oil circulating tank. Then lubricating oil flows to the main engine lubricating oil cooler, thermostatic valve and full-flow filter in sequence. Finally, it reaches to the engine. All pumps and fine filters are arranged in duplicate with one as a standby. The lubricating oil is collected into the oil sump and then drained to the lubricating oil circulating tank for reuse. The lubrication system is shown in Fig. 3. The list of lubrication system components is given in Table 1.

Figure 3. Marine diesel engine lubrication system
Table 1. The components of main engine lubrication system

| Label | Component                          | Label | Component                          |
|-------|------------------------------------|-------|------------------------------------|
| (1)   | Main engine                        | (11)  | Make up pump                       |
| (2)   | Exhaust gas receiver               | (12)  | Bearings                           |
| (3)   | Exhaust gas turbocharge            | (13)  | Main engine cam lubricating oil tank|
| (4)   | Air receiver                       | (14)  | Main lubricating oil back flush filter|
| (5)   | Air cooler                         | (15)  | Main lubricating oil pump          |
| (6)   | Lubricating oil sump               | (16)  | Main engine cam lubricating oil pump|
| (7)   | Cylinder oil daily tank            | (17)  | Main engine lubricating oil cooler |
| (8)   | Cylinder oil storage tank          | (18)  | Main engine cam lubricating oil cooler|
| (9)   | Cylinder oil make up pump          | (19)  | Main engine cam lubricating oil filter|
| (10)  | Lubricators                        | (20)  | Bypass filter                      |

We choose fourteen major monitoring parameters of lubrication system in the diesel marine as follows: main lubricating oil pump discharge press, main lubricating oil press outlet lubricating oil cooler, main lubricating oil press inlet main engine, main lubricating oil press inlet main engine bearings, main lubricating oil filter differential press, main lubricating oil temperature (°C) inlet lubricating oil cooler, main lubricating oil temperature (°C) outlet lubricating oil cooler, main lubricating oil temperature (°C) inlet main engine, main lubricating oil temperature (°C) outlet main engine, camshaft lubricating oil press inlet main engine, camshaft lubricating oil temperature inlet main engine, camshaft lubricating oil temperature outlet main engine, camshaft lubricating oil cooler inlet pressure and camshaft lubricating oil filter differential pressure. In addition, we choose nine common faults to do fault diagnosis experiments. They are normal condition, main lubricating oil pump wear, main lubricating oil pump failure, main lubricating oil back flush filter dirty, main lubricating oil cooler dirty, main engine cam lubricating oil pump wear, main engine cam lubricating oil pump failure, main engine cam lubricating oil filter dirty, and main engine cam lubricating oil cooler dirty.

3.2. Data Collecting and Preprocessing

In this paper, the fault samples are acquired from marine engine room simulator. We did 154 fault simulation experiments and collected 2156 (154×14) data samples. We chose 60% data samples as training samples, and the remaining as testing samples.

The initial data is preprocessed by means of Eq.(7), which confirm all the data are in the interval of [0, 1].

\[ x_i = \frac{x_i - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \]  

(7)

3.3. Initialize the population of PSO using Chaotic Systems

A basic PSO algorithm uses a random strategy to initialize population. This method may generate the inhomogeneous solutions since the PSO is extremely sensitive to the initial population. In order to solve this problem, we introduce chaos variable to produce a uniformly distributed population. Here, a two-dimensional Arnold mapping is applied and shown in Eq. (8):

\[
\begin{cases}
  x_{n+1} = (x_n + y_n) \mod 1 \\
  y_{n+1} = (x_n + 2y_n) \mod 1
\end{cases}
\]  

(8)

Where \( x_n \) and \( y_n \) are the variables in the range (0–1).

Firstly, we randomly generate the vectors \( x_1 \) and \( y_1 \); then, \( m \) chaotic variables are generated using Eq. (8). Finally, we initialize the population using the chaotic variables.

\[ x_1 = (x_{11}, x_{12}, ..., x_{1m}), x_{1n} \in [0,1] \]  

(9)
\[ y_1 = (y_{11}, y_{12}, \ldots, y_{1n}), y_{1n} \in [0,1] \] 

3.4. Determine the topology of ELM

We choose a three-layer (14-15-9) ELM. In addition, we choose the fault diagnosis accuracy as fitness function value of PSO algorithm.

4. Fault Diagnosis and Analysis

In order to evaluate the performance of the proposed model, we choose fault diagnosis accuracy (FDA), wrong fault diagnosis ratio (WFDR) and run-time of model as the criteria. In addition, we choose BP Neural Network (BPNN) and Support Vector Machine (SVM) as the compared algorithms. MATLAB R2018a is used for the algorithm design and a computer (Intel (R) Core (TM) i7-3770 CPU @ 3.40GHZ and 8.00 GB of RAM) is used for algorithm verification. In order to get the optimal algorithm parameters, we repeatedly tested the different value of each parameter. Finally, the BP neural network structure is as follows: 14-15-9 three-layer; hyperbolic tangent sigmoid transfer function for both hidden and output layer neurons; learning rate: 0.1. We adopt the initial parameters of GA as follows: population size: 50 and iterative number: 100. We choose the initial parameters of SVM as follows: the penalty factor: 20 and kernel function parameter: 4. All the experiments are repeated five times and the average values of criteria are listed out in Table 2.

The Table 2 shows the results of fault diagnosis. Firstly, we test the training samples. The average FDA of the proposed method is 97.66%, and it is higher than other methods, which are 79.44%, 81.74%, and 93.83%, respectively. The average WFDR of the proposed method is 2.34%, and it is lower than other methods, which are 20.56%, 18.26% and 6.17%, respectively. Then, we test the testing samples. The average FDA of the proposed method is 95.67%, and it is higher than other methods, which are 75%, 79.43%, and 91%, respectively. The average WFDR of the proposed method is 4.33%, and it is lower than other methods, which are 25%, 23.57% and 9%, respectively. Finally, the average run time are calculated. We can see the average run time of the proposed method is 2.7s and the others are 0.02s, 4.03s, and 0.01s, respectively. The Table 2 also shows the deference of FDA using optimized and random weights (also thresholds) of ELM. By comparison, the FDA of training sample is enhances from 93.83% to 97.66% (testing samples FDA from 91% to 95.67%). After the above analyses denote the proposed model has higher fault diagnosis accuracy than others.

| Method  | FDA Training | FDA Testing | WFDR Training | WFDR Testing | Run time (s) |
|---------|--------------|-------------|---------------|--------------|--------------|
| SVM     | 79.44%       | 75%         | 20.56%        | 25%          | 0.002        |
| BP      | 81.74%       | 76.43%      | 18.26%        | 23.57%       | 4.03         |
| ELM     | 93.83%       | 91%         | 6.17%         | 9%           | 0.001        |
| Proposed model | 97.66% | 95.67% | 2.34% | 4.33% | 2.7          |

5. Conclusion

In this paper, a combinational faults diagnosis model is proposed. The proposed model uses improved PSO algorithm to optimize ELM. Fault diagnosis is done among nine fault cases in lubricating system of marine diesel engine. Accuracy of the proposed method is demonstrated by the results in training and testing samples. Our contribution of the proposed model is the higher accuracy (97.66% in training samples and 95.67% in testing samples). In addition, the running time of the proposed method is relatively short (2.7s), which can apply most situation. In this paper, a simple fault diagnosis model is developed. We can diagnose fast and accurately the fault cases of complex marine diesel engine lubricating system just by analyzing some sensor parameters in lubricating system.
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