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Optimization of Hydrogen-fueled Engine Ignition Timing Based on L-M Neural Network Algorithm

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Abstract

In view of the improvement measures of the optimization control algorithm for the ignition system of the hydrogen-fueled engine, the L-M neural network algorithm, Powell neural network algorithm and the traditional BP neural network algorithm are used to optimize the ignition system. The results showed that L-M algorithm not only can accurately predict the hydrogen-fueled engine ignition timing, but also has high precision, high convergence speed, a simple model and other outstanding advantages in the training process, which can greatly reduce the workload of human engine bench tests. Only a small amount of engine bench test is carried out, and the obtained sample data can be used to predict the ignition timing under the whole working conditions. The mean square error of the optimization results based on L-M algorithm arrives at 0.0028 after 100 times of calculation, the maximum value of absolute error arrives at 0.2454, and the minimum value of absolute error arrives at 0.00426.

Keywords*: Hydrogen-fueled Engine, L-M Algorithm, Neural Network, Optimization*

1. Introduction

Research on hydrogen as fuel of internal combustion engine began in the middle of nineteenth century. It fell behind for about 100 years compared with the research on traditional internal combustion engine. Although at this stage, the traditional gasoline engine and diesel engine technologies become more and more perfect and mature, but it’s unable to directly use the traditional internal combustion engine for hydrogen combustion due to the particularity of hydrogen as a fuel. Its technology is not perfect and there is no commercial promotion. However, hydrogen is considered to be the most promising clean energy source in this century, with its advantages of low emission, renewable energy and so on. In the process of combustion, the ignition limit of hydrogen is wide, the combustion speed is high and the calorific value is high. This results pre-ignition, inlet backfire and other abnormal combustion phenomenon in the combustion process of internal combustion engine, so that the engine cannot operate normally [1]. How to avoid the abnormal combustion phenomenon without reducing the output power of the hydrogen-fueled engine is the research focus of the relevant researchers in various countries.

Changwei, et al., have studied on the effect of hydrogen and methanol mixture combustion on the emission characteristics of hydrogen-fueled engine [2]. J.M. Gomes Antunes, et al., have studied on the influence of the high pressure direct injection technology on the hydrogen combustion characteristics of diesel engine, and the influence of homogeneous charge compression ignition technology and hydrogen injection timing and length on the performance of the hydrogen-fueled engine [3]. Xing-hua, Fu-shui Liu, et al., have studied the effects of hydrogen injection timing under different rotation speed and equivalence ratio on the formation of hydrogen mixture gas and its effect on the prevention of backfireby using computational fluid dynamics simulation [4]. The effect of EGR system on the combustion and performance of a compression ignition hydrogen-fueled engine was studied by Vinod Yadav Singh, et al., [5]. However, these studies are based on a large number of bench test or simulation process, and only a part of the operating conditions of the hydrogen-fueled engine characteristics are studied, which can't take into account the operation, emission and combustion characteristics of all the working conditions of the hydrogen-fueled engine.

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Because of the high combustion speed and low ignition energy of hydrogen, the optimization of ignition system is considered to be the most effective way to control the combustion. However, based on the previous calibration ignition MAP, it is often unable to carry out the control of ignition timing in all conditions, which requires a lot of manpower, material resources and time. Therefore, an optimization algorithm is proposed in this paper to realize the Optimal Control of the ignition system of the hydrogen-fueled engine, which can avoid a lot of manual calibration work, in order to optimize the ignition and combustion process of the hydrogen-fueled engine and avoid the abnormal combustion phenomenon. The algorithm not only realizes the modeling of nonlinear mapping model from engine speed and load to the optimal ignition advance angle, but also solves problems of easily falling into the local minimum, low convergence speed and low accuracy by the traditional BP network algorithm. The simulation results show that the optimal control scheme of the ignition advance angle of the hydrogen-fueled engine based on L-M neural network is of high accuracy and high speed. Only a small amount of engine test is carried out, and the obtained sample data can be used to predict the ignition timing under the whole working conditions. In the process of engine operation, the current condition parameters are imported into the optimized neural network control system, and then the network can output the current optimal ignition timing to realize the optimal control. And then it can be extended to control other operation parameters of the engine, so as to optimize the control of the power and emission of the hydrogen-fueled engine and avoid abnormal combustion.

2. Algorithm Theory

2.1. BP Neural Network Algorithm

BP neural network(the back-propagation neural network), a kind of non feedback forward network, is used to solve the input/output nonlinear optimization problem and the internal neurons are presented as a layered arrangement. It includes input layer, hidden layer and output layer, in which the hidden layer neurons can have multiple layers, the weighted sum of the output of each neuron and the input of the next layer of neurons [6]. It includes input layer, hidden layer and output layer, in which the hidden layer neurons can have multiple layers. The weighted sum of the neurons output value for each layer is the input value of a single neuron in the next layer. The work process is divided into training and testing process, and the training process is divided into the forward propagation process of the input information and the reverse propagation process of the error. In the training process, the connection weights between each two neurons and thresholds of each neuron in neural network are backward modified by the error between the output value of the output layer and actual sample value, until the error satisfies a desired accuracy requirement. The weights and thresholds of the network are fixed after training, and then enter the testing process. During the test process, only the forward propagation of information exists. The objective function is defined by the mean square error (MSE) of the actual output and the desired output, and the calculation formula is derived by using the gradient descent method. The structure of a traditional three layer BP neural network model is shown in Figure 1.

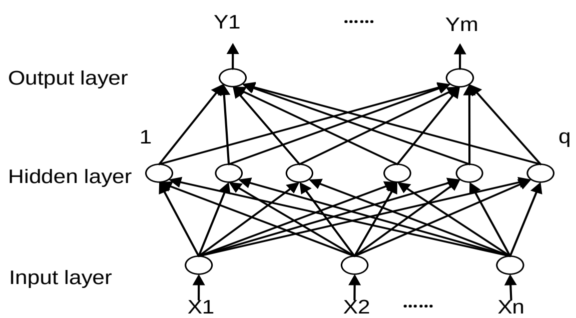

Figure 1. The structure of a BP neural network

Gradient descent method used to optimize the weights and thresholds of the BP algorithm is the most widely used method in the field of artificial neural network algorithm and it has become one of the important models of neural network. But it has some shortcomings, such as low convergence speed, the convergence speed is related with the choice of the initial values, and it is easy to fall into local minimum. Therefore, researchers are committed to improving the neural network optimization algorithm to enhance its effectiveness [7, 8]. In fact, as long as it is a random search algorithm, there will be the problem of local extremum, but the possibility of different size. The search strategy is selected according to the nature of the target function is a good alternative.

2.2. L-M Algorithm

Levenberg-Marquardt (L-M) algorithm is one of the optimization algorithms, which is the most widely used nonlinear least squares optimization algorithm [9], with the advantages of both gradient method and Newton method. The algorithm is also derived from the Gauss-Newton method.

The basic idea of the Newton method is to replace the original objective function with the quadratic function. The minimum point of the original objective function is replaced by the minimum point of the quadratic function and gradually approaches the point. If the general objective function $F(X)$ has a continuous two order partial derivative, $X^{(k)}$ is the near point of the minimum point of $F(X)$, then the Taylor expansion at the point $X^{(k)}$ is:

$$F(X)\approx F\left(X^{(k)}\right)+\nabla F\left(X^{(k)}\right)^T\left(X-X^{(k)}\right)+\frac{1}{2}\left(X-X^{(k)}\right)^T H\left(X^{(k)}\right)\left(X-X^{(k)}\right) \tag{1}$$

Where,

$$H\left(X^{(k)}\right)=\left[\frac{\partial^2 F\left(X^{(k)}\right)}{\partial x_i \partial x_j}\right]\ (i, j=1,2,\ldots n) \tag{2}$$

Is the Hessian matrix for the function $F(X)$ at the point $X^{(k)}$.

The above Taylor binomial expansion is used as an approximate substitute function $\Phi(X)$, that is:

$$\Phi(X)=F\left(X^{(k)}\right)+\nabla F\left(X^{(k)}\right)^T\left(X-X^{(k)}\right)+\frac{1}{2}\left(X-X^{(k)}\right)^T H\left(X^{(k)}\right)\left(X-X^{(k)}\right) \tag{3}$$

If the function $\Phi(X)$ has the minimum value point X_φ^*, then its gradient value is equal to zero, namely $\nabla\Phi(X)=0$. Then the equation (4) is get.

$$H\left(X^{(k)}\right)\left(X_\varphi^*-X^{(k)}\right)=-\nabla F\left(X^{(k)}\right) \tag{4}$$

Since the point X_φ^* can be used to replace the minimum point approximately, the iterative formula is:

$$X^{(k+1)}=X^{(k)}-H^{-1}\left(X^{(k)}\right)\nabla F\left(X^{(k)}\right) \tag{5}$$

The convergence speed of the Newton method is high, but it has strict requirements on the properties of the objective function. In addition to the function must have first and second order continuous partial derivatives, in order to guarantee the stability decline of the objective function, the Hessian matrix must be positive definite everywhere, if not, the Newton method will fail.

In order to overcome the deficiency of Newton method, Levenberg and Marquardt proposed the L-M optimization algorithm. In fact, the algorithm is a correction to the Newton method. In order to prevent the Hessian matrix being singular, the L-M method overcomes requirements of full rank of matrix $H\left(X^{(k)}\right)$ of the Newton method by introducing a damping parameter λ_k. The iterative formula is:

$$X^{(k+1)} = X^{(k)} - H^{-1}\left(X^{(k)} + \lambda_k I\right)\nabla F\left(X^{(k)}\right) \quad (6)$$

Where the parameter $\lambda_k \geq 0$ and it carries on an adaptive renewal in each iteration process, and I is the identity matrix. L-M algorithm avoids the stringent requirements of Hessian matrix of the Newton method. The same with the Newton method, the algorithm is fast, simple and easy to operate, and it is especially productive when the structure of the objective function is simple. Because of the control parameter λ_k, the L-M algorithm not only possesses the local search property of Newton method, but also possesses the global convergence property of the gradient method. It retains the advantages of the two algorithms, the number of iterations is small, the efficiency of the network training is high.

2.3. Powell Conjugate Gradient Method

Powell algorithm is a kind of local search method without calculating derivative, which is designed for unconstrained optimization problem. Powell algorithm uses the successive approximate conjugate direction to search for the solution, which can quickly converge [10]. This algorithm is divided into several stages. Each stage is started from the optimal point of the last stage and $(n+1)$ times of searches are done in succession. Firstly the n times of searches are done along n linear independent directions, and then a best direction is selected by using the search results and the former n directions are replaced by the $(n+1)$th direction. Then a new search stage is started. Powell algorithm has a high convergence speed in dealing with a class of optimization problem that the objective function which is very complex and its functional characteristics is not clear due to avoiding the calculation of the derivative term. But because of its n search directions in the iteration process can probably turn into linearly dependent and the conjugate direction can not be formed, which leads to the failure of the algorithm. In view of this situation, Powell has improved the original algorithm, and after each stage of the new direction search, it is necessary to check whether it can be used as a direct search direction for the next stage of iteration. If the direction does not meet the requirements, it is necessary to redetermine the optimal solution in the source search direction groups that has the maximum value of the function decline. The so called Powell algorithm is actually the Powell correction algorithm. The determination condition is also known as Powell condition:

1) Firstly, the contrast function values are calculated by equation (7), (8) and (9).

$$X_{n+1}^{(k)} = 2X_n^{(k)} + X_0^{(k)} \quad (7)$$

$$F_1 = F\left(X_0^{(k)}\right),\ F_2 = F\left(X_n^{(k)}\right),\ F_3 = F\left(X_{n+1}^{(k)}\right) \quad (8)$$

$$\Delta = \max\left\{F\left(X_{i-1}^{(k)}\right) - F\left(X_i^{(k)}\right), i = 1,2,...m,...n\right\} = F\left(X_{m-1}^{(k)}\right) - F\left(X_m^{(k)}\right) \quad (9)$$

Where $S_m^{(k)}$ is the direction of the maximum value of the objective function decline, and $F\left(X_m^{(k)}\right)$ is the objective function value.

2) If the following inequalities

$$\begin{cases} F_3 < F_1 \\ \left(F_1 - 2F_2 + F_3\right)\left(F_1 - F_2 - \Delta\right) < \frac{1}{2}\Delta\left(F_1 - F_3\right)^2 \end{cases} \quad (10)$$

Are both satisfied, then the direction needs to change, otherwise the original direction is still adopted.

3. Modeling and Training of L-M Neural Network Control System

In view of the obvious disadvantages of BP algorithm, the L-M algorithm is adopted to avoid the local optimal solution in the search process. If it is applied to the training process of neural network, it can jump out of local optimal solutions and obtain the global optimal solution. This is beneficial to improve the reliability of the solution, reduce the number of iterations, and improve the convergence precision. As the selected objective function itself is not complicated, the adoption of L-M algorithm achieves a very good effect. So in this paper, L-M algorithm is adopted to train the neural network which is to use L-M algorithm to calculate the optimal weights and thresholds of the neural network to get the exact value of the global optimal solution. The algorithm makes the neural network modeling, training, simulation and so on to achieve the desired effects, so as to effectively use the algorithm for hydrogen-fueled engine ignition system optimization modeling and prediction of the ignition MAP under the whole working conditions. And compared with the traditional BP algorithm and Powell algorithm, the results show that the L-M algorithm has higher precision, higher convergence speed and a very simple model. The neural network trained by this algorithm can be used to simulate the ignition system of the hydrogen-fueled engine. With the characteristics of fast, accurate and sensitive, it can also optimize and control the hydrogen-fueled engine.

Three layer neural network is selected, the inputs of the input layer are the hydrogen-fueled engine working condition parameters, namely, the engine speed $n\left(r/\min\right)$ and the load $\rho\left(\%\right)$ parameters, the output of the network is the optimal ignition advance angle $\theta\left(°CA\right)$. So the input layer of neural network contains 2 neurons, and the output layer contains 1 neurons. The number of neurons in the hidden layer is determined by experience or formula. In this model, the number of neurons in the hidden layer is 5. The “sigmoid” function is selected as the transfer function between each two neurons. After the neural network model is established, the training process of the network can be carried out. In this paper, three algorithms are used to train the neural network weights and thresholds, and the training objective function is the mean square error (MSE). Namely,

$$f = \frac{1}{K}\sum_{i=1}^{K}\left(y_i - \overline{y}\right)^2 \tag{11}$$

Where K is the number of training samples, y_i is the predictive output of neural network, $\overline{y}$ is the actual output of network.

The optimization procedure based on L-M neural network in this paper is as follows:

Step1: Initialization

The control parameter λ_k of L-M algorithm is initialized, the maximum number of iterations E and the network allowable error ε are given and the weights and thresholds of the neural network vector W are used as the initial solution. And the network is established in this step.

Step2: Random selection of the training samples

Step3: Calculation of the objective function value

The mean square error (MSE) for training samples is calculated by:

$$F\left(W\right) = \frac{1}{K}\sum_{i=1}^{K}\left(y_i - \overline{y}\right)^2 \tag{12}$$

And it is served as the objective function.

Step4: Judgment

Whether the results satisfy the termination condition is judged by the maximum number of iterations E or the network allowable error ε, if it is, the procedure transfers to step6; if not, the procedure transfers to step5 to continue the iteration.

Step5: Iteration renewal

The calculation of the Hessian matrix $H\left(W^{(k)}\right)$ of the current solution and its gradient $\nabla F\left(W^{(k)}\right)$ and the renewal of control parameter λ_k are done in this step. The weights and thresholds are updated according to the iterative formula (6) and procedure transfers to step3.

Step6: Output

A set of weights and thresholds are outputted as the optimal solution, and the procedure ends.

The flow chart is shown in Figure 2.

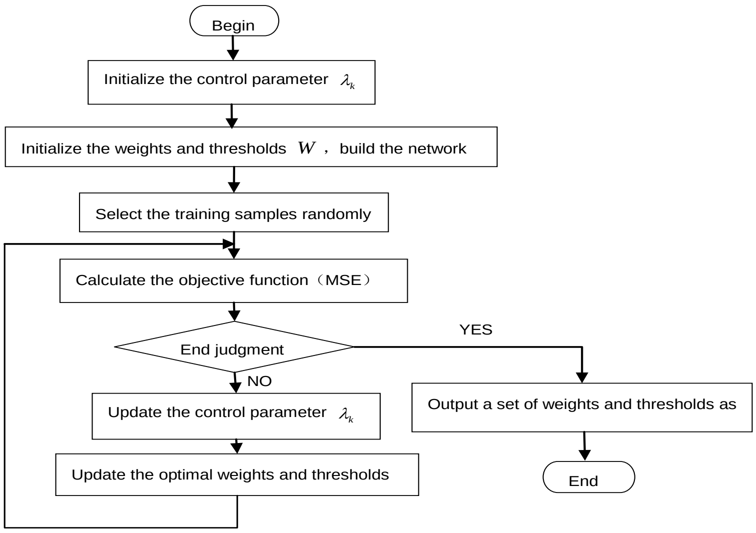

Figure 2. The flow chart of BP neural network training process by L-M algorithm

4. Engine Test System and Electric Control Unit

4.1. Engine Test System

The hydrogen-fueled engine bench test is modified by a single cylinder four stroke valve water cooled engine, and its parameters are as shown in Table 1 below. The test system consists of the hydrogen supply system, air supply system, exhaust system, ignition system, electronic control unit, various test sensors and signal conditioning circuit, computer monitoring system, dynamometer, heat-dissipation module and various control valve systems. The test sensors include: the hydrogen flow sensor, air flow sensor, intake pressure sensor, speed sensor, throttle position sensor, cooling water temperature sensor, etc., with the ability to carry on a comprehensive testing and monitoring of the hydrogen-fueled engine under multiple working conditions. By using the test bench to calibrate the ignition data, combined with the intelligent algorithm proposed in this paper, the whole condition calibration and optimization control of the engine ignition system can be carried out.

Table 1. The parameters of the hydrogen-fueled engine

Cylinder diameter（mm）	Piston travel（mm）	Displacement（L）	Compression ratio	Maximumpower（KW）	Maximum speed
94	85	0.5899	9.7	30	6000

4.2. The Electric Control Unit

In the process of engine running, the electronic control unit (ECU) reads the operation parameters from the various sensors [11], after the analysis and processing is carried out, an instruction is issued to each engine actuator to control the operation of the engine. At this stage, the complexity of the engine electronic control unit determines the degree of adaptation of the engine in various conditions, and its role is equivalent to the brain of human [12]. Therefore, after the completion of the hydrogen-fueled engine optimization control algorithm, the control algorithm needs to be written into the electronic control unit. According to the ignition system control strategy proposed in this paper, the hydrogen-fueled engine ignition MAP is manufactured and imported into ECU.The schematic diagram of the electronic control unit is shown in Figure 3.

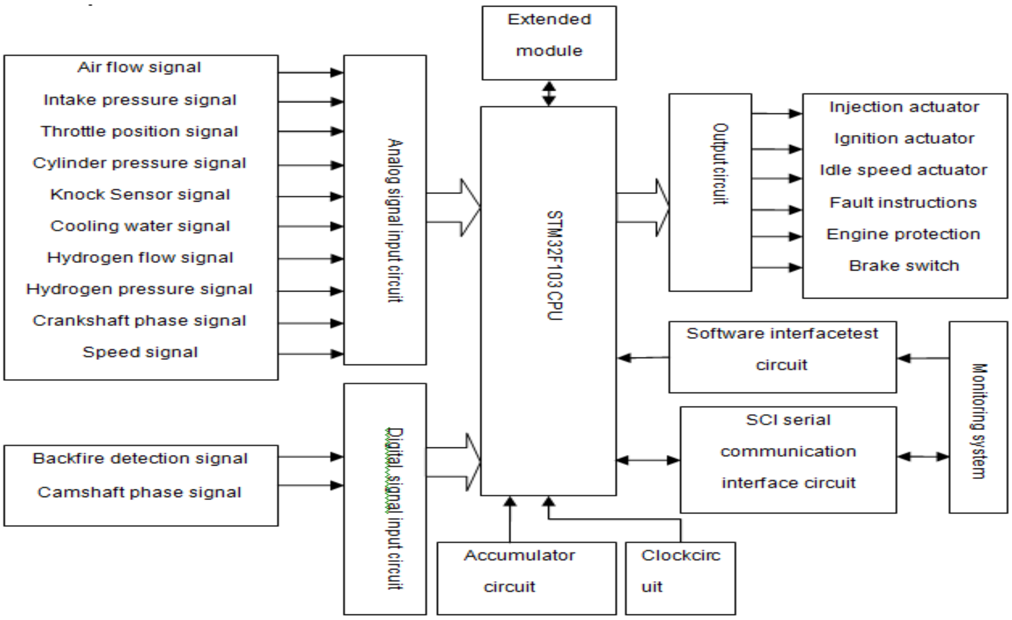

Figure 3. The electronic control unit

5. Experiment Simulation
5.1. Simulation
The BP neural network optimization model based on L-M algorithm is established in this paper, and compared with the Powell neural network algorithm and the traditional BP algorithm by using MATLAB neural network toolbox for simulation calculating. The parameters of neural network are set to: the number of input layer neurons $n=2$, the number of hidden layer neurons $q=5$, the number of output layer neuron $m=1$, the maximum number of iterations $E=100$ and the network allowable error $\varepsilon=10^{-3}$. The parameters of L-M algorithm are set to: the initial control parameter $\lambda_k=10$ and the number of samples $K=84$.

5.2. Result Analysis
In order to verify the optimization effectiveness of the L-M neural network algorithm for ignition timing of the hydrogen-fueled engine, firstly, the training samples are used to train the network, and then the test samples are used to test the trained network. The results show that the L-M neural network algorithm has high accuracy and high speed when used to optimize the ignition timing, which completely meets the design requirements. Its optimization effect is superior to the traditional BP network algorithm, and compared with the Powell algorithm which is more suitable for complex functions, it also has a higher convergence speed and accuracy. When the iteration number satisfies the termination condition, the mean square error of the L-M algorithm is 0.0028, the Powell algorithm is 0.005785 and the BP algorithm is 0.1656. The convergence curves of the three algorithms are shown in Figure 4, 5 and 6.

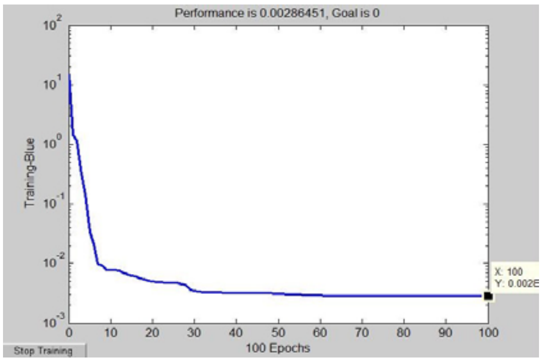

Figure 4. The convergence curve of L-M algorithm

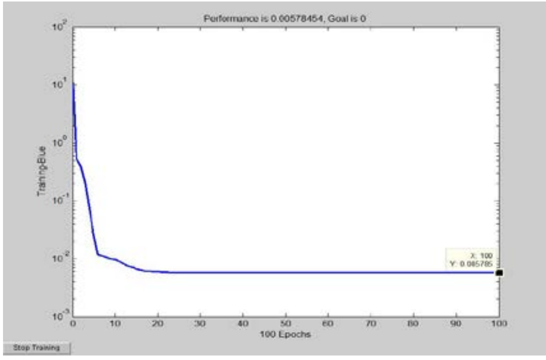

Figure 5. The convergence curve of Powell algorithm

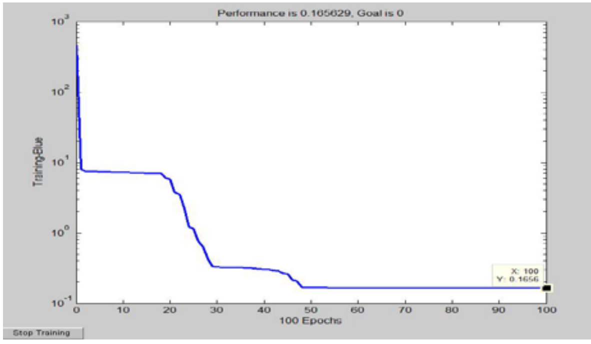

Figure 6. The convergence curve of BP algorithm

The absolute error curves between the simulated and actual values of all samples are shown in Figure 7, 8 and 9. Among them, the maximum absolute error of the L-M algorithm is 0.24564, the Powell algorithm is 0.2679, and the BP algorithm is 1.447. This shows that the optimization effect of L-M algorithm is the best with the least error and highest speed.

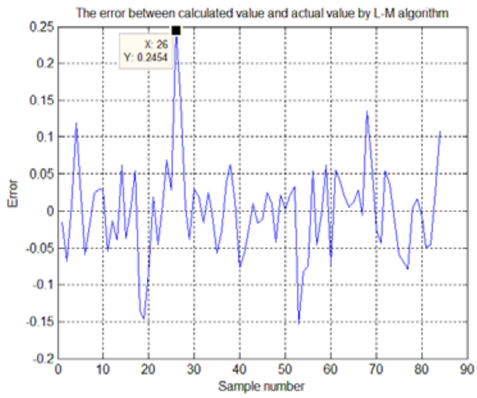

Figure 7. The absolute error curve of L-M algorithm

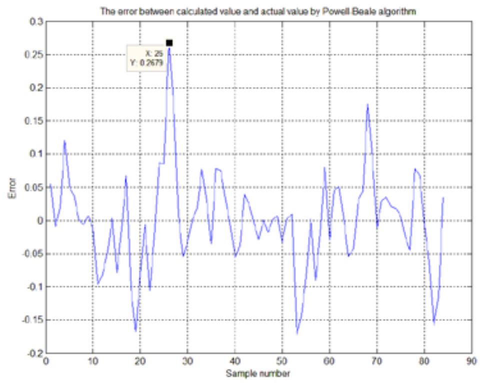

Figure 8. The absolute error curve of Powell algorithm

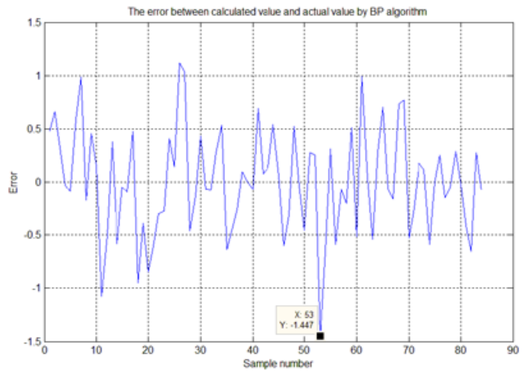

Figure 9. The absolute error curve of BP algorithm

The calculated results of MAP diagram of hydrogen-fueled engine ignition system based on L-M neural network optimization algorithm are shown in Figure 10.

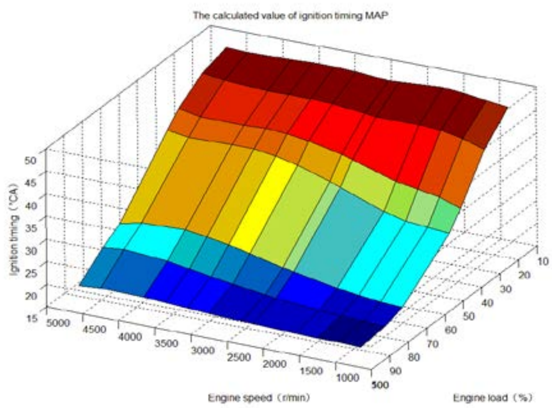

Figure 10. The calculated ignition MAP diagram based on L-M neural network algorithm

6. Conclusion

The ignition timing optimization model of the hydrogen-fueled engine based on the L-M neural network algorithm is constructed in this paper. It has high precision, high convergence speed, a simple model and other advantages in the network training process. It combines the advantages of Newton method and gradient method, and avoids the characteristic of local extremum. Compared with the traditional BP algorithm and Powell algorithm, it has a better optimization effect. The calibration and optimization control of the ignition timing of the hydrogen-fueled engine under whole working conditions is realized. The optimization model has a very strong practicability, and it is significant in the experimental study of the hydrogen-fueled engine.

Acknowledgements

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