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Retraction

Retracted: Fault Diagnosis of Automobile Engine Based on Improved BP Neutral Network

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Y. Ling and C. Niu, "Fault Diagnosis of Automobile Engine Based on Improved BP Neutral Network," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 2287776, 11 pages, 2022.

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Research Article

Fault Diagnosis of Automobile Engine Based on Improved BP Neutral Network

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With the continuous enrichment of automobile functions and the complexity of automobile structure, the difficulty of automobile fault diagnosis is constantly increasing. The study of fault diagnosis methods with high real-time performance, accuracy, and predictability is of great significance to improve automobile safety performance and ensure driving safety. Since the convergence speed of the traditional BP neural network algorithm is slow and the accuracy is insufficient in the process of automobile engine fault diagnosis, this paper improves convergence speed of the algorithm by introducing the momentum term, and the weights and thresholds of the neural network are optimized by using GA selection, crossover, and genetic characteristics, to propose a genetic algorithm (GA) optimization BP neural network fault diagnosis method. The average absolute error of the traditional BP neural network algorithm is 0.5976, while the average absolute error of the improved BP neural network algorithm in this paper is 0.1027. The comparative simulation results show that the proposed improved algorithm is better than the traditional BP neural network algorithm in diagnosis precision, accuracy, and other key indicators.

1. Introduction

Automobile has become a necessity in people's life today; once the engine fails, it will bring great troubles to consumers if it cannot be found in advance, handled in time, and repaired accurately, and even threatens the safety of life and property and it also will greatly affect the customer satisfaction and reputation of automobile enterprises; some automobile enterprises even have to protect consumers through market actions and recalls, and they need to spend huge amounts of money to save them at the same time. It can be seen that timely warning, rapid processing, accurate diagnosis, and timely maintenance of faulty engines are important basis for ensuring the normal operation of vehicles and escorting people's travel safety.

With the continuous enrichment of automobile functions and the complexity of automobile structure, the difficulty of automobile fault diagnosis is constantly increasing. The study of fault diagnosis methods with high real-time performance, accuracy, and predictability is of great significance to improve automobile safety performance and ensure driving safety. As one of the core components of an automobile, the engine is a part with a high fault rate. It is very important in the field of automobile manufacturing and maintenance to be able to timely and accurately judge the type of engine fault.

Engine fault diagnosis refers to real-time monitoring of vehicle information and status, analysis of engine running status, and timely judgment of fault types and early warning information once abnormalities are found. With the continuous progress of technology, fault diagnosis has gone through four stages: manual diagnosis, instrument-assisted manual diagnosis, expert system diagnosis, and intelligent diagnosis. Specific is as follows: In the 1950s, in the manual inspection stage, the internal structure of the automobile is relatively simple, and there are not many electronic equipment parts. Therefore, the corresponding fault diagnosis can be completed by relying on manual experience. In the 1950s to 1970s, manual inspection and simple instrument and equipment fusion diagnosis stage: the use of multimeter, vacuum meter, and other equipment and instruments to test

the relevant assembly and parts, reducing the technical level of testing personnel requirements. In the 1980s and 1990s, in professional equipment diagnosis stage, various precision detection means with computer as the core are widely used, such as engine analysis instruments and electronic unit detection instruments, which further improve the accuracy of fault diagnosis. In the 1990s, in the intelligent diagnosis stage, the application of artificial intelligence theory and technology integration of modern advanced ideas, the development of various systems to achieve automatic detection, which provides a basis for rapid diagnosis and safely use of vehicles. Among them, manual diagnosis is mainly to identify the cause of starting engine fault through the method of human experience judgment, which is suitable for the vehicle system with relatively simple structure. Instrument-assisted manual diagnosis improves the efficiency and accuracy of diagnosis with the help of some instruments and equipment. Expert diagnosis system, relying on professional fault diagnosis equipment, can judge the fault type through information integration and computer analysis [1]. Intelligent diagnosis combines artificial intelligence algorithm, computer technology and expert experience and integrates with the engine to form an on-board fault diagnosis system, which further improves the real-time performance and safety of fault diagnosis. It is the most widely used engine fault diagnosis method at present [2].

2. Related Work

As early as 1950, industrialized countries began to produce single detection equipment and performance debugging equipment for fault diagnosis and debugging of engines. After 1960, due to the increase in demand and the increase in the number of cars, there are some simple car maintenance, testing stations, and the application of more professional equipment, to solve the common problems of the car. With the development of economy, the development of automobile industry is particularly significant, and the old car repair technology, especially the traditional manual experience diagnosis, cannot meet the development needs at that time [3]. Some developed countries drew lessons from mature mechanical diagnosis and repair technology in other fields and apply them to automobile troubleshooting. After 1970, detection technology was developed that integrated automatic detection and control, data acquisition and analysis, result printing and other functions, and conducted out-of-car diagnosis for a number of functions of specific vehicles [4]. In 1978, Sarna and Steyaert [5] learned from the experience of the military industry and applied the fault diagnosis expert system to military automobile engines, obtaining a large amount of data. As the heart of automobile, the engine failure rate is very high, so the study of engine fault diagnosis has become a hot topic. More electronic control system technology has been applied to automobile fault diagnosis, and the development of fault diagnosis technology has become more refined and complicated [6]. After 1980, advanced on-board diagnosis system was put on the historical stage in developed countries, and many automobile manufacturers installed fault self-diagnosis function for their products. At this time, a fault diagnosis expert system was widely used as an advanced out-of-car diagnosis tool. Wu et al. [2] applied the supercharacteristics of neural network to engine fault diagnosis and automobile control system. People found that neural network has strong fault tolerance, large capacity, good learning performance, and super nonlinear mapping characteristics and can quickly find, classify, and diagnose potential faults. In 1989, Venkatusubramanian and Chen [7] in the United States studied and designed the application of neural network in vehicle fault diagnosis to make vehicle diagnosis more intelligent. Compared with the traditional diagnosis method, intelligent fault diagnosis has the advantages of faster speed and online diagnosis, and the experimental analysis had proved the feasibility of applying neural network to fault diagnosis. Sharkey et al. [1] conducted a large number of studies and fault experiments on engines and proposed the diagnosis strategy of multineural network, which has more powerful diagnosis function and is far superior to the diagnosis of single-strategy expert system. In the early 1990s, multineural network diagnosis was further developed. The expert system of automobile fault diagnosis developed to the direction of multimodel and multiknowledge diagnosis, and the research objects were more extensive and popularized in more automobile systems. Hamilton and Lu [8] upgraded the fault diagnosis system and developed the automobile suspension unit technology by studying the state monitoring and other technologies. Staszewski and Worden [9] gave people a new understanding of automobile gearbox failure by using the neural network mode and special vibration signal extraction through specific recognition. The integrated diagnosis system for automobile brake system is a new technology developed by M L. Smith for Eaton, which is applied to the diagnosis of the brake system. After regular integration with the fact data, the fact data and virtual diagnostic input information are interacted by neural network reasoning, which makes the fault diagnosis more perfect.

Since 1985, automatic diagnosis technology such as machine learning has been applied in automobile fault diagnosis abroad. Among them, the TEST expert system was developed by Ford Company, and the RuleMaster expert system was unveiled by Renault Company in France. In the 21st century, with the rise of cloud computing, big data, neural network, and other emerging technologies, foreign automobile fault diagnosis technology continues to "automation, intelligent" direction of development, greatly promoting the improvement of fault diagnosis technology and development. The above methods have been applied in engine fault diagnosis, but there is still space for improvement in diagnosis speed and accuracy.

Unlike the SVM applied in automobile engine fault detection [10], the neural network algorithm has been applied in many fields [11], and it has been applied to automobile engine fault detection, such as automobile engine fault detection by probabilistic neural network [12], neural network, and expert system for fault diagnosis of automobile engine [13], a mixed model based on neural network and wavelet transform for fault diagnosis of automobile engine [14], and some others NN-based method for fault diagnosis

of automobile engine like and neural network torsional vibration [15], fuzzy neural network [16], or single neural network [17]. Compared with other NN-based method, the BP neural network-based method is used less, but there are already some researches about fault diagnosis throughout the BP network [18]. In recent research about fault diagnosis of automobile engine [19], a genetic algorithm is applied in it and has get the outperform result already [20, 21]. Therefore, in this paper, we employed the improved BP neutral network and GA algorithm for fault diagnosis of automobile engine.

Therefore, since the convergence speed of the traditional BP neural network algorithm is slow and the accuracy is insufficient in the process of automobile engine fault diagnosis, this paper improves convergence speed of the algorithm by introducing the momentum term, and the weights and thresholds of the neural network are optimized by using GA selection, crossover, and genetic characteristics, to propose a genetic algorithm (GA) optimization BP neural network fault diagnosis method. The comparative simulation results show that the proposed improved algorithm is better than the traditional BP neural network algorithm in diagnosis precision, accuracy, and other key indicators.

3. Fault Diagnosis of Gasoline Engine

3.1. An Overview of Gasoline Engines and Common Faults. Since the rapid diagnosis of engine faults, the first need is to understand the basic structure of the engine and common faults. The basic structure of gasoline engine includes crank connecting rod mechanism, valve mechanism, ignition system (diesel engine without ignition system), fuel supply system, lubrication system, cooling system and starting system, and "two major institutions and five systems". There are thousands of parts and components, as well as a variety of complex electronic circuit systems. Material composition of the various parts of the sort is various, plus parts of complex production process, the process capability of suppliers is not stable, component and system design of unsound, insufficient durability test design, and the process of many factors that led to the engine system such as the frequent failure rate, so quick, correct, and effective fault diagnosis is especially important for every automobile manufacturing company.

3.2. Typical Fault Signs of Gasoline Engines. Gasoline engines developed by different manufacturers have different varieties and specifications, and the types of faults are also different, which can be roughly divided into mechanical system failure, ignition system failure, electronic control system failure, and fuel system failure. In view of typical faults of gasoline engines, relevant theoretical materials are collected and summarized according to relevant experience, and the causes of typical engine faults are sorted out as follows:

(1) The gasoline engine cannot start: according to a large number of data, the pressure reading of normal operation of gasoline engine should be 250-300 kPa. From engine idling to short time throttle, the engine fuel pressure should not exceed this range. If the fuel pressure is normal, the oil transmission system fault can be eliminated. At this time, check the following electrical components:

(i) Crankshaft position sensor: the crankshaft position sensor can transmit the ignition reference signal and the speed parameters of the gasoline engine. If the electronic control unit does not have the ignition reference signal and speed parameters are normal, the fault of the sensor can be eliminated

(ii) Start signal: the start signal is provided by a wire between the electronic control unit and the electromagnetic coil of the starter. The electronic control unit also uses this signal to start and intensify. The inspection found that the signal disappeared, the above function can not be produced, and the engine can not start, which proves that the component is damaged.

(iii) Cooling water temperature sensor: to ensure that the engine cold state needs to provide special fuel material. Cooling water temperature sensor detects cooling water temperature and transmits water temperature information to electronic control unit. The data transmitted by this sensor is affected by the resistance value. When the sensor fails, the resistance value is high, and the electronic control unit cannot issue correct instructions, so the engine cannot start

(iv) Throttle or throttle position sensor: when the throttle reaches the fully open position, the valve limit switch transmits throttle signal information to the electronic control unit through the throttle position sensor; this signal is an important signal of engine startup information, if after receiving the throttle open signal and the start signal, the electronic control unit injector pulse control, start the engine. If the throttle sensor is faulty, the "unloading" signal is continuously emitted, resulting in the normal operation of the gasoline engine

(v) Electronic control unit: the electronic control unit is the command center of all the sensors; the sensor input information is analyzed by it and then causes the injector to produce a specific pulse. If all input information is normal, check the electronic control components and wiring faults

(vi) Fuel injection system failure: the fuel injector is an important factor for the normal start of the engine. Common faults include unstable injection pressure, poor atomization of injector, and oil leakage of injector. These factors can affect the normal start of the engine

(vii) Ignition line failure: late ignition, spark plug failure, premature ignition time are the main fault of ignition line, and point over line failure will affect the engine start.

(2) Cold start difficulty of gasoline engine: it refers to normal start of gasoline engine under normal or thermal condition, and difficult to start under cold condition. Analysis of its causes includes cooling water temperature sensor failure, electric fuel pump failure, and idle control valve failure. Among them, the cooling water temperature sensor failure directly affects the fuel injection volume, which indirectly affects the engine start. Failure of the electric fuel pump resulted in insufficient fuel pressure, which made it difficult to start the engine. When the cooling water temperature sensor sends the signal that additional fuel is needed, the idle control valve will provide extra air, and the valve can not work properly due to mechanical failure and electronic component failure

(3) The gasoline engine often flameout during idle speed: If the ignition system works normally, the following components need to be tested

Idle motor or its circuit is damaged; low idle speed is the main cause of engine stall.

(i) Fuel system: there may be many reasons for failure, such as no electrical signal in the fuel pump; Insufficient fuel pressure, failure of oil pump and pressure regulator and other reasons may cause insufficient fuel flow of injector, or damage or blockage of circuit in fuel system such as oil pump and fuel filter

(ii) Electronic control unit: idle control module in the electronic control unit is out of control, and the fuel injector cannot correctly identify the amount of fuel injection, causing the gasoline engine to stop running

(4) Unstable idle speed of gasoline engine: low idle speed or incorrect ignition timing is the main reason for unstable idle speed, in addition, the factors causing unstable idle speed of gasoline engine may also have the following points:

(i) Injector: the cylinder is not maintained in time and is seriously polluted, which causes the injector to be blocked, the actual oil injection amount of the injection pipe to drop sharply, and the mixture concentration in the cylinder is insufficient, which causes the engine to idle unstable and flameout easily

(ii) Fuel pressure regulator: the main role is to adjust the fuel pressure, fuel pressure regulator failure is an important factor affecting the fuel pressure and intake manifold absolute pressure sensor transmission data, its vacuum hose leakage will eventually lead to idle instability and easy to flameout

(iii) Intake manifold absolute pressure sensor: through the vacuum change in the manifold, it affects the electronic control unit fuel injection and ignition timing angle. The common fault causes are short circuit or circuit break of the sensor itself, vacuum tube damage, transmission voltage uncontrollable, and other factors. Damage to vacuum hose of intake manifold pressure sensor, abnormal leakage, or blockage will cause engine idle instability and easy flameout

(iv) A cylinder misfire: the fault of the coil, spark plug, and high-voltage line may be an important cause of a cylinder misfire. At present, most electronically controlled gasoline engines are computer numerical control ignition systems with direct ignition as the main mode. The reasons for the failure are ignition coil damage, high voltage line break, spark plug does not fire, electric coil break, nozzle does not spray oil can cause the engine idle unstable, easy to flameout.

(v) Intake system leakage: the intake system is affected by the change of engine speed, and the amount of air intake or leakage will affect idle speed, resulting in idle speed instability

(vi) Idle control system working disorder: electrical failure of electronically controlled gasoline engine, idle control valve mechanical failure caused by stagnation and loose closed air leakage, disturb the original closed loop idle control system working time will cause idle unstable phenomenon, easy to flameout

(5) High fuel consumption: the biggest possible fault is the throttle position sensor: when the throttle reaches the fully open position, the valve limit switch provides a fully open throttle signal to the electronic control unit through the throttle position sensor, which is the role of the throttle position sensor. When the throttle fails, the electronic control unit mistakenly thinks that the throttle is fully open, which mistakenly increases the amount of fuel, resulting in high fuel consumption

(i) Fuel pressure system: the level of fuel pressure will affect fuel consumption, which affects the economy of the vehicle. Too high fuel pressure can cause too much fuel to be injected each time the injector is turned on. Too low fuel pressure will result in too thin mixture concentration and insufficient fuel injection combustion will affect fuel consumption

(ii) Cooling water temperature sensor: this sensor is an important equipment to detect engine temperature. If the sensor short-circuit, circuit break, or deviation from the calibration value and other faults, it will lead to the continuous emission of cold state intensification signal, resulting in the electronic control unit adjustment imbalance, too much oil injection

3.3. Gasoline Engine Fault Diagnosis Method. In this paper, based on the basic method of gasoline engine fault diagnosis, it can increase the degree of intelligence and rapid intelligent fault diagnosis. Existing fault diagnosis methods mainly depend on the advanced sensor technology, in the car without disassembly or according to the cars under the condition of incomplete dissolution, rapid, accurate, and objective acquisition engine work status of all the information, and dynamic tracking, by large data samples, the expert database, analysis and processing, separation and identification, the final diagnosis of the engine. With the upgrading of market demand, computer application technology, mobile Internet technology, sensor technology, artificial intelligence technology are also constantly developing and improving, efficient and accurate information collection, integration and judgment without the premise of disassembling the vehicle have long been possible.

4. Method Introduction

Engine electronic control is not only the basis of fault diagnosis but also an effective part of later experimental data collection. Only by fully understanding the basic common methods of fault diagnosis can we provide strong prior knowledge for the later artificial intelligent fault diagnosis model. At present, although there are many types and kinds of electronic control system of automobile engine, the control principle and structure composition are basically the same. The engine is started by injection and ignition and other devices, and finally, the engine runs normally.

The electronic control system is composed of electronic sensors, actuators, and electronic control units of gasoline engines. The sensor is the equipment that transmits the data information signal of the engine under various working conditions. It can be placed and used in different parts of the engine according to the vehicle model and the size of the sensor space. After the sensor collects the signal under each working condition of the engine, the signal source information should be converted into the electronic control unit which can recognize the received electrical signal and transfer the electrical signal to the electronic control unit. The electronic control unit is an important part of the electronic control system of gasoline engine. It takes the engine working condition parameters transmitted by sensors as input, selects the high quality execution command according to the corresponding control strategy, and transmits the execution command to the actuator, so as to realize the effective control of gasoline engine running condition. It is worth mentioning that the electronic control unit includes a fault diagnosis function. If the engine fails, the electronic control unit can store the fault parameters, and under certain conditions, enter the fault limping control mode to ensure that the vehicle can be driven to a safe area or repair shop. The actuator consists of the igniter, idle control valve, fuel pump, exhaust gas recirculation valve and fuel injector, the signal from the electronic control unit, the input actuator, and the actuator converts the input source signal into mechanical motion output through conversion. They run the engine together.

4.1. Engine Failure Type Introduction. The process of fault diagnosis is to accurately locate the component where the fault occurs (the cause of the fault) according to the fault symptom, so establishing the relationship between the fault symptom and the cause of the fault is the primary task of fault diagnosis. According to the common faults of gasoline engine in Section 3, the design of the relationship between the fault phenomena and the main components of the fault causes can be seen in Table 1.

As can be seen from Table 1, the cause of the fault result is the fault symptom, as follows.

(1) Fault diagnosis of engine startup difficulty, their corresponding signs (fault phenomena) contain the idle or fault of idle speed control valve, ignition coil, throttle fault or inlet pipe leakage, air flow sensor failure, the spark plug failure, crankshaft position sensor failure, intake manifold absolute pressure or temperature sensor fault, fuel supply system, ignition timing wrong, failure of fuel injector, ignition coil, storage battery without electricity, and so on

(2) Sometimes engine stall fault diagnosis, its corresponding fault symptoms include ignition coil fault, air flow sensor fault, spark plug fault, and improper ignition timing

(3) Engine acceleration tempering diagnosis, its corresponding fault symptoms include oxygen sensor fault, intake pipe absolute pressure problem or temperature sensor fault, fuel supply system fault, fuel injector fault, throttle fault or intake pipe leakage, ignition timing is wrong, idle speed is improper

(4) Fault diagnosis of engine flameout due to unstable idle speed, its corresponding fault symptoms include idle or fault of idle speed control valve, ignition coil, air flow sensor, throttle fault or inlet pipe leakage, spark plug fault, intake manifold absolute pressure or temperature sensor fault, ignition timing is wrong, injectors, ignition coil fault, cylinder carbon, and oxygen sensor fault

(5) The engine speed is difficult to control the diagnosis, its corresponding fault symptoms include oxygen sensor fault, ignition coil, intake manifold absolute pressure or temperature sensor, fuel pressure instability and fault of fuel injector, air filter, spark plug fault, of the opening of the throttle fault or inlet pipe leakage and sensor fault, ignition timing is wrong, and air flow meter fault

(6) Fault diagnosis of engine panting or weak acceleration, its corresponding fault symptoms include ignition system timing, intensity, air filter, intake manifold absolute pressure or temperature sensor fault, ignition coil, fuel pressure, throttle fault or inlet pipe leakage and spark plug fault, cylinder carbon accumulation, and fuel injector fault

(7) Engine detonation fault diagnosis, its corresponding fault symptoms include cylinder carbon

Table 1: Relationship between common fault sites and fault causes of gasoline engines.

Fault phenomena	Starting difficulty	Sometimes stall	Backfire when accelerating	Idle is unstable or stalled	Idle speed is too high	To gasp or accelerate weakly	Explosive shock	The temperature of gasoline engine is too high	The exhaust muffler blasts the gun
Fault causes									
Idle or idle control valve fault	√		√	√	√				√
Ignition coil fault	√	√		√		√			
Improper ignition timing	√	√	√	√	√	√	√	√	√
The spark plug fault	√	√		√		√	√		√
The openness sensor fault			√	√	√	√			√
Throttle fault or intake pipe leakage	√		√	√	√	√			√
The air filter fault									
The fuel injector fault									
Fuel supply system fault				√		√			
The air flow sensor fault	√		√	√	√	√			√
Intake pipe absolute pressure problem or temperature sensor fault	√	√		√	√	√			
Oxygen sensor fault	√		√	√	√			√	
Crankshaft position sensor fault			√	√					√
Cooling or lubrication system fault								√	
Cylinder carbon accumulation				√		√	√	√	
Battery without power	√								

accumulation, spark plug carbon accumulation too much or failure, and ignition timing is not accurate

(8) Fault diagnosis of engine overtemperature, corresponding fault symptoms include cylinder carbon accumulation, temperature sensor failure, and cooling or lubrication system fault,

(9) Engine exhaust muffler shooting fault diagnosis, its corresponding fault symptoms include fire system timing is not accurate, fuel pressure instability, throttle fault or intake pipe leakage, oxygen sensor fault, spark plug fault, fuel injector fault, idle speed improper, etc.

4.2. The Basic Process and Defects of BP Neural Network Fault Diagnosis. The neural network input vector $A_k = (a_1, a_2, \cdots, a_n)$ and the expected output vector $Y_k = (y_1, y_2, \cdots, y_m)$ are defined: input and output vectors $S_k = (s_1, s_2, \cdots, s_d)$ and $B_k = (b_1, b_2, \cdots, b_d)$ of hidden layer units; input and output vector $L_k = (l_1, l_2, \cdots, l_m)$ and $C_k = (c_1, c_2, \cdots, c_m)$ of output layer units; input and output vector $L_k = (l_1, l_2, \cdots, l_m)$ and $C_k = (c_1, c_2, \cdots, c_m)$ of output layer units. The connection weight between the input layer and the hidden layer is $\{W_{ij}\}$, $i = 1, 2, \cdots, n$, $j = 1, 2, \cdots, d$, and that between the hidden layer and the output layer is $\{V_{jt}\}$, $t = 1, 2, \cdots, m$. The output threshold of each unit in the hidden layer is $\{\theta_j\}$, and the output threshold of each unit in the output layer is $\{\gamma_t\}$. Using S-type function as response function, signal transmission rules of BP neural network can be established as follows.

The equation of neural network output and mean square error of expected output error are

$$\begin{cases} E_k = \sum_{t=1}^{h} \frac{\left(\delta_j^k\right)^2}{2}, \\ \delta_j^k = \left(y_j^k - C_j^k\right). \end{cases} \tag{1}$$

The weight and threshold correction function from the hidden layer to the output layer are

$$\begin{cases} \Delta V_{jt} = -\alpha \dfrac{\partial E_k}{\partial V_{jt}} = \alpha \delta_t^k C_t^k \left(1 - C_t^k\right) b_j, \\ C_t^k = f\left(\sum_{j=1}^{d} V_{jt} b_j - \gamma_t\right), \end{cases} \tag{2}$$

$$\begin{cases} \Delta \gamma_t = \alpha d_t^k, \\ d_t^k = \delta_t^k C_t^k \left(1 - C_t^k\right). \end{cases} \tag{3}$$

The weight and threshold correction function from the input layer to the hidden layer are

$$\begin{cases} \Delta W_{ij} = -\beta \dfrac{\partial E_k}{\partial W_{ij}} = \beta e_j^k a_j, \\ e_j^k = \left[\sum_{t=1}^{h} d_t^k V_{jt}\right] b_j \left(1 - b_j\right), \end{cases} \tag{4}$$

$$\Delta \theta_j = \beta e_j^k. \tag{5}$$

In the formula, k represents the number of training samples, n represents the number of input parameters, m represents the number of output parameters, d represents the number of hidden layers, and α and β are modified parameters. δ_j^k represents the error, E_k represents the mean square error, d_t^k represents the generalization error of each unit in the output layer, and e_j^k represents the generalization error of each unit in the hidden layer.

The BP neural network has been widely used in fault diagnosis due to its strong learning ability and nonlinear approximation characteristics. Its basic process is as follows:

Step 1: obtain sample data corresponding to engine fault phenomena and symptoms, and normalize the data to form a fault mode pair sample set.

Step 2: initialize the connection weights and thresholds of the neural network, and provide the processed mode pairs to the neural network for online learning and training.

Step 3: fault symptom data is taken as the input of neural network, and the output data is obtained after weighted processing by hidden layer and output layer.

Step 4: calculate the sum of squares of errors between the output data and the expected output according to formula (1), reverse transfer and modify the weight threshold according to formulas (2)–(5);

Step 5: repeat steps 3 and 4 until the sum of squares of error is minimal.

Although the BP neural network has strong nonlinear mapping ability, it still has the following defects:

(1) The learning convergence rate is slow, requiring large training samples for hundreds of times of repeated learning

(2) Easy to fall into local minimum

(3) The selection of parameters such as the number of hidden layer units and the initial weight threshold depends on manual experience and has certain blindness

4.3. Improved BP Neural Network Fault Diagnosis Method

4.3.1. Introduce Momentum Term to Improve Convergence Rate. In traditional BP neural network algorithm, from formula (2) to (4), it can be seen that in the modification of the weight and threshold only considers the gradient descent at the current moment, that is, only considers the influence of error factors and does not consider the gradient direction at the previous moment, which easily leads to the oscillation of the learning process, falling into the local minimum value, and the convergence rate is slow.

To solve this problem, we can introduce the weight and threshold correction variable of the previous moment into the correction formula, so as to transfer the weight change of each time, which can make the adjustment of the weight change to the average direction of the bottom of the error surface, and help to make the network jump out of the local minimum of the error surface. The modified formula of weight threshold is as follows.

It can make the weight adjustment change to the average direction at the bottom of the error surface and help to make the network jump out of the local minimum of the error surface. The modified formulas of weight and threshold are as follows:

$$\begin{cases} \Delta W_{ij}(k+1) = (1 - m_c)\beta e_j^k a_j + m_c \Delta W_{ij}(k), \\ \Delta \theta_j(k+1) = (1 - m_c)\beta e_j^k + m_c \Delta \theta_j(k), \end{cases} \tag{6}$$

$$\begin{cases} \Delta V_{ij}(k+1) = (1 - m_c)\alpha d_t^k b_j + m_c \Delta V_{ij}(k), \\ \Delta \gamma_j(k+1) = (1 - m_c)\alpha d_t^k + m_c \Delta \gamma_j(k), \end{cases} \tag{7}$$

where m_c is momentum factor, and when $m_c = 0$, the modified formula is consistent with that of the traditional algorithm, that is, only the gradient descent of the current output error is considered; When $m_c = 1$, the improved weight and threshold changes are consistent with the previous weight and threshold changes, that is, only the gradient descent of the previous training output error is considered. Thus, when the momentum term is increased, in the local minimum region, i.e., e_j^k and d_t^k approach 0, there is still the following:

$$\begin{cases} \Delta W_{ij}(k+1) = m_c \Delta W_{ij}(k), \\ \Delta \theta_j(k+1) = m_c \Delta \theta_j(k), \end{cases} \quad \begin{cases} \Delta V_{ij}(k+1) = m_c \Delta V_{ij}(k), \\ \Delta \gamma_j(k+1) = m_c \Delta \gamma_j(k). \end{cases} \tag{8}$$

Table 2: BP neural network training samples.

Serial number	Sample input	Expected output	Fault parts
1	101110001	00001	Idling or idle control valve fault
2	110101000	00010	The ignition coil fault
3	111111111	00011	The ignition was wrong on time
4	110101101	00100	The spark plug fault
5	001111001	00101	The openness sensor fault
6	101111000	00110	Throttle fault or intake pipe leakage
7	000101000	00111	The air filter fault
8	101111011	01000	The fuel injector fault
9	101111001	01001	The fuel supply system fault
10	110111000	01010	The air flow sensor fault
11	101110010	01011	The intake pipe fault
12	011000001	01100	The oxygen sensor fault
13	100000001	01101	Crankshaft position sensor is faulty
14	000000100	01110	Cooling or lubrication system fault
15	000101110	01111	Cylinder carbon
16	100000000	10000	Battery without power

Table 3: Simulation results of partial training data based on the traditional BP neural network.

The target output	Actual output based on the traditional BP neural network					Diagnostic number	Diagnostic results
00001	0.0025	-0.0085	0.0043	0.0133	1.0006	1	True
00010	0.0019	-0.0044	0.0053	0.9987	0.0032	2	True
00011	0.0074	-0.0013	0.0075	0.9976	1.0074	3	True
00100	-0.0054	0.0038	0.9974	0.0031	0.0129	4	True
00101	0.0024	0.0023	0.9968	0.0052	0.9996	5	True
00110	-0.0031	0.7386	0.2512	0.2544	0.5055	9	False
00111	-0.0065	0.0088	0.9979	0.9972	0.9955	7	True
01000	-0.0031	0.7386	0.2512	0.2545	0.5055	9	False
01001	-0.0031	0.7386	0.2512	0.2545	0.5055	9	True
01010	-0.0005	0.9961	0.0008	0.9972	0.0007	10	True
01011	-0.0163	0.9827	-0.0031	1.0156	1.0012	11	True
01100	0.0074	0.9995	1.0043	0.0125	-0.0019	12	True
01101	0.4946	0.4968	0.4988	0.0110	0.4988	0	False
01110	0.0047	0.9971	1.0012	0.9977	0.0002	14	True
01111	-0.0006	0.9968	1.0001	1.0055	1.0067	15	True
10000	0.4946	0.4968	0.4988	0.0111	0.4988	0	False

Thus, the correction value of 0 can be avoided effectively and the output of neural network can jump out from the local minimum.

4.3.2. Genetic Algorithms Optimize the Weights and Threshold Initial Values. Since the fault prediction system is a nonlinear system, the selection of initial weight threshold of BP neural network has a great influence on the length of training time, the speed of convergence, and whether it will fall into local extremum, from the point of the traditional BP neural network fault diagnosis process, the initial weights of the selection of threshold is often dependent on human experience; this brings a lot of uncertainty to the establishment of BP neural network model, while genetic algorithm simulates biological evolution model and, through selection, crossover, and variation, can retain the individuals with good fitness value and eliminate the individuals with bad fitness value, so as to obtain the initial weight and threshold of the best fitness value.

4.4. Introduction of the Proposed Method. The improved BP neural network fault diagnosis algorithm flow is as follows:

Step 1: obtain sample data corresponding to engine fault phenomena and symptoms, and normalize the data to form a fault mode pair sample set.

Table 4: Simulation results of partial training data based on the improved BP neural network.

The target output	Actual output based on the improved BP neural network					Diagnostic number	Diagnostic results
00001	0.0001	-0.0001	0.0000	-0.0001	0.9999	1	True
00010	0.0002	-0.0002	-0.0003	0.9998	0.0001	2	True
00011	-0.0002	0.0000	-0.0002	1.0000	1.0003	3	True
00100	-0.0003	-0.0005	0.9992	0.0000	0.0008	4	True
00101	0.0001	0.0001	1.0000	0.0002	0.9995	5	True
00110	0.0000	0.0000	0.9998	0.9999	0.0002	6	True
00111	0.1751	0.4825	-0.0322	0.6006	0.2937	7	False
01000	0.0000	1.0001	0.0000	0.0001	0.0003	8	True
01001	-0.0001	1.0000	0.0003	0.0000	1.0000	9	True
01010	0.0003	0.9996	-0.0003	0.9997	0.0003	10	True
01011	-0.0000	0.9999	-0.0000	1.0000	1.0001	11	True
01100	0.0000	1.0000	0.9999	-0.0000	0.0001	12	True
01101	-0.0001	0.9996	1.0001	0.0001	0.9998	13	True
01110	0.0001	0.9997	0.9990	1.0000	0.0008	14	True
01111	0.0000	0.9999	0.9999	1.0000	1.0000	15	True
10000	1.0000	0.0000	-0.0002	0.0001	0.0003	16	True

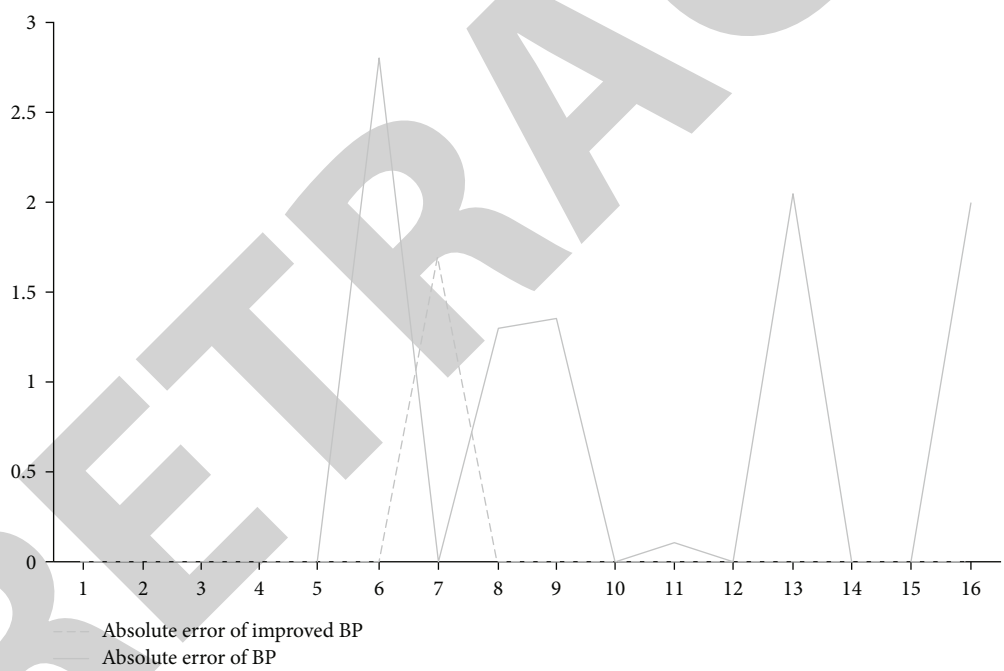

Figure 1: Absolute error of simulation data output.

Step 2: genetic algorithm is used to optimize the initial connection weights and thresholds of the neural network, and the processed mode pairs are provided to the neural network for online learning and training.

Step 3: fault symptom data is taken as the input of neural network, and the output data is obtained after weighted processing by hidden layer and output layer.

Step 4: calculate the sum of the squares of error between the output data and the expected output according to Formula (1) and modify the weight threshold by introducing the improved formulas (6) and (7) of momentum item

Step 5: repeat steps 3 and 4 until the sum of squares of error is minimum.

Step 6: use the trained improved BP neural network fault diagnosis model to diagnose the fault phenomenon and judge the fault type.

5. Experiment and Result Analysis

In order to verify the superiority of the improved algorithm proposed in this paper, MATLAB simulation was used to conduct fault diagnosis simulation experiments on the

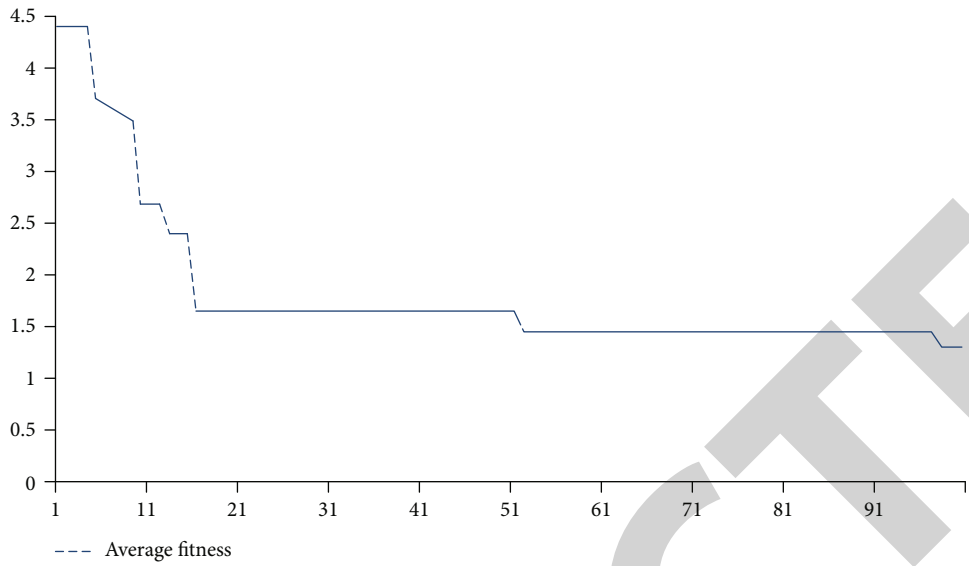

Figure 2: Fitness of genetically optimized BP network.

traditional BP neural network and the improved BP neural network in this paper, respectively. 16 kinds of common engine fault phenomena and corresponding relationships of causes as shown in Table 1 were used as fault diagnosis objects.

In the process of simulation, the causes of faults are numbered with numbers 1-16 and binarized as the target output of the training sample. The phenomenon of faults is represented by 0 and 1, respectively, and constitutes the input of the training sample. Then, the training sample pairs can be obtained, as shown in Table 2.

In the process of simulation, the causes of faults are numbered with numbers 1-16 and binarized as the target output of the training sample. The phenomenon of faults is represented by 0 and 1, respectively, and constitutes the input of the training sample. Then, the training sample pairs can be obtained, as shown in Table 2. Parameters of the neural network are set as follows: number of training samples $k = 50$, number of input parameters $n = 9$, number of output parameters $m = 5$, number of hidden layers $d = 10$, and modified parameter $\alpha = 0.2$ and $\beta = 0.2$, momentum factor $m_c = 0.9$, iteration times $d = 100$, population size $l = 10$, crossover probability $\mu = 0.3$, and mutation probability $\gamma = 0.01$.

The neural network training model was established by MATLAB; after the fault sample mode training, the first 16 groups of neural network data were selected for testing and analysis. The simulation result data shown in Tables 3 and 4, the simulation error curve shown in Figure 1 and the optimization curve of genetic algorithm fitness value shown in Figure 2 could be obtained, respectively.

By analyzing the simulation results in Tables 3 and 4, it can be seen that the traditional BP neural network not only has certain diagnostic ability for training samples but also has some error diagnosis. The diagnostic accuracy of 16 groups of sample data is 75%, while the fault diagnosis accuracy of the improved BP neural network algorithm in this paper is 93.75%; the diagnostic accuracy increased by 18.75%.

Table 5: Diagnostic errors of the two neural networks for each group of data.

Diagnostic number	Evaluation index formula	Traditional BP neural network	Improved BP neural network
1		0.0292	0.0004
2		0.0161	0.0010
3		0.0260	0.0007
4		0.0278	0.0024
5		0.0135	0.0009
6		2.7461	0.0005
7		0.0247	1.6311
8	$\text{error}_k = \sum_{i=1}^{m} \left\| y_i^k - C_i^k \right\|$	1.2756	0.0005
9		1.2646	0.0004
10		0.0087	0.0016
11		0.0535	0.0002
12		0.0266	0.0002
13		2.0112	0.0009
14		0.0113	0.0022
15		0.0161	0.0002
16		2.0109	0.0006

With the output absolute error value as the evaluation index, the diagnostic error data of the traditional BP neural network and the improved BP neural network in this paper for each group of data are shown in Table 5, the error distribution of the 16 groups of data is shown in Figure 1, and the fitness value optimization of the genetic algorithm is shown in Figure 2.

As can be seen from Table 5 and Figure 1, in the output results of 16 groups of test data, the error of each group of data of the improved algorithm in this paper is smaller than that of the traditional algorithm. The average absolute error of the traditional BP neural network algorithm is 0.5976,

while the average absolute error of the improved BP neural network algorithm in this paper is 0.1027. The diagnostic accuracy was improved by 82.8%. As can be seen from Figure 2, the genetic algorithm continuously optimized the fitness value through selection, crossover, and genetic characteristics, so that the initial weight threshold of the neural network reached the optimal value when the number of iterations was $d = 96$, and the optimal fitness value was 1.3827.

6. Conclusion

In the process of the automobile engine fault diagnosis, the authors of this paper show the the traditional BP neural network algorithm problems such as lack of slow convergence speed and precision. By introducing the momentum term to improve the convergence speed of the algorithm, and using the GA selection, crossover, and genetic characteristics to optimize the weight and threshold value of the neural network, a fault diagnosis method of the BP neural network optimized by legacy algorithm (GA) is proposed in this paper. The average absolute error of the traditional BP neural network algorithm is 0.5976, while the average absolute error of the improved BP neural network algorithm in this paper is 0.1027. The simulation results show that the improved algorithm proposed in this paper has a certain degree of improvement over the traditional BP neural network algorithm in diagnosis precision, diagnosis accuracy, and other key indicators, so it has a certain application value.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

References

[1] A. Sharkey, N. E. Sharkey, and G. O. Chandroth, "Diverse neural net solutions to a fault diagnosis problem," *Neural Computing & Applications*, vol. 4, no. 4, pp. 218–227, 1996.

[2] J. D. Wu, C. K. Huang, Y. W. Chang, and Y. J. Shiao, "Fault diagnosis for internal combustion engines using intake manifold pressure and artificial neural network," *Expert Systems with Applications An International Journal*, vol. 37, no. 2, pp. 949–958, 2010.

[3] E. Mendes and E. Mendes, "Introduction to Bayesian networks," in *Practitioner's Knowledge Representation*, Springer, Berlin, Heidelberg, 2014.

[4] M. Khalil, "An expert system to evaluate the wear between cylinder kit parts for the vehicle engine," *SAE Technical Papers*, 2010.

[5] D. S. Sarna and J. W. Steyaert, *Diagnostic Equipment Development for Military Vehicle Applications*, Automotive Engineering Congress & Exposition, 1978.

[6] K. A. Marko, L. A. Feldkamp, and G. V. Puskorius, "Automotive diagnostics using trainable classifiers: statistical testing and paradigm selection," in *1990 IJCNN International Joint Conference on Neural Networks*, San Diego, CA, USA, 2012.

[7] V. Venkatasubramanian and K. Chan, "A neural network methodology for process fault diagnosis," *AICHE Journal*, vol. 35, no. 12, pp. 1993–2002, 1989.

[8] B. Hamilton and Y. Lu, "Diagnosis of automobile failures using fuzzy logic," in *Proceedings of the 8th International Conference on Industrial and Engineering Applications of Artificial Intelligence and Expert Systems*, pp. 337–344, Melbourne, Australia, 1995.

[9] W. J. Staszewski and K. Worden, "Classification of faults in gearboxes - pre-processing algorithms and neural networks," *Neural Computing & Applications*, vol. 5, no. 3, pp. 160–183, 1997.

[10] D. J. Wang, M. Li, C. Liu, and J. N. Sun, "Fault diagnosis of automobile engine based on support vector machine," *Applied Mechanics and Materials*, vol. 80-81, pp. 1060–1064, 2011.

[11] Z. Bao and C. Wang, "A multi-agent knowledge integration process for enterprise management innovation from the perspective of neural network," *Information Processing & Management*, vol. 59, no. 2, p. 102873, 2022.

[12] C. Du, W. Li, F. Yu, F. Li, and X. Zeng, "Misfire fault diagnosis of automobile engine based on time domain vibration signal and probabilistic neural network," *International Journal of Performability Engineering*, vol. 16, no. 9, p. 1488, 2020.

[13] Y. Z. Men and F. L. Wang, "Research on the application of neural network and expert system in the fault diagnosis of automobile engine," *Journal of Machine Design*, vol. 24, no. 12, pp. 64-65, 2007.

[14] J. D. Wu and C. H. Liu, "Investigation of engine fault diagnosis using discrete wavelet transform and neural network," *Expert Systems with Applications*, vol. 35, no. 3, pp. 1200–1213, 2008.

[15] C. Y. Du, K. Ding, Z. J. Yang, and C. L. Yang, "Diagnosis for engine misfire fault based on torsional vibration and neural-network analysis," *Advanced Materials Research*, vol. 433-440, pp. 7240–7246, 2012.

[16] L. L. Jiang, Y. Ni, L. H. Tang, and Y. He, "Fault diagnosis expert system of automobile engine based on neural networks," *Key Engineering Materials*, vol. 460-461, pp. 605–610, 2011.

[17] R. Guo, H. Li, and L. Zhang, "A study about fault diagnosis of automobile engine based on neural network," 2012.

[18] R. Guo, H. Li, and L. Zhang, "A study about fault diagnosis of automobile engine based on neural network," in *Proceedings of the 2nd International Conference on Electronic & Mechanical Engineering and Information Technology (EMEIT 2012)*, pp. 2040–2043, 2012.

[19] C. Du, W. Li, Y. Rong, F. Li, F. Yu, and X. Zeng, "Research on the application of artificial intelligence method in automobile engine fault diagnosis," *Engineering Research Express*, vol. 3, no. 2, p. 026002, 2021.

[20] K. Zhang and D. Lu, "Fault diagnosis of engine misfire base on support vector machine," *Digital Technology & Application*, vol. 1, pp. 250–253, 2011.

[21] L. F. Kong, S. S. Zhu, and Z. Wang, "Gradient genetic algorithm-based oil fault diagnosis model for automobile engine," in *2011 2nd International Conference on Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC)*, pp. 2127–2130, 2011.