TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol.12, No.2, February 2014, pp. 1367 ~ 1373
DOI: http://dx.doi.org/10.11591/telkomnika.v12i2.3839

Accord Ignition Diagnosis Based on Improved GA-BP

Tie Wang*, Chao Wang, Jing Wu
School of Vehicle and Traffic, Shenyang Ligong University
No.6, nanping center Road, Hunnan New District, Shenyang, China
*Corresponding author, e-mail: wangtielucky@126.com

Abstract

BP neural network as a kind of intelligent method is widely used in fault diagnosis, due to the single BP neural network's error is big, GA algorithm is often used in optimizing BP neural network, but the standard GA algorithm's searching efficiency is low and it is easy to fall into local convergence. According to the characters of Accord car ignition diagnosis and BP neural network, this article puts forward an improved scheme of the standard GA algorithm optimizing BP net, calculate and analyze different simulation results gotten by MATLAB program. Through calculation: the single BP neural network's convergence step number is 101, the final mean square error is 0.000997167; the convergence step number that standard GA algorithm optimizes the BP neural net is 83, the final mean square error is 0.000142126; the convergence step number that GA algorithm improved optimizes the BP neural net is 73, the final mean square error is 0.000137508. By the comparison, the improved GA algorithm has a better search efficiency and it's computation can avoid falling into a local convergence.

Keywords: *failure diagnosis, BP neural network, improved GA algorithm*

1. Introduction

Along with the progress of science and technology, the mechanical fault is becoming more and more complicated. At the end of the last century, the researchers gradually developed many artificial intelligence methods, such as expert system and neural network. Those methods always used in the field of fault diagnosis, BP (Back Propagation) neural network is the most widely used among them.

BP neural network's application and operation are simple [1-3], but the limitations of network's structure and the randomness of its weights and thresholds cause it have a big error and a slow convergence speed and unable to search the global optimal solution. GA (Genetic Algorithm) as the representative of the intelligent algorithm often is used to optimize BP neural network's initial weights and thresholds, it not only can reduce the error of the neural network, but also can improve the BP neural network's training speed[4-6]. In the practical application, we find the standard GA algorithm also has some disadvantages, mainly includes two aspects:

(1)Search efficiency is low.

(2)Easy premature and stuck in local minima.

2. The Basic Idea of Improving GA

GA [7-9] is an algorithm which is based on biological genetic simulation, it simulates the natural process, mainly concludes selection, crossover and mutation. The basic idea of GA algorithm is starting from any initial group, using the random selection, crossover and mutation operation, produce a new group which is more adapt to the environment and make the group evolve into a better regional in all search space; the evolution is continuously converge to points that obtain the optimal solution of the problem. Various improved GA can increase the efficiency and make the results more accurate.

2.1. GA Adaptive Improvement

(1) The standard genetic algorithms crossover probability is often a value from 0.6 to 1, but it is easy to cause the algorithm un-converge. Crossover operation is the process of global search, in the early stage of the evolution, population's diversity is high, the single crossover

Received July 6, 2013; Revised August 31, 2013; Accepted September 17, 2013

can get large search space, in the later stage of the evolution, individual's differences is small, so it need to use multiple point crossover. When the fitness of the population remains constant, the operations may have entered into the local optimal, so the cross point should be changed, strides out from the current part [10]. We selects pc as the adaptive crossover probability.

When $F(i) \geq Favg$, pc is:

$$pc = \frac{pc1 + pc2}{2} + \frac{pc1 - pc2}{2} \times \frac{F(i) - Favg}{F\max - Favg} \tag{1}$$

When $F(i) < Favg$, pc is:

$$pc = pc2 \tag{2}$$

Here, pc1 is the upper limit of the crossover probability, pc2 is the lower limit of the crossover probability, F(i) is the fitness value of individual i, Favg is the average fitness value, Fmax is the largest individual fitness value in contemporary population.

(2) Mutation probability is similar with crossover probability, the mutation probability of standard genetic algorithm is also fixed. The conclusion of theory analysis are when the fitness of population is concentrated, the mutation probability should be increased, when the fitness of population is decentralized, the mutation probability should be reduced, so that we can maintain the diversity of population, increase the search scope of optimal value, avoid falling into local extreme points. This article selects pm as the adaptive crossover probability.

When $F(i) \geq Favg$, pm is:

$$pm = \frac{pm1 + pm2}{2} + \frac{pm1 - pm2}{2} \times \frac{F\max - F(i)}{F\max - Favg} \tag{3}$$

When $F(i) < Favg$, pm is:

$$pm = pm2 \tag{4}$$

Here, pm1 is the upper limit of the mutation probability, pm2 is the lower limit of the mutation probability.

2.2. Improving Fitness

Abnormal fitness value may exist in the initial population, this phenomenon often leads the optimization of the population to a wrong direction, or the algorithm converges to a local minimum. At the end of the calculation, the algorithm is close to convergence, because the individual's fitness value in the group is quite close, continuing optimization is difficult, at this time, the fitness of the individual should be changed: first, the individual's fitness value should be spread out, second, the individual's fitness value should be enlarged, then improve the ability to choose [11]. Fitness values to improve as following formula:

$$F1 = \frac{F \times 2Favg}{F\max - F\min} \tag{5}$$

$$F' = \frac{F1 + |F\min|}{F\max + F\min} \tag{6}$$

Here, F is the unimproved fitness value, F1 is the fitness value after dispersed, F' is the improved fitness value, Fmin is the minimum fitness value of contemporary population.

3. Fault Diagnosis by BP Net

In this article, Accord car with F23A1 engine is experimental model, and ignition failure of this model is the experimental case.

Four ignition failures of the experimental model can be gotten by the maintenance manual [12-13].

Fault a: Engine is difficult to start, the engine lack power and be easy to flameout.

Fault b: Engine idling is instability and fuel economy decline, the pollutants of tail gas exceed the standard.

Fault c: Engine has Poor fuel economy, is easy blasting and bad engine power.

Fault d: The actual engine displacement decreases, the engine power become bad, when the vehicle is running accompany with engine knock, and increase the wear of the engine.

Those four kinds of ignition faults are mainly determined by ignition voltage, firing voltage, firing time and oscillating voltage. Through the oscilloscope, the fault data in various speeds can be obtained. In the article, the sample data is the failure data when the engine's speed is 3000r/min. Fault data table as Table 1 (The four parameters are expressed by A, B, C, and D, and the data have been normalized):

Table 1. Fault Sample Data Table

	A	B	C	D
	0.6585	0.0697	0.2623	0.0656
Fault a	0.6721	0.0669	0.2473	0.0546
	0.6995	0.0656	0.2432	0.0478
	0.9317	0.0546	0.2131	0.0137
Fault b	0.9590	0.0697	0.2090	0.0109
	1.0000	0.0751	0.2036	0.0096
	0.9863	0.1148	0.2268	0.1038
Fault c	0.9590	0.0874	0.2227	0.0915
	0.9317	0.0683	0.2295	0.0751
	0.8770	0	0.2063	0.0191
Fault d	0.9044	0.0328	0.2049	0.0178
	0.9317	0.0260	0.1995	0.0123

Through the Table 1, we determine the neuron number of BP neural network's input layer be 4. For output layer, there are four kinds of fault condition, each fault condition is corresponding to the vector as Table 2 shown, and all 2 dimensional vectors of Table 2 is composed by 0 and 1.

Table 2. The Fault Corresponding Output Table

Fault type	The corresponding output
Fault a	(0, 0)
Fault b	(0, 1)
Fault c	(1, 0)
Fault d	(1, 1)

The hidden layer's node number of BP neural network is always determined by formula (7).

$$L < \sqrt{m+n} + a \tag{7}$$

Here, m is the node number of input layer, n is the node number of output layer, L is the node number of hidden layer, a is a real number. In this article, the hidden layer node number of BP neural network is 10.

Set the basic parameters of BP neural network: the node number of input layer is 4, the node number of hidden layer is 10, the node number of output layer is 2, the learning efficiency is 0.01, the largest training steps is 20000, the minimum training error is 0.001 [14].

Figure 1 is the training error simulation figure of single BP neural network.

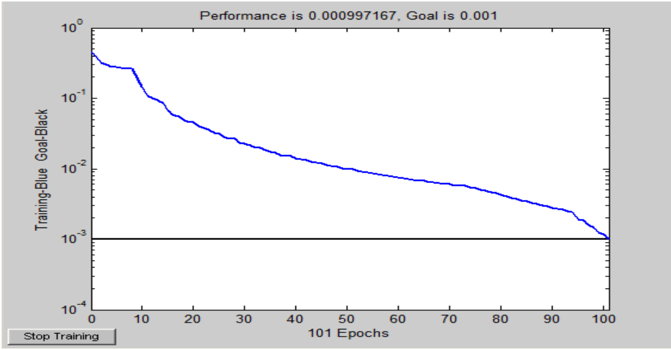

Figure 1. The Training Error Simulation Figure of Single BP Neural Network

It can be seen form Figure 1, when the epochs is 101, the network is convergence, the mean square error is M1 when the network is convergence, M1= 0.000997167.

This article chose the four representative faults as the diagnostic sample when the engine's speed is 3000r/min, the diagnostic sample is used to diagnose the trained network. The test sample data is shown in Table 3. (The data have been normalized).

Table 3. The Test Sample Data Table

	A	B	C	D
Fault a	0.7013	0.0583	0.2489	0.0484
Fault b	1.0000	0.0612	0.2020	0
Fault c	0.9716	0.0882	0.2219	0.0882
Fault d	0.8862	0.0114	0.1977	0.0085

Put test data input the trained network, we can get the output result Y1.

$$Y1=\begin{bmatrix} 0.0320 & 0.0191 & 0.9958 & 0.9888 \\ 0.0081 & 0.9993 & 0.0219 & 0.9947 \end{bmatrix}$$

The desired output is O:

$$O=\begin{bmatrix} 0 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 \end{bmatrix}$$

Through Y1 and O, we can get the single BP neural network's simulation error E1.

E1=(0.0200, 0.0099, 0.0130, 0.0082)

4. Standard GA Optimizing BP Net

In this article, F as the fitness function is expressed as formula (8).

$$F = N \times \frac{1}{\sum_{k=1}^{n} (O_k - Y_k)^2} \tag{8}$$

Here, O is the predict output, Y is the actual output, n is the node number of hidden layer nodes.

Set the basic parameters of the standard GA: individual number is NIND=40, the maximum genetic algebra is MAXGEN=20, the generation gap is GGAP=0.95, the crossover probability is pc=0.7, the mutation probability is pm=0.01. Neural network's parameters are constant.

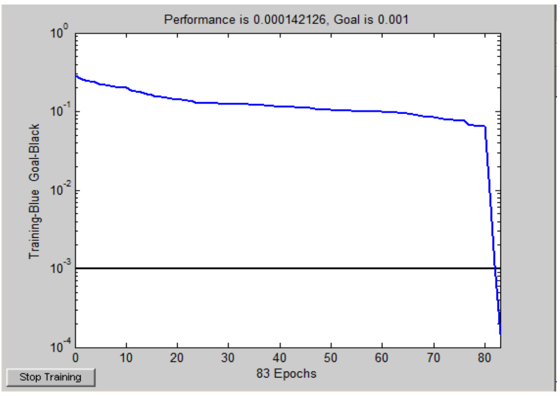

Figure 2. The Training Error Simulation Figure of Standard GA Optimizing BP Net

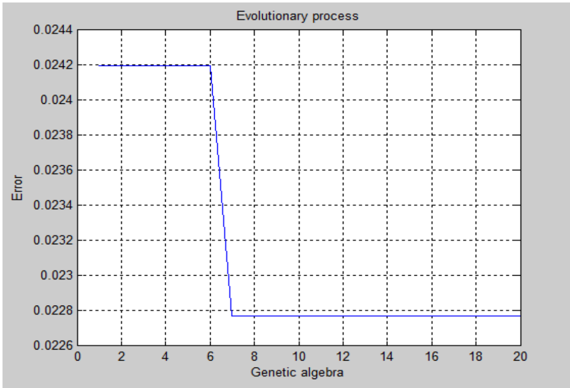

Figure 3. Evolutionary Process of Standard GA

Figure 2 is training error simulation that using standard GA optimize BP neural network.

It can be seen from Figure 2, when the network's training steps is 83, the network become convergence, the mean square error is M2=0.000142126.

Figure 3 is the evolution process figure of the standard GA algorithm. It can be seen from Figure 3 when the iteration number is 10 times, the error is very small [15].

Through the training, we can get Y2, Y2 is network's output that the standard GA optimize BP net.

$$Y2=\begin{bmatrix} 0.0057 & 0.0059 & 0.9999 & 0.9791 \\ 0.0020 & 0.9992 & 0.0125 & 0.9972 \end{bmatrix}$$

E2 is the final error of standard GA to optimizing BP neural network used in fault diagnosis.

E2=(0.0039, 0.0034, 0.0063, 0.0119)

5. Improved GA Optimizing BP Net

Set the basic parameters of the improved GA algorithm: Individual number is NIND=40, the maximum genetic algebra is MAXGEN=20, the generation gap is GGAP=0.95, the upper limit of the crossover probability is pc1=0.8, the lower limit of the crossover probability is pc2=0.6, the upper limit of the mutation probability is pm1=0.012, the lower limit of the mutation probability is pm2=0.008. Neural network's parameters are constant.

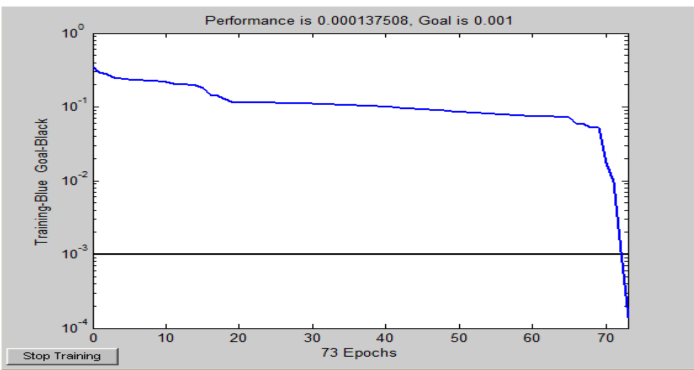

Figure 4. Training Error Simulation Figure of Improved GA Optimizing BP Net

Figure 4 is network training error simulation figure that use the improved GA to optimize BP net.

It can be seen from Figure 4, when the network's training steps is 73, the network become convergence, and the mean square error is M3=0.000137508.

Figure 5 is the evolution process figure of improved GA.

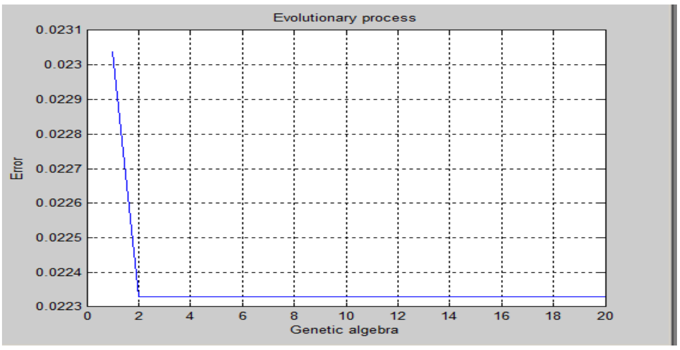

Figure 5. The Evolutionary Process Figure of Improved GA

It can be seen from Figure 5, the error become smaller and the number of iterations becomes less.

The contrast of the network's training result is shown in Table 4.

Table 4. The Contrast of the Network's Training Result

	Training steps	mean square error
Single BP	101	0.000997167
Standard GA-BP	83	0.000142126
Improved GA-BP	73	0.000137508

Through the training, we can get Y3, that Y3 is network's output of improved GA optimizing the BP net.

$$Y3=\begin{matrix} 0.0102 & 0.0050 & 0.9998 & 0.9809 \\ 0.0005 & 0.9999 & 0.0059 & 0.9981 \end{matrix}$$

E3 is the final error of improved GA to optimizing BP net used in fault diagnosis.

E3=(0.0054, 0.0025, 0.0030, 0.0105)

The contrast of final simulation error is shown in the Table 5 (The average error rates are expressed by AER).

Table 5. The Contrast of Final Simulation Error

	Fault a	Fault b	Fault c	Fault d	AER
E1	0.0200	0.0099	0.0130	0.0082	1.28%
E2	0.0039	0.0034	0.0063	0.0119	0.64%
E3	0.0054	0.0025	0.0030	0.0105	0.54%

6. Conclusion

BP neural network as a kind of intelligent method is widely used in fault diagnosis, due to the single BP neural network's error is big, GA algorithm is widely used in the optimization of

BP neural network, but the standard GA searching efficiency is low and fall into local convergence easily. This article puts forward three kinds of improvement scheme to GA optimizing BP neural network that diagnose F23A1engine ignition fault of Accord car.

This article respectively made the single BP neural network's error simulation experiment, the standard GA optimizing BP neural network's error simulation experiment and the improved GA to optimizing BP neural network's error simulation experiment. It can be seen from the comparison among Figure 1,、Figure 2 and Figure 4, optimized BP neural network's error is smaller than single BP neural network, the training steps of the optimized BP neural network become less, at the same time, compared with the standard GA to optimize the BP neural network, the improved GA to optimize the BP neural network's convergence speed is faster, and the performance is better. Through Figure 3,、Figure 5 and Table 5, we can conclude that compared with the standard GA to optimize the BP neural network, the error of improved GA optimizing the BP neural network is smaller, the number of iterations is less. The improved GA algorithm can improve the search efficiency, it's computing result can avoid falling into local convergence.

References

[1] Tie Wang, Chao Wang. Bora Engine CH Emissions Diagnosis Based on Neural Network. *TELKOMNIKA Indonesian Journal of Electrical Engineering.* 2012; 10(8): 2343-2350.
[2] Yan Feng, CuiPing Wei. The Novel Model of Construction Green Building System by BP Neural Network Method. *International Journal of Digital Content Technology and its Applications*. 2013; 7(5): 296-305.
[3] FAN Li-lin, ZHU Xiao-jing. The Application Research of BP Neural Network Algorithm in the Automotive After-sales Service System. *Advances in Information Sciences and Service Sciences*. 2013; 5(6): 344-351.
[4] Ma Qiang, Ma Shaohua, Mao Zonglei. Using Genetic Algorithm to Optimize BP Neural Network. *Science Mosaic.* 2008; 21(12): 196-197.
[5] Liu Jinrong, Wang Shaojin, Ren Fang, Yang Zhaojian. Fault Diagnosis of Hoist Braking System Based on BP Neural Network Optimized by Genetic Algorithm. *Coal Mine Machinery*. 2011; 32(5): 246-248.
[6] Luo Chengfeng. Estimating urban impervious surface percentage with BP neural network based on genetic algorithm. *Science of Surveying and Mapping*. 2011; 36(1): 48-50.
[7] Jeffrey O Kephart. Learning from Nature. *American Association for the Advancement of Science.* 2011; 331(6018): 682-683.
[8] Hanmin Liu, Qinghua Wu, Xuesong Yan. Solve Combinatorial Optimization Problem Using Improved Genetic Algorithm. *Advances in Information Sciences and Service Sciences.* 2013; 5(1): 1-8.
[9] Chris Bakal, Rune Linding, Flora Liense, Elleard Heffern, Enrique Martin-Blanco, Tony Pawson, Norbert Perrimon. Phosphorylation Networks Regulating JNK Activity in Diverse Genetic Backgrounds. *Science.* 2008; 322(5900): 453-456.
[10] Wang Siyan. A New Study on the Self-adaptive Genetic Algorithm, Master Degree Thesis, North China electric power university, He Bei. 2009.
[11] Luan Qinglin, Lu Huibin. Research on the Application of the Improved Genetic Algorithm on Neural Network Optimization. *Journal of Telemetry, Tracking and Command*. 2008; 29(1): 51-54.
[12] Car breakdown speed-searches handbook series. Editorial Board, Honda Accord sedan breakdown speed-searches the Handbook, Standards Press of China, BeiJing. 2005.
[13] Li Ping. Guangzhou Honda car repair instances compilation (Four). *Auto Maintenance.* 2005; 5(5): 39-44.
[14] Shen Zhe, Ge Guangying, Tian Cunwei. Problems Analyses in design of BP neural network. *Science & Technology Information.* 2011; 28(6): 238-240.
[15] Xu Yanfei, Xing Haiqiong. The Application and Research Analysis of Genetic Algorithm. *Intelligent Computer and Applications.* 2010; 26(03): 113-115.