Study on BP Neural Network Optimization by Improved Decay Parameter Genetic Algorithm

Yi Jiang and Fan Zhang

Electronic Communication Engineering School, Anhui Xinhua University, Hefei 230088, China
Email: salas0527@163.com

Abstract. BP neural network optimized by standard genetic algorithm is hard to meet the balance between global search capability with local search capability. Therefore, the decay parameters genetic algorithms were presented to improve the convergence rate and accuracy. The results of this approach were compared with that of the standard genetic algorithm as well as the improved genetic algorithm by MATLAB simulation software. The simulation results show that the decay parameter genetic algorithm has better accuracy and robustness than the standard genetic algorithm, and greatly gives consideration to both the global search ability and the ability of local search. As a result, the precision and speed on the system fault diagnosis are dramatically improved.

1. Introduction

Artificial neural network is a model with strong nonlinear mapping capability developed from bionics since 1980s. BP Propagation as one of the most widely used networks, has been a research hotspot [1]. The learning algorithm based on error inverse propagation has good nonlinear mapping ability, generalization ability and fault tolerance ability, but it also has some problems, such as slow convergence speed of the learning process, the possibility of local minimum of error and function.

Genetic Algorithm also known as evolutionary algorithm, is based on Darwin’s theory of evolution and heredity. It has strong global searching ability and fast convergence speed [2-4]. The combination of genetic algorithm and BP neural network can realize fast global search and solve the local minimum problem. However, the standard genetic algorithm uses fixed crossover probability and mutation probability, which makes it difficult for the system to balance the contradiction between global search and local search. Therefore, the BP neural network model of the improved decay parameter genetic algorithm is proposed to establish the nonlinear mapping relationship between fault types and data-based fault symptoms, so as to improve the accuracy and speed of fault diagnosis.

2. Standard Algorithm Genetic Neural Network

Standard genetic algorithm codes the problem to be solved in a certain form to generate corresponding solution set, and then carries out genetic operation on the coding string according to the guidance of fitness function to realize survival of the fittest, and then generates new populations through selection, crossover and mutation until the optimal solution appears [5]. Figure 1 shows the schematic diagram of BP neural network optimized by genetic algorithm. It can be seen that the optimization of neural network weight threshold matrix by genetic algorithm is achieved by error feedback. Figure 2 shows the specific flow of the algorithm. The specific steps are as follows:
Figure 1. Schematic diagram of BP neural network optimized by genetic algorithm.

Figure 2. Flow chart of standard genetic algorithm.

1. Produce the initial population: The initial population can be randomly generated. If the initial population is \( n \), \( n \) chromosomes constitute the initial population.

2. Calculated fitness: Fitness is used to evaluate an individual and is the basis of genetic algorithm. The fitness value of each individual is calculated. The larger the value is, the higher the fitness is, the more suitable the living environment is, and the better the individual evaluation is, thus providing a basis for the next selection, crossover and mutation operation.

3. Coding: Common coding techniques include binary code, gray code, integer or alphabetic code uniquely recognized by the computer. In this paper, binary coding is adopted, that is, weight and threshold are represented by binary coding form of the same number of bits, so as to form a chromosome.

4. Genetic manipulation: The selection, crossover, and mutation operations are also included in this step.

5. Decoding operation: The decoding operation is used to generate the weight, threshold matrix. Form a new generation population with the inherited new individuals, return step 2, and repeat steps 2–4 until the predetermined error range or the predetermined number of iterations is reached.

3. An Improved Decay Parameter Genetic Neural Network
In genetic algorithm, crossover is the main means to produce new individuals, and mutation is one of
the methods to produce new individuals. If the probability of crossover and mutation is too low, genetic algorithm search may fall into a state of dullness and fail to meet the requirements of global search. If crossover and mutation probability are too high, genetic algorithm will degenerate into random search. Since the standard genetic algorithm adopts fixed crossover probability and mutation probability, it is difficult to balance the contradiction between global search and local search [6-7]. Therefore, this paper proposes an improved decay parameter genetic algorithm. On the basis of the standard genetic algorithm, the attenuation factor is introduced to act on the crossover probability and mutation probability, making them gradually smaller in the process of iteration, so as to give consideration to both the global search ability and the local search ability. The local process is shown in figure 3.

![Image of flow chart](Figure 3. Partial flow chart of decay parameter genetic algorithm.)

Attenuation factor:

$$\beta = 1 - \frac{k \times g}{g_{\text{max}}}$$  \hspace{1cm} (1)

where, k is the constant between 0 and 1, and when k is 0, it corresponds to the standard genetic algorithm, g is the genetic algebra, and $g_{\text{max}}$ is the maximum cutoff algebra. As the number of iterations increases, $\beta$ decreases linearly from 1 to 1-k.

On the basis of the standard genetic algorithm, decay factor $\beta$ is introduced to constitute the decay crossover probability is $\beta \rho_c$, decay mutation probability is $\beta \rho_m$, $\rho_c$ and $\rho_m$ are fixed crossover probability and mutation probability in the standard genetic algorithm respectively.

As the number of iterations increases, the attenuation factor $\beta$ correspondingly decreases linearly from 1 to 1-k, thereby the crossover probability decreases from $\rho_c$ to $(1-k)\rho_c$, and the mutation probability decreases from $\rho_m$ to $(1-k)\rho_m$, respectively. Thus, the dynamic balance between global search and local search can be realized by adjusting the constant $k$.

4. Algorithm Comparison Verification

4.1. The Sample Parameters

The experimental data in Ref. [8] were used to compare and verify the improvement of algorithm performance before and after the genetic algorithm improvement. The sample input vector includes the average maximum combustion burst pressure of each cylinder, exhaust manifold temperature, scavenging chamber temperature, turbocharger speed, scavenging chamber pressure, scavenging exhaust duct pressure loss coefficient, compressor outlet temperature, and a load parameter. A total of 8 variables are used as BP neural network input variables. Output variables are composed of common engine failure variables in the experimental data, including: #1 failure-free; #2 the efficiency of supercharger decreases; #3 heat transfer of cold air deteriorates; #4 turbine protective grating is blocked; #5 the turbine is partially blocked. A total of 5 variables are used as output variables of BP
neural network.

4.2. **Decay Parameter Genetic Algorithm Optimization Steps**

The parameters to be set for genetic algorithm include population size, maximum genetic algebra, generation gap, crossover probability, mutation probability and attenuation factor [9]. By determining the input and output vector choose the structure of the BP neural network for the 8-17-5, the weights of the neural network hidden layer number is 156 (17×8), the threshold of 17 (17×1), the number of output layer weights 85 (5×17), the threshold of 5 (5×1), using improved genetic algorithm for the decay parameter 243 weight threshold is optimized, the steps as follows, optimize the flow chart shown in figure 4.

1. **Determination of population size**

   Generally speaking, choosing a large number of population size can deal with more individuals at the same time, so it is easy to find the global optimal solution. However, the disadvantage is that the time of each iteration is increased. The experiment shows that the increase of population size will lead to an exponential increase in the calculation amount. However, when the population is too small, the population diversity decreases, and the genetic algorithm falls into the local minimum value, which will greatly increase the possibility of premature phenomenon. Therefore, the population size of this algorithm is set as 40.

2. **The error E is calculated by the feedback algorithm**

   Weight and threshold are decoded to generate weight and threshold matrix, and assigned to BP neural network to calculate the objective error function E.

3. **Calculate fitness and rank it**

   The reciprocal of the objective error function is defined as the fitness function, and the individual fitness function is calculated and sorted [10].

4. **Encoding**

   The encoding method adopts 10-bit binary encoding.

5. **Genetic operations**

   When the generation gap is set as 0.95, 38 (40×0.95) optimal individuals are selected from 40 individuals. The crossover probability was set as 0.7, and the variation probability as 0.01, that is, the crossover was carried out with the probability of 0.7, and the variation was carried out with the probability of 0.01β. Among them, the k in the attenuation factor was set as a constant between 0 and 1.

6. **After several Matlab simulation experiments and observation of the error evolution curve, it can be found that the error does not change after the number of iterations is 30~70, so the genetic algebra Gen is set as 40. If the genetic algebra is not reached, step (2) is entered to start the next cycle, while the minimum error of each generation is recorded.**

7. **The optimal individual is decoded and the optimal weight and threshold are output. The optimal weight and threshold are given to BP neural network, and the training samples and test samples are input to get the corresponding output samples.**

4.3. **The Effect Comparison of Genetic Algorithm before and after Improvement**

11 numbers between [0, 1] and k were genetically manipulated to obtain 11 groups of weight threshold matrix, which were used to evaluate the effect of attenuation factor. The evaluation results were shown in table 1.

It can be seen from the table that when k=0.5, the error is the smallest. Therefore, k in the equation (1) is taken as 0.5, and the attenuation factor is shown in equation (2):

\[ \beta = 1 - 0.5 \times \frac{g}{g_{\text{max}}} \]  

When k=0 is the standard genetic algorithm, and when k=0.5 is the decay parameter genetic algorithm. Tables 2 and 3 are the output results of BP neural network given by the optimized weight
threshold of standard genetic algorithm and decay parameter genetic algorithm.

Diagram:

The initial weight and threshold populations are determined according to the selected BP neural network structure.

The error $E$ is calculated by neural network feedback algorithm.

The fitness value $P$ is calculated and sorted.

Coding

Genetic operations

Decoding

$\text{gen} = \text{gen} + 1$

N

Complete the evolutionary algebra $\text{gen}$

Y

The optimal neural network weight threshold is assigned to BP neural network.

Decay crossover probability $\beta \rho_c$

Probability of decay variation $\beta \rho_m$

Figure 4. Flow chart of initial weight matrix of BP neural network optimized by decay parameter genetic algorithm.

Table 1. Evaluation results of attenuation factor.

| Decay factor | Training sample error | Test sample error |
|--------------|-----------------------|------------------|
| 0            | 0.25919               | 0.00845          |
| 0.1          | 0.26795               | 0.00945          |
| 0.2          | 0.24018               | 0.00912          |
| 0.3          | 0.22973               | 0.00728          |
| 0.4          | 0.21153               | 0.00715          |
| 0.5          | 0.19824               | 0.00624          |
| 0.6          | 0.23847               | 0.00698          |
| 0.7          | 0.21462               | 0.00827          |
| 0.8          | 0.24092               | 0.00865          |
| 0.9          | 0.23981               | 0.00901          |
| 1            | 0.26343               | 0.00972          |
Table 2. Output results of standard genetic algorithm.

| Fault types       | Standard genetic algorithm |
|-------------------|-----------------------------|
| #2 serious failure| 0.0001 0.9952 0.0003 0.0165 0.0000 |
| #3 moderate failure| 0.0002 0.0006 0.4916 0.0000 0.0007 |
| #4 serious failure | 0.0000 0.0018 0.0000 0.9842 0.0001 |
| Training sample error | 0.25919 |
| Test sample error   | 0.00845 |

Table 3. Output results of decay parameter genetic algorithm.

| Fault types       | Decay parameter genetic algorithm |
|-------------------|-----------------------------------|
| #2 serious failure| 0.0000 0.9891 0.0003 0.0000 0.0000 |
| #3 moderate failure| 0.0000 0.0017 0.4966 0.0005 0.0002 |
| #4 serious failure | 0.0001 0.0005 0.0002 0.9961 0.0001 |
| Training sample error | 0.19824 |
| Test sample error   | 0.00624 |

It can be seen from tables 2 and 3 that compared with the standard genetic algorithm, the output of decay parameter genetic algorithm is more similar to the theoretical output, and the training sample error and test sample error are smaller. Error training curves are shown in figures 5 and 6.

![Figure 5. Error training curve of standard algorithm genetic neural network.](image1)

![Figure 6. Error training curve of genetic neural network with decay parameters.](image2)

As can be seen from the comparison between figures 5 and 6, the number of training steps of the decay parameter genetic algorithm is shorter, from 14 steps to 4 steps, so the convergence speed is faster. The error evolution curve is shown in figures 7 and 8.

From figures 7 and 8 contrast can be seen that decay parameter in the early stage of the iterative genetic algorithm has stronger global searching ability, in the later has better local search ability, better balance the contradiction between the global search and local search and overcome the disadvantages of standard genetic algorithm, greatly improving the accuracy and robustness of fault diagnosis.
5. Conclusion

Based on the standard genetic algorithm and the concept of decay factor, an improved decay parameter genetic algorithm is proposed to optimize BP neural network and establish fault diagnosis model. The simulation results show that the improved decay parameter genetic neural network can overcome the deficiency of the standard genetic algorithm in both global and local search ability, and has better accuracy and robustness, and can be fully applied to system fault diagnosis.

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