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AN ELECTRICAL MOTOR FAULT DETECTION SCHEME BASED ON IMPROVED GENETIC ALGORITHM AND OPTIMAL NEURAL NETWORK

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ABSTRACT

With the development of Computer technology, data fusion and artificial intelligence theories, there are many new solutions for motor fault diagnosis. In terms of the motor fault characteristics, integrated diagnosis is implemented to solve this problem in this article, which adopts an improved genetic algorithm and optimizing neural network methods. That diagnosis method can not only reduce the difficulty of fusion system optimization, but also simulate the effect between different faults in coupling fault mode and achieve a precise diagnosis result. The research of the motor fault monitoring and diagnosis technology with this new method has the important theoretical value and engineering practical significance.

Keywords: *Fault Diagnosis, Improved Genetic Algorithm, Neural Network*

1. INTRODUCTION

In recent years, with the rapid development of fault diagnosis technology, Research results continuously have emerging [1,2,3]. As the main power of modern industry, electrical motor's role is self-evident. If there were the electrical motor of dragging production equipment fault, it will make production process interrupt and lead to a vast of economic losses. Thus, it has the important theoretical value and engineering practical significance to focus on the research of the motor fault monitoring and diagnosis technology [4,5,6].

When the motor fault occurs, several comparatively independent working systems will be involved in it. Therefore, the motor fault diagnosis is more complicated than other normal mechanism diagnosis, which covers multiple technology fields, including Electric Machinery, thermodynamics and heat transfer, high voltage techno1ogy, material engineering, machine diagnosis, electronically measure, information engineering, Computer technology, and so on. Because of several interactive systems working together, the fault reason and symptom for motor is multiform that one trouble may cause another one and result in multi-fault coupling finally. The inter-coupling effect in kinds of fault types increases the difficulty of motor fault diagnosis. With the development of Computer technology, data fusion and artificial intelligence theories, there is a new solution for motor fault diagnosis. According to the motor fault characteristics, integrated diagnosis is applied to solve this problem, with employing modern calculation methods, such as wavelet analysis, fuzzy algorithm, artificial immune theory, multi-sensor information data fusion etc.

Motor fault types are various: both slow change fault and fault, and electrical failure and mechanical failure; in linear and nonlinear system fault, fault, its relationship to perplexing. Motor a fault tends to become other fault generated incentives. So the study of multiple fault coupling case for the exact diagnosis problem has been the motor fault diagnosis problem of a key, and due to coupling fault by the runtime environment, the motor load and fault severity influence, so it is also the motor fault diagnosis problem in [7][8]. Many domestic and foreign scholars on the motor coupling fault diagnosis method based on [9,10,11,12,13], the majority of these methods that employ mathematical modeling to the individual fault coupling are analyzed, not to other coupling fault situation of development. At the same time, these models are simplified model is set up on the basis of, so in the actual diagnosis is very difficult to guarantee the accuracy of diagnosis,

This article discusses the fault diagnosis methods of an improved genetic algorithm optimizing the neural network. When it comes to motor fault diagnosis application, we can use the predicted

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characteristic parameters to determine whether a motor is failure or not. As a result, the process of fault characteristic parameter and the obvious effect can be captured.

2. IMPROVEMENT OF GENETIC ALGORITHM

2.1 The Basic Thought About Genetic Algorithm

Genetic Algorithm is a sort of random search algorithm which refers biosphere natural selection and natural genetic mechanism by American professor J. Holland. It originated from Darwin's theory of evolution. In other word, it's a calculation model which simulates Darwin genetic selection and natural selection of biological evolution process.

2.2 The Main Steps On Genetic Algorithm

Genetic Algorithm is a random search method on the simulation of biological evolution. It mainly consists of three basic operations: choice, crossover and variation, which refers the Fig.1.

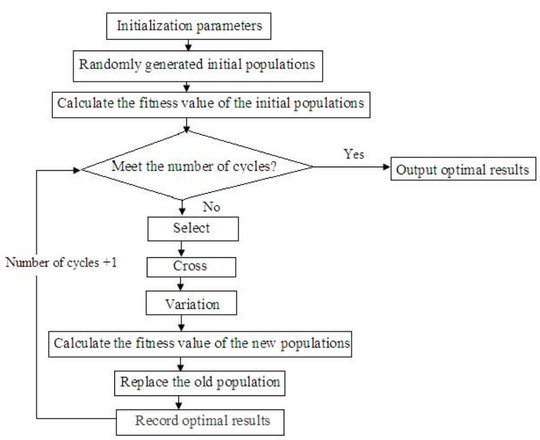

Figure 1: Standard Genetic Algorithm Flow Chart

Step 1. Generating of initial population.
Step 2. Calculating the fitness of each individual in the initial population, and judging whether it can conform to the optimal condition, if it fits, outputting the corresponding optimal solution. Otherwise, use the following procedures.
Step 3. According to the size of the fitness, select individual, the higher the degree of the fitness the greater the chance of being selected, and may be eliminated.
Step 4. In terms of a certain cross method and cross probability Pc, executing cross operation.
Step 5. Based on a certain mutation method and mutation probability Pm, executing variation operation.
Step 6. Return to the step 2.

2.3 The Procedure About Modified Genetic Algorithm

In view of existing premature problems of standard genetic algorithm, this article brings in multiple population then makes optimize grabble. Next, breaking thorough standard genetic algorithm for genetic optimization framework simply. The algorithm structure of multiple populations just as Figure 2.

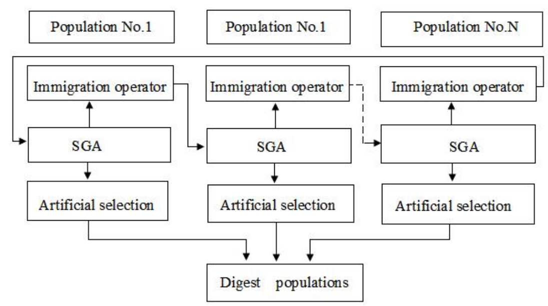

Figure 2: Multi-Population Genetic Algorithm Structure Diagram

From the structure of the algorithm diagram, we can know, the improved genetic algorithm takes different control parameters by each population. The value of cross Pc and variation Pm determines the balance between algorithm global search and the ability of local search.

3. GENETIC ALGORITHM IMPROVEMENT AND THE BP NEURAL NETWORK OPTIMIZATION ALGORITHM

GA is a global searching algorithm, which takes BP Neural Network and genetic algorithm fusion together organically. Then it makes up the random defects of BP Neural Network on its connection weights and threshold. Not only could it play an important role in mapping ability in BP Neural Network, but also, bring a quicker convergence and a stronger learning ability to BP Neural Network. Based on this, the scientists propose a kind of improved genetic algorithm to optimize the BP neural network predicted model which reduces the risk of plunging into a local minimum and can make BP network has high convergence accuracy. First, this model determines the topological structure of BP neural network, with the number of input or output parameters in a time series.

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Secondly, we can figure out the optimal moderate value to correspond the individual to optimizing the weights and the threshold of BP neural network. Finally, the optimal individual assigns a new value to the weights and the threshold and trains the model to get the optimal result.

3.1 Algorithm Flow

Genetic algorithm was used to optimize the BP network weights algorithm flow chart as Figure 3.

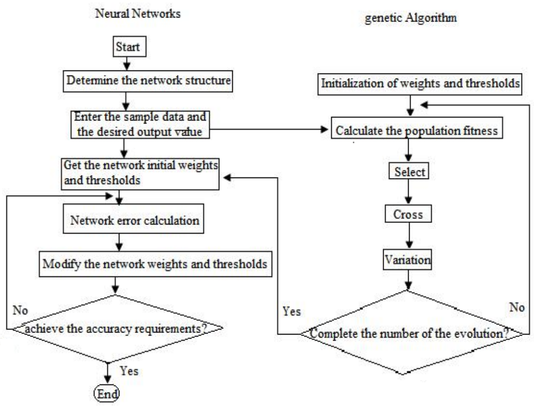

Figure 3: Genetic Algorithm Optimize The BP Network Weights Algorithm Flow Chart

3.2 The Realization Of The Algorithm

The improved genetic algorithm optimizing neural network algorithm realization's steps are as follows:

Step 1. Parameter setting: the operation parameters which need to be chosen by genetic algorithm are: Individual coding string length L, Population size M, Crossover probability Pc. Mutation probability Pm., termination algebra T, the generation gap G, etc.

Step 2. Generating of original population.

Step 3. The appraisal of each individual evaluation function. Choose network individual on the basis of $P_i = f / \sum_{i=1}^{N} f_i$, f_i is the individual i's adaptive value, can use square-error and E to measure. Namely:

$$\cdot\begin{cases} f_i = 1/E(i) \\ E(i) = \sum_{M}\sum_{P}(T_p - z_p)^2 \end{cases} \qquad (1)$$

Where i is the number of chromosome, use the selection operator, crossover operator and mutation operator Pm Pc to format the new individuals, produce the next generation of population.

Step 4. Put the new individual into the population and calculate the new individual's evaluation function.

Step 5. Estimate whether the algorithm is over. If you find the satisfied individual, the algorithm is over, conversely, repeat steps 3, 4 until meet the evaluation function of the default standard, and the program using termination conditions for G generation inside the highest adaptive value has no significant change.

4. IMPROVED FAULT DIAGNOSIS OF GENETIC ALGORITHM OPTIMIZING NEURAL NETWORK

4.1 Data Collection

In order to examine the advantage of this algorithm in motor fault diagnosis, research motor fault diagnosis data, which Series models are Y630-10/1180 and so on from Guangdong Xing Huada Motor Co., Ltd. table 1 is the motor normalized after the fault sample data.

Table I: Fault Sample Data

No	Feature samples	Motor Status
1	0.0442,0.0880,0.1147,0.0563,0.3347,0.1150,0.1453,0.0429,0.1818,0.0378,0.0092,0.2251,0.1516,0.0858,0.0670	trouble-free
2	0.0940,0.0522,0.1345,0.0090,0.1260,0.3619,0.0690,0.1828,0.1592,0.1335,0.0733,0.1159,0.2286,0.1292,0.0720	trouble-free
3	0.1387,0.2558,0.0900,0.0771,0.0882,0.1670,0.2450,0.0508,0.1328,0.2090,0.0947,0.1393,0.0393,0.1430,0.0126	trouble-free
4	0.2101,0.0950,0.1298,0.1359,0.2601,0.1001,0.0753,0.0890,0.0389,0.1451,0.0128,0.1590,0.2452,0.0512,0.1319	trouble-free
5	0.2593,0.1800,0.0711,0.2801,0.1501,0.1298,0.1001,0.1891,0.2531,0.0875,0.0058,0.1803,0.0992,0.0802,0.1002	Crack
6	0.5460,0.1977,0.1248,0.0624,0.0832,0.1640,0.1002,0.0059,0.1503,0.1837,0.1295,0.0700,0.0359,0.1149,0.1230	Crack
7	0.1506,0.1310,0.0500,0.0078,0.0348,0.0451,0.0707,0.0880,0.3690,0.2222,0.0562,0.5157,0.1872,0.1614,0.1425	Crack
8	0.0871,0.0060,0.1793,0.1002,0.0789,0.0909,0.2603,0.1715,0.0702,0.2711,0.1491,0.1330,0.0968,0.1911,0.2545	Crack
9	0.1102,0.0683,0.0621,0.2597,0.2602,0.1167,0.0048,0.1002,0.1521,0.2281,0.3205,0.2599,0.2235,0.1201,0.1171	Fracture
10	0.0655,0.0774,0.2273,0.2056,0.0925,0.0078,0.1852,0.3501,0.1680,0.2668,0.1759,0.2347,0.1829,0.1811,0.2922	Fracture
11	0.1155,0.0050,0.0978,0.1511,0.2273,0.3220,0.2634,0.2258,0.1165,0.1154,0.1074,0.0657,0.0610,0.2623,0.2588	Fracture
12	0.1064,0.1909,0.1586,0.0116,0.1698,0.3644,0.2718,0.2494,0.0724,0.1909,0.1340,0.2409,0.2842,0.0450,0.0824	Fracture

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From table 1 can be seen that this motor failure mode basically has 3 kinds: respectively for trouble-free, crack and fracture, according to three failure form, we adopt the following output form: trouble-free (1,0,0), crack (0,1,0) and fracture (0,0,1).

4.2 Simulation of Algorithm Realization

Simulated experiments were selected to demonstrate the analytic results, which were run at Matlab7.0 on a personal computer with an AMD X4 620 processor and 2GB of memory. According to the algorithm process, it can use Matlab software of the simulation program of the algorithm, set up corresponding simulation parameters: the population size is 40, the biggest genetic algebra is 50, crossover probability is 0.7, and the variation probability is 0.01. In order to verify the validity of the established network, 12 groups sample data will be divided into two parts, the front nine group for training data, the behind three groups data for testing data.

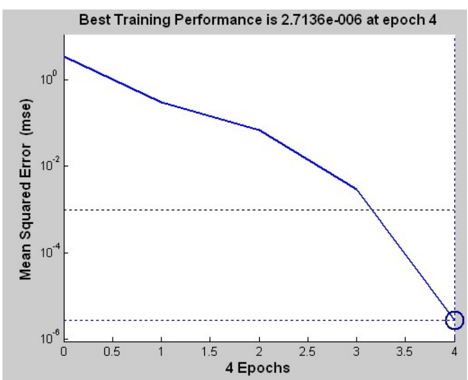

Figure 4: The BP Neural Network Training Error Before Optimization

1) Using random weights and threshold

Figure 4 is the BP neural network training error curve diagram before optimization, Best training performance is 2.7136e-006 at epoch 4. The BP neural network output test sample prediction results as follows:

$$ty = \begin{array}{ccc} 0.9997 & 0.0070 & 0.0002 \\ 0.0397 & 0.9227 & 0.0065 \\ 0.0076 & 0.0272 & 0.9806 \end{array}$$

The test sample simulation error is: 0.0825

The training sample simulation error is: 0.4201

2) Using optimization of the weights and threshold

Figure 5 is the BP neural network training error curve diagram after optimization, and Figure 6 is genetic algorithm error evolution curve diagram, Best training performance is 2.0157e-006 at epoch 2 in Figure 5. After optimization, the optimized BP neural network output test sample prediction results as follows:

$$ty = \begin{array}{ccc} 0.9971 & 0.0031 & 0.0001 \\ 0.0126 & 0.9967 & 0.0098 \\ 0.0077 & 0.0012 & 0.9983 \end{array}$$

The test sample simulation error is: 0.0236

The training sample simulation error is: 0.1558

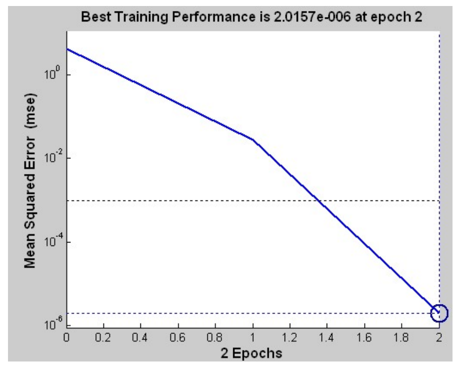

Figure 5: Training Error Curve After Optimization

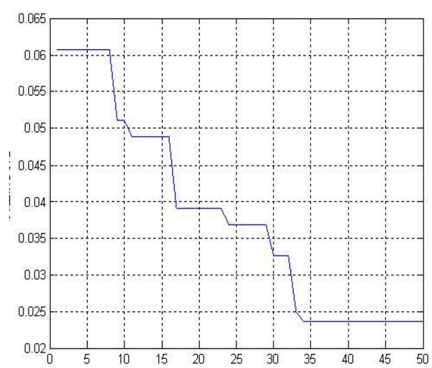

Figure 6: Genetic Algorithm Error Evolution Curve

3) Contrasting the optimization of before and after optimization

In comparison, we can find that after using the optimization algorithm, the best training performance is 2.0157e-006 need 2, while Best training performance is 2.7136e-006 at epoch 4 before and after optimization, the training epochs are decreased by 50% .The test sample simulation error downs from 0.0825 to 0.0236 and the sample simulation error reduces by 71.4%, at the same time, the training sample simulation error decline from 0.4201 to 0.1558 and reduces by 62.9%. So through the optimization, testing and training effect has made a lot of improvement.

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5. CONCLUSION

This paper represents an improved genetic algorithm optimizing the neural network method and applies method in the motor fault diagnosis. By the improved genetic algorithm optimizing neural network for fault diagnosis the training epochs are decreased by 50% .The test sample simulation error reduces by 71.4%, at the same time, the training sample simulation error reduces by 62.9% , the forecast effect and forecast accuracy of the BP neural network is improved greatly. Therefore, this algorithm can be applied to other industries and fields.

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