The application of BP neural network optimized by genetic algorithm in logistics forecasts

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Abstract

This paper points out disadvantages of traditional forecast methods and elaborates the advantages of the method based on BP neural network. On this basis, the paper puts forward a logistics forecasting model of BP neural network optimized by genetic algorithm. The new method uses historical data to establish and train BP neural network and thus obtain logistics forecasting model. The results implemented by MATLAB show that, neural network possesses memorizing and learning capability, and can forecast logistics development trend perfectly, which is proved by a large amount of actual forecast results. Compared with BP neural network model, the model has the advantages of less number of iterations, convergence speed and strong generalization ability.

Keywords: BP neural network, genetic algorithm, optimized, MATLAB

1 Introduction

In logistics management, if the trend of the market can be grasped through prediction, it would be possible for the management to make decisions on research strategies in advance and take more effective technological strategies to gain even better results. Moreover, enterprises can prevent or minimize the adverse effects on their development and foster more favourable conditions with a more sensible decision on logistics development strategic goals. Since the prediction is determined by many factors, such as market supply and demand, economic situations and transportation, systematic efforts are needed to establish a predicting model [1].

In recent years many innovative and practical predicting methods have been proposed by scholars both home and abroad such as moving average method, exponential smoothing method, neural network method, chaos and nonlinearity investigation, regression analysis, time series, grey theory and Markov analytic approach. However, each of the models or the analysis methods has its own advantages and disadvantages as far as its limitation and applicability are concerned [2]. For example, the moving average forecasting method is based on the time series by item. It forecasts the further phenomenon by calculating exponential smoothing value and cooperating with the time series forecast model. To some extent, this method is more accurate in reflecting the recent changes and the trends [3]. The exponential smoothing method as a time series is based on the moving average method. It calculates the exponential smoothing value, and then forecasts the phenomenon of the future by time series prediction model [4]. Regression analysis method is based on historical logistics data, and the regression mathematical model is established to forecast the future logistics. This kind of logistics forecasting method is effective and accurate, but it must establish the mathematical model, which is very complex. The traditional cost prediction of logistics operation is based on regression analysis. This kind of prediction method is simple and easy to use, but its prediction error is bigger and it cannot meet the requirements of cost control in the process of modern logistics operation [5].

By contrast, the neural network has a good ability of curve fitting, anti-interference ability and learning ability, so the neural network is an effective method to logistics prediction.

The neural network has many good qualities, such as self-organization, self-adaption and is good at making decisions from the approximate, uncertain and even conflicting knowledge environment, and avoids calculating the weights and correlation coefficient artificially [6]. But the traditional neural network has the problems of local minimum and slow convergence, so BP neural network optimized by genetic algorithm is established for the logistics forecasts model. The model combines the self-adaptive and self-organization of BP neural network with rapid global search ability of genetic

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algorithm, solves the problems of slow convergence speed and is easy to fall into local minimum. The practical simulation results prove that the method has stronger practicability.

2 Basic principle of BP neural network optimized by genetic algorithm

Usually the BP algorithm adjusts the weights between neurons through some learning rules. In the learning process, the topological structure and network learning rules are constant. However, a neural network information processing function depends not only on the strength of the connections between neurons, but also on the network topology (neurons connection), characteristics of input and output neurons, and the weights and thresholds of neurons [7].

The traditional BP neural network has shortcomings of long training time, slow convergence and easy to fall into local minimum, but the local searching ability of genetic algorithms can make up for the deficiency of BP neural network. And BP neural network has great dependence on the weights and thresholds, but if the initial values are closer to the true ones, the time of network training will be shorten obviously. This paper uses the basic genetic algorithm to optimize BP neural network weights and thresholds, leads the weights and thresholds close to the real values, rather than a simple random assignment. Then, the paper adopts the trained BP network as the model of logistics forecasts. Simulation results demonstrate that the genetic algorithm has a significant effect to accelerate the convergence speed.

The algorithm that optimizes BP neural network weights and thresholds with basic genetic algorithms is described as follows:

1) Encode BP neural network weights and thresholds with the real, and produce an initial population $W=(W_1,W_2,\cdots W_p)^T$ randomly, which has *P* individuals. Each individual is a string of real numbers, containing the connection weights of the input layer and hidden layer, hidden layer thresholds, hidden layer and output layer weights and the output layer thresholds.

2) Use the reciprocal of an error function as the fitness function. The error produced by the mean square error function of the desire output and the actual output of the network, determine the fitness of each individual by fitness function. Smaller the error is, greater the fitness is.

3) Use the roulette bet method as the selecting method. In the method, the selected probability of each individual is proportional to the fitness. The selected probability increases with increasing of fitness. Select the part of higher fitness individuals as the parents, and eliminate the lower ones.

4) Handle the parents to produce progeny by crossover and mutation operators. If the offspring's fitness is higher than the parent's, the parent's individual will be eliminated, and the new offspring will become the parent. Keep the number of parent individuals as a constant.

5) Repeat step (2)-(4), a new round of selection, crossover and mutation will be executed to the new group, until the termination condition is satisfied.

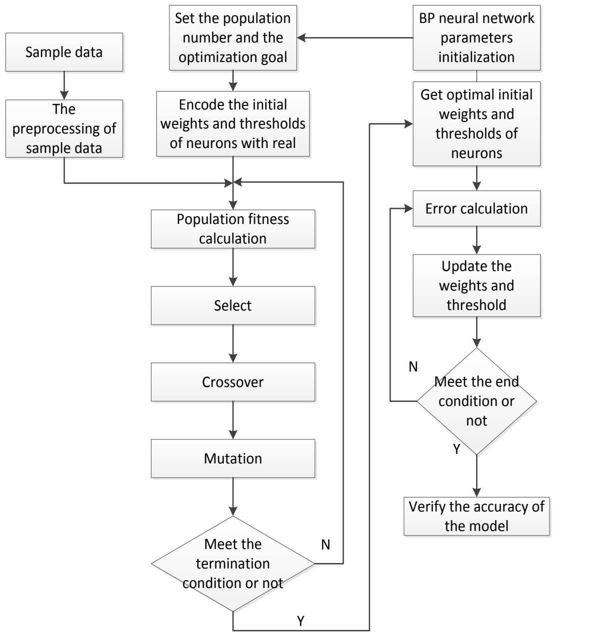

FIGURE 1 Procedure of BP neural network optimized by genetic algorithm

6) Decompose the optimal individuals of current groups into the connection weights and thresholds of BP neural network, and use the optimal weights and thresholds as the initial values of BP neural network.

7) Train BP neural network with preset algorithm parameters.

8) Stop training when the training objective is satisfied.

The procedure of BP neural network optimized by genetic algorithm is shown as Figure 1 the training objective is satisfied.

3 BP neural network model optimized by genetic algorithm

3.1 BP NEURAL NETWORK MODEL

BP neural network is a multilayer feed forward neural network. The network is composed of input layer nodes, hidden layer nodes (hidden layer can be one or more), and output layer nodes.

There is no universal theory guidance for selecting how much hidden layers and hidden layer nodes of each layer, but after a lot of practice, predecessors have accumulated some experience. Theoretical analysis shows that, BP network with a single hidden layer can map the arbitrary continuous nonlinear function. Only when the learning is not a continuous function (such as a saw tooth wave), two hidden layers are needed.

Increasing the hidden layer number can improve the training accuracy and reduce the errors, but the network will become complicated and time-consuming. In fact, the nodes of the hidden layer can be increased to improve the training accuracy, when the increased number of nodes is not significantly to reduce the error, trying to increase the number of hidden layers [8]. So this network uses three layers network, namely the input layer, the hidden layer and the output layer.

1) Design the input and the output layer. The design of input and output layer is according to the specific problems, there are 2 evaluation indexes and one evaluation result, so the input layer is set to n=2, the output m=1.

2) Design the hidden layer. In the BP network, hidden layer nodes are used to extracting and storing the samples inherent law from the samples, so setting the numbers of hidden layer nodes depend on the training sample size and complexity. There is no exact formula for the calculation of the hidden layer nodes, but the summary based on network structure obtained an empirical formula. The hidden layer nodes number $l=\sqrt{n+m}+\alpha$, n and m are the input and output layer nodes numbers, α is a constant between [1,10]. After repeated testing, this paper determines the hidden layer node number is 7.

3) Design the driving function. In the BP neural network, which is established in this paper, hidden layer transferring function uses bipolar *S* type function.

$$f(x)=\frac{1-e^{-x}}{1+e^{-x}}. \quad (1)$$

The output layer transferring function uses linear function.

$$f(x)=x. \quad (2)$$

The structure shown as Figure 2:

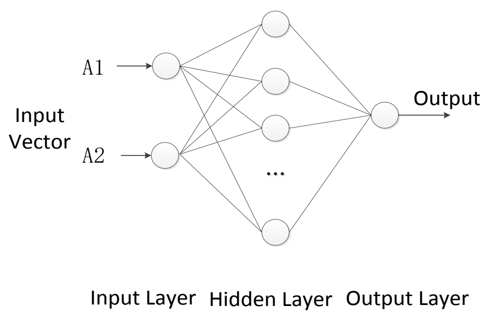

FIGURE 2 The structure of BP neural network model of logistics forecasts

3.2 THE CODING METHOD SELECTION

Genetic algorithm needs to encode the initial weights and thresholds of BP network, and BP network weights values and thresholds values composed of many real values. So it will be the real if uses binary coding. This will affect the learning accuracy, so this paper adopts real coding method.

Assume each chromosome in the population contains *S* gene, then

$$S=R\times S_1+S_1\times S_2+S_1+S_2 \quad (3)$$

where R is the number of input layer nodes; S_1 is the number of hidden layer nodes; S_2 is the number of output layer nodes. So, the chromosome length $S=2\times7+7\times1+7+1=29$, a total of 29 parameters need to be optimized.

3.3 FITNESS FUNCTION DESIGN

In the genetic algorithm the value of fitness function directly determines the direction of evolution population. The fitness function is designed generally based on the objective function of optimization. In the network designed in the paper, the objective function makes the mean square error of all the sample output to the minimum, namely the minimum of Equation (4).

$$E_{MSE}=\frac{1}{p}\sum_{p=1}^{p}(\mathrm{d}_p-\mathrm{y}_p)^2, \quad (4)$$

where P is the number of training samples; d_p is the desired output of the p samples; y_p is the actual output of the *p* sample.

As the individuals with higher adaptive value are selected to evolve in genetic algorithm, the adaptive value function uses the reciprocal of sample output variance.

$$f=\frac{1}{E_{MSE}}. \quad (5)$$

3.4 DESIGN OF GENETIC OPERATION

Genetic operations include selection, crossover and mutation.

1) Selection. The selection operation is based on fitness proportional selection method, higher the fitness is, greater the probability of selection is. Selection probability of each individual is shown as follows:

$$p_i=f_i\Big/\sum_{i=1}^{N}f_i. \quad (6)$$

2) Crossover. The crossover adopts the real crossover method, namely the chromosome marked *i* and chromosome marked *j* cross at Position *r*.

$$a_{ir}=a_{ir}(1-c)+\mathrm{a}_{jr}c, \quad (7)$$

$$a_{jr}=a_{jr}(1-c)+\mathrm{a}_{ir}c, \quad (8)$$

where *c* is a random number between [0, 1].

3) Mutation. Select the *j* genes of the individual marked *i* to compile operation.

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{max}) r_2 (1 - g/G_{max})^2 & r_1 \geq 0.5 \\ a_{ij} + (a_{min} - a_{ij}) r_2 (1 - g/G_{max})^2 & r_1 < 0.5 \end{cases}, \quad (9)$$

where a_{max} and a_{min} are the upper and lower bounds of gene a_{ij}; r_1 is a random number between [0, 1]; r_2 is another random number; g is the current iterations; G_{max} is the maximum number of evolution.

3.5 DESIGN OF TERMINATION CONDITIONS

In the BP neural network algorithm, when the optimal individual fitness reaches a given threshold, or the best individual fitness and population fitness will not rise any more, even or the number of iterations reaches a preset algebra, the algorithm will be terminated.

In this paper the algorithm selects the default algebra as 100 generation, and terminates when the iterations reaches a preset algebra.

3.6 BP NEURAL NETWORK PREDICTION

Take the weights and thresholds optimized by genetic algorithm as the BP neural network weights and thresholds, then use them to predict.

4 The example research

4.1 EXAMPLE

The case in [9] is used to analyse the enterprise material purchasing. The historical data samples of enterprise market demand, market price and the amount of material procurement are shown in Table 1:

TABLE 1 Sample data

Resources /t	2540	2960	2570	…	3110
Price /Yuan	1.60	1.75	1.63	…	1.78
Market purchases /t	235	273	238	…	289

4.2 TRAINING AND RESULTS

200 groups of data as the training sample are used to train BP neural network model, network structure is BP (2,7,1). The BP neural network is trained and optimized by genetic algorithm with MATLAB. The results are shown as Figure 3 and Figure 4.

The model, which uses BP neural network had gained the goal after 235 generations, but the model that uses BP neural network optimized by genetic algorithm had attained the goal just after 76 generations. The results show that convergence speed is greatly improved by genetic algorithm optimization.

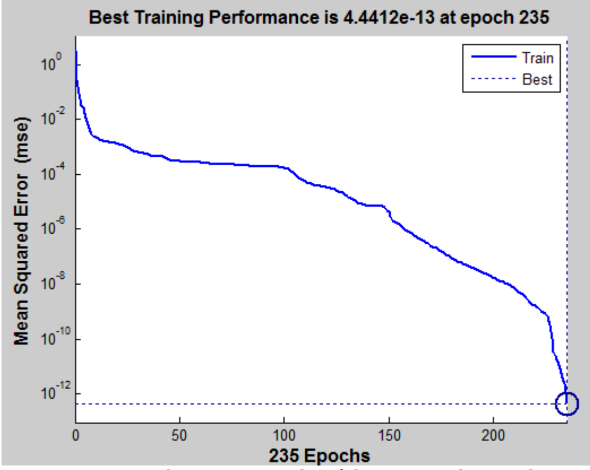

FIGURE 3 The training results of the BP neural network

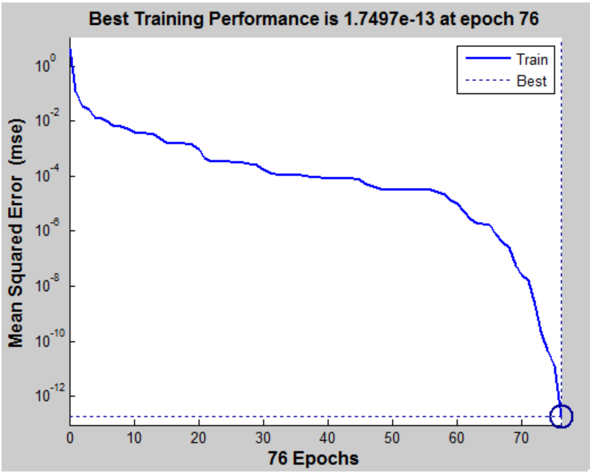

FIGURE 4 The training results of the BP neural network optimized by genetic algorithm

4.3 SIMULATION AND PREDICTION

After training the neural network 11 groups of data, which is not trained are used to test. The results are shown as follows (Figure 5 and 6).

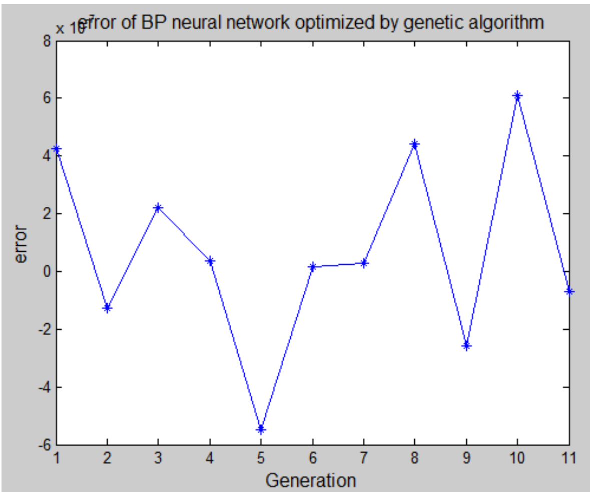

FIGURE 5 The error of the BP neural network optimized by genetic algorithm

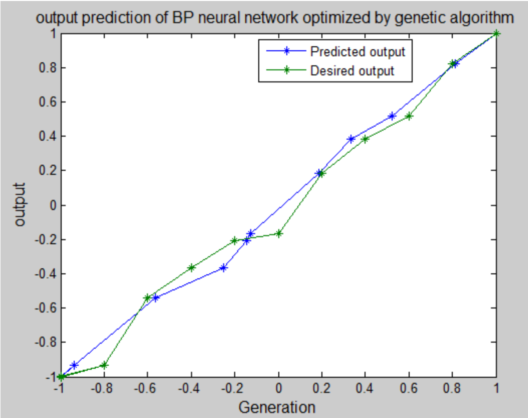

FIGURE 6 The contrast of the predicted output and desired output

The results show that the BP neural network optimized by genetic algorithm has good performance in logistics forecasting. The predicted output is very similar to the desired one. The errors are small and mostly are around 0 errors. The results proved that the network was trained successful and had better generalization ability.

5 Conclusions

This article analyses disadvantages of traditional forecasting methods and elaborates the advantages of the method based on BP neural network. Through introducing the genetic algorithm, a new logistics forecasting model based on BP neural network is proposed and applied to a logistical process. The simulation results show that the BP neural network optimized by genetic algorithm improved the convergence speed greatly, and it does not fall easily into local minimum.

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