Research on Equipment Materials Demand Forecast based on Genetic BP-Neural Networks

Tiening WANG[1, a], Longtao WU[1, a]

[1] Department of technique Support Engineering, Academy of Armored Forces Engineering, Beijing 100072, China

[a]email: tony9076@163.com

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Abstract. Accurate demand forecasting is an important precondition to carry out an active and detailed oriented equipment materials support. Learning and self-adaptive ability of BP-neural networks is used to learn the law of equipment demand, with genetic algorithm combined to improve the convergence speed of BP-neural networks. An optimized algorithm combining BP-neural networks and genetic algorithm is proposed for forecasting equipment materials demand. The simulation result shows that the proposed method owns high precision and fast convergence compared with original BP-neural networks.

Introduction

With the proceeding of equipment materials support and the wide application of information system, a large amount of equipment management data has been accumulated. Finding a way to fully use the big data can help the army improve equipment materials support efficiency[1].

Equipment materials support[2] can be described as a complicated and dynamic system influenced by many factors, and the complexity of support process is caused by randomness, uncertainty and fuzziness of the process, which makes it impossible to build precise mathematical models.

BP-Neural Networks[3] is a kind of multi-level feed forward network trained by Back Propagation algorithm, having a lot of good qualities such as large-scale parallel process, distributed storage, capability of self-learning, etc. By analyzing the law in historical data, it can output unknown result by new data. Although widely used in various fields, BP-Neural Networks has its own drawbacks. One is that the initial weights and thresholds are chosen randomly, which means sometimes the improper value may impede the optimization. Genetic Algorithm[3], capable of global searching, is one of the heuristic searching algorithms. This article combines advantages of the two algorithms and applies them to the forecast of materials demand.

Model of BP-Neural Networks

The process of BP learning algorithm can be divided into two stages[4]:

(1) The first stage is the forward propagation stage. Take the learning sample as input, and by the iteration process layer by layer with pre-set weights and threshold, calculate the real output value of every unit;

(2) The second stage is the backward stage. When the output layer does not get the expected value, it would calculate the deviation caused by weights and threshold, and adjust them.

Standard BP-Neural Networks learning algorithm trains the weights of nonlinear differentiable functions based W-H learning rule. It has been proved by practice that a 3-layer BP-Neural Network can imitate intricate nonlinear reflection as long as there are enough hidden layers. Here are the steps of learning algorithm for a 3-layer BP-Neural Network[5]:

STEP 1, initiate the network. Assign a number within (-1, 1) to the weights, and give values to error function e, calculation precision ε and maximum learning times M.

STEP 2, select input samples and corresponding expected output.

SETP 3, calculate input and output of hidden layer and output layer.

STEP 4, by the expectation output and actual output, calculate partial derivative using error function to output layer.

STEP 5, use connection value from hidden layer to output layer and error function of output layer and hidden layer to calculate partial derivative to neurons in hidden layers.

STEP 6, correct connection value by the output values of neurons in output layer and hidden layer.

STEP 7, correct connection weight by input value of hidden and output layer's neurons.

STEP 8, calculate global errors.

STEP 9, check if the error meet requirement. If the process has reach maximum iteration times or the error is smaller the precision threshold, stop the algorithm. Otherwise, select n the k+1-th sample, go back to STEP 3.

Structure of BP-Neural Networks

(1) Identify Nodes of input layer and output layer

The demand for materials mainly comes from equipment repair and maintain, and the using time and frequency of equipment are the main causes of equipment malfunction. Here large-scale repair times (x_1), medium repair times (x_2) and routine repair time (x_3), maintenance times (x_4), equipment using time (x_5) and equipment using frequency (x_6) are taken as input of the network, and number of nodes is 6. Demand amount of materials is the only output variable of the network, thus the output node number is 1.

(2) Number of hidden layers and number of neurons

Generally, number of hidden layers is related number of neurons, the increase of hidden layers will improve the precision but lower convergence speed. In short, less hidden layers need more hidden neurons and vice versa. For the same function, the increase of neurons' number can reduce the local extreme value, but on the other hand, convergence speed will drop. Since any continuous function in closed intervals can be approached by a BP-Neural Network, number of hidden layers in this article is 1.

Number of hidden layer neurons (N_h) and Number of input layer neurons (N_{in}) have such a relation:

$$N_h = 2N_{in} + 1$$

The number of hidden layer neurons (N_h), number of training samples (N_{train}) and number of input nodes (N_{in}) have following relations:

$$0.11N_{train} < N_h(N_{in} + 1) < 0.30N_{train}$$

The article collect influence data relevant to materials demand from 2003 to 2012 as input data, and the materials consumption data per month is used as a sample, 120 in total. The number of hidden layer neurons is 5.

(3) Selection of activation function

According to the demand of neural networks and output to reach, the article chose the common Sigmoid Function as the transfer function between layers, simply called S-Function. It can output values Even if the input values are relatively small, while when the input values are comparatively large, it tends to output a constant, avoiding over-flow.

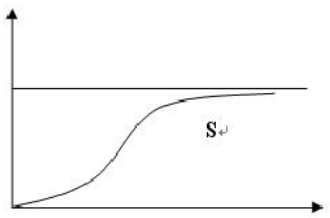

Fig.1. curve of Sigmoid Function

Assignment of initial weights and thresholds of BP-Neural networks using GA

In order to increase the convergence speed and reduce the possibility of falling into local extreme values, Genetic Algorithm is introduced to optimize the assignment of initial weights and thresholds. Here are the steps:

(1) Initiate the population. Every individual is coded with a string of doubles, made up of connection value from input layer to hidden layer, threshold of hidden layer, connection value from hidden layer to output layer and threshold of output layer.

(2) Identify the fitness function. Take the reciprocal of the absolute error between forecasted output value and target output value as fitness function:

$F = 1 \Big/ \sum_{k=1}^{n} \sqrt{(yo(k) - o(k))}$,

n is number of sample, $yo(k)$ is forecasted output value under effect of k-th sample, $o(k)$ is target output value of k-th sample.

(3) Process of selection. Select some individuals from the population as the parents to reproduce later generations. Possibility of each individual to be chosen is:

$P_i = F_i \Big/ \sum_{i=1}^{c} F_i$, c is volume of population, F_i Fitness of individual i.

(4) Process of crossing. 2 matched individuals exchange part of their genes in a specific rate, generating 2 new individuals. Crossing algorithm between individual a and b in position j is as follows:

$$\begin{cases} g_{aj} = g_{aj} r + g_{bj}(1-r) \\ g_{bj} = g_{bj} r + g_{aj}(1-r) \end{cases}$$

g_{aj}、g_{bj} are respective Gene of a and b in position j, $r \in [0,1]$.

(5) Process of variation. Impose variation on in position j of gene g_{kj} of individual k at a specific possibility, aim for increasing population diversity. The variation algorithm is as follows:

$$gki = \begin{cases} g_{kj} + (g_{kj} - g_{\max})(1 - s/s_{\max})\sqrt{r_1}, r_2 \geq 0.5 \\ g_{kj} + (g_{kj} - g_{\min})(1 - s/s_{\max})\sqrt{r_1}, r_2 < 0.5 \end{cases}$$

$g_{\max}, g_{\min}$ are the upper and lower limitation of gene g_{kj}, $r_1, r_2 \in [0,1]$.

(6) Calculating fitness function. If the result satisfies the requirement for ending, return the weights and thresholds. Otherwise, the algorithm goes back to step 3 to repeat.

Simulation and analysis

Take the data of factors affecting the demand of one kind of material from 2003 to 2012 as input, data of one month can be seen as one sample , so 120 samples in total can be used for training. The article forecasts the material demand from January to June of 2013, and the real demand data in this period is the test sample.

Parameters including Initial population, crossing possibility, variation possibility of GA are 30, 50%, 10% respectively. Parameters including target error, learning rate, training steps are 0.05, 0.1, 500 respectively . Build forecasting models by original BP-Neural networks and genetic BP-Neural networks respectively and compare the two models by Absolute Percent Error (APE) and Root Mean Square Error (RMSE), calculated as following formulas:

$$APE = \frac{|y(k) - y_o(k)|}{y_o(k)} \times 100\%, RMSE = \sqrt{\frac{(y(k) - y_o(k))^2}{n}}$$

k is month, $n = 6$ is the number of month, $y(k)$ is forecasting output value, $y_o(k)$ is expectation output value.

The following two figures and the table are the simulation result.

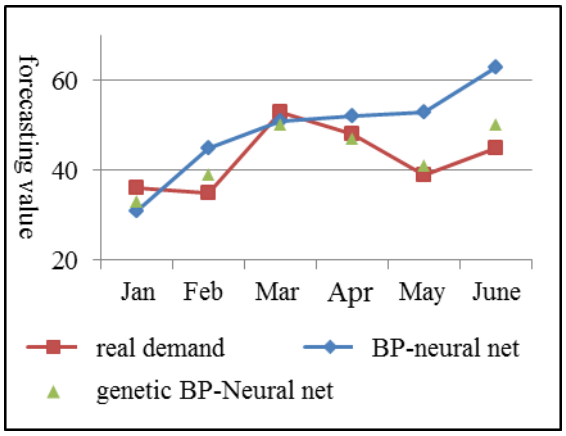

Fig.2. real demand forecast

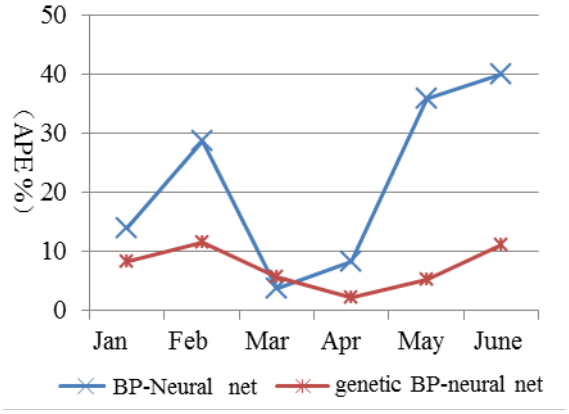

Fig.3. APE

Table 1：RMSE of demand forecasting

Month	Real demand	BP-NN		Genetic BP-NN	
		Forecast value	Training time	Forecast value	Training time
Jan	36	31	176	33	125
Feb	35	45	352	39	142
Mar	53	51	121	50	88
Apr	48	52	373	47	153
May	39	53	537	41	76
Jun	45	63	422	50	94
RMSE		10.53		3.27	

The simulation result above shows evidently that RMSE of genetic BP-neural networks is smaller than that of original BP-neural networks, and the forecasting precision is higher; The maximum APE of genetic-neural networks is about 10%, while the number of original BP-neural networks is 30% higher, which proves the better generalization ability of genetic BP-neural networks; also, the training times of genetic BP-neural networks is less enough to indicate that the genetic algorithm optimized the initial weights and thresholds and boosted the convergence speed.

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