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General Aircraft Material Demand Forecast Based on PSO-BP Neural Network

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Abstract

Accurately determine the air material demand has been an important research topic in the general aviation enterprise, the selection of forecasting methods is very important to scientifically determine air material demand. Consider general aircraft material demand forecast problem, forecast method is proposed using particle swarm optimization (PSO) algorithm to optimize the BP neural network. Firstly analyzed the main influence factors of general aircraft material demand, and then introduces the basic principle and algorithm process of PSO algorithm and BP neural network and PSO-BP neural network forecast model is constructed, finally simulation experiments are carried out by using historical statistics of general aviation enterprise, the prediction accuracy is higher than BP neural network and good results have been achieved. The method also can be used to forecast other kinds of material resources.

Keywords*: general aircraft; air material demand; BP neural networks; particle swam optimization algorithm*

1 Introduction

Air material demand forecast plays a very important role in the general aviation enterprise air material security system. Forecast accuracy will directly affect the security of air material, inaccurate forecast will cause air material shortage or waste, accurate forecast can not only effectively reduce the cost of air materials also satisfy high guarantee ratio, demand forecast has become the technical advantages of enterprises to participate in market competition, so the air material demand forecast has been an important research topic in the field of general aviation. At present, the research on this issue has made some results[1-6]. Lv [1] analyzed the classification and characteristics of air material, established practical formulas for calculating the demand of circular, non-circular, and expendable spares. By analyzing the demand of the following spare parts, Zhao [2] proposes a forecast model based on Bayesian prior distribution so as to improve the air material management and the utilization of reserve funds. Li [3] considered the fault distributing of air material, maintain capability of aviation army and the air material number of loading, queuing theory is used to forecast the repairable air material demand, the relevant arithmetic is designed and actualized. In view of the six types of performance failure rate of aviation equipment, first determine what kind of air material corresponding to the failure distribution function, then estimate the parameter values of repair degree by applying a generalized renewal process, finally calculate the demand of air material by Monte Carlo method in [4].

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Due to the influence factors of air material is diverse, nonlinear, it is difficult to establish a precise mathematical model using traditional numerical method, while the neural network algorithm is suitable for solving the problem of nonlinear mapping relationship. At present, the air material forecast based on neural network algorithm has attracted the attention of scholars[5, 6]. In the practice, 80% ~ 90% of the neural network model using the BP network or its modified forms, it's the essence of artificial neural network[7], which is also the most mature one. Dong [5] analyzed the many factors that affect air material demand to remove the relevance of the original input data and reduce the data dimension by using principal component analysis, Proposed forecast model based on PCA-BP neural network, and achieved good result through simulation. However, due to the BP neural network training using the gradient descent method, easily fall into local optimum, lead to its low reliability and poor generalization ability. Aiming at the shortage of the BP neural network, Shang [6] constructed forecast model of BP neural network improved by genetic algorithm. Through simulate forecast demand of military aircraft material, results proved that precision accuracy of this model is higher than BP neural network. However, it's worth noting that although BP neural network model optimized by genetic algorithm can overcome some defects of BP neural network and good results were obtained, but the operation of genetic algorithm is so complex that its training time increases exponentially with the size and complexity of practical problems, this leads to vastly reduced efficiency of the algorithm. PSO algorithm is simple in operation so as to avoid the complex genetic operation, has the advantage of high efficiency and global optimization which can effectively overcome the defects of BP neural network is easy to fall into local optimum.

Research of general aircraft material demand forecast based on PSO-BP neural network has not been reported in the literature so far. It should be noted that domestic research on the general aircraft material demand forecast has just started, in the existing literature, mostly to forecast material demand of military aircraft or transport aircraft, and demand forecast of general aircraft material are mostly based on the traditional material classification and experience. Because of the extensive management pattern does not take full advantage of accumulated historical data, which causes inaccurate prediction. In order to guarantee successful completion of the mission, general aviation enterprise need to store excess air material, with large inventory to ensure supply leading to air material inventory occupies lots of funds. Therefore, scientifically determine general aircraft material demand is very necessary, thus can be achieved high level of safeguard rate while reduced air material stock funds.

In response to these phenomena, this paper analyzed the main influence factors of general aircraft material demand firstly, then introduces the related theory of PSO algorithm and BP neural network model and PSO-BP neural network forecast model is constructed, finally the feasibility and validity of this method are proved with example simulation by using MATLAB tool.

2 Influencing Factors Analysis of General Aircraft Material Demand

The influence factors of general aircraft material demand is more complex, so it is impossible to tradeoff analysis on all factors, only need to extract the key influence factors. Take a certain type of general aircraft material as an example to analyze the air material consumption and combined with literature research and expert opinion, the following five factors are selected as the main influencing factors:

2.1 Accumulated Flight Time within Compute Cycles（P_1）

The time of usage has direct effect on the air material life, the more time of flight, the more air material usage frequency, will inevitably intensify the wastage of it, thus affecting the demand of air material.

2.2 Air Materiel Failure Rate（P_2）

Air materiel failure rate as a function of time, it refers to the air material in good condition at a certain moment, after which time, the conditional probability of failure per unit time. Failure rate is the inherent characteristic of product, it depends on the level of product design and manufacturing. The lower the air materiel failure rate, the smaller the demand.

2.3 Mean Time between Failures of air Materiel（P_3）

Mean time between failures (MTBF) is the important indicator of measuring the reliability of air material, it refers to the average time of spare parts from use until failure. The longer the MTBF means that the higher the reliability of air material, the smaller the demand.

2.4 Technical Level of Maintenance Crew（P_4）

As the main body of air material safeguards activities, the technical level of maintenance crew will directly affect the overall effectiveness of air materiel security system. The mastership degree and working ability of maintenance crew need some time to train and foster, the higher the skill level of maintenance personnel and the stronger ability to repair fault, the smaller the demand. In order to facilitate quantitative study, this paper selects the proportion of low technical level personnel as a measure index.

2.5 Environmental Factor（P_5）

High temperature, high humidity, strong sunlight, strong winds and other environmental factors will affect the use and storage of air material. For example, metal spare parts will be eroded because of damp or oxidation; high pressure and high temperature can damage the electronic equipment etc. Environmental impacts can be quantified as integer from 1 to 7, the larger the integer indicates that the severer of environment, the greater effect on air material demand.

3Construction of PSO-BP neural Network Forecast Model

3.1 The Principle and Process of Particle Swarm Optimization (PSO) Algorithm

（1）The Principle of PSO Algorithm

PSO algorithm derived from the study of birds of prey behavior, is a global optimization technique based on swarm intelligence, which was proposed by Dr. Eberhart and Dr. Kennedy in 1995[8]. First initialize a particle swarm in the solution space, where each particle represents a potential optimal solution, then to characterize the particles with position, velocity and fitness values of these three indicators, the fitness value represents the pros and cons of the particles.

Assumed that in M-dimensional search space, there is a population composed with N particles, set off population is $X=(X_1,X_2,\mathrm{L},X_N)$, The ith element of the set is $X_i=[X_{i1},X_{i2},\mathrm{L},X_{iM}]^T$ which denotes the position of the ith particle in M-dimensional search space. The velocity of each particle can be expressed as $V_i=[V_{i1},V_{i2},\mathrm{L},V_{iM}]^T$, the individual extremum of each particle $P_i=[P_{i1},P_{i2},\mathrm{L},P_{iM}]^T$,the global extremum of population $P_g=[P_{g1},P_{g2},\mathrm{L},P_{gM}]^T$. Fitness value of each particle can be calculated by the fitness function.

Each iteration, the particle through individual extremum and global extremum update its velocity and position, update formula can be expressed as follow[9]:

$$V_{im}^{k+1} = \omega V_{im}^{k} + c_1 r_1 (P_{im}^{k} - X_{im}^{k}) + c_2 r_2 (P_{gm}^{k} - X_{im}^{k}) \text{ , } (c_1 \geq 0, c_2 \geq 0) \tag{1}$$

$$X_{im}^{k+1} = X_{im}^{k} + V_{im}^{k+1} \tag{2}$$

Where X_{im} represents particle's position, $i = 1,2,\text{L},N$, $m = 1,2,\text{L},M$; V_{im} is the particle's velocity; P_{im} is the particle's individual extremum; P_{gm} is the global extremum; c_1 and c_2 is the acceleration factor; r_1 and r_2 is the random number which distribution between zero and one; ω is the inertia weight; and k is the number of iterations.

（2）PSO Algorithm Flow

The flow chart of PSO algorithm is shown as Fig.1.

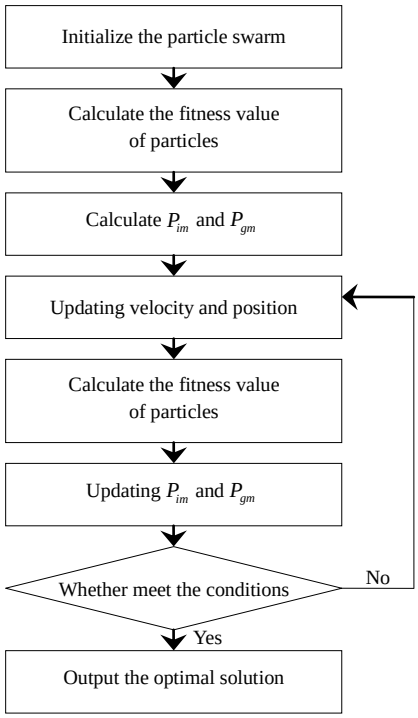


Figure 1. The Flow Chart of PSO Algorithm

Initialize the particle swarm is randomly set the initial position x and velocity v of each particle. Fitness value (F) of each particle can be calculated by the fitness function. Determine individual extremum and global extremum according to the initial particle fitness value. Update velocity and position by formula (1) and formula (2). Update particle's individual extremum and global extremum according to the fitness value of particle in the new population. If the termination condition (position is good enough or the maximum number of iterations is reached) is reached, output the optimal solution, otherwise return to step 4.

3.2 BP Neural Network

（1）Basic Theory of BP Neural Network

Back-Propagation Neural Network (BPNN) is a multilayer feed-forward neural

network, the main features of the network is information forward propagation and the error back propagation[10]. The BPNN can achieve any nonlinear mapping of the input and output. Due to the general BPNN with three layers structure can meet the demand of prediction problem, so this paper used in the three layers BPNN, its topology structure is shown as Fig.2.

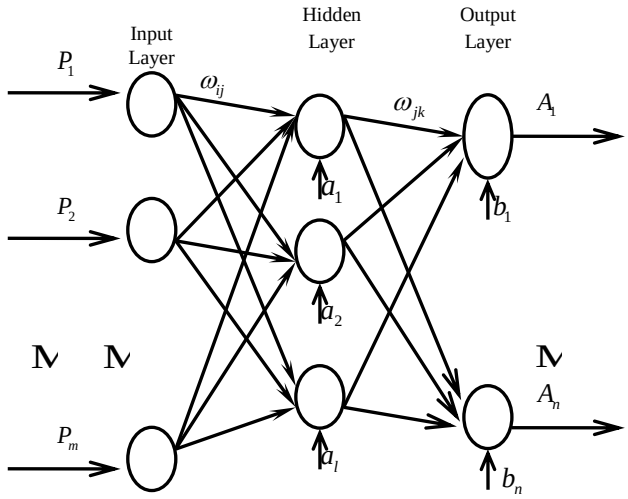


Figure 2. The Topology Structure of Three Layers BPNN

Where $(P_1, P_2, \ldots, P_m)$ is the input vectors of BPNN; $A_1, A_2, \ldots, A_n$ is the output vectors of BPNN; ω_{ij} and ω_{jk} is the weights of BPNN; $(a_1, a_2, \ldots, a_l)$ is the threshold of hidden layer node, and $(b_1, \ldots, b_n)$ is the threshold of output layer node. Such a network can reflect function mapping relationship between *m* independent variables and n dependent variable.

(2) Training process of BPNN

BP neural network to be trained before being used to predict, the training process is divided into the following six steps:

Step 1: Network initialization. According to the input and output sequences of practical problems to determine the number of input layer nodes m, the number of hidden layer nodes *l* and output layer nodes *n*, initialize the connection weights ω_{ij} and ω_{jk} between layers, initialize the threshold of hidden layer node $(a_1, a_2, \ldots, a_l)$ and the threshold of output layer node $(b_1, \ldots, b_n)$.

Step 2: Calculate the *j*th neuron (H_j) of hidden layer output value, where $H_j = f(\sum_{i=1}^{m} \omega_{ij} p_i - a_j)$, $(j = 1, 2, \ldots, l)$.

Step 3: Calculate the *k*th neuron (A_k) of hidden layer output value, where $A_k = \sum_{j=1}^{l} H_j \omega_{jk} - b_k$, $(k = 1, 2, \ldots, n)$.

Step 4: Error calculation. According to the forecast output (A) and the expected output (T), calculate the forecast error (e) .where $e_k = T_k - A_k$, $(k = 1, 2, \ldots, n)$.

Step 5: Updating weights and thresholds. According to the error in step 4 update the connection weights between layers and the threshold of hidden layer node & the threshold of output layer node. The updating formula can be listed as follows:

$$\omega_{ij} = \omega_{ij} + \eta H_j (1 - H_j) p(i) \sum_{k=1}^{n} \omega_{jk} e_k \text{ , } (i = 1, 2, \ldots, m; j = 1, 2, \ldots, l)$$

$$\omega_{jk} = \omega_{jk} + \eta H_j e_k \text{ , } (j = 1, 2, \ldots, l; k = 1, 2, \ldots, m)$$

$$a_j = a_j + \eta H_j (1 - H_j) \sum_{k=1}^{n} \omega_{jk} e_k \ , (j = 1, 2, \mathrm{L} \ , l)$$

$$b_k = b_k + e_k \ , (k = 1, 2, \mathrm{L} \ , n)$$

Where η [11]represents the learning rate of neural network, which can be expressed as $\eta = 0.99 / max[det(P * P^T)]$, $\eta \in (0,1)$.

Step 6: Decide whether stop training, If the termination condition is reached, output the optimal solution, otherwise transferred to the fourth step. Stop training while end condition is reached, otherwise return to step 2.

The training process of BP neural network is shown as Fig .3.

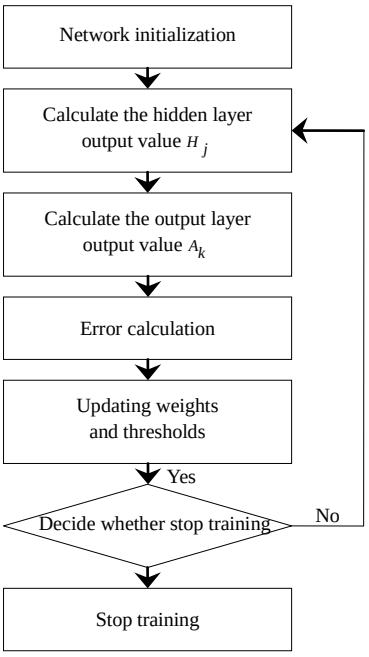


Figure 3. Training Process of BPNN

In the forward propagation process, input vector gradually processing through the input layer and hidden layer spread to the output layer. Calculate error value of output layer if the output does not reach the expected value, and then the error back propagation to modify the weights and thresholds of each neuron until reach the target[12].

3.3 Construction of PSO-BP neural Network Forecast Model

The training process of BPNN depends on the initial weights and thresholds selection, but the network weights and thresholds is random initialized, that will cause the blindness of training and easily fall into local optimum, lead to low reliability and poor generalization ability of the trained network. BPNN based on particle swarm optimization is to use particle swarm algorithm to optimize the initial weights and thresholds of network, the PSO algorithm is simple in operation and has good optimization efficiency, it also has the characteristic of global optimization and high computing precision[13]. Therefore, particle swarm algorithm can be used to optimize the BPNN to improve the global searching ability and generalization ability of network, thus the optimized network can have higher forecast accuracy.

3.3.1 Determination Structure of PSO-BP Neural Network

We put the earlier analysis of the five main demand influencing factors $(P_1, P_2, \text{L}, P_5)$ as input samples, the actual demand (T) for air material as object samples of output, which can determine the structure of BPNN: the number of input layer node is 5 and output layer node number is 1, according to the optimal number of hidden layer nodes selection formula[14] $l = \sqrt{(\text{m}+\text{n})} + c$, where $c \in (0,10)$, in this paper, the number of hidden layer nodes is set to 7, thus building a single hidden layer PSO-BPNN, which structure is 5-7-1.

3.3.2 The Training and Forecast of PSO-BP Neural Network

The training and forecast process of PSO-BPNN are illustrated as follows:

(1) PSO algorithm parameter setting. According to research in this paper, set the acceleration factor $c_1 = c_2 = 1.49$; inertia weight $\omega = 1$; the number of iterations is 400; the size of the population is 50; other parameters using the system defaults.

(2) According to the BPNN structure of the previously constructed calculate the length of weights and thresholds, that is $5 \times 7 + 7 \times 1 + 7 + 1 = 50$. Use PSO algorithm encode the connection weights between layers and the threshold of each node into real vector, represents the particles in population, so the dimension *M* of the particle's velocity and position vector are 50. Use MATLAB intrinsic function *rands(1,50)* to generate initial position and velocity of the population.

(3) Compute the fitness value of each particle by the fitness function, get the optimal solution by continuously updating speed and position. According to the actual situation, this paper choose the sum of relative error of BP neural network test output as fitness function: $F = \sum_{i=1}^{n} (|A_i - T_i| / T_i)$.

(4) The optimal solution of PSO is assigned to the weights and thresholds of BPNN, and set the operating parameters of BPNN for training. Combined with the actual needs, in this paper, the BPNN training parameters are set as follows: Training times is 600; the learning rate is 0.1; the expected error is 1*e*-006, other parameters using the system defaults.

(5) Use trained PSO-BPNN to forecast, comparative analysis of the error between actual demand and forecast demand.

The flow chart of PSO-BPNN algorithm is shown as Fig.4.

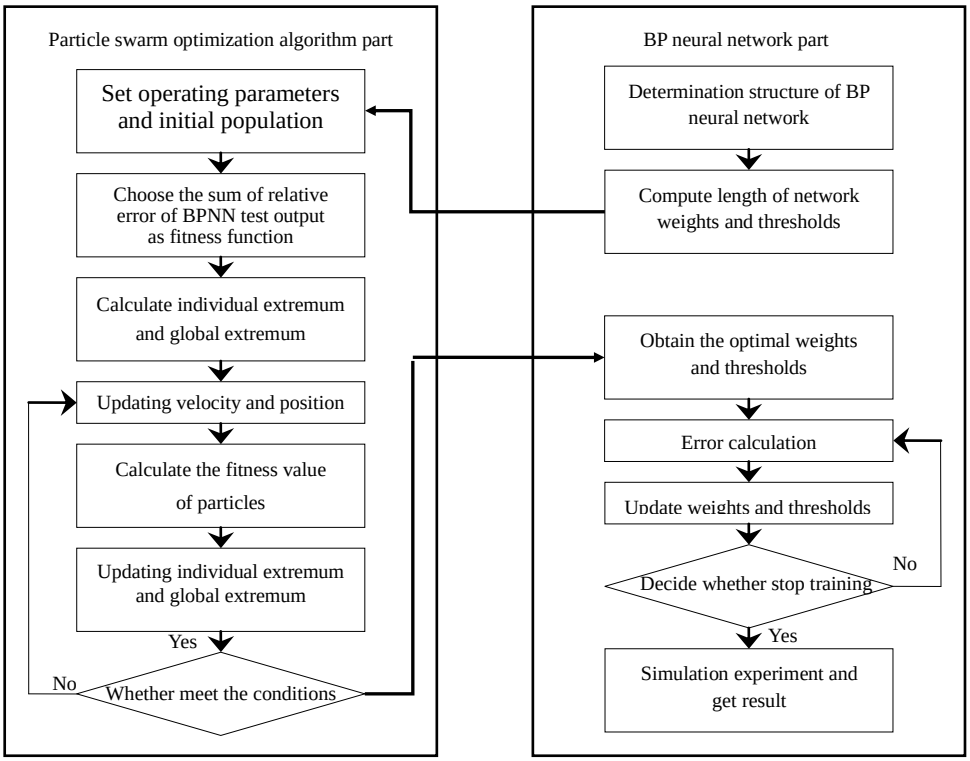


Figure 4. The Flow Chart of PSO-BPNN Algorithm

4 Actual Example and Analysis

We used the five influence factors $(P_1, P_2, \text{L}, P_5)$ of general aircraft material demand as independent variables and the actual demand for air materials *(T)* as dependent variable. 24 batches of a certain air material demand historical statistical data of general aviation enterprise are listed in Table 1:

Table 1. Historical Statistical Data of Air Material Demand

Batch	P_1（h）	P_2（piece/10^3h）	P_3（h）	P_4（%）	P_5	T（piece）
1	22	2.1	480	15.2	4	24
2	20	2.0	430	14.8	5	27
3	32	4.3	370	14.2	3	33
4	38	4.5	450	13.3	2	30
5	23	2.1	390	9.2	4	21
6	40	5.6	345	11.3	2	36
7	34	4.4	320	10.5	3	38
8	31	4.1	380	9.5	1	15
9	42	5.7	416	8.4	3	42
10	46	5.2	435	7.6	5	48
11	34	4.3	285	6.7	1	18
12	37	4.6	276	5.8	6	45
13	32	4.2	425	13.2	5	37
14	43	5.8	356	12.5	4	51
15	27	2.3	328	10.4	2	28
16	25	2.1	405	9.2	3	26
17	36	4.5	368	8.3	2	39
18	28	2.3	295	10.5	3	32
19	47	5.7	452	9.8	2	43
20	50	6.1	272	8.2	2	63
21	35	4.3	320	7.5	3	49
22	37	4.1	380	6.8	4	39
23	42	5.2	346	5.9	6	54
24	29	2.4	372	5.5	5	29

This paper selects 1 to 18 batches as neural network training data and 19 to 24 batches as test data. By respectively using BPNN and PSO-BPNN simulation test on the data, simulation results are shown in Fig.5.

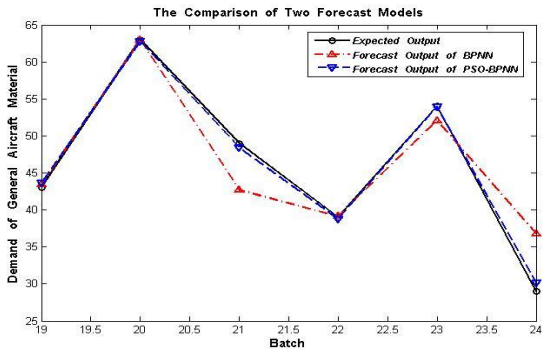
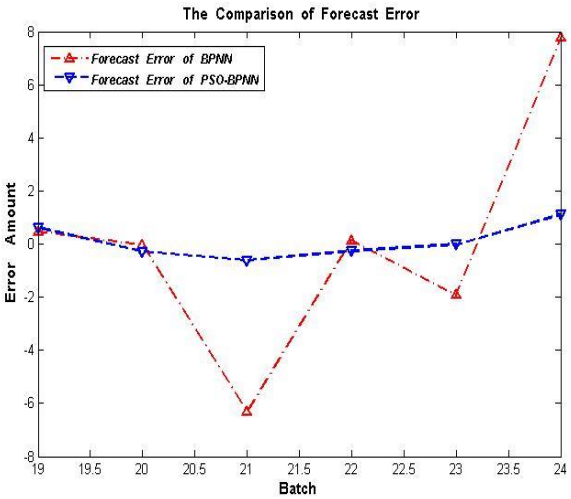


Figure 5. Simulation Results

By comparative analysis the true value and the forecast value of BPNN model and PSO-BPNN model, get the error curve and the relative error curve, which has shown in Fig.6 and Fig.7, detailed data are shown in Table 2.



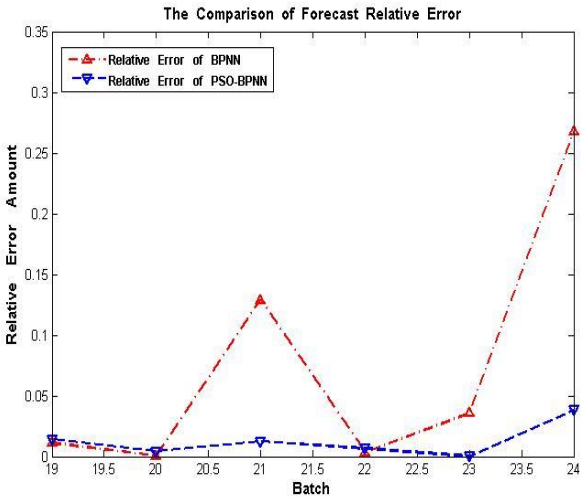


Figure 6. Forecast Error Curve **Figure 7. Forecast Relative Error Curve**

Table 2. Error Analysis

Batch		19	20	21	22	23	24
actual demand		43	63	49	39	54	29
BPNN	forecast value	43.4731	62.9712	42.6758	39.1336	52.0831	36.7533
	error amount	0.4731	−0.0288	−6.3242	0.1336	−1.9169	7.7533
	relative error amount	0.0110	0.0004	0.1291	0.0034	0.0355	0.2674
PSO-BPNN	forecast value	43.6146	62.7271	48.3904	38.7488	53.9801	30.1113
	error amount	0.6146	−0.2729	−0.6094	−0.2512	−0.0199	1.1113
	relative error amount	0.0143	0.0043	0.0124	0.0064	0.0003	0.0384

According to the table above, the sum of the relative error amount of BPNN is 0.4468, the sum of the relative error amount of PSO-BPNN is 0.0761. Simulation results show that forecast accuracy of PSO-BP neural network is higher than the BP neural network and a more accurate prediction results are achieved, can be used as an effective method to forecast the demand of general aircraft material in the future.

5. Conclusion

This article studies the problem of general aircraft material demand forecast based on PSO-BP neural network, that can be effectively compensate for the shortcomings of traditional BP neural network, example shows that this method has higher accuracy and good results are obtained. This forecast model based on intelligent algorithm can solve complex nonlinear function relation and have good learning ability and generalization ability, it has high practical value

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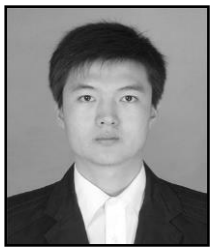

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