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General Aircraft Material Demand Forecast Based on Modified PSO Optimized BP Neural Network

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Abstract

Air material demand forecast is an important content of air material management, How to scientifically determine the general aircraft material demand has always been a key research subject of general aviation enterprise. Consider the general aircraft material demand forecast problem, forecast method is proposed by using Modified Particle Swarm Optimization (MPSO) algorithm to optimize the BP neural network. Firstly analyzed the main influence factors of general aircraft material demand, then introduces the basic principle of BP neural network and PSO algorithm and its improvement and MPSO-BP neural network forecast model is constructed, finally case analysis is carried out by using historical data of general aviation enterprise. The results show that the model prediction accuracy is improved effectively and good results have been achieved.

Keywords*: general aircraft; air material demand; BP neural networks; Particle Swam Optimization*

1. Introduction

General aircraft material demand forecast directly affect air material security and cost management of general aviation enterprise, inaccurate forecast will cause air material shortage or waste, accurate prediction can not only meet the high safeguard rate but also greatly reduce the cost, So how to scientifically determine the general aircraft material demand has always been a key research subject of general aviation enterprise. At present, the research on this issue has made some results [1-6]. Jia [1] researched a forecast method for consumption of air material based on ARIMA model, put forward a method that regards the number of air materials' consumption as time sequence during use, and the relevant ARIMA(p, d, q) model is constructed. Yang [2] combined the advantages of univariate and multivariate forecast methods which are both based on LSSVM, then weight coefficient of the combination forecast method is optimized based on entropy theory, finally the calculation method for forecast steps is presented. Taken the air material demand forecast as the research object, considering the operational availability of equipment and the limitation of cost, the simulation method of Monte Carlo is used to establish the model in [3], *etc.*

Due to the influence factors of air material is complex, non-linear, it is difficult to establish accurate mathematical model using traditional numerical method. Therefore, the scholars turned to the research field of neural network which has obvious advantages in dealing with non-linear problems. In the practice, 80%-90% of the neural network model using the BP network or its modified forms, it's one of the most mature in artificial neural network, which is also embodies the most essence part of neural network [6]. Song [4] analyzed the main factors of air material demand firstly, then a forecasting method is

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proposed based on the GM-BP neural network. The proposed method uses the grey forecast model to train the training samples and gets the BP neural network input samples, then BP neural network is used to get the air material demand results. 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, the BP neural network has the defects such as easy to fall into local optimum and slow convergence speed *etc.* Aiming at the defects of BP network, many scholars use PSO algorithm to improve. PSO algorithm is a kind of swarm intelligence optimization algorithm, which is simple and easy to implement, but when applied to high-dimensional complex problems often appear the phenomenon of premature convergence and slow late convergence speed, which can not guarantee convergence to the optimal value. In this paper, the PSO algorithm is improved to overcome these shortcomings, general aircraft material demand forecast model is constructed by using Modified Particle Swarm Optimization algorithm to optimize the BP neural network.

So far, research of general aircraft material demand forecast based on MPSO-BP neural network has not been reported in the literature. 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 mathematical modeling method, which causes inaccurate prediction. General aviation enterprise can not achieve a balance between high level of safeguard rate and low inventory cost, usually can use excess inventory to ensure timely supply leading to air material inventory occupies lots of 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 BP neural network and PSO algorithm and its improved theory, general aircraft material demand forecast model is constructed by using MPSO-BP neural network. Finally, the feasibility and validity of this method are proved with example analysis by using MATLAB tool.

2. Influencing Factors Analysis of General Aircraft Material Demand

Due to the influence factors of general aircraft material demand is complex and non-linear, it is impossible to consider all factors, only need to analyze 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.

3. BP Neural Network

3.1 Basic Theory of BP Neural Network

Back-Propagation Neural Network (BPNN) is a feed-forward network consists of input layer, a number of hidden layer and output layer, it has advantages of powerful information processing ability, good self-learning ability and parallel processing *etc.*, which is presently one of the most widely applied neural network models. Scholars have proved that, with a single hidden layer neural network can carry on the arbitrary accuracy to any nonlinear mapping approaching [7]. This paper uses three layer network structure containing a single hidden layer, its topology structure is shown as Figure1.

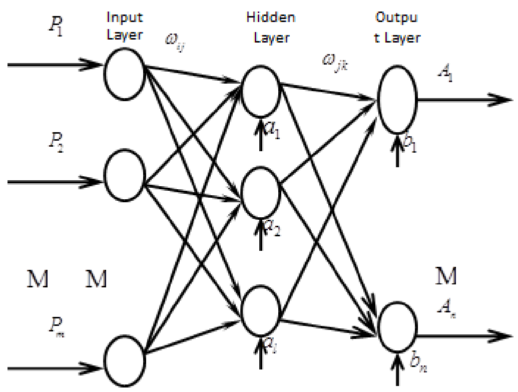

Figure 1. The Topology Structure of Three Layers BPNN

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

3.2. The Training of BPNN

BP neural network to be trained before being used to forecast, the main features of raining process is information forward propagation and the error back propagation[8]. Forward propagation is the input vector gradually processing through the input layer and hidden layer spread to the output layer. Error back propagation means that calculate error value when the forecast output and the expected output is not consistent, and then the error signal transfer through the output layer and hidden layer spread to the input layer to modify the weights and thresholds of each neuron until reach the target. 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 $(a_1, a_2, \cdots, a_l)$ and the threshold of output layer node $(b_1, \cdots, b_n)$.

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

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

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

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:

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

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

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

$$b_k = b_k + e_k, \quad (k = 1, 2, \cdots, n)$$

Where η [9] 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 Figure .2.

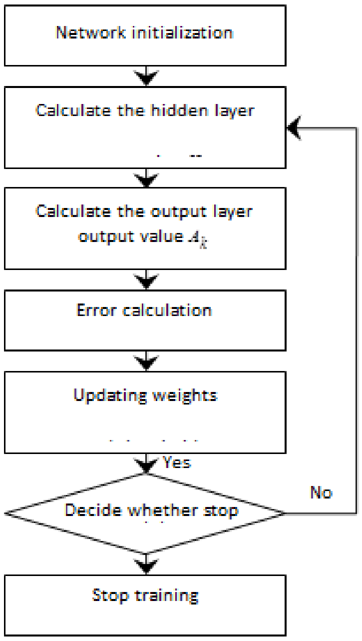

Figure 2. Training Process of BPNN

4. The Modified of PSO Algorithm

4.1. The Basic PSO Algorithm

PSO algorithm [10] was first proposed by Dr. Eberhart and Dr. Kennedy in 1995, which is an intelligent optimization algorithm comes from the study of the birds feeding behavior, it has become an important branch of evolutionary algorithm. The mathematical meaning is: assumed that in M-dimensional search space, there is a population composed with N particles, set of population is $X=(X_1,X_2,\cdots,X_N)$, where each particle represents a potential optimal solution. The fitness value of each particle position $X_i=[X_{i1},X_{i2},\cdots,X_{iM}]^T$ can be calculated by the fitness function, which indicates the pros and cons of the particles. Each particle $V_i=[V_{i1},V_{i2},\cdots,V_{iM}]^T$ has a velocity determine its direction and distance of flying. Thus with the position, velocity, and the fitness value can represent characteristics of the particles. First, get a group of particles through random initialization, and then through the iteration to optimization. Each iteration, the particle through individual extremum $P_i=[P_{i1},P_{i2},\cdots,P_{iM}]^T$ and global extremum $P_g=[P_{g1},P_{g2},\cdots,P_{gM}]^T$ update its velocity and position, update formula can be expressed as follow [11]:

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

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

Where V_{im} is the particle's velocity; X_{im} represents particle's position; c_1 and c_2 is the acceleration factor; r_1 and r_2 is the random number which distribution between zero and one; $m=1,2,\cdots,M$, $i=1,2,\cdots,N$; and k is the number of iterations.

4.2. The Modified PSO Algorithm

In order to overcome the defects of basic PSO algorithm, this paper adopts adaptive mutation and linear decreasing inertia weight strategies to improve it.

(1) Adaptive mutation

Learn from the mutation of genetic algorithm, mutation operation is introduced to the basic PSO algorithm. That is, after each of the particle velocity and position update, to re-initialize the particle at a certain probability, based on MATLAB programming code is as follows:

```
if rand>0.9
    k=ceil (M*rand);
    pop (j, k)=rand;
end
```

Where j is the number of population size; M is the dimension of particle's velocity vector and position vector.

The introduction of mutation operation increased the population diversity, so that the particles can jump out the optimal position of previously searched, carry out the search in a larger space in order to obtain better global optimization capability, thus can avoid the particles fall into local optimum.

(2) The setting of linear decreasing inertia weight

In order to improve the convergence performance of the basic PSO algorithm, Shi and Eberhart added inertia weight [12] in the velocity update formula which can be expressed as follows:

$$V_{im}^{k+1} = \omega V_{im}^{k} + c_1 r_1 (P_{im}^{k} - X_{im}^{k}) + c_2 r_2 (P_{gm}^{k} - X_{im}^{k}) , \quad (c_1 \geq 0, c_2 \geq 0) \tag{3}$$

Through the experiment found that the larger ω is conducive to jump out of local optimal for global search, while the smaller ω is conducive to local search to accelerate the algorithm convergence. According to these analyzes, they proposed using a linear decreasing inertia weight which can be expressed as follows:

$$\omega = \omega_{start} - (\omega_{start} - \omega_{end}) * k / T_{max} \tag{4}$$

Where ω_{start} is the initial inertia weight; ω_{end} is the inertia weight of iteration to the maximum number; k is the number of iterations; and T_{max} is the maximum iterations. In general, when the inertia weight value $\omega_{start} = 0.9$ and $\omega_{end} = 0.4$ is the best performance of the algorithm. As the iteration proceeds, the inertia weight linearly decreasing from 0.9 to 0.4, larger ω makes the algorithm keeps the good global exploring ability at beginning of iteration, while smaller ω is conducive to the algorithm maintains a good global exploring ability, thus balance the particles' global search ability and local search ability, improve the convergence performance and accuracy of particle swarm.

4.3 MPSO Algorithm Flow

The flow chart of MPSO algorithm is shown as Figure3.

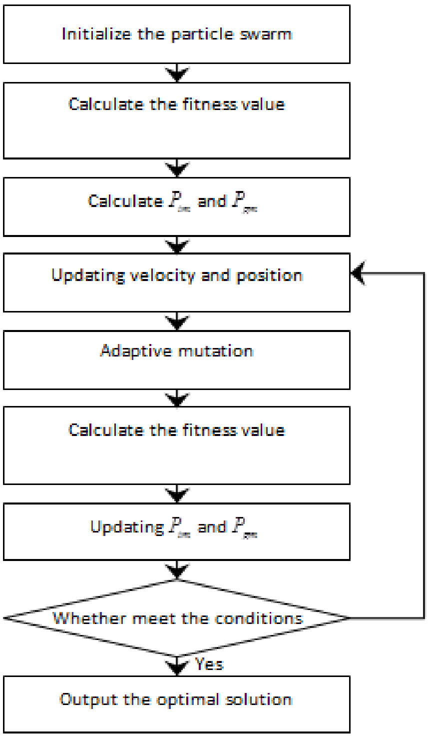

Figure 3. The Flow Chart of MPSO Algorithm

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 (2), formula (3) and formula (4). 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.

5. Construction of MPSO-BP Neural Network Forecast Model

Due to the BP neural network training using the gradient descent method, the learning results depends on the initial weights and thresholds, This can cause oscillation and poor generalization ability of the network , eventually led to the trained network is easy to fall into local optimum and the reliability of the network is poor. MPSO-BP neural network is to use the Modified Particle Swarm Optimization algorithm to find a better network weights and thresholds of network, MPSO algorithm is easy to implement, has a fast convergence speed and better global optimization ability. Therefore, Modified Particle Swarm Optimization algorithm can be used to optimize the BP neural network to improve learning performance and convergence performance of the network, minimize the global error of BP neural network, has a higher prediction precision.

5.1 Determination Structure of MPSO-BP Neural Network

We put the earlier analysis of the five main demand influencing factors $(P_1, P_2, \ldots, P_5)$ as input samples, the actual demand (T) for air material as object samples of output, which can determine the structure of MPSO-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 [13] $l = \sqrt{(\mathrm{m+n})} + c$, where $c \in (0,10)$, in this paper, the number of hidden layer nodes is set to 7, thus building a single hidden layer MPSO-BPNN, which structure is 5-7-1.

5.2 The Training and Forecast of MPSO-BP Neural Network

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

(1) MPSO algorithm parameter setting. According to research in this paper, set the acceleration factor $c_1 = c_2 = 1.49$; ω use the linear decreasing inertia weight which shown as equation (4), where $\omega_{start} = 0.9$, $\omega_{end} = 0.4$; 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 selected the BP neural network test outputs' mean square error of relative error as fitness function $error = mse((A_i - T_i)./T_i)$.

(4) After each of the particle update, to re-initialize the particle at a certain probability, obtained the optimal solution through adaptive mutation and constantly iterative update. Combined with the example, based on MATLAB programming code is as follows:

```
if rand>0.9
      k=ceil (50*rand);
     pop (j, k)=rand;
 end
```

(5) The optimal solution of MPSO is assigned to the weights and thresholds of BPNN, and set the operating parameters of network for training. Combined with the actual needs, in this paper, the network 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.

(6) Use trained MPSO-BPNN to forecast, Analysis of the forecast effect.

The flow chart of MPSO-BPNN algorithm is shown as Figure4.

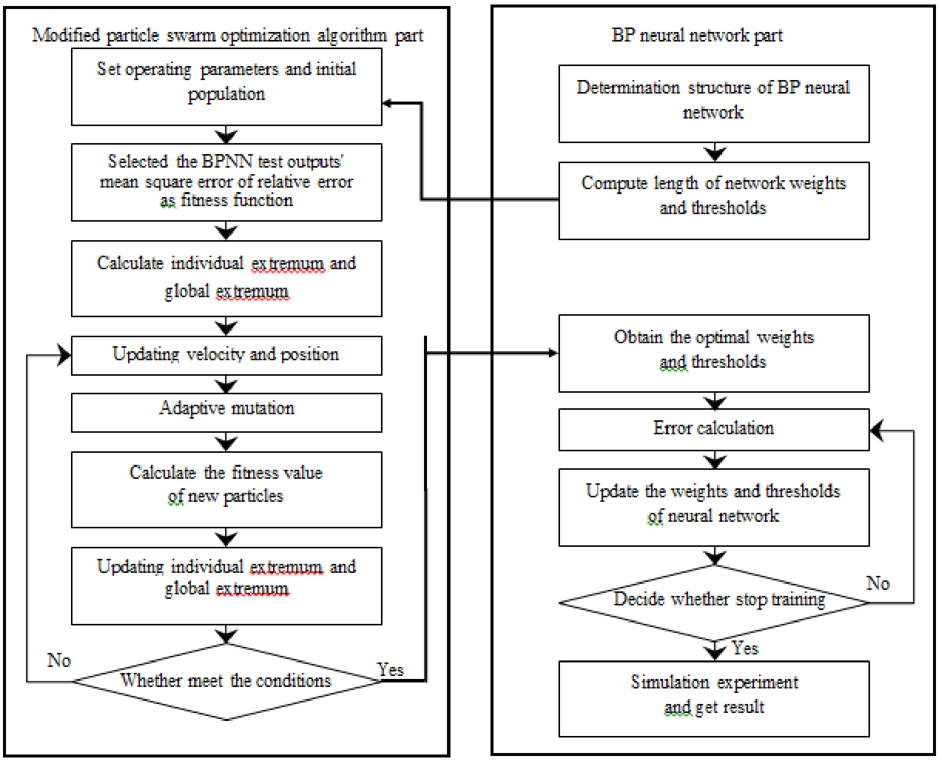

Figure 4. The Flow Chart of MPSO-BPNN Algorithm

6. Actual Example and Analysis

We used the five influence factors $(P_1, P_2, \ldots, P_5)$ 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	P1（h）	P2（piece/103h）	P3（h）	P4（%）	P5	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. To illustrate the effectiveness of the proposed model, respectively using BPNN forecast model and PSO-BPNN forecast model compared with MPSO-BPNN forecast model, simulation results are shown in Figure5.

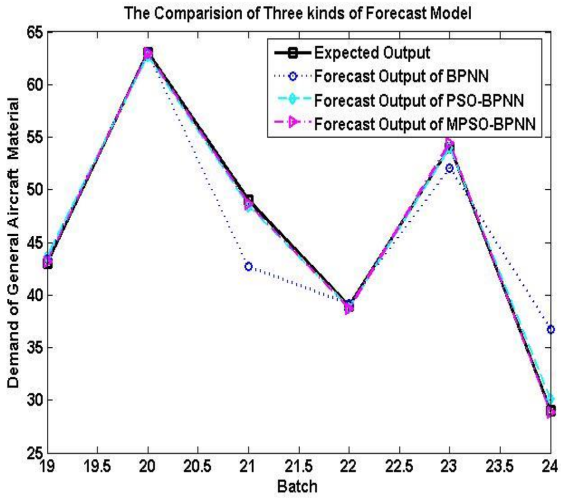

Figure 5. Comparison between the Forecast Output Results

By comparative analysis the true value and the forecast value of BPNN model, PSO-BPNN model and MPSO-BPNN model, get the error curve and the relative error curve, which has shown in Figure6 and Figure7, detailed data are shown in Table 2.

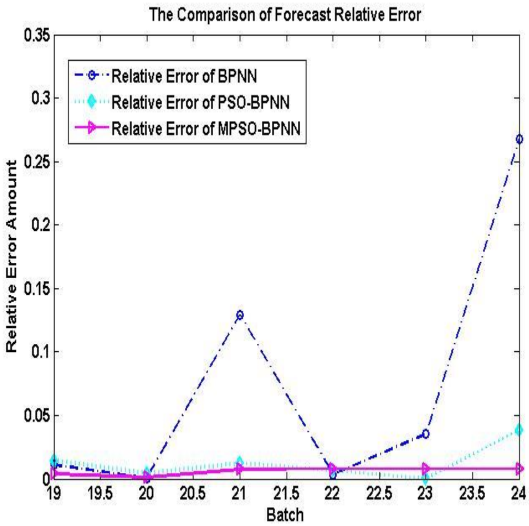

Figure 6. Forecast Error Curve

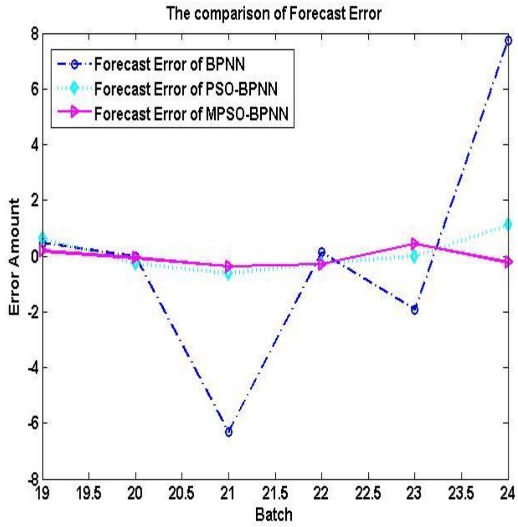

Figure 7. Forecast Relative Error Curve

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	-0.6096	-0.2512	-0.0199	1.1113
	relative error amount	0.0143	0.0043	0.0124	0.0064	0.0004	0.0384
MPSO-BPNN	forecast value	43.1674	62.9327	48.6306	38.6979	54.4331	28.7653
	error amount	0.1674	-0.0673	-0.3694	-0.3021	0.4331	-0.2347
	relative error amount	0.0039	0.0011	0.0075	0.0077	0.0080	0.0081

Comparison of MPSO algorithm and basic PSO algorithm, we can see the optimal individual fitness value changes in the process of optimization, which has shown in Figure8.

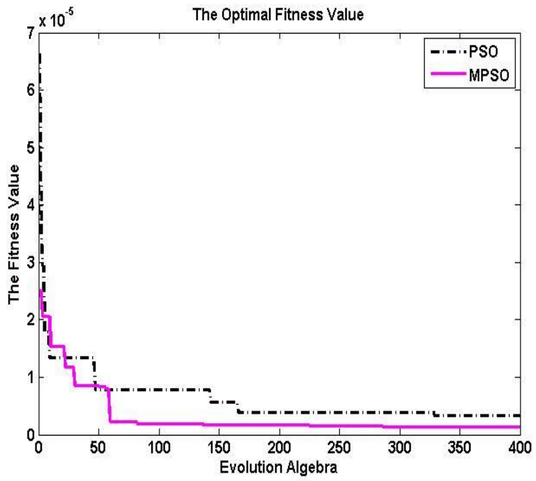

Figure 8. Curve of Best Individual Fitness Value Changes

It can be seen from Figure8, The MPSO algorithm's fitness value after 60 iterations has been better than the basic PSO algorithm's optimal fitness value after 400 iterations, shows that the convergence speed of the MPSO algorithm is faster and the convergence accuracy is higher. According to the Table 2, the sum of the relative error amount of BPNN is 0.4468, the sum of the relative error amount of PSO-BPNN is 0.0762 and the sum of the relative error amount of MPSO-BPNN is 0.0363. Simulation results show that the MPSO algorithm has better convergence efficiency and accuracy, the forecast accuracy of MPSO-BP neural network is higher than the BP neural network and the PSO-BP neural network, a more accurate predict results are obtained, can be used as an effective method to forecast the demand of general aircraft material in the future.

7. Conclusion

This article studies the problem of general aircraft material demand forecast based on MPSO-BP neural network that can be effectively overcomes some defects of BP neural network and PSO algorithm. It is proved that compared with the BP neural network model and PSO-BP neural network model, this method has better nonlinear fitting and generalization ability, it improves the convergence efficiency and reduces the possibility of trapped into local minimum. This method has higher forecast precision and good application effect in the general aircraft material demand forecasting. However, it should be pointed out the problem of general aircraft material demand forecast is a new research project. Further study on other intelligent optimization algorithm to improve the performance of BP neural network and improve the scientific and accuracy of its predictions are the focus of the next step research work.

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