Research Article

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Computer technology of multisensor data fusion based on FWA–BP network

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Abstract: Due to the diversity and complexity of data information, traditional data fusion methods cannot effectively fuse multidimensional data, which affects the effective application of data. To achieve accurate and efficient fusion of multidimensional data, this experiment used back propagation (BP) neural network and fireworks algorithm (FWA) to establish the FWA–BP multidimensional data processing model, and a case study of $PM_{2.5}$ concentration prediction was carried out by using the model. In the $PM_{2.5}$ concentration prediction results, the trend between the FWA–BP prediction curve and the real curve was basically consistent, and the prediction deviation was less than 10. The average mean absolute error and root mean square error of FWA–BP network model in different samples were 3.7 and 4.3%, respectively. The correlation coefficient R value of FWA–BP network model was 0.963, which is higher than other network models. The results showed that FWA–BP network model could continuously optimize when predicting $PM_{2.5}$ concentration, so as to avoid falling into local optimum prematurely. At the same time, the prediction accuracy is better with the improvement in the correlation coefficient between real and predicted value, which means, in computer technology of multisensor data fusion, this method can be applied better.

Keywords: FWA–BP network, multisensor data, computer technology

1 Introduction

The dimension of sensor data increases with the development of science and technology. Multisensor data fusion can solve the problem of data dimension increase and nonlinear system [1]. However, when multisensor data fusion is used to process multidimensional data, the complexity of model operation is high, and the data fusion method needs to be further improved [2]. In the fusion calculation of multisensor data, the neural network has good self-learning and self-adjusting capabilities and can be used to solve nonlinear problems [3]. In the research on the relationship between multisensor data and target objects, back propagation (BP) neural network can fully exploit the nonlinear relationship between them, and constantly adjust and optimize the parameters in BP neural network by using the BP method [4]. The data information is stored in the trained optimization model, and the final fusion result is obtained by fusing the input data information. However, BP neural network has the problems of slow convergence speed and premature falling into local optimization when making predictions [5]. Research shows that different scholars have introduced genetic algorithm (GA), artificial ant colony algorithm, etc., to optimize the BP neural network's parameters [4,6]. The introduction of different algorithms can make BP neural network's prediction accuracy improve effectively. However, in-depth research shows that these algorithms also have limitations, which will lead to slowing down of the search speed of the algorithm and get local optimal results. Fireworks algorithm (FWA) is a new type of swarm intelligence optimization algorithm, which has a wider search scope and simpler algorithm than other

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algorithms. FWA simulates the principle of simultaneous explosion and diffusion of operators in the process of fireworks explosion, forming a diverse fireworks population. At the same time, the FWA has stronger global search ability, and can conduct global optimization on the input data information. The introduction of FWA can optimize the parameters of other algorithms and improve their performance. Therefore, FWA is innovatively introduced in this experiment to optimize the BP neural network, so as to solve the problems of slow convergence speed and premature falling into local optimization of BP neural network during model training. With the progress of urbanization, air pollution has a serious impact on people's lives and health. Fine particulate matter ($PM_{2.5}$) is the main factor affecting air quality. The traditional $PM_{2.5}$ prediction model takes into account the relationship between the concentrations of ozone, inhalable particles (PM_{10}), and other pollutants. However, in the traditional prediction model, the processing of original data requires multisensor data fusion, resulting in low accuracy of prediction results. Therefore, in the case application analysis of the optimization model, the dimension reduction analysis is conducted on the original data, and then the optimization model is used to predict the $PM_{2.5}$ concentration to verify the performance of the optimization model.

2 Related work

Multisensor data fusion technology uses computers to comprehensively analyze information and data from multiple sources or from different sensors under certain rules. Multisensor data fusion technology has been effectively applied in many fields such as position testing, defect inspection and monitoring, and ultrasonic testing [7,8]. During the environmental weather forecast, it will be affected by the clouds in the air, which will reduce the accuracy of the weather forecast. Multisensor data fusion technology can be used to eliminate the impact of cloud coverage in the air. It has good prediction accuracy when dealing with extreme situations, and promotes the development of data integration technology [9]. To understand the life span of wood and its reliability in use, scholars analyzed the factors affecting wood weathering from the molecular, micro and macro perspectives. Different sensors are used for data fusion, and then a model is established to study the dynamics of wood weathering [10]. When acquiring the drilling depth of the exploration rig, researchers use multiple sensors to measure and combine the weighted fusion algorithm to measure the final drilling depth. This method has high fault tolerance. The application of multisensor data fusion technology has improved the accuracy of borehole depth measurement [11].

To further improve multisensor data fusion technology's accuracy and performance, researchers use different algorithms to improve the data fusion method. Common multisensor data fusion methods include Kalman filtering method, artificial neural network method, etc. Among them, neural network has unique advantages in information processing, application range, and operating environment [12,13]. Therefore, in the research of multisensor data fusion technology, neural network has received extensive attention. The selection criteria of neural network models need to be consistent with the characteristics and requirements of sensors in the fusion system, such as learning rules, network structure, etc. At the same time, neural network model can establish the connection between input information, output information, and decision-making system, determine and optimize parameters according to known sensor information, and complete the training of neural network. After training, neural network can be used in the actual process of multisensor data fusion [14]. And BP has a strong learning ability and a wide range of data fusion. It can perform more complex data fusion processing in multisensor data fusion. BP neural network can make full use of network flow and other data information to predict traffic volume in urban network flow prediction. The results show that the trend of predicted volume and actual traffic volume is consistent within a certain error range [15]. Optimizing the input of the network can improve the performance of the multisensor data fusion model. Research shows that using particle swarm optimization (PSO) to optimize BP neural network's parameters, the multisensor data fusion method established on the basis of the optimized model can speed up the network convergence and improve the data fusion and its accuracy [16]. The combination of neural network and sensor can monitor the industrial operation state. After the fusion of different heterogeneous data, the problems such as fault monitoring and noise pollution can be effectively fused. The industrial operation state is accurately monitored, which is conducive to troubleshooting and effectively guarantees industrial production [17].

The FWA has strong global optimization capability. In the radio network spectrum allocation, the FWA can solve the channel interference problem based on the user's cognitive coding and channel auxiliary coding, and has advantages in solving the spectrum allocation problem [18]. For the scheduling of the heating system, the improved FWA can formulate a multi-objective intelligent scheduling strategy, solve the multi-objective optimization problem, reduce energy waste, and do not affect the normal operation of the heating system [19]. In the relevant research, FWA can optimize the parameters of neural network, and the introduction of FWA can improve the data prediction accuracy and training effect of neural network. Among the data information related to time series, the neural network model optimized by FWA can maintain the relationship between current data information and past data information, and realize the prediction of fluctuating exchange rate [20]. From the above research, we can see that the neural network has advantages in the application of multisensor data fusion, but a single algorithm is easy to fall into the problem of local optimal solution, so further optimization of the neural network is needed. Based on FWA's advantages, such as strong global search ability, this experiment innovatively introduces FWA to optimize BP neural network, which solves the problems of slow convergence speed of traditional algorithm and premature falling into local optimization. In the $PM_{2.5}$ prediction model, the relationship analysis of multiple pollutants is required, and the data fusion of multiple sensors is required for data processing. In the analysis of the practical application of the method, this experiment selects $PM_{2.5}$ concentration prediction to verify and analyze the optimization algorithm, hoping to improve the multisensor data fusion technology through example analysis.

3 Research on the technology of multisensor data fusion based on FWA–BP

3.1 Data processing and optimization of BP neural network

BP neural network has good self-learning and self-adjusting ability, which can be used to solve nonlinear problems. In the research of the relationship between multisensor data and target objects, BP neural network can fully mine the nonlinear relationship between them, and constantly adjust and optimize the parameters of BP neural network by using the BP method. The data information is stored in the trained optimization model, and the final fusion result is obtained by fusing the input data information. Figure 1 shows the BP neural network's structure.

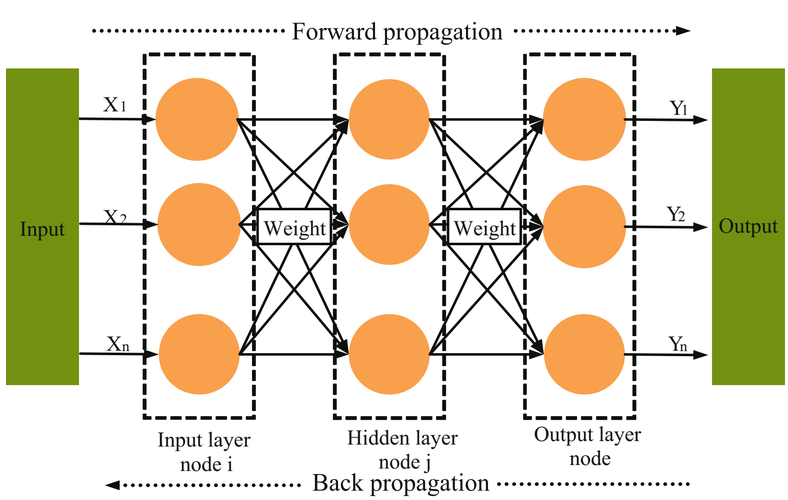

Figure 1: Structure diagram of BP network.

Due to the strong correlation between the data during multisensor data fusion, the data can only be input into the BP after processing, otherwise the running speed of the network and the accuracy of prediction will be reduced. Therefore, it is necessary to reduce the dimension of the input data information, and the method used in this experiment is the Principal component analysis (PCA). The number of input nodes can be reduced and the correlation between multisensor data can be reduced by inputting data into BP neural network after dimension reduction. In the dimension reduction step of PCA, in n units of time, m data are collected and matrix X is composed of these data samples, and then the data are standardized using formula (1) to obtain the standardized matrix U.

$$\mu_{ij} = \frac{x_{ij} - \overline{x_j}}{s_j}, \quad i = 1, 2, \ldots, n; j = 1, 2, \ldots, m, \tag{1}$$

where $\overline{x}$ is the mean value, $\overline{x_j} = \frac{1}{n}\sum_{i=1}^{n} x_{ij}$, s is the standard deviation, and $s_j = \sqrt{\frac{\sum_{i=1}^{n}(x_{ij} - \overline{x_j})^2}{n-1}}$. Thus, the correlation coefficient matrix R of U can be obtained, as shown in formula (2).

$$R = \frac{U^T U}{n - 1}, \tag{2}$$

where T is the maximum number of iterations. Then, the characteristic equation $|R - \lambda E_m| = 0$ of R can be obtained. Solve the eigenvalues in the characteristic equation, and take the first p principal components whose contribution rate is higher than 85% as the sample characteristics. Arrange the eigen values in the order from large to small, and convert the eigen vectors corresponding to the features of the first p principal component samples into matrix A^T, as shown in formula (3).

$$A^T = (u_1,\ u_2,\ \ldots, u_p), \quad p < m, \tag{3}$$

where u represents the eigen vector, and the first p principal components $Y = AX$ can be obtained to reduce the dimension of data. BP neural network is easy to generate local minima during model training and has slow convergence speed, which will reduce the network performance. As a single BP neural network is easy to fall into local optimization and the convergence speed of the function is slow, this experiment uses FWA to optimize. FWA is a new type of swarm intelligence optimization algorithm, which has a wider search scope and simpler algorithm than other algorithms. FWA simulates the principle of simultaneous explosion and diffusion of operators in the process of fireworks explosion, forming a diverse fireworks population. FWA constantly seeks the optimal solution in the process of continuous explosion, and the sparks generated by explosion can be regarded as a feasible solution. In the FWA, first, the fireworks population should be initialized, and then the fitness value of each firework should be calculated to obtain the explosive sparks and Gaussian sparks. All fireworks are arranged in the order of fitness value from large to small, and the first N fireworks are selected to generate candidate fireworks population. When the candidate fireworks population meets the termination conditions, the optimization process ends and the fireworks with the best fitness can be obtained, as shown in Figure 2.

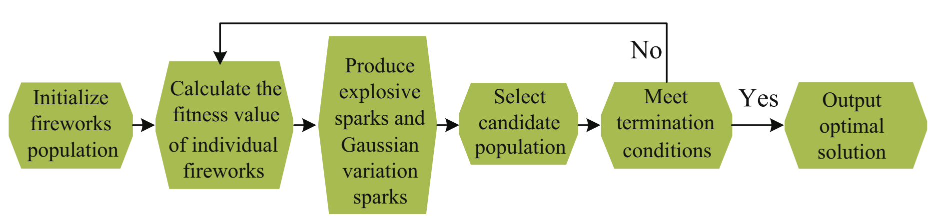

Figure 2: Specific process of FWA.

In the FWA, the initial number N of fireworks and the dimension n of each firework should be determined. The dimensions of fireworks are set with upper and lower limits, and the initial fireworks generated are controlled within the upper and lower limits of the dimensions. In the original FWA, according to different mapping rules and selection strategies, explosive sparks and Gaussian sparks will be generated. The explosion spark can be searched in the neighborhood. To realize explosion operation, first the explosion radius A_i and spark number S_i of the spark are defined using formulas (4) and (5), respectively.

$$A_i = E_r \times \frac{f(x_i) - y_{\min} + \varepsilon}{\sum_{i=1}^{N}(f(x_i) - y_{\min}) + \varepsilon}, \tag{4}$$

where x_i represents the fireworks that need to be exploded, $f(x_i)$ represents the fitness value of fireworks, $y_{\max}$ and $y_{\min}$ represent the worst and best solutions of fitness function, respectively, E_r and E_n represent the parameters controlling the range and quantity of spark explosion, respectively, and ε represents a minimum real value, which is used to avoid the situation where the denominator is 0 during the calculation. The calculation of spark number S_i can be seen in formula (5).

$$S_i = E_n \times \frac{y_{\max} - f(x_i) + \varepsilon}{\sum_{i=1}^{N}(y_{\max} - f(x_i)) + \varepsilon}. \tag{5}$$

According to the range and number of fireworks explosions, the explosion operation of each firework can be realized. During the explosion operation, it should randomly determine the number of dimensions D_{select} = rand × D to be offset for each firework, and generate the explosive fireworks ex_i after offset by formula (6).

$$ex_{ik} = x_{ik} + h, \tag{6}$$

where x_{ik} represents the dimension k that fireworks i need to offset, and ex_{ik} represents the sparks generated after fireworks i explode. The explosive sparks' random numbers are generated within the explosion radius, and A_i is expressed by h in formula (7).

$$h = A_i \times \text{rand}(1, -1). \tag{7}$$

Gaussian spark can increase FWA population's diversity, and Gaussian mutation operation is required to generate Gaussian spark. First, it is necessary to select the number of Gauss sparks with g from the initial fireworks, and then calculate the Gauss sparks after dimension offset by using formula (8).

$$\hat{x}_{i,k} = x_{i,k} \times e, \tag{8}$$

where $x_{i,k}$ represents the dimension k that needs to be offset for Gaussian fireworks i, and represents the sparks generated after the explosion of Gaussian fireworks i; and the random number of Gaussian distribution is expressed as e. In the explosion operation and Gaussian mutation operation, sparks may be generated beyond the explosion range, so using mapping rules to limit fireworks within the limits is necessary. For sparks that exceed the boundary in the k-dimension, it is necessary to remap them within the explosion range by using formula (9).

$$\widehat{x}_{i,k} = x_{\text{LB},K} + |x_{ik}| - \{|x_{ik}|/(x_{\text{UB},K} - x_{\text{LB},K})\} \times (x_{\text{UB},K} - x_{\text{LB},K}). \tag{9}$$

where $x_{\text{UB},K}$ and $x_{\text{LB},K}$ represent the upper and lower bounds of the boundary in the k-dimension in formula (9), respectively. The whole fireworks population K is composed of initial fireworks, explosive sparks, and Gaussian sparks. It is necessary to select one firework with optimal fitness from the whole fireworks population, and use the selection strategy formula (10) to select $N - 1$ fireworks from the remaining fireworks as the fireworks population for the next iteration.

$$p(x_i) = \frac{R(x_i)}{\sum_{j=K} R(x_j)}, \tag{10}$$

where $p(x_i)$ represents the probability of fireworks x_i being selected in the whole fireworks population, and $R(x_i)$ represents the sum of European distances d between fireworks x_i and all other fireworks, as shown in formula (11).

$$R(x_i) = \sum_{j=1}^{K} d(x_i - x_j) = \sum_{j=1}^{K} \|x_i - x_j\|. \tag{11}$$

For the calculation of fitness value of each firework population's generation, if the optimal fitness value obtained achieves the maximum number of iterations or meets the requirements, the optimization process of FWA can be ended. Figure 3 shows the multisensor data fusion's process.

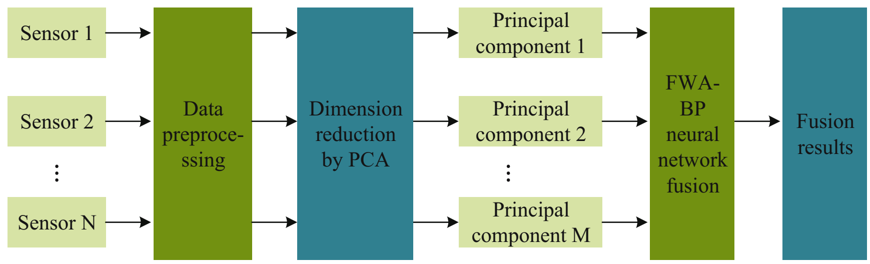

Figure 3: Flow chart of multisensor data fusion.

3.2 Establishment of multisensor data fusion model based on FWA–BP

BP includes input layer, hidden layer, and output layer to form a multi-layer feedforward network. Data are input from the input layer, feature extraction is performed by the hidden layer, and results are classified or predicted by the output layer. The feature extraction of data is mainly carried out in the hidden layer, and the increase in the number of hidden layers will increase the complexity and training time of the neural network. The number of nodes in each layer has an important impact on the function of the neural network. The generalization ability of the network is related to the number of nodes in the hidden layer, but there is no clear method to determine the specific number of nodes in the hidden layer in BP. To ensure hidden layer nodes number does not increase the complexity of the network structure and the over fitting problem, formula (12) was selected in this experiment to optimize and adjust the number of hidden layer nodes n.

$$n^* = \sqrt{m^* + p^*} + d^*, \tag{12}$$

where m^* and p^* represent the input layer and output layer's node numbers, respectively, and d^* represents the adjustment constant. When the performance of BP neural network cannot be improved by increasing the node numbers, the current number of nodes is selected as the optimal number of nodes in the hidden layer. The multisensor data are the data information that BP needs to process in this experiment, and the nonlinear relationship between the data and the target object needs to be mined. Sigmoid nonlinear function is selected as the activation function of the hidden layer, which is divided into two types, logsig and tansig. Formula (13) is used for the calculation of logsig function.

$$\log\text{sig}(x) = \frac{1}{1 + e^{-x}}, \tag{13}$$

where e represents the base of natural logarithm. Formula (14) is used for the calculation of tansig function.

$$\tan\text{sig}(x) = \frac{1 - e^{-x}}{1 + e^{-x}}. \tag{14}$$

Purelin linear function is selected as output layer's activation function, as shown in formula (15).

$$\text{purelin}(x) = x. \tag{15}$$

In the establishment of FWA–BP neural network fusion model, the topological structure and transfer function of BP neural network should be determined first, and the weights and thresholds should be initialized. Then, the fireworks function is used to optimize the BP network's parameters, and obtain initialized fireworks population. In the optimization process, all the parameters should be coded in the form of fireworks, and the mapping between parameters and fireworks dimension space should be established. Formula (16) is the dimension calculation method for each firework, which limits the dimension range to [−1, 1], and randomly initializes each firework.

$$D = n_{\mathrm{IW}(1,1)} + n_{b(1,1)} + n_{\mathrm{IW}(2,1)} + n_{b(2,1)}, \tag{16}$$

where the weight value between input and hidden layer is represented by $n_{\mathrm{IW}(1,1)}$, the weight value between the hidden layer and the output layer is represented by $n_{\mathrm{IW}(2,1)}$, and the number of threshold values of neurons in the hidden layer and the output layer are respectively expressed as $n_{b(1,1)}$ and $n_{b(2,1)}$. The sum of square errors is selected as BP network's fitness function, and the fitness value of each firework is calculated using formula (17).

$$f(x_i) = \sum_{i=1}^{s}(t_i - y_i)^2, \tag{17}$$

where s represents the output layer's neuron numbers, and t and y represent the expected output value and the actual output value, respectively. Then, the explosion spark and Gaussian spark are obtained by using formulas (4)–(7), and the initial fireworks population is composed to generate the whole fireworks population K. Calculate the fitness values of all fireworks, and then sort them from large to small. The next generation fireworks population is composed of the fireworks with the best fitness value and the remaining $N - 1$ fireworks are selected by formulas (10) and (11) to achieve the optimization of fireworks population. When the candidate fireworks population meets the termination conditions, the optimization process ends and the fireworks with the best fitness can be obtained. The weights and threshold parameters of BP neural network can be obtained after the fireworks with the best fitness are decoded. The network parameters are initially updated to obtain the initially established FWA–BP model. To optimize the algorithm's parameters, Levenberg Marquardt (L–M) algorithm is selected, and the error function is the sum of square errors. When the target error or iteration number reaches the maximum, the training is completed as shown in Figure 4, and the final FWA–BP neural network fusion model is obtained.

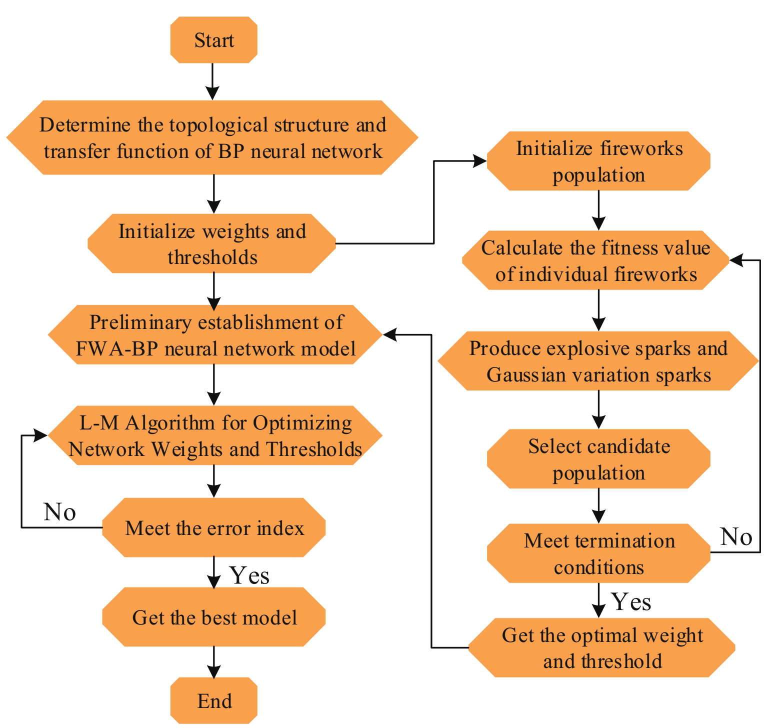

Figure 4: FWA–BP neural network fusion model.

4 Simulation analysis of multisensor data fusion technology

4.1 Processing of raw data based on PCA

With the progress of urbanization, air pollution has a serious impact on people's lives and health. Air Quality Index, a dimensionless index, is a quantitative index used to describe air quality, which is of great significance for the prevention of and reduction in air pollution. The air quality of city A in April was analyzed, and the air quality sub index values of the true concentrations of six pollutant indicators, such as fine particulate matter ($PM_{2.5}$) and inhalable particulate matter (PM_{10}), are calculated, respectively. The monitoring and prediction of $PM_{2.5}$ concentration is of great significance to the evaluation of air quality. The relationship between six pollutant indicators and $PM_{2.5}$ concentration is analyzed, and the data fusion method is used to predict the $PM_{2.5}$ concentration. Table 1 shows the collection of raw data of six pollutants.

Table 1: Original data of air quality of City A in April

Date	$PM_{2.5}$ (μg/m^3)	PM_{10} (μg/m^3)	O_3 (μg/m^3)	CO (μg/m^3)	SO_2 (μg/m^3)	NO_2 (μg/m^3)
1	66	83	344	0.9	3	39
2	39	65	228	0.6	3	39
3	50	92	269	0.9	20	62
4	80	134	278	1.2	14	68
5	87	140	311	1.2	17	62
6	74	107	113	1.7	18	59
7	14	39	150	0.5	3	41
8	41	87	174	1.1	11	81
9	41	80	207	0.9	9	65
10	101	128	173	1.8	9	63
11	60	62	188	1.1	5	48
12	36	84	215	0.8	9	134
13	72	126	269	1.4	12	62
14	57	102	336	0.9	5	57
15	152	218	362	1.8	21	74
16	189	224	305	1.5	5	62
17	132	161	255	1.4	5	53
18	92	108	264	1.1	6	54
19	182	198	239	1.8	8	68
20	66	57	215	1.2	3	41
21	98	95	231	1.5	8	51
22	44	62	221	0.9	3	47
23	35	66	258	0.8	3	57
24	74	131	335	1.1	9	78
25	153	188	255	1.8	15	72
26	191	77	311	1.7	6	50
27	29	60	194	0.6	5	51
28	29	68	180	0.6	8	63
29	63	126	329	1.5	17	78
30	110	180	366	1.8	23	80

The cumulative contribution rate of the first four principal components can reach 87.9% after PCA dimensionality reduction for the data of these six pollutants. To reduce the correlation between multisensor data, the original data is reduced to four dimensions, which simplifies the structure of BP neural network and facilitates the subsequent model training and testing. Table 2 shows some sample data of the first four principal components.

Table 2: Four principal components' partial sample data

Component 1	Component 2	Component 3	Component 4	$PM_{2.5}$
−4.951	1.220	−0.308	−0.682	13
−1.223	−1.848	−0.759	1.023	9
5.172	1.078	−0.319	−0.572	37
…	…	…	…	…
−1.056	−1.815	0.451	0.913	13
2.640	0.671	−0.242	−0.561	62
0.661	−0.506	0.077	0.132	41

"…" indicates omitted normalized data.

To eliminate the impact of dimension on the prediction accuracy of FWA–BP network model, it is necessary to normalize the sample data of the above four principal components, and scale all data to the range of [0, 1]. Table 3 shows the data normalization results.

Table 3: Four principal components' partial data

Component 1	Component 2	Component 3	Component 4	$PM_{2.5}$
0.22605	−0.08536	0.5676	0.11550	1.00000
0.33814	−0.95832	0.22319	0.09757	1.00000
0.06028	0.14443	0.46981	0.01221	1.00000
…	…	…	…	…
0.16412	0.36663	0.58190	0.01221	1.00000
0.25663	−0.08536	0.33000	0.73337	1.00000
0.87879	0.62102	0.84001	0.64603	1.00000

"…" indicates omitted normalized data.

4.2 Performance verification and performance comparison results of FWA–BP network model

The verification of the model is carried out in the MATLAB program. After many experiments, the parameter settings in the BP neural network and FWA can be obtained. The number of variables in the input layer of BP neural network is 4, the number of nodes in the hidden layer is set to 12, and the variable in the output layer is $PM_{2.5}$ concentration. The parameters in the FWA are set as $N = 10$, $E_r = 5$, $E_n = 30$, $g = 10$, and $T = 100$. The FWA optimizes BP's parameters preliminarily, and optimizes FWA–BP's parameters through further training. The samples to be tested are input into the model after parameter optimization, and the results are shown in Figure 5.

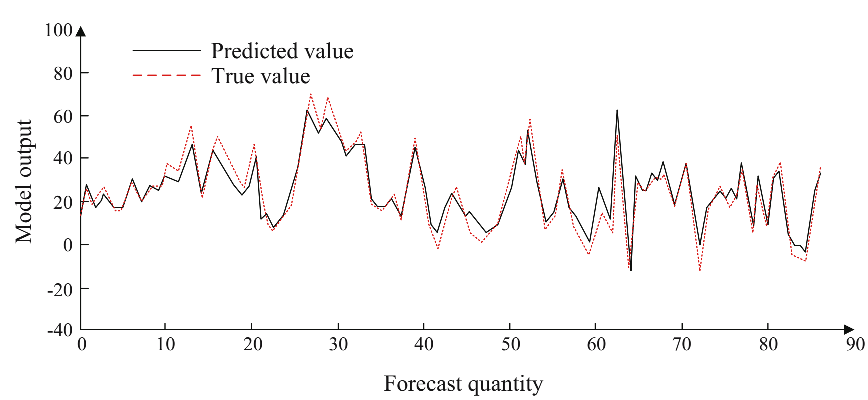

Figure 5: Comparison between predicted value and real value.

From Figure 5, in the prediction results, the error between the predicted $PM_{2.5}$ concentration of FWA–BP network model and the true value is small, and the maximum sample prediction deviation is less than 10. The trend between the predicted curve and the real curve is basically consistent, which indicates that the prediction accuracy of $PM_{2.5}$ concentration of FWA–BP network model is high. To achieve the superiority of FWA–BP network model, experimental comparison of fusion effect between FWA–BP and traditional BP, PSO–BP, and GA–BP is made [4,6]. Figure 6(a) shows the comparison results of mean absolute error (MAE) index, and Figure 6(b) shows the experimental results of root mean square error (RMSE).

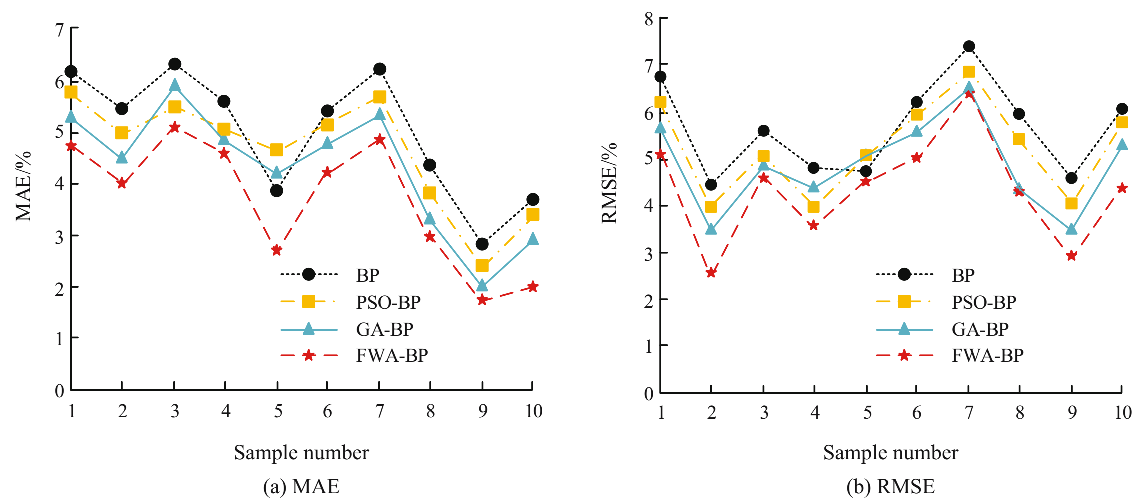

Figure 6: Comparison of (a) MAE and (b) RMSE.

From Figure 6(a), the maximum MAE of FWA–BP network model in different samples is 5.2%, the minimum is 1.7%, and the average is 3.7%. From Figure 6(b), the maximum RMSE of FWA–BP network model in different samples is 6.4%, the minimum is 2.5%, and the average is 4.3%. The MAE and RMSE values of FWA–BP network models in different samples are lower than those of traditional BP, PSO–BP, and GA–BP. FWA–BP network model's error value has a certain volatility, but it is more accurate than other models when predicting $PM_{2.5}$ concentration. To further analyze the performance of FWA–BP network model, correlation coefficient R is introduced to compare the performance between FWA–BP, traditional BP, PSO–BP, and GA–BP. In Figure 7, the results of inputting relevant data into MATLAB software for correlation analysis can be obtained.

From Figure 7, the correlation coefficient R value of FWA–BP network model is 0.963, which is 16.2, 5.2, and 1.0% higher than that of traditional BP, PSO–BP, and GA–BP. FWA–BP network model has higher correlation coefficient between real value and predicted value and better prediction accuracy when predicting $PM_{2.5}$ concentration. During the model training, the fitness values of FWA–BP, traditional BP, PSO–BP, and GA–BP are plotted. Figure 8 shows the result of the convergence comparison of different algorithms.

From Figure 8, compared with FWA–BP's final fitness values, traditional BP, PSO–BP, and GA–BP are relatively large, which reach the convergence state earlier and get local optimal result. It shows that during the training process, with the increase in iteration times, FWA–BP algorithm can continuously optimize the fitness value of firework individuals, obtain new candidate populations, and finally obtain a better fireworks population, so as to avoid falling into the local optimal state prematurely. This is because the FWA continuously optimizes the weights and threshold parameters of the BP neural network in the training process, and the L–M function selected in the training process reduces the error value of the FWA–BP network model, thus obtaining more accurate prediction results. The above results show that FWA–BP algorithm has stronger ability of global optimization, and the multisensor data fusion model based on this algorithm has higher fusion accuracy. It has higher accuracy in predicting $PM_{2.5}$ concentration, and has better practicability.

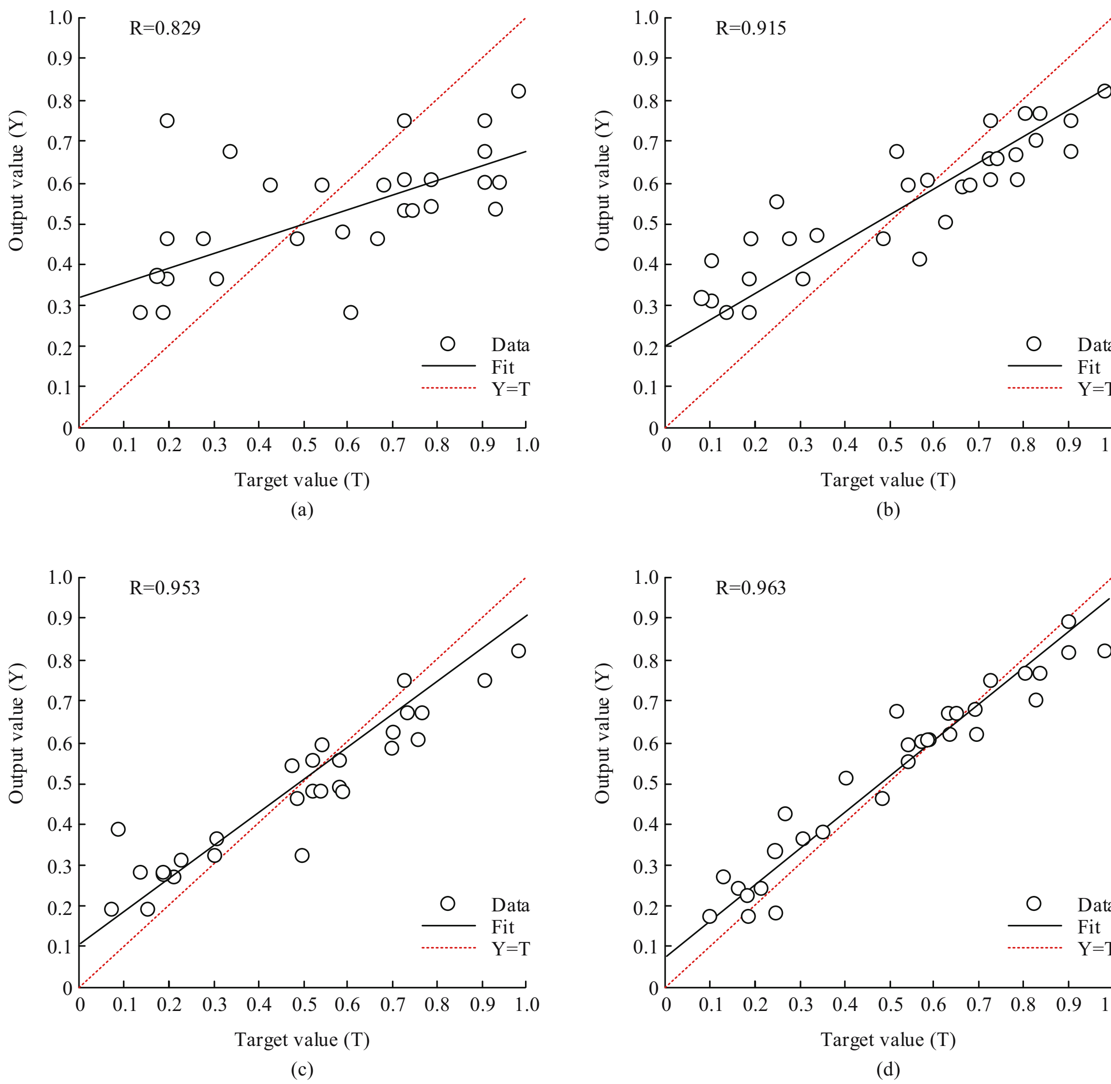

Figure 7: Correlation analysis results chart. (a) BP, (b) PSO–BP, (c) GA–BP, and (d) FWA–BP.

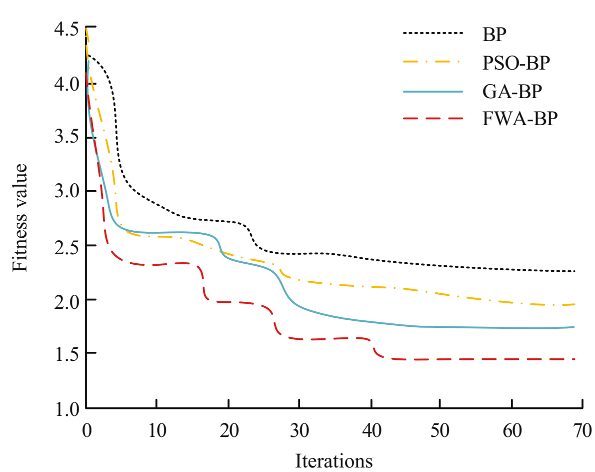

Figure 8: Comparison chart of fitness curves.

5 Conclusion

The FWA can realize the effective fusion of multidimensional sensor data after optimizing the BP neural network. In the $PM_{2.5}$ concentration prediction results, the error between the predicted $PM_{2.5}$ concentration of FWA–BP network model and the true value is small, the maximum sample prediction error is less than 10, and the trend between the prediction curve and the true curve is basically consistent. In different samples, the maximum MAE of FWA–BP network model is 5.2%, the minimum is 1.7%, and the average is 3.7%. The maximum RMSE of this model is 6.4%, the minimum is 2.5%, and the average is 4.3%. The correlation coefficient R of FWA–BP network model is 0.963, which is 16.2, 5.2, and 1.0% higher than the traditional BP, PSO–BP, and GA–BP, respectively. FWA–BP network model can be continuously optimized during model construction, which can avoid falling into local optimization. When predicting $PM_{2.5}$ concentration, FWA–BP algorithm has higher correlation coefficient between real value and predicted value, and better prediction accuracy. This research combines FWA with BP neural network, and gives a play to the advantages of multi-dimensional data processing of artificial neural network. However, in the $PM_{2.5}$ concentration prediction, the prediction results still have some volatility, and the optimization performance of BP neural network needs to be improved to further improve the prediction performance of the model.

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Author contributions: To achieve accurate and efficient fusion of multidimensional data, this experiment used back propagation (BP) neural network and fireworks algorithm (FWA) to establish the FWA–BP multidimensional data processing model, and a case study of PM2.5 concentration prediction was carried out by using the model. Xiao Hai conducted experiments, recorded data, analyzed the results, and wrote a manuscript. Xiao Hai agreed to the published version of the manuscript.

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