

Air Quality Index Prediction Using Error Back Propagation Algorithm and Improved Particle Swarm Optimization

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Abstract. As the latest evaluation standards of air quality released by the State Environmental Protection Department, the Air Quality Index (AQI) is influenced by sulfur dioxide (SO₂), nitrogen dioxide (NO₂), particulate matter with particle size below 10 microns (PM10), particulate matter (PM2.5), carbon monoxide (CO) and ozone (O₃) in the air. The variation of AQI shows nonlinearity and complexity. In order to improve prediction accuracy, this paper proposes an air quality prediction model based on Error Back Propagation (BP) algorithm. The model is optimized by Particle Swarm Optimization (PSO) algorithm using dynamic inertia weight and experience particles. The experimental results show the improved PSO-BP model significantly reduces iteration time, effectively improves the prediction accuracy, and provides a new method for the AQI prediction.

Keywords: BP · PSO · Dynamic inertia weight

1 Introduction

With the development of social economy, cities' developments have been accelerated and the car ownership has increased. The contents of SO₂, NO₂, PM10, PM2.5 and O₃ in the atmosphere have increased gradually; Environmental pollution problems have been increasingly serious. As the State Environmental Protection Department released the latest air quality assessment standards in 2012, the air quality has become a major issue in relation to the future fate of mankind [1]. The study around this problem also came into being.

AQI is a single non-dimensional numerical form and is used to quantitatively describe the air quality. Its value looks seemingly disorderly, but the variation in a long time shows a certain rule. AQI is comprehensively influenced by SO₂, NO₂, PM10, PM2.5, CO and O₃; its value shows the characteristics of non-linear and abrupt changes. So AQI is a complicated nonlinear system. We can find the internal relation of influencing factors by the historical monitoring data, and then establish a prediction function to realize AQI prediction. Its principle is similar to the Artificial Neural Network (ANN). At present, the air quality forecasting application of ANN is still in the exploratory stage. The BP neural network is one of the most widely used neural network models and has the typical characteristics of neural networks [2]. However, the BP algorithm has slow

convergence and is easy to fall into a local minimum. To solve these problems, scholars have put forward many improved methods. For example, Li et al. [3] introduced a variable learning rate and an additional momentum into the BP algorithm to jump out of the local minimum of the error surface. But the training speed of this method is not very satisfactory. Zhang et al. [4] used the PSO algorithm to improve the learning strategies of the BP neural network. In this paper, the learning speed of BP algorithm is improved, but for the high dimension complex problem, the PSO algorithm is faced with the premature convergence problem.

This paper adopts the dynamic inertia weight and experience particles [5] to improve the standard PSO algorithm; it uses the improved algorithm to optimize the BP network learning strategy and then builds the PSO-BP prediction model to realize AQI simulation. The experimental results show that the improved PSO-BP algorithm not only could shorten the algorithm iteration time, but also could improve the convergence speed and the prediction accuracy.

2 Standard BP Neural Network

The BP neural network is a multilayer feed forward network with the one-way transmission. It is composed of input layer, hidden layer and output layer, its main characteristic is the signal forward propagation and the error back propagation [6]. The standard BP is a feed forward neural network with three layers topological structure and has only one hidden layer. The research shows if we select the suitable connection weights and the transfer function, a neural network with enough neurons and only one hidden layer could approximate any smooth, measurable function between the input and output [7]. Therefore, this paper uses the standard BP neural network as the network prototype.

The standard BP neural network adopts the sigmoid function to calculate the network output of each level. The sigmoid function is a non-decreasing continuous function; its value is a floating point number between -0.5 and 1.5 . The function represents the state continuous neuron model and is processed very conveniently.

When the total error of input samples can't achieve the desired effect, the network enters the error back propagation stage. Using the formula (1), the BP algorithm calculates the weights between the hidden layer and the output layer. The weights can be used to inversely modify the weight matrix to achieve the optimization algorithm. The formula (1) is defined as

$$\begin{cases} \Delta w_{jk} = \eta \delta_k^y z_j = \eta (d_k - y_k) y_k (1 - y_k) z_j \\ \Delta v_{ij} = \eta \delta_j^z x_i = \eta \left(\sum_{k=1}^m \delta_k^y w_{jk} \right) z_j (1 - z_j) x_i \end{cases} \quad (1)$$

Where Δw_{jk} and Δv_{ij} are the adjusting weights. δ_k and δ_j are the error signals of each level. η is a proportional coefficient and its value is a random number between 0 and 1. x_i is an input component. z_j is an output component of the hidden layer. y_k is an output component of the output layer. d_k is an expected output component.

3 Improved PSO Algorithm

The PSO algorithm [8, 9] is a kind of typical swarm intelligence algorithm, it can simulate the foraging behavior of birds in the nature to find an optimal solution through individuals collaborating and information sharing. In 1998, Shi and Eberhart in the academic paper “A Modified Particle Swarm Optimizer” [10] introduced an inertia weight into the evolution equation, thus the standard PSO algorithm was born.

The inertia weight is a very important parameter in the standard PSO algorithm. The larger the inertia weight is, the stronger the exploration ability is; the smaller the inertia weight is, the stronger the development ability is [11]. In this paper, we have studied literatures [12–15], compared and analyzed the advantages and disadvantages of the linear inertia weight. At last, we linearly increase the value of the inertia weight before 1000 iterations, and then linearly decrease its value, so as to balance the exploration ability and development ability of the improved PSO algorithm. So we define the dynamic inertia weight as a function of the iteration time and the function is defined as

$$w(k) = \begin{cases} 1 \times \frac{t}{MaxNum} + 0.25, & 0 \leq \frac{t}{MaxNum} \leq 0.5 \\ -1 \times \frac{t}{MaxNum} + 1.25, & 0.5 < \frac{t}{MaxNum} \leq 1 \end{cases} \quad (2)$$

where k is the current iteration. $MaxMum$ is the maximum iteration time.

In the algorithm learning process, the fitness of each particle has showed the weakening “choice” behavior, [5] introduced experienced particles into the speed evolution equation to adjust the individual extreme and the global extreme, so as to improve the algorithm convergence speed and accuracy. The updated formulas of the individual extreme (3) and the global extreme (4) are defined as

$$Pb'_i(t) = \begin{cases} Pb_i(t), & i < 2 \\ r_1 \times Pb_i(t) + r_2 \times Pb_m(t) + r_3 \times Pb_n(t), & i \geq 2 \end{cases} \quad (3)$$

$$Pgb'(t) = r_1 \times Pb_1(t) + r_2 \times Pb_2(t) + r_3 \times Pb_3(t) \quad (4)$$

where Pb_i is the current individual extreme value. Pb_m and Pb_n are the experienced individual extreme values; they are randomly selected from previous ones in the same generation. Pb'_i is the updated individual extreme value. Pgb' is the updated global extreme value. Pb_1 , Pb_2 and Pb_3 are three best individual extremes from the same generation. r_1 , r_2 and r_3 are random values between -0.5 and 1.5 , and $r_3 = 1 - r_1 - r_2$.

4 Simulation Design and Analysis

The simulation experiment selects 13 groups of Wuhan between May 1, 2016 and May 13, 2016 as the samples; they come from the China air quality on-line monitoring and analysis platform (<http://www.aqistudy.cn/>). PM_{2.5}, PM₁₀, CO, NO₂, O₃ and SO₂ are

the network inputs, AQI is the target data. The first 12 groups are training samples, NO. 13 data is a test sample. Through experimental comparison, the network structure of improved PSO-BP model is 6-8-1; the population size is 20; the particle dimension is 65. The initial position component is a random number between -1 and 1 . The current velocity component is a random number between -0.5 and 0.5 . The maximum iterations number is 2000 and the minimum error is 0.001.

Firstly, the algorithm convergence analysis and the network output curve analysis are shown as Fig. 1(a) and (b).

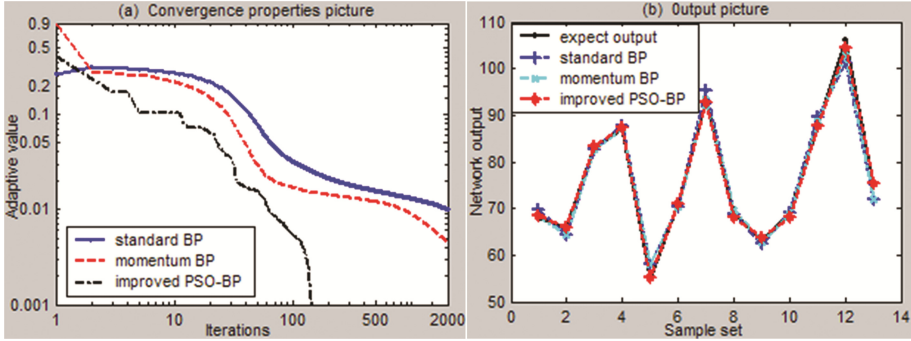


Fig. 1. (a) Convergence properties picture; (b) Output picture

By Fig. 1(a) and (b), the convergence speed of the standard BP algorithm and the momentum BP algorithm are slow in the late training; they can't reach the minimum convergence precision; the predicted values have the obvious deviation. The improved PSO-BP algorithm keeps a good convergence rate, it can reach the minimum error at 143 iterations; Its deviation values only show in No. 8, No. 9, No. 10 and No. 12. So the improved algorithm has the better effect of convergence and forecast than others.

Secondly, the relative error value comparison of three algorithms is shown in Table 1.

In Table 1, the deviation value of the improved PSO-BP algorithm in No. 8, No. 9, No. 10 and No. 12 is between 1.13 and 1.45, other values are all smaller than 0.9. So the algorithm doesn't have large deviation value. Its Ave_Error value is only 0.64%, which is smaller than other two algorithms. So the improved PSO-BP algorithm in this paper is obviously better than others.

Table 1.

NO.	Expected output	Standard BP		Momentum BP		Improved PSO-BP	
		Predicted value	Error (%)	Predicted value	Error (%)	Predicted value	Error (%)
1	68	69.801345	2.65	68.402343	0.59	68.568022	0.84
2	66	64.478980	2.30	64.435718	2.37	65.873440	0.19
3	83	82.555808	0.54	82.613787	0.47	83.318232	0.38
4	87	87.602480	0.69	87.068520	0.08	87.304945	0.35
5	55	58.106085	5.65	58.013594	5.48	55.155547	0.28
6	71	70.300322	0.99	70.347997	0.92	70.951919	0.07
7	93	95.401679	2.58	93.363184	0.39	92.745650	0.27
8	69	68.808340	0.28	69.869844	1.26	68.178084	1.19
9	63	62.557808	0.70	62.927736	0.11	63.714685	1.13
10	69	69.101081	0.15	68.885957	0.17	68.165413	1.21
11	88	89.685779	1.92	88.707819	0.80	87.670740	0.37
12	106	101.425017	4.32	103.009014	2.82	104.462997	1.45
13	75	71.917179	4.11	72.021966	3.97	75.448108	0.60
Ave_Error (%)		2.07		1.49		0.64	

5 Conclusion

In this paper, the dynamic inertia weight and experience particles are used in the improved PSO-BP algorithm to optimize network weights and thresholds. This integration method makes full use of the neural network learning ability and the global optimization of PSO algorithm. It provides a new method for predicting AQI. In the future, this paper will start from the nonlinear adjustment method of inertia weight, and further improve the global optimization of PSO algorithm.

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