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Research on pso-bpnn based model for forecasting typhoon rainfall

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Abstract. In view that there are great errors in forecasting typhoon rainfall by back propagation neural network (BPNN) based models, it is proposed in this paper that these models can be optimized by particle swarm optimization (PSO). In this paper, one basic BPNN-based model and one PSO-BPNN model are separately built for performing simulation experiments with the same data. According to the experimental results, the optimized model can forecast typhoon rainfall much more precisely, which demonstrates that the PSO-BPNN model is effective for forecasting typhoon rainfall.

Key words. Typhoon, rainfall, bp neural network, particle swarm optimization.

1. Introduction

As an extremely destructive natural phenomenon, typhoon brings about storm, heavy rain, surge, storm surge and even tsunami in affected areas, so buildings and others would be broken down in case of typhoon. Meanwhile, tremendous losses will be caused by a tsunami if any. Waterlog is one of great disasters that result from continuous rainstorm and that can't be neglected when a typhoon takes place. To minimize disasters of typhoon, it is important to forecast potential rainfall, predict possible severity of waterlog and take preventive measures in advance. Over the past years, it has become a hot research topic to forecast rainfall. There have been many theories and methods for forecasting typhoon rainfall, including fractal theory, autoregressive model, fuzzy system, analysis of time series and Markov forecasting [1], which are more representative traditional methods. In spite of some specific distinctive advantages for rainfall forecast under certain conditions, they have something in common that all their forecasting algorithms are dependent upon a function or relations of several functions, so predictive values of their forecasting models tend to

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be regular. Under specific regional conditions, changes to rainfall generally appear to be complicated, dynamic and non-linear. Therefore, these traditional methods are inappropriate for precise typhoon rainfall forecasting.

Having developed to be relatively mature, back propagation (BP) neural network has been demonstrated t be feasible for rainfall forecasting [2, 3]. At present, rainfall is mostly forecast by artificial neural network in two ways, including forecasting meteorological data and predicting rainfall of the (n=1)th year based on rainfall of n consecutive years [4-6], among which the former method is more suitable for forecasting typhoon rainfall that has been proven to have smaller errors since rainfall is associated with meteorological factors in typhoon days.

In consideration of considerable errors in making forecasts with BP neural network, the BP neural network (BPNN) based model for forecasting typhoon rainfall is optimized by particle swarm optimization (PSO) in this paper, and simulated in Matlab. The experimental results suggest that the optimized BPNN-based model can forecast typhoon rainfall more precisely.

2. Problems with BPNN-based Model for Forecasting Typhoon Rainfall and Corresponding Solutions

2.1. BP Neural Network

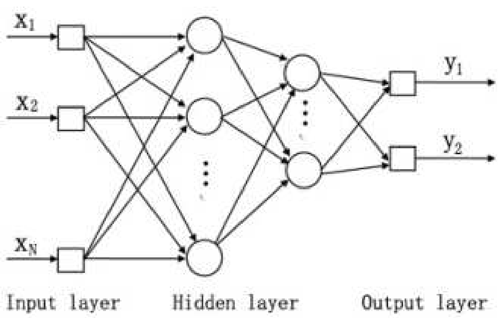

Fig. 1. Architecture of a bp neural network with a single hidden layer

Put forward by a group of scientists represented by Rinehart and McClelland in 1986, BP network is trained based on error back propagation algorithms as multilayer feed forward network [7], and is one of neural networks that are utilized most widely at present. It is capable of learning and storing numerous mapping relationships between input and output modes without prior revelation or depiction of their mathematical formulas or equations. The steepest descent method is just its learning rule. The weights and thresholds of BP neural network are constantly adjusted via back propagation, so as to minimize error sum of squares in these networks. The topological structure of a BP neural network is made up of an input layer, a hidden layer and an output layer. There could be only one hidden layer (namely a single hidden layer) or several hidden layers on a BP neural sub-network. The BP neural network with a single hidden layer is composed of an input layer, a hidden layer and an input layer, a hidden layer and an output layer. Commonly known as 3-layer BP neural network, it has multiple strengths, including simple architecture, mature algorithms, self-taught learning and adaptation. Hence, such 3-layer BP neural network is one of the most common BP neural networks that are applied most extensively. Fig 1 shows the architecture of a BP neural network with a single hidden layer.

2.2. Problems with BPNN-based Model for Forecasting Typhoon Rainfall and Corresponding Solutions

A standard BPNN-based model for forecasting typhoon rainfall (hereunder referred to as BPNN-based Forecasting Model) is generally made up of three layers, namely an input layer, a hidden layer and an output layer. Concerning input data, several leading factors that impact rainfall are chosen as independent variable, while output data are pure rainfall values. The forecasting model is trained based on historical data. The outputs from a BP neural network are not so precise that their errors will be still rather significant in spite of sufficient sample trainings, which indicates that the relatively considerable errors are attributable to architecture of the BP neural network. As a result, it is difficult to increase the output precision just from the perspective of the network. To make the outputs from a BP neural network more precise, the network can be improved by algorithm optimization, which is one of optional methods. As a met heuristic population-based intelligent optimization algorithm, PSO is highly convergent and stable. The BP neural network is improved by PSO under its architecture to create a new PSO-BPNN based model for forecasting typhoon rainfall (hereunder referred to as PSO-BPNN based forecasting model), which can output data more precisely than the BP forecasting model.

3. PSO and Optimization of Forecasting Models

3.1. PSO and Optimization

PSO is one of representative population-based intelligent optimization algorithms. Optimization means finding a group of parameters for measuring some performances on the premise of satisfying certain constraint. For practical problems, optimization is to choose the optimal from numerous schemes. Its history can be traced back to extreme value problems of the Ancient Greek such as isoperimetric problems and grain filling problems. By 1940s, optimization had gradually developed into a discipline with the appearance of numerous complex optimization problems in an endless stream and development of technologies like functional analysis. At present, optimization technologies are widely used in many fields such as national defines, transport, energy and materials.

3.2. PSO-BPNN Based Model for Forecasting Typhoon Rainfall

In the process of PSO, what is optimized is essentially the weight matrix of the BP neural network.

First of all, dimensions of particles are determined. Weights of the BP network and elements of the threshold matrix are arranged in rows based on given orders, to make up a D-dimension row vector and compose coordinates of points in the D-dimension space which indicate positions of particles in the space. Thereby, mappings can be created one to one from the weight matrix of the BP neural network to the D-dimension space and denoted as F.

Subsequently, fitness function shall be determined for PSO.

In this paper, the sum of the absolute output errors of the BP neural network is regarded as fitness function. The lower the function, the greater the fitness. The fitness function is solved as follows: The coordinate of a particle in the D-dimension space is transformed into weight and threshold matrices of the BPNN-based forecasting model by inverting F. forecasts are made based on test data and the sum of absolute errors is calculated, in order to determine fitness value of particles. Particles with lower fitness function will be better.

In this way, two key elements of the PSO-BPNN based model are determined.

4. Simulation Experiment of Models

4.1. Data Sources and Experimental Conditions

Data of the simulation experiment were collected from 2015 observations of two rainfall observation stations in Wenzhou and data about rainfall observations for No.09 typhoon in 2005, which covered central atmospheric pressure, elevation of rainfall observation stations, distance from typhoon center, central atmospheric pressure of typhoon and rainfall within six hours. Data of both observation stations are shown in Table 1 and Table 2 as follows. The simulation experiment was performed in Matalab2012a.

In the forecasting model, longitude/latitude of monitoring station, elevation of rainfall observation station, distance from the center of typhoon and central atmospheric pressure of typhoon are considered as major factors that affect rainfall, which is deemed as result.

In other words, in training the forecasting model and optimizing weights, 15 rows of data in Table 1 are converted into a matrix, which is further transposed into matrix A. A is made up of 4 rows and 15 columns, among which the first three rows compose matrix P of training data, and expected value T is indicated on the fourth row. In the process of simulating forecast, 16 rows of data in Table 2 are transformed into a matrix, which is further transposed into matrix B composed of 4 rows and 16 columns, among which the first three rows are training data and expected value is listed on the fourth row.

Table 1. Observation Station A

Elevation of Rainfall Observation Station	Distance from the Center of Typhoon	Central Atmospheric Pressure of Typhoon	Rainfall within Six Hours
540	490	950	17.2
540	434	950	68.6
540	394	950	53.7
540	216	950	131.8
540	111	950	168.8
80	482	950	19.9
80	428	950	36.8
80	348	950	8.1
80	217	950	12.6
80	112	950	23.4
80	35	970	42.6
80	68	975	5.8

Table 2. Observation Station B

Elevation of Rainfall Observation Station	Distance from the Center of Typhoon	Central Atmospheric Pressure of Typhoon	Rainfall within Six Hours
70	451	950	17.2
70	394	950	68.6
70	308	950	53.7
70	175	950	131.8
70	71	950	168.8
490	561	950	12.4
490	459	950	24
490	403	950	46.6
490	319	950	61.7
490	185	950	113
490	81	950	115.7

4.2. Model Simulation and Results

P and T are training and test samples respectively, which are separately employed in the architecture of BP neural network and PSO-BPNN based model for simulation.

The basic PBNN-based model for forecasting typhoon rainfall is built based on standard function of the toolbox of MATLAB2010a, namely net_ BP=newff (P,T, hiddennum), where hiddennum is number of hidden nodes. Assuming that hiddennum is taken to be 5, net_ BP is just a 3-5-1 (number of nodes on output, hidden and output layers) BBNN-based model for forecasting typhoon rainfall.

To get a PSO-BPNN based model for forecasting typhoon rainfall, the basic BPNN-based model is improved by PSO and has the same architecture as BPNN. In other words, the optimized model is also made up of 3 nodes on its output layer, 5 nodes on the hidden layer and 1 node on the output layer.

Concerning PSO, particles are associated with net_BP as follows: Whereas there are 21 (3*5+5*1=21) weights in the net_BP model, 6 (5+1) thresholds, the sum of weights and thresholds equal to 27, the sequences composed by weights and thresholds of the BP model correspond to coordinates of points in the D-dimension (D=27) space and particles have 27 dimensions (D=27).

Parameters of PSO are taken as follows: As cognitive coefficient, c1 is taken to be 1.4900, and c2 is taken to be 1.4900 as social coefficient. To save computation cost, the inertia factor ω is assumed to be 1.0. The number of maximum iterations (denoted by MaxGen) is critical for PSO. In this paper, MaxGen is taken to be 20, 50, 80 and 100 respectively, among which 100 has been demonstrated to be more suitable for the case of this paper and corresponding convergence is shown in Fig 1.

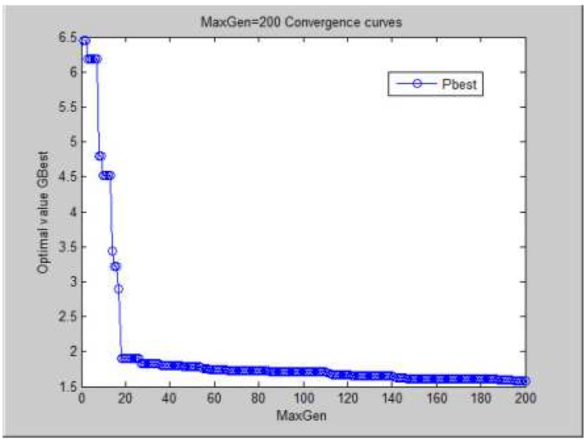

Fig. 2. Convergence curve (maxgen=200)

Fig 2 is the convergence curve of PSO when the maximum number of iterations is set to be 200. It may be observed from this figure that the convergence curve descends rather slowly when the MaxGen is above 160.

Fig 3 shows the test results of both models. After a comparison of test results and actual values, it is found that the predictive values are pretty fit in with actual values in the PSO-BPNN based forecasting model, which means that the optimized BP model can forecast typhoon rainfall more precisely than the basic BPNN model.

Fig 4 indicates statistical errors in testing the basic BPNN and the PSO-BPNN based forecasting models. It can be observed that output errors are lower in all 17 groups of test data in the PSO-BPNN based forecasting model than the basic

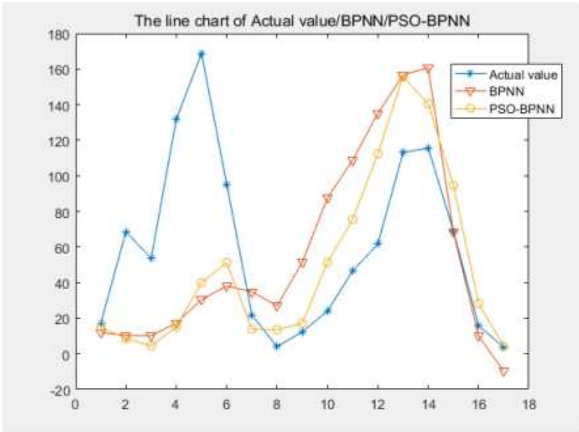

Fig. 3. Actual values, output data for testing basic bpnn and pso-bpnn models

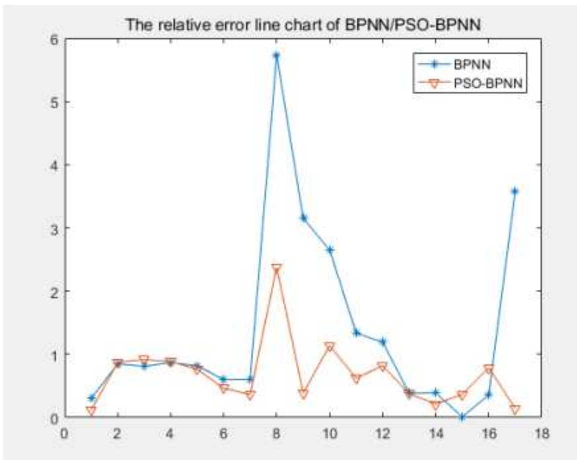

Fig. 4. Output error rate in testing basic bpnn and pso-bpnn models

BP model, which suggests that the optimized model is more effective for predicting typhoon rainfall more precisely than the basic BPNN model.

5. Conclusions and Outlooks

In this paper, a basic BPNN-based model and a PSO-BPNN based model are respectively built for forecasting typhoon rainfall. These two models are simulated by utilizing raw data about rainfall of a typhoon in certain area as training and test samples. The experiment has demonstrated that the precision has been significantly improved in the optimized forecasting model. This implies that it is effective to increase precision of the basic BPNN-based model in forecasting typhoon rainfall by improving it through PSO.

PSO is a typical heuristic swarm intelligence algorithm, where remarkable theoretical and practical outcomes have been attained over the past few years. Similar algorithms such as ant colony optimization, monkey optimization, and fish swarm algorithm and firefly algorithm have become hot research topics. In the future, the basic BPNN-based models for forecasting typhoon rainfall shall be optimized by these algorithms, in an attempt to explore more effective and precise schemes to increase the precision of BPNN-based models in forecasting typhoon rainfall.

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