

Telecommunication traffic forecasting based on BP neural network trained by PSO

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Abstract: Telecommunication traffic forecasting based on BP neural network which is optimized by particle swarm optimization (PSO) algorithm is presented. PSO is a novel random optimization method based on swarm intelligence, which has more powerful ability of global optimization. Here, we use the telecommunication traffic ranging from 1989 to 2005 in China as the sample to the neural network, which has been trained by PSO, are employed to illustrate the presented model. The experimental results prove that the proposed method optimized by PSO can quicken the learning speed of the network and improve the forecasting precision compared with the conventional BP method and show that the method is not only simple to calculate, but also practical and effective.

Key words: BP neural network; particle swarm optimization; telecommunication traffic forecasting

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1 Introduction

Telecommunications industry is an important part of the national economy. Telecommunication traffic represents the amount of information needed to pass the telecommunications, which is important for performing many power utility functions, such as equipment accounting, short-term maintenance, production organization, etc. Therefore, accurate telecommunication traffic forecasting plays an important role in planning the professional telecom network engineering.

To solve the forecasting problem, artificial neural network (ANNs) methods have been proposed. ANNs are able to give better performance in dealing with the nonlinear relationships among their input variables^[1]. The conventional back propagation algorithm (BP) is successfully applied to complex nonlinear problems. However, using BP method needs the transfer function of each neuron must be different. Moreover, it has been proven that gradient techniques are slow to train and are sensitive to the initial guess which can possibly be trapped in a local minimum^[2].

To overcome these shortcomings, here we introduce particle swarm optimization algorithm (PSO) to optimize the BP network to solve the telecommunication traffic forecasting problem. The PSO algorithm is applied to the neural network in the training phase, to obtain a set of weights that will minimize the error function in competitive time. Weights are progressively updated until the convergence criterion is satisfied. The objective function to be minimized by the PSO algorithm is the

predicted error function^[3].

In the following sections, we first briefly describe some essentials of PSO, then present sufficient algorithm optimized by PSO. Then, the algorithm is applied for telecommunication traffic forecasting. At last, we give the conclusions of this paper.

2 Particle swarm optimization algorithm

Particle swarm optimization (PSO) is an optimization algorithm based on the community intelligence principle, which was originally proposed by Kennedy et al^[4]. The PSO algorithm is based on the biological and sociological behavior of animals such as schools of fish and flocks of birds searching for their food. PSO imitates this behavior by creating a population with random search solution, and each potential solution is represented as a particle in a population (called swarm). The social sharing of information among the particles of a population may provide an evolutionary advantage^[5]. Each particle is flown through the multi-dimension search space with random and adaptable velocity in order to find the lower function values (global minimum).

Supposing the dimension for a searching space is d , the total number of particles is m , the position of the i_{th} is expressed as $\mathbf{x}_i = (x_{i1}, x_{i2}, \dots, x_{in})^T$, the velocity of the i_{th} is expressed as $\mathbf{v}_i = (v_{i1}, v_{i2}, \dots, v_{in})^T$, the best position of the i_{th} particle is denoted as $\mathbf{p}_i = (p_{i1}, p_{i2}, \dots, p_{in})^T$, the corresponding fitness is represented as local best ($p_{best,i}$), the best position of the whole swarm is denoted as $\mathbf{p}_g = (p_{g1}, p_{g2}, \dots, p_{gn})^T$, and its fitness is represented as global best (g_{best}).

Therefore, particles are manipulated according to the equations:

$$v_{id}(t+1) = wv_{id}(t) + c_1r_1(p_{id}(t) - x_{id}(t)) + c_2r_2(p_{gd}(t) - x_{id}(t)) \quad (1)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (2)$$

where $d=1, 2, \dots, n$; $i=1, 2, \dots, n$; n is the size of the population; w is the inertia weight; c_1 and c_2 are two positive constants; r_1 and r_2 are uniformly distributed random numbers in the range $[0, 1]$. In addition, the velocity of the particle is limited to the range $[v_{\min}, v_{\max}]$, w can be determined by Eq.(3).

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{t_{\max}} \times t \quad (3)$$

where w_{\max} and w_{\min} are separately maximum and minimum of w , t_{\max} is the maximum iteration time, t is the present iterative time.

3 BP neural network trained by PSO

In artificial neural networks, back propagation network is a powerful tool for prediction of nonlinearities. It consists of three layers: input layer, hidden layer and output layer. All of the layers are fully interconnected with each other by weights as shown in Fig.1.

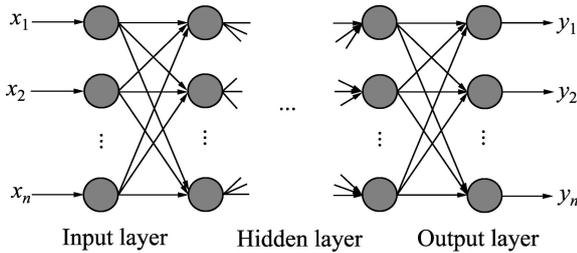


Fig.1 BP neural network architecture

The BP training algorithm is an iterative gradient descent algorithm designed to minimize the mean square error E between the actual output of a multilayer feed forward perceptron and the desired output and updates the weights by moving them along the gradient-descent direction^[6]. However, unless the mean square error E is positive, otherwise it can possibly be trapped in a local minimum. The PSO algorithm, on the contrary, is a global algorithm, which has a strong ability to find global optimistic results. Therefore, by combining the PSO with the BP, a new algorithm referred to as PSO-BP hybrid algorithm is formulated in this paper.

The specific procedure for this PSO-BP algorithm can be summarized as follows:

Step 1: Normalize the sample data groups according to Eq. (4), then define the structure of the BP network according to the input and output sample.

$$y_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (4)$$

where x_i is defined as an initial group of data among the collected data groups. x_{\max} and x_{\min} express the maximum and minimum data group among the collected data groups, respectively.

Step 2: Define the topological structure of BP network and initialize the weight and threshold value. Define n and G_{\max} , initialize the inertia weight factor $w(0)$, P_{best} and g_{best} , set c_1 and c_2 .

Step 3: Define the fitness function according to the mean of output error sum of squares as follows:

$$f = \frac{1}{n} \sum_{j=1}^n \sum_{k=1}^m (y_k - t_k)^2 \quad (5)$$

Where y_k is the actual forecasting output value, t_k is the target value, n is the numbers of training sample, m is the nodes of output. According to Eq.(5), define the fitness of each particle $f(x_i)$, if this position is better than $p_{\text{best},i}$, $p_{\text{best},i}$ will be replaced by this position; otherwise, $p_{\text{best},i}$ remains.

Step 4: Choose the maximum of the $p_{\text{best},i}$ as the current g_{best} of the particle.

Step 5: According to Eq.(3), update the inertia weight. Use Eqs.(1) and (2) to update the position and speed of each particle.

Step 6: Set $t=t+1$.

Step 7: Judge the stopping criteria, if the maximal iterative times are met, stop the iteration, and the positions of particles are the optimal solution. Otherwise, the procedure is repeated from step 3.

4 Simulation experiment in telecommunication traffic forecasting

In order to test the performance of the algorithm given above, the paper takes the telecommunication traffic from 1989 to 2005 in China as the process data. This paper adopts a typical 3-tier BP NN model which is optimized by PSO algorithm. Here we choose the 1994–2002 data as the train sample, and among these data we select the former four years as the input sample, the following data as the output sample. In addition, we choose the data from 2004 to 2005 as the test sample. The programs of PSO-BP are compiled by MATLAB R2008a. After many experiments and comparison, the parameters are as follows: the structure parameter of network is 4-11-1; the size populations are 20, the size

dimensions are 10; c_1 and c_2 are all equaled to 2.0; the iteration will repeat until the t_{max} equals 2 000; and the minimum expected distortion is 1×10^{-4} ; velocity threshold $v_{max}=20$. In order to save the limited space, this specific program progress is omitted.

We compare the forecast results by PSO-BP algorithm and BP algorithm as shown in Table 1. Figs.2 and 3 show predicting results with BP method and PSO-BP algorithm, respectively.

It's obvious that PSO-BP algorithm has more small deviation than the BP algorithm. The PSO-BP forecasting results are very close to the target output

Table 1 Simulation results with different artificial neural networks

Year	Target output	Conventional BP algorithm		PSO-BP algorithm	
		Actual output	Relative error	Actual output	Relative error
1993	0.028 5	0.032 7	0.148 4	0.018 7	0.343 7
1994	0.047 4	0.044 8	-0.055 9	0.040 4	0.148 6
1995	0.072 7	0.073 0	0.004 8	0.064 3	0.115 1
1996	0.102 4	0.104 3	0.018 8	0.097 9	0.043 5
1997	0.138 6	0.141 7	0.022 4	0.138 3	0.001 7
1998	0.193 8	0.194 4	0.003 1	0.185 6	0.042 4
1999	0.269 4	0.272 9	0.012 8	0.255 5	0.051 7
2000	0.392 2	0.393 7	0.003 9	0.383 8	0.021 3
2001	0.372 3	0.372 9	0.003 9	0.380 4	0.021 6
2002	0.468 1	0.467 9	-0.000 4	0.463 0	0.010 8
2003	0.579 3	0.579 4	0.000 2	0.576 1	0.005 5
2004	0.805 4	0.660 4	-0.180 0	0.860 2	0.068 0
2005	1.000 0	0.765 8	-0.234 2	0.903 1	0.096 9

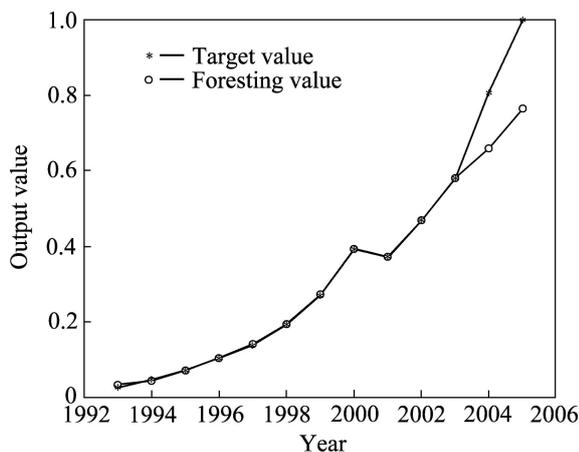


Fig.2 Prediction with BP algorithm

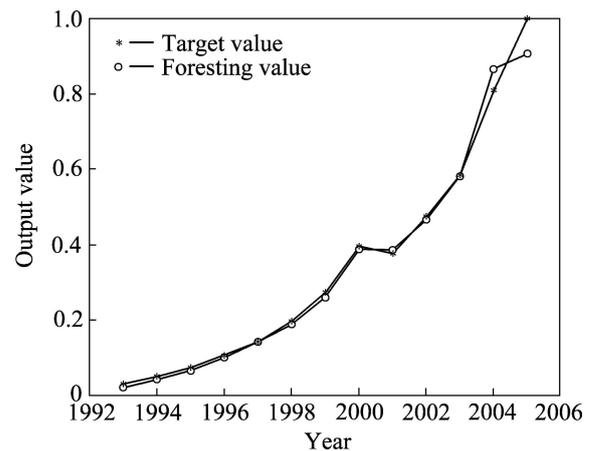


Fig.3 Prediction with PSO-BP algorithm

results. Especially for the test sample in 2004, the error of PSO-BP algorithm is 6.8%, and the error of conventional BP algorithm is 18%. Therefore, the PSO-BP is more effective, and can effectively improve the forecasting precision in some degree.

5 Conclusions

In this paper, a BP-based PSO algorithm is applied to forecast telecommunication traffic. The PSO-BP algorithm takes full advantages of the better performance of global optimized search of PSO and the local optimized search of BP neural networks. The result also suggests that the model presented above can provide highly accuracy in the field of forecasting. We will test the proposed algorithm across a wide range of important problems and applications in the next future work.

References

- [1] Sanchez-Sinencio E, Lau C. Artificial neural networks, paradigms, applications, and hardware implementations[M]. NJ: IEEE Press, 1992: 34-46.
- [2] Rumelhart D E, Hinton G E, Williams R J. Learning representation by back propagating errors[J]. Nature, 1986, 323: 533-536.
- [3] Bashir Z A, El-Hawary M E. Applying wavelets to short-term load forecasting using PSO-based neural networks[J]. IEEE Transactions on Power System, 2009, 24(1): 20-27.
- [4] Kennedy J, Eberhart R. Particle swarm optimization[C]//Proc IEEE Int'l Conf on Neural Networks IV. Perth, Australia, 1995: 1942-1948.
- [5] Eberhart R C, Simpson P K, Dobbins R W. Computational intelligence, in PC tools[M]. New York: Academic Press Professional, 1996: 355-357.
- [6] El-Telbany M, El-Karmi F. Short-term forecasting of Jordanian electricity demand using particle swarm optimization[J]. Electric Power Systems Research, 2008, 78: 425-433.

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