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The improvement and application of forecasting method in gm(1,1) model

SHILIANG ZHANG[2], TINGCHENG CHANG[2]

Abstract. In this article, GM algorithm will be put into BP (GM-BP improved model), By alternating GA algorithm and LM algorithm to correct BP neural network weights and thresholds and optimize the neural network, making full use of the local search ability of LM algorithm and the global search ability of genetic algorithm (GA) to complete each other. It not only enhance the local search ability of genetic algorithms, avoid neural network training fall into local minimum point, and prompt the entire GM-BP model with a strong search capabilities, but also improve the accuracy of the network of training and shorten training time, with a better generalization ability. Therefore GM-BP model is of great significance to deepen the understanding of the evolution of the system.

Key words. Grey system, gm(1,1), ga, algorithm.

1. Introduction

In the GM (1,1) model, the predict results depend on the length of the data sequence. A prediction gray range, which presents a horn shaped, is combined with the upper and lower bounds of the future predicted value.That is to say the farther the prediction time, the greater the range of predicted ash, and it is difficult to obtain satisfactory results [1]. Combining the model GM with other models is an effective method to improve the prediction accuracy. In 2005, Hu Qiao and He Zhengjia put forward a hybrid intelligent forecasting model, which was based on improving gray system, supporting vector machines, and fuzzing nervous system. When the model is applied to the vibration prediction of a unit, forecast results show that the prediction of a mixed prediction method is more accurate than the prediction

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[2]Workshop 1 - Department of Computer and Information Engineering, Ningde Normal University, Ningde, Fujian, China; e-mail: shiliangzh@163.com

of a single prediction method [2]; In 2006, Shan Jinle and Xiao Nong combined the improved MA moving average forecasting model with the gray prediction model GM (1,1) and later put forward a combination forecasting model??which was based on the time series. The prediction results show that the prediction method can achieve a higher accuracy [3];In the same year, Cui Jifeng and Qi Jianxun put forward a hybrid-forecasting model, basing on the gray prediction, the ARIMA, and the improved BP neural network. The model is applied to China's energy demand forecasting, the prediction results show that the prediction of a combination prediction model is more accurate than the prediction of the single prediction model [4]; In 2010, Wen Shengqiang and Zhou Pengfei proposed a hybrid-forecasting model of three-weight combination, basing on the gray theory and the neural network theory, and applied these prediction models into the traffic volume prediction. The prediction results show that selecting an appropriate method for solving hybrid forecasting model and parameters can be very effective to improve the prediction accuracy of the prediction model [5].

2. GM-BP model

Firstly, from the genetic algorithm, it can be got a global approximate solution as a initial value. And then alternately train optimization neural network algorithm with LM and genetic algorithm. The accuracy or partial maximum number can achieve the switching of LM optimization neural network algorithm to the genetic algorithm. The exchange of the genetic algorithm to LM optimize neural network algorithm can be operated by a complete genetic operator (selection operator, cross operator, mutation operator). Cross-training with each other, as their initial weight or the initial group, until the limit of the maximum number is reached.

Optimize the initial weights of the genetic algorithm and position some of the better search space in the solution space firstly. Iterate the population of each new individual by alternating LM algorithm to produce the fitness requirements of the network weights and thresholds. The algorithm is carried on in phases. The first phase of the mission is to produce N neural networks and encode it into the initial group of the genetic algorithms. And then calculate the fitness function with selection, crossover and mutation. When reaches the individual of the specified fitness function, or the number of iterations reaches the specified criteria to enter the second phase of the optimization process, encoding the neural network connection weightsw_i and the node threshold $\varphi_i$into a string of genetic genotype space. Fitness function is based on the network energy function E of the neural network output error of the network node, let F = C / E, C is a constant. The selection process uses the gap 0.9 for the genetic manipulation. The second phase of the mission of the group is to be decoded for each individual to obtain the connection weights and thresholds corresponding network; according to the local maximum training times, all these new individuals form a new group with LM algorithm of the connection weights and thresholds network is corrected and the connection weights and thresholds networks new corresponds individual code generation.

Establishing BP network model for residual sequence$q^{(0)}(k)$, if the predicted order is s, using s date, which is before residual sequence. Using information of $q^{(0)}(k-1), q^{(0)}(k-2), ..., q^{(0)}(k-s)$ to predict the value of k, that is to say, using the date before s,$q^{(0)}(k-1), q^{(0)}(k-2), ..., q^{(0)}(k-s)$, as the input sample of network training and the value of $q^{(0)}(k)$ as the predicted output value of BP network model. Putting GA algorithm and LM algorithm into BP optimization algorithm, with a sufficient number of residual series sample training this network, makes the different input vectors corresponds with output values (proven values). The network obtained the training value through the adaptive learning, which called neural network rights threshold and threshold values. Using the trained BP network model to predict a new residual value$\hat{x}^{(0)}(k,1)$, the predictive value of BP-GM hybrid model outputs. $\hat{x}^{(0)}(k,1) = \hat{x}^{(0)}(k) + \hat{q}^{(0)}(1)$, Improved algorithm GM-BP flow is shown in Fig.1.

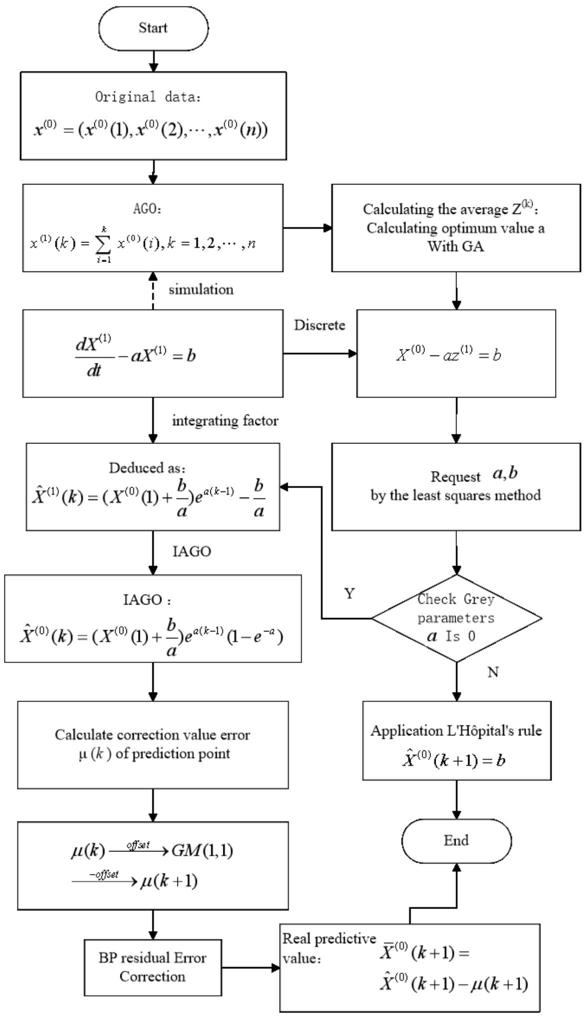

Fig. 1. The flow of improved algorithm GM-BP

3. Model analysis

Basing on the total water consumption of Ningde from 2004 to 2014, the data of this thesis is selected from Ningde City Water Resources Bulletin, as shown in table 1(unit:100 million cubic meters). BP neural network model parameters are as follows: selecting the data of recent three years as the input parameter, the number of input layer neurons is 3, and implied layer is 1, hidden layer nodes is 6, the output layer nodes is 1, the learning rate is 0.06, the maximum number of training is 5,000 times, training convergence precision is 0.0001, the mean square error is limited to 0.001. The GA algorithm and LMS algorithm are realized by the C# program. Intermediate values, which are generated by the algorithm, are stored in the database by calling the neural network toolbox of the Matlab software package to design BP neural networks. It uses the trained neural network model to the computing of the objective function and then it will get the water forecast results. It can be calculated from the data in the table1, residuals mean is -2.250, mean S1 and S2 mean are 34.607 and 1.603, respectively, a = -0.09612, b = 13.95586, variance ratio C = 0.215234, which shows that the model accuracy is excellent and can be used for prediction.

Table 1. Compare the results of total annual water consumption with different model in Ningde

year	fact	GM(1,1)		BP		GM-BP	
	$x^{(0)}(k)$	$\hat{x}^{(0)}(k)$	relative error	fitting value	relative error	fitting	
2004	10.89	10.89	0	-	-	-	
2005	14.2	15.75	10.9	-	-	-	
2006	17.36	17.34	0.14	-	-	-	
2007	18.56	19.09	2.83	17.68	4.72	17.78	
2008	19.13	21.01	9.83	18.77	1.90	20.16	
2009	20.83	23.13	11.05	19.72	5.31	20.98	
2010	23.23	25.46	9.62	24.90	7.18	24.23	
2011	25.16	28.03	11.42	27.03	7.43	26.51	
2012	27.21	30.86	13.42	25.36	6.8	26.72	
2013	30.65	33.98	10.85	28.12	8.26	31.23	
2014	33.22	37.40	12.6	31.21	6.06	34.27	

4. Results and analysis

GM-BP Model, basing on the BP neural network, contains the advantages of grey theory, GA algorithm and LM algorithm. It takes advantages of the local search

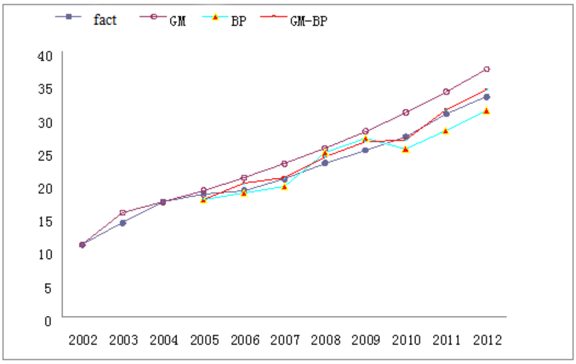

Fig. 2. Compare different model fitting results

ability of LM algorithm and the global search ability of genetic algorithm when alternately using the weights and thresholds of GA algorithm and LM algorithm in the network training. It not only enhance the local search ability of genetic algorithms, but also avoid falling into the minima of neural network training, and improve the accuracy of network training and shorten the time of network training. It prompts the entire GM-BP model with a strong search capability to find out the historical information and data sequence change trend. Combining with the nonlinear processing, self-learning and adaptive ability of the BP neural network, it can excavate the nonlinear information of total water consumption in further. It is a good reflection to the change process of total water consumption and improves the fit prediction accuracy significantly. From the table 2, it can be easily find out that the average relative error of the GM (1, 1) model is 9.27%, the BP model is 5.96%, and the GM-BP model is 3.35%. Thus, the GM-BP model is applicable to predict the total water consumption. It has a good versatility since it can be widely used to predict the water consumption everywhere.

5. Conclusions

In this paper, based on the grey artificial neural network model, which is combined of grey theory and artificial neural networks, it uses the neural networks to correct residuals of GM(1,1) model and applying into the prediction of Ningde urban water. The testing results show that, using the gray artificial neural network model not only can improve the utilization of information, and avoid the information distortion phenomenon that the positive and negative data offset when accumulate data system in sequence, but also greatly reduce the amount of network computing and improve the learning speed of the network. The GM model combine with other models can inherit each its merits, the hybrid model has a faster convergence speed, higher prediction accuracy than other standard algorithm models.

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