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Electric Energy Demand Forecast of Nanchang Based on Cellular Genetic Algorithm and BP Neural Network

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Abstract

A kind of power forecast model combined cellular genetic algorithm with BP neural network was established in this article. Mid-long term power demand in urban areas was done load forecasting and analysis based on material object of the actual power consumption in urban areas of Nanchang. The results show that this method has the characteristic of the minimum training times, the shortest consumption time, the minimum error and the shortest operation time to obtain the best fitting effect.

Keywords: *Cellular genetic algorithm, BP neural network, City power, Forecast*

1. Introduction

The modern intelligent forecast methods are mainly including grey forecast, fuzzy forecast, expert system forecast, artificial neural network forecast, optimized combination forecast, wavelet analysis method, system dynamics method and the algorithm combined with the above method [1-6]. Due to its strong robustness and dealing with questions having the characteristics of randomness, global and parallel, genetic algorithm is also being used in forecast research. But genetic algorithm also has some shortcomings which is easy to make problem solving in local optimum, such as slow convergence speed and poor global convergence performance. Genetic neural network combined with genetic algorithm and BP algorithm has begun to be used for short-term electric power load forecast in the past two years [7, 8]. The quantity demand of energy for cities was in the rapid increase with the acceleration of urbanization speed. In order to satisfy the energy demand of production, business and residents of life, Predicting energy demand of city accurately achieved real low carbon and ecologization, which satisfied energy demand and improved energy efficiency at the same time. Our research team tried to use traditional genetic algorithm combining with BP to forecast mid-long term power demand of urban areas and obtained better conclusion [9].

Cellular genetic algorithm is the combination of cellular automata mechanism and genetic operation and is also a branch of genetic algorithm. Cellular automata (CA) is a kind of discrete dynamic model of time and space, which simulates life system of the dynamic evolution process by adding certain evolution rules and is widely used in geography simulation and ecological simulation system. CGA combines the genetic algorithm (GA) with Cellular Automata (Cellular Automata, referred to as the CA) organicly as a calculation tool and its thought is mainly from the following two simple views [10]. Repeated simple operation rules can lead to complex system behavior in the cellular automata. Repeated local interaction can eventually become to realize global calculation purpose. According to this thought, complicated global optimization problems can be defined by some simple learning rules to solve and the learning rules are the core of the cellular automata, which is the evolution rules. The specific principle of cellular genetic algorithm is that one individual in the population of genetic algorithm is treated as one cellular through cellular automata model and these individuals are mapped to two-dimensional grid at random, then adding the evolution rules and finally the process of optimal solution by population search. The genetic algorithm is introduced into cellular automata Simulation of urban expansion process, which can get optimized space parameters weight, CA conversion rules of the relevant parameters optimization, reduce model operation time, and improve the simulation accuracy.

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The first of cellular genetic algorithm model is put forward by Robertson in 1987 and some his researches are reported successively by some foreign countries, especially very good application to the urban traffic problem [11]. Nearly two years, researches on yuan cell genetic algorithm have focused on the mechanism and algorithm and done very little applied research in the domestic [12, 13].

A power forecast model of combination with cellular genetic algorithm and BP neural network was intended to establish in this paper. Mid-long term power demand in urban areas was done load forecasting and analysis based on material object of the actual power consumption in urban areas of Nanchang from 1995 to 2009, and compared with traditional genetic algorithm and the algorithm combined with traditional genetic algorithm and BP neural network.

2. Establishment of Model

The main ideas of cellular genetic algorithm combining with BP neural network was that neural network was used to test the number of the best network nodes in the hidden layer and genetic algorithm was used to optimize a smaller range in overall optimal characteristics of network weights, then reused BP algorithm to continue optimization. Its procedures were as follows.

2.1. Determination of the Number of Hidden Layer Node

The data was ensured in the interval 0~1 by normalization. One hidden layer was established between input and output of the BP neural network model of total power forecasting. Inputs and outputs were set as five dimensions and one dimension according to actual needs, respectively.

It could be seen in Table 1 that training times were least when the number of hidden nodes was 12, but it had the biggest network error. Training time was shorter and network error was bigger when the number of hidden nodes was 16. The BP neural network with 20 hidden nodes had the best approximation effect of function and shorter training time, which reached target error only needing five training times. Comprehensive considering network performance and training speed, the number of hidden nodes was set as 20.

2.2. Determination of Training Function

According to the convenience of data collection, taking total power consumption in urban areas of Nanchang from 1995 to 2009 as an object in this paper, six different training functions were selected to compare in the same experimental conditions and its results were taking average of 100 times repeat experiments , such as traingd, traingdm, traingda, trainbr, trainrp and trainlm. The above parameters were set the same as net. TrainParam. Epochs, Net. TrainParam. Goal Net and TrainParam. Lr equal to 10000, 0.0001 and 0.01, respectively. The average training time and average training times (10000 steps) of different training function are shown in Table 2.

From Table 2, it could be seen that the training speed of traingda improved bigger than that of traingd and traingdm and its network reached expectant performance error after 517 iterations. However, training effect of trainbr and trainrp was superior to that of traingda, and trainlm had the fastest convergence speed, the least average training times and the least mean square error, so the effect of trainlm was better.

2.3. Cellular Genetic Algorithm Optimized BP

The process as follows:

Step one: Producing initial population, initialization of parameters, the length of each individual chromosomes in the group is 5×20+20*1+20+1=141

Step two: individual was placed in space grid in turn, determination of objective function

$$E(i) = \sqrt{\sum_{m=1}^{10} (y_m - T_m)^2} \tag{1}$$

$$F(i) = 1/E(i), \quad (1 \le i \le N) \tag{2}$$

Where, N for population scale, i signify individual in the position of cellular grid, m for learning samples equal to 1, 2, 3... 10, y_m for training value, T_m for expectations.

Step three: taking each cellular grid position as a center to choose cell neighbors, in which according to roulette method to choose based on fitness size, genetic crossover and mutation operators were done between choice individual and individual in center position.

Step four: if fitness of new individual produced by variational individuals was improved, father generation individuals were alternated.

Step five: algorithm achieved maximum evolution algebra introduced or turn to step 3.

Step six: output optimal solution.

Step seven: the best individual was decoded as initial weight values and threshold of BP network.

Step eight: began training of BP network and updated weights and threshold constantly until satisfied requirement of accuracy.

Table 1. The training situation of the number of different hidden nodes

The number of hidden nodes	Mean square error (10^{-4})	Training times	Training Time (s)
10	0.9256	14	0.5913
11	0.1049	5	0.4967
12	0.9447	2	0.4779
13	0.1205	3	0.4983
14	0.2787	5	0.5130
15	0.1621	3	0.5054
16	0.2800	4	0.4830
17	0.1359	4	0.5018
18	0.2395	5	0.5151
19	0.3431	3	0.4913
20	0.0118	5	0.5084
21	0.5588	5	0.5261
22	0.1737	4	0.5068
23	0.8848	5	0.5128
24	0.0147	3	0.4955

Table 2 The average training time and average training times of different training function

Training function	Average training times	Average training time (s)	Mean square error (10^{-4})
traingd	-	33.1541	5.0243
traingdm	-	32.9554	5.0217
traingda	517	2.0638	0.9998
trainbr	172	2.6474	0.3411
trainrp	51	0.6488	0.9764
trainlm	5	0.5056	0.0118

Table 3 Experimental results

Algorithm	Training times	Running time (s)	Permissible error
BP neural networks	-	33.4335	0.0001
BP neural networks optimized by GA	9	0.910286	0.0001
BP neural networks optimized by CGA	5	0.590787	0.0001

3. Simulation Research

The total power consumption five years before was set as sample data of network and that of one year after was set as expectant target according to the total power consumption of

Nanchang city from 1995 to 2009. The main parameters Settings of algorithm were as follows: the biggest evolution algebra was 500, population scale was 400, grid size was 20x20, using real number coding, cross rate was 0.8, variation probability was 0.05, initial value of Weights and threshold was in the interval from 0 to 1. Experimental results of algorithm are shown in Table 3.

It could be seen that the effect of BP neural network optimized by GA and CGA was far better than that of traditional BP algorithm from Table 3. BP neural network optimized by CGA needed the minimum training times and the shortest consumption time and had the minimum error. Power consumption of urban areas of Nanchang from 2000 to 2009 was forecasted further. The results was shown in Table 4 and its fitting curve was shown in Figure 1.

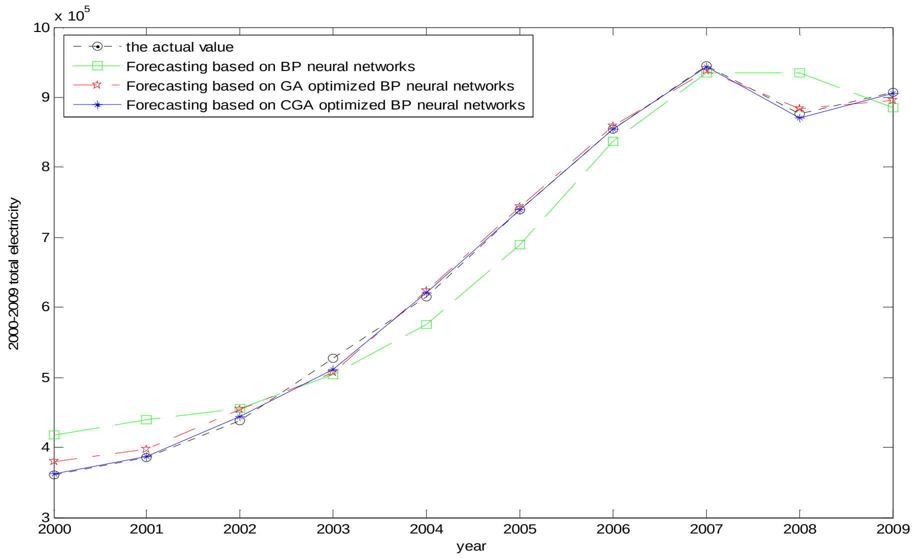

Figure 1. Forecast fitting curve of different BP neural network

Figure 1 shows forecast fitting curve of different BP neural network. The forecast curve of BP neural network optimized by CGA was fittest into actual power consumption curve. So, whether from running time or the point of fitting effect, BP neural network optimized by CGA was better than that of the other two algorithms. The power consumption in urban areas of Nanchang from 2010 to 2025 was forecasted by this algorithm and its results were shown in Table 5.

Tabal 4 Compared with forecast of total power consumption in Nanchang city from 2000 to 2009 by three algorithms

Years	actual value (ten thousand kwh)	BP neural networks		GA optimized BP neural networks		CGA optimized BP neural networks	
		forecast value (ten thousand kwh)	Error	forecast value (ten thousand kwh)	Error	forecast value (ten thousand kwh)	Error
2000	36.0835	**41.7149**	**0.1350**	**38.0333**	**0.0513**	**36.2300**	**0.0041**
2001	38.5977	**43.9782**	**0.1223**	**39.9860**	**0.0327**	**38.7166**	**0.0031**
2002	43.7378	**45.6201**	**0.0413**	**45.4256**	**0.0372**	**44.4064**	**0.0151**
2003	52.7274	**50.3190**	**-0.0479**	**50.6466**	**-0.0411**	**52.3220**	**-0.0077**
2004	61.4828	**57.5420**	**0.0685**	**65.4672**	**0.0369**	**62.1299**	**0.0104**
2005	73.8684	**68.8972**	**0.0722**	**76.9414**	**0.0281**	**73.8671**	**-1.6357e-05**
2006	85.4364	**83.7422**	**-0.0202**	**87.5347**	**0.0129**	**85.4217**	**-1.7258e-04**
2007	94.5496	**93.3552**	**-0.0126**	**93.6421**	**-0.0096**	**94.3755**	**-0.0018**
2008	87.6851	**92.8135**	**0.0585**	**89.5248**	**0.0210**	**87.6558**	**-3.3415e-004**
2009	90.6520	**88.5792**	**0.0234**	**89.5144**	**-0.0127**	**90.6285**	**-2.5930e-004**

Table 5 Forecast of total power consumption in Nanchang city from 2010 to 2025

Year	Total power consumption (ten thousand kwh)	Year	Total power consumption (ten thousand kwh)
2010	93.6326	2017	177.7629
2011	107.7790	2018	178.8885
2012	121.9816	2019	190.6643
2013	152.6796	2020	202.8590
2014	164.6812	2021	212.4974
2015	172.4755	2022	212.5338
2016	173.8297	2023	213.5356

4. Conclusion

The urban industrial structure and city planning have a corresponding changed With the acceleration of urbanization process. The scale and population of urban area have large increased relatively. Power demand has increased greatly, such as industrial, commercial, residential life and so on. Market operation has also brought a lot of uncertain factors with big change of randomness and relevance, which brings certain difficulties to forecast urban energy demand accurately. Cellular genetic algorithm got better solution of function optimization problem through introducing a two-dimensional cellular automaton processing complex function optimization problems. Complex global optimization problems could be achieved by cellular genetic algorithm. Material object study showed that the effect of BP neural network optimized by GA and CGA was far better than that of traditional BP algorithm. BP neural network optimized by CGA needed the minimum training times and the shortest consumption time and had the minimum error. Meanwhile, BP neural network optimized by CGA was better than that of the other two algorithms whether from running time or the point of fitting effect

References

[1] Jun-Xiao, Debao-Sun, Yuanqing-Qin. Application of the grey model in electric power predicting and its optimization. T*echniques of Automation and Applications*. 2005; 24(2): 19-21.

[2] Gwo-Ching Liao, Ta-peng Tsao. Application of fuzzy neural networks and artificial intelligence for load forecasting. *Electric Power Systems Research*. 2004; 70: 237-244.

[3] Yaonian-Liu, Wei-Wang, Dongfeng-Yang. Mid-long term electric capacity Forecasting based on fuzzy cluster theory. *Journal of Northeast China Institute of Electric Power Engineering*. 2004; 24(04): 39-42.

[4] Haiping-Huang. Combination estimate for electric demand of china based on BP neural networks. *Science Technology and Engineering*. 2004; 7(04): 612-616.

[5] GJ Chen, KK Li, TS Chung, et al. Application of an innovative combined forecasting method in power system load forecasting*. Eletric Power System Research*. 2001; 59: 131-137.

[6] Mara Lu cia M Lopes, Carlos R. Minussi,Anna Diva P Lotufo. Electric load forecasting using a fuzzy ART&ARTMAP neural network. *Applied Soft Computing*. 2005; 5: 235-244.

[7] Wu-Wang, Yuanmin-Zhang, Ziliang-Cai. Neural network based genetic algorithm optimizing for short-term load forecasting. *Relay*. 2008; 36(09): 39-42.

[8] Zhiwu-Liang, Jiekang-Wu, Minghua-Chen, et al. Short-term load forecasting based on genetic algorithm and simulated annealing algorithm optimized elman neural networks. *Modern Electric Power*. 2008; 25(02): 13-17.

[9] Yugui-Cheng, Ming-Li, Mingyu-Lin. Forecasting and analysis on long-term/mid-term electric load of city by GA-BP neural networks. *Journal of Computer Applications*. 2010; 1.

[10] M Tomassini. *Spatially Structured Evolutionary Algorithmsser*. Artificial Evolution in Space and Time Series, Natural Computioning Series. Springer. 2005.

[11] Nagel K, Schreckenberg M. A cellular automaton model for freeway traffic. *Physics I France*. 1992; 2: 2221-2229.

[12] LU Yu-ming, LI Ming, LI Ling. The cellular genetic algorithm with evolutionary rule. *Acta Electronica Sinica*. 2010; 38(7): 1603-1607.

[13] Wan Cheng, Yang Xiao-qin, LU Yu-ming. Study on cellular genetic algorithms in dynamic environment. *Electronic Component & Device Applications*. 2010; 12(7): 78-79.