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SciVerse ScienceDirect
Energy Procedia 12 (2011) 180 – 184
Energy Procedia

ICSGCE 2011: 27–30 September 2011, Chengdu, China

Application of a Load Forecasting Model Based on Improved Grey Neural Network in the Smart Grid

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Abstract

An important feature of smart grid is the intelligent power distribution function based on load forecasting with high accuracy. Accurate prediction of load is the key indicator of power intelligence. As a result of this, this paper combines Genetic Algorithm with grey prediction model, uses Genetic Algorithm to optimize the initial value and the background value of traditional GM (Grey Model), combines the new GM with BP neural network and constructs a tandem Grey Neural Network model, which is used in load forecasting in smart grid. This model can solve the forecasting problem of non-isometric series, greatly improve the accuracy of prediction model, optimize data quality, strengthen the intelligence on operation and deployment, and provide more realistic, workable scientific reference for the decision support of smart grid. Finally the proposed method is applied to predict the load of some area. The results prove the effectiveness of the method.

Keywords: BP neural network, genetic algorithm, improved GM (1, 1), load forecasting, smart grid

1. Introduction

Recently, smart grid has become internationally popular topic. Different countries and organizations research it in their own way and try various technologies in generation, transmission, distribution and use. The decision-making function of smart grid is based on a large number of collected data. By means of the advanced communications technology, smart grid can obtain the real-time data of each electricity terminal, predict the load and allocate electricity reasonably. Smart grid can improve the utilization factor of energy, use renewable energy, solve the energy crisis, reduce environmental pollution and optimize energy configuration.

The ability of predicting data determines the quality of smart grid. If the predicted value of load is too

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doi:10.1016/j.egypro.2011.10.025

low, it will lead to allocate low power and power cut. If the predicted value of load is too high, it will lead to unnecessary cost and energy waste. So it is very necessary to predict exactly.

GM (1, 1) (Grey Model with First Order Differential Equation and one Variable) is used to forecast the load frequently, because of its advantages such as requiring short samples, operating conveniently and so on. But the GM is not so perfect. To make up the deficiency of traditional GM (1, 1), this paper uses genetic algorithm which having the advantages such as strong robustness, randomness, global search and parallel processing to improve the fitting ability of the GM (1, 1), combines the optimized GM (1, 1) with BPNN to improve the nonlinear approximation ability of the GM and builds a kind of GBP (Grey BP Neural Network) dynamic prediction model. Finally the proposed method is applied to predict the load of some area. The results prove the effectiveness of the method.

2. Grey BP Neural Network

2.1. The principle and the limitations of traditional GM (1, 1)

The principle of traditional GM (1, 1) can be briefly summarized as follows. To eliminate the randomness and the volatility, original data $X^{(0)}=(x^{(0)}_{(1)},x^{(0)}_{(2)},x^{(0)}_{(3)},\cdots,x^{(0)}_{(n)})$ are accumulated once obtainin $X^{(1)}=(x^{(1)}_{(1)},x^{(1)}_{(2)},x^{(1)}_{(3)},\cdots,x^{(1)}_{(n)})$. Then, the differential equation about $X^{(1)}$ is built as follow,

$$\frac{dX^{(1)}}{dt}+aZ^{(1)}=b \tag{1}$$

In (1), $Z^{(1)}$ is the background value of $X^{(1)}$, and

$$z^{(1)}_{(k)}=0.5x^{(1)}_{(k)}+0.5x^{(1)}_{(k-1)} \qquad k=2,3,4\cdots n \tag{2}$$

After using the least-square method to calculate the parameters a and b, the grey prediction model about $X^{(1)}$ is built as follow,

$$\hat{x}^{(1)}_{(k+1)}=(x^{(1)}_{(0)}-\frac{b}{a})e^{-ak}+\frac{b}{a} \qquad k=1,2,3,\cdots \tag{3}$$

The initial condition is $x^{(1)}_{(0)}=x^{(0)}_{(1)}$.

By the subtraction operation to $\hat{X}^{(1)}$, $\hat{X}^{(0)}$ (the prediction of $X^{(0)}$) is found.

There are three factions which lead to low prediction precision. (1) The selection of initial value is not scientific; (2) Little attention is paid to new data; (3) The construction of background value is unreasonable. On account of foregoing reasons, some improvements are made to traditional GM (1, 1).

2.2. Metabolic GM (1, 1) (MGM (1, 1))

In the development process of any grey system, some random disturbance and driving factor will join into the system with the passage of time. In the traditional GM (1, 1), once the parameters is acquired, they will be fixed, it means that new data for the GM are neglected. This is the reason that the GM (1, 1) has high accuracy only near the initial point. Metabolic GM (1, 1) thinking about new information is more reasonable.

In the Metabolic GM (1, 1), parameters a and b are regarded as variables over time. The GM (1, 1) built with initial data sequence is used to forecast firstly, the result is regarded as new information and added to the initial data sequence. In the same time, the oldest data is removed. By this way, a new data sequence is formed. Then a new GM (1, 1) will be built with new data sequence, and it will be used to obtain the next forecast result. And this new result is added to newer data sequence and replaces the oldest data in this sequence. The work will be repeated until forecast goal is reached.

2.3. MGM (1, 1) based on genetic algorithm (GAMGM (1, 1))

The choice of initial value and the identification of parameters are the two steps of setting up GM (1, 1). As mentioned above, the initial condition of $x^{(1)}$ which is the solution of the grey differential equation is $x^{(1)}_{(0)} = x^{(0)}_{(1)}$. This initial condition is proved unscientific by least-square theory and practices.

The accuracy of GM (1, 1) model depends on parameters a and b, the value of parameters depends on the form of background value. The background value is the key factor impacting on the accuracy and the adaptability of GM (1, 1). The traditional formula of background value is smooth and has not universal applicability. In order to make improvements, the following formula is advanced to calculate the background value.

$$z^{(1)}_{(k+1)} = px^{(1)}_{(k+1)} + (1-p)x^{(1)}_{(k)} \qquad k = 1, 2, \cdots, n-1 \tag{4}$$

Obviously, the effect of background value to prediction accuracy is reflected by the parameter p.

In order to gain the optimum GM (1, 1), genetic algorithm is applied to optimize $x^{(1)}_{(0)}$ and p.

Genetic algorithm formed by means of the imitation of natural biological evolution, is a kind of optimization algorithm with the merits of global and parallel search. Genetic algorithm can find out optimal solutions by the random search among multiple points within the solution space.

The specific steps of optimizing GM (1, 1) with genetic algorithm are as follows.

(1) Coding

To optimize initial value and parameter p simulta- neously, MAMGM (1, 1) regards $x^{(1)}_{(0)}$ and p as one genome to code. The values of these two variables are real numbers, so the way of coding is real number coding.

(2) Initialization population

For each individual in the population, the initial value of $x^{(1)}_{(0)}$ can be any value in initial data sequence $X^{(0)}$, and the initial value of p can be a random number between 0 and 1.

(3) Calculating the fitness of each individual

In genetic algorithm, fitness function is the only information guiding search. To minimize the residual, the fitness function is selected as follows.

$$f = \frac{1}{1+\sum_{k=1}^{n}\sigma_k} = \frac{1}{1+\sum_{k=1}^{n}\left|\hat{x}^{(0)}_{(k)} - x^{(0)}_{(k)}\right|} \tag{5}$$

(4) Selection

In this paper, preserving the best individuals and roulette wheel selection method are combined. Firstly, the individuals having the largest and the second largest fitness among the parent individuals are selected and directly copied to the next generation without cross and mutation, and then other individuals are selected by roulette wheel selection method. Suppose N is the population size, according to this method, the probability of the individuals i to be selected is

$$P_{si} = \frac{f_i}{\sum_{k=1}^{N} f_k} \tag{6}$$

(5) Crossover

For the individuals coded with real number, suppose X and Y are individuals involved in crossover, the two new individuals are:

$$X' = kY + (1-k)X, \qquad Y' = kX + (1-k)Y \tag{7}$$

In (7), k is a random number between 0 and 1.

The adaptive crossover probability is selected as follows,

$$P_C = \begin{cases} k_1(f_{\max} - f')/(f_{\max} - f_{avg}) & f' > f_{avg} \\ k_2 & f' < f_{avg} \end{cases} \tag{8}$$

In (8), $f_{\max}$ is the largest fitness, f_{avg} is the average fitness of population, f' is the larger fitness among the two crossover individuals, k_1 and k_2 are constants between 0 and 1.

(6) Mutation

For the individuals coded with real number, suppose Z is the individual that is selected according to a random probability to mutate, then the result is:

$$Z' = U_{\min} + r \times (U_{\max} - U_{\min}) \tag{9}$$

In (9), $U_{\min}$ and $U_{\max}$ are left and right border of individual A .

The adaptive mutation probability is selected as follows,

$$P_m = \begin{cases} k_3(f_{\max} - f)/(f_{\max} - f_{avg}) & f > f_{avg} \\ k_4 & f < f_{avg} \end{cases} \tag{10}$$

In (10), the meanings of $f_{\max}$ and f_{avg} are the same as above, f is the fitness of individual which is to be mutate, k_3 and k_4 are constants between 0 and 1.

(7) Repeating above operations until forecast goal being reached.

2.4. Grey BP neural network

Grey forecast method has not only numerous advantages as mentioned, but also has inevitable shortcomings. The neural network has strong abilities of nonlinear approximation, self-study, organization and adaptive. Combining these two methods can cover the shortages of each other. A series grey neural network model combining GAMGA (1, 1) with BPNN is advanced in this paper. The model is not only simple but also can give full play to the advantages of the grey theory and neural network.

The working process of GBP is as follows. (1) A GAMGM (1, 1) is built using the original data and is applied to forecast, (2) a BPNN, which regards the forecast results of GAMGM (1, 1) as inputs and the real value as target, is built and trained, and its parameters are obtained, (3) the trained BPNN is applied to forecast, the inputs are the forecast results of the GAMGM (1, 1) and the outputs are the final forecast results.

2.5. Load forecasting model based on GBP

Table 1. Load Data of some Area

year	2000	2001	2002	2003	2004
Load (kW/h)	98.96	112.26	123.52	135.45	142.92
year	2005	2006	2007	2008	2009
Load (kW/h)	163.88	186.46	227.63	276.25	364.14

This paper selects the load data of some area from 2001 to 2009 (shown in Table 1) as sample data to verify performance of the model.

With the data of 2000 to 2007, the writer built GAMGM (1, 1) and got the fitting data of 2000 to 2007 and the prediction data of 2008 and 2009. Considering the fitting data as the input sample and the real data of 2000 to 2007 as the targets, the BPNN is trained. Considering the prediction data of 2008 and 2009 got above as the inputs, the trained BPNN is applied to forecast and the outputs of the BPNN are the final forecast results of the load of 2008 and 2009 as are shown in table 2.

Obviously, comparing with the GAMGM (1, 1), the GBP model has stronger prediction ability and adaptive ability. And the low relative errors prove that the GBP model is an effective method to load forecast.

3. Conclusion

An improved GM (1, 1) based on genetic algorithm was advanced. The way, which using genetic algorithm to optimize the initial value and the background value of the grey differential equation, strengthens the data handing ability of the GM (1, 1). The grey BPNN model combined the advantages of grey prediction model and the BP neural network availably.

It is proved that the GBP prediction model based on genetic algorithm is obviously better than traditional GM (1, 1) in the stability and the prediction precision. It is obvious that genetic algorithm as an efficient, parallel and global searching method, can be widely applied in the optimization of grey neural network to improve the accuracy of prediction for small data.

Table 2. Load Data of some Area

year	2000	2001	2002	2003	2004
Real value	98.96	112.26	123.52	135.45	142.92
Fitting (Prediction)	98.96	111.09	121.09	136.06	141.55
Relative Error%	0	1.04	1.97	0.45	0.96
year	2005	2006	2007	2008	2009
Real value	163.88	186.46	227.63	276.25	364.14
Fitting (Prediction)	167.45	185.21	222.76	285.37	352.49
Relative Error%	2.18	0.67	2.14	3.3	3.2

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