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APPLICATION OF GREY NEURAL NETWORK TO FORECASTING OF CERAMIC INDUSTRIAL OUTPUT

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ABSTRACT

Ceramic industrial output is susceptible to the influence of various factors, with the characteristics of the nonlinear and stochastic volatility. Grey neural network model combines the advantages of grey GM(1,1) model and neural network model, which suits for few sample data and volatile random questions. In this paper, the ceramic industrial output of Jingdezhen from 2002 to 2010 are used as research object to build grey neural network model and check its precision through analysis of some practical examples. The result shows that grey neural network model not only has higher precision, but also better shows the data sequence trend than the grey GM(1,1) model does.

Keywords: *Grey Neural Network Model (GNNM), GM(1,1) Model, Nonlinear, Forecasting*

1. INTRODUCTION

GM(1,1) builds model after few sample data accumulating, which can weaken the randomness of the original data, find the data conversion rule, and finally realize forecast [1]. But forecasting for linear sequence only is the disadvantage of this model. Neural network model is the network system of imitating the human brain to deal with problems, which has the ability of high nonlinear operation, self-learning, self-organization, and can consider influences of random factors in the forecast [2]-[4]. But a lot of data as input variables are the shortcomings of this model. In recent years, although the two forecasting models have been widely employed in various fields such as electric power, population, stock, agriculture and so on, the forecasting precisions must be improved [5]-[9]. If the grey forecasting model is combined with the neural network model organically to constitute the grey neural network model, the combined model will have the advantages of both and realize the optimization of the forecast methods.

Jingdezhen city is the world-famed ceramic capital and the city government has attached great importance to the development of ceramic industry in recent years. Continuous improvement of ceramic industrial output forecast accuracy will be benefitial to the city government to formulate macroeconomic policies. With the influence of the policy, economic and other factors, ceramic industrial output of Jingdezhen in recent years increases nonlinearly and the volatility is bigger, the traditional forecasting methods will cause greater errors. In this paper, the ceramic industry output of Jingdezhen will be forecasted by grey neural network model

Section 2 and section 3 introduce the theory of grey GM(1,1) model and grey neural network model respectively. In section 4, the grey neural network model is applied in the forecasting of Jingdezhen ceramic industrial output. Finally, we give the conclusion to the whole paper in section 5.

2. GREY GM(1,1) MODEL

Grey GM(1,1) model does the first-order accumulated generating operation for original sequence firstly, lets the accumulated sequence show a certain regularity, and then fits discrete data with a continuous function or different equation, solves the equation and gets the forecasting value finally. The GM(1,1) model can be expressed as follows [1].

1). Listing the original sequence.

$$X^{(0)} = \left\{x^{(0)}(i)\right\} \quad (i = 1, 2, \cdots, n) \qquad (1)$$

where $x^{(0)}(i) > 0$.

2). Doing one-time accumulation generating operations for $x^{(0)}$, get the new sequences $X^{(1)}$

$$X^{(1)} = \left\{x^{(1)}(i)\right\} = \left\{\sum_{i=1}^{n} x^{(0)}(i)\right\} \quad (i = 1, 2, \cdots, n) \qquad (2)$$

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3). Establishing grey first-order differential equation by $X^{(1)}$

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = u \qquad (3)$$

4). Getting the forecasting model

$$\hat{x}^{(1)}(k+1) = (x^{(0)}(1) - \frac{u}{a})e^{-ak} + \frac{u}{a} \qquad (4)$$

5). Calculating the forecasting value

$$\begin{aligned}\hat{x}^{(0)}(k+1) &= \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \\ &= (1-e^{a})e^{-ak}(x^{(0)}(1) - \frac{u}{a})\end{aligned} \qquad (5)$$

3. GREY NEURAL NETWORK MODEL

Grey neural network model is denoted by GNNM(h, n), wherein, h is the order of the differential equations, n is the number of sequences involved in the modeling. In this paper, GNNM(1, n) is studied, which is a one-order multi-variable differential equation and needs multi-input variables. Grey neural network model lets a grey differential equation be mapped to a neural network topology structure, in neural network training process, the weights are revised constantly, grey parameters continue to refinement, and the predictive ability of data will be strengthened in this process.

A. Establish Grey Neural Network Model

Defining the original sequence $X^{(0)}$ as $x(t)$, one-time accumulation generating operation sequence $X^{(1)}$ as $y(t)$, the forecasting result $\hat{x}^{(0)}(k+1)$ as $z(t)$. According to Eqn. (3), grey differential equation of n parameters is expressed as:

$$\frac{dy_1}{dx} + ay_1 = b_1y_2 + b_2y_3 + \cdots + b_{n-1}y_n \qquad (6)$$

Where $y_1, y_2, \cdots, y_n$ are system input parameters, y_1 is system output parameter, $a, b_1, b_2, \cdots b_{n-1}$ are differential equation coefficients.

The time response equation of Eqn. (6) is

$$\begin{aligned}z(t) = (y_1(0) - \frac{b_1}{a}y_2(t) - \frac{b_2}{a}y_3(t) - \cdots \\ -\frac{b_{n-1}}{a}y_n(t))e^{-at} + \frac{b_1}{a}y_2(t) \\ +\frac{b_2}{a}y_3(t) + \cdots + \frac{b_{n-1}}{a}y_n(t)\end{aligned} \qquad (7)$$

Set $d = \frac{b_1}{a}y_2(t) + \frac{b_2}{a}y_3(t) + \cdots + \frac{b_{n-1}}{a}y_n(t)$.

Then Eqn.(7) can be converted into Eqn.(8) which can be shown as

$$\begin{aligned}z(t) &= \left(\left(y_1(0) - d\right) \times \frac{e^{-at}}{1+e^{-at}} + d \times \frac{1}{1+e^{-at}}\right) \\ &\quad \times (1+e^{-at}) \\ &= \left(\left(y_1(0) - d\right) \times \left(1 - \frac{1}{1+e^{-at}}\right) + d \times \frac{1}{1+e^{-at}}\right) \\ &\quad \times (1+e^{-at}) \\ &= \left(\left(y_1(0) - d\right) - y_1(0) \times \frac{1}{1+e^{-at}} + 2d \times \frac{1}{1+e^{-at}}\right) \\ &\quad \times (1+e^{-at})\end{aligned} \qquad (8)$$

Transformed Eqn.(8) is mapped to an extensional BP neural network, then get grey neural network model with n input parameters and 1 output parameters. Network topology is shown in Fig.1.

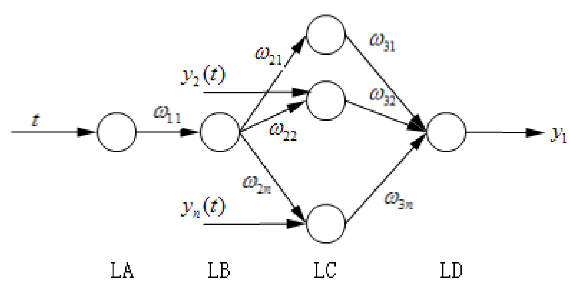

Fig.1 BP Neural Network Structure

Wherein, t is the serial number of input parameters; $y_2(t), \cdots y_n(t)$ are network input parameters; $\omega_{21}, \omega_{22}, \cdots \omega_{2n}, \omega_{31}, \omega_{32}, \cdots \omega_{3n}$ are network weights; y_1 is network forecasting value; LA, LB, LC, LD are layers of grey neural network model.

Set $d = \frac{b_1}{a}y_2(t) + \frac{b_2}{a}y_3(t) + \cdots + \frac{b_{n-1}}{a}y_n(t)$, then, the network initial weights are assigned as follows

$$\begin{aligned}&\omega_{11} = a \\ &\omega_{21} = -y_1(0), \omega_{22} = u_1, \omega_{23} = u_2, \cdots, \omega_{2n} = u_{n-1} \\ &\omega_{31} = \omega_{32} = \cdots = \omega_{3n} = 1 + e^{-at}\end{aligned} \qquad (9)$$

The threshold of output node in layer LD is

$$\theta = \left(1+e^{-at}\right)\left(d - y_1(0)\right) \qquad (10)$$

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B. Learning Process

1). Initializing network structure by the features of training data, initializing the parameters a, b, calculating u by the parameters a and b.

2). According to network weights definition, calculating $\omega_{11},\omega_{21},\omega_{22},\cdots\omega_{2n},\omega_{31},\omega_{32},\cdots\omega_{3n}$.

3). Calculating output of each layer for each input node $(t,y(t)), t=1,2,3,\cdots N$.

Layer LA: $a=\omega_{11}t$

Layer LB: $b=f(\omega_{11}t)=\dfrac{1}{1+e^{-\omega_{11}t}}$

Layer LC: $c_1=b\omega_{21}, c_2=y_2(t)b\omega_{22}, c_3=y_3(t)b\omega_{23},\cdots,c_n=y_n(t)b\omega_{2n}$

Layer LD: $d=\omega_{31}c_1+\omega_{32}c_2+\cdots+\omega_{3n}c_n-\theta_{y_1}$

4). Calculating the error of network output and desiring output, and adjusting the weights and thresholds by the errors.

The error of layer LD: $\delta=d-y_1(t)$

The error of layer LC:

$$\delta_1=\delta\left(1+e^{-\omega_{11}t}\right),\delta_2=\delta\left(1+e^{-\omega_{11}t}\right),\cdots,$$
$$\delta_n=\delta\left(1+e^{-\omega_{11}t}\right)$$

The error of layer LB:

$$\delta_{n+1}=\frac{1}{1+e^{-\omega_{11}t}}\left(1-\frac{1}{1+e^{-\omega_{11}t}}\right)\times\left(\omega_{21}\delta_1+\omega_{22}\delta_2+\cdots+\omega_{2n}\delta_n\right)$$

Adjust the connection weights from layer LA to layer LB.

$$\omega_{11}=\omega_{11}+at\delta_{n+1}$$

Adjust the threshold.

$$\theta=\left(1+e^{-\omega_{11}t}\right)\left(\frac{\omega_{22}}{2}y_2(t)+\frac{\omega_{23}}{2}y_3(t)+\cdots+\frac{\omega_{2n}}{2}y_n(t)-y_1(0)\right)$$

5). Determining whether the training is ended, if not, return step 3).

Finally, forecasting the result by training grey neural network.

4. FORECASTING EXAMPLE

Ceramic industrial output from 2002 to 2010 in Jingdezhen is shown in Table I, which comes from Jingdezhen Bureau of Statistics. Table I shows that ceramic industrial output of Jingdezhen is affected by many factors, so that the output has large volatility. In this paper, we choose the output of ceramic for daily, art ceramic, construction sanitary ceramic and industrial ceramic as major influencing factors, and forecast ceramic industrial output of Jingdezhen.

Table I Ceramic Industry Output values from 2002 to 2010 in Jingdezhen

Year	Ceramic Industry Output values (Unit: 100 thousand yuan)				
	the total output value of Jingdezhen ceramic industry	ceramic for daily	art ceramic	construction sanitary ceramic	industrial ceramic
2002	168000	70900	79600	5700	11800
2003	175000	82700	57500	8500	26300
2004	205000	97600	67600	9500	30300
2005	246000	111500	85700	11500	37300
2006	320000	135100	119560	18200	47140
2007	420000	179000	156000	25000	60000
2008	701500	231500	220600	167400	82000
2009	1003000	306000	326900	232600	137500
2010	1551700	488800	509300	355400	203600

In this example, input data is 5 dimensions and output data is 1 dimension, so that the structure of grey neural network is 1-1-5-1. That is, layer LA has 1 node, the time series t is input data, layer LB has 1 node. Layer LC has 5 nodes, from node 2 to node 5, there are normalized output data of ceramic for daily, art ceramic, construction sanitary ceramic and industrial ceramic respectively, forecast result is output data in layer LC. There are 9 rows of data in Table I, all data are divided by 10000 firstly, which can reduce volatility of data. Use data in 2002-2006 as model building data set, learn and

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train 100 times, and use data in 2007-2010 as ex-post testing set to compare the forecasting accuracy. Initialization weights and thresholds of grey neural network are random data, which leads to different forecasting results. After many times of forecast comparison, when a=0.5, b1=0.55, b2=0.58, b3=0.38, b4=0.25, the forecasting result is best.

Table Ⅱ Comparison of forecasting results

Year	Actual value	GM(1,1)		GNNM	
		Forecasting value	Relative error	Forecasting value	Relative error
2002	168000	168000	0.00%	--	--
2003	175000	80756	53.85%	--	--
2004	205000	117350	42.76%	--	--
2005	246000	170526	30.63%	--	--
2006	320000	247798	22.56%	--	--
2007	420000	360086	14.27%	460186	-9.57%
2008	701500	523256	25.41%	714142	-1.80%
2009	1003000	760366	24.19%	1000780	0.22%
2010	1551700	1104920	28.79%	1571275	-1.26%

Table Ⅲ Comparison of verification indices

	Relative error	osterior ratio	Small error probability	Relational grade
GM(1,1)	26.95%	0.0811	0.8889	0.68
GNNM	3.21%	0.0071	1	0.65

Table Ⅳ Criterion of accuracy grade

	good	medium	pass	fail
relative error	<1%	<5%	<10%	>=10%
posterior ratio	<0.35	<0.5	<0.65	>=0.65
small error probability	>0.95	>0.8	>0.7	<=0.7

From Tables Ⅱ-Ⅳ it can be seen that the relative error of GM(1,1) is about 8 times of GNNM, posterior ratio and small error probability of GNNM are better than of GM(1,1), and GNNM gets quite satisfactory forecasting result. Where, posterior ratio of GNNM decreases greatly, which means that the error focused on the small-scale and achieves higher precise prediction. Fig. 2 shows GNNM converges fast and the network gets optimization quickly. In Fig. 3, the forecasting curve of GNNM is more close to the actual curve than the curve of GM(1,1), especially the forecasted value after 2008. This shows GNNM has the better forecasting effectiveness and accuracy.

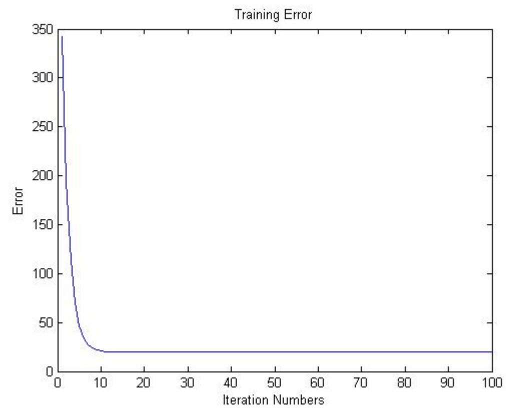

Fig. 2 Training Error

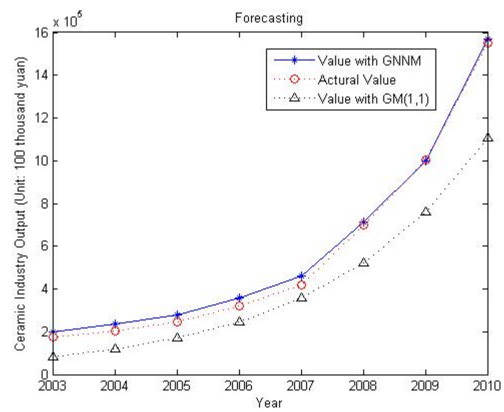

Fig. 3 Curve of Forecasting with Different Models

5. CONCLUSION

This paper discusses the modeling idea and the key steps of the grey neural network model about the ceramic industrial output forecasting. This model is applied to forecast in Matlab 7, and good result is obtained. The grey neural network model is built by combining grey model and neural network model, which expands the application scope of GM(1,1) and improves the forecasting precision. In addition, the parameters of the grey neural network model influence the forecasting results greatly. In the future research, genetic algorithm can be used to optimize the parameters, which make prediction results more realistically reflect the actual situation.

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