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A New VWBFGM (1,1r) –BPNN Model Based on Power Function $x^{-\alpha}$ Transformation for University Graduates' Employment Forecasting

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Abstract—**In The continuously increasing enrolment of higher education has created some employment problems. It is very meaningful that we scientifically forecast and analysis the graduates employment trends. Based on the basic principle of Grey Model with First Order Differential Equation and one Variable (GM(1,1)) and Power Function $x^{-\alpha}$ Transformation, in this paper, a new Variable Weights Buffer First-entry none linear Grey Model with First Order Differential Equation and one Variable (VWBFGM(1,1r)) model was established by minimum total residual sum of square. Furthermore, a VWBFGM(1,1r) (Variable Weights Buffer First-entry Grey Model with First Order Differential Equation and one Variable)- BPNN (Back-Propagation) neural network model is established. The single variable change rate of the proposed VWBFGM(1,1r) - BPNN model is less than or greater than the index component, can be used for fitting a single sequence of non-negative data and forecasting widely, and also can interfuse the advantages in the uncertainty domain in radial basis function neural network.**

Keywords- ***VWBFGM (1,1r) –BPNN Model, University Graduates' Employment Forecasting, Power Function $x^{-\alpha}$ Transformation***

I. INTRODUCTION

With the rapid development of China's higher education and the continuously increasing enrolment of many higher education, the enrollment growth is larger than the social economic growth and market of high level talented person's demand growth. Thus the employment situation of college students in recent years is more and more serious, the graduates employment prospects and employment trends also become sensitive topic in recent years. In recent years, the difficult employment of college students has become one of the most prominent social problems in China, which in the context of the global crisis is particularly prominent. The employment rate of college graduates is a measure of the schools is one of the most important quality index, accurate and reliable employment trend prediction can provide the reference for graduate school decision making new development strategy. It is a very valuable information that we do a good job of predicting the trend of employment of graduates of the college and university students himself. Ease the employment predicament, need to explore various factors affecting the employment of college students, so as to determine the key factors affecting the employment of College Students. In recent decades, many advanced theories have been produced in studies on Employment Forecasting [1-15]. By using of a Bayesian vector autoregressive (BVAR) estimation technique, which incorporate the interindustry input-output table relationships into the labor market forecasting model, LeSage et al. [1] presented the results of using input-output tables as a source of Bayesian prior information in a national employment forecasting model. By incorporating regional input-output coefficients instead of national coefficients, using the coefficients both to specify the prior means in one model and to weight the variances of a Minnesota-type prior in a second model, and including final-demand effects and links to national and world economies, Partridge et al. [2] advanced previous regional Bayesian vector autoregression (BVAR) employment -forecasting approach -es, compared out-of-sample forecasts produced by the generalized BVAR models to forecasts produced from an autoregressive model, an unconstrained VAR model, and a Minnesota BVAR model. Based on a combination of top-down and bottom-up techniques, Blien et al. provided an outline of a method useful for projecting employment in all 327 (western) German districts for a time span of two years. By using the mean square forecast error (MSFE) metric, in [5], Rapach et al.

examined different approaches to forecasting monthly US employment growth in the presence of many potentially relevant predictors, first generated simulated out-of-sample forecasts of US employment growth at multiple horizons using individual ARDL models based on 30 potential predictors, considered different methods from the extant literature for combining the forecasts generated, and investigated the performance of the forecast combining methods over the last decade, as well as five periods centered on the last five US recessions. By means of the regional level a Bayesian approach, LeSage [8] analyzed forecasts of turning points in a multicountry setting. To forecast the industrial employment figures of the Southern California economy, Puri et al. [10] constructed a Bayesian vector autoregressive model. In [11], Wang et al. established an ARIMA model on the employment information of computer industry from 2002 to 2007 in China, and gived a prediction of situation in 2008 by using the proposed model. In [15], Zeng et al. constructed a GM(1,1) model to predict the tuition defaulting situation in 2010 based on the tuition defaulting situation from 2005 to 2009 in a university in Jiangxi Province of China. But the GM(1,1) models usually fail to reduce errors between predicted value and actual value if the raw data is irregular and small. The grey system theory, which was firstly brought forward by Deng in [16], has developed rapidly in recent years[17-23].

Based on the basic principle of Grey Model with First Order Differential Equation and one Variable (GM(1,1)) and power function $x^{-\alpha}$ transformation, motivated by [19-20], a new VWBFGM(1,1^r) (Variable Weights Buffer First-entry Grey Model with First Order none linear Differential Equation and one Variable) model was established by minimum total residual sum of square. Furthermore, a VWBFGM(1,1r) - BPNN (Back-Propagation) neural network model is established. The single variable change rate of the proposed VWBFGM(1,1r) - BPNN model is less than or greater than the index component, can be used for fitting a single sequence of non-negative data and forecasting widely, and also can interfuse the advantages in the uncertainty domain in radial basis function neural network, the smooth degree of discrete data after power function $x^{-\alpha}$ transformation is enhanced. So the VWBFGM(1,1^r) - BPNN method based on power function $x^{-\alpha}$ transformation can widen range of application of grey model.

II. VWBFGM(1,1^R) MODEL

A. GM(1,1^r) model based on Power Function $x^{-\alpha}$ Transformation

The design thought of grey modeling is: the original data sequence (assuming that all data is positive) after a cumulative, form an increasing sequence, the new sequence data connection point close to exponential function curve, the more the number of accumulated, formed by connecting data points will be more close to an exponential function. Then according to the exponential function can be extrapolated to the next (i.e. the first forecast) accumulation and, after the final regressive reduction to obtain original sequence prediction value. The construction procedure of GM(1,1^r) model is carried out as follows[22]:

Consider the original predicted data sequence $x^{(0)}$:

$$u^{(0)}=\{u^{(0)}(1),u^{(0)}(2),\cdots,u^{(0)}(n)\},$$

Process the original data sequence based on power function $x^{-\alpha}$ transformation

$$x^{(0)}=\{x^{(0)}(1),x^{(0)}(2),\cdots,x^{(0)}(n)\}$$

where

$$x^{(0)}(k)=\left(u^{(0)}(k)\right)^{-\alpha},i=1,2,\cdots,n.$$

and then the first-order accumulated generating operation (1-AGO) of $x^{(0)}$ is given by :

$$x^{(1)}=\{x^{(1)}(1),x^{(1)}(2),\cdots,x^{(1)}(n)\}. \quad (1)$$

where the first-order accumulated generating operation sequence as

$$x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i),k=1,2,\cdots,n.$$

The differential equation of (1) constituted by the one-order grey model can be expressed as:

$$\frac{dx^{(1)}(t)}{dt}+ax^{(1)}(t)=b, \quad (2)$$

where a and b are the grey developmental coefficient and the grey control parameter respectively.

Rewriting (2) as

$$\frac{dx^{(1)}(t)}{dt}+a\left(x^{(1)}(t)\right)^{r}=b, \quad (3)$$

Deriving the equation (3), we have

$$\frac{d^2x^{(1)}(t)}{dt^2}+ar\left(x^{(1)}(t)\right)^{r-1}\frac{dx^{(1)}(t)}{dt}=0, \quad (4)$$

From (4), it is easy to see that the change rate of $x^{(0)}$ is nonlinear, that is

$$\frac{dx^{(0)}(t)}{dt}+ar\left(x^{(1)}(t)\right)^{r-1}x^{(0)}(t)=0, \quad (5)$$

Deriving the equation (3) in term of r, one can obtain

$$\frac{d\left(\frac{dx^{(1)}(t)}{dt}\right)}{dr}+a\left(x^{(1)}(t)\right)^{r}\ln x^{(1)}(t)=0, \quad (6)$$

From (6), the single variable change rate of the GM(1,1^r) model is less than the index component when $r<1$, the single variable change rate of the GM(1,1^r) model is greater than the index component when $r>1$. The model (6) can reflect the original sequence information.

r is calculated by using of direct search method. The parameters a and b can be solved by means of the least-square method as follows:

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y_N ,$$

where

$$B = \begin{bmatrix} -\frac{1}{2}(x^{(1)}(1)+x^{(1)}(2))^r & 1 \\ -\frac{1}{2}(x^{(1)}(2)+x^{(1)}(3))^r & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(x_m^{(1)}(n-1)+x_m^{(1)}(n))^r & 1 \end{bmatrix}$$

and

$$Y_N = [x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n)]^T .$$

The prediction value of the grey model with respect to the data sequence $x^{(1)}$ is given by

$$\hat{x}^{(1)}(k) = (x^{(0)}(1) - \frac{b}{a})e^{-a(k-1)} + \frac{b}{a}, k = 2,3,\cdots, \quad (7)$$

from (7), the modeling value $\hat{x}^{(0)}$ can be derived to be

$$\hat{x}^{(0)}(1) = \hat{x}^{(1)}(1) = x^{(0)}(1) .$$

And $\hat{x}^{(0)}(k)$ analogue value will be:

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1)$$

$$= (x^{(0)}(1) - \frac{b}{a})(1-e^a)e^{-a(k-1)}, k = 2,3,\cdots .$$

B. FGM(1,1^r) model based on Power Function $x^{-\alpha}$ Transformation

The modeling procedure of FGM(1, 1) is carried out in detail as follows by inserting an arbitrary number in front of the original series to extract the messages from its first entry.

Let $u^{(0)}$ be the original predicted data sequence:

$$u^{(0)} = \{u^{(0)}(0), u^{(0)}(1), u^{(0)}(2), \cdots, u^{(0)}(n)\},$$

where the first entry $x^{(0)}(0)$ is an arbitrary number.

Process the original data sequence based on power function $x^{-\alpha}$ transformation

$$x^{(0)} = \{x^{(0)}(0), x^{(0)}(1), \cdots, x^{(0)}(n)\}$$

where

$$x^{(0)}(k) = \left(u^{(0)}(k)\right)^{-\alpha}, i = 0,1,2,\cdots,n.$$

and the first-order accumulated generating operation (1-AGO) of $x^{(0)}$ is given by:

$$x^{(1)}(k) = \sum_{i=0}^{k} x^{(0)}(i), k = 0,1,2,\cdots,n.$$

Based on the series

$$x^{(1)} = \{x^{(1)}(0), x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\},$$

(8)

the grey generated model can be given by the differential equation

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b, \quad (9)$$

where a and b are the grey developmental coefficient and the grey control parameter respectively.

The grey derivative for the first-order grey differential equation with 1-AGO data as the intermediate information can be conventionally expressed as

$$\frac{dx^{(1)}(t)}{dt} = \lim_{\Delta t \to 0} \frac{x^{(1)}(t+\Delta t) - x^{(1)}(t)}{\Delta t},$$

and

$$\frac{dx^{(1)}(t)}{dt} = \frac{\Delta x^{(1)}(t)}{\Delta t} = x^{(1)}(t+1) - x^{(1)}(t) = x^{(0)}(t+1) .$$

Rewriting (9) as

$$\frac{dx^{(1)}(t)}{dt} + a\left(x^{(1)}(t)\right)^r = b,$$

(10)

Deriving the equation (10), we have

$$\frac{d^2x^{(1)}(t)}{dt^2} + ar\left(x^{(1)}(t)\right)^{r-1} \frac{dx^{(1)}(t)}{dt} = 0, \quad (11)$$

From (11), it is easy to see that the change rate of $x^{(0)}$ is nonlinear, that is

$$\frac{dx^{(0)}(t)}{dt} + ar\left(x^{(1)}(t)\right)^{r-1} x^{(0)}(t) = 0,$$

(12)

Deriving the equation (10) in term of r, one can obtain

$$\frac{d\left(\frac{dx^{(1)}(t)}{dt}\right)}{dr} + a\left(x^{(1)}(t)\right)^r \ln x^{(1)}(t) = 0,$$

(13)

r is calculated by using of direct search method. The parameters a and b can be solved by means of the least-square method as follows:

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y_N ,$$

where

$$B=\begin{bmatrix} -\frac{1}{2}(x^{(1)}(0)+x^{(1)}(1))^r & 1 \\ -\frac{1}{2}(x^{(1)}(1)+x^{(1)}(2))^r & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(x_m^{(1)}(n-1)+x_m^{(1)}(n))^r & 1 \end{bmatrix}$$

and

$$Y_N=[x^{(0)}(1),x^{(0)}(2),\cdots,x^{(0)}(n)]^T.$$

The prediction value of the GM model with respect to the data sequence $x^{(1)}$ is given by

$$\hat{x}^{(1)}(k)=(x^{(0)}(1)-\frac{b}{a})e^{-a(k-1)}+\frac{b}{a},k=1,2,3,\cdots.(14)$$

From (14), the modeling value $\hat{x}^{(0)}$ can be derived to be

$$\hat{x}^{(0)}(0)=x^{(0)}(0)$$

And

$$\hat{x}^{(0)}(k)=\hat{x}^{(1)}(k)-\hat{x}^{(1)}(k-1)$$

$$=(x^{(0)}(1)-\frac{b}{a})(1-e^{a})e^{-a(k-1)},k=1,2,3,\cdots.$$

C. VWBFGM(1,1^r) model based on Power Function $x^{-\alpha}$ Transformation

For weakening the fluctuations of the original load sequences, strengthening the trend of modeling sequence and improving forecast accuracy, we use variable weights buffer operator and background value optimization to improve the FGM(1,1^r) (First-entry Grey Model with First Order none linear Differential Equation and one Variable) model to build the VWBFGM(1,1^r) (Variable Weights Buffer First-entry Grey Model with First Order none linear Differential Equation and one Variable) model. The modeling process is as follows. Let

$$U^{(0)}=\left[u^{(0)}(0),u^{(0)}(1),\cdots,u^{(0)}(n)\right].$$

Process the original data sequence based on power function $x^{-\alpha}$ transformation

$$x^{(0)}=\{x^{(0)}(0),x^{(0)}(1),\cdots,x^{(0)}(n)\}$$

where

$$x^{(0)}(k)=\left(x^{(0)}(k)\right)^{-\alpha},i=0,1,2,\cdots,n.$$

Pretreatment of the original data sequence using variable weight buffer operator D to weaken the randomness and enhance tendency,

$$\begin{cases} Y^{(0)}=\left[y^{(0)}(1),y^{(0)}(2),\cdots,y^{(0)}(n)\right] \\ y^{(0)}(k)=\lambda x^{(0)}(n)+(1-\lambda)x^{(0)}(k),k=1.2.\cdots,n \end{cases}$$

Then the first-order accumulated generating operation sequence as

$$\begin{cases} Y^{(1)}=\left[y^{(1)}(0),y^{(1)}(1),\cdots,y^{(1)}(n)\right] \\ y^{(1)}(k)=\sum_{i=0}^{k}y^{(0)}(i),k=0,2,\cdots,n \end{cases}$$

Tectonic the variable weights background value $Z^{(1)}$

$$\begin{cases} Z^{(1)}=\left[z^{(1)}(1),z^{(1)}(2),\cdots,z^{(1)}(n)\right] \\ z^{(1)}(k)=\eta y^{(1)}(k-1)+(1-\eta)y^{(1)}(k),k=1,2,\cdots,n \end{cases}$$

where η is background value generating weighting coefficient, $0\le\eta\le1$.Now, Let us establish GM (1,1) Model

$$\frac{dy^{(1)}(t)}{dt}+az^{(1)}(k)=b, \tag{15}$$

where a and b are model parameters.

Rewriting (15) as

$$\frac{dy^{(1)}(t)}{dt}+a\left(z^{(1)}(t)\right)^r=b, \tag{16}$$

Deriving the equation (16), we have

$$\frac{d^2x^{(1)}(t)}{dt^2}+ar\left(x^{(1)}(t)\right)^{r-1}\frac{dx^{(1)}(t)}{dt}=0, \tag{17}$$

From (17), it is easy to see that the change rate of $x^{(0)}$ is nonlinear, that is

$$\frac{dx^{(0)}(t)}{dt}+ar\left(x^{(1)}(t)\right)^{r-1}x^{(0)}(t)=0, \tag{18}$$

Deriving the equation (15) in term of r, one can obtain

$$\frac{d\left(\frac{dx^{(1)}(t)}{dt}\right)}{dr}+a\left(x^{(1)}(t)\right)^r\ln x^{(1)}(t)=0, \tag{13}$$

r is calculated by using of direct search method. We can find the values of a and b by the following equation,

$$[a,b]^T=\left(B^TB\right)^{-1}B^TY$$

$$B=\begin{bmatrix} -(z^{(1)}(1))^r & 1 \\ -(z^{(1)}(2))^r & 1 \\ -(z^{(1)}(3))^r & 1 \\ \vdots & \vdots \\ -(z^{(1)}(n))^r & 1 \end{bmatrix}, \quad Y=\begin{bmatrix} y^{(0)}(1) \\ y^{(0)}(2) \\ y^{(0)}(3) \\ \vdots \\ y^{(0)}(n) \end{bmatrix}.$$

The result of model is

$$\hat{y}^{(0)}(k)=\left(y^{(0)}(0)-\frac{b}{a}\right)e^{-a(k-1)}+\frac{b}{a},k=0,1,\cdots,n.$$

Cumulative diminishing gets predictive value

$$\hat{y}^{(0)}(k)=\hat{y}^{(1)}(k)-\hat{y}^{(1)}(k-1)$$

III. VWBFGM(1,1^R) - BPNN MODEL

BP network, which is named by it's learning algorithm: Error Back Propagation, was proposed by Rumelhart, Hinton and Williams in [24]. It is perhaps the most widely used supervised training algorithm for multi-layered feed forward neural networks. In university graduates' employment forecasting, the randomicity of errors and disturbance will decrease the VWBFGM(1,1^r) (Variable Weights Buffer First-entry Grey Model with First Order none linear Differential Equation and one Variable) model's accuracy. Thus we decompose the original predicted data sequence $x^{(0)}$ to the representation of regular change of the parameters $x'^{(0)}$ and the representation of error and disturbance during data acquisition and process $w^{(0)}$,

$$x^{(0)}=x'^{(0)}+w^{(0)},$$

where $x'^{(0)}$ is modeled and predicted by the VWBFGM(1,1^r) (Variable Weights Buffer First-entry Grey Model with First Order none linear Differential Equation and one Variable) model, $w^{(0)}$ is apt to model and predict with BP network because of it's capability for nonlinear problem.

The procedures of deriving VWBFGM(1,1r) - BPNN model are as follows:

Step 1: model the original predicted data sequence $x^{(0)}$ with VWBFGM(1,1r) model and get the estimate output $\hat{x}^{(0)}$;

Step 2: structure BPNN for $w^{(0)}$, where $w^{(0)}=x^{(0)}-\hat{x}^{(0)}$;

Step 3: correct the estimate sequence $\hat{x}^{(0)}$ of the VWBFGM(1,1r) model with the output of the BPNN and attain the corrected parameter serial $x'^{(0)}$.

REFERENCES

[1] J. P. LeSage, M. Magura, "Using interindustry input-output relations as a Bayesian prior in employment forecasting models," International Journal of Forecasting, vol. 7, no. 2, 1991, pp. 231–238.

[2] M. D. Partridge, D. S. Rickman, "Generalizing the Bayesian Vector Autoregression Approach for Regional Interindustry Employment Forecasting," Journal of Business & Economic Statistics, vol. 16, no. 1, 1998, pp. 62–72.

[3] M. Magura, "IO and spatial information as Bayesian priors in an employment forecasting model," The Annals of Regional Science,. Springer-Verlag, 1998, vol. 32, pp. 495-503.

[4] U. Bliena, A. Tassinopoulos, "Forecasting Regional Employment with the ENTROP Method," Regional Studies, vol. 35, no. 2, 2001, pp. 113-124.

[5] D. E. Rapach, J. K. Strauss, "Forecasting US employment growth using forecast combining methods," Journal of Forecasting, vol. 27, no. 1, 2008, pp. 75-93.

[6] R. H. Murillo, M. T. Owyang, "The information content of regional employment data for forecasting aggregate conditions," Economics Letters, vol.90, 2006, pp. 335-339.

[7] F. J. Trıvez, J. Mur, "A short-term forecasting model for sectoral regional employment," The Annals of Regional Science,. Springer-Verlag, 1999, vol. 33, pp. 69-91.

[8] J. P. LeSage, "Forecasting turning points in metropolitan employment growth rates using Bayesian techniques," Journal of Regional Science, vol. 30, no. 4, 1990, pp. 533–548.

[9] M. Mayor, A. J. López, R. Péreza, "Forecasting Regional Employm -ent with Shift–Share and ARIMA Modelling," Regional Studies, vol. 34, 2000, pp. 503-514.

[10] A. Puri, G. Soydemir, "Forecasting industrial employment figures in Southern California: A Bayesian vector autoregressive model," The Annals of Regional Science,. Springer-Verlag, 1998, vol. 32, pp. 495-503.

[11] X. G. Wang, Y. L. Liu, "ARIMA Time Series Application to Employment Forecasting," Proceedings of 2009 4th International Conference on Computer Science & Education, 2009, pp. 1124-1127.

[12] M. Han, D. F. Guo, "Application of Prediction Feature Selection of Undergraduates Based on S VM in Employment," Journal of Hangzhou Normal University (Natural Science Edition), vol.8, no. 5, pp. 358–362, 2009(In Chinese).

[13] X. L. Yan, Y. H. Nie, "Application of the clusterng analysis in the forecast of enployment of graduates," Journal of Guangxi Universi -ty of Technology, vol. 16, no. 4, 1994, pp. 82–84.

[14] J. J. Wang, J. X. Wang, Q. S. Huang, "The Design and Realizes about Employment Forecast System of Graduate Based on Data Warehouse,"Journal of Chuxiong normal University, vol. 24, no. 3, 2009, pp. 20–26.

[15] W. L. Zeng, Y. P. Wan, "Grey prediction of college students' tuition defaulting based on GM(1,1) model: a case study in a university in Jiangxi Province," Journal of Nanchang Institute of Technology, vol. 30, no. 1, 2011, pp. 24–26.

[16] Julong Deng. Grey Theory Basis. Wuhan: Huazhong University of Science and Technology Press, 2002, 2.

[17] Y Wang, "The Application of Grey Model System in Forecasting of Water Demand," Systems Engineering, vol.14, no. 1, 1996, pp.60-64.

[18] T. L. Tien, "The indirect measurement of tensile strength by the new model FGMC(1, n)," Measurement, vol. 44, 2011, pp.1884-1897.

[19] H. Y. Tang, F. Ma, K. Yang, B. Lu, "A study of information renewal GM (1 ,1) model for predicting urban medium and long-term water demand", Engineering Journal of Wuhan University, 2004, vol. 37, no. 6, pp.32-35.

[20] T. L. Tien, "The indirect measurement of tensile strength of material by the grey prediction model GMC(1,n)," Measurement Science & Technology, vol.16,2005, pp.1322–1328.

[21] T. L. Tien, "A new grey prediction model FGM(1, 1)", Mathematical and Computer Modelling, vol. 49, 2009, pp.1416–1426.

[22] H. S. Zhang, "The Grey Model GM (1, 1r) and Application of Per Capita Living-Space in the Country," Systems Engineering-theory & Practice, vol. 1, pp.74-76, 1994. (in Chinese)

[23] F. Zha, B. Q. Hu, "Prediction of gyro motor's state based on grey model and BP neural network," 2009 Second International Conference on Intelligent Computation Technology and Automation, 2009, pp. 87-90.

[24] D. E. Rumelhart, G. E. Hinton, R. J. Wilhams, "Learning internal representations by error propagation ," Parallel Distributed Processing, pp.318-362, 1986.