Regional Logistics Demand Forecasting: a Method Based on Improved Grey Neural Network

Lin Wang[1, 3], Zhonghua Yang[1, 3,*], Chen Xue[2]

1 *School of Management*
Wuhan University of Science & Technology
Wuhan 430081, China
2 *School of Machinery & Automation*
Wuhan University of Science & Technology
Wuhan 430081, China
3 Hubei Province Industrial Policy and Management Research Center
Wuhan 430081, China

***Abstract* — Regional logistics demand prediction directly affects regional economy development and logistics planning. Grey prediction, BP neural network, grey neural network and other methods have been widely used in the prediction of complex nonlinear logistics demand system. In this study, an improved grey neural network model was proposed based on these models. First, in this model, the grey influence factors and the grey targets were completely taken as inputs, and the actual targets were taken as outputs. Then, the weights of neural network were optimized by continuous positive input and feedback adjustment to improve the prediction accuracy. Finally, an experiment was conducted to verify the effectiveness of the proposed model by analyzing the historical logistics demand data of Hubei province. The results show that the improved grey neural network is feasible and effective. The experiment results demonstrate the promising application of the proposed method in regional logistics demand forecasting.**

Keywords - Regional logistics; Demand prediction; BP neural network; Improved grey neural network

I. INTRODUCTION

As an important component of the regional economy, regional logistics plays a key role in national and regional economies in two significant ways [1]. First, regional logistics is one of the major expenditures for businesses, thereby affecting and being affected by other economic activities. Second, regional logistics supports the movement of many economic transactions; it is an important aspect of facilitating the sale of all goods and services [2]. Regional logistics demand is the total volume of logistics flow within the activities including transportation, storage, packing, loading and unloading, handling, and distribution procession [3, 4]. Regional logistics forecasting is the key step in regional logistics system planning and logistics resources rationalization, and scientific prediction of regional logistics demand will provide quantitative basis for regional logistics planning, development policy and situation analysis of logistics market supply and demand.

Regarding regional logistics demand forecasting, various quantitative forecasting methods have been developed by scholars in recent years. Those forecasting methods can be roughly divided into regression analysis method, grey forecasting method, artificial neural network (ANN), and support vector machine (SVM) [5-7]. Due to the limitation of single forecasting method, it is difficult to obtain satisfactory results. The hybrid modeling methods which integrate the effective information of the single model and improve the prediction accuracy, thus make it is widely applied to solve complex system predictive issue. Specifically, because the grey neural network model combined the advantages of fewer samples and simpler calculation of grey theory and the characteristics of high accuracy, good robustness and strong nonlinear approximation ability of neural network modeling, it is widely used in the prediction of the nonlinear logistics demand[8].This paper establishes a hybrid forecasting method based on grey neural network model, which take both parameters and targets of the grey prediction as the input of BP neural network and revise weights in neural network training. Experiment results demonstrate that the model has better prediction accuracy, feasibility and reliability than existing methods.

The reset of this paper is organized as follows. Section 2 analyzed the factor of regional logistics demand forecasting, and the index system of regional logistics demand forecast was established. Section 3 gave the solution methodology, a hybrid forecasting model based on improved grey neural network was studied, and the network configuration was confirmed using the stepwise checkout and iterative gradient descent methods. Section 4 presented an illustrative example of logistics demand prediction in Hubei province to explore the application of the improved grey neural network. Conclusions are summarized in Section 5.

DOI 10.5013/IJSSST.a.17.01.13 ISSN: 1473-804x online, 1473-8031 print

II. LITERATURE REVIEW

II.1. LOGISTICS DEMAND PREDICTION

Regional logistics demand is the total volume of logistics flow within the activities including transportation, storage, packing, loading and unloading, handling, and distribution procession in a certain period of time[2]. Logistics demand prediction is a forecast for the future logistics demand based on historical data on the change of logistics demand and the relationship among the factors affecting the change of logistics demand. Because regional economy is the inherent and determinative factor of regional logistics demand, it is feasible to forecast regional logistics demand by economic indexes which can accelerate the harmonious development of regional logistics industry and regional economy. Research showed that the regional economic scale, industrial structure and economic space layout are the significant respects of regional logistics demand [9, 10]. Therefore, this paper selects the total freight volume as the logistics demand target and constructs the forecast index system as shown in Fig.1.

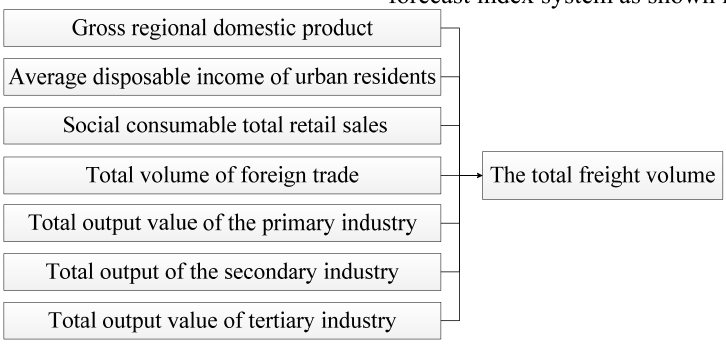

Figure 1. Forecast Index System

II.2. FORECASTING MODEL OF LOGISTICS DEMAND

There are several kinds of models often used in forecasting regional logistics demand. Trend extrapolation method extrapolates the future development trends bases on the hypothesis that the regional logistics will develop steadily [11]. Grey system method predicts the change of logistics demand by the generation and development of original data sequence and excavation of inherent rules of the original data[12]. Regression method obtains the change rules through the analysis between explained variable and explanatory variables. Support Vector Regression (SVR) is also considered as a useful technique for data prediction [3]. Moreover, Kopela and Tuominen presented an Analytic Hierarchy Process-based approach to demand forecasting [13]. In order to enhance the forecasting efficiency and precision, extended Kalman Filter is applied to training artificial neural network in Miao and Xi's study [14].

Each method has unique characteristics. The performance of the regression analysis method is not satisfactory because this method is parametric; additionally, it is developed on the assumption that the time series being forecasted are linear and stationary. However, it is difficult to give a precise regional logistics demand forecasting expression. Therefore, because of its strong fitting function and good fault tolerance ANN has been widely used in the regional logistics forecasting. Moreover, due to its unique non-parametric, non-assumable, noise-tolerant and adaptive properties, ANN is more effective in describing the dynamics of a non-stationary time series. But ANN has an over-fitting problem and a local minimum problem, which often lead to predicted result distortion [15]. SVM has provided another novel approach to improve the generalization properties of ANN [16]. Although SVM has become a dominant and popular tool in many fields, SVM in the regional logistics demand prediction of research is still at the fledgling stage.

Because of nonlinear, stochastic, dynamic and uncertain characteristics of the logistics demand forecasting system, the forecasting model should develop toward the nonlinear, multi-parameter direction. The combined forecasting methods which integrate the effective information of the single model and improve the prediction accuracy, thus make it is widely applied to solve complex system predictive issue [12]. The purpose of this paper is to establish a combined forecasting model to predict regional logistics demand, which is an important procedure on decision making of regional logistics planning. In order to improve the accuracy of the prediction, a combined method is established based on grey neural network model, which take both parameters and targets of the grey prediction as the input of BP neural network and revise weights in neural network training.

III. SOLUTION METHODOLOGY

III.1. GM (1, 1)

The grey system theory was proposed by Deng[17]. The grey model (GM) is one of the best features in grey system theory. Generally, the grey model is written as GM (m, n), where m is the order and n is the number of variable of the modeling equation. The grey theory applies to the concern of sample of small data, in which systems for the "uncertainty" , "multi-input" , "discrete data" , and" incomplete data" can effectively be addressed.

DOI 10.5013/IJSSST.a.17.01.13 ISSN: 1473-804x online, 1473-8031 print

GM (1, 1) is the most commonly used grey prediction model, which uses the first order differential equation to formulate laws about its variables changing with time. After the input of original sequence X (0), and accumulate X (0) to X (1) if the step ratio meets the modeling conditions. Then a differential equations are established for X (1).

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

Using least-squares method it can be obtained:

$$\hat{A} = [a,b]^T = (B^T B)^{-1} B^T Y_n \tag{2}$$

Where

$$B = \begin{bmatrix} -\frac{1}{2}(X^{(1)}(1) + X^{(1)}(2)) & 1 \\ -\frac{1}{2}(X^{(1)}(2) + X^{(1)}(3)) & 1 \\ \cdots & \cdots \\ -\frac{1}{2}(X^{(1)}(n-1) + X^{(1)}(n)) & 1 \end{bmatrix} \tag{3}$$

$$Y_n = (X^{(0)}(2), X^{(0)}(3), X^{(0)}(4), \ldots, X^{(0)}(n))^T \tag{4}$$

After using the least-square method to calculate the parameters, the solutions of the differential equations are used to restore the cumulative sequence forecast value and the prediction values of the original discrete data driven by using IAGO process are as follows:

$$\hat{X}^{(0)}(j) = \hat{X}^{(1)}(j) - \hat{X}^{(1)}(j-1) \tag{5}$$

III.2. BP NEURAL NETWORK

BP neural network is the most widely used feed-forward neural network, and its structure consists of input layer, hidden layer and output layer[18]. The hidden layer may have many layers. The upper and lower layers are connected with each other while each layer has no connection between neurons. BP neural network is parallel distributive processor based on human thinking, it includes two courses. One is the forward propagation, and the actual output value of each unit is processed by the hidden layer scale by scale. Another is the error back-propagation. If the output layer fails to get the wishful output, the difference between the targets and the wishful output will be calculated by the recursive calculation. Then the weight values are adjusted according to the error. This positive feedback adjustment process will continuously circulate until the error is narrowed to the extent permitted[18].

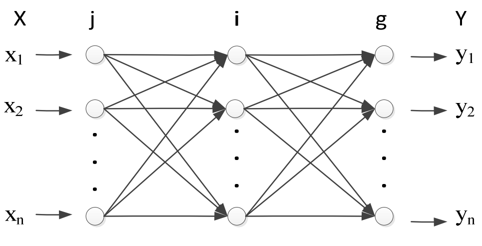

Figure 2. BP Neural Network

III.3. GREY NEURAL NETWORK

GM (1, 1) and BP neural network have not only numerous advantages as mentioned, but also has inevitable shortcomings. Combining these two methods can play their strengths and overcome the shortages of each other. Grey neural network utilizes the character of grey theory to predict the input parameters, and then the BP neural network is employed to input and output training sample data. The model is built by using data accumulation based on grey prediction, which reduces the randomness of the data and clears the law of data change. Besides, the good applicability of BP neural network to deal with nonlinear relationship between inputs and desired outputs helps to obtain a better predicting effect. The following Fig. 3 is a three layer of grey neural network architecture with n inputs and one output.

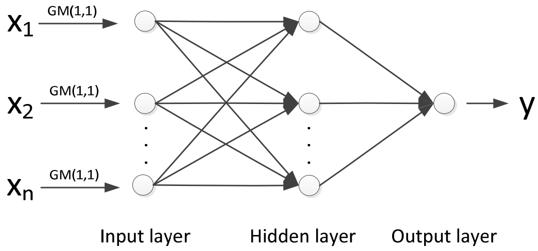

Figure 3. Grey Neural Network

III.4. IMPROVED GREY NEURAL NETWORK

The input of the improved grey neural network model includes not only the grey prediction parameters, but also the grey prediction results. Accordingly, it reduces the heterogeneity of the input factors by combining the forecast data with the actual results which can make full use of the forecasting function of the grey model. Then, through the training of BP neural network algorithm, more satisfactory results can be got. An improved neural network structure with n+1 inputs and one output is shown as Fig. 4.The output value of grey model is added to the bottom as one input of BP neural network.

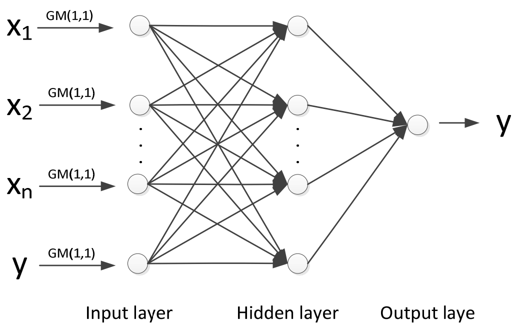

Figure 4. An Improved Grey Neural Network

The steps of the improved grey neural network model:

Step1: use *GM* (1, 1) to predict the influence factors (x_1, x_2,..., x_n) and results y of the test training examples;

Step2: put the grey forecasting data of the *GM* (1, 1) model as input and the actual results as the output to construct the neural network model;

Step3: get the satisfactory results of training by learning a number of training samples and continuous adjustment of weight.

IV. Application of Improved Grey Neural Network

IV.1. Data Sources

According to comprehensiveness, relevance, accessibility and independence principle of predictive index, the total freight volume of Hubei Province (y, million tons) is regarded as indicator of regional logistics demand forecast, and selected the total output value of Hubei Province (x_1, billion yuan), average disposable income of urban residents in Hubei Province(x_2, yuan), total retail sales of social consumer goods in Hubei Province(x_3, billion yuan), total import and export volume of Hubei Province(x_4, billion yuan), total output value of the primary industry in Hubei Province(x_5, billion yuan), total output value of the secondary industry in Hubei Province(x_6, billion yuan)and total output value of the tertiary industry in Hubei Province(x_7, billion yuan)as influencing factors. The original data of the paper comes from "Hubei Statistical Yearbook", listed in the table 1.

Logistics demand data in Hubei Province from 2002 to 2012 are used as training samples, and the data from 2013 to 2014 are taken as test samples. After the grey prediction of data, BP neural network, grey neural network model and the improved grey neural network model are respectively adopted to process data to compare the prediction accuracy of the three models.

TABLE 1 The Original Data

Year	x_1	x_2	x_3	x_4	x_5	x_6	x_7	y
2002	4212.82	6789.0	2129.38	39.55	707.00	1709.90	1795.93	42064
2003	4757.45	7322.0	2358.69	51.10	798.35	1956.02	2003.08	44661
2004	5633.24	8022.8	2619.47	67.72	1020.09	2320.60	2292.55	47073
2005	6590.19	8786.0	2985.83	90.92	1082.13	2852.12	2655.94	50317
2006	7617.47	9803.0	3461.09	117.38	1140.41	3365.08	3111.98	52885
2007	9333.40	11485.0	4115.78	148.58	1378.00	4143.06	3812.34	58523
2008	11328.92	13153.0	5109.74	205.67	1780.00	5082.07	4466.85	75778
2009	12961.10	14367.0	5928.41	172.29	1795.90	6038.08	5127.12	82714
2010	15967.61	16058.4	7013.90	259.07	2147.00	7767.24	6053.37	97007
2011	19632.26	18373.9	8275.20	335.19	2569.30	9815.94	7247.02	110168
2012	22250.45	20839.6	9562.50	319.59	2848.77	11193.10	8208.58	126195
2013	24668.49	22906.4	10885.90	363.89	3098.16	12171.56	9398.77	139740
2014	27367.04	24852.0	11806.27	430.64	3176.89	12840.22	11349.93	154736

IV.2. GREY FORECAST PROCESSING

The grey forecasting model is built by the forecast index system .The model shows that the average variance ratio is less than 0.35, small error probability is 1, the model accuracy is excellent, and the model can meet the requirements of data prediction. And then the fitting data of 2002 to 2017 (Table 2) are available according to the grey model based on the data of 2002 to 2012.

IV.3. Forecasting Ability Test and Result Analysis

First, we use the Matlab to build the model and carry out the training data from 2002 to 2012.Three models all take the original data y in table 1 as targets, with different input for training. BP neural network model uses x_1-x_7 from 2002 to 2012 in the original data table 1 as inputs (7 dimensional input, 1 dimensional output); grey neural network uses x_1-x_7 from 2002 to 2012 in table 2 *GM* (1,1) as inputs (7 dimensional input, 1 dimensional output); improved grey neural network uses x_1-x_7 and Y input from 2002 to 2012 in table 2 *GM* (1,1) data as inputs (8 input, 1 dimensional output).

Different neural networks with different weights are constructed based on these. In this paper, the improved grey neural network model of the middle layer of invisible nodes number is 8.After many experiments, the weights W_1, W_2, threshold B_1 and B_2 are determined and listed in the following table.

TABLE 2 *GM* (1, 1) MODEL PREDICTION RESULTS

Year	x_1	x_2	x_3	x_4	x_5	x_6	x_7	y
2002	4213.0	6789.0	2129.0	39.55	707.00	1710.0	1796.0	42060
2003	5250.0	7247.0	2399.0	80.72	894.40	2386.0	2005.0	39350
2004	6138.0	8125.0	2788.0	94.68	1011.4	2815.0	2345.0	44620
2005	7177.0	9109.0	3240.0	111.1	1143.8	3321.0	2743.0	50600
2006	8391.0	10211	3765.0	130.3	1293.5	3918.0	3209.0	57380
2007	9811.0	11448	4376.0	152.8	1462.8	4623.0	3753.0	65060
2008	11471	12834	5085.0	179.2	1654.2	5454.0	4390.0	73780
2009	13413	14388	5909.0	210.2	1870.7	6435.0	5136.0	83660
2010	15682	16130	6867.0	246.6	2115.5	7592.0	6007.0	94870
2011	18336	18084	7981.0	289.3	2392.4	8956.0	7027.0	107570
2012	21439	20273	9275.0	339.3	2705.4	10567	8219.0	121980
2013	25066.0	22728.0	10778.0	398.0	3059.50	12467.0	9614.0	138320
2014	29308.0	25480.0	12526.0	466.9	3459.90	14708.0	11246.0	156850
2015	34267.7	28565.5	14556.5	547.6	3912.72	17352.7	13154.9	177855.7
2016	40066.5	32024.4	16916.46	642.4	4424.8	20472.7	15387.6	201678.7
2017	46846.5	35902.1	19659.1	753.5	5003.9	24153.7	17999.3	228692.7

TABLE 3 THE IMPROVED GREY NEURAL NETWORK WEIGHTS AND THRESHOLDS

W_1	0.1781	0.3545	0.1396	-0.0764	-0.1719	-0.1209	0.3609	0.2445
	0.1026	0.0803	-0.0151	-0.0053	0.1384	0.2592	0.1794	0.2022
	-0.0815	0.3680	-0.0471	-0.2506	0.0379	0.2037	0.2468	0.4074
	0.1073	-0.1457	0.1700	0.0712	-0.2100	-0.2092	-0.0614	-0.2381
	0.0268	-0.0610	0.1950	-0.2336	0.2363	0.2537	0.2026	0.4116
	0.0264	0.2249	0.0172	-0.2750	0.0529	0.1301	0.3699	0.3533
	-0.0460	0.1423	0.2462	-0.3213	0.0832	-0.1502	0.3197	0.5521
	0.0443	0.1726	0.1670	-0.2414	-0.1356	-0.0399	0.3154	0.4783
W_2	0.5294	0.0492	0.6140	-0.4978	0.5256	0.7966	0.8885	1.0743
B_1	-0.1007	0.3316	-0.0279	0.3690	0.1718	0.0953	0.1020	-0.1416
B_2	-1.9445							

Then the data from 2013 to 2014 was selected as test sample; import the prediction values in 2013 and 2014 from table 2 into trained networks. The trained neural network model, grey neural network model and improved grey neural network model are applied to forecast the logistics demand in Hubei Province. Finally, comparing the actual values and getting the algorithms errors of the three models to verify performance of the model (table 4).

TABLE 4 RELATIVE ERROR OF TEST SAMPLE IN 2013-2014

Models		**BP neural network**		**Grey neural network**		**Improved grey neural network**	
Year	Actual value	Predicted value	Relative error (%)	Predicted value	Relative error (%)	Predicted value	Relative error (%)
2013	139740	132190	5.40%	134490	3.76%	134590	3.69%
2014	154736	142260	8.06%	146610	5.25%	147170	4.89%
Average relative error		6.73%		4.50%		4.29%	

Obviously, the average relative error of the improved grey neural network model is the smallest, the grey neural network is the second, and the average relative error of BP neural network model is the biggest. In the process of modeling and prediction, BP neural network is simply to use the grey model to get the input data. And the grey system and neural network are integrated by the grey neural network model, which make full use of the correction function of the grey forecast error in neural network training process to have a better prediction effect. What's more, on the basis of the grey neural network, the improved grey neural network integrated the nonlinear effect of grey indicators and grey targets on the regional logistics demand, with higher forecasting accuracy and stronger predictive power.

IV.4. Regional Logistics Demand Forecast

The eight dimensional grey forecast values from 2015 to2017 are imputed into the trained improved grey neural network and the forecast values of logistics demand in Hubei Province in the next three years can be got. In the next three years, Hubei Province logistics demand will show a growth trend with rapid growth rate, as shown in Table 5.

TABLE5 Logistics Demand Prediction in 2015~2017

Year	The forecast value of logistics demand
2015	158160
2016	167060
2017	173710

V. Conclusion

The limited prediction accuracy of the traditional BP neural network model and the grey neural network model is caused by high nonlinearity and uncertainty of regional logistics demand forecast data. Therefore, a novel combined forecasting model was built based on improved grey BP neural networks, which can tap useful information to improve prediction accuracy through continuous learning to the historical data, thus greatly improve the accuracy of regional logistics demand prediction.

The results of the practical examples show that the model established in this paper is feasible for regional logistics demand forecasting. Additionally, through the analysis and forecast of historical data, it can get the macro development trend of logistics demand in Hubei Province, and provide reliable data support for regional logistics industry and regional economic development.

Acknowledgment

This work was supported by Humanity and Social Science Youth Foundation of Ministry of Education of China (Grant No.12YJC630266), and the Social Science Research Foundation of Education Bureau of Hubei Province (Grant No.2011jyty130). Additional Funding was received from the Youth Foundation for Talents of Wuhan Science & Technology University (Grant No.2010xz039).

References

[1] Cheong, I. K. Suthiwartnarueput, "ASEAN's initiatives for regional economic integration and the implications for maritime logistics reforms". International Journal of Logistics Management, vol.26, No.3, pp. 479-493, 2015.

[2] Banomyong, R., P. Cook, P. Kent, "Formulating regional logistics development policy: the case of ASEAN". International Journal of Logistics, vol.11,No.5,pp.359-379, 2008.

[3] Chen, S., M. Gan, Y.Y. Tang, "Analysis of predicting the diversity regional logistics demand based on SVR: the case of Sichuan in China". Applied Mathematics & Information Sciences, vol.7, No.2, pp. 645-651, 2013.

[4] Zhang, D.Z., et al., "A robust optimization model for green regional logistics network design with uncertainty in future logistics demand". Advances in Mechanical Engineering, vol.7, No.12, pp. 280-290, 2015.

[5] Albertson, K. J. Aylen, "Forecasting the behaviour of manufacturing inventory". International Journal of Forecasting, vol.19, No.1, pp. 299-311, 2003.

[6] Carbonneau, R., K. Laframboise, R. Vahidov, "Application of machine learning techniques for supply chain demand forecasting". European Journal of Operational Research, vol.184, No.3, pp. 1140-1154, 2008.

[7] Samvedi, A., V. Jain, "A grey approach for forecasting in a supply chain during intermittentdisruptions". Engineering Applications of Artificial Intelligence, vol.26, No.3, pp. 1044-1051, 2013.

[8] Ma, Y., L. Peng, "Coupled Model of Artificial Neural Network and Grey Model for Tendency Prediction of Labor Turnover". Mathematical Problems in Engineering, No.2, pp.1-6, 2014.

[9] Hou, R., B.X. Zhang, "A Method for Forecasting Regional Logistics Demand Based on MLP Neural Network and Its Application". Systems Engineering-theory & Practice, vol.25, No.12, pp. 43-47, 2005.

[10] Chen, S., M. Gan, Y. Tang, "Analysis of predicting the diversity regional logistics demand based on SVR: the case of Sichuan in China". Applied Mathematics & Information Sciences, vol.7,No.2, pp. 645-651, 2013.

[11] Sun,S.C., Z.Y.Duan,C.Chen, "Freight Transport Demand Forecasting in Urban Logistics Planning: A Case Study of Yiwu City". Applied Mechanics & Materials, No.505-506, pp. 915-921, 2014.

[12] He,F.B.,J.Chang, "Combined forecasting of regional logistics demand optimized by a Genetic Algorithm". Grey Systems Theory & Application, vol.4, No.4, pp. 454-458, 2014.

[13] Korpela,J., M.Tuominen, "Inventory forecasting with a multiple criteria decision tool". International Journal of Production Economics, vol.45, No.1-3, pp. 159-168, 1996.

[14] Miao, X., B. Xi, "Agile forecasting of dynamic logistics demand". Transport,vol.23, No.1, pp. 26-30, 2008.

[15] Kang, S., S. Cho, "Approximating support vector machine with artificial neural network for fast prediction". Expert Systems with Applications, vol.41, No.10, pp. 4989-4995, 2014.

[16] Ling, P., X. Rong, "A Novel and Principled Multiclass Support Vector Machine". International Journal of Intelligent Systems, vol.30, pp. 1047-1082, 2015.

[17] Deng, J.L., "Introduction to Grey system theory". Journal of Grey System, vol.1, No.1, pp. 1-24, 1989.

[18] Xiao, Z., et al., "BP neural network with rough set for short term load forecasting". Expert Systems with Applications, vol.36, No.1, pp. 273-279, 2009.