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An Elman Model Based on GMDH Algorithm for Exchange Rate Forecasting

LI Qiumin[a],[b],*; TIAN Yixiang[a]; ZHANG Gaoxun[a]

[a]School of Management and Economics, University of Electronic Science and Technology of China, Chengdu, China.
[b]Department of Arts and Science, Chengdu College of University of Electronic Science and Technology of China, Chengdu, China.
*Corresponding author.

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Abstract

Since the Elman Neural Networks was proposed, it has attracted wide attention. This method has fast convergence and high prediction accuracy. In this study, a new hybrid model that combines the Elman Neural Networks and the group method of data handling (GMDH) is used to forecast the exchange rate. The GMDH algorithm is used for system modeling. Input variables are selected by the external standards. Based on the output of the GMDH algorithm, valid input variables can be used as an input for the Elman Neural Networks for time series prediction. The empirical results show that the new hybrid algorithm is a useful tool.

Key words: Elman Neural Networks; GMDH; Forecast

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INTRODUCTION

The exchange rate is the charge for exchanging currency of one country for currency of another. It essentially reflects the contrast value of the currencies between the different countries. As the relative price of two currencies exchange rates becomes an important link and bridge of international economic exchanges. The exchange rate not only affects a country's domestic economic equilibrium, but also determines its external balance. With the global economic integration, the formation of a unified international market situation as well as all-round opening of national economies, world financial markets have become more complex and changes in exchange rates have shown more complex and dynamic characteristics.

The traditional exchange rate forecasting methods that are based on the exchange rate determination theory, build on linear models between the exchange rate and the economic variables that affect the exchange rate. Such as the PPP (Purchasing Power Parity Theory) by Cassel (1930), Interest Parity Theory by Keynes (1923), and the Efficient Markets Hypothesis by Fama (1970). However, the traditional model of exchange rate determination based on a linear model cannot explain many visions in reality, for example, the "fat tail" in the statistical distribution, clusters of volatility. More and more studies show that exchange rate system has complex non-linear characteristics. Mandelbrot (1963) found that the distribution of stock returns has "fat tails", and does not follow a normal distribution. Hsieh (1989) tested the nonlinear dependence in daily exchanges in five major foreign exchange rates. De Grauwe and Dewachter (1993) showed that the non-linearity of the exchange rate speculative dynamics leads to chaotic motion of the exchange rate dynamics.

Therefore, a large number of non-parametric models and non-linear methods have been applied to the study exchange rate forecast performance in recent years. Alvarez-Diaz and Alvarez (2005) exploited the non-linear structures of the yen/US$ and Pound sterling/ US$ exchange rate employing forecasting techniques, such as Genetic Programming and Neural Networks. Alvarez-Diaz and Alvarez (2007) employed an Evolutionary Neural Network that combines genetic programming and neural network methodologies to forecast exchange rate returns for the Japanese yen and the British pound against the US dollar. Francis and Cao (2001) examined the feasibility of SVM in financial time series forecasting by comparing it with a multi-layer back-propagation (BP) neural network. The experiment showed that SVM outperformed the BP neural network. Nikkinen (2011) applied wavelet cross-correlation techniques to analyze linkages in the option-implied exchange rate expectations over different time-scales.

Different methods of time series forecasting of exchange rates produce different effects. But the prediction accuracy is not very good due to the complexity and variability of the time series. In recent years, some researchers studied time series prediction with the use of multiple neural network algorithms. Since the aforementioned hybrid model combines the advantages of the various, its outcome is obviously superior compared to that of single forecasting models.

Onwubolu（2008）proposed a hybrid modeling approach based on the group method of data handling (GMDH) and differential evolution (DE) population-based algorithm in time series prediction problems of exchange rates. His results show that the proposed DE–GMDH algorithm appears to outperform the standard GMDH algorithm and the polynomial neural network (PNN) model. Samsudin (2011) proposes a novel hybrid forecasting model which combines the group method of data handling (GMDH) and the least squares support vector machine (LSSVM) that works as river flow time series forecasting. But Samsudin didn`t give the estimating equations.

In this article, we simulated the model structure by GMDH algorithm; select the input variables based on the output of the model equations, and then forecast the time series by the Elman neural networks. The GMDH and the Elman neural networks are used together to improve the predictive ability of the model. The former algorithms are used for system modeling and input variables are selected by external standards. Based on the output of the GMDH algorithm, valid input variables act as an input in the Elman neural networks for time series prediction.

1. THE ELMAN NEURAL NETWORKS

The Elman neural networks are a new class of neural networks introduced by Elman (1990). The Elman Neural Networks is comprised by four layers: the input layer, the middle layer, the receiving layer and the output layer. The connections of the input layer, the middle layer and the output layer are similar to the feed forward network.

The input layer unit only functions as the signal input. The output layer unit functions as the linear weighting. The transfer function of the middle layer unit can use a linear function or a non-linear function. It is generally a Sigmoid function. The receiving layer is used to record the output value of the middle layer on the previous time. The receiving layer is a time delay operator equivalent to state feedback.

The output of the middle layer is delayed and stored by the receiving layer, and then self linked to the input of the middle of them. This self-linking mode is sensitive to the data of the historical status. The adding of the internal feedback network increases the capacity of the processing dynamic information of the network itself. So the purpose of dynamic modeling is achieved.

The nonlinear state space representation of the Elman Neural Networks is:

$$\begin{cases} y(k) = g(W_3 x(k)) \\ x(k) = f(W_1 x_c(k) + W_2(u(k-1))) \\ x_c(k) = x(k-1) \end{cases} . \quad (1)$$

Where $y(k)$ is the n-dimensional output vector, $u(k)$ is r-dimensional input vector，$x(k)$ is -dimensional output vector of the middle layer, $x_c(k)$ is the output vector at the moment k of the receiving layer, W_1，W_2，W_3 are denoted the connection weights of the middle layer to the output layer, the input layer to the middle layer, an the receiving layer to the middle layer respectively. $g(\cdot)$ is the transfer function of the output neurons, is a linear combination of the output of the middle layer. $f(\cdot)$ is the transfer function of the neurons in the middle layer. It is generally a Sigmoid function.

The BP algorithm is used to correct weights of the Elman Neural Networks. The squared error function is taken as learning index function.

$$E(\omega) = \sum_{k=1}^{n} [y_k(\omega) - \tilde{y}_k(\omega)]^2 . \quad (2)$$

Where $\tilde{y}_k(\omega)$ is the expected output vector.

2. THE GROUP METHOD OF DATA HANDLING ALGORITHM (GMDH)

The Group Method of Data Handling (GMDH) algorithm is a multivariate analysis method for modeling and identifying uncertainty on linear or nonlinearity systems. This algorithm was first introduced by Ivakhnenko in 1970. The GMDH algorithm uses advantages of both self-organizing principle and multilayer neural networks to select the best relationships between variables. The main idea of GMDH is the use of feed-forward networks based on short-term polynomial transfer functions combined with emulation of the self-organizing activity behind NN structural learning (Farlow, 1984). Barron (1988) gave a comprehensive overview of some early developments of the network to improve the performance of the GMDH algorithm, and introduced the Polynomial Network Training algorithm (PNETTR). Elder (1996) proposed the Synthesis of Polynomial Network (ASPN) algorithm to improve the GMDH algorithm. Muller and Lemke (2000) developed and improved self-organizing data mining algorithms. Further enhancements of the GMDH algorithm have been realized in the "Knowledge Miner" software.

The GMDH algorithm has gradually become an effective tool in many fields such as modeling, forecasting, and decision support and pattern recognition of complex systems, data mining, intelligent classification. The GMDH method has been successfully applied in several fields, such as, economics, climate, finance, ecology, medicine, manufacturing and military systems. (Abdel-Aal, Elhadidy, & Shaahid, 2009; Ivakhnenko & Ivakhnenko, 1995; Kondo, Pandya, & Zurada, 1999; Mehrara, Moeini, Ahrari, & Erfanifard, 2009; Dorn, Braga, Llanos, & Coelho, 2012).

The GMDH model is a multivariate analysis approach for modeling and identification of complex systems. Each layer of the model is formed by a simple element node. Based on the forward pass of neurons, the output variable will be obtained in the next layer through the polynomial transfer function.

The first step of the model is as follows: divide the normalized variables $X=[x_1, \cdots, x_M]$ into the training set and testing set.

In the second step: Build $C^2_M = M(M-1)/2$ new variables in the training set to enter the Kolmogorov-Gabor polynomial function.

$$y = a_0 + \sum_{i=1}^{M} a_i x_i + \sum_{i=1}^{M}\sum_{j=1}^{M} a_{ij} x_i x_j + \sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{k=1}^{M} a_{ijk} x_i x_j x_k + \cdots . \tag{3}$$

Where y is the output variable, $x_1, x_2, \cdots, x_n$ are the input variables, a is the coefficient.

In the third: The output variable y is obtained in the first layer. The variable which error`s value increased will be removed based on the root mean square error criterion.

Finally, in the fourth step: select $n_1 \le C^2_M$ variables as new inputs to enter the transfer Equation (3).

Repeat the steps 2 to 4 until the errors of the test data in each layer stop decreasing. At that point the iterative computation procedure is terminated.

The aforementioned steps of the GMDH algorithm are executed iteratively until there is no improvement based on the external criterion. The optimal model parameters and the model structure will be obtained through pushing back along the last layer.

3. THE HYBRID MODEL

GMDH algorithm can simulate the internal structure of the system, can select the output variables automatically according to the minimum variance criterion, and has explicit expressions of the model structure. In this paper, we simulate the model structure by GMDH algorithm; select the input variables based on the output of the model equations, and then forecast the time series by the Elman neural networks. The GMDH and the Elman neural networks are used together to improve the predictive ability of the model. The major steps are as follows:

A) The data are standardized and divided into training set and testing set;

B) The combinations of two input variables enter each layer. The number of input variables is $C^2_M = \frac{M!}{(M-2)!2!}$. The final output model will be obtained by the minimum root mean square error criterion.

$$y=a_0+a_1x_i+\cdots a_m x_j+a_{m+1}x_k x_l+\cdots+a_n x_p x_q. \tag{4}$$

The polynomial coefficients are estimated by the least squares method.

c) The variables chosen by GMDH model will be the input variables of the Elman neural networks. The model structure is shown in Figure 1.

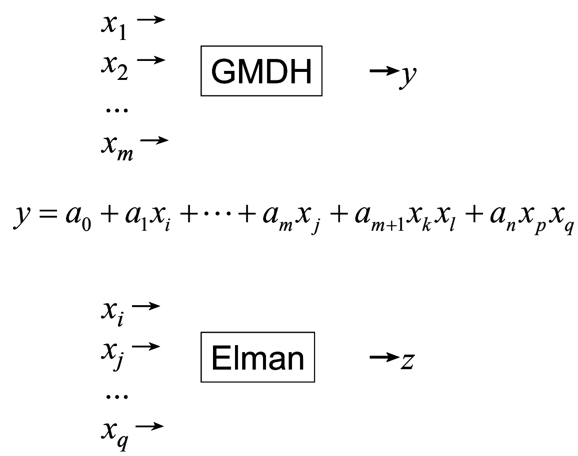

Figure 1
Model Structure of the New Hybrid Model

d) The root means square error (RMSE) and the R-squared are used to judge the prediction performance of the models. The prediction of model with the smallest RMSE and largest R-squared is the preferred one. The root means square error (RMSE) and the R-squared are defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_i - o_i)^2}, \tag{5}$$

$$R = \frac{\frac{1}{n}\sum_{t=1}^{n}(y_i-\bar{y})(o_i-\bar{o})}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_i-\bar{y})^2}\sqrt{\frac{1}{n}\sum_{t=1}^{n}(o_i-\bar{o})^2}}. \tag{6}$$

Where o_i and y_i are the observed values and the predicted value of the i th sample respectively. $\bar{o}$ is the mean of the observed values. n is the number of the sample.

4. EMPIRICAL ANALYSES

The hybrid model is tested with two exchange rates: the US dollar against the Japanese yuan and the British pound. The data used in this study are daily closing prices of exchange rates between June 25, 2007 and July 28, 2011. The invalid data (as holiday days and weekend) is excluded. The full samples are divided into a training set (the first 900 samples), and a testing set (the remaining 101 samples). The data is collected from the CCER Chinese financial and economic database.

First the GMDH model was used to fit on the time series of exchange rate. The closing price x_t is the output variable. The five lags of closing price x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}, x_{t-5} are output variables. Estimation results are as follows:

The US dollar against the Japanese yuan：

$$x_t=0.071736+0.999743x_{t-1.} \tag{7}$$

The US dollar against the British pound：

$$x_t=0.202372+0.872041x_{t-1}-0.198723x_{t-2}. \tag{8}$$

The first lag was chosen as the input variable in the Elman neural networks of the US dollar against the Japanese yuan. The first two large were chosen as the input variables in the Elman neural networks of the US dollar against the British pound. The closing price x_t is the output variable.

The kernel function, also know as RBF, is:

$$K(x_i,x_j)=\exp(-\eta\left\|x_i-x_j\right\|^2),\eta>0 \ . \tag{9}$$

Where η is the kernel parameter, representing the width of the RBF. In this paper, we set $\eta=0.5$.

In order to compare the predictive accuracy, this paper models the exchange rate based on the GMDH, the Elman neural networks and the new hybrid models. The RMSE values and the *R-squared* values of three prediction models are shown in Table 1:

Table 1
The RMSE Values and the *R* Values of Three Models

	RMSE	R^2	RMSE	R^2
	USD/JPY	USD/JPY	USD/GBP	USD/GBP
GMDH	0.375969	0.950052	0.386434	0.954634
Elman neural networks	0.339454	0.964214	0.354153	0.970104
hybrid model	0.256943	0.975118	0.225971	0.981203

As shown in Table 1, the RMSE of the new hybrid model is the smallest, and the *R*-squared of the new hybrid model is biggest among the three models under considerations. It is evident that the predictive accuracy of the new hybrid model outperforms that of the GMDH, the Elman neural networks in the testing process.

The hybrid model is used to predict the exchange rate of USD/JPY and USD/GBP in March to April 2011. The results are shown in Table 2.

Table 2
Comparison of the Real Values and the Prediction Results of the Hybrid Model

	USD/JPY			USD/GBP		
Date	**Real values**	**Prediction results**	**Relative error (%)**	**Real values**	**Prediction results**	**Relative error (%)**
2011-03-07	82.3654	82.3542	-0.0136%	0.6150	0.6161	0.1868%
2011-03-08	82.2754	82.2511	-0.0295%	0.6171	0.6180	0.1548%
2011-03-09	82.8749	82.9409	0.0796%	0.6190	0.6192	0.0347%
2011-03-10	82.7953	82.8505	0.0667%	0.6170	0.6196	0.4230%
2011-03-11	82.9245	82.9966	0.0869%	0.6222	0.6269	0.7521%
2011-03-14	81.9951	81.9426	-0.0640%	0.6222	0.6271	0.7878%
2011-03-15	81.8552	81.8006	-0.0667%	0.6187	0.6284	1.5655%
2011-03-16	81.1153	81.3250	0.2585%	0.6221	0.6286	1.0382%
2011-03-17	79.3904	81.9895	3.2738%	0.6251	0.6288	0.5956%
2011-03-18	81.0996	81.3222	0.2745%	0.6205	0.6186	-0.3082%
2011-03-21	80.9502	81.3147	0.4503%	0.6167	0.6148	-0.3018%
2011-03-22	80.9748	81.3134	0.4182%	0.6130	0.6121	-0.1343%
2011-03-23	81.0549	81.3161	0.3223%	0.6113	0.6133	0.3259%
2011-03-24	80.9595	81.3141	0.4380%	0.6153	0.6179	0.4253%

To be continued

Continued

	USD/JPY			USD/GBP		
Date	Real values	Prediction results	Relative error (%)	Real values	Prediction results	Relative error (%)
2011-03-25	80.995	81.3131	0.3927%	0.6205	0.6226	0.3419%
2011-03-28	81.5951	81.5703	-0.0304%	0.6248	0.6250	0.0392%
2011-03-29	81.5754	81.5551	-0.0249%	0.6253	0.6249	-0.0625%
2011-03-30	82.4597	82.4632	0.0042%	0.6245	0.6229	-0.2578%
2011-03-31	83.1155	83.2072	0.1103%	0.6213	0.6226	0.2135%
2011-04-01	83.4399	83.5473	0.1287%	0.6239	0.6182	-0.9066%
2011-04-06	85.1247	85.1136	-0.0130%	0.6126	0.6128	0.0308%
2011-04-07	85.0148	85.0095	-0.0062%	0.6130	0.6127	-0.0443%
2011-04-08	84.3353	84.3899	0.0647%	0.6124	0.6119	-0.0869%
2011-04-11	84.1105	84.1868	0.0907%	0.6114	0.6120	0.0977%
2011-04-12	83.6896	83.7940	0.1247%	0.6126	0.6136	0.1721%
2011-04-13	83.6345	83.7406	0.1269%	0.6147	0.6141	-0.0919%
2011-04-14	83.0948	83.1847	0.1082%	0.6148	0.6145	-0.0596%
2011-04-15	82.615	83.0074	0.4750%	0.6114	0.6173	0.9653%
		Average error	0.2434%		Average error	0.2106%

As shown in Table 2, In addition to individual data, the error between the predictive value and the true value is less than 1%. The average errors of the USD/JPY and USD/GBP exchange rates are 0.2434% and 0.2106%, respectively. So the predicted results of the new hybrid model are better.

CONCLUSION

In this paper, the GMDH algorithm and the Elman neural networks are combined to form a new hybrid model. Based on the explicit model structure of the GMDH algorithm, the variables are selected as new input variables of the Elman neural networks for time series prediction. The hybrid model can avoid man-made choice of input variables of the Elman neural networks. The hybrid model takes advantage of the explicit output structure of the GMDH algorithm and the convergence of the Elman neural networks to improve the predictive accuracy. The new hybrid model is tested with two exchange rates: the US dollar against the Japanese yuan and the British pound. The forecast results of the new hybrid model outperform those of the GMDH and the Elman neural networks. Specifically, the results of the empirical analysis show that the RMSE of the new is smallest and the R-squared of new is biggest among the models evaluated. It is thus evident that the predictive power of the new hybrid model outperforms those of the GMDH and the Elman neural networks. Hence, there is evidence that the hybrid model, that combines the advantages of the various algorithms and the prediction of the hybrid model, is better than that based on a single algorithm. Therefore, the new hybrid model can be successfully used to predict the exchange rate time series.

REFERENCES

Abdel-Aal, R., Elhadidy, M., & Shaahid, S. (2009). Modeling and forecasting the mean hourly wind speed time series using GMDH-based abductive networks. *Renewable Energy*, *34*(7), 1686–1699.

Alvarez-Diaz, M., & Alvarez, A. (2005). Genetic multimodel composite forecast for non-linear forecasting of ex-change rates. *Empirical Economics, 30*(3), 643-663.

Alvarez-Diaz, M., & Alvarez, A. (2007). Forecasting exchange rates using an evolutionary neural network. *Applied Financial Economics Letters, 3*(1), 5-9.

Barron, A. R. (1988). *Statistical learning networks: A unifying view* (pp. 192-203). in Proceedings of the 20th symposium Computing Science and Statistics. Alexandria: American Statistical Association.

Cassel, G. (1930). *Money and foreign exchange after 1914*. London：Macmillan.

De Grauwe, P., & Dewachter, H. (1993)． A chaotic model of the exchange rate：The role of fundamentalists and chartists ． *Open Economies Review, 4*(4), 351-379.

Dorn, M., Braga, A. L. S., Llanos, C. H., & Coelho, L. S. (2012). A GMDH polynomial neural network-based method to predict approximate three-dimensional structures of polypeptides. *Expert Systems with Applications*, *39*, 12268–12279.

Elder, J. F. (1996). *A Statistical Perspective on Knowledge Discovery in Databases*.California: AAAI Press, MIT Press.

Elman, J. L. (1990). Finding structure in time. Cognitive Science, (02), 179-211.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383-417.

Farlow, S. J. (1984). *Self-organizing methods in modeling*. Marcel Dekker, New York and Basel.

Francis, E. H. T., & Cao, L. J. (2001). Application of support vector machines in financial time series forecasting. *International Journal of Management Science, 29,* 309-317.

Hsieh, D. A. (1989). Testing for nonlinear dependence in daily foreign exchange rates. *Journal of Busines, 62*(3), 329-368.

Ivakhnenko, A. G. (1970). Heuristic self-organization on problems of engineering cybernetics. *Automatic*, *6*(3), 207-219.

Ivakhnenko, A. G., & Ivakhnenko, G. A. (1995). The review of problems solvable with algorithms of the Group Method of Data Handling (GMDH). *Pattern Recognition and Image Analysis*, *5*(4), 527–535.

Keynes, J. M. (1923). *A track on monetary reform*. London: Macmillan.

Kondo, T., Pandya, A. S., & Zurada, J. M. (1999). Logistic GMDH-type neural networks and their application to the identification of the X-ray film characteristic curve. *In Proceedings of the IEEE international conference on systems, man and cybernetics, 1,* 437–442.

Mandelbrot, B. B. (1963). The variation of certain speculative prices． *Journal of Business, 36*(4), 394-419.

Mehrara, M., Moeini, A., Ahrari, M., & Erfanifard, A. (2009). Investigating the efficiency in oil futures market based on GMDH approach. *Expert Systems with Applications*, *36*, 7479-7483.

Muller, J. A., & Lemke, F. (2000). *Self-organizing data mining*. Dresden, Berlin. Libri Books.

Nikkinen, J., Pynnonen, S., Ranta, M., & Vahamaa, S. (2011). Cross-dynamics of exchange rate expectations: a wavelet analysis. *International Journal of Finance & Economics, 16*(3), 205–217.

Onwubolu, G. C. (2008). Design of hybrid differential evolution and group method of data handling networks for modeling and prediction. *Information Sci*, *178*, 3616– 3634.

Samsudin, R., Saad, P., & Shabri, A. (2011). A hybrid GMDH and least squares support vector machines in time series forecasting. *Neural Network World, 21*(3), 251-268.

Saunders, C., Gammerman, A., & Vovk, V. (1998). *Ridge regression learning algorithm in dual variables* (pp.515-521). Proceedings of the 15th International Conference on Machine Learning ICML-98, Madison, WI, USA.

Shuhaida, I., Shabri, A., & Samsudin, R. (2011). A hybrid model of self-organizing maps (SOM) and least square support vector machine (LSSVM) for time-series forecasting. *Expert Systems With Applications, 38,* 10574- 10578.

Suykens, J. A. K. (2001). Nonlinear modeling and support vector machines, *IEEE Instrumentation and Measurement Technology Conference*, *Budapest, Hungary,* 287–294.

Vapnik, V. (1998). *Statistical learning theory.* New York, NY.: JohnWiley.

