2011 3rd International Conference on Information and Financial Engineering
IPEDR vol.12 (2011) © (2011) IACSIT Press, Singapore

Forecasting Chinese Foreign Exchange with Monetary Fundamentals using Artificial Neural Networks

Chun-Teck Lye [1], Tze-Haw Chan [2] and Chee-Wooi Hooy [2+]

[1] Centre for Foundation Studies & Extension Education, Multimedia University, 75450, Melaka, Malaysia.

[2] School of Management, Universiti Sains Malaysia, 11800, Pulau Pinang, Malaysia.

Abstract. We employ artificial neural networks (ANNs) and unconditional Vector Autoregressive model (VAR) to perform one-month-ahead out-of-sample predictions of both official and market Yuan/USD exchange rates using monetary fundamentals from 1992:M3 to 2010:M10. The optimal ANNs are attained systematically based on random validation sets. We empirically demonstrated that the generalized regression neural network is superior to the multilayer feedforward network in Chinese foreign exchange forecasting. ANNs generally outperformed in market rate forecasts in which suggest that market rates are supported by monetary fundamentals. On the contrary, official rates do not explained well by monetary fundamentals.

Keywords: Feedforward, generalized regression, monetary model, random walk, vector autoregression.

1. Introduction

Although the modeling-forecasting of foreign exchange rate is widely acknowledged as a difficult task, it is always the center of attraction in the field of empirical research. In late 1970s, many researchers have advocated the monetary approaches to exchange rate determination (see e.g., Dornbusch, 1976; Frenkel, 1976; Bilson, 1978; Frankel, 1979). Still, in an influential paper, Meese and Rogoff (1983) challenged the credibility of these monetary models. Their study showed that the conventional linear models' forecasts of future nominal and real exchange rates were not as good as the naïve random walk benchmark model. As more and more evidence of complex nonlinearities in foreign exchange fluctuations surfaced (see e.g., Baillie and McMahon, 1989; Brooks, 1996; Soofi and Cao, 1999), nonparametric and nonlinear methods as well as the artificial neural network (ANN) have been progressively applied to scrutinized the problem, by different samples and assorted explanatory variables. Nevertheless, the overall empirical evidences are at best mixed (see e.g., Plasmans *et al.*, 1998; Yao and Tan, 2000; Kamruzzaman and Sarker, 2004; Panda and Narasimhan, 2007; Bissoondeeal *et al.*, 2008). The issue becomes more challenging when the focal point involves Chinese Yuan. Yuan has always been claimed as undervalued and maintained within rigid band regulated by Chinese authority. Whether Yuan can be predicted by fundamentals remains an open question.

In light of these studies, we examine the performance of the multilayered feedforward network (MLFN), generalized regression neural network (GRNN) and unconditional Vector Autoregressive model (VAR) models in forecasting the monthly Yuan/USD from March 1992 to October 2010. We systematically attain the optimal ANNs by using simple random validation sets built with anticipation to avoid seasonal pattern. Unlike previous works, the forecasts of both the Chinese official and market exchange rates, in addition to the predicted rates based on the discrete and differential monetary fundamentals are assessed. In all cases, the naïve random walk is taken as the benchmark. Out of the 224 historical data, the most recent 24 observations are reserved for out-of-sample test while the remaining data are used for model building/training and validation.

[+] Corresponding author. Tel.: +604-6532897; fax:+604-6577448.
E-mail address: cwhooy@usm.my

2. Data and Methodology

This paper considers the monetary exchange rate models advocated by Meese and Rogoff (1983) [1], which can be subsumed into the general specification:

Model 1 (differential): $y_{t+1} = f\left((m-m^*)_t, (p-p^*)_t, (r-r^*)_t, (i-i^*)_t, B_t, B_t^*\right)$ (1)

Model 2 (discrete): $y_{t+1} = f\left(m_t, m_t^*, p_t, p_t^*, r_t, r_t^*, i_t, i_t^*, B_t, B_t^*\right)$ (2)

where an asterisk denotes foreign variable, y is the exchange rate, m is the money supply, p is the real income, r is the short-term interest rate, i is the rate of inflation and B is the cumulated trade balance. All series that sourced from the International Financial Statistics, IMF, are transformed into natural logarithm and we employ the naïve random walk (RW) without drift as our benchmark model. The forecasts of the RW is acquired by $y_{t+1} = y_t$, with y_{t+1} and y_t being the one-step-ahead and present time series observations, respectively. As comparable to RW, we also perform one-step-ahead prediction in all the ANN and VAR forecasting models.

Although ANNs are efficient in time series forecasting, researches has also shown that ANNs often encounter issues such as overfitting problems and difficulties in finding the optimal network (see Zhang *et al.*, 1998). Therefore, we use systematic experiment that based on random validation set which is formed by random selection of data from successive equal-width interval to avoid seasonal pattern, to determine the respective optimal architecture and smoothing parameter in MLFN and GRNN. In favor of a parsimonious MLFN model, we use 3-layer (input-hidden-output) feedforward network as earlier findings disclosed single hidden layer is sufficient in function approximation (see Cybenko, 1989; Hornik *et al.*, 1989). The transfer functions employed in the hidden and output layers of MLFN are sigmoid and linear functions, respectively. We also restrict the maximum number of hidden nodes in the MLFN to twenty, i.e., twofold the number of monetary input variables according to the practical guideline provided by Wong (1991). The MLFN is trained with the Levenberg-Marquardt backpropagation (see Hagan and Menhaj, 1994). Alternatively, the GRNN that was first proposed by Specht (1991) is a class of neural network that is closely associated to the radial basis function network (see Powell, 1987). GRNN does not require iterative training as in the backpropagation network. Table 1 summarizes the key steps in the determination of optimal ANN models.

Table 1: The Summarized Procedures in the Determination of ANN Models

Step 1:	Stratify the 200 historical data into 20 successive equal-width intervals. Randomly select one observation from each interval to form the validation set.
Step 2:	Construct MLFN with initial n_h=2 hidden nodes (or GRNN with initial s=0 smoothing parameter).
Step 3:	Train MLFN with n_h hidden nodes and repeat this step for 100 times. Initiate the weights and biases for each repetition (or simulate GRNN with s using random validation set).
Step 4:	Evaluate the MSE and save the network that yielded the smallest MSE.
Step 5:	Increase n_h by 1 (or s by 0.005). Repeat steps 2 to 5 and do until n_h=20 (or s=10).
Step 6:	Select the optimal network (or optimal smoothing parameter) that gives the smallest MSE for out-of-sample predictions.

To evaluate forecast performance, we employ the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Theil's Inequality Coefficient (Theil-U):

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}_t - y_t)^2} \qquad MAE = \frac{1}{T}\sum_{t=1}^{T}\left|\hat{y}_t - y_t\right|$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{\hat{y}_t - y_t}{y_t}\right| \times 100 \qquad Theil-U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}_t - y_t)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}_t)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t)^2}}$$

where y_t is the actual observation, $\hat{y}_t$ is the forecasted value, and T is the number of predictions. The model that yields a smaller value in all such criteria signifies its superiority against other model.

[1] The monetary fundamentals are given by the quasi-reduced forms of the Frenkel-Bilson's flexible-price monetary model (Frenkel, 1976; Bilson, 1978), Dornbusch-Frankel's stickey-price monetary model (Dornbusch, 1976; Frankel, 1979) and Hooper-Morton's stickey-price asset model (Hooper and Morton, 1982).

3. Empirical Discussion

We utilize five random validation sets to diminish the preconception on model's performance that may be formed based on a particular validation set. The entire modeling-forecasting procedures are repeated for each of the random validation set. The respective optimal number of nodes in the hidden layer and the smoothing parameter in the MLFN and GRNN for the official and market rates are shown in Table 2. The results showed that the overall optimal parameters and the number of hidden nodes obtained are consistent.

Table 2: Optimal Number of Hidden Nodes and Smoothing Parameter

Validation set	Smoothing parameter				Nodes in hidden layer			
	GRNN1		GRNN2		MLFN1		MLFN2	
	Official Rate	Market Rate	Official Rate	Market Rate	Official Rate	Market Rate	Official Rate	Market Rate
1	0.160	0.130	0.195	0.145	19	19	20	18
2	0.125	0.175	0.180	0.190	19	17	20	20
3	0.160	0.150	0.175	0.165	20	16	18	20
4	0.180	0.165	0.200	0.180	20	13	20	20
5	0.135	0.145	0.145	0.155	20	17	20	20

Note: GRNN1 and MLFN1 represent the differential models whereas GRNN2 and MLFN2 represent the discrete models.

Additional tests were performed to further examine the consistency of the ANN models built based on the random validation sets. The outcomes summarized in Table 3 showed that the analysis of variance tests failed to reject the null hypothesis of equal means in all ANN models, i.e. there are no statistical significant differences in the out-of-sample forecasting performance between the ANN models. Hence, the results verified the generalization and robustness of the ANN forecasting models constructed based on the random validation sets and justified their utilization in this paper.

Table 3: ANOVA Test for Random Validation Sets

Validation set	GRNN1		GRNN2		MLFN1		MLFN2	
	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
				Official Rate				
1	2.3452	0.0152	2.3443	0.0167	2.3299	0.0816	2.3460	0.0852
2	2.3439	0.0173	2.3443	0.0173	2.3357	0.0717	2.3367	0.0883
3	2.3452	0.0152	2.3443	0.0175	2.3432	0.0569	2.3664	0.0711
4	2.3457	0.0144	2.3442	0.0165	2.3328	0.0492	2.3622	0.0901
5	2.3443	0.0167	2.3444	0.0189	2.3426	0.0782	2.3537	0.1023
	[0.995]		[1.000]		[0.948]		[0.772]	
				Market Rate				
1	1.9204	0.0028	1.9203	0.0027	1.9217	0.0230	1.9023	0.0619
2	1.9207	0.0022	1.9205	0.0023	1.9116	0.0277	1.9239	0.0364
3	1.9205	0.0025	1.9204	0.0025	1.9160	0.0184	1.9110	0.0533
4	1.9206	0.0023	1.9205	0.0024	1.9159	0.0205	1.9365	0.0684
5	1.9205	0.0026	1.9204	0.0026	1.9211	0.0173	1.9231	0.0396
	[0.994]		[0.999]		[0.472]		[0.221]	

Note: *p*-values for the Analysis of Variance test are presented in parentheses. GRNN1 and MLFN1 represent the original differential models whereas GRNN2 and MLFN2 represent the reduced form discrete models

The overall out-of-sample forecasting performance of the forecasting models is summarized in Table 4. For official rate predictions, all forecasting models (except for VAR1 in 6-month forecast horizon) failed to outperform the random walk benchmark model. The result is reasonable as the local government regulates the official rate and it might be independent of the dynamics of monetary fundamentals. As for the market rate predictions, the best forecasting model (GRNN2) outperformed the RW in 6- and 12-month forecast horizons. In both official and market rates, we found evidences of superiority in GRNN models over the MLFN models in exchange rate forecasting. Such results are consistent with the findings of Leung, *et al.* (2000). Our study also revealed that GRNN2 perform better than GRNN1 while MLFN1 and VAR1 better than MLFN2 and VAR2 respectively. In general, the forecasting performance of the models is better in market rate predictions as compared to the official rate.

Next, we proceed with the *t*-test on the out-of-sample forecast errors. The results are presented in Table 5. In both official and market rates forecasts, the respective MLFN1 and VAR1 models statistically significantly outperformed the MLFN2 and VAR2. Conversely, the outperformance of GRNN2 is not significant in comparison to the GRNN1. The results also showed that the best forecasting models in market rate predictions are superior to the best forecasting models in official rate. Alternatively, the outperformance of the best forecasting models in both official and market rates forecasts is not statistically significance as compared to the random walk benchmark model.

Table 4: Forecasting Performance in Different Forecast Horizons

Forecast horizon	Performance Measures	GRNN1	GRNN2	MLFN1	MLFN2	VAR1	VAR2	RW
				Official Rate				
6-month	RMSE	0.02029	0.01916	0.10717	0.14532	0.01422	0.02134	0.01642
	MAE	0.01816	0.01588	0.07404	0.10617	0.01272	0.02081	0.01268
	MAPE	0.77938	0.68158	3.17725	4.55668	0.54559	0.89355	0.54363
	Theil-U	0.00435	0.00411	0.02320	0.03113	0.00305	0.00457	0.00353
12-month	RMSE	0.02340	0.02326	0.08141	0.10808	0.01962	0.02913	0.01344
	MAE	0.02196	0.02101	0.05159	0.07025	0.01776	0.02702	0.01060
	MAPE	0.93210	0.89124	2.20294	3.00053	0.75243	1.14585	0.45174
	Theil-U	0.00499	0.00496	0.01739	0.02297	0.00418	0.00617	0.00286
24-month	RMSE	0.02410	0.02233	0.06543	0.08537	0.03270	0.14308	0.01342
	MAE	0.02115	0.01915	0.04282	0.05312	0.02749	0.10916	0.01125
	MAPE	0.90230	0.81619	1.83078	2.26659	1.17494	4.67025	0.48037
	Theil-U	0.00514	0.00476	0.01397	0.01816	0.00695	0.02981	0.00286
				Market Rate				
6-month	RMSE	0.00073	0.00072	0.03339	0.07393	0.00195	0.01177	0.00081
	MAE	0.00047	0.00044	0.02362	0.05370	0.00178	0.00841	0.00056
	MAPE	0.02432	0.02265	1.22894	2.79377	0.09268	0.43774	0.02921
	Theil-U	0.00019	0.00019	0.00871	0.01926	0.00051	0.00306	0.00021
12-month	RMSE	0.00056	0.00055	0.02569	0.06497	0.00298	0.04106	0.00058
	MAE	0.00038	0.00035	0.01663	0.04081	0.00265	0.03136	0.00034
	MAPE	0.02001	0.01836	0.86525	2.12322	0.13801	1.63233	0.01778
	Theil-U	0.00015	0.00014	0.00669	0.01688	0.00077	0.01060	0.00015
24-month	RMSE	0.00549	0.00540	0.02154	0.05356	0.01073	0.10811	0.00373
	MAE	0.00260	0.00250	0.01367	0.02972	0.00715	0.08719	0.00157
	MAPE	0.13623	0.13121	0.71260	1.54745	0.37434	4.55520	0.08217
	Theil-U	0.00143	0.00141	0.00562	0.01395	0.00279	0.02755	0.00097

Note: GRNN1, MLFN1 and VAR1 represent the differential models. GRNN2, MLFN2 and VAR2 represent the discrete models

Table 5: Comparison Tests on Out-of-Sample Forecast Errors

Hypothesis	6-month	12-month	24-month
		Official Rate	
GRNN2 < GRNN1	0.193	0.286	0.091*
MLFN1 < MLFN2	0.088*	0.085*	0.089*
VAR1 < VAR2	0.000***	0.000***	0.000***
		Market Rate	
GRNN2 < GRNN1	0.587	0.343	0.439
MLFN1 < MLFN2	0.003***	0.000***	0.000***
VAR1 < VAR2	0.000***	0.000***	0.000***
		Overall	
$\text{Market}_{\text{Best}}$ vs $\text{Official}_{\text{Best}}$	GRNN2 < VAR1 0.000***	GRNN2 < VAR1 0.000***	GRNN2 < GRNN2 0.000***
$\text{Official}_{\text{Best}}$ vs $\text{RW}_{\text{Benchmark}}$	VAR1 < RW 0.503	VAR1 > RW 0.000***	GRNN2 > RW 0.000***
$\text{Market}_{\text{Best}}$ vs $\text{RW}_{\text{Benchmark}}$	GRNN2 < RW 0.216	GRNN2 < RW 0.611	GRNN2 > RW 0.040**

Note: *, ** and *** denote significant at 10%, 5% and 1% significance level respectively. In all cases, one-tailed *t*-tests are used and the corresponding *p*-values are presented.

4. Conclusion

This paper examined the significance of monetary fundamentals in explaining the dynamics of both Chinese official and market exchange rates vis-à-vis the US dollar using unconditional VAR, multilayer feedforward network and generalized regression neural network. The random walks performed better in official rate predictions whereas ANNs generally outperformed in market rate forecasts, suggesting that market rates are supported by monetary fundamentals. More specifically, the GRNN models can provide a more convincing result of the differential and discrete models as compared to other forecasting models in market rates predictions. On the contrary, official rates ignore the effects of cross-border monetary transmission mechanism and do not explained well by monetary fundamentals. In addition, the unconditional VAR estimations underperform in most cases. Perhaps, a structural system approach should be adopted to explicate the Yuan/USD movements, e.g. the VARX modeling put advanced by Garratt, *et al*. (2003). All in all, we anticipated that the performance of ANNs in modeling-forecasting the Yuan/USD can be enhanced if updated series, structural break and more deterministic variables are introduced into the ANN models.

5. Acknowledgements

The authors would like to thank the government of Malaysia for the support through the FRGS (1/2009).

6. References

[1] A. Garratt , K. Lee, M. H. Pesaran, and Y. Shin. A Long Run Structural Macro-econometric Model of the UK. *Economic Journal* 2003: 412-455.

[2] A.S. Soofi, and L. Cao. Nonlinear deterministic forecasting of daily Peseta-Dollar exchange rate. *Economics Letters* 1999, **62**: 175-180.

[3] C. Brooks. Testing for non-linearity in daily sterling exchange rates. *Applied Financial Economics* 1996, **6**: 307-317.

[4] C. Panda, and V. Narasimhan. Forecasting exchange rate better with artificial neural network. *Journal of Policy Modeling* 2007, **29**: 227-236.

[5] C. Xie, B. Sun, J. Zhang, and Y. Xiang. Which neural network is appropriate for CNY/USD exchange rate series forecast? *International Journal of Computational Science* 2009, **3**: 535-553.

[6] D.F. Specht. A general regression neural network. *IEEE Transactions on Neural Networks* 1991, **2**: 568-576.

[7] F.S. Wong. Time series forecasting using backpropagation neural networks. *Neurocomputing* 1991, **2**: 147-159.

[8] G. Cybenko. Approximations by superpositions of a sigmoidal function. *Mathematics of Control, Signals, and Systems* 1989, **2**: 303-314.

[9] G. Zhang, and M.Y. Hu. Neural network forecasting of the British pound/US dollar exchange rate. *International Journal of Management Science* 1998, **26**: 495-506.

[10] G. Zhang, B.E. Patuwo, and M.Y. Hu. Forecasting with artificial neural networks: the state of the art. *International Journal of Forecasting* 1998, **14**: 35-62.

[11] J. Kamruzzaman, and R.A. Sarker. ANN-based forecasting of foreign currency exchange rates. *Neural Information Processing - Letters and Reviews* 2004, **3**: 49-58.

[12] J. Plasmans, W. Verkooijen, and H. Daniels. Estimating structural exchange rate models by artificial neural networks. *Applied Financial Economics* 1998, **8**: 541-551.

[13] J. Yao, and C.L. Tan. A case study on using neural networks to perform technical forecasting of forex. *Neurocomputing* 2000, **34**: 79-98.

[14] K. Hornik, M. Stinnchcombe, and H. White. Multi-layer feed forward networks are universal approximators. *Neural networks* 1989, **2:** 359–366.

[15] M.J.D. Powell. Radial basis functions for multivariable interpolation: A review, in Algorithms for the approximation of functions and data. In: J.C. Mason, and M.G. Cox (eds). *Clarendon Press*, Oxford, England, pp. 143-167.

[16] M.T. Hagan, and M. Menhaj. Training feedforward networks with the Marquardt algorithm. *IEEE Transactions on Neural Networks* 1994, **5**: 989-993.

[17] M.T. Leung, A.S. Chen, and H. Daouk. Forecasting exchange rates using general regression neural networks. *Computers and Operations Research* 2000, **27**: 1093-1110.

[18] P. Hooper, and J. Morton. Fluctuations in the dollar: a model of nominal and real exchange rate determination. *Journal of International Money and Finance* 1982, **1**: 39-56.

[19] R. Baillie, and P. McMahon. *The foreign exchange market: theory and econometric evidence.* Cambridge University Press, New York, 1989.

[20] R.A. Meese, and K. Rogoff. Empirical exchange rate models of the seventies: do they fit out of sample? *Journal of International Economics* 1983, **14**: 3-24.

[21] R.K. Bissoondeeal, J.M. Binner, M. Bhuruth, A. Gazely, and V.P. Mootanah. Forecasting exchange rates with linear and nonlinear models. *Global Business and Economics Review* 2008, **10**: 414-429.

[22] X.F. Hui, Z. Li, and Q.Q. Wei. Using fuzzy neural networks for RMB/USD real exchange rate forecasting. *Journal of Harbin Institute of Technology* 2005, **4:** 189-192.

[23] Z.C. Liu, X.Y. Liu, and Z.R. Zheng. Modeling and prediction of the CNY exchange rates using RBF neural networks versus GARCH models. *Applied Mechanics and Materials* 2010, **39**: 375-382.