Forecasting Malaysian Exchange Rate: Do Artificial Neural Networks Work?

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FORECASTING MALAYSIAN EXCHANGE RATE: DO ARTIFICIAL NEURAL NETWORKS WORK?

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Abstract
Being a small and open economy, the stability and predictability of Malaysian foreign exchange are crucially important. However, despite the general failure of conventional monetary models, foreign exchange misalignments and authority intervention have both caused the forecasting process an uneasy task. The present paper employs the monetary-portfolio balance exchange rate model and its modified version in the analysis. We then compare two Artificial Neural Networks (ANNs) estimation procedures (MLFN and GRNN) with random walk (RW) in the modeling-prediction process of RM/USD during the post-Bretton Wood era (1990M1-2008M8). The out-of-sample forecasting assessment reveals that the ANNs have outperformed the RW, which in particular, the MLFNs outperform GRNNs where as the latter outperform the RW models with consistency in both the exchange rate models by all evaluation criteria. In addition, the findings also show that the modified model has superior forecasting performance than the first model. In brief, economic fundamentals are vital in forecasting and explaining the RM/USD exchange rate. The finding is beneficial in policy making, investment modeling as well as corporate planning.

Keywords: Artificial Neural Networks, Forecasting, modified monetary-portfolio balance model, RM/USD

JEL classification: C45, C53, F31

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1.0 Introduction

Since the collapse of Bretton Wood system, the modeling-forecasting of foreign exchange rate has become a popular but challenging task (Hu *et al.*, 1999; Leung *et al.*, 2000; Panda and Narasimhan, 2007; Zhang and Hu, 1998). In the classical view (balance of payment approach), currency changes are simply determined by the current demand and supply for imports and exports. In modern age, however, the global turnover in foreign exchange is much higher than can be explained by international trade alone. The classical model may determine where the exchange rate has to converge to, yet, provides very little guidance to the short term fluctuations.

By end-1970s, Dornbusch, Frenkel, Mussa and others advocated the monetary approaches to exchange rate determination. Monetary approaches are asset pricing view of the exchange rate. The central idea is that agents have a portfolio choice decision between domestic and foreign assets. Those instruments (either money or bonds) have expected return that could be arbitraged and such arbitrage opportunity determines the process of the exchange rate. These relatively new approaches show that the exchange rate must depend not only on supply and demand of international trading, but also on market expectations of future developments in the 'fundamentals' including outputs and money supplies. The workhorse model of policy analysis remains the Mundell-Fleming framework[1], fitting well in the theoretical shield and seemed to hit the nail on the head in explaining why flexible exchange rates had been volatile in the post-Bretton Wood era.

Still, in an influential series of papers, Meese and Rogoff (1983a, 1983b, 1988), challenged the credibility of these monetary exchange rate models. Their empirical findings show that the models' forecasts of future nominal and real exchange rates were not as good as than those of a naïve random walk. The result was unusual, as the random walk model does not utilize any information on fundamentals. Even more surprisingly, the out-performance of the random walk held for conditional out-of-sample forecasts as well, that is for forecasts that use realized values of the fundamentals - economic variables other than the lagged exchange rate and does not have an economic interpretation[2]. A bulk of subsequent studies scrutinized the Meese-Rogoff puzzle using different samples, various econometric specifications and assorted explanatory variables. Nevertheless, the overall empirical evidence is at best mixed and the Meese-Rogoff's finding of the poor forecasting ability (out-sample) of exchange rate models relative to the simple random walk has never been convincingly overturned, even in the recent works by Cheung *et al*. (2003), Frankel and Ross (1995), Kilian and Taylor (2001), Rossi (2004), among others.

The unsolved issue is far more important when applies to Malaysia. The Malaysia experience offers some interesting insights. First, Malaysia is a small and open economy with the exchange rate regime playing an important role in the economic development. Malaysian trade openness is now among the highest in the world, about 200% of its GDP. Though Malaysia has tried to diversify the economy activities and expand the domestic consumption in the past decade, half of its aggregate demand still relies on its external trade. Malaysia is

[1] Modified mainly to allow for some expected regression of the exchange rate towards a long-run 'normal' level (Krugman, 1993).

[2] This is against the theoretical sense, since real exchange rates are not traded assets or market variables, whose price is subject to arbitrage conditions. Nominal exchange rates, though, are market variables, but there is no reason to expect them to be random walks in the presence of nominal interest rate differentials or risk premia.

thus inevitably and largely vulnerable to foreign exchange risk and volatilities. Second, Malaysia has practiced various exchange rate regimes in the past four decades, from the Bretton Wood system, managed floating, free floating to the basket of currency-floating era. Third, government interventions are always evident even when floating regime is in place. The form of intervention goes from selling small amounts of foreign currency, domestic instruments, to sterilization and even buying stocks in the domestic stock markets. Forth, exchange rate misalignments were captured overtimes during the economic boom of early 1990s and during the 1999-2005 economic recovery. With all the consideration mentioned, can Malaysian Ringgits predicted by fundamentals? Our paper will study the case of Malaysian Ringgit against USD in the post-Bretton Wood era (1990M1-2008M8) and hopefully provides the answer. To precisely capture the short run fluctuations of Malaysian Ringgit in the post-Bretton Wood era, the present study employs the modified monetary-portfolio balance model and compares two estimation procedures in the modeling-prediction process. Most specifically, these include the Random Walk (RW) and the Artificial Neural Networks (ANNs).

The present study is organized in the following manner. In section 2, we share a brief and recent literature on ANNs and exchange rate forecasting, followed by the review of Malaysian foreign exchange regime in Section 3. The theoretical representation of recent exchange models, the estimation procedures and data description are elaborated in Section 4. Section 5 provides the discussion of empirical results and finally, in the closing Section 6, conclusions are drawn.

2.0 Brief Literature Review

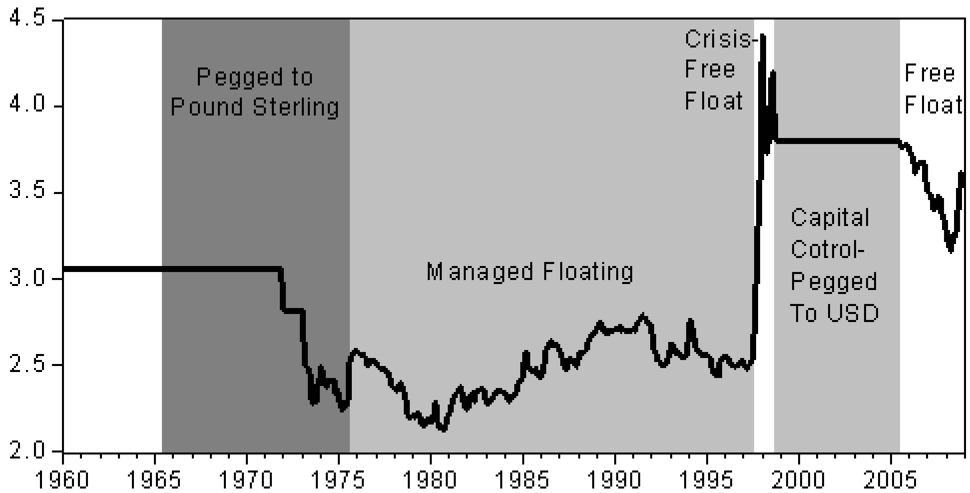
While time series econometrics has been popularized by economists since 1980s, the application of ANNs in financial forecasting is more of recent. ANNs are recognized in function approximation and system modeling due to the ability to learn and generalize from experience, as the mimic of the biological neural system. ANNs have shown to be a promising tool in financial time series analysis and forecasting (see Bishop, 1995; Hill et al., 1996; Yao and Tan, 2000; Yaser and Atiya, 1996; Yu, 1999). Notably, ANNs are capable in nonstationary time series and nonlinear modeling, especially in foreign exchange rate forecasting on account of its several distinctive properties such as nonlinearity, nonparametric, self-adaptive, noise-tolerant, and flexible nonlinear function mapping capability without priori assumptions about the data (see also Cao and Tay, 2001; Kamruzzaman and Sarker, 2004; Yao and Tan, 2000; Zhang et al., 1998). Gencay (1999), for instance, compared the performance of neural network with those of random walk and generalized autoregressive conditional heteroskedasticity (GARCH) models in forecasting daily spot exchange rates for the British pound, Deutsche mark, French franc, Japanese yen, and the Swiss franc. The results show that forecasts generated by neural network are superior to those of random walk and GARCH models. More recent, Panda and Narasimhan (2007) had successfully compared the forecasting accuracy of neural network with that of linear autoregressive and random walk models in the study of one-step-ahead prediction of weekly Indian rupee/US dollar exchange rate. They found that neural network is superior in-sample forecast than linear autoregressive (LAR) and random walk models. Neural network is also found to outperform both linear autoregressive and random walk models in out-of-sample forecasting.

In addition, the application of ANNs to short-term currency performance was fruitful in numerous studies and the results suggested that ANN models do have some advantages when frequent short-term forecasts are required (Kuan and Liu, 1995). Also, Nasr et al. (2006) concluded that the best ANN model is able to forecast exchange rates during periods of extreme fluctuations, as a result of the research in which they built various feed-forward ANN models and trained them by the backpropagation algorithm to forecast the exchange rate movements during periods of currency crises characterized by excessive volatility. Such advantages best describe our Malaysia model which that involves high frequency observations and currency crisis period.

3.0 Malaysian Foreign Exchange Regime

Malaysian Ringgit (RM) was formerly known as Malaysia Dollar (M$). M$ was created in June 1967 to replace the old Sterling-link Malaysian/Straits Dollar. In year 1971, M$ was linked to Pound Sterling (£) at fixed rate of 7.4369M$/£. With floating of Sterling and dismantling of Sterling Area, Malaysia adopted US Dollar with fluctuation range for Effective Rate as intervention currency in place of Sterling in 1972. The intervention of Malaysian Central Bank was to maintain the stability in the value of domestic currency in relation to basket of foreign currencies. Due to devaluation of US Dollar in February 1973, the Official Rate of Malaysian Dollar was realigned to 2.53M$/US$, based on currency's unchanged gold content. In 21 June 1973, Malaysia placed a controlled, floating effective rate (see Figure 1).

Figure 1: Malaysian Exchange Rate Regime, 1960M1-2009M1



In 1975, the Malaysian Dollar was officially changed to Ringgit (RM) and the controlled, floating effective rate was replaced. The external value of Ringgit was determined based on the weighted basket of foreign currencies of the Malaysia major trading partners. The same exchange rate determination was sustained up till the Asian Financial Crisis 1997/98. During the crisis year, the overvalued Ringgit depreciated sharply against the US dollar by more than 40%. To stabilize the financial market, Malaysia imposed capital control and returned to fixed exchange rate that pegged to US dollar at RM3.80 in September 1998. As part of the economic recovery strategy, Malaysia has committed to export-led growth policy based on maintenance of their undervalued and pegged currencies against the USD. On July 21, 2005, Malaysia responded to China's de-pegging announcement within an hour after the 7-year pegging. Akin to the Chinese policy, BNM allows the ringgit to operate in a managed floating system based on a basket of several major currencies.

4.1 Exchange Rate Models

The monetary-type of exchange rate models can be broadly subdivided into sticky price, flexible price and interest rate differential models. Monetary models concentrate on the economic outputs, monetary variables, interest rates of domestic and foreign countries, but not on the consume prices, which are influential of long-run exchange rates. On the other hand, the portfolio balance model focuses on the imperfect substitutability between domestic and foreign assets because of the risk premium. Attention is given on the demand of a set of portfolio, indexed as accumulated current account. When combined, the monetary-portfolio balance model of exchange rate can be represented by the following functional form,

$$S_{t+1} = f(m_t - m_t^*, ip_t - ip_t^*, r_t - r_t^*, \pi_t - \pi_t^*, TB_t, TB_t^*) \quad (1)$$

where * denotes foreign variables. S_{t+1} being the bilateral exchange rate, $(m_t - m^*_t)$ is the differential form of relative nominal money supply, $(ip_t - ip^*_t)$ is the differential form of relative industrial production, $(r_t - r^*_t)$ is the nominal short term interest, $(\pi_t - \pi^*_t)$ is the differential form of inflation differential, whereas TB and TB^* are the cumulated trade balance. And, $_t$ and $_{t+1}$ are the respective series in present time and one period time ahead. More specific, function (1) can be generalized and estimated by two separated models:

Model 1:

$$S_{t+1} = \alpha + \beta_1(m_t - m_t^*) + \beta_2(ip_t - ip_t^*) + \beta_3(r_t - r_t^*) + \beta_4(\pi_t - \pi_t^*) + \beta_5 TB_t + \beta_6 TB_t^* + \varepsilon_t \quad (2)$$

Model 2:

$$S_{t+1} = \alpha + \delta_1 m_t + \delta_2 m_t^* + \delta_3 ip_t + \delta_4 ip_t^* + \delta_5 r_t + \delta_6 r_t^* + \delta_7 \pi_t + \delta_8 \pi_t^* + \delta_9 TB_t + \delta_{10} TB_t^* + \nu_t \quad (3)$$

In both models, the αs, βs and δs are parameters to be estimated whereas ε_t and ν_t are disturbance terms. All series are transformed into natural logarithm before estimation.

4.2 Estimation Procedure and Data description

ANN composes of individual processing nodes in which the architecture (the arrangement of the connection between nodes, the flow of signals, and the number of layers of the network), is closely related to the learning algorithm that will consequently determine the function and the performance of the network. In general, a network is trained by adjusting the values (weights) of the connections between nodes and the biases, in order to acquire a target output for a particular input provided. (see *inter alia*, Hammerstrom, 1993; Hush and Horne, 1993; Rumelhart *et al*., 1995). Despite the random walk estimation, we examine the performance of two types of ANNs: Multi-layered feedforward network (MLFN) and General Regression Neural Network (GRNN) in predicting the exchange rate of Malaysia ringgit against the US dollar.

The backpropagation algorithm is the most popular learning techniques for multi-layered feedforward network[3]. Basically, the learning algorithm involves changing the value of the weights and the biases in an iterative manner so that the output generated by the network approximates the underlying function of the training data. In a typical backpropagation neural network, the error i.e. the difference between the network output and the target, is back-propagated through the network and used to adjust the weights such that the error decreases by iteration. The output of the network is compared to the target, and the algorithm adjusts the network's weights and biases until the performance function, for instance, the mean square error (MSE) is minimized and is within a specified tolerance limit. Specifically, Hornik *et al*. (1989) revealed that if a sufficient number of hidden nodes are used, the standard backpropagation networks using an arbitrary transfer function can approximate any measurable function precisely in a satisfactory manner. On the other hand, the GRNN was first proposed and developed by Specht (1991). GRNN is a class of neural network that is closely associated to the radial basis function network (see Powell, 1987). GRNN is based on the kernel regression - a standard statistical technique, and it does not require an iterative training procedure as what the backpropagation network required. GRNN usually involves more nodes than a standard feedforward backpropagation network due to the limitation of the radial basis function nodes, in which it can only respond to relatively small regions of input space, but the procedures of designing a GRNN usually require less time than training a standard feedforward backpropagation network. The performance of GRNN has been proven in some of the preceding studies done in non-parametric functional approximations[4].

The procedures in achieving of the best neural network are rather subjective and the most common way in determining the optimum number of hidden nodes is via systematic experimentation or by trial and error[5]. In order for this study to achieve a more parsimonious MLFN model and to avoid the overfitting problem, we use a 3-layer (input-hidden-output) feedforward network with one hidden layer following the findings that show a single hidden layer is sufficient for ANNs function approximation (Cybenko, 1989; Hornik *et al*., 1989). We also restrict the maximum number of hidden nodes in both MLFN models to 20, i.e., twofold the number of input nodes in Model 2 based on the practical guideline provided by Wong (1991). The number of hidden nodes is determined through systematic experimentation procedures as shown in Table 1. The model employs sigmoid transfer function in the hidden layer, and linear function in the output layer and it is trained with the Levenberg-Marquardt backpropagation (see Hagan and Menhaj, 1994). In addition, a preprocessing is done by normalizing the data into the interval $[-1,\ 1]$ to improve the efficiency of network training, and the mean square error (MSE) is used as the performance function. We train each MLFN network 100 times by using 100 sets of different initial weights and biases for each number of hidden nodes (starting from n_h=2 until n_h=20). The best MLFN that yielded the least MSE among all the trials will be selected as the optimal model for out-of-sample forecasting. As a result (after the step 1 to step 7 in Table 1), the optimal MLFN models for exchange rate Model 1 and Model 2 are 6-18-1 and 10-17-1 respectively.

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[3] The backpropagation algorithm is one of the most commonly used learning algorithm for multi-layer feedforward networks and it performance is acknowledged by others. For instance, Adya and Collopy (1998), Kamruzzaman and Sarker (2004), Nikola and Jing (2000), Walczak, (2001), Yao and Tan (2000).

[4] See for instance, Chen and Leung (2001), Leung *at el*. (2000), Wittkemper and Steiner (1996).

[5] See for instance, Kamruzzaman and Sarker (2004), Panda and Narasimhan (2007), Zhang and Hu (1998).

Table 1: The summarized procedures in the MLFN model

Step 1:	Stratify the 200 historical data into 20 successive intervals with 10 data in each interval. Randomly select one data from each interval. The selected 20 data (or 10%) shall be use for validation, where as the remaining 180 data (or 90%) for training.
Step 2:	Construct a 3-layer feedforward network with n_h nodes in the hidden layer (initial n_h=2).
Step 3:	Train the network by using the data set obtained in step 1. Repeat this step for 100 times. Initiate the weights and the biases of the network each time before the training start over.
Step 4:	Save the network that yielded the smallest MSE.
Step 5:	Increase the number of nodes (n_h) by one.
Step 6:	Repeat step 2 to 5 until n_h=20.
Step 7:	Select the best network that yielded the smallest MSE (out of the 19 networks built separately for n_h from 2 to 20) for out-of-sample forecasting.
Step 8:	Use the optimal network to forecast the predicted value (y_{t+1}) for a set of input variables (x_t).
Step 9:	Initiate the weights and the biases of the network and retrain the network by using the data set obtained in step 1, together with the last data used in step 8 (x_t and y_{t+1}).
Step 10:	Forecast the predicted value (y_{t+2}) for a set of input variables (x_{t+1}) by using the network trained.
Step 11:	Repeat step 9 and 10 until all out-of-sample data are tested.

As for the GRNN, the procedures to obtain the optimal GRNN model in this paper mainly focus on attaining best smoothing factor (or spread constant). The larger the smoothing factor in the GRNN, the smoother the network function will be. However, a larger smoothing factor does not necessarily promise superior accuracy. With initial spread constant s=0, and gradually increase by 0.005 until s=20, the spread constant of the GRNN that yielded the smallest MSE among all the 2000 trials will be chosen as the best spread constant s_b (as shown in step 1 to step 5 in Table 2) and it will be utilized for out-of-sample forecasting. Consequently, the best spread constant s_b chosen for exchange rate Model 1 and Model 2 are 0.065 and 0.095 respectively.

Table 2: The summarized procedures in the GRNN model

Step 1:	Stratify the 200 historical data into 20 successive intervals with 10 data in each interval. Randomly select one data from each interval. The selected 20 data (or 10%) shall be use in determining the best spread constant s_b, where as the remaining 180 data (or 90%) for model construction.
Step 2:	Construct a GRNN with spread constant s by using the remaining 90% of the data obtained in step 1, (initial s=0).
Step 3:	Obtain the MSE with the network built by simulating the selected 10% of the data obtained in step 1.
Step 4:	Repeat step 2 and 3 by increasing the spread constant s by 0.005 in each repetition until s=10.
Step 5:	Select the spread constant s_b of the GRNN that yield the smallest MSE (out of the 2000 GRNNs built respectively for s from 0 to 10) for out-of-sample forecasting.
Step 6:	Construct a GRNN with spread constant s_b by using all the 200 data to forecast the predicted value (y_{t+1}) for a set of input variables (x_t).
Step 7:	Rebuild a GRNN with the same spread constant s_b by using all the 200 data, together with the last data used in step 6 (x_t and y_{t+1}).
Step 8:	Forecast the predicted value (y_{t+2}) for a set of input variables (x_{t+1}) by using the GRNN.
Step 9:	Repeat step 7 and 8 until all out-of-sample data are tested.

In this paper, the RW and ANN models use 200 historical monthly data of the exchange rate of Malaysia ringgit against the US dollar from the period of January 1990 to August 2006 for model building. The remaining 24 monthly historical data from September 2006 to August 2008 were kept for testing i.e. out-of-sample forecasting. All monthly data are sourced from the International Financial Statistics (IFS), IMF. In view of the fact that the benchmark RW model is a one-step-ahead forecasting model since it employs existing observation S_t to forecast the succeeding value S_{t+1}, we conduct the similar forecasting for ANN models in order to make a more rational comparison between these models. Hence, all the ANNs are retrained every time when a more recent observation is available. The process is repeated until all the 24 monthly out-of-sample data are utilized. We rely on four popular criteria to evaluate the models' out-of-sample performance, namely the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Theil's Inequality Coefficient (Theil-U):

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{S}_t - S_t\right)^2} \tag{4}$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|\hat{S}_t - S_t\right| \tag{5}$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{\hat{S}_t - S_t}{S_t}\right| \times 100 \tag{6}$$

$$Theil - U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{S}_t - S_t\right)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{S}_t\right)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(S_t\right)^2}} \tag{7}$$

where S_t is the actual observation, $\hat{S}_t$ is the forecasted value, and T is the number of predictions. In a comparative study, model that yields a smaller value in all such criteria signifies its superiority against other models.

5.0 Data Analyses and Results Discussion

The applicability of a forecasting model is determined by its prediction quality. The prediction quality is determined by comparing the forecasted outputs to the actual known values of the test. As shown in the previous section, the MLFNs with the structure of 6-18-1 and 10-17-1 are selected respectively for Model 1 and Model 2, where as in the GRNNs, the spread constant for Model 1 and Model 2 are 0.065 and 0.095 respectively. The forecasted values over the 24-month forecasting horizon obtained from the ANN and RW models, in contrast to the actual values are plotted in the following Figure 2 and Figure 3 respectively for Model 1 and Model 2, to provide a clearer picture of the forecasted values.

Figure 2: Actual and forecasted values (24-month horizon) of Model 1

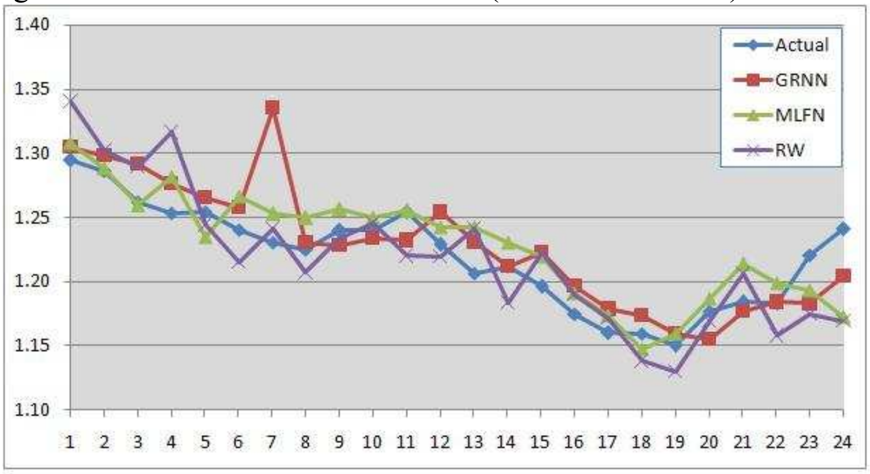
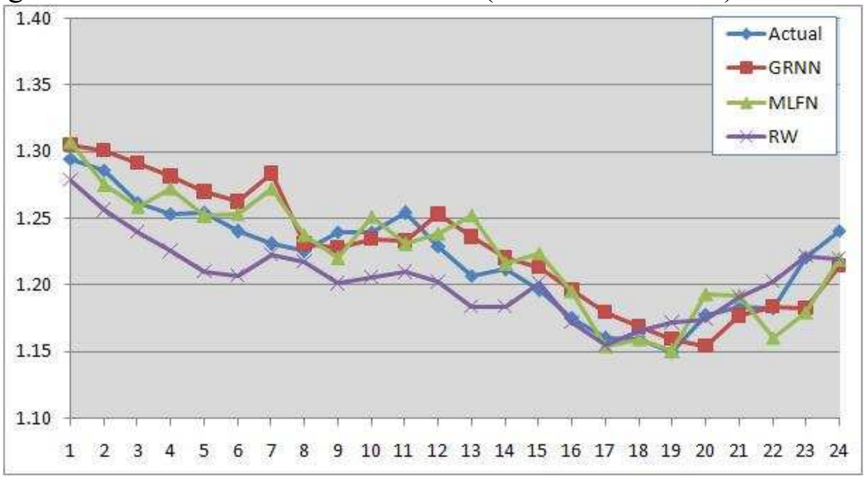


Figure 3: Actual and forecasted values (24-month horizon) of Model 2



In general, we can see that generally all the forecasting models are able to forecast quite accurately (as shown in Figure 2) except it is noticeable that the predicted value at the 7th month of the GRNN departs significantly from the actual value. After further study, we believe that the reason of this departure maybe due to the sudden abrupt in inflation rate of Malaysia which significantly altered the inflation logarithmic differential ($\ln\pi_t - \ln\pi^*_t$), from 0.1111 in the 6th month to –0.6348 in the 7th month. Besides that, it is clear that the differences between the actual values and the various forecasted values after the 21st month enlarged. This probably caused by the larger inflation differential as well in the 22nd month to 24th month (with values in the range of 0.8672 to 0.8809), which are much greater than other data with inflation logarithmic differential values merely between the ranges of –1.1069 to 1.1108. Conversely, the overall forecast performances of the predicting models (as shown in Figure 3) are considerably better, i.e. the forecasting performance of all predicting models under the modified version of monetary-portfolio balance exchange rate model (Model 2) is better than the basic version (Model 1). However, the difference between the actual value and the predicted value in the 7th month of the GRNN and MLFN still observable, which most likely because of the sudden swift in the Malaysia inflation rate as well.

To evaluate the forecasting performance of the GRNN and MLFN models, we employ RMSE, MAE, MAPE and Theil-U as performance evaluation criteria, and the RW model is taken as a benchmark. The evaluation results for the out-of-sample performance are reported in Table 3. The parenthesis value in Table 3 represents the ranking of the model in each setting. The results show that the out-of-sample forecasts of ANNs are more accurate than the random walk forecasts by all criteria in both Model 1 and Model 2. Specifically, the results in this study show that the MLFN models outperform the GRNN models by all criteria as well. These findings are consistent across the four performance selection criteria over the 24-month forecasting horizon. In addition, the results also indicate the superiority of the Model 2 (Equation 3) in forecasting exchange rate in comparison to Model 1 (Equation 2). We believe that the outperformance of Model 2 could be due to its larger number of predictor variables, i.e., 10 predictor variables in Model 2 in contrast to 6 predictor variables only in Model 1.

Table 3: Assessment of forecasting (24-month horizon)

Criteria	**Model 1 (Equation 2)**			**Model 2 (Equation 3)**		
	RW1	**GRNN1 [0.065]**	**MLFN1 [6-18-1]**	**RW2**	**GRNN2 [0.095]**	**MLFN2 [10-17-1]**
RMSE	0.03030 (3)	0.02892 (2)	0.02343 (1)	0.02391 (3)	0.02207 (2)	0.02065 (1)
MAE	0.02516 (3)	0.02076 (2)	0.01919 (1)	0.01984 (3)	0.01878 (2)	0.01644 (1)
MAPE	2.05296 (3)	1.69823 (2)	1.57512 (1)	1.60917 (3)	1.53574 (2)	1.34604 (3)
Theil-U	0.01242 (3)	0.01181 (2)	0.00957 (1)	0.00986 (3)	0.00901 (2)	0.00845 (1)

Note: Figures in the parentheses ( ) are the respective ranking of the model according to each criterion.

6.0 Conclusion

This paper employed two Artificial Neural Networks (ANNs) estimation procedures, i.e. MLFNs and GRNNs to forecast the process of RM/USD under the monetary-portfolio balance exchange rate model (Model 1) and its modified version (Model 2) over 1990M1-2008M8 period. The out-of-sample forecasting assessment reveals that both the ANNs estimations outperformed the benchmark random walk. In particular, the MLFNs outperform GRNNs, where as the latter outperform the RW models. The superiority of ANNs over RW models suggests that the economic fundamentals are vital in forecasting and explaining the RM/USD exchange rate. Furthermore, this paper also shows that the Model 2 has superior out-of-sample forecasting performance than Model 1. The forecasting performance is consistent in both the exchange rate models by all evaluation criteria in the 24-month forecasting horizon. The superior forecasting performance of Model 2 modeled by MLFNs in predicting exchange rate is beneficial in assisting the policy makers to carry out a more appropriate and comprehensive monetary policy that will subsequently entail price stability and the enhancement of economy environment. It is also useful to investors for profitable trading strategy, as well as for multinational companies in corporate planning. Lastly, we anticipate that if more deterministic variables can be identified, in addition to the usage of more recent data, the performance of ANNs in modeling and forecasting the exchange rate can be enhanced.

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