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FORECASTING MALAYSIAN RINGGIT: BEFORE AND AFTER THE GLOBAL CRISIS

Chan Tze-Haw[1], Lye Chun Teck[2] and Hooy Chee-Wooi[3]

[1] *Graduate School of Business, Universiti Sains Malaysia, 11800 Pulau Pinang, Malaysia*
[2] *Faculty of Business, Multimedia University, Jalan Ayer Keroh Lama, 75450 Ayer Keroh, Melaka, Malaysia*
[3] *School of Management, Universiti Sains Malaysia, 11800 Pulau Pinang, Malaysia*

*Corresponding author: thchan@usm.my

ABSTRACT

The forecasting of exchange rates remains a difficult task due to global crises and authority interventions. This study employs the monetary-portfolio balance exchange rate model and its unrestricted version in the analysis of Malaysian Ringgit during the post-Bretton Wood era (1991M1–2012M12), before and after the subprime crisis. We compare two Artificial Neural Network (ANN) estimation procedures (MLFN and GRNN) with the random walks (RW) and the Vector Autoregressive (VAR) methods. The out-of-sample forecasting assessment reveals the following. First, the unrestricted model has superior forecasting performance compared to the original model during the 24-month forecasting horizon. Second, the ANNs have outperformed both the RW and VAR forecasts in all cases. Third, the MLFNs consistently outperform the GRNNs in both exchange rate models in all evaluation criteria. Fourth, forecasting performance is weakened when the post-subprime crisis period was included. In brief, economic fundamentals are still vital in forecasting the Malaysian Ringgit, but the monetary mechanism may not sufficiently work through foreign exchange adjustments in the short run due to global uncertainties. These findings are beneficial for policy making, investment modelling, and corporate planning.

Keywords: Artificial Neural Networks, forecasting, modified monetary-portfolio balance model, Malaysian Ringgit, global crisis

INTRODUCTION

Since the collapse of the Bretton Wood system, the modelling-forecasting of foreign exchanges has become a popular but challenging task (Hu, Zhang, Jiang, & Patuwo, 1999; Leung, Chen, & Daouk, 2000; Panda & Narasimhan, 2007; Zhang & 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 the 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 must converge to, yet it provides very little guidance regarding short-term fluctuations.

By the end of the 1970s, Dornbusch (1976), Frenkel (1976), Bilson (1978) and Frankel (1979), among others, advocated monetary exchange rate models for exchange rate determinations[1]. More recently, the influential work of Meese and Rogoff (1983a, 1983b, 1988) has challenged the reliability of these models as they empirically showed that the naive random walk benchmark model outperformed the monetary models in short-term out-of-sample exchange rates predictions[2]. A large number of subsequent studies scrutinised the Meese-Rogoff puzzle using different samples, various econometric specifications and assorted explanatory variables. The overall empirical evidence is at best mixed, and 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 Frankel and Ross (1995), Kilian and Taylor (2001), Cheung, Chinn and Garcia (2003), Rossi (2005), Engel and West (2005), Nwafor (2006), and Rogoff and Stavrakeva (2008), among others.

While the development of novel exchange rate theory has halted for nearly a decade, the new issue of foreign exchange forecasting has risen lately due to the recent global crisis in 2008. The policy responses of interest rate cuts and quantitative easing (QE) by central banks of Europe, the US and Japan have resulted in positive outcomes in the short run. Substantial central bank credits were channelled to the financial sector and provided monetary stimulus to accelerate economic growth. However, such moves have also augmented the risk of import inflation and currency depreciation of the host country, which simultaneously create additional pressures on emerging-market currencies (including the Malaysian Ringgit). Increasing concerns that QE will thrust the world into a global currency war and over the intricacy of regional export competition have collectively raised queries about whether the forecasting of foreign exchanges by economic fundamentals is still possible.

The impacts of global changes are especially significant for a small and open economy such as Malaysia due to the export-oriented development strategy[3]. The stability and predictability of Malaysian foreign exchanges are vulnerable to global risk and volatilities. Over the past four decades, Malaysia has practiced various exchange rate regimes, including the Bretton Wood system, managed floating, free floating and the currently used approach of currency-floating. However, government interventions are always evident, even when a floating regime is in place. The forms of intervention range from selling small amounts of foreign currency, domestic instruments, to sterilisation and even buying stocks in the domestic stock markets. Exchange rate misalignments were still captured at times during the economic boom of the early 1990s and during the 1999–2005 economic recovery (see Lee & Azali, 2005, Lee, Azali, Yusop, & Yusoff, 2008). Given the aforementioned considerations, we ask whether the Malaysian Ringgits exchange rate can be predicted by economic and monetary fundamentals? This paper will provide new insights by studying the case of the Malaysian Ringgit against the USD in the post-Bretton Wood era (1991M1–2012M12) before and after the subprime crisis.

To precisely capture the short-run fluctuations of the Malaysian Ringgit in the post-Bretton Wood era, the present study employs the modified monetary-portfolio balance model and compares three estimation procedures in the modelling-prediction process. Specifically, these procedures include Random Walks (RW), the Vector Autoregressive (VAR) method and the emerging technology of Artificial Neural Networks (ANNs). Presently, ANNs are often viewed as a class of machine-learning algorithms that draw inspiration from biological neural systems (Aamodt, 2010). This technique gained considerable momentum in the early 1990s, but limited attention has been given to the Malaysian Ringgit due to minor trading volumes in the foreign exchange market. This new technology is set to continue throughout the decade (Taylor & Lisboa, 1993) and the new millennium. These networks have proven to be good at solving many tasks in areas such as modelling and forecasting, signal processing, and expert systems (Lippmann, 1987). The neural network method has demonstrated its ability to address complex problems, and this method may enhance an investor's forecasting ability.

The present study is organised in the following manner. Next section briefly reviews the recent literature on ANNs and foreign exchange forecasting. The theoretical depiction of our foreign exchange models is then provided, followed by the estimation procedures and data description. Subsequently, the paper elaborates the Malaysian foreign exchange regime and discusses the empirical results. In the final section, the paper concludes.

ANNs AND FOREIGN EXCHANGES

While time series econometrics has been popularised by economists since the 1980s, the application of ANNs in financial forecasting is more recent. ANNs are recognised in function approximation and system modelling as the mimicking of the biological neural system due to the ability to learn and generalise from experience. ANNs have been shown to be a promising tool in financial time series analysis and forecasting (see: Bishop, 1995; Hill, O'Connor, & Remus, 1996; Yao & Tan, 2000; Yaser, & Atiya, 1996; Yu, 1999; Bissoondeeal, Binner, Bhuruth, Gazely, & Mootanah, 2008). Notably, ANNs are capable of handling non-stationary time series and nonlinear modelling, especially in foreign exchange forecasting, on account of their distinctive properties, such as nonlinearity, nonparametric, self-adaptive, noise-tolerant, and flexible nonlinear function mapping capability without a priori assumptions about the data (see also Cao & Tay, 2001; Kamruzzaman & Sarker, 2004; Yao & Tan, 2000; Zhang, Patuwo, & Hu, 1998). Gencay (1999), for instance, compared the performance of a neural network with that of random walk and generalised 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 showed that the forecasts generated by the neural network are superior to those of the random walk and GARCH models.

More recently, Panda and Narasimhan (2007) successfully compared the forecasting accuracy of a neural network with that of linear autoregressive and random walk models in the study of one-step-ahead predictions of weekly Indian rupee/US dollar exchange rates. They found that the neural network generates superior in-sample forecasts than the linear autoregressive (LAR) and random walk models. Neural networks are also found to outperform both linear autoregressive and random walk models in out-of-sample forecasting. Note that limited studies of the Malaysian Ringgit are found in the literature. Among them, Lye, Chan and Hooy (2011) studied the RM/USD during 1991–2008 using the monetary models advocated by Meese and Rogoff (1983a, 1983b) and Sarantis and Stewart (1995) with inclusion of autoregressive (AR) terms. They confirmed that generalised regression neural network (GRNN)'s outputs outperform random walks and that potential misalignments are temporal and can be corrected by monetary adjustments. Lye, Chan and Hooy (2012) then studied the short-run predictability of monthly Chinese Yuan and Malaysian Ringgit against the USD using the GRNN with discrete and relative monetary fundamentals during 2005–2010. They arrived at a similar conclusion in that the GRNN outperformed random walks for both currencies. However, in both studies, the multi-layered feedforward network (MLFN) and the VAR approach were not applied.

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 & Liu, 1995). Additionally, Nasr, Dibeh and Abdallah (2006) concluded that the best ANN model is able to forecast exchange rates during periods of extreme fluctuations, and as a result of this research, they constructed various feed-forward ANN models and trained them using the backpropagation algorithm to forecast exchange rate movements during periods of currency crises characterised by excessive volatility. Such advantages best describe our Malaysia model, which involves high frequency observations and a currency crisis period.

EXCHANGE RATE MODELS

The monetary-type exchange rate models can be broadly subdivided into sticky price, flexible price and interest rate differential models (Meese & Rogoff, 1983a; 1983b; 1988). Alternatively, the portfolio balance model focuses on the imperfect substitutability between domestic and foreign assets because of the risk premium (Hallwood & MacDonald, 2000). Attention is given to the demand of a set of portfolios, indexed as accumulated current account. When combined, the monetary-portfolio balance model of exchange rates 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} is 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, and TB and TB^* are the cumulated trade balance. In addition, $_t$ and $_{t+1}$ are the respective series in present time and one period time ahead. More specifically, function (1) can be generalised 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:

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

Model (1) relaxes the assumptions of identical income elasticity for foreign and domestic countries: the neutrality of money and interest parity inherent in Model (2)—the less-restricted or often called unrestricted form of monetary-portfolio balance model. 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 logarithms before estimation.

Estimation Procedure and Data Description

ANN are composed of individual processing nodes in which the architecture (the arrangement of the connections between nodes, the flow of signals, and the number of layers in the network) is closely related to the learning algorithm that will consequently determine the function and performance of the network. In general, a network is trained by adjusting the values (weights) of the connections between nodes and the biases to acquire a target output for a particular input provided. (see inter alia; Hammerstrom, 1993; Hush, & Horne, 1993; Rumelhart, Durbin, Golden, & Chauvin, 1995). Despite the random walk estimation, we examine the performance of two types of ANNs; MLFN and GRNN, in predicting the exchange rate of the Malaysia Ringgit against the US dollar (RM/USD).

The backpropagation algorithm is the most popular learning technique for multi-layered feedforward networks[4]. Basically, the learning algorithm involves changing the values of the weights and the biases in an iterative manner such 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 with each 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 minimised and is within a specified tolerance limit. Specifically, Hornik, Stinnchcombe and White (1989) concluded 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.

The GRNN was first proposed and developed by Specht (1991). GRNN is a class of neural networks that is closely associated with the radial basis function network (see Powell, 1987). GRNN is based on the kernel regression, a standard statistical technique, and does not require an iterative training procedure such as that required by the backpropagation network. 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; however, the procedures for 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 conducted in non-parametric functional approximations[5]. If $D_i = (x - p_i)$ is the distance between the training sample and the point of prediction, the output of the GRNN can be defined as:

$$\hat{y}(X) = \frac{\sum_{i=1}^{n} w_i \exp\left(-D_i^{\mathrm{T}} D_i / 2s^2\right)}{\sum_{i=1}^{n} \exp\left(-D_i^{\mathrm{T}} D_i / 2s^2\right)} \tag{4}$$

where s is the smoothing parameter, and w_i is the weight of the point of prediction. The procedures for achieving the best neural network are rather subjective, and the most common method for determining the optimum number of hidden nodes is via systematic experimentation or by trial and error[6]. For this study to achieve a more parsimonious MLFN model and to avoid the over-fitting problem, we use a three-layer (input-hidden-output) feedforward network with one hidden layer based on 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 the systematic experimentation procedures, as shown in Table 1.

Table 1
The summarised procedures in the MLFN model

Step 1:	Stratify the 264 historical data into 24 successive intervals with 11 data in each interval. Randomly select one data from each interval. The selected 24 data (or about 10%) shall be use for validation, where as the remaining 240 data (or about 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.

The model employs a sigmoid transfer function in the hidden layer and a linear function in the output layer, and it is trained using Levenberg-Marquardt backpropagation (see Hagan & Menhaj, 1994). In addition, a pre-processing is performed by normalising 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 step 1 through step 7 in Table 1), the optimal MLFN models for exchange rates in Model 1 and Model 2 are 6-18-1 and 10-17-1, respectively.

Table 2
The summarised procedures in the GRNN model

Step 1:	Stratify the 264 historical data into 24 successive intervals with 11 data in each interval. Randomly select one data from each interval. The selected 24 data (about 10%) shall be use in determining the best spread constant s_b, whereas the remaining 240 data (or about 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.

For the GRNN, the procedures to obtain the optimal GRNN model in this paper mainly focus on attaining the 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 the initial spread constant $s = 0$, and gradually increasing 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 through step 5 in Table 2), and it will be utilised for out-of-sample forecasting. Consequently, the best spread constant s_b chosen for exchange rates Model 1 and Model 2 are 0.065 and 0.095, respectively.

In this paper, the RW and ANN models use 240 historical months of data (20 years) of the exchange rate of the Malaysia Ringgit against the US dollar from the period of January 1991 to December 2010 for model building. The remaining 24 months of historical data (2 years) from January 2010 to December 2012 were kept for testing, i.e., out-of-sample forecasting. The remaining 60 months are further split into 24 months and 36 months. All monthly data are sourced from the International Financial Statistics (IFS), IMF. As the benchmark RW model is a one-step-ahead forecasting model because it employs existing observation S_t to forecast the succeeding value S_{t+1}, we conduct similar forecasting for the ANN models to make a more rational comparison between these models. Hence, all the ANNs are retrained each time a more recent observation is available. The process is repeated until all the 24 monthly out-of-sample data are utilised. 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, the model that yields a smaller value in all such criteria is superior to the other models.

MALAYSIA FOREIGN EXCHANGE REGIME

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

In 1975, the Malaysian Dollar was officially changed to the Ringgit (RM), and the controlled but floating effective rate was replaced (see Figure 1). The external value of the Ringgit was determined based on the weighted basket of foreign currencies of Malaysia's major trading partners. The same exchange rate determination was sustained until the Asian Financial Crisis of 1997/98. During the crisis year, the overvalued Ringgit depreciated sharply against the US dollar by more than 40%. To stabilise the financial market, Malaysia imposed capital control and returned to a fixed exchange rate that pegged to the 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 21 July 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. Though fluctuation of the Malaysian Ringgit against the USD was evident during the Subprime crisis in 2008/09, Malaysian banks do not have much impact due to global financial turmoil; the collective exposure of Malaysian banks to the sub-prime mortgage-backed Collateralised Debt Obligations was estimated to be less than US$100 million. However, the manufacturing and export sectors were heavily impacted by the decline of global demand.

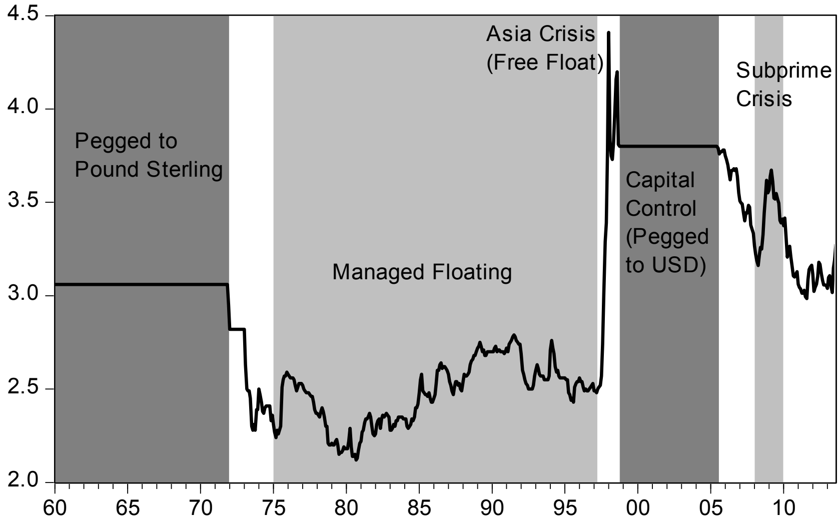

Figure 1. Malaysian Exchange Rate Regime, 1960M1–2012M12

EMPIRICAL 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. As shown in the previous section, the MLFNs with the structure of 6-18-1 and 10-17-1 are selected for Model 1 and Model 2, respectively, whereas in the GRNNs, the spread constants 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 for Model 1 and Model 2, respectively, to provide a clearer picture of the forecasted values.

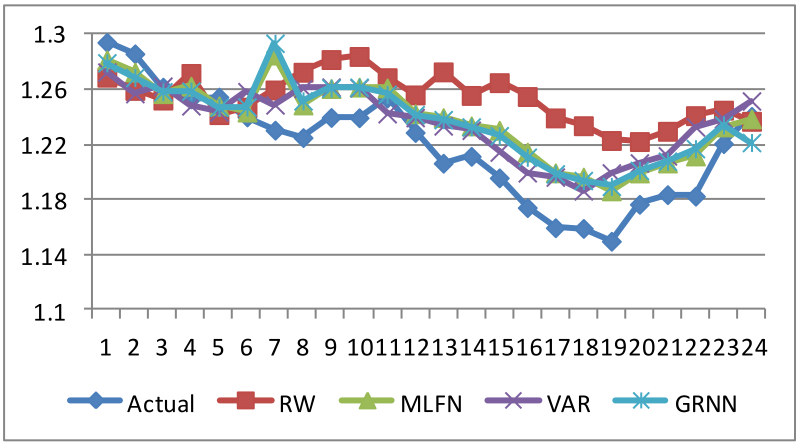

Figure 2. Actual and forecasted values (24-month horizon) of Model 1

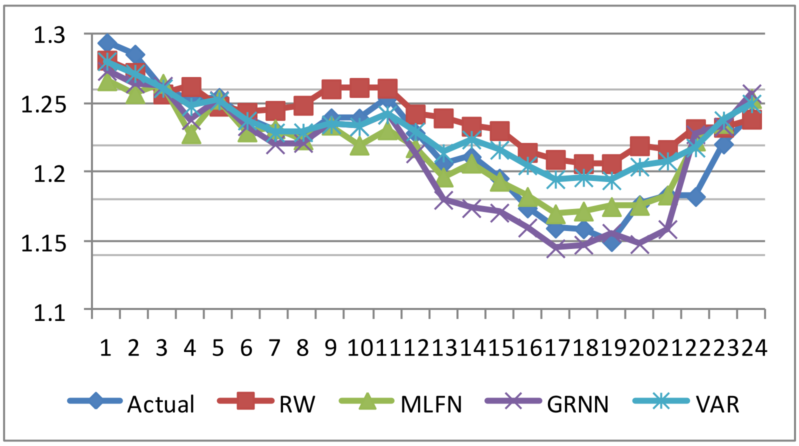

Figure 3. Actual and forecasted values (24-month horizon) of Model 2

Overall, we can see that all the forecasting models are generally 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 for this departure could be due to the sudden abrupt change in the inflation rate in Malaysia that 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. Otherwise, it is clear that the differences between the actual values and the various forecasted values after the 21st month increased. This result is most likely also caused by the larger inflation differential in the 22nd month to the 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 only 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) are 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 is still observable, which most likely occurred because of the sudden change in the Malaysia inflation rate as well.

To evaluate the respective forecasting capability of the monetary models based on the GRNN and MLFN methods, we employ RMSE, MAE, MAPE and Theil-U as performance evaluation criteria. At the same time, the RW and VAR model are taken as benchmarks. The evaluation results for the out-of-sample performance, with and without the subprime crisis period, are reported in Table 3 and Table 4, respectively. The values in parentheses in both tables represent the ranking of the model in each setting.

Table 3
Assessment of forecasting (24-month horizon) without subprime crisis

	Model 1 (Equation 2)				**Model 2 (Equation 3)**			
	RW	VAR	GRNN	MLFN	RW	VAR	GRNN	MLFN
RMSE	0.03030 (3)	0.03225 (4)	0.02892 (2)	0.02343 (1)	0.02391 (3)	0.03117 (4)	0.02207 (2)	0.02065 (1)
MAE	0.02516 (3)	0.03925 (4)	0.02076 (2)	0.01919 (1)	0.01984 (3)	0.02128 (4)	0.01878 (2)	0.01644 (1)
MAPE	2.05296 (4)	1.91163 (3)	1.69823 (2)	1.57512 (1)	1.60917 (3)	1.61699 (4)	1.53574 (2)	1.34604 (1)
Theil-U	0.01242 (3)	0.02325 (4)	0.01181 (2)	0.00957 (1)	0.00986 (4)	0.00917 (3)	0.00901 (2)	0.00845 (1)

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

The results without the subprime crisis (Table 3) show that the out-of-sample forecasts of the ANNs are more accurate than the RW and VAR forecasts by all criteria in both monetary Model 1 and Model 2. Specifically, the results in this study show that the MLFN models also outperform the GRNN models by all criteria. These findings are consistent across the four performance selection criteria over the 24-month forecasting horizon. The result is consistent with Panda and Narasimhan (2007), who investigated the Indian Rupee/USD and arrived at a similar conclusion. However, the predictability is subject to the setting of appropriate numbers of hidden nodes. In addition, the results also indicate the superiority of the unrestricted form of monetary Model 1 (Equation 3) in forecasting the 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 compared to 6 predictor variables in Model 1.

Next, we proceed with the assessment of forecasting that includes the subprime crisis period (Table 4). Similar to results without the subprime crisis, the out-of-sample forecasts of MLFN and GRNN outperform both RW and VAR forecasts by all criteria for both monetary Model 1 and Model 2. Comparison of the neural networks technique with the VAR and RW walk models confirms the recent findings by Lye et al. (2011, 2012), who showed that the neural networks approach could significantly improve the predictability of the Malaysian Ringgit. In fact, our finding provides new insights in addition to those of the aforementioned previous studies that found superiority of ANNS over RW, but without both the estimation of MLFN and the assessment of subprime crisis period.

Table 4
Assessment of forecasting (24-month horizon) with subprime crisis

	Model 1 (Equation 2)				**Model 2 (Equation 3)**			
	RW	VAR	GRNN	MLFN	RW	VAR	GRNN	MLFN
RMSE	0.0851 (4)	0.0348 (3)	0.0226 (2)	0.0233 (1)	0.0387 (4)	0.0306 (3)	0.0315 (2)	0.0132 (1)
MAE	0.0640 (4)	0.0406 (3)	0.0374 (2)	0.0393 (1)	0.0568 (4)	0.0357 (4)	0.0280 (2)	0.0213 (1)
MAPE	5.7783 (4)	0.0329 (3)	0.0296 (2)	0.0312 (1)	2.4906 (4)	0.0293 (3)	0.0451 (3)	0.0170 (1)
Theil-U	0.0387 (4)	0.0293 (3)	0.0306 (2)	0.0324 (1)	0.0329 (2)	0.0851 (4)	0.0348 (3)	0.0322 (1)

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

Though the forecasting has slightly weakened when post-crisis data included, the present study is consistent with Nasr et al. (2006) in finding that the best ANN model is able to forecast exchange rates during periods of extreme fluctuations, e.g., the subprime crisis. Additionally, the unrestricted monetary Model 2 has consistently reported superior out-of-sample forecasting performance than the restricted Model 1. To some extent, this finding supports the novel finding of Baharumshah and Liew (2006), who found that both the non-linear Smooth Transition Autoregressive model and the linear Autoregressive model of purchasing power parity outperform, or at least match, the performance of the RW model. In other words, the RM/USD can be predicted by monetary fundamentals in a less restrictive manner.

CONCLUSION

This paper employs two Artificial Neural Network (ANN) estimation procedures, i.e., MLFNs and GRNNs, to forecast the process of RM/USD under the monetary-portfolio balance model (Model 1) and its unrestricted version (Model 2) over 1991M1-2012M12. The out-of-sample forecasting assessment reveals that both ANN estimations outperformed the benchmark random walks and VAR models. In particular, the MLFNs outperform the GRNNs, whereas the latter outperform the RW and VAR models. Our result is consistent with those of Engel and West (2005) and Baharumshah and Masih (2005), among others, in the assessment of monetary models for predicting foreign exchange movements among developed and emerging markets; however, we disagree with the Meese-Rogoff puzzle that foreign exchange forecasts were not as good as those of a naïve random walk. Our result holds true even when the post-subprime crisis period was included.

Furthermore, this paper shows that the unrestricted monetary model has superior out-of-sample forecasting performance compared to the restricted monetary model. This finding suggests that the economic fundamentals are vital in forecasting and explaining the RM/USD movements, but the assumptions of money neutrality, absolute purchasing power parity and identical income elasticity do not hold in strong form across Malaysia-US. In fact, we expect that the monetary mechanism may not sufficiently work through foreign exchange adjustments in the short run due to global uncertainties, whereas fiscal policy has carried more of the burden of economic stabilisation during 2008–2012.

In conclusion, the superior performance of Model 2, modelled by MLFNs in predicting RM/USD, is beneficial in assisting Malaysian policy makers to conduct a more appropriate and comprehensive policy that will subsequently entail monetary stability and sustainable economy development. It is also useful for investors to formulate investment and trading strategies, as well as for multinational companies in corporate planning. Finally, it is anticipated that if more deterministic variables can be identified, in addition to the usage of updated series, the performance of ANNs in modelling and forecasting the foreign exchange can be further enhanced.

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NOTES

1. Monetary approaches are asset pricing views 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 returns that could be arbitraged, and such arbitrage opportunities determine the process of the exchange rate. The Mundell-Fleming framework remains the workhorse model of policy analysis, which fit well in the theoretical framework and appeared highly effective in explaining why flexible exchange rates had been volatile in the post-Bretton Wood era.
2. They have shown that the monetary models' forecasts of future nominal and real exchange rates were not as good as than those of a naïve random walk. This 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 also held for conditional out-of-sample forecasts, which use realized values of the fundamentals - economic variables rather than the lagged exchange rate, which does not have an economic interpretation. This is against prevailing theory because real exchange rates are not traded assets or market variables, whose prices are subject to arbitrage conditions. Nominal exchange rates, however, 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.
3. Malaysian trade openness is now among the highest in the world, approximately 200% of its GDP. Though Malaysia has tried to diversify its economy activities and expand its domestic consumption in the past decade, the aggregate demand still largely relies on its external trade.
4. The backpropagation algorithm is one of the most commonly used learning algorithms for multi-layer feedforward networks and its performance is acknowledged by others, for instance, Adya and Collopy (1998), Kamruzzaman and Sarker (2004), Gradojevic and Jing (2000), Yao and Tan (2000).
5. See, for instance, Chen and Leung (2005), Leung et al. (2000), Wittkemper and Steiner (1996).
6. See, for instance, Kamruzzaman and Sarker (2004), Panda and Narasimhan (2007), Zhang and Hu (1998).

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