Application of Dynamic Models for Exchange Rate Prediction

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***Abstract*—The need of exchange rate forecasting in order to prevent its disruptive fluctuations has encouraged the monetary policy makers and economists for many years to find a powerful method to predict it. The determinants of exchange rate make its behavior to be complex, volatile and non-linear. In most of the studies done by researchers for exchange rate prediction, linear models such as econometric models and non-linear models such as neural networks have been applied. The lack of studies on the application of dynamic networks is the most important motivation of this study. In this paper Neural Network Autoregressive with Exogenous Input (NNARX) as a dynamic non-linear neural network, Artificial Neural Network (ANN) as a static neural network, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) as a non-linear econometric model and Autoregressive Integrated Moving Average (ARIMA) as a linear econometric model are applied to forecast the Singaporean Dollar over US Dollar (SGD/USD) exchange rate in three time horizons. Comparison of the performance of different models is measured by different criteria. Results reveal that among all models, NNARX outperformed other models and among nonlinear models, NNARX outperformed ANN and both outperformed the GARCH model.**

***Index Terms*—ANN, Dynamic networks, Exchange rate, NNARX.**

I. Introduction

Assessing the future changes in exchange rate is the main concern of policy makers and economist since it plays an important role in the economy [1]. The better understanding of the movements of exchange rate will provide the confidence for policy makers to keep inflation stable [2]. Central banks must be aware of the fluctuations of exchange rate and its consequences. In international market whereby there are financial turmoil and instability in economic growth in different countries, multinational corporations must scrutinize the exchange rate in order to get a competitive advantage over their competitors. Hence the above mentioned are some reasons why different organizations are interested to predict the exchange rate. Recently, numerous studies have been done for time series forecasting using ARIMA model. Since it is well documented that many economic time series are non linear, while a linear correlation is assumed among the time series, so this model cannot capture the nonlinear pattern and its estimation is not satisfactory. Therefore application of nonlinear models becomes more important since nonlinear models can predict the time series variables with higher accuracy than linear models. Artificial intelligence (AI) is widely accepted as a nonlinear models for time series forecasting as they can learn the past behavior of variables and recognize the complexity and nonlinearity in the pattern of data set. AIs can be applicable in robotics, medicine, pattern recognition, forecasting, manufacturing, power systems, optimization, etc [3].

As an example of intelligent systems, a neural network is a processor that has the ability for storing experiential knowledge and making it available for use at a latter stage. ANNs can model the complex nonlinear relationship among the data set without any prior assumption [4].

Neural networks are categorized into two types; dynamic networks and static networks. Static networks as in feed forward neural network have no feedback element and contain no delay in the network. The output of network is calculated directly from inputs through the feed forward connections. In dynamic networks, output not only depends on inputs but also depends on previous inputs, outputs and the state of network. Dynamic networks can learn the sequential or time-varying patterns [5].

Neural networks have been used for time series forecasting by numerous researchers. Lapedes and Farber [6] reported the first attempt of neural network application for time series prediction and found that it can outperform the conventional methods. Wu [7] compared the performance of neural networks and ARIMA model for Taiwan Dollar/US Dollar exchange rate. His result reveals that the performance of neural networks is better than ARIMA for one step ahead as well as six steps ahead prediction. Zhang and Hu [8] find the result of their paper in favor of neural networks compared to other econometric models. Gencay [9] compare the performance of neural networks with GARCH model in daily spot exchange rate for GBP, DM, and JPY. His finding shows the higher accuracy of neural networks compared to GARCH model.

Kuan and Liu [10] used back propagation and recurrent neural networks for out of sample forecasting performance on five exchange rates against the US Dollar and find the advantage of ANNs over econometric models.

Ince and Trafalis [11] proposed parametric techniques such as ARIMA and VAR, and nonparametric techniques such as neural networks. He reported that comparison among these models show the advantage of ANNs over econometrics models.

There are very few literature on the application of dynamic neural networks to time series forecasting compared to static neural networks. Hence this motivates us to perform this

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study to compare between these two types of networks. In this paper, we compare the neural network autoregressive with exogenous input (NNARX) as a dynamic neural network, feed forward ANN as a nonlinear static neural network, GARCH as a nonlinear model when we consider the volatility and ARIMA as a linear model for prediction. In order to compare the performance of these models, the common performance measures such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Theil's U statistics (U) are used. We compare the performance of the above mentioned models for three time horizons (3, 6 and 12) steps ahead for SGD/USD monthly exchange rate.

II. Methodology

A. Autoregressive Integrated Moving Average

Box-Jenkins [12] is one of the most popular approaches for time series prediction that is known as ARIMA method. The assumption underlying the ARIMA model is that the future value of a variable is a linear function of past observations and random errors. In this model it is possible to find an adequate description of data set. This method consists of four steps: i) model identification, ii) parameter estimation, iii) diagnostic checking and iv) forecasting. In the identification step, it can be seen that if a model generated from an ARIMA process it may contain some autocorrelation properties, so there will be some potential models that can fit the data set but the best fitted model is selected according to AIC information criteria. Stationarity is a necessary condition in building an ARIMA model used for forecasting, so data transformation is often required to make the time series to be stationary. In this paper, the Augmented Dickey Fuller unit root test [13], Phillips Perron unit root test [14] and Zivot-Andrews unit root test [15] are used to test the stationarity of the series. Based on the result obtained, the data set is stationary at first difference even with the existence of structural break.

Once a tentative model is obtained, estimation of the model parameters is applicable. The parameters are estimated such that an overall measure of errors is minimized. The third step is diagnostic checking for model adequacy. Autocorrelation and also serial correlation of the residuals are used to test the goodness of fit of the tentatively obtained model to the original data. When the final model is approved then it will be used for prediction of future value of exchange rate. The ARIMA model can be written as follows when the data set is stationary:

$$Z_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Z_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

The above equation implies that the forecasted value is depended on the past value and previous shocks.

B. Generalized Autoregressive Conditional Heteroscedasticity

Volatility is one of the features in exchange rate data set and can be measured through the GARCH model. In this model, the conditional variance of a time series depends on the past variance and squared residuals of the process, and it has the advantage of incorporating heteroscedasticity into the estimation procedure of the conditional variance. GARCH model is the reduced form of a more complicated dynamic structure for the time varying conditional second order moments [16]. The GARCH model can be presented by the following form:

$$y_t = \mu_t + \varepsilon_t \tag{2}$$

$$\varepsilon_t / \Omega_{t-1} \sim N(0, \sigma_t^2) \tag{3}$$

$$\sigma_t^2 = \dot{\omega} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \tag{4}$$

where y_t is equal to log (e_t / e_{t-1}), e_t is the exchange rate, μ_t is the mean of y_t conditioned on past information (Ω_{t-1}) and the following inequality restrictions $\acute{\omega}$ >0, β_j >0, α_j >0 are imposed to ensure that the conditional variance (σ^2_t) is positive. The size and significance of α_j indicate the magnitude of the effect imposed by the lagged error term (ε_{t-j}) on the conditional variance (σ^2_t). In other forms of interpretation, the size and significance of α_j indicate the ARCH process in the residuals (volatility clustering in the data).

C. Artificial Neural Networks

Neural Network is a modeling method based on human brain that can learn the rules on the foreign exchange rate through past data, save these rules and forecast the future exchange rate. For ANN, there is no need to specify any particular model because ANN can be adapted based on the features presented in the data set.

The great advantage of neural networks is their flexible ability to model the nonlinear patterns. The model is adapted based on the features of the data set and called data driven approach [17]. This approach is useful for many empirical researches in which there is no theoretical guideline available to suggest an appropriate data generating process.

ANNs are the appropriate methods to forecast the exchange rate due to some unique features. First, ANNs are self adaptive in that there are few assumptions about the models, so neural networks are less impressible in model misspecification problem. Second, Generalization ability, after learning the pattern of data set given to them, ANNs can infer the unseen part of population, even if data set contain noisy information. Third, ANNs are Non linear, based on time series prediction models like ARIMA, always assumed that the time series generated from a linear process. Fourth, ANNs are universal functional estimators; it means a network can estimate any continuous function to any desired accuracy [18].

Feed Forward Neural Network is the most widely used network in which all layers except input layer receive weights from their previous layer. This network is consisted of three layers; input layer which includes explanatory variables (inputs) in the model. Hidden layer; lies between the input and output layers. There can be many hidden layers, which allow the network to learn, adjust, and generalize from the previously learned facts (data sets) to the new input. The number of hidden layers and nodes in the network are determined by experimentation, and this paper follows this technique. Output layer is including the output of network.

Single hidden layer feed forward network is represented as follow for time series modeling and forecasting, it has three layers of simple processing units connected by acyclic links:

$$y_t = w_0 + \sum_{j=1}^{q} w_j . g(w_{0,j} + \sum_{j=1}^{p} w_{i,j} . y_{t-i}) + \varepsilon_t \quad (5)$$

where, w_{ij} (i = 0,1,2,…,p, j=1,2,…,q) and w_j (j=0,1,2,…,q) are model parameters called connection weights; p is the number of input nodes; and q is the number of hidden nodes. Fig. 1 represents the simple structure of feed forward neural network:

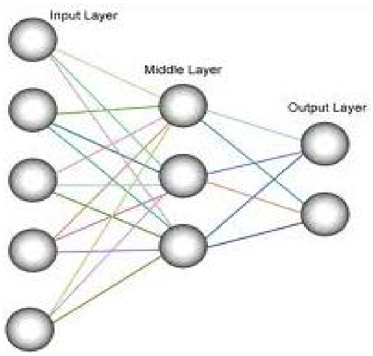

Fig. 1. Three layers neural network.

Neurons must use transfer function to generate the output. Transfer function represents a degree of nonlinearity which is valuable for neural networks applications.

Activation function can take several forms; the type of this function is specified by the situation of the neuron within the network. The logistic and tangent hyperbolic activation functions are mostly used as the hidden layer transfer function that can be represented as in Equations 6 and 7 respectively:

$$Sig(x) = 1/(1+e^{-x}) \quad (6)$$

$$tahn(x) = (1-e^{-2x})/(1+e^{-2x}) \quad (7)$$

D. Neural Network Autoregressive with Exogenous Input

In dynamic networks, output not only depends on inputs but also depends on previous inputs, outputs and the state of network. Dynamic networks can learn the sequential or time-varying patterns [11]. NNARX is a recurrent dynamic network, with feedback connections enclosing several layers of the network. The NNARX model is based on the linear ARX model, which is commonly used in time-series modeling and forecasting. The NNARX model can be represented as follows:

$$y_t = f(y_{t-1}, y_{t-2}, ..., y_{t-n_y}, u_{t-1}, u_{t-2}, ..., u_{t-n_u}) \quad (8)$$

where the next value of the dependent output signal y_t is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal. The output is feedbacked to the input of the feed-forward neural network as part of the standard NNARX architecture as shown in Fig. 2 left side. Since the true output is available during the training, we could create a series parallel architecture in which the true output is used instead of feeding back the estimated output as shown in Fig. 2 right side. This has two advantages, first is that the input to the feed-forward network is more accurate, second is that the resulting network has purely feed-forward architecture and static back propagation can be used for training [19].

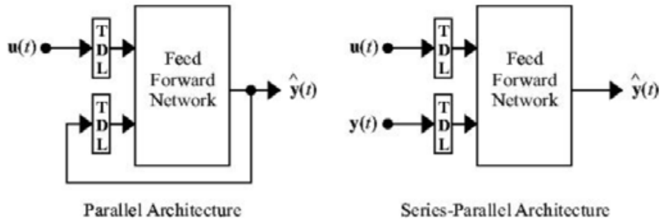

Fig. 2. NNARX network.

Dynamic networks can be trained in the same gradient-based algorithm that is applied in back propagation. Although the method of training is same with static networks but the performance of this algorithm in dynamic networks is different from static networks because the gradient is computed in a more complex way [19]. The diagram of resulting network is represented in Fig. 3.

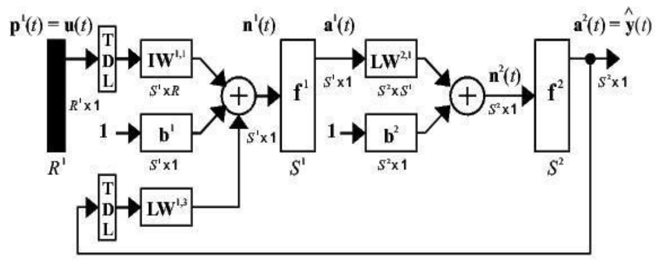

Fig. 3. A typical NNARX model.

III. Performance Comparison

In order to compare the performance of different models, the following criteria are used:

- Root Mean Square Error

$$RMSE = \sqrt{\sum_{t=1}^{n} (F_t - X_t)^2 / n} \quad (9)$$

- Mean Absolute Error

$$MAE = [\sum_{t=1}^{n} |F_t - X_t|]/n \quad (10)$$

- Mean Absolute Percentage Error

$$MAPE = [\sum_{t=1}^{n} \left| \frac{F_t - X_t}{X_t} \right|]/n \times 100 \quad (11)$$

- Theil's U statistics

$$U = \sqrt{\frac{\sum_{t=1}^{n} (F_t - X_t)^2}{n}} / [\sqrt{\frac{\sum_{t=1}^{n} (X_t)^2}{n}} + \sqrt{\frac{\sum_{t=1}^{n} (F_t)^2}{n}} \quad (12)$$

For all the above formula, F denotes the forecasted value and X is the actual value, RMSE and MAE criteria depend on the scale of the dependent variable. These should be used as relative measures to compare the forecast value for the same series across different models; the smaller value means the better the forecasting performance of that model. MAPE and Theil's U are scale invariant. The Theil's U lies between zero and one where zero indicates a perfect fit.

IV. Data Set

Monthly exchange rate data set for Singaporean Dollar over USD are collected from data stream (Thomson) from January 1971 to April 2010 and it is divided into two parts: first is the training part which includes January 1971 to April 2009 and the second part is the testing (prediction) part which includes May 2009 to April 2010. The Eviews software is used in the estimation of ARIMA and GARCH models, while for AIs, Matlab 2009 software is used. SGD/USD exchange rate data series is represented in Fig. 4.

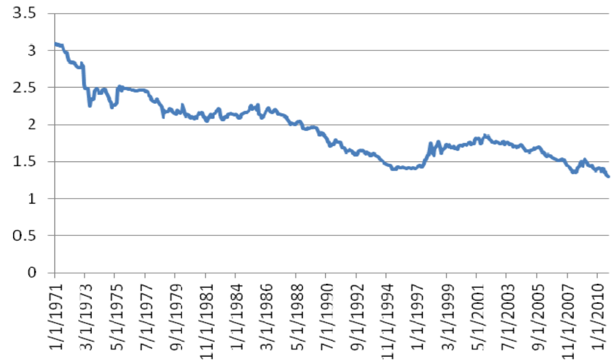

Fig. 4. SGD/USD monthly exchange rate.

V. Empirical Findings

A. Unit Root Test

Before we proceed to the modeling of exchange rate, unit root test is performed to ensure that the data set is stationary. As mentioned earlier, ADF, PP and ZA unit root test procedures are used in this study [20]. The results for stationary test reveal that SGD/USD is stationary at first difference. Although there is a sign of Stationarity in level-constant based on ZA test, but as long as the Stationarity of this series is not approved when trend is considered, we conclude that this series is stationary at first difference according to the ZA test. Unit root results are presented in Table I.

TABLE I: Unit Root Test Results

Stationary Tests		Level Constant	Level Trend-Constant	1st Differen. Constant
ADF	Critical	-2.87	-3.42	-2.87
	t-statistics	-2.50	-3.05	-20.33
PP	Critical	-2.87	-3.42	-2.87
	t-statistics	-2.48	-3.08	-20.31
ZA	Critical	-4.93	-5.08	-4.93
	t-statistics	-4.97	-4.42	-20.52

We provide diagnostic checking for both ARIMA and GARCH models to ensure that they are suitable for estimation and forecasting. For ARIMA model we run the autocorrelation test and serial correlation test. For GARCH model we apply the autocorrelation test as well as Heteroscedasticity test. The result for autocorrelation test and serial correlation test for ARIMA is presented in Table II and Table III respectively, while Table IV and Table V represents the autocorrelation and heteroscedasticity test for GARCH model respectively.

TABLE II: Autocorrelation Test for ARIMA

Lag	Probability	Lag	Probability
1	0.191	7	0.800
2	0.317	8	0.842
3	0.511	9	0.867
4	0.667	10	0.916
5	0.777	11	0.948
6	0.701	12	0.968

TABLE III: Serial Correlation Test for ARIMA

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	1.208061	Prob. F(2,456)	0.2997
Obs*R-squared	2.419200	Prob. Chi-Square(2)	0.2983

Based on the results obtained in the tables above, ARIMA model satisfies the diagnostic checking tests.

TABLE IV: Autocorrelation Test for GARCH

Lag	Probability	Lag	Probability
1	0.684	7	0.921
2	0.921	8	0.917
3	0.906	9	0.953
4	0.965	10	0.968
5	0.826	11	0.965
6	0.900	12	0.980

TABLE V: Heteroscedasticity Test for GARCH

Heteroscedasticity Test: ARCH			
F-statistic	0.163604	Prob. F(1,456)	0.6860
Obs*R-squared	0.164263	Prob. Chi-Square(1)	0.6853

Similarly, based on the results obtained in the tables above, GARCH model also satisfies the diagnostic checking tests.

The best model for Feed Forward ANN and also NNARX was found through the lowest epochs (number of network training times) among different hidden layers that result lower errors. Hence, we select the network which consists of one input layer with 1 neuron, three hidden layer with 15, 20, 15 neurons and one output layer with one neuron (1,15,20,15,1) both for in sample as well as out of sample forecasting. While for NNARX a network consists of one input layer with two neuron, one hidden layer with 25 neurons and one output layer with one neurons is selected (2,25,1).

Applying the best fitted models for exchange rate prediction gives the following values for both in sample and out of sample forecasting. Table VI presents the results for in sample forecasting while Table VII, VIII, IX presents the results for out of sample forecasting respectively.

Based on the results obtained in table VI, among econometric models, surprisingly it can be seen that when volatility of exchange rate is considered through GARCH model for in-sample forecasting, the performance of forecasting of this model does not improved except for U statistics (it can be shown through the comparison of different criteria). When AIs is used, the performance of forecasting by these models increases because these models used the pattern recognition of the past behavior of the exchange rate. Thus, by considering the dynamic network (NNARX) for prediction, the forecasting performance improved dramatically.

TABLE VI: IN-SAMPLE FORECASTING RESULTS

Models	ARIMA (0,1,0)	GARCH (1,1)	ANN (1,15,20,15,1)	NNARX (2,25,1)
RMSE	0.016429	0.016443	0.008482	0.00019189
MAE	0.010785	0.010815	0.005927	0.00006200
MAPE	126.08	144.23	0.944168	0.016960
U stat.	0.9074	0.8755	0.006617	0.00016658

TABLE VII: OUT OF SAMPLE FORECASTING RESULTS (3 STEPS AHEAD)

Models	ARIMA (0,1,0)	GARCH (1,1)	ANN (1,15,20,15,1)	NNARX (2,25,1)
RMSE	0.010596	0.010158	0.01586	0.007932
MAE	0.007823	0.007598	0.01294	0.007130
MAPE	132.40	174.20	2.9993	0.07964
U stat.	0.7953	0.7256	0.01780	0.003967

TABLE VIII: OUT OF SAMPLE FORECASTING RESULTS (6 STEPS AHEAD)

Models	ARIMA (0,1,0)	GARCH (1,1)	ANN (1,15,20,15,1)	NNARX (2,25,1)
RMSE	0.11376	0.010918	0.01381	0.007690
MAE	0.009069	0.008844	0.01143	0.007683
MAPE	147.57	181.72	2.6466	0.15535
U stat.	0.8046	0.7370	0.01554	0.003871

TABLE IX: OUT OF SAMPLE FORECASTING RESULTS (12 STEPS AHEAD)

Models	ARIMA (0,1,0)	GARCH (1,1)	ANN (1,15,20,15,1)	NNARX (2,25,1)
RMSE	0.011890	0.011629	0.010399	0.007358
MAE	0.009351	0.009239	0.008566	0.007328
MAPE	139.81	163.65	1.9348	0.30053
U stat.	0.8356	0.7803	0.011650	0.003751

According to the results obtained in table VII, VIII and IX, generally, in all forecasting horizons, the performance of the dynamic model (NNARX) is better than the other models (linear and nonlinear). More specific, when we consider the volatility inside the model through the GARCH model, the performance of its prediction becomes better than ARIMA model in all forecasting horizons (out of sample forecasting result's for GARCH model is different from in sample forecasting result's, i.e., this model outperform the ARIMA model for all time horizons). As the number of forecasting horizons increases, the performance of ARIMA and GARCH model decreases. When it comes to the comparison for ANN and both previous models, ANN performance increases as the number of forecasting horizons increases. Finally the dynamic model (NNARX) outperformed all the previous models because in all forecasting horizons, its performance is better. In addition, as the number of forecasting horizon for prediction increases, NNARX performance increases as well. Thus it can be concluded that for longer forecasting horizon, the performance of artificial intelligence are better compared to the econometric models. A better forecasting performance can be obtained for a shorter forecasting horizon using econometric models, while artificial intelligence is better for the longer forecasting horizon.

VI. CONCLUSIONS

Recently, the application of different models for predicting the most important variables in the economy such as exchange rate, stock market and interest rate for decision making in foreign direct investment, international trade and investment becomes more important. In this paper four different models are applied to predict the SGD/USD exchange rate for three forecasting horizons, i.e. 3, 6 and 12 steps ahead. Since the exchange rate exhibits a nonlinear pattern and exhibits volatility in its own behavior, nonlinear models predict better than linear models. The results reveal that the performance of econometric models get worse when we consider longer forecasting horizon, while the performance of artificial intelligence is better in the longer forecasting horizon. It can be concluded that nonlinear models is better than linear models. Among the nonlinear models, NNARX outperformed the ANN and GARCH models.

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