

Forecasting Exchange Rate in India: An Application of Artificial Neural Network Model

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Abstract

The paper employs Artificial Neural Network (ANN) to forecast foreign exchange rate in India during 1992-2009. We used two types of data set (daily and monthly) for US dollar, British pound, euro and Japanese yen. The performance of forecasting is quantified by using various loss functions namely root mean square error (RMSE), mean absolute error (MAE), mean absolute deviation (MAD) and mean absolute percentage error (MAPE). Empirical results confirm that ANN is an effective tool to forecast the exchange rate. The technique gives the evidence that there is possibility of extracting information hidden in the foreign exchange rate and predicting it into the future. The evaluation of the proposed model is based on the estimation of the average behaviour of the above loss functions.

Keywords: Exchange Rate, Neural Network

1. Introduction

Modelling and forecasting a financial variable is a very key activity in the financial markets and certainly useful for various players like practitioners, regulators and policy makers. Forecasting is also a critical element of financial and managerial decision making (Majhi et al., 2009). It is established fact that increased volatility of a variable and/or using weak forecasting technique in the financial markets is harmful to economic development due to their adverse impact on international trade and foreign investment (Chang and Foo, 2002). Hence, forecasting a variable in the financial markets is a matter of imperative importance, especially in the country like India. Various econometric models are readily available to forecast a variable in the financial markets. In particular, Autoregressive Integrated Moving Average (ARIMA) is an extensive model of time series forecasting in which past observation of same variable are collected and analyzed to develop a model describing the relationship and then used to extrapolate the time series into the future. One of the limitations associated with this ARIMA model is that it does not capture the non-linear pattern of the time series variable (Timmermann and Granger, 2004). In fact, Autoregressive Conditional Heteroskedasticity (ARCH) is another extensive model to capture the volatility issue in the financial market forecasting. The volatility foreign exchange rate is the stylized facts, which have been documented since the abandonment of the Bretton Woods system of fixed parities more than 30 years ago. There are two interesting features in the issue of foreign exchange volatility. First, it is the phenomenon of volatility clustering where large exchange rate changes are typically followed by other large changes, eventually giving way to more tranquil periods (Baillie and Bollerslev, 1991). Second, periods of high exchange rate volatility have displayed remarkable persistence, in some cases lasting years (Engel and Bollerslev, 1986). We have extensive literature on the issue of forecasting exchange rate volatility (see Vilasuso, 2002; Engle and Russel, 1997; Engle and Russel, 1995; Bollerslev and Domowitz, 1993; Glosten and Milgrom, 1985). Though the above models are very useful in out-of-sample forecast accuracy, present paper uses Artificial Neural Network, an alternative model, to capture the non-linear pattern of time series forecasting. We specifically use this technique for forecasting exchange rate in India. Exchange rate forecasting is one of the main endeavors for researchers and practitioners in the international finance, especially in the floating exchange rate era (Hu et al., 1999).

The rest of the paper is organized as follows: Section II discusses the methodology of ANN and data descriptions. Section III presents the empirical results and its discussion thereof. Section IV concludes with policy implications.

2. Methodology and Data Descriptions

Artificial Neural Network (ANN) is an emerging computational technique that provides a new avenue for exploring dynamics of various economic and financial applications. The ANN is an information process technique for modelling mathematical relationships between input variables and output variables. It is a class of generalized non-linear non parametric models inspired by studies of the brain and nerve system (Alon et al., 2001). Based on the construction of the

human brain, a set of processing elements or neurons (nodes) are interconnected and organized in layers (Malliaris and Salchenberger, 1996). In the recent times, this technique is extensively used in financial markets, particularly to forecast inflation, interest rate, stock price, exchange rate, etc. The comparative advantage of ANN over more conventional econometric model is that they can model complex, possibly non-linear relationships without any priori assumptions about the underlying data generating process (White, 1990).

There are two ways ANN can be designed: feed forward and feedback networks. Feedback networks contain neurons that are connected to them, enabling neuron to influence other neurons. Kohonen self-organizing network and Hopfield network are the type of feed forward network (Wang, 2009). On the contrary, back propagation neural network take inputs from the previous layer and send outputs to the next layer. The present study uses back propagation neural technique for the forecasting exchange rate in India. In general, ANN structure is composed of three layers: input layer, hidden layer and output layer (Figure 1). Each layer has a certain number of processing elements called neurons. Signals are passed between neurons over connection links. Each connection link has an associated weight, which, in a typical neural net, multiplies the signal transmitted. Each neuron applies an activation function (usually nonlinear) to its net input (sum of weighted input signals) to determine its output signal (Figure 2). A neural network performance is highly dependent on its structure. The interaction allowed between various nodes of the network is specified using the structure. The forecasting set up of ANN consists of followings steps (Zhang, 2004): data preparation, neural network set up (input variable selection, choice of structure, transfer function, etc.) and evaluation and selection.

2.1 The Structure of ANN

In this investigation, the feed-forward back-propagation ANN is employed and its procedure is outlined below (Erims et al., 2007).

Step 1: Evaluate the net input to the j^{th} node and that to the k^{th} node in the hidden layer as follows:

$$\begin{aligned} net_j &= \sum_{i=1}^n w_{ij}x_i - \theta_j, \\ net_k &= \sum_{j=1}^n w_{jk}x_j - \theta_k \end{aligned} \quad (1)$$

where i is the input node, j is the hidden layer node, k is the output layer, w_{ij} is the weights connecting the i^{th} input node to the j^{th} hidden layer node, w_{jk} is the weights connecting the j^{th} hidden layer node to the k^{th} output layer, θ_j is the threshold between the input and hidden layers, θ_k the threshold connecting the hidden and output layers.

Step 2: Evaluate the output of the j th node in the hidden layer and the output of the k th node in the output layer as follows:

$$\begin{aligned} h_j &= f_h \left(\sum_{i=1}^n w_{ij}x_i - \theta_j \right), \\ y_k &= f_k \left(\sum_{j=1}^n w_{jk}x_j - \theta_k \right) \end{aligned} \quad (2)$$

where,

$$\begin{aligned} f_h(x) &= \frac{1}{1 + \exp(-\lambda_h x)}, \\ f_k(x) &= \frac{1}{1 + \exp(-\lambda_k x)} \end{aligned} \quad (3)$$

and where h_j is the vector of hidden-layer neurons, y_k is the output of the output-layer neurons, $f_h(x)$ and $f_k(x)$ are logistic sigmoid activation functions from input layer to the hidden layer and from hidden layer to output layer respectively and λ_h and λ_k are the variables, which control the slope of the sigmoid function. The output of each neuron is obtained by applying an activation functions $f_h(x)$ and $f_k(x)$. The nodes are used to perform the non-linear input/output transformations using a sigmoid activation function. Since the actual adaptation seems to be a non-linear form, the sigmoid function influences strongly the ANN predictions in this study.

Step 3: For the calculation of errors in the output and hidden layers can be expressed as follows:

The output layer error between the target and the observed output is expressible as

$$\begin{aligned} \delta_k &= -(d_k - y_k)f'_k, \\ f'_k &= y_k(1 - y_k), \text{ for sigmoid function} \end{aligned} \quad (4)$$

where δ_k is the vector of errors for each output neuron (y_k) and d_k the target activation of output layer. The term δ_k depends only on the error ($d_k - y_k$) and f'_k is the local slope of the node activation function for output nodes. The hidden layer error is expressible as

$$\delta_j = f'_h \sum_{k=1}^n w_{kj} \delta_k, \quad (5)$$

$$f'_h = h_j(1 - h_j), \text{ for sigmoid function}$$

where δ_j is the vector of errors for each hidden layer neuron, δ_k is a weighted sum of all nodes and f'_h the local slope of the node activation function for hidden nodes.

Step 4: Adjust the weights and thresholds in the output layer and hidden layer as follows:

$$w_{kj}^{t+1} = w_{kj}^{(t)} + \alpha \delta_k h_j + \eta (w_{kj}^{(t)} - w_{kj}^{(t-1)}),$$

$$w_{ji}^{t+1} = w_{ji}^{(t)} + \alpha \delta_j h_i + \eta (w_{ji}^{(t)} - w_{ji}^{(t-1)}), \quad (6)$$

$$\theta_k^{t+1} = \theta_k^{(t)} + \alpha \delta_k, \theta_j^{t+1} = \theta_j^{(t)} + \alpha \delta_j$$

where α is the learning rate, η the momentum factor, and t the time period.

2.2 Model Selection and Evaluation

The paper uses four loss functions to be the criteria to evaluate the forecasting performance relative to change exchange rate.

$$RMSE = \left(T^{-1} \sum_{t=1}^T (Y_t - \hat{Y}_t)^2 \right)^{0.5} \quad (7)$$

$$MAE = T^{-1} \sum_{t=1}^T |Y_t - \hat{Y}_t| \quad (8)$$

$$MAD = T^{-1} \sum_{t=1}^T (Y_t - \hat{Y}_t) \quad (9)$$

$$MAPE = T^{-1} \sum_{t=1}^T \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \times 100 \quad (10)$$

The forecasting performance is better when the values are smaller. However, if the results are not consistent among these three, we choose the MAPE (Makridakis, 1993) to be the benchmark with relative stable than other criteria. Matlab 7.1 has been used to investigate the ANN model in the present study. The software is used to train the net, test it and evaluate it. The following procedures have been used to do the same:

- The weights are chosen randomly.
- The minimum test error is initialized to the maximum real value.
- The training data set is passed to the network more than once.
- Perform back propagation using the mean squared error as the stop criterion for learning, while never exceeding the maximum number of cycles, or perform back propagation using a fixed number of epochs.
- The net is tested using the testing data set, and measures of the final performance of the learning and testing set are computed.
- Evaluate the testing set. In this method, the calculated values are printed in an output file, which contains actual prediction and the corresponding testing error.
- If the test error is less than the minimum test error, the weights are saved and the test error will be the minimum test error.
- Otherwise, net will be trained in a second phase and new error measures to be recorded.

- Finally, the network evaluation is performed, which consists of calculating the root mean square errors (RMSE) and the mean absolute error (MAE).

3. Results and Discussion

In this investigation, an Artificial Neural Network (ANN) projection of exchange rate in India is carried out. To obtain the least error convergence, the configurations of the ANN are set by selecting the number of hidden layers and nodes, the learning rates and momentum coefficients. In order to determine the best structure of the ANN model, the sensitivity of the ANN model is examined for the different nodes, which are randomly selected in the hidden layer. The neural network is formed for US dollar, Britain pound, Euro and Japanese yen by using two inputs (year and each actual exchange rate in terms of INR), one output (future project its data) and 1-5 nodes for the hidden layer. In the algorithm, learning rates and momentum coefficients are 0.7 for learning processes, in which 20×20 interactions are used to obtain the good fits. The summary of the ANN results are presented in Tables 1-2. We first find out the appropriate structure to forecast the exchange rate and then use the same for training as well as testing samples. For the sake of convenience, these forecasting are termed as in- sample and out-of-sample respectively. The detail descriptions of these results are described below:

3.1 Training of the ANN

Since the only flexible layer in the proposed ANN is the intermediate one, we try to optimize the forecast accuracy by experimenting with the number of inputs and the hidden neurons, both of which are immediately pertinent to the hidden layer. We utilize Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) as the selection criteria. We choose five possible candidates from a wide range of neurons. These are then applied across various input nodes classified as per the length of the input vector. These are selected to partially meet the size necessary for achieving high prediction accuracies. The experimented results are reported in Table 1.

The empirical results clearly indicate that the performance of our ANN architecture is very accurate, when the number of inputs for daily rate is set to 8 for US dollar, 1 for British pound, 1 for Euro and 15 for Japanese yen. Similarly, the accuracy is accurate when the number of inputs for monthly exchange rate is set to 14 for US dollar, 12 for British pound, 10 for Euro and 8 for Japanese yen. In each case the hidden nodes are taken at five different levels, i.e., 1, 2, 3, 4 and 5. But we have presented the average results of five hidden nodes (see Table 1). This is justified on the basis of RMSE and MAE. In the next section, we examine the validity of trained ANN architecture by in-samples and out-of-samples.

3.2 In-Sample Forecasting

The purpose of in- sample forecasting is to validate the ANN architecture by the in- sample data. The Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE) test are used here for forecasting accuracy measures. The results of these tools are reported in Table 2. The RMSE of neural networks along with MAE and MAD is very much low and varies from 0.02 to 0.40. This consistency proves their accurate prediction power and absolutely true for both daily data and monthly data. The results are also supported by MAPE.

4. Conclusion and Policy Implications

Modelling and forecasting exchange rate is usually carried out by the regression technique. The shortcoming of this technique is that data analyzed often exhibit some non-linearity that cannot be captured by a linear model. Therefore, we used Artificial Neural Network (ANN), a highly flexible form of non-linear models, to forecast the same. The model performs coupling global revolutionary search of the network topologies as well as the input series and initial heuristic near-optimal weights. The method improves the forecasting significantly by adequate training, cross-validation and testing. The empirical findings suggest that neural network is an advanced method in forecasting exchange rate in India. It recommends that the linear unpredictability of exchange rate could be improved and non-linearity can be captured by using the neural network modelling. The superiority of this model is that the information that is hidden in exchange rate could be better extracted by using artificial neural network. The policy implication of this study is that ANN can be used to forecast foreign exchange rate in India, which is certainly useful for various financial players including policy makers of the country. To conclude, ANN model could be applied to forecast exchange rate policy in India and that will, in turn, achieve the desired objective of economic growth in the country.

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Table 1. Training Factors and Their Effect on Network Performance

IN	HID	RMSE	MAE	IN	HID	RMS E	MAE
DAILY				MONTHLY			
USD							
8	1-5	.067	0.052	14	1-5	0.116	0.087
POUND							
1	1-5	0.062	0.047	12	1-5	0.112	0.089
EURO							
1	1-5	0.063	0.047	10	1-5	0.091	0.072
YEN							
15	1-5	0.061	0.049	08	1-5	.086	0.067

Table 2. Measuring Forecast Performance for In-Sample and Out-Sample Data

STATISTICS	IN	OUT	IN	OUT	IN	OUT	IN	OUT
	DAILY		MONTHLY		DAILY		MONTHLY	
	USD				POUND			
	RMSE	0.04	0.04	0.03	0.05	0.07	0.06	0.06
MAE	0.02	0.02	0.02	0.04	0.05	0.05	0.04	0.06
MAD	0.25	0.14	0.57	0.19	0.38	0.19	0.05	0.10
MAPE	11.1	3.5	94.6	25.8	89.6	84.1	36.3	9.25
	EURO				YEN			
RMSE	0.06	0.06	0.17	0.08	0.04	0.04	0.06	0.08
MAE	0.05	0.05	0.14	0.06	0.02	0.03	0.04	0.06
MAD	0.40	0.20	0.37	0.11	0.25	0.14	0.47	0.12
MAPE	96.1	89.6	87.9	9.29	10.8	3.56	35.9	9.68

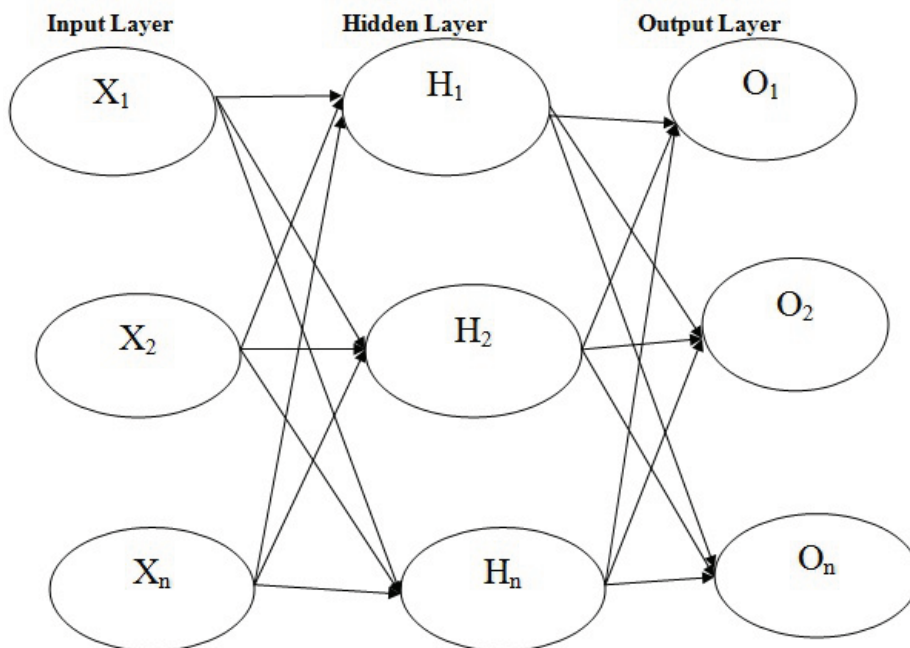


Figure 1. Neural Network Structure

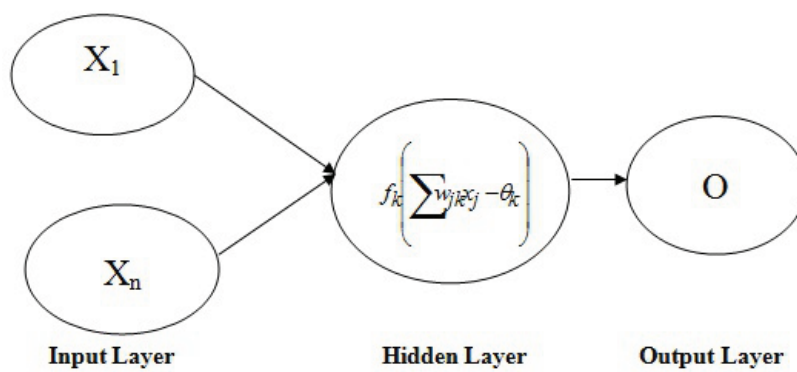


Figure 2. A Node in Neural Network Structure