Applying Artificial Neural Networks to Foreign Exchange Modeling for the Prediction of Indian Rupee Rates

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Abstract

The foreign exchange market is the largest financial market in the world with a daily turnover in excess of five trillion USD. The Indian economy is the fastest growing, with an annual GDP growth of 8%. The purpose of this project is to model the value of the Indian rupee relative to the USD. Specifically, an artificial neural network was developed to relate a diverse set of economic, social, and political variables to changes in the value of the Indian rupee. The prediction horizon for the model is one week, which allows the market enough time to react to political and economic developments, but is also short enough to make profitable predictions. The model was developed through four stages. In stage one all potential variables were delineated. In stage two, the list of potential variables was refined into a group of 55 key variables, which would be incorporated into the model. Then, historical data for each variable was downloaded, partitioned, and normalized as necessary. In stage three, each variable was eased into the model; if the model improved in accuracy as a result, the variable was kept. In stage four, the profitability of the model was assessed and the model was revised as necessary. The final model correctly predicted the movement of the Indian rupee 62% of the time. Additionally, for the year of 2017, the model has earned an annualized net return of 12.03%. This research has the potential to increase rupee stability, fueling foreign investment into India.

Introduction

The foreign exchange, or FOREX for short, is the global market for the exchanging, buying, and selling of currencies. The FOREX market is by far the largest financial market in the world, with an estimated $3.2 trillion traded each day (USA Federal Reserve, 2009). As a result of the sheer size of the FOREX market, shifts in exchange rates can impact many economic decisions at all levels (corporations, governments, financial institutions, or even consumers). Because of this, an application which could accurately model this market would prove invaluable to the world of high finance (USA Federal Reserve, 2009).

Fortunately, this market provides a good opportunity for model-based predictions, with previous studies concluding that “rates evolve to fit a trend not completely random” (Vincenzo, 2011). However, current models are not yet “good enough to attempt to use … for profit in the real market” (Shahbazi, 2016). The goal of this research was to develop an econometric model capable of turning a profit (the benchmark for success) in the FOREX market.

Specifically, this model attempted to predict the value of the Indian Rupee one week into the future. The Indian Rupee was chosen because India’s annual rate of GDP growth exceeds 7%, putting it on track to become one of the major world economic powers in the coming years. Additionally, the Indian government is very open with their financial data (unlike China). These factors mean that an accurate predictive model of the Indian Rupee would not only be viable, but also immensely valuable. A one-week prediction horizon was chosen because it is short enough to make profitable predictions, yet long enough to account for social/economic/political developments.

Many different types of FOREX modelling have been attempted over the years, with artificial neural networks emerging recently and showing great promise in the field (Chaudhuri, 2016). Because of this, it was decided that the predictive model would be an artificial neural network (ANN). This allows the model to take into account a vast amount of diverse information which it can base its predictions off of.

Briefly, an artificial neural network, or ANN, is a network of interconnected nodes, based on the biology of the human brain. This network consists of multiple “layers” of nodes, through which information travels. The flow of data through these ANNs starts at the input layer, travels through at least one “hidden” layer, and arrives at the output layer (Smith, 2008). Each node, or “neuron”, has a transformation function, usually tan-sigmoid, which is applied to the values that pass through it. Additionally, each neuron contains a “weight”, which is a quantification of the significance of its output. This allow the network to dynamically modify itself to adapt to different sets of data. This optimization of the network takes place during a training period, in which the ANN is given inputs, and their respective desired outputs. This type of training is called backpropagation, and through repeated training trials an ANN can detect patterns across very large and varied datasets (Smith, 2008). This pattern detecting ability within non-linear and volatile data is precisely what makes ANNs so useful in modelling exchange rates (Wanjawa, 2014).

ANNs have been looked at for their potential in time series forecasting (such as predicting exchange rates) for a long time (Hill et. al, 1994). Early research in this area has shown that ANNs are superior to traditional linear models for predicting financial time series. Because of this, ANNs for financial forecasting are a popular research subject, providing a wealth of information on which to base this project.

Recently, researchers from the Calcutta Business School examined different forecasting methods in predicting the movement of the USD/INR (rupee) currency pair. Among the input variables chosen were the 3-month rupee exchange rate, crude oil price, India VIX, and other stock market indices. The results of their experiment showed that a Multi-Layered Feed-Forward Neural Network (MLFFNN), the type of network which this project employed, performed better than the other models (Chaudhuri, 2016). They also presented the topology of their network, which can be used a base for future adaptation (Chaudhuri, 2016).

While previous research has made good progress in this area, there is still potential for further investigation. Specifically, research thus far has failed to take into account a diverse set of input variables. This means that artificial neural networks which have been developed to model the FOREX market, so far, do not take into consideration each country's dynamic political and economic environment. This led to the research question of this project: Would the inclusion of a diverse set of input variables improve the accuracy of an artificial neural network developed to predict the value of the Indian Rupee?

To answer this question, it was hypothesized that if a more diverse set of inputs - factors which could have some bearing on the political or economic environment of the country - are taken into account, then a more accurate artificial neural network could be developed, because the value of a nation's currency is inherently tied to its economic and political standing. For example, how much money is being printed, interest rates, central bank reserves, etc, could be taken into account. This would allow the model to take into consideration India's unique political and economic environment, week by week.

The model was developed through four stages. In stage one all potential variables were delineated. In stage two, the list of potential variables was refined into a group of 40 key variables, which would be incorporated into the model. Then, historical data for each variable was downloaded, partitioned, and normalized as necessary. In stage three, each variable was eased into the model; if the model improved in accuracy as a result, the variable was kept. In stage four, the profitability of the model was assessed and the model was revised as necessary.

By comparing the accuracy of this model to that of previously developed ANNs, the impact of the inclusion of a diverse set of input variables was determined.

Materials and Methods

In the first stage, all potential variables were delineated. To do this, a massive amount of research on the Indian economy was examined. These resources included monetary reports by the Reserve Bank of India (RBI), previous research on the prediction of the Indian Rupee, news articles on the political and economic climate of India, and other such sources. In all, a preliminary list of roughly 200 distinct variables were identified for further investigation. This became the starting point for stage two.

In stage two, the preliminary list of variables was refined into a group of 55 key variables, 40 of which were not used by previous researchers. To do this, each member of the preliminary list was checked for two key features. The first feature is a frequency of at least one week. Because the model seeks to predict one week into the future, all of its inputs must be published with a frequency of one week or less. The second feature is access to 10 years of historical data, which became the training set for the model. If the variable was not published openly for the past 10 years, then it could not be used by the model for future predictions, because the model would lack sufficient training data. This process led to the preliminary list being refined into the following list, which served as the input variable set for the neural network (italicized words represent categories, bolded words represent subcategories):

Variables Used by Chaudhuri (Control)

Currency

- USD/INR

- Trade-Weighted Dollar
- Dollar Adjusted Rupee

Market Returns

- NIFTY Returns (rs)
- Dow Jones Returns
- Hang Seng Returns
- DAX Returns

Commodities

- Crude Oil (COP)

Volatility Indexes

- CBOE Vix

RBI Liabilities & Assets

Notes

- Notes Issued,
- Notes in Circulation
- Notes held in Banking Department

Deposits

- Deposits
- Scheduled Commercial Banks
- Scheduled State Co-operative Banks
- Other Banks
- Others

Liabilities

- Other Liabilities

- Total Liabilities /Assets

Foreign Exchange Reserves

Foreign Currency

- Foreign Currency Assets

Rupee Securities

- Rupee Securities (including T - Bills)

Loans & Advances

- Others

Assets

- Other Assets

Foreign Currency Assets

- (Rupees Billion)
- (US Dollar Million)

Gold Reserves

- (Rupees Billion)
- (US Dollar Million)

Reserve Tranche Position

- (Rupees Billion)
- (US Dollar Million)

SDRs

- (Rupees Billion)
- (US Dollar Million)

Total

- (Rupees Billion)

- (US Dollar Million)

Reserve Money: Sources & Components

Components

- Currency in circulation (total)
- Other deposits with RBI
- Bankers' deposits with RBI

Reserve Money

- Reserve Money (Liabilities/Components)

Sources

- RBI's Claims on - Government (net)
- RBI's Claims on - Central Govt
- RBI's Claims on Banks & Commercial sector
- RBI's Claims on Banks (Including NABARD)
- RBI's claims on Commercial sector (Excluding NABARD)
- Net foreign exchange assets of RBI Net non-monetary liabilities of RBI

Cash Reserve Balances of Commercial Banks

Cash Balance

- Actual Cash Balance with RBI
- Cash Balance as Percent of Average Daily Cash Reserve Requirement
- Average Daily Cash Reserve Requirement

Treasury Bills Outstanding

14 Day Intermediate

- Governments
- Others

- Total

91 Day

- Banks

- Others

- Total

182 Day

- Banks

- Others

- Total

364 Day

- Banks

- Others

Historical data for the above variables was then downloaded, partitioned, and normalized, which was done in Microsoft Excel. This resulted in 55 columns of data, each containing 520 timesteps (once a week for the past ten years).

This historical data was collected from a few key sources. The main source of this data was the Reserve Bank of India's website (rbi.org.in), in particular their online Data Warehouse (https://dbie.rbi.org.in/DBIE/dbie.rbi?site=home). Other sources include Google Finance (https://www.google.com/finance), Yahoo Finance (https://finance.yahoo.com), and the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/).

It is important to note that exchange rates take the form of a proportion between two currencies, and as such are impacted by changes in the value of either one. Since this research is only concerned with predicting the absolute value of the Indian Rupee, the Trade-Weighted

Dollar (the value of the US Dollar, adjusted for inflation) was used to normalize the exchange rate, so that the model was only working with the real, not relative, value of the Indian Rupee.

In stage three, this massive amount of data was imported into Matlab, which was equipped with the Neural Network toolbox, and the model was generated. During network generation, the amount of hidden layer nodes, as well as the amount of delays, could be freely set. Network delays are the amount of weeks into the past with which the model bases its prediction. To properly optimize the network, the amount of hidden layer nodes were varied at the following levels: {10, 20, 30, 40}. Network delays were varied at the following levels: {2,3}. These levels were chosen because they were used by previous researchers in this area (Chaudhuri, 2016). This gave a total of 8 experimental groups, shown in Figure 1 below.

In stage four, the profitability of the optimal model (30 hidden layer nodes with 2 delays) was assessed, both theoretically and realistically. This was done by simulating the return rates of utilizing this model for FOREX trading.

Data

Figure 1: Results of all 8 experimental groups. Optimal network is highlighted.

TOPOLOGY		RESULTS		
Hidden Nodes	Delays	R Value	MSE	Success Rate
10	2	0.9977	0.97	58%
20	2	0.9989	0.28	52%
30	2	0.9982	0.59	62%
40	2	0.9976	0.98	57%
10	3	0.996	1.15	43%
20	3	0.9846	5.05	50%
30	3	0.996	1.49	47%
40	3	0.995	1.61	51%

Results

Figure 2: Actual rupee value (black line), and predicted rupee value (red marks)

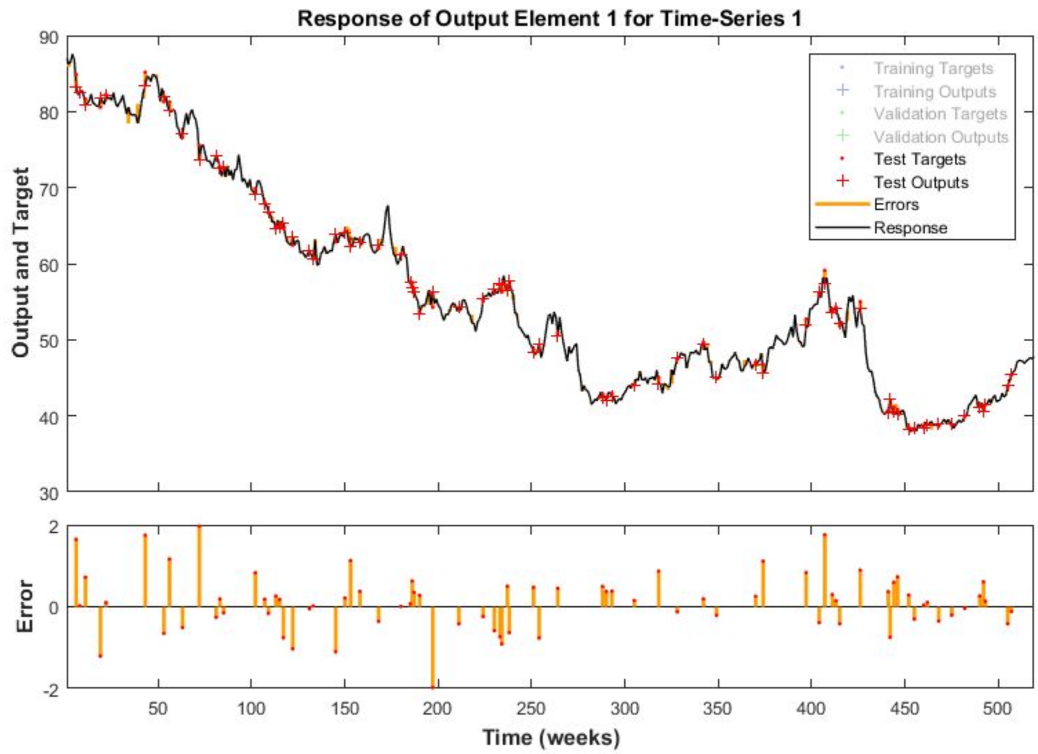

Figure 3: Experimental return on a $1,000 principle, for the first 19 weeks of 2017

Looking at figure 1, it is evident that the optimal model contains 30 hidden layer nodes, with 2 delays. With neural networks, it is important to strike a balance between too much and too little information. Too little, and the network runs into the same challenge as previous research: it lacks the data necessary to make meaningful predictions. Too much, and the network is bogged down with excess noise. 30 hidden layer nodes with 2 delays appears to be the optimal balance between these two. Additionally, this model achieved a success rate of 62%, which means that 62% of the time it can correctly predict whether the value of the Indian Rupee will go up or down. This makes it profitable if implemented. An experimental implementation is shown in figure 3, with an annualized net return of 12.03%. Additionally, the R value of this model is 0.9982. This is significant because previous research obtained an R value of 0.9923, showing an increase in accuracy. This improvement strongly supports the initial hypothesis, which stated that the inclusion of a diverse variable set would have a beneficial impact on the performance of an ANN.

Discussion

The goal of this research was to develop an artificial neural network capable of predicting Indian Rupee rates one week into the future more accurately than previous research, through the inclusion of a diverse variable set. Because the R value increased from 0.9923 to 0.9982, it can be concluded that the newly developed model, containing 30 hidden layer nodes and two delays, is more accurate than previously developed networks. Additionally, with a success rate of 62%, the model is theoretically profitable in the long-run, assuming that gains will surpass loses.

Furthermore, this model was assessed for experimental performance. This was done by taking the network, which was trained on data from January 2007 to December 2016, and simulating its performance with 20 weeks of data from January 2017 to May 2017 (data which it had never seen before). The results of this test are shown in figure 3, and with an annualized net return of 12.03%, are highly encouraging. As the year continues, more data will become available for testing, and the model will be further optimized.

As it is, this model has a multitude of possible applications in the world of high finance. Most obviously, by exchanging between US dollars and Indian rupees with the help of this model, a trader would stand to make a respectable profit. Additionally, entities (such as governments, banks, and businesses) which seek to invest in India could use this model to hedge their actions, and minimize their risk exposure. Since much of the data used in this project was obtained from the Reserve Bank of India, they could use this model to predict the economic impact of proposed monetary policies, such as changing the reserve requirement or issuing an increased number of banknotes.

However, the network is by no means perfect, and contains a number of flaws. For example, while the model takes into account many different economic inputs, it does not include many political variables. As a consequence, political developments which may have a significant impact on the value of the rupee could be overlooked by the model. One such event was the sudden demonetization of all ₹500 and ₹1,000 banknotes in November 2016. If political factors, such as geopolitical tensions and public sentiment, could be accurately quantified, they would make a valuable addition to this model. In this regard, there is great potential for future work.

Another area worthy of future exploration is the application of the methodology used in this research to a different currency. As long as enough pertinent data is available, there is nothing stopping a similar model from being developed for another country with another currency. With increasing globalization, other BRICS countries (Brazil, Russia, India, China, South Africa) could be of particular interest in the coming years.

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