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Currency Exchange Rates: A Review in Forecasting

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Abstract—*The forex rate time series is composed of two composite structures, a long term trend and a short term oscillation. Fundamental analysis works on the long-term approach. Technical analysis is used to predict the near future trends in the market. Artificial Neural Networks is a method used for predicting the future exchange rate. Support Vector Machine is another method used popularly. In this paper, we review currency exchange prediction methods using three different papers. We look into neural networks and see how it is used successfully for forecasting algorithms. We then observe recurrent neural networks with expert methods. We then learn about Support Vector Machines and see how different kernels are used to predict the future exchange rate and give different accuracies.*

1. INTRODUCTION

The foreign exchange market is a global market for currency trade. International banks are its main participants. The market operates on several levels, from big banks to small financial firms, which are involved in foreign exchange trading. Trades between these firms can be very large, going up to millions of dollars. The foreign exchange market assists investments using currency conversion. The market works between a wide range of buyers and sellers around the clock, five days a week. Forex has very little supervisory entity regulating its actions because of the sovereignty issue between currencies.

In a floating exchange rate regime, there are a couple of factors that decide the exchange rate of that currency. International parity conditions, tradable goods and investment portfolios are a few of these factors. However, these economic factors do not help with respect to technical analysis. Technical indicators look at past patterns for predicting the future price levels. If not the levels, it tries to predict the direction that it is going in. They are called technical, as it is not involved with any fundamental factors like revenue, profit margins and so on. These indicators are of most help during short term movements. Thus, long term investors cannot make much use of technical indicators, apart from finding the good entry and exit points, by analyzing the long-term trend.

One of the methods commonly used is the backpropagation method. This method calculates the gradient of a loss function with respect to weights in the network. The optimization method updates the weights, trying to reduce the loss function. It is used as a supervised learning method. This is because we use past data to predict future patterns. Thus, we have a desired output which we want the system to reach till.

In machine learning, support vector machines (SVM) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. A SVM algorithm checks the data and assigns them to different categories, making it a classifier. Once the categories are decided, the new examples are mapped to this space and predicted to go one way depending on the category they fall into.

2. REFERENCE PAPERS DESCRIPTION

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

This paper shows that Artificial Neural Network (ANN) is an alternative model in time series prediction to capture the non-linear pattern of time series such as currency exchange rates. Artificial Neural Network processes information and establishes a relation between input and output variables. The system mentioned in this paper uses a feed-forward back propagation neural technique for prediction. The paper uses four loss functions to be the criteria to evaluate the forecasting performance relative to change exchange rate, root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and mean absolute deviation (MAD).

These four loss functions are the criteria used to evaluate the prediction performance relative to currency exchange rate. If results are inconsistent then MAPE is chosen to be benchmarked. MATLAB 7.1 was used to train, test and evaluate the network.

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 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 goodfits. firstly the appropriate structure to forecast the exchange rate is found out and then used for training as well as testing samples.

Only the hidden layer is flexible so determining the appropriate number of input and hidden neurons is essential to optimize forecast accuracy. Results show that performance of ANN architecture is very accurate when number of inputs for daily rate and monthly exchange rate is set for every currency. Its justified on basis of RMSE and MAE

The empiricalfindings suggest that neural network is an advanced method in forecasting exchange rate in India since the information that is hidden in exchange rates could be better extracted by using artificial neural network.

2.2 Application of Neural Network for Forecasting of Exchange Rates and Forex Trading

In this paper, exchange rates prediction and trading algorithm was developed by Delphi method and prediction compatibility. The proposed algorithm used up to 8 expert methods, which are applied for human decision making with recurrent neural network (RNN). Algorithms used are Evolino-based Long Short-Term Memory (LSTM) by using of genetic learning algorithm and EVOlution of recurrent systems with LINear Outputs (EVOLINO).

Evolino is used to discover good Recurrent Neural Network hidden node weights using linear regression or quadratic programming to compute optimal linear mappings from the hidden state to the output. It is found that Evolino based LSTM (Long Short-Term Memory) learns on average faster and it is able to generalize substantially better that gradient-based LSTM. Evolino is useful to superimpose oscillators such as double and triple sine and it makes good accurate prediction.

The expert prediction model has three main stages Delphi method, compatibility of neural networks predictions and reliability of forecasting. Neural network prediction shows contradictory, unstable observation. Delphi method makes it possible to achieve a certain consensus or clustering of forecasts. Three steps were needed for this: (a) finding of historical orthogonal data; (b) forming of eight data sets; (c) calculating of medians and quartiles. In this upper and lower range quartile can be determined. Then value of lower range quartile Q1 evaluates cuts off lowest 25 % of data and upper range quartile Q3 cuts off highest 25 % of data. Thus two quartiles and median forms four desirable intervals. It is a continuously iterated procedure until consensus is determined.

In next stage if evaluation of experts gives good compatibility of responses then evaluation of the performance could be considered reliable. Compatibility can be obtained by variational response and interquartile coefficients. Variational performance measured in min max of intervals. Variational response is the difference between the first and third quartiles $Q_3 - Q_1$.

In last stage, actual values and forecast values at some-time step *t* was investigated. The Pearson's correlation coefficient was chosen for verification of the accuracy and reliability of the model. This model shows 83 % accuracy for three trading days and five trading day's prediction's accuracy was 35% and the correctly predicted market directions were 78 % of all trading days.

By this paper, we can conclude that neural network prediction has characteristics such as reliability and compatibility. Expert's methods can improve the quality of forecasting and make profit accordingly. Proposed model shows consistent profit growth and compatibility of forecasting of LMST.

2.3 SVM Based Models for Predicting Foreign Currency Exchange Rates

SVM-based forecasting model necessitates the selection of appropriate kernel function and values of free parameters: regularization parameter and ε–insensitive loss function. The paper checks the effect of various kernel functions on the indicators - linear, polynomial, spline and radial. It then performs a prediction of six different currencies against the Australian Dollar and analyzes it.

Exchange rate prediction is one of the challenging applications of modern time series forecasting and very important for the success of many businesses and financial institutions. The rates are inherently noisy, non-stationary and deterministically chaotic [6]. Historical data of such rates are assumed to exhibit all behaviors, which is why it is the major input for the prediction process.

The ARIMA method has been used quite frequently. However, ARIMA is a general univariate model and it is developed based on the assumption that the time series being forecasted are linear and stationary [7]. The neural network method was found to have accurate results, which is why there was a lot of research done on it. However, the paper explains that the neural network model had disadvantages based on network size, over fitting of data and so on, which is why the research was done on SVM instead. They also state that SVM has the ability to minimize structural risk, which was an advantage over the empirical risk minimization employed by the neural network model.

SVMs originate from Vapnik's statistical learning theory. They formulate the regression problem as a quadratic optimization problem. SVMs perform by nonlinearly mapping the input data into a high dimensional feature space by means of a kernel function and then do the linear regression in the transformed space.

The Kernel function is given as $K(x, x_i)$

Kernel function: The value of the kernel function is equal to the inner product of two vectors x_i and x_j in the feature space $\varphi(x_i)$ and $\varphi(x_j)$ satisfying Mercer's condition [8]. The kernel functions used in this study are the followings:

Linear: $K(x_i, xj) = \langle x_i \cdot x_j \rangle$

Polynomial: $K(x_i, xj) = (\langle x_i \cdot x_j \rangle + 1)$ d, d=degree

Radial Basis: $K(x_i, xj) = \exp(-||xi-xj||2/2\sigma 2)$, σ=width

Spline: $K(x_i, xj) = 1 + \langle x_i \cdot x_j \rangle + (1/2) \langle x_i \cdot x_j \rangle \min(\langle x_i \cdot x_j \rangle) - (1/6) \min(\langle x_i \cdot x_j \rangle)^3$

Technical indicators were found to be more efficient compared to the market data. Because of this, the authors chose time delay moving average as technical data. The advantage of such an indicator is that it smoothens out the irregularity formed between market days [6]. The system has five indicators of moving average over a period of days. The periods were 5 days, 10 days, 20 days, 60 days and 120 days. Apart from this, the sixth indicator was the closing rate of the previous week, X_i. Exchange rate for the period i+1 is predicted. These six indicators are used as inputs to construct support vectors.

The evaluation of the performance was done against six widely used metrics [9]: Normalized Mean Square Error (NMSE), Mean Absolute Error (MAE), Directional Symmetry (DS), Correct Up trend (CU) and Correct Down trend (CD).

The authors used 500 sets of weekly data for training and the rest 65 was left for testing. They tested four types of kernels against six currencies to check which kernel gave the best result. They checked the US Dollar, British Pound, Japanese Yen, Singapore Dollar, New Zealand Dollar and Swiss Franc against the Australian Dollar.

They realized that it is not just one kernel which gives a higher accuracy during prediction. Based on the predicted error, they observed that the linear kernel worked best for the US Dollar, while both linear and polynomial worked for the Great British Pound. However, the Singapore Dollar, the New Zealand Dollar and the Swiss Franc all favor the polynomial kernel. Thus, they concluded that the polynomial kernel works for all except the US Dollar.

In terms of trend prediction, radial and polynomial were the top dogs in terms of better results. They also reigned in terms of correct directional changes. This continued for Correct Up and Correct Down trend. However, they inferred that they couldn't select one particular type of kernel that would give good performance, yet with low prediction errors. In terms of prediction, if one method gave less prediction error but high direction matching errors, there is less success. They gave the example of the prediction being in the opposite direction of the actual result leading to 0% success that week. Thus, they concluded that no specific kernel could be used to forecast all currency exchange rates.

3. CONCLUSION

This paper is a review of forecasting currency exchange rates using different methods. We learn about neural networks and how the multiple inputs are taken into consideration for prediction of the forex rate. There is a method in recurrent networks that shows an improvement in forecasting, thus increasing profits. However, we need to evaluate the performance against some standard measures. We learn that RMSE, MAD and MAPE are some certain measures that can be used. Different types of kernels are used to predict the exchange rate in the SVM method. It is seen that each currency exchange rate has a different one applied to them and a uniform one cannot be determined in general.

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