Design and Development of an Algorithm to Predict Fluctuations of Currency Rates

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Abstract— Dealing with businesses with the foreign market always took a special place in a country's economy. Political and social factors came into play making currency rate changes fluctuate rapidly. Currency rate prediction has become an important factor for larger international businesses since large amounts of money exchanged between countries. This research focuses on compare the accuracy of mainly three models; Autoregressive Integrated Moving Average (ARIMA), Artificial Neural Networks(ANN) and Support Vector Machines(SVM). series of data import, export, USD currency exchange rate respect to LKR has been selected for training using above mentioned algorithms. After training the data set and comparing each algorithm, it was able to see that prediction in SVM performed better than other models. It was improved more by combining SVM and SVR models together.

Keywords— Autoregressive Integrated Moving Average (ARIMA), Artificial neural networks (ANN), Feed forward neural networks (FFNN), Root Mean Squared Error (RMSE), Support vector Regression(SVR), Support vector machines (SVM)

I. INTRODUCTION

Predicting USD/LKR currency exchange rate is a challenge. There are various factors that effect to the USD/LKR currency exchange rates. Inflation, Interest rates, Speculation, Balance of payments (country's current account), government debt, terms of trade, political stability & performance, recession, speculation are some of them. These factors cannot be predicted easily and always fluctuates. Therefore it is very difficult to predict the USD/LKR currency exchange rate. Increasing or decreasing Inflation rates also affect the currency exchange rates. If the values of goods and services increase the inflation rate is low. A country with higher inflation rate depreciate its currency. It is a one of examples of the way these social, political, geographical and economical factor affecting to the currency exchange rate.

Businessman who is buying and selling using huge amount of money need to have some idea of currency exchange rates. Because if a businessman wants buy a huge bulk, It can make some profit from buying it in a day which has lower currency exchange rate. Businesses like selling cars, selling phones, selling clothes, selling shoes, selling electrical equipment's, selling medicine need to buy huge amount of goods to sell. Another scenario of investing huge amount of money is when businessmen wants to buy expensive machines and software to the business operation. Businessmen have to invest big amount of money for buying these goods

and services. Because they are paying big amount of money even a change of one point of currency exchange rate is affect the profit of the business. Not only businessmen, student who study in abroad also have huge benefit of knowing the currency exchange rate beforehand. When their parents send money the fee will be change according to the currency exchange rate. Therefore it is important to predict the currency exchange rate to save money. Investor who like to invest in Sri Lanka market can also save money from predicting the USD/LKR currency exchange rate. Investor can decide right time to invest in the Sri Lankan Market. It is import to predict currency exchange rate to give the investor an idea of Sri Lankan market. It can give an idea of how long they can invest in the Sri Lankan market.

II. LITERATURE SURVEY

When predicting currency exchange rate historical data is very important [1]. There are some theories to predict currency exchange rate which has their own limitations. There are some approaches like fundamental approach, technical approach and some models such as Purchasing Power Parity Model (PPP), Relative Economic Strength Model, Econometric Model, Time Series Model, etc. [2]. In here time series is a famous and conventional technique which is used to model the exchange rates [1]. This is a completely technical model which doesn't include any economic theories [2]. ARMA is a popular model which can be get as an example for time series linear model. But the problem of this kind of linear model is that, most complex real-world economic time series are non-linear though it is assumed to be linear. As the determinants of the exchange rate have grown with higher complexity, nonlinear and volatile, non-linear models have a much better performance than linear models [3]. ANFIS, Artificial Neural Network (ANN), chaotic dynamic, self-exciting threshold autoregressive model, autoregressive random variance (ARV) model, auto regressive conditional heteroskedasticity (ARCH) and Generalized ARCH (GARCH) are examples for nonlinear model which are used for forecasting foreign exchange rate [4]. ANN is also a well-known nonlinear model which can be used as an alternative for the linear traditional forecasting methods.

Modeling a mechanism to identify the behavior of exchange rate totally correctly is still an unsolved issue which has exposed to the researches. Building an accurate model for identifying the behavior of the exchange rate and forecasting is a huge challenge as there can be many reasons which can impact on this directly or indirectly such as economic, political, social, short run and long run, etc. [5]. When regarding some

existing models, Autoregressive Integrated Moving Average (ARIMA) model of Box and Jenkins' has been widely used for a long period that assuming the time series being forecasted is a linear and stationary [6], [7]. This method has some considerable limitations as most of time series are not linear. This issue has been well-addressed by Fahimifard, Homayounifar, Sabouhi and Moghaddamnia [3] in their research. They have used ANFIS and ANN as the nonlinear models and GARCH and ARIMA as the linear models with a common dataset and check forecasts. By this comparing they revealed the accuracy of the prediction of non-linear models specially ANFIS model forecasts is greater than linear models [3]. In Chandrasekara and Tilakaratnes' research [1] they have used some different type of neural network models and looked for a better mechanism for forecasting USD/LKR exchange rate. The three types of neural network models were employed: (I) Feedforward neural network (FFNN; static neural networks) with the Backpropagation (BPR) algorithm; (II) FFNN with the Scaled Conjugate Gradient (SCG) algorithm; (III) Time Delay neural network (TDNN; dynamic neural

network) [1]. In their research, they have found that TDNN performs better and has the ability to predict unseen data with 76% prediction accuracy [1]. There are also some other researches which has been done from neural networks and comparing those various types.

When considering about ARIMA to forecasting future values in the research done by Prapanna Mondal, Labani Shit and Saptarsi Goswami they have conducted a study on fifty six stocks from seven sectors. All the stocks that are selected by them are listed in National Stock Exchange (NSE). They have selected 23 months of data for the set empirical study. Which they have used to evaluated the accuracy of the ARIMA model in predicting the stock prices. In their study, they have also changed the time period of previous or historic data and studied its effect on accuracy [7].

In the research of Joarder Kamruzzaman, Ruhul A Sarker, Iftekhar Ahmad, a nonlinear technique is called Support Vector Machine (SVM) has been used. They have indicated that using SVM algorithm can positively affect to the predictions rather than neural networks or ARIMA based traditional methods [8].

III. METHODOLOGY

A. Collecting the Data set

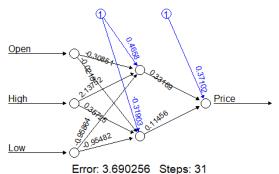
The selection of input data directly effect for better performing algorithms. The selected data set contains factors which are varies according to the time. Among available factors; imports, exports, open price, low price, high price, USD/LKR and relevant dates have been selected as the using dataset. these factors are effect to the currency fluctuation in Sri Lanka. This information was available on the official websites of Sri Lanka Census and Statistic Department and Central Bank of Sri Lanka.

B. Variable weight on LKR in Sri Lanka

Lot of variables are affecting to fluctuation of currency in a country. But variable weights are depend on country wise. In here testing is done to find how these variables are affecting to Sri Lankan currency and what are the variables weight of Sri Lankan currency is. In here neural network use to train the data set. Open price, high price and low price are used as inputs and by using these inputs to predict the price variable.

Price ~ Open value + High value + Low value

When the neural network is running input weight assigned by randomly. It is main feature of the neural network. Each time input weight is changed. Finally calculate the mean squared error by using both actual values and predicted values. When the compare with that MSE in each and every time can be identify which variable is most effect to the fluctuation of Sri Lankan currency.



E1101. 3.090230 Steps. 31

Figure 3.1: Different weight is assigned in inputs

C. Algorithm types

According to the past researches, most researches have proven that ARIMA ,Artificial Neural Networks and Support Vector Machines performs better than other models. So, in this research paper, Feed Forward Neural Networks with Back-Propagation, ARIMA, Radial Basis Functional Neural Networks and Support Vector Machine have been selected to test predictions with USD/LKR data. After comparing predictions of algorithms the best algorithm or combination of algorithms will be selected.

a. ARIMA (Autoregressive Integrated Moving Average)

ARIMA is a forecasting technique that forecasts the future values of a time series based totally on its own inactivity. Its main use is in the area of short-term forecasting which requires at least 50 historical data points.

It works best when the data set to display is stable or consistent pattern over time with a minimum amount of outliers.

Sometimes called Box-Jenkins (after the original authors), ARIMA is usually preferable to exponential smoothing techniques when the data is reasonably long and the correlation between past information is stable. If the data is short or highly unstable, then some smoothing method may perform better. If dataset doesn't contain at least 40 data points, it is better to consider some other method than using ARIMA.

Monthly value of USD/LKR from 2012 to 2017 was used. 75% was used to train the model and 25% was used to test the predictions

The flow of the system used in ARIMA algorithm is shown below in Figure 3.2.

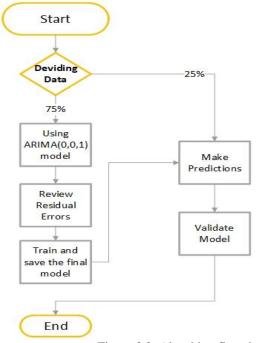


Figure 3.2: Algorithm flowchart

By adding the residual error to make the final model makes predictions accurate. Residual error of 3.228540 was calculated with the data set.

At the end predictions give out a RMSE 0.794 which makes ARIMA not effective compared with SVM and SVR models.

b. Feed Forward Neural Networks

Below Figure 3.3 shows the structure of the neural network which have been used in this section. This consists of two-size input layer, ten-size hidden layer and one-size output layer.

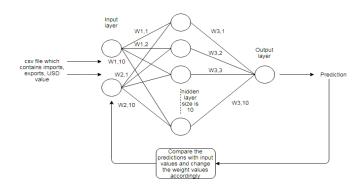


Figure 3.3: Neural network structure

To train the algorithm set of imports, exports, USD/LKR values have been used. Gradient descent was used to identify the minimum point of cost function. Backpropagation was used to change the weight values with respect to the cost values. The way weight values are changed according to this,

$$W(n)_{\text{new}} = W(n-1)_{\text{old}} + \frac{dJ}{dW(n-1)old} \alpha + \beta$$

The weight value of the n^{th} training cycle is $W(n)_{new}$ which is derived by $W(n-1)_{old}$ the previous cost value and the rate of change of cost(J) with respect to $W(n-1)_{old}$ the cost value. α and β are learning rate parameters. In the final trained model, their values were 10 and 0.0002 respectively.

c. Radial Basis Functional Neural Networks

In here RBFNN use to forecast the future Sri Lankan currency respect to the USD. Data set is consisting with open values, high value, low value and actual value variables. In this function these variables are used as inputs and using these inputs, try to forecast future LKR values. Between this forecasting value and actual values on same day, it can be seen clearly, there are some differences. By changing number of levels in hidden layer, tried to decrease the difference of this error. But it could not be succeeded. In here data set is very small and no of variables are less. RBFNN function is more suitable for the large data sets which are consisted with large number of variables.

d. Support Vector Machines and Support vector regression

i. Support vector regression

In this research one of the goal is to find best parameter values of parameter C(cost) and parameter gamma for SVR according to USD/LKR data. Figure 3.4 shows the flowchart of support vector regression.

The best value is determined by comparing calculated RMSE values for different values of each parameter combinations. Then using these parameters root mean squared error(RMSE) is calculated for three different kernels. The kernels used are radial basis kernel, polynomial kernel and linear kernel. After calculating RMSE, the best kernel for SVR algorithm is chosen by comparing RMSE values.

INPUTS USD/LKR exchange rates) Determine Determine Determine parameter C and parameter C and parameter C and Gamma for RBF Gamma for Linear Gamma for kernel kernel Polynomial kernel Predict the currency Predict the currency Predict the currency rate using the rate using the rate using the RBF Linear kernel in Polynomial kernel in kernel in SVR SVR SVR Choose the kenel which has lowest

Figure 3.4:Support vector regression flowchart

ii. Support vector machines

The best cost parameter value and best gamma parameter value for USD/LKR data are determined by comparing RMSE values for support vector machines(SVM). Other than that best value for the parameter epsilon is also calculated. Then the data set is labeled as 0 and 1 . '0' represents USD/LKR currency exchange rate increasing. '1' represents USD/LKR currency exchange rate decreasing. After that data

is divided as training data and testing data. Using these best parameters predictions are taken and root mean squared errors(RMSE) are calculated for three different kernels. The kernels used is radial basis kernel polynomial kernel and linear kernel. Kernels will be compared,

after calculating RMSE values. Flowchart of Figure 3.5 illustrates the flow of support vector machine part of the research.

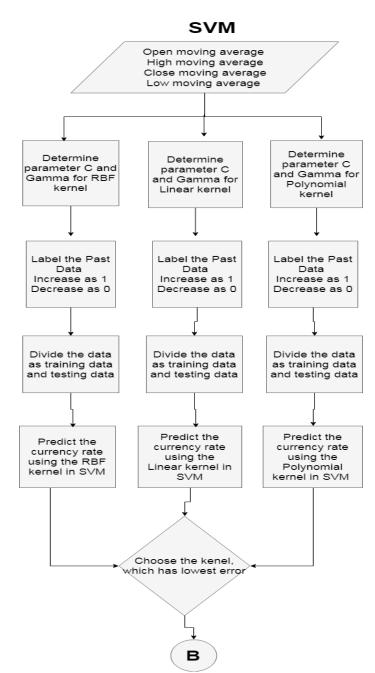


Figure 3.5: Support vector machines flowchart

iii. Combining SVR and SVM

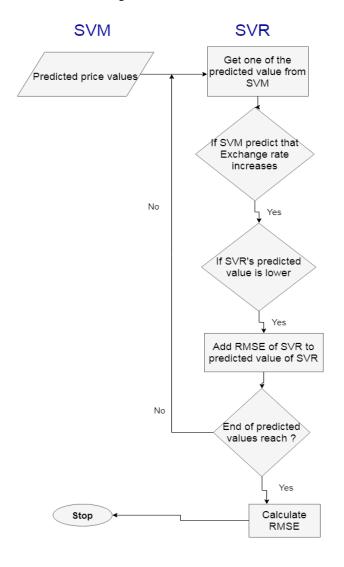


Figure 3.6: Flowchart of Combining SVR and SVM

After determining the best kernels with optimized parameters for support vector machines and support vector regression, best kernels with optimized parameters for SVM and best kernel with optimized parameters for SVR are combined together. Then compare RMSE value of before combining the algorithms with RMSE value of after combining the algorithms.

Figure 3.6 describes how support vector machines and support vector regression algorithms combination works. Predicted values from support vector machines are the input to the support vector algorithm. SVM take these predicted values which basically '0' s and '1' s. '1' means currency rate is increasing and '0' means USD/LKR currency rate is decreasing. Then it checks two conditions. First it checks

whether USD/LKR currency exchange rate increases or decreases according to the prediction of support vector machines. Then it checks whether USD/LKR currency exchange rate increases or decreases according to the prediction of support vector regression algorithm. Only if support vector machines predicted rise of currency exchange rate and support vector regression predict fall of currency exchange rate, add half of the RMSE value of support vector regression algorithm(basically the error) to the value predicted by support vector regression. Then the RMSE value of the combined algorithm is calculated. The value of RMSE before the combining algorithms and value of RMSE after the combining are compared to identify the difference.

iv. ANN and SVM combined model

ANN and SVM were combined to check results to determine whether it can increase the accuracy. SVM and ANN contained their own errors. So that these separate algorithms tried to combine to check to see what will happen to the accuracy. Imports, exports, USD/LKR values of Sri Lanka has been used to train the model. In this model, SVM was used to predict import, export rate instead of predicting USD/LKR value. And the ANN was used to get that predicted imports, exports values and predict the USD/LKR value.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Determine the best values for parameters in SVM and SVR

One of the objective in this research is to find best values for cost parameter, gamma parameter, and epsilon parameter for USD/LKR currency exchange rate prediction. In order to find out best parameter grid search can be used.

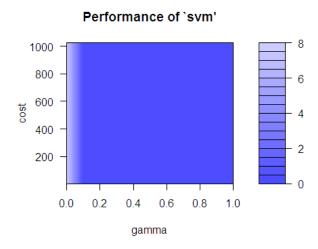


Figure 4.1: Best value for gamma and C parameters

The figure 4.1 shows gamma and cost parameters with respect to the RMSE values using radial basis kernel. In figure 4.1 right side bar represent RMSE value. The results shows cost parameters does not make much difference and best gamma value is between 0.1 to 1.

Same results were showed, when considering polynomial kernel and linear kernel.

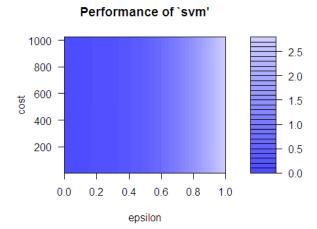


Figure 4.2: Best value for epsilon and C parameters

Figure 4.2 illustrate best values for parameter C and epsilon. the grid shows that best values for C could be any value and best epsilon is between 0 to 0.8.

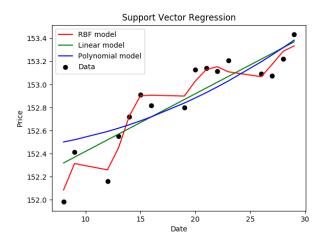


Figure 4.3. Using support vector regression

The figure 4.3 Illustrate predictions of three different kernels. The graph shows that the prediction using radial basis kernel is better than the polynomial kernel or the linear. Radial basis kernel shows the best fit for the data.

b. Comparing Monthly predictions of SVR and ARIMA

The Below figure 4.4 shows the monthly prediction using ARIMA. It uses red line to show prediction and blue line to show the actual data.

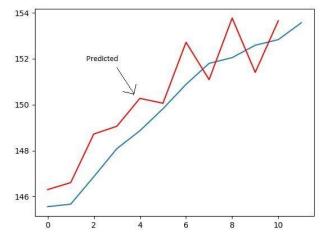


Figure 4.4. Monthly prediction using ARIMA

In below, Figure 4.5 shows the monthly prediction using SVR.

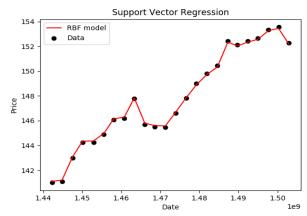


Figure 4.5. Monthly prediction using SVR

When the data analysis is done for Support vector regression method it provides more accurate results compared to neural network methods. When comparing Figure 4.4 and Figure 4.5, Even when RMSE values is considered ARIMA gives a RMSE value of 0.794 and SVR gives out a RMSE value of 0.0987. It proves SVR is better than ARIMA to predict USD/LKR exchange rate.

c. Comparing Daily predictions of SVR and ANN

The Below Figure 4.6 represent daily prediction of USD/LKR exchange rate using ANN. Red line to represent prediction and blue line to represent actual data.

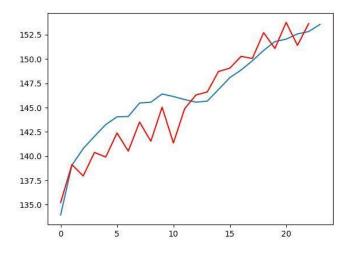


Figure 4.6. Daily prediction using ANN

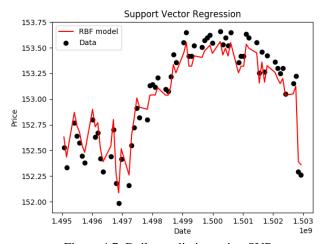


Figure 4.7. Daily prediction using SVR

Figure 4.7 shows the Daily prediction using SVR. When comparing Figure 4.6 and Figure 4.7, it proves that daily SVR is the more accurate method than ANN to predict the USD/LKR exchange rate.

d. Results of combining SVR and ANN

To identify the accuracy of the model, RMSE value was considered and without combining SVR and ANN, it gave 3.6765. In the combined model of SVR and ANN, it gave 3.6765 which is almost same value as ANN by itself.

e. Results of combining SVR and SVM

Before combining the SVR and SVM, RMSE value is 0.0987. After combining the SVR and SVM, RMSE value is 0.0900. RMSE value reduced by 0.0087 by combining the SVR and SVM.

V. CONCLUSION

In this paper, several different methods have been used to predict the USD/LKR currency exchange rates. When predicting the currency rates with methods ARIMA, SVM and ANN, Support Vector Machines Provide more accuracy than neural network and ARIMA methods compared to the result analysis. Based on the results combination of SVM and SVR provide better result than other algorithms. Therefore, combination of SVM and SVR is an accurate and effective way to predict the USD/LKR exchange rates.

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