Multi-Step-Ahead Prediction of Exchange Rates Using Artificial Neural Networks: A Study on Selected Sri Lankan Foreign Exchange Rates

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***Abstract* - The exchange rate is a very important economic indicator for countries with market economies as its fluctuations heavily affect the most areas in the economy. Accordingly, predicting future values of foreign exchange rates is very important in policymaking. This study was conducted to perform multi-step ahead predictions on foreign exchange rates of Sri Lankan Rupee against three international currencies using Artificial Neural Network models, to measure the accuracies of these models and identify shortcomings if present. Multi-Layer Perceptron, Simple Recurrent Neural Network, Long Short-Term Memory, Gated Recurrent Unit and Convolutional Neural Network architectures were employed for this study. Most of the models except few Gated Recurrent Unit models were able to predict 10-days-ahead exchange rates with a higher level of accuracies (97%-99%). According to the findings Stateful Simple Recurrent Neural Networks with one input layer, a hidden layer, a flatten layer and an output layer performed as the best architecture to predict the three exchange rates selected.**

Keywords - Multi-step ahead prediction, exchange rates, Sri Lankan Rupee (LKR), MLP, SRNN, LSTM, GRU, CNN

I. INTRODUCTION

Most of the countries in the world have their own currencies and used as a medium of exchange in economic activities. When a country is involved in economic transactions (e.g. imports and exports) with another country that uses a different currency, needs to exchange their currencies at a given rate. This rate is called as "Foreign Exchange Rate." The foreign exchange rate can be defined as the number of units of one currency exchanged for a single unit of another currency. In most countries' foreign exchange rates are determined by the supply and demand for foreign currencies [1].

Since most of the countries adopted open economies, the exchange rate is very much important as it affects the imports, exports, foreign investments, inflation, worker remittances and reserve position of a country, etc. So, it is very important to predict the future values of foreign exchange rates for future economic planning [1], [2]. Therefore, government institutions, business organizations, investors, researchers, etc. are very interested in the prediction of foreign exchange rates.

As foreign exchange rates are a kind of time-series data, several time-series analysis models have been used for the prediction of foreign exchange rates. Because of the non-linear, complex and uncertain nature of foreign exchange rates, traditional statistical methods are not successful in forecasting exchange rates accurately. Due to that reason several machine learning techniques have been employed in the prediction of foreign exchange rates. Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) are the widely used machine learning models for such predictions [2].

Normally, time series forecasting involves predicting the value in the next time step based on past observations. This is called as one-step-ahead forecasting. If the prediction is done for multiple-time-steps-ahead based on past observations this is called as multi-step-ahead prediction [3]. There are four commonly used strategies for multi-step-ahead predictions namely – direct multi-step forecast, recursive multi-step forecast, direct-recursive hybrid multi-step forecast and Multiple-Output Forecast [3]. Compared to one-step-ahead forecasting, multi-step-ahead forecasting is more difficult due to the accumulation of errors, reduction of accuracy and increased uncertainty and accurate prediction of time series prediction over long future horizons has become an interesting research area [4].

Since Sri Lanka is a developing country that adopted the open economy since 1977, changes in exchange rates heavily affect most areas of the economy. So, the accurate prediction of exchange rates is very important for policymakers of the country as well as business organizations and foreign investors. This study was conducted in order to perform multi-step-ahead predictions of Sri Lankan foreign exchange rates using Artificial Neural Network (ANN) models, to measure the accuracies of these models and to identify shortcomings of these models if present. Since Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and Convolutional Neural Network (CNN) models are widely used and found more accurate in predicting financial time series data [5], [6], [7] the above three architectures were employed for model building. Since a study on predicting daily stock prices in the Sri Lankan stock market suggests Simple Recurrent Neural Network (SRNN) and Multi-Layer Perceptron (MLP) architectures in predicting financial time series data [8] can be used effectively, MLP and SRNN architectures were also employed in this study.

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In section II of this paper, a review of past research work is presented. Section III describes the theoretical framework and section IV describes the research methodology. In section V results of the study are presented and section VI includes discussion, conclusion and future research work.

II. LITERATURE REVIEW

A. *Exchange Rate Prediction Using Machine Learning Techniques*

A study was done to analyze the extent of the volatility of exchange rates of British Pound (GBP) and Indian Rupee (INR) in terms of US Dollar (USD) and make predictions [9]. It applied GARCH and EGARCH models to analyze the volatility and applied Artificial Neural Networks (ANN) to make predictions. Findings confirmed the volatility and asymmetry in both foreign exchange (FOREX) markets and forecast were done for a period of 12 months based on best models.

A study was conducted to predict three exchange rates – Euro/USD, USD/Japanese Yen (JPY) and USD/Turkey Lira (TRY) – using four machine learning techniques – Multi-Layer Perceptron (MLP), Radial Basis Function (RBF), Long Short-Term Memory (LSTM), and Support Vector Regression (SVR) [5]. Results revealed that SVR is the best-performed technique while MLP is the least performed technique.

A study was conducted to predict exchange rates EUR/USD, GBP/USD and USD/JPY in daily, monthly and quarterly steps. It was found that the short-term prediction method provides good accuracy and can be used to predict the exchange rate for one-step-ahead in practical systems [10]. The same researcher conducted another study to predict exchange rates of currency pairs EUR/USD, GBP/USD and JPY/USD using Deep Convolutional Neural Networks (CNNs). Results show that deep CNNs achieve significantly higher classification accuracy in predicting the direction of change in foreign exchange rates [6].

Another study was done using 2D CNNs to predict the exchange rates of Euro/USD, USD/JPY and GBP/USD and suggested that CNNs outperform MLP, SVR, and GRU models and improve the accuracy of long-term forecasting effectively [7].

An Indian study on one-step-ahead prediction of daily Indian Rupee (INR)/USD exchange rate suggested that ANN and linear autoregressive models outperform the random walk model in in-sample and out-of-sample forecasts [11]. A study conducted in 2007 by the same researchers confirmed the findings of the previous study [12].

A study was conducted to compare the accuracy of mainly three models: Autoregressive Integrated Moving Average (ARIMA), Artificial Neural Networks (ANN) and Support Vector Machines (SVM) using a series of data of imports, exports and USD/LKR currency exchange rates [13]. Among the selected models SVM performed better than other models.

Many studies have found that the use of hybrid machine learning models produces more accurate results than using individual models alone. A study was done to predict daily exchange rates of Sri Lankan Rupees (LKR) to Euro and Yen with a hybrid forecasting model using Empirical Mode Decomposition (EMD) and Feed-forward Neural Network (FNN). Results revealed that the proposed hybrid model produced better results compared with widely used Non-linear Autoregressive (NAR) and Support Vector Regression (SVR) models [14]. Two novel ANN models – named functional link artificial neural network (FLANN) and cascaded functional link artificial neural network (CFLANN) – were developed using nonlinear inputs and simple ANN structure with one or two neurons to predict exchange rates of USD/GBP, USD/INR, and USD/JPY. Results suggested that CFALNN models perform the best [15].

B. *Multi-Step-Ahead Prediction*

A study was done to compare the performance of 5 multi-step-ahead prediction strategies: direct, recursive, direct-recursive (DirREC), Multi-Input Multi-Output (MIMO) and a combination of both DirRec and MIMO strategies (DirMO). After doing several experiments on 3 datasets it was found that DirREC strategy is the best among all strategies for multi-step-ahead prediction using neural networks [4]. Another study was done to examine two different approaches in multi-step-ahead prediction – independent value prediction and parameter prediction using multiple linear regression, Recurrent Neural Networks (RNN) and hybrid of hidden Markov model with multiple linear regressions. Results suggest that multi-stage prediction tends to suffer from error accumulation problems when the prediction period is long and RNN models give better results in both independent value and parameter prediction approaches [16].

The optimal MLP topology was designed and tested by means of a Pareto-based multi-objective genetic algorithm to predict the exchange rate Euro/USD up to three days ahead of the last data available. The developed model was able to largely predict the exchange rate of Euro/USD three days ahead [17].

III. THEORETICAL FRAMEWORK

Five neural network architectures were employed in this study. They were Multi-Layer Perceptron (MLP), Simple Recurrent Neural Network (SRNN), Long Short Term Memory (LSTM), Gated Recurrent Unit (GRU) and Convolutional Neural Network (CNN).

MLP or Feed-forward Neural Networks is the simplest, oldest and most commonly used architecture where the data flow from the input layer to the output layer is strictly feed-forward [18]. SRNN, LSTM, and GRU are types of Recurrent Neural Networks (RNN) which contain at least one feedback connection. RNNs are able to store correct pattern and they are based on more recent history. SRNNs (also called as Elman-Jordan Neural Networks) are three-layer networks with a set of context units. In Elman networks, context units are connected to the hidden layer while in Jordan networks context units are connected to the output layer. An LSTM network contains LSTM blocks instead of regular neurons. An LSTM block contains 3 gates – input gate, output gate and forget gate. GRU is also a kind of RNNs with a gating mechanism. Compared to LSTMs, GRUs do not contain an output gate [19].

A Convolutional Neural Network (CNN) is a deep learning architecture with the ability to differentiate one image from others by assigning importance to various aspects/objects in the image [20]. Although CNN's are a special kind of neural network designed for working with two-dimensional image data, they can also be used with one dimensional and three-dimensional data including financial time series data [21]. In this Study 1-dimensional architecture (1D CNN) was used. The 1D CNN is very effective in deriving interesting features from shorter segments of the overall dataset [21].

IV. METHODOLOGY

A. *Selection of Data*

Daily exchange rates of US Dollars (USD), Great Britain Pounds (GBP) and EURO on Sri Lankan Rupee (LKR) from 3rd January, 2005 to 30th May, 2019 (3473 trade days) were selected for this study (see Figs. 1-3). Above mentioned 3 exchange rates were selected as those currencies are the major currencies in the world economy and those are the most commonly trading currencies with LKR. Data were obtained from the official website of the Central Bank of Sri Lanka [1].

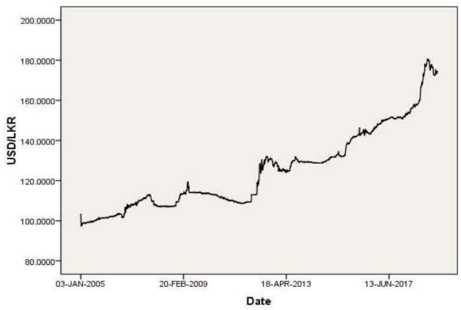

Fig. 1. Time plot of USD/LKR data

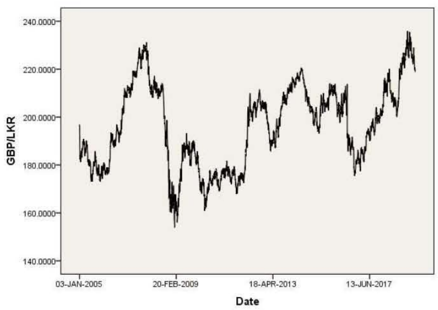

Fig. 2. Time Plot of GBP/LKR data

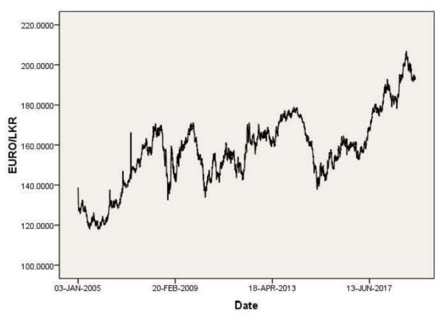

Fig. 3. Time plot of EURO/LKR data

B. *Selection of Variables*

Past 30 days exchange rates were selected as input variables to predict future 10 days exchange rates. So, each model has 30 input variables (neurons) and 10 output variables (neurons). Accordingly, the input and output variables are as follows (where X=exchange rate and t=current time):

Input Variables: X(t-1) to X(t-30)

Output Variables: X(t) to X(t+9)

C. *Neural Network Topology*

As stated in section III, 5 neural network architectures (MLP, SRNN, LSTM, GRU and 1D CNN) were employed for model building. There are several suggestions in finding the optimum number of hidden neurons. One method suggests the addition of the number of input and output neurons and division by two. Another method suggests multiplication of the number of input neurons by two and adding one (2×N+1) [22]. By using these two methods for this study to calculate the optimum number of hidden units it can be found that the number of optimum hidden units are in the range of 45 – 60. Therefore, for each neural network architecture, 12 neural network models were developed by varying the number of hidden neurons from 5 to 60. Accordingly, there were 60 neural network models for each exchange rate category. So, the total number of models developed was 180. The table below shows the internal architecture of each 12 models developed for each exchange rate category using a single ANN architecture.

TABLE 1: ANN MODELS WITH NO. OF HIDDEN UNITS

Model Number	No. of Input Neurons	No. of Hidden Neurons	No. of Output Neurons
1	30	5	10
2	30	10	10
3	30	15	10
4	30	20	10
5	30	25	10
6	30	30	10
7	30	35	10
8	30	40	10
9	30	45	10
10	30	50	10
11	30	55	10
12	30	60	10

Accordingly, MLP, SRNN, LSTM & GRU models have an input layer of 30 neurons/units, a hidden layer with 5-60 neurons/units, a flatten layer and an output layer of 10 neurons/units. One Dimensional CNN models have an input layer of 30 neurons/units, a convolutional layer with a kernel size of 5, a 1D max-pooling layer, a flatten layer, a hidden layer with 5-60 neurons/units, and an output layer of 10 neurons/units.

D. *Data Preprocessing*

The data were normalized into the range of [0,1] using the Min-Max Scalar function (see Eq. 1).

$$X_p = \left(\frac{X - \min X}{\max X - \min X} \right) \quad (1)$$

X_p – Normalized value
X – Original value
minX – Minimum value of the dataset
maxX – Maximum value of the dataset

E. Training and Performance Evaluation

From each of the data series most recent data was selected for testing and the rest was selected for training. Each dataset (USD/LKR, GBP/LKR, and EURO/LKR) consists of 3473 values. From each dataset, 80% was allocated for training and the remaining 20% was allocated for testing. Since the size of the dataset is exceeding 3,000, no cross-validations were used.

"Keras" deep learning library running on the Anaconda platform on Windows 10 operating system was used to data pre-processing, model building, training, and testing. For each model "Softsign" activation function, Mean Squared Error (MSE) function and Root Mean Square Propagation (RMSProp) training algorithm were used in the training. All the recurrent neural network models (SRNN, LSTM, and GRU) were "Stateful" which keeps the last state and uses it as the initial state for the next sequence of the dataset. The stopping condition for all the models was 200 iterations.

During training, runtimes were calculated for each model. The following table shows the average runtime (in minutes) for each architecture (for all three datasets) during training.

TABLE 2: AVERAGE RUNTIMES (MINUTES) DURING TRAINING

Runtime (Minutes)	MLP	SRNN	LSTM	GRU	1D CNN
Average	3.68	9.63	34.66	26.09	29.13
ST. Dev.	0.35	1.06	11.87	3.73	14.80
Minimum	2.95	7.76	26.27	21.08	10.11
Maximum	4.08	11.13	68.98	32.53	52.10

After training, predictions were done using the test dataset. Then the predicted values which were in the normalized format were converted to the raw format and compared with actual values. To measure the performance of each model Mean Absolute Deviation (MAD) (see Eq. 2) and Mean Absolute Percentage Error (MAPE) (see Eq. 3) were calculated. To measure the correlation between the actual and predicted values Pearson's correlation coefficient was used. Pearson's correlation coefficient is the test statistic used to measure the association between two continuous variables [23].

$$MAD = \frac{1}{n}\sum_{t=1}^{n} |\hat{y}_t - y_t| \tag{2}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \frac{|\hat{y}_t - y_t|}{y_t} \tag{3}$$

where t - current time, y - actual value, $\hat{y}$ - predicted value.

To find the best architectures, average errors of each architecture were calculated. And to find whether the ANN models developed are performing better than linear regression models, multivariate regression models were built for each dataset using the training data and predictions were done using test datasets. Also, P-values were calculated using Paired Sample T-tests to identify the significant differences among the models.

V. RESULTS OF THE STUDY

A. USD/LKR Dataset

According to the figures in the Section 5A, Stateful Simple Recurrent Neural Network (SRNN) models produce comparatively lower errors while Stateful Gated Recurrent Unit (GRU) models produce both comparatively lower and higher errors. SRNN model with 45 hidden units has the lowest error (MAD - 0.6567, MAPE - 0.40%) while GRU model with 60 hidden units has the highest error (MAD - 569.3317, MAPE - 363.25%). Other models produce errors (MAPE) ranging from 3.0% - 10.0%. SRNN model with 5 hidden units obtained the highest correlation between actual and predicted values (0.99632) while GRU models have the lowest positive (0.05941) and negative correlations for actual and predicted values (-0.0989). Other models are having relatively strong correlations between 0.95 and 0.99. So, based on error values and correlation coefficients SRNN model with 45 hidden units is the best model among USD/LKR models and it can be suggested that Stateful SRNN models accurately predict future values of USD/LKR exchange rate compared with other neural network architectures.

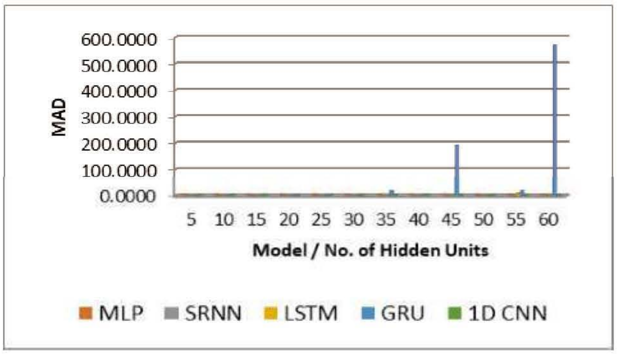

Fig. 4. Forecast Errors (MAD) - USD/LKR Models

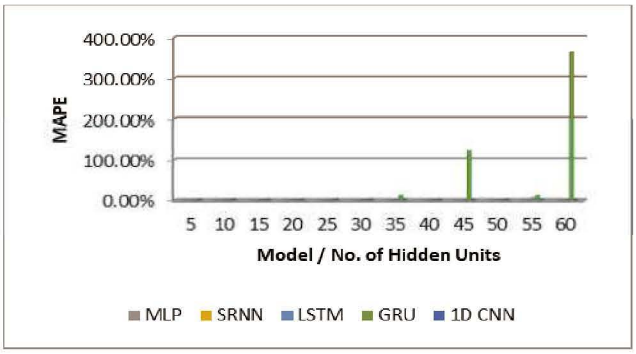

Fig. 5. Forecast Errors (MAPE) - USD/LKR Models

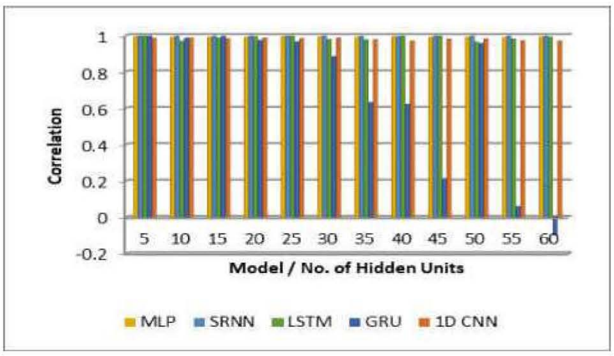

Fig. 6. Correlation (Actual Vs. Predicted) - USD/LKR Models

B. GBP/LKR Dataset

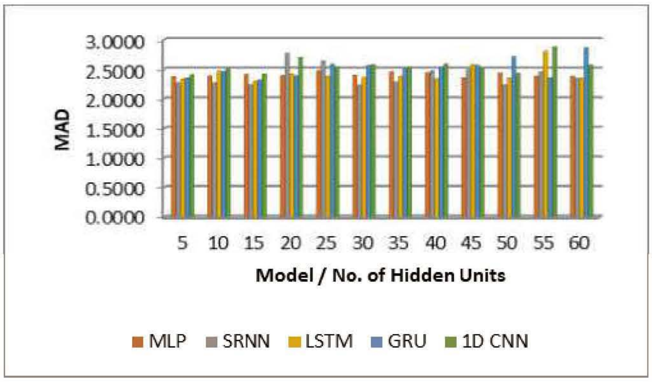

Fig. 7. Forecast Errors (MAD) - GBP/LKR Models

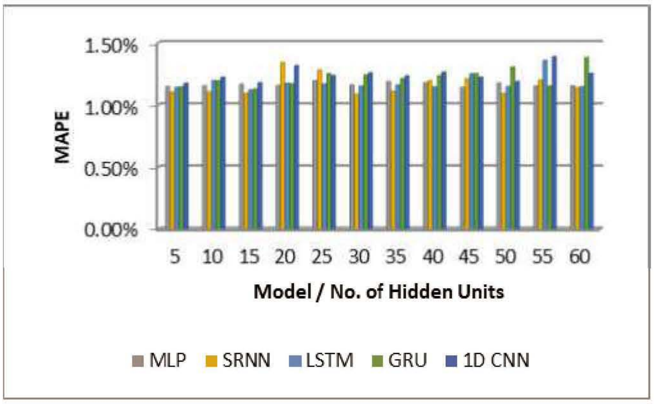

Fig. 8. Forecast Errors (MAPE) - GBP/LKR Models

Unlike in USD/LKR dataset, all GBP/LKR models produce errors with less deviations. And when considering the correlation between actual and predicted datasets all the models have strong correlations ranging from 0.97-0.98. SRNN model with 30 hidden units has the lowest error (MAD-2.2286, MAPE-1.09%) while 1D CNN model with 55 hidden units has the highest error (MAD-2.8770, MAPE-1.39%). SRNN model with 10 hidden units has the highest correlation (0.98230). Averagely, the accuracies of all the models are nearly 98%. On most occasions, SRNN models have the lowest errors and highest correlations. So, it can be stated that Stateful SRNN models more accurately predict future values of GBP/LKR exchange rate compared with other neural network architectures.

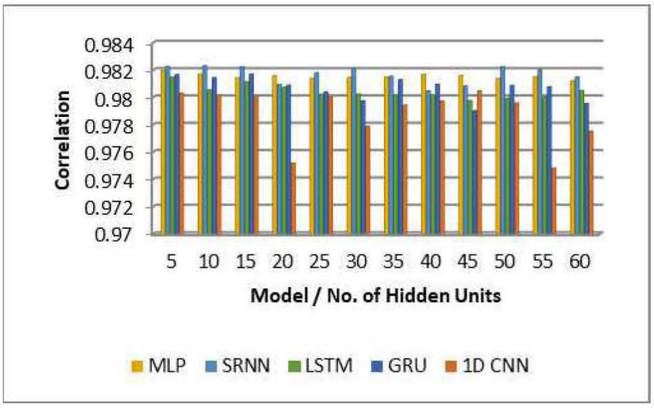

Fig. 9. Correlation (Actual Vs. Predicted) - GBP/LKR Models

C. EURO/LKR Dataset

In EURO/LKR dataset, SRNN and LSTM models produce comparatively lower errors and 1D CNN and MLP models produce comparatively higher errors. But compared to USD/LKR dataset, there were no large deviations in error terms but compared to GBP/LKR dataset there are some deviations among models. All the models have strong correlations ranging from 0.97-0.98. SRNN model with 30 hidden units has the lowest error (MAD-1.6097, MAPE-0.90%%) while MLP model with 20 hidden units has the highest error (MAD-3.9343, MAPE-2.11%). The accuracies of EURO/LKR models are ranging from 97%-99%.

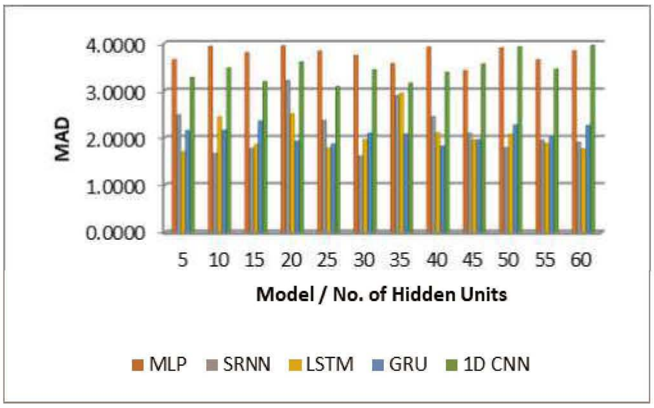

Fig. 10. Forecast Errors (MAD) - EURO/LKR Models

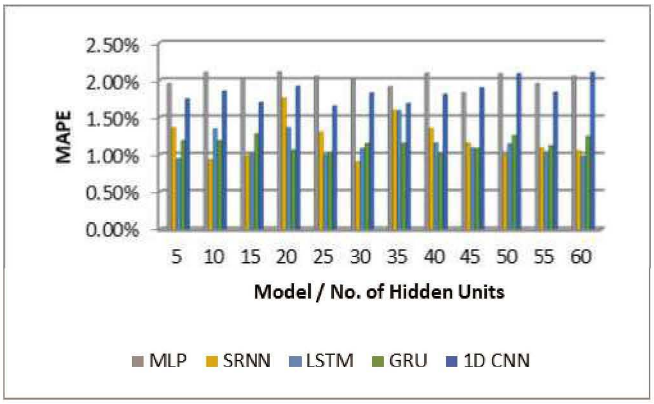

Fig. 11. Forecast Errors (MAPE) - EURO/LKR Models

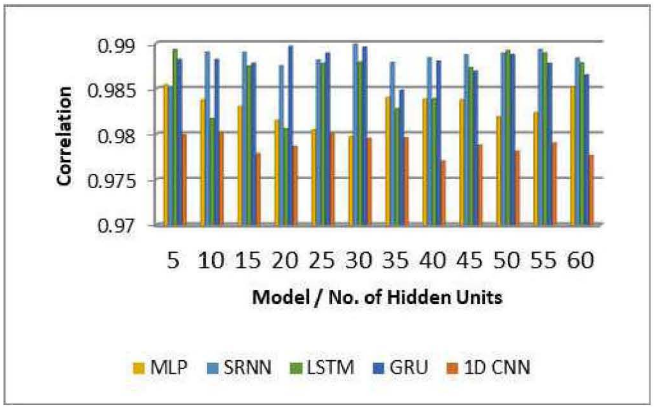

Fig. 12. Correlation (Actual Vs. Predicted) - EURO/LKR Models

D. Finding the Best Architecture

TABLE 3: AVERAGE MAPE OF EACH ARCHITECTURE

Architecture	Average MAPE		
	USD	GBP	EURO
MLP	7.210	2.404	3.757
SRNN	0.986	2.388	2.177
LSTM	2.022	2.420	2.073
GRU	68.192	2.514	2.073
CNN	5.191	2.550	3.450
Multivariate Regression	0.583	4.497	3.814

TABLE 4: PAIRED SAMPLES T-TEST

NN Architecture		Paired Samples t-test Significance p value (2 tailed test)		
		USD	GBP	Euro
Pair 1	MLP - SRNN	.000	.761	.000
Pair 2	MLP - LSTM	.000	.737	.000
Pair 3	MLP - GRU	.232	.033	.000
Pair 4	MLP - CNN	.000	.005	.003
Pair 5	SRNN - LSTM	.179	.578	.446
Pair 6	SRNN - GRU	.190	.107	.566
Pair 7	SRNN - CNN	.000	.004	.000
Pair 8	LSTM - GRU	.197	.199	.996
Pair 9	LSTM - CNN	.004	.001	.000
Pair 10	GRU - CNN	.218	.586	.000

In USD dataset multi-variate regression model has the lowest error when compared with ANN models. But in the other two (GBP & EURO) datasets ANN models perform better than multi-variate regression models (Refer Table 3). According to the results of the T-test (Table 4) in USD dataset SRNN and LSTM models are performing better than other ANN models. In GBP dataset MLP, SRNN and LSTM models perform better than other two models. In EURO dataset SRNN, LSTM and GRU models perform better than other two models.

VI. DISCUSSION, CONCLUSION AND FUTURE RESEARCH WORK

Previous studies discussed in Section II have employed several machine learning techniques including different ANN architectures to predict exchange rates in different countries. These studies have employed time series variables as well as other technical and fundamental variables for model building. In this study, only the time series variables (past data) were employed. When compared with previous studies this study has used data from a long-time period (nearly 14 years). When considering all the ANN models in three datasets, Stateful Simple Recurrent Neural Networks (SRNN) (with one input layer, a hidden layer, a flatten layer and an output layer) are performing better than other ANN architectures in predicting USD/LKR, GBP/LKR, and EURO/LKR exchange rates. Most of the models except few GRU models in USD/LKR dataset were able to predict 10-days ahead exchange rates with 97%-99% accuracies. Except in USD/LKR dataset ANN models performed better than linear regression models. Some GRU models performed badly and regression model performed better than ANN models in USD/LKR dataset because that dataset has a linear trend with fewer fluctuations. Future studies can focus on minimizing these shortcomings. In addition, other technical and fundamental analysis variables affecting exchange rates can be incorporated for model building. Also, models can be built by combining different exchange rates.

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