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Prediction of Exchange Rates using Neural Networks and Performance by Friedman's Test

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Abstract:
Forecasting of exchange rates plays a pivotal role in global trade, stocks and making the policies of exports and imports. USD exchange rates used widely for many business areas. In this paper an attempt is made to predict INR/USD exchange rates using Feed forward Neural Networks and Box-Jenkins methodology. The forecasting performance of the developed models were tested using error measures like MAE, MAPE and RMSE. The results shows FFNN model has better model than ARIMA model. The predicted exchange rates would vary between 83.06 and 83.28 for the out sample and this variation is exchange rates would help the business people and also for framing the government policies in the future.

Keywords: Exchange Rates, Box Jenkins methodology, FFNN, MAE, MAPE and RMSE

1. Introduction

The value of one currency for the purpose of conversion to another is called exchange rate. In finance, and exchange rate is the rate at which one currency will be exchanged for another. Reserve Bank of India buys foreign exchange when the exchange rate is low and sells the same when it is sufficiently high.

The exchange rate is a key financial variable affects decisions made by foreign exchange investor, exporters, importers, banks, business, financial institutions, policy makers and tourists in the developed as well as developing world. Foreign exchange rates are affected by many highly correlated economic, political and even psychological factors. The interaction of these factors is in a very complex fashion. Therefore to forecast the changes of foreign exchange rates is generally very difficult. Researchers and practioners have been striving for an explanation of movement of exchange rates. Thus various kinds of forecasting methods have been developed by many researchers and experts. Currency forecasts are useful in the international aspects of project evaluation, strategic planning, pricing, working capital management and the analysis of portfolio investments.

Most conventional econometric models are not able to forecast exchange rates with significantly higher accuracy. In recent years, there has been a growing interest to opt the state–of–the–art artificial intelligence technology to solve the problem. One stream of these advanced techniques focuses on the use of artificial neural networks (ANN) to analyse the future movements in the Foreign exchange Market. Neural networks applications in time series forecasting is discussed by Krishna Reddy and Kalyani 2005[4] and Zhang et-al1998 [13]. Modelling exchange rates using Box-Jenkins methodology, Neural networks and its applications presented by Huang and Lai 2004[2] Kuan and Liu, 1995[5], Kamruzzaman,2004[3].

2. Review of Forcasting Methods

2.1 Box-Jenkins Methodology

In this section, the modelling of exchange rates INR-USD in India per 10gm using Box-Jenkins methodology is discussed. The Box-Jenkins procedure is concerned with the fitting of an ARIMA model of the following form for the a given set of data $\{Z_t : t=1, 2, \ldots\ldots n\}$ and the general form of ARIMA (p, d, q) model is given by

$$\emptyset(B)\nabla^{d}Z_{t} = \theta(B)a_{t}$$

Where $\emptyset(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - - - - - - \emptyset_p B^p$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - - - - \theta_q B^q$$

and $\nabla^{d} = (1 - B)^{d}$

where $B^K Z_t = Z_{t-k}$ *and* a_t is a white noise process with zero mean and variance σ_a^2. The Box-Jenkins procedure consists of the following four stages. (i) Model Identification, where the orders d, p, q are determined by observing the behavior of the corresponding autocorrelation function (ACF) and partial autocorrelation function (PACF). (ii) Estimation, where the parameters of the model are estimated by the maximum likelihood method. (iii) Diagnostic checking by the "Portmanteau Test", where the adequacy of the fitted model is checked by the LJung-Box statistic, applied to the residual of the model. (iv) Forecast is obtained from an adequate model using minimum mean squared error method. If the model is judged to be inadequate, stages (i) to (iii) are repeated with different values of d, p, and q until an adequate model is obtained L Jung G.M. et al., 1979 [9].

2.2 NEURAL NETWORKS MODEL

An artificial neural networks (ANN) is a mathematical model which is inspired by the structure and functional aspects of biological neural networks is a powerful forecasting model. It consists of an interconnected group of artificial neurons, and it processes information using a approximate approach to computation. In this paper we develop a feed forward neural networks (FFNN) model for fore casting exchange rates. Feed forward neural network (FFNN) structure is a three layer network and it consists of an input layer, a hidden layer and an output layer. Total number of input neurons needed in this model is one, and it representing the values of lag1 (previous day exchange rate). In this model only one output unit is needed and it indicates the forecasts of exchange rate for INR-USD. The following table displays information about the neural networks model, including the dependent variable, number of input and output units, rescaling method, number of hidden layers and units and activation functions.

Network Information

Input Layer	Covariates	1	Lag1
	Number of units [a]		1
	Rescaling method of covariates		standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of units in Hidden Layer 1[a]		3
	Activation Function		Hyperbolic Tangent
Output Layer	Dependent Variables	1	INR-USD
	Number of Units		1
	Rescaling method for scale Dependents.		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares
a. Excluding the bias unit.			

Back propagation Theorem is used in learning of the network. The network is trained using back propagation algorithm until the sum of squares of error is small for the training set. Haykin, 1999, Rama Krishna et al., 2013, [1,11].

2.3 Testing Equality Of Forecasting Performance Of The Models

To compare the multiple forecasting models with respect to absolute errors Friedman's test is used. Under the null hypothesis that all models are equivalent in performance the Friedman's test statistics is given by

$$\chi_F^2 = \frac{12}{nk(k+1)} \sum_{j=1}^{k} R_j^2 - 3n\,(k+1)$$

is approximately distributed as χ^2 with k-1 degrees of freedom and where k=1 number of models, n = number observations in each model.

The data are daily FEDAI indicative from 1st January,2019 to 23rd October, 2023 from http://dbie.rbi.org.in and the same is divided into training sample (till 29th September, 2023) and out-of-sample (from 3rd April, 2023 to 23rd October, 2023). The ARIMA and FFNN models fitted to the training sample and validated on the out of sample. The actual time series data was plotted in Figure-1 and it shows more fluctuations in the INR-USD exchange rates over a period of time.

3. BUILDING ARIMA MODEL

The development of ARIMA model for any variable involves Identification, Estimation, Diagnostics Checking and Forecasting.

The time plot of daily exchange rates from 1st January, 2019 to 23rd October 2023 is given in figure-1.

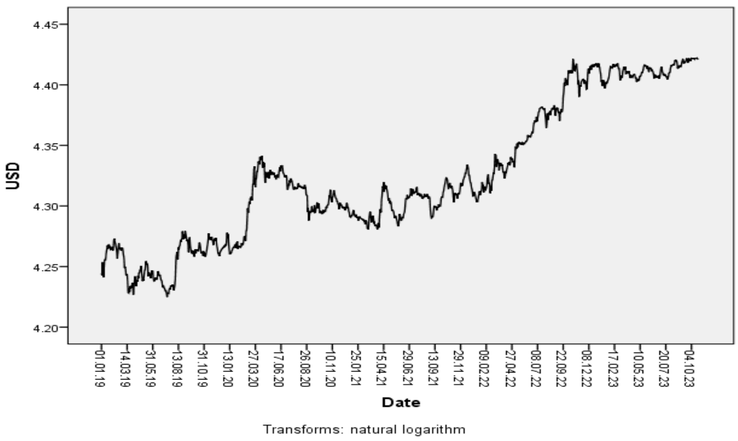
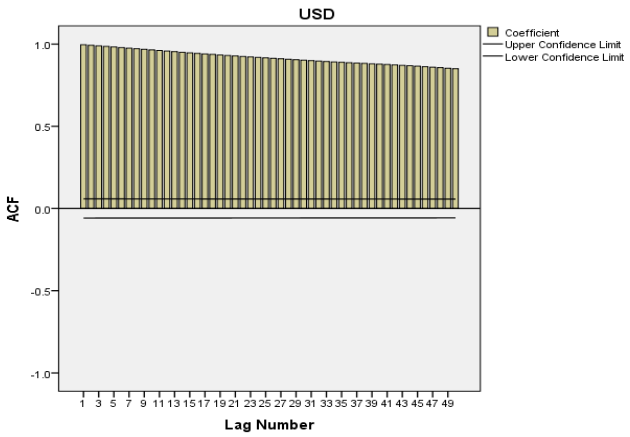


Figure-1: Time Plot of Daily Exchange Rates.

The sample autocorrelation function is computed to check whether the series is stationary or non-stationary. The sample ACF for 50 lags is given in figure-2.



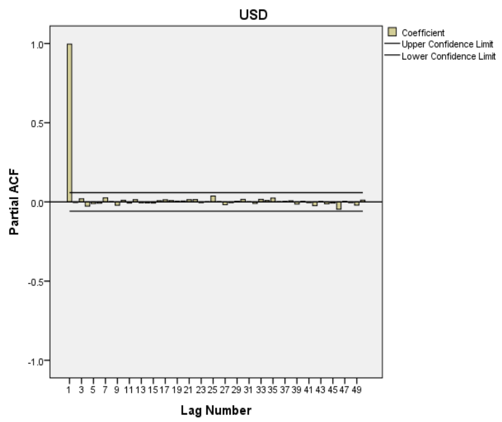


Figure-2 : Auto Correlation Function   Figure-3 : Partial Auto Correlation Function

From the figure-2 & 3, it is observed that the time plot as a downward trend and ACF dies out slowly for higher lags, this indicates the time series is not stationary. ARIMA model is estimated only after transforming the variable under forecasting into a stationary series. Non stationarity in variance is corrected through natural log transformation and non-stationarity in mean is corrected through appropriate differencing of the data. The time plot of transformed series is given in figure-4.

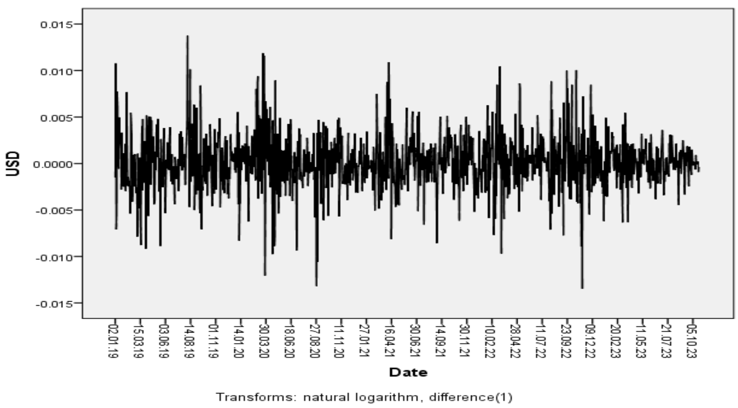


Figure-4 : Time plot of Transformed Series

In this case is observed that difference of order 1 (d=1) is sufficient to achieve stationary in mean the newly constructed variable $W_t = \nabla^1 \ln(Z_t)$ can now be examined for stationarity and it is observed that W_t is stationary in Mean and variance.

The next step is to identifying the values of $p\ and\ q$ for autocorrelations and partial auto correlations of various orders W_t are computed.

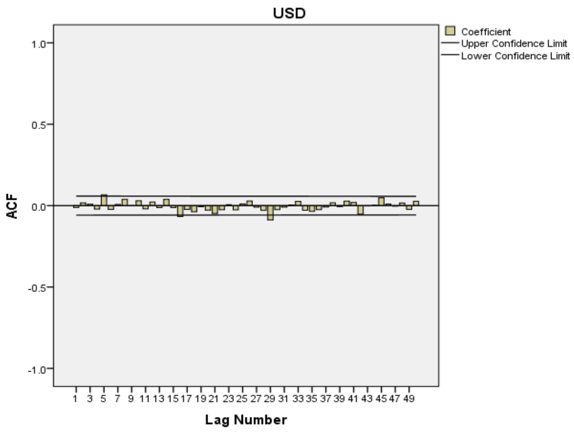


Figure-5 : ACF for transformed series.

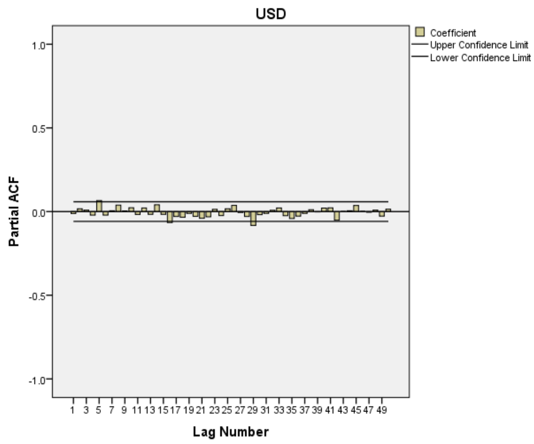


Figure-6: PACF for transformed series

From the above ACF and PACF and the SPSS skilled creator was accustomed to determine the most effective ARIMA model for the prediction of USD exchange rates, as this plan to estimate the best – filtering ARIMA for one or additional variable series, therefore eliminating the necessity to spot an applicable model through trial and error methodology. It is discovered that, ARIMA (1, 1, 1) model fits the data well and therefore the same is tested on the validation set.

Table 1 : ARIMA Model (1, 1, 1) Parameter Estimates

					Estimate	SE	t
USD-Model_1	USD	No Transformation	AR	Lag 1	-0.993	0.018	-55.842
			Difference		1		
			MA	Lag 1	-0.990	0.022	-44.335

From the above table ARIMA (1, 1, 1) significant with respective parameters as well as adequacy of the model. Hence the fitted model for the forecasting of USD exchange rate is

$$(1 + 0.993\mathrm{B})\nabla^1 I_n(Z_t) = (1 + 0.990B)a_t$$

Diagnostic checking is done through examining autocorrelations and partial autocorrelations of the residual of various orders.

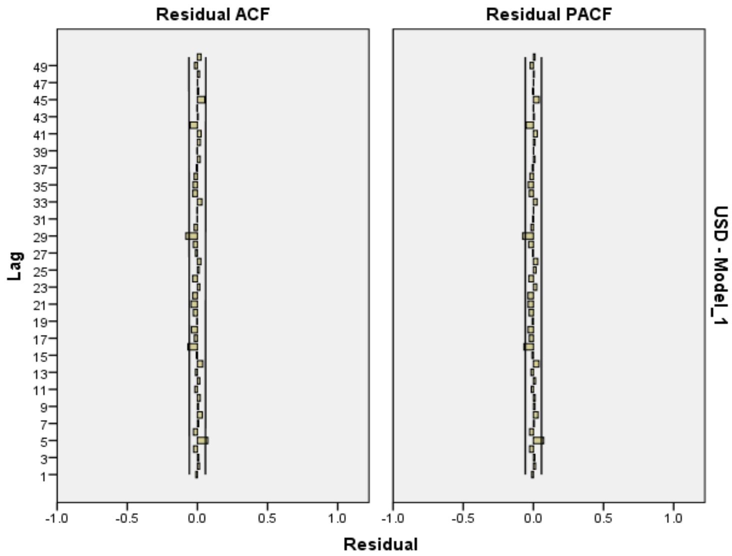


Figure 7: Residual ACF and PACF

As the result indicates none of these auto correlations of residuals is significantly different from 0 at the level 0.05. The adequacy of the model is tested using L Jung-Box statistic.

L Jung-Box statistic is 21.846 for 16 d. f. and the significant probability corresponding to

L Jung-Box Q statistic is 0.147 which is greater than 0.05.Therefore null hypothesis of model adequacy and we conclude that (1, 1, 1) model is an adequate model for a given time series. Future exchange rates or forecasted using minimum square error method and the forecast for the period 3rd October 2023 to 23rd October 2023 are following table.

Table1 2: Forecasts of Exchange Rates using ARIMA (1, 1, 1)

Date	USD original values	USD Predicted Values
03.10.23	83.18	83.05
04.10.23	83.26	83.19
05.10.23	83.24	83.25
06.10.23	83.24	83.25
09.10.23	83.25	83.23
10.10.23	83.26	83.26
11.10.23	83.24	83.25
12.10.23	83.18	83.25
13.10.23	83.26	83.18
16.10.23	83.26	83.27
17.10.23	83.26	83.26
18.10.23	83.26	83.26
19.10.23	83.27	83.25
20.10.23	83.2	83.28
23.10.23	83.17	83.19

The Graphical representation of out of sample forecasts are given in the following table

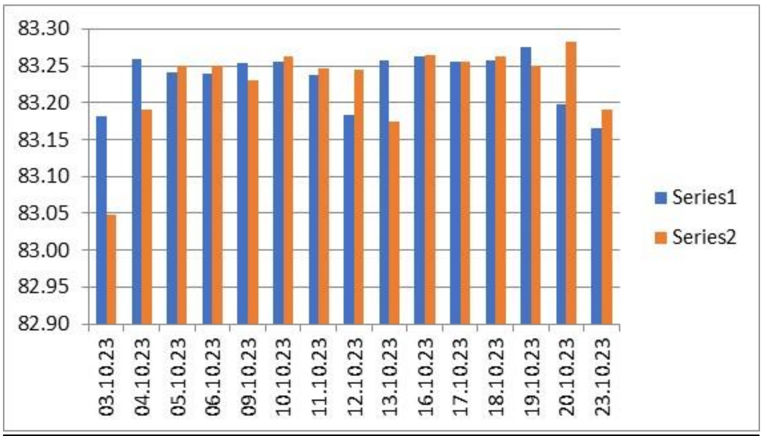


Figure 8: Out of sample forecasts using ARIMA

Table 3 : ARIMA (1, 1, 1) Model Performance

	MAE	MAPE	MSE	RMSE
In sample	0.105	0.138046	0.01105	0.105119
Out sample	0.075	0.090167	0.00865	0.093005

From the above table it is observed that ARIMA model as lowest errors measures in fitting stage and out of sample MAPE is less than 5. Therefore the model is an appropriate model for forecasting the exchange rates. Like any other measure this ARIMA technique also doesn't guaranty perfect forecast. Nevertheless, it can be successfully used for forecasting long time series data and it should be updated from time with incorporation of current data.

4. BUILDING OF FEED FORWARD NEURAL NETWORKS (FFNN)

The Feed Forward Neural Networks model for forecasting of daily exchange rates is developed using SPSS packages. The FFNN model having one input layer, hidden layers and an output layer. The hyperbolic tangent function is takes as an activation function under the back propagation algorithm. The FFNN model was trained till the testing sample error is smaller than the training sample.

Table 4 : Descriptive statistics

	N	Minimum	Maximum	Mean	Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Statistic
USD	1164	68.3665	83.2746	75.646088	4.3568512
lag1	1163	68.37	83.27	75.6396	4.35313
Valid N (list wise)	1163				

By applying trial and error method, the optimum number of hidden neurons is four and in the hidden layer and the optimum network is 1-4-1 since this network has minimum MAE, MAPE and RMSE. The following figure of feed ward neural network gives clear idea about selected model for the given data.

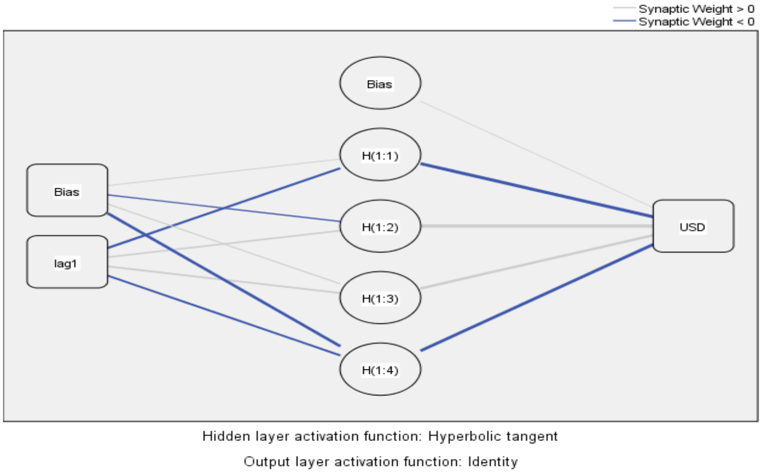


Figure 9: FFNN model for prediction of INR-USD exchange rates.

The FFNN Model 1-4-1 parameters are obtained and given in the following table

Table 5 : FFNN 1-4-1 Model Parameter Estimates

Parameter Estimates						
		Predicted				
		Hidden Layer 1				Output Layer
Predictor		H(1:1)	H(1:2)	H(1:3)	H(1:4)	USD
Input Layer	(Bias)	0.161	-0.204	0.184	-0.398	
	lag1	-0.317	0.262	0.285	-0.317	
Hidden Layer 1	(Bias)					0.104
	H(1:1)					-1.161
	H(1:2)					1.434
	H(1:3)					0.380
	H(1:4)					-0.791

The hidden activation functions are as follows :

H_{11} = Tanh[0.161-0.317(Z_{t-1} –75.6396)/ 4.3531)]

H_{12} = Tanh[(-0.204-0.262(Z_{t-1} –75.6396)/ 4.3531)]

H_{13} = Tanh[(0.184-0.285(Z_{t-1} –75.6396)/ 4.3531)]

H_{14} = Tanh[(-0.398 -0.317(Z_{t-1} –75.6396)/ 4.3531)]

Where Z_{t-1} is the rescaled input variable and the forecasting model is

$$\hat{Z}_t = \mu_z + \sigma_z\,(0.104 - 1.161H_{1:1} + 1.434H_{1:2} + 0.380H_{1:3} - 0.791H_{1:4})$$

The forecasting performance of FFNN model is given below

Table 6 : FFNN 1-4-1 Model Performance

	MAE	MAPE	MSE	RMSE
In sample	0.117651	0.150968	0.01525	0.12349
Out sample	0.171566	0.206274	0.029436	0.171569

From the above table it is observed that the FFNN model has lowest error measures in fitting stage and forecasting stage. Since MAPE is less than 5 therefore the FFNN model is an appropriate model for forecasting the exchange rates.

Table 7 : Out sample forecasts using FFNN 1-4-1

Date	USD	Predicted Values
03-Oct-23	83.1812	83.00856
04-Oct-23	83.2588	83.07481
05-Oct-23	83.2413	83.05989
06-Oct-23	83.2388	83.05776
09-Oct-23	83.2542	83.07089
10-Oct-23	83.2556	83.07208
11-Oct-23	83.2368	83.05605
12-Oct-23	83.1834	83.01044
13-Oct-23	83.2574	83.07362
16-Oct-23	83.2632	83.07856
17-Oct-23	83.2555	83.072
18-Oct-23	83.2571	83.07336
19-Oct-23	83.2746	83.08826
20-Oct-23	83.1982	83.0231
23-Oct-23	83.1663	82.99581

The graphical representation of out sample forecasts is given below. This presents the forecasts generated from FFNN model is close to original series and it indicates a good performance of FFNN model.

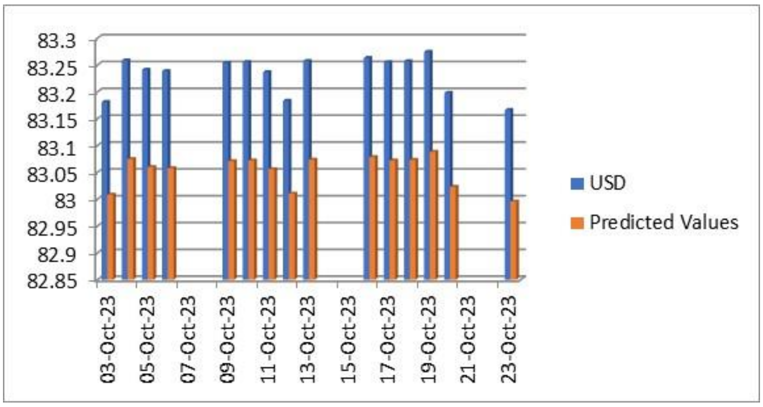


Figure 10: Forecasts of USD-INR exchange rates using FFNN model

5. COMPARISION AND CONCLUSIONS

The performance of ARIMA, FFNN models and its graphical representation is given below:

Table 8 : Performance of the ARIMA and FFNN models

Model	In sample			Out sample		
	MAE	MAPE	RMSE	MAE	MAPE	RMSE
ARIMA	0.105	0.138046	0.105119	0.075	0.090167	0.093005
FFNN	0.117651	0.150968	0.12349	0.171566	0.206274	0.171569

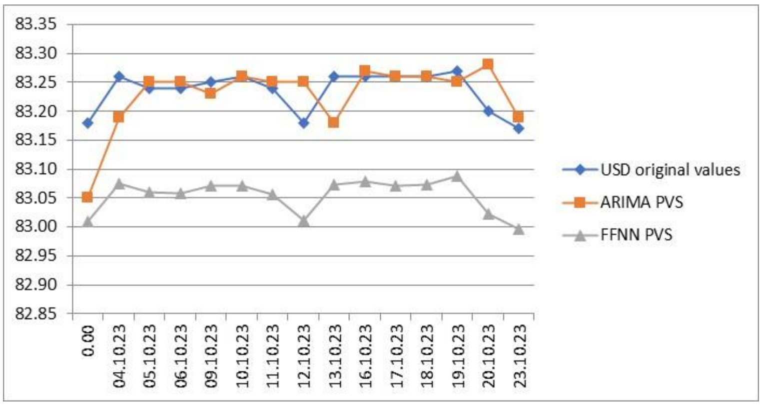


Figure 11: Out of sample forecasts of ARIMA and FFNN models

From the above table, it is observed that ARIMA and FFNN models has moderately minimum error measures in-sample and out-of-sample. One can use either ARIMA or FFNN model to forecasts of daily exchange rates for USD. But by adopting FFNN model can study the complexity and non linearity of the data. Hence it was concluded that FFNN and ARIMA models are equally performed for the daily exchange rates of USD

Table 9 : Friedman's Test for out of sample forecasts

sample	model	Mean ranks	n	Chi-square	p-value
Out-of-sample	ARIMA	1.03	15	14.00	< 0.001
	FFNN	1.97			

It is noticed that the significant possibility is less than 0.05, therefore the invalid speculation is dismissed and presume that there is a critical difference in the performance of the models. But based on the mean ranks of the models ARIMA gets first rank and FFNN gets the second rank. Therefore ARIMA model moderately performs better than FFNN model.

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