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Forecasting INR/USD Exchange Rates using Hybrid and Neural Network Model

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Abstract:
Prediction of exchange rates plays a vital role in international trade, stocks and framing 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 Hybrid model that joins the forecasts of ARIMA as well as FFNN. The forecasting accuracy of developed models, were tested used the error measures like MAE, MAPE & RMSE. The results shows hybrid model has greater accuracy compared to ARIMA and FFNN model. The predicted exchange rates would vary between 70.80 and 71.39 for the next one month and this variation is exchange rates would help the business people and also for framing the govt policies within the upcoming future.

Keywords: *Exchange Rates, Box Jenkins methods, FFNN, Combined Forecasts, MAE, MAPE, and RMSE.*

I. INTRODUCTION

The value of one currency for the purpose of conversion to another is called exchange rate. In finance, exchange rate is the rate wherein a single currency will be replaced on behalf of other. Reserve Bank of India buys foreign exchange when the exchange rate is low and sells the same when it is sufficiently high.

A significant financial variable that impacts the decisions provided by foreign exchange investor, exporters, importers, banks, business, financial institutions, policy makers and tourists in the developed as well as developing world is referred as the exchange rate.

The high interrelated economic, political as well as equal psychological parameters affects the Foreign exchange rates. Moreover, the correlation of the parameters is a quite complicated parameter. Thus, it is a complex issue in forecasting the variations in the foreign exchange rates. An effort is made by the investigators and practitioners for explaining the exchange rates movement. Therefore, various investigators as well as experts have developed several forecasting techniques. Within international aspects of working capital management the analysis of portfolio investments, project evaluation, pricing, & strategic planning, a significant role is played by the Currency forecasts. (Ref.1 and Ref.2).

Using the highly accurate ones, the exchange rates are not forecasted by the various conventional econometric models. The selection of state–of–the–art artificial intelligence technology for solving the issue is done recently. The ANN (Artificial Neural Networks) applications focused by one of the advanced methods for analysing the upcoming movements within the Foreign exchange Market. Neural networks applications in the time series forecasting the discussed by Krishna Reddy and Kalyani 2005 (Ref.3) and Zhang et-al 1998 (Ref.5). Modelling exchange rates using Box-Jenkins methodology, Neural networks and its applications presented by Huang and Lai 2004 (Ref.7), Kuan and Liu, 1995 (Ref.8), Kamruzzaman, 2004 (Ref.9), Naveen Kumar, 2008 (Ref.4).

II. REVIEW OF FORCASTING METHODS BOX –JENKINS METHODOLOGY

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

$$\emptyset(B)\nabla^d Z_t = \theta(B)a_t \qquad (1)$$

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 in white noise process with the zero mean & variance σ_a^2. Box-Jenkins procedure consists of following four stages. (i) The performance of the equivalent Autocorrelation Function (ACF) as well as Partial Autocorrelation Function (PACF) determines the orders d, p, q of the model identification.
(ii) Estimation, where the parameters of model are estimated with help of maximum likelihood method.
(iii) Diagnostic checking by the "Portmanteau Test", where, the LJung-Box statistic, applied to residual of model verifies adequacy of the fitted model. (iv) Forecast is obtained from an adequate model using the minimum mean square error method. The model is judged to be inadequate, stages i-iii are frequently with the different values of d, p, and q till an adequate model is then obtained (Box et al., 1994)[Ref.1], (L Jung G.M. et al., 1979) [Ref.7].

A. *NEURAL NETWORKS MODEL*

A mathematical pattern which is based on the structural as well as efficient features of biological neural networks is a powerful forecasting pattern is referred as an artificial neural networks (ANN). A correlated group of artificial neurons is involved in it, and it processes information using an approximate approach to computation. A feed forward neural networks (FFNN) model on behalf of forecasting exchange rates is developed in this unit. A 3 layer network that includes an input layer, a hidden layer in addition to an output layer is referred as Feed Forward neural network (FFNN). Total number of input neurons needed in this model is one, and it representing values of lag1 (previous day exchange rate). In this model only a single output unit is required and the forecasts of exchange rate for INR-USD are indicated by it. The table 1 displays the information about neural networks model, including dependent variable, rescaling method, No. of hidden layers & units & activation functions, No. of input & output units.

TABLE 1
Network Information

Input Layer	Covariates	Lag1
	Number of units [a]	1
	Rescaling method of covariates	Adjusted normalized
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	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. Network is trained by using back the propagation algorithm until the sum of squares of error is small for the training set; Haykin, 1999, Rama Krishna et al., 2013, [Ref 14 and 15].

III. THE HYBRID METHODOLOGY

Appendixes, both the ARIMA &the ANN models have been achieved the success in their own linear or nonlinear domains. However, none of these is a

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universal model that is suitable to any circumstances. The complicated nonlinear problems might not be suitable for the ARIMA model's approximation. However, mixed results were obtained by applying the ANNs for the issues of model linear. For example, using simulated data showed that when there are outliers or multicollinearity in data, neural networks can significantly outperform linear regression models. Kamruzzaman, J., & Sarkar R.A., 2004 (Ref.9) also found that performance of ANNs for linear regression issues relays upon noise level as well as sample size. Therefore, it is unfair for applying the ANNs for certain data types without a consideration. Finding the features of the information within the real time is quite complex and the hybrid method including linear as well as nonlinear modelling methods can be used practically. The capturing of the various features of the fundamental models can be performed with the combination of various patterns.

Considering a time series for composing a linear autocorrelation structure as well as the nonlinear component is quite realistic. That is,

$$Z_t = L_t + N_t \qquad (2)$$

Where, the linear component is denoted by L_t and nonlinear component is represented by N_t. The estimation of the above components is performed by the given information. Initially, the linear component is allowed to be modelled by the ARIMA and later the remaining ones out of the linear model would include the relationships of the nonlinear ones. Assume that residual at time t out of the linear model is denoted by e_t, then

$$e_t = Z_t - \hat{L}_t \qquad (3)$$

Where, forecast value for time t out of predicted relationship is represented by $\hat{L}_t$ (i). For diagnosing the linear model's adequacy, a significant role is played by the residuals. In case of the existence of linear correlation structures within the residuals, a linear model is insufficient. On the other hand, detecting some of the nonlinear patterns within the information cannot be performed by analysing the residuals. Actually, the communal diagnostic statistics on behalf of the relationships of the nonlinear autocorrelation are not available at present. Thus the pattern might moreover inadequate within the appropriately modelled that nonlinear relationships, although the verification of the model is qualified. The ARIMA constraints are indicated by certain essential nonlinear patterns within the residuals. The detection of the nonlinear relationships is done by the residual modelling with the help of ANNs. The model of ANN using n input nodes is presented as

$$e_t = f\left(e_{t-1,}e_{t-2}, \dots \dots . . e_{t-n}\right) + \epsilon_t \qquad (4)$$

Where, a nonlinear function which is defined using the neural network is represented as f and the random error is denoted as ϵ_t.Error term is not needed randomly whenever the model f is not considered as a suitable model. Thus, identifying the appropriate model is quite complex. The forecast from (ii) is denoted as $\widehat{N}_t$, the combined forecast is presented as

$$\hat{Z}_t = \hat{L}_t + \widehat{N}_t \qquad (5)$$

Two stages are involved within the presented approach of the hybrid system. The linear part of the issue is analysed by using the ARIMA model in the initial stage. Later, the residuals out of the ARIMA model is modelled by a neutral network. The details regarding the nonlinearity are involved within linear model residuals as the nonlinear structure cannot be captured by the developed ARIMA model.

The estimations of error terms on behalf of ARIMA model are utilized by outcomes of neutral network. Therefore, with the help of various model, using the model linear and nonlinear patterns are beneficial and the complete forecasting as well as modelling is enhanced by combining the forecasts.

The subjective judgement of model order along with adequacy are frequently required in constructing the ARIMA and ANN models as said earlier. There is a possibility that the hybrid method could be utilized by the suboptimal models. For instance, the low order autocorrelation is focused by the present Box-Jenkins methodology practice. Whenever the low ordered correlations are insignificant, a model is assumed as adequate

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although the essential higher order correlations are existing. The hybrid model's efficiency is affected by the presented sub optimality. The component model out to be suboptimal for producing greater forecasts as stated by Granger and Anderson, 1978 (Ref.16).

Generally, combining the respective forecasts which are on the basis of various data sets is quire efficient (Ref. 15).

Data source:-

The data are daily FEDAI indicative from 1st January, 2014 to 29th November, 2019 from http://dbie.rbi.org.in and the same is divided into training sample (till 31st October, 2019) and out-of-sample (from 1st November, 2019 to 30th November, 2019). The ARIMA and ANN models fitted to training sample and validated on out of the 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.

IV. Building ARIMA Model

ARIMA Identification, Estimation, Diagnostics Checking and Forecasting are the steps that are involved for developing ARIMA model of any variable.

The major steps of the Box-Jenkins method is described as follows.The daily exchange rate's time plot is from 01-Jan-2014 to 30-Nov-2019 is given in figure-1.

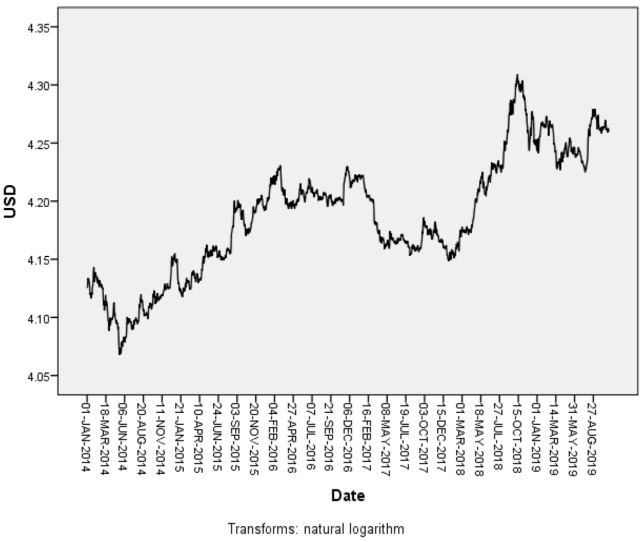

Figure-1: Time Plot of Daily Exchange Rates.

Autocorrelation function model is computed to check whether series is stationary or non-stationary. Sample ACF for 30 lags is given in figure-2.

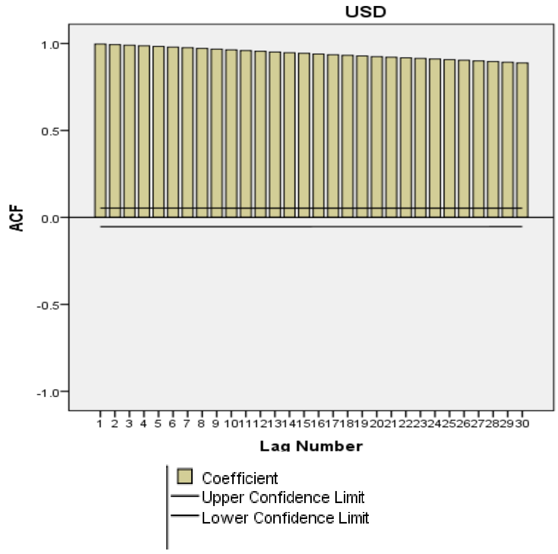

Figure-2: Auto Correlation Function

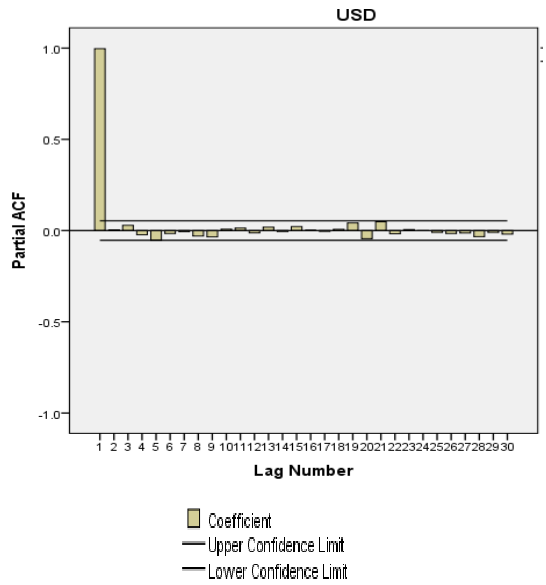

Figure-3: Partial Auto Correlation Function

From figure-2 & 3, the ACF expires gradually on behalf of the high lags and the time plot is detected as a decreasing path as observed and the time series is indicated as alterable. Later to the transformation of the variable within a stationary series under forecasting, the estimation of the ARIMA model is done. With the help of the log transformation that is occurred natural, the correction of the Non

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stationarity is done in variance and the suitable differentiation of the information is used for correcting the non-stationarity. Figure-4 gives the time plot of transformed series.

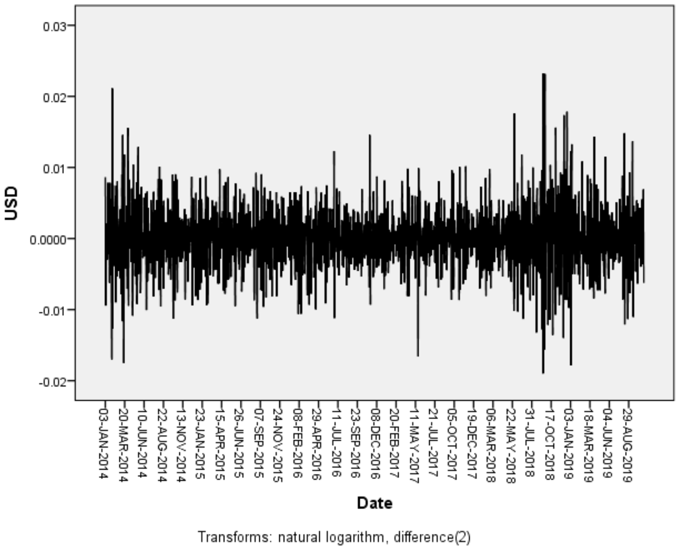

Figure-4 : Time plot of Transformed Series

In this case is observed that difference of order 2 (d=2) is adequate for attaining stationary in mean the recently built variable $W_t = \nabla^2 \ln(Z_t)$ can now be verified for stationarity and it is detected that W_t is stationary in Mean as well as variance.

Identification of the p and q values for the autocorrelation is the succeeding step and computing the partial auto correlations of various orders W_t is performed later.

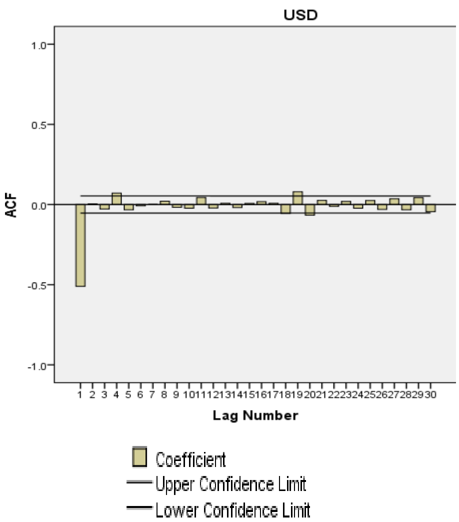

Figure-5: ACF for transformed series.

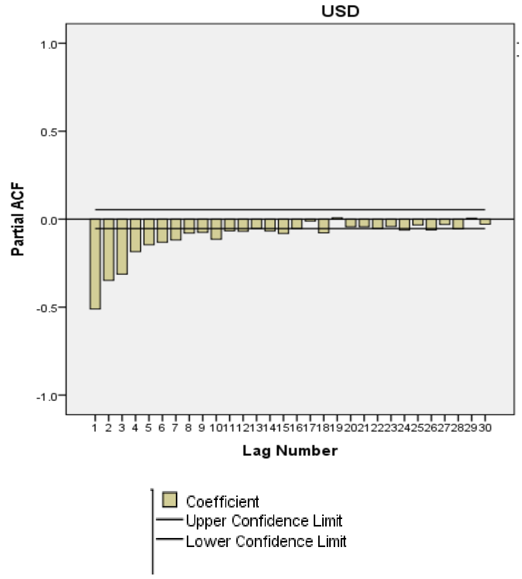

Figure-6: PACF for transformed series.

The order of p is at most 3 and order of q at most 3 is observed as presented in ACF and PACF above. The SPSS skilled creator was accustomed to determine the most effective ARIMA model for prediction of USD exchange rates, as this plan to automatically determine and 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, 2, 1) model fits data well and therefore the same is tested on the validation set.

TABLE 2

ARIMA (1, 2, 1) Model Parameters

					Estimate	SE	t	Sig.
USD-Model_1	USD	Natural Logarithm	Constant		-5.54E-08	2.63 E-07	-0.21	0.83
			AR	Lag 1	-0.022	0.027	-0.813	0.42
			Difference		2			
			MA	Lag 1	0.999	0.005	204.91	0

From the above table ARIMA (1, 2, 1) significant using respective features in addition to sufficiency of the model. Hence, the fitted model for the forecasting of USD exchange rate is one

$$(1 + 0.022B)\nabla^2 I_n(Z_t) = (1 - 0.99B)a_t$$

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With the examination of the autocorrelations & partial autocorrelations of residual of various orders, the verify diagnostic is performed.

The adequacy of the model is tested using L-Jung-Box Q-Test statistic, L-Jung box value is 17.843 for 16d.f. and the significant probability value corresponding to L-Jung Box Q-Statistic is 0.333 which is greater than 0.05. Therefore selected ARIMA (1, 2, and 1) model represents a sufficient model for the given series.

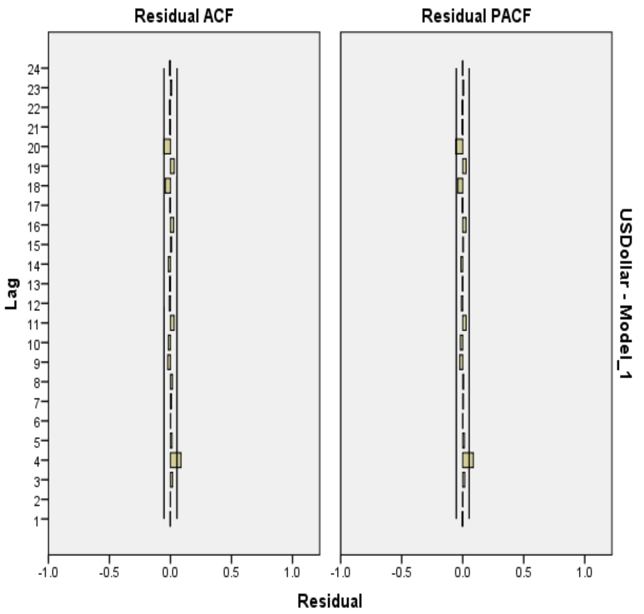

Figure 7: Residual ACF and PACF

As the result indicates no auto correlation of residuals are essentially altered from 0 by 0.05 level. Adequacy of model is tested using Ljung-Box statistic. Ljung-Box statistic is 17.843 for 16 d.f. and the significant probability corresponding to Ljung-Box *Q* statistic is 0.33 which is greater compared to 0.05. Therefore null hypothesis of model adequacy and we conclude that (1, 2, 1) model is a sufficient model for a specified time sequence. Future exchange rates or forecasted using minimum square error method and the forecast for the period 1st November 2019 to 30th November 2019 are following table.

TABLE 3
Forecasts of exchange rates using Arima(1,2,1)

Date	US Dollar	Forecasts
01.11.2019	70.88	70.82
04.11.2019	70.68	70.82
05.11.2019	70.73	70.83
06.11.2019	70.89	70.83
07.11.2019	71.01	70.84
08.11.2019	71.25	70.85
11.11.2019	71.45	70.85
13.11.2019	71.7	70.86
14.11.2019	72.05	70.86
15.11.2019	71.71	70.87
18.11.2019	71.71	70.87
19.11.2019	71.81	70.88
20.11.2019	71.68	70.88
21.11.2019	71.8	70.89
22.11.2019	71.85	70.89
25.11.2019	71.65	70.9
26.11.2019	71.59	70.9
27.11.2019	71.36	70.91
28.11.2019	71.51	70.91
29.11.2019	71.73	70.92

Graphical representation of out of sample forecasts is given below

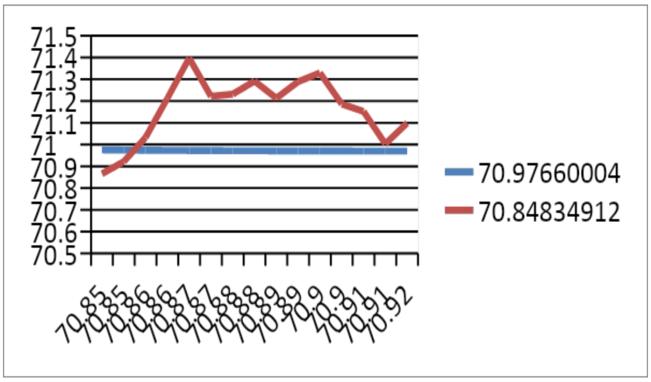

Figure8: Forecasts of INR-USD exchange Rates.

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TABLE 4 ARIMA (1, 2, 1) Model Performance.

	MAE	MSE	MAPE	RMSE
In-Sample	0.170312	0.05161	0.003607	0.227178
Out-Sample	0.606655	0.481456	0.812594	0.693871

ARIMA model as lowest errors measures in fitting stage and out of sample MAPE is less than 5 as it is detected from the table presented above. Therefore, for forecasting the exchange rates, this model is a suitable one. This ARIMA technique also doesn't guaranty faultless forecast similar to the additional methods. In order to forecast the long-time sequencing data, it can be utilized effectively and with the current data incorporation, it must be updated from time.

Feed forward Neural Networks (FFNN)

Using the SPSS packages, the develope the Feed Forward Neural Networks model is done in order to forecast daily exchange rates. The FFNN model having one input layer hidden layers & an output layer. 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.

Structure of Neural Network

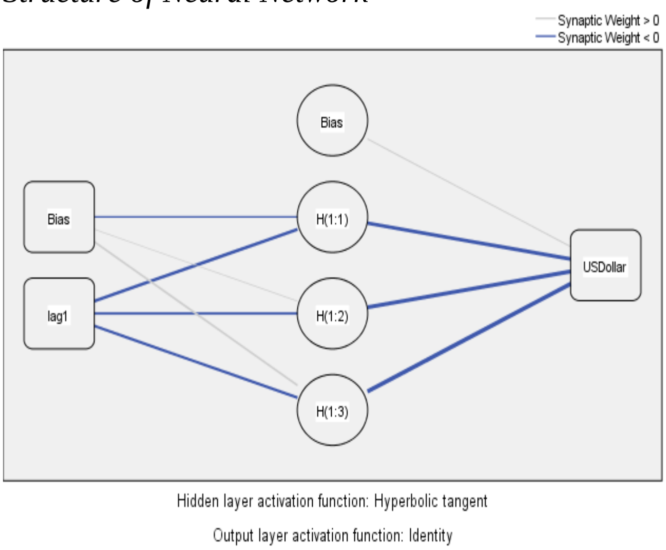

Figure 9: Feed Forward Neural Network model for prediction of INR-USD exchange rates.

Case Processing Summary

TABLE 5 Parameter Estimates

		Predicted			
		Hidden Layer 1			Output Layer
Predictor		H(1:1)	H(1:2)	H(1:3)	USDollar
Input Layer	(Bias)	-.084	.030	.086	
	lag1	-.427	-.316	-.359	
Hidden Layer 1	(Bias)				.078
	H(1:1)				-.719
	H(1:2)				-1.070
	H(1:3)				-1.249

The hidden activation function is:

$H_{11} = \tanh[(-0.084-0.427(Z_{t-1} - 65.8882)/3.39851)]$

$H_{12} = \tanh[(0.030-0.316(Z_{t-1} - 65.8882)/3.39851)]$

$H_{13} = \tanh[(0.086-0.359(Z_{t-1} - 65.8882)/3.39851)]$

The forecasting performance of FFNN model is given below.

TABLE 6
Model Performance

	MAE	MSE	MAPE	RMSE
In-Sample	0.20959	0.08	0.002627	0.279322
Out-Sample	0.55252	0.389142	0.665662	0.623813

From above table it is observed that 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 FFNN Forecasts

Date	US Dollar	Forecasts
01.11.2019	70.88	70.9838785
04.11.2019	70.68	70.9815473
05.11.2019	70.73	70.9795972
06.11.2019	70.89	70.9779655
07.11.2019	71.01	70.9766
08.11.2019	71.25	70.9754572
11.11.2019	71.45	70.9745005
13.11.2019	71.7	70.9736996
14.11.2019	72.05	70.973029
15.11.2019	71.71	70.9724676
18.11.2019	71.71	70.9719974
19.11.2019	71.81	70.9716037

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20.11.2019	71.68	70.971274
21.11.2019	71.8	70.9709979
22.11.2019	71.85	70.9707666
25.11.2019	71.65	70.9705729
26.11.2019	71.59	70.9704107
27.11.2019	71.36	70.9702749
28.11.2019	71.51	70.9701611
29.11.2019	71.73	70.9700658

Graphical Representation of FFNN Model

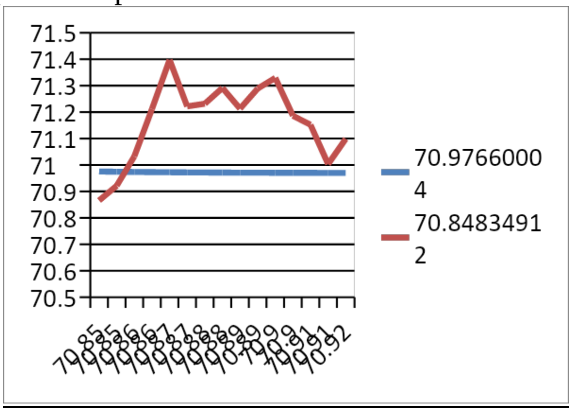

Figure 10: Forecasts of USD-INR exchange rates

Hybrid Modelling

In developing the Hybrid model, the ARIMA model can apply to linear component then residuals out of the linear model will comprise only the relationship of non-linearity. ARIMA model to linear component of model ARIMA (1, 2, 1) model is obtained then FFNN model to the error components is obtained as follows:

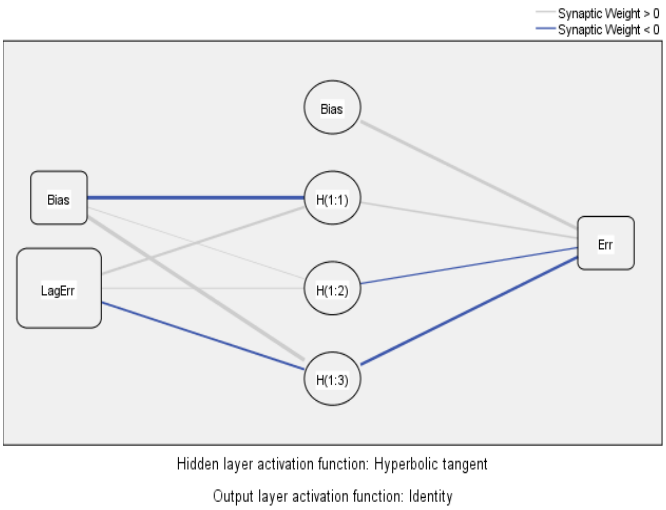

Figure 11: FFNN model for Error components

TABLE 8

Parameter Estimates					
		Predicted			
		Hidden Layer 1			Output Layer
Predictor		H(1:1)	H(1:2)	H(1:3)	Err
Input Layer	(Bias)	-1.419	0.001	1.949	
	lagErr	0.591	0.314	-0.588	
Hidden Layer 1	(Bias)				1.293
	H(1:1)				0.514
	H(1:2)				-0.327
	H(1:3)				-0.911

TABLE 9 The predicted values using Hybrid model are calculated as follows.

Date	US Dollar	Forecasts
01.11.2019	70.88	70.833434
04.11.2019	70.68	70.8283491
05.11.2019	70.73	70.8414325
06.11.2019	70.89	70.8397475
07.11.2019	71.01	70.8483491
08.11.2019	71.25	70.8657495
11.11.2019	71.45	70.9214487
13.11.2019	71.7	71.0323486
14.11.2019	72.05	71.2117018
15.11.2019	71.71	71.3974393
18.11.2019	71.71	71.2217018
19.11.2019	71.81	71.2317018
20.11.2019	71.68	71.2914059
21.11.2019	71.8	71.2130396
22.11.2019	71.85	71.2888562
25.11.2019	71.65	71.329332
26.11.2019	71.59	71.1862776
27.11.2019	71.36	71.1520594
28.11.2019	71.51	71.0030577
29.11.2019	71.73	71.0989405

Graphical representation of Hybrid model

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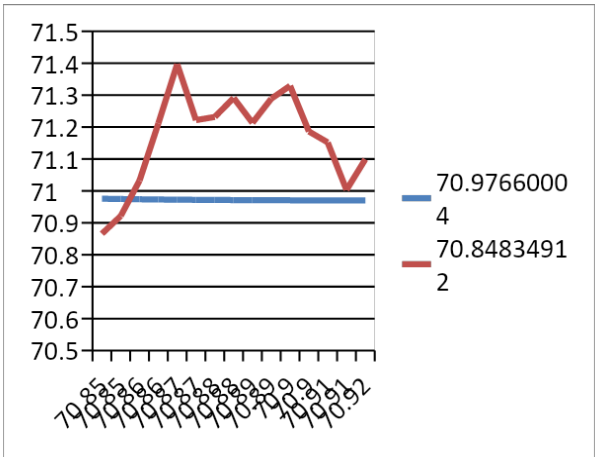

Figure 11: Forecasts of USD/INR Exchange Rates

TABLE 10

Various Calculations of errors of Hybrid Model are as follows.

	MAE	MSE	MAPE	RMSE
In-sample	0.17	0.052291991	0.257663029	0.228674421
Out-sample	0.40	0.20420424	0.552497713	0.451889632

V. Conclusion

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

Predicted values of ARIM, FFNN & Hybrid model are as follows:

TABLE 11

Performance of the models

Model	In-Sample				Out-Sample			
	MAE	MSE	MAPE	RMSE	MAE	MSE	MAPE	RMSE
ARIMA	0.1703	0.5162	0.0036	0.2272	0.6067	0.4815	0.8126	0.6939
FFNN	0.20959	0.08	0.0026	0.2793	0.5525	0.3891	0.6657	0.6238
HYBRID	0.17	0.0523	0.2577	0.2287	0.40	0.2042	0.5525	0.4579

From the above table, it is observed that Hybrid model has minimum error measures in-sample as well as out-of-sample data as compared to ARIMA and FFNN models. FFNN model has minimum error measures than that of ARIMA model and Hybrid model has minimum error measures than that of FFNN models. Hence it was concluded that Hybrid model performing well as forecasting foreign exchange rates than that of Arima and FFNN models.

TABLE 12

Forecasts using ARIMA, FFNN and HYBRID MODELS

Date	USD	ARIMA Predicted Values	FFNN Predicted Values	Hybrid Predicted Values
01.11.2019	70.88	70.82	70.98387845	70.833434
04.11.2019	70.68	70.82	70.98154727	70.8283491
05.11.2019	70.73	70.83	70.97959717	70.8414325
06.11.2019	70.89	70.83	70.97796551	70.8397475
07.11.2019	71.01	70.84	70.97660004	70.8483491
08.11.2019	71.25	70.85	70.97545718	70.8657495
11.11.2019	71.45	70.85	70.97450049	70.9214487
13.11.2019	71.7	70.86	70.97369958	71.0323486
14.11.2019	72.05	70.86	70.97302902	71.2117018
15.11.2019	71.71	70.87	70.97246756	71.3974393
18.11.2019	71.71	70.87	70.9719974	71.2217018
19.11.2019	71.81	70.88	70.97160369	71.2317018
20.11.2019	71.68	70.88	70.97127399	71.2914059
21.11.2019	71.8	70.89	70.97099786	71.2130396
22.11.2019	71.85	70.89	70.97076661	71.2888562
25.11.2019	71.65	70.9	70.97057293	71.329332
26.11.2019	71.59	70.9	70.97041072	71.1862776
27.11.2019	71.36	70.91	70.97027486	71.1520594
28.11.2019	71.51	70.91	70.97016107	71.0030577
29.11.2019	71.73	70.92	70.97006576	71.0989405

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