Forecasting USD to INR foreign exchange rate using Time Series Analysis techniques like HoltWinters Simple Exponential Smoothing, ARIMA and Neural Networks

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Abstract

Forecasting the exchange rates is both a challenging and important task for the modern traders, people working in the financial markets and general population across the globe. In this paper we will be utilizing the time series concepts to do an analysis and predict the daily exchange rates of the Indian Rupee (INR) against the United States Dollar (USD). This paper will investigate and compare different forecasting techniques like ARIMA, Holt-Winters simple exponential smoothing and Neural networks. Further, utilizing the above techniques investigate the behavior of daily exchange rates of the Indian Rupee (INR) against the United States Dollar. (Daily exchange rates from 19th November 2007 to 18th December 2017 were used for the analysis [1].

1 Introduction

Money in the form of currency, in today's world is an essential component for our lives like food, water and air is required. It is used to intermediate the exchange of goods and services and also other money transactions among people, countries etc. Before we address the issue of Foreign exchange rate, we need to discuss why money as currency was adoped as a medium of exchange by people across the world and adopting of money in the form of currency by every nation.

Why money adopted as medium of exchange: Money in fact has replaced the old barter system, where goods were exchanged according to individual needs. The barter system was very cumbersome and inefficient as it was based on "coincidence of wants", which was very problematic.

The following explanation will clarify 'why Barter system was inefficient and problematic?'For instance, a person has goats but need mangoes, he then must find someone who has mangoes and also has the desire for goat meat. What if he finds someone who has the need for goat meat but doesn't have mangoes and can only offer you cakes? Then to get your goat meat, he or she must find someone who has mangoes and wants cakes! oooff!...and so on -what a cumbersome, tiring process, just for having some mangoes!

The problem doesn't end here. Even if the person find someone with whom to exchange goat meat for mangoes, he may not find it feasible to buy a Kg of them in exchange of a whole goat. Then he is required to devise a way to divide his goat and determine how many mangoes he is willing to take for certain parts of his goat meat, a very very messy way to trade just for 1 Kg. of mangoes. Money as a commodity for exchange of goods and trade could solve all these issues and proven very convenient medium of exchange. Therefore nations adopted money in the form of currency of a nation.

Why need for exchange rates

Exchange rates for inter nation currencies are prices just like price of any other commodity. The exchange rates change based on the economics of supply and demand. The currency of nation 'A' appreciates relative to currency of nation 'B' if the citizens of nation 'B' want to buy A's currency.

Why would 'B' need to buy A's currency? The answer is to buy the goods, services, and investments produced by nation A.

Here are some examples of events that would cause currency of nation A to appreciate relative to currency of nation B.

1. Nation A producing some goods, which nation B wants, or nation 'A' producing better quality of those at a lower cost and efficiently, then nation B will need A's currency in order to buy those.

2. Nation A has desirable investments to offer, like savings accounts, financial assets, or real assets, where if money invested by B can grow faster than in own country, then nation B wants to invest in Nation A to get high returns and also save for the future.

3. Nation A is not printing more currency and restrict money supply so that money in circulation expands slower to nation B, then because of reduced availability of A's currency relative to B's, if 'B' need to buy A's currency, it has to pay more for that.

4. Nation A's currency is more acceptable for international trade and if nation 'B' wants to trade with some other nation 'C'. which refuse to accept currency of B, but accepts the currency of 'A' as a medium of exchange from B, then demand for currency fo A will increase and it will appreciate more.

Therefore, because of the existence of different currencies in use transactions between nations and between people who live in different nations need exchange rates for currencies. And the relative economic strength approach compares growth in different countries to forecast the direction of exchange rates. A strong economy like USA and high growth attracts foreign investors, which in turn the reason for increasing demand and acceptance of USD world wide currency.

The price of a currency gets stronger or weaker against another currency on a daily basis and are determined by foreign exchange markets in operation. the currency exchange rates thus affect people and the economy of a nation. All the activities like International travel, exports, imports and the economy need currency exchange, thus making forecating of exchange rate correctly an important excercise.

2 Methodology

The four most popular methods for forecasting exchange rates are discussed here before implementing the Time Series Model, which is used in this project. It is very difficult to show which model is superior.

Purchasing Power Parity (PPP)

PPP being the conventional model in use ,is the most popular method. The forecasting approach uses the popular 'one price theory law', which states that identical goods in different countries should have identical prices.

For example, according to this law the cost of a product like pencil in India should be the same as a pencil in the USA after considering the exchange rate, but excluding costs like transaction and shipping. Or to put in simple terms there should be no incentive for someone to buy pencils cheap in one country and sell them in another for a profit.

Therefore PPP approach forecasts wd include changes due to inflation to determine the exchange rate that will offset price changes due to inflation existing in the country. For example, suppose that prices in India are expected to rise by 4% over the next year as compared to USA, where the rise will be only 2%.

Means inflation differential between the two countries is: 4% - 2% = 2%

This means prices in India are expected to rise faster as compared to prices in USA Or as per the PPP approach, the Indian INR wd have to depreciate by appx. 2% as compared to USA to keep parity in prices between both India and USA.

So, assuming that the current exchange rate of 1USD = INR64 then as per the the PPP model would forecast an exchange rate of: (1 + 0.02) x (INR 64 per \$1) = INR 65.28 per USD 1.

Meaning now one USD will fetch INR 65.28 instead of INR 64 previously. Thus INR has weaken against USD. or USD is stronger as compared to INR.

Relative Economic Strength Approach

This approach forecast the exchange rates, considering the strength of economic growth in different countries. The rationale is that potentially high growth and a strong economic environment is more likely to attract foreign investors. And for that, an investor would have to purchase the currency of the country, where he/she/they interested to invest. Thus the increased demand would result in currency to appreciate.

This approach also looks at all investment flows as already discussed above.

This approach doesn't forecast the value of exchange rate, gives the investor a general sense of whether a currency will appreciate or depreciate based on the overall feel about the future strength of the economic activities and strength. This approach is thus not used as stand alone, but used in combination with other methods to develop a more complete forecast.

Econometric Models

This model analyze factors that investors believe can affect the price of currency. The factors are normally based on economic theory. Any new variable can be added or the existing one is deleted, depending upon its influence on the exchange rate.

For example, suppose a forecaster for an Indian company has been tasked with forecasting the USD/INR exchange rate over the next year. He believes an econometric model would be a good method to forecast. He considers that most influential factors are:

a) Interest rate differential(INT) between the USA and India.
b) Difference in growth rates(GDP),
c) Differences in Income growth rate(IGR).

Based on these factors the econometric model will forecast rate according to the below written equation:
USD/INR (1-year) = Current rate + a(INT) + b(GDP) + c(IGR)

The coefficients a, b and c determine how much a certain factor affects the exchange rate and whether the effect is positive or negative. Though this model is probably the most complex, but once built, could gather data easily and can generate quick forecasts.

Time Series Model

This is the model I have used for my project. This approach is purely technical in nature and is independent of the complexities of every economic theory. The rationale for this model uses the idea that past behavior and price patterns can be used to predict future exchange price behavior and patterns. The HoltWinters Simple Exponential Smoothing, Auto Regressive Moving Average (ARMA) process based (ARIMA) model and Autoregressive Neural Network is used. The data in this approach is simply a time series of univariate data that is entered into a computer program to estimate the parameters and essentially create a model for forecasting of USD/INR exchange rate.

2.1 Dataset

2.1.1 About Dataset

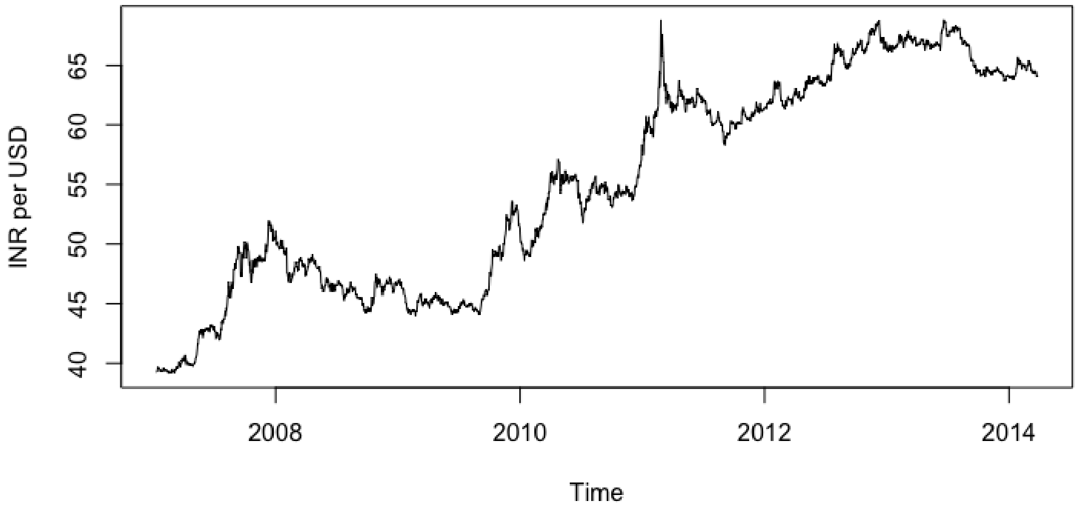

Figure 1: Time series plot of closing price of USD against INR

USD to INR exchange rate data is collected from Investing.com[1]. It is a 10 year historical data recorded daily from 11/19/2007 to 12/18/2017. Its attributes are Closing Price, Opening Price, High Price and Low Price and contains a total of 2632 records/observation.

2.1.2 Data Transformations

Initially the value type it had were double which were converted to numeric type on loading. Missing values have been checked. And there is any missing value in the data.

2.1.3 Analysis

All the analysis have been done on 'Price' Variable. Or simply the closing price. Univariate time series analysis have been carried out. Time Series plot of the closing 'Price' can be seen in Figure 1

2.2 Time Series Analysis

2.2.1 Data Analysis

Decomposition

When a time series is separated into its constituent components which it is composed of is known as decomposition of time series. A time series is composed of Trend, Random/Stochastic and Seasonal component. A time series is said to be seasonal or non-seasonal consisting of trend (upward or downward). Further classified into an additive or multiplicative. Decomposing a time series helps us understand it in a better way. Hence better model classification and forecasts. Here it is assumed to be an additive time series which is given by an equation

$$y_t = S_t + T_t + R_t \tag{1}$$

S_t is the seasonal component. T_t is the trend component and R_t is the random component. In the case of additive model, as is the case here, seasonal fluctuations or the variations around trend does not vary much with time series.

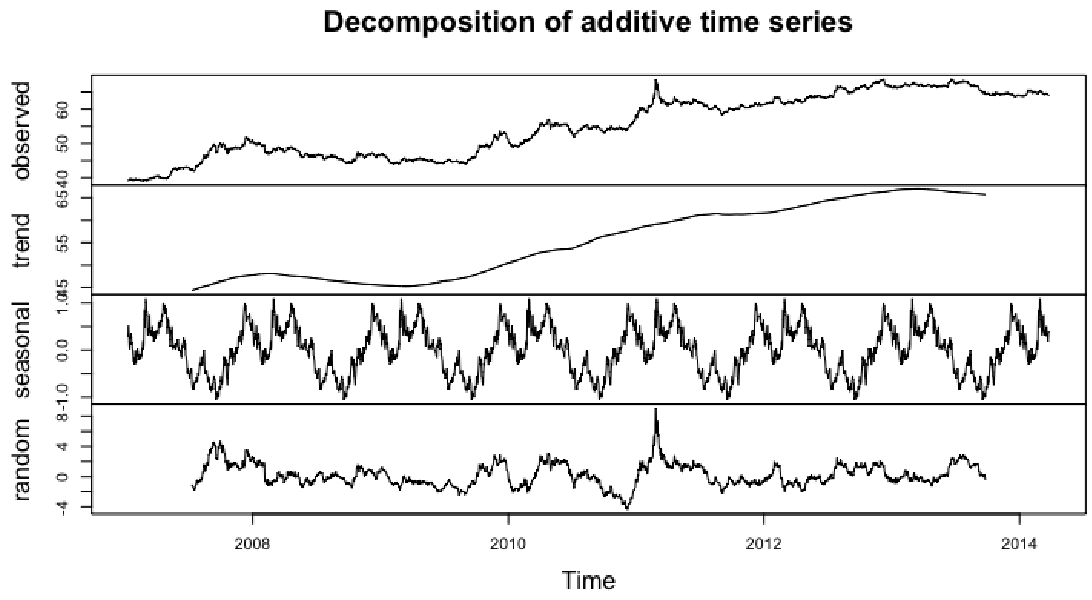

Figure 2: Additive decomposition of the time series

Seasonality Adjustment

If seasonal component is removed from the original time series data, then the resultant is called Seasonally Adjusted series. Generally seasonal adjustment is carried out when we are not interested by the affects of seasonality in the time series. Here in the case of USD to INR exchange rate forecasting, seasonality is not of primary interest. Therefore series has been adjusted for seasonality. To do seasonality adjustment in an additive time series seasonal differencing has been carried out:

$$y_{t\ adjusted} = y_t - S_t \tag{2}$$

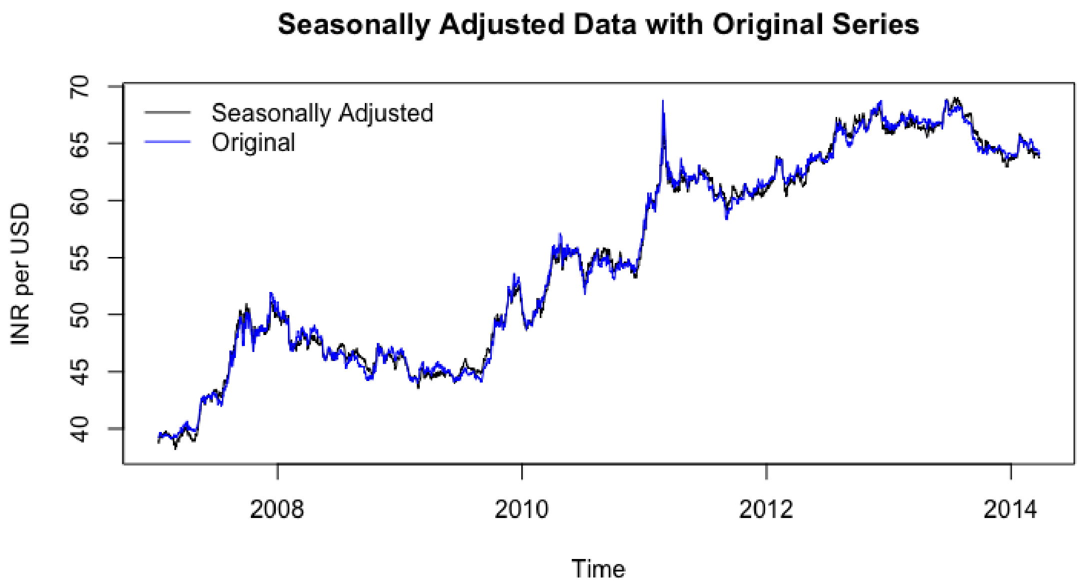

Figure 3: Seasonally adjusted data with original data

Analysis

From Figure-3 we can see there is not much of a difference between the Seasonally Adjusted series and the Original series. It can be concluded that the series does not have much of seasonal variations in the trend.

2.2.2 Forecasting Time Series

HoltWinters Simple Exponential Smoothing

Exponential smoothing is used to make short-term predictions/forecasts. As the time series has been adjusted for seasonality and in-fact did have close to nil seasonality, therefore simple smoothing can be carried out. This way level can be estimated at any point in time. It is dependent on α to estimate the level at any point in time series and $0 < \alpha < 1$. The original data set has been split into training and testing. Approximately 20% of the total observations have been split into test data. Which is 524 records.

Holt-Winters exponential smoothing without trend and without seasonal component.

Smoothing parameters	**Values**
alpha α	0.9957723
beta β	FALSE
gamma γ	FALSE
Coefficients	[,1] a 67.13616

For simple exponential smoothing, parameters β and γ are set to FALSE. The output tells that the estimated value of the α parameter is 0.9957723. Which is not close to zero and means that the forecasts are based on only recent observations. If α is large that is close to 1, more weight is given to the more recent observations. For the extreme case where $\alpha = 1$, $\hat{y}_{T+1|T} = y_T$ and the forecasts are equal to the naive forecasts. Fitted values of the forecasts:

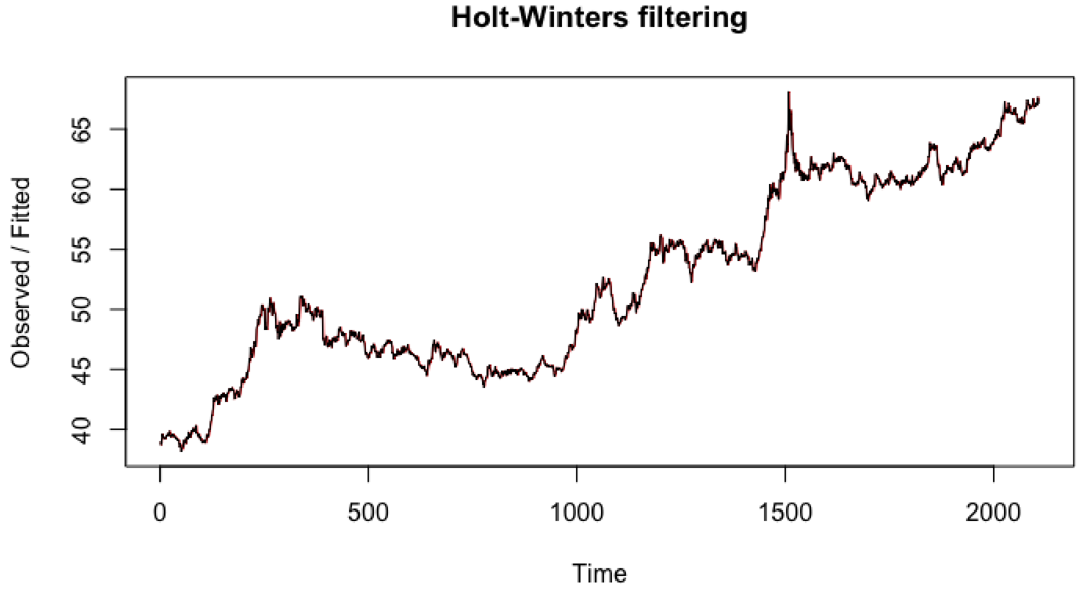

Figure 4: HoltWinters Filtering

Error for the in-sample forecast or (Sum of squared error) SSE is: 176.0695

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1	Theil's U
Training	0.0134	0.28907	0.20564	0.02446	0.392	0.999	-0.0017	NA
Testing	-1.030	1.808	1.44	-1.610	2.21	7.003	0.986	8.52

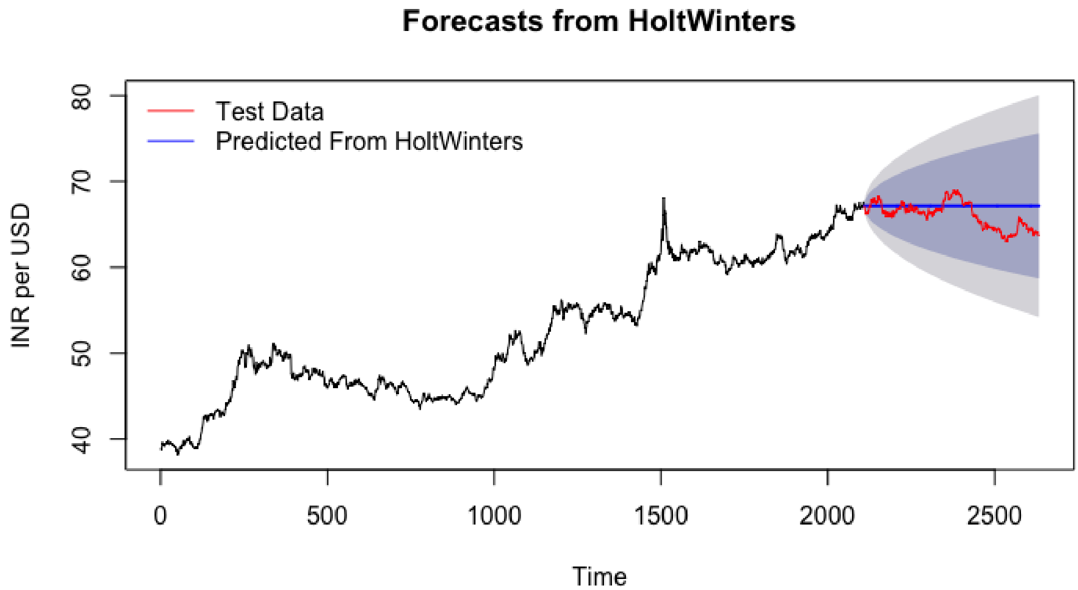

Figure 5: Forecasts from HoltWinters

Dark gray is the 80% confidence interval, the light gray is the 95% confidence interval, and the blue line is the actual prediction. The red line is the test data. We can see how much it deviates from the blue line and get an idea. The forecast errors are stored in the "residuals" of the list variable returned by HoltWinters(). Also, If the model cannot be improved upon, there should be no correlations between forecast errors for successive predictions. To check correlations between forecast errors and successive predictions we plotted ACF of residuals:

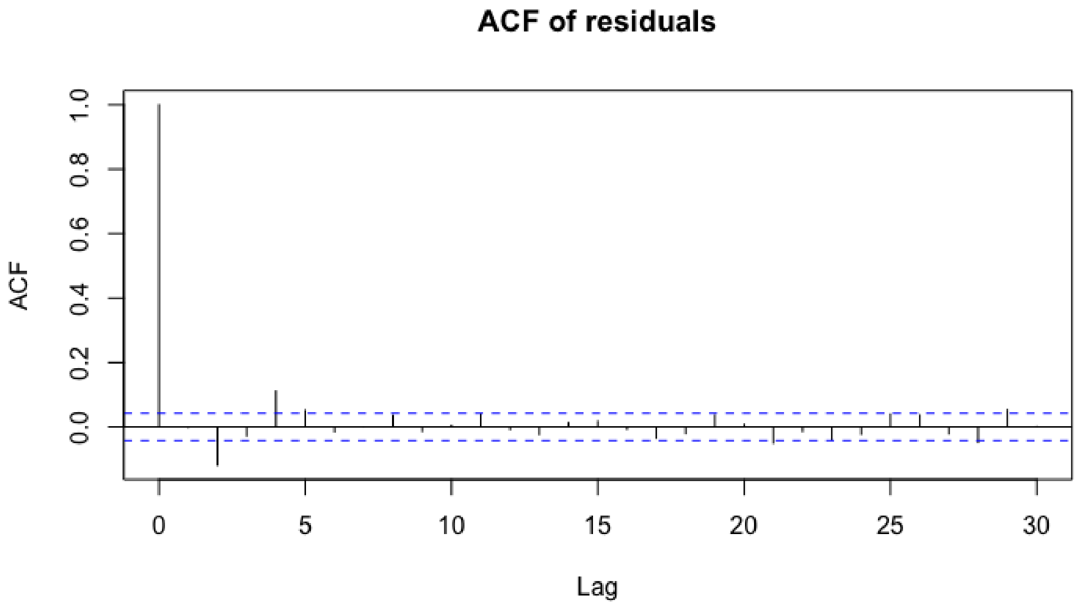

Figure 6: ACF of residuals

Also, Ljung Box test in our case rejects the Null hypothesis that there is no correlation in residuals. Data: usdinr.hw.forecast$residuals X-squared = 107.61, df = 30, p-value = $1.124e-10$.Which means the residuals does contain data. But ACF and bell curve suggest the opposite and also validates our model. Suggesting mean 0 and constant variance. Also, forecast errors are normally distributed. Suggesting that the forecast model is good.

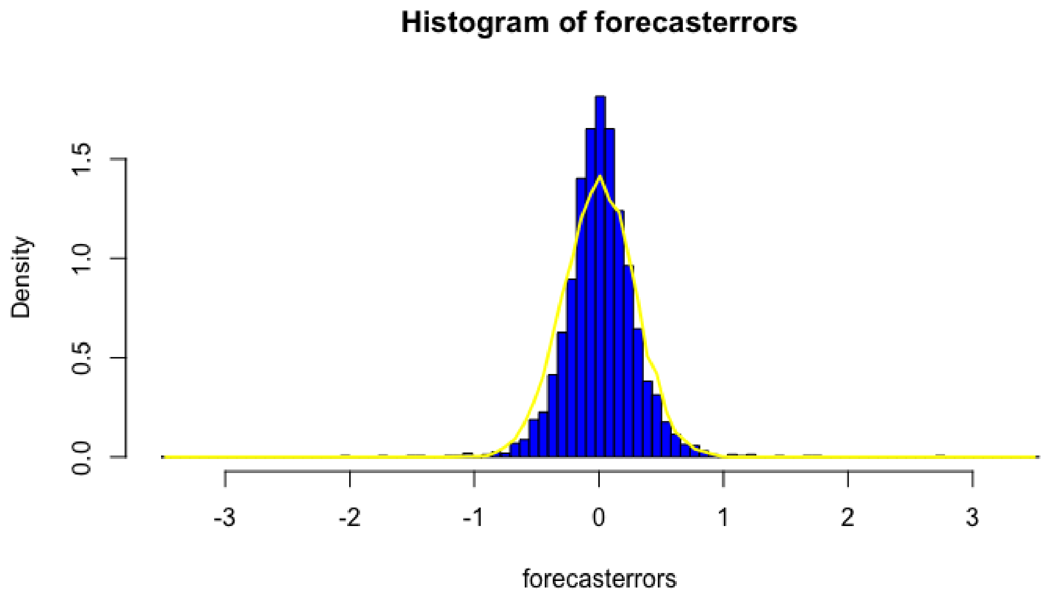

Figure 7: Histogram of forecast-errors

Forecasting with ARIMA

The first and foremost step which is required to build ARIMA model is to determine the stationarity of the time series. With the help of ACF and PACF we define the distribution of the sample data. If the series is not stationary, we have to do a differencing. The steps to ARIMA modeling can be summarized by this:

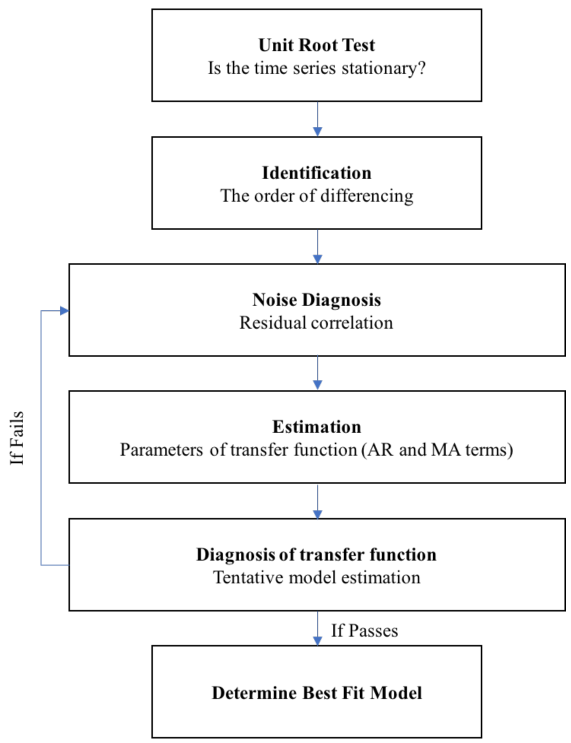

Figure 8: ARIMA modeling steps

Unit root test

Augmented Dickey-Fuller Test
H_0: Non-stationary series
H_A: Stationary series
data: usdinr.seasonalAdjusted Dickey-Fuller = -2.0384, Lag order = 13, p-value = 0.562 alternative hypothesis: stationary

KPSS Test for Level Stationarity
H_0: Stationary series
H_A: Non-stationary series
data: usdinr.seasonalAdjusted
KPSS Level = 20.407, Truncation lag parameter = 11, p-value = 0.01

ACF plot

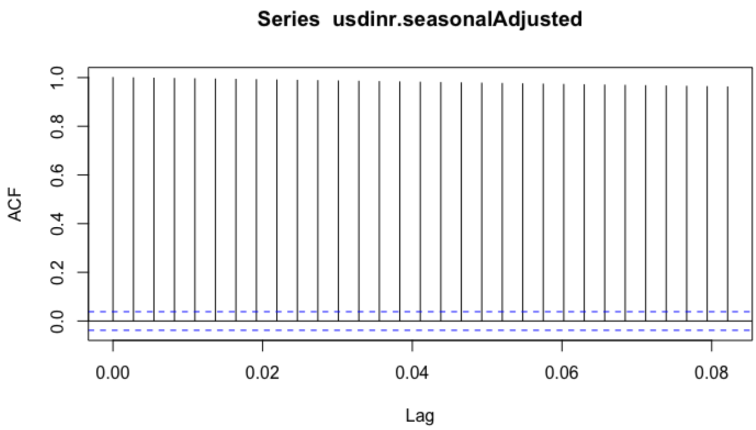

Figure 9: ACF

PACF plot

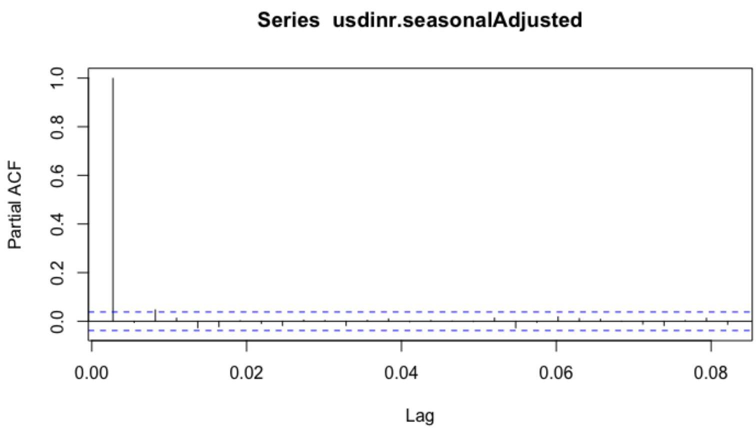

Figure 10: PACF

The above ACF is decreasing or one cay say decaying very slowly and remains well above the significance range (dotted blue lines). This is an indication of a non-stationary time series. Also the above stationarity test suggests us that the time series is not stationary. Which makes sense after looking at the ACF.

Identification

Taking first order difference, the series becomes:

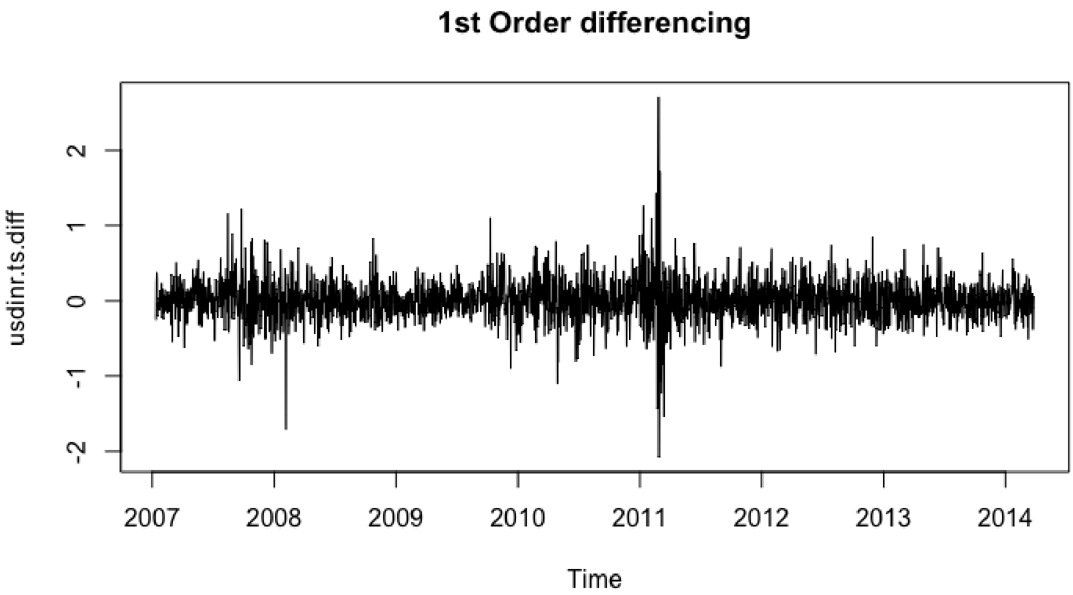

Figure 11: Series after 1st order differencing

Augmented Dickey-Fuller Test
data: usdinr.ts.diff
Dickey-Fuller = -12.962, Lag order = 13, p-value = 0.01

KPSS Test for Level Stationarity
data: usdinr.ts.diff
KPSS Level = 0.12852, Truncation lag parameter = 11, p-value = 0.1

ACF of the differenced series

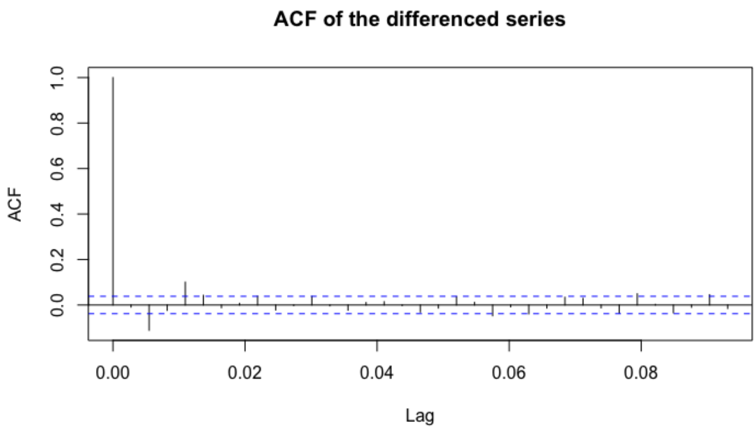

Figure 12: ACF of the Series after 1st order differencing

PACF of the differenced series

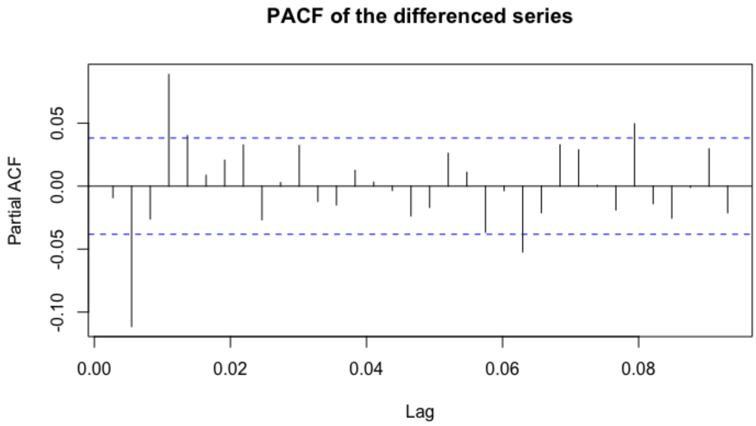

Figure 13: PACF of the Series after 1st order differencing

Augmented Dickey-Fuller Test and KPSS tells us that the series is stationary after 1st order differencing. Also the ACF depicts the same.

Model Estimation

After trying different combinations of ARIMA(p,1,q) we found the AIC, MAPE and Model Size. Akaike's Information Criterion (AIC), is used to select predictors for regression, and also to determine the order of an ARIMA model. It can be written as

$$\text{AIC} = -2\log(L) + 2(p+q+k+1) \tag{3}$$

Where L is Likelihood. $k = 1$ For ARIMA the corrected AICc is:

$$\text{AICc} = \text{AIC} + \frac{2(p+q+k+1)(p+q+k+2)}{T-p-q-k-2} \tag{4}$$

Generally a good model is obtained by minimizing the AIC or BIC. Here we are using AIC for model selection and MAPE (Mean Absolute Percentage Error)

˜	p	q	AIC	MAPE	Size
	1	0	702.8136	0.3654995	1
	0	1	702.7668	0.3654574	1
	2	0	672.7122	0.3652117	2
	0	2	677.7229	0.3650563	2
	1	1	699.1057	0.3648059	2
	2	1	674.1232	0.3652099	3
	1	2	679.6058	0.3650729	3
	3	0	673.1204	0.3652044	3
	0	3	679.3208	0.3651040	3
	4	0	653.6493	0.3653110	4
	0	4	655.1254	0.3653721	4
	2	2	659.4763	0.3647929	4
	3	1	669.2605	0.3652270	4
	1	3	675.9580	0.3652043	4
	5	0	651.1156	0.3652259	5
	0	5	650.7404	0.3654830	5
	1	4	651.7220	0.3656124	5
	4	1	649.7228	0.3654667	5
	2	3	656.9540	0.3643502	5
	3	2	657.0599	0.3644240	5
	6	0	652.8627	0.3653482	6
	0	6	652.6443	0.3654304	6

5 1	651.4575	0.3654977	6
1 5	652.6603	0.3654423	6
4 2	651.5520	0.3655032	6
2 4	653.5145	0.3655621	6
3 3	658.9559	0.3643564	6

Plotting the graph with model complexity and size to select model:

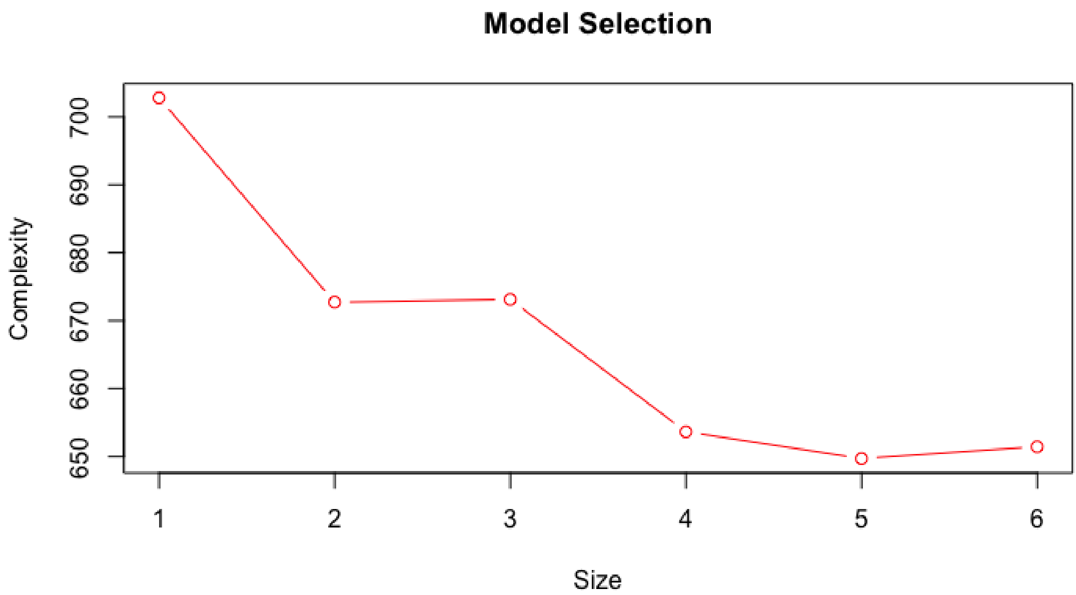

Figure 14: Model complexity and Size plot

We can see from the Figure-14, the model with size 5 that is $ARIMA(4,1,1)$ has the lowest AIC value. Therefore going ahead with it. Also, auto.arima() selects this model for us: Series: usdinr.seasonalAdjusted ARIMA(4,1,1) with drift

Coefficients:

ar1	ar2	ar3	ar4	ma1	drift
0.4752	-0.0957	0.0294	0.0996	-0.4908	0.0094
s.e					
0.1663	0.0215	0.0283	0.0200	0.1672	0.0055

σ^2 estimated as 0.0747: log likelihood=-317.42 AIC=648.83 AICc=648.88 BIC=689.96

Forecasting using $ARIMA(4, 1, 1)$ with Drift

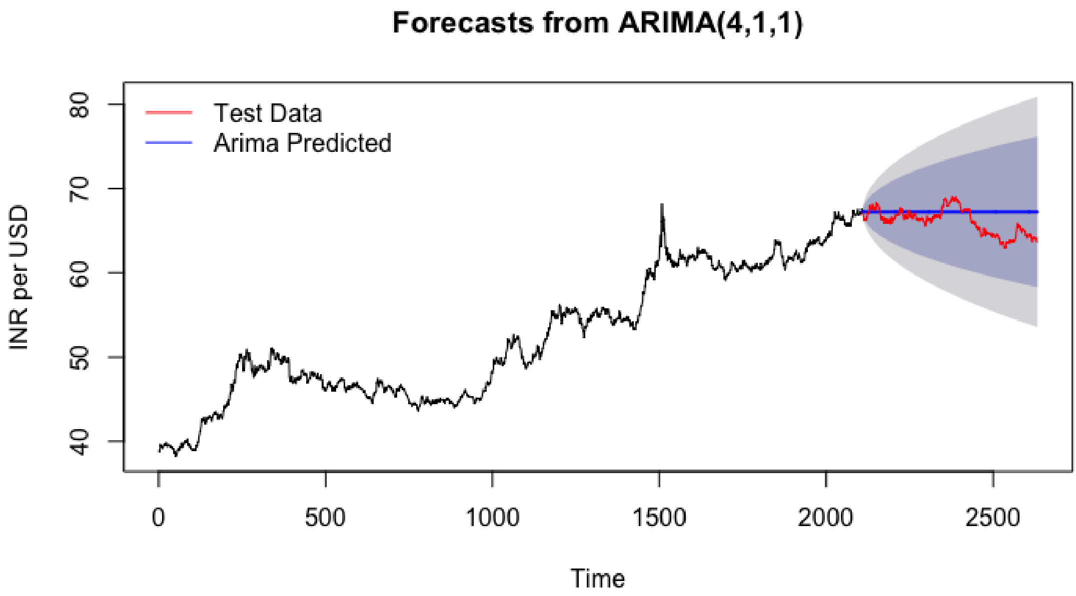

Figure 15: Forecasting with $ARIMA(4, 1, 1)$

Dark gray is the 80% confidence interval, the light gray is the 95% confidence interval, and the blue line is the actual prediction. The red line is the test data. We can see how much it deviates from the blue line and get an idea. The forecast errors are stored in the "residuals" of the list variable returned by the ARIMA. The original data set has been split into training and testing. Approximately 20% of the total observations have been split into test data. Which is 524 records.

ARIMA(4,1,1) with drift

Coefficients:

ar1	ar2	ar3	ar4	ma1
0.4908	-0.1013	0.0313	0.1130	-0.5016
s.e				
0.1616	0.0241	0.0304	0.0226	0.1627

σ^2 estimated as 0.08129: log likelihood = -345.75, aic = 703.5

The AIC changed because data was split into training and testing. But it should not change the result much because at the end we want to train our model on all the data. In which this model is the best.

Accuracy Summary

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1	Theil's U
Training	0.0125	0.2850	0.2053	0.0229	0.3922	0.9984	-0.0016	NA
Testing	-1.117	1.859	1.484	-1.741	2.279	7.216	0.9863	8.7684

Model Verification

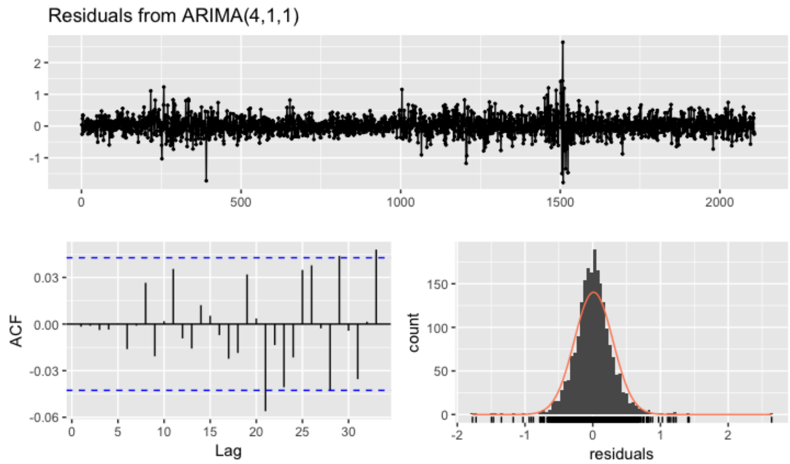

Figure 16: Model Residuals $ARIMA(4,1,1)$

As seen from the ACF and PACF plots for the $ARIMA(4,1,1)$ residuals almost all the correlations are below the threshold limit are except 1 or two by chance. This means that the residuals are behaving like white noise and do not hold important information. Residuals are distributed normally as well. Further, Ljung Box estimates on residuals tells the same:

Box-Ljung test
X-squared = 56.963, df = 45, p-value = 0.1088

Therefore this model can be validated and used for the purpose of forecasting.

Forecasting with Neural Network

A neural network is similar to how biological neurons are organized. And they can be thought of biologically inspired network of nodes organized in layers similar to how neurons in a brain are. The independent variables or predictors are the inputs and form the bottom layer, and the predictions/forecasts or output makes the top layer. There may be many layers in between, and is containing hidden nodes and are famously known as deep belief networks, though out of scope of this paper. All the predictors are attached with a weight known as coefficients. These weights are selected using a algorithms to make learning. These algorithms are there to minimize the cost function like linear regression, and activation function like (sigmoid). Output is obtained by the linear combination.

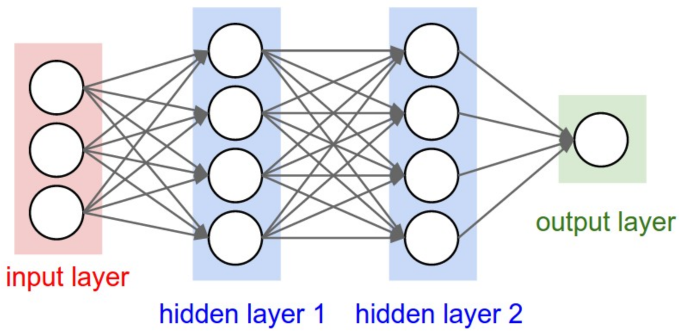

Figure 17: Neural Network architecture Reference: http://cs231n.github.io/neural-networks-1/

In time series data lagged values of the data are used as the input to a neural network. Similar to autoregression model. This neural network is called as autoregression or NNAR model. Considering only feed-forward networks with one hidden layer, and use the notation NNAR(p,k) to indicate there are p lagged inputs and k nodes in the hidden layer. In this paper we are limiting the scope of neural network to simple model without any complexities involved. Neural network is also not based on a well formed stochastic/random model and therefore it is not simple to get the prediction intervals unlike other autoregression models. Below Figure-18 is the forecast made by the neural network that is defined by $NNAR(1, 1)$.

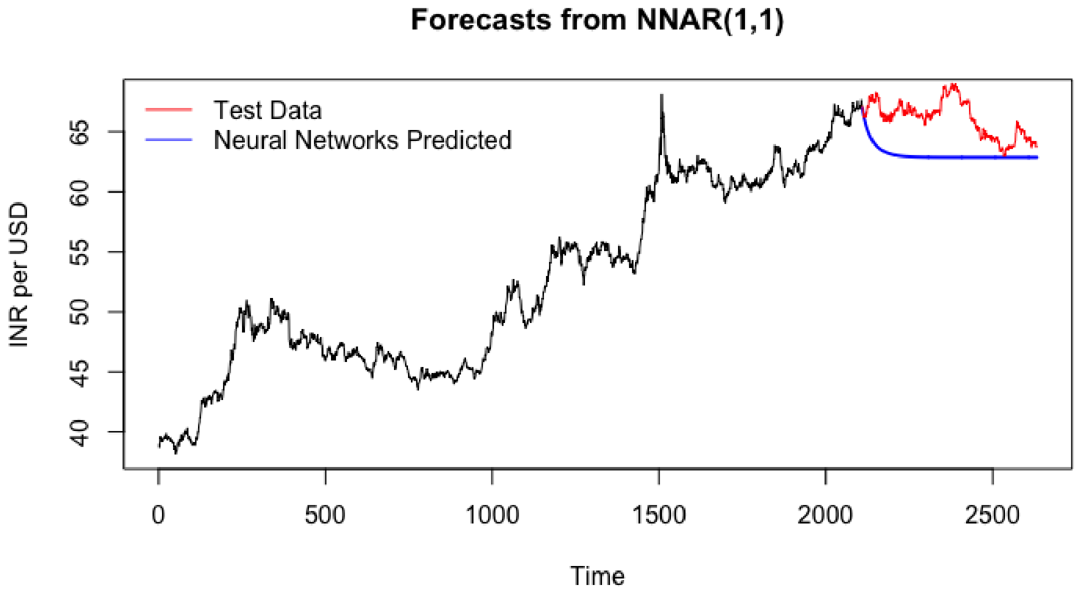

Figure 18: Forecast with NNAR(1,1)

The blue line is the actual prediction made by the neural network. The red line is the test data. We can see how much it deviates from the blue line and get an idea. The original data set has been split into training and testing. Approximately 20% of the total observations have been split into test data. Which is 524 records.

Accuracy Summary

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1	Theil's U
Training	0.00128	0.2911	0.2084	-0.0005	0.3974	1.0136	0.0232	NA
Testing	3.0767	3.417	3.076	4.610	4.6104	14.957	0.9837	15.483

2.2.3 Comparing test and and train data taking m=24 observations from each

HoltWinters Simple Exponential Smoothing Train Data **Test data**

Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95	Original
2109	67.13616	66.76601	67.50631	66.57006	67.70226	67.17393
2110	67.13616	66.61379	67.65853	66.33727	67.93506	66.85192
2111	67.13616	66.49685	67.77548	66.15841	68.11391	66.72144
2112	67.13616	66.39820	67.87412	66.00755	68.26477	66.53713
2113	67.13616	66.31127	67.96105	65.87461	68.39772	66.38837
2114	67.13616	66.23267	68.03965	65.75439	68.51793	66.18744
2115	67.13616	66.16038	68.11195	65.64383	68.62849	66.16632
2116	67.13616	66.09309	68.17924	65.54091	68.73141	66.31655
2117	67.13616	66.02988	68.24245	65.44425	68.82808	66.19868
2118	67.13616	65.97009	68.30223	65.35281	68.91951	66.50060
2119	67.13616	65.91322	68.35910	65.26584	69.00649	66.22287
2120	67.13616	65.85889	68.41344	65.18274	69.08959	66.39363
2121	67.13616	65.80677	68.46556	65.10303	69.16930	66.72200
2122	67.13616	65.75662	68.51571	65.02633	69.24600	66.44510
2123	67.13616	65.70822	68.56410	64.95232	69.32000	66.70475
2124	67.13616	65.66142	68.61090	64.88074	69.39158	67.06817
2125	67.13616	65.61606	68.65627	64.81136	69.46096	67.16922
2126	67.13616	65.57201	68.70032	64.74400	69.52833	66.95080
2127	67.13616	65.52917	68.74316	64.67848	69.59385	67.02543
2128	67.13616	65.48744	68.78489	64.61466	69.65767	66.97612
2129	67.13616	65.44674	68.82558	64.55241	69.71991	67.37291
2130	67.13616	65.40700	68.86532	64.49164	69.78069	67.91157
2131	67.13616	65.36815	68.90417	64.43222	69.84010	67.91347
2132	67.13616	65.33014	68.94218	64.37409	69.89823	67.78782

Forecast function gives you the forecasts of the next 24 days, along with 80% prediction interval for the forecast, and a 95% prediction interval for the forecast as can be seen. Take in the example above the forecast of USD to INR on 22nd day that is at point 2130 is 67.136 with a 95% prediction interval of (64.49164, 69.78069) and original price is 67.91157.

$ARIMA(4, 1, 1)$ **Train Data** **Test data**

Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95	Original
2109	67.18607	66.82068	67.55146	66.62726	67.74489	67.17393
2110	67.26949	66.75552	67.78345	66.48344	68.05553	66.85192
2111	67.27130	66.66452	67.87808	66.34331	68.19929	66.72144
2112	67.23080	66.54701	67.91459	66.18503	68.27657	66.53713
2113	67.21913	66.44786	67.99041	66.03956	68.39870	66.38837
2114	67.22699	66.36883	68.08516	65.91455	68.53944	66.18744
2115	67.23097	66.29366	68.16828	65.79748	68.66446	66.16632
2116	67.22718	66.21733	68.23704	65.68275	68.77162	66.31655
2117	67.22385	66.14469	68.30301	65.57342	68.87428	66.19868
2118	67.22361	66.07778	68.36944	65.47122	68.97600	66.50060
2119	67.22416	66.01475	68.43357	65.37453	69.07379	66.22287
2120	67.22392	65.95397	68.49388	65.28170	69.16615	66.39363
2121	67.22337	65.89542	68.55131	65.19245	69.25428	66.72200
2122	67.22311	65.83935	68.60686	65.10684	69.33938	66.44510
2123	67.22309	65.78553	68.66065	65.02453	69.42165	66.70475
2124	67.22306	65.73357	68.71256	64.94508	69.50105	67.06817
2125	67.22298	65.68326	68.76270	64.86818	69.57778	67.16922
2126	67.22292	65.63451	68.81132	64.79366	69.65217	66.95080
2127	67.22289	65.58721	68.85856	64.72134	69.72444	67.02543
2128	67.22288	65.54124	68.90451	64.65103	69.79472	66.97612
2129	67.22286	65.49647	68.94925	64.58258	69.86315	67.37291
2130	67.22285	65.45283	68.99287	64.51584	69.92986	67.91157
2131	67.22284	65.41023	69.03544	64.45069	69.99498	67.91347
2132	67.22283	65.36861	69.07706	64.38704	70.05862	67.78782

Forecast function gives you the forecasts of the next 24 days, along with 80% prediction interval for the forecast, and a 95% prediction interval for the forecast as can be seen. Take in the example above the forecast of USD to INR on 22nd day that is at point 2130 is 67.22285 with a 95% prediction interval of (64.51584, 69.92986) and original price is 67.91157.

$NNAR(1,1)$ **Train Data** **Test data**

Point	Forecast	Original
2109	66.94409	67.17393
2110	66.76445	66.85192
2111	66.59506	66.72144
2112	66.43510	66.53713
2113	66.28385	66.38837
2114	66.14066	66.18744
2115	66.00496	66.16632
2116	65.87621	66.31655
2117	65.75393	66.19868
2118	65.63768	66.50060
2119	65.52707	66.22287
2120	65.42174	66.39363
2121	65.32135	66.72200
2122	65.22559	66.44510
2123	65.13419	66.70475
2124	65.04689	67.06817
2125	64.96345	67.16922
2126	64.88365	66.95080
2127	64.80728	67.02543
2128	64.73416	66.97612
2129	64.66411	67.37291
2130	64.59697	67.91157
2131	64.53258	67.91347
2132	64.47080	67.78782

Forecast function gives you the forecasts of the next 24 days. There is no 80% or 90% interval in the prediction. Take in the example above the forecast of USD to INR on 22nd day that is at point 2130 is 64.59697 versus the original price that is 67.91157.

2.3 Performance of models

Forecasting error is calculated as difference between an observed and its corresponding forecast. Error means the part that was not predicted accurately. Forecasting error can be written as:

$$e_{T+h} = y_{T+h} - \hat{y}_{T+h|T} \tag{5}$$

Where training set is given by $\{y_1, \ldots, y_T\}$ and testing set is given by $\{y_{T+1}, y_{T+2}, \ldots\}$
In this paper to measure accuracy percentage error has been used. Specifically using Mean absolute percentage error $MAPE$ which is one of the most commonly used performance measure. Another reason for choosing percentage error is that they are always unit-free. MAPE is defined as:

$$\left(\frac{1}{n}\sum \frac{|Actual - Forecast|}{|Actual|}\right) * 100 \tag{6}$$

MAPE of Models

Dataset	Holt-Winters Simple	ARIMA(4,1,1)	NNR(1,1)
Training Dataset	0.3920981	0.3922883	0.3976794
Test Dataset	2.2110790	2.2792695	4.6494720

Even though all the models were close, but as can be seen, HoltWinters Simple Exponential Smoothing performed better than both $ARIMA(4, 1, 1)$ and $NNR(1, 1)$ with MAPE on Training set = 0.3920981 and Testing set = 2.2110790 for this dataset. Then comes a close second $ARIMA(4, 1, 1)$ and surprisingly Neural networks $NNR(1, 1)$ did not perform as good as the HoltWinters Simple Exponential Smoothing and $ARIMA(4, 1, 1)$.

3 Conclusion

Since a time series is a sequence of numerical data points in successive order, the time series tracks the movement of the chosen data points of exchange price, over a specified period of time with data points recorded at regular intervals. There is no minimum or maximum time interval that must be included, allowing the analysts and investors to gather data easily.

BREAKING DOWN 'Time Series' is very easy. A time series can be taken on any variable that changes over time. In foreign exchange forecasting it is common to use a time series to track the price of a currency over time. This can be tracked over the short term, such as on the hour over the course of a business day, or the long term, at close on the last day of every month over the course of ten years.

Time Series Analysis can also examine how the changes associated with the chosen data point compare to shifts in other variables over the same time period.

For example, suppose we want to analyze a time series of daily closing USD exchange prices for a given currency over a period of one year. We can obtain a list of all the closing prices for the currency from each day for the past year and list them in chronological order.

We can also determine any seasonality associated with exchange rate, whether it goes through peaks and valleys at regular times each year. Analysis would require taking the observed prices and correlating them to a chosen season such as summer and winter, or festival and holiday seasons.

In short "Time series forecasting" uses information regarding historical values and associated patterns to predict future activity. This may relate to trend, cyclical fluctuation and issues of seasonality.

Though forecasting exchange rates is a very difficult task, and the results obtained by any of the four models may not be absolutely correct, but since Time series analysis is based on chronological data, the approach is quite close to neural network analysis even though surprisingly it did not perform as well as HoltWinters Simple Exponential Smoothing and $ARIMA(4, 1, 1)$. Data is updated continuously, moment by moment,hour by hour, day by day, taking fluctuation due to various factors whether political, policy, economic, cyclic, seasonality into consideration, which is what the AI or neural network approach is based on - continuous reactions based on various factors.

Since the predictions may not be correct, and it is for this reason many companies and investors simply hedge their currency risk. However, there are others who see value in forecasting exchange rates and want to understand the factors that affect their movements.

4 Future Work

As it was a univariate time series analysis. In the future macro-economic variables and trends can be included to do a multivariate analysis along with utilization of machine learning methods like ensembles and deep belief networks to further improve forecasting.

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