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Statistical Techniques For Stock Price Prediction In India

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Abstract

Construction of model and analysis of stock market involve more interest from the researchers in the last decade. This article examined whether the current closing stock market price depends on the closing stock price of the previous days. Based on the results it is clear (N50) that the stock market price does not depend on the previous price. Regression analysis method has been used to identify the most influential factor in the Indian stock market price. In terms of factors, the price of Crude oil changes in the share price of India. Two time series models were used in this study for future prediction and which method is applicable to this data. The results of the Fuzzy Time Series (FTS) model are better than the Autoregressive Integrated Moving Average (ARIMA) model because the percentage error (MAPE) in the FTS is less than the ARIMA.

Keywords: *Stock Price, Nifty50, Correlation, ARIMA, FTS*

1. INTRODUCTION

Time series plays a vital role in the branches of Stock prices, Global surface temperature, Economy Population growth and agricultural production. Time Series is a series of values of variable arranged in chronologically order over a period of time. The stock market is an unpredictable extraordinary environmental business system. The word stock means a fraction of the capital of a company and the word exchange means a place for purchasing and selling something. National Stock Exchange (NSE) is a stock exchange in India, which is set up in 1992. Through this research paper, the timing of the daily closing stock price on Nifty50 was viewed with Time Series Analysis. Based on the available decision, the Nifty50 Daily closing

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stock price appears to have a decreasing trend in the future. Through the review of the literature, it is possible to see how much of the real-life situation has been used in this regard. Okpara (2010), the Nigerian stock market return price is random walk process or not using the run test technique. It is shown that the successive stock price changes are independent and the Nigerian stock market follows a random walk process. Box and Jenkins (1970) proposed the Autoregressive Integrated Moving Average model using the stationary concept for the forecast purpose. Banerjee (2014) applied the ARIMA model to forecast in Indian Stock Exchange the future stock indices. Jin et al (2015) used ARIMA model to predict in Shanghai Composite Stock Price Index and they are considered to closing stock price. Saini et al (2016) endeavoured to present the forecasting of daily stock data of SBI for a period of 2 years using the Box-Jenkins method. Ashik and Kannan (2017) discussed ARIMA model applied by Nifty50 closing stock market price for forecasting. Song and Chissom (1993) have initiated the study of time-invariant and time-variant forecasting models using fuzzy time series for enrollment data of the University of Alabama. Also, compare the predicted values of the fuzzy time series with those of non-linear regression models. Mangale et al (2017) involve the strength of fuzzy logic to expect stock price used long-term valuation fundamental approach. In this work, the National Stock market of India is the random behaviour of the previous day stock price. Two types of time series models have been used in this study. They are the Autoregressive Integrated Moving Average (ARIMA) and Fuzzy Time Series (FTS).

2. RANDOM WALK

This subsection presents a preliminary analysis of the basic characteristics and stylized facts of the National Stock Exchange of Indian stock market indices. Randomness, the efficient market hypothesis and presence of chaos also examined. An empirical investigation of the Indian stock market is examined (close price). Mainly, all the available empirical information about the time series of Nifty50 indices of National Stock Exchange respectively has been analyzed. Deviations from the normality of the data are highlighted and the probability distribution of closing stock price also presented. There has been no uniform randomness in the phenomenon of stock on the basis of the run test. This establishes the significance of the first hypothesis namely, NSE is not uniformly random; there are only periods of randomness. Coming to the second hypothesis concerning the stock market inefficiency, the run test has

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ensured the non-uniformity of randomness. The dataset was collected from January 2012 to December 2016 with 1218 observations.

NSE is Normality or Not

Generally, the stock market price is fluctuation movements because there is affected by many terms and economic policies. The daily stock market closing price of Nifty50 for the period 2012 - 2016 has been plotted in figure 1. It is clear those movements of Nifty50 index depicts a similar pattern reflecting the performance of the economy.

Figure 1: Time Plot of Closing Stock Price for N50

The descriptive statistics clearly say that the values of skewness and kurtosis clearly indicate that the closing stock price movements in markets do not follow a Normal distribution. Check the normality test for closing stock price in table 1.

Table 1: Normality Test of Close and Return Price for N50

Closing Stock Price		
	Close	**Sig**
Observations	1218	
Skewness	-.112	
Kurtosis	-1.542	
Kolmogorov-Smirnov	.143	.000
Shapiro-Wilk	.052	.000

This ascertains the values of Kolmogorov-Smirnov and Shapiro-Wilk statistics which are significant at 1% and 5% level critical values. (Referring table – 1) Therefore it is concluded

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that NSE closing stock price distribution is non-normal. It is also observed that close is negatively skewed of the Nifty50 index. The histogram (with density curve) and normal q-q plot of Nifty50 are presented in figure 2. In order to check the deviations from normality, quantile graph has been plotted for the Nifty50 index. From this plot, there has been a deviation from normality as many points deviate from 45-degree line in close price either side. From figure 2, is a clear indication of non-normality of Nifty50 close and return series.

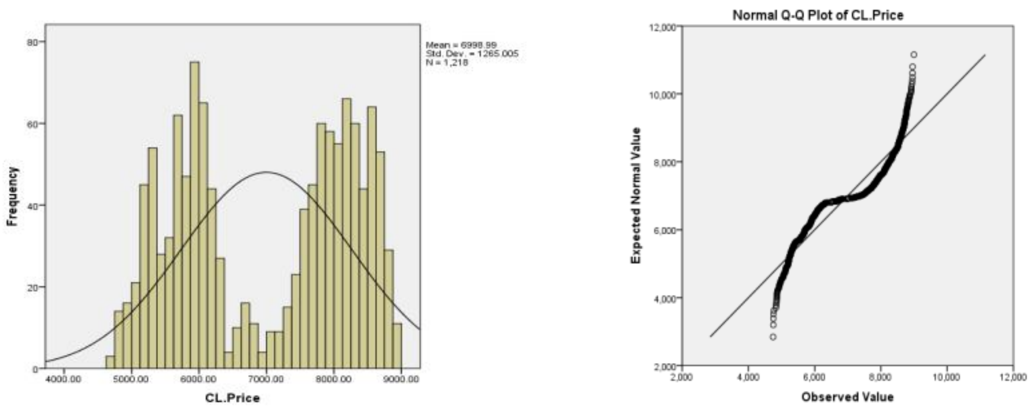

Figure.2: Histogram and Q-Q plot of Close Price for N50

Randomness Test

In order to test the randomness of the data or to test the random walk hypothesis, the run test has been conducted for the mean and median of closing stock price for the Nifty index. The test details are presented in table 2. The significance value of Z-statistics gives sufficient evidence to conclude that the price change is not at random; thus the random walk hypothesis of NSE close stock price has been rejected. From the run test find out price changes are random or not. **H_0:** Closing price changes are random; **H_1:** Closing price changes are dependent. Test reference values are taken as mean and median. $|Z| \geq 1.96$ indicates the rejection of the null hypothesis at 5% level of significance. In closing stock price, the Z scores for the mean (Z=-34.512) and median (Z=-34.284) falls beyond the range -1.96 and 1.96. The Z score indicates rejects the null hypothesis at 5% level of significance.

Table 2: Run Test of Close and Return Price for N50

NSE (Nifty50)			
Run Test (Mean)	**Close**	**Run Test (Median)**	**Close**
Test Value	6998.98	Test Value	7364.80
Cases < Mean (Test Value)	578	Cases < Median (Test Value)	609
Cases >= Mean (Test Value)	640	Cases >= Median (Test Value)	609
Total	1218	Total	1218

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Number of Runs	8	Number of Runs	12
Z – Value	-34.512	Z – Value	-34.284
Sig.	.000	Sig.	.000

The p-value is less than or equal to significance level (0 < 0.05; α = 5%), the decision is to reject the null hypothesis and conclude that the order of the data (close price) is not random. From the hypothesis, this shows that the successive price change is not random.

3. MULTIPLE LINEAR REGRESSION ANALYSIS

Correlation Co-efficient

Correlation is concerned with measuring the strength or degree of relationship between variables. The measure of correlation is called correlation coefficient which shows the direction and degree correlation. It measures the closeness of the relationship between variables. The word 'relationship' is of importance and indicates that there is some connection between the variables under consideration. [Total Observations (N): 258]

Table 3: Correlation Analysis

Variables		N50	Crude Oil	Gold	USD
N50	*Correlation*	1	**.686****	.600**	.062
	Sig.		.000	.000	.319
	Covariance	243106.828	151381.720	456803.218	17.269
Crude Oil	*Correlation*	**.686****	1	.327**	.353**
	Sig.	.000		.000	.000
	Covariance	151381.720	200146.560	226069.453	88.816
Gold	*Correlation*	.600**	.327**	1	-.355**
	Sig.	.000	.000		.000
	Covariance	456803.218	226069.453	2387348.674	-308.604
USD	*Correlation*	.062	.353**	-.355**	1
	Sig.	.319	.000	.000	
	Covariance	17.269	88.816	-308.604	.316

In this work, we have studied in the relationship between Nifty50 stock price, Crude oil price, Gold price and Foreign Exchange (USD) price. From table 3, computing the linear association strength of among variables. In these results, the correlation between N50 and Crude Oil is 0.686, which indicates that the relationship is positive. The correlation between N50 and Gold is 0.600, and the correlation between N50 and USD is 0.062. These values indicate that both relationships are positive.

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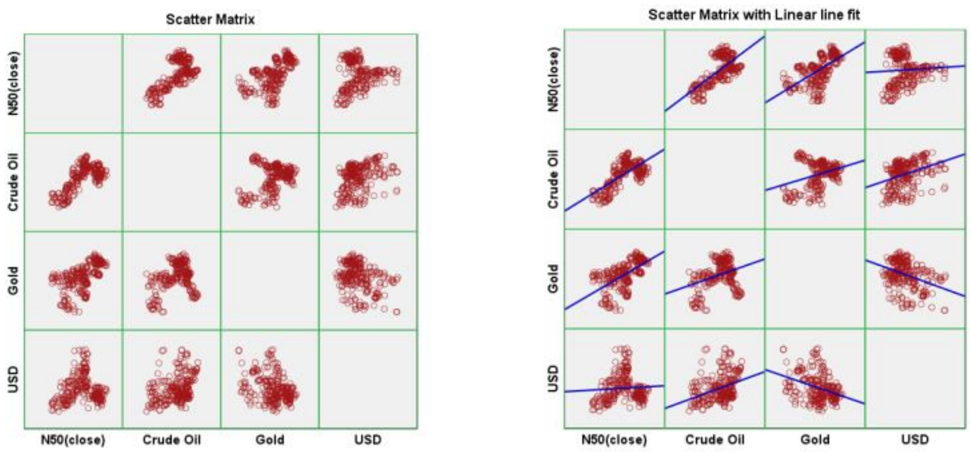

Figure 3 Scatter Matrix and Linear line fit of stock price

The correlation between Gold and USD is -0.355, which indicates that the relationship is negative. The correlation between Crude Oil and Gold is 0.327, and the correlation between Crude Oil and USD is 0.353. These values indicate that both relationships are positive. In figure 3, additional evidence of relationship check for graphically, draw the scatter matrix and linear line fit of the dataset. The N50 and Crude oil variables tend in the same direction together, the coefficient is highly positive for the other combinations.

Regression Analysis

The nifty50 closing stock price is the dependent variable and other three (Crude, Gold and USD) are independent variables. Table 4 shows the multiple linear regression model summary and overall fit statistics. We find that the adjusted R^2 of our model is .625 with R^2 = .629. This means that the linear regression explains 62.9% of the variance in the data. The Durbin-Watson d = .088, which is between the two critical values of 0 < d < 2 (positive autocorrelation trend). Therefore, we can assume that there is no first-order linear auto-correlation in our multiple linear regression data.

Table 4: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.793	.629	.625	302.05223	.088

Predictors: (Constant), USD, Crude oil, Gold; Dependent Variable: N50 (close)

The next output table is the F-test. The linear regression's F-test has the null hypothesis that the model explains zero variance in the dependent variable (R^2 = 0). The F-test is highly significant, thus we can assume that the model explains a significant amount of the variance in N50 closing stock price.

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Table 5: ANOVA

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	3930462.044	3	1310154.681	143.601	.000
	Residual	2317382.712	254	9123.550		
	Total	6247845.756	257			

Dependent Variable: N50 (close); Predictors: (Constant), USD, Crude oil, Gold

Table 6 shows the multiple linear regression estimates including the intercept and the significance levels. If we force all variables into the multiple linear regressions, we find that only Crude oil and Gold price are significant predictors. We can also see that crude oil has a higher impact than gold price by comparing the standardized coefficients **(Beta = .534 versus Beta = .435)**. The information in the table above also follows us to check for multicollinearity in our multiple linear regression models. Tolerance should be > 0.1 (or VIF < 10) for all variables.

Table 6: Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Collinearity Statistics	
		B	Std.Error	Beta			Tolerance	VIF
1	Constant	614.087	3019.817		.203	.839		
	Crude oil	.589	.053	.534	11.186	.000	.641	1.561
	Gold	.139	.015	.435	9.104	.000	.640	1.563
	USD	24.816	42.347	.028	.586	.558	.627	1.595

Dependent Variable: N50 (close)

Lastly, we can check for normality of residuals with a normal P-P plot. The plot shows that the points generally follow the normal (diagonal) line with no strong deviations. This indicates that the residuals are normally distributed.

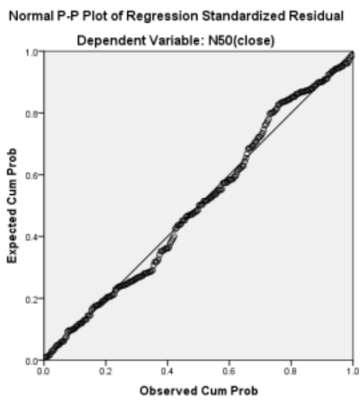

Figure 4 Normal p-p plot of Regression Standardized Residual of N50.

4. COMPARISON OF TIME SERIES MODELS

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The comparison is a consideration or estimate of the similarities or dissimilarities between two things or others. In this section consider about two statistical models (ARIMA and FTS). The testing period of the dataset is the daily closing stock price (N50) from July to December of 2016.

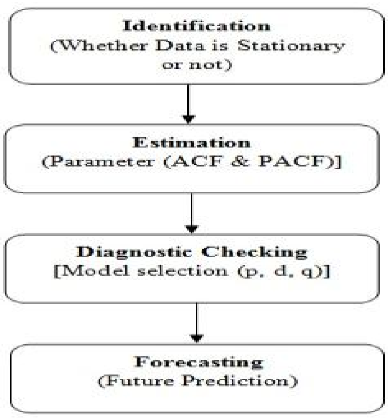
Autoregressive Integrated Moving Average (ARIMA) Model

In time-series study, an ARIMA model is a mixture of Auto-regressive and Moving Average with a difference. This model is fitted to time series data either to better identify with the data or to predict upcoming points in the series. It is also known as the Box-Jenkins method. In case the data is found to be non-stationary is achieved by differencing technique and it's reduced. Generally, Box-Jenkins method is marked ARIMA (p, d, q) where parameters are p, d, q refers to autoregressive (φ), difference (∇) and moving average (θ) also can be expressed as

$$y_t = c + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \ldots + \varphi_p y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \qquad (1)$$

φ – Autoregressive model; θ – Moving Average model; ∇ (Difference) – $Y_t - Y_{t-1}$; c – constant.

Box-Jenkins methods for modelling and analyzing time series are characterized by four steps:



Model selection can be made based on the minimum values of Bayesian Information Criteria (BIC) given by

$$BIC = -2\log(L) + k\log(n) \qquad (2)$$

5. RESULTS AND DISCUSSION

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Figure 5: Time Plot of Daily Closing Stock Price for N50

In figure 5, the time plot of the daily closing stock price during the test period. It is mountain outlook of the stock market. That means which is some days increasing trend then down the field. This is remained to up and down of hills situation. So that the Nifty50 stock price is volatility movements. In the previous section results; we know that the Indian stock market is independent upon the previous day effect. Additional to facilitate time series models applied for testing periods.

ARIMA Model

An ARIMA model, a First-order differencing is computed for the data after that time plot of the differencing data is shown in figure 6. The differencing data shows a stationary pattern, and an Autocorrelation and Partial Autocorrelation (figure 7) are also done on the differencing data, which displays a short-term autocorrelation and confirms the stationary of the differencing data.

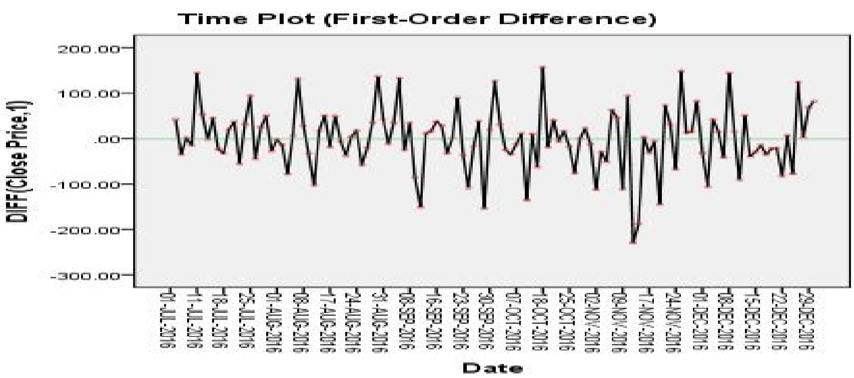

Figure 6: Time Plot of First-Order Difference for N50

According to the identification rules on time series, the corresponding model can be established. If a partial correlation function of a stationary sequence is truncated, and the

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auto-correlation function is tailed, it can be concluded the sequences for the AR model; if the partial correlation function of a stationary sequence is tailed, and the auto-correlation function is truncated, it can be strong that the MA model can be fitted for the sequence.

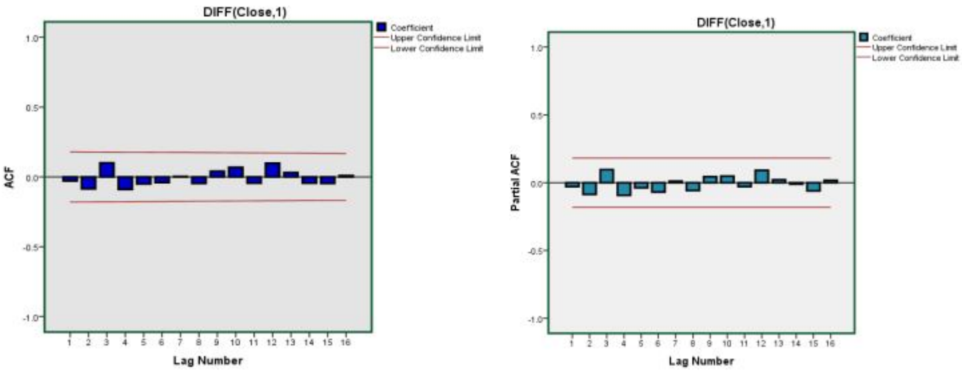

Figure 7 ACF and PACF Plot of First-Order Difference

Based on the results from an ARIMA model can be fitted to the original Nifty 50 data, also the parameters in ARIMA (p,1,q) need to be determined. From figure 7 of the Autocorrelation and Partial Autocorrelation are safe to the concluded. This means that it is enough to choose the model in the set of $\{p, q \leq 3\}$. The first ordered difference of ACF and PACF that the order of p and q can be find using Criteria method. We entertained Nine interim ARIMA models and choose that model which has minimum BIC values. The models and corresponding BIC values are presented in table 6. From table 7, nine tentative models considered for Nifty 50 closing stock price. The most suitable model is ARIMA (0, 1, 1) due to having the lowest BIC, MAE, and RMSE value for diagnostic first-order difference daily closing stock price in Nifty50.

Table 7: BIC Value of Suitable ARIMA (p, d, q) Model

Model (p, d, q)	BIC	MAE	RMSE
ARIMA (0, 1, 0)	9.252	80.563	100.110
ARIMA (0, 1, 1)	**8.612**	**51.303**	**71.226**
ARIMA (1, 1, 0)	9.048	70.783	88.616
ARIMA (1, 1, 1)	8.657	52.382	71.422
ARIMA (0, 1, 2)	8.671	53.019	71.910
ARIMA (1, 1, 2)	8.705	52.407	71.725
ARIMA (2, 1, 0)	8.884	60.873	80.012
ARIMA (2, 1, 1)	8.695	51.709	71.362
ARIMA (2, 1, 2)	8.732	52.080	71.252

In table 8, the more suitable ARIMA (0, 1, 1) model parameters estimated. That means p = 0, q = 1 lag with a first difference and MA(q) is occurring the negative values for not transform

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data. As the results indicate, none of these correlations is notably different from zero at a reasonable level.

Table 8: Model Parameters of ARIMA (0, 1, 1) N50

	Parameters	Estimate	SE	T	Sig
No Transformation	Constant	-1.215	6.147	-.198	.844
	Difference (d)	1			
	MA Lag 1 (q)	.035	.092	.375	.708

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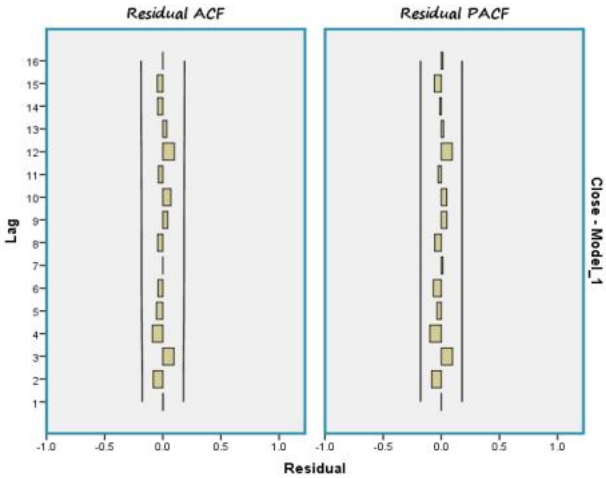

Figure 8: Residual ACF & PACF plot of ARIMA (0, 1, 1)

This proves that the chosen ARIMA model is an appropriate model. The ACF and PACF of the residuals (figure 8) also indicate 'good fit' of the model.

FTS Model

Step 1: Define the universe of discourse to accommodate the time series data. It needs the minimum and maximum closing stock prices and set as D_{min} and D_{max}.

MIN = 7908.25 and MAX = 8952.50 [D_1: 8.25, D_2: 47.50]; Thus universe of discourse U is defined as [$D_{min} – D_1$, $D_{max} + D_2$], here D_1 and D_2 are two positive numbers. In the present case of closing stock prices is U = [7900, 9000]

Step 2: Partition the universe of discourse into 5 equal length intervals U_1, $U_{2,}$…, U_5 such that U_1 = [7900, 8120]; U_2 = [8120, 8340]; U_3 = [8340, 8560]; U_4 = [8560, 8780]; U_5 = [8780, 9000]

Step 3: Define fuzzy sets on the universes of discourse using the historical linguistic data

A_1 = Large Decrease, A_2 = Decrease, A_3 = Increase, A_4 = Large Increase,

A_5 = Very Large Increase

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Step 4: Fuzzification of the time series data.

$U_1, U_2, \ldots, U_5 = [A_1, A_2, \ldots, A_5]$

Step 5: Computation of fuzzy numbers (Using "IF-THEN RULE" condition).

IF (Current Observation < max (U_1), "1", IF (Current Observation < max (U_2), "2", IF (Current Observation < max (U_3), "3", IF (Current Observation < max (U_4), "4", IF (Current Observation < max (U_5), "5")))))

Step 6: The logical relationship associated with the fuzzy numbers.

Table 9: Logical relationship of FTS method

$A_2 \rightarrow A_3$	$A_2 \rightarrow A_2$	$A_2 \rightarrow A_3$	$A_3 \rightarrow A_3$	$A_4 \rightarrow A_3$	$A_3 \rightarrow A_3$	$A_4 \rightarrow A_3$
$A_3 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_3 \rightarrow A_3$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$
$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_5 \rightarrow A_4$
$A_5 \rightarrow A_5$	$A_5 \rightarrow A_5$	$A_5 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_5$	$A_4 \rightarrow A_4$	$A_5 \rightarrow A_5$
$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_3$
$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_4$	$A_3 \rightarrow A_3$	$A_3 \rightarrow A_3$
$A_3 \rightarrow A_3$	$A_3 \rightarrow A_2$	$A_1 \rightarrow A_1$	$A_1 \rightarrow A_1$	$A_1 \rightarrow A_1$	$A_1 \rightarrow A_1$	$A_1 \rightarrow A_2$
$A_2 \rightarrow A_2$	$A_2 \rightarrow A_1$	$A_2 \rightarrow A_2$	$A_1 \rightarrow A_2$	$A_2 \rightarrow A_2$	$A_2 \rightarrow A_2$	$A_2 \rightarrow A_2$
$A_1 \rightarrow A_1$	$A_1 \rightarrow A_1$	$A_1 \rightarrow A_1$	$A_1 \rightarrow A_1$	$A_1 \rightarrow A_2$		

Step 7: Identifying the fuzzy numbers, then find the count (COUNT-IF RULE) and sum (SUM-IF RULE) conditions for the fuzzy number. Compute the average of each fuzzy groups (direct approach) A_1 to A_5 replaced by U_1 to U_5 intervals.

Table 10: Compute the prediction value of the FTS model

Fuzzy Numbers	Count	Sum	Prediction
A_1	20	160899.90	8044.99
A_2	19	156142.55	8218.03
A_3	19	161556.50	8502.97
A_4	55	476630.40	8666.01
A_5	9	79783.40	8864.82

6. COMPARISON RESULTS

In table 11, a comparison of error rates (RMSE & MAPE) for among models. The FTS model is more appropriate for the daily closing stock price because forecast accuracy is more sufficient for the other model.

Table 11: Prediction Accuracy of ARIMA & FTS

Models	Fit (Specify)	RMSE	MAPE
ARIMA	(0, 1, 1)	69.4311	0.6165
FTS	L.I = 5	61.6640	0.5746

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In figure 9, the FTS model prediction price is more fit and related to close (represent blue line) price. So that FTS line is a minimum risk of strong evidence for upcoming trading days.

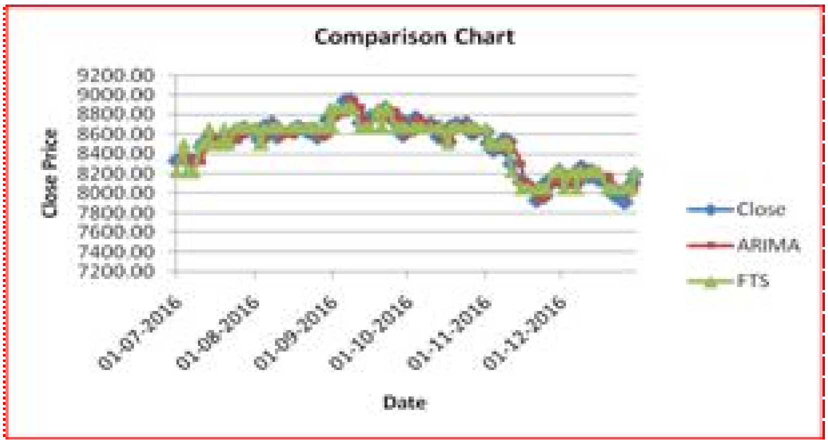

Figure 9: Actual and Prediction (methods) graph of close stock price

In figure 10, the prediction accuracy of Root Mean Square Error and Mean Absolute Percentage Error for the daily closing stock price. The Fuzzy Time Series (FTS) model occurs minimum errors of the other model.

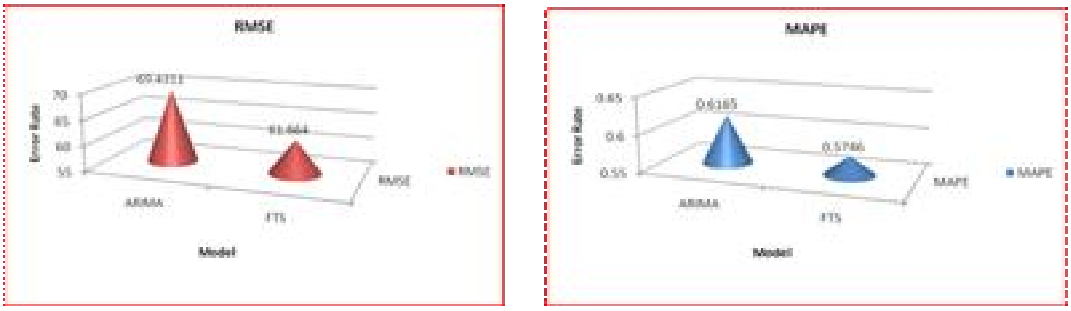

Figure 10: Error Rates of RMSE & MAPE

In table 12, prediction closing stock price of last 7 days of among three methods compared to actual closing stock price. This is numerical evidence for prediction accuracy for N50.

Table 12: Comparison of Actual and Prediction (7 days) for N50

Date	Close	ARIMA		FTS	
		Prediction	**SE**	**Prediction**	**SE**
22-12-2016	7979.10	8070.8	91.70	8044.99	65.89
23-12-2016	7985.75	8057.71	71.96	8044.99	59.24
26-12-2016	7908.25	8043.36	135.11	8044.99	136.74
27-12-2016	8032.85	8003.67	29.18	8044.99	12.14
28-12-2016	8034.85	8015.37	19.48	8044.99	10.14
29-12-2016	8103.60	8023.38	80.22	8044.99	58.61

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30-12-2016	8185.80	8089.95	95.85	8218.03	32.23
Prediction Accuracy		MAPE	0.93	MAPE	**0.67**

SE: Standard Error, MAPE: Mean Absolute Percentage Error

From figure 11, prediction of last 7 days closing stock price of among three methods and compared to actual closing stock price. It is graphically evidence for FTS as more appropriate to the ARIMA model.

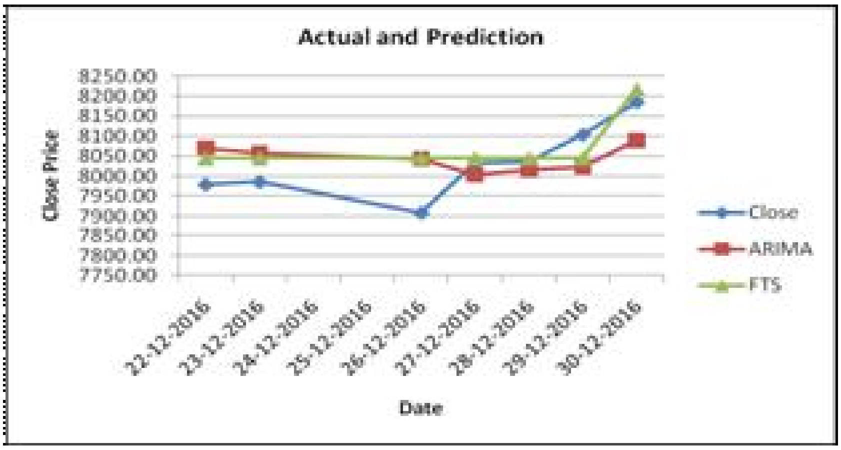

Figure 11: Comparison Graph of Last 7 Observations for N50

7. CONCLUSION

From the results of this study, India stock price is non-random. It is also known that crude oil prices are the cause of this non-random. The Fuzzy Time Series model is respectively relevant for future prediction. Due to the stagnant economic nature of India, such results are natural. There is no doubt that the policy and legal issues announced by the Government of India also affect the stock market.

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