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A Comparative Study of Various Forecasting Techniques in Predicting BSE S&P Sensex

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ABSTRACT

The study aims to compare various forecasting techniques in predicting the stock movements of BSE S&P 500. The study also aids in creating awareness in the investors, whether to invest or not and at the same time which type of tool the investors can consider as a basis for analyzing the future trend. The risk-return relationship is a fundamental concept in not only financial analysis, but in every aspect of life. In the current study, the data of the BSE S&P 500 collected for the period of Jan 2005 to Dec 2015. The tools which are used for data analysis are Simple moving average, weighted moving average, exponential smoothing and ARIMA. The selection of the best model is taken based on the values of minimum RMSE and MAD.

Key words: RMSE, MAD, ARIMA, simple moving average, weighted moving average, exponential smoothing

INTRODUCTION

Recently forecasting stock market return is gaining more attention, maybe because of the fact that if the direction of the market is successfully predicted the investors may be better guided. The profitability of investing and trading in the stock market to a large extent depends on predictability. If any system can be developed which can consistently predict the trends of the dynamic stock market, it would make the owner of the system wealthy. Moreover the predicted trends of the market will help the regulators of the market in making corrective measures. Another motivation for research in this field is that it possesses many theoretical and experimental challenges. The most important of these is the Efficient Market Hypothesis (EMH); see Eugene Fama’s (1970) “Efficient Capital Markets”. The hypothesis says that in an efficient market, stock market prices fully reflect available information about the market and its constituents and thus any opportunity of earning excess profit ceases to exist. So it is certain that no system is expected to outperform the market predictably and consistently. Hence, modeling any market under the assumption of EMH is only possible on the speculative, stochastic component not on the changes in value or other fundamental factors. Another related theory to EMH is the Random Walk Theory, which states that all future prices do not follow any trend or pattern and are random departures from the previous prices.

Review of Literature

Forecasting techniques can be categorized into two broad categories: quantitative and qualitative. The techniques in the quantitative category include mathematical models such as moving average, straight-line projection, exponential smoothing, regression, trend-line analysis, simulation, life-cycle analysis, decomposition, Box-Jenkins, expert systems, and neural network. The techniques in the qualitative

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category include subjective or intuitive models such as jury or executive opinion, sales force composite, and customer expectations (Kress, 1985; Mentzer & Kahn, 1995).

Typically, the two forms of forecasting error measures used to judge forecasting performance are mean absolute deviation (MAD) and mean absolute percentage error (MAPE). For both MAD and MAPE, a lower absolute value is preferred to a higher absolute value. MAD is the difference between the actual sales and the forecast sales. Absolute values are calculated over a period of time, and the mean is derived from these absolute differences. MAPE is used with large amounts of data, and forecasters may prefer to measure error in percentage (Wilson & Keating, 1994)

In many papers ARIMA model has been used as a benchmark model in order to compare the forecasting accuracy of the ANN. Jung-Hua Wang; Jia-Yann Leu developed a prediction system of recurrent neural network trained by using features extracted from ARIMA analysis. The results showed that the performance of the ARIMA was better than that of the basic forecasting techniques and at the same time ARIMA is also considered as better forecasting technique compared to Machine Learning Techniques. It was also asserted that useful prediction can be made even without the use of extensive data or knowledge.

Statement of the Problem

In the current scenario there are large numbers of forecasting techniques available in the market for prediction. We are not sure which forecasting technique is efficient and which techniques' input we have to consider as an input for decision making at the time of investment. The investor can generate the return only when he predicts the market trend perfectly. So this study mainly concentrates on analyzing and comparing most commonly used different forecasting techniques and finding out the most suitable technique in predicting the stock market indices through which we can minimize the risk.

Objectives of the Study

The main objective of the study is to develop the forecasting models to forecast most popular Stock Market Indices by using different types of techniques like Simple Moving Average, Weighted Moving Average, Exponential Smoothing, Time Series Analysis, Regression and Auto Regression Integrated Moving Average. And to fit, the best suited time series models for the data collected with the help of forecasting accuracy measures like RMSE and MAD. The following are the specific objectives of the current study:

a. To evaluate various forecasting models available in financial forecasting process and to discuss about their advantages and disadvantages.

b. To examine the volatility behaviour of selected financial indices for a particular period of time by using plots like ACF and PACF.

c. To analyze and build the financial model for forecasting selected stock market indices.

Hypothesis of the Study

H_1: There is no significant difference between Simple Moving Average, Weighted Moving Average, Exponential Smoothing, Time Series Analysis, Regression and Auto Regression Integrated Moving Average in predicting BSE S&P sensex.

Research Methodology:

Research Type: Quantitative Research

Research Design: Conclusive Research

SOURCES OF THE DATA:

Secondary Source: The study is purely based on secondary data. The data for the study is collected from **www.bseindia.com**

Description of Research Data: In the current study, the monthly data from BSE S&P sensex, collected for the period from Jan 2005 to Dec 2015 (120 observations), is taken from the Historical indices of BSE index collected from www.bseindia.com etc.,

Plan of Analysis/ Tools for Analyzing Secondary Data:

Simple Moving Average, Weighted Moving Average, Exponential Smoothing, Time Series Analysis, Regression and Auto Regression Integrated Moving Average with Single Input.

Empirical Analysis:

Simple Moving Average:

A moving average forecast uses a number of most recent historical actual data values to generate an estimate. The moving average for 'n' number of times in the moving average is calculated as:

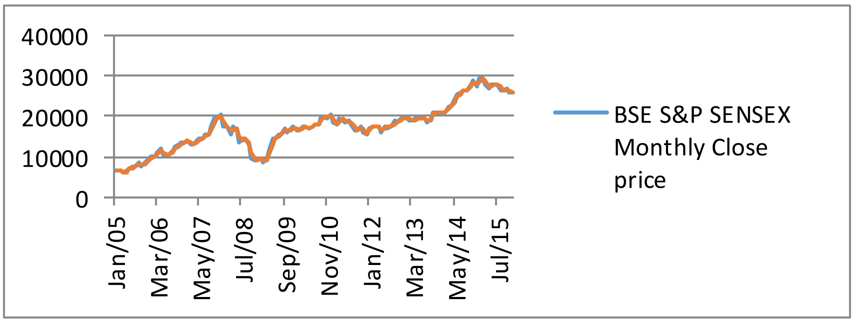
Moving average= {Σ (demand in previous n periods)/(N)};N may be 2, 3, 4, 5 ….., In the current analysis I used 2 months, 5 months, 7 months and 10 months moving average for predicting BSE S&P 500

Error measurement for Two months, Five months, Seven months and 10 months moving average:

Tools	RMSE	MAD
2 months simple moving average	525.0896728	400.762595
5 months simple moving average	1193.197351	934.330438
7 months simple moving average	1570.462242	1217.92139
10 months simple moving average	2050.224992	1627.86528

From the above table when the numbers of past months are increasing as input for the prediction, then automatically the performance of the tool is decreasing because the value of RMSE and MAD is increasing. Simple Moving average is efficient when fewer months' past data are chosen. For predicting BSE S&P 500 using simple moving average technique the best tool is two months' simple moving average

Actual vs Predicted graph using 2 months simple moving average of BSE S&P sensex 500



Exponential Smoothing: It is a sophisticated weighted moving average method that is even now comparatively easy to comprehend and use. It requires only three items of data: this period's forecast, the authentic demand for this time and α which is referred to as smoothing constant and having a value between 0 and 1. The formula used is:

Next period's forecast = This period's forecast + (α*(This period's actual demand-This period's forecast))

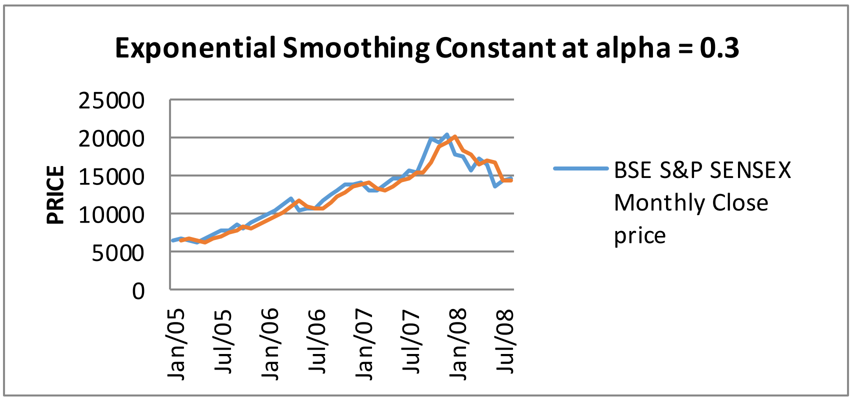
In the current study for predicting two different stock market indices, the researcher has taken three different values of smoothing constants, they are 0.3, 0.5 and 0.7.

Error Measurement in predicting BSE S&P 500 using Exponential Smoothing Constant

Exponential Smoothing	RMSE	MAD
when alpha = 0.3	1111.237087	862.6004772
when alpha = 0.5	1250.299299	978.8569667
when alpha = 0.7	1584.799117	1231.062689

From the above error measurement table it is clear that when the value of smoothing constant is increasing there is a large difference between the actual closing price and predicted prices. It means when the value of alpha is minimal, the error values are minimal which indicates that the predicted monthly closing prices are closer to the actual monthly closing prices of BSE S&P 500. The optimal value of alpha for exponential smoothing technique should be always less than 0.5, it means the value of alpha always has to lie between 0 – 0.5 for better prediction. The respective graphs for the selected model that is alpha = 0.3 for BSE S&P 500 are shown in the following Figure.

Actual vs Predicted graph of BSE S&P sensex 500 using Exponential Smoothing constant at alpha=0.3 .



Weighted Moving Average: In the **weighted moving average method** each earlier period demand in the moving average can have its own weight and the sum of the weight equals to one. For *example,* in a 2 period weighted moving average model, the most recent period might be assigned a weight of 0.70, the second most recent period might be assigned a weight of 0.30 and in a 3 months weighted moving average the weights assigned as follows as 0.5, 0.3 and 0.2 and where as in five months weighted moving average the weights are assigned as follows from latest to oldest as 0.4, 0.25, 0.2, 0.1 and 0.05. Then forecast,

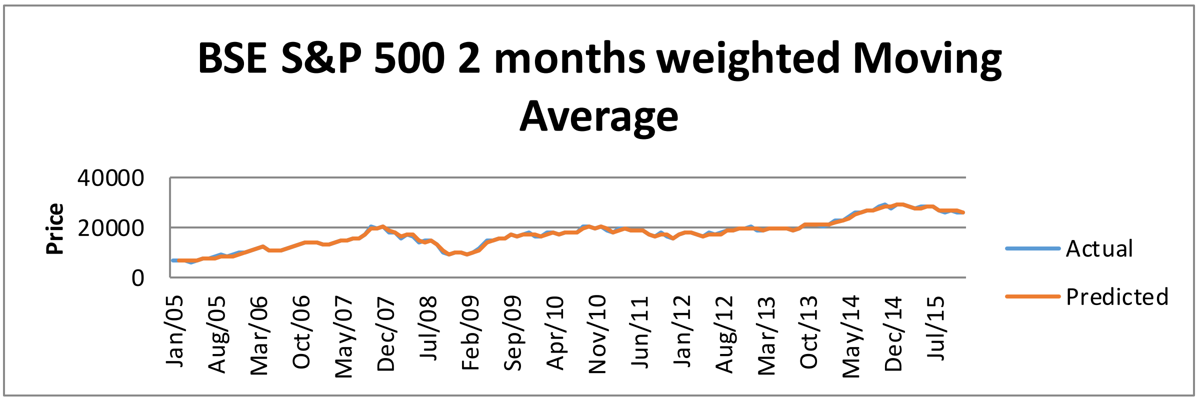
$$F_{t+1} = \{(0.5\, D_t + 0.3\, D_{t-1} + 0.2\, D_{t-2}) / (\text{sum of weights})\}$$

Error Measurement for BSE S&P 500 Using Weighted Moving Average

Tools	RMSE	MAD

2 months weighted moving average	97.1581914	73.82851145
3 months weighted moving average	174.1796746	129.6149615
5 months weighted moving average	231.9906292	177.8105078

Actual Vs Predicted Values Line Graph for BSE S&P 500 Using 2 months weighted moving average



Time Series Analysis for BSE S&P 500:

Under this model, my dependent variable is monthly closing price and independent variable is time. Here the researcher predicting the monthly closing price of BSE S&P 500 against time (month) as input. The below table gives the details of regression statistics, from here it is evident that the value of R-square is 0.801 which is nearer to one. So, the model what we generated is efficient.

Regression Statistics for BSE S&P 500 Financial model Generated by Using Time Series Analysis

Regression Statistics	
Multiple R	0.895008216
R Square	0.801039706
Adjusted R Square	0.799565927
Standard Error	2603.341045
Observations	60

	Coefficients
Intercept	-156686.0326
Date	4.307919619

$$Y = -156686.0326 + 4.307X$$

Where y = monthly closing price of BSE S&P 500

X= time

With the help of the above equation, the monthly closing prices of BSE S&P 500 and the residual errors by using Root Mean Sum Error (RMSE) and Mean Absolute Deviation (MAD) can be determined and it is as follows:

Error Measurement of BSE & NSE Sensex Using Time Series Analysis

	RMSE	**MAD**

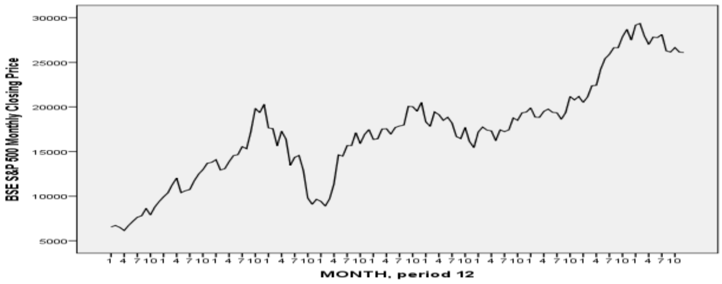
BSE S&P 500	2070.677248	2584.26869

ARIMA (Auto Regressive and Integrated Moving Average): Building of Arima Model for Prediction of BSE S&P 500:

In this section, modeling of prediction of closing prices of BSE S&P 500 is discussed. The development of ARIMA model for any variable involves mainly four steps: Identification, Estimation, Diagnostic Checking and Forecasting.

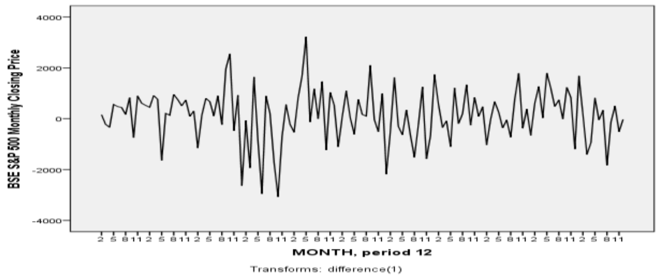
Model Identification:

Time series plots reveal that the data is non-stationary which is shown in the below figure.



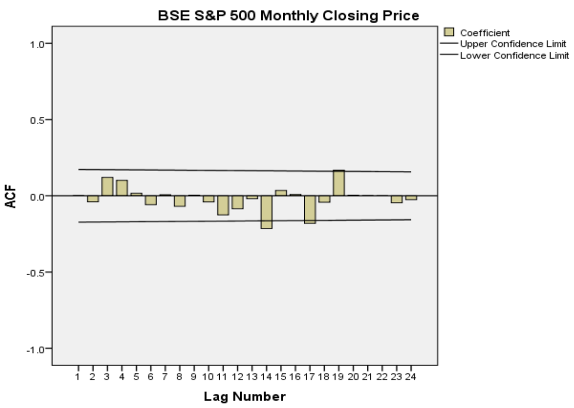
Time series plots of Stock Market Indices

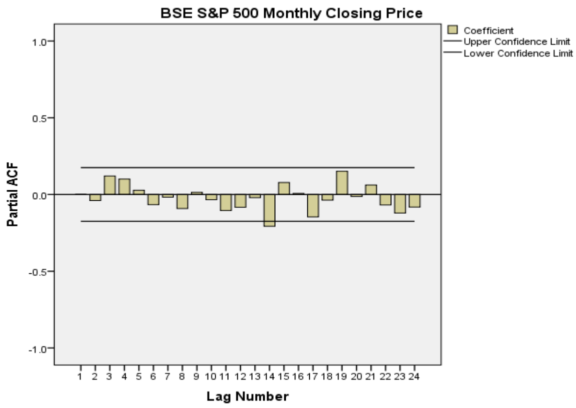
Non-stationarity in mean is corrected through appropriate differencing of the data. In this case, a non-seasonal difference of order 1 (i.e. d=1) is sufficient to achieve stationarity in mean and variance. The newly constructed variable can now be examined for stationarity.



Time series plot with non-seasonal difference of order 1 for Stock Market Indices

The above figure, shows that the data is stationary in mean and variance. The next step is to identify the values of p and q. The ACF and PACF for 24 lags are computed for the identification of parameters of ARIMA model is shown in below figure





Sample Autocorrelation Function and Partial Autocorrelation Function

Different ARIMA models are considered for different values of *p, d* and *q* and an ARIMA model is selected as a best model for forecasting based on maximum R-squared values and minimum RMSE value for predicting different exchange rates and indices considered in this study.

RMSE Values of Exchange Rates and Stock Market Indices using ARIMA for Different Values of p,d,q Under Time as input

Model Fit statistics

Model	p, d, q	Number of Predictors	Model Fit statistics					
			Stationary R-squared	R-squared	RMSE	MAPE	MAE	Normalized BIC
BSE S&P 500 Monthly Closing Price	1 0 0	1	.945	.945	1350.319	6.103	856.731	14.527
BSE S&P 500 Monthly Closing Price	0 0 1	1	.681	.681	3267.052	18.932	2540.793	16.294
BSE S&P 500 Monthly Closing Price	1 0 1	1	.945	.945	1365.159	6.118	857.665	14.586
BSE S&P 500 Monthly Closing Price	1 1 0	1	.005	.966	1048.749	4.980	781.865	14.022
BSE S&P 500 Monthly Closing Price	0 1 1	1	.005	.966	1048.749	4.980	781.870	14.022
BSE S&P 500 Monthly Closing Price	**1 1 1**	**1**	**.022**	**.967**	**1043.870**	**4.964**	**779.034**	**14.050**
BSE S&P 500 Monthly Closing Price	1 1 2	1	.024	.967	1046.976	4.946	774.851	14.093

BSE S&P 500 Monthly Closing Price	2 1 1	1	.024	.967	1046.911	4.944	774.450	14.093
BSE S&P 500 Monthly Closing Price	1 2 2	1	.501	.965	1062.947	5.032	788.880	14.125
BSE S&P 500 Monthly Closing Price	2 2 1	1	.490	.965	1074.232	5.070	793.935	14.146
BSE S&P 500 Monthly Closing Price	1 2 1	1	.489	.965	1070.803	5.075	795.471	14.102
BSE S&P 500 Monthly Closing Price	2 1 2	1	.033	.967	1046.219	4.875	763.561	14.129
BSE S&P 500 Monthly Closing Price	2 2 2	1	.502	.966	1065.853	5.035	786.678	14.168

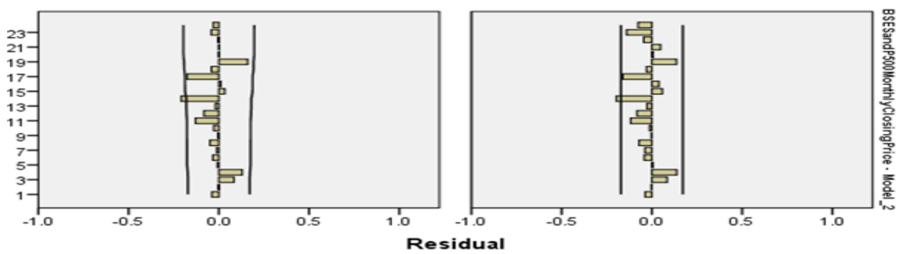
ARIMA Model Parameters for Exchange Rates and Stock Market Indices under Time as Input

					Estimate	SE	T	Sig.
BSE S&P 500 Monthly Closing Price	BSE S&P 500 Monthly Closing Price	No Transformation	Constant		58.552	200.135	.293	.770
			AR	Lag 1	-.907	.101	-9.022	.000
			Difference		1			
			MA	Lag 1	-.966	.075	-12.895	.000

$$Y_t = -58.55 - 0.907Y_{t-1} - 0.966\ e_{t-1}$$ ---------------------------- BSE S&P 500

Diagnostic Checking

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



The sample ACF and PACF plots of the residuals for Different Exchange Rates and Stock Market Indices under Time as Input using ARIMA

As results indicate, none of these autocorrelations is significantly different from zero at the level 0.05.

This proves that the model is an appropriate model.

Portmanteau Test: For this purpose, the various autocorrelations of residuals for 24 lags were computed and the same along with their significance are tested by Ljung-Box Q test statistic. Let the hypotheses on the model be

H_o : The selected model is adequate V/s H_1 : The selected model is inadequate

Significance Testing Using Ljung-Box Q Test Statistic Using ARIMA under Model I

Statistics	DF	Sig.	ARIMA (p,d,q)	Description
19.173	16	.260	1 1 1	Monthly Close Price of BSE S&P 500

Since the probability corresponding to Ljung-Box Q statistic is greater than 0.05, then accept H_o and concluded that the selected ARIMA model is an adequate model for prediction of three popularly traded exchange rates and three indices listed under BSE S&P Index. There is no difference between actual and predicted values. The forecast values for all the selected data and the respective graphs are presented as follows:

FINDINGS

- When the number of past months is increasing as input for the prediction, then automatically the performance of the tool is decreasing because the value of RMSE and MAD is increasing, in the case of Simple Moving average, weighted moving average and exponential smoothing constant.
- These techniques are efficient when fewer months' past data are chosen.
- The forecasting techniques are selected based on minimum values of RMSE and MAD.
- The optimal value of alpha for exponential smoothing technique should be always less than 0.5, it means the value of alpha always has to lie between 0 – 0.5 for better prediction.
- The value of smoothing constant is increasing there is a large difference between the actual closing price and predicted prices. It means when the value of alpha is minimal the error values are minimal which indicates that the predicted monthly closing prices are closer to the actual monthly closing prices.
- But there is quite reverse situation raised under auto regressive integrated moving average because when the number of inputs are increasing the prediction is very closer to actual values.
- When the inputs are increasing in ARIMA, then automatically the values of p and q are increasing for minimizing the gap between the actual and predicted values.

SUGGESTIONS

- It's very important for the investors to analyze the movements of stock prices in future and decide whether to buy or sell the stocks. To find this out, it is better to take the decision based on advanced forecasting techniques.
- If the investor is not efficient in analyzing the data using advanced forecasting techniques then at that time compared to simple moving average he has to use weighted moving average technique because according to Random walk hypothesis – current price has more impact on future prediction. Even in weighted moving average we give more weightage to recent and current months for analyzing the future patterns.
- If the investor wants to take the decision based on using only time series models at that time it is advised for the investor to use only weighted moving average compared to simple moving average and exponential smoothing.
- It is also advised that stock markets are full of fluctuations and in order to have a better prediction, first the investor has to stabilize the market by differencing the data.
- Instead of considering time or previous months closing price as inputs for prediction, if we increase the number of parameters as input like time, monthly open price, high price and low price, then it leads to better prediction with minimal error.

CONCLUSION

In the current study, a comparative study is made between basic and advanced models which can be used very widely for the prediction. Usually the prediction is done by considering the previous data as input. In the current study the techniques used are simple moving average, weighted moving average, exponential smoothing constant, time series analysis and an ARIMA. From this analysis it is observed that if the input data is smoothened then the future values can be predicted which are very closer to actual, which happened in ARIMA. Whereas in SMA WMA and ES the researcher has not done the smoothing of the input data, and due to this, techniques are efficient only when number of input are less, whereas it is a quite reverse in ARIMA.

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