

STUDY OF EFFECTIVENESS OF TIME SERIES MODELING (ARIMA) IN FORECASTING STOCK PRICES

Prapanna Mondal¹, Labani Shit¹ and Saptarsi Goswami²

¹ Student, Bachelor of Technology
Department of Computer Science and Engineering
Institute of Engineering and Management

² Asst. Professor
Department of Computer Science and Engineering
Institute of Engineering and Management

ABSTRACT

Stock price prediction has always attracted interest because of the direct financial benefit and the associated complexity. From our literature review, we felt the need of a study having sector specific analysis with a broad range of stocks. In this paper, we have conducted a study on the effectiveness of Autoregressive Integrated Moving Average (ARIMA) model, on fifty six Indian stocks from different sectors. We have chosen ARIMA model, because of its simplicity and wide acceptability of the model. We also have studied the effect on prediction accuracy based on various possible previous period data taken. The comparison and parameterization of the ARIMA model have been done using Akaike information criterion (AIC). The contribution of the paper, are a) coverage of a good number of Indian stocks b) Analysis of the models based on sectors c) Analysis of prediction accuracy based on the varying span of previous period data.

KEYWORDS

Stock price prediction, Indian Stocks, Sector, Time Series, ARIMA.

1. INTRODUCTION

A time series is a set of well-defined data items collected at successive points at uniform time intervals. Time series analysis is an important part in statistics, which analyzes data set to study the characteristics of the data and helps in predicting future values of the series based on the characteristics. Forecasting is important in fields like finance, industry, etc. [1] Autoregressive and Moving Average (ARMA) model is an important method to study time series. The concept of autoregressive (AR) and moving average (MA) models was formulated by the works of Yule, Slutsky, Walker and Yaglom [1]. Autoregressive Integrated Moving Average (ARIMA) is based on ARMA Model. The difference is that ARIMA Model converts a non-stationary data to a

stationary data before working on it. ARIMA model is widely used to predict linear time series data. [3] The ARIMA models are often referred to as Box-Jenkins models as ARIMA approach was first popularized by Box and Jenkins. The general transfer function model employed by the ARIMA procedure was discussed by Box and Tiao (1975) [3]. ARIMA model is often referred to as ARIMAX model when it includes other time series as input variables. [18] Pankratz (1991) refers to the ARIMAX model as dynamic regression. [3] The ARIMA procedure offers great flexibility in univariate time series model identification, parameter estimation, and forecasting.

Stock prices are not randomly generated values rather they can be treated as a discrete time series model and its trend can be analyzed accordingly, hence can also be forecasted. There are various motivations for stock forecasting [12], one of them is financial gain. A system that can identify which companies are doing well and which companies are not in the dynamic stock market will make it easy for investors or market or finance professionals make decisions.

Having an excellent knowledge about share price movement in the future helps the investors and finances personals significantly [2]. Since, it is necessary to identify a model to analyze trends of stock prices with relevant information for decision making, it recommends that transforming the time series using ARIMA is a better approach than forecasting directly, as it gives more accurate results [6]. But only predicting will not help if one cannot figure out the efficiency of the result. Thus, this paper focuses on finding the accuracy of predicted values using ARIMA model on the NSE stocks for various companies from various sectors.

In this paper, we have mainly focused on the amount of accuracy of forecasting stock values for various sectors which will help investors understand the market and make a decision to invest in the stock market. The organization of the paper is as follows. In section II, we discuss about the various applications of ARIMA model. In section III, we provide details about the dataset on which we have conducted our experiment. In section IV, we discuss about our experimental steps in details. Section V shows the experimental results and in section VI we conclude.

2. RELATED WORKS

Stock forecasting has been the topic of many surveys and review articles to evaluate the accuracies of different statistical technique [8] [9] [10]. At present most of the study is based on stock market trend prediction using ARIMA-based neural networks [11].[13] ARIMA is used as both analytical and forecasting models in the PACAP CCER China Database, developed by the Pacific

Basin Capital Markets (PACAP) Research Center at the University of Rhode Island (USA) and the SINOFIN Information Service Inc, affiliated with the China Center for Economic Research (CCER) of Peking University (China). [2] ARIMA has been applied to solve real world problems in the stock market by forecasting the stock prices with the top four companies in Nifty Midcap-50 using MATLAB along with performance measure.[15] Combining fuzzy regression model and ARIMA model, fuzzy ARIMA (FARIMA) model was developed for the purpose of forecasting the exchange rate of NT dollars to US Dollars. [16] Another purpose for which ARIMA model have been used was for predicting or forecasting price more specifically electricity price of the next day. Mostly the studies and experiments that were conducted were based on forecasting stock prices of a particular stock, whereas our study emphasizes more on a sector specific study related to stock forecasting.

3. DATASETS

We have taken historical data of National Stock Exchange (NSE) fifty six companies from seven sectors, eight companies in each sector from the official website of NSE India [19]. We have taken twenty three months of training data from April 2012 to February 2014 and predicted next months' data. We have also divided our dataset into three different time periods, one is of six months' from September 2013 to February 2014, another is of twelve months' from March 2013 to February 2014 and the other is of eighteen months' from September 2012 to February 2014.

4. METHODOLOGY

4.1 STEP I: MODEL SELECTION , FITTING AND FORECASTING:

4.1.1 Model identification: (ARIMA) model is derived by general modification of an autoregressive moving average (ARMA) model. This model type is classified as ARIMA(p,d,q), where p denotes the autoregressive parts of the data set, d refers to integrated parts of the data set and q denotes moving average parts of the data set and p,d,q is all non-negative integers.

ARIMA models are generally used to analyze time series data for better understanding and forecasting. Initially, the appropriate ARIMA model has to be identified for the particular datasets and the parameters should have smallest possible values such that it can analyze the data properly and forecast accordingly. [14] The Akaike Information Criteria (AIC) is a widely used measure of a statistical model. It is used to quantify the goodness of fit of the model. When comparing two or more models, the one with the lowest AIC is generally considered to be closer with real data. AICc is AIC with a correction for finite sample sizes.

The AIC does not penalize model complexity as heavily as the BIC (Bayesian Information Criterion) does. [7] Burnham & Anderson shows that AIC and AICc and BIC all can be derived in the same framework and using AIC/AICc for model selection is theoretically proved to be more advantageous than using BIC for selecting a model. As suggested by Yang (2005) [14], AIC is asymptotically optimal in selecting the model, under the assumption that the true model is not in the candidate set (as is virtually always the case in practice); BIC relies on the assumption that the true model is in the candidate set which makes it asymptotically less optimal. Hence, we preferred checking AICc values of data sets for selecting the model to checking the BIC values for the aforementioned.

According to Box-Jenkins method, in ARIMA (p, d, q) the value of p and q should be 2 or less or total number of parameters should be less than 3 [5]. Therefore, for checking AICc of the model we have only checked for p and q values 2 or less. The model with the least AICc value is selected [5]. We are showing our experimental results for model selection for stock of the company "Emami Limited". We have used R [20] for conducting our experiments.

MODEL	AICc
0,1,0	-2175.07
0,1,1	-2173.66
1,1,1	-2173.29
2,1,1	-2173.59
2,0,1	-2173.03
2,0,2	-2174.07
2,1,2	-2171.66
1,0,2	-2175.97
2,3,2	-2136.32

Table 1: AICc values of dataset of "Emami Limited" for different models

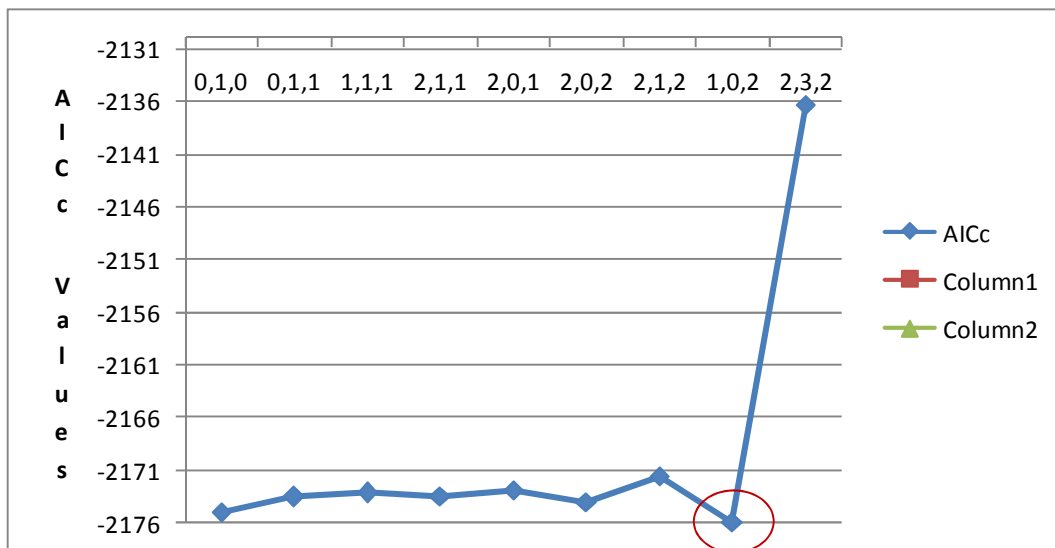


Figure 1: AICc values for different models

Depending on AICc, model ARIMA(1,0,2) is selected for the above mentioned stock.

4.1.2 Parameter Estimation:

The parameters estimated as per the model identified are as follows:

Coefficients				
	ar1	ma1	ma2	Intercept
	0.9863	-0.0158	-0.082	6.2366
S.E.	0.0073	0.0453	0.045	0.0714

Table 2: Estimated parameters for ARIMA(1,0,2) for dataset of Emami Limited

The coefficients show the AR and MA terms of the particular ARIMA model. S.E. denotes the standard error.

4.1.3 Checking the model:

The partial autocorrelation function (PACF) identifies the appropriate lag p in an extended ARIMA(p,d,q) model. Both ACF and PACF are used to check whether the model selected by AICc criterion is appropriate.

Model	ACF	PACF
MA (q): moving average of order q	Cuts off after lag q	Dies Down
AR (p): autoregressive of order p	Dies Down	Cuts off after lag p
ARMA (p,q): mixed autoregressive-moving average of order (p, q)	Dies Down	Dies Down
ARIMA (p, d, q): Autoregressive Integrated Moving Average of order (p, d, q)	Dies Down	Dies Down

Table 3: Role of ACF and PACF in selecting models

The identified model does not show significant lag in ACF and PACF of the residuals, hence the identified model was selected to analyze the aforementioned dataset.

After identifying the model, it was fitting for twenty three months', eighteen months', twelve months' and six months' stock prices and accordingly next thirty days' data were predicted.

4.2 STEP II: MEASURING THE ACCURACY OF PREDICTION AND STANDARD DEVIATION OF ACCURACY:

After prediction, the accuracy was measured in percentage. The actual data for 30 days that were predicted previously was collected from the same source and compared to measure the accuracy. We have used Mean Absolute Error (MAE) [17] method to compute the accuracy. The method is elaborated below:

- i) Firstly, the predicted values and the actual values are stored in a single matrix with two columns, namely PredictedVal and ActualVal containing the predicted and original values respectively.*
- ii) Then the error between the 2 columns are computed,*
$$err = | ActualVal - PredictedVal |$$
- iii) Next, we calculate the accuracy by,*
$$acc = 1 - err / ActualVal$$
- iv) Next, the percentage of accuracy is calculated by, $(acc * 100) \%$.*
- v) The individual accuracies are averaged to get the accuracy of for each sector.*
- vi) It is done for six, twelve, eighteen and twenty three months' training data separately.*

Lastly, we check the standard deviation of the accuracy of forecasting for each sector to get precise results. A smaller standard deviation indicates data members have closer value of the mean and a larger standard deviation denotes that the data are deviated from the mean to larger extent.

4.3 STEP III: PAIRED T-TESTING:

We conducted paired t-test for each pair of accuracies (all combinations possible) to test whether the difference between accuracy of prediction for different training datasets is significant. A paired t-test checks the difference between paired values within two samples. Each test produces a p-value. The p-values for each pair tests whether the coefficient of the null hypothesis is zero. A smaller p-value indicates that the null hypothesis can be rejected, and a higher p-value suggests that changes in the predictor are statistically insignificant.

Here, our null hypothesis is, the changes in the accuracy for different size of training datasets is not significant. If a p - value is lesser than this will be rejected, and it will be concluded that the differences between accuracy of prediction for different sizes of data is significant. Else, it will be accepted. The results are displayed in table 13.

5. EXPERIMENTAL RESULTS

The high price of stocks is taken into consideration for implementation. All the implementation works are done through R [20]. All the series are stationary.

The accuracy of prediction for different sectors are computed by averaging the accuracies obtained by the algorithm of top eight companies in that sector. The result is given below in Table 3.

Sector	Accuracy of prediction (in %) for twenty three months' training data	Accuracy of prediction (in %) for eighteen months' training data	Accuracy of prediction (in %) for twelve months' training data	Accuracy of prediction (in %) for six months' training data
1. Information Technology (IT)	91.06	93.77	93.79	94.03
2. Infrastructure	91.29	91.56	91.58	90.88
3. Bank	90.51	89.37	89.57	88.54
4. Automobile	87.89	85.32	85.78	85.91
5. Power	92.28	92.21	92.21	92.03
6. Fast Moving Consumer Goods (FMCG)	95.93	95.70	95.44	95.85
7. Steel	90.46	89.14	90.29	89.41

Table 4: Accuracy of prediction using ARIMA for seven sectors

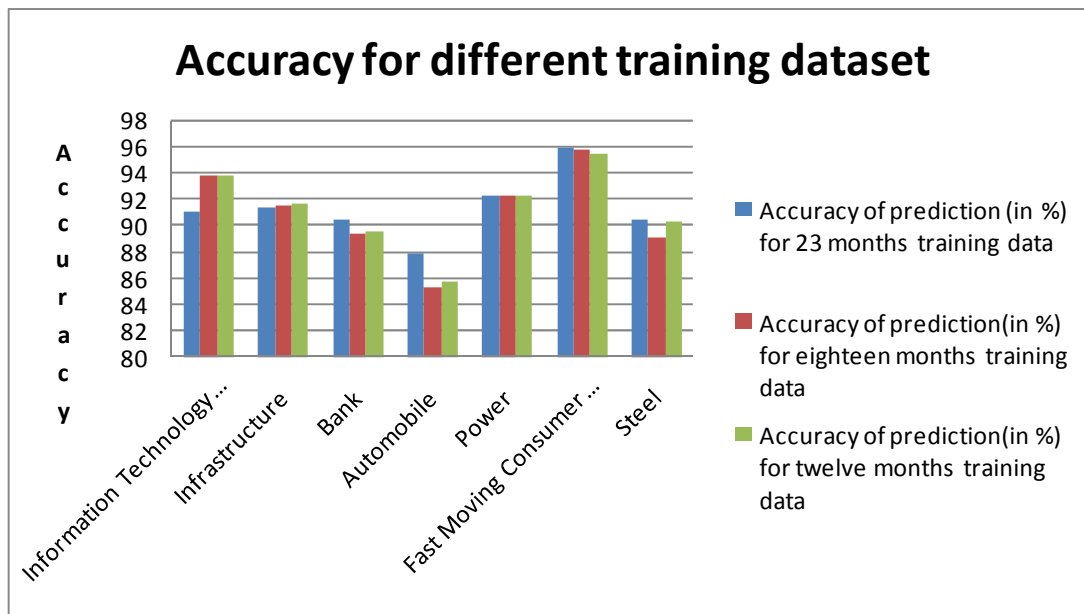


Figure 2: Accuracy for different training data sets

Next we show the result for each company in table 5,6,7,8,9,10,11 for the automobile sector, banking sector, infrastructure sector, steel sector, FMCG sector, IT sector and power sector respectively.

1. Automobile sector:

Company name	Accuracy of prediction(in %) for twenty three months' training data	Accuracy of prediction(in %) for eighteen months' training data	Accuracy of prediction(in %) for twelve months' training data	Accuracy of prediction(in %) for six months' training data
Ashok Leyland	85.99	85.32	85.66	84.37
Bajaj	93.02	93.82	94.72	94.45
Hero Moto Corp.	92.23	92.09	92.23	95.80
Hind Motors	86.67	91.74	93.05	93.41
Mahindra & Mahindra	94.84	94.26	94.45	94.26
Maruti Suzuki	84.99	85.04	78.85	85.65
Tata Motors	95.58	95.32	95.73	94.45
TVS	69.78	44.31	51.55	43.88

Table 5.Results for automobile sector

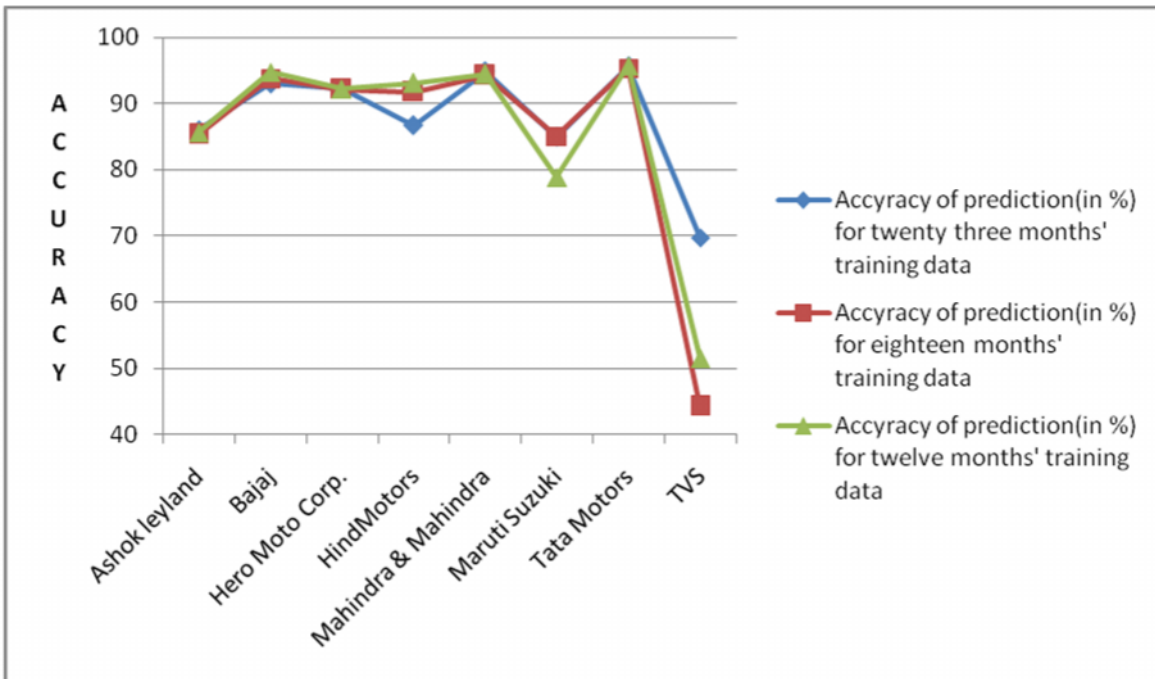


Figure 3: accuracy for automobile sector

2. Banking Sector:

Company name	Accuracy of prediction (in %) for twenty three months' training data	Accuracy of prediction (in %) for eighteen months' training data	Accuracy of prediction (in %) for twelve months' training data	Accuracy of prediction (in %) for six months' training data
Axis bank	85.49	85.48	86.64	83.94
State bank of India	92.70	85.41	85.39	85.31
Bank of India	87.34	87.79	87.45	87.23
Bank of Baroda	84.49	83.98	84.86	82.74
HDFC	92.98	90.94	90.90	90.14
ICICI	88.26	88.97	89.16	85.36
IDBI	94.94	94.96	94.71	96.14
PSB	97.86	97.38	97.46	97.45

Table 6 Results for banking sector

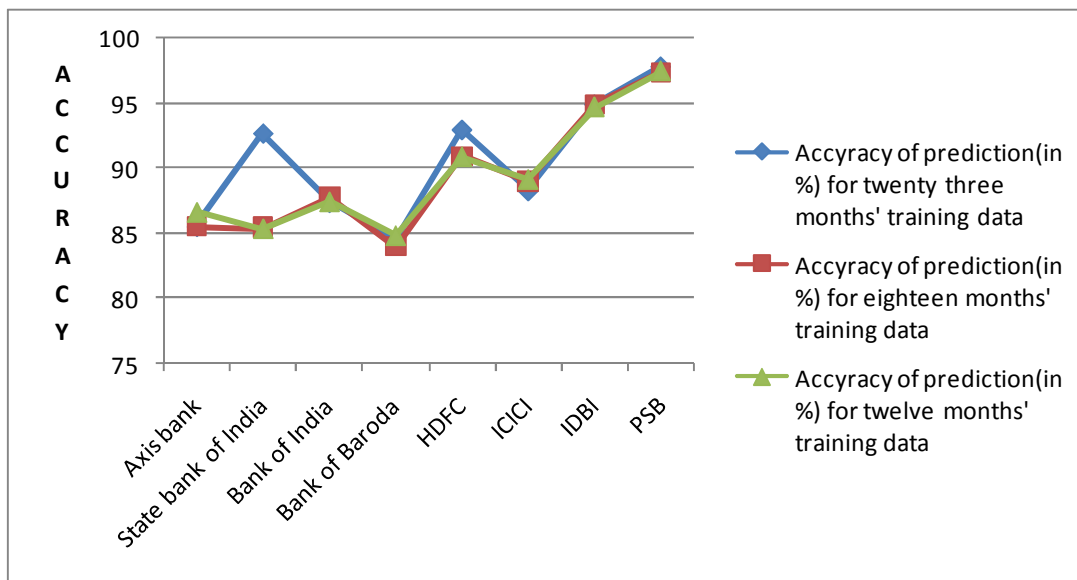


Figure 4:Accuracy for Banking sector

3. Infrastructure sector:

Company name	Accuracy of prediction (in %) for twenty three months' training data	Accuracy of prediction (in %) for eighteen months' training data	Accuracy of prediction (in %) for twelve months' training data	Accuracy of prediction (in %) for six months' training data
Ramky	82.84	91.01	91.93	92.08
JPIInfotech	95.19	95.51	96.57	95.97
RelIndia	92.13	91.48	91.94	91.21
GMRInfra	94.13	91.97	91.59	90.56
DLF	90.34	90.09	89.50	89.09
Simplex	84.84	85.03	84.82	78.56
Gammon	96.08	96.15	96.12	95.85
GodrejProperties	89.81	91.23	90.15	93.75

Table 7. Results for infrastructure sector

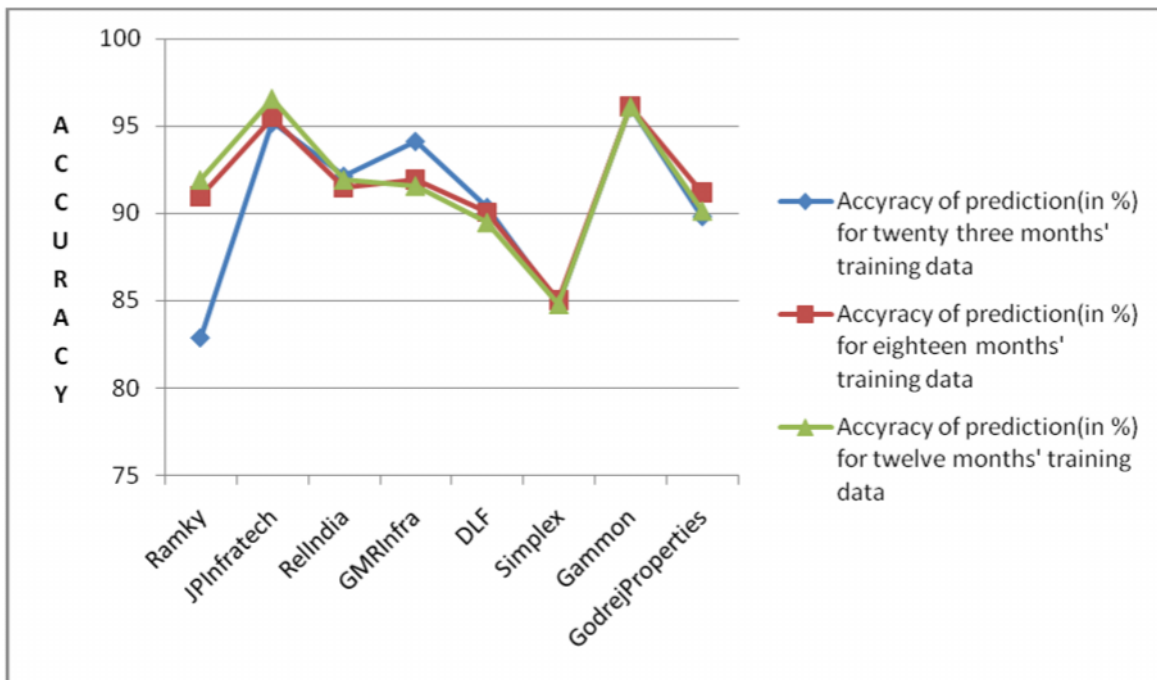


Figure 5:Accuracy for the infrastructure sector

4. Steel sector:

Company name	Accuracy of prediction (in %) for twenty three months' training data	Accuracy of prediction (in %) for eighteen months' training data	Accuracy of prediction (in %) for twelve months' training data	Accuracy of prediction (in %) for six months' training data
Tata Steel	95.16	96.43	96.33	96.27
Jindal Steel	94.99	95.96	95.76	94.07
VSSL	77.75	76.94	77.83	78.53
Visa Steel	96.75	95.56	95.47	89.66
SAIL	93.31	93.15	93.47	93.45
Bhusan Steel	98.94	97.67	98.17	96.99
Adhunik Steel	78.89	74.13	74.51	75.39
Sal Steel	87.91	90.51	90.84	90.91

Table 8. Results for steel sector

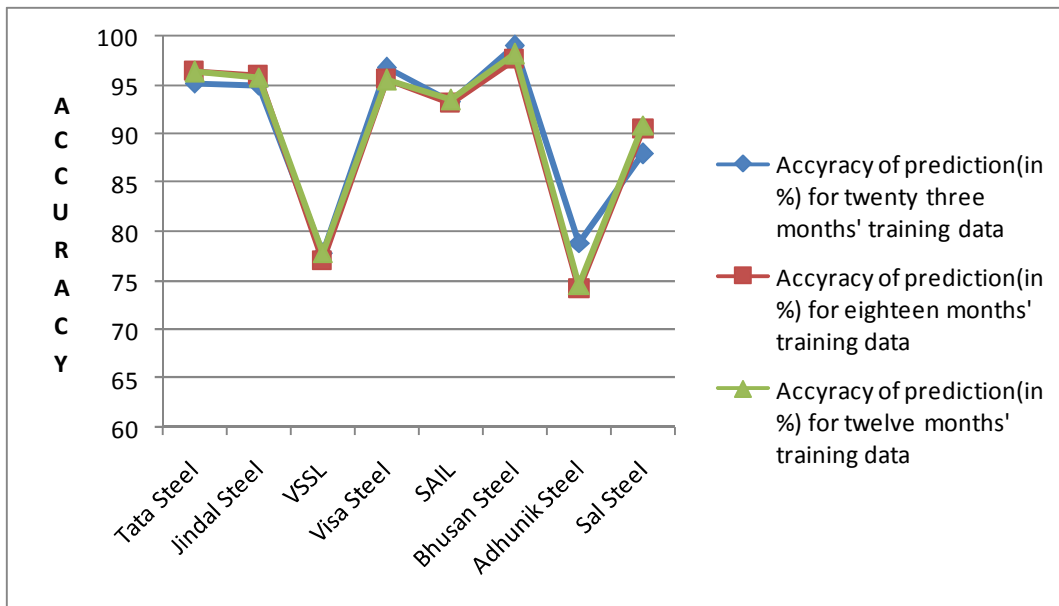


Figure 6. Accuracy for steel sector

5. FMCG:

Company name	Accuracy of prediction (in %) for twenty three months' training data	Accuracy of prediction (in %) for eighteen months' training data	Accuracy of prediction (in %) for twelve months' training data	Accuracy of prediction (in %) for six months' training data
Hindustan Unilever	96.36	96.90	97.04	97.66
Gillette	96.59	95.79	94.86	96.05
Colpal	97.56	98.41	98.55	96.58
ITC	92.05	92.03	93.38	94.01
Godrej	95.16	95.11	93.80	94.43
Emami	96.15	95.28	94.82	97.20
Nestle India	97.28	96.99	96.39	95.29
Dabur	96.27	95.11	94.68	95.56

Table 9. Results for FMCG sector

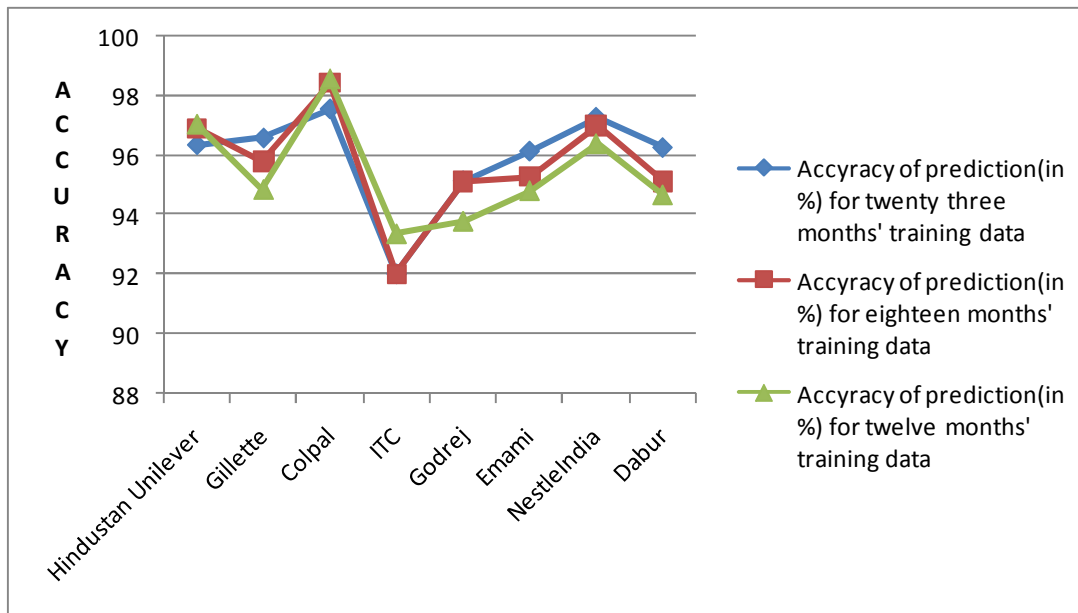


Figure 7: accuracy for FMCG sector

6. IT:

Company name	Accuracy of prediction (in %) for twenty three months' training data	Accuracy of prediction (in %) for eighteen months' training data	Accuracy of prediction (in %) for twelve months' training data	Accuracy of prediction (in %) for six months' training data
Tata Consultancy service	98.12	98.22	98.32	98.38
Infosys	93.85	93.48	93.68	93.54
Tech Mahindra	98.36	98.17	98.34	98.39
Wipro	97.56	97.56	96.04	97.38
HCLTech	97.48	97.23	97.51	97.11
Polaris	78.83	77.46	78.38	79.16
OFSS	97.65	97.68	97.44	97.36
Mindtree	90.81	90.61	90.61	90.35

Table 10. Results for IT sector

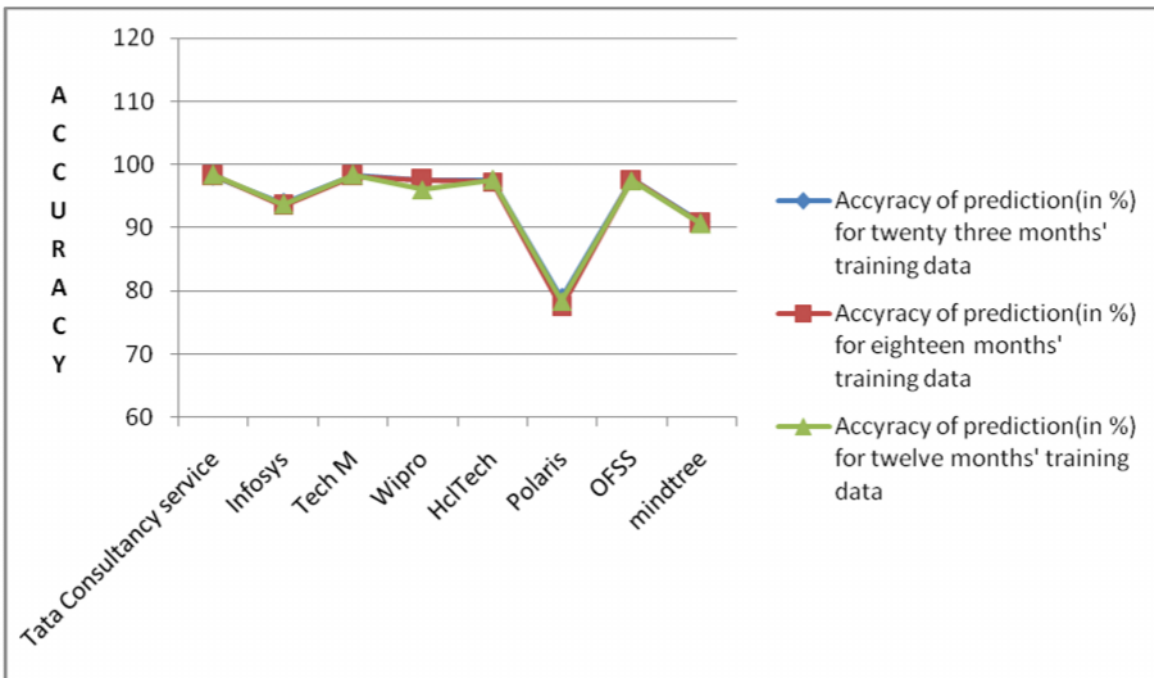


Figure 8: accuracy of IT sector

7. Power:

Company name	Accuracy of prediction (in %) for twenty three months' training data	Accuracy of prediction (in %) for eighteen months' training data	Accuracy of prediction (in %) for twelve months' training data	Accuracy of prediction (in %) for six months' training data
Tata Power	97.82	97.65	97.54	97.02
Reliance Power	96.84	97.47	96.41	97.25
Birla Power	86.61	86.41	86.69	86.67
NTPC	84.18	85.23	83.34	85.58
GPIL	93.43	93.40	94.77	96.28
GIPCL	95.36	94.93	95.38	95.07
Powergrid	96.26	95.66	96.19	95.89
JP Power	87.74	86.98	87.33	82.48

Table 11. Results for power sector

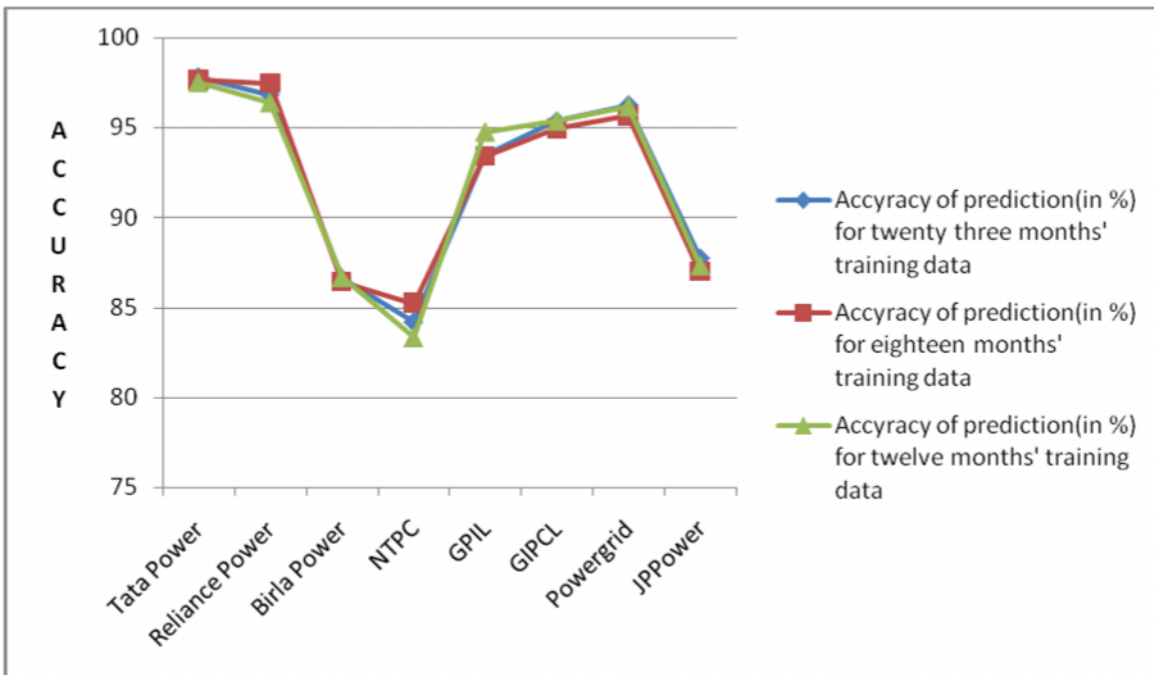


Figure 9: accuracy for Power sector

In the next table, we show the standard deviation of accuracy of prediction for each sector.

Sector	Standard deviation of twenty three months' training data	Standard deviation of eighteen months' training data	Standard deviation of twelve months' training data	Standard deviation of six months' training data
Automobile	8.401289	16.99188	14.96798	17.47848
Banking	8.238547	15.67122	13.36196	15.77012
Infrastructure	5.073215	3.744663	4.009234	5.63259
Steel	7.619857	8.663484	8.441142	7.718103
Fast Moving Consumer Goods	3.123484	2.468907	2.240957	2.035353
Information Technology	6.310874	6.693157	6.341761	6.193422
Power	4.980284	4.873199	5.168635	5.683261

Table 12: Standard deviation of accuracy of forecasting for different sectors

	Twenty three months' data	Eighteen months' data	Twelve months' data
Eighteen months' data	0.2902	–	–
Twelve months' data	0.3138	0.5896	–
Six months' data	0.1983	0.3874	0.3053

Table 13: Null hypothesis testing of accuracy of forecasting for different training data

6. CONCLUSION:

In this paper, we have conducted a study on fifty six stocks from seven sectors. All the stocks that are selected are listed in National Stock Exchange (NSE) [19]. We have selected twenty three months' of data for the set empirical study. We have evaluated the accuracy of the ARIMA model in predicting the stock prices. AICc has been used to select the best ARIMA model. In our study,

we have also changed the time period of previous or historic data and studied its effect on accuracy.

For all the sectors, Accuracy of ARIMA model in predicting stock prices is above 85%, which indicates that ARIMA gives good accuracy of prediction. If we discuss about specific sectors, forecasting stocks in FMCG sector using ARIMA model give result with best accuracy. On the other hand accuracy of predictions for the banking sector and automobile sector using ARIMA model is lower as compared to that of other sectors. Hence, we need a better model for forecasting stocks of the companies in aforementioned sector.

From the standard deviations of accuracy of forecasting of seven sectors, we see that Automobile sector, steel sector and the banking sector has a high standard deviation which means the values are spread over a large range, and there might be some stocks for which ARIMA model does not produce good results. For Information Technology sector, the standard deviation is not too low or not too high, whereas we are getting an above 90% accuracy in prediction for this sector. There may be a possibility that stock prices of companies of IT sector vary within a high range due to changes in value of the dollar and other factors.

We see that p-values for all possible combinations are high, hence we cannot reject the null hypothesis, i.e. the null hypothesis will be accepted which is, the changes in the accuracy for different size of training datasets is not significant.

REFERENCES

- [1] Chen, S., et al. "The time series forecasting: from the aspect of network." arXiv preprint arXiv:1403.1713 (2014).
- [2] Devi, B. Uma, D. Sundar, and P. Alli. "An Effective Time Series Analysis for Stock Trend Prediction Using ARIMA Model for Nifty Midcap-50."
- [3] Box, George EP, and George C. Tiao. "Intervention analysis with applications to economic and environmental problems." *Journal of the American Statistical Association* 70.349 (1975): 70-79.
- [4] Kofi agyarko ababio, June 2012, "Comparative study of stock price forecasting using arima and arimax models".
- [5] L-- Stern Group Ly Pham, Time Series Analysis with ARIMA – ARCH/GARCH model in R
- [6] Al Wadia, Mohd Tahir Ismail S, "Selecting Wavelet Transforms Model in Forecasting Financial Time Series Data Based on ARIMA Model", *Applied Mathematical Sciences*, Vol. 5, 2011, no. 7, 315 – 326
- [7] Anderson, David Raymond. *Model based inference in the life sciences: a primer on evidence*. New York: Springer, 2008.
- [8] Chatfield, Chris. *The analysis of time series: an introduction*. CRC press, 2013.
- [9] Christodoulos, Charisios, Christos Michalakelis, and Dimitris Varoutas. "Forecasting with limited data: Combining ARIMA and diffusion models." *Technological forecasting and social change* 77.4 (2010): 558-565.
- [10] Pai, Ping-Feng, and Wei-Chiang Hong. "An improved neural network model in forecasting arrivals." *Annals of Tourism Research* 32.4 (2005): 1138-1141.
- [11] Nayak, S. C., and B. B. Mishra. "A Neuro-Genetic Technique for Index Prediction.
- [12] Liang, Jiuzhen, Wei Song, and Mei Wang. "Stock price prediction based on procedural neural networks." *Advances in Artificial Neural Systems* 2011 (2011): 6.
- [13] Jarrett, Jeffrey E., and Eric Kyper. "ARIMA modeling with intervention to forecast and analyze chinese stock prices." *International Journal of Engineering Business Management* 3.3 (2011): 53-58.

- [14] Yang, Yuhong. "Can the strengths of AIC and BIC be shared? A conflict between model identification and regression estimation." *Biometrika* 92.4 (2005): 937-950.
- [15] Tseng, Fang-Mei, et al. "Fuzzy ARIMA model for forecasting the foreign exchange market." *Fuzzy sets and systems* 118.1 (2001): 9-19.
- [16] Contreras, J., Espinola, R., Nogales, F. J., & Conejo, A. J. (2003). ARIMA models to predict next-day electricity prices. *Power Systems, IEEE Transactions on*, 18(3), 1014-1020.
- [17] Willmott, Cort J., and Kenji Matsuura. "Advantages of the mean absolute error (MAE) over the root mean square error(RMSE) in assessing average model performance." *Climate Research* 30.1 (2005): 79.
- [18] A. Pankratz, *Forecasting with Dynamic Regression models*, Wiley Interscience, 1991.
- [19] http://www.nseindia.com/products/content/equities/equities/eq_security.htm.
- [20] R Development Core Team (2008). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL <http://www.R-project.org>.