Stock Price Prediction Using the ARIMA Model

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Abstract— Stock price prediction is an important topic in finance and economics which has spurred the interest of researchers over the years to develop better predictive models. The autoregressive integrated moving average (ARIMA) models have been explored in literature for time series prediction. This paper presents extensive process of building stock price predictive model using the ARIMA model. Published stock data obtained from New York Stock Exchange (NYSE) and Nigeria Stock Exchange (NSE) are used with stock price predictive model developed. Results obtained revealed that the ARIMA model has a strong potential for short-term prediction and can compete favourably with existing techniques for stock price prediction.

Keywords- ARIMA model, Stock Price prediction, Stock market, Short-term prediction.

I. INTRODUCTION

Prediction will continue to be an interesting area of research making researchers in the domain field always desiring to improve existing predictive models. The reason is that institutions and individuals are empowered to make investment decisions and ability to plan and develop effective strategy about their daily and future endevours. Stock price prediction is regarded as one of most difficult task to accomplish in financial forecasting due to complex nature of stock market [1, 2, 3]. The desire of many investors is to lay hold of any forecasting method that could guarantee easy profiting and minimize investment risk from the stock market. This remains a motivating factor for researchers to evolve and develop new predictive models [4].

In the past years several models and techniques had been developed to stock price prediction. Among them are artificial neural networks (ANNs) model which are very popular due to its ability to learn patterns from data and infer solution from unknown data. Few related works that engaged ANNs model to stock price prediction are [5, 6, 7]. In recent time, hybrid approaches has also been engaged to improve stock price predictive models by exploiting the unique strength of each of them [2]. ANNs is from artificial intelligence perspectives.

ARIMA models are from statistical models perspectives. Generally, it is reported in literature that prediction can be done from two perspectives: statistical and artificial ³Charles K. Ayo

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intelligence techniques [2]. ARIMA models are known to be robust and efficient in financial time series forecasting especially short-term prediction than even the most popular ANNs techniques ([8, 9, 10]. It has been extensively used in field of economics and finance. Other statistics models are regression method, exponential smoothing, generalized autoregressive conditional heteroskedasticity (GARCH). Few related works that has engaged ARIMA model for forecasting includes [11, 12, 13, 14, 15, 16].

In this paper extensive process of building ARIMA models for short-term stock price prediction is presented. The results obtained from real-life data demonstrated the potential strength of ARIMA models to provide investors short-term prediction that could aid investment decision making process.

The rest of the paper is organized as follows. Section 2 presents brief overview of ARIMA model. Section 3 describes the methodology used while section 4 discusses the experimental results obtained. The paper is concluded in section 5.

II. ARIMA MODEL

Box and Jenkins in 1970 introduced the ARIMA model. It also referred to as Box-Jenkins methodology composed of set of activities for identifying, estimating and diagnosing ARIMA models with time series data. The model is most prominent methods in financial forecasting [1, 12, 9]. ARIMA models have shown efficient capability to generate short-term forecasts. It constantly outperformed complex structural models in short-term prediction [17]. In ARIMA model, the future value of a variable is a linear combination of past values and past errors, expressed as follows:

$$Y_{t} = \phi_{t} + \phi_{t}Y_{t-1} + \phi_{t}Y_{t-2} + \dots + \phi_{p}Y_{t-p} + \varepsilon_{t} - \theta_{t}\varepsilon_{t-1} - \theta_{t}\varepsilon_{t-2} - \dots - \theta_{q}\varepsilon_{t-q}$$
(1)

where,

 Y_t is the actual value and \mathcal{E}_t is the random error at t, ϕ_i and θ_j are the coefficients, p and q are integers that are often referred to as autoregressive and moving average, respectively.



The steps in building ARIMA predictive model consist of model identification, parameter estimation and diagnostic checking [18].

III. METHODOLOGY

The method used in this study to develop ARIMA model for stock price forecasting is explained in detail in subsections below. The tool used for implementation is Eviews software version 5. Stock data used in this research work are historical daily stock prices obtained from two countries stock exchanged. The data composed of four elements, namely: open price, low price, high price and close price respectively. In this research the closing price is chosen to represent the price of the index to be predicted. Closing price is chosen because it reflects all the activities of the index in a trading day.

To determine the best ARIMA model among several experiments performed, the following criteria are used in this study for each stock index.

- Relatively small of BIC (Bayesian or Schwarz Information Criterion)
- Relatively small standard error of regression (S.E. of regression)
- Relatively high of adjusted R²
- Q-statistics and correlogram show that there is no significant pattern left in the autocorrelation functions (ACFs) and partial autocorrelation functions (PACFs) of the residuals, it means the residual of the selected model are white noise.

The subsections below described the processes of ARIMA model-development.

A. ARIMA (p, d, q) Model for Nokia Stock Index

Nokia stock data used in this study covers the period from 25th April, 1995 to 25th February, 2011 having a total number of 3990 observations. Figure 1 depicts the original pattern of the series to have general overview whether the time series is stationary or not. From the graph below the time series have random walk pattern.

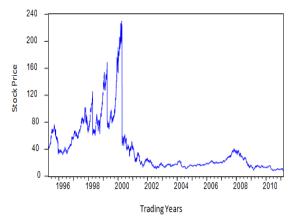


Figure 1: Graphical representation of the Nokia stock closing price index

Figure 2 is the correlogram of Nokia time series. From the graph, the ACF dies down extremely slowly which simply means that the time series is nonstationary. If the series is not stationary, it is converted to a stationary series by differencing. After the first difference, the series "DCLOSE" of Nokia stock index becomes stationary as shown in figure 3 and figure 4 of the line graph and correlogram respectively.

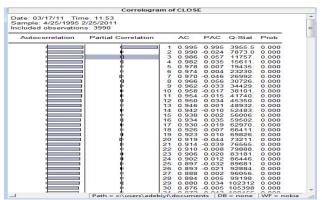


Figure 2: The correlogram of Nokia stock price index

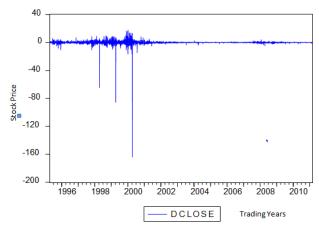


Figure 3: Graphical representation of the Nokia stock price index after differencing

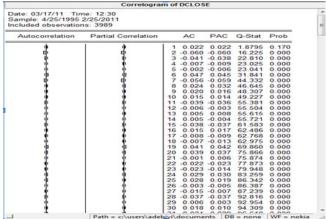


Figure 4: The correlogram of Nokia stock price index after first differencing

In figure 5 the model checking was done with Augmented Dickey Fuller (ADF) unit root test on "DCLOSE" of Nokia stock index. The result confirms that the series becomes stationary after the first-difference of the series.

Null Hypothesis: DCLOSE has a unit root Exogenous: Constant .ag Length: 1 (Automatic based on SIC, MAXLAG=30)						
- J J			t-Statistic	Prob.*		
ugmented Dickey-F		stic	-46.89879	0.0001		
est critical values:	1% level		-3.431805			
	5% level		-2.862068			
	10% level		-2.567094			
*MacKinnon (1996) one-sided p-values.						
pendent Variable:	D(DCLOSE)	ation				
ugmented Dickey-F ependent Variable: lethod: Least Squar ate: 03/17/11 Tim ample (adjusted): cluded observations	D(DCLOSE) es e: 12:37 /28/1995 2/25/	2011	t-Statistic	Prob.		
ependent Variable: ethod: Least Squar ate: 03/17/11 Tim ample (adjusted): 4 cluded observations Variable	D(DCLOSE) es e: 12:37 /28/1995 2/25/ s: 3987 after a Coefficient	2011 djustments Std. Error				
pendent Variable: thod: Least Squar te: 03/17/11 Tim mple (adjusted): 4 luded observations Variable DCLOSE(-1)	D(DCLOSE) es es: 12:37 /28/1995 2/25/ s: 3987 after a Coefficient -1.037429	2011 djustments Std. Error 0.022121	-46.89879	0.0000		
pendent Variable: ethod: Least Squar ate: 03/17/11 Time imple (adjusted): 4 cluded observations Variable	D(DCLOSE) es e: 12:37 /28/1995 2/25/ s: 3987 after a Coefficient	2011 djustments Std. Error				
spendent Variable: ethod: Least Squar ate: 03/17/11 Time ample (adjusted): 4 cluded observations Variable DCLOSE(-1) D(DCLOSE(-1)) C	D(DCLOSE) es es: 12:37 /28/1995 2/25/ s: 3987 after a Coefficient -1.037429 0.060437	2011 djustments Std. Error 0.022121 0.015814 0.056703	-46.89879 3.821732 -0.146267	0.0000 0.0001		
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pendent Variable: thod: Least Squar tle: 03/17/11 Tim mple (adjusted): 4 cluded observations Variable DCLOSE(-1) D(DCLOSE(-1)) C squared justed R-squared E of regression	D(DCLOSE) es =: 12:37 :=: 12:37 :28/1995 2/25/ :: 3987 after a: Coefficient -1.037429 0.060437 -0.008294 0.491018 0.490762 3.580364	2011 djustments Std. Error 0.022121 0.015814 0.056703 Mean deper	-46.89879 3.821732 -0.146267 Indent var dent var	0.0000 0.0001 0.8837		
spendent Variable: ethod: Least Squar ate: 03/17/11 Tim mple (adjusted): 4 cluded observations Variable DCLOSE(-1) D(DCLOSE(-1)) C squared djusted R-squared E. of regression m squared resid	D(DCLOSE) es : 12:37 /28/1995 2/25/ s: 3987 after a Coefficient -1.037429 -0.060437 -0.008294 0.491018 0.490762 3.580364 51070.94	2011 djustments Std. Error 0.022121 0.015814 0.056703 Mean deper S.D. depen Akaike info	-46.89879 3.821732 -0.146267 Indent var dent var criterion	0.0000 0.0001 0.8837 0.000100 5.017265 5.389558 5.394292		
pendent Variable: thod: Least Squar te: 03/17/11 Tim mple (adjusted): 4 luded observations Variable DCLOSE(-1) D(DCLOSE(-1)) C squared justed R-squared justed R-squared justed R-squared	D(DCLOSE) es =: 12:37 :=: 12:37 :28/1995 2/25/ :: 3987 after a: Coefficient -1.037429 0.060437 -0.008294 0.491018 0.490762 3.580364	2011 djustments Std. Error 0.022121 0.015814 0.056703 Mean depen S.D. depen Akaike info	-46.89879 3.821732 -0.146267 Indent var dent var criterion iterion	0.0000 0.0001 0.8837 0.000100 5.017265 5.389558		

Figure 5: ADF unit root test for DCLOSE of Nokia stock index.

Table 1 shows the different parameters of autoregressive (p) and moving average (q) among the several ARIMA model experimented upon . ARIMA (2, 1, 0) is considered the best for Nokia stock index as shown in figure 6. The model returned the smallest Bayesian or Schwarz information criterion of 5.3927 and relatively smallest standard error of regression of 3.5808 as shown in figure 6.

Dependent Variable: Method: Least Squar Date: 03/19/11 Time Sample (adjusted): 4/ Included observations Convergence achieve	es e: 16:08 /28/1995 2/25/ e: 3987 after ac	djustments		
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C AR(2)	-0.007997 -0.059938	0.053504 0.015813	-0.149458 -3.790524	0.8812 0.0002
R-squared Adjusted R-squared S.E. of regression Sum squared resid .og likelihood Durbin-Watson stat	0.003593 0.003343 3.580866 51098.07 -10742.14 1.958555		dent var criterion terion	-0.007988 3.586866 5.389588 5.392744 14.36807 0.000153

Figure 6: ARIMA (2, 1, 0) estimation output with DCLOSE of Nokia index.

Figure 7 is the residual of the series. If the model is good, the residuals (difference between actual and predicted values) of the model are series of random errors. Since there are no significant spikes of ACFs and PACFs, it means that the residual of the selected ARIMA model are white noise, no other significant patterns left in the time series. Therefore, there is no need to consider any AR(p) and MA(q) further.

	Correlogram	of Residu	als		
ate: 03/17/11 Tin ample: 4/26/1995 cluded observation statistic probabili	2/25/2011	MA term(:	=)		
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
h	1 0	1 0.02	1 0.024	2.2903	
di di	l de	2 -0.05	3 -0.058	15.495	0.000
di .		3 -0.03	3 -0.036	21.331	0.000
4	1 0	4 -0.00	5 -0.007	21.433	0.000
10	1 0		0.004		0.000
ф	1 0		0.047		0.000
d)			4 -0.057		0.000
ф	1 0			45.262	0.000
•	1 0	9 0.02	3 0.018	47.298	0.000
•	1 9	10 0.01	7 0.016	48.502	0.000
di .	1 0	11 -0.03			0.000
10.	1 0	12 -0.00			0.000
10.	1 0		7 0.011	54.223	0.000
- 4	1 0		7 -0.002		0.000
dı.	1 0	15 -0.03			0.000
•	1 9	16 0.01			0.000
40	1 1	17 -0.00			0.000
4	. •	18 -0.00			0.000
40	1 1	19 0.04			0.000
4	1 9	20 0.04		75.295	0.000
4.	1 1	21 0.00			0.000
•	1 •	22 -0.02		76.928	0.000
•	1 •	23 -0.02		78.629	0.000
4	1 9		1 0.032	82.424	0.000
4	1 9	25 0.03		85.972	0.000
40	1 1	26 -0.00			0.000
•	1 4	27 -0.01;			0.000
q.	1 0	28 -0.03			0.000
4.	1 4	29 0.00	0.005	91.809	0.000
	Path = c:\users\adeb		0 0 0 0	3 = none	0 000

Figure 7: Correlogram of residuals of the Nokia stock index.

In forecasting form, the best model selected can be expressed as follows:

$$Y_t = \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \varepsilon_t \tag{2}$$

where, $\mathcal{E}_t = Y_t - \hat{Y_t}$ (i.e., the difference between the actual value of the series and the forecast value)

TABLE I: STATISTICAL RESULTS OF DIFFERENT ARIMA PARAMETERS FOR NOKIA STOCK INDEX

ARIMA	BIC	Adjusted R ²	S.E. of
			Regression
(1, 0, 0)	5.3936	0.9907	3.5824
(1, 0, 1)	5.3950	0.9907	3.5817
(2, 0, 0)	6.1061	0.9811	5.1157
(0, 0, 1)	8.8324	0.7126	19.9942
(0, 0, 2)	8.8871	0.6964	20.5490
(1, 1, 0)	5.3956	0.0002	3.5860
(0, 1, 0)	5.3937	0.0000	3.5859
(0, 1, 1)	5.3953	0.0002	3.5854
(1, 1,2)	5.3941	0.0035	3.5800
(2, 1, 0)	5.3927	0.0033	3.5808
(2, 1, 2)	5.3947	0.0031	3.5812

The bold row represent the best ARIMA model among the several experiments.

B. ARIMA (p, d, q) Model for Zenith Bank Index

The stock data of Zenith bank used in this study covered the period from 3rd January, 2006 to 25th February, 2011 with total of 1296 observations. Figure 8 is the original pattern of the series. From the graph there was upward movement of the index from 2006 and downward movement is observed

from 2008 possibly because of world financial crisis experienced at that time.

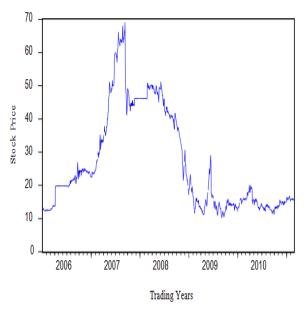


Figure 8: Graphical representation of the Zenith Bank stock index closing price.

Figure 9 is the correlogram of the time series of Zenith bank stock index. From the graph of the correlogram, the ACF dies down extremely slowly which simply means that the time series is nonstationary. If the series is not stationary, there is need to convert to stationary series by differencing. After the first difference, the series "DCLOSE" of Zenith bank stock index becomes stationary as shown in figure 10 and figure 11 of the line graph and correlogram of the series after first differencing.

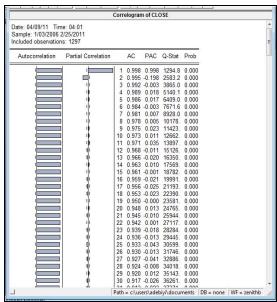


Figure 9: The correlogram of Zenith Bank stock price index

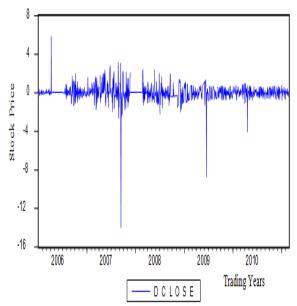


Figure 10: Graphical representation of the Zenith bank stock index first differencing

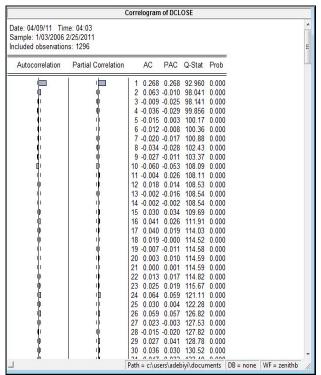


Figure 11: The correlogram of Zenith bank stock price index after first differencing.

Figure 12 is the ADF unit root test on "DCLOSE" of the series which also indicates the first difference of the series becomes stationary.

nenti roctoopeeti roper	col inschaan	10:1		DOL	0.05			
		ted Dickey-Ful	ler Unit Root	Test on DCL	OSE			
Null Hypothesis: DCL Exogenous: Constant	Null Hypothesis: DCLOSE has a unit root							
Lag Length: 0 (Autom		SIC, MAXLA	G=22)					
			t-Statistic	Prob.*				
Augmented Dickey-Fr	uller test stati:	stic	-27.33425	0.0000				
Test critical values:	1% level 5% level		-3.435188 -2.863564					
	10% level		-2.567897					
*MacKinnon (1996) or	ne-sided p-valu	ies.						
Augmented Dickey-Fi Dependent Variable: I Method: Least Square Date: 04/09/11 Time Sample (adjusted): 1/ Included observations	D(DCLOSE) s : 04:04 05/2006 2/25/	2011	t-Statistic	Prob.				
DCLOSE(-1) C	-0.732475 0.001779	0.026797 0.021843	-27.33425 0.081457	0.0000 0.9351				
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	0.366226 0.365736 0.786049 798.9102 -1524.772 1.994624	Mean deper S.D. depend Akaike info Schwarz cri F-statistic Prob(F-stati	dent var criterion terion	0.000139 0.986995 2.357948 2.365927 747.1610 0.000000				
		Path = c	:\users\adebiy	vi\document:	S DB = none WF = zenithb			

Figure 12: ADF unit root test for DCLOSE of Zenith bank stock index.

Table 2 shows the different parameters of autoregressive (p) and moveing average (q) of the ARIMA model in order to get the best fitted model. ARIMA (1, 0, 1) is relatively the best model as indicated in figure 13. The model returned the smallest Bayesian or Schwarz information criterion of 2.3736 and relatively smallest standard error of regression of 0.7872 as shown in figure 13.

Dependent Variable: Method: Least Squar Date: 04/09/11 Time Sample (adjusted): 1/Included observations Convergence achieve Backcast: 1/03/2006	es :: 04:24 04/2006 2/25/ :: 1296 after ac	djustments			
Variable	Coefficient	Std. Error	t-Statistic	Prob.	
C AR(1) MA(1)	27.76649 0.997704 0.254140	11.97506 0.001829 0.026934	2.318694 545.5149 9.435526	0.0000	
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	0.997254 0.997250 0.787215 801.2819 -1527.370 1.966274		dent var criterion terion	26.70431 15.01153 2.361682 2.373642 234805.8 0.000000	
Inverted AR Roots Inverted MA Roots	1.00 25				

Figure 13: ARIMA (1, 0, 1) estimation output with DCLOSE of Zenith bank index.

Figure 14 is the correlogram of residual of the seies. From the figure it is obvious there is no significant spike of ACFs and PACFs. This means that the residual of this selected ARIMA model are white noise. There is no other significant patterns left in the time series and there is no need for further consideration of another AR(p) and MA(q).

	L	orrelogram	of Resid	luais				
Date: 04/09/11 Tin								
Sample: 1/04/2006								
cluded observation								
l-statistic probabili	ties adjusted for 2 AF	lMA term(s)						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob			
ılı .	1 0	1 0.017	0.017	0.3672				
ıb	10	2 0.064	0.064	5.7132				
10	1 10	3 -0.015	-0.018	6.0217	0.014			
¢i	d di	4 -0.030	-0.034	7.1976	0.027			
101	1 10	5 -0.005	-0.002	7.2318	0.065			
10	1 1	6 -0.007	-0.003	7.3005	0.121			
ψ	10	7 -0.010						
4	0	8 -0.030						
10	l III	9 -0.004						
Qi	į į	10 -0.060						
10	l ili	11 0.008						
10	1 1	12 0.019						
10	1 10	13 -0.004						
10	10	14 -0.005						
1)))	15 0.025		14.723				
10	1 1		0.030					
10	1 1	17 0.031						
10	10	18 0.016						
Ψ.	ų ų	19 -0.011						
ų.	111	20 0.008		17.724				
ų.	111	21 -0.004		17.742				
ų.	1	22 0.014		17.991				
ų.	1 1		0.009	18.086				
y.	1 19		0.063					
T	1 12		0.006		0.439			
Y.	1 19	26 0.055						
4	1 4							
¥.	1 9	28 -0.025						
1		29 0.029	0.029	29.782	0.324			
1		Path = c:\use				DR = none	WF = zenithb	

Figure 14: Correlogram of residuals of the Zenith bank stock index.

In forecasting form, the best model selected can be expressed as follows:

$$Y_{t} = \phi_{1}Y_{t-1} - \theta_{1}\varepsilon_{t-1} + \varepsilon_{t}$$
 where. (3)

$$\mathcal{E}_t = Y_t - \hat{Y}_t$$
 (i.e., the difference between the actual value of the series and the forecast value)

TABLE II: STATISTICAL RESULTS OF DIFFERENT ARIMA PARAMETERS FOR ZENITH BANK STOCK INDEX

ARIMA	BIC	Adjusted	S.E. of
		\mathbb{R}^2	Regression
(1, 0, 0)	2.4385	0.9970	0.8151
(1, 0, 1)	2.3736	0.9972	0.7872
(2, 0, 0)	3.3682	0.9925	1.2974
(0, 0, 1)	6.9285	0.7372	7.6951
(0, 0, 2)	6.9815	0.7228	7.9018
(1, 1, 0)	2.3659	0.0708	0.7860
(0, 1, 0)	2.4338	0.0000	0.8151
(0, 1, 1)	2.3693	0.0669	0.7873
(1, 1,2)	2.3714	0.0701	0.7863
(2, 1, 0)	2.4370	0.0031	0.8144
(2, 1, 2)	2.4412	0.0036	0.8142

The bold row represent the best ARIMA model among the several experiments

IV. RESULTS AND DISCUSSION

The experimental results of each of stock index are discussed in the subsection below.

A. Result of ARIMA Model for Nokia Stock Price Prediction

Table 3 is the result of the predicted values of ARIMA (2, 1, 0) considered the best model for Nokia stock index. Figure 15 gives graphical illustration of the level accuracy of the predicted price against actual stock price to see the performance of the ARIMA model selected. From the graph, is obvious that the performance is satisfactory.

TABLE III: SAMPLE OF EMPIRICAL RESULTS OF ARIMA (2,1,0) OF NOKIA STOCK $\,$ INDEX.

Sample Period	Actual Values	Predicted Values
1/3/2010	13.28	13.58
2/3/2010	13.51	13.69
3/3/2010	13.86	13.80
4/3/2010	13.78	13.91
5/3/2010	14.13	14.02
8/3/2010	14.17	14.13
9/3/2010	14.12	14.24
10/3/2010	14.56	14.35
11/3/2010	14.49	14.45
12/3/2010	14.84	14.56
15/3/2010	14.81	14.67
16/3/2010	15.14	14.77
17/3/2010	15.42	14.88
18/3/2010	15.28	14.98
19/3/2010	15.07	15.09
22/3/2010	15.11	15.19
23/3/2010	15.26	15.30
24/3/2010	15.07	15.40
25/3/2010	15.20	15.50
26/3/2010	15.46	15.60
29/3/2010	15.42	15.71
30/3/2010	15.41	15.81
31/3/2010	15.54	15.91

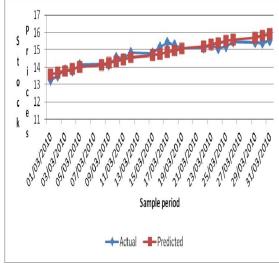


Figure 15: Graph of Actual Stock Price vs Predicted values of Nokia Stock Index

B. Result of ARIMA Model for Zenith Bank Stock Price Prediction

In this case, ARIMA (1, 0, 1) was selected as the best model for Zenith bank stock index after several adjustment of the autoregressive (p) and moving average (q) parameters in Eviews software used. Table 4 contained the predicted values of the model selected and figure 16 is the graph of predicted price against actual stock price to demonstrate the correlation of accuracy. From the graph, the performance of the ARIMA model selected is quite impressive as there are some instances of closely related of actual and predicted values.

TABLE IV: SAMPLE OF EMPIRICAL RESULTS OF ARIMA (1,0,1) OF ZENITH BANK INDEX

Sample Period	Actual Values	Predicted Values
1/3/2010	16.19	15.83
2/3/2010	15.98	15.86
3/3/2010	15.71	15.89
4/3/2010	15.50	15.91
5/3/2010	15.70	15.94
8/3/2010	15.75	15.97
9/3/2010	15.86	15.99
10/3/2010	16.00	16.02
11/3/2010	16.19	16.05
12/3/2010	16.99	16.08
15/3/2010	17.83	16.10
16/3/2010	17.71	16.13
17/3/2010	17.50	16.16
18/3/2010	16.85	16.18
19/3/2010	17.69	16.21
22/3/2010	18.00	16.24
23/3/2010	18.00	16.26
24/3/2010	17.85	16.29
25/3/2010	17.89	16.31
26/3/2010	18.11	16.34
29/3/2010	19.01	16.37
30/3/2010	19.96	16.39
31/3/2010	18.97	16.42

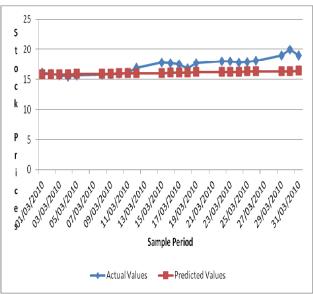


Figure 16: Graph of Actual Stock Price vs Predicted values of Zenith Bank Stock Index

V. CONCLUSION

This paper presents extensive process of building ARIMA model for stock price prediction. The experimental results obtained with best ARIMA model demonstrated the potential of ARIMA models to predict stock prices satisfactory on short-term basis. This could guide investors in stock market to make profitable investment decisions. With the results obtained ARIMA models can compete reasonably well with emerging forecasting techniques in short-term prediction.

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