International Journal of Development Mathematics Vol 2 Issue 2 Page No. 345 - 357

INTERNATIONAL JOURNAL OF DEVELOPMENT MATHEMATICS

ISSN: 3026-8656 (Print) | 3026-8699 (Online)

journal homepage: https://ijdm.org.ng/index.php/Journals

Application of ARMA Model in Forecasting Nigerian Stock Price Index (NSPI)

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ARTICLE INFO

Article history:
Received 20 Januarry 2025
Received in revised form 03 May 2025
Accepted 20 June 2025

Keywords:
Times Series, Metrics, ARMA, Performance Comparison, Stock Price Index.

MSC 2020 Subject classification:
62-XX, 62M10, 91B84.

ABSTRACT

This was designed to study and compare the performance of the autoregressive (AR), Moving average (MA) and Autoregressive moving average (ARMA) models in forecasting the Nigeria Stocks Price Index (NSPI). The data used for this study are secondarily sourced from 'All share index' of the Nigeria stock exchange rate between 2009 and 2024. A test for stationarity of the original data was carried out using the augmented Dickey-fuller (ADF) test and the test showed the non-stationarity of the observed data, hence a test for stationarity for differenced data set was carried out to achieved stationarity. The results from the analysis showed that the ARMA (1,0,1) model outperforms the AR (1) and MA (1) models with a lower Akaike information criterion (AIC), Mean square error (MSE), Mean absolute error (MAE) and Root mean Square Error (RMSE). The study therefore recommends that investors and financial institutions use the ARMA (1, 0, 1) model to forecast the Nigeria Stock price index for precision of results.

1. Introduction

A stock price index is a measure of the overall performance of a group of stocks traded on the stock exchange. It represents the value of a hypothetical portfolio of stocks and is used to track the performance of the stock market as a whole. Iliya et al (2024) stated that the stock market prices serve as a key indicator of market sentiment, economic performance and investor confidence, with a growing demand for accurate stock market predictions. An AR model predicts future values based on a linear combination of pass values of the index, on the other hand, MA model predict future values base on a linear combination of past forecast errors in forecast of the Nigeria stock price index. Glosten (1993) and Masoud (2013) defined the stock market as a very sophisticated marketplace as it is central to the creation and development of a strong and competitive economy. Information on the stock market provides investors with the status of the market value of the assets, and this serve as guild to business on their investment. According to Thompson (2019), due to its inherent volatility, the NSPI's accuracy in forecasting future values is questionable, as the unpredictable nature of the index can make it challenging to make precise prediction. Hence a comparative study between Autoregressive (AR) moving average (MA) and Autoregressive moving average (ARMA) models in forecasting the Nigeria stock price index (NSPI) could explore the accuracy of the three models in predicting future values of the NSPI. This could be done by comparing the forecast error, which is the difference between the actual value and the forecast value, for each model (Olomola, 2001). Additionally, the study could explore the computational complexity of the three models, as well as the ease of implementation and interpretation. The study could also consider factors such as seasonality, trend and volatility when evaluating the performance of the three models. The NSPI is a stock market index that tracks the performance of the Nigerian stock market. It is calculated by the Nigerian stock Exchange (NSE) and is a widely used indicator of market performance. The NSPI is known for its high volatility, which makes it difficult to predict. AR, MA and ARMA models are commonly used in financial forecasting, as they

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https://doi.org/10.62054/ijdm/0202.20
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are able to capture historical trends and patterns in the data. However, the high volatility of the NSPI can make it difficult to accurately forecast future values. According to Tan (2013) the NSPI's volatility is a major challenge for investors as it can experience significant fluctuation in value making it difficult to predict future values. The NSPI is its high volatility. This means that the NSPI experiences large fluctuation in value over time, making it difficult to predict future values. The NSPI is its seasonality. Seasonality refers to the tendency for the NSPI to follow certain pattern over time, such as an increase in value during certain months or quarters. This seasonality can be caused by a variety of factors, including economic conditions, investor sentiment and company earning. Understanding the seasonality of the NSPI can be useful in developing more accurate forecast. Forecasting the NSPI is important for investors and financial analysts for several reasons. First, it can help them make informed investment decision (Sylvester and Enabulu, 2011). Predicting future values of the NSPI could ensure investors make more informed decision about when to buy or sell stocks. Additionally, financial analysts can use forecasts of the NSPI to develop model and strategies for managing risk. Forecast can also be used to assess the performance of investment portfolios and identity opportunities for improvement. Finally, accurate forecast of the NSPI can help to increase the efficiency of the Nigerian stock market and improve investor confidence. The NSPI's vitality undermines its accuracy as the large fluctuations in value can lead to unreliable forecasts of future price (Michael, 2017). There are several challenges associated with forecasting the NSPI. The high volatility of the NSPI can make it difficult to develop accurate forecast (Maana, 2015). The NSPI have a limited availability of historical data, which can make it difficult to develop model that accurately capture the dynamics of NSPI change in macroeconomics environment such as changes in interest rates or inflation, can affect the NSPI in ways that are difficult to predict. NSPI is affected by unpredictable events, such as political development or natural disaster, which can make it difficult to develop accurate forecasts. Autocorrelation is a challenge associated with forecasting the NSPL, is the presence of relationship between the current value of the NSPL and it past values. This can make it difficult to distinguish between random fluctuation in the NSPL and true changes in trend. The NSPI's unpredictable fluctuation in values, present challenges for forecasting future values, as the index can experience rapid and large swings in price (David, 2017). Jena (2018) opined that to overcome this challenge, analysts may use time-series model that account for autocorrelation, such ARIMA (autoregressive integrated moving average) model. With these models, there is still the possibility of over fitting. Autoregressive (AR) moving average (MA) and autoregressive moving average (ARMA) are three common approaches for forecasting the NSPI. AR models use past values of the NSPI to predict its future values, while MA models ARIMA (Autoregressive integrated moving average) model. With these models, there is still the possibility of over fitting. Volatility is the risk or uncertainty in stock prices, which can be measure using a number of approaches, including the use of annualized standard deviation of daily changes in securities prices (Chen Hsu, 2012). According to Malkiel and Xu (1999), it is fluctuation, rather than unidirectional changes, in stock prices that is term "volatility". Volatility of stock price is a form of reaction to the incomplete information in the market (i.e. uncertainty) (Poterba, 2000). Salisu and Fasanya (2012) in their study, noted that volatility guild investor in dire decision making because they are not only interested in the returns but also in the risk and uncertainty involve. Policy aim at reforming the financial market may not be effective if proper attention is not paid to the issue of volatility. Osazevbaru (2014) posited that volatility in stock market may cause a rise in the cost of capital which could have consequence in economic growth. Empirically, evidences from literature reviewed show that AR and MA models have been applied more extensively on volatility studies than other methods (Hamzaoui et al, 2016). They all contribute to the literature on volatility studies that autoregressive model are capable of specifying time variation in both conditions of skewness and kurtosis. Taking into consideration the past behavior in model estimation, the autoregressive model entails linearly unpredictable stochastic process which are conditionally leptokurtic and conditionally heteroskedatic, thus, they possess the tendency to be more accurate forecasting models (Ibrahim, 2017). Other volatility forecasting models in literature include Artificial Neural Network (ANN) following an evidence in (Neenwi et al, 2013). Yahaya (2023) studied stock market liquidity and volatility on the Nigerian Exchange Limited (NGX). The study found and evidence of volatility clustering (GARCH = 1.0056) on the NGX. Abdullahi (2024) analyzes the effect of COVID-19 pandemic on the performance of Nigerian stock market. The study made use of a number of models that include autoregressive distributed lag, vector autoregression, exponential generalized autoregressive conditional heteroskedasticity. The result show that the Nigerian stock market is not

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immune from the negative effects of crisis; but its performance when compared to other markets in the study was fairly good. This study therefore aims to determine a more accurate and robust forecasting method for the Nigeria Stocks Price Index (NSPI) by comparing the AR and MA and ARMA models. According to Thompson (2019) due to inherent volatility, the NSPI's accuracy in forecasting future values is questionable, as the unpredictable nature of the index can make it challenging to make precise prediction. Hence a comparative study between Autoregressive (AR) moving average (MA) and Autoregressive moving average (ARMA) models in forecasting the Nigeria stock price index (NSPI) could explore the accuracy of the three models in predicting future values of the NSPI.

2. Methods

This study sourced historical stock price index and divided it into a training and testing sets. The study applied autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) models to the training set to forecast the future stock price. The AR model is a type of linear regression model that uses past values of the variable being forecasted to predict future values.

The AR (p) model is given by;

$$X_{(t)} = C + \varnothing_1 X_{t-1} + \varnothing_2 X_{t-2} + \ldots + \varnothing_p X_{t-p} + \varepsilon_{(t)} \tag{1}$$

Where;

$X_{(t)}$ is the value of the time series at time t

C is the constant term or mean of the series $\varnothing_1, \varnothing_2, \ldots, \varnothing_p$ are the parameters of the model

$\varnothing_1 X_{t-1} + \varnothing_2 X_{t-2}, \ldots, \varnothing_p X_{t-p}$ are the past value of the series.

$\mathcal{E}_{(t)}$ is the error term or white noise

An MA (q) model is expressed by the formula;

$$X_{(t)} = C + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_{t-q} \tag{2}$$

where; X_t is the value of the series at time t, C is the mean of the series, q is the order of the MA model, indicating how many logged error terms are used θ_1, θ_2, … are the parameters of the model, $\mathcal{E}_t$ is white noise or error terms.

ARMA (p, q) model is given by the formula below;

$$X_{(t)} = C + \varnothing_1 X_{t-1} + \varnothing_2 X_{t-2} + \ldots + \varnothing_p X_{t-p} + \varepsilon_{(t)} + C + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_{t-q} \tag{3}$$

Where;

X_t is the current value of the series at time t, C is the constant term or mean of the series $\varnothing_1, \varnothing_2 \ldots, \varnothing_p$ is autoregressive parameters $\theta_1, \theta_2 \ldots, \theta q$ is moving average parameters, $\mathcal{E}_{(t)}$, $\mathcal{E}_{(t-1)}$, $\mathcal{E}_{(t-2)}$ …, $\mathcal{E}_{(t-q)}$ are the error terms or white noise.

Using the error metrics approach, the following will be used as the model accuracy measures;

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 \tag{4}$$

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$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| \tag{5}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \tag{6}$$

2.1 Data Presentation

Table 1: Monthly Nigeria Stock Price Index

Year	Month	Price	Year	Month	Price
2009	February	25382.5	2017	January	26251.39
2009	April	23271.69	2017	February	32459.17
2009	May	26100.64	2017	March	35953.44
2009	June	21483.02	2017	March	39257.53
2009	July	28713.67	2017	April	33276.68
2009	August	21349.18	2017	May	37120.28
2009	September	24237.85	2017	June	38198.6
2009	November	22293.53	2017	July	28192.46
2009	December	23656.42	2017	August	26325.93
2010	January	25738.79	2017	September	33261.66
2010	February	27503.36	2017	October	35005.57
2010	March	21658.69	2017	November	33810.56
2010	April	24609.3	2017	December	25164.91
2010	May	24445.05	2018	January	37625.59
2010	June	25422.79	2018	February	34037.91
2010	July	25367.83	2018	March	38669.23
2010	August	24984.8	2018	April	43127.92
2010	September	27753.13	2018	May	35446.47
2010	October	22060.36	2018	June	41022.31
2010	November	24846.64	2018	July	42898.9
2010	December	22993.77	2018	August	37392.77
2011	January	25300.46	2018	September	32327.59

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2011	February	26168.72	2018	October	38928.02
2011	March	24310.03	2018	November	42638.83
2011	April	19785.04	2018	December	35266.29
2011	May	25696.46	2019	January	27146.57
2011	June	26684.49	2019	February	30432.13
2011	July	22775.55	2019	March	31529.92
2011	August	25813.71	2019	April	27306.81
2011	September	27269.3	2019	May	28847.81
2011	October	23832.14	2019	June	29830.7
2011	November	21106.67	2019	July	28566.79
2011	December	25309.17	2019	August	27779
2012	January	20725.3	2019	September	30046.7
2012	February	26670.22	2019	October	32715.2
2012	March	20902.95	2019	November	26925.29
2012	April	20950.01	2019	December	28871.93
2012	May	23239.09	2020	January	26279.61
2012	June	22622.44	2020	February	25041.89
2012	July	27287.85	2020	March	24045.4
2012	August	20840.97	2020	April	28415.31
2012	September	27685.54	2020	May	29415.39
2012	October	21184.58	2020	June	34250.74
2012	November	20824.25	2020	July	25182.67
2012	December	23141.08	2020	August	22734.07
2013	January	36403.95	2020	September	25199.84
2013	February	39564.79	2020	October	23871.33
2013	March	37870.87	2020	November	28659.45
2013	April	38037.85	2020	December	29618.52
2013	May	36010.28	2021	January	38811.11
2013	June	29202.01	2021	February	39198.75

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2013	July	37382.49	2021	March	40123.71
2013	August	36098.07	2021	April	37994.19
2013	September	37249.93	2021	May	38921.78
2013	October	33258.45	2021	June	39157.29
2013	November	36986.94	2021	July	40439.85
2013	December	36907.81	2021	August	39533.97
2014	January	41529.11	2021	September	39494.7
2014	February	40773.5	2021	October	41176.14
2014	March	42598.46	2021	November	37947.18
2014	April	38554.19	2021	December	42353.31
2014	May	41480.62	2022	January	50937.01
2014	June	42832.82	2022	February	47351.43
2014	July	40672.94	2022	March	46631.46
2014	August	41517.1	2022	April	48881.93
2014	September	38767.29	2022	May	53201.38
2014	October	41380.05	2022	June	47202.3
2014	November	39022.1	2022	July	49664.07
2014	December	41751.55	2022	August	53100.21
2015	January	29175.35	2022	September	44454.67
2015	February	31441.71	2022	October	52215.12
2015	March	34388.12	2022	November	49475.42
2015	April	30143.02	2022	December	51778.08
2015	May	34930.02	2023	January	51222.34
2015	June	27269.71	2023	February	63040.87
2015	July	33621.75	2023	March	68143.34
2015	August	27585.26	2023	April	55930.97
2015	September	30705.62	2023	May	54327.3
2015	October	34439.52	2023	June	65325.37
2015	November	29032.29	2023	July	52214.62

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2015	December	31047.99	2023	August	52512.48
2016	January	25701.6	2023	September	62569.73
2016	February	27835.22	2023	October	67395.74
2016	March	27028.39	2023	November	59000.96
2016	April	25817.69	2023	December	53804.46
2016	May	27232.62	2023	January	71112.99
2016	June	25988.4	2024	February	99222.33
2016	July	27246.98	2024	March	101330.9
2016	August	26441.03	2024	April	101858.4
2016	September	27861.03	2024	May	98234
2016	October	23514.04	2024	July	83042.96
2016	November	26707.1			
2016	December	29247.27			

Source: Investing Economies Bulletin, 2024

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3.0 RESULTS

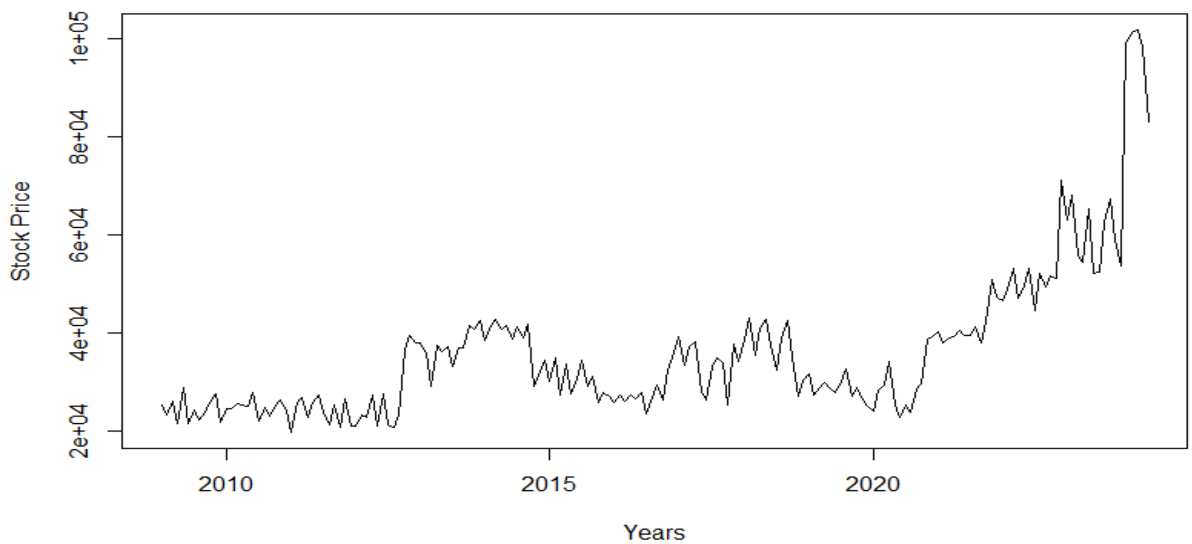

Figure 1: Data visualization showing time plot of the original Nigeria Stock Price Index 2009-2024.

Table 2: Test for stationarity for original dataset

Augmented Dickey-Fuller Test	
Statistic	***Estimate***
Dickey-Fuller	-0.374
Lag Order	5
P-value	0.9865
Alternative hypothesis: stationary	

Table 2 presents the results of the Augmented Dickey-Fuller (ADF) test for stationarity on the original dataset. The Dickey-Fuller test statistic is -0.374, with a p-value of 0.9865. Since the p-value is significantly higher than the conventional threshold of 0.05, we cannot reject the null hypothesis, which implies that the original time series is non-stationary. This suggests that the dataset exhibits trends, seasonality, or other patterns over time, making it inappropriate for direct use in time series modeling without further transformation.

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Table 3: Test for stationarity for differenced dataset

Statistic	***Estimate***
Dickey-Fuller	-7.3282
Lag Order	5
P-value	0.01

Table 3 shows the ADF test results after differencing the dataset. The Dickey-Fuller test statistic is now -7.3282, with a p-value of 0.01. The substantially lower p-value allows us to reject the null hypothesis, indicating that the differenced dataset is stationary. This transformation has effectively removed the non-stationary components, making the time series suitable for further analysis, such as applying an autoregressive model.

Table 4: Model Parameter estimates

Model	**Estimate**	**Intercept**	**SE**	**AIC**
AR(1)	-0.2640	335.5855	0.0725	3696.36
MA(1)	-0.3754	351.5959	0.0809	3691.05
ARMA(1,0,1)	AR(1) 0.3456 MA(1) -0.6754	347.0447		3690.11

Table 5: Performance Metrics for AR, MA, and ARMA Models

Model	**AIC**	**BIC**	**RMSE**	**MAE**
AR(1)	3696.357	3705.986	6063.363	4563.338
MA(1)	3691.047	3700.675	6093.567	4634.443
ARMA(1,0,1)	3690.108	3702.946	5658.464	3755.235

Based on the performance metrics presented, the ARMA(1,0,1) model is the best choice among the three models evaluated. This is because the ARMA(1,0,1) model has the lowest AIC value of 3690.108, indicating it has a more balanced fit and outperformed the AR(1) and MA(1) models. The ARMA(1,0,1) model also has the lowest BIC of 3702.946. Like AIC, BIC penalizes model complexity, and a lower BIC value indicates a preferable model. The ARMA(1,0,1) model's lower BIC suggests it is more parsimonious in terms of data fitting. The ARMA(1,0,1) model has the lowest RMSE of 5658.464, which means it has the smallest average squared deviation between predicted and observed values. This indicates that ARMA(1,0,1) provides more accurate forecasts compared to the AR(1) and MA(1) models. Similarly, the ARMA(1,0,1) model has the lowest MAE of 3755.235, suggesting that its forecasts are closer to the actual values on average. This measure of forecast accuracy further supports the ARMA(1,0,1) model as the best

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model option in NSPI forecast.

Table 6: Forecasts with Prediction Intervals

Month	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Aug 2024	260.1301	-7432.344	7952.605	-11504.494	12024.750
Sep 2024	355.5080	-7337.051	8048.067	-11409.246	12120.260
Oct 2024	330.3254	-7362.240	8022.890	-11434.437	12095.090
Nov 2024	336.9743	-7355.591	8029.540	-11427.789	12101.740
Dec 2024	335.2188	-7357.347	8027.784	-11429.545	12099.980
Jan 2025	335.6823	-7356.883	8028.248	-11429.081	12100.450
Feb 2025	335.5599	-7357.005	8028.125	-11429.204	12100.320
Mar 2025	335.5922	-7356.973	8028.158	-11429.171	12100.360
Apr 2025	335.5837	-7356.982	8028.149	-11429.180	12100.350

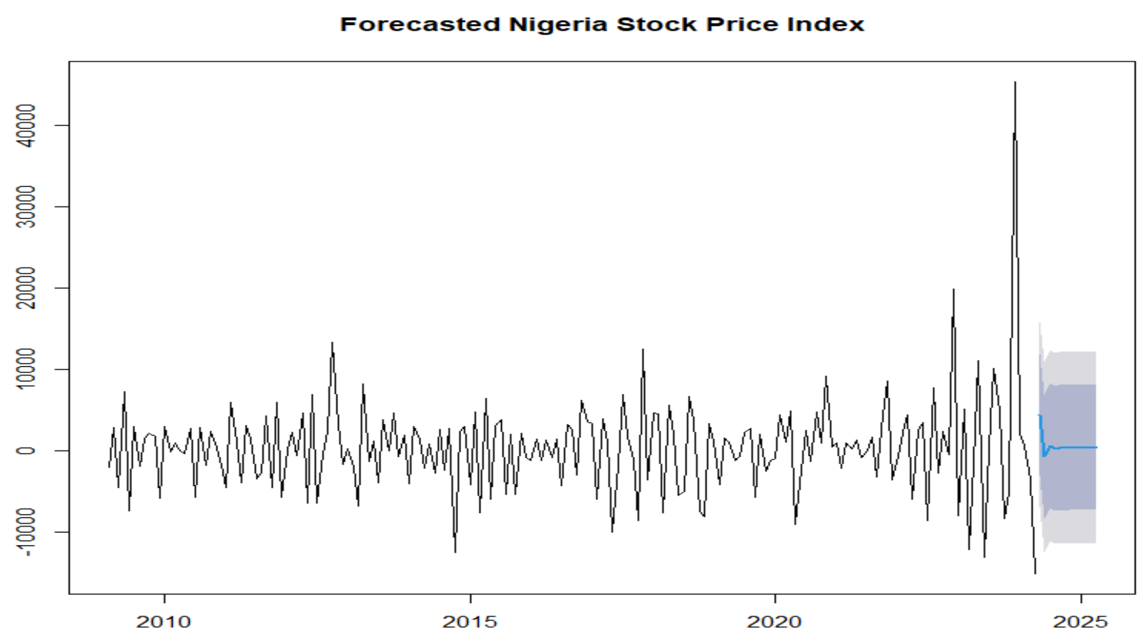

Figure 2: Time plot of the forecast data

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The forecasts for the Nigeria Stock Price Index show a range of predictions for each month with associated confidence intervals. The result shows that as we progress through the months, the forecasts stabilize around 335.5, with very narrow prediction intervals by March 2025 and April 2025. This suggests that the model predicts a stable value around this range for future months, with the confidence intervals becoming quite tight.

4. Discussion of Results

Figure 1 is the time plot of the original Nigeria Stock Price Index from 2009-2024. The data visualization from the plot indicates the presence of trend and heavy fluctuations I the series; this may be attributed to instability in the Nigerian stock market. Table 2 displays the results of the Augmented Dickey-Fuller (ADF) test on the original dataset, which shows a Dickey-Fuller test statistic of -0.374 with a p-value of 0.9865. This high p-value indicates that we cannot reject the null hypothesis, implying that the original time series is non-stationary. This suggests the presence of trends, seasonality, or other patterns in the data, making it unsuitable for direct time series modeling. In contrast, Table 3 presents the ADF test results after differencing the dataset. The Dickey-Fuller test statistic is -7.3282 with a p-value of 0.01, a significantly lower p-value that allows us to reject the null hypothesis. This indicates that the differenced dataset is stationary, making it appropriate for further analysis and time series modeling. Tables 4 and 5 indicate that among the models evaluated, the ARMA(1,0,1) model is identified as the best choice based on the model parameter estimates and the performance metrics. ARMA(1,0,1) has the lowest Akaike Information Criterion (AIC) value of 3690.108, the lowest Bayesian Information Criterion (BIC) of 3702.946, the smallest Root Mean Squared Error (RMSE) of 5658.464, and the lowest Mean Absolute Error (MAE) of 3755.235. These metrics indicate that the ARMA(1,0,1) model has a balanced fit with relative efficiency, providing accurate forecasts with minimal deviation from observed values. The forecasts generated by the ARMA(1,0,1) model for the Nigeria Stock Price Index suggest that future values will stabilize around 335.5. Table 6 shows that the prediction intervals narrow significantly by March 2025 and April 2025, indicating increasing confidence in the stability of future forecasts. Figure 2 is the time plot of the forecast data which collaborated the stability of future forecasts as indicated in Table 6. This results are in line with the findings of Kodongo (2012), Hamzaoui and Yahaya (2023).

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5. Conclusion

This study examines the time series analysis on the ‘All share index’ of the Nigeria stock exchange rate between 2009 and 202………………………..4 by comparing autoregressive (AR), Moving Average (MA) and the Autoregressive Moving Average (ARMA). T/.he test for stationarity for the original data was carried out using the augmented Dickey-fuller (ADF) test and the test showed that the original time series is non-stationary. Hence the test for stationarity for differenced data set was carried out and the result showed that the differenced data set is stationary. This transformation remove the non-stationary components, making it suitable for further analysis. This study compare the performance of the autoregressive (AR), Moving average (MA) and Autoregressive moving average (ARMA) models in forecasting the Nigeria stocks price index. The result showed ARMA (1,0,1) model outperform the AR (1) and MA (1) models with a lower Akaike information criterion (AIC), Mean Square Error (MSE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The study contribute to the understanding of time series forecasting models in the contest of the Nigerian stock market. The findings have implications for investors, financial institutions and policy makers seeking to optimize investment strategies and manage risk. Further research should build on this study’s findings to explore alternative model and data sources. The study therefore recommends that investors and financial institutions should use the ARMA (1, 0, 1) model for forecasting the Nigeria Stock price index for precision of results; further research should explore the use of Alternative models, such as neural networks and GARCH models; and the study’s findings should be used to inform investment decisions and risk management strategies in the Nigeria stock market.

6. Acknowledgement

We acknowledge the contributions of our final year students in making this study a fruition. We also thank the staff and managements of the Delta State Polytechnic and the National Bureau of Statistics for their moral support in the course of the research work.

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