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Forecasting Road Traffic Accidents in Lagos State, Nigeria

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Abstract
Road traffic accidents (RTAs) indicate significant challenges worldwide, with developing countries like Nigeria facing severe impacts due to rapid urbanization, inadequate infrastructure, and poor traffic law enforcement. Lagos State, a densely populated metropolitan area, has recorded a consistent increase in RTAs, contributing to high economic costs and public health strain. This study examines temporal patterns in RTAs in Lagos from 2014 to 2023, employing advanced time series analysis to forecast trends for 2024–2028 with the use of Seasonal Autoregressive Integrated Moving Average (SARIMA) Model. The findings reveal notable seasonal variations, with December consistently reporting the highest accident rates, likely influenced by festive activities. SARIMA (0,1,1)(2,0,0)[12] emerged as the best-fit model, demonstrating robust performance in capturing seasonal and trend components due to the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values of 697.9351 and 705.8249 respectively. *Predictions indicate a continued upward trend in RTAs, emphasizing the need for proactive interventions. The study offer actionable insights for urban planners, policymakers and stakeholders to prioritize safety measures, optimize resource allocation, and implement data-driven strategies for mitigating RTAs. The study underscores the utility of predictive modeling in solving the problems of urban traffic accidents in Lagos and similar contexts globally. The study provides a framework for both motorists and traffic regulatory agencies to work together towards enhancing road safety. By leveraging data and predictive modeling, stakeholders can create a safer urban environment, ultimately reducing the incidence of road traffic accidents.*

Keywords: Accident trend, Road traffic accident, Traffic safety, Forecasting, Modeling sustainability

Introduction
Road traffic accidents (RTAs) pose significant challenges to societies in both developed and developing countries, leading to loss of life and substantial costs, especially in fast-growing metropolitan areas like Lagos, Nigeria. RTAs are projected to become the fifth leading cause of death globally by 2030 (Mannering & Bhat, 2014). For decades, statistical analysis and modeling have played a crucial role in extracting insights from RTA data. Experts in this field advocate for the use of statistical methods, analysis, and forecasting to uncover the root causes of RTAs and provide a basis for developing policies and economically driven interventions (Zhang, Pang, Cui, Stallones, & Xiang, 2015).
In Nigeria, the burden of RTAs is particularly acute, with the country recording one of the highest rates of road traffic fatalities in Africa (Akinwunmi, 2020). Road traffic accidents in Lagos State, Nigeria, have shown an upward trend, reflecting similar patterns observed in other developing regions (Adeyemi & Adegoke, 2020). Factors such as increasing urbanization, growing vehicle ownership, poor infrastructure, and inconsistent traffic law enforcement contribute to this rise in RTAs (World Health Organization, 2018). Previous studies have highlighted the significance of trend analysis and examining in identifying high-risk periods and formulating targeted interventions (Chukwuma, 2021). For instance, seasonal variations in traffic accidents can be influenced by factors such as weather conditions, holiday travel patterns, and local events (Ogunyemi, 2020).

Time series analysis has proven to be a powerful tool for examining and forecasting temporal data. This approach enables researchers to identify seasonal patterns, trends, and irregularities, facilitating informed decision-making. Among various time series forecasting methods, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is recognized for its robustness in capturing both seasonality and trends in data. SARIMA has been extensively applied in traffic-related studies, demonstrating its effectiveness in modeling road traffic volumes, accident frequencies, and other transportation phenomena (Jia *et al*., 2018; Zhang *et al*., 2019). Balogun *et al* (2014) applied time series techniques to a long-time dataset of road accidents in Lagos State, the study revealed a positive cubic trend in accident numbers, meaning that rather than increasing linearly, the growth in accidents followed a more complex acceleration pattern, the finding indicate that current accident levels are significantly influenced by the past levels. However, the study by Fagoyinbo *et al* (2014), forecasting road accident using least square method shows that trend of total road accidents and fatalities in Lagos State was declining, a change largely attributed to sustained government interventions.

This study focuses on the time series analysis and forecasting of RTAs in Lagos between 2024 and 2028 using the SARIMA modeling approach. By leveraging historical accident data, this research aims to identify key temporal patterns and develop a reliable forecasting model.

The SARIMA model has been widely used in various regions to analyze and predict RTA trends. Agyemang *et al*. (2023) explored the use of SARIMA and Facebook Prophet models for forecasting RTAs in Ghana. The study demonstrated SARIMA's ability to accurately model seasonal patterns in accident data, highlighting its effectiveness in road safety planning. Moreover, the comparative analysis showed SARIMA's robustness in regions with consistent seasonal patterns.

In Lagos, Nigeria, RTAs have been a growing concern due to increasing urbanization and vehicular congestion. However, application of SARIMA remains a gap in the literature regarding this context. Studies in similar urban environments have demonstrated the model's potential. For instance, research in Bogotá, Colombia, highlighted the effectiveness of SARIMA in analyzing urban traffic data with spatiotemporal variations, offering valuable insights for accident mitigation strategies (Ramírez & Valencia, 2021)

However, Shafiq *et al*. (2020) emphasized the need for predictive models to support legal and policy frameworks for road safety. Their review of global RTA trends pointed to SARIMA's utility in forecasting accident occurrences, providing actionable data for policymakers

The insights gained from this analysis will provide actionable recommendations for policymakers, stakeholders and urban planners in Lagos to enhance road safety and reduce the societal impacts of RTAs.

Materials and Methods

Description of study area

Lagos State, situated in Nigeria's southwestern geopolitical zone, is the smallest state by land area but the most populous and economically vital in the country. Covering about 3,577 square kilometers, it shares borders with Ogun State to the north and east, the Atlantic Ocean to the south, and the Republic of Benin to the west. The state comprises 20 Local Government Areas (LGAs) and includes Lagos Island, which is the historical and economic center, and the Lagos Mainland, home to a diverse and dense urban population. Lagos State is one of the most densely populated and heavily trafficked cities in Nigeria, so forecasting helps in predicting future accident case, enabling government agencies to plan for the future occurrence accidents.

Data Collection and Analysis

This study used a secondary dataset comprised of monthly accident records sourced from the Federal Road Safety Commission for the period of ten years (2014-2023) to know the accident rate for the ten years in the study region. Time series was used to visualize the data to identify trends, seasonality and potential outliers and the data was transformed to ensure stationarity, a prerequisite for ARIMA modeling using firstorder differencing. The Augmented Dickey-Fuller (ADF) test was employed to confirm the stationarity of the time series.

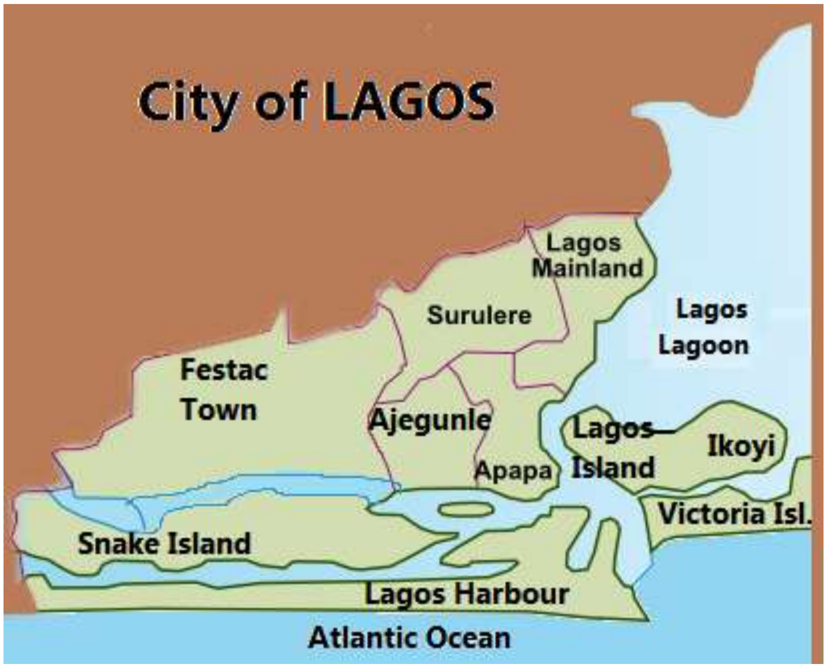

Figure 1: Map of Lagos State Nigeria

Model Selection and Estimation

Several Autoregressive Integrated Moving Average (ARIMA) and SARIMA models were evaluated to examine the best fit for the data. The optimal model was chosen using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which help balance model fit and complexity. The SARIMA model's parameters were determined through maximum likelihood estimation. The model equation was derived to represent the relationship between the differenced series and its lagged values.

An ARIMA (p, d, q) model for a time series sequence (X_t, t =1,2, ..., n) can be written as

$$\phi(\beta)(1-\beta)^d X_t = \theta(\beta)A_t \qquad (1)$$

where p is the order of the AR process, d is an order of differences, q is the order of the MA process, At is the white noise sequence, ϕ is a polynomial of degree p, B is a back shift operator, and θ is a polynomial of degree q. However, an ARIMA model could not analyze time series with seasonal characteristics; therefore, seasonal autoregressive integrated moving average (SARIMA) models have been developed. SARIMA models perform better than the traditional average, linear regression, and simple ARIMA models for data with seasonal variations. In fact, SARIMA models are capable of considering the trend and seasonality. The full model for SARIMA (p,d, q)(P, D,Q)m can be written as

$$Y^*_t = \beta_o + \beta_1 Y^*_{t-1} + \ldots + \beta p Y^*_{t-p} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta q\, e_{t-q} \qquad (2)$$

Where p = order of AR (Autoregressive), d = order of differencing q = order of MA (Moving Average), Y*t is the differenced data and β_o, β_1, $\beta_{2....}$, β_p and θ_0, θ_1, θ_2, …, θ_q are AR(p) and MA(q) parameters respectively.

Forecasting

The SARIMA model was used to forecast road traffic accidents for the period January 2024 to December 2028. Forecast intervals were calculated to provide upper and lower bounds for the predictions.

Results and Discussion:

The data on monthly road traffic accidents from Lagos State in Table 1 reported from 2014 to 2023 reveals a steady increase in incidents over the years, with December consistently recording the highest numbers, likely due to festive season travel. Seasonal variations show February as a low-incidence month, while April and mid-year months fluctuate, possibly influenced by weather and holiday activities.

Table 1: Monthly Road Traffic Accidents for Lagos State 2014-2023

Month/year	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Jan	14	11	13	14	18	26	30	36	29	33
Feb	7	10	9	15	12	23	23	18	30	15
Mar	6	11	11	12	14	23	29	23	23	48
Apr	16	12	21	19	18	37	31	25	34	28
May	11	12	15	18	19	19	26	28	22	25
Jun	8	14	12	14	22	14	20	33	29	22
Jul	11	12	16	16	16	28	26	12	24	19
Aug	8	14	7	19	14	24	29	17	29	24
Sep	14	17	22	16	20	18	26	29	26	18
Oct	13	16	17	12	7	15	18	19	30	20
Nov	11	13	21	10	16	19	33	31	21	19
Dec	19	22	19	24	25	39	50	41	54	44

Source: FRSC (2023)

Decomposition of additive time series

The decomposition plot in Fig.1 shows the original data, the trend, seasonality and the random of the data in which the trend of the data indicates that there is a linear increment in the number of road accident and the seasonality plot shows the presence of seasonality in the plot. Augmented Dickey-Fuller test results of Dickey-Fuller = -4.5326, Lag order = 4 and p-value = 0.01 indicate that the time series model plot shows the stationarity in the data with differencing the original data.

Time series model estimation

Suitable seasonal ARIMA models were estimated. Supported by AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) values, multiple SARIMA models were fitted, and the estimated orders in Table 2.

As a result, the best time series model found is SARIMA (0, 1, 1) (2, 0, 0)[12] due to the lowest AIC and BIC values of 697.9351 and 705.8249 respectively and the best model to forecast the possible road accident.

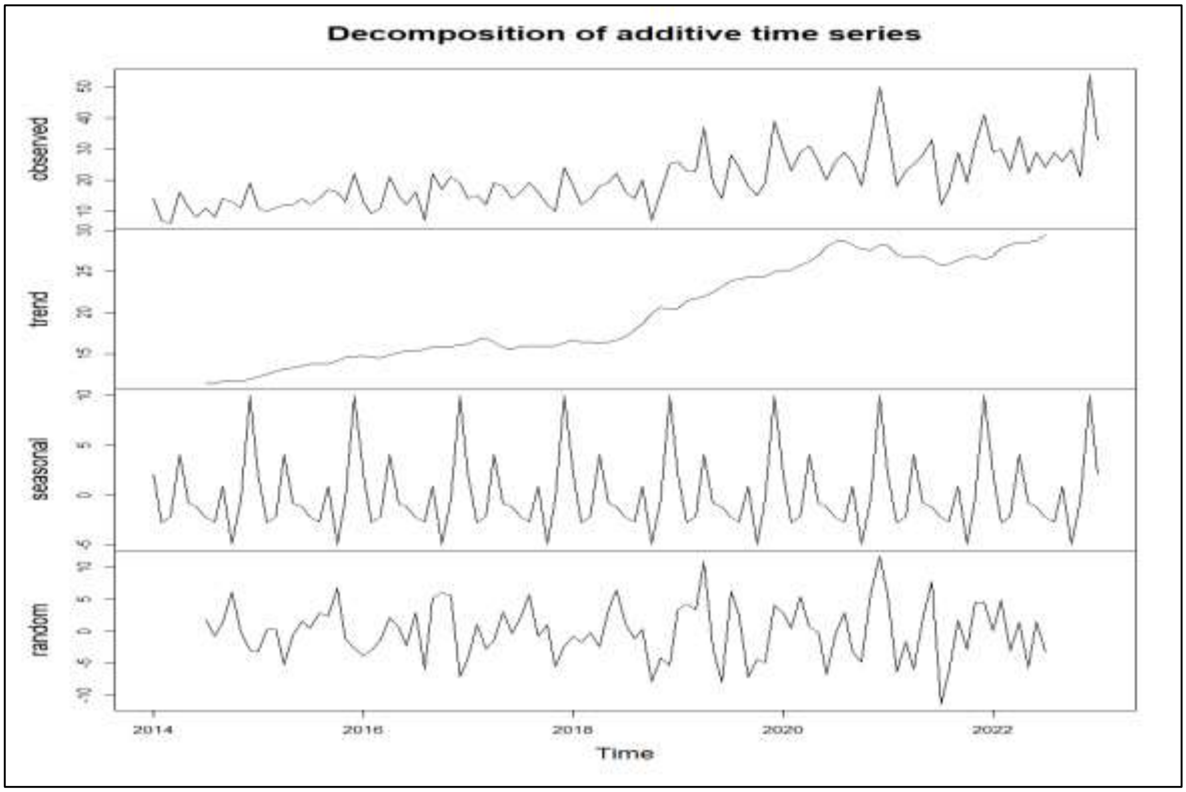

Figure 2: Decomposition plot indicating the observed, trend, seasonality and random of the data

Table 2: Model Estimation

ARIMA (p, d, q) (P, D, Q)[m]	AIC	BIC
ARIMA (0, 1, 1) (2, 0, 0)[12]	697.9351	705.8249
ARIMA (3, 1, 1) (1, 0, 0)[12]	702.1002	760.7835
ARIMA (2, 1, 0) (2, 0, 0)[12]	719.1354	714.8441
ARIMA (2, 1, 2) (2, 0, 0)[12]	699.8449	727.3333
ARIMA (1, 1, 0) (2, 0, 0)[12]	731.7779	742.5064
ARIMA (1, 1, 2) (2, 0, 0)[12]	698.7513	710.4615

Model Parameter

The parameters estimated for an ARIMA model were indicated in Table 3 highlighting significant components i.e. the constant, moving average (MA) and auto-regressive terms. The coefficient estimate for the MA component at lag 1 is 0.932. This high value (close to 1) indicates strong autocorrelation at this lag. The t-statistic is 22.814, with a p-value of less than 0.001, indicating that this parameter is highly significant. Lag 1: The coefficient estimate is 0.354 with a t-statistic of 3.373 and a p-value of 0.001. This suggests that the seasonal autoregressive component at lag 1 is significant and contributes to the model.
Lag 2: The coefficient estimate is 0.240 with a t-statistic of 2.054 and a p-value of 0.042. This indicates that the seasonal autoregressive component at lag 2 is also statistically significant.
Moving Average (MA) term at lag 1 is highly significant, indicating strong short-term autocorrelation. Seasonal Auto-Regressive (AR) terms at lags 1 and 2 are also significant, reflecting the influence of seasonal patterns. The coefficient estimated for constant, MA and AR was used to form the model equation as shown in Equ.2 which was used for the prediction. These results suggest that the model effectively capture both short-term dependencies and seasonal effects.

Table 3: ARIMA Model Parameters

	Estimate	SE	t-statistic	P val.	Remark
Constant	0.125	0.091	1.369	0.174	
Differencing	1				
MA Lag 1	0.932	0.041	22.814	<0.001	Significant
AR, Seasonal Lag1	0.354	0.105	3.373	0.001	Significant
Lag 2	0.240	0.117SS	2.054	0.042	Significant

$$Y_t = 0.125 + 0.932\, e_t + 0.354 * Y_{t-12} + 0.240 * Y_{t-24} + e_t \quad (3)$$

Where:

Y_t is the value of the time series at time t

e_t is the error term at time t

e_{t-1} is the error term at time t-1 (the previous time period)

Y_{t-12} is the value of the time series at time t-12 (the same time period in the previous year)

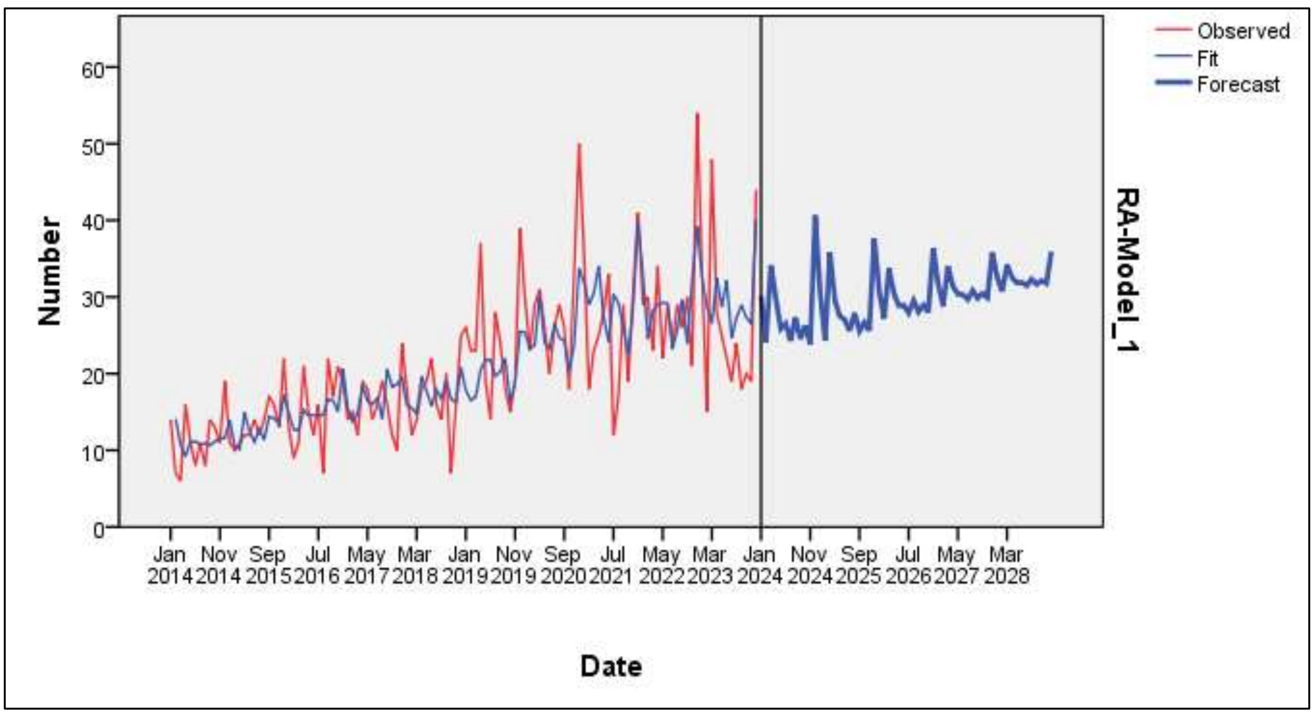

Figure 3: Observed, Fit and Predicted Road Traffic Accident

Table 4: Forecasted accident with lower and upper boundary

MONTH/YEAR	PREDICTED NUMBERS	LOWER BOUNDARY	UPPER BOUNDARY
JAN 2024	30	18	42
FEB 2024	24	12	36
MAR 2024	34	22	47
APR 2024	30	17	42
MAY 2024	26	13	38
JUN 2024	27	14	39
JUL 2024	24	12	37
AUG 2024	27	15	40
SEP 2024	25	12	37
OCT 2024	26	14	39
NOV 2024	24	11	36
DEC 2024	41	28	53
JAN 2025	31	17	44
FEB 2025	24	11	38
MAR 2025	36	22	50
APR 2025	30	16	43
MAY 2025	27	14	41
JUN 2025	27	13	41
JUL 2025	26	12	40
AUG 2025	28	14	42
SEP 2025	26	12	40
OCT 2025	27	13	41
NOV 2025	26	11	40
DEC 2025	38	23	52
JAN 2026	31	16	46
FEB 2026	27	12	42
MAR 2026	34	18	49
APR 2026	30	15	46
MAY 2026	29	13	44
JUN 2026	29	13	45
JUL 2026	28	12	44
AUG 2026	30	14	45
SEP 2026	28	12	44
OCT 2026	29	13	45
NOV 2026	28	12	44
DEC 2026	36	20	52
JAN 2027	32	15	48
FEB 2027	29	12	45
MAR 2027	34	17	51
APR 2027	31	15	48
MAY 2027	30	14	47
JUN 2027	30	13	47
JUL 2027	30	13	47
AUG 2027	31	14	48
SEP 2027	30	13	47
OCT 2027	30	13	48

NOV 2027	30	13	47
DEC 2027	36	18	53
JAN 2028	33	15	50
FEB 2028	31	13	49
MAR 2028	34	16	52
APR 2028	33	15	51
MAY 2028	32	14	50
JUN 2028	32	14	50
JUL 2028	31	13	50
AUG 2028	32	14	51
SEP 2028	32	13	50
OCT 2028	32	14	51
NOV 2028	32	13	50
DEC 2028	36	17	55

The predicted values for each month from January 2024 to December 2028, along with the corresponding lower and upper boundaries of the predictions are shown in Table 4. The predicted values follow a general trend, with fluctuations throughout the years. The pattern suggests that, while there are minor monthly and yearly variations, the predicted values remain relatively stable over the 5-year period, typically oscillating between lower and upper boundaries. The general trend appears to show some seasonal variability which is in line with the work of Balogun *et al* (2014), with slightly higher values often observed in the latter months of each year, particularly in December (such as 53 in December 2024 and 55 in December 2028), this may due to festival period in the last part of the year.

Conclusion

The forecasting of road traffic accidents (RTAs) in Lagos, Nigeria, using the SARIMA modeling approach was carried out and based on the findings, it is concluded that:

i. Predictions for the period 2024–2028 revealed a continued upward trend in Road Traffic Accident occurrences, this implies that road users will be facing an increasingly hazardous driving environment, underlining the urgent need for comprehensive safety interventions and improved infrastructure.

ii. There is persistent increase in Road Traffic Accidents over the years, with significant seasonal variations, particularly during December which consistently records the highest predicted values.

iii. The SARIMA (0,1,1)(2,0,0)[12] model was identified as the most suitable for capturing the underlying patterns in the data due to its robustness in handling seasonal characteristics.

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