Air temperature time series modelling and prediction using neural network and SARIMA model

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Accurate modelling and forecasting of air temperature play a vital role in many facets of human life and environmental endeavours. This study specifically focuses on determining the superior method for modelling and predicting air temperature in Warri, a city located in the southern region of Delta State, Nigeria. The dataset used in this research was provided by NiMet (2000–2020). To accomplish the modelling and prediction task, we employed two prominent methods: the Seasonal Autoregressive Integrated Moving Average (SARIMA) and the Neural Network Time Series Autoregressive (NNETAR) models. Initially, the dataset exhibited non-stationary behaviour, as evident from the time plot series and confirmed by conducting the Augmented Dickey-Fuller (ADF) test. However, after applying the first difference, the data was transformed into a stationary series. Further analysis using the Hegy and Canova-Hasen tests revealed the presence of seasonality in the series, with a seasonal order of 1. Upon achieving stationarity, we proceeded to evaluate various models, and both the SARIMA (2,1,2) (1,0,1) [12] and NNAR (22,1,12) [12] models demonstrated the best performance. However, when assessing the accuracy measures, the NNAR (22,1,12) [12] model outperformed the SARIMA (2,1,2) (1,0,1) [12] model. Having identified the superior model, we utilised the fitted NNAR (22, 1, 12) [12] model to forecast the air temperature for the next five years. This approach provides valuable insights into the future climate trends of Warri City and supports informed decision-making in various sectors.

Keywords: modelling; forecasting; air temperature; SARIMA model; NNAR model

1. Introduction

Air temperature is one of the meteorological variables that show how cold or hot the air is, and it also affects atmospheric and land surface processes. The air temperature is one of the key factors in predicting other meteorological variables like the relative humidity, wind speed, wind direction, and precipitation patterns, and it also affects the growth and reproduction of plants and animals (Chen *et al*., 2018). Forecasting air temperature is important for weather prediction for the protection of human lives and properties and also due to its significant effect on other various sectors such as industry, energy, and agriculture (Sardans *et al*., 2006 and Sharma *et al*., 2011). Accurate air temperature prediction increases energy consumption and establishes a plan for human activities, and business development (Green, 2003; Smith *et al*., 2007). The fifth IPCC assessment report revealed that the mean temperature increased by 0.85^0Cfrom 1880 to 2012 (IPCC, 2018). Since air temperature is usually affected by many climate elements, it is important to predict the changes in temperature for the projected duration and conduct quantitative analyses of air temperature fluctuations so that necessary steps are taken to mitigate adverse effects (Lee *et al*., 2020 and Mitu and Hasan, 2021). In temperature research forecasting, time series analysis is considered an essential component (Balibey and Turkyilmaz, 2015; Wanishsakpong and Owusu, 2019 and Dimri *et al*., 2020).

The Time series model deals with the collection and analysis of past values in developing an appropriate model for describing the inherent structure and characteristics of the series (Adhikari and Agrawal, 2013). Time series forecasting is the use of an appropriate model on past observed values to forecast future values (Raicharoen *et al*., 2003). Many time series models have been developed in the literature to improve the accuracy and efficiency of time series forecasting. The time series models used in data production can be classified under four main categories: regression models, including Autoregressive Integrated Moving Average (ARIMA) with SARIMA as its seasonal component, artificial neural network approaches, numerical weather prediction models, and hybrid models (Nishimwe and Reiter, 2022).

ARIMA model is one of the most widely used and well known for its notable forecasting accuracy and efficiency in representing various types of time series with simplicity and is associated with the Box-Jenkins methodology for optimal construction as described by Khandelwa *et al.* (2015), with the assumption that the time series is linear and follows a statistical normal distribution. Seasonal ARIMA (SARIMA) is better suited and shows a better fit when the time series is longer with the availability of multiple periodicities (Shih and Rajendran, 2019). Tylkowsi and Hojan (2019) studied short-term hydrometeorological variables prediction with multiple measurement stations in the coastal zone using the SARIMA method, which provided reliable information that helped in environmental planning and decision making based on monthly averaged predictions for air temperature, total atmospheric precipitation, and average sea level. Kreuzes *et al.* (2020) found that neural networks (NN) are better suited for forecasting when the datasets comprise nonlinear time series that has been consistently available for many years, and also for linear time series. Neural networks fall under the broader category of machine learning (ML) techniques and are seen as part of artificial intelligence (AI) where the sample data, known as the training dataset, is used to make predictions or decisions without being explicitly programmed to do so (Kuhn and Johnson, 2018). ARIMA and its seasonal counterpart, SARIMA, and neural networks have been used by many researchers to tackle problems in some weather prediction like air temperature, humidity, solar radiation, wind speed, and so on (Wang *et al*., 2006; Jain and Kumar, 2007; Di *et al*., 2014; Grigonyte & Butkevi, 2016; Dwivedi *et al*., 2019; Lai and Dzombak, 2020; Ray *et al*., 2021 and Shad *et al*., 2022). Reza and Debnath (2020) compared the two models to forecast the price of commodities with neural network time series showing better performance both in prediction ability with R-squared statistics and also in forecasting capabilities. Ahmar and Boj (2021) also compared the two models to forecast infection fatality rate of COVID-19 in Brazil with neural network coming out better than ARIMA. Therefore, in this paper, we analyse the air temperature using NNETAR (Neural Network time Series Autoregressive) and ARIMA (Autoregressive Integrated Moving Average) model methodologies, which have been adopted by other researchers as stated in the literature, to determine if the Neural network has a superior performance to ARIMA model using the air temperature data for Warri, Delta State, Nigeria.

2. Materials and Methods

2.1 Study area and data source

This study was held in Warri, Delta State, Nigeria, at the following coordinates: latitude 5° 31' 2.5"N and longitude 5° 45.004'E (Figure 1). The study area covers an area of 826 square kilometres, including the suburbs of Agbarho, Udu, and Uvwie, and is located on the State's southern boundaries. It is now the economic hub of Delta State, with various road networks and enterprises, including a refinery, a seaport and a gas industry. Warri is Delta State's busiest metropolis, with a plethora of socioeconomic activity taking place from dawn to dusk. In Warri, the rainy season is warm and gloomy, and the dry season is hot and partially cloudy. The temperature seldom drops below 61°F or rises over 92°F in a year. The data used for this research was obtained from the Nigerian Meteorological Agency (NiMet). The temperature data spans from January 2000 to December 2020.

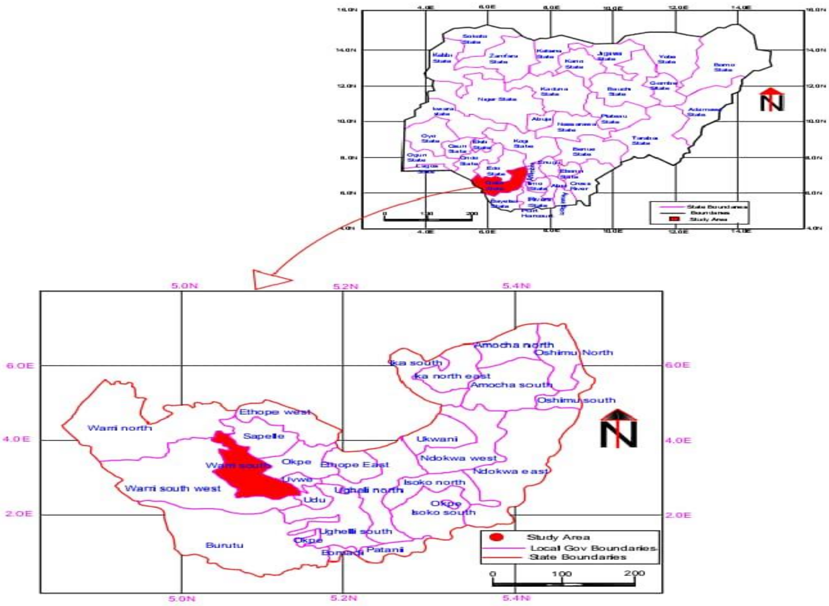

Figure 1: Showing the map of Warri City in Delta State of Nigeria

2.2 Model Identification and Selection

When constructing a Box-Jenkins model, the first step is to examine the time series data to determine whether or not it exhibits stationarity and seasonality. The Augmented Dickey-Fuller test, the time series plot, the seasonal plot, and the autocorrelation plot are the tools that we use to examine whether or not there is stationarity and seasonality in the data. If the time series data is not stationary, Box-Jenkins differencing is used to achieve stationarity in the series. The autocorrelation function (ACF) and partial autocorrelation function (PACF) will determine whether an autoregressive or moving average component should be used, and in what sequence.

2.3 Augmented Dickey-Fuller Test

To detect whether or not a time series sample contains a unit root, an Augmented Dickey-Fuller test, often known as an ADF, is performed. It is an improved version of the Dickey-Fuller test that may be used to a collection of time series models that are more complicated. A negative value represents the test statistic that the Augmented Dickey-Fuller (ADF) makes use of. The more negative it is, the stronger the rejection of the hypothesis that there is still a unit root holds, at some level of confidence (Mushtaq and Rizwan 2011). The ADF test is based on the following regression equation:

$$\Delta\gamma_t = \rho\gamma_{t-1} + \propto + \beta t + \gamma_1\Delta\gamma_{t-1} + \gamma_2\Delta\gamma_{t-2} + \cdots + \gamma_p\Delta\gamma_{t-p} + \varepsilon_t, \quad (1)$$

where ρ represents the coefficient of the lagged value of the time series (γ_{t-1}), $\Delta\gamma_t$ is the first difference of the time series, γ_{t-1} is the lagged value of the time series, $\propto$ is the intercept term, βt is the trend term, γ_1, γ_2, ..., γ_p, are the coefficients of the lagged differences of the time series and ε_t is the error term.

2.4 Model Parameter Estimation

When utilising computing algorithms to determine the optimal coefficients for the given ARIMA or SARIMA model, the maximum likelihood estimate or nonlinear least-squares estimation are two of the most often used approaches.

2.5 Model Diagnostic and Forecasting

Model-checking ensures the estimated model meets stationary univariate process requirements, with independent residuals, constant mean and variance. Misspecification can be detected through graphing, Ljung-Box tests, and autocorrelation plots. If inadequate, a more accurate model is created. The model is used to characterize and predict time series observations for the next five years.

2.6 Stochastic Models

2.6.1 Autoregressive Integrated Moving Average (ARIMA) model

In this research, we employed the ARIMA model introduced by Box and Jenkins in 1976 for time series modelling and forecasting, which has been widely utilised in several academic papers. A time series model consists of a deterministic trend and a stochastic residual for the trend, with the residual intended to reflect natural variation (Romilly, 2005). ARIMA is a subset of the autoregressive moving average (ARMA) model. This model is fitted to time series data to improve understanding of the data or to anticipate the next point in the series (forecasting). They are used in certain circumstances when data show non-stationary behaviour and an initial differencing step may be used to eliminate the non-stationary behaviour. The model is often referred to as an ARIMA (p,d,q) model, where p, d and q are non-negative integers indicating the order of the autoregressive, integrated, and moving average components of the model. ARIMA models are a critical component of the Box-Jenkins method for time series modelling. The model is written as:

$$\Phi_p(B)W_t = \theta_q(B)Z_t \quad (2)$$

$$\Phi_p(B)(1-B)^d X_t = \theta_q(B)Z_t \quad (3)$$

The model for X_t is non-stationary because the AR operator just on the left has a d root on the unit circle; d is often 1, and the random walk is ARIMA (0,1,0). In equation (2), d is the number of non-seasonal difference order, W_t is an ARMA process and $W_t = (1-B)^d X_{t;}$ where $\Phi_p(B)$ is a polynomial of autoregressive with order p is denoted by AR(p); $\theta_q(B)$ is a polynomial of moving average with order q is denoted by MA(q), B is the backward shift operator and Z_t is a white noise process.

2.6.2 Seasonal Autoregressive Integrated Moving Average (SARIMA) model

It is an extension of the ARIMA model that incorporates seasonality. When the time data exhibits seasonality the seasonal component is added to the ARIMA to become SARIMA. The notation for *s* SARIMA model is SARIMA (p, d, q) (P, D, Q)$_s$, where p is autoregressive order(AR) for the non-seasonal component, d is the order of differencing (I) for the non-seasonal component, q is the moving average order(MA) for the non-seasonal component, P is autoregressive order(AR) for the seasonal component, D is the order of differencing (I) for the seasonal component, Q is the moving average order(MA) for the seasonal component, *s* is the seasonal period or frequency of the data.

The generalised form of SARIMA model can be written as:

$$\Phi_p(B)\Phi_P(B^s)W_t = \theta_q(B)\theta_Q(B^s)Z_{t,} \quad (4)$$

where

$$\Phi_P(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} -,,, - \Phi_P B^{ps} \quad (5)$$

$$\theta_Q(B^s) = 1 - \theta_1 B^s - \theta_2 B^{2s} -,,, - \theta_Q B^{Qs} \quad (6)$$

$$\nabla_s^D = (1-B^s)^D \quad (7)$$

where $\Phi_P(B^s)$ is a polynomial of seasonal autoregressive with order P and seasonal period m is denoted by SAR(P); $\theta_Q(B^s)$is a polynomial of the seasonal moving average with Q and seasonal period S is denoted by SMA(Q) and ∇_s^D is the seasonal differencing operator.

2.7 Neural Network Autoregressive (NNETAR) model

In this study, we employed feed-forward neural network architecture to model and forecast the time series data. The neural network was trained using lagged values of the target variable (y) as inputs. A single hidden layer with a specified number of nodes was utilised for learning the underlying patterns in the data. The inputs to the neural network corresponded to lagged values ranging from 1 to p and m-M.P., where m represents the frequency of the target variable (y). Additionally, if x_{reg} (exogenous variables) were provided, their columns were also included as inputs. Any rows containing missing values in y or x_{reg} were excluded from the training process, along with the corresponding lagged values. To obtain robust predictions, a total of repeated networks were fitted, each initialised with random weights. When making predictions, these individual networks were averaged to generate the final forecast. The neural network was specifically trained to predict the target variable in a single step, but recursive procedures were employed for generating multi-step forecasts. The fitted model for non-seasonal data is referred to as an NNAR (p, k) model, where k denotes the number of hidden nodes in the neural network. This model can be considered analogous to an autoregressive (AR) model of order p, but with the advantage of nonlinear functions capturing the relationships between inputs and outputs. For seasonal data, the fitted model is called an NNAR (p, P, k) [m] model, which can be compared to an ARIMA (p, 0, 0) (P, 0, 0) [m] model. However, the neural network model introduces nonlinearity, enabling it to capture more complex patterns in the data. It is worth noting that traditional time series prediction approaches such as Box-Jenkins, ARMA, or ARIMA assume linear relationships between inputs and outputs. In contrast, neural networks offer the advantage of being able to predict any nonlinear function without prior knowledge of the specific features of the data series.

2.8 Model performance measures

The present study used a comparative study on the two models' numerical performance (ARIMA, SARIMA & NNETAR) on the air temperature data for Warri city in Delta State of Nigeria. Forecast accuracy was evaluated using the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE), and the Mean Absolute Scaled Error (MASE).

2.8.1. The Akaike Information Criterion (AIC)

The AIC (Akaike, 1974) is a fine-grained approach for assessing a model's probability to predict/estimate future values based on in-sample fit. A good model is the one with the minimum AIC value among all other models.

$$AIC = 2K - 2ln(\hat{L}), \tag{8}$$

where L is the likelihood function, *n* represents the number of measured values, and *K* denotes the number of estimated parameters.

2.8.2. The Root-Mean-Square Deviation (RMSD)

The RMSD or root-mean-square error (RMSE) is a widely used statistic that expresses the difference between predicted values by a model (sample or population values) and actual values.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_t - \hat{y}_t)^2}, \tag{9}$$

where y_t denotes the observation of rainfall at the t-th time point and $\hat{y}_t$ denotes estimate of y_t while forecast error will be

$$\varepsilon = y_t - \hat{y}_t \tag{10}$$

2.8.3. Mean Absolute Error (MAE)

The Mean Absolute Error is a statistic that indicates the average degree of errors in a collection of predictions without regard for their direction. It is the average of the absolute differences between prediction and actual observation across the test sample, where all individual deviations are given equal weight.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \tag{11}$$

2.8.4. Mean Absolute Scaled Error (MASE)

MASE is a metric for determining prediction accuracy. The prediction values' mean absolute error is divided by the in-sample one-step naïve forecast's mean absolute error.

$$\text{MASE} = mean\left(\frac{|e_j|}{\frac{1}{T-m}\sum_{t=m+1}^{T}|y_t - y_{t-m}|}\right) \tag{13}$$

3. Results and Discussion

Table 1 provides descriptive statistics for a 20-year period in which the average air temperature was 27.82 °C, the maximum temperature was 30.90 °C, and the minimum temperature was 20 °C. The skewness of the air temperature distribution is -0.88; this indicates that the distribution is negatively skewed, which means that the mean temperature is less than the median temperature and the mode temperature (suggesting that the majority of days over a 20-year observation period are cooler).

Table 1: Descriptive Statistics

variable	n	mean	sd	median	trimmed	mad	min	max	range	skew	Kurtosis	se
Warri	241	27.82	1.33	27.9	27.86	1.48	20	30.9	10.9	-0.88	3.58	0.09

Source: Authors' Calculations

3.1 Time plots for Warri meteorological stations in Delta State

Figure 2 shows the time plot of monthly series for air temperature for Warri city in Delta State for a period of 2000 to 2020. The figure revealed that there is an irregular trend in the data series. We noticed that the mean of the series is not constant and the data is therefore not stationary.

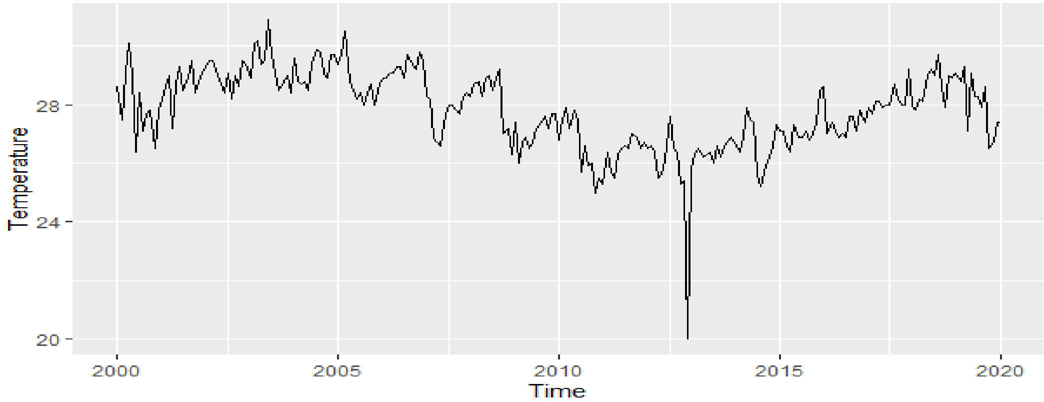

Figure 2: Time plot showing Warri Air temperature from 2000-2021

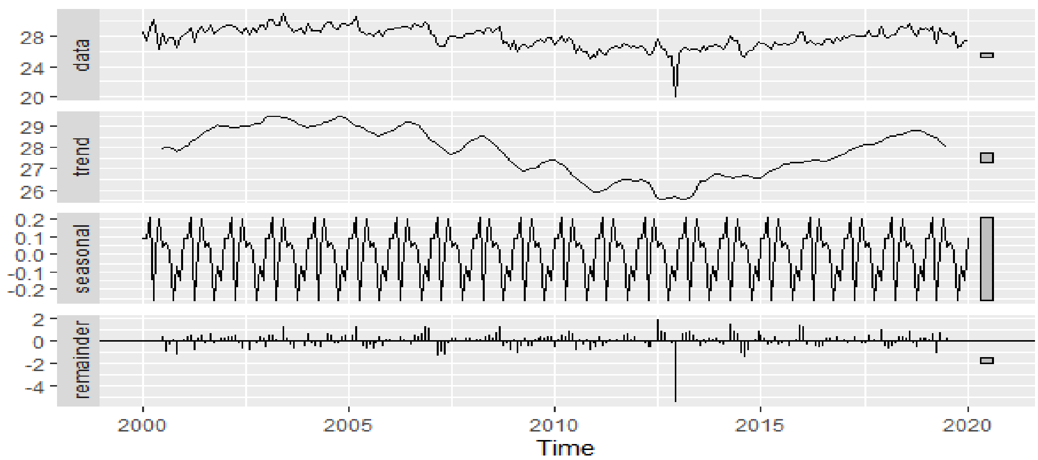

Figure 3: The series' additive time series decomposition into a random, seasonal, trend and observed variation

3.2 Stationarity and Seasonality test

To test for stationarity or unit root test, the Augmented Dickey-Fuller test is used. Table 2 displays the stationarity results obtained when applied to the dataset. The results in Table 2 suggest the data series for Warri air temperature did not attain stationarity since the p-value (0.4319) for the series is greater than the 5% level of significance but shows seasonality with order 1. We difference the data to attain stationary and the result is shown below in Table 3.

Table 2: Augmented Dickey-Fuller Test for the series

Meteorological Stations	DF statistic	Lag-order	p-value	Seasonality	
				Decision	**Order**
Warri	-2.3423	6	0.4319	Yes	1

Table 3: Differenced Result for Stationarity

Meteorological Stations	DF statistic	Lag-order	p-value	Seasonality	
				Decision	**Order**
Warri	-4.5725	6	0.01	Yes	1

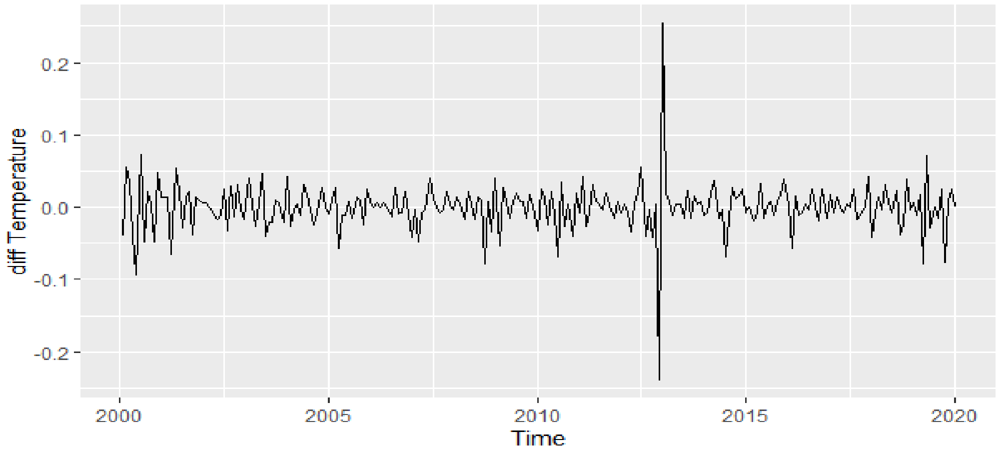

Figure 4: The Time Plot after Differencing

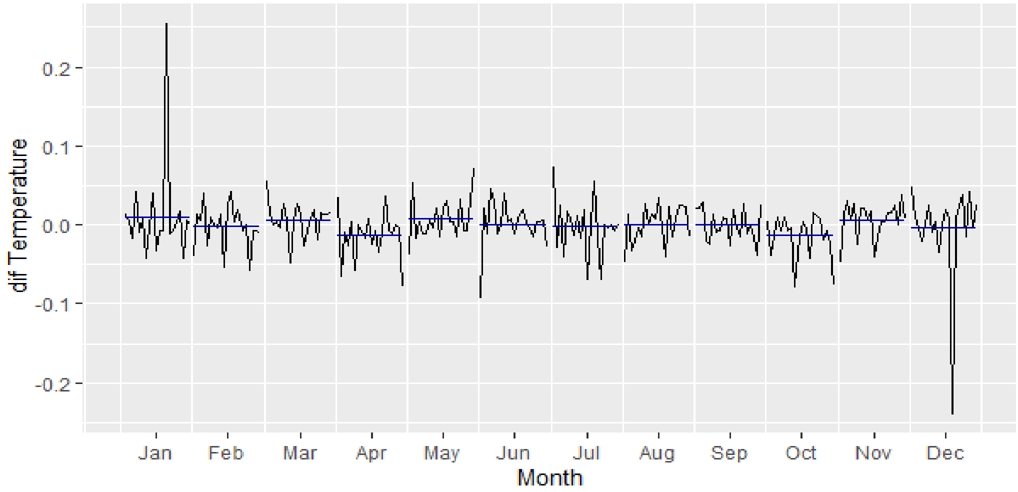

Figure 5: Seasonal Time Plot after Differencing

3.3 Model Identification

The Autocorrelation Function (ACF) was used to identify the probability time series models that best describe the monthly air temperature series for the meteorological stations in the Warri city of Delta State.

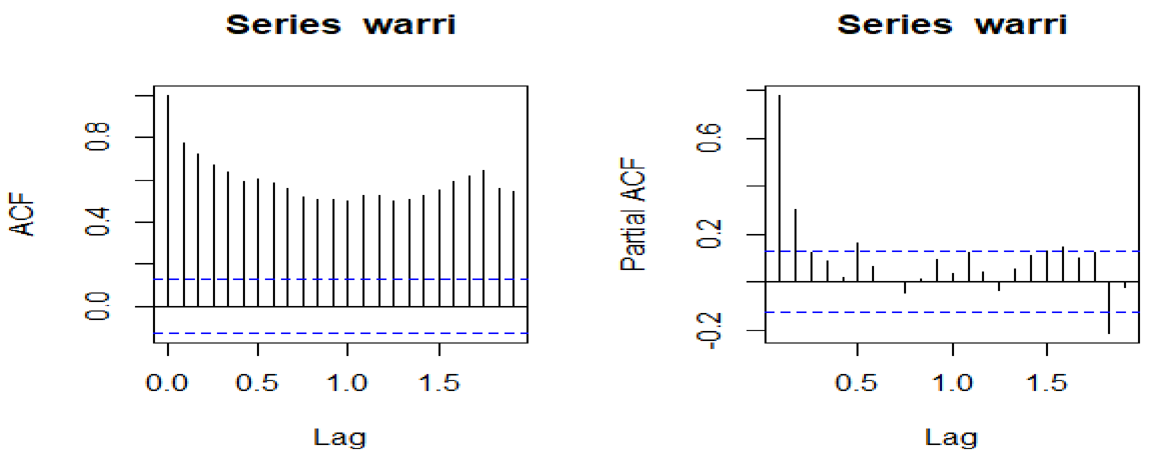

Figure 6: The ACF and PACF Plots of Monthly Air Temperature for Warri City in Delta State

3.4 Parameter Estimation

After the data series was transformed to achieve stationarity, data series also exhibits seasonality and the ACF examined, we then concluded that the data series follows the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. Table 4 shows the parameter estimation table for the model that best describes the monthly air temperature for Warri City in Delta State. These tables likely provide information on the specific values assigned to the autoregressive, moving average, and seasonal components of the SARIMA model, along with any other relevant parameters. By estimating the parameters of the SARIMA model, one can capture the underlying patterns and dynamics in the monthly air temperature data, allowing for accurate modelling and forecasting of temperature fluctuations in Warri City.

Table 4: Model Estimation of Monthly Air Temperature for Warri City

Model		Model	AR1	AR2	MA1	MA2	SAR1	SMA1	
		Estimate	-0.3338	0.327	-0.186	-0.5727	-0.6127	0.4904	
SARIMA	**(2,1,2)**	S.E.	0.3178	0.1038	0.3226	0.2574	0.2233	0.2431	
(1,0,1) [12]		**Performance**	**AIC**	**Log-likelihood**	**ME**	**RMSE**	**MAE**	**MAPE**	**MASE**
		criteria	571.73	-278.87	-0.011	0.77	0.5315	1.9528	0.5237
		Model	**AR1**	**AR2**	**MA1**	**MA2**	**SAR1**	**SMA1**	**SAR2**
SARIMA	(1,1,1)	Estimate	0.2579		-0.9771		0.1658		0.2057
(2,0,0) [12]		S.E.	0.0641		0.0164		0.0617		0.0609
		Performance	**AIC**	**Log-likelihood**	**ME**	**RMSE**	**MAE**	**MAPE**	**MASE**
		criteria	739.8	-364.9	0.047	1.026	0.60433	2.699	0.794
		Model	**AR1**	**AR2**	**MA1**	**MA2**	**SAR1**	**SMA1**	**SMA2**
SARIMA	(0,1,2)	Estimate			-7128	-0.2478		0.1294	0.1533
(0,0,2) [12]		S.E.			0.0611	0.0605		0.065	0.056
		Performance	**AIC**	**Log-likelihood**	**ME**	**RMSE**	**MAE**	**MAPE**	**MASE**
		criteria	746.69	-368.35	0.046	1.042	0.629	2.8	0.826

3.5 Model Diagnostic and Forecasting

The residual from each fitted SARIMA model was checked using the autocorrelation plots at different lags. The ACF plot does not show any autocorrelation among the residuals, which shows we can use the SARIMA model for forecasting. This section aims to check how well the selected models fit the actual data; this is an iterative procedure used to evaluate model aptness by examining whether the model assumptions are satisfied. Model adequacy is concerned with the residuals' analysis. To check the estimated models' adequacy, we first look at the standardised residual plot of the models. Figure 7 show the residual plots, histogram and the ACF of the models fitted the mean air temperature data. The residuals' standardised time plots do not show any strange behaviour or specific direction; therefore, these plots do not suggest any major irregularities with the model. The histogram of the residuals has a bell shape, which is a good indication of the normality of the distribution.

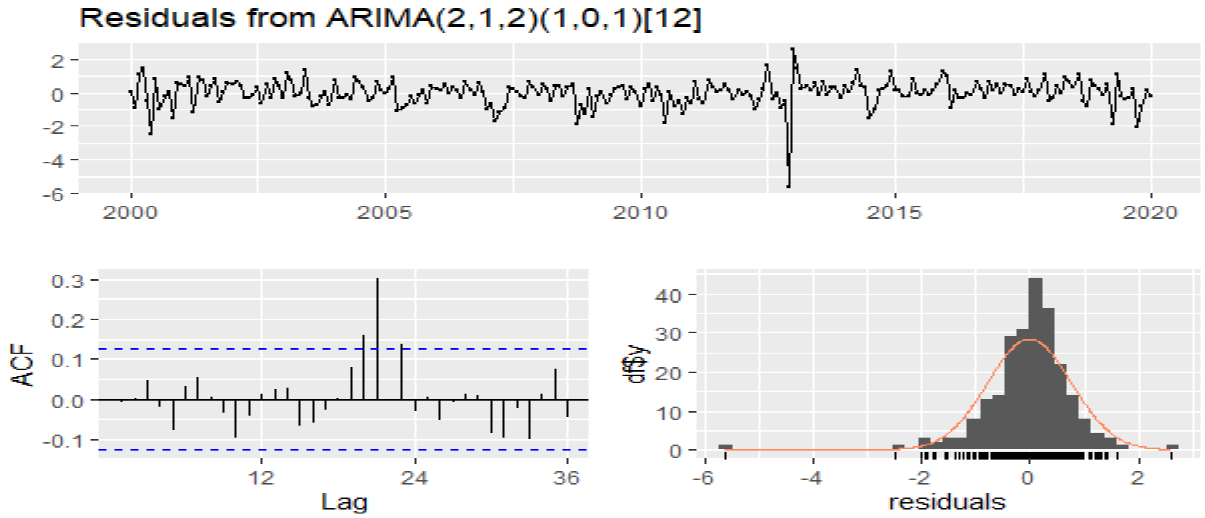

Figure 7: The standardised residual plot

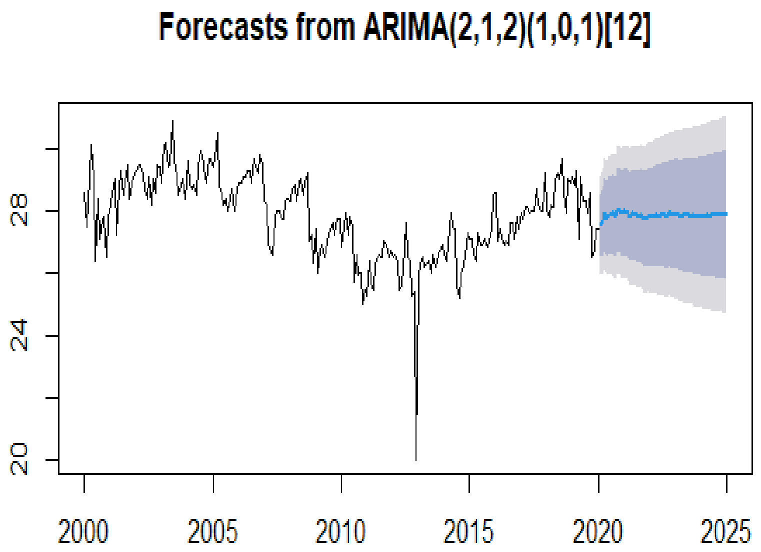

Figure 8: 5 years' ARIMA model forecast for monthly mean air temperature for Warri City

3.6 Modelling of Warri air temperature data using NNETAR

A feed-forward neural network model was fitted to the air temperature series from Warri's meteorological station in Delta State Nigeria using lagged values of the time series data as inputs and a single hidden layer with a number of nodes. On the data series, the Neural Network Autoregressive (NNETAR) model was used, and the best NNETAR model that suites the data series has an NNAR(22,1,12)[12] model with 20 networks on the average, each of which is a 22-12-1 network with 289 weights.

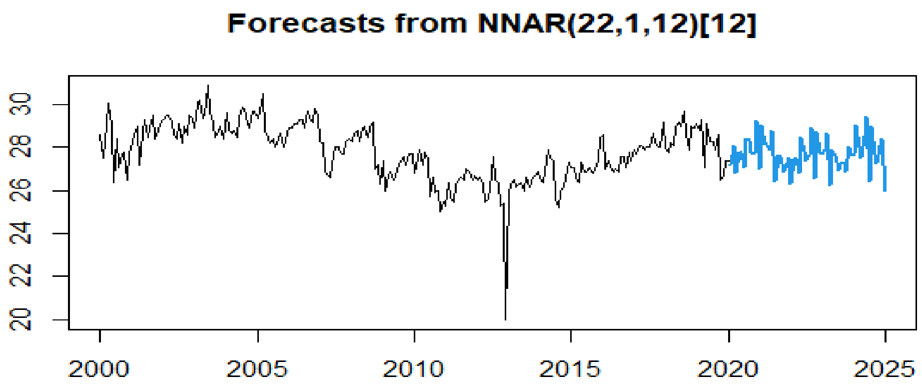

Figure 9: 5 years' NNETAR model forecast for monthly mean air temperature for Warri City

Table 5: NNETAR Model Estimation of Monthly Air Temperature for Warri City

Met Station	Model	ME	RMSE	MAE	MAPE	MASE	ACF1
Warri	NNAR(22,1,12)[12]	-0.0003	0.01621	0.01048	0.4020	0.01032	0.0093

The NNAR(22,1,12)[12] model is a neural network model that incorporates 22 lagged values of the dependent variable, performs differencing of order 1 to achieve stationarity, and captures seasonal patterns with a lag of 12. It was determined to be the best model among several neural network models evaluated using the R software. The ACF (Autocorrelation Function) at lag 1, which is 0.0093, indicates a very small positive correlation between the series and its lagged value. However, the value is close to zero, suggesting that the correlation is weak. Additionally, the RMSE (Root Mean Squared Error) value of 0.1621 suggests that the model's predictions are relatively close to the actual air temperature values. Furthermore, the model's performance is also reflected in the low Mean Absolute Scaled Error (MASE) of 0.01032, which indicates that the model's forecast are relatively accurate. Overall, the NNAR(22,1,12)[12] model shows promising results in capturing the patterns and predicting air temperature values, as evidenced by its relatively low ACF, RMSE, and MASE values.

Table 6: Point forecast for ARIMA and NNETAR model for 5 years

SARIMA 5 Years' Forecast						**NNETAR 5 Years' Forecast**
Months	**Point Forecast**	**Lo.80**	**Hi.80**	**Lo.95**	**Hi.95**	**Point Forecast**
Feb-20	27.53740373	26.53591	28.5389	26.00575	29.06906	27.16806
Mar-20	27.63729388	26.52632	28.74827	25.93821	29.33638	28.06357
Apr-20	27.8974217	26.71367	29.08117	26.08703	29.70781	26.84152
May-20	27.74804466	26.53553	28.96055	25.89367	29.60242	27.79775
Jun-20	27.84249184	26.59632	29.08866	25.93664	29.74834	27.79096
Jul-20	27.84481074	26.57732	29.1123	25.90636	29.78326	27.09598
Aug-20	27.90845935	26.61489	29.20203	25.93011	29.88681	28.38878
Sep-20	27.78724325	26.47319	29.10129	25.77758	29.79691	28.36747
Oct-20	27.99106182	26.65362	29.32851	25.94562	30.03651	27.75093
Nov-20	28.0471132	26.68934	29.40489	25.97057	30.12365	27.69033

Table 6 Cont'd:

Dec-20	27.89976491	26.52007	29.27946	25.7897	30.00983	29.24516
Jan-21	27.96185169	26.56204	29.36166	25.82102	30.10268	27.01701
Feb-21	27.93953756	26.53455	29.34452	25.7908	30.08827	29.03381
Mar-21	27.94800375	26.53165	29.36436	25.78187	30.11414	28.13426
Apr-21	27.78560927	26.35634	29.21488	25.59972	29.97149	28.16845
May-21	27.90091971	26.45677	29.34506	25.69229	30.10955	27.9163
Jun-21	27.83412613	26.37539	29.29286	25.60318	30.06507	28.78197
Jul-21	27.84346498	26.36954	29.31739	25.5893	30.09763	26.40405
Aug-21	27.79795808	26.30929	29.28662	25.52124	30.07467	27.67726
Sep-21	27.87791634	26.37432	29.38151	25.57837	30.17747	27.55393
Oct-21	27.74901208	26.23083	29.26719	25.42716	30.07086	26.89163
Nov-21	27.71787648	26.18508	29.25067	25.37367	30.06208	27.00307
Dec-21	27.80576625	26.25862	29.35292	25.4396	30.17193	27.54628
Jan-22	27.76957222	26.2081	29.33104	25.38151	30.15764	26.33678
Feb-22	27.78184698	26.1945	29.3692	25.3542	30.20949	27.46024
Mar-22	27.77772951	26.17129	29.38417	25.3209	30.23456	27.54335
Apr-22	27.87641157	26.25197	29.50085	25.39205	30.36077	26.84556
May-22	27.80638458	26.16568	29.44709	25.29715	30.31562	28.45082
Jun-22	27.84683416	26.18979	29.50388	25.3126	30.38107	27.82352
Jul-22	27.84147367	26.1688	29.51415	25.28334	30.3996	27.39384
Aug-22	27.86907941	26.18067	29.55749	25.28688	30.45128	27.66939
Sep-22	27.82030067	26.11656	29.52404	25.21465	30.42595	28.91975
Oct-22	27.8991175	26.18001	29.61822	25.26997	30.52826	26.53466
Nov-22	27.9183158	26.18412	29.65251	25.2661	30.57053	28.70951
Dec-22	27.86437438	26.11513	29.61362	25.18913	30.53962	27.77801
Jan-23	27.88662076	26.12252	29.65072	25.18866	30.58458	27.70991

Table 6 Cont'd:

Feb-23	27.87904609	26.10549	29.6526	25.16662	30.59147	27.91804
Mar-23	27.8816101	26.09608	29.66714	25.15087	30.61235	28.64354
Apr-23	27.82111811	26.02327	29.61896	25.07155	30.57068	26.24715
May-23	27.86404624	26.05321	29.67488	25.09461	30.63348	27.90938
Jun-23	27.83924529	26.01562	29.66287	25.05026	30.62823	27.66484
Jul-23	27.84254353	26.00594	29.67915	25.0337	30.65139	26.96444
Aug-23	27.8256194	25.97626	29.67498	24.99726	30.65398	27.28405
Sep-23	27.85551326	25.99334	29.71768	25.00757	30.70346	27.33295
Oct-23	27.8072176	25.93241	29.68202	24.93995	30.67448	26.90917
Nov-23	27.79545992	25.90803	29.68288	24.90889	30.68203	28.02035
Dec-23	27.82850512	25.9286	29.72841	24.92284	30.73417	27.61821
Jan-24	27.81487796	25.90252	29.72723	24.89018	30.73957	27.69277
Feb-24	27.81951671	25.89144	29.74759	24.87078	30.76825	29.07936
Mar-24	27.8179474	25.87605	29.75984	24.84808	30.78782	28.04205
Apr-24	27.85500839	25.89965	29.81037	24.86455	30.84547	27.54179
May-24	27.82870813	25.86044	29.79698	24.8185	30.83892	28.54839
Jun-24	27.84390245	25.86273	29.82507	24.81397	30.87384	29.43604
Jul-24	27.84188223	25.84807	29.8357	24.79261	30.89116	26.41847
Aug-24	27.85225089	25.84579	29.85871	24.78364	30.92086	28.99668
Sep-24	27.83393584	25.81499	29.85288	24.74623	30.92164	27.69891
Oct-24	27.86352537	25.83212	29.89493	24.75676	30.97029	27.29085
Nov-24	27.87072924	25.82699	29.91447	24.74509	30.99636	28.08165
Dec-24	27.85048298	25.79444	29.90652	24.70604	30.99492	28.44064
Jan-25	27.85883217	25.79059	29.92707	24.69573	31.02193	25.98067

Table 6 shows the point forecast for both the SARIMA model and the NNETA.

3.7 Predictive Performance Comparison between SARIMA and NNETAR model

The predictive performance is compared between SARIMA and NNETAR models for all the time series data under study. Predictive accuracy or performance is reported in Table 7.

Table 7: Comparison between SARIMA and NNETAR Model

Met Stations	Model	RMSE	MAPE	MAE	MASE
Warri	SARIMA (2,1,2) (1,0,1) [12]	0.77	1.9528	0.5315	0.5237
	NNAR(22,1,12)[12]	**0.01621**	**0.402**	**0.01048**	**0.01032**

Table 7 illustrates that the NNETAR model emerged as the superior choice for modeling and forecasting the mean air temperature of Warri City. This conclusion is supported by its significantly lower values for RMSE (0.01621), MAPE (0.402), MAE (0.01048), and MASE (0.01032) compared to the corresponding metrics of the SARIMA model.

4. Summary and Conclusion

In this study, two separate forecasting models, SARIMA and NNETAR, were developed to predict and forecast the mean monthly air temperature in Warri, Delta State, Nigeria. The data exhibited non-stationarity but had seasonal patterns, requiring differencing to achieve stationarity. Among the SARIMA models tested, SARIMA (2,1,2) (1,0,1) [12] was identified as the best model using an iterative technique with auto.arima in R.

In this analysis, we compare the SARIMA model (2, 1, 2) (1, 0, 1) [12] with the NNAR (22, 1, 12) [12] model based on multiple metrics: MASE, MAPE, MAE, ME and RMSE. The NNAR model demonstrates significantly lower MASE (0.01032) compared to the SARIMA model (0.5237), indicating its superior accuracy and forecasting performance. Similarly, the NNAR model exhibits a substantially lower MAPE (0.402) compared to the SARIMA model (1.9528), indicating a smaller average percentage difference between predicted and actual values. Moreover, the NNAR model achieves a significantly lower MAE (0.01048) than the SARIMA model (0.5314), indicating improved accuracy in predicting air temperature values.

Both models display relatively small ME values, suggesting that the predictions slightly underestimate the actual values with negligible differences between the models. Notably, the NNAR model outperforms the SARIMA model in terms of RMSE, with values of 0.01621 and 0.770, respectively. This lower RMSE signifies better accuracy and smaller prediction errors.

To summarize, based on the provided metrics, the NNAR (22, 1, 12) [12] model demonstrates superior performance compared to the SARIMA (2, 1, 2) (1, 0, 1) [12] model. The NNAR model exhibits lower values for MASE, MAPE, MAE and RMSE, indicating higher accuracy and improved forecasting capabilities.

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