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SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE MODEL FOR PREDICTION OF ELECTRICAL ENERGY DEMAND OF A BASE TRANSCEIVER STATION

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Abstract

Efficient energy management is essential for the continuous operation of Base Transceiver Stations (BTS), which are critical to mobile communication infrastructure. Power shortages can lead to service disruptions, necessitating accurate energy demand forecasting for optimal energy planning. This study developed a dual SARIMA models using 36 months (May 2021–April 2024) of field-measured hourly and daily electrical energy data from a BTS in Abeokuta, Nigeria with average load of 4.2 kW. The long-term daily model SARIMA $(0,1,0)(1,0,1)_7$ *captures weekly traffic seasonality, while the short-term hourly model SARIMA*$(1,0,0)(0,1,2)_{24}$ *addresses diurnal peaks. The performance of the model was evaluated using Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Results showed that the long-term approach had a lower MAPE (7.67%) compared to the short-term approach (13.32%), indicating better accuracy. However, the short-term approach outperformed in terms of RMSE (0.63 kW) and MSE (0.40 kW), compared to 0.78 kW and 0.62 kW, respectively, for the long-term approach. Utilizing the forecasted energy demand, HOMER Pro software was employed to design an optimized hybrid energy system integrating solar energy and a biogas co-fired generator. Results yielded an economically optimal solar-biogas-battery configuration: 40 kW Canadian Solar PV, 16 kW CAT biogas generator, and 32.8 kWh LiFePO*$_4$ *storage delivering zero unmet loads. Key metrics include Levelized Cost of Energy (COE) of $0.01666/kWh, Net Present Cost (NPC) of $15,000, and 8-year payback, representing a 75% cost reduction versus diesel-only alternatives. SARIMA forecasting thus bridges precise BTS load prediction with cost-effective renewable sizing, enabling sustainable telecom expansion across off-grid regions.*

1.0 INTRODUCTION

communication and high-quality video streaming [1,2]. While mobile telecommunication has experienced significant growth in acceptability by the teeming population, insufficient power supply for the BTS operation could impede the benefits [3-5]. A previous study [6] investigated key areas on the efficiency of energy usage in communication networks and reported that up to 80% of the energy used by networks can be conserved.

Energy forecasting has traditionally used conventional forecasting techniques like Box-Jenkins and exponential smoothing [7-9]. While these methods are robust for linear time-series data,

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previous studies have often struggled to capture the complex, non-linear, and multi-seasonal patterns inherent in telecommunications load profiles [10,11]. This inability to efficiently predict power requirements can lead to overheating and damaging of key BTS components due to electrical stress arising from inadequate power supply.

Time series forecasting models have gained significant traction, especially for weather related problems. The approach has proven its ability to forecast weather and solar radiation data for the short and medium terms [12]. The study by [13-15] opined that electrical load forecasting is essential for planning to meet the continuous supply of electricity demand. Furthermore, [16] investigated the power consumption of BTS and the inherent benefits of using conserved power without affecting the network's quality of service (QoS). From sustainable batteries to power-efficient electronics, the study discussed the common goal of these storage systems and devices to improve power efficiency [17,18].

Hence, by employing a time series forecasting model, this study aims to predict the short and long-term energy demand of a typical BTS at the Federal University of Agriculture, Abeokuta, Nigeria. The paper is structured thus: a review of relevant literature is presented in Section 2; materials and methods applied in this study are contained in Section 3; the results and discussion appear in Section 4, and the conclusion is presented in Section 5.

This section discusses a few of energy forecasting techniques in power systems and telecommunication infrastructures that have been proposed in the literature, highlighting the different methods and their limitations. For instance, [19] employed ARIMA and Holt-Winters models for regional energy prediction; however, the study lacked a comparative framework to determine the contextual applicability of these models.

In another study, [20] used multiple linear regression (MLR) to find correlations within 195 scenarios. The use of MLR by Ciulla and D’Amico offered a user-friendly statistical approach but failed to account for the inherent seasonality of energy data, leading to insufficient results. The challenge of model generalization is also prevalent. Dudek [21] and [22] utilized pattern-based local linear regression for short-term loads to reduce complexity, but this localized approach often inhibits performance when applied to historical patterns that deviate from training data. Hybrid methodologies have been proposed to bridge these gaps [23-27] to address data unavailability. While innovative, the complexity of such hybrid systems can introduce uncertainties regarding model stability and reliability. Consequently, [28] expanded on the use of combined bagging and forecasting methods in the energy sector with a combination of ARIMA and exponential smoothing methods. However, the inability of the models employed to model non-linear data still limits the effectiveness of the methods employed.

According to [29], a multiple equation time-series model can outperform complex non-linear forecasting models. However, its use in other regions with different load characteristics or market structures remains untested. Moreover, the reliance on a linear model might limit the ability to capture patterns in the data. Also, the model assumed stationarity in the time series data, which differs from real-world scenarios where load patterns can change due to various external factors. This assumption could lead to inaccuracies in forecasting results.

In the telecommunications sector, Regmi and Pandey [30] and Obinna and Osawaru [31] utilized ridge and linear regression models to examine the relationship between traffic load and power consumption. While effective in reducing multi-collinearity, these linear approaches often underestimate consumption by omitting environmental variables and failing to capture sudden operational spikes or non-linear dynamics.

Collectively, these studies highlight a persistent need for forecasting methods that can simultaneously handle non-linearity, account for multi-period seasonality (diurnal and weekly), and process high-resolution datasets. This study addresses these deficiencies by developing a dual-scale SARIMA model specifically optimized for the unique load characteristics of a Nigerian Base Transceiver Station.

2.0 MATERIALS AND METHOD

The quality of data collected directly affects the accuracy of the results in a machine learning task. Hence, it is important to collect and apply good-quality datasets. The BTS from which the historical power consumption data is obtained is owned by MTN Nigeria and managed by IHS towers. Data spanning 36 months of BTS instantaneous power consumption in kW was retrieved from on-site data loggers. Figure 1 shows the location area of the BTS. The purpose of collecting the different kinds of data is to enable informed decisions about the energy

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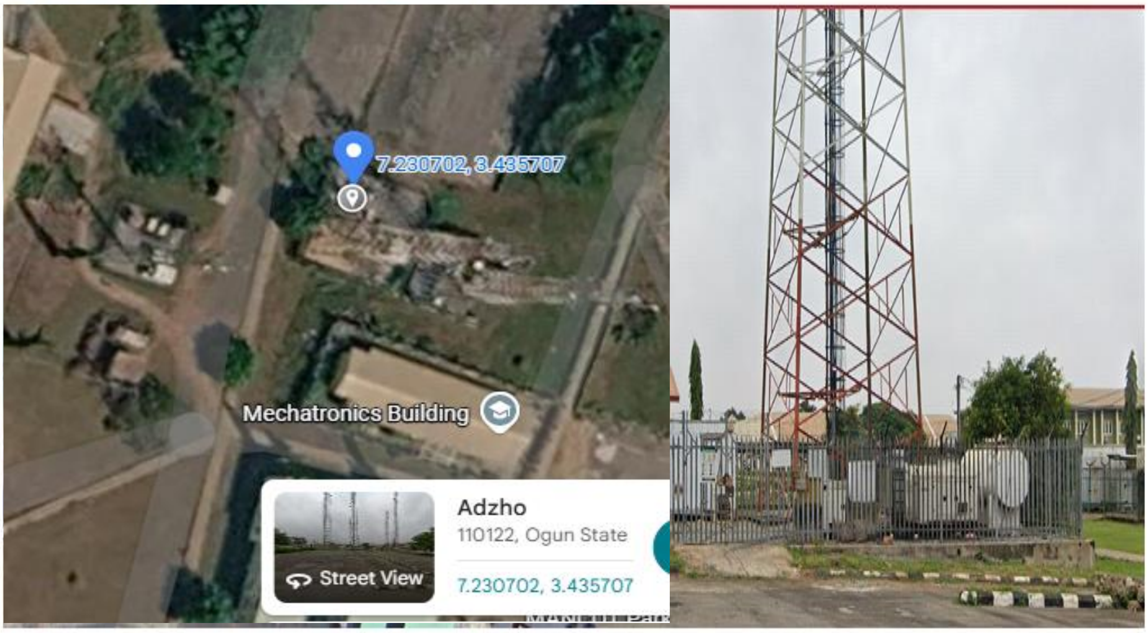
consumption of the BTS and predict its energy demand.



(a) (b)

Figure 1: (a) Location of the selected BTS (b) sample image of the BTS and its immediate environment

Energy consumption data was retrieved from on-site data loggers covering a 36-month period. Microsoft Excel was employed for data organization, while the forecasting models were implemented using the Pandas, Numpy, statsmodels and SARIMAX libraries in a Python-based Google Colab environment. The SARIMA model is a generalization seasonal autoregressive moving average technique suitable for handling non-stationary time series and takes care of the time signal after de-noising and outputs its forecast for a subsequent time point [32,33]. The following makes up the SARIMA model [34]:

1. AR (auto-regression): This part of the model uses the dependence relationship between an observation and several lagged observations. It is represented by lag order (p).

2. I (integration) order is the differencing order of raw observations. It is used to make the time series to become stationary. It is represented by the degree of difference (d).

3. MA (moving average): This part of the model is the representation of relationship between an observation and the error terms created when moving average model is used on observations with a time lag. It is represented by the order of the moving average (q).

4. S (Seasonal): This handles the length of the seasonal cycle adopted in the model. For instance, 12 for monthly data, 7 for daily weekly seasonality and 24 for hourly data).

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model extends ARIMA to handle seasonality in BTS energy data, which exhibits hourly or daily cycles [33-35]. Generally denoted as SARIMA(p,d,q)(P,D,Q)$_{s,}$, SARIMA captures both seasonal and non-seasonal patterns in time series data, making it ideal for BTS energy forecasting with diurnal peaks and weekly trends. It is mathematically expressed as:

$$(1 - \textstyle\sum_{i=1}^{p} \phi_i L^i)\,(1 - \sum_{j=1}^{P} \Phi_j L^{js})^d\,(1 - B)^D\, Y_t = C + (1 + \sum_{k=1}^{q} \theta_k L^k)\,(1 + \sum_{m=1}^{Q} \Theta_m L^{ms}) \qquad (1)$$

where B=1- L is the backshift operator ($LY_t = Y_{t-1}$), d and D are non-seasonal and seasonal differencing orders for stationarity, p, q (P, Q) are AR (MA) orders, s is the seasonal period (e.g., s=24 and 7 for hourly and weekly BTS data respectively), ϕ_i, Φ_j are non-seasonal/seasonal AR coefficients, θ_k, Θ_m are MA coefficients, C is the constant (drift), and $\epsilon_t \sim WN(0, \sigma^2)$ is white noise.

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The selection criteria often used in practice are the Akaike (AIC) and Bayesian information criteria (BIC). The AIC measures the balance between over-fitting and model complexity while BIC is specifically inclined to an increased penalty for complex models. The AIC is expressed as

$$AIC = -2 \log\log(\text{maximum likehood}) + \frac{n+k}{n-2-k} \quad (2)$$

where k is an independently adjusted number of the parameters and n is total number of data points while the expression for the BIC is

$$BIC = -2 \log\log(\text{maximum likehood}) + \frac{k \log\log n}{n} \quad (3)$$

For BTS application, fit using statsmodels.tsa.statespace.sarimax.SARIMAX in Python after Box-Cox transformation, ADF test for stationarity, and ACF/PACF for orders, validate residuals via Ljung-Box.

The implementation was done in Python programming language environment to determine the SARIMA model's parameters $(p, d, q)_s$. The flowchart of the implementation process is shown in Figure 2.

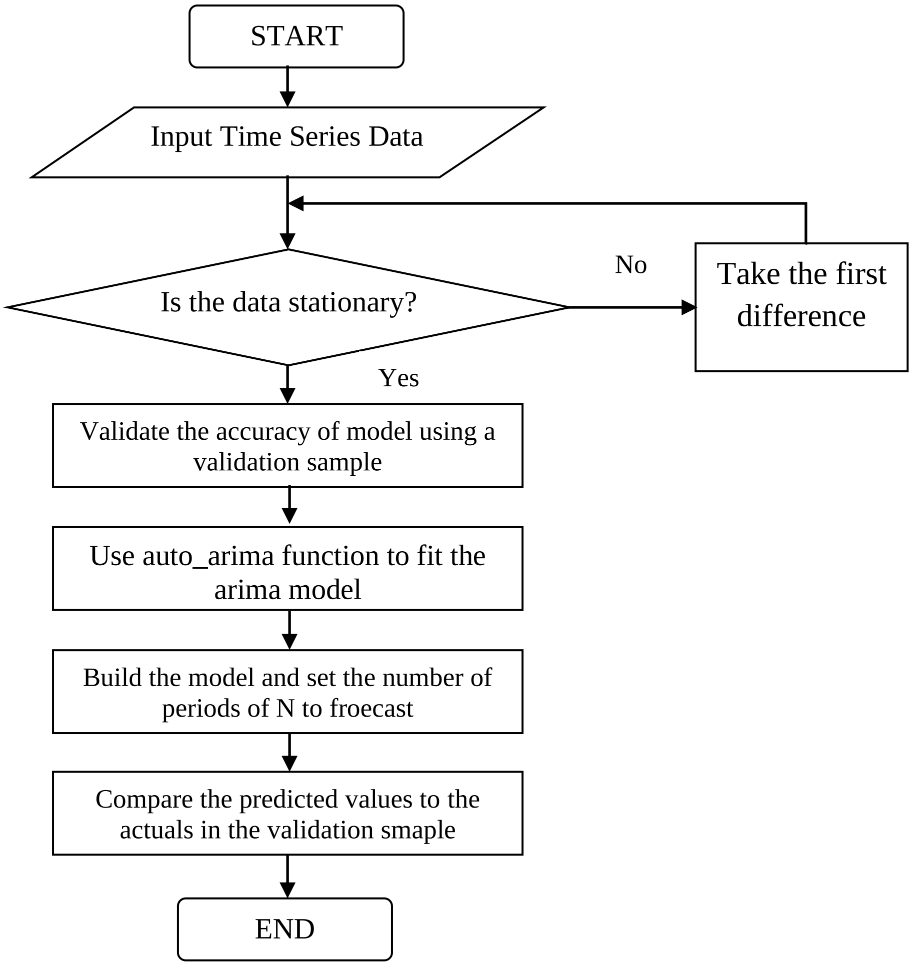

Figure 2: SARIMA model implementation for energy demand forecasting of the BTS

Energy usage data collected hourly served as input for training and testing the model. The data is split such that 80% was used to train the model while the remaining 20% was employed for testing.

Based on the forecast values of energy demand using the proposed models, there is need for the design of a potential energy sources' mix from available renewable energy sources in the study area.

2.1 Design of Potential Energy Mix

Hybrid optimization of multiple energy resources (HOMER) software was used to optimize the mix of renewable and non-renewable energy sources to provide the forecasted energy value to the BTS. The choice is informed going by results from previous and related studies [36] where HOMER Pro software was successfully applied for the optimization of micro-grids and energy supply systems. The

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components of the simulated environment include a solar energy source and gas-fired source among others. Due to the solar irradiance of the BTS location as well as proximity of the study area to gas supply station, solar power and gas fired generator mix was considered as an energy source to meet the BTS need.

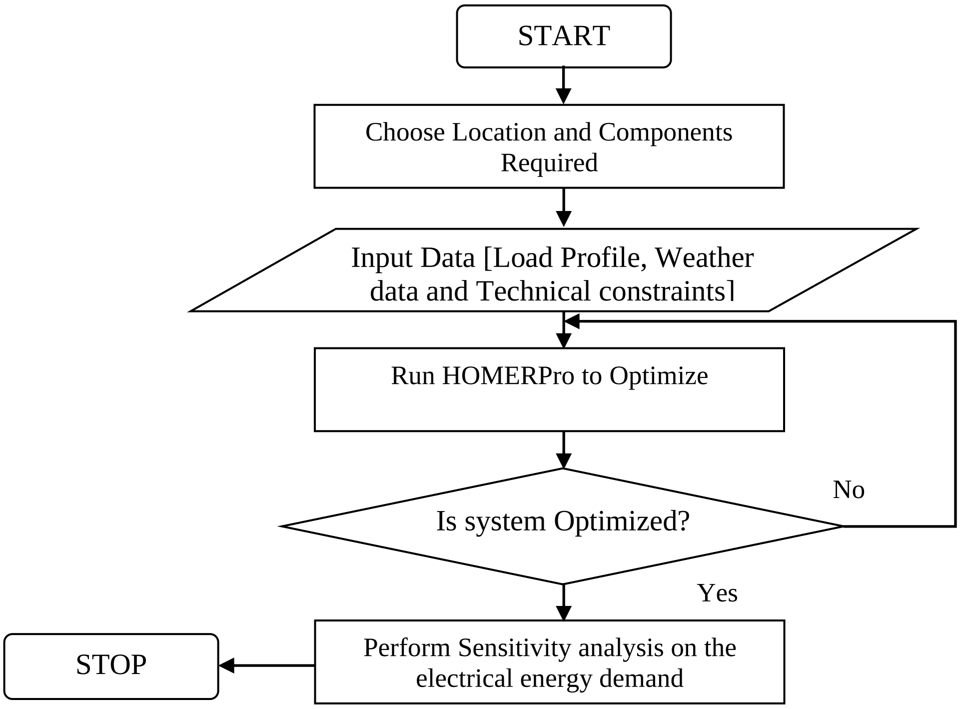

Figure 3: Flowchart of HOMER pro optimisation technique for the energy source mix

2.2 Model Performance Metrics

Model accuracy was evaluated using three standard metrics for energy forecasting: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) expressible in the form:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \qquad (4)$$

$$RMSE = \sqrt{\left[\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2\right]} \qquad (5)$$

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \qquad (6)$$

where y_t is actual BTS energy consumption (kWh) at time t, $\hat{y}_t$ is the SARIMA forecast, and n is the number of validation observations.

3.0 RESULTS AND DISCUSSION

Figure 4 shows the hourly distribution of electrical energy usage data collected.

The observed electrical energy usage is seen to vary as the month changes. For instance, in December 2023, the average daily usage is 7.5 kW while in January 2024, the value is 9 kW. These variations are often caused by weather, increased traffic load and downtime which may be due to equipment failures. Peak and off-peak periods are also noticed in the data distribution for March 2023 and December 2023, as shown in Figures 5 (a) and (b). Off-peak periods in the time series plot with a sharp reduction in energy usage are crucial for further analysis.

The hourly load profile of the BTS for a day is shown in Figures 5 (a) and (b), respectively. Figure 5(a) shows the peak hourly load profile, and Figure 5(b) shows the daily off-peak hourly load profile for the BTS. The figure 5(b) shows the maximum load power during the off-peak period is 7.50 kW, and the minimum load power is below 5.75 kW. For the peak period, figure 5(a) shows the maximum load power is 9.1kW and the minimum load power is 6.1kW. It can be observed from the figures that the load demand peaked in the afternoons and was at the lowest values in the early mornings around dawn for both peak and off-peak periods. The augmented Dickey-Fuller (ADF) test tested the dataset for stationarity. The application of the ARIMA model was approached in two ways. long-term prediction and short-term prediction. The long-term approach captured the daily energy usage for the entire three years of data collected, while the short-term approach captured the

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hourly energy usage for three months (December 2023 - February 2024) selected from the data collected. The stationarity test was carried out using the Augmented Dickey-Fuller (ADF) on the data sets for the two approaches, and the results are presented in Table 1. For the long-term approach, the ADF test yielded a p-value < 0.05, suggesting stationarity. However, to ensure the removal of any residual stochastic trends and to maintain model stability across the 3-year window, a first-order differencing ($d=1$) was integrated into the SARIMA model as determined by the auto_arima optimization. For the short-term approach, the ADF test indicated non-stationarity ($p > 0.05$), necessitating seasonal differencing ($D=1$) to stabilize the mean.

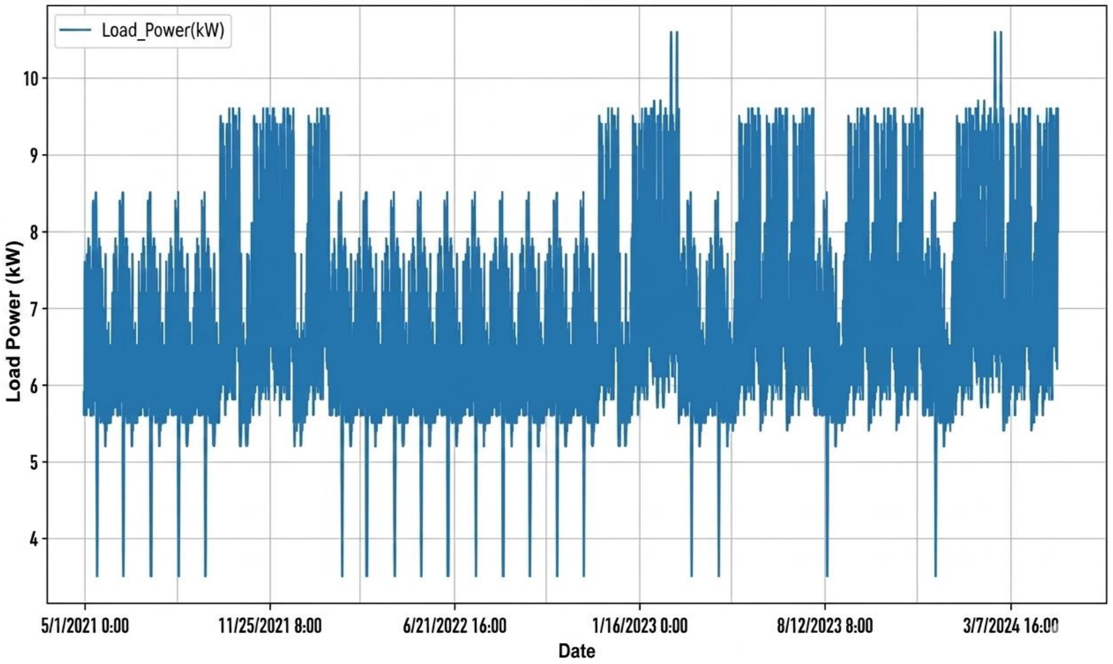
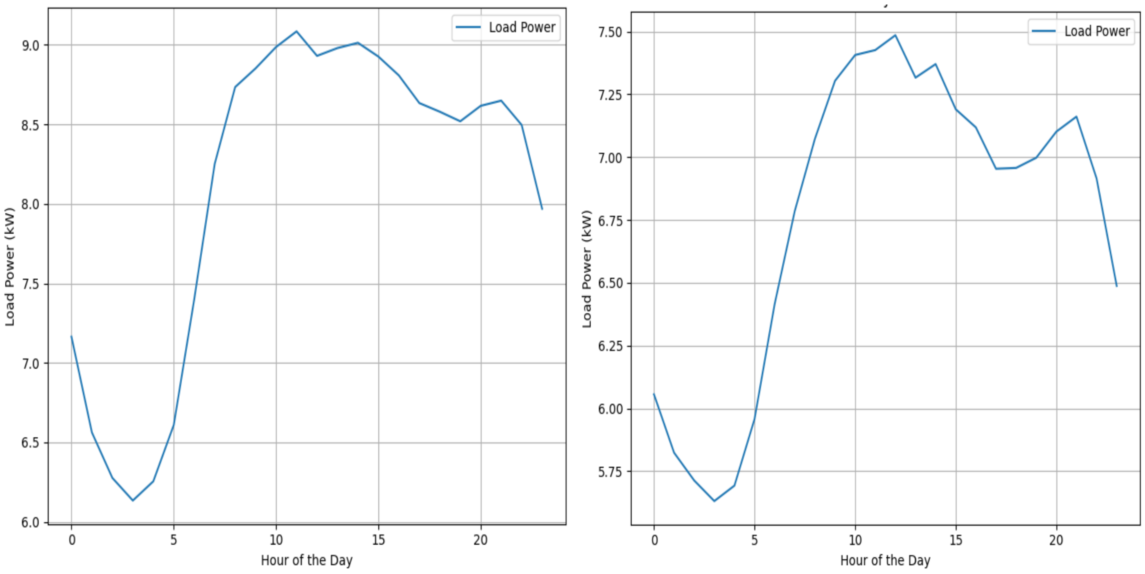


Figure 4: Hourly load profile of the mtn BTS (in kW) for may 2021 – april 2024



(a) (b)

Figure 5: Hourly load profile of the BTS (a) peak (b) off-peak

The model parameters were selected using the relevant Python programming function, which gives the best model parameters suited for the data by finding the parameters with the lowest akaike's information criteria (AIC) and the time taken to fit them. Table 2 shows the results of the auto_arima function on the two datasets for the different approaches.

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Table 1: Results of the ADF stationarity test on short- and long-term predictions

Period (Frequency)	**ADF Test (p-value)**	**P > 0.05?**	**Stationarity**
Long Term	0.000771	False	True
Short Term	0.256	True	False

Table 2: Results of the model AIC and parameters tuning

Period (Frequency)	**Model Parameters**	**AIC**	**Time taken(s)**
Long Term	$(0, 1, 0)\ (1, 0, 1)_7$	623.484	0.37
Short Term	$(1, 0, 0)\ (0, 1, 2,)_{24}$	644.885	3.00

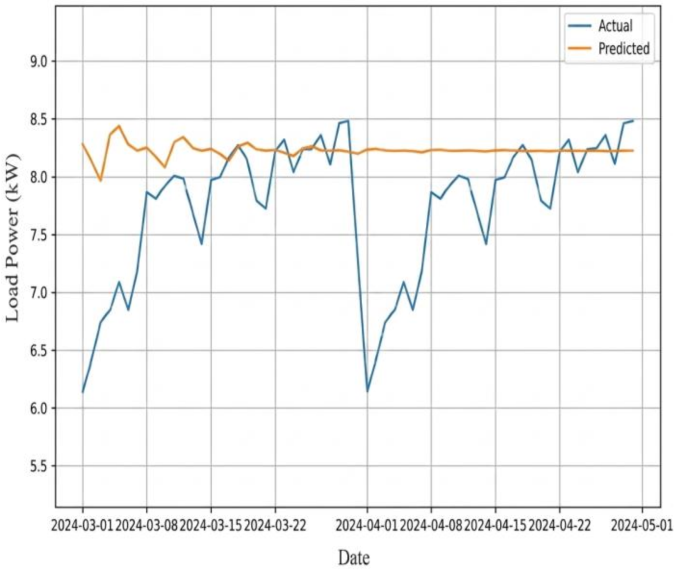

Figure 6: Variations of Daily load profile test data and predicted data for Long-Term approach (May 2021 – April 2024)

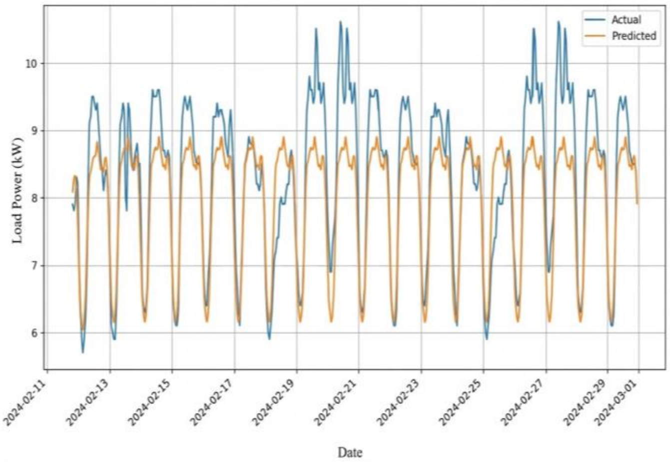

Figure 7: Variations of hourly load profile test data and predicted data for short-term approach (December 2023–February 2024)

The results shown in Table 2 for the long-term approach indicate that a first-order differencing was carried out in the model's non-seasonal component (p, d, q). The model's seasonal component $(P, D, Q)_s$ comprised the seasonal AR and MA component of the first order with a seasonal period of seven (7) days.

The lowest AIC obtained from the different models tested was 623.484, and the time taken to get the desired value was 0.37 seconds. Conversely, for the short-term approach, results obtained showed that a first-order differencing was carried out in the seasonal component $(P, D, Q)_m$ of the model, and the second order of the MA model was selected with a seasonality index (m) of 24 hours. The lowest AIC obtained from the different models tested was 644.85, and the time taken to get the desired value was 3 seconds.

For the long-term and short-term approaches, 80% of the data was used to train the model, and testing was done using 20% of the data. Figures 6 and 7 show the plot of the actual and predicted values for the two approaches. Figure 7 show that the short-term prediction is closer to the actual values.

The entire dataset for long-term and short-term energy prediction approaches was used in their separate approaches with the SARIMA model. The fitted model was used to predict new values of electrical power demand for the BTS. Figures 8 and 9 show the plot of the future values.

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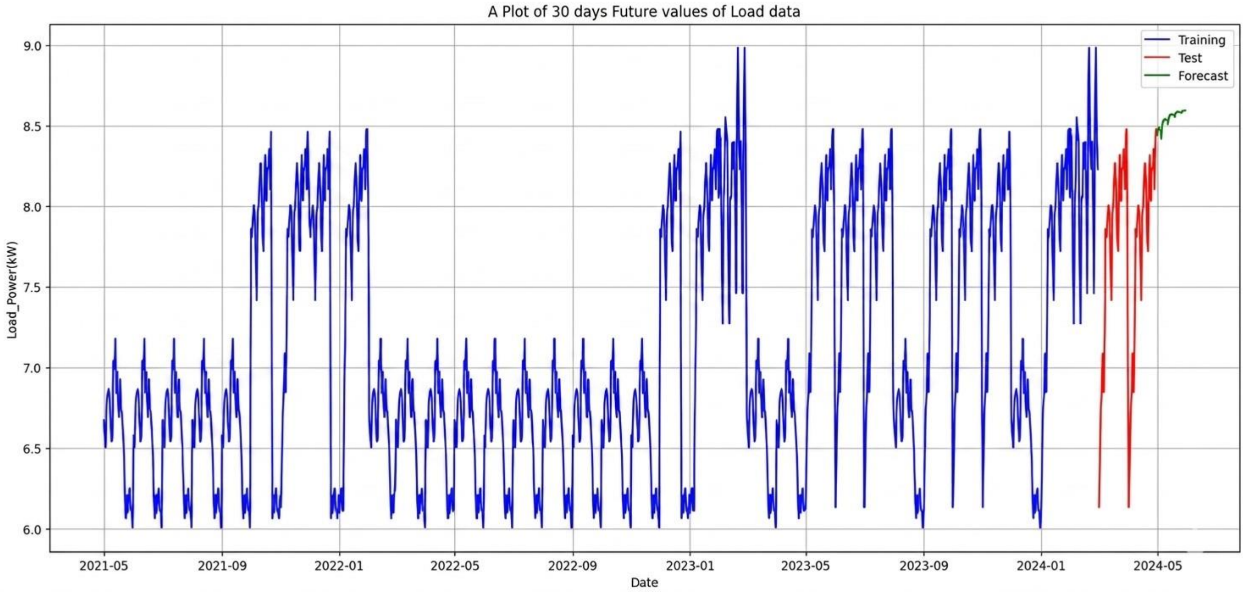

Figure 8: Profile of collected daily load data (blue and red font) with 30 days forecast (green font)

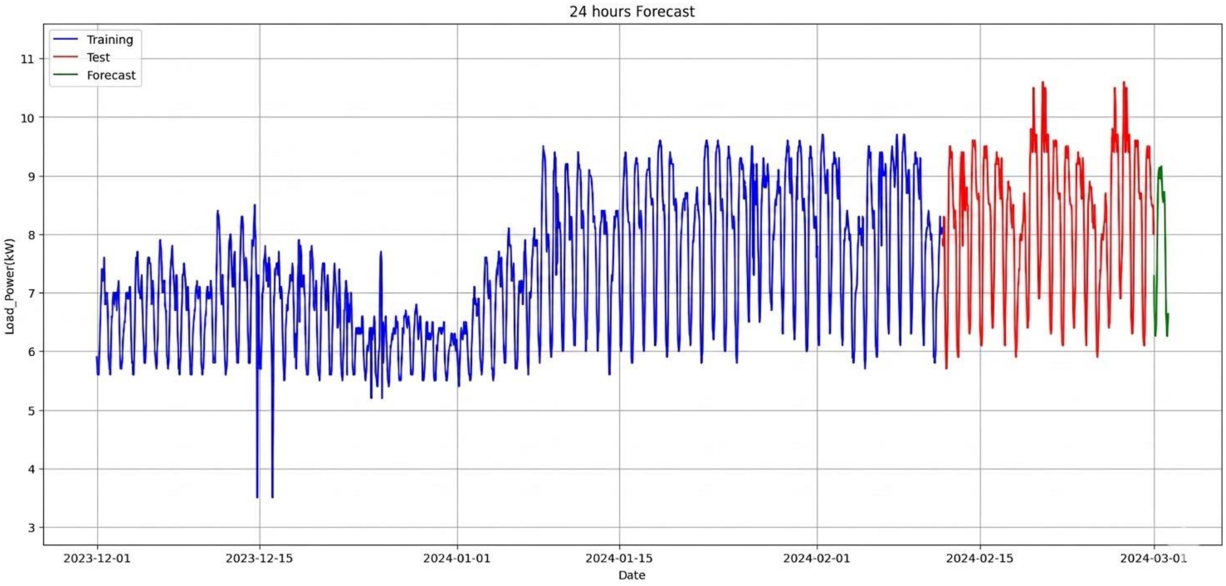

Figure 9: Profile of collected hourly load data (blue and red font) with 24 hours forecast (green font)

3.1 Performance Metrics Comparison

The performance metrics, including the mean square error (MSE), root mean square error (RMSE), and mean absolute percentage error (MAPE), were used to measure data in the validation period. Table 3 shows the MSE, RMSE and MAPE for the two approaches selected, indicating that the predictive model for long-term energy demand performs better in terms of MAPE. The results present a nuanced trade-off in forecasting accuracy. The long-term approach achieved a lower MAPE (7.67%), due to the daily aggregation of data which smoothens out high-frequency noise. However, the short-term approach demonstrated superior precision with a lower RMSE (0.63 kW) and MSE (0.40 kW). Despite the higher percentage error, the short-term model is the preferred approach for operational management. Its lower RMSE indicates fewer extreme deviations from actual values, which is critical for preventing electrical stress and potential hardware failure during sudden peak periods.

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Table 3: Performance metrics comparison of the periods selected

Load Profile	Long-term approach	Short-term approach
MAPE (%)	7.67	13.32
RMSE (kW)	0.78	0.63
MSE (kW)	0.62	0.40

3.2 Comparison with Previous Studies

This section compared results obtained from this study with those of two previous works using MAPE as an index. Results of the comparison are summarized in Table 4.

This result is numerically competitive when compared to the 11.49% reported by Ciulla and D'Amico [20] and the 8.25% achieved by Samuel *et al.* [37] using Artificial Neural Networks (ANN) for campus-wide load forecasting. However, it is important to note that direct comparison across these studies is constrained by variations in geographic location, data resolution (daily vs. hourly), and the specific characteristics of the datasets used. While the different environmental and operational contexts of the referenced works prevent an absolute claim of model superiority, the results suggest that the SARIMA framework is a robust and reliable tool for daily electrical energy demand prediction in the specific context of Nigerian telecommunications infrastructure. Such accuracy supports more informed energy planning and contributes to the reduction of operational waste in localized power systems.

Table 4: Comparison of model performances

Model References	Dataset	Method Used	MAPE (%)
[20]	12 Dec 2012-1 Feb-2018 Daily Energy consumption of Ohio/Kentucky from PJM’s Website	ARIMA	11.49
[37]	Hourly energy consumption data for Covenant University, Ogun state, Nigeria	ANN	8.25
Current Study	Daily energy consumption data of a BTS located in FUNAAB	SARIMA	7.67

3.3 HOMER Pro Optimization Results

The forecasted hourly load profile of the electrical energy demand was used to serve as the input electrical load of the system designed using the HOMER pro software. The designed system is shown in Figure 10. The monthly electrical output of optimising multiple energy sources, including biogas-powered generators and solar energy, are shown in Figure 11. The generation sources include Canadian Solar All-Black CS6K-290MS with a nominal capacity of 40kW and a biogas co-fired CAT20-KVA-50Hz generator. The annual production is 90,417 kWh/yr.

The power output from the Caterpillar Inc. generator system, rated at 16 kW using biogas as fuel, is 99kWh/day of the year. The selected energy storage system comprises of Ten (10) PowerPlus Energy LiFe4833 batteries, with a storage system's nominal capacity of 32.8 kWh. The annual throughput is 7,094 kWh/year. It has an autonomy of 3.27 hours. The total load capacity of the optimised system is 70,317 kWh/year, with the total electrical production capacity at 90,417 kWh/year. This leaves excess electricity produced at 18,015 kWh/year and zero unmet electrical loads. The optimized hybrid energy system demonstrates significant economic viability for sustaining the BTS infrastructure. The total Net Present Cost (NPC) is calculated at $15,000, with an annual operating cost of $517. Most notably, the Levelized Cost of Energy (COE) is $0.01666/kWh.

The cash flow and NPC distribution is depicted in Figures 12 and 13 respectively. This low COE indicates that the integration of solar and biogas resources provides a highly cost-effective alternative to traditional fossil-fuel-based power generation. By reducing reliance on expensive fuel logistics and minimizing maintenance through a leaner system design, the proposed configuration ensures long-term financial sustainability alongside its technical reliability.

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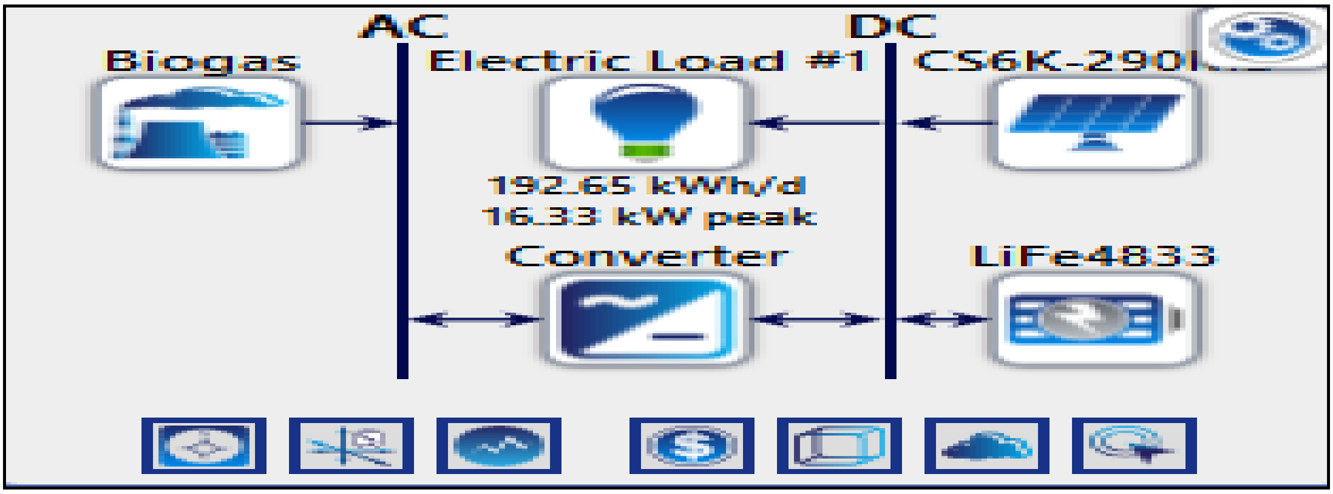


Figure 10: System design for optimization

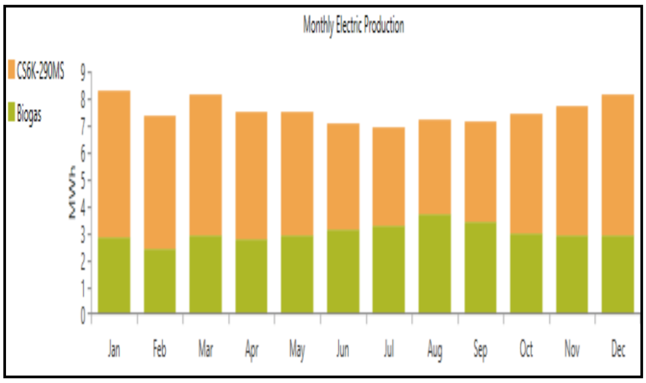


Figure 11: Monthly electrical output from the designed system

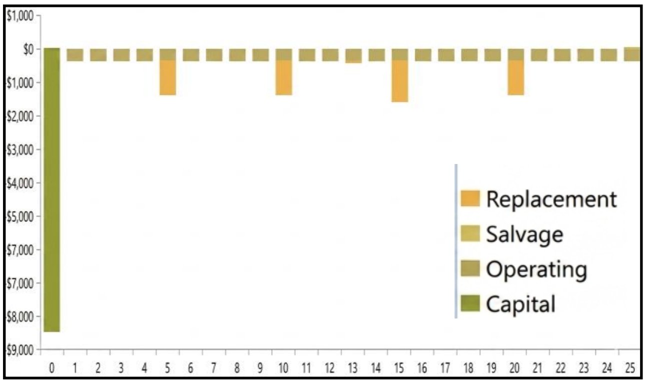
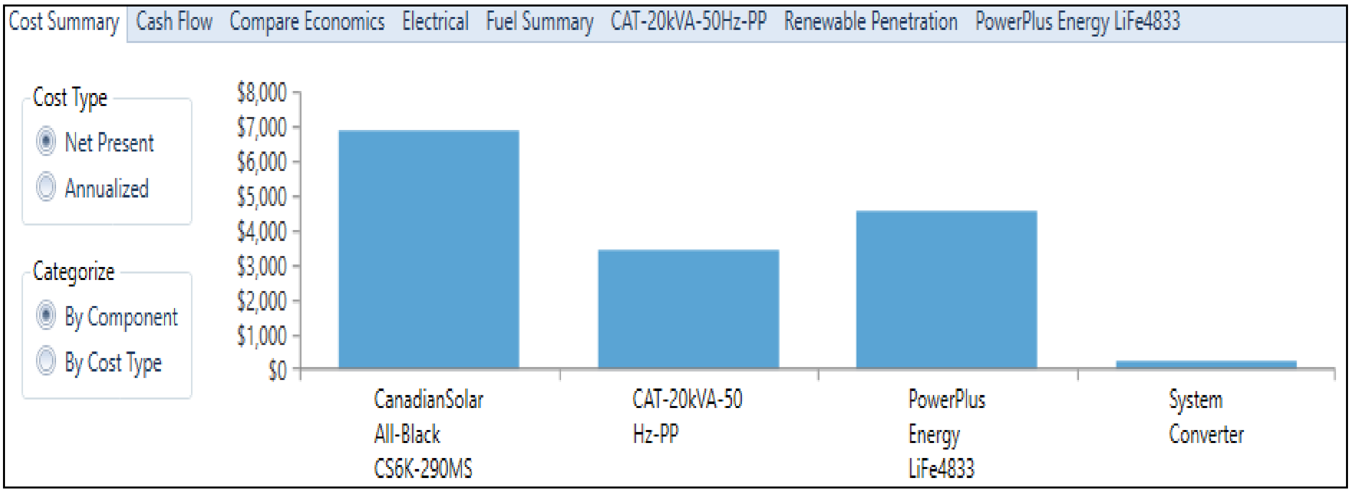


Figure 12: Cash flow and economic metrics of the Designed System



Cost Type
● Net Present
○ Annualized

Categorize
● By Component
○ By Cost Type

Figure 13: The NPC distribution by component of the designed system

4.0 CONCLUSION

This study demonstrates the effectiveness of SARIMA-based models for predicting the electrical energy demand of telecommunication infrastructure in Nigeria. By evaluating 36 months of historical data, two distinct forecasting approaches were validated: a long-term daily model (SARIMA (0,1,0)(1,0,1)$_7$ and a short-term hourly model (SARIMA (1,0,0) (0,1,2)$_{24}$. The findings indicate that while the daily model achieved a lower MAPE (7.67%), the hourly model provided superior precision with a lower RMSE (0.63 kW), making it more suitable for

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real-time operational management and protecting sensitive BTS hardware from sudden load variations. The integration of these forecasts into HOMER Pro enabled the design of an optimized hybrid energy system. By resizing the solar PV array and battery bank to meet the BTS load with a strategic 50% surplus, the system achieved a highly competitive Levelized Cost of Energy (COE) of $0.01666/kWh. This technical-economic optimization ensures zero unmet load while providing a sustainable and cost-effective alternative to diesel-dependent power solutions in the region.

The study's findings contribute to improving energy planning for telecommunication infrastructure by demonstrating the effectiveness of SARIMA-based forecasting models and optimized renewable energy systems. Accurate energy demand predictions and renewable energy integration can enhance operational efficiency, reduce costs, and support sustainability goals, providing a robust framework for future telecommunication energy management.

4.1 Limitations and Future Work

Despite the robust performance of the SARIMA models, this study is limited by the exclusion of exogenous variables such as ambient temperature and real-time traffic load fluctuations, which can influence energy demand. Future research should investigate the application of SARIMAX models to incorporate these environmental factors. Additionally, further studies could explore the economic potential of utilizing excess energy for community energy sharing or the implementation of smart-grid technologies to further enhance the resilience of telecommunication networks.

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