LONG-TERM LOAD FORECASTING FOR OPTIMAL POWER SYSTEM PLANNING AND DECISION-MAKING

Abstract:

The study focused on long-term load forecasting for power system planning, specifically examining the electric load demand from consumers on distribution transformers within Port Harcourt, located in Rivers State, Nigeria. The study encompassed a comprehensive review of both statistical and artificial intelligence-based approaches. Historical load data for distribution transformer readings spanning 2008 to 2017 were acquired from the Port Harcourt Electricity Distribution Company (PHEDC) and subjected to analysis using the curve-fitting technique.For the period between 2015 and 2030, a yearly load forecast simulation was conducted using the Fourier Series model, implemented with MATLAB software. This simulation aimed to provide insights into future load demand, facilitating careful and informed decision-making in the investment, operation, and maintenance of power system equipment. The effectiveness of the forecasting investigation was assessed using the Root Mean Square Error (RMSE), confirming the efficiency, reliability, and validity of the employed model.The study's forecasted results are presented as a valuable guide and practical tool for policymakers and the utility company (PHEDC) to enhance proper planning and decision-making processes. Additionally, considering the observed trend in the results, it was suggested that installing additional transformer units in the region would be necessary to alleviate the loads on existing overloaded transformer units within the network.

KEYWORDS: Distribution transformer,Long-term load forecasting, Mean absolute percentage error, Root mean square error, PHEDC.

I. INTRODUCTION

Port Harcourt isthe largest city in the south-south region of Nigeria and amongst thefastest growing cities in the country economically (Amadi, 2015), hence the need to ensure steady electricity power supply by ascertaining the load demand and forecasting the future load growth in the area. In electric power systems, the term "Load forecast" is used to describe an estimation of where and how much load will grow on a network and allow for effective decision-making and planning of network expansion projects. According to Friedrich (2015), load forecasting holds paramount significance in facilitating the proper operation, maintenance, and planning of electric power systems. The temporal scope of load forecasting is categorized into Very Short-Term (minutes to an hour ahead), Short-Term (day or week ahead), Mid-Term (one month to one year), and Long-Term (one to fifty years). Both long- and mid-term forecasts are crucial for strategic planning in the development of electric power systems, encompassing the scheduling of construction for new generation or transmission facilities, maintenance planning, and long-term demand-side measurement and management.

Long-term load forecasting is essential for power system planning and decision-making since it provides valuable information about the amount of electricity needed to fulfil future demand. Load forecasting is a crucial aspect of efficient power system management and is carried out by several entities including individual researchers, research organizations, consulting businesses, utilities, and regulatory bodies. Amara (2015) emphasizes the critical role of precise load forecasting in power system operation, recognizing the nonlinear and volatile nature of electricity load. Addressing this complexity necessitates the use of suitable forecasting tools, which can be broadly classified into artificial intelligence (AI) and statistics-based approaches.

In the context of the deregulated economy in the electric industry, load forecasting holds diverse applications, including energy purchasing, generation planning, load switching, contract evaluation, and infrastructure development. Badr *et al.* (2021), highlight the extensive attention load forecasting has received, particularly for enhancing the performance of Smart Grids. Applications range from electricity theft detection and smart meter (SM) false reading detection to energy cost optimization, power management, and microgrids.

Moreover, Hafeez *et al.* (2020) contribute to the discourse by emphasizing the significance of load forecasting in Smart Grids, especially in the context of grid-interactive and efficient building energy processes. Load forecasting emerges as a pivotal element in advanced management and operation planning, playing a vital role in the efficient control of building energy costs through model predictive control for building energy management.

This study aims to forecast future load demand in the Stadium Road area of Port Harcourt city, Rivers State, Nigeria, using the curve-fitting approach. The importance of long-term load forecasting in power system planning and decision-making by managers, as well as its industrial applications, has been taken into consideration.

II. LITERATURE REVIEW

Various forecasting approaches and techniques have been applied for a range of objectives in solving power system difficulties, including planning, protection, control, analysis, fault detection, load forecasting, and related duties. Mehr et al. (2018) applied the regression techniques for estimating the yearly load in southern Turkey, supplementing it with the addition of Genetic Algorithm structures alongside the standard coefficients.

A long-term load forecast of Bonny Island has been carried out by Adebayo (2019) using the Regression analysis of sample load data. A reduction in load during the rainy season and an increment in load consumption during the dry season were recorded as revealed by the model results. It reveals that there could be minimal power supply and demand during this period. This calls for the energy suppliers; the Nigerian Liquefied Natural Gas (NLNG) and the Shell Petroleum Development Company (SPDC) plan for major maintenance, and upgrade operations on the power generation and distribution system can take place during this period.

Farrag *et al.* (2021) employed parametric techniques to develop a statistical framework, exploring the modal functions connecting the load and pertinent variables, the report emphasizes essential approaches such as linear regression and grey models. The parameters for these models are obtained from the load data, and the performance of the model is evaluated through an analysis of forecast errors. This approach utilizes a mathematical perspective to establish relationships between inputs (such as loads and other influential variables) and outputs (the predicted load). Widely adopted methods in this context include AR-MA with External Variables (ARMAX), Auto-Regressive (AR) Moving Average (AR-MA), Auto-Regressive Integrated Moving Average (ARIMA), and ARIMA with external variables (ARIMAX).

According to Guo *et al.* (2021), long-term load forecasting plays a crucial role in macro managerial decisions, specifically in determining the volume of investments for future long-term programs. The report emphasizes its predominant use in managing energy resources, as well as in the planning or updating of power plants in the upcoming years. It is instrumental in decision-making related to grid development, contractual reviews, and closures. Agreeing with this perspective, Arthurs, as indicated by Friedrich (2015), considering the distribution network, underscores the importance of long-term load forecasting for periods extending to a year or more. The report emphasizes its exceptionalimportance in estimating grid expansion, stating that the rise in the number of distribution equipment and plants within the existing grid ought to be initiated early enough to meet the evolving load wants. Although various methods exist for forecasting grid load, these methods, while appearing distinct, fundamentally operate on the same principle—the forecasting of load based on operative parameters. The law governing the correlationthat exists within two processes in this context is termed the load model.

The emergence of Artificial Intelligence (AI), and more especially Artificial Neural Networks (ANN), has had a considerable effect on load forecasting in the energy sector. In recent years, ANN-based models have garnered a lot of interest due to their ability to recognize difficult non-linear relationships within datasets. This fact has contributed to their broad popularity. Improvements in load forecasting have been made possible by artificial intelligence, more notably artificial neural networks (ANN), which has led to an increase in the reliability and accuracy of forecasts within the energy industry, which is constantly evolving.

Elkateb*et al.* (1998) introduced a Monthly Load Forecasting (MTLF) model using an independentmethod to predict loads in the Jeddah regionmonthly. Weather factors and Load were the only variable factors the model considered. The authors asserted that an artificial intelligence-based approach would yield superior results, drawing comparisons between outcomes from statistical methods and artificial intelligence. Doveh*et al*. (1999) proposed an Artificial Neural Network (ANN) model, demonstrating its superior accuracy over statistical techniques when carrying out yearly forecasting every month. In the same manner, Ghiassi *et al.* (2006) presented a dynamic ANN-based MTLF model, comparing it to a statistical technique and concluding that the forecasted values from the employedapproach yielded a better result. Notably, the main advantage the model gives in this article is its independence from a specific forecasting method.

In the study conducted by Unutmaz*et al.* (2021), recursive neural networks were employed for long-term load forecasting. The article utilized a three-layer artificial neural network (ANN) with the backpropagation learning method, emphasizing the crucial factor of economic development. The outcomes of the forecast spanning from 2008 to 2014 were compared with those generated by traditional methods, revealing a superior performance of the proposed approach. In Gul *et al.* (2021), attention was directed towards the impact of new energies on load changes, with a focus on evaluating the methodology using data from a solar power facility in Istanbul. In developed nations, a significant portion of energy is sourced from wind turbines and solar panels, both strongly influenced by weather conditions, including cloud cover and wind patterns. The researchemployed time intervals of 5 to 35 minutes to forecast the energy output of solar and wind generation sources. The basic multi-layer Artificial Neural Network (ANN) was employed in the study and optimization was achieved through the Levenberg–Marquardt method.

In a study conducted by Shirzadi*et al.* (2021), algorithms, including Random Forest (RF) and Support Vector Machine (SVM), as well as deep learning models like the Nonlinear Autoregressive Exogenous Neural Network (NARX) and Long Short-Term Memory (LSTM), were employed for power consumption modelling. Mochalin*et al.* (2014), referencing Shirzadi *et al.* (2021), noted that the 2019 forecast was generated using hourly power consumption data from 2010 to 2018 and weather data.

Shirzadi *et al.* (2021) conducted a study employing classical machine-learning algorithms such as Random Forest (RF) and Support Vector Machine (SVM), as well as deep learning models including the Nonlinear Autoregressive Exogenous Neural Network (NARX) and Long Short-Term Memory (LSTM), to model power consumption. Mochalin*et al.* (2014), while referring to Shirzadi et al. (2021), highlighted that the 2019 forecast was developed based on hourly power consumption data spanning 2010–2018 and weather data. According to Shirzadi *et al.* (2021), evaluating the accuracy of the forecast involved the application of MAPE and RMSE, revealing that the NARX model yielded a more precise forecasting result.The implications for power system planning and decision-makingcentrearound addressing challenges and capitalizing on opportunities in the evolving energy landscape. Key considerations include predicting and managing demand growth, integrating renewable energy sources effectively, modernizing ageing infrastructure, complying with environmental regulations, embracing energy storage, safeguarding against cybersecurity threats, adapting to decentralization and distributed energy resources, and making economically sound investments. A comprehensive and flexible approach is essential to create a resilient, sustainable, and efficient power system that meets current and future needs.

An optimal approach for forecasting electric load would involve the ability to identify non-linear correlations between electric load and diverse economic and other factors, while also being adaptable to changes. Among various models, the Fourier series, based on curve fitting analysis, is selected to meet these criteria. The research proposal aims to employ the Fourier series model in forecasting consumer electric load consumption on distribution transformers.

III. MATERIALS AND METHOD

This research study proposes the regression technique for forecasting future load consumption. The Fourier series model which is capable of forecasting the non-linear pattern of electrical load consumption is considered. This model is generally based on the principles of time series. In addition, some statistical analysis would be carried out to aid the decision-making as accuracy will be decided by the results of the analysis.

The selected approach is formulated mathematically as a function that delineates a curve offering the optimal fit for a given dataset. This method serves as a predictive technique, exploring the correlation between a dependent variable (Load consumption) and an independent variable (Year).

The mathematical expression for the model is given as:

$$\mathrm{f(x)} = \mathrm{a_0} + \sum_{\mathrm{n=1}}^{\infty} (\mathrm{a_n} \cos \mathrm{x}w + \mathrm{b_n} \sin \mathrm{x}w) \qquad 3.1$$

with;

$f(x)$: Dependent variable (transformer load consumption in KW)

x: Independent variable (Time in Years)

w: Periodicity and,

a_0, a_n and b_n are the Fourier coefficients of the model.

$$a_0 = \frac{1}{\pi}\int_{-\pi}^{\pi} f(x)dx \qquad 3.2$$

$$a_n = \frac{1}{\pi}\int_{-\pi}^{\pi} f(x) cosxwdx \qquad 3.3$$

$$b_n = \frac{1}{\pi}\int_{-\pi}^{\pi} f(x) sinxwdx \qquad 3.4$$

3.1 EvaluationMetric

The selection of an appropriate metric hinges on the characteristics of the data. In instances of significant data variability, it is advisable to employ the Mean Absolute Percentage Error (MAPE) metric; otherwise, the Root-Mean Squared Error (RMSE) metric suffices. The RMSE, a widely used metric for assessing accuracy in continuous variables, gauges how closely the data points cluster around the best-fit line or how dispersed they are from the regression line. A lower RMSE value signifies a more accurate fit. This can be expressed in mathematical terms as:

$$\mathbf{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} = \sqrt{MSE} \qquad 3.5$$

$\hat{y}_i$ represents the predicted value derived from the fit

y_i denotes the observed data value

n is the sample size

3.2 Data Source and Types

The historical load data for the period 2008 to 2017 used in the research was acquired from the Rumuola sub-station of the Port Harcourt Electricity Distribution Company (PHEDC) in Port Harcourt, Nigeria.The data are the distribution transformer readings for the transformers within the sub-station, specifically for the Stadium Road region within Port-Harcourt, Rivers State, Nigeria. The historical load data is presented in Table 1. MATLAB software has been utilized in the development of the Algorithm as well as simulating the data.

Table 1: Historical Load Data

YEAR	STADIUM ROAD LOAD (KW)
2008	3581.00
2009	3466.00
2010	4128.15
2011	4012.00
2012	4612.24
2013	4232.67
2014	4436.68
2015	4956.01
2016	4363.63
2017	4623.47

Source: *PHEDC sub-station, Rumuola, Port Harcourt.*

3.3 Future Load Forecasting

MATLAB code was developed to call up the Fourier model and take in data as input data for the forecasting simulation. For validation of the forecasting result, it was decided to forecast from 2015 to 2030 instead. The result is presented in Table 2.

IV. RESULTS AND DISCUSSION

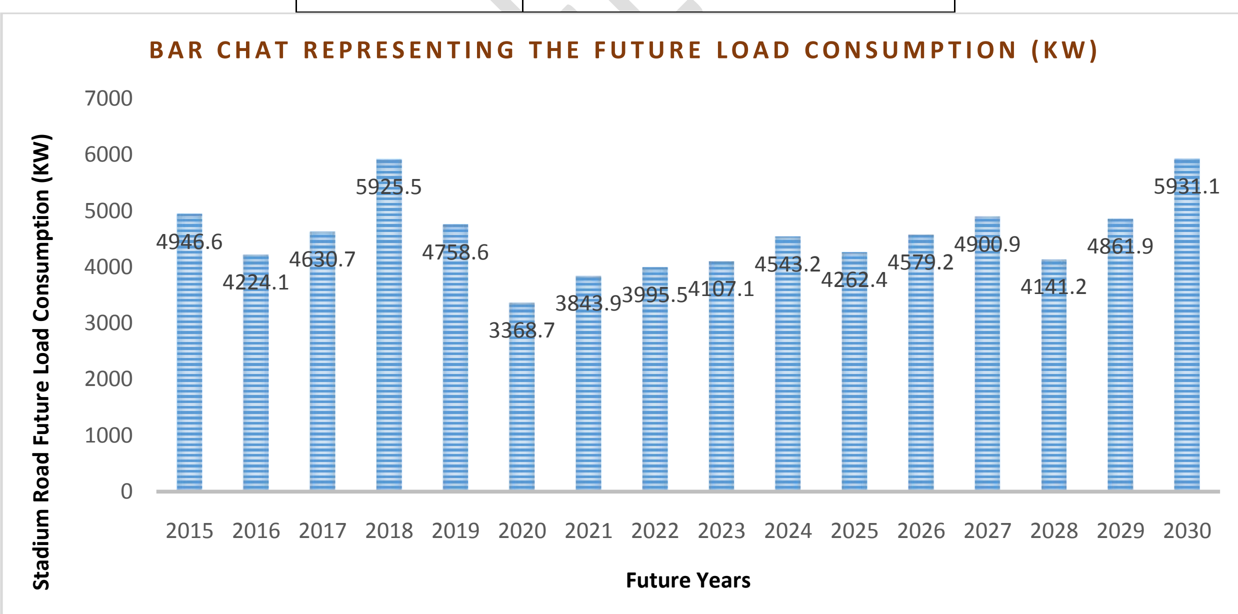
4.1 Forecasting Results and Evaluation

The performance of the fitted curves as well as the goodness of fit has been analyzed. The curve fitting evaluation is done by graphical display and numerical measures. The graphical displays allow for the entire dataset view but the numerical measures compress that information into a single number and it is presented in Table 2.

Table 2: Forecasted future load consumption

YEARS	FORECASTED LOAD

2015	4946.6
2016	4224.1
2017	4630.7
2018	5925.5
2019	4758.6
2020	3368.7
2021	3843.9
2022	3995.5
2023	4107.1
2024	4543.2
2025	4262.4
2026	4579.2
2027	4900.9
2028	4141.2
2029	4861.9
2030	5931.1



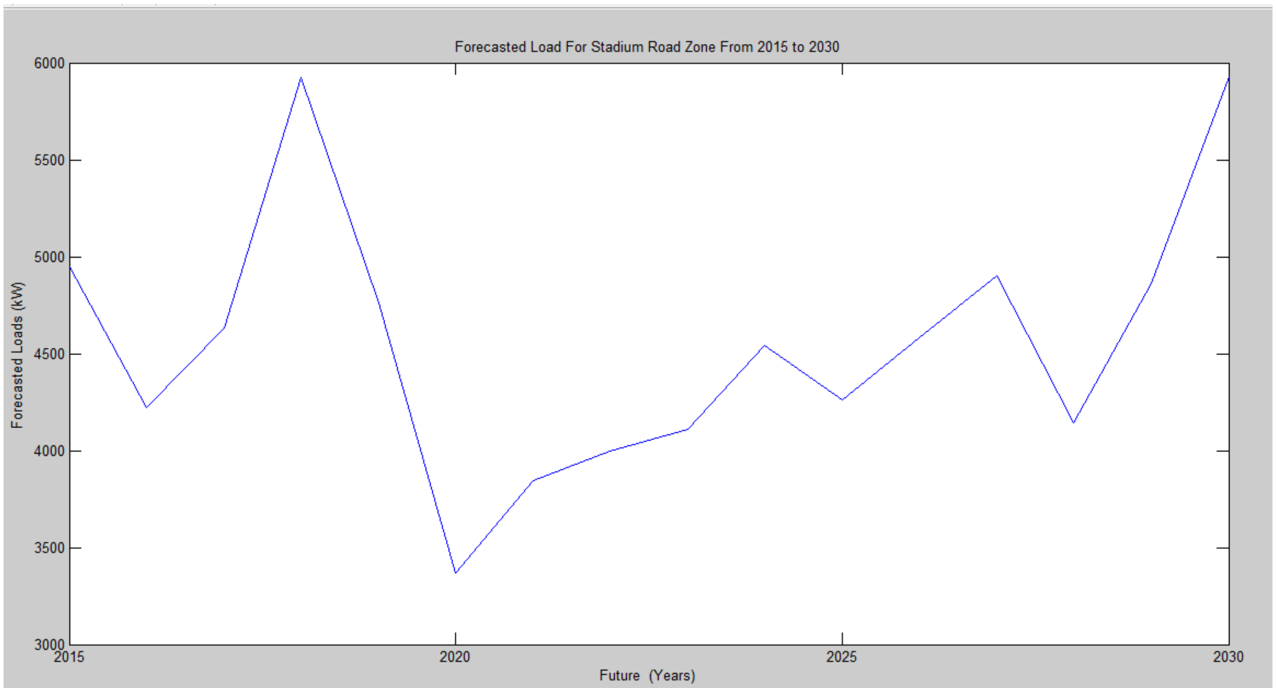


Figure 1: The Model Forecasted Performance For Stadium Road Region

The anticipated trajectory indicates a decline in consumption from 2015 to 2016, followed by a gradual upswing until 2018. Subsequently, the electric load consumption rate for the Stadium Road region is expected to experience a significant decrease from 2018 to 2020, succeeded by a gradual ascent leading up to 2024. A minor dip in consumption is projected for the year 2025. However, in the same year, the consumption rate is foreseen to surge until 2027, followed by a sudden drop in 2028. Finally, there is a projected substantial increase in consumption up to 2030, marking the conclusion of the research period.

Throughout this timeframe, fluctuations in load consumption are anticipated, potentially resulting in some distribution transformers being underutilized while others may be overutilized at various points in the future. The primary objective is to ensure the optimal operation of distribution transformers concerning the connected load to achieve efficiency. Additionally, there is a likelihood of certain transformers within the region experiencing overload conditions, particularly in 2018 and 2030, respectively.

Some key factors responsible for the fluctuations in electric load consumption every year can be attributed to: Economic Conditions, Population Growth, Weather Patterns, Energy Efficiency Measures, Technological Advances, Government Policies and Regulations, Infrastructure

Investments, Natural Disasters, Market Dynamics, and Global Events. Understanding the interplay of these factors is crucial for energy planners, policymakers, and industry stakeholders to anticipate and respond to changes in electric load consumption from year to year.

Moreover, the ever-progressing landscape of technology, energy policies, and societal dynamics plays a pivotal role in shaping the dynamic patterns of electricity consumption over an extended period.

4.2 Assessing the Accuracy of Forecasted Results

To gauge the effectiveness of the forecasting model, an evaluation of the goodness of fit is undertaken by calculating the accuracy of the forecasted outcomes. This is achieved through the computation of the Root Mean Square Error (RMSE) values, as detailed in Table 3.

Table 3: Goodness of fit for the Forecasted data

Region	RMSE Value
Stadium Road	0.002193

The data given in Table 3 illustrates that the employed model utilized for the forecasting produces a negligible error value, signifying a notably high degree of accuracy. This suggests that the forecasted load consumption is anticipated to align closely with the actual values in the forthcoming years within that particular region.

4.3 Error Analysis and Validation

There is no guarantee that a forecast will be done without any error. For this reason, errors resulting from the forecasting model wereanalyzed to check whether the forecasted load is as near as possible to the actual load as this will guarantee the forecasting accuracy.

To ensure the accuracy of the forecast, it was imperative to validate data for the years 2015 - 2017, as the raw information for these years is readily accessible and displayed in Table 4.

Table 4: Validation andAnalysis of the Model Error

	Stadium Road Region		

Years	Actual Values	Forecasted Values	Error
2015	4955.00	4946.60	8.40
2016	4273.67	4224.10	49.57
2017	4533.67	4630.70	-97.03

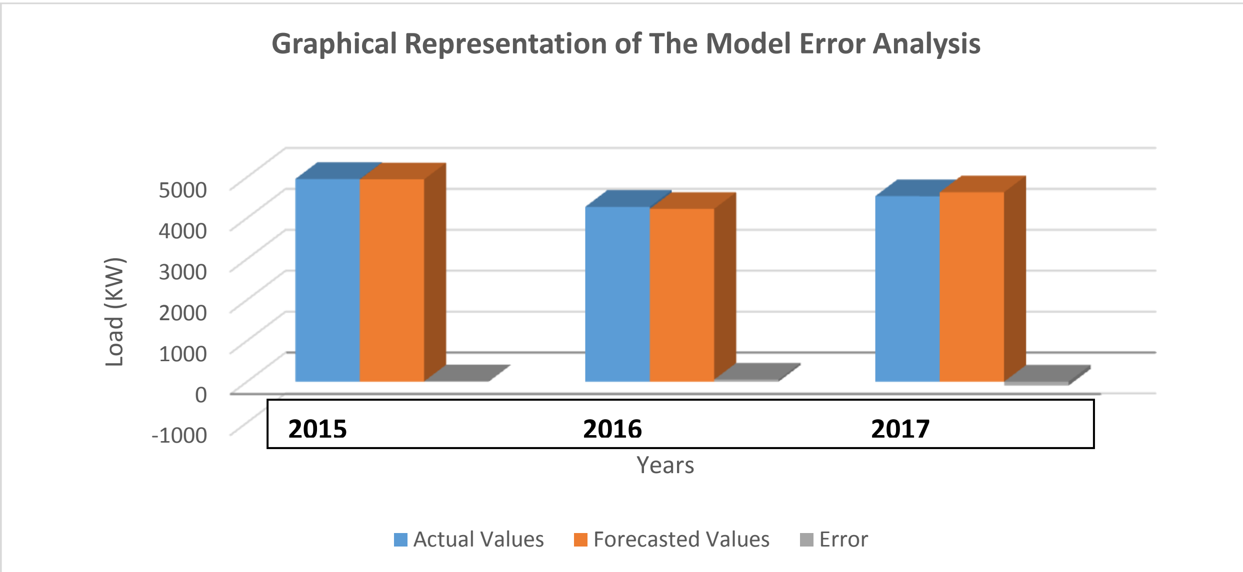


Figure 2: Model Error Analysis

To verify the precision of the forecasted results, it was necessary to project from previous years where the load data were already accessible. Table 4 illustrates the actual and predicted load values, along with the forecasting errors, for the years 2015, 2016, and 2017. Analysis of Table 4 reveals that the forecasted consumption will demonstrate a similar pattern according to the applied model.

Upon comparing the actual and forecasted loads, it is evident from Table 4 and Figure 2 that there is no noteworthy difference between the two. This indicates that the forecasting model recorded a negligible error. Consequently, a high degree of accuracy has been attained.

V. CONCLUSION

The Fourier model employed in the analysis returned a significantly reduced error in terms of RMSE value as an indication that a more precise forecast has been achieved. The result obtained from the forecasting process shows that the choice of the Fourier model in terms of its ability to forecast load consumption is correct and high in accuracy. Hence the model has proven to be efficient, reliable and a valid forecasting technique.

The study outcomes presented in both numerical and graphical formats, offer a valuable and applicable guide for policymakers and the utility company (PHEDC).

This information enables them to effectively strategize and prepare for the capacity of distribution transformers and operations. The goal is to ensure a reliable energy supply to all consumers in the region by anticipating future load consumption or demand. Furthermore, this understanding prompts the (PHEDC) to strategically plan significant maintenance and upgrade operations on the distribution system. Additionally, the study proposes supplementary units of transformers to ease the strain on the current overloaded transformer units connected to the network.

This work serves as a factual approach to eliminating underutilization and overutilization of the transformers which accounts for the wastage of energy and prevention of system downtime and failure respectively. Timely planning, adherence and implementation of this approach could result in significant financial savings.

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