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# Long-term Load Forecasting for Optimal Power System Planning and Decision-Making

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***Authors' contributions***

*This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.*

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## ABSTRACT

Forecasting the future load growth of an area based on its load demand is often a proactive measure to ensure a steady electricity power supply to that area. 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 City, 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

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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. Considering the observed trend in the results, it is suggested that installing additional transformer units in the region would be necessary to alleviate the loads on existing overloaded transformer units within the power system network.

*Keywords: Distribution transformers; electric load demand; long-term load forecasting; power system planning; Root Mean Square Error (RMSE).*

## 1. INTRODUCTION

Port Harcourt is the largest city in the south-south region of Nigeria and amongst the fastest growing cities in the country economically [1] 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 [2] 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 [3] 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. [4] 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. [5] 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.

## 2. 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.

Zhou et al. [6] looked at how load forecasting techniques in the electricity sector may be improved by using AI, more especially LSTM-RNN. The LSTM-RNN-based forecasting model was validated using German electricity energy consumption data as a case study, with a focus on the country's peak years, 2006 to 2017. The impact of influencing variables on load forecasting, including seasonality, society, and climate, is also covered in the article. The paper's conclusions show that, with a high confidence interval, the LSTM-RNN-based forecasting model performs better than the best of the assessed alternative techniques. The findings imply that LSTM-RNN is a useful artificial intelligence method for load forecasting, especially when it comes to correctly estimating patterns of non-linear energy use.

For power electronics-based system design, Sandelic et al. [7] proposed a long-term forecasting method that uses models based on artificial intelligence and statistics that offer forecasting profiles and their probability of occurrence with a high time resolution over the course of the long-term planning horizon. The study's findings demonstrate that the created model's forecast profiles' accuracy makes them appropriate for use in power electronics reliability evaluations. The study's conclusions also demonstrated the efficacy of the suggested long-term forecasting approach for power electronics-based system design, which makes use of models based on artificial intelligence and statistics to generate forecasting profiles and their likelihood of occurring over the course of a long-term planning horizon with high temporal resolution.

Wang et al. [8] used an ensemble learning-based LSTM-Informer model to address the long-term power load forecasting issue. In order to determine prediction accuracy, the study compared the suggested LSTM-Informer model with sophisticated single models, such as the Transformer, Autoformer, Reformer, and Informer models. The paper's conclusions demonstrate that, on two schemes of comparison, the ensemble learning-based LSTM-Informer model performs better in long-term power load forecasting than sophisticated single models. In both input-length-shorter-than-output-length and output-length-longer-than-input comparison methods, the suggested model performs better. Additionally, the suggested LSTM-Informer model offers a useful method for precise long-term power load forecasting, particularly in scenarios involving a lot of data. The study's findings further emphasise how crucial it is to take input and output lengths into account for model performance. They also offer direction for future investigations into ensemble models and deep learning-based techniques for long-term power load forecasting.

Yang and Shi [9] put up a strategy that combines deep learning with causal effect computation to increase the prediction accuracy of non-stationary time series data. The Informer architecture, a stack consisting of an encoder, a temporal attention module, and a decoder, is the foundation of the technique known as Causal-Informer. Targeted maximum likelihood estimation is used to calculate the causal influence among the variables once the causal graphs derived from the observed data have been obtained. Comparing the paper's findings to other well-known deep learning techniques such as Informer, LSTM, Prophet, and ARIMA, it appears that the suggested approach, Causal-Informer, can enhance the prediction performance of non-stationary time series data.

To increase the accuracy of load forecasting for power systems, Hu et al. [10] proposed a new model based on data mining and deep learning that takes into account historical load data, weather information, date types, real-time electricity prices, etc. This is accomplished by combining the load curve clustering DBFCM method, feature fusion extraction CNN, and parameter optimisation IVIA-BLSTM. The goal of the study was to improve the accuracy of the load prediction model and address the difficulties associated with machine learning methods for load forecasting for power systems, particularly when dealing with complicated, non-smooth, nonlinear time series, and "noisy" data. According to study results, the suggested LVMD-DBFCM-CNN-IVIA-BLSTM model performs better for power load forecasting than many benchmark models, including Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), Support Vector Regression (SVR), and General Regression Neural Network (GRNN).

Lukong et al. [11] used historical or previous demand data as an information source to evaluate the relationships between energy demand and various factors influencing consumption, such as long-term trends, cyclical variation, seasonal variation, and random variation in the input variables. This allowed them to capture the past growth in demand and use it to predict demand in Cameroon. The study's conclusions recommend a data-driven strategy to forecast Cameroon's energy consumption, with GDP and H serving as key factors and historical or previous demand data as supporting data. The study concludes that a data-based strategy for analysing the links between energy demand and different factors impacting consumption may successfully anticipate Cameroon's energy demand. Because the method depends on variables whose impacts are controllable, it is appropriate for controlled short-term forecasts. In this sense, LSTM is found to be a useful prediction tool. The study also points out that the unpredictability of certain elements influencing energy consumption makes long-term predictions difficult, and the suggested method might not work well for these kinds of projections.

Mehr et al. [12] 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.

Adebayo [13] used regression analysis of sample load data to anticipate the long-term load on Bonny Island. The model findings showed that there was a decrease in load during the wet season and an increase in load consumption during the dry season. It indicates that there could not be much of a power supply or demand at this time. This means that the energy providers, Shell Petroleum Development Company (SPDC) and Nigerian Liquefied Natural Gas (NLNG), must schedule significant maintenance and upgrades for the electricity generating and distribution infrastructure that can happen during this time.

In order to create a statistical framework, Farrag et al. [14] used parametric techniques. They looked at the modal functions that connected the load and relevant variables, and they highlighted key strategies such grey models and linear regression. These models' parameters are derived from the load data, and a study of forecast errors is used to assess the model's performance. This method establishes correlations between inputs (such loads and other significant factors) and outputs (the expected load) using a mathematical perspective. In this context, Auto-Regressive (AR) Moving Average (AR-MA), Auto-Regressive Integrated Moving Average (ARIMA), ARIMA with external variables (ARIMAX), and AR-MA with External Variables (ARMAX) are widely used approaches.

Guo et al. [15] assert that long-term load forecasting is essential for making macromanagerial decisions, particularly when it comes to figuring out how much money to invest in upcoming long-term projects. The study highlights how widely used it is for developing or modernising power plants in the next years, as well as for managing energy resources. When making decisions on grid development, contractual reviews, and closures, it plays a crucial role. In line with Friedrich's [2] analysis, Arthurs emphasises the significance of long-term load forecasting for durations of a year or more, taking the distribution network into account. The paper highlights how crucial it is to estimate grid expansion, noting that the increase in the number of plants and distribution equipment inside the current grid should be started early enough to satisfy changing load demands. While there are many different approaches of forecasting grid load, they all work on the same concept of anticipating demand based on operating factors, despite their apparent differences. In this case, the load model refers to the law guiding the connection between two processes.

The energy sector's load forecasting has been significantly impacted by the rise of Artificial Intelligence (AI), and specifically Artificial Neural Networks (ANN). The capacity of ANN-based models to identify challenging non-linear correlations within datasets has attracted a lot of attention in recent years. Their wide appeal has been aided by this characteristic. Artificial intelligence (AI), particularly artificial neural networks (ANN), has enabled advances in load forecasting, leading to a rise in prediction accuracy and dependability in the dynamic energy sector.

In order to forecast loads in the Jeddah region on a monthly basis, Elkateb et al. [16] devised the Monthly Load Forecasting (MTLF) model, which uses an independent technique. The only variable parameters that the model took into account were load and weather conditions. The authors compared and contrasted the outcomes of statistical approaches with artificial intelligence, arguing that the latter would provide better results. When doing monthly annual forecasting, Doveh et al. [17] showed that their Artificial Neural Network (ANN) model outperformed statistical methods in terms of accuracy. Ghiassi et al. [18] demonstrated a dynamic ANN-based MTLF model in a similar fashion. They compared it to a statistical method and found that the predicted values from the used strategy produced a superior outcome.

Notably, the model's independence from a particular forecasting technique is its primary benefit as presented in this article.

Recursive neural networks were used in the study of Unutmaz et al. [19] for long-term load forecasting. Using a three-layer artificial neural network (ANN) and the backpropagation learning technique, the article emphasised how important economic development is. When the predicted results from 2008 to 2014 were compared with the results from conventional approaches, the suggested method performed better. The influence of new energies on changes in load was the focus of Gul et al. [20] who evaluated the technique with data from an Istanbul solar power facility. A large amount of energy in industrialised countries comes from solar panels and wind turbines, both of which are heavily impacted by weather factors like wind and cloud cover. The energy production of solar and wind generation sources was forecasted by the research using time intervals ranging from 5 to 35 minutes. The Levenberg-Marquardt approach was utilised in the study to optimise a basic multi-layer Artificial Neural Network (ANN).

Power consumption modelling was done in a study by Shirzadi et al. [21] using deep learning models like the Nonlinear Autoregressive Exogenous Neural Network (NARX) and Long Short-Term Memory (LSTM), as well as algorithms like Random Forest (RF) and Support Vector Machine (SVM). According to Mochalin et al. [22] who cited Shirzadi et al. [21] hourly power consumption data from 2010 to 2018 and meteorological data were used to create the 2019 prediction.

In order to model power consumption, Shirzadi et al. [21] used both deep learning models, such as the Nonlinear Autoregressive Exogenous Neural Network (NARX) and Long Short-Term Memory (LSTM), and classical machine-learning algorithms, such as Random Forest (RF) and Support Vector Machine (SVM). Citing Shirzadi et al. [21] Mochalin et al. [22] emphasised that hourly power consumption data from 2010 to 2018 and meteorological data were used to generate the 2019 prediction. Shirzadi et al. [21] state that the NARX model produced a more accurate forecasting result when MAPE and RMSE were applied to assess the forecast's accuracy. The consequences for planning and decision-making in the power system are centred on how to take advantage of opportunities and solve problems in the changing energy environment. Anticipating and controlling demand growth, incorporating renewable energy sources efficiently, updating ageing infrastructure, adhering to environmental rules, embracing energy storage, protecting against cyberattacks, adjusting to decentralisation and distributed energy resources, and making financially prudent investments are all important factors to take into account. A thorough and adaptable strategy is necessary to provide a reliable, sustainable, and effective power system that satisfies present and future demands [23,24].

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 [25].

## 3. MATERIALS AND METHODS

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 Evaluation Metric

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:

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

$\hat{y}_i$ 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 in 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.

## 4. 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 |

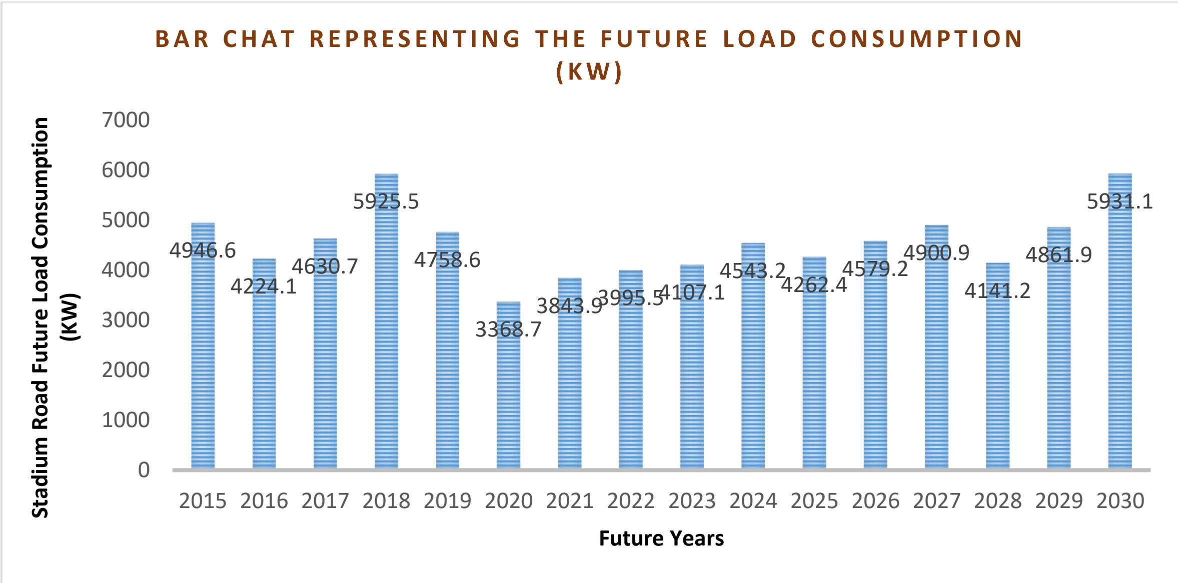


**Fig. 1. Bar chart representing the future load consumption for stadium road region**

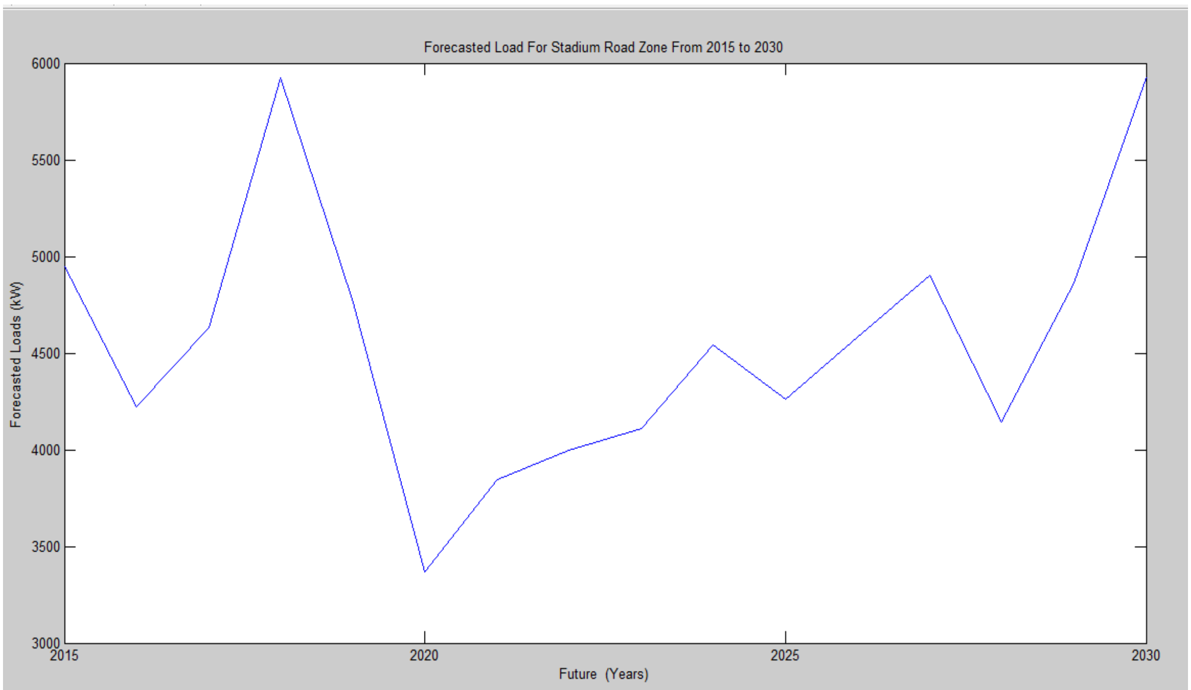


**Fig. 2. The model forecasted performance for stadium road region**

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.

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.

**Table 3. Goodness of fit for the forecasted data**

| Region | RMSE Value |
|---|---|
| Stadium Road | 0.002193 |

### 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 were analyzed 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.

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 forecasted (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.

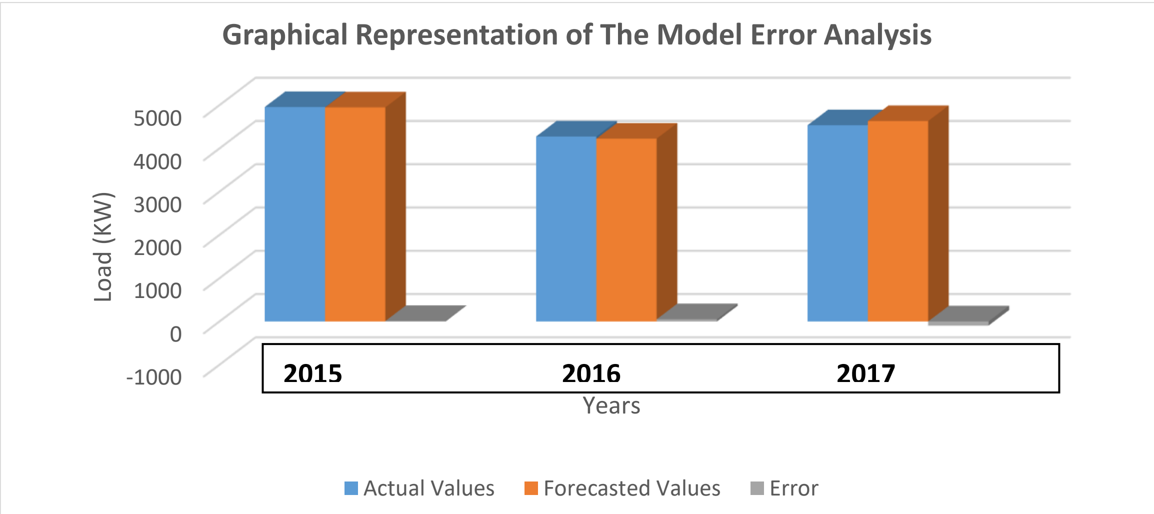


**Fig. 3. Model error analysis**

**Table 4. Validation and analysis 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 |

Upon comparing the actual and forecasted loads, it is evident from Table 4 and Fig. 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.

## 5. CONCLUSION

The Fourier model used in the analysis yielded a substantially lower inaccuracy in terms of the RMSE value, indicating that a more accurate forecast had been made. The outcome of the forecasting procedure demonstrates that the Fourier model was a proper and very accurate option in terms of its capacity to predict load consumption. As a result, the model has been shown to be an effective, trustworthy, and legitimate forecasting method. When comparing long-term load forecasting techniques, a blend of statistical and artificial intelligence-based methods stands out for its ability to capture complex patterns and adapt to changing conditions. Unlike other approaches, such as econometric models or time series analysis alone, this combination offers enhanced accuracy and flexibility, making it particularly effective for anticipating load variations over extended time horizons.

The study's findings, which are displayed in graphical and numerical forms, provide the utility company (PHEDC) and policymakers with a useful and appropriate reference.

This information is capable of helping the Utility to plan and get ready for distribution transformer capacity and operations. Anticipating future load consumption or demand is the first step towards ensuring a dependable energy supply for all users in the region. Additionally, this knowledge motivates the Utility (PHEDC) to proactively schedule important distribution system maintenance and upgrades. To lessen the burden on the present overloaded transformer units linked to the network, the research also suggests adding more transformer units.

This study provides a methodical strategy to avoiding under- and overuse of distribution transformers, which often results in energy waste. The strategy thus prevents system failure, downtime and in addition contributes to energy conservation. Proper preparation, following through, and putting this strategy into practice might save a lot of money.

## COMPETING INTERESTS

Authors have declared that no competing interests exist.

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