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Soft Computing Based Load Forecasting Using Artificial Neural Networks: A Case Study of Lagos, Nigeria.

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ABSTRACT

This study introduces a soft computing approach using Artificial Neural Networks (ANN) for load forecasting, specifically focusing on predicting the minimum and maximum load power. The goal is to allocate the expected power to suitable load centers efficiently. The analysis utilizes a 3-year (2021 to 2023) historical dataset of load consumption in Lagos, a city in Western Nigeria. A Multi-layered Perceptron (MLP) network generates short-term load forecasts for the area. The inputs for the network include monthly data, while the output parameters are load data obtained from the Eko Electricity Distribution Company (EEDC), which are used to predict power needs in the geographical area. The ANN training employs supervised learning and the back-propagation algorithm (BPA), implemented using MATLAB and SIMULINK. The input and target data are preprocessed and normalized within the range of -1 and 1. The network is continuously trained until desirable regression values and a disparity graph are achieved. The study demonstrates significant success with regression values of 0.96, 0.97 and 0.97 obtained over three consecutive years (2021/2022, 2022/2023 and 2023/2024) which indicate that the model accurately predicts the load of the year 2024. The developed model holds promise for independent power companies in Nigeria to enhance load allocation planning and forecast expected revenue.

INTRODUCTION

The effective operation of any power system is dependent on accurate load forecasting. Making decisions about power generation, purchasing, energy planning, and system security can benefit from its insightful recommendations. Accurate load forecasting is crucial for operational decisions in control systems, including load demand analysis and help commitment decisions (Magalhães *et al*., 2024). Electric utilities can perform these tasks efficiently; thanks to precise load estimates, which save money on operation and maintenance costs and improve infrastructural development and power supply systems (Huan *et al*, 2020; Veeramsetty *et al*, 2022). Power consumption data that may be examined on an hourly, daily, weekly, monthly, and annual basis is generally used to evaluate load predictions (Feinberg and Genethliou, 2005).

Forecasting involves estimating the future values of certain characteristics (Alquthami *et al*., 2022). Energy organizations strive to provide customers with a reliable and sufficient power supply. However, power production, transmission, and distribution are expensive and valuable resources. On the other hand, load demand is not constant, it is subject to fluctuations because of several variables, including environmental factors, lack of storage space, and poor maintenance practices. Furthermore, it is difficult to forecast the precise growth in the number of clients. (Ali *et al*, 2016)

Load forecasting can be broadly classified into three categories: short-term, medium-term, and long-term. Short-term load forecasting focuses on analyzing power consumption, data ranging from one hour to one week and it is primarily used for planning power generation and transmission. Medium-term forecasts cover a span of one week to one year and are mainly utilized for scheduling fuel purchases. Long-term forecasting involves examining consumption data for more than one year. It is essential for establishing and developing the supply and distribution system (Emhamed *and* Jyoti, 2004).

One of the key tasks in running a power system is load forecasting. Since electricity is a commodity and a trading item, accurate forecasting is important for managing production and purchasing in an economically sensible manner for an electric utility. Since electricity cannot be stored, accurate forecasting is motivated by this fact. In Nigeria, forecasting is necessary to calculate the amount of energy the power plants must produce each day and prepare the plants before the production.

Due to the persistent imbalance between demand and supply in the Nigeria power industry, an Electricity Distribution Company should be able to forecast, in the short to medium term, the total energy it will get from the National Grid so that it can plan on how to re-allocate the same power. Power forecasting has been an integral part of the planning, operation and maintenance of a power system most especially in the Nigerian power sector.

Professor Lotfi Zadeh in 1996 introduced the concept of "soft computing" to make use of Consumers' tolerance for imperfection, uncertainty, and partial facts to achieve traceability, robustness, inexpensive solution costs, and a better relationship with actuality (Senthil, 2017). These include fuzzy logic, stochastic process, linear regression, exponential smoothing and data mining models. But recently, ANN has been widely employed for power forecasting. The domain of soft computing also encompasses probabilistic reasoning, as it provides mechanisms to handle randomness and uncertainty. Numerous statistical and soft computing techniques have been specifically designed to enable accurate and reliable short-term forecasting (Wu *et al*., 2022; Feng *et al*., 2022; Gao *et al*., 2022; Hsu *and* Yang, 1991)

Various exogenous and meteorological factors make load forecasting a complex and challenging task Wu *et al*. (2022) highlighted the inevitability of short-term power load forecasting for the reliable and efficient operation of power systems. The study discusses various soft computing techniques, including neural networks (NN), fuzzy logic (FL), and genetic algorithms (GAs), for short-term load forecasting. Hsu and Yang (1991) proposed a new approach utilizing Artificial Neural Networks (ANNs) for short-term load forecasting. The study emphasizes the need to determine the hourly load pattern along with the peak and valley loads of the day to accurately forecast hourly loads. In the first phase, a neural network based on self-organizing feature maps was developed to identify days with similar hourly load patterns, categorizing them as the same day type. The load pattern of the target day is then obtained by averaging the load patterns of past days that belong to the same day type.

Ivana *et al*. (2013) and Jun *et al*. (2019) focused on enhancing the efficiency of the smart grid and integrating renewable energy sources to ensure sustainable electricity provision. To optimize energy usage, a multi-agent approach was proposed, employing load forecasting for residential demand response. This approach utilized Reinforcement Learning Agents (RLAs) to control household electrical devices. These agents leveraged current electricity load data and 24-hour load predictions to manage electricity consumption while maintaining overall demand within transformer capacity. The study involved simulations in a small neighbourhood with nine homes, each equipped with an agent-controlled Electric Vehicle (EV). The performance of agents using 24-hour load predictions was compared to those relying solely on current load information or operating without any load data.

Park *et al*. (1991) introduced an artificial neural network (ANN) approach for electric load forecasting. The ANN was trained to capture the relationship between past, current, and future temperatures and loads. By interpolating load and temperature data within a training dataset, the ANN generated load forecasts. The study assessed the accuracy of these forecasts using actual utility data, reporting average absolute errors of 1.40% for 1-hour-ahead and 2.06% for 24-hour-ahead predictions. In comparison, an existing forecasting technique applied to the same data yielded an average error of 4.22% for 24-hour-ahead forecasts. These results demonstrated the superior performance of the ANN approach in load forecasting.

Ajeigbe *et al*. (2020), Suthasinee *et al*. (2022), and Ming *et al*. (2023) addressed the importance of accurately predicting optimal domestic power peak demand for long-term electricity construction planning. The authors emphasized that precise predictions can help electricity suppliers reduce construction costs and provide customers with lower electricity rates. However, existing prediction methods still require improvement in accuracy. To address this challenge, the study introduced a modified Artificial Emotional Neural Network (AENN) based on an improved Jaya optimizer. Additionally, an Extreme Learning Machine (ELM) was incorporated to compute expanded features within the AENN. The proposed model was applied to a real case study of Thailand's power peak demand using a rolling mechanism. Comparative analyses with state-of-the-art AENN models, including an artificial neural network with Levenberg-Marquardt, AENN methods based on the winner-take-all approach, and an improved brain emotional learning-based AENN model, demonstrated that the developed predictive model offered superior performance, enhanced stability, and improved generalization capabilities. Overall, the proposed model showed significant potential in improving the accuracy and effectiveness of predicting optimal domestic power peak demand.

Seung (2009) and Duan (2022) presented a method for mid-term daily peak load forecasting using a recurrent artificial neural network (RANN). While artificial neural network (ANN) algorithms are commonly applied to short-term load forecasting, these studies addressed the challenges associated with long-term and mid-term forecasting, including limited training data and accumulated errors over extended estimation periods. The proposed method introduced a structure that replaced input data for special days and incorporated a recurrent-type neural network. The RANN demonstrated strong performance in estimating sudden and nonlinear increases in demand, particularly during heat waves. Case study results using load data from South Korea highlighted the effectiveness of the proposed RANN model.

Building on the gaps identified in the reviewed literature, this research aims to develop an ANN-based application for forecasting grid load consumption using available load data from the Enugu Electricity Distribution Company (EEDC) in Lagos State, Nigeria. The anticipated outcomes of this research include improved equipment maintenance scheduling, reduced manpower requirements, enhanced revenue forecasting for EEDC, and better planning for load allocation to customers. Additionally, the system will enable EEDC to make informed adjustments to load distribution based on the expected power supply (MW) from the Transmission Company.

Artificial Neural Network Model

This study includes a thorough analysis and evaluation of related works. It analyzes the load forecasting techniques that are already used and accepted before attempting to develop a new technique using ANNs.

The proposed model is used to simulate the load parameters of a power utility in Nigeria and apply artificial neural networks to forecast its future loads.

The design uses a set of load data for neural network training and testing as illustrated in Figure 1. The better ANN model for this research will then be given and described after the ANN training and optimization. With the activation function (f) applied to the weighted sum of inputs, the given ANN model will be effective and of good stability and adaptability when applied to achieve the desired result.

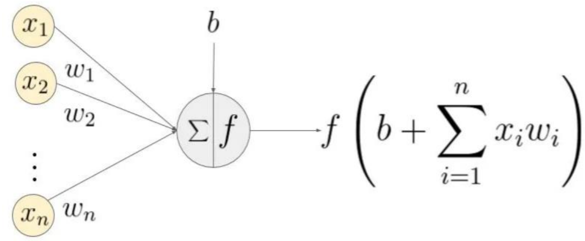


Figure 1: A neuron showing the input $(x_1 - x_n)$, their corresponding weights $(w_1 - w_n)$, a bias (b) and activation function (f) applied to the weighted sum of inputs

The implementation is developed by simulating the developed model using MATLAB 9.7 R2019b (MathWorks, 2021) i.e. using proper training and learning algorithms based on a comprehensive dataset, and the different importance of every influencing factor can be directly gotten from its different net weight. Also, application programs and software packages proved very essential. These include Microsoft Office Word and Microsoft Excel.

Database of ANNS.

The data used in this work was obtained from the database of EEDC. The data shows the daily minimum, maximum and average load consumed. It spans over three years (Jan, 2021-Dec, 2023).

Quality of the data set.

EEDC is a utility company, which has nine (9) sub-business units under its control. Each sub-business unit gathers the data received from the grid daily and sends them to the main headquarters for collation. For this work, the data gathered is sufficient for data training. An expanded database incorporating more input, in turn, would provide for a more complete adaptability of the network.

Going through the data gathered, some days have zero-megawatt (0MW), which means that there was a system collapse. These days are considered and taken care of by proper re-arrangement process.

Properties of the Lagos load curve.

In Nigeria, there exist two main seasons. These are the Dry season and Rainy/Wet seasons. The dry season spans from November to April of the following year while raining/wet season spans from May to October (Nigeria, 2023). The load consumed from the grid varies from season to season, day to day, week to week, month to month and year to year as shown in Figure 2.

In this work, the load curve to be forecasted consists of daily load values, with their daily averages. This means that the power curve can be seen as a day series of real numbers, each being the average of one day (Liao *et al*, 2019; Yu *et al*., 2019). Although the number of observations is restricted to 31 days per month, the model can be applied with slight modifications to cases where the interval between observations is shorter. The daily electric load consumed from the grid is used throughout this work as the test case. The data ranges from Jan. 2021 to Dec. 2023. The load curve over one year is shown in Figure 2. The seasonal trend can be seen; in the Dry season, the average power received is about twice as high as in the rainy season. The extent of this property is a special characteristic of EEDC's load conditions, and it is due to the differences between the weather seasons of the year. The working day-weekend pattern followed by the majority of generating stations is where the weekly rhythm gets its start. Customers often use more electricity during the weekdays than they do on weekends and holidays (Wu *et al*., 2023), which results in a larger load consumption (Zhu *et al*., 2021; Yu *et al*., 2019).

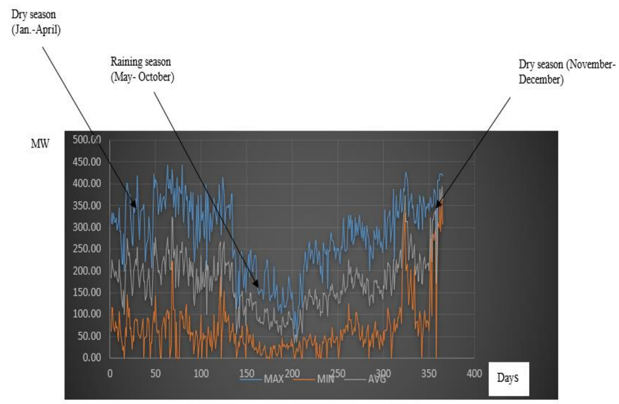


Figure 2: Curve representing power consumed from the grid for the year 2023 (Jan.-Dec.)

Figure 3 displays the load for two consecutive weeks from March 27 to April 10, 2023. The shapes start with nearly five remarkably similar patterns, which are the load curves from Monday through Friday. Then come two distinct Saturday and Sunday patterns. This weekly pattern keeps repeating itself. On the other hand, the daily rhythm is the outcome of consumers acting in unison throughout the day. Since most Consumers sleep at night, the burden is minimal then. The majority of consumers also frequently engage in multiple activities at once throughout the day (viewing TV, working computers, etc.). Over the year, the daily pattern varies. Figure 4 displays the load curves on average Tuesdays at various times of the year.

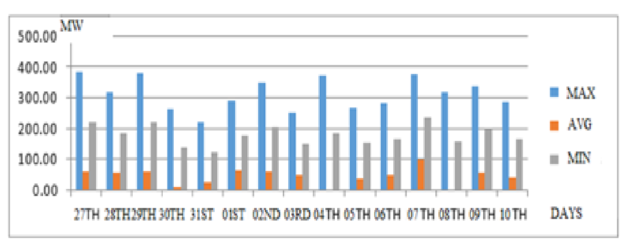


Figure 3: The load consumed over the period March 27th – April 10th, 2023. The first day is Monday.

Variations naturally occur between days within the same season, as illustrated in Figure 4. Consequently, power forecasting often categorizes days into different types, each with distinct load patterns.

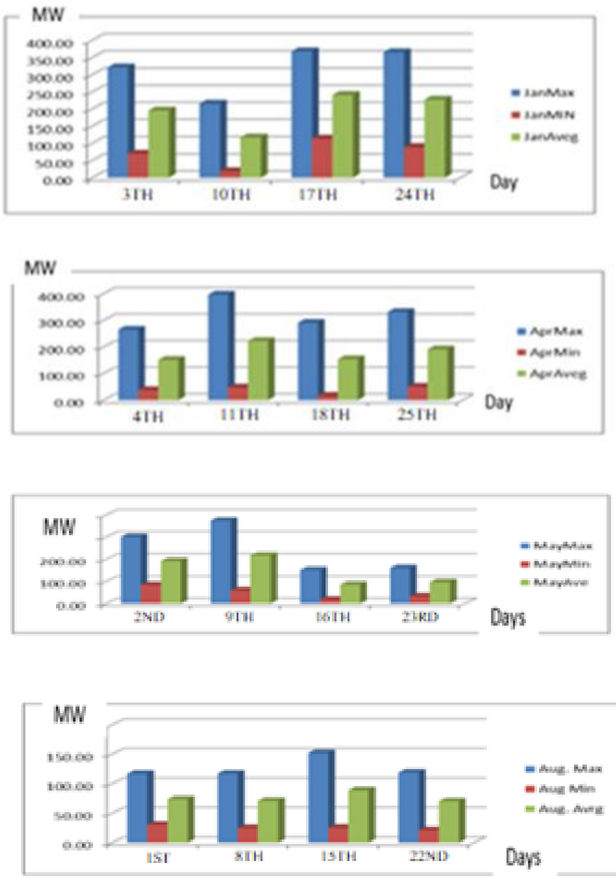


Figure 4: The load charts of four Tuesdays at different seasons.

The load curves on Saturdays and Sundays differ from those on other days, while Mondays and Fridays are sometimes separated from other working days due to the minimal impact of the weekend on electricity consumption from the grid. The classification of festive periods, such as Eid-el-Fitr, Christmas, and other special days, presents a greater challenge. In some cases, these days are grouped with Sundays; however, their load profiles can vary significantly (Hsu and Yang, 1991). This is depicted in Figure 4. The load drawn from the grid throughout the year 2021 to 2023 is used as our forecasting data in this work. The MLPNN technique used by the MATLAB program codes to execute these data (in Microsoft Excel Format) is demonstrated in the next section.

The ANN Training Dataset

To construct input/target pairs for the NN, the historical data load parameter values (collected by the EEDC, Lagos, Nigeria) were used in the MATLAB/SIMULINK environment. The network was given the created training dataset, which is depicted in Table 1. The target (t) represents the load data to be projected, whereas the input (p) represents the months in each year.

Table 1: Training dataset for the ANN (i.e., Input fed into the network)

Months of the Year (2021)	**Months of the Year (2022)**	**Months of the Year (2023)**
1	1	1
2	2	2
3	3	3
4	4	4
5	5	5
6	6	6
7	7	7
8	8	8
9	9	9
10	10	10
11	11	11
12	12	12

RESULTS AND DISCUSSIONS

The LM method (trainlm) was utilized in this research since it is a quick training algorithm for networks of a reasonable size (Duan, 2022). For use when the training set is huge, it offers a memory reduction feature. The following graphs and outcomes were produced by this algorithm:

The disparity graph

This demonstrates the degree of disparity between the desired output (i.e., the projected data) and the simulated (ANN) output (i.e., the predicted results). The charts and tables with their corresponding values are shown in Figures 5a, 5b and 5c and Tables 3a, 3b *and* 3c respectively.

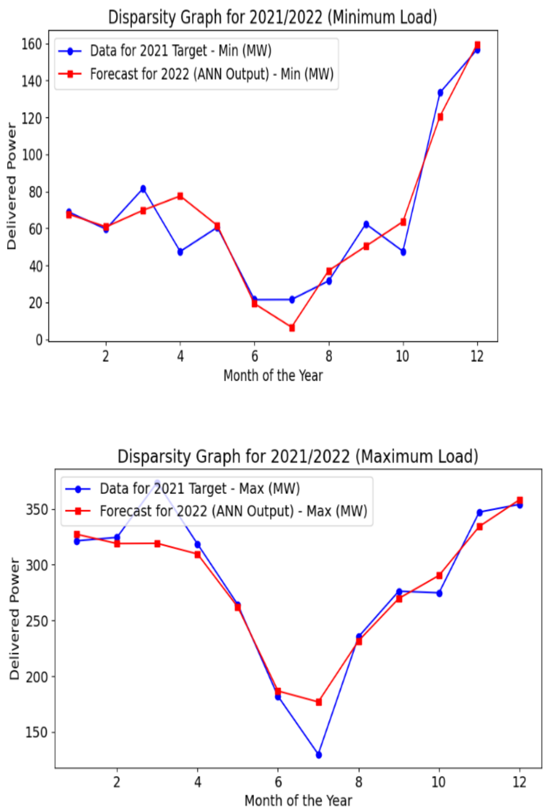
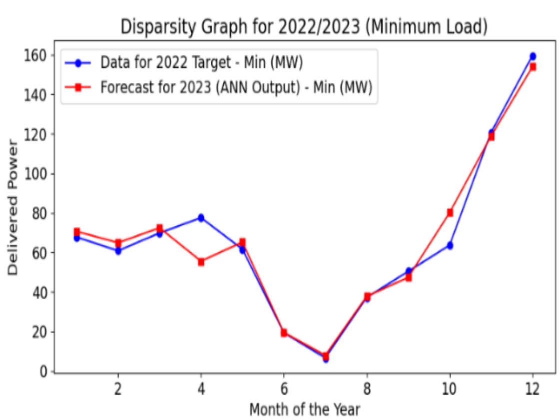


Figure 5a: The Disparity Graph for Year 2021/2022



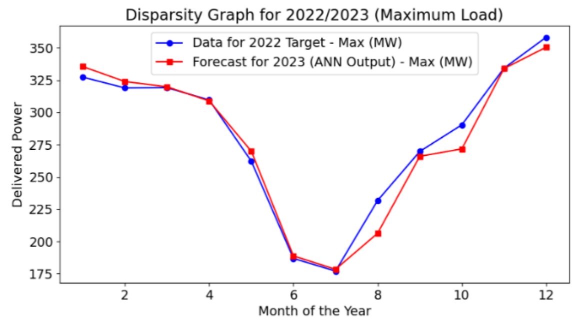


Figure 5b: The Disparity Graph for Year 2022/2023

Table 2: Target (MW) (i.e. the corresponding results of each fed input)

Year 2022 Target 't'		Year 2023 Target 't'		Year 2024 Target 't'	
Max (MW)	Min (MW)	Max (MW)	Min (MW)	Max (MW)	Min (MW)
321.43	68.82	327.33	67.72	335.53	70.65
324.52	59.7	318.97	60.87	323.93	64.93
373.79	81.62	319.15	69.83	319.86	72.47
318.62	47.58	309.66	77.57	308.91	55.61
264.34	60.62	262.18	61.64	269.94	65.24
182.07	21.53	186.80	19.36	188.77	19.49
130.1	21.6	176.98	6.67	178.34	7.96
235.38	31.67	231.72	37.24	206.32	37.82
276.26	62.47	269.72	50.41	265.94	47.39
274.81	47.69	290.38	63.67	271.74	80.13
347.2	133.45	334.27	120.67	333.99	118.89
354.1	156.79	358.25	159.62	350.53	153.94

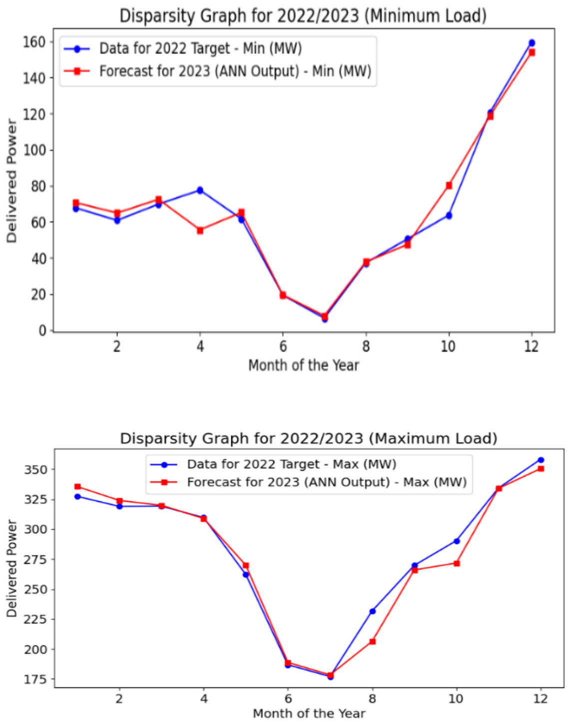


Figure 5b: The Disparity Graph for Year 2022/2023

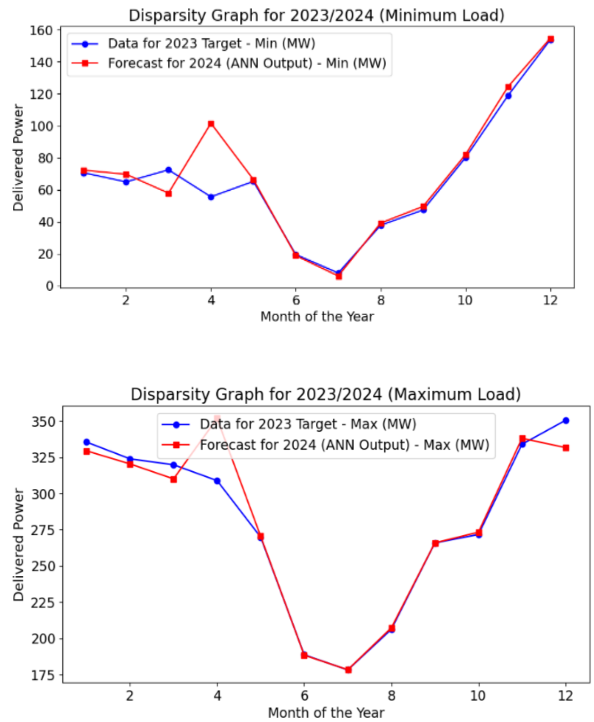


Figure 5c: The Disparity Graph for Year 2023/2024

Table 3a: The disparity table between the target and the forecasted output for the year 2021/202

Data for 2021 Target		**Forecast for 2022 (ANN Output)**	
Max (MW)	Min (MW)	Max (MW)	Min (MW)
321.43	68.82	327.3322	67.7178
324.52	59.7	318.9665	60.8664
373.79	81.62	319.1515	69.8322
318.62	47.58	309.6565	77.5679
264.34	60.62	262.1798	61.6423
182.07	21.53	186.7991	19.363
130.1	21.6	176.9763	6.665
235.38	31.67	231.7186	37.2364
276.26	62.47	269.7179	50.409
274.81	47.69	290.3817	63.6669
347.2	133.45	334.2738	120.6746
354.1	156.79	358.2485	159.6192

Table 3b: The disparity table between the target and the forecasted output for the year 2022/2023

Data for 2022 Target		**Forecast for 2023 (ANN Output)**	
Max (MW)	Min (MW)	Max (MW)	Min (MW)
327.3322	67.7178	335.53	70.65
318.9665	60.8664	323.93	64.93
319.1515	69.8322	319.86	72.47
309.6565	77.5679	308.91	55.61
262.1798	61.6423	269.94	65.24
186.7991	19.363	188.77	19.49
176.9763	6.665	178.34	7.96
231.7186	37.2364	206.32	37.82
269.7179	50.409	265.94	47.39
290.3817	63.6669	271.74	80.13
334.2738	120.6746	333.99	118.89
358.2485	159.6192	350.53	153.94

Table 3c: The disparity table between the target and the forecasted output for the year 2023/2024

Data for 2023 Target		**Forecast for 2024 (ANN Output)**	
Max (MW)	Min (MW)	Max (MW)	Min (MW)
335.53	70.65	329.46	72.24
323.93	64.93	320.45	69.71
319.86	72.47	310.11	57.93
308.91	55.61	351.81	101.64
269.94	65.24	270.55	66.43
188.77	19.49	188.49	18.85
178.34	7.96	178.46	6.1
206.32	37.82	207.38	39.2
265.94	47.39	265.99	49.58
271.74	80.13	273.33	82.01
333.99	118.89	338.1	124.41
350.53	153.94	331.69	154.82

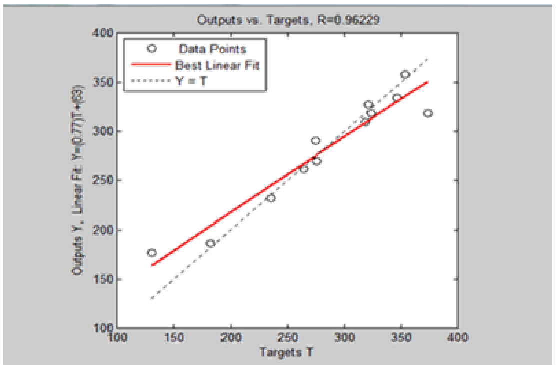
The relationship or similarity between the outputs and the targets is indicated in this section. The network was constantly trained after the initial input and output data were introduced until a good regression value was obtained. For the subsequent years, this was done similarly. For the years 2021–2022, 2022–2023, and 2023–2024, R is equal to *0.96, 0.97, and 0.97*, respectively. The degree to which the outputs and targets are connected and changed together is depicted in Figure 6 as *96%, 99%, and 97%*, respectively. Table 4 shows mathematical models generated by the network which can be used to predict the load using past historical data. $f(x)$ represents each historical power (Maximum and minimum) and x represents the months of the year which serves as input.

Table 4: Mathematical models used to predict Load for years 2022, 2023 and 2024 respectively.

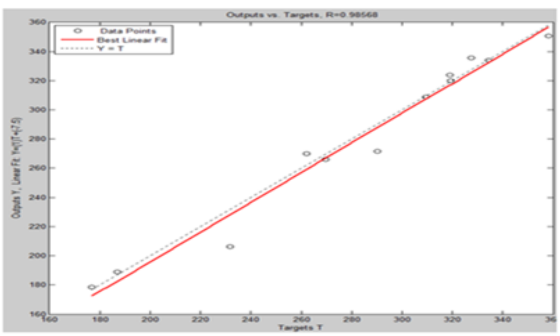
S/N	**Year**	**Mathematical model**
1	**2021/2022**	$f(x) = p_1x^3 + p_2x^2 + p_3x^1 + p_4$ $p_1 = -0.01703$, $p_2 = 2.741$, $p_3 = -113.7$ and $p_4 = 1578$ $\boldsymbol{Goodness\ of\ Fit}$ $SEE: A = (0.77)T + (63)$ R-square: 0.96
2	**2022/2023**	$f(x) = p_1x^3 + p_2x^2 + p_3x^1 + p_4$ $p_1 = -0.00006366$, $p_2 = 0.07518$, $p_3 = -2.185$ and $p_4 = 123.8$ $\boldsymbol{Goodness\ of\ Fit}$ $SEE: A = (1)T + (75)$ R-square: 0.99
3	**2023/2024**	$(x) = p_1x^3 + p_2x^2 + p_3x^1 + p_4$ $p_1 = -0.02078$, $p_2 = 4.775$, $p_3 = -127.8$ and $p_4 = 1760$ $\boldsymbol{Goodness\ of\ Fit}$ $SEE: A = (0.987)T + (68)$ R-square: 0.97

Summary of Findings

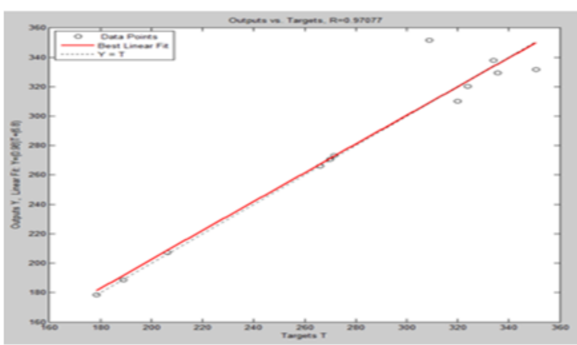
From the aforementioned findings, Table 4 shows the three mathematical models obtained by carrying out a curve-fitting analysis using the MATLAB tool application. This was followed by an identical curve fitting procedure to validate the previously forecasted load using MATLAB codes. All the results obtained were found to be equivalent. Figure 5(a-c) graphically illustrates how the measured output data fitted the predicted mathematical model.



Regression=0.96, ***Best Linear Fit: A= (0.77) T + (63)***



Regression =0.99, Best ***Linear Fit: A= (1) T + (75)***



Regression =0.97, ***Best Linear Fit: A= (0987) T + (68)***

Figure 6: Regression graph for years 2021/2022, 2022/2023 and 2023/2024

It can be further shown that the predicted power during the rainy season differs from that during the dry season. The amount of power provided by the grid during the dry season, from November to April, is more during the rainy season; from May to October. This should be considered in addition to learning what to anticipate from the grid in the coming years. Overall, this shows a high level of accuracy in neural networks' capacity to predict power. The optimal Linear Fit equation, A = (1) T + (75), can be used to represent the provided artificial neural network regression model (ANNRM). According to this equation, the output variable A is predicted using a linear relationship with the input variable T. T is multiplied by a weight of 1, and a constant bias term of 75 is also added.

An artificial neural network is used in this regression model to determine the relationship between the input variable T and the output variable A. A set of input-output pairs with the matching values of T and A are used as training data to train the neural network. The neural network modifies its internal parameters, such as weights and biases, during the training phase to reduce the discrepancy between the projected output and the actual output.

To forecast values for unknown inputs, the neural network regression model seeks to capture the underlying patterns and correlations between T and A. The model implies a direct proportionality between T and A by employing a linear connection with a weight of 1. The bias term of 75 denotes an output offset that is inserted as a constant and may be used to adjust any systemic or baseline effects.

CONCLUSION

The results obtained from carrying out this study confirmed the relevance as well as the efficiency of neural networks in power supply prediction. The ANN approach has proved to be accurate and computationally fast. The use of normalized preprocessing and post-processing techniques proved undoubtedly essential for the overall performance of the ANN.

The training algorithm used, usually applicable to function approximation problems, trained the NN on average, about much faster than the usual BPAs. However, it must be noted that the algorithm described and used to execute this work is not for pattern recognition problems or tasks involving very large numbers of weights. What happens is that a relatively poor performance could result and the intended goal of prediction may appear erratic.

It is recommended that all of the nation's universities be encouraged to implement thorough research on ANN applications. It is important to instill in students an understanding of how simple it is to use ANN to anticipate the weather, electricity loads, stock market, and other events. Additionally, a more thorough investigation of this study could explore other factors of power supply. An ANN can be used, for example, to control the speed and position of a DC motor. To determine which method is the most effective, all currently used approaches for forecasting the availability of electricity should be reviewed and contrasted with the ANN approach.

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