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Research article

Modeling influence of weather variables on energy consumption in an agricultural research institute in Ibadan, Nigeria

Rahaman Abu[1], John Amakor[1,2], Rasaq Kazeem[1,3,*], Temilola Olugasa[1], Olusegun Ajide[1], Nosa Idusuyi[1], Tien-Chien Jen[3] and Esther Akinlabi[4]

[1] Department of Mechanical Engineering, University of Ibadan, Ibadan, 200005, Nigeria
[2] International Institute of Tropical Agriculture, Ibadan, 200285, Nigeria
[3] Department of Mechanical Engineering Science, University of Johannesburg, Auckland Park, Johannesburg, 2006, South Africa
[4] Department of Mechanical and Construction Engineering, Faculty of Engineering and Environment, Northumbria University, Newcastle, NE7 7XA, United Kingdom

* **Correspondence:** Email: ra.kazeem@ui.edu.ng; Tel: +2348033877073.

Abstract: Climate change is having a significant impact on weather variables like temperature, humidity, precipitation, solar radiation, daylight duration, wind speed, etc. These weather variables are key indicators that affect electricity demand and consumption. Hence, understanding the significance of weather elements on energy needs and consumption is important to be able to adapt, strategize, and predict the effect of the changing climate on the required energy of an organization. This study aims to investigate the relationship between changing weather elements and electricity consumption, employing Multivariate Linear Regression (MLR), Support Vector Regressions (SVR), and Artificial Neural Network (ANN) models to predict the effect of weather changes on energy consumption. The following approaches were engaged for this study: Creating a catalog of weather elements and parameters of energy need or its consumption; analyzing and correlating electrical power consumption to weather factors; and developing prediction models—MLR, SVR, and ANN to predict the significance of the change in the variables of weather on the electrical energy consumption. Among the weather variables considered, temperature emerged as the most influential factor affecting electricity consumption, displaying the highest correlation. The monthly total pattern for electricity use for the case study area followed a similar pattern as the mean apparent temperature. Of the three models (MLR, SVR, and ANN) developed in this study, the ANN model yielded the best predictive performance, with Mean Square Error (MSE), Mean Absolute Error (MAE), and Mean Absolute

Percentage Error (MAPE) of 2.733%, 1.292%, and 4.66%, respectively. Notably, the ANN model outperformed the other models (MLR and SVR) by more than 20% across the predictive performance metrics employed.

Keywords: ANN; weather variable; MLR; energy consumption; SVR

1. Introduction

Access to an adequate, secure, and sustainable energy supply is important for economic and social development [1]. It has been established that the rate of industrialization of any country is dependent on the amount of energy available in that country and the extent to which this energy is utilized. According to [2], It is critical to provide enough energy to meet basic human needs while mitigating negative environmental impacts. As global weather conditions change, energy consumption in weather-sensitive industries or sectors is likely to change. The most visible and studied impacts are changes in building space conditioning efficiency as a result of increased space cooling demands [3]. According to [3], climate changes the way consumers react to short-term weather shocks and how people will adjust in the long run by switching to durable goods. The demand for electricity is affected by several factors, which can be referred to as economic variables, calendar effects, and climate variables [4]. Climate change is having a moderately significant impact on weather factors such as precipitation, humidity, temperature, solar radiation, daylight duration, wind speed, and so on, all of which influence electricity demand and consumption [5–8]. The authors in [9] concluded that it is imperative to comprehend these weather variabilities and their effects on the power system to be able to recommend, plan, and manage the change to renewable energy generation. Moreover, it is important to include these weather variables in electricity demand models to increase the predicting power and accuracy of models as well as give energy managers an insight into the factors influencing electricity demand [4]. Of particular note is the steady temperature rise in Nigeria, attributed to global warming, with data revealing an alarming 3 ℃ per decade rise in mean minimum temperature over the span of four decades [10]. Recent research has focused on the link between climate change and energy usage, with studies by [11] exploring the Agricultural Energy Internet's role in revolutionizing agriculture, highlighting relevant technologies and energy consumption patterns. [12] emphasized the benefits of optimizing collaboration between photovoltaic greenhouses and rural energy systems, showing substantial energy cost savings through load control. In another study, [13] investigate the construction of the Agricultural Energy Internet, its impact on agricultural electrification and carbon emissions reduction, and stress the role of digital twin and virtual power plant technologies.

Several researchers have created energy models to simulate the influence of parameters such as the economy, weather conditions, demographics, population, and calendar data on different facets of electrical energy demand and usage (minimum and peak load, heating and cooling, demand daily and monthly consumption, etc.). [14] developed a high-accuracy ANN model for forecasting energy load for short-term using a Long Short-Term Memory (LSTM) network and tested it using historical data. [15] forecasted electrical energy consumption by developing two ANN models; the first model was a univariate completely connected ANN model with three Electrical Energy Consumption (EEC) input units, and the second model was a partly connected multivariate ANN model that has both EEC and Degree Day (DD) as input units. [16] created a model for predicting electricity use in Saudi Arabia based on past data for weather parameters (relative humidity, solar radiation, average air temperature), economic parameters or indicators (gross domestic product (GDP) per capita) and demography (population). [17] utilized ANN and SVR (SVR) to predict electricity use in Turkey based on a catalog of electricity consumption that spans forty years (1970 to 2011). [18] developed a predicting model comprised of two sub-models using demographic, economic, and weather variables to forecast electricity consumption in Saudi Arabia. [19] examined the effect of weather parameters on monthly electric energy demand in the United Kingdom using three different models: Box and Jenkin's model, ANN, and the socioeconomic model (S-E). [20] developed a model for predicting short-term electricity requirements that incorporates previous data on consumption into a functional vector autoregressive state space model. [4] modeled the impact of temperature on daily maximum electricity need in South Africa using the generalized extreme value distribution and piecewise linear regression model. These models, often categorized as parametric and non-parametric, provide varying degrees of precision in forecasting electricity needs, measured through diverse statistical methods such as MSE, MAPE, MAE, and Sum of Square Error (SSE). Some of these models, specifically the non-parametric models (SVR, ANN, etc.), are data dependent, and as such, the resultant models are designed according to the dataset. It is, therefore, important to have an in-depth understanding of the influence and impact of weather variables on energy demand and consumption to be able to adapt, plan, and forecast the impact of the changing climate on the energy needs of an organization. This study aims to provide a comprehensive understanding of the effect of weather factors on energy demand and consumption to support adapting, planning, and forecasting the effect of climate change on an organization's electricity requirements by modeling the influence of changes in weather variables (such as temperature, relative humidity, solar radiation, sunshine hours, evaporation) on the electricity demand and consumption at a typical agricultural research institute and forecasting the impact of change in these variables on electricity demand [21].

2. Materials and methods

This study employed the following methodology to analyze and model the impact of weather variables on electrical energy consumption:

i. A comprehensive database was created, comprising daily data from the years 2011 to 2018 and 2008 to 2018 for monthly data. This database included records of weather variables and energy demand or consumption parameters.
ii. The electrical energy demand (maximum and minimum power, average load etc) was analyzed and correlated to weather variables. These variables included minimum and maximum temperatures, as well as minimum and maximum values of relative humidity, wind speed, solar radiation, and sunshine hours.
iii. To quantify the impact of changes in weather variables on electrical energy demand, several multivariate models were employed. These models included multiple linear regression, support vector regression, and artificial neural networks.
iv. The predictive performance of the models was accessed using statistical methods such as mean absolute error, mean square error, and mean absolute percentage error.

2.1. Location of study

The location of the study was the International Institute of Tropical Agriculture (IITA), situated in Ibadan, Oyo State, Nigeria. IITA's coordinates are approximately Latitude 07°30' N and Longitude 03°55' E, with an altitude of 227 meters above sea level. This region is classified under the Köppen climate classification as having a tropical wet and dry climate, denoted by the abbreviation "Aw". Such climates are typically characterized by distinct wet and dry seasons, with the wet season typically occurring in the summer months and the dry season in the winter months [22]. The Institute is situated on a 1000-hectare land, housing research farms, offices, and residential and commercial buildings. Electricity supply to the IITA campus is sourced from both the public utility, specifically the Ibadan Electricity Distribution Company (IBEDC), and four 1.5 MVA self-generation power plants.

2.2. Weather data

Weather and temperature are key determinants of electricity use. With regards to [23], heating and cooling requirements account for more than 40% of energy usage in both residences and industries and are heavily determined by weather conditions. The weather data was obtained from the IITA weather observation station established in Ibadan, Nigeria. The daily data for the weather (minimum and maximum temp., sunshine hours, minimum and maximum rel. humidity, solar radiation, and wind speed) spanning from the year 2011 to 2018 was obtained, and the monthly data for the weather (minimum and maximum temperature) spanning from 2008 to 2018 was collated for this study.

2.3. Energy data

Energy data for this study were obtained from IITA Power Unit. Energy parameters, namely average power factor, maximum, minimum, and average loads (in WM), generator hours (hrs), public utility consumption, public utility hours (hrs), generator consumption, and total use, were recorded daily for this study.

2.4. Data preprocessing

In the data preprocessing phase, we applied normalization and standardization techniques to the acquired energy and weather datasets. The primary aim of normalization is to prevent variables with larger numeric ranges from overshadowing those with smaller numeric ranges. Additionally, we introduced a new categorical variable known as "day-index" to distinguish between working days (assigned a value of 1) and non-working days (assigned a value of 0). This differentiation was made with the understanding that working days significantly impact the population in the study area, subsequently influencing energy consumption. As highlighted by [24], there exists a direct correlation between population and energy consumption. Empirical observations also supported this, revealing a decrease in population during non-working days. To account for demographic, population, and activity fluctuations in the study area, we introduced two additional variables, "month index" and "year index". These variables played a crucial role in enhancing the performance of the models applied in this study. The dataset was further divided into three segments, with a distribution ratio of sixty percent for training, twenty percent for validation, and twenty percent for testing. This division facilitated rigorous testing and validation, ensuring the robustness and reliability of the models developed.

Table 1 shows the linear correlation coefficient between weather variables and total energy consumption obtained from the daily data from 2011 to 2018. A substantial negative correlation of −0.74 is observed between daily maximum temperature and minimum relative humidity. This indicates that as the maximum temperature increases, the minimum relative humidity decreases. Also, a high positive correlation was observed between the daily maximum temperature and the sunshine hours, as well as between sunshine hours and solar radiation. These findings highlight the interplay between weather variables, shedding light on how changes in one variable can influence another. The influence of changing population and activities becomes evident when observing the strong positive correlation between total consumption and the day index. This correlation is further enhanced when considering the year index and month index, as demonstrated in Table 2 with the correlation coefficient between Average Temperature and Total Consumption increasing to 0.87 for working day and 0.86 for non-working days for the year 2015 which is a similar trend in all other years in this study.

Table 1. Correlation coefficient between daily weather variables and total electricity consumption (Total cons) (2011–2018).

	Wind speed	Max. rel. hum.	Min. rel. hum.	Max. temp.	Min. temp.	Avg. temp.	Sunshine hr.	Solar radiation	Day index	Total cons
Wind speed	1	−0.21	−0.16	0.3	0.15	0.31	0.22	0.13	0.031	0.033
Max. rel hum	−0.21	1	0.4	−0.15	0.27	0.019	−0.12	−0.17	0.039	0.048
Min. rel. hum.	−0.16	0.4	1	−0.74	0.15	−0.49	−0.56	−0.34	0.0355	−0.11
Max. temp.	0.3	−0.15	−0.74	1	0.21	0.87	0.68	0.49	−0.015	0.31
Min. temp.	0.15	0.27	0.15	0.21	1	0.66	0.026	0.11	0.063	0.42
Avg. temp.	0.31	0.019	−0.49	0.87	0.66	1	0.53	0.43	0.02	0.45
Sunshine hr.	0.22	−0.12	−0.56	0.68	0.026	0.53	1	0.62	0.0051	0.23
Solar radiation	0.13	−0.17	−0.34	0.49	0.11	0.43	0.62	1	−0.032	0.33
Day index	0.031	0.039	0.035	−0.015	0.063	0.02	0.0051	−0.032	1	0.67
Total cons	0.033	0.048	−0.11	0.31	0.42	0.45	0.23	0.33	0.67	1

Table 2. Correlation between daily weather variables and total consumption considering the day index (2015).

Variables	Total cons (Index 1)	Total cons (Index 0)
Wind speed	0.26	0.34
Max. rel. hum.	0.3	0.31
Min. rel. hum.	−0.24	−0.29
Max. temp.	0.61	0.62
Min. temp.	0.76	0.75
Avg. temp.	0.87	0.86
Sunshine hr.	0.3	0.36
Solar radiation	0.29	0.34

Among the analyzed weather variables, it is evident that average daily temperature exerts the most significant influence on total electricity consumption, whereas wind speed exhibits the least impact on consumption.

2.5. Energy models

2.5.1. MLR model

In this study, the dependent variable was energy utilization; specifically, electricity consumption (kWh), while the independent variables, such as day index, year, and temperature, are listed in Table 3. This regression analysis was used to measure the effect of changes in weather factors on electricity use in the study area.

Table 3. Variables for the study.

Designation	Model inputs (Independent variables)
A	Day index
B	Year index
C	Month index
D	Max. temp.
E	Min. temp.
F	Sunshine hour
G	Solar radiation
H	Min. rel. hum.
	Model output (Dependent variable)
Y	Total consumption (Total cons)

The model of the MLR can be represented with Eq 1.

$$Y = Z_0 + AZ_1 + BZ_2 + CZ_3 + DZ_4 + EZ_5 + FZ_6 + GZ_7 + HZ_8 \tag{1}$$

This model was executed with the daily energy and weather data obtained from IITA using a Python programming language. The values for the coefficient of the independent variable Z_1 to Z_8 were obtained for the linear regression model in Eq 2.

$$Y = 7.2366A + 0.7981B + 0.0401C + 0.4317D + 0.8126E + 0.1006F + 0.0956G + 0.0124H - 1618.32 \tag{2}$$

2.5.2. SVR model

SVR is adopted to minimize the generalization error bound. Suppose there are given training data $\{(x_1, y_1), \dots \dots .(x_t, y_t)\} \subset X \times R$ where X represents the space of the input patterns. In SVR, a function $f(x)$ with the most deviation ε from the obtained targets y_i for all the training data, and a small coefficient *w* is given in Eq 3.

$$f(x) = (w, x) + b \; with \; w \in X, b \in R \tag{3}$$

For minimization of the norm, $\|w^2\| = (w, w)$. A convex optimization problem is expressed in Eq 4:

$$minimize \; 0.5\|w\|^2$$

$$subject \; to \; \{y_i - (w, x_i) - b \le \varepsilon \; (w, x_i) + b - y_i \le \varepsilon \tag{4}$$

In cases in which *f(x)* exists, Eq 4 is feasible and accurately approximates all pairs (x_i, y_i). Some errors are permissible at times [25]. This model was likewise executed with the daily energy and weather data obtained from IITA using a Python programming language.

2.5.3. ANN model

There are many ANN structures used in machine learning problems, but the Multilayer Perceptron (MLP). MLP is the most commonly used ANN type. The MLP is a fully connected structure ANN framed up with an input layer, one or more hidden layers, and an output layer, as illustrated in Figure 1 [26].

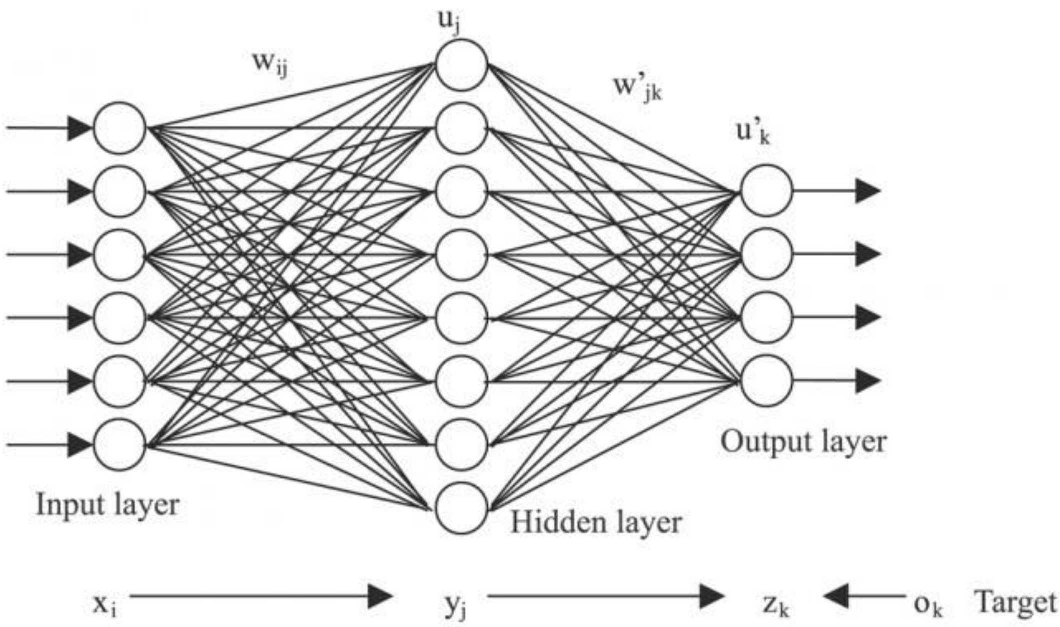

Figure 1. General representation of an ANN.

Tables 4–7 show the parameters (input, scaling, structure, selection, and training) for developing the ANN model. This model was executed using the daily energy and weather data obtained from IITA using the Python programming language sklearn (module) library.

Table 4. Input selection algorithm's description and values.

Input	Description	Value
Trials number	Number of trials for every neural network	3
Selection loss goal	Goal value for the selection error	0
Tolerance	Tolerance for selection error during algorithm training	0.01
Maximum selection failures	The maximum number of iterations when the selection error increases	10
Maximum number of inputs	The neural network's maximum number of inputs	9
Minimum correlation	The minimum value for considering correlations	0
Maximum correlation	Maximum value for considering correlations	1
Maximum number of iterations	Maximum number of iterations to execute the algorithm	100
Maximum time	The maximum time for the input selection algorithm	3600
Plot selection error history	Make a graph of each iteration's selection errors	true
Plot training loss history	Make a graph of each iteration's selection errors	true

Table 5. Input scaling values.

Input	Minimum	Maximum	Mean	Deviation
Wind speed (km/hr)	0	7.7	3.28	1.09
Max. rel. hum. (%)	73	100	93.8	4.88
Min. rel. hum. (%)	0	97	51.6	17.7
Solar radiation (MJ/m²/day)	3.53	27.8	14.7	3.75
Sunshine hour (hr.)	0	11.1	5.75	2.86
Year index	1	8	4.49	2.26
Day index	0	1	0.674	0.469
Min. temp. (°C)	16	27	22.5	1.68
Max. temp. (°C)	22.5	38	31.4	2.67

Table 6. Perceptron layer values and activation functions.

Layer	Inputs number	Perceptron number	Activation function
Hidden layer	9	100	Hyperbolic tangent
Output layer	100	1	Linear

Table 7. ANN model training—Quasi-Newton method results.

Parameter	Value
Final parameters norm	20
Final training error	0.0168
Final selection error	0.0164
Final gradient norm	0.0166
Elapsed time	00:01
Epochs number	50
Stopping criterion	Maximum number of iterations

3. Results and discussion

A plot of monthly total electricity consumption and average temperature from 2008 to 2018 is depicted in Figure 2. It is observed that an increase or decrease in average temperature results in the same electricity consumption. The maximum electricity consumption was observed between February and April, which is the hottest period (peak dry season) in the year. The lowest average temperature and the minimum electricity consumption were observed between July and September (peak rainy season) in the year based on the data obtained.

Figure 3 illustrates the linear regression for the dependent variable, daily total electricity consumption (Total_Cons), for the MLR model. The predicted values of the test set data were plotted against the actual to test the loss in the model. A line of best fit is shown.

The values of the MLR model are shown in Table 8. For a perfect model, 1 will be the correlation between the actual value and the predicted value of the dependent variable (Total_Cons).

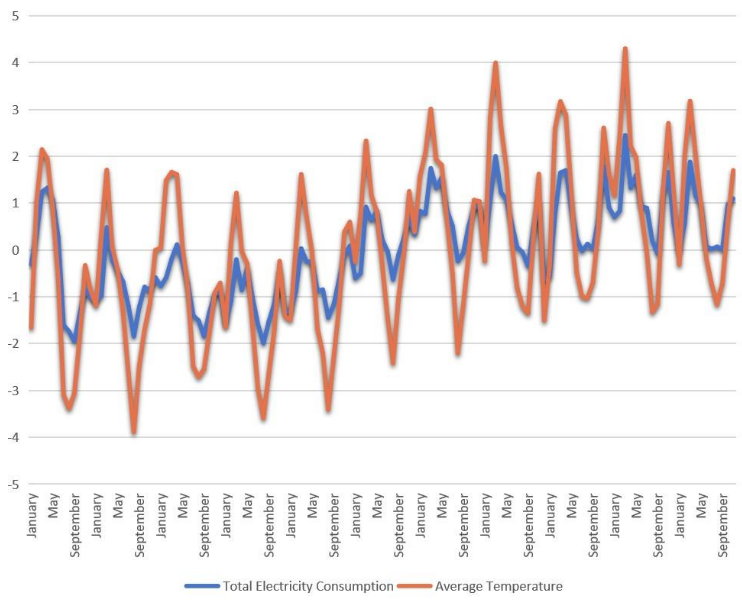

Figure 2. Monthly energy consumption and average temperature pattern (2008–2018).

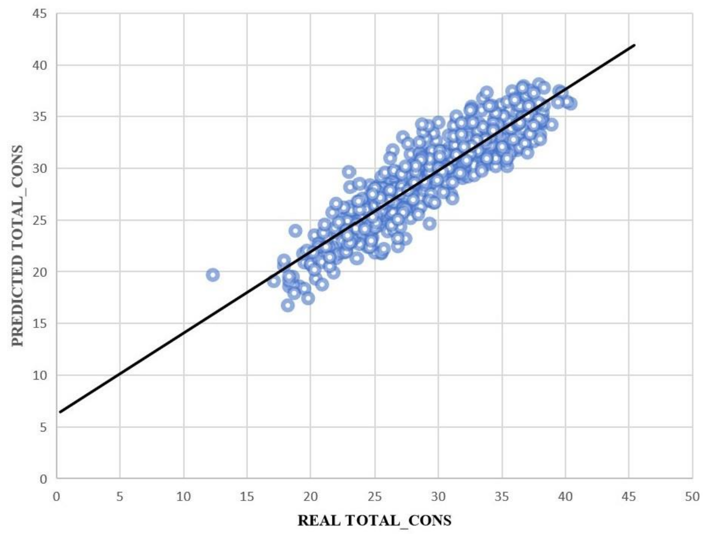

Figure 3. MLR model linear regression chart between predicted and actual electricity consumption.

Table 8. MLR model linear regression parameters between actual and predicted electricity use.

Category	Value
Intercept	6.207
Slope	0.786
Correlation	0.904

Figure 4 shows the linear regression for the dependent variable, daily total electricity consumption (Total_Cons), for the support vector machine-regression model. The predicted values of the test set data were plotted versus the actual ones as dots to test the loss in the model. The line shows the best linear fit. Also, the values for the linear regression analysis for the support vector machine-regression model are shown in Table 9.

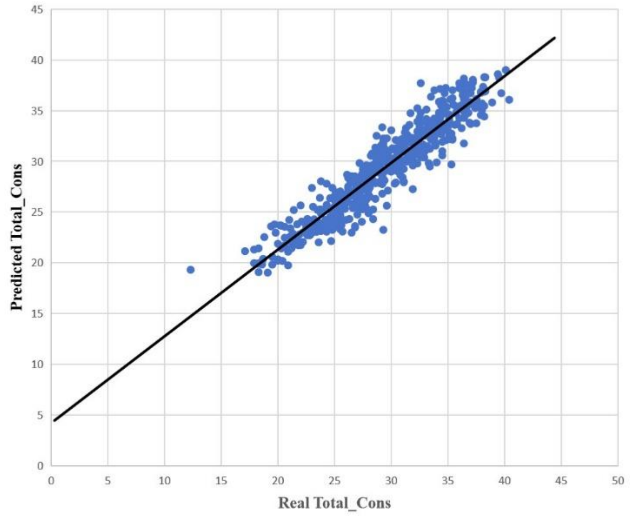

Figure 4. SVR model linear regression chart between the predicted and actual electricity use.

Table 9. SVR model linear regression parameter between the predicted and actual electricity use.

Category	Value
Intercept	4.19
Slope	0.855
Correlation	0.942

Figure 5 shows the linear regression for the dependent variable, daily total electricity consumption (Total_Cons) for the ANN model. The predicted values of the test set data were plotted against the actual to test the loss in the model. A line of best fit is shown. The values of the ANN model are shown in Table 10. For a perfect model, the correlation between the actual value and the predicted value of the dependent variable (Total_Cons) will be 1. However, the correlation obtained with ANN is the best and closest to 1 when compared to the MLR and SVR models.

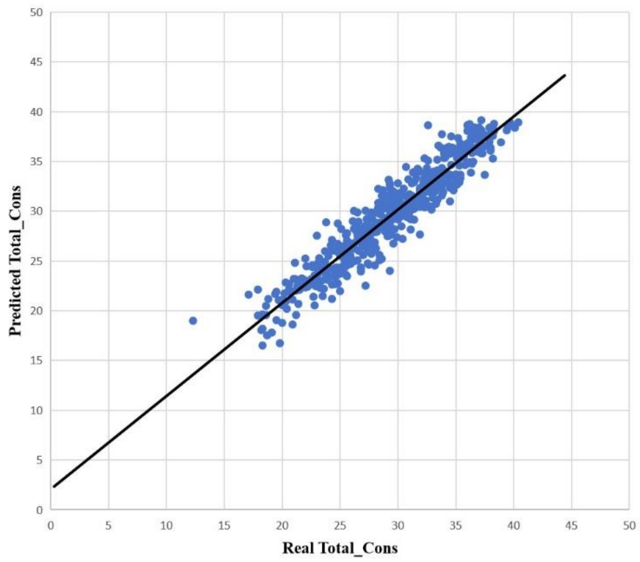

Figure 5. ANN model linear regression chart between the actual and predicted electricity use.

Table 10. ANN linear regression parameters between the actual and predicted electricity use.

Category	Value
Intercept	2.048
Slope	0.937
Correlation	0.949

3.1. *MLR model result*

Figure 6 shows a plot of the forecasted daily electricity use from the MLR model and the real daily electricity use from IITA. The MLR model has an MSE of 4.893, MAE of 1.773, and MAPE of 6.213%, as shown in Table 11.

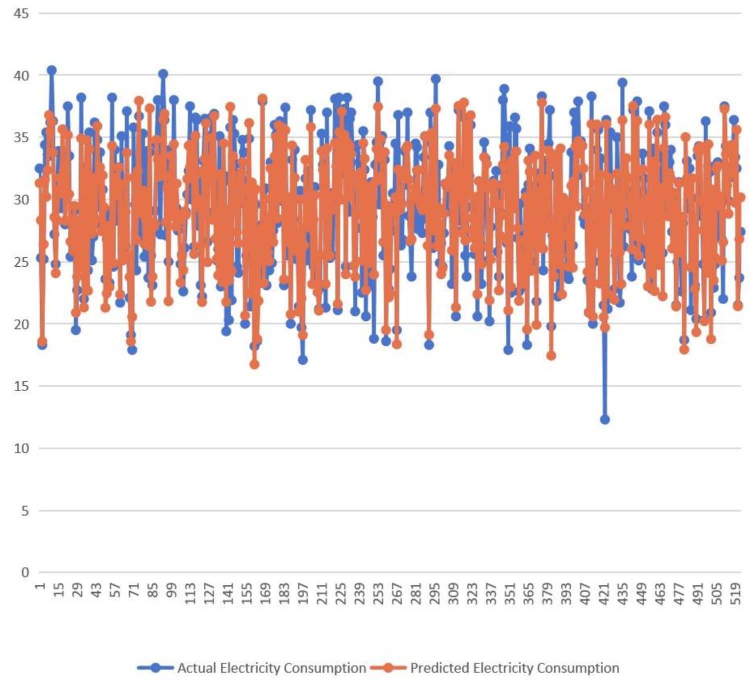

Figure 6. MLR model—A plot of predicted daily electricity consumption to actual daily electricity consumption.

The performance of the linear regression model was improved by using polynomial transformation (PT) of the input variables to the fourth order, resulting in a better-fitted model with an MSE of 3.33, MAE of 1.376, and a MAPE of 4.886% using the test dataset, as shown in Table 11.

3.2. *SVR model result*

A plot of the forecasted daily electricity usage from the SVR model and the real daily electricity consumption from IITA is shown in Figure 7. The SVR model has an MSE of 3.057, MAE of 1.355 and MAPE of 4.826%, as shown in Table 11. The SVR model showed an improvement over the MLR model, as observed from the error value.

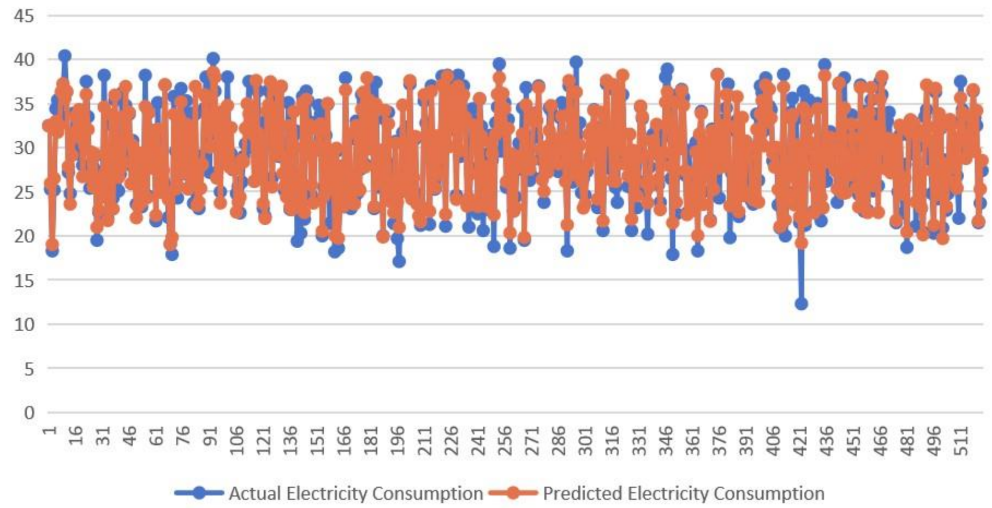

Figure 7. SVR model—Plot of predicted daily electricity consumption to actual daily electricity consumption.

3.3. ANN model result

Figure 8 shows a plot of the forecasted daily electricity consumption from the ANN model and the actual daily electricity consumption from IITA. The ANN model has an MSE of 2.733, MAE of 1.292, and MAPE of 4.66%, as shown in Table 11.

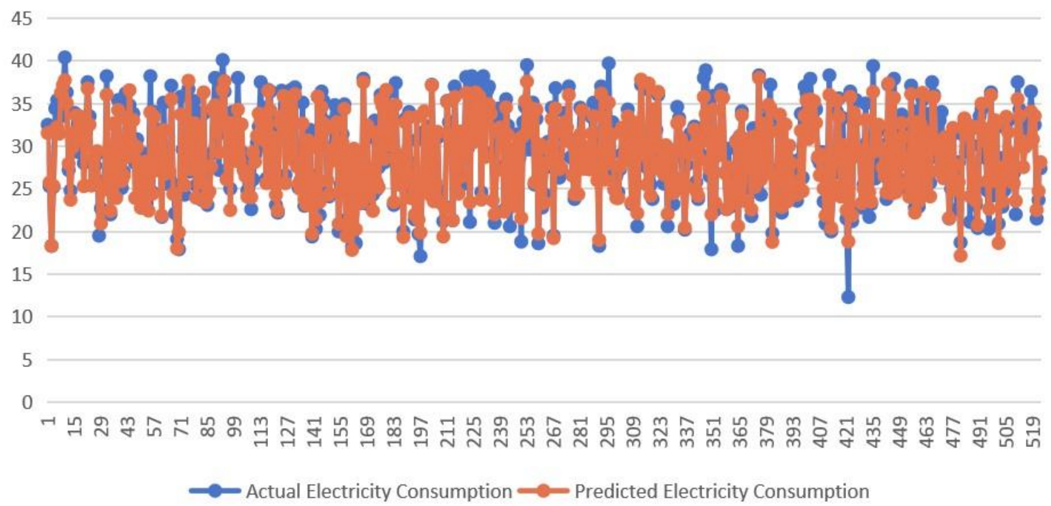

Figure 8. ANN model—Plot of predicted daily electricity consumption to actual daily electricity consumption.

The fitness of these models was tested using various statistical methods (R-squared, MSE, MAE, and MAPE) as seen in the results, as well as the distribution plot of the predicted test data and the actual test data as seen in Figures 3–5.

Table 11. Predictive performance of the models.

Error indices	MLR model	MLR (PT) model	SVR model	ANN model
MAE	1.773	1.376	1.355	1.292
MSE	4.893	3.330	3.057	2.733
MAPE	6.213%	4.886%	4.826%	4.660%

4. Conclusions

This study sheds light on the critical influence of weather variables on electricity consumption, with temperature standing out as the most significant factor, displaying the highest correlation. The monthly total electricity usage pattern in the case study area closely mirrored the mean apparent temperature, emphasizing the direct impact of weather on energy needs. Models were created to predict the anticipated daily electricity use when given the values of the weather variables. ANN model produced the best result concerning error and predictive performance compared to SVR and MLR models. ANN model outperformed the other models (MLR and SVR) by more than 20% across the predictive performance metrics employed in this study. To optimize energy utilization, we advocate for the implementation of building management systems equipped with sensors (such as temperature, humidity, and occupancy sensors) and incorporated with a robust control system to effectively manage the energy consumption in the buildings and take full advantage of the changes in weather variables.

Organizations may consider generating renewable energy from solar as this energy can be used to offset the increase in electricity consumption during the months with high average temperatures as such months also have an equivalent high solar radiation (average temperature has a high positive correlation with solar radiation and sunshine hours). The scope of this study was constrained by the limited size of the case study area and the availability of historical data. This limitation arises from the irregular and unstable power supply in Nigeria, which hinders the collection of comprehensive energy data encompassing a broader geographical expanse. Given the challenging nature of gathering electricity data in a country grappling with erratic power supply, particularly in the Nigerian context, obtaining data representative of more extensive geographical areas, such as cities or states, proves to be a significant challenge. The challenges posed by this prevailing condition underscore the need for future research to encompass broader geographical regions such as cities or states. By doing so, we can have a more comprehensive insight into energy patterns, aiding in robust energy planning and effective climate change response within Nigeria and across the African continent.

Use of AI tools declaration

The authors declare that they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflicts of interest.

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