



## Comparison of Load Demand Forecasting Using Machine Learning and Classical Multivariate Regression Analysis

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### ABSTRACT

To avoid an energy catastrophe, variable electrical load and ever-increasing load demand must be predicted or projected. Both suppliers and consumers benefit from forecasting the day-ahead electrical load. With precise load estimates, the reduction of electricity waste and the sensible dispatch of electric generator units can be considerably enhanced. This article is focused on comparing Artificial Neural Network ANN (nonlinear model) and classical Multivariate Linear Regression MLR (linear model) techniques for Short Term Load Forecasting (STLF). The live load data from a sub-station of the Abuja Electricity Distribution Company (AEDC), situated in the Federal Capital of Abuja, and is procured for the presented simulation study. For the simulation study using a neural network and MLR methodology, the obtained live data is divided into three categories: validation, training, and testing. The simulation results were checked against live load data from the chosen site and confirmed to be within allowable limits. The Coefficient of Determinate ( $R^2$ ), Correlation Coefficient ( $R$ ), Mean Square Error (MSE), and Root-Mean-Square Error (RMSE) were calculated to demonstrate the effectiveness of the proposed machine learning based STLF, and it can be safely concluded that ANN (nonlinear models) gives far more accurate results than MLR (linear model), and is reliable in predicting the load forecast. This would aid in determining the variation in electric load well in advance and providing an opportunity or scope for preparedness to meet the abrupt spike in load demand, thereby achieving the requirements of active load forecasting in the power system arena.

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### INTRODUCTION

Load forecasting is the predicting of electrical power required to meet the short term, medium term or long-term demand. The forecasting helps the utility companies in their operation and management of the supply to their

customers. Electrical load forecasting is an important process that can increase the efficiency and revenues for the electrical generating and distribution companies. It helps them to plan on their capacity and operations in order to reliably supply all consumers with the required energy.[1]

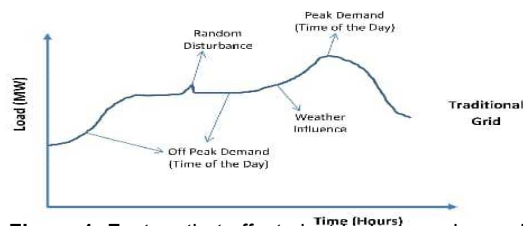


Figure 1: Factors that affect electrical power demand



Some limitation of the traditional forecasting models is that some assumptions may not always hold true, resulting in false and misleading results when estimating the values of a variable using the regression equation, when data has cyclical or seasonal fluctuations, predictions aren't reliable. One of the reasons we use machine learning for forecasting is to overcome some of these limitations. But with machine learning, it needs less formal statistical training, has the capability of implicitly detecting complex relationships between dependent and independent variables, has the capability of detecting all possible interactions between predictor variables, has access to multiple training algorithms[2]. Abuja faces a serious challenge for a growing demand for electricity, providing reliable power supply and keeping electricity price affordable to consumer's electricity availability in Abuja has worsened over the years. The city has been unable to meet demand because of its policies, regulations and management of operations. Its failure to provide adequate and reliable energy is well documented, specifically its impact on the city economy. Electricity in Abuja is generated through thermal and hydro power sources. The main source of electricity generation comes from fossil fuels especially gas which accounts for 86% of the capacity in Nigeria with the remainder generated from hydropower sources[3]. The power generation statistics for Nigeria 2019 reflected that a total of 33,448,633 MWh of energy was generated by power stations. Electricity is generated by 13 companies which are called generating companies (GenCos). Privatized GenCos generated 19,692,683 MWh, Independent Power Plants (IPP) GenCos generated 7,798,253 MWh while the NIPP GenCos generated 5,957,697MWh. However, Egbin recorded the highest energy generation with 3,786,313MWh accounting for 11.32% while Alaoji NIPP recorded the lowest with 209,453MWh accounting for 0.63% of total energy generated in 2019.

Total Energy sent out by GenCos stood in 2019 at 32,799,114MWh. Privatized GenCos sent out 19,233,151 MWh, IPP GenCos sent out 7,648,700 MWh while the NIPP GenCos sent out 5,917,262 MWh. Energy consumed by the Eleven Discos in 2019 stood at 28,026,503 MWh, Ikeja Discos recorded the highest energy consumption with 4,087,971 MWh accounting for 14.95% while Yola Disco recorded the lowest with 1,122,534 MWh accounting for 4% of total energy consumed in 2019[4]. The introduction of sustainable demand forecasting in Abuja presents an opportunity for diversifying its energy supply, reduce its dependence on fossil fuels, and the impact of global warming caused by greenhouse gas emissions, in other words improving the quality of life for its people. They offer an opportunity to save the capital investment for the transmission and distribution of electricity. Demand forecasting, data availability determines the power out of a system and helps to size the system and its components. So, it is very important to have accurate data based on the available energy demand. For this reason, the data of Abuja, Nigeria is assessed, particularly the distribution of electricity.

The main contributions of this work are:

1. Designing a cost-effective and a reliable energy system that would meet the electrical load demand of in Abuja and Nigeria at large.
2. Carrying out the optimization process based on an average hourly ambient temperature, electricity supply and electricity used over a period of one year, instead of using a single day or month data.
3. Applying neural network model and a multivariate regression analysis model in order to predict load demand variability in Abuja.
4. The work would serve as a guide for proffering a comprehensive solution to Nigeria's lingering energy crisis, which when used can solve electricity generation, transmission, and distribution problems.



**Figure 2:** A Transmission Station in Abuja

## LITERATURE REVIEW

The literature contains many articles on the best configuration of machine learning forecasting.[5] purposes the model of mid-term energy consumption load forecasting (MTLF) by using artificial neural network based on the two and the three years ahead. This load demand forecasting is a useful tool for a unit commitment and a fuel reserve planning in the power system. Both two and three years ahead forecasting uses two patterns for comparing the accuracy in this research. [6]proposes the level suitability of a wavelet transform and a neural network method that are very significant technique for a load forecasting. An accurate forecast of the load demand is an essential activity for fuel reserve planning in a power system. Level adjustment of wavelet is demonstrated in this research based on mid-term load demand forecasting in Thailand. [7] Presented five exponential smoothing methods are considered for load forecasting for lead times from a half-hour-ahead to a year-ahead. Forecasting load demand with high accuracy is required to prevent energy wasting and system failure. [8] Matching Electricity Supply with Demand in Nigeria.[9] paper are about an approach for evaluating existing short term load forecasting and predicting such discrepancies. Our approach is based on generating and using deep convolutional - recurrent neural networks that are able to process the data, either as time series, or as 2-D information. [10] presents a

generalized technique for modelling historical load data in the form of time-series with different cycles of seasonality (e.g., daily, weekly, quarterly, annually) in a given power network. The proposed method separately models both non-seasonal and seasonal cycles of the load data using autoregressive (AR) and moving-average (MA) components, which only rely on historical load data without requiring any additional inputs such as historical weather data (which might not be available in most cases).[11] paper is to review, identify, evaluate and analyse the performance of Artificial Intelligence (AI) based load forecast models and research gaps.[12] presents a novel design of interval type-2 fuzzy logic systems (IT2FLS) by utilizing the theory of extreme learning machine (ELM) for electricity load demand forecasting.[13] presents a review of electricity demand forecasting techniques. The various types of methodologies and models are included in the literature. Load forecasting can be broadly divided into three categories: short-term forecasts which are usually from one hour to one-week, medium forecasts which are usually from a week to a year, and long-term forecasts which are longer than a year.[14] presented a deep learning model to forecast the load demand of residential buildings with a one-hour resolution, while considering its complexity and variability. [15] This paper presents a review of electricity demand forecasting techniques. The various types of methodologies and models are included in the

literature. Load forecasting can be broadly divided into three categories: short-term forecasts which are usually from one hour to one-week, medium forecasts which are usually from a week to a year, and long-term forecasts which are longer than a year.[16] present a meta-learning system is developed using exogenous weather variables as meta-features. The proposed system selects the best predictor among a pool of candidate forecasting algorithms including ARIMA, ARIMAX, MLR, NAR, NARX, and SVR. In statistical approaches, the volatility of the mean and variance of the load demand is modelled by GARCH process.[17] presents, the results of two models are compared to other previous studies of Iraq's energy system to provide the yearly unsuppressed load forecast in the long term.[18] presents reviews a few single hidden layer network configurations with random weights (RWSLFN). The RWSLFN was extended to eight variants based on the presence or absence of input layer bias, hidden layer bias and direct input-output connections.[19] present several regression tools are analysed using larger datasets for urban area electrical load forecasting. The regression tools which are used are Random Forest Regressor, k-Nearest Neighbour Regressor and Linear Regressor. [20]examines several prediction approaches for day and week ahead electrical load of a community of houses that are supplied by a common residential transformer, in particular: artificial neural

networks; fuzzy logic; auto-regression; auto-regressive moving average; auto-regressive integrated moving average; and wavelet neural networks.[21] paper depicted the novel data mining based methods that consist of six models for predicting accurate future heating and cooling load demand of water source heat pump, with the objective of enhancing the prediction accuracy and the management of future load.[22] paper discusses the use of machine learning strategies, specifically, Support Vector Machines, for predicting future peak load demand based on historical data. Support Vector Regression is implemented here using RStudio software package.[23] Presents the survey of electricity demand forecasting for power system management. As such, machine learning has been use in different fields of study and its application has improve the performance of engineering disciplines [24 - 26]

## METHODOLOGY

### Artificial Neural Network ANN:

There are two forms of ANN in general. Feedforward and Feedback. In Feedforward ANN the information flow in this network is unidirectional. A computer that transfers information to another device that does not receive it. There are also no feedback loops in this. Despite the fact that it is used to identify a pattern. Owing to the fact that they have set inputs and outputs.

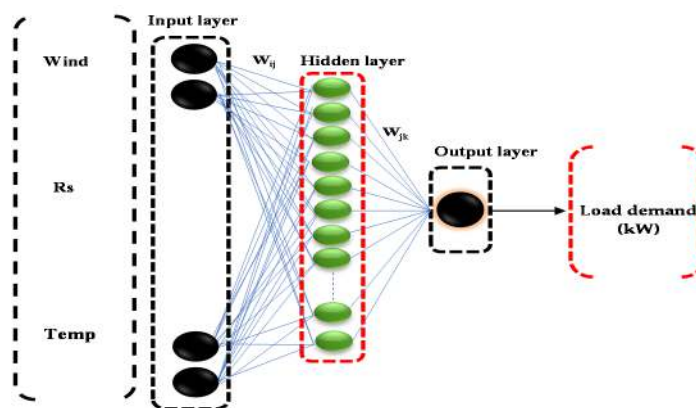


Figure 3: Architecture of ANN used in this study

### Multivariate Regression Analysis

A model with two input variables has the following equation:

$$y = \beta_0 + \beta_1x_1 + \beta_2x_2 \quad (1)$$

What if the inputs are three variables? Only three dimensions are possible in human visualizations. There can be an infinite number of dimensions in the field of machine learning. The equation for a three-input-variable model is as follows:

$$y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \beta_3x_3 \quad 2)$$

Below is the generalized equation for the multivariate regression model-

$$y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_nx_n \quad (3)$$

Where n represents the number of independent variables,  $\beta_0 \sim \beta_n$  represents the

coefficients and  $x_1 \sim x_n$ , is the independent variable.

The multivariate model helps us in understanding and comparing coefficients across the output. Here, small cost function makes Multivariate linear regression a better model.

### METHODOLOGY

Artificial Neural Networks (ANN) and Machine Learning Algorithms (MRA) are proposed and compared in this paper to predict load demand variability (see, Fig. 3.6). The forecasting models are trained and validated using real data from Nnamdi Azikiwe International Airport's weather station for solar radiation (kW/m<sup>2</sup>), temperature (°C), and wind speed (m/s) ([climate.onebuilding.org](http://climate.onebuilding.org)). Figure 3. gives the flowchart of the proposed predictive models. The main variables related to the goal variable can be determined using a variety of methods. The input-output relationship between the main variables and the target variable, as provided by equation, is used to construct two models in this paper.

$$\text{Load demand (kW)} = \begin{cases} M1 = \Phi(\text{Temperature} + \text{wind}) \\ M2 = \Phi(\text{Temperature} + \text{wind} + \text{solar radiation}) \end{cases} \quad (4)$$

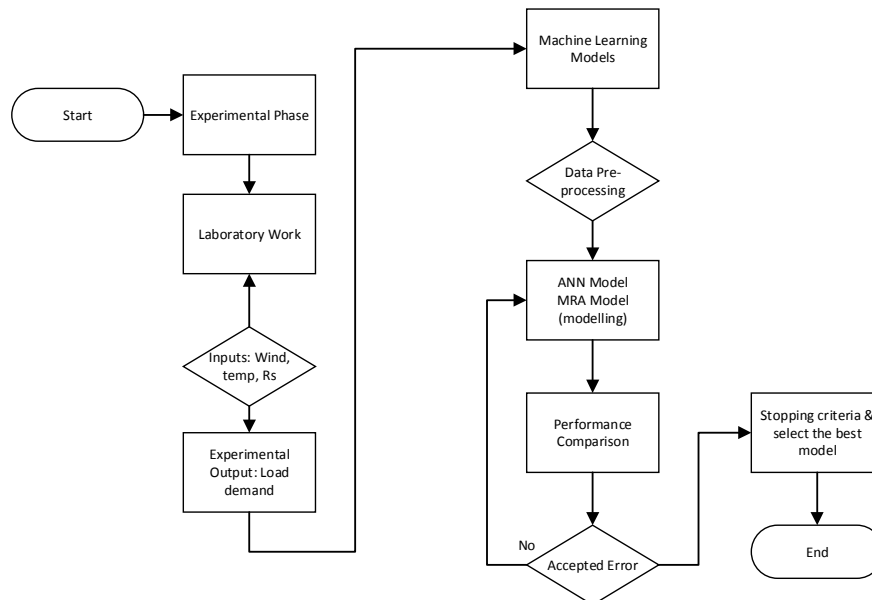


Figure 4: The flowchart of the proposed predictive models

### Evaluation Criteria of the Models

Several performance assessment metrics are used to evaluate the ANN and MRA models, including the correlation coefficient (R), coefficient of determination (R<sup>2</sup>), mean square error (MSE), and root mean square error (RMSE). The R<sup>2</sup> value in training and validation indicates the difference between observed and computed values; for the best network, the R<sup>2</sup> value should be high. The stronger the prediction, the higher the R<sup>2</sup>, which ranges from 0 to 1, with higher values suggesting better agreement. The R is an important factor to consider when determining the robustness of the relationship between expected and simulated data points. The root mean square error (RMSE) is a statistical parameter that is often used to compare the forecasting errors of several models. Better predictions are typically indicated by a lower RMSE value.

To achieve high accuracy predictions, the process of selecting the best predictive model is critical. As a result, four statistical parameters were used to evaluate the efficiency of each predictive method in this analysis. These quantitative parameters are:

$$R^2 = 1 - \frac{\sum_{j=1}^N [(O)_{obs,j} - (O)_{com,j}]^2}{\sum_{j=1}^N [(O)_{obs,j} - \overline{(O)_{obs,j}}]^2} \quad (5)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (O_{obs_i} - O_{com_i})^2}{n}} \quad (6)$$

$$R = \frac{\sum_{i=1}^N (O_{obs} - \overline{O_{obs}})(O_{com} - \overline{O_{com}})}{\sqrt{\sum_{i=1}^N (O_{obs} - \overline{O_{obs}})^2 \sum_{i=1}^N (O_{com} - \overline{O_{com}})^2}} \quad (7)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (O_{com,i} - O_{pre,i})^2 \quad (8)$$

Where  $n$ ,  $O_{obs_i}$ ,  $\overline{O_{obs}}$  and  $O_{com_i}$  are data number, observed data, averaged value of the observed data and computed values, respectively.

### RESULTS AND DISCUSSION

Short-term load forecasting has been achieved for a remote area located in Abuja, Nigeria. The load demand forecasting was done using the ANN and MLR models. The model input combinations are derived in this study utilizing the Spearman-Pearson correlation, which depicts the link between variables (solar radiation, temperature, wind speed, and surveyed/historic load demand). The inverse or direct relationship between the variables has no bearing on the strength of the correlation. Figure 4.1 shows the correlation analysis between the variables. From this figure, it can be seen that the variables contribution to load demand are 51%, 42% and 61% by wind speed, solar radiation and temperature respectively.

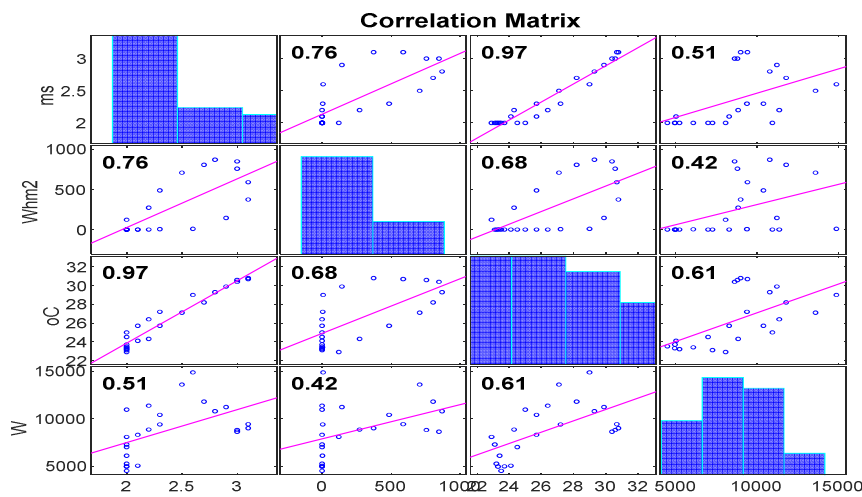


Figure 4. Correlation Analysis between Variables

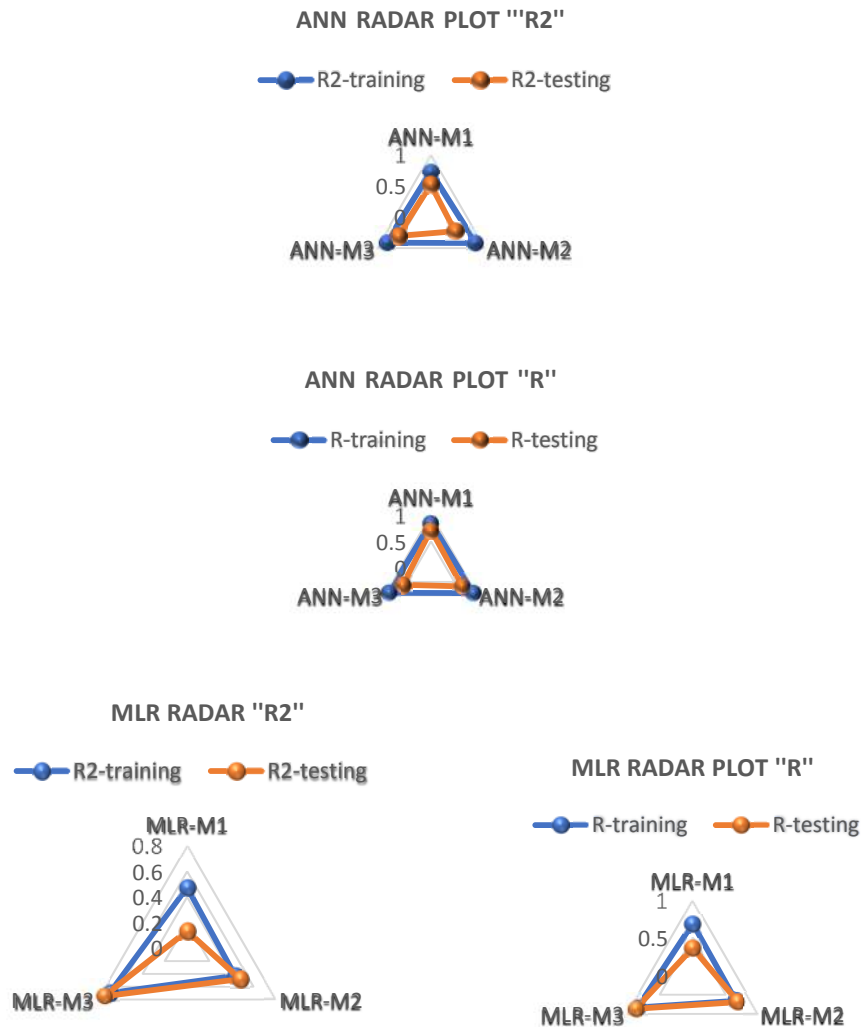


$R^2$ , MSE, R, and RMSE are used to assess the models' prediction accuracy. MATLAB software (R2020b) is used to implement the ANN and MLR models, while Microsoft Excel is used to implement the MLR model (version 2016). To avoid overfitting caused by various causes, determining adequate hidden nodes is a critical part of any ANN modelling. There is no specific criterion for identifying the proper number of hidden neurons, as stated in various scientific and technical studies, hence trial and error methods are used. The **Lavenberg-Marquardt** algorithm is used in training the ANN model, due to its excellent performance in relevant studies. It is found to improve convergence speed and training effectiveness by resolving non-linear least squares problems. In order to find the appropriate structure for ANN modelling, many types of membership functions and iterations are tested

using trial and error. Table 4.1 shows the performance outcomes of the two models.

Table 1 shows that all of the nonlinear ANN models achieved the requisite prediction accuracy, however the linear model MLR did not. This can be justified by looking at the performance evaluation criteria's values ( $R^2$ , RMSE, R and MSE). Higher values of  $R^2$  and R or lower values of RMSE and MSE indicate a higher accuracy of prediction. Furthermore, when compared to M1, the results showed that M2 has a high capability. This revealed that temperature, wind speed, and sun radiation could be used to accurately anticipate load. Figure 4.2 depicts the radar plots in terms of R and  $R^2$  values for both the calibration and verification phases. The values of R and  $R^2$  for both calibration and verification exceed 0.5 for linear MLR models and 0.6 for nonlinear ANN models, as seen in the radar graphs.

	Calibration				Verification			
	$R^2$	R	MSE	RMSE	$R^2$	R	MSE	RMSE
ANN-M1	0.73093	0.85494	0.01667	0.12911	0.52431	0.72409	0.03914	0.19785
ANN-M2	0.83831	0.91559	0.01001	0.10009	0.45033	0.67107	0.04523	0.21268
ANN-M3	0.82048	0.90580	0.01112	0.10546	0.60414	0.60414	0.60414	0.60414
MLR-M1	0.47418	0.68861	0.03258	0.18050	0.13447	0.36671	0.03476	0.18645
MLR-M2	0.43315	0.65814	0.03512	0.18741	0.48151	0.69390	0.03565	0.18882
MLR-M3	0.70074	0.83710	0.01854	0.13617	0.75074	0.87028	0.04059	0.20148

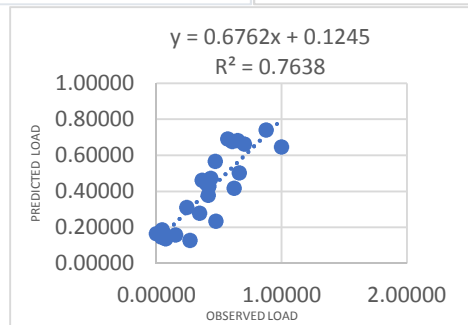
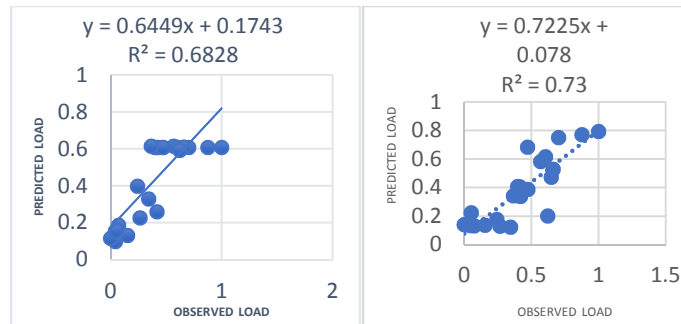


**Figure 5:** Calibration and verification of ANN and MLR using radar plots

Additional study of the simulation results reveals that these nonlinear models' promising ability can be related to their great ability to anticipate complicated dynamic systems. Figure 5 shows the goodness of fit ( $R^2$ ) results as well as the agreement between observed and anticipated values. The figure vividly indicates the high agreements between the observed and predicted

values associated with M2. Even if MLR models are the most recently developed models for load prediction, linear models must still be introduced in order to comprehend the deterministic pattern of the data. Several studies have justified the application of non-linear and linear models to analyse data from chaotic processes and the results of both models are compared.

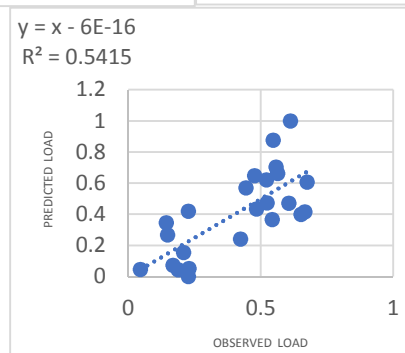
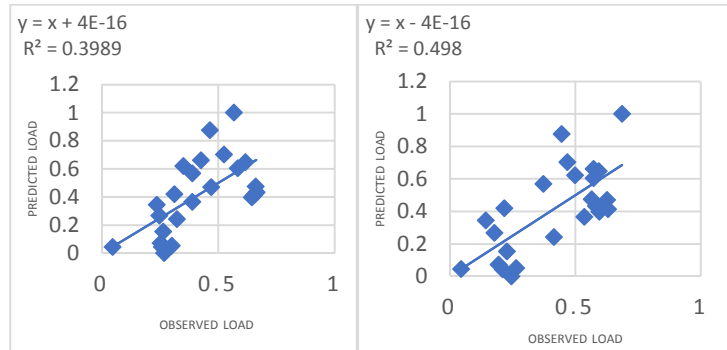




ANN- M1

ANN-M2

ANN-M3



MLR-M1

MLR-M2

MLR-M3

Figure 6 shows that the strongest agreements (highest  $R^2$ ) between observed and predicted values are found in ANN- (M1 and M3)

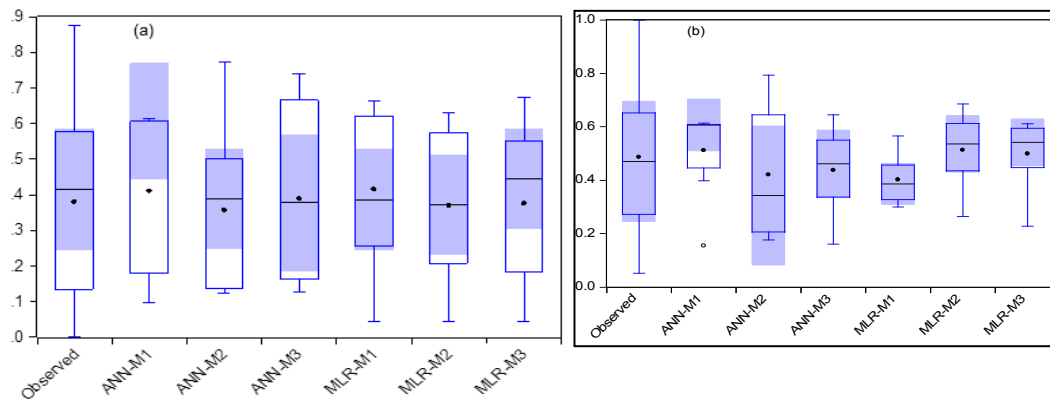
models. In the verification phase, the ANN model surpassed MLR by 16 % in terms of performance accuracy. The linear aspect of the MLR model is

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clearly one of its flaws. Further study of the data demonstrates that the load demand might be anticipated with reasonable accuracy using ANN-M1.

Additional exploratory analysis is conducted using boxplots for the models, which is a graphical representation that shows a statistical summary for a data set. The box and whisker plots are described as a powerful numerical tool for data presentation that can be summarized. The closeness between the predicted and observed load is demonstrated using the boxplots. By looking at the whiskers and quartiles, it can be deduced that the level of the overall spread values between the predicted and observed load precisely resembles that of ANN-M3. Note that the data used for this purpose is not normalized. The ANN-M3 was found to be the best among all the

models by considering the level of the spread values between the predicted and observed load. In the modelling process, the model tries to visualize the data at the training and testing phase, different behaviour exists, and transfer property to the AI model. Likewise, for the data-intelligent algorithm, an over-fitted model is obtained when the verification accuracy is higher than the calibration accuracy, which leads to an improvement model by decreasing the bias and variance. As can be seen in figure 6 (a) and (b), promising results were reported, where the boxplot model provides clear information on how the values in the data are evenly distributed, which can assist in comparing the distribution between large datasets. Thus, the variation is similar to the data spread but different to the quantitative accuracy of the models.



**Figure 6:** Box plot between the predicted and observed load for (a) Calibration and (b) Verification phases

## CONCLUSION

This work proposes an approach for applying machine learning models to optimize the design of an energy system while also forecasting load demand. The neural predictor ANN-M3 is used to feed real data for solar radiation, temperature, wind speed, and expected load demand into mathematical models for each component of the energy system. The PSO method is used to determine the ideal sizing of the energy system, which is then simulated for three different generation systems (PV, temperature, and wind systems). The results revealed that the temperature in the system is the most cost-effective candidate for achieving the load demand

needs. ANN, a well-known AI-based model, and MLR, a linear model, are both used to anticipate load demand fluctuation. As a result, a comparison analysis was conducted to determine the predictive accuracy of these models. The investigation demonstrated that machine learning nonlinear based models are accurate in predicting load demand with low error. Explicitly, the verification phase findings revealed that the ANN model outperformed MLR by 16 %.

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