Characterization Of Daily Peak Load In Uyo Using Artificial Neural Networks (ANN) Model

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Abstract— **Characterization of daily peak load in Uyo using Artificial Neural Networks (ANN) model is presented. The data items employed in the study included the daily temperature (with mean of 28.2979 Degree Centigrade), daily rainfall (with mean of 10.8423 mm), daily wind speed (mean of 5.4735 km/h), population (with mean of 429,533.8007), gross domestic product (with mean of 2,354.8274 USD) and the daily Electric Peak load demand (with mean of 35.8029 MW). The base case ANN model was implemented without the SHAP tool while the SHAP tool was later applied which helped to interpret the ANN model and thereby determine the contribution of each of the input variables to the ANN model prediction performance. The results in the ANN model baseline case had MSE value of 0.456185, RMSE value of 0.675415, MAE value of 0.5436 and R^2 value of 0.935688. Again, the results showed that the feature importance using SHAP value improved the ANN model performance with 41.01% improvement in MSE, 23.19% improvement in RMSE, 26.28% improvement in MAE and 2.82% improvement in R^2. In addition, that the peak load increased from 50.4 MW in 2024 to 56.5 MW in 2028.**

Keywords— Daily Peak Load, Machine Learning Model, Artificial Neural Networks (ANN), Load Forecasting, Power System Planning

1. Introduction

Over the years, there has been the problem of epileptic power supply in various cities across Nigeria [1,2,3]. This is due to the persistent power shortage from the national grid in Nigeria [4,5]. This has necessitated the need for load shedding. By proper grouping of the consumers into discrete clusters the power distribution companies can manage the rationing of the available power from the national grid through some form of load shedding approach [6,7,8]. Such load shading system requires appropriate knowledge of the load demand pattern of each user cluster [9,10,11].

On the other hand, there has been rapid development in Uyo city in recent years [12,13]. This has necessitated the expansion of the power system within Uyo metropolis. Such power system expansion project requires the projection of expected future energy demand in the city [14,15]. As such, energy forecasting model is required to address such issue [16,17]. Accordingly, in this work, characterization of daily peak load in Uyo using Artificial Neural Networks (ANN) model is presented [18,19,20]. The ANN model will be used to determine the energy demand of Uyo city in the years ahead thereby enabling the power system planning to accommodate expected energy demand patterns in the years ahead. Such model are developed based on some carefully selected weather and macro-economic parameters as well a previous years load demand dataset. The ANN model developed is also optimized using SHAP values for optimal feature selection during the ANN model training and validation [21,22].

2. Methodology

2.1 The ANN) Model Architecture , Hyperparameters and Evaluation Metrics

The structure of Artificial Neural Networks (ANN) model used in this study consisted of one input layer, two hidden layers and one output layer. Each layer processed the data as inputs and passed it out as output to the succeeding layer. The type of ANN used in this study was multiple perceptron. After choosing the type of ANN structure, the hyperparameters were tuned to minimise the loss function using Bayesian optimization technique. The perceptron took inputs, adjusted the weights and produced output using the activation function. The internal structure of the ANN model is shown in Figure 1 and summarized in

Table 1, while the Hyperparameters tuning values are shown in Table 2.

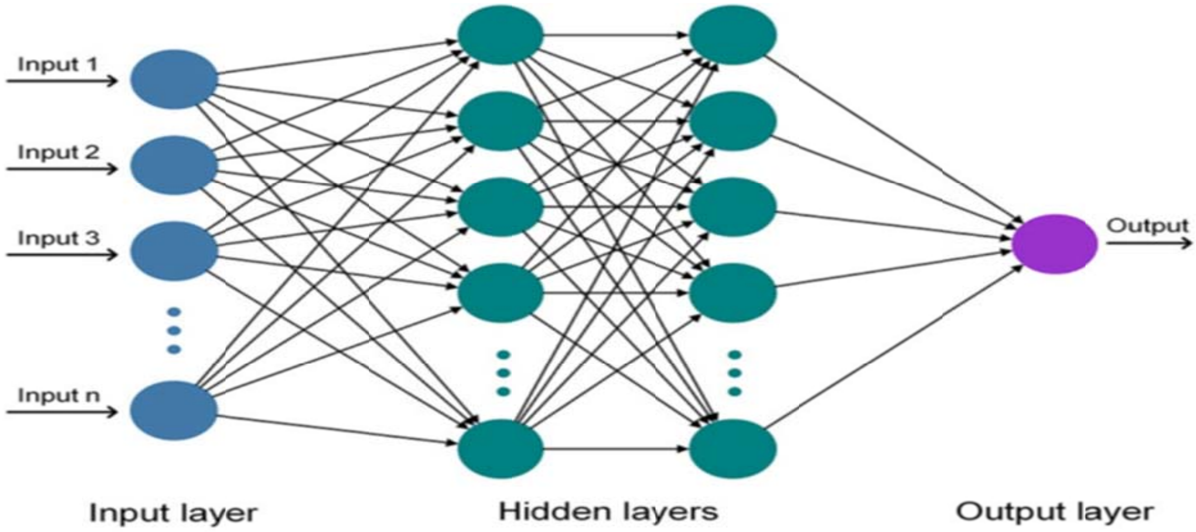


Figure 1: The ANN Architecture.

Table 1: Summary of ANN model parameters settings

Layer(type)	Output shape	Param
Flatten (Flatten)	(None, 36)	0
dense (Dense)	(None, 128)	4736
Dense_1 (Dense)	(None, 64)	8256
Dense_2 (Dense)		
Total params: 13,057		
Trainable params: 13,057		
Non-trainable params: 0		

Table 2: Hyperparameters of ANN Model Tuning

Parameters	Values
Number of Layers	4
Number of Neurons	36
Activation Function	ReLU
Learning Rate	0.001
Batch Size	1
Number of Epochs	200

Given that the model has n data records, $x_{Act(i)}$ as the ith actual data record, $x_{Pred(i)}$ as the ith predicted data record and $x_{MeanAct}$ as the mean of the actual dataset , then the model is evaluated based on MSE (Mean Square Error), RMSE (Root Mean Square Error, MAE (Mean Absolute Error) and R^2 (R-Squared) where;

$$\text{MSE}=\frac{\sum_{i=1}^{i=n}\left(x_{Act(i)}-x_{Pred(i)}\right)^2}{n} \quad (1)$$

$$\text{MAE}=\frac{\sum_{i=1}^{i=n}\left|x_{Pred(i)}-x_{Act(i)}\right|}{n} \quad (2)$$

$$\text{RMSE}=\sqrt[2]{\left(\frac{\sum_{i=1}^{i=n}\left(x_{Pred(i)}-x_{Act(i)}\right)^2}{n}\right)} \quad (3)$$

$$R^2 = \frac{\sum_{i=1}^{i=n}\left(x_{Act(i)} - x_{Pred(i)}\right)^2}{\sum_{i=1}^{i=n}\left(x_{Act(i)} - x_{MeanAct}\right)^2} \quad (4)$$

Where,

$$x_{MeanAct} = \frac{\sum_{i=1}^{i=n}\left(x_{Act(i)}\right)}{n} \quad (5)$$

Further to the ANN model training and validation, the feature importance for the ANN model was assessed using XAI tools (SHAP) which helped to interpret the ANN model and thereby determine the contribution of each of the input variables to the ANN model prediction performance. The base case ANN model was implemented without the SHAP tool while the SHAP tool was later applied and the performance of the various versions of the ANN models were compared.

2.2 The Case Study Dataset

The data items employed in the study includes the daily temperature, daily rainfall, daily wind speed, population, gross domestic product and the daily Electric Peak load demand. The 24 years daily mean temperature dataset (shown in Figure 2) has 5,113 data records with mean of 28.2979 Degree Centigrade. The daily rainfall data with mean of 10.8423 mm is presented in Figure 3. The daily wind speed data with mean of 5.4735 km/h is presented in Figure 4. The daily population data with mean of 429,533.8007 is presented in Figure 5. The GDP/Capita data with mean of 2,354.8274 USD is presented in Figure 6. Finally, the daily peak load demand data with mean of 35.8029 MW is presented in Figure 7.

The data items were preprocessed and with 70% training set, 15% validation set and 15 % testing set, the data was employed in the ANN model training and evaluation. The daily peak load was the target variable predicted while the data items were used as input for training the ANN model based on the ANN model parameters settings in Table 1 and the ANN model hyperparameters tuning presented in Table 2.

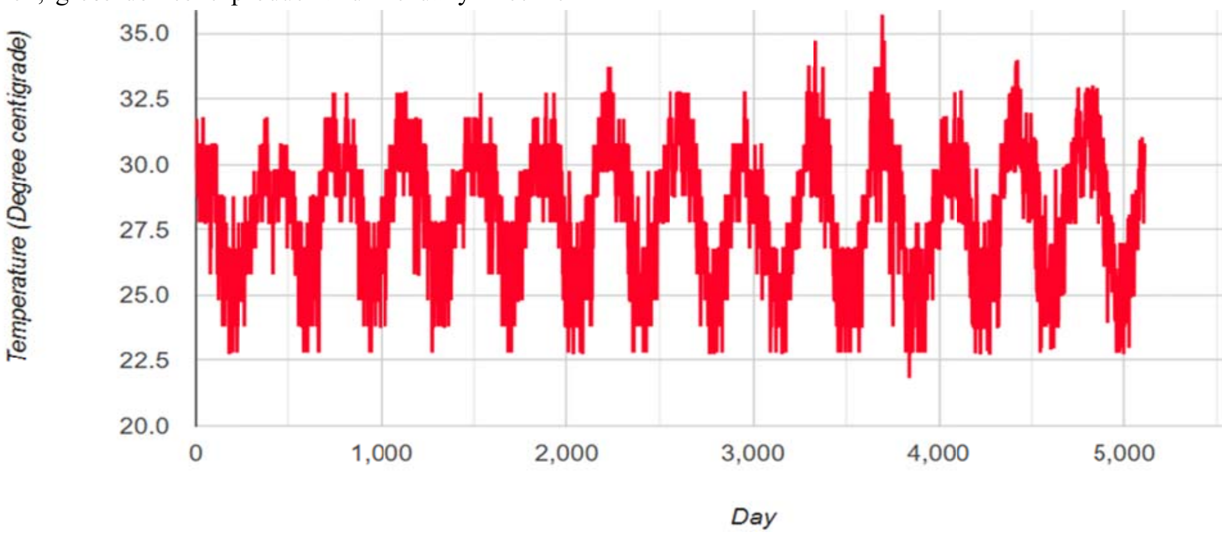


Figure 2 The line chart of the 24 years daily mean temperature dataset having 5,113 data records with mean of 28.2979 Degree Centigrade

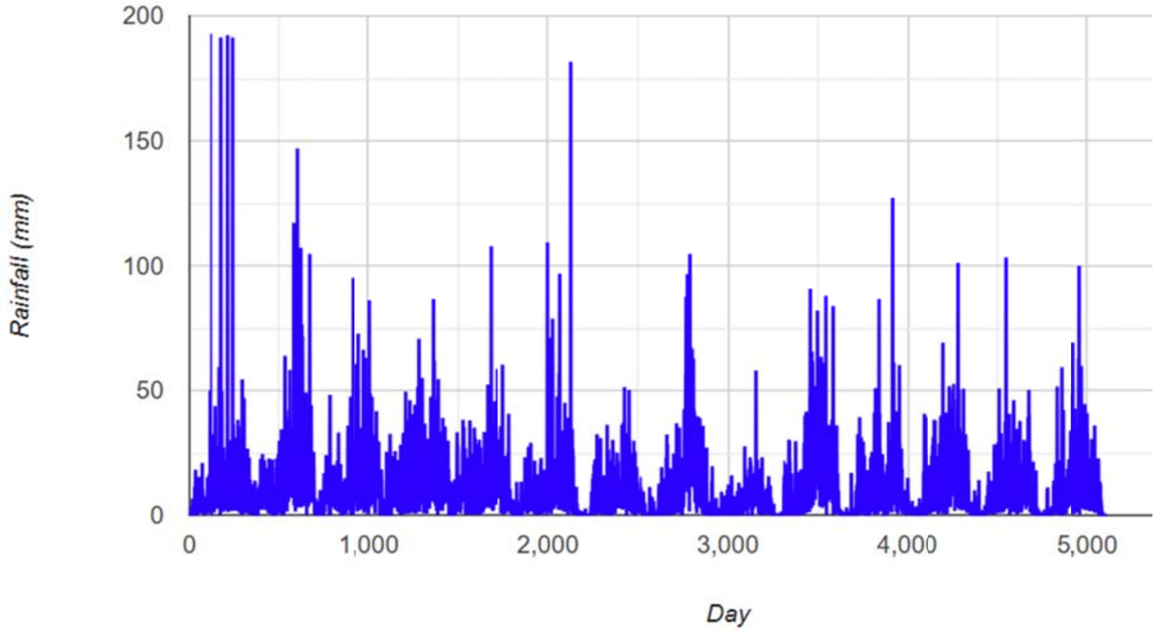


Figure 3 The line chart of the 24 years daily mean rainfall dataset having 5,113 data records with mean of 10.8423 mm

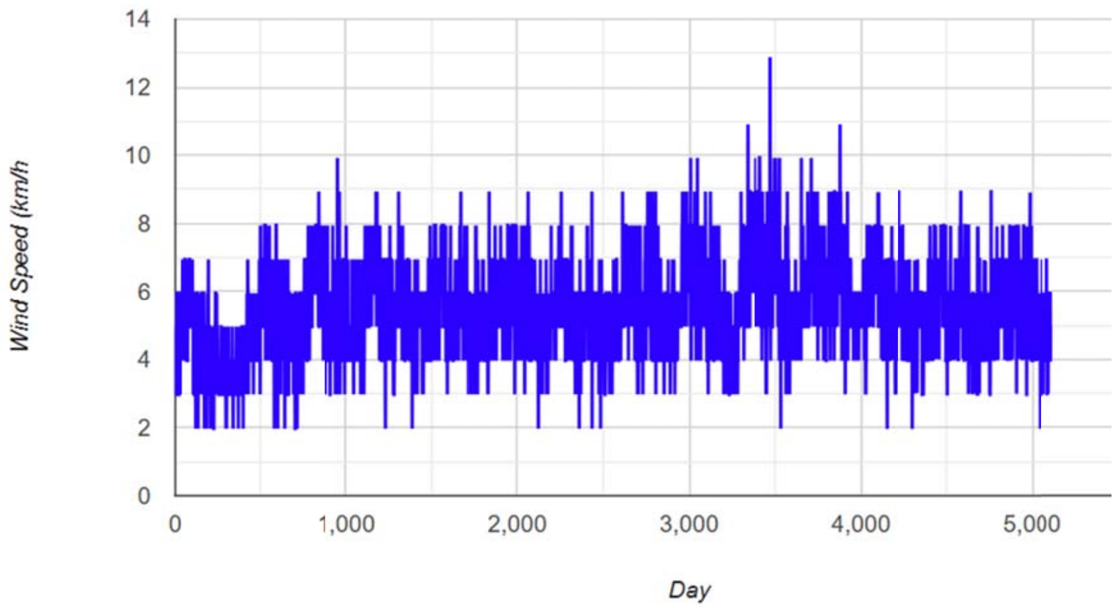


Figure 4 The line chart of the 24 years daily mean wind speed dataset having 5,113 data records with mean of 5.4735 km/h

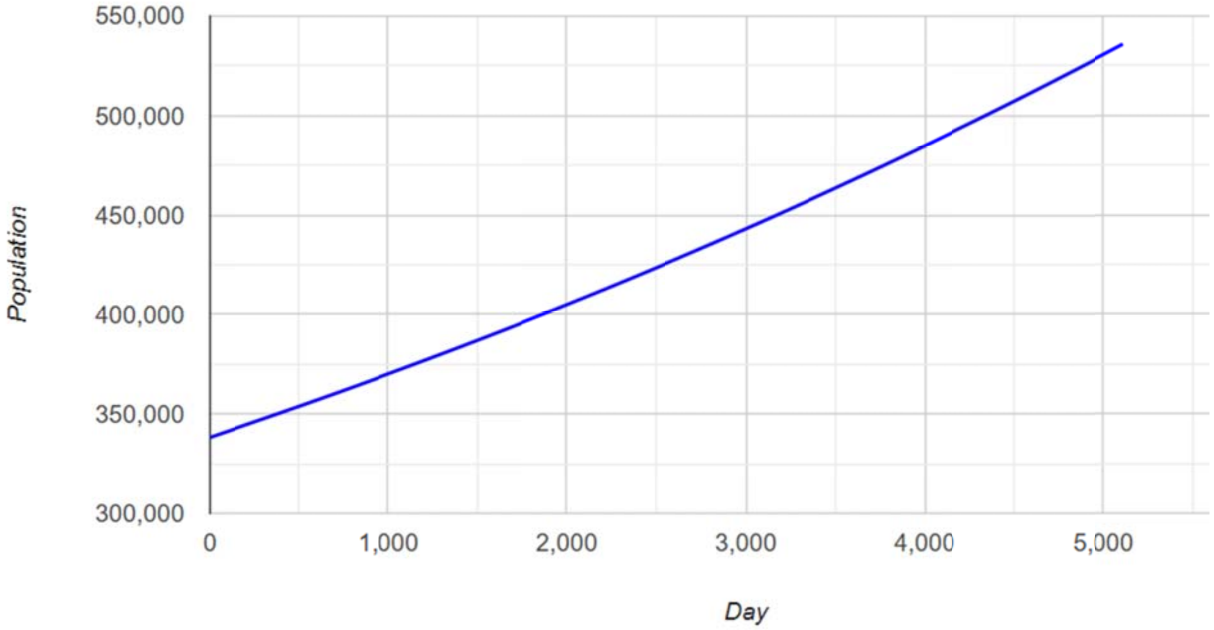


Figure 5 The line chart of the 24 years daily population dataset having 5,113 data records with mean of 429,533.8007

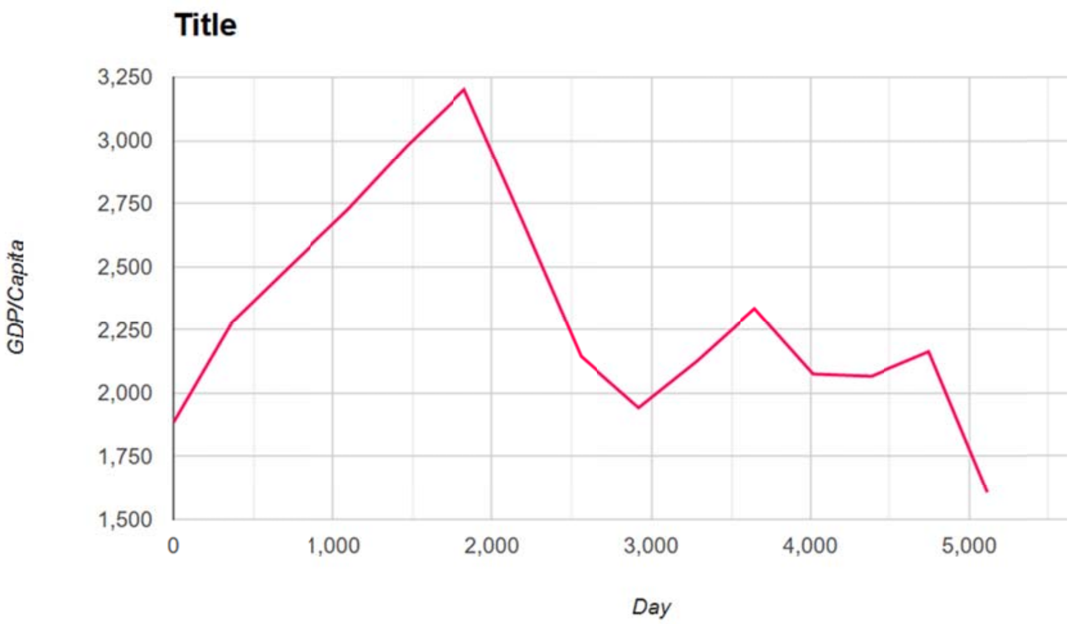


Figure 6 The line chart of the 24 years GDP/Capita dataset having 5,113 data records with mean of 2,354.8274 USD

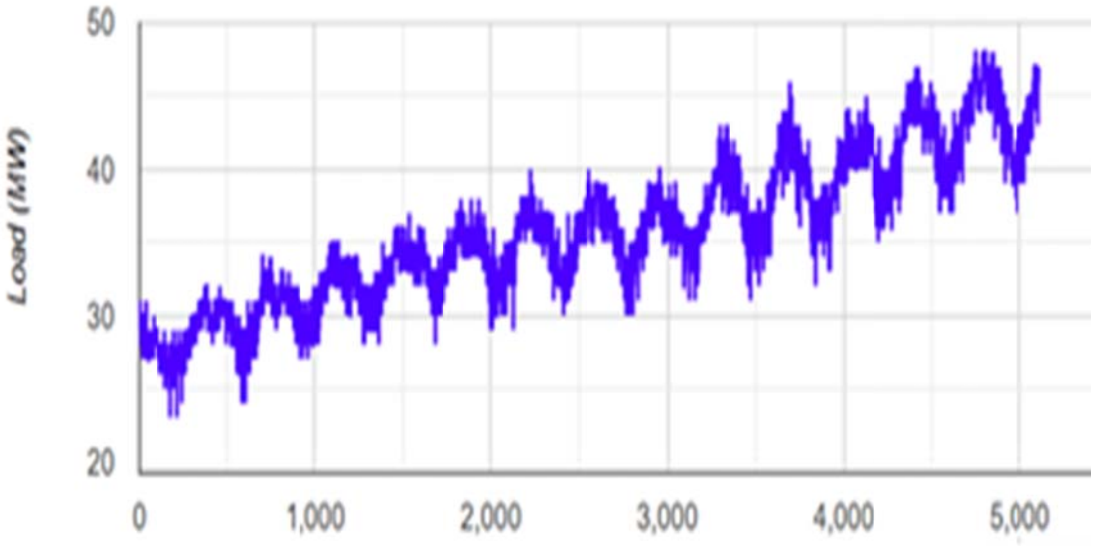
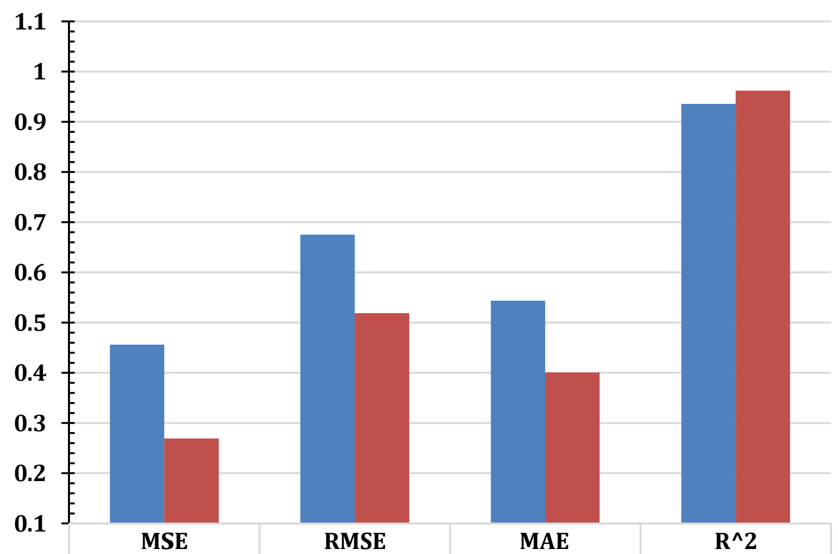


Figure 7 The line chart of the 24 years daily peak load demand dataset having 5,113 data records with mean of 35.8029 MW

3. Results and discussion

The results of the performance of the ANN model for the baseline case and ANN model after feature importance using SHAP value are shown in Figure 8, Figure 9 Figure 10. Figure 9 shows the plot for the performance of the ANN model after introducing feature importance using SHAP value. According to the results in Figure 8, the ANN model baseline case has MSE value of 0.456185, RMSE value of 0.675415, MAE value of 0.5436 and R^2 value of 0.935688. According to the results in Figure 10, the feature importance using SHAP value improved the ANN model performance with 41.01% improvement in MSE, 23.19% improvement in RMSE, 26.28% improvement in MAE and 2.82% improvement in R^2.

The results of the peak load demand using the baseline ANN model and using the ANN after it has undergone the feature selection with the SHAP values are shown in Figure 11. The load forecasting result using the ANN model after feature selection is shown in Figure 12 and Figure 13. The results show that the peak load increased from 50.4 MW in 2024 to 56.5 MW in 2028.



	MSE	RMSE	MAE	R^2
ANN model for the baseline case	0.456185	0.675415	0.5436	0.935688
ANN model after feature importance using SHAP value	0.269106	0.518754	0.400731	0.962062

Figure 8 The bar chart for the performance of the ANN model for the baseline case and ANN model after feature importance using SHAP value

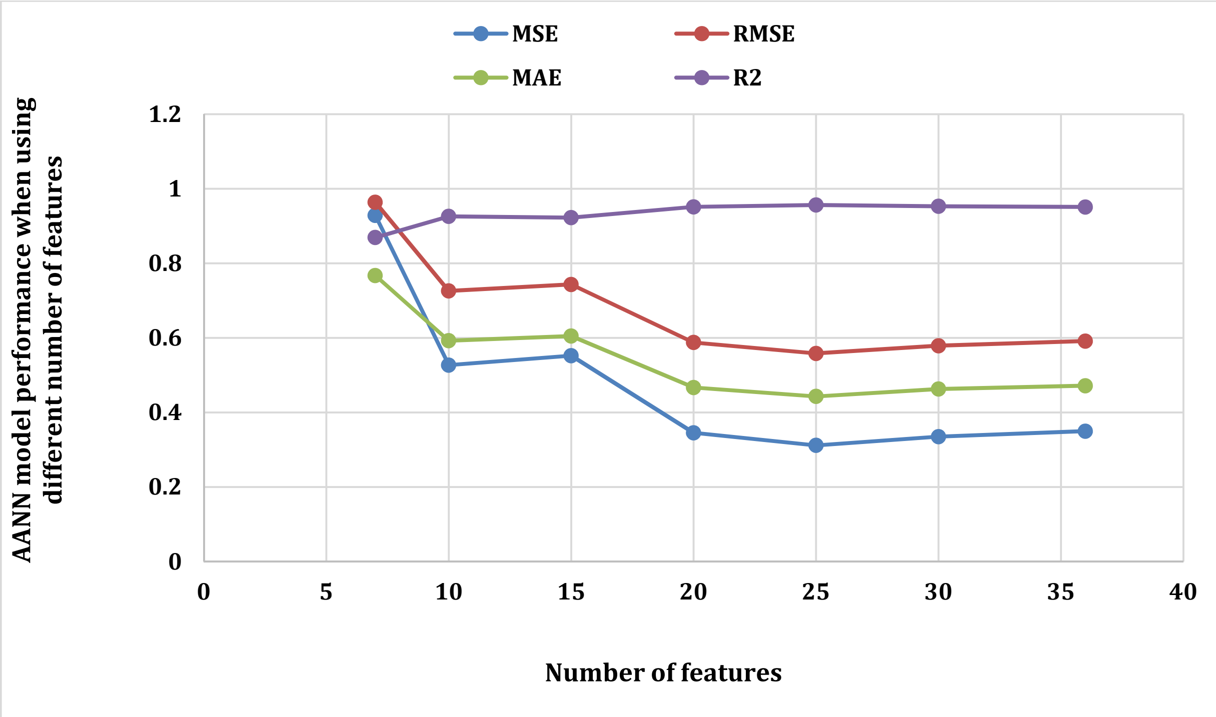


Figure 9 The plot for the performance of the ANN model after introducing feature importance using SHAP value

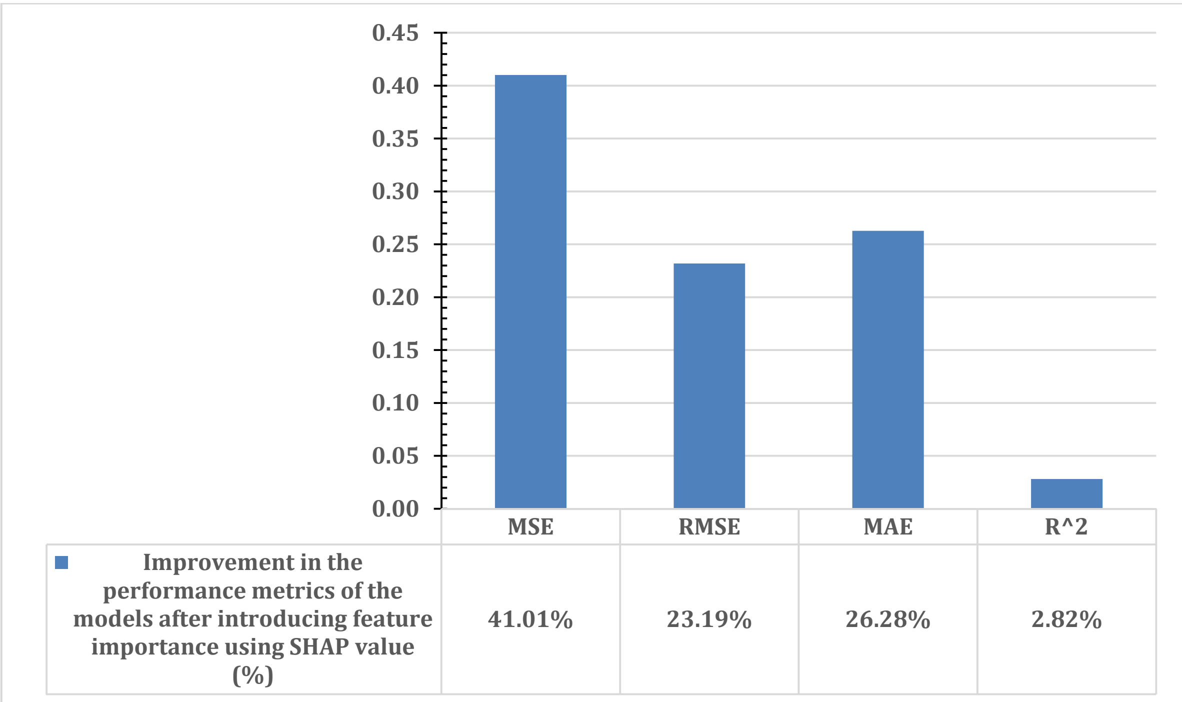
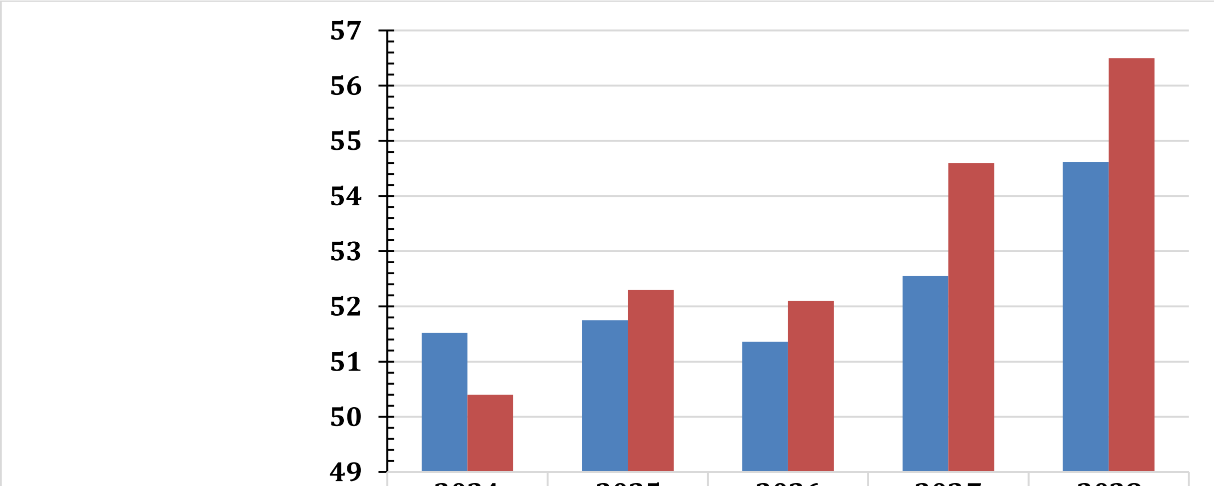


Figure 10 Improvement in the performance metrics of the models after introducing feature importance using SHAP value



	2024	2025	2026	2027	2028
ANN (the baseline case)	51.52	51.75	51.36	52.55	54.62
ANN (after using SHAP models)	50.4	52.3	52.1	54.6	56.5

Figure 11 The peak load demand using the baseline ANN model and using the ANN after it has undergone the feature selection with the SHAP values.

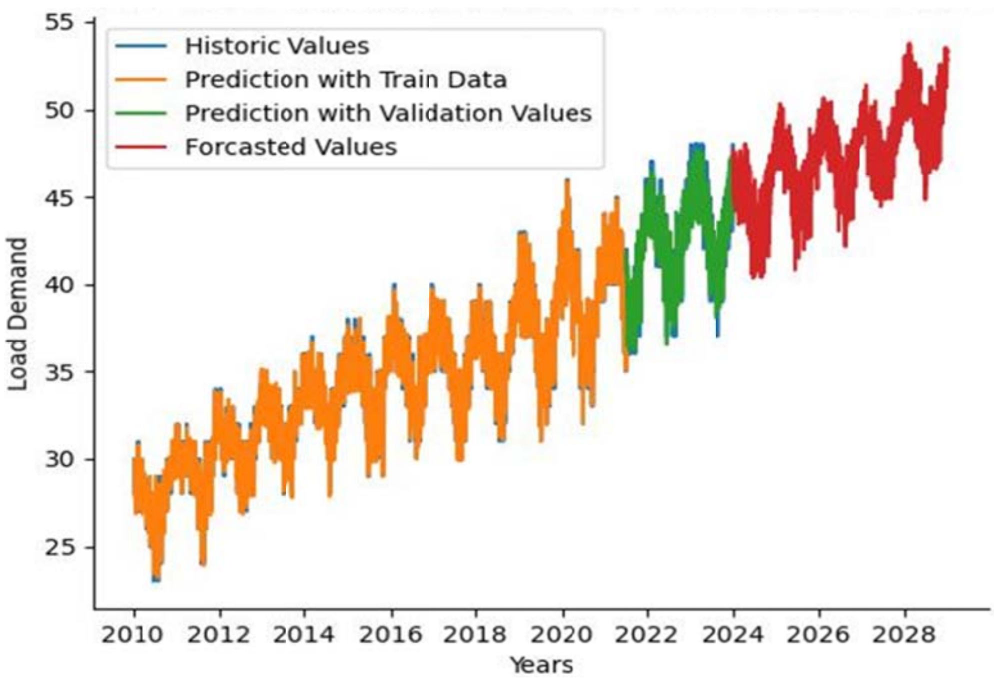


Figure 12: Load Forecasting Result using ANN after Feature Selection.

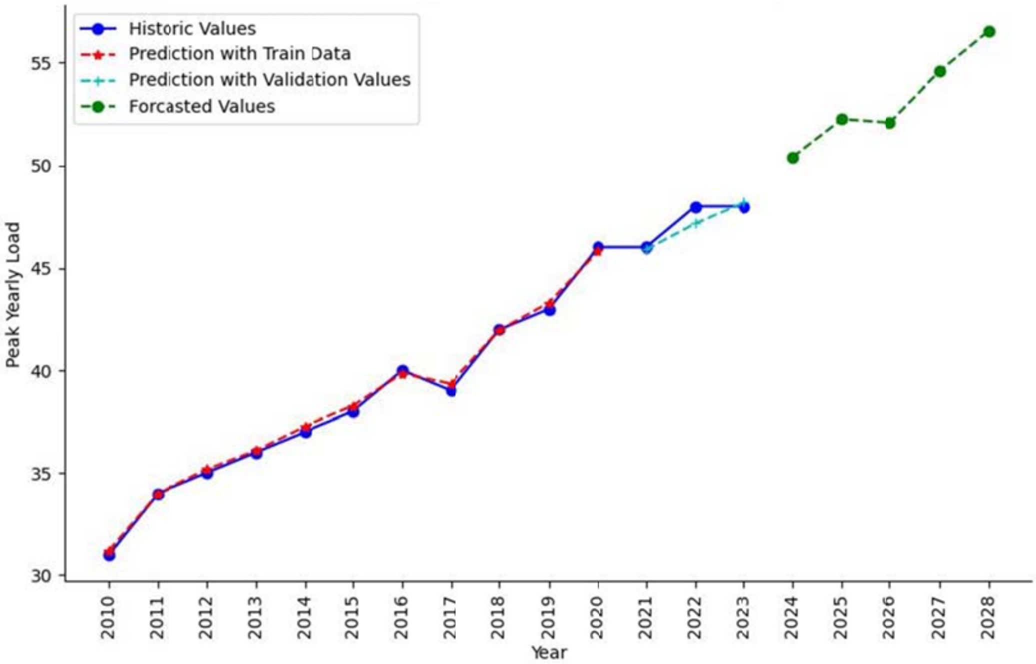


Figure 13: Plot of Yearly Peak Load Forecast with ANN after Feature Selection.

4. Conclusion

The Artificial Neural Networks (ANN) model is use for characterizing the annual peak load demand for a case study metropolis. Some weather parameters and macro-economic parameters were used as the explanatory variables while the peak load is the response variable. The ANN model was further modelled and evaluated with different number of features to examine the impact of features on the ANN model performance. The results showed that using different feature selection using the SHAP values had significant improvement on the performance of the ANN model. Eventually, the ANN model with the best performance was used to forecast the peakload demand for some years ahead.

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