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Long-Term Load Forecasting In Uyo Metropolis Using Long Short-Term Memory (LSTM) Model

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Abstract **In this study, Long-term load forecasting in Uyo metropolis using Long Short-Term Memory (LSTM) model is presented. The parameters used for the model training are 24 years' daily time series data on temperature, rainfall and wind speed, population, gross domestic product and the daily Electric Peak load demand. The dataset was normalized and split into 70 % training set, 15 % validation set and 15 % testing set. SHAP technique was applied on the LSTM model to determine the influence of each input variables on the forecasted load demand results. The results show that in the baseline case, the LSTM model had MSE of 0.12726, RMSE of 0.356735, MAE of 0.292638 and R^2 of 0.982059. Also, the results show that the daily peak load increased from 51.5 MW in 2024 to in 61.2 MW in 2028. In all, the feature selection using the SHAP technique did not yield any significant improvement in the prediction performance of the LSTM model.**

Keywords— Long-term Load Forecasting, Long Short-Term Memory (LSTM), Electric Peak Load Demand, Feature Selection, SHAP Technique

1. Introduction

In the power industry, energy demand forecasting is essential for power system planning [1,2,3]. Power system planning can be for the installation of new equipment or power network [4,5]. The planning can also be for upgrading or expansion of existing power system [6,7]. In another scenario, power system planning can entail electrical load management which may involve load shedding, energy cost management, among other options [8,9]. Each of these power system planning options require adequate knowledge of the prevailing energy consumption pattern and possibly the future energy demand 10,11,12]. Such energy demand pattern can be modelled using analytical or machine learning model.

In order to use the analytical or machine learning model for electric energy demand pattern and then to forecast future energy demand, some time series data values are needed , especially the time series energy demand data along with some weather and economic parameters that correlate well with energy demand of the case study area [13,14,15]. In this work, Long Short-Term Memory (LSTM) algorithm is used to model the electric energy demand in Uyo [16,17,18]. The LSTM model utilized three weather parameters, two economic parameters and time series daily load demand to depict the load demand of Uyo city and then use the model to forecast the energy demand for about ten years ahead. The study is essential for power system planning for the city of Uyo.

2.0 Description of the Long Short-Term Memory (LSTM) Model

The Long Short-Term Memory (LSTM) model architecture is presented in Figure 1. The LSTM architecture involved the memory cell which is controlled by the input gate, the forget gate, and the output gate. The input gate chooses which data is passed to the memory cell [19,20,21]. The forget gate chooses what data to remove from the memory cell while the output gate chooses what part of the information to output. This structure allows LSTM models to retain important data or delete insignificant data as it is passed through the model. In the LSTM architecture shown in Figure 1 X_t represents input time step, h_t represents output, C_t represents cell state, f_t represents forget gate, i_t represents input gate and O_t represents output gate.

The internal working of the forget gate is expressed in Equation 1 where, W_f represents forget gate weight matrix, h_{t-1}, and x_t are chain of present input and the preceding concealed state, b_f represents bias related to forget gate and σ is the sigmoid activation function. The forget gate function as a filter and allows data near one to pass while rejecting information with values near zero. By this action, the forget gate determined which parts of the long-term memory to retained.

$$f_t = \sigma(W_f \cdot [h_{t-1}, X_t] + b_f) \quad (1)$$

The input gate performed the work of a filter which allowed information considered important to proceed pass the filter. Equation 2 describes the working of input gate.

$$i_t = \sigma(W_i \cdot [h_{t-1}, X_t] + b_i) \quad (2)$$

where, W_i represents weight matrix of input gate, h_{t-1}, and xt are chain of present input and the preceding concealed state, b_i represents bias related to input gate, and σ represents the sigmoid activation function.

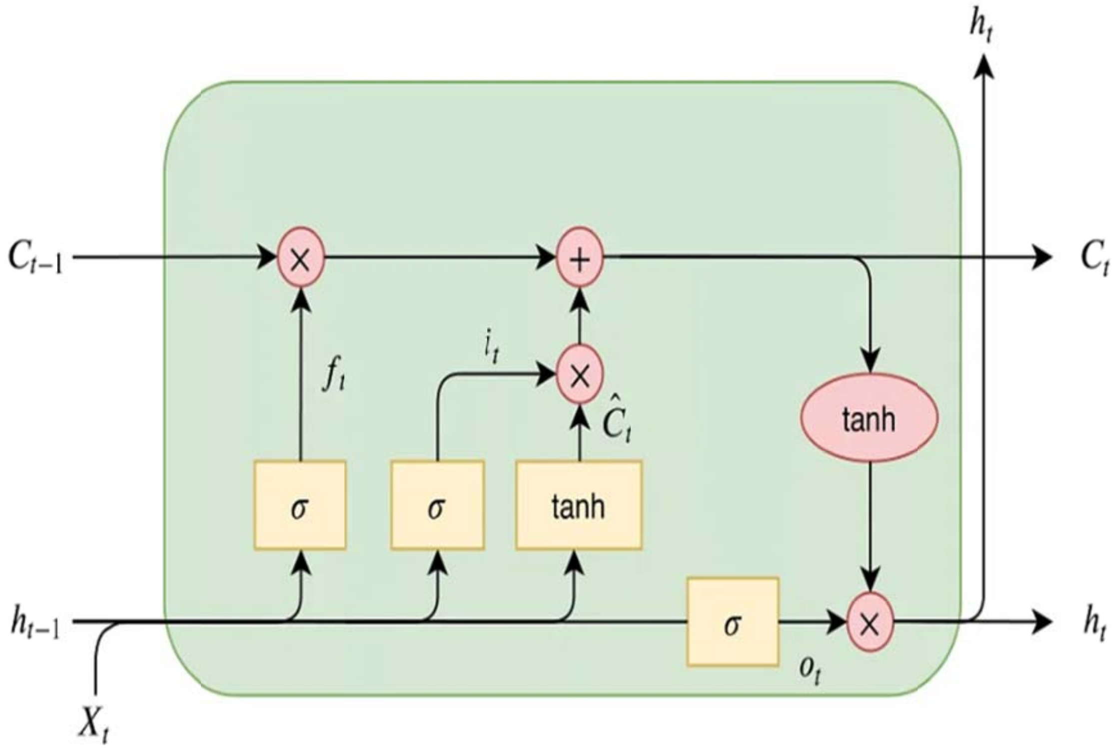

Figure 1: Long Short-Term Memory (LSTM) model **Architecture.**

The last step of LSTM model had the output gate that makes decision for the model. The input to the output gate was made up of updated cell state, preceding concealed state, and current input data. The output gate functions as the last filter and sent out only information that is considered significant. Equation (3) describes the working of output gate as follows:

$$O_t = \sigma(W_o \cdot [h_{t-1}, X_t] + b_o) \quad (3)$$

where, W_o represents weight matrix of output gate, [h_t-1, x_t] are chain of present input and the preceding concealed state, b_o represents bias related to output gate, and σ represents the sigmoid activation function.

3. Methodology

3.1 Data collection

The data used for the study includes the weather parameters (temperature, rainfall and wind speed), macro-economic variables (population and gross domestic product (GDP and finally the daily electric peak load demand. The daily peak load data for 2010 to 2023 was obtained from the repository at the Afaha Ube transmission station in Uyo. The GDP, data for the year 2010 to 2023 was obtained from the Akwa Ibom State Ministry of Economic Development, Uyo. Similarly, population data for Uyo which was estimated at 305,961 by the 2006 national population census, was projected to grow annually at a rate of 3.4% (National Population Commission, Uyo). The using Equation 1 obtained from Akwa Ibom state ministry of economic development, the population data of Uyo for 2010 to 2023 was projected and used as input to the models.

$$P_n = P_0 \times (1 + r)^n \quad (1)$$

where P_n is the projected population figure for the n^{th} year, P_0 is the population census figure of 2006, r is the population growth rate for Uyo, and n is the number of years.

Again, the historical daily maximum temperature, rainfall, and wind speed data for Uyo, were retrieved online at worldweatheronline.com, accessed on June 5, 2024.

3.2 Training and Validation of LSTM Model

Exploratory data analysis was conducted on the case study dataset which provided some descriptive statistical on the various variable used in the study. Afterwards, the data items were normalized using minmax method. The normalized dataset was split into 70 % training set, 15 % validation set and 15 % testing set. The LSTM model parameters settings are presented Table 1 and the optimal hyperparameter tuning values that gave the best performance are shown in Table 2. After the training, the model performance was validated using the validation dataset.

After the training and validation, the model was used to forecast the daily peak load demand. Also, SHAP technique was applied on the **LSTM** model to determine the influence of each input variables on the forecasted load demand results.

Table 1: Summary of LSTM model

Layer(type)	Output shape	Param
Lstm_2(LSTM)	(None, 6, 64)	18176
Lstm_3 (LSTM)	(None, 64)	33024
Dense_1 (Dense)	(None, 1)	65
Total params		51,265
Trainable params		51,265
Non-trainable params		0

Table 2: Hyperparameters of LSTM 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

4. Results and Discussion

4.1 Model-Specific Feature Impacts

The results in Figures 2 and Figures 3 show the impact of each of the variables on the performance of the LSTM model. The input features used are represented by the vertical axis while the impact of the variables is shown on the horizontal axis. Specifically, Figure 3 shows the feature importance based on SHAP values for the LSTM model. The performance of the LSTM model in the base case without the feature selection study using the SHAP value is shown in Figure 4. It shows that in the baseline case, the LSTM model had MSE of 0.12726, RMSE of 0.356735, MAE of 0.292638 and R^2 of 0.982059.

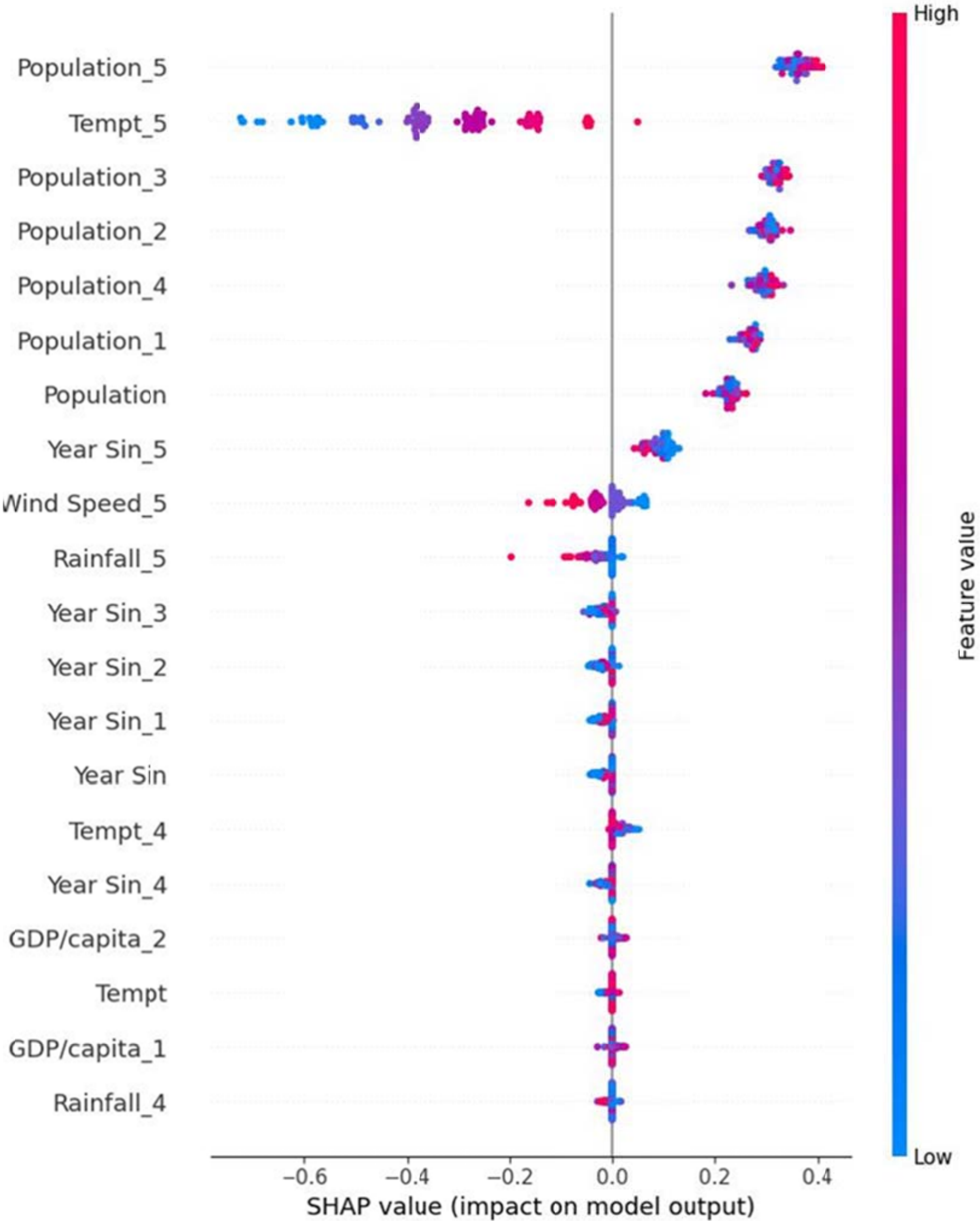

Figure 2: Impact of each Feature on LSTM Model.

Again, the performance of the LSTM model when using different features selected using the SHAP value is shown in Table 3 and Figure 5. The results showed that the LSTM model gave the best performance when the about 22 features are used.

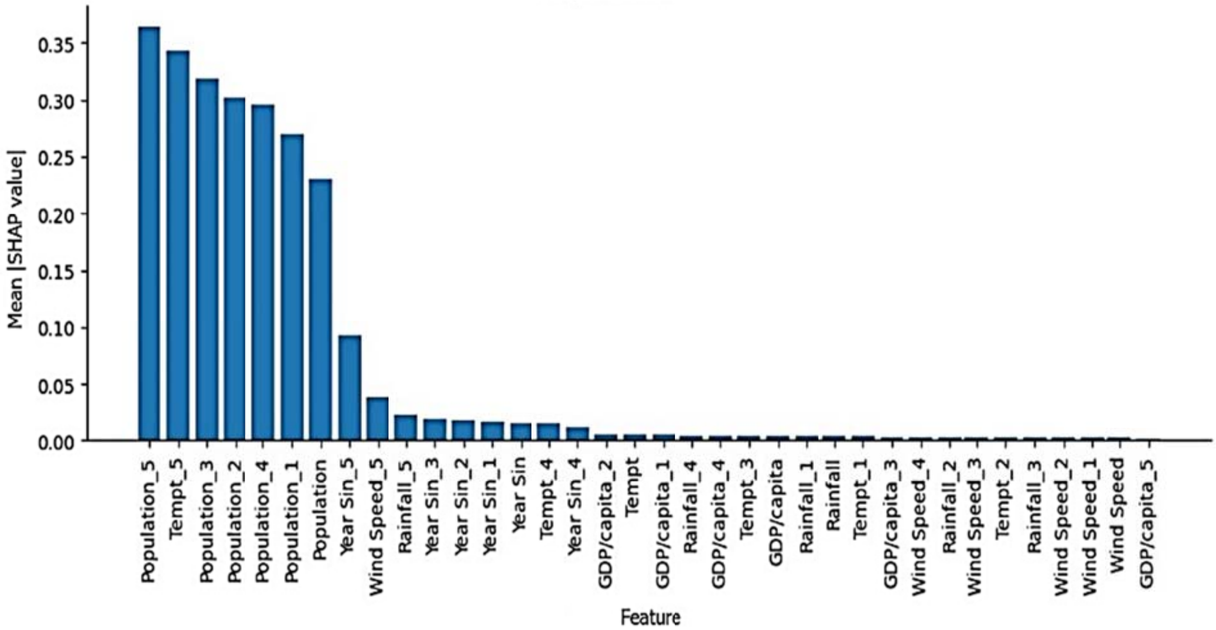

Figure 3 Feature Importance Based on SHAP Values for LSTM

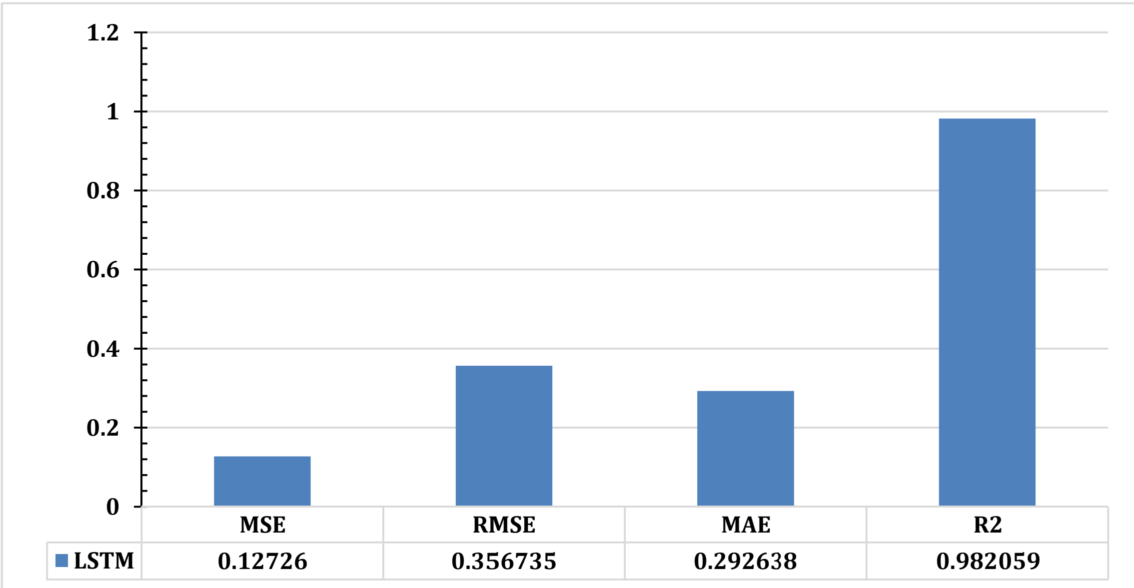

Figure 4 The performance of the LSTM model in the base case without the feature selection study using the SHAP value.

Table 3 The performance of the LSTM model when using different features selected using the SHAP value.

Model	Number of Features	MSE	RMSE	MAE	R2
LSTM	7	0.911096	0.954513	0.810745	0.871556
LSTM	10	0.721045	0.849143	0.740948	0.898349
LSTM	15	0.499107	0.706475	0.596319	0.929637
LSTM	20	0.15917	0.398962	0.324881	0.977561
LSTM	25	0.129132	0.359349	0.290461	0.981795
LSTM	30	0.176426	0.420031	0.335267	0.975128
LSTM	36	0.202525	0.450028	0.356378	0.971449

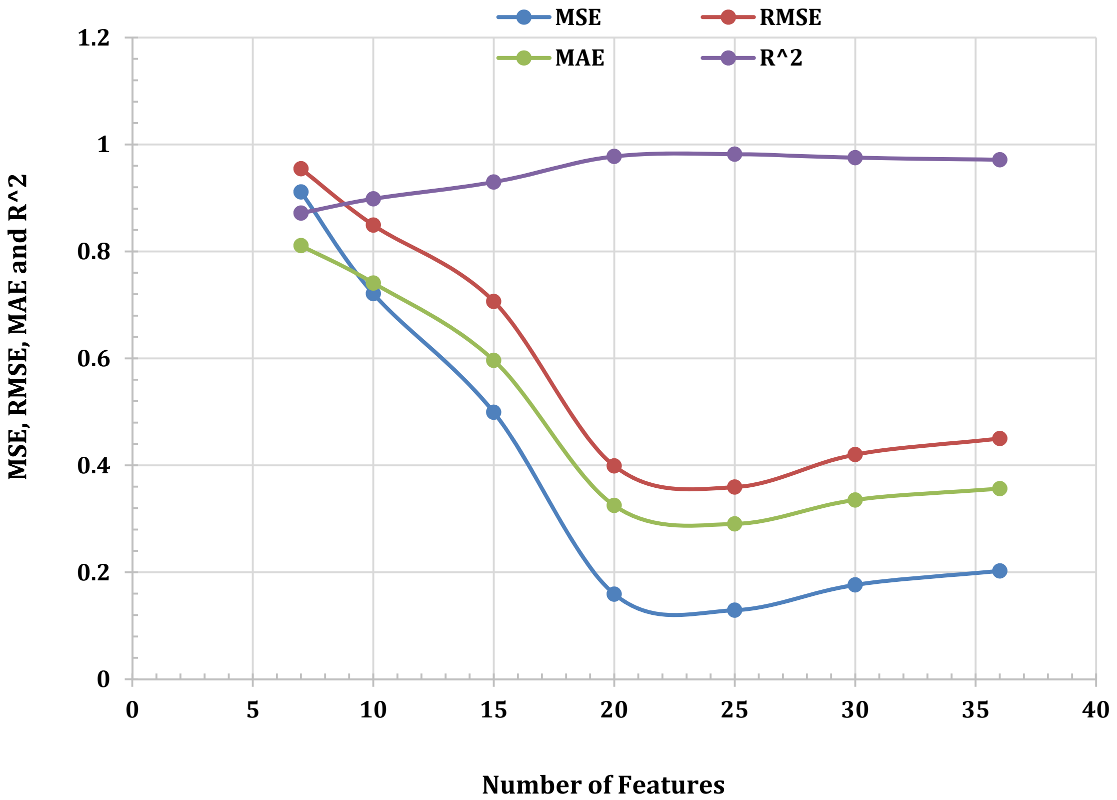

Figure 5 The line chart of the performance of the LSTM model when using different features selected using the SHAP value

4.2 Forecasting future peak load demand

The results in Figure 8 show the annual peak load demand in MW using baseline models and using the LSTM after the feature selection with the SHAP values. Furthermore, the load forecasting result using LSTM after feature selection is shown in Figure 7 for the training and the validation dataset. The plot of yearly peak load forecast with LSTM after feature selection is shown in Figure 8. The results show that the daily peak load increased from 51.5 MW in 2024 to in 61.2 MW in 2028.

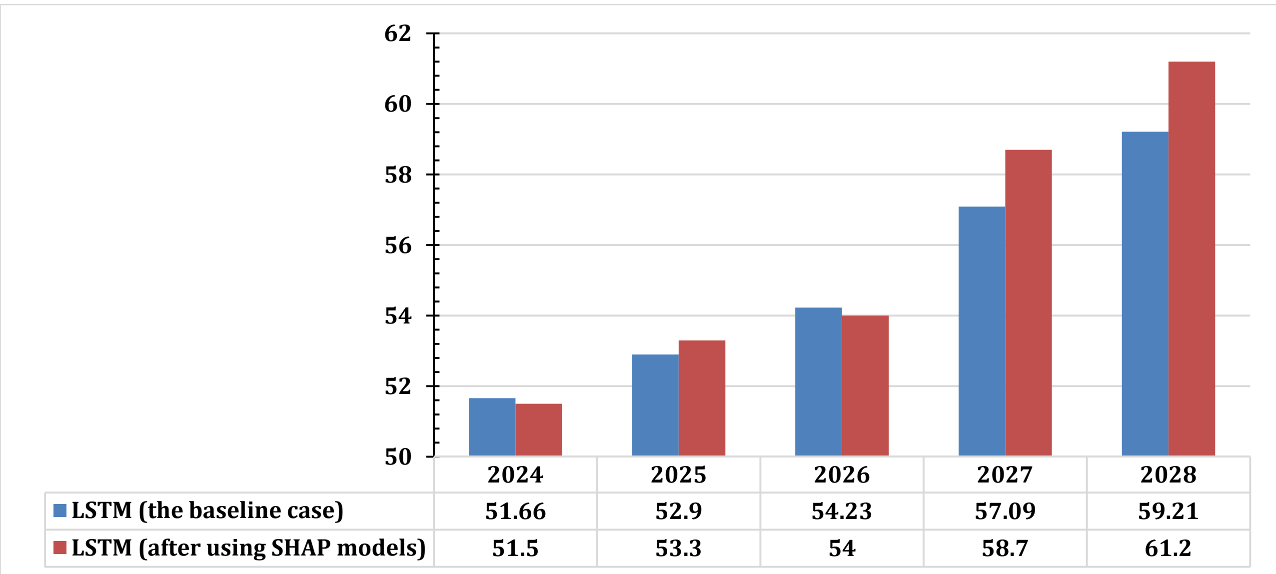

Figure 6 The annual peak load demand in MW using the baseline model and using the LSTM after the feature selection with the SHAP values.

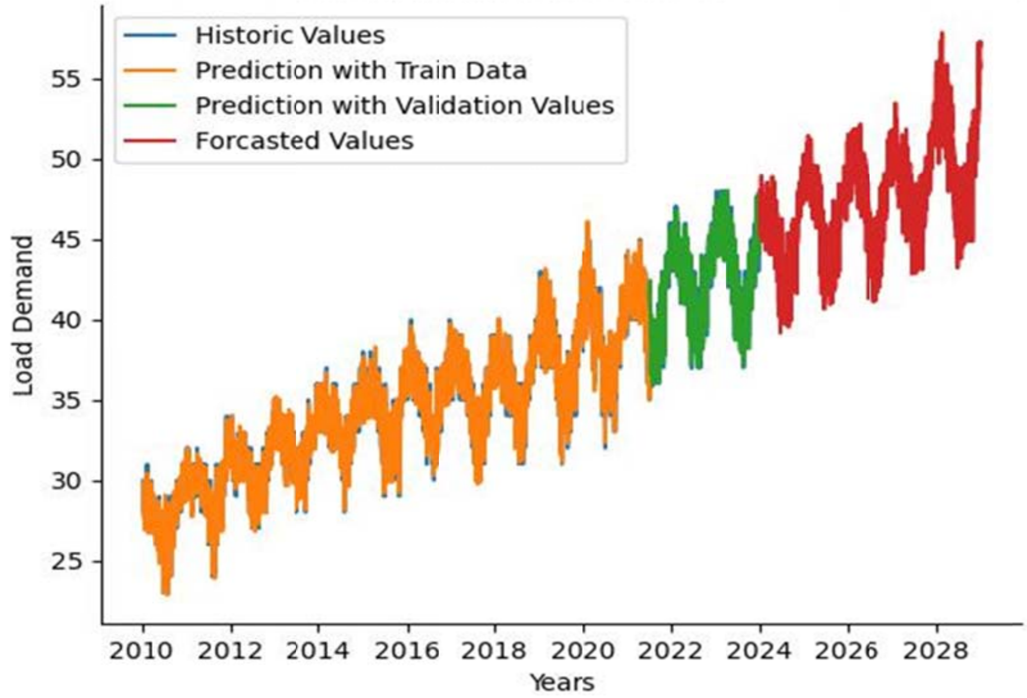

Figure 7: Load Forecasting Result using LSTM after Feature Selection.

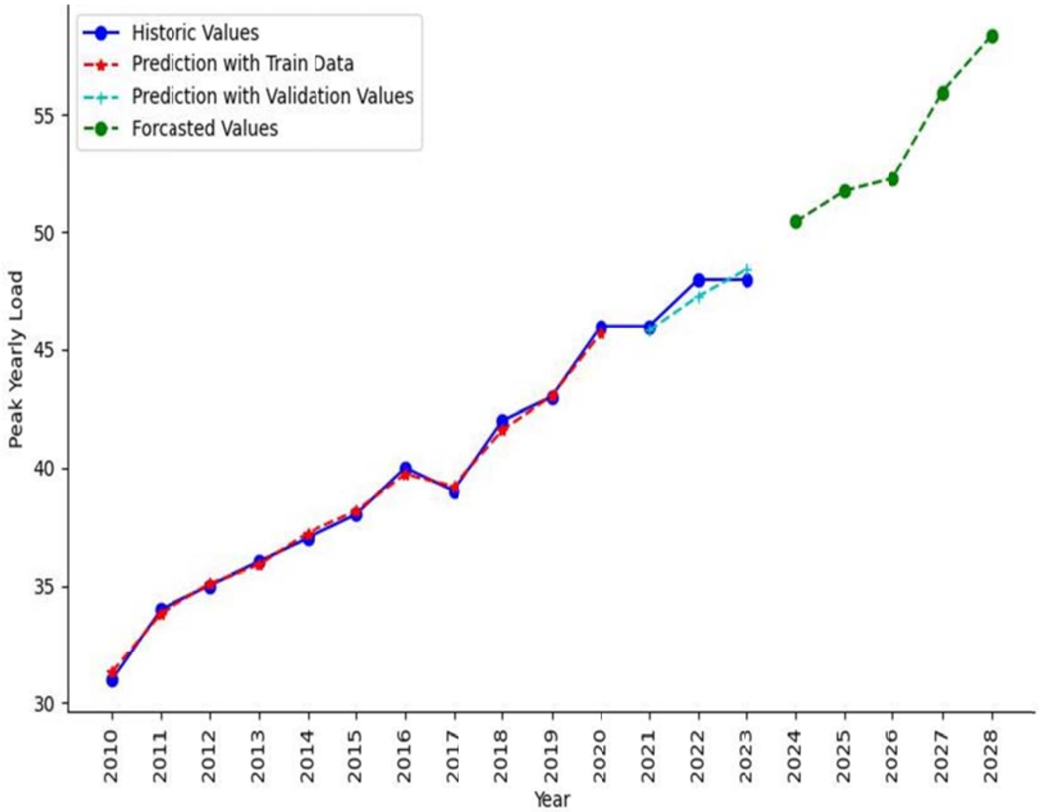

Figure 8: Plot of Yearly Peak Load Forecast with LSTM after Feature Selection.

4. Conclusion

Long Short-Term Memory (LSTM) model is presented for the forecasting of daily peak load demand of a given city using some weather parameters and macro-economic variables as the independent variables while the daily peak load is the dependent variable. In the study, SHAP technique was applied on the LSTM to examine the influence of feature selection on the prediction performance of the LSTM. In all, the feature selection using the SHAP technique did not yield any significant improvement in the prediction performance of the LSTM model.

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