Considering renewable energy sources in electricity load forecasting

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Eser Omer Talha
Student ID: x22242724

School of Computing
National College of Ireland

Supervisor: Dr. Muslim Jameel Syed

National College of Ireland

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Considering renewable energy sources in electricity load forecasting

Eser Omer Talha
x22242724

Abstract

Uses of renewable energy sources have been increased and integrated into power grid which means is managing these sources in the grid is becoming vital in terms of grid reliability and stability. Hence, forecasting of the most promising sources, wind and solar, is becoming more important for efficient and effective power grid operation. On the other hand, designing stable and reliable smart grid requires an accurate forecasting of electricity load**,** which uses historical load/demand data and its related factors to forecast. In this case, we aimed to develop accurate forecasting models by comparing their results to find out the best model for this task. Therefore, we utilized different machine learning models in both traditional and advanced deep learning models to make comparisons. More weather parameters were used in understanding correlations between them. The proposed models were used to forecast 2-hour and 1-week ahead electrical load of NEMA zone in New England. The proposed LSTM model exhibits remarkable performance to all other models by obtaining with lowest values of 0.047, 0.062, 0.003, with metrics of MAE, RMSE, MSE, respectively. R^2 value of 0.902, which was close to 1, as well. For wind power forecasting side, RMSE, MSE, MAE, and R^2 of proposed XGBoost are, 0.208, 0.043, 0.162, and 0.078, respectively. In solar power forecast, proposed XGBoost is evaluated with four metrics e.g. MAE, MSE, R^2, RMSE, and 0.088, 0.024, 0.714, 0.155, respectively.

1 Introduction

1.1 Background and Motivation

Planning and operation of power systems is a crucial step for energy management within the power companies or utilities in order to prevent additional energy purchase costs in last minutes or unexpected blackouts situations. Hence, making an accurate electricity load forecasting is vital and it can ensure the several things such as making stable and reliable power grid operations, reducing operational costs, and keeping balance between supply and demand of power network (Inman, Pedro, & Coimbra, 2013). In contrast, inaccurate and unreliable load forecasting can cause significant losses for electricity utilities or companies and even can make unstable the whole entire power system which can end up with blackouts situation or damage on critical parts. In order to predict electricity load, we need to consider factors such as weather data, historical power load, economic factors, and other factors that influence the forecast in the future period.

In the literature, load forecasting is generally categorized into three time zones: short-term (STLF), medium-term (MTLF), and long-term (LTLF). In addition, different forecast time zone provides different purposes. For instance, the time range for short-term is from an hour up to one/few weeks (Che , Peter, Laurent, Wang, & Friedland, 2013) which can allow system operators to make critical decisions during the planning and operation of power network as well as scheduling electricity systems efficiently. On the other hand, the time range of medium-term comprises from few weeks up to several months and it is being used to make maintenance schedule, or load dispatch coordination. Lastly, the period of long-term is from several months to several years which is good for long term system planning such as expanding transmission lines or adding new power sources into the grid.

Additionally, due to rapid growth in renewable energy sources, we should assess their impact on future power systems. In that case, solar and wind power has been receiving high attention among others because they have potential to be the main power supply in the future. However, their uncertainty, which is called intermittent sources, can cause significant challenge in terms of economic and safety operation of the system. Therefore, by making reliable wind and solar forecasting can ensure stable and safe operation of the power system with a high proportion of new energy (Foley, Leahy, Marvuglia, & McKeogh, 2012). Moreover, it can increase the uncertainty of wind and solar power's adverse effect, make effective dispatching plan in time, and reduce the operation costs.

Electricity load has been forecasted using a variety of methods in existing research, such as artificial intelligence models, traditional statistical methods, and hybrid models. Traditional or conventional methods e.g., autoregressive integrated moving averages (ARIMA), exponential smoothing (ES) are easy to implement with high calculation speed, however, accuracy efficiency of these models is not satisfactory due to non-linearity features, or chaotic relationships of electrical load data (Guan, Luh, L. D., & Z., 2013). For this reason, researchers have shifted their attention towards artificial intelligence models, which play a significant role in dealing with complex nonlinear relationships and providing accurate predictions. In this sense, to forecast accurately electricity load, combined deep learning models have been developed and proposed because of fact that they obtain better results than traditional machine learning models due to their ability to deal with complex data structures.

In our paper, we mainly focus on predicting medium and short-term electricity load by considering renewable energy forecasting simultaneously. We utilized the most commonly used advanced deep learning algorithms in this field, RNN (recurrent neural networks), LSTM (long short-term memory networks) as well as other machine learning models such as random forest, support vector machine, and XGBoost. Our main motivation of this study is to design more robust and accurate AI models to reduce prediction errors of electricity load forecasting in order to implement them in real-case applications, along with renewable forecasting.

1.2 Contributions

- Our study aimed to integrate forecasting of renewable energy sources alongside electricity load to address the increased penetration of renewables in the power grid.
- We proposed and employed state-of-the-art deep learning models e.g. RNN (Recurrent Neural Networks), LSTM (Long Short-Term Memory networks), GRU (Gated Recurrent Units), and by utilizing dropout and batch normalization layers.
- Our work also used conventional machine learning models such as XGBoost, SVR, and RF to compare their results towards to the deep learning models.
- More weather parameters such as humidity, temperature, pressure, cloud cover and precipitation probability were utilized to understand relationships between electricity load.

1.3 Research questions

Our study will attempt to forecast electricity load of the NEMA in New England, by considering related weather parameters as well as solar and wind energy forecasting. The following four research questions will be answered in this study:

Which kinds of weather parameters such as temperature, humidity, or pressure can influence electricity load forecasting?

How do machine learning models can enhance load forecasting using distinct types of methods such as traditional, or advanced machine learning models in terms of accuracy and computational efficiency?

Why do we need to consider simultaneously renewable energy sources forecasting such as wind and solar, when we make forecast of electricity load?

What are the benefits of making accurate forecasts for companies or energy markets?

1.4 Research Objectives

- To examine the weather parameters' impact on load forecasting of electricity
- Compare the different machine learning methods in terms of accuracy and computational expensive

2 Related Work

In this section of the paper, we are going to review current literature of load forecasting in both medium and short term. As we forecast two different objects, we divided this section into two subsections such as electricity load forecasting, and renewable forecasting. Researches have made remarkable progress on electricity load forecasting in recent years by utilizing machine learning algorithms, however, the proposed methods by far still lack robustness and generalizability in varying conditions. We discussed the techniques below.

2.1 Electricity load forecasting

The authors in (Zhang, Chen, Cao, & Tan, 2023) highlighted the benefits of using multi-task learning due to its ability to perform different task simultaneously. It uses less memory by sharing the same model for different tasks as well as increasing the inference speed. Therefore, CNN-LSTM multi-task learning model was implemented to deal with some issues such as poor convolution effect or high repetitive data. In addition, the generalizability of the model can be developed by utilizing multi-task learning. The proposed model gained better results than baseline models. Two forecast time which are 10-day short, and 3-month medium term is used to forecast electricity load. Authors mentioned that one-dimensional CNN is rarely used for STLF predictions due to the use of LSTM and GRU methods. However, it is the first time a novel method, which uses 1-D CNN based on VPN (Video Pixel Networks) method, was constructed and time series predictions of one-step and multi-step ahead are employed using real-world load data in (Yazici, Beyca, & Delen, 2022).

A novel method called enhanced elite-based PSO (EEPSO), which is a two loops-based structure including outer and inner, was proposed and implemented to forecast 24 ahead electric load in power systems in (Hong & Chan, 2023). The outer loop provides optimization of hyperparameters like kernel size and the whole structure of the model, whereas inner loop optimizes the weights in the networks and the parameters. The conclusion of this study shows that the proposed method can be more efficient in finding the optimal hyperparameters and parameters of the CNN than traditional-and-error approaches. In this paper (Ma et al., 2024), a hybrid model was constructed by utilizing the advantages of empirical wavelet transform (EWT), short-term memory network (LSTM), convolutional neural network (CNN), and recurrent neural network (RNN). In other word, they called their proposed method in short format; EWT-CNN-S-RNN + LSTM. The statistical features are extracted from EWT decomposition in fixed mode. On the other hand, they utilized Bayesian optimization algorithm to optimize or find best parameters to overcome model gradient explosion problem. Lastly, forecasting of short-term load is carried out by RNN and LSTM.

They mentioned in (Haque & Rahman, 2022) that many research papers do not provide enough detail on how to configure the optimal network architecture. Hence, their main target is to address this issue and propose a method that can select the optimal network architecture of a hybrid network, which is called LSTM-RNN, to forecast short-term electricity load via heuristic analysis. In addition, the hyperparameters of the proposed method and selection of optimal input features were selected by heuristic analysis which makes differ than other studies. In another study (Bashir, Haoyong, Tahir, & Liqiang, 2022) focused on some common issues such as low speed convergence, high complexity of AI models and so on. To overcome these issues, they proposed a hybrid method that uses prophet and Long-short term memory. Linear and non-linear data were used by the proposed prophet model in order to make prediction of load data; however, it still remains residual non-linear data. And then, LSTM was used to train these residual data. Lastly, these forecasted data is used in back propagation neural network in order to increase the prediction accuracy.

A novel data preprocessing system is constructed to eliminate the undesirable characteristics by recognizing and correcting outliers and make the data better to forecast short-term electricity in (Meng, and others, 2023). Moreover, they used random forest algorithm to select high-impact parameters to get rid of irrelevant variables which makes more robust the model. In addition to these steps, loess (STL) and Hodrick Prescott (HP) filters were combined to create seasonal-trend decomposition which enables to explore more depth latent trend characteristics in the complex data. Forecasting step on the other hand is carried out by feed-forward neural network (FNN). Their proposed preprocessing methods demonstrate that the quality of more complex data can be improved.

In this work (Stamatellos & Stamatelos, Short-Term Load Forecasting of the Greek Electricity System, 2023), two types of FF ANN models were applied with particularly designed input training dataset for day-ahead short-term electricity load forecasting in Greek electricity markets. They compared forecasting capabilities of used two model with Greek system operator's predictions against the actual data reported in the European platform. This study (Aguilar Madrid & Antonio, 2021) primarily focuses on 168h forecasts, short-term electricity load, by utilizing a bunch of machine learning algorithms. The XGB model achieved better results and outperforms other machine learning methods. This work demonstrated several important things such as confirming temperature value has direct relationship with load forecasting. Authors in (Khan, Short-Term Electricity Load Forecasting Using a New Intelligence-Based Application, 2023) developed a novel integrated model for short-term load forecasting by combining radial basis function network, the wavelet transform decomposition, and the thermal exchange optimization (TEO) algorithm. By doing this, they aimed to enhance the accuracy and robustness of load forecasting models.

As a result of reviewing researches, we see that various deep learning and traditional machine learning has been employed for electric load forecasting. These methods encompass basic algorithms such as random forest, XGB regressor, decision tress and more complex or robust algorithms such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory networks (LSTMs).

Authors	**Algorithms**	**Datasets**	**Period**	**Limitations and gaps**
Zhang et. al.	Proposed hybrid MTMV-CNN-LSTM model	10th Teddy Cup Data Mining Challenge.	10-day and 3-month	--
Yazici et. al.	One-dimensional CNNs based on Video Pixel Networks (VPNs)	Obtained from CK Bogazici Electric.	1-hour and 24-hour ahead	--
Hong et. al.	A proposed novel EEPSO-based CNN	Taken from Taiwan power company.	24-hour ahead	It needs to add more search techniques
Fan et. al.	Proposed EWT-CNN-S-RNN + LSTM model	Australian Energy Market Operator.		--
Haque et. al.	Regularized LSTM-RNN	Obtained from Dominion Energy.	30-min and 24-h ahead	Need to considered occupancy and equipment status of building
Bashir et. al.	Prophet + LSTM	Belgium based Elia Grid data	24-h, 1-week, and 1-month ahead	--
Meng et. al.	Proposed DP-HSTL-FNN	Taken from UMass Trace Repository	1-hour ahead	More relevant data needed
Stamatellos et. al.	Feed Forward ANN	ENTSO-E	24-hour ahead	Additional weather parameters should be discussed
Madrid et. al.	KNN, SVR, RF, XGB	Panama Case Study	72-hour ahead	Lack of historical load records such as holidays
Khan et. al.	Proposed WT-RBF-TEO model	the Pennsylvania-New Jersey-Maryland electricity market, and	Seasonally	--

		Spanish electricity market

Table 1: Comprehensive recent Literature Review of Electricity Load Forecasting

2.2 Renewable Forecasting (Wind and Solar)

Making an accurate forecasting of wind and solar power are crucial for power systems due to their potential to being most uses resources to generate clean energy. As we mentioned above, many machine learning techniques are being applied to forecast them. For instance, Authors in (Wu & Wang, 2021) built an ensemble neural network framework that includes ELM, LSTM, SVM, and BP neural network for forecasting of wind and solar in China. On the other hand, eliminating vanishing and exploding gradient problems was the main purpose of this study (Kumar, Mathur, Bhanot, & Bansal, 2020) to accurately forecast of wind speed and solar irradiance. Therefore, they utilized a long short-term memory (LSTM) algorithm, which is advanced method of RNN. In another study (Carneiro, Rocha, Carvalho, & Fernández-Ramírez, 2022) employed a ridge regression to combine the results of four ML techniques: MLP, CFBP, SOM, and RBF and they pointed out that combining results of these models can gain better performance, compared with single methods. Furthermore, joint forecasting method based on attention neural network was proposed by authors in (Zhang, Yan, Han, Yongqian, & Song, 2022) In addition, they aimed to reduce workload by making predictions of each station at the same time. Moreover, three types of deep learning models such as encoder-decoder LSTM, multi-head CNN, and multi-channel CNN are employed and compared towards to two popular traditional models i.e., RegARMA, and NARX. The authors in (Blazakis, Katsigiannis, & Stavrakakis, 2022) used a Quantile Regression Deep Neural Networks (QRDNN) along with Hypernetworks (HN), and Quality-Driven loss Deep Neural Networks (QDDNN).

3 Research Methodology

This section of the paper describes our data, models we used, and evaluating metrics.

3.1 Data Understanding

The data was taken from New England ISO hourly load data, which is publicly available, for a period of 132 months from 2012/1/1 to 2022/12/31. Dataset comprises whole load zones in New England such as VT, NH, ME, or CT, with their relevant weather parameters e.g., DrBbulb, DewPnt. In our study, experiments are conducted on NEMA. In addition, we obtained additional hourly weather parameters including humidity, pressure, temperature, cloud cover, and precipprob from Visual Crossing Weather Data website from exactly same weather station they mentioned in the raw data to assess other weather parameters impact on load forecasting. Furthermore, wind and solar power are forecasted by using a same weather parameter to generate a case study for high penetration renewable forecasting, which is crucial step for future power system.

3.2 Data Preparation

Data preparation is the main key to provide an accurate and reliable electricity load forecasting. Therefore, we utilize some effective python libraries such as NumPy, Pandas, and Matplotlib to perform data manipulations, cleaning data properly, and plot visualizations. On the other hand, we used most packages, which are TensorFlow and Keras, that allow us to build deep learning networks. All the experiments were carried out by python language.

3.3 Machine Learning Algorithms

3.3.1 LSTM

Long-short term memory (LSTM) (Hochreiter & Schmidhuber, 1997) is made based on architecture of artificial recurrent neural network (RNN) and it was proposed to overcome vanishing and exploring gradients, which might occur when RNN model training on data. Furthermore, it basically has feedback connections, enables them to exploit temporal dependencies across data. On the other hand, it identifies memory cells, which can retain meaningful information in long sequences. Memory cells comprising three main components which are an input, forget, and output gate. Additionally, the flow of the information can be regulated by these gates in and out of the memory cell.

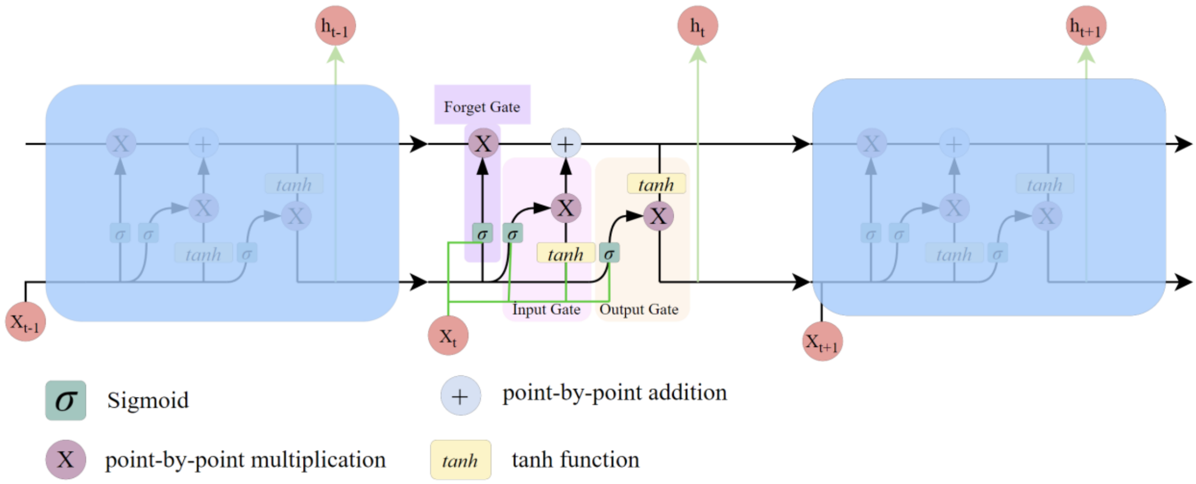

Figure 1: The Memory Cells in The LSTM Algorithm

In forget gate that makes decisions to discard essential information from the time before that the cell state. Secondly, it updates the state of the cell in two minor steps: keep flow of information to the inputs so that old cell state can exist, second, the tanh layer produces more information for updating. In the third step, we combine the first two stages of laying work in order to update and obtain a new cell state. Lastly, we filter and scale output screen from the produced new cell state to gain output information from the hidden layer. The one memory cell of the LSTM is shown in Fig.1. We constructed LSTM network with 200 units followed by dropout, which is rate of 0.15 and batch normalization layers as input layer. After then, three more hidden layers were used along with one dense additional layer. In the final layer, we used only one dense layer to ensure that model output is single continuous value, which is suitable for regression task. The total parameters of the model were 2,432,305. We summarized our proposed LSTM layer and is shown in Fig.2.

Layer (type)	Output Shape	Param #
lstm_4 (LSTM)	(None, 1, 200)	172,000
batch_normalization_5 (BatchNormalization)	(None, 1, 200)	800
dropout_5 (Dropout)	(None, 1, 200)	0
lstm_5 (LSTM)	(None, 1, 200)	320,800
batch_normalization_6 (BatchNormalization)	(None, 1, 200)	800
dropout_6 (Dropout)	(None, 1, 200)	0
lstm_6 (LSTM)	(None, 1, 150)	210,600
batch_normalization_7 (BatchNormalization)	(None, 1, 150)	600
dropout_7 (Dropout)	(None, 1, 150)	0
lstm_7 (LSTM)	(None, 100)	100,400
batch_normalization_8 (BatchNormalization)	(None, 100)	400
dropout_8 (Dropout)	(None, 100)	0
dense_2 (Dense)	(None, 50)	5,050
batch_normalization_9 (BatchNormalization)	(None, 50)	200
dropout_9 (Dropout)	(None, 50)	0
dense_3 (Dense)	(None, 1)	51

Figure 2: Proposed LSTM network

3.3.2 RF

Random forest (Breiman, 2001) is a type of supervised machine learning algorithm that utilizes both bagging (Breiman, Bagging predictors, 1996) and feature randomness (Amit & Geman, 1997) to build an uncorrelated forest with produced multiple decision trees by algorithm. To better understanding of the model, feature randomness produces a randomly chosen subset of features, whereas bagging trains several models separately on random subsets of the data and uses voting or averaging to aggregate their predictions. In our experiment, we set hyperparameter of the model such as max_depth = 50, random_state = 0, and n_estimators = 1000.

3.3.3 SVR

Support vector machine was introduced by Vapnik (Vapnik, 2000) and it is a kernel-based machine learning model which can be used for classification and regression task. The basic working principle is to find an optimal line that maximizes the distance between each class in an N-dimensional space. In our study, we utilized only 'RBF' kernel due to its capability to deal with non-linearity of the nature of time-series data.

3.3.4 RNN

Recurrent neural networks were constructed particularly to interpret and analyse time-series data. In other words, they are well-known models that able to process time-series or sequential data vector at each step in the sequence. RNNs uses hidden layers that act as a memory to keep information from previous time steps, which allows the network to utilize earlier information in the sequence. Prediction to the next sequence is made by using current input and stored memory, which makes powerful when we are dealing with sequential data. Fig.3 illustrates the working principle of RNNs.

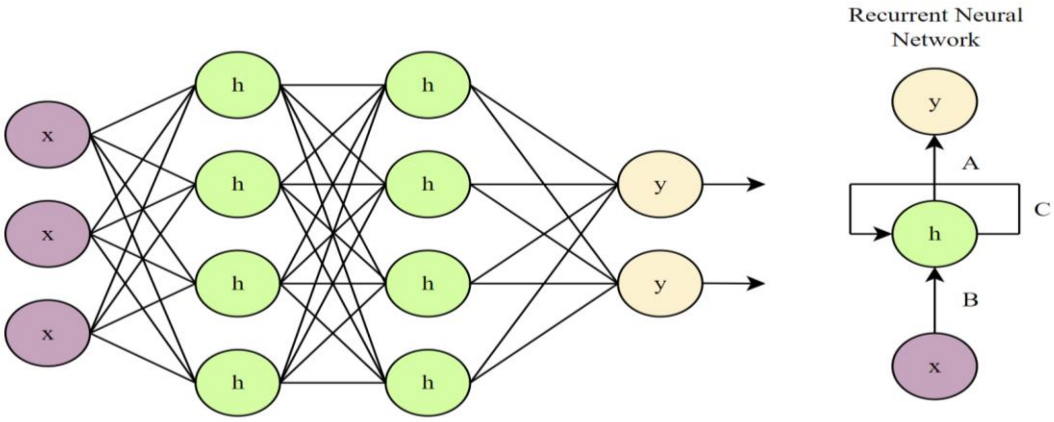

Figure 3: RNN with its Working Mechanism of Recurrent Neural Networks

We built a recurrent neural network using simpleRNN layers following with the last dense layer in our study. Additionally, a dropout layer was used as we used in LSTM to prevent overfitting issue with rate of 0.15. The input layer consisted of 250 units with a tanh activation function, whereas six hidden layers were used to enable the model to learn more abstract and complex features from data. in the last layer of the model, which is output layer, dense with one unit was employed for our regression task. Total parameters of the proposed model were 1,279,355. We illustrated our proposed simple RNN model in Fig.4.

Layer (type)	Output Shape	Param #
simple_rnn (SimpleRNN)	(None, 14, 250)	63,000
dropout_10 (Dropout)	(None, 14, 250)	0
simple_rnn_1 (SimpleRNN)	(None, 14, 250)	125,250
dropout_11 (Dropout)	(None, 14, 250)	0
simple_rnn_2 (SimpleRNN)	(None, 14, 250)	125,250
dropout_12 (Dropout)	(None, 14, 250)	0
simple_rnn_3 (SimpleRNN)	(None, 14, 150)	60,150
dropout_13 (Dropout)	(None, 14, 150)	0
simple_rnn_4 (SimpleRNN)	(None, 14, 100)	25,100
dropout_14 (Dropout)	(None, 14, 100)	0
simple_rnn_5 (SimpleRNN)	(None, 14, 100)	20,100
dropout_15 (Dropout)	(None, 14, 100)	0
simple_rnn_6 (SimpleRNN)	(None, 50)	7,550
dropout_16 (Dropout)	(None, 50)	0
dense_4 (Dense)	(None, 1)	51

Figure 4: Proposed Simple RNN Model

3.3.5 GRU

The gated recurrent units (GRUs) are a gating method in recurrent neural networks established in 2014 (Cite-13). GRUs are similar to long short-term memory (LSTM) networks with a forget gate but have fewer parameters since they lack an output gate. GRUs have been shown to outperform LSTMs on specific tasks such as polyphonic music modeling, speech signal modeling, and natural language processing. They have also demonstrated better performance on smaller and less frequent datasets. GRUs, which represent an improvement on the classic RNN's hidden layer. A GRU is composed of three gates: an update gate, a reset gate, and a temporary output, and demonstrated in Fig.5.

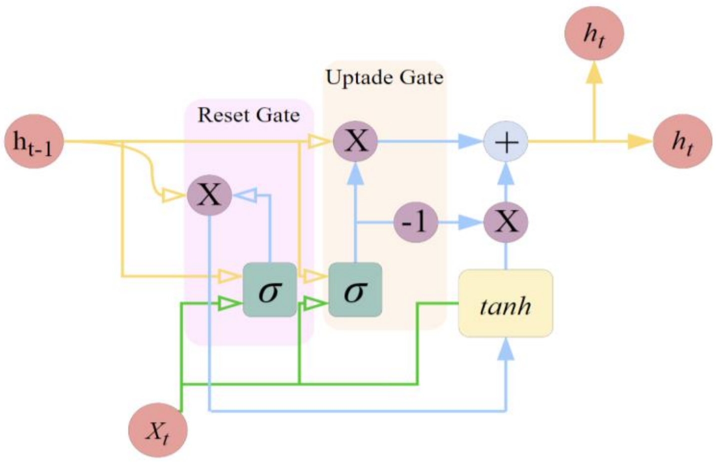

Figure 5: GRU

We constructed a basic gated recurrent network along with utilizing two fully connected layers for our regression task and it is illustrated in Fig.6. The last layer of the model with one dense layer was used to obtain one single continuous value for regression task. Total parameters of the model were 1,632,581.

Layer (type)	Output Shape	Param #
gru_24 (GRU)	(None, 14, 64)	12,864
batch_normalization_39 (BatchNormalization)	(None, 14, 64)	256
gru_25 (GRU)	(None, 14, 128)	74,496
batch_normalization_40 (BatchNormalization)	(None, 14, 128)	512
gru_26 (GRU)	(None, 14, 256)	296,448
batch_normalization_41 (BatchNormalization)	(None, 14, 256)	1,024
gru_27 (GRU)	(None, 128)	148,224
batch_normalization_42 (BatchNormalization)	(None, 128)	512
dense_24 (Dense)	(None, 64)	8,256
dropout_18 (Dropout)	(None, 64)	0
batch_normalization_43 (BatchNormalization)	(None, 64)	256
dense_25 (Dense)	(None, 32)	2,080
dropout_19 (Dropout)	(None, 32)	0
batch_normalization_44 (BatchNormalization)	(None, 32)	128
dense_26 (Dense)	(None, 1)	33

Figure 6: Proposed GRU Model

3.3.6 XGBoost

(Tianqi & Carlos, 2016) proposed a boosting learning algorithm which is called eXtreme Gradient Boosting (XGBoost) in 2016. The main purpose of this model is to build a poor classifier through a regression and classification tree. And then, these multiple weak classifiers are integrated into a strong classifier. In other words, each iteration produces a new tree, and it consistently learns the residuals between the true value and the predicted values of the current tree which enables to gather the multiple trees' results. In addition, this model is designed to be more efficient and less computationally expensive. We illustrated the main working principle of XGBoost in Fig.7

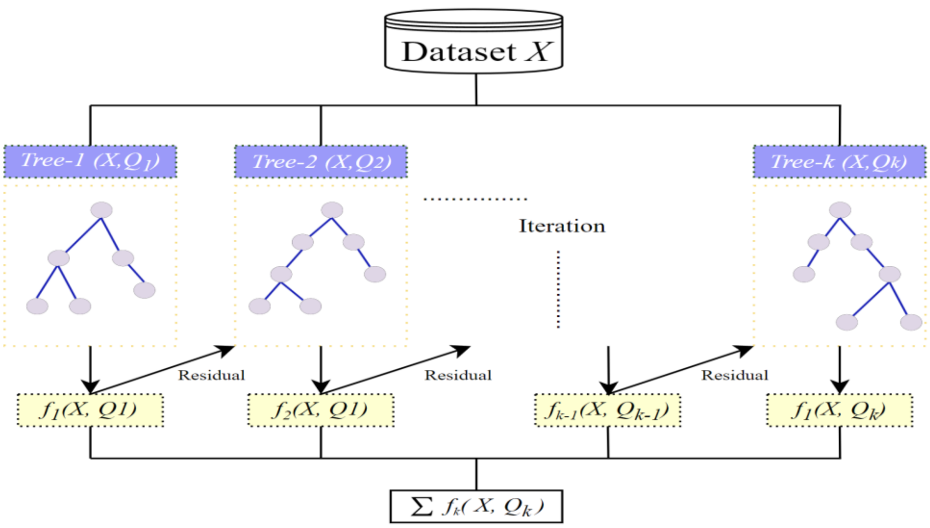

Figure 7: XGBoost

3.4 Performance Metrics

In our study, we evaluated the accuracy of forecasting performance using the mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2).

4 Design Specification

The design of the proposed methods is shown in Fig.8.

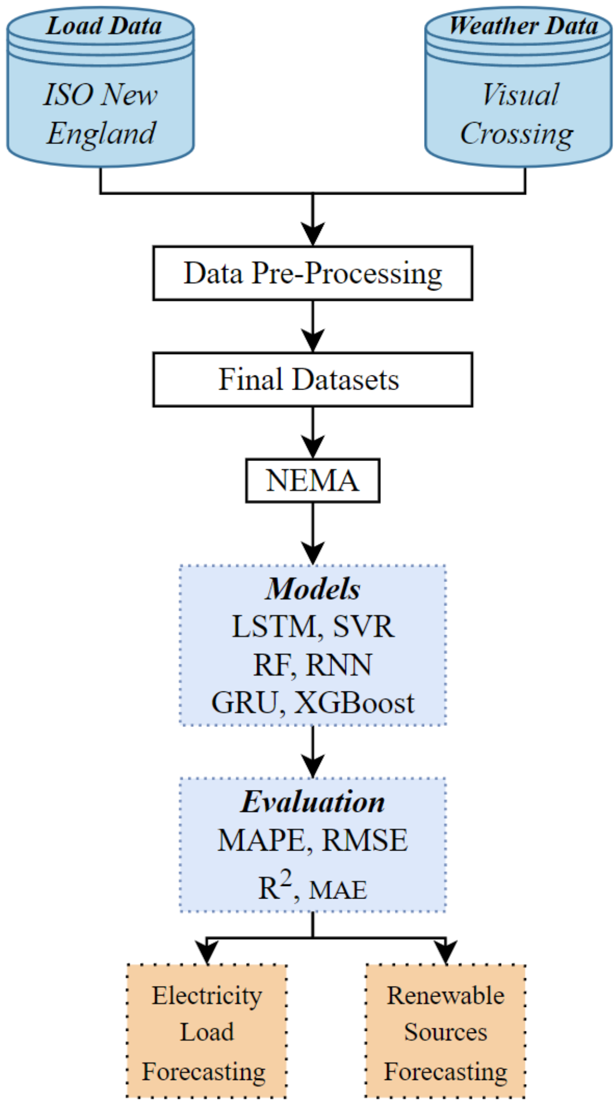

Figure 8: Proposed Method

5 Implementation

This section of the paper discusses the how proposed models were implemented and evaluated, the data acquisition, setup we used.

5.1 Data Pre-Processing

For data pre-processing, first step was the removing unnecessary features from the original dataset and only kept Date, Hr_End, and DA_Demand columns that will be used for load forecasting. NaN values were found in the column of weather parameters: Solar radiation, and Solar energy and filled with mean () value techniques and there was no NaN value in the load data.

Second step was outliers' detection and outliers were found in DA_Demand, and sealevelpressure. To deal with outliers, we employed the interquartile range method, IQR for short, that calculates lower and upper limit to consider conditions, which are if any data points greater than upper limit, or if any data points less than lower limit, will be considered as outliers. After then, we used the capping technique that keeps minimum and maximum values as threshold and make values to the data points accordingly. Fig.9 displays each feature before and after outliers are removed.

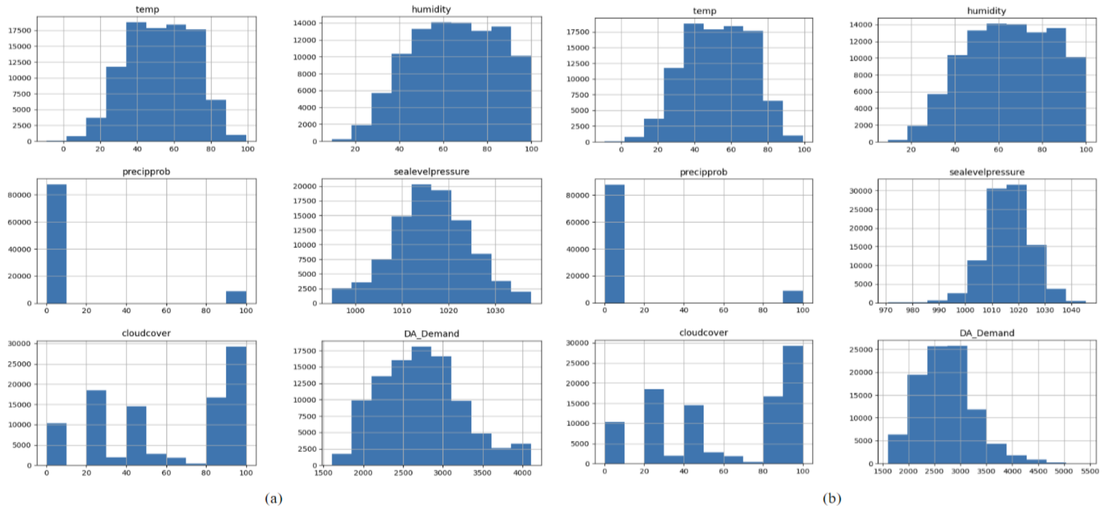

Figure 9: (a) represents after outliers removed, and (b) shows the data features before the outliers process

After all pre-processing steps, one dataset was created for NEMA zones separately including relevant weather parameters. Additionally, we consider precipitation probability and wind speed for solar radiation forecasting, whereas pressure, precipitation probability, and temperature were used for wind speed correlation.

5.2 Feature Engineering

Feature engineering is a technique that selects, transforms, and manipulates the raw data into necessary features that used in both supervised, and unsupervised learning. In our study, we created time series features based on time series index. We can see all the added features in Fig.10, which is found in many research paper.

datetime	temp	humidity	precipprob	sealevelpressure	cloudcover	DA_Demand	hour	dayofweek	quarter	month	year	season	dayofyear	dayofmonth	weekofyear
2012-01-01 00:00:00	38.8	86.63	0	1012.9	0.0	2214.5	0	6	1	1	2012	1	1	1	52
2012-01-01 01:00:00	39.0	85.76	0	1012.8	1.7	2104.3	1	6	1	1	2012	1	1	1	52
2012-01-01 02:00:00	38.9	85.79	0	1013.6	0.9	2043.2	2	6	1	1	2012	1	1	1	52
2012-01-01 03:00:00	40.6	81.48	0	1014.5	0.0	2020.2	3	6	1	1	2012	1	1	1	52
2012-01-01 04:00:00	42.2	76.90	0	1015.0	0.0	2026.9	4	6	1	1	2012	1	1	1	52
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2022-12-31 19:00:00	53.2	99.74	100	1010.4	100.0	2506.5	19	5	4	12	2022	1	365	31	52
2022-12-31 20:00:00	52.2	99.73	100	1008.9	100.0	2319.9	20	5	4	12	2022	1	365	31	52
2022-12-31 21:00:00	53.2	99.67	100	1008.2	100.0	2322.9	21	5	4	12	2022	1	365	31	52
2022-12-31 22:00:00	52.2	99.68	100	1007.2	100.0	2183.2	22	5	4	12	2022	1	365	31	52
2022-12-31 23:00:00	52.2	99.80	100	1006.2	100.0	1936.6	23	5	4	12	2022	1	365	31	52

Figure 10: After adding necessary features for short- and medium-term forecasting

5.3 Data Exploration

Confusion matrix is being used to explore relationships between variables and it is useful tool in Python. Fig.11 shows that there is direct correlation between temperature and demand, as used in many research paper as main parameter. Moreover, Humidity has direct correlation with cloud cover and precipitation probability. On the other hand, cloud cover has direct relationship with precipitation probability.

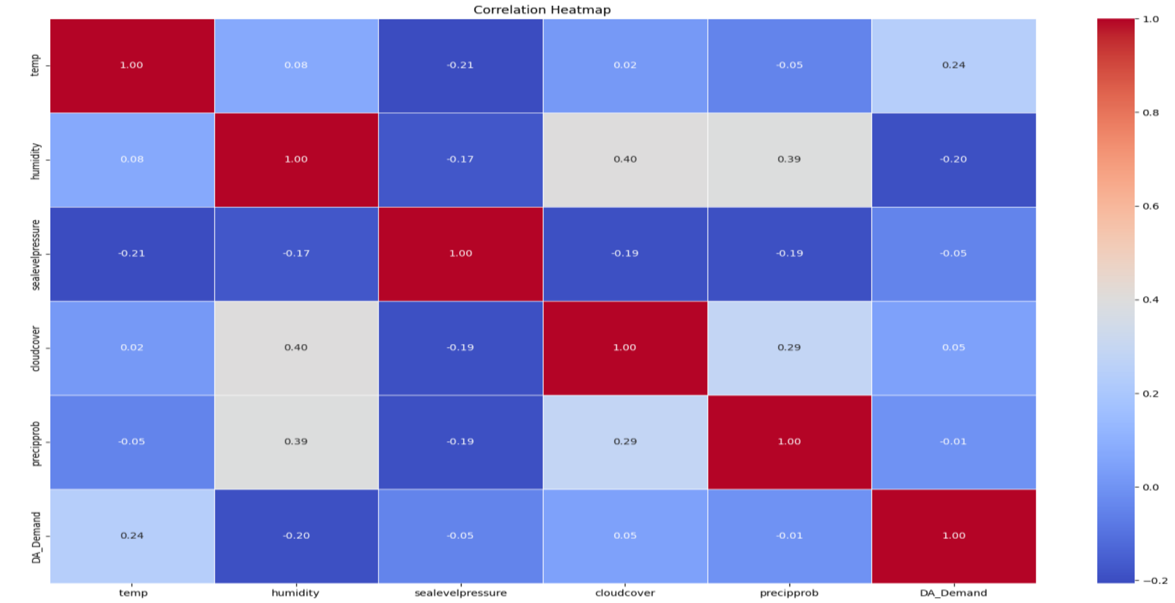

Figure 11: Correlation Matrix of Final Dataset

5.4 Data Split

We used data from 1st January of 2012 until 31st September 2021 as training data, while data from 1st January of 2022 to 31st December of 2022 used as testing data for electricity load forecasting as well as renewable forecasting. Entire utilized data ranges can be seen in Fig.12.

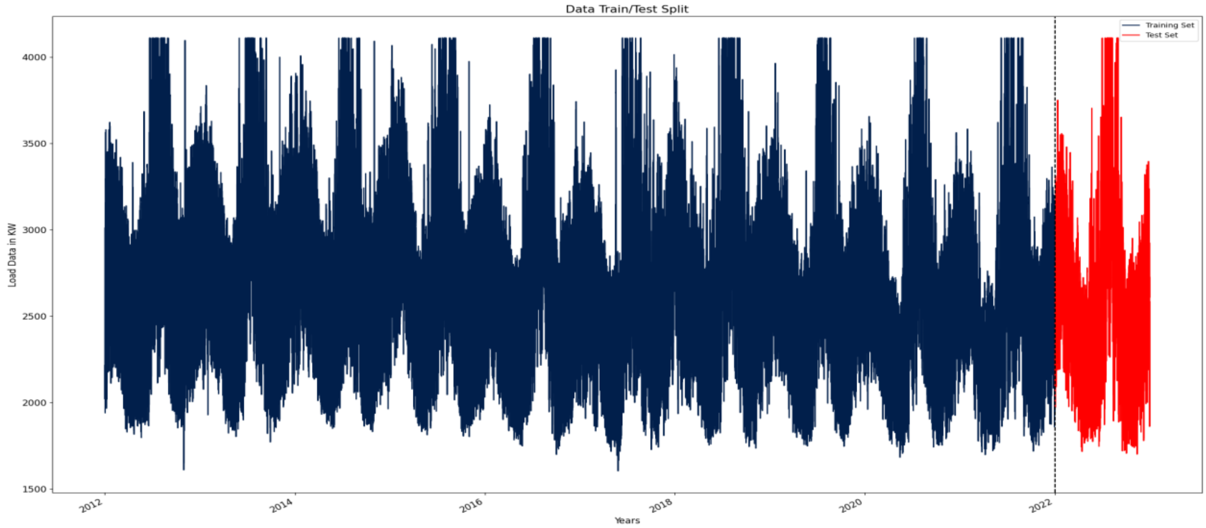

Figure 12: Data Test/Train Split

5.5 Implementation, Evaluation, and results of our proposed models

The section of the paper discusses implementation and evaluation of our models.

5.6 Implementation

We are considering two case study such as NEMA load zones as well as renewable forecasting using the best models obtained. Our target variable is DA_Demand. The data was divided into both training, which comprises 10 years, and testing, which comprises only one year.

5.7 Evaluation

Our models were evaluated using most common performance metrics e.g. mean squared error (MSE), mean absolute error (MAE), R squared (R^2), and root mean square deviation (RMSE).

5.8 Experiment / Case Study 1 for NEMA load zone

NEMA, Northeast Massachusetts and Boston for long, is predicted in this case study and proposed models evaluation was made on testing dataset. All the models were trained five times. 1-week (720h) and 2-day ahead (48h) were targeted for forecasting time zones, which are short and medium-term. To evaluate our model, October was selected for short term, while December was used for medium term.

5.8.1 LSTM

5.8.1.1 Implementation

The LSTM was trained five times with 100 epochs, and 128 batch size. Additionally, we employed early stopping, reduce late learning, and Adam optimizer.

5.8.1.2 Evaluation

Proposed LSTM model was evaluated on test dataset and the results are shown in Fig. 13 and Fig. 14. MAE was obtained 0.047, whereas MSE was 0.003. Additionally, R^2 and RMSE gained 0.902, and 0.062 respectively. Training time of the model 4.05 minutes.

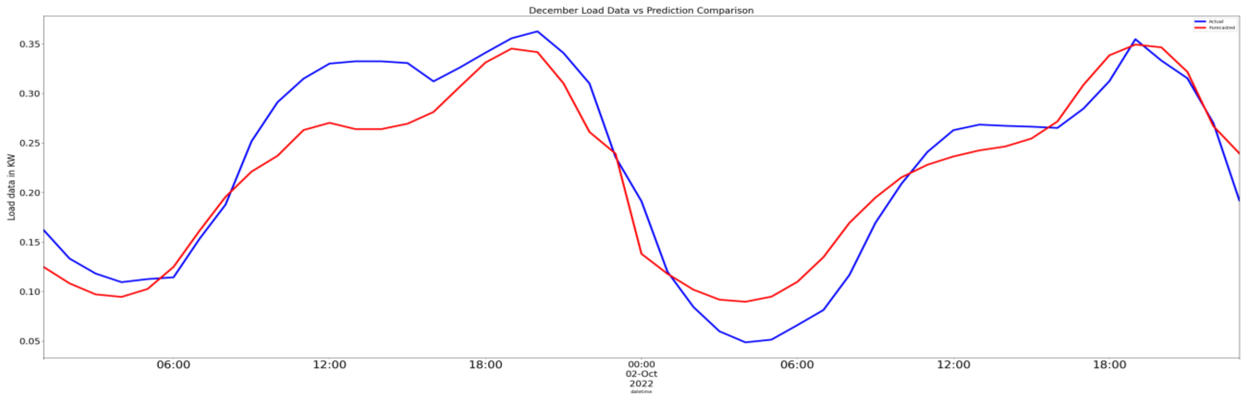

Figure 13: 2-hour Ahead Forecasting

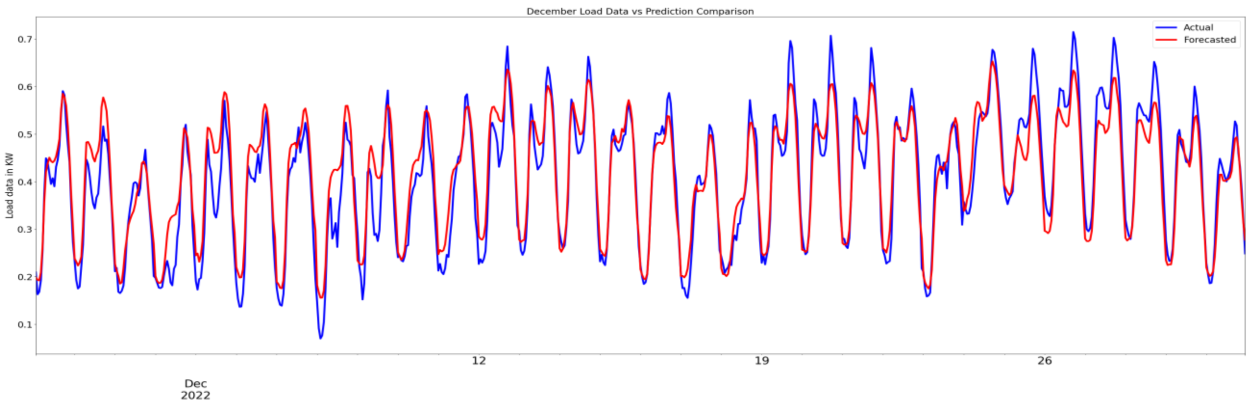

Figure 14: 1-Month Ahead Forecasting

5.8.2 Support Vector Machine

5.8.2.1 Implementation

The SVM model was used, and RBF kernel is utilized in our work.

5.8.2.2 Evaluation

The performance of our model was measured by error metrics for regression task. RMSE was 0.083, whereas MAE obtained the value of 0.065. MSE was 0.006, and R^2 was 0.822. Total training of the proposed model took 0.7 min which is less than LSTM model. Fig.15 shows that forecasted values of SVM for 2-hour ahead forecasting , while Fig.16 shows the 1-month ahead forecasting. As a results, we see that error metrics increased which is performance of the proposed LSTM obtained better results than SVM and R^2 value decreased.

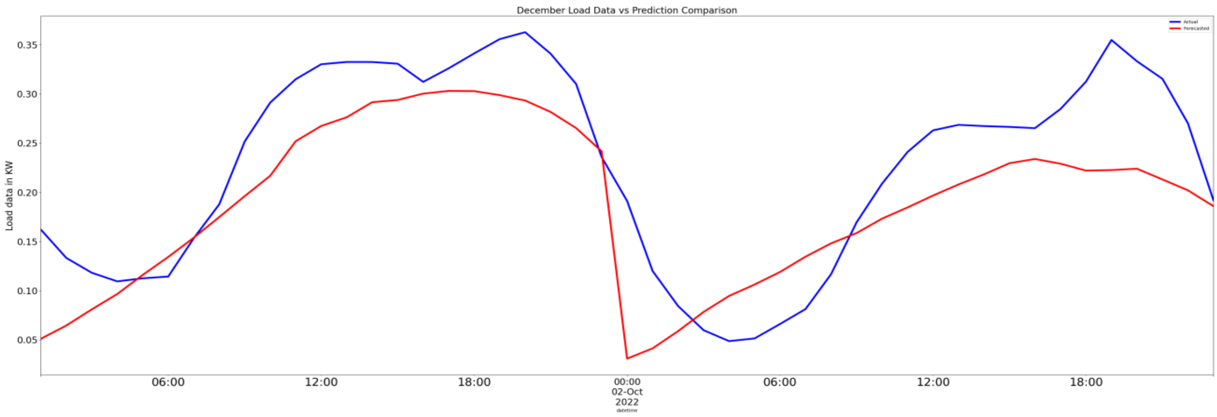

Figure 15: 2-hour Ahead Forecasting

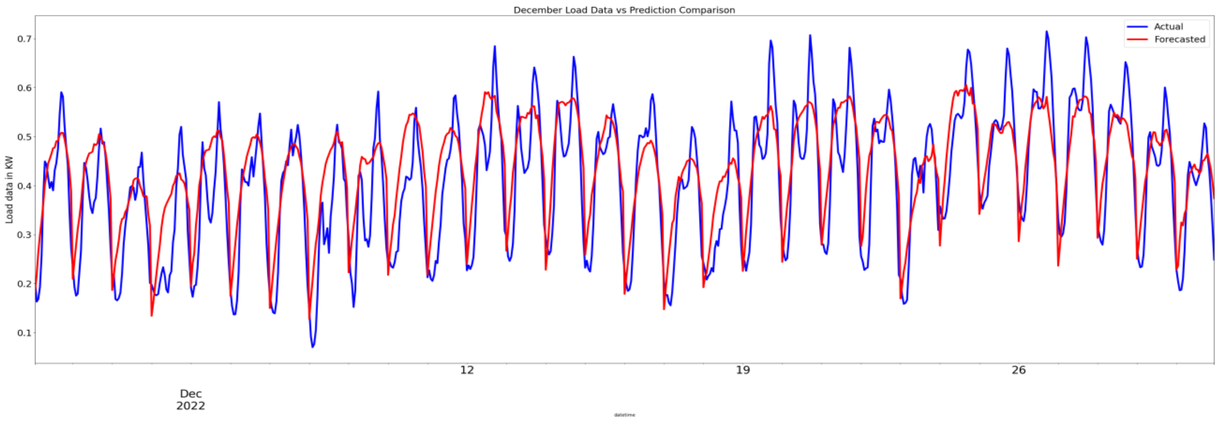

Figure 16: 1-Month Ahead Forecasting

5.8.3 Random Forest

5.8.3.1 Implementation

The parameters of the proposed model were set max_depth= 50, random_state=0, and n_estimators= 1000.

5.8.3.2 Evaluation

Short-term forecasting results are demonstrated on Fig.17, whereas Fig.18 represents the results of medium-term forecasting. According to these figures, we can understand that random forest showed better results than SVM. The values of MAE, and MSE are 0.047, 0.003 and rest of the metrics shows the values of 0.899, and 0.063, R^2, RMSE, respectively. We need to highlight that the proposed RF's performance is very close to the LSTM due to both model's abilities to capture non-linear relationships in the data. On the other hand, Total training time increased to 6.78 minutes, which makes it more computational expensive.

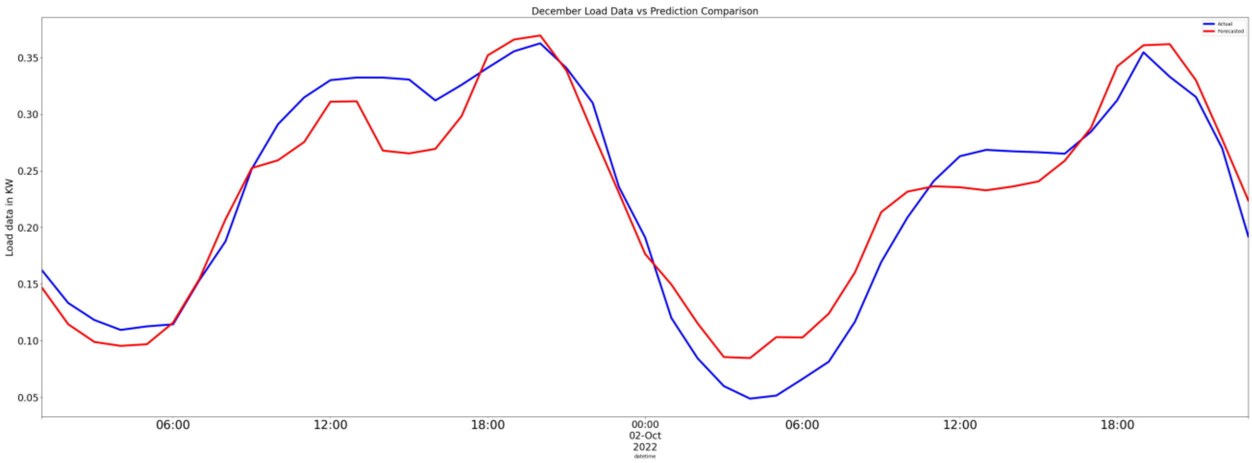

Figure 17: 2-hour Ahead Forecasting

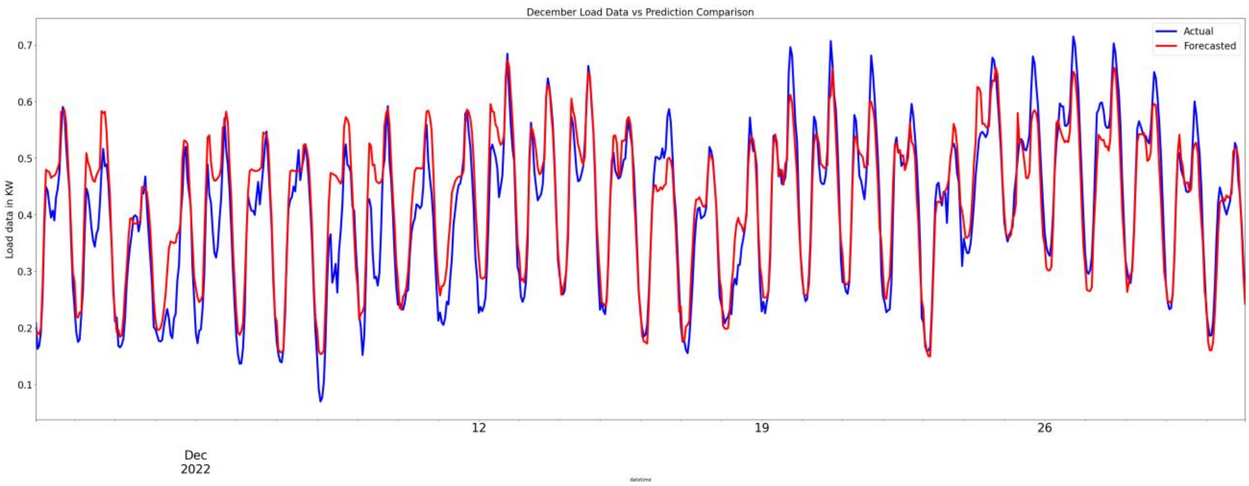

Figure 18: 1-Month Ahead Forecasting

5.8.4 XGBoost

5.8.4.1 Implementation

The parameters of the proposed model were set base_score = 0.5, n_estimators=6000, max_depth=5, learning_rate=0.2, random_state = 48, booster='gbtree', and objective='reg: linear'.

5.8.4.2 Evaluation

Fig.19 displays the better forecasted results, for 2-hour ahead forecasting, than SVM in terms of MAE value, which is 0.054, while LSTM and RF are obtained less values of MAE than SVM. This suggests that the proposed model in question exhibits a higher predictive capability. The value of MSE is also 0.005 higher than LSTM and RF that forecasted values are less close than the actual values. On the other hand, R^2, which measures the variance proportion, is gained with value of 0.87, which is less than LSTM and RF. Lastly, the value of RMSE is 0.071. Fig.20 also demonstrates the forecasted value of XGBoost for 1-month ahead forecasting. The total training time of the proposed model took 0.39 min that makes it less computationally expensive and also highlights its efficiency. This model could be used in case of situations where computational resources and time are limited and critical.

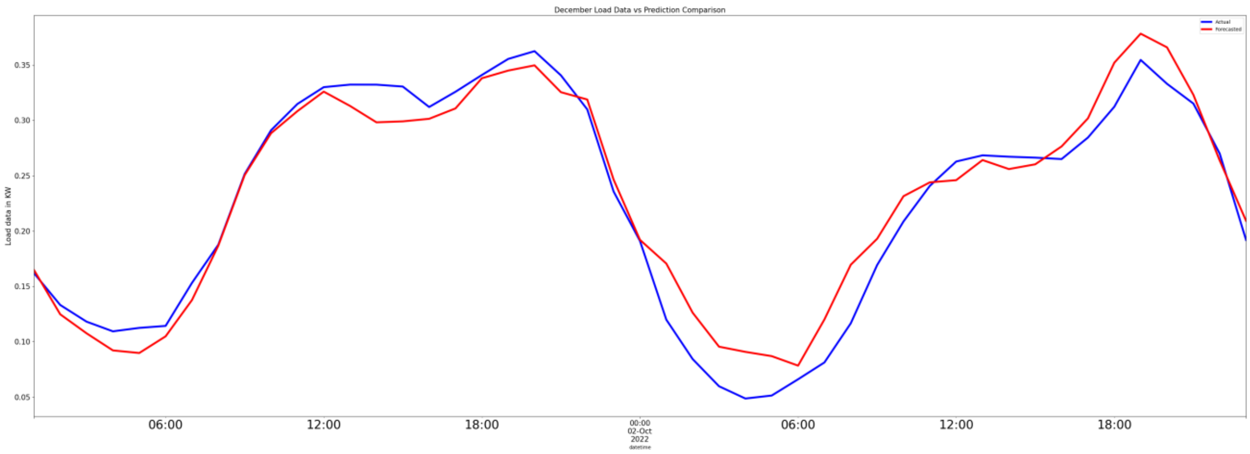

Figure 19: 2-hour Ahead Forecasting

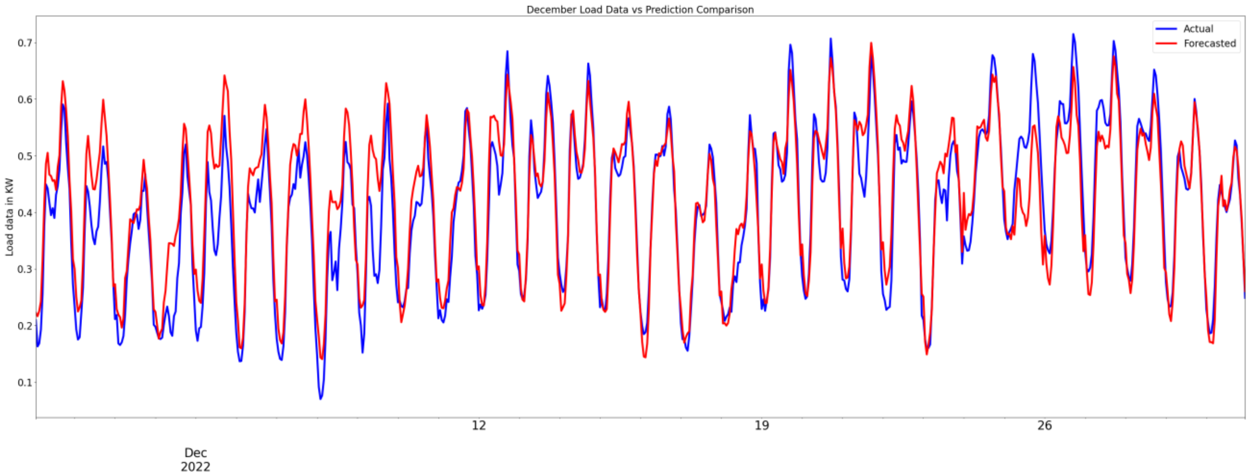

Figure 20: 1-Month Ahead Forecasting

5.8.5 GRU

5.8.5.1 Implementation

The proposed GRU model was trained five time with 50 epoch, and 128 batch size amounts. In addition, early stopping function was employed to reduce the training time.

5.8.5.2 Evaluation

We demonstrated the forecasted values of GRU predictions in Fig.21, which represents the results for 2-hour ahead forecasting, while Fig.22 shows the forecasted results for 1-month ahead forecasting. The proposed GRU are shown better results than SVM and XGBoost in terms of MAE with value of 0.050, however, LSTM and RF still holds the less value of its which makes them more robust towards those methods. 0.064 value is achieved by proposed GRU which the model still making less efficient than LSTM and RF. Moreover, the value of R^2 has increased compared to XGBoost and SVM with the value of 0.892. Furthermore, RMSE error metrics has achieved value of 0.064 which makes slight differences among RF and LSTM. The total training time of the proposed GRU is reported to be 19.20 min., which has the highest training time among others. Moreover, having a higher training time indicates that this model may not be suitable for critical situations where quick decisions are required.

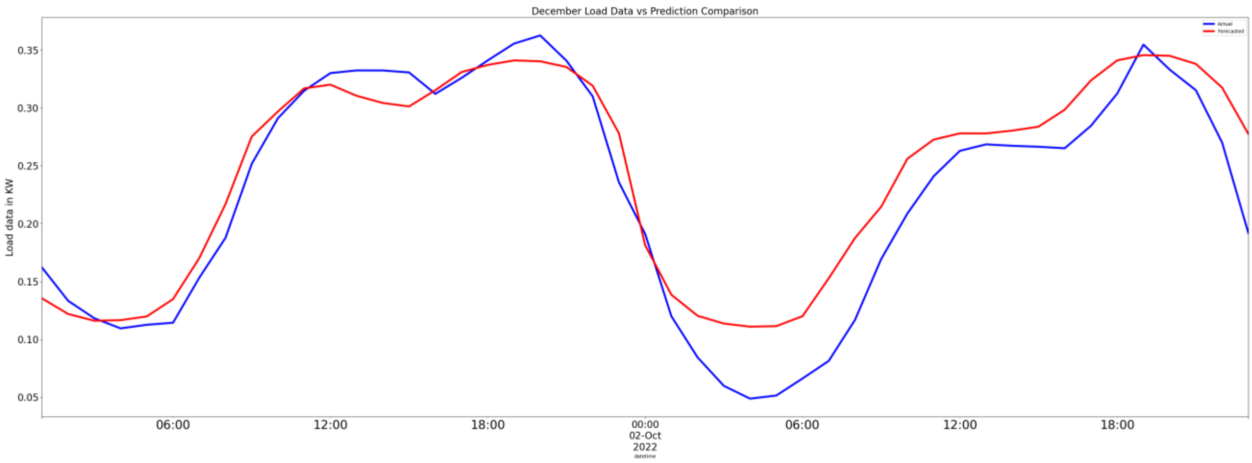

Figure 21: 2-hour Ahead Forecasting

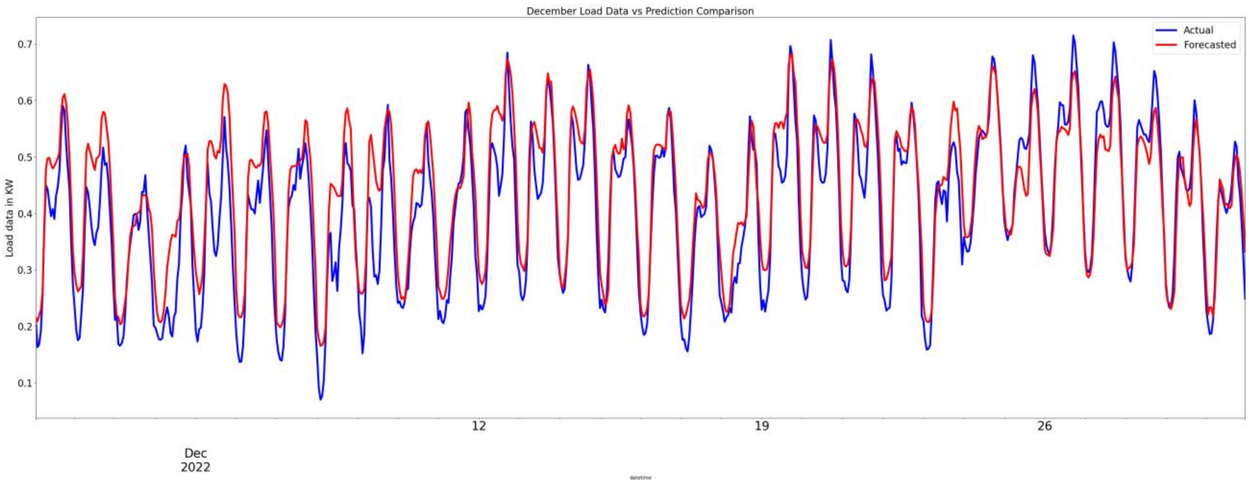

Figure 22: 1-Month Ahead Forecasting

5.8.6 RNN

5.8.6.1 Implementation

We trained proposed RNN model five times by setting epochs to 50 with 128 batch size. We again used early stopping function to stop the model where it does not improve in terms of loss.

5.8.6.2 Evaluation

RNN model is the last used proposed model among others in this study. The value of R^2 is 0.896 which is greater than XGBoost, SVM, and GRU models. Additionally, the obtained value is very close to RF, and LSTM. This closeness could be expected due to sharing the same abilities. On the other hand, RMSE is decreased with the values of 0.063 than proposed XGBoost, and SVM. The value of MSE is shown to be 0.004, which shares the same value as the proposed GRU model, while LSTM and RF keep the lowest value of MSE. Lastly, the value of the MSE is obtained as 0.048. The total training time of the model was recorded as 20.15 minutes. This proofs that the proposed RNN model is the most expensive among other models in terms of computationally, which makes it less robust model for this task. In addition, obtained forecasted data points are illustrated in both Fig.23, which is used for 2-hour forecasting, and Fig.24 that represents the 1-month ahead forecasting results.

In this section of the paper, we discussed obtained results and compared with each other to better understand of performance of the models. And also, we enhanced the evaluation section by utilizing graphs, which allow us to see each data point in the specific time range.

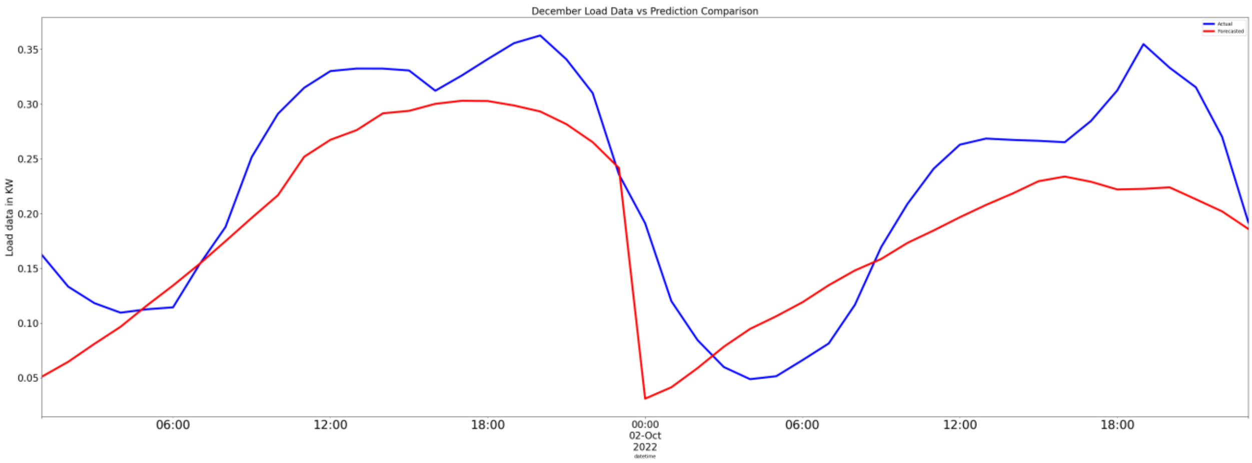

Figure 23: 2-hour Ahead Forecasting

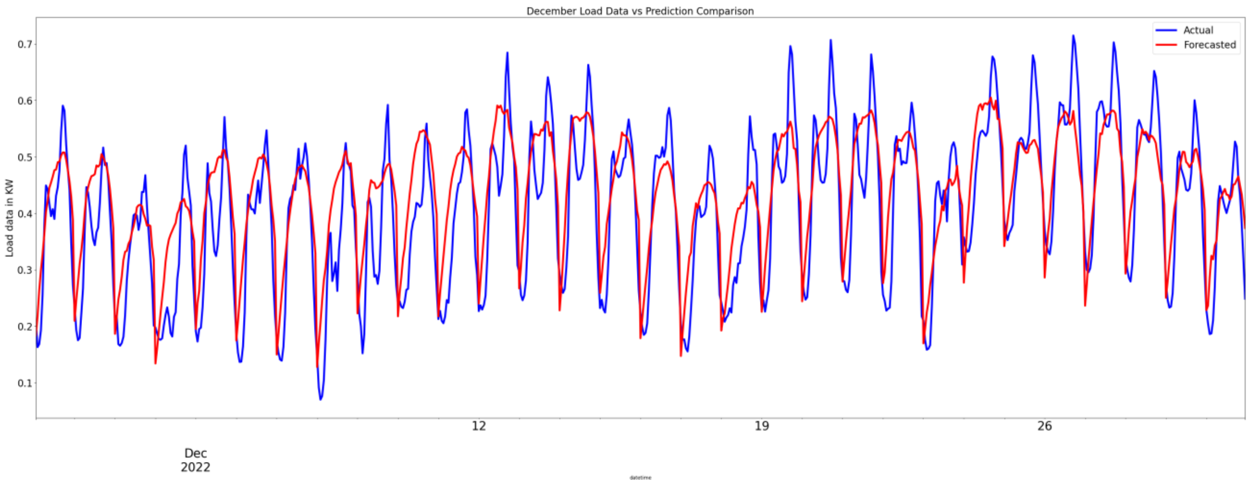

Figure 24: 1-Month Ahead Forecasting

5.7 Experiment / Case Study 2 for Renewable Forecasting

To ensure the reliable and safe planning and operation of electric power system, it is essential to work on electricity load forecasting, along with most common renewable sources such as wind and solar power. Therefore, we created a case study 2 that encompasses forecasting of wind and solar power. For wind power forecasting, temperature, precipitation probability, pressure, were used with others are that hourofday, and dayofyear. On the other hand, precipitation probability, windspeed, dayofyear, and hourofday features were used for solar power forecasting.

5.7.1 Implementation

The parameters of the proposed model were set base_score = 0.5, n_estimators=10000, max_depth=5, learning_rate=0.2, random_state = 48, booster='gbtree', and objective='reg: linear'. Same proposed model used in both wind and solar power forecasting.

5.7.2 Evaluation

The forecasted values of proposed XGBoost are shown for both wind and solar power in Fig. 25 and Fig.26. These results, specifically, point out that how the wind and solar energy are unpredictability, and has the inherent variability, which makes the challenge to develop robust, or efficient forecasting models for these renewable energy sources.

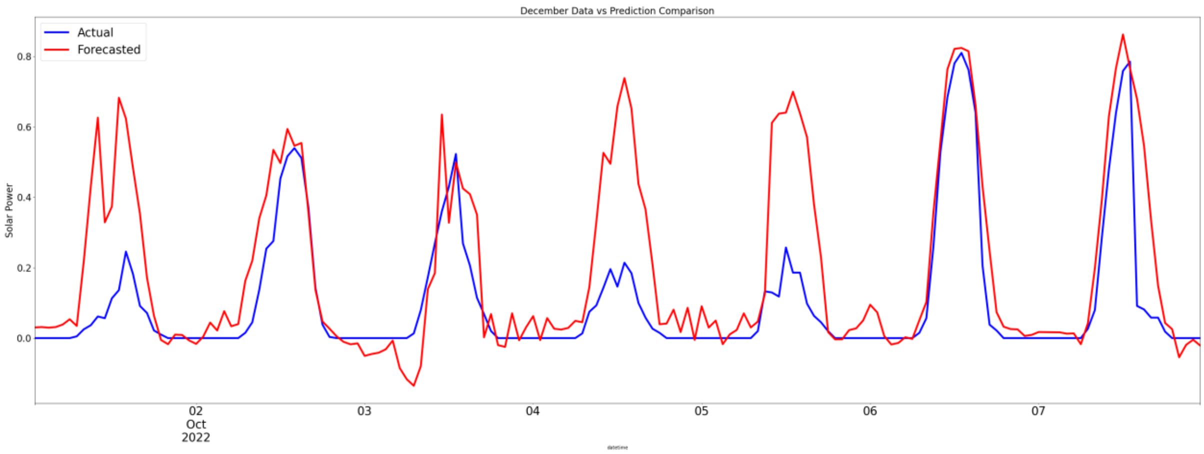

Figure 25: Forecasted Values of XGBoost for Solar Radiation

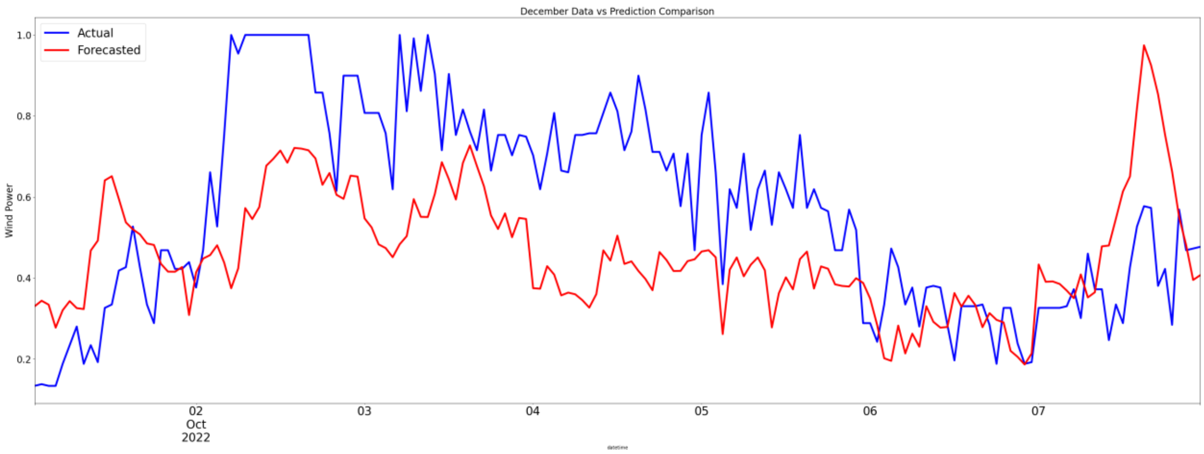

Figure 26: Forecasted Values of XGBoost for Wind Speed

6 Discussion and comparison

We evaluated our model with four different evaluation methods for both electricity load and renewable forecasting. First, R^2 of proposed LSTM model forecast is 0.902 with highest value, which is close to 1, among other models. Second best model in terms of R^2 was proposed RF model with value of 0.899, while R^2 value of proposed GRU is 0.892. Other models' values of R^2 are 0.871, 0.822, 0.896, and obtained by XGBoost, SVM, and RNN, respectively. Secondly, MAE of proposed SVM is 0.065 with highest value, whereas XGBoost in the second highest MAE value with 0.054. MAE values of LSTM, and RF are obtained lowest value of 0.047. The rest of the models' MAE error metric, which are RNN, and GRU, are 0.048, and 0.050, respectively. RMSE of proposed SVM with the highest value is 0.083, while proposed XGBoost is obtained the RMSE values of 0.071. 0.063 values of RMSE are obtained from both model RNN, and RF. In addition, 0.062, and 0.064 values of RMSE are gained from proposed LSTM, which is lowest one, and GRU, respectively. Lastly, MSE of proposed SVM is 0.006. Additionally, MSE of proposed LSTM, and RF are 0.003, which is the lowest value. On the other hand, proposed RNN and GRU is gained the same values of 0.004, while MSE of proposed XGBoost is 0.005.

In the side of renewable forecasting are discussed as well. For wind power forecasting side, RMSE, MSE, MAE, and R^2 of proposed XGBoost are, 0.208, 0.043, 0.162, and 0.078, respectively. In solar power forecast, proposed XGBoost is evaluated with four metrics e.g. MAE, MSE, R^2, RMSE, and 0.088, 0.024, 0.714, 0.155, respectively.

7 Conclusion and Future Work

In conclusion of our study, we intend to forecast of electricity load of NEMA zone in New England, along with renewable energy sources forecasting which is important for planning of power system in power grid. The data used in this paper originally captured as an hourly electricity load including related weather parameters for the NEMA zone of New England between 2012 and 2022. In the implemented methodology, data was passed through data pre-processing to feed our proposed models with clear data. Our primary objectives of this paper were to present comparison of deep learning and traditional machine learning algorithms in terms of their performance results to find out that which model can be used in real-time applications for the operators or companies whose plans the power systems in the power grid. Additionally, providing correlated relationship between load demand and weather parameters could be helpful in developing models for forecasting of electricity load. As a result, our developed and proposed LSTM model exhibits remarkable performance to all other models by obtaining with lowest values of 0.047, 0.062, 0.003, with metrics of MAE, RMSE, MSE, respectively. R^2 value of 0.902, which was close to 1, as well. In other words, LSTM networks are good at capturing long-term dependencies, and handling sequential data efficiently, which are necessary abilities for accurate electricity load forecasting.

7.1 Future Recommendations

Our study has not discussed calendar effects that comprises of holidays, and school days and we did not develop any hybrid model, although we still gained remarkable results by utilizing single models. Therefore, we will consider calendar effect, and developed hybrid models in future work. Furthermore, more electricity production sources in both renewable and unrenewable need to be considered to implement any kind of AI models in real-time application as we are using any available sources for producing electricity in the real-time.

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