A DISSERTATION

ON

A MACHINE LEARNING APPROACH FOR LOAD FORECASTING

Submitted in Partial Fulfillment for the Requirements for the Award of the Degree of

MASTERS of TECHNOLOGY in **ELECTRICAL ENGINEERING**
(with **Specialization** in **POWER SYSTEM ENGINEERING)**

Under
ASSAM SCIENCE AND TECHNOLOGY UNIVERSITY

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SESSION: 2021-2023

CANDIDATE'S DECLARATION

This is to clarify that the project entitled "**A MACHINE LEARNING APPROACH FOR LOAD FORECASTING**" has been carried out and presented by:

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And also I would like to show my sincere thanks to the Assam Electricity Grid Corporation Limited for helping in supplying the past load dataset.

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Place:

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CONTENT I

CONTENT II

CONTENT III

ABSTRACT

In this study, an approach has been suggested that will forecast the load or burden depending on weekends and weekdays because electrical energy has to be generated whenever there is a need for it. Therefore, it is essential for electric power companies to prepare for the demand on their systems. The proposed LSTM (Long Short Term Memory) model is interfaced with the Python programming language in the Spyder software and uses the real-time past load consumption data of the year 2018 from the power department to predict load for the 53rd week using 8742 samples of load, which includes all the weekdays and weekends for that particular year. For utility maximisation, loss reduction, voltage control, unit commitment, and power system operational studies, the short-term electric load forecasting period, which spans from one hour to one week, is primarily used. The method's MAPE (Mean Absolute Percentage Error) is 0.23, indicating accurate predictions, and a MAD (Mean Absolute Deviation) of 2.21 units, which is much better than recent studies done on the other models, which have MAPE (Mean Absolute Percentage Error) of 2.00, 2.26, 1.09, and 1.04 for ANN-PSO (Particle Swarm Optimisation), ANN-GA (Genetic Algorithm), MS (Multi-scale)-CNN, and SVR, respectively. The proposed LSTM (Long Short Term Memory) model had a high forecast accuracy of over 90%. This analysis of historical data using the suggested model is capable of giving us useful insights on how a variable changes over time. Thus, the project has demonstrated how to analyse and forecast time series data in a detailed and understandable manner using a machine learning model and a variety of statistical formulas, which helped in the search for the most accurate prediction model with the lowest error rate.

Keywords - *Short Term Load Forecasting, Hour, LSTM, Machine learning, Load forecast, Artificial Intelligence, Accuracy, RMSE, MAD, MSE, MAPE.*

CHAPTER: 1
INTRODUCTION

1.1. GENERAL

Without studying load forecasting, studies of power system design, operation, and dependability are inadequate. The three categories of short-term load forecasting (STLF), mid-term load forecasting (MTLF), and long-term load forecasting (LTLF) allow the load forecasting process to be categorised according to the sort of study that will be performed. An essential step in the successful operation of electricity systems is short-term load forecasting. Load forecasting accuracy is crucial for operations including economic power dispatch, storage planning, and energy market transactions [1]. The STLF is a difficult nonlinear issue that involves large amounts of data and requires advanced computation techniques in order to attain higher accuracy in the findings [2]. It is influenced by a wide range of elements, including meteorological, social, and economic considerations. Over the years, several strategies have been put forth by researchers to address the STLF problem. The autoregressive integrated moving average (ARIMA) and its variants were used in several researches [3] and [4]. However, the limitations of conventional statistical approaches in adjusting the forecasting model to the dynamic nature of load inspired new research on modern calculating methods, including genetic algorithms [5] and fuzzy logic [6]. By enabling the creation of highly effective models to characterise the nonlinear interdependence of numerous factors that affect power demand, machine learning techniques also offer effective ways to handle this complex problem. Support vector regression (SVR) and artificial neural networks (ANN) are the two applications used most commonly [7]. This evidence demonstrates the significance of using the big data idea to improve the operational efficiency of power systems. All of these strategies perform better when trained using significant amounts of data of different sorts.

The conventional approach does not take into consideration the nonlinear and historical aspects of the load data when estimating the short-term power load. In order to address this issue, load forecasting research has recently extensively implemented several deep learning techniques. The use of LSTM is advocated as a power load forecasting approach. With more accuracy than the conventional model, this approach is used to forecast the amount of power required in a specific place. The LSTM model has been shown to have fewer errors and a greater predictive impact.

1.2. Machine learning

A branch of artificial intelligence (AI) and computer science called machine learning focuses on using data and algorithms to simulate how humans learn, gradually increasing the accuracy of the system. Now that machine learning is so popular right now, it is crucial to be familiar with various machine learning models as well. We are already aware with statistical modelling on time series. We're going to start with the Long Short-Term Memory model, which is the most widely used model in the time series field.

A type of recurrent neural network is the LSTM. Therefore, it is crucial to comprehend neural networks and recurrent neural networks before moving on to LSTM.

Neural Networks

An artificial neural network is a layered structure of connected neurons, inspired by biological neural networks. It is not one algorithm but combinations of various algorithms which allows us to do complex operations on data.

Recurrent Neural Networks

It is a group of neural networks designed specifically to handle historical input. RNN neurons possess a cell state or memory, and input is processed in accordance with this internal state with the help of neural network loops. RNNs have recurrent modules of 'tanh' layers that give them the ability to store information. But not for a long time, which is why LSTM models are required.

LSTM

It is a special type of recurrent neural network that can discover long-term dependencies in data. There are three different types of load forecasting, depending on the forecasting horizon: short-term load forecasting (STLF), which covers predictions up to one week in the future; medium-term load forecasting (MTLF), which covers predictions between one week and one year; and long-term load forecasting (LTLF), which predicts the loads up to one year in the future.

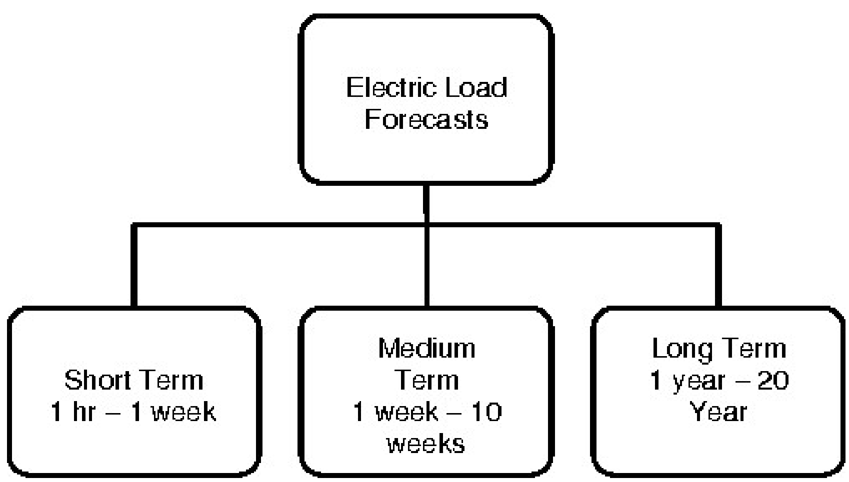


Fig.1.2: Types of Electric Load Forecasts

This is achieved because the recurring module of the model has a combination of four layers interacting with each other.

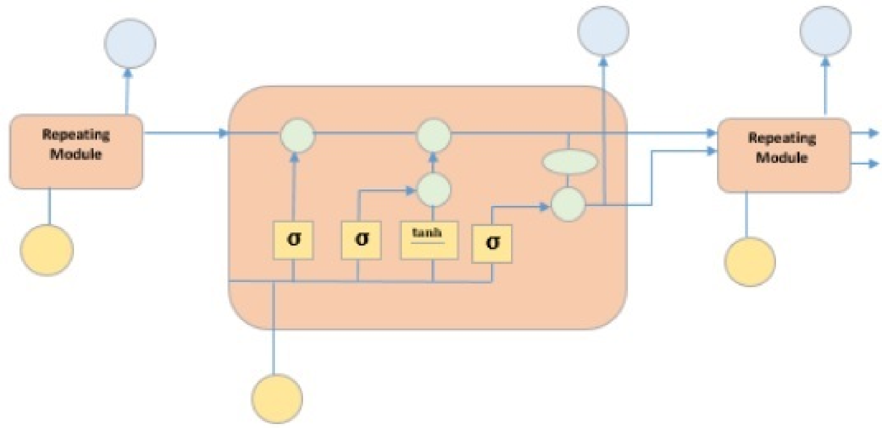


Fig.1.2: LSTM Module

In the image above, input is shown as yellow circles, point wise operators are shown as green circles, four neural network layers are shown as yellow boxes, and cell state is shown as blue circles. The ability to selectively learn, unlearn, or retain knowledge from each of the units is provided by an LSTM module, which has a cell state and three gates. By allowing just a few linear exchanges, the cell state in LSTM aids in the information's uninterrupted flow across the units. Each component contains an input, output, and forget gate that can add or remove data from the cell state. A sigmoid function is used by the forget gate to determine which information from the previous cell state should be forgotten. The input gate uses a point-wise multiplication operation of "sigmoid" and "tanh" to control the information flow to the current cell state. The output gate ultimately determines which data should be transferred to the following hidden state.

1.3. Project objectives

1. To predict the load type based on past dataset attributes and improves the accuracy of load forecasting using machine learning.
2. To enhance the performance of the overall prediction results.
3. Comparative study with other recent models.

CHAPTER: 2

LITERATURE REVIEW

In the last ten years, a range of methodologies have been used in the field of load forecasting. The most often used models are those that use regression. Artificial intelligence (AI) in various forms [8, 9], like particle swarm optimization (PSO), auto-regressive moving average (ARMA), and its modified version [10–13] are examples of time series models. [14, 15] are some of the other approaches that have been successfully used. These methods have shown to be quite successful. Additionally, hybrid approaches [16, 17], which combine many individual strategies, have been examined in the literature. Combining time-series analysis with breakdown has helped certain forecasting efforts be successful while using less computational power.

Electricity forecasting is required to help the power-producing firm provide enough power for expected consumer use. Short-term, medium-term, and long-term electricity predictions are applicable [20]. The purpose of the study is to determine which electricity forecast type should be used. Typically, forecasts in the short-term category range from an hour to a week. The long-term forecast category typically predicts beyond a year, whereas the medium-term forecast category typically predicts within a week to a year [21] [22]. Predicting the short-term electrical load was the main concentrate of most investigations [20]. Because electricity cannot be stored for an extended period of time, it must be given immediately to the user. The short-term forecast will assist in determining the anticipated electrical load demand, at the very least for the upcoming hour [20].

Accuracy has a big impact on the economy. Savings can be significant even with a very minor reduction in forecasting errors. Accurate forecasting results in significant operational and maintenance cost reductions, better power supply and delivery system reliability, and wise development decisions. Overestimating the amount of load results in wasteful reserve and increased operating expenses. Underestimating load forecasts limits the system from having the necessary spinning and standby reserve and stability, which could result in the network's collapse. Geographical location, the consumer mix in the service area, weather conditions, seasonal effects, time of day, day of week, and random disturbances are just a few of the variables that might affect STLF. Up until now, it has been challenging to predict future loads, particularly on days with harsh weather, on vacations, and on other unusual days. It is now possible to enhance the prediction of outcomes thanks to the recent development of new mathematical, data mining, and artificial intelligence techniques [24].

Over the past few years, various methods for load forecasting have been developed. At first, a variety of mathematical models were put forth, but they were operationally costly, lacked the robustness to account for weekends and holidays, and couldn't adequately simulate the meteorological factors. [25] While regression models may analyse the relationship between load and affecting factors, they are computationally intensive. An investigation has been done on the use of artificial intelligence (AI) approaches to the load forecasting issue as a result of AI tools' improved short-term load forecasting performance versus conventional methods [23]. In the literature, machine learning, fuzzy inference, neural networks, and fuzzy-neural models are examples of AI techniques.

CHAPTER: 3

SYSTEM PROPOSAL

3.1. Existing system

The accuracy of short-term load forecasting is currently improved using the LSTM model approach. In addition to utilising the useful information and possible features present in the vast previous input data, the suggested method uses a deep network to learn the temporal information through the LSTM network. The unpredictability of power loads will increase due to the growing load of electric vehicles and the ongoing promotion of distributed renewable energy, making it harder to anticipate the load with any degree of accuracy.

3.2. Disadvantages

1. Theoretical Limits.
2. Loss of Information.
3. Incorrect Forecast Results.

3.3. Proposed system

1. The proposed model is introduced to overcome all the disadvantages that arise in the existing system.
2. In our proposed system we are going to use Machine learning algorithms for the prediction of weekend/weekday load.
3. It enhances the performance of the overall prediction results.

3.4. Advantages

1. High performance.
2. Provide accurate prediction results.
3. Reduces the information loss and the bias of the inference due to the multiple estimates.

CHAPTER: 4

SYSTEM DIAGRAMS

4.1. Architecture diagram

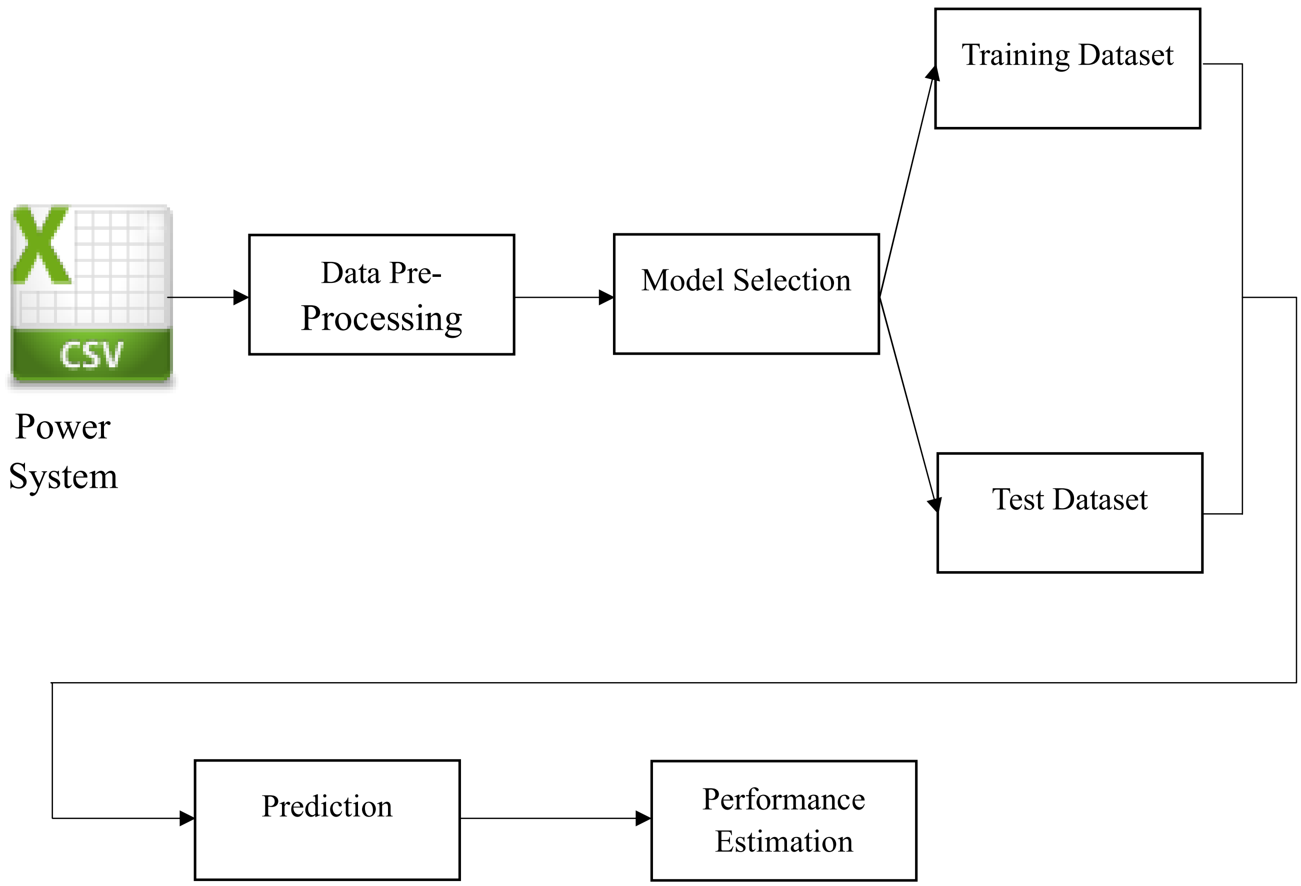


Fig.4.1: Systematic model of LSTM

4.2. Flow diagram

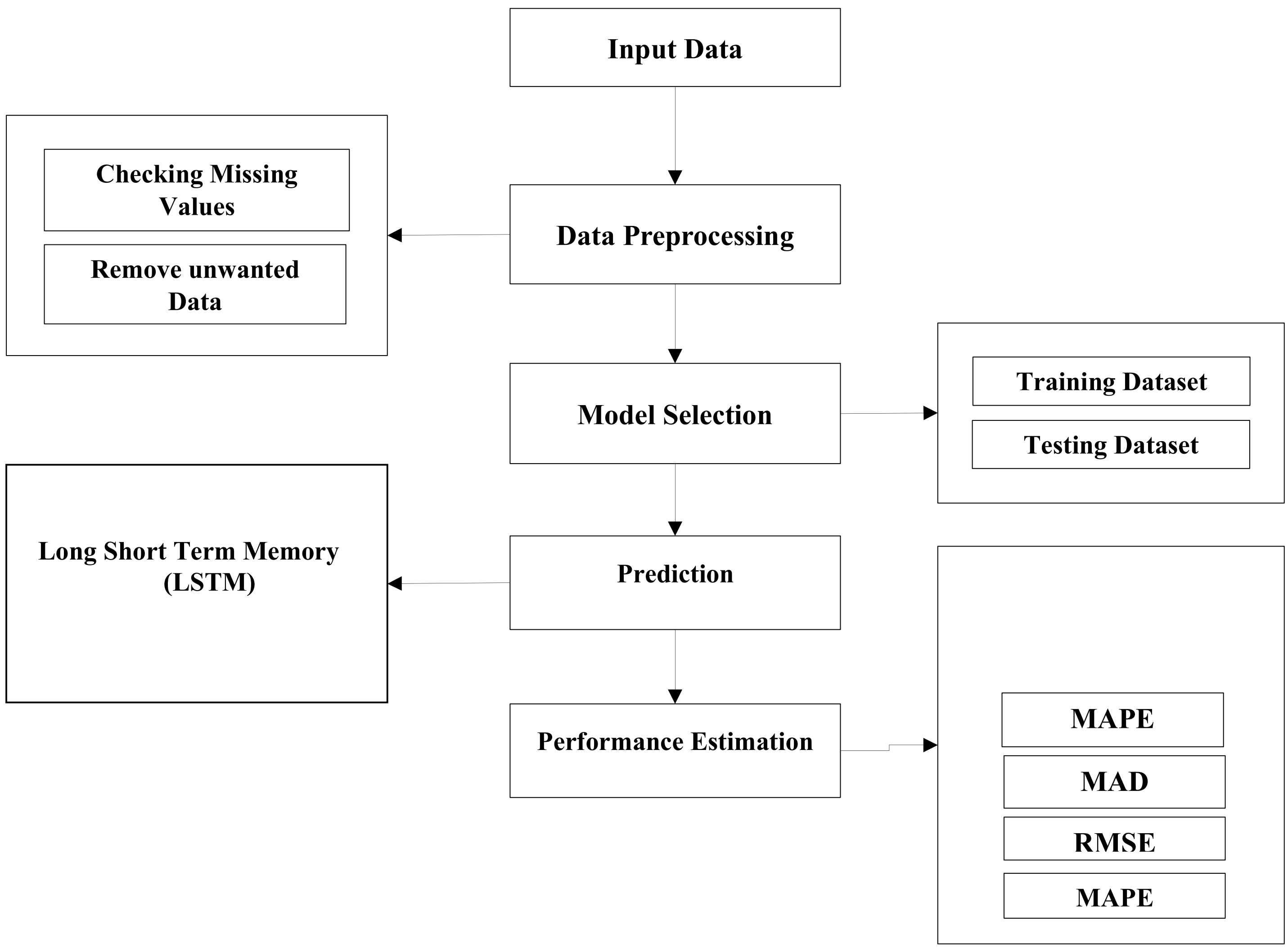


Fig.4.2: Flowchart diagram of LSTM model working

CHAPTER: 5

METHODOLOGY

5.1. Modules

1. Data Selection and Loading
2. Data Preprocessing
3. Data Splitting
4. Forecasting Method

5.2. Modules description

5.2.1. Data selection and loading

1. The data selection is the process of selecting the data for weekday/weekend prediction from power system load past data.

2. The dataset contains the information date, time in hour and load in KW

3. The load data for the year 2018 is being taken on an hourly basis.

5.2.2. Data preprocessing

1. Data pre-processing is the process of removing the unwanted data from the dataset.

2. Missing data removal: In this process, the null values such as missing values and Nan values are replaced by 0.

3. Getting data: That categorical data is defined as variables with a finite set of rescaled values. That most machine learning algorithms require array input and output variables.

5.2.3. Splitting dataset into train and test data

1. Data splitting is the act of partitioning available data into two portions, usually for cross-validate purposes.
2. One Portion of the data is used to develop a predictive model and the other to evaluate the model's performance.
3. Separating data into training and testing sets is an important part of evaluating data mining models.
4. Typically, when we separate a data set into a training set and testing set, most of the data is used for training, and a smaller portion of the data is used for testing.

Long short term memory, or LSTM, is a neural network that has numerous uses, including the prediction of time series. An LSTM network produces the greatest time series analysis and load prediction results based on the LSTMs' structure and basic learning. Long Short Term Memory networks have been proven to be the appropriate solution for nearly all of these sequence forecasting challenges when taking into account the most recent research findings. LSTMs outperform intermittent neural networks and conventional feed-forward neural networks in a range of applications.

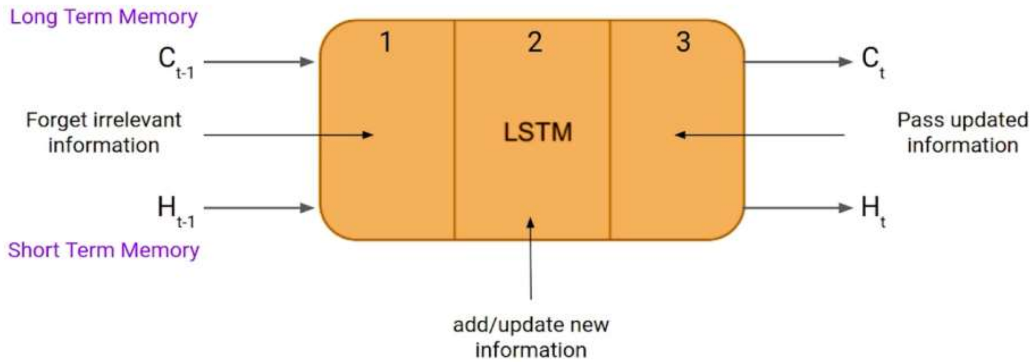


Fig.5.1: Basic depiction of the LSTM cell

The sigmoid function must be utilized to thoroughly convert the previously added input before adding new data to a basic neural network. A change to the entire set of data outcomes as a result. This implies that the distinction between information that is "important" and information that is "not so important" is ignored. However, the information is only significantly multiplied and added by LSTMs. In LSTMs, information travels through the cell state layer. This technique allows LSTMs to either entirely forget or retrieve information. from Figure 1. The hidden state is referred to as the short-term memory in this context, while the cell state is the long-term memory.

The accompanying diagram describes the internal structure of an LSTM network in more detail:

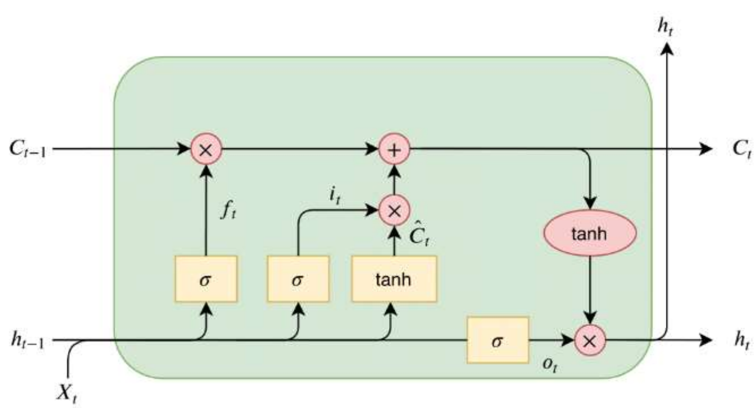


Fig.5.2: LSTM Architecture

A standard LSTM network consists of a large number of memory cells. The cell state and the hidden or concealed state are the two states that are being transferred to the new cell. The memory blocks are in charge of creating flashback effects, and three basic techniques known as gates are used to modify this memory.

a. **Forget Gate**

An LSTM network cell's first action is to decide whether to keep or throw away the information from the previous timestamp. Below is the forget gate equation.

$$\mathbf{f_t = \sigma (x_t * U_f + W_f)}$$

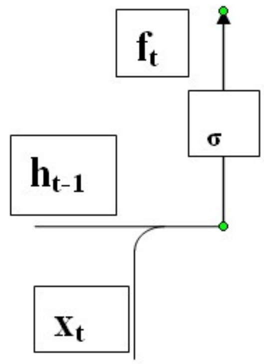


Fig.5.3: Forget Gate, Internal Architecture

Here,

σ: sigmoid activation function

X_t: input to the current timestamp.

U_f: weight associated with the input

H_{t-1}: Hidden state of the previous timestamp

W_f: It is the weight matrix associated with hidden state

$C_{t-1} * f_t = 0$ ...if $f_t = 0$ (forget everything)

$C_{t-1} * f_t = C_{t-1}$ ...if $f_t = 0$ (forget everything)

The network will forget everything if f_t is 0, but it won't forget anything if f_t is set to 1.

b. **Input Gate**

The input gate calculates the value of the new information being carried by the input. The equation for the input gate is shown below.

$$\mathbf{i_t = \sigma (x_t * Ui \ + H_{t-1} * Wi)}$$

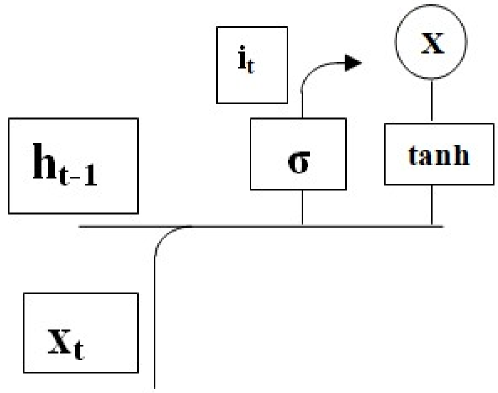


Fig.5.5: Input Gate, Internal Architecture

Here,

σ: sigmoid activation function

X_t: Input at the current timestamp t

U_i: weight matrix of input

H_{t-1}: A hidden state at the previous timestamp

W_i: Weight matrix of input associated with hidden state.

- **New information**
  $\mathbf{N_t = tanh\ (x_t * U_c + H_{t-1} * W_c\ )}$

The hidden state at timestamp t-1 in the past and the input x at timestamp t determine the new data that needed to be transmitted to the cell state at this moment. In this instance, Tanh is the activation function. The fresh information's value ranges from -1 to 1, according to the tanh function. If the value of N_t is negative, the information is taken out of the cell state, and if it is positive, it is added to the cell state at the current timestamp.

However, the N_t won't be added to the cell state right away. The updated equation is given here.

$\mathbf{C_t = f_t * C_{t-1} + i_t * N_t}$

c. **Output Gate**

The Output gate's equation, which is quite identical to the ones for the preceding two gates, is shown below.

$\mathbf{O_t = \sigma\ (x_t * Uo\ \ +H_{t-1} * W_o)}$

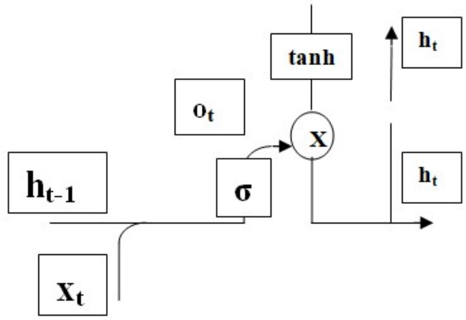


Fig.5.6: Output Gate, Internal Architecture

It will also be between 0 and 1 due to this sigmoid function. To determine the current hidden state, we will now compute o_t and tanh using the updated cell state. As displayed below.

$Ht = o_t * tanh(C_t)$

It will also have a value between 0 and 1 because of this sigmoid function. We will now compute the most recent hidden state using the updated cell state's o_t and tanh functions. As displayed below.

Output = Softmax (H_t)

Here the token with the maximum score in the output is the prediction.

Activation function

Tanh : The Tanh function is used to modify the function output threshold. [1, 1], is the value range.

$$f(x) = \frac{1-e^{-2x}}{1+e^{-2x}}$$

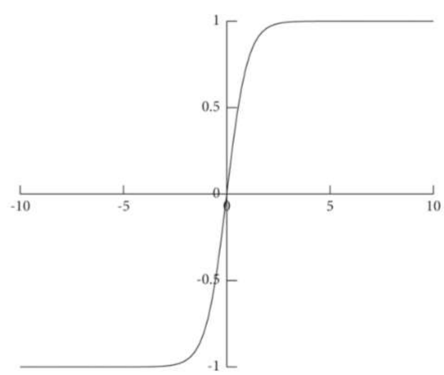


Fig.5.7: Tanh activation function graph

Sigmoid: The Sigmoid activation function has a value range of (0, 1) and is comparable to the Tanh activation function.

$$\sigma = \frac{1}{1+e^{x}}$$

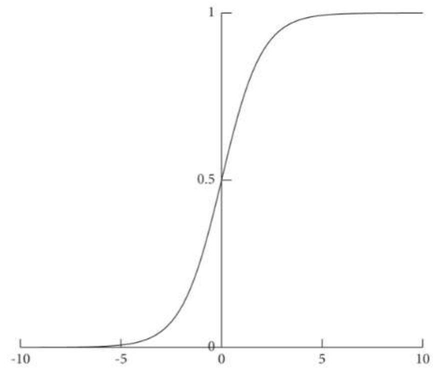


Fig.5.7: Sigmoid activation function graph

d. **Perfromance estimation parameters**

1) Mean Square Error

It is the average of square of difference between the predicted values and true values. It has the same units as the true and predicted values squared and is always positive.

$$\frac{1}{n}\sum_{t=1}^{n}(y'_t - y_t)^2$$

Where

y'_t is the predicted value
y_t is the actual value
n is the total number of values in the data set

2) Root Mean Square Error

It is the square root of the mean square error. It is also always positive and is in the range of the data.

$$\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y'_t - y_t)^2}$$

Where

y'_t is the predicted value
y_t is the actual value
n is the total number of values in the data set

3) Mean Absolute Percentage Error

It is the average percent difference between the actual value and the value that is projected divided by the true value.

$$\frac{1}{n}\sum_{t=1}^{n}\frac{y'_t - y_t}{y_t} \times 100\%$$

Where

y'_t is the predicted value
y_t is the actual value
n is the total number of values in the data set

4) Mean Absolute Deviation

It is the mean of the absolute deviations from the centre.

$$\frac{1}{n}\sum_{t=1}^{n}|x_i - m(X)|$$

Where

m(X) is the average value of the dataset
x_i is the data values in the dataset
n is the total number of values in the data set

CHAPTER: 6

MODELLING STUDY SETUP ANALYSIS

6.1. Dataset

The power department provided the raw, real-time data. On an hourly basis, the load dataset for 2018 was collected, and 8742 samples were there for a year. The dataset includes the date, time in hours, and load in KW that were utilised to predict the load.

Table 6.1: Arrangement of real time past raw data

SL.NO.	DATE AND TIME (IN HOUR)	LOAD CONSUMPTION (IN KW)
1	01-01-2018 00:00	958.9889
2	01-01-2018 01:00	927.2573
3	01-01-2018 02:00	917.108
4	01-01-2018 03:00	892.7452
5	01-01-2018 04:00	871.409
6	01-01-2018 05:00	867.6174
7	01-01-2018 06:00	834.0206
8	01-01-2018 07:00	826.7753
9	01-01-2018 08:00	862.4476
10	01-01-2018 09:00	908.8466
11	01-01-2018 10:00	907.9955
12	01-01-2018 11:00	955.3573
13	01-01-2018 12:00	929.1913
14	01-01-2018 13:00	951.5704
15	01-01-2018 14:00	944.4715
16	01-01-2018 15:00	916.5776
17	01-01-2018 16:00	915.0416
18	01-01-2018 17:00	896.9411
19	01-01-2018 18:00	1012.6848
20	01-01-2018 19:00	1083.0473
21	01-01-2018 20:00	1080.5878
22	01-01-2018 21:00	1075.2159
23	01-01-2018 22:00	1049.0289

6.2. Proposed algorithm

Step 1: Download the Libraries.

Step 2: Realise how to visualise dataset for load prediction.

Step 3: Publish the dataframe shape, check that there are no null values.

Step 4: Identify the features and setting the target variable and normalise the data.

Step 5: Generating a test and a training dataset for load prediction.

Step 6: Construct the LSTM (Long Short Term Memory) model for load prediction.

Step 7: Final load prediction.

Step 8: Evaluation of LSTM (Long Short Term Memory) model's projected vs. real values.

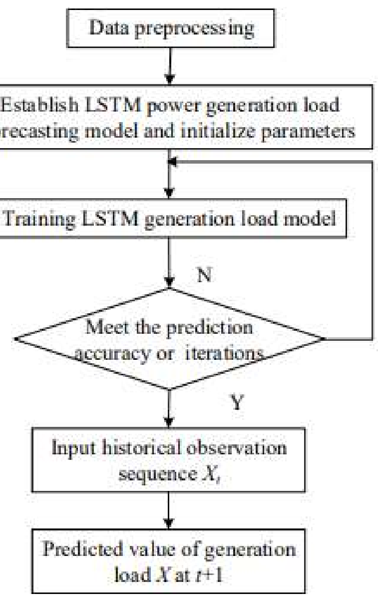


Fig.6.1: Flowchart of load forecasting based on LSTM

7.3. Software Requirements

1. O/S : Windows 10
2. Language : Python
3. SPYDER platform for Python programming

Python

One of the few languages that can be both simple as well as effective is Python. We are pleasantly astonished to discover how simple it is to focus on the problem's solution rather than the syntax and organization of the programming language. Python is a strong programming language that is simple to learn, according to the official introduction. Its object-oriented programming methodology is clear but efficient, and it includes good high-level data structures. Python's interpreted nature, logical syntax, and flexibility in typing make it the perfect language for scripting and quick application development across a wide range of platforms.

7.4. Working model

In our proposed approach, the LSTM (Long Short Term Memory) model is interfaced with the Python programming language in the spyder software using the KERAS library. All 8742 samples in total are present in this model for an entire year which is then divided into weekdays and weekends (Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday) separately.

Here, we have a data frame with 1269 samples for a specific day.

The training dataset uses 67% of the samples, whereas the testing dataset uses 33% of the samples where the

ADAM optimizer is used, which stands for adaptive moment estimation for training and optimizing the model's parameter and learning rates to find optimal configuration of the dataset. The learning rate is an adjustment parameter in an optimization method used in machine learning and statistics that controls the step size at each iteration while working towards a minimum of a loss function. A learning rate of 0.01 is applied in this model.

The proposed model included 50 epochs, which is the term for one complete iteration of the algorithm through the training set of data, with batch sizes of 848 and batch numbers of 1. Following this, a network with two hidden layers, also known as an LSTM (Long Short Term Memory) layer, is constructed. Each LSTM (Long Short Term Memory) layer has 128 numbers of units or neurons with a dropout of 0.2 or 20% and 1 dense layer for the last output.

In machine learning, the term verbose describes the particular setting used for model training and validation. When verbose is enabled, the algorithm will give more thorough updates on its progress as the model goes through training iterations. One line per epoch is the verbose for a value 2 utilised in this model.

The input layer in the illustration given below receives the input data, which is then transferred to the LSTM 1 layer, which has 128 units/neurons. By randomly changing a portion of the input units to 0 during training, a dropout layer with a dropout rate of 0.2 is applied after LSTM 1 to assist prevent overfitting. The second LSTM layer (LSTM 2) receives the output of the dropout layer and forwards it with 128 units/neurons. The output of the second LSTM is similarly sent through a second dropout layer with a dropout rate of 0.2. The final output is created by feeding the dropout layer's output into the dense layer with one unit.

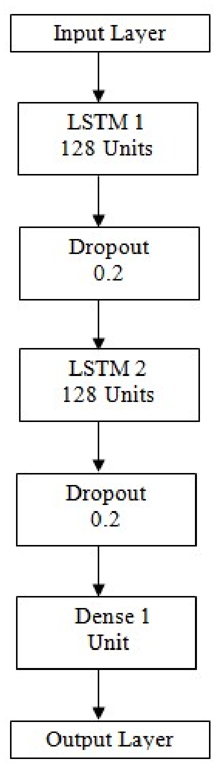


Fig.6.2: Flowchart of LSTM (Long Short Term Memory) layer

CHAPTER: 7

RESULT AND DISCUSSIONS

7.1. Prediction

1. It's a process of predicting weekend/weekday load from past load dataset.
2. This project effectively predicted the weekend/weekday load from dataset by enhancing the performance of the overall prediction results.

7.2. Result generation

This research successfully predicted the weekends and weekdays load from the historical dataset by improving the performance of the overall prediction findings. Based on the overall projection, the final result is generated and displayed below, along with predicted values and graphs for the weekdays and weekends.

Here, the original dataset is displayed in blue, the training dataset's predictions are displayed in green, and the predicted timeframes for the test dataset are displayed in red:-

MONDAY

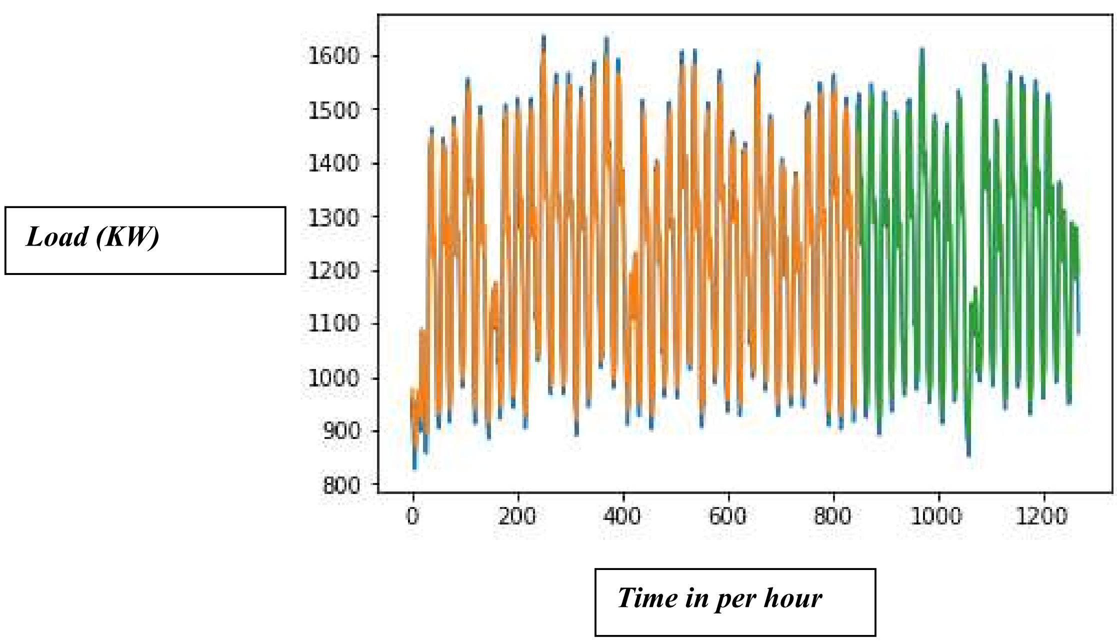
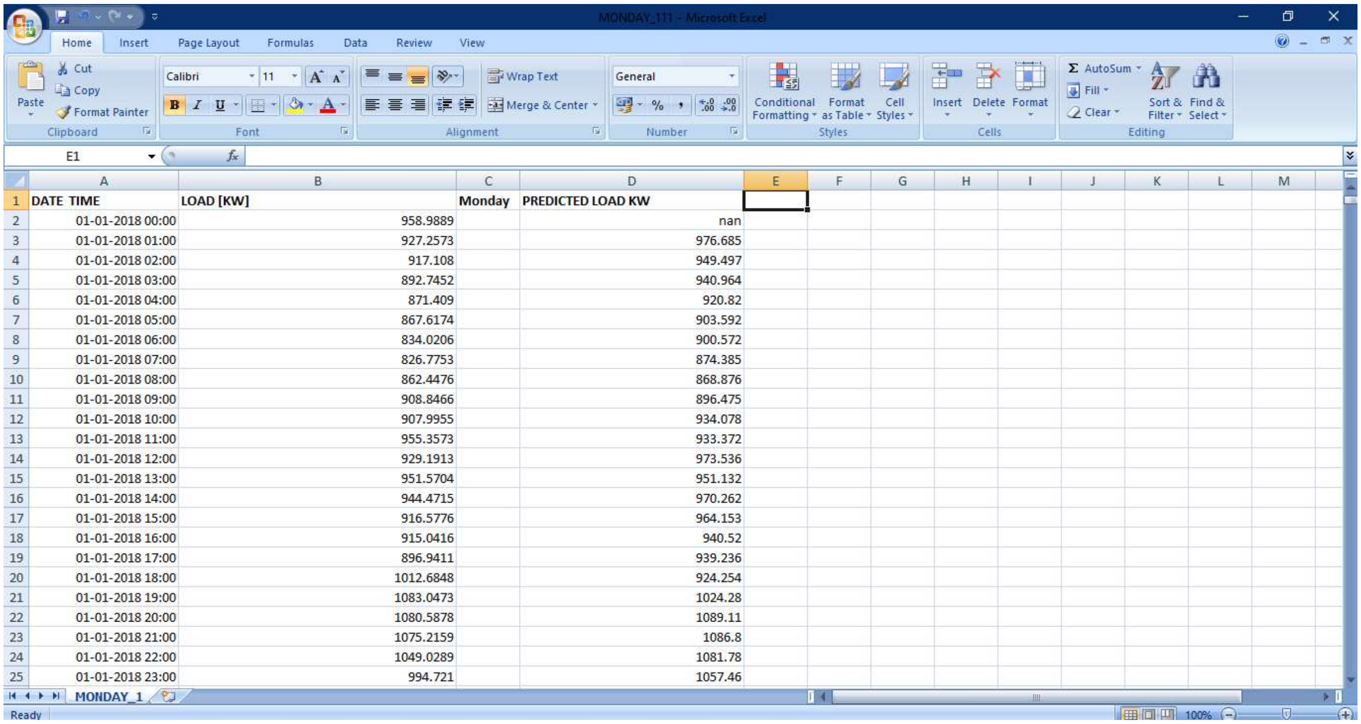


Fig.7.1: Actual load v/s Predicted load for all Mondays in a year



	A	B	C	D
1	DATE TIME	LOAD [KW]	Monday	PREDICTED LOAD KW
2	01-01-2018 00:00	958.9889		nan
3	01-01-2018 01:00	927.2573		976.685
4	01-01-2018 02:00	917.108		949.497
5	01-01-2018 03:00	892.7452		940.964
6	01-01-2018 04:00	871.409		920.82
7	01-01-2018 05:00	867.6174		903.592
8	01-01-2018 06:00	834.0206		900.572
9	01-01-2018 07:00	826.7753		874.385
10	01-01-2018 08:00	862.4476		868.876
11	01-01-2018 09:00	908.8466		896.475
12	01-01-2018 10:00	907.9955		934.078
13	01-01-2018 11:00	955.3573		933.372
14	01-01-2018 12:00	929.1913		973.536
15	01-01-2018 13:00	951.5704		951.132
16	01-01-2018 14:00	944.4715		970.262
17	01-01-2018 15:00	916.5776		964.153
18	01-01-2018 16:00	915.0416		940.52
19	01-01-2018 17:00	896.9411		939.236
20	01-01-2018 18:00	1012.6848		924.254
21	01-01-2018 19:00	1083.0473		1024.28
22	01-01-2018 20:00	1080.5878		1089.11
23	01-01-2018 21:00	1075.2159		1086.8
24	01-01-2018 22:00	1049.0289		1081.78
25	01-01-2018 23:00	994.721		1057.46

Fig.7.2: Image of excel sheet showing actual load and predicted load for Monday in KW arranged together

TUESDAY

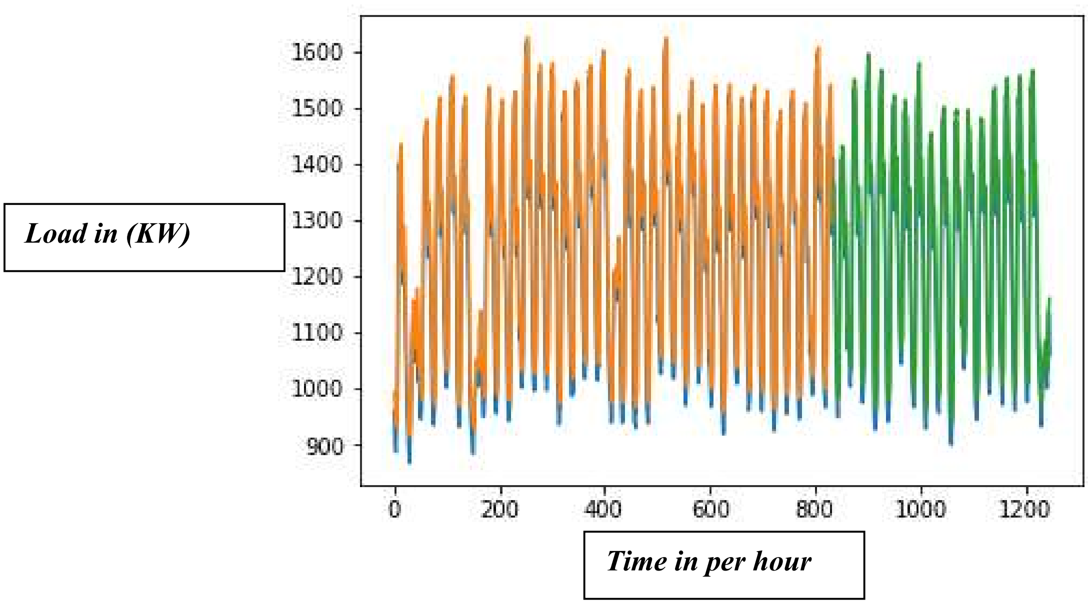
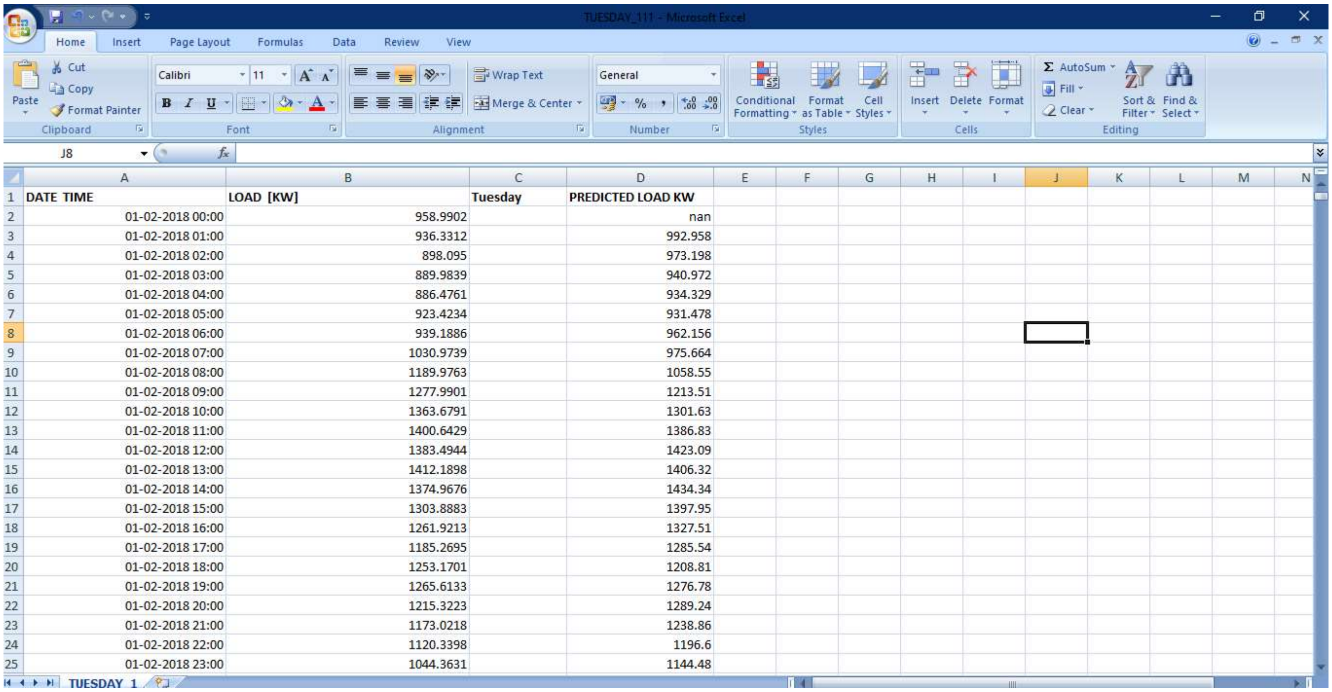


Fig.7.3: Actual load v/s Predicted load for all Tuesday’s in a year



DATE TIME	LOAD [KW]	Tuesday	PREDICTED LOAD KW
01-02-2018 00:00	958.9902		nan
01-02-2018 01:00	936.3312		992.958
01-02-2018 02:00	898.095		973.198
01-02-2018 03:00	889.9839		940.972
01-02-2018 04:00	886.4761		934.329
01-02-2018 05:00	923.4234		931.478
01-02-2018 06:00	939.1886		962.156
01-02-2018 07:00	1030.9739		975.664
01-02-2018 08:00	1189.9763		1058.55
01-02-2018 09:00	1277.9901		1213.51
01-02-2018 10:00	1363.6791		1301.63
01-02-2018 11:00	1400.6429		1386.83
01-02-2018 12:00	1383.4944		1423.09
01-02-2018 13:00	1412.1898		1406.32
01-02-2018 14:00	1374.9676		1434.34
01-02-2018 15:00	1303.8883		1397.95
01-02-2018 16:00	1261.9213		1327.51
01-02-2018 17:00	1185.2695		1285.54
01-02-2018 18:00	1253.1701		1208.81
01-02-2018 19:00	1265.6133		1276.78
01-02-2018 20:00	1215.3223		1289.24
01-02-2018 21:00	1173.0218		1238.86
01-02-2018 22:00	1120.3398		1196.6
01-02-2018 23:00	1044.3631		1144.48

Fig.7:4: Image of excel sheet showing actual load and predicted load for Tuesday day in KW arranged together

WEDNESDAY

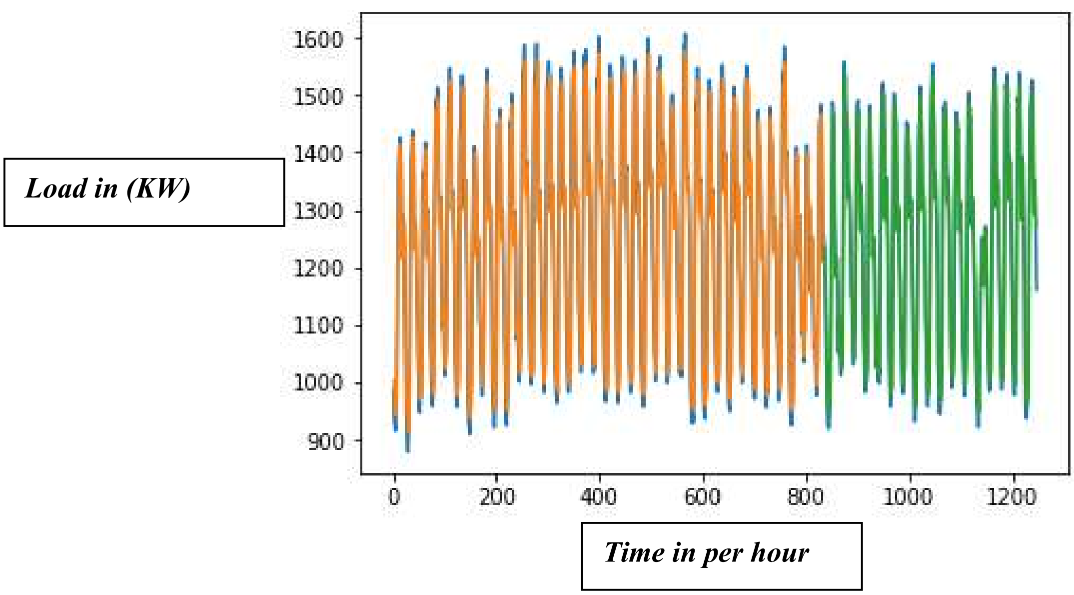
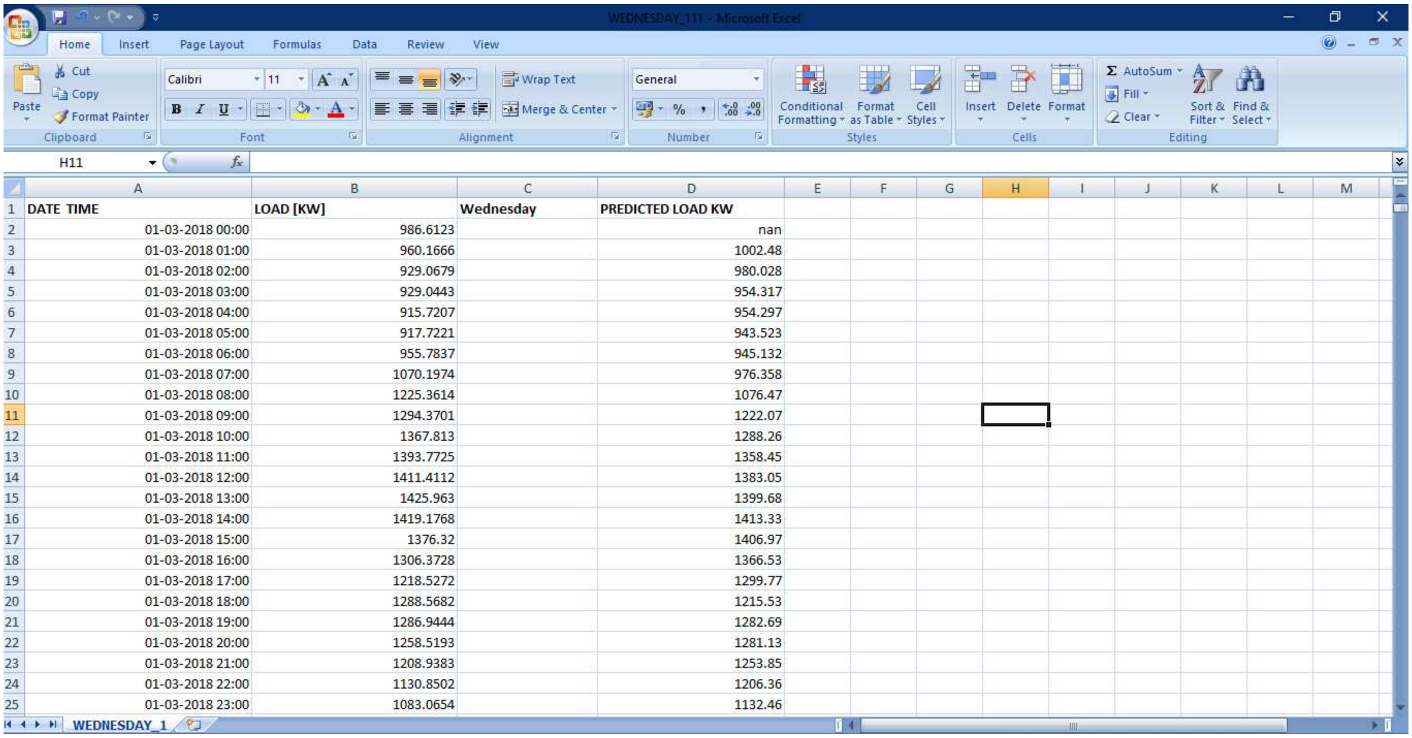


Fig.7.5: Actual load v/s Predicted load for all Wednesday's in a year



	A	B	C	D
1	DATE TIME	LOAD [KW]	Wednesday	PREDICTED LOAD KW
2	01-03-2018 00:00	986.6123		nan
3	01-03-2018 01:00	960.1666		1002.48
4	01-03-2018 02:00	929.0679		980.028
5	01-03-2018 03:00	929.0443		954.317
6	01-03-2018 04:00	915.7207		954.297
7	01-03-2018 05:00	917.7221		943.523
8	01-03-2018 06:00	955.7837		945.132
9	01-03-2018 07:00	1070.1974		976.358
10	01-03-2018 08:00	1225.3614		1076.47
11	01-03-2018 09:00	1294.3701		1222.07
12	01-03-2018 10:00	1367.813		1288.26
13	01-03-2018 11:00	1393.7725		1358.45
14	01-03-2018 12:00	1411.4112		1383.05
15	01-03-2018 13:00	1425.963		1399.68
16	01-03-2018 14:00	1419.1768		1413.33
17	01-03-2018 15:00	1376.32		1406.97
18	01-03-2018 16:00	1306.3728		1366.53
19	01-03-2018 17:00	1218.5272		1299.77
20	01-03-2018 18:00	1288.5682		1215.53
21	01-03-2018 19:00	1286.9444		1282.69
22	01-03-2018 20:00	1258.5193		1281.13
23	01-03-2018 21:00	1208.9383		1253.85
24	01-03-2018 22:00	1130.8502		1206.36
25	01-03-2018 23:00	1083.0654		1132.46

Fig.7.6: Image of excel sheet showing actual load and predicted load for Wednesday in KW arranged together

THURSDAY

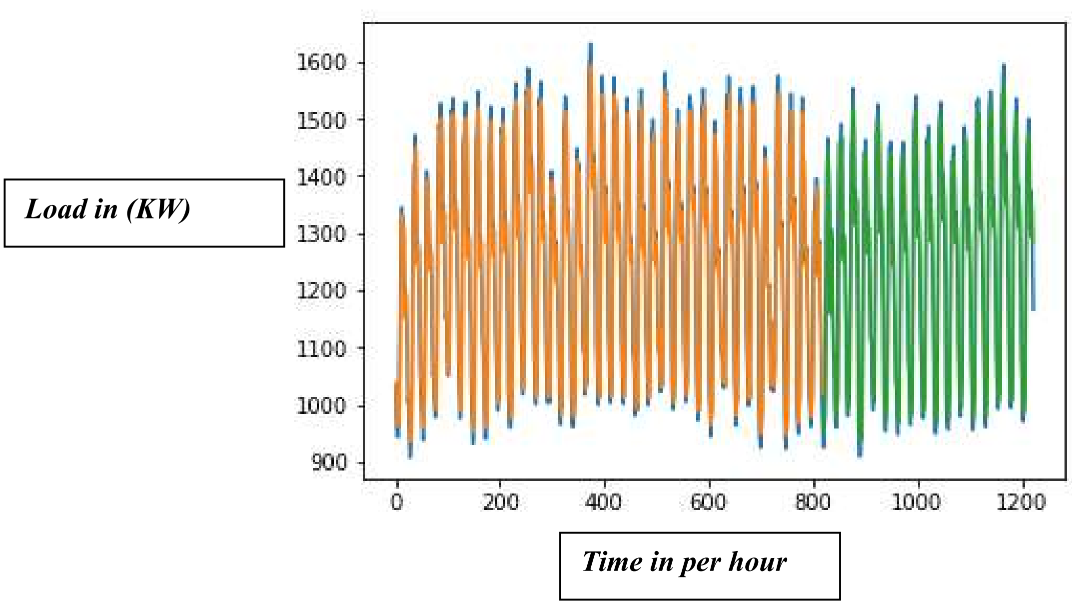
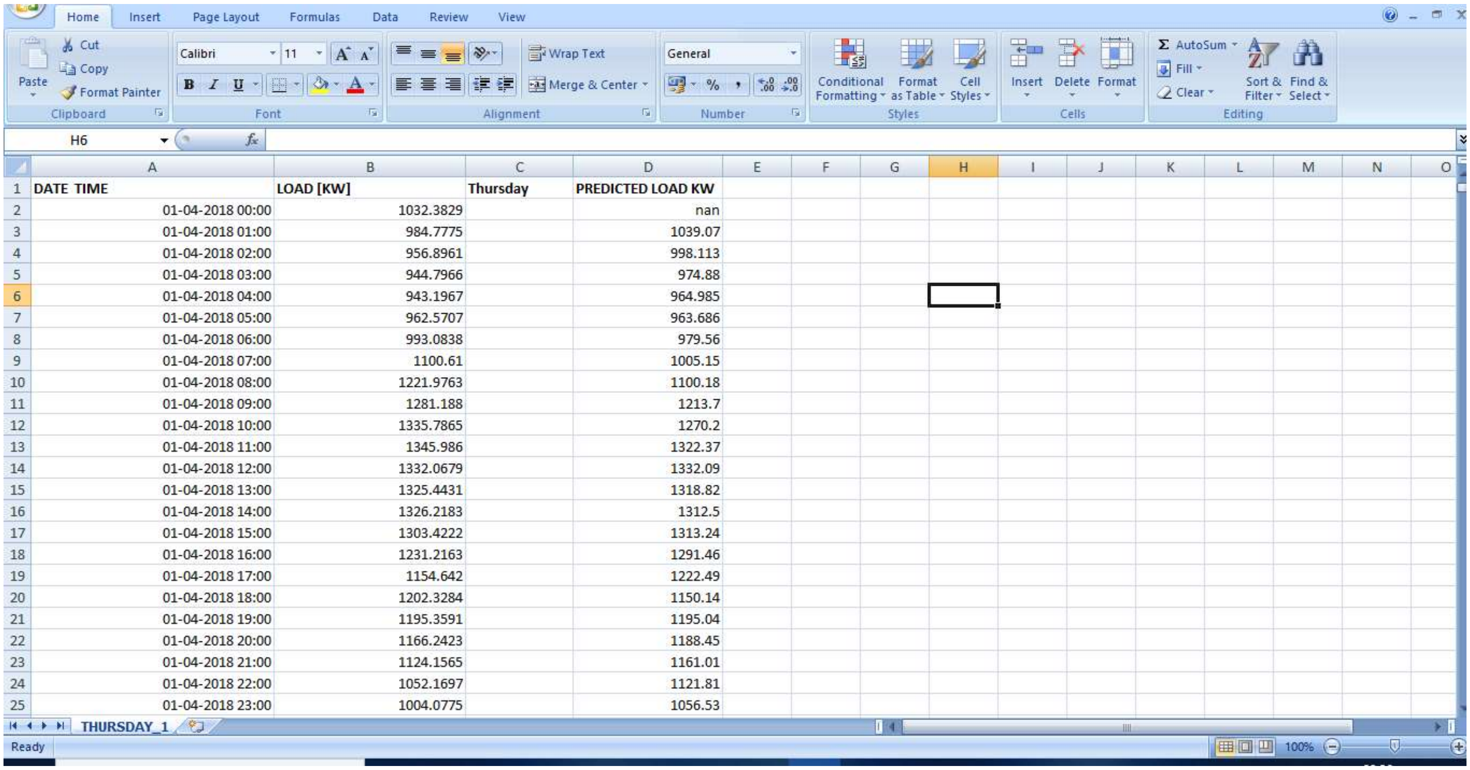


Fig.7.7: Actual load v/s Predicted load for all Thursday's in a year



	DATE TIME	LOAD [KW]	Thursday	PREDICTED LOAD KW
2	01-04-2018 00:00	1032.3829		nan
3	01-04-2018 01:00	984.7775		1039.07
4	01-04-2018 02:00	956.8961		998.113
5	01-04-2018 03:00	944.7966		974.88
6	01-04-2018 04:00	943.1967		964.985
7	01-04-2018 05:00	962.5707		963.686
8	01-04-2018 06:00	993.0838		979.56
9	01-04-2018 07:00	1100.61		1005.15
10	01-04-2018 08:00	1221.9763		1100.18
11	01-04-2018 09:00	1281.188		1213.7
12	01-04-2018 10:00	1335.7865		1270.2
13	01-04-2018 11:00	1345.986		1322.37
14	01-04-2018 12:00	1332.0679		1332.09
15	01-04-2018 13:00	1325.4431		1318.82
16	01-04-2018 14:00	1326.2183		1312.5
17	01-04-2018 15:00	1303.4222		1313.24
18	01-04-2018 16:00	1231.2163		1291.46
19	01-04-2018 17:00	1154.642		1222.49
20	01-04-2018 18:00	1202.3284		1150.14
21	01-04-2018 19:00	1195.3591		1195.04
22	01-04-2018 20:00	1166.2423		1188.45
23	01-04-2018 21:00	1124.1565		1161.01
24	01-04-2018 22:00	1052.1697		1121.81
25	01-04-2018 23:00	1004.0775		1056.53

Fig.7.8: Image of excel sheet showing actual load and predicted load for Thursday in KW arranged together

FRIDAY

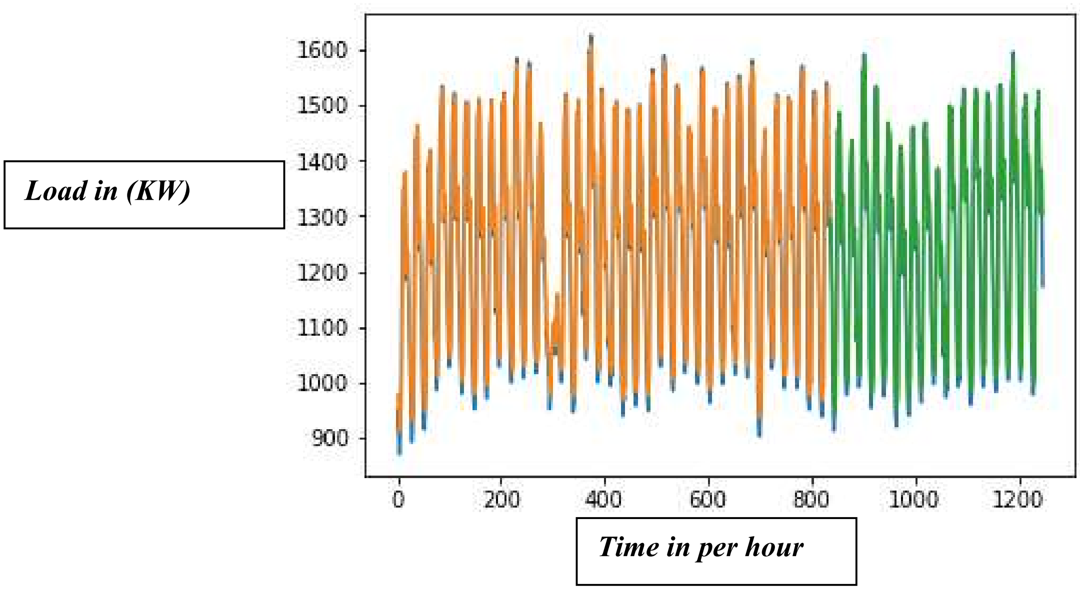
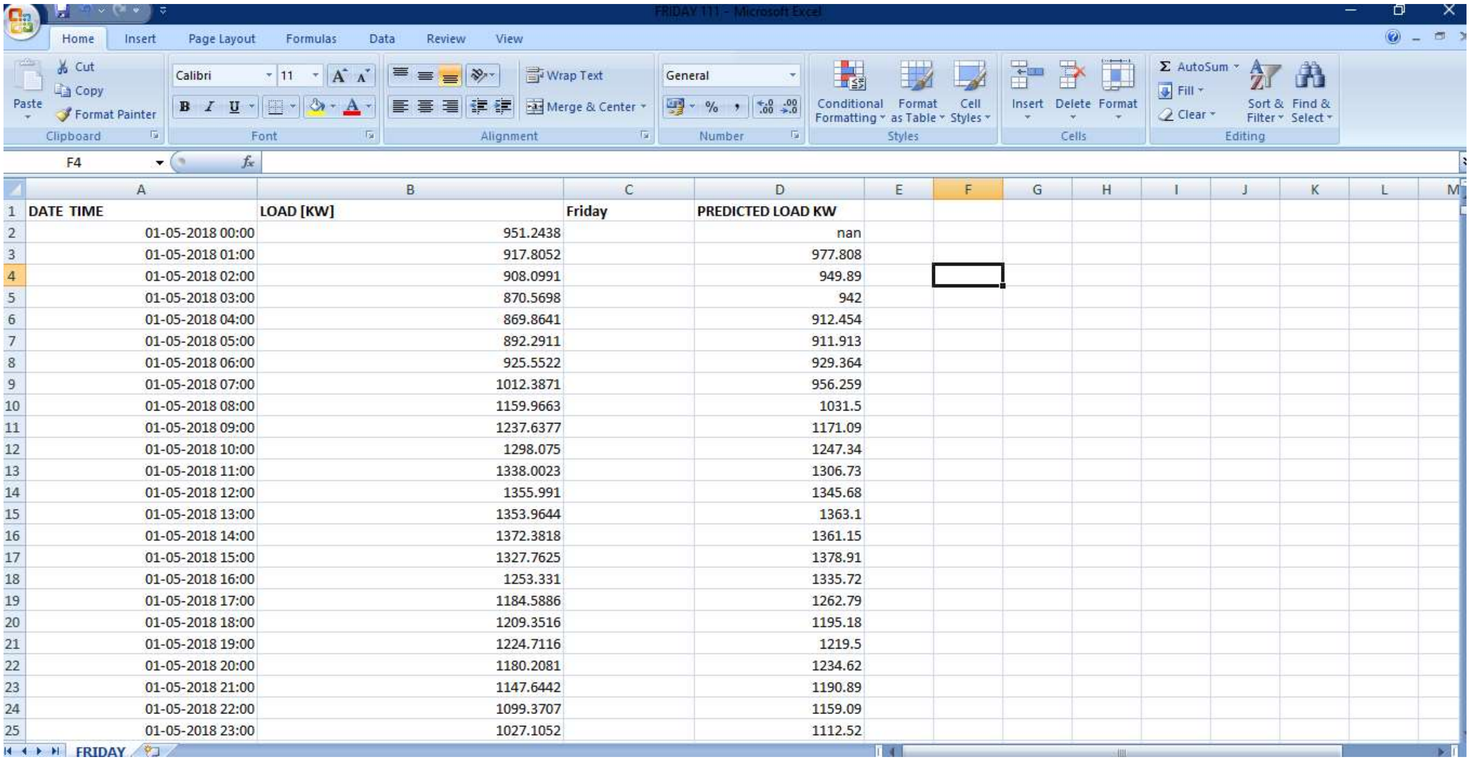


Fig.7.9: Actual load v/s Predicted load for all Friday's in a year



DATE TIME	LOAD [KW]	Friday	PREDICTED LOAD KW
01-05-2018 00:00	951.2438		nan
01-05-2018 01:00	917.8052		977.808
01-05-2018 02:00	908.0991		949.89
01-05-2018 03:00	870.5698		942
01-05-2018 04:00	869.8641		912.454
01-05-2018 05:00	892.2911		911.913
01-05-2018 06:00	925.5522		929.364
01-05-2018 07:00	1012.3871		956.259
01-05-2018 08:00	1159.9663		1031.5
01-05-2018 09:00	1237.6377		1171.09
01-05-2018 10:00	1298.075		1247.34
01-05-2018 11:00	1338.0023		1306.73
01-05-2018 12:00	1355.991		1345.68
01-05-2018 13:00	1353.9644		1363.1
01-05-2018 14:00	1372.3818		1361.15
01-05-2018 15:00	1327.7625		1378.91
01-05-2018 16:00	1253.331		1335.72
01-05-2018 17:00	1184.5886		1262.79
01-05-2018 18:00	1209.3516		1195.18
01-05-2018 19:00	1224.7116		1219.5
01-05-2018 20:00	1180.2081		1234.62
01-05-2018 21:00	1147.6442		1190.89
01-05-2018 22:00	1099.3707		1159.09
01-05-2018 23:00	1027.1052		1112.52

Fig.7.10: Image of excel sheet showing actual load and predicted load for Friday in KW arranged together

SATURDAY

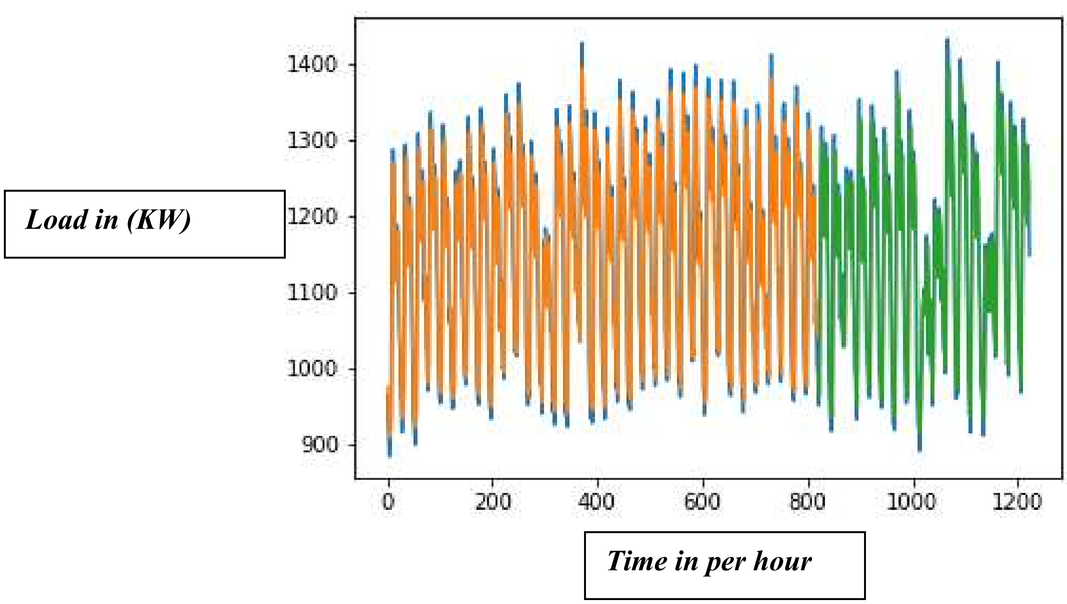
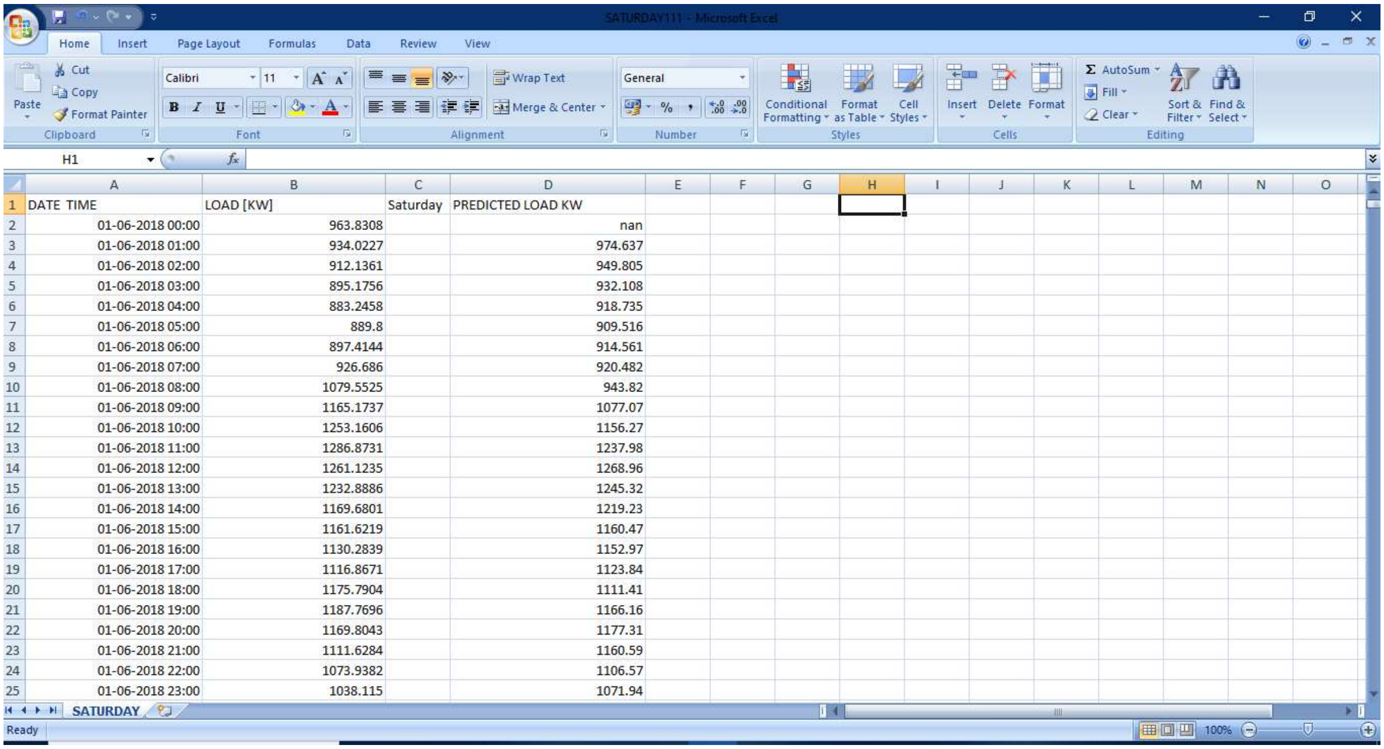


Fig.7.11: Actual load v/s Predicted load for all Saturday's in a year



	A	B	C	D
1	DATE TIME	LOAD [KW]	Saturday	PREDICTED LOAD KW
2	01-06-2018 00:00	963.8308		nan
3	01-06-2018 01:00	934.0227		974.637
4	01-06-2018 02:00	912.1361		949.805
5	01-06-2018 03:00	895.1756		932.108
6	01-06-2018 04:00	883.2458		918.735
7	01-06-2018 05:00	889.8		909.516
8	01-06-2018 06:00	897.4144		914.561
9	01-06-2018 07:00	926.686		920.482
10	01-06-2018 08:00	1079.5525		943.82
11	01-06-2018 09:00	1165.1737		1077.07
12	01-06-2018 10:00	1253.1606		1156.27
13	01-06-2018 11:00	1286.8731		1237.98
14	01-06-2018 12:00	1261.1235		1268.96
15	01-06-2018 13:00	1232.8886		1245.32
16	01-06-2018 14:00	1169.6801		1219.23
17	01-06-2018 15:00	1161.6219		1160.47
18	01-06-2018 16:00	1130.2839		1152.97
19	01-06-2018 17:00	1116.8671		1123.84
20	01-06-2018 18:00	1175.7904		1111.41
21	01-06-2018 19:00	1187.7696		1166.16
22	01-06-2018 20:00	1169.8043		1177.31
23	01-06-2018 21:00	1111.6284		1160.59
24	01-06-2018 22:00	1073.9382		1106.57
25	01-06-2018 23:00	1038.115		1071.94

Fig.7.12: Image of excel sheet showing actual load and predicted load for Saturday in KW arranged together

SUNDAY

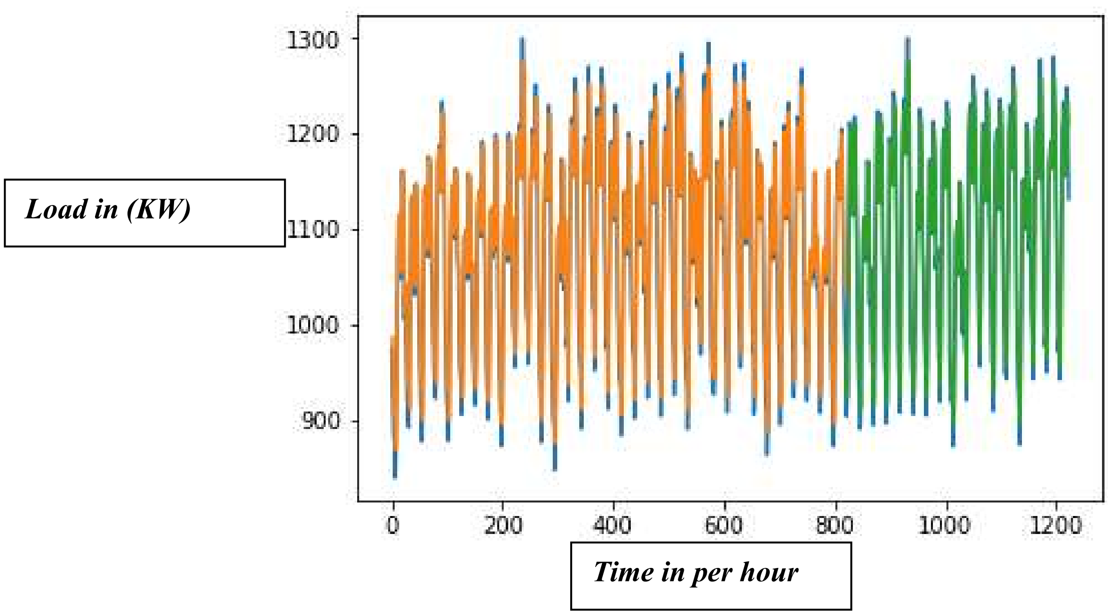
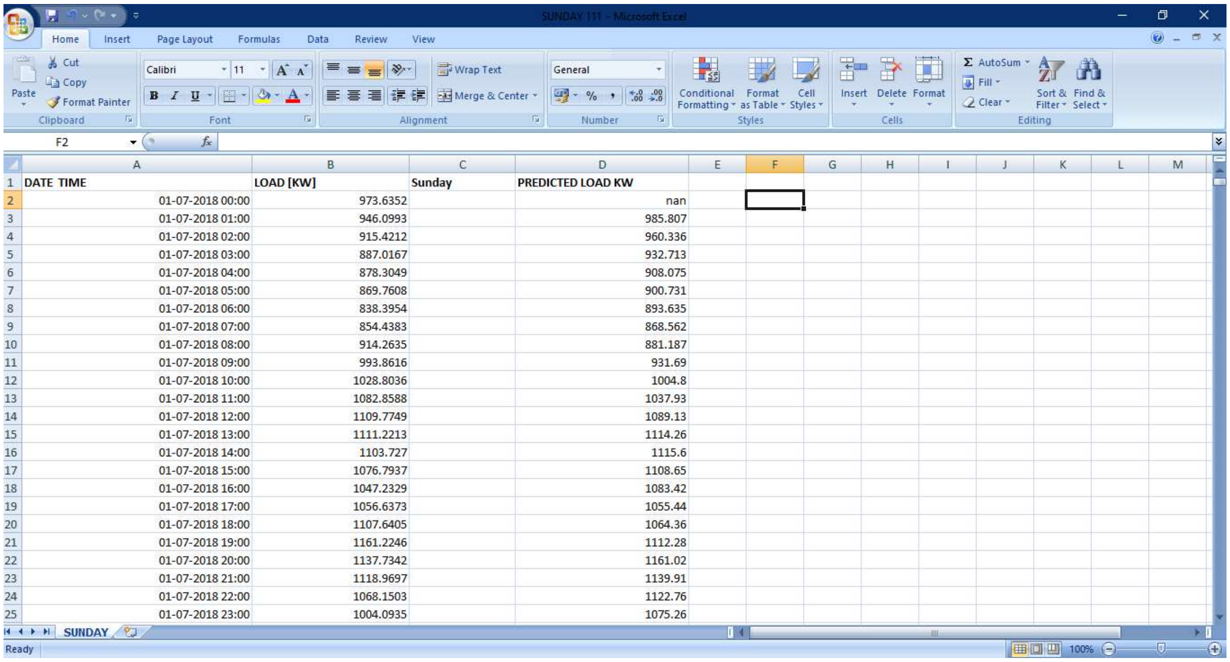


Fig.7.13: Actual load v/s Predicted load for all Sunday's in a year



	A	B	C	D
1	DATE TIME	LOAD [KW]	Sunday	PREDICTED LOAD KW
2	01-07-2018 00:00	973.6352		nan
3	01-07-2018 01:00	946.0993		985.807
4	01-07-2018 02:00	915.4212		960.336
5	01-07-2018 03:00	887.0167		932.713
6	01-07-2018 04:00	878.3049		908.075
7	01-07-2018 05:00	869.7608		900.731
8	01-07-2018 06:00	838.3954		893.635
9	01-07-2018 07:00	854.4383		868.562
10	01-07-2018 08:00	914.2635		881.187
11	01-07-2018 09:00	993.8616		931.69
12	01-07-2018 10:00	1028.8036		1004.8
13	01-07-2018 11:00	1082.8588		1037.93
14	01-07-2018 12:00	1109.7749		1089.13
15	01-07-2018 13:00	1111.2213		1114.26
16	01-07-2018 14:00	1103.727		1115.6
17	01-07-2018 15:00	1076.7937		1108.65
18	01-07-2018 16:00	1047.2329		1083.42
19	01-07-2018 17:00	1056.6373		1055.44
20	01-07-2018 18:00	1107.6405		1064.36
21	01-07-2018 19:00	1161.2246		1112.28
22	01-07-2018 20:00	1137.7342		1161.02
23	01-07-2018 21:00	1118.9697		1139.91
24	01-07-2018 22:00	1068.1503		1122.76
25	01-07-2018 23:00	1004.0935		1075.26

Fig.7.14: Image of excel sheet showing actual load and predicted load for Saturday in KW arranged together

By using these training and testing values of the dataset, the desired hourly prediction of the load is done. Here in the graphs, the blue colour indicates the actual load, and the red colour indicates the predicted load. Following are the figures shown below:-

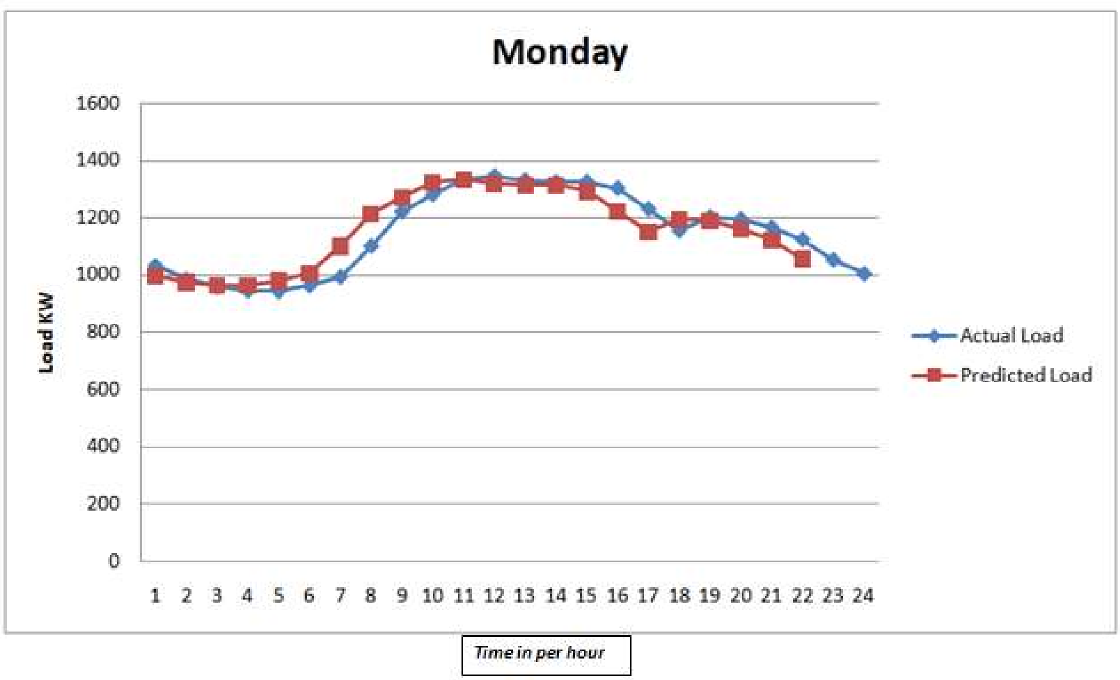


Fig.15: Actual v/s predicted load of Monday

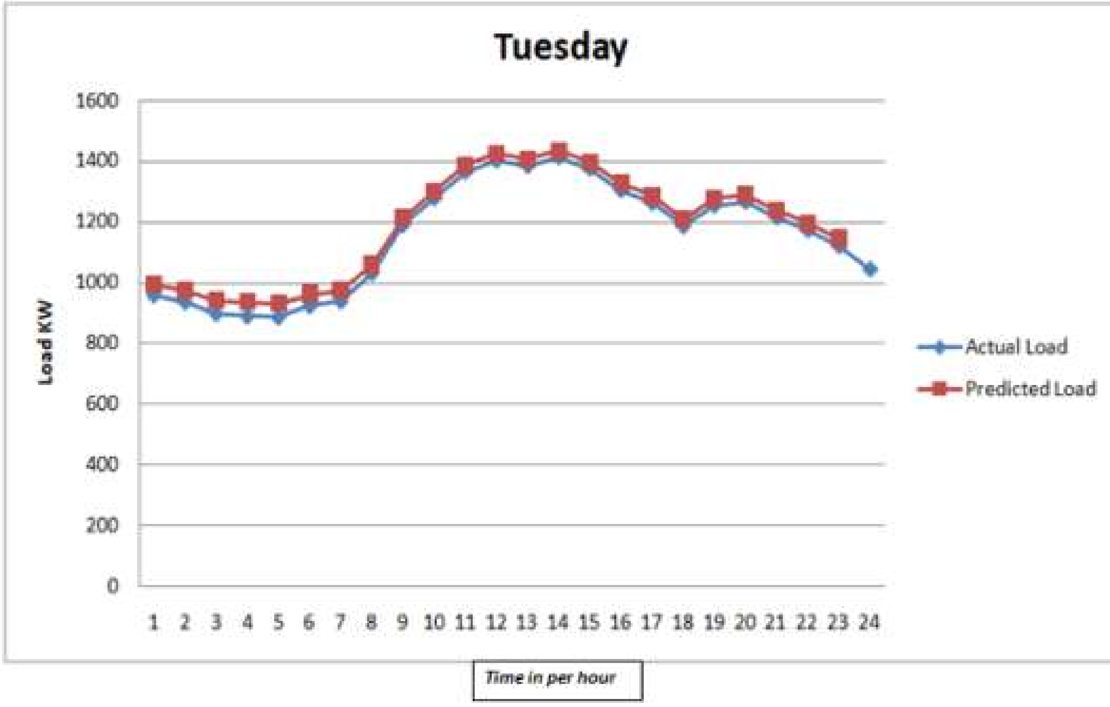


Fig.16: Actual v/s predicted load of Tuesday

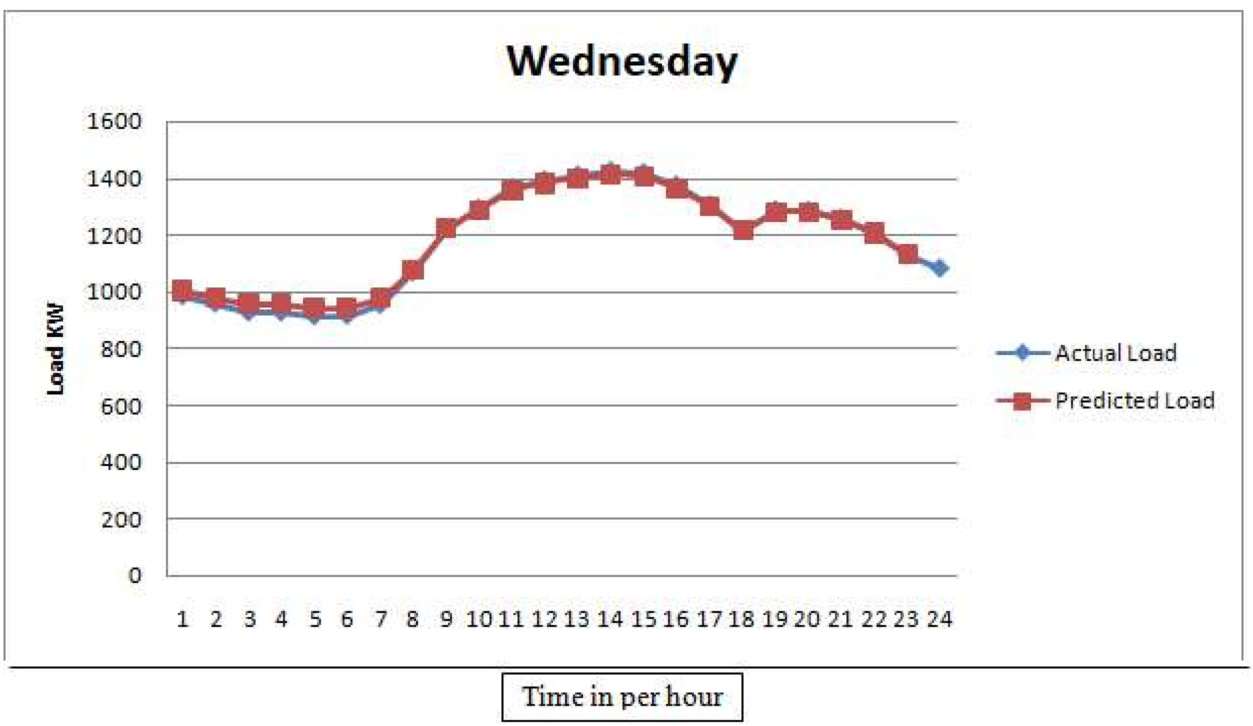


Fig.17: Actual v/s predicted load of Wednesday

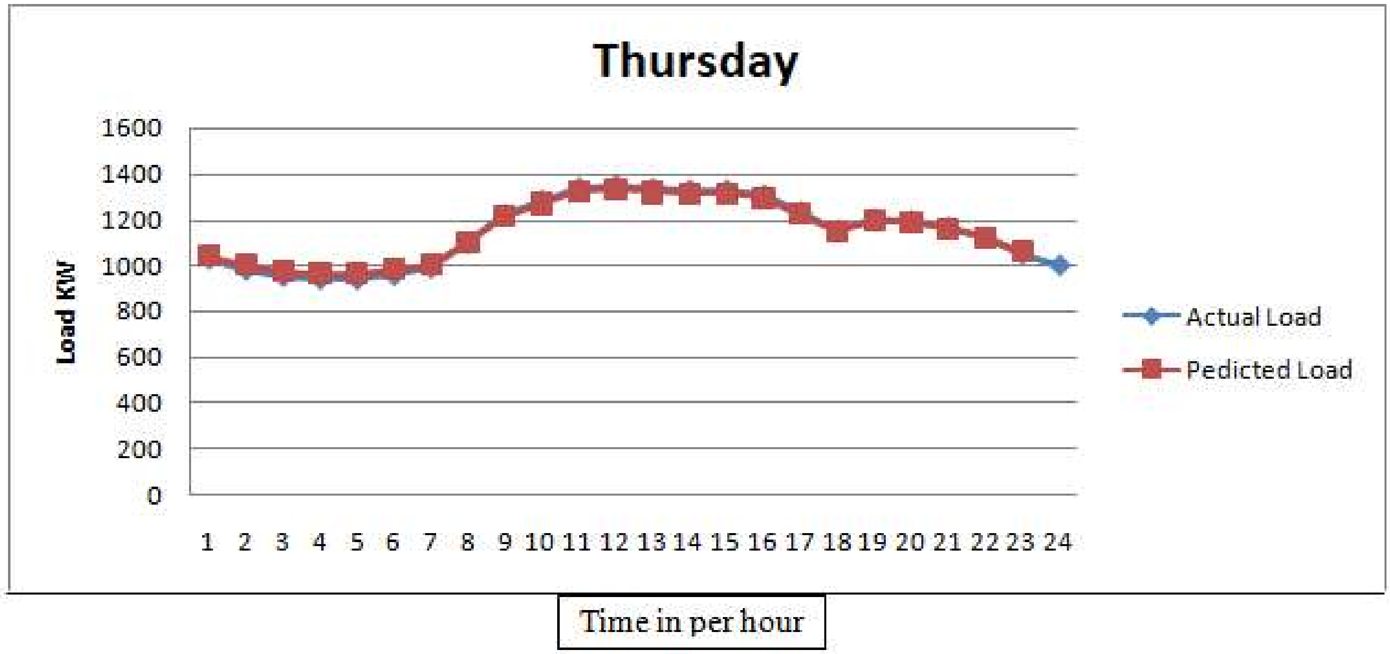


Fig.18: Actual v/s predicted load of Thursday

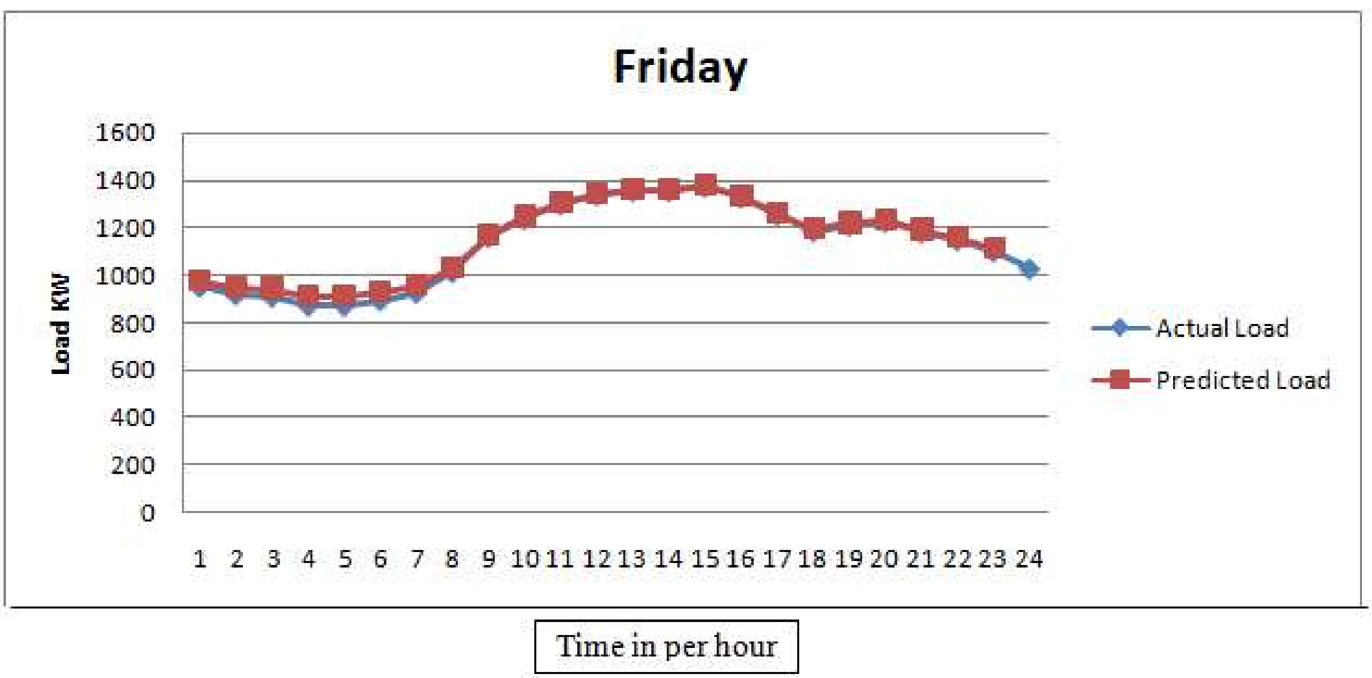


Fig.19: Actual v/s predicted load of Friday

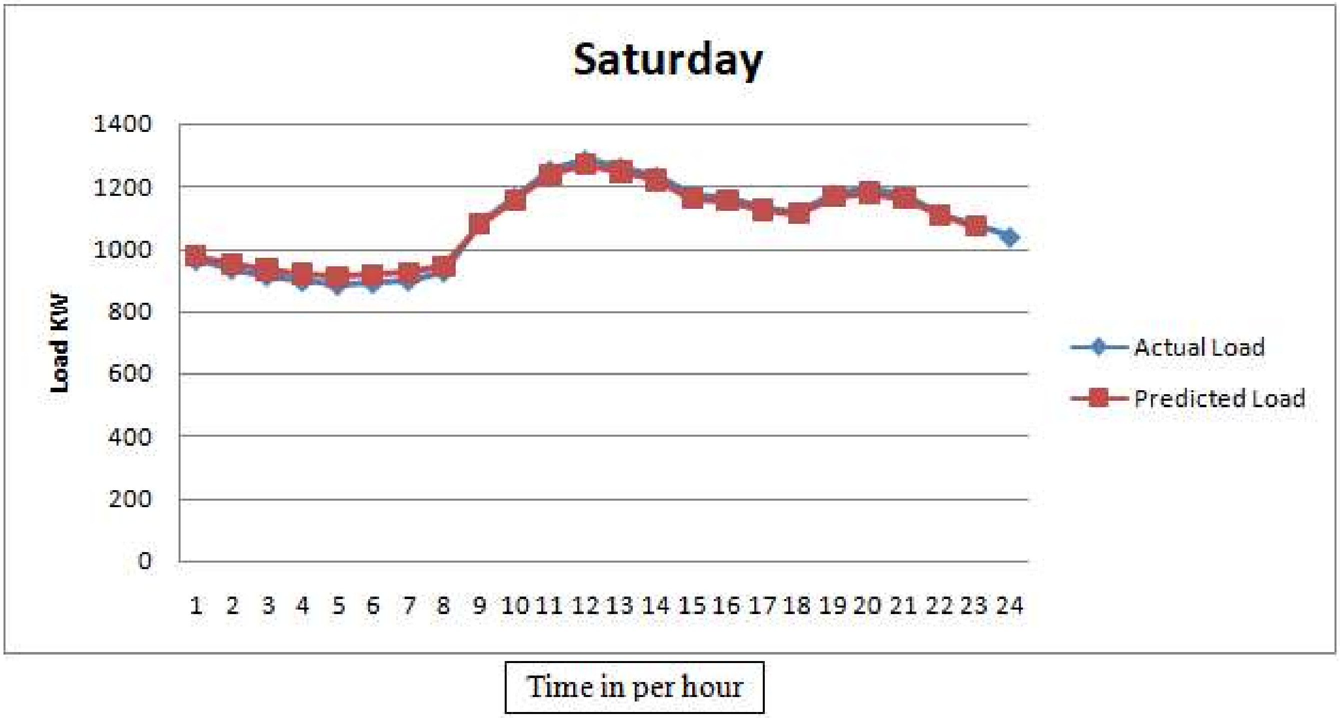


Fig.20: Actual v/s predicted load of Saturday

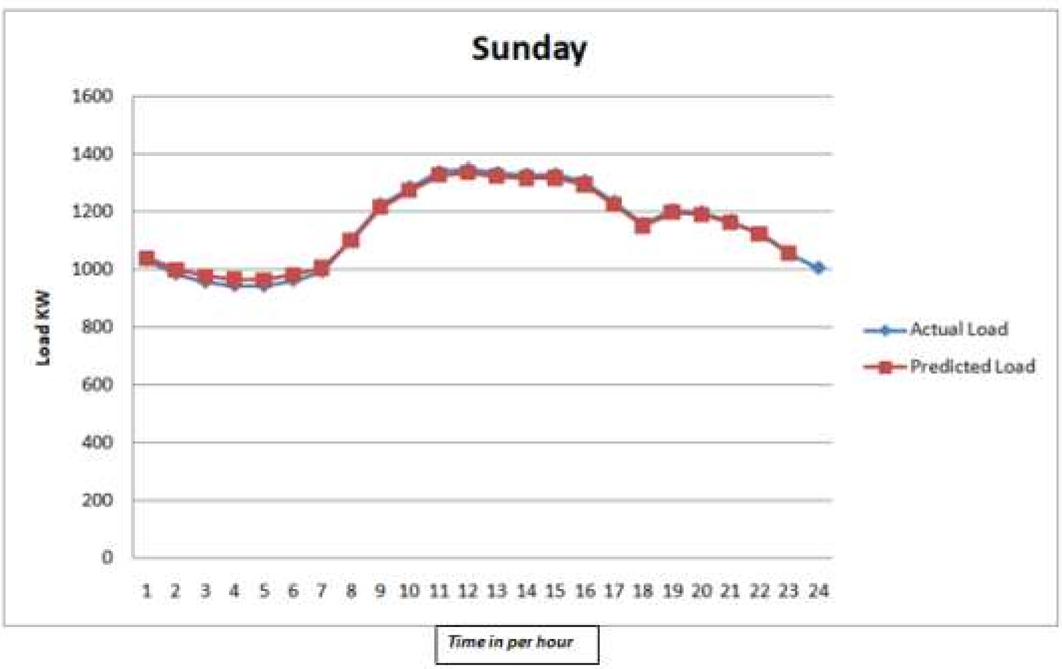


Fig.21: Actual v/s predicted load of Sunday

As a result, the performance estimation of the LSTM model for each weekday and weekend is based on the above forecast is shown below in the table below:-

Table 7.1: Performance Estimation of weekdays/weekends

PERFORMANCE ESTIMATION							
METHODS	MONDAY	TUESDAY	WEDNESDAY	THURSDAY	FRIDAY	SATURDAY	SUNDAY
MAD	2.24671	2.57394	1.923336	2.46784	2.7274	1.8461	1.80489
MSE	111.04988	145.75429	81.3829	133.98525	163.65164	74.97824	71.66825
MAPE	0.24229	0.27489	0.20031	0.25059	0.29716	0.197651	0.190772
RMSE	10.53802	12.07287	9.02124	11.57519	12.79264	8.65899	8.46571

Here,

MAD = Mean Absolute Deviation

MSE = Mean Square Error

MAPE = Mean Absolute Percentage Error

RMSE = Root Mean Square Error

Thus from the above result we plot the bar graphs of the following methods used for performance estimation.

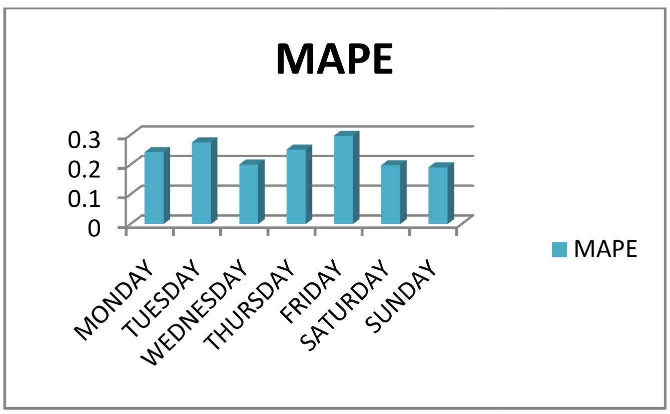


Fig.22: Bar graph for MAPE of the predicted weekdays and weekends

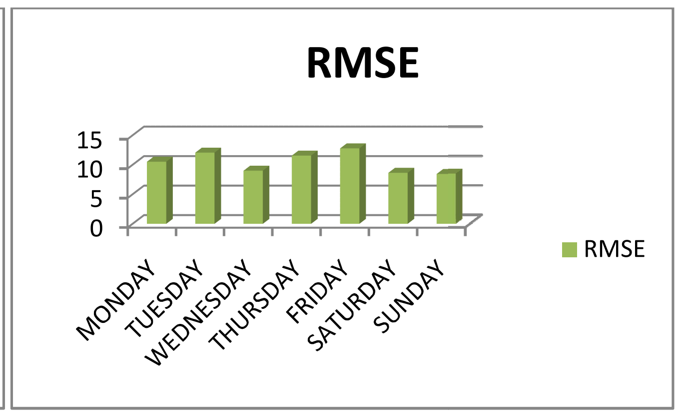


Fig.23: Bar graph for RMSE of the predicted weekdays and weekends

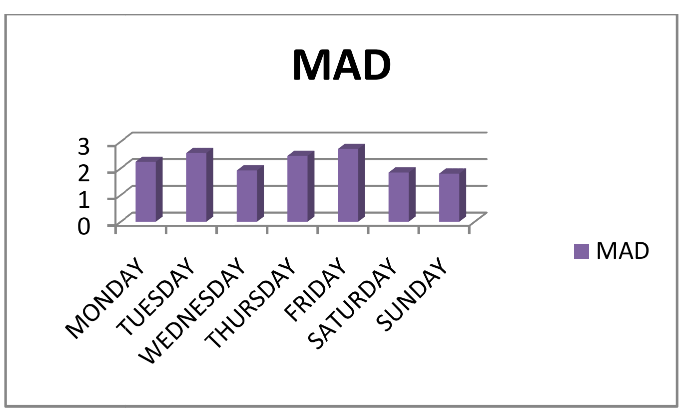


Fig.24: Bar graph for RMSE of the predicted weekdays and weekends

Table 7.2: Comparison of the outcome with the most present report established

Serial No.	Model	Dataset	MAPE (%)
1	ANN-PSO [19]	Real data of load consumption of Fars province in Iran	2.00
2	ANN-GA [19]	Real data of load consumption of Fars province in Iran	2.26
3	MS-CNN [18]	Ireland's 2014-2018 load dataset	1.09
4	SVR [18]	Ireland's 2014-2018 load dataset	1.04
5	LSTM (Proposed model)	2018 Real time load data	0.23

The proposed approach is evaluated using actual load consumption data gathered from the power department as a case study for predicting the power load consumption for 24 hours for the 53rd week using all 52 weekdays and weekends for the year 2018.

The proposed method's overall MAPE (Mean Absolute Percentage Error), which was tested using past load data, was found to be 0.23, indicating that the predictions are effectively near to the actual values. As a result, the difference between the predicted and actual values shows greater accuracy and fewer deviations from the mean, or a MAD (Mean Absolute Deviation) of 2.21 units.

The results indicate a high forecast accuracy of more than 90% using the suggested LSTM model, which has significant implications for the economy and society.

The Long Short Term Memory (LSTM) approach, among the following models for prediction, has the best MAPE (Mean Absolute Percentage Error) values, according to the comparison Table II as shown above. LSTMs (Long Short Term Memory) are therefore especially strong because they can learn long-term dependencies in data and because they have the ability to store past information, making them very useful for prediction tasks.

CHAPTER: 8

CONCLUSION AND SUGGESTIONS

The advancement of electrical load forecasting is the main topic of this study, which also looks at how well the LSTM (Long Short-Term Memory) neural network predicts load demand. Testing the proposed method on the load data, it was shown that the proposed method has an overall MAPE (Mean Absolute Percentage Error) of 0.23, which indicates that the predictions are very close to the actual values. Thus, it indicates a higher accuracy and smaller deviations from the mean value between the predicted and actual values, i.e., a MAD (Mean Absolute Deviation) of 2.21 units.

Using the proposed LSTM model, the findings show a high forecast accuracy more than 90%, which has important consequences for the economy and society.

Accurate electrical load demand forecasting helps save operating costs and guarantee the secure operation of power utility organizations. According to the survey, load utilization is highest during the workweek and lowest throughout the weekend. The performance of the hourly forecasting model in identifying these trends is good.

The LSTM model provides an easy approach for handling the supplied information in comparison to complex equations. The forecasting precision of LSTM can be increased yet more by including other variables. The correct data, such as duration and associated attributes, can help LSTM effectively recognize periodicity and patterns.

According to the study, LSTM performs better at load forecasting than traditional methods. Additionally, the LSTM is appropriate for processing and classifying sequential data due to its capacity to learn long-term associations between data time steps. Speech recognition, sentiment analysis, language modeling, and video analysis are examples of common LSTM applications.

In order to take into account periodicity and patterns directly from the data, without the need for specific extraction, the study contends that using data from several decades can further develop LSTM forecasting. This makes way for further improvements and new developments in LSTM-based forecasting methods.

Overall, the findings from the study highlight the utility of LSTM in electrical load forecasting and its applicability to a variety of fields that need sequential data processing.

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