Short Term Load Forecasting

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***Abstract*— We define Load forecasting as a method to predict the future quantity of power or energy required to meet the supply. In simpler terms Load forecasting is about estimating future consumptions based on various data and information available as per consumer behavior. Majorly it is used by power companies and limit their resources consumption. There are various types of load forecasting namely short-term which is applicable for a few hours, medium-term for a few weeks up to a year and long-term, whose time period is over a year. Short-term Load Forecasting can help to estimate the load flows and to make decisions that can prevent overloading. Timely implementations of such choices result in improvement of network responsibleness and to reduced occurrences of apparatus failures or blackout.**

Introduction

In today's deregulated economical world, we see that sustainable living is the only way to go and for that we need to know how much power is to be used and try not to waste excess resources. This is where load forecasting comes into picture. It has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development. We know that electrical energy can't be stored, it is whenever there is a demand for it. Therefore, it is imperative that electrical appliances energy intake load is foretold. This estimation is called load forecasting. It is necessary for power system planning.

In this paper we will be focusing on Short term load forecasting and some methods on how it can be implemented.

The period of short term load forecasting usually ranges from an hour to a week. It gives us an approximation on the energy usage and prevents overloading.

Let's discuss the roles of Load forecasting:

➢For proper planning of Power System.

• To forecast the future need for additional new generating facilities.

• To determine the size of the plants.

• On correct values of demand, load forecasting will prevent over designing of conductor sizes.

➢ For proper planning of Transmission and Distribution facilities.

•Wastage due to unplanning like the purchase of equipment which is not immediately required can be avoided.

➢ For proper Financing.

➢ For proper Grid Formation.

The load on a Power Station never remains constant rather it varies time to time, the variation of load with time is known as load curve. They are usually measured or plotted per hour or so on a daily, monthly, annual basis and hence the names:

•Daily load curves.
•Monthly load curves.
•Annual load curves.

With the Load curves we can determine: Variation of load during different times, Total no. of units generated, Maximum demand, Average load on a power station, Load Factor.

There are some factors that determine the results of load forecasting namely:

•Weather conditions (Temperature and Humidity).
•Class of customers (residential, commercial, industrial, agricultural, public, etc.).
•Special Events (public holidays, etc.).
•Electricity price.

The data we have used is taken from ENTSO-E Power Statistics Data whose link can be found in the reference section [5]

•We have collected corresponding weather data from NCEI ISD [6]

•Factors applied : Time of the day, Day of the week , ENTSO-E Hourly Load, Weather condition.

Data processing is done as follows:

Firstly, a function is defined to convert a vector of time series into a 2D matrix, next the dataset is split dataset: 90% for training and 10% for testing, now the training set is shuffled. (but do not shuffle the test set).

OBJECTIVES:

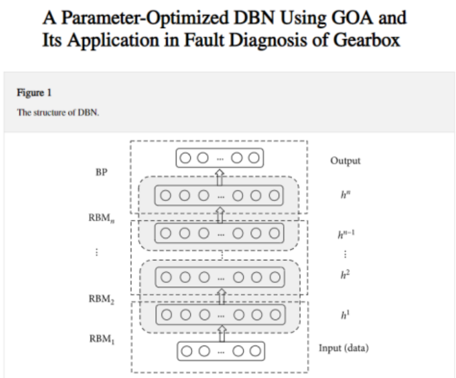
1.Determine the time and factors affecting short-term forecasting
2.Use various models to do short term forecasting
3.Take outputs and compare the models and make inference

METHODOLOGY:

Network Training :

1.DBN:

It is generally referred to as a probability generation network composed of several Restricted Boltzmann Machines (RBMs) [13, 14]. The network basically is composed of three layers: a visible layer, a hidden layer, and an output layer. So the hidden and the visible layers are joined using weights, and all the neuron each of them have their own offsets to represent their weight. The output layer and therefore the previously hidden layer form a BP neural network which is especially wont to adjust the initial parameters of the hidden layer to realize supervised training of the entire network. In the DBN learning process, the data is input from the bottom layer and then through the various hidden layers to complete the training process. The learning process here is split up into two sections: pretraining and fine tuning. The figure below shows a DBN structure with n layers hidden.



2. K-means clustering:
The K-means algorithm is a typical clustering algorithm. The basic notion of the algorithm is to split the samples into different clusters by continuous iteration until the objective function reaches its optimal value.

The specific procedure is as follows:
(1) Choosing K appropriate points as the initial clustering centers., in this project, we have set k=365
(2) Calculate the value of d:
(3) Classify all the points of load according to their nearest center points, thus dividing all the sample points into K clusters.
(4) Calculate the middle of the mass of the K clusters and update them as new agglomeration centers.
(5) Repeat the steps 2,3,4 and, keep iterating until the clustering centers stop shifting.

Then while predicting we compare the input temperature and other data points with the mass centers to find the cluster the input points belong to produce the load output.

3.LSTM:
3.1. Training the LSTM Network
The LSTM network is meant to be told each the long and short-run options of the coaching knowledge. Toward this finish, the kind of input file has connexion to the effectiveness of learning. If the info is provided that is leading toward wrong direction or isn't enough to form the options clear, the LSTM or RNN can learn consequently and can not predict or forecast accurately. as an example, the yearly seasonality within the provided knowledge is simply for one year. The LSTM can take into account it a seamless trend and can predict wrong and can lead toward zero values step by step. However, if the info of quite one year is given, LSTM will learn to predict the yearly seasonality too. Similarly, the choice of input file additionally contributes when deciding the accuracy of the network performance. The coaching method knowledge that has all types of seasonality and trends except the yearly seasonality.
• optimizer="rmsprop"
• No. of Training Iterations (Max Epochs) = 100
batch size=512
*activation = linear

model summary:

```
Layer (type)            Output Shape            Param #
=================================================================
lstm (LSTM)             (None, None, 50)        10400
_________________________________
dropout (Dropout)       (None, None, 50)        0
_________________________________
lstm_1 (LSTM)           (None, 100)             60400
_________________________________
dropout_1 (Dropout)     (None, 100)             0
_________________________________
dense (Dense)           (None, 1)               101
=================================================================
Total params: 70,901
Trainable params: 70,901
```

3.2. Forecast
The trained LSTM network in the previous subsection is used to forecast over the horizons of the given range or the particular hour entered by the user.

LITERATURE SURVEY:

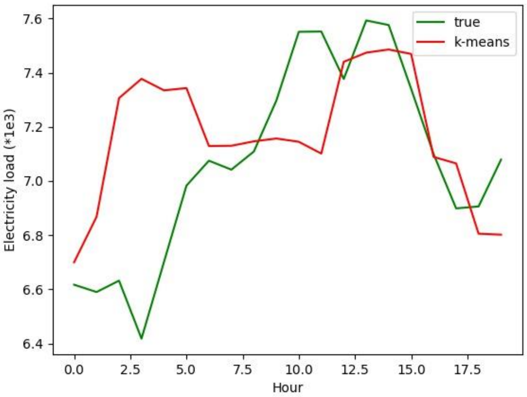
In the paper [1] the definition of what load forecasting is and why is it so necessary in our day-to-day life is enlightened upon. This paper is a theoretical one which grazes upon all the types of forecasting used short, long and medium. It also talks about how forecasting is not always accurate and also talks about second opinions. It also tells us about the advantages and disadvantages of forecasting and touches upon few methodologies involved in forecasting.

In the paper [2] Data have an internal structure, such as autocorrelation, trend, or seasonal variation is what the Time series forecasting assumes. It detects and explores such a structure. This project takes place in the City of Ravne, Slovenia where a 5 days span of short-term load forecasting is done for industrial plant. They present five different load-forecasting techniques: linear regression, ARIMA, Winter's multiplicative and real time Data Mining. In linear regression phase two time series are used namely: energy and production at the electric arc furnace. Then the forecasting model is broken down into two parts: ARIMA with predictor "loads" and Winter's multiplicative without any predictor; in this case the electric arc furnace is off. The concept of Data Mining at ARMA (Autoregressive and Moving Average Models) and Data Mining at ART (Autoregressive Tree Models) is discussed. For better quality of forecasting they used the Microsoft technology: Analysis Server .SQL server, and the WEB server.

In the paper[3] which also happens to be our base paper, A notion of similar months approach based seasonal ARIMA which is abbreviated as SARIMA is used to forecast. Through comparison with similar days-based approach on similar tasks, they demonstrate that this method may be a viable method for brief term electric load forecasting of power systems also as in building energy management applications.

OUTPUT RESULTS AND ANALYSIS:

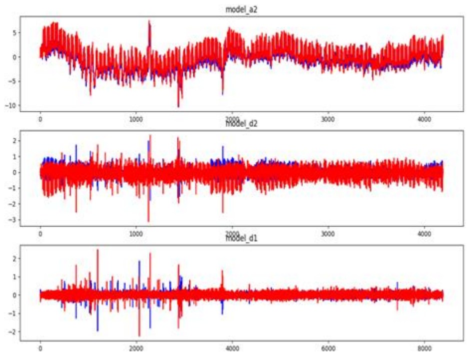
K-means clustering:




```
train — -zsh — 80×30
gagan@Gagans-Mac train % python main.py
Enter
1 for Clustering model
2 for LSTM model
3 for ARIMA
4 for SVR
5 for DBN
6 for prediction using all the algorithms:1
Loading data...
Processing data...
Enter 1 to predict load for given hour and 2 to predict load for a range of hour
s: 1
1 2016-11-30 23:00:00+00:00
2 2016-12-01 00:00:00+00:00
3 2016-12-01 01:00:00+00:00
4 2016-12-01 02:00:00+00:00
5 2016-12-01 03:00:00+00:00
6 2016-12-01 04:00:00+00:00
7 2016-12-01 05:00:00+00:00
8 2016-12-01 06:00:00+00:00
9 2016-12-01 07:00:00+00:00
10 2016-12-01 08:00:00+00:00
Select time from the above list to predict the date :3
Finiding centroids and labels with iter=10
Predicting...
------K-means--------
      date/time.              |   Predicted values(kW)   |    Actual values(kW)
   2016-12-01 01:00:00+00:00       6.916438935167263               6.664
exiting
gagan@Gagans-Mac train %
```

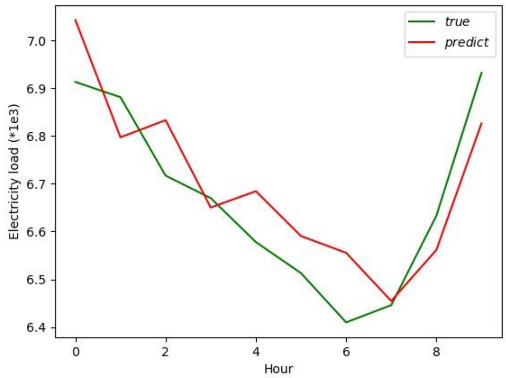
```
train — -zsh — 80×45
gagan@Gagans-Mac train % python main.py
Enter
1 for Clustering model
2 for LSTM model
3 for ARIMA
4 for SVR
5 for DBN
6 for prediction using all the algorithms:1
Loading data...
Processing data...
Enter 1 to predict load for given hour and 2 to predict load for a range of hour
s: 2
Enter the range of hours to predict the load
from:30
to:50
Finiding centroids and labels with iter=10
Predicting...
------K-means--------
      date/time.              |   Predicted values(kW)   |    Actual values(kW)
   2016-12-02 04:00:00+00:00       6.699836672448484              6.617
   2016-12-02 05:00:00+00:00       6.867893926012442              6.59
   2016-12-02 06:00:00+00:00       7.306209885970026              6.632
   2016-12-02 07:00:00+00:00       7.377367981365129              6.418
   2016-12-02 08:00:00+00:00       7.334846851780681              6.701
   2016-12-02 09:00:00+00:00       7.343127104784101              6.983
   2016-12-02 10:00:00+00:00       7.1291475214401325              7.075
   2016-12-02 11:00:00+00:00       7.130144285785578              7.042
   2016-12-02 12:00:00+00:00       7.1464512002522005              7.109
   2016-12-02 13:00:00+00:00       7.156951272301746              7.297
   2016-12-02 14:00:00+00:00       7.144868059627317              7.551
   2016-12-02 15:00:00+00:00       7.1013429996150474              7.552
   2016-12-02 16:00:00+00:00       7.4401908769444045              7.377
   2016-12-02 17:00:00+00:00       7.4740337751068795              7.593
   2016-12-02 18:00:00+00:00       7.485689582689764              7.576
   2016-12-02 19:00:00+00:00       7.469310710124681              7.34
   2016-12-02 20:00:00+00:00       7.08893252376386              7.099
   2016-12-02 21:00:00+00:00       7.064963496063327              6.899
   2016-12-02 22:00:00+00:00       6.805470724738807              6.906
   2016-12-02 23:00:00+00:00       6.801770090192932              7.079
MAPE is  0.037152291644663334
MAE is  256.0215742467418
MSE is  127393.48866255411
RMSE is  356.92224456112865
NRMSE is  0.3037636123924499
gagan@Gagans-Mac train % _
```

ARIMA:




```
[996, 996, 1992]
(20758,)
20758 20758
MAPE is  0.08765869918367696
MAE is  566.4280580572758
MSE is  530302.3990327556
RMSE is  728.2186478199769
NRMSE is  0.08055897932487063
gagan@Gagans-Mac train % _
```

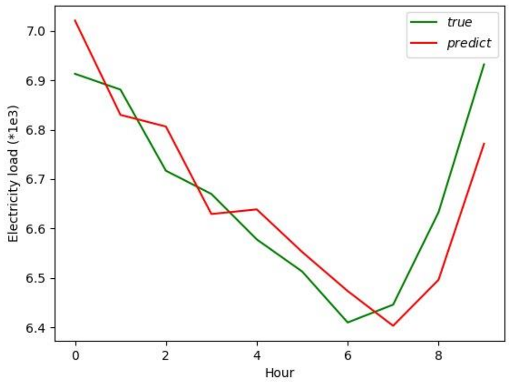
DBN:




```
train — -zsh — 85×37
gagan@Gagans-Mac train % python main.py
Enter
1 for Clustering model
2 for LSTM model
3 for ARIMA
4 for SVR
5 for DBN
6 for prediction using all the algorithms:5
importing Libraries
Enter 1 to train the model, Enter 2 to use the existing trained model : 2
Enter 1 to predict load for given hour and 2 to predict load for a range of hours: 1
1 2016-11-30 23:00:00+00:00
2 2016-12-01 00:00:00+00:00
3 2016-12-01 01:00:00+00:00
4 2016-12-01 02:00:00+00:00
5 2016-12-01 03:00:00+00:00
6 2016-12-01 04:00:00+00:00
7 2016-12-01 05:00:00+00:00
8 2016-12-01 06:00:00+00:00
9 2016-12-01 07:00:00+00:00
10 2016-12-01 08:00:00+00:00
Select time from the above list to predict the date :9
------DBN-------
      date/time.              |   Predicted values(kW)   |    Actual values(kW)
   2016-12-01 07:00:00+00:00       [8.312915]               8.339
gagan@Gagans-Mac train %
```

```
gagan@Gagans-Mac train % python main.py
Enter
1 for Clustering model
2 for LSTM model
3 for ARIMA
4 for SVR
5 for DBN
6 for prediction using all the algorithms:5
importing Libraries
Enter 1 to train the model, Enter 2 to use the existing trained model : 2
Enter 1 to predict load for given hour and 2 to predict load for a range of hours: 2
Enter the range of hours to predict the load
from:45
to:50
------DBN-------
      date/time.             |   Predicted values(kW)   |    Actual values(kW)
   2016-12-02 19:00:00+00:00       [7.4405394]                  7.34
   2016-12-02 20:00:00+00:00       [7.1705246]                  7.099
   2016-12-02 21:00:00+00:00       [6.969784]                  6.899
   2016-12-02 22:00:00+00:00       [6.7992425]                  6.906
   2016-12-02 23:00:00+00:00       [6.7908025]                  7.079
MAPE is  [0.01804061]
MAE is  [127.56055]
MSE is  22937.869135665893
RMSE is  151.45253096487326
NRMSE is  0.3434297754305516
gagan@Gagans-Mac train %
```

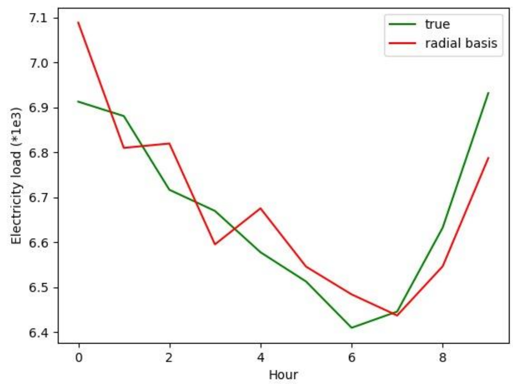
LSTM:




```
train — -zsh — 85×29
gagan@Gagans-Mac train % python main.py
Enter
1 for Clustering model
2 for LSTM model
3 for ARIMA
4 for SVR
5 for DBN
6 for prediction using all the algorithms:2
importing Libraries
Loading data...
Processing data...
Enter 1 to train the model, Enter 2 to use the existing trained model : 2
Enter 1 to predict load for given hour and 2 to predict load for a range of hours: 1
1 2016-11-30 23:00:00+00:00
2 2016-12-01 00:00:00+00:00
3 2016-12-01 01:00:00+00:00
4 2016-12-01 02:00:00+00:00
5 2016-12-01 03:00:00+00:00
6 2016-12-01 04:00:00+00:00
7 2016-12-01 05:00:00+00:00
8 2016-12-01 06:00:00+00:00
9 2016-12-01 07:00:00+00:00
10 2016-12-01 08:00:00+00:00
Select time from the above list to predict the date :8
1/1 - 1s - loss: 0.0156
------LSTM--------
      date/time.             |   Predicted values(kW)   |    Actual values(kW)
   2016-12-01 06:00:00+00:00       [7.6270456]                  7.502
gagan@Gagans-Mac train % _
```

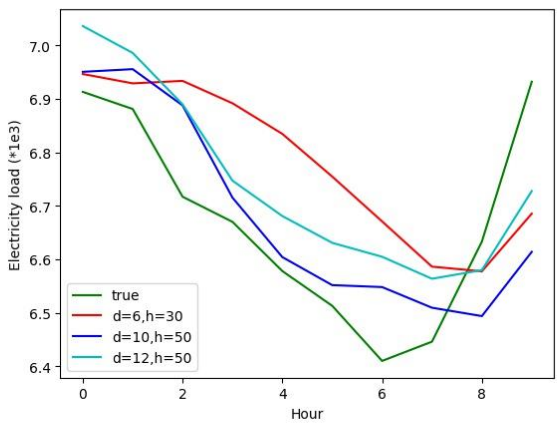
```
train — -zsh — 85×37
gagan@Gagans-Mac train % python main.py
Enter
1 for Clustering model
2 for LSTM model
3 for ARIMA
4 for SVR
5 for DBN
6 for prediction using all the algorithms:2
importing Libraries
Loading data...
Processing data...
Enter 1 to train the model, Enter 2 to use the existing trained model : 2
Enter 1 to predict load for given hour and 2 to predict load for a range of hours: 2
Enter the range of hours to predict the load
from:40
to:50
1/1 - 1s - loss: 0.0207
------LSTM--------
      date/time.             |   Predicted values(kW)   |    Actual values(kW)
   2016-12-02 14:00:00+00:00       [7.3155046]                  7.551
   2016-12-02 15:00:00+00:00       [7.569568]                  7.552
   2016-12-02 16:00:00+00:00       [7.590535]                  7.377
   2016-12-02 17:00:00+00:00       [7.4062705]                  7.593
   2016-12-02 18:00:00+00:00       [7.5842195]                  7.576
   2016-12-02 19:00:00+00:00       [7.3574595]                  7.34
   2016-12-02 20:00:00+00:00       [7.1702514]                  7.099
   2016-12-02 21:00:00+00:00       [6.9520693]                  6.899
   2016-12-02 22:00:00+00:00       [6.790515]                  6.906
   2016-12-02 23:00:00+00:00       [6.8583794]                  7.079

The MSE on the test data set is 0.021 for 10 test samples.
MAPE is  [0.01561327]
MAE is  [113.94336]
MSE is  20650.771358060836
RMSE is  143.70376250488656
NRMSE is  0.20706594020877025
gagan@Gagans-Mac train % _
```

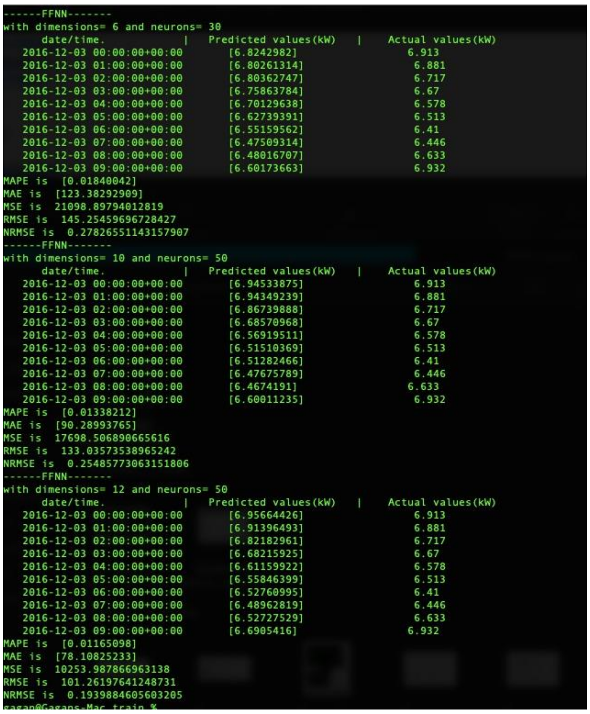
SVR:

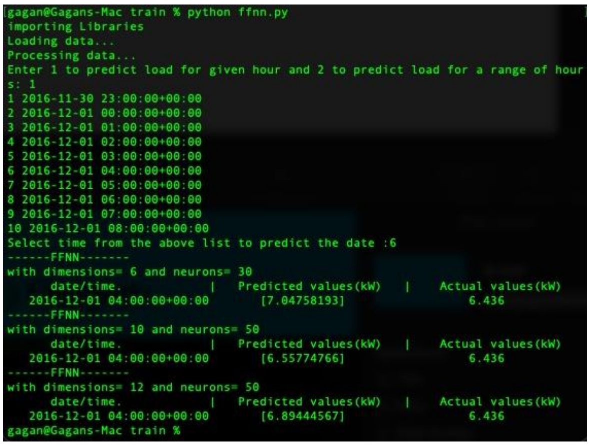



```
gagan@Gagans-Mac train % python main.py
Enter
1 for Clustering model
2 for LSTM model
3 for ARIMA
4 for SVR
5 for DBN
6 for prediction using all the algorithms:4
Loading the data...
Processing the data...
Enter 1 to predict load for given hour and 2 to predict load for a range of hours: 1
1 2016-11-30 23:00:00+00:00
2 2016-12-01 00:00:00+00:00
3 2016-12-01 01:00:00+00:00
4 2016-12-01 02:00:00+00:00
5 2016-12-01 03:00:00+00:00
6 2016-12-01 04:00:00+00:00
7 2016-12-01 05:00:00+00:00
8 2016-12-01 06:00:00+00:00
9 2016-12-01 07:00:00+00:00
10 2016-12-01 08:00:00+00:00
Select time from the above list to predict the date :6
------SVR--------
      date/time.             |   Predicted values(kW)   |    Actual values(kW)
   2016-12-01 04:00:00+00:00       6.557618931866196                6.436
gagan@Gagans-Mac train % _
gagan@Gagans-Mac train % python main.py
Enter
1 for Clustering model
2 for LSTM model
3 for ARIMA
4 for SVR
5 for DBN
6 for prediction using all the algorithms:4
Loading the data...
Processing the data...
Enter 1 to predict load for given hour and 2 to predict load for a range of hours: 2
Enter the range of hours to predict the load
from:40
to:50
------SVR--------
      date/time.             |   Predicted values(kW)   |    Actual values(kW)
   2016-12-02 14:00:00+00:00       7.30440724070379                7.551
   2016-12-02 15:00:00+00:00       7.5606384598899155                7.552
   2016-12-02 16:00:00+00:00       7.6278084428942545                7.377
   2016-12-02 17:00:00+00:00       7.483347267166508                7.593
   2016-12-02 18:00:00+00:00       7.707847355051918                7.576
   2016-12-02 19:00:00+00:00       7.431195621304315                7.34
   2016-12-02 20:00:00+00:00       7.100369500045345                7.099
   2016-12-02 21:00:00+00:00       6.931747265589568                6.899
   2016-12-02 22:00:00+00:00       6.808810070345578                6.906
   2016-12-02 23:00:00+00:00       6.789198506788039                7.079
MAPE is  0.01720196323181058
MAE is  125.98435597714032
MSE is  25601.662197883088
RMSE is  160.0051942840703
NRMSE is  0.23055503499145577
gagan@Gagans-Mac train % _
```

Feed Forward:







Comparison Table:

Forecast Horizon (10 hours)	MAPE	NRMSE
K-means	0.037	0.303
ARIMA	0.087	0.080
LSTM	0.015	0.207
SVR	0.017	0.230
DBN	0.018	0.343
Lstm without dropouts	0.026	0.3

We have implemented short term load forecasting using various models and clearly the LSTM model is clearly the most accurate model by which short term forecasting can be achieved with most accuracy compared to other models. We make this inference by plotting a table consisting of MAPE(Mean Absolute Percentage Error) and NRMSE(Normalized Root Mean square Error) values displayed to us on the output and when plotted we see that MAPE and NRMSE values for LSTM is the least.

CONCLUSIONS

In this paper we discussed how power stations play a vital role in reducing wastage of energy and how short-term forecasting plays a pivotal role to achieve the results. We also went through various models on which Short-term forecasting can be implemented and made a comparison based on the outputs displayed. We have thoroughly discussed about the datasets we used and also defined load curves and different types of load curves. A mention of factors affecting the results of short-term forecasting were also mentioned. We have successfully managed to complete this project of short-term load forecasting using various models namely:

- K-means Clustering
- Auto Regressive Integrated Moving Average (ARIMA)
- Long Short-Term Memory (LSTM)
- Deep Belief Network (DBN)
- Support Vector Regression (SVR)
- Feed Forward Neural Network

The Predicted, true value almost same with very little error.

REFERENCES

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3. https://ieeexplore.ieee.org/document/9071939
4. https://www.techopedia.com/definition/30629/load-forecasting-electric-power-engineering
5. https://www.entsoe.eu/data/power-stats/
6. https://www.ncdc.noaa.gov/isd/data-access