EV Charging Forecasting

This Report is Submitted
for Partial Fulfillment of Requirements
for the Degree of
(B. Tech) Bachelor of Technology
in
Computer Science
Engineering
by

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to the
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Motilal Nehru National Institute of Technology, Allahabad
Prayagraj, Uttar Pradesh (India)
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UNDERTAKING

We hereby declare that the work presented in this report title "*EV Charging Forecasting*", submitted to the Computer Science and Engineering Department, Motilal Nehru National Institute of Technology, Allahabad, Prayagraj, Uttar Pradesh (India) for the award of the ***(B. Tech) Bachelor of Technology*** degree in ***Computer Science Engineering***, is my own work and we have not submitted or plagiarized this same work for award of other degree.

August 2021
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CERTIFICATE

Certified that the work contained in the report titled "*EV Charging Forecasting*", by *Naval Kumar (20184043), Jagshish Singh (20184053), Rajat Maheshwari (20184163), Piyush Nirala (20184197)*, has been done under my guidance and supervision. This work hasn't been submitted elsewhere for any other degree.

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August 2021

Preface

Load forecasting on different-different time scales have different roles in energy systems and transportation. We are facing a very high rise in the prices of patrol and diesel, which directly affect the transportation.

In this project we will use various models for predicting the requirement of electrical energy at the stations by applying different methods to forecast demand of energy at a particular station. We intend to come up with an idea so that electric vehicle charging can be done in smooth and easy way to the nearest charging Station.

Acknowledgements

Completion this work required a great amount of effort, support, and guidance from many people. We feel honored and privileged to have all that we are developing in this project. We would also like to thank our mentor, Dr.Dinesh Kumar(Assistant Professor) for his complete support, oversight and guidance in all manner for this project. We would also like to thank and acknowledge our professors, mates for their support and for allowing us to successfully completion our project.

Contents

Chapter 1

Introduction

1.1 Motivation

Short-term forecasting is an important issue in the power management system and the main key measure sustainable and efficient operation of energy systems.

Load forecasting at non-identical time scale has various and corresponding roles in energy systems. In recent years, plug in electric vehicles have increasingly used and become popular in big cities,also the number of electric cars are growing faster.

In this paper, artificial neural networks and a long short term memory model based on deep learning are monitored and compared, to predict EV charging load by charging station view.

Result of our method shows :-

- The Long short term memory model has shown better performance.
- This model provided higher accuracy in predicting short-term EV load forecasting compared to traditional performance artificial neural networks.

Terms need to be known before moving forward:

- Feature: Features are individual measurable property or characteristic of a phenomenon being observed. These require classification.
- Label: Labels are the final release. We can also look at the output classes as labels.
- Classification: By classification, we will need to divide the data into a limited number of previously defined classes.
- Model: A machine learning model is a mathematical representation of a real-life problem. There are different algorithms that perform different functions with different levels of accuracy.
- Training: Much like us humans, machines in order to learn first need to be taught some "right" answers. This is the essence of training a Machine Learning model. While training the machine learning model, we transmit an algorithm with training data. The learning algorithm detects patterns in training data so that the input parameters match the target. The final result of the training process is a Machine Learning model that we can use to make predictions.

Chapter 2

Related Work

In 1995, Storn and Price proposed the Differential Evolution algorithm. It worked on simple logic and took reasonable time to reach global optimum values.

Since then, the algorithm has been used by many researchers in the fields of machine learning and artificial intelligence, both of which have numerical optimization at their core.

The algorithm has also been successfully modified and used by researchers to solve various real-life multi-objective problems.

In 2003, Xue et al. introduced Multi-Objective Differential Evolution (MODE). In this, the fitness of a solution is determined using two factors. One is the Pareto ranking(for exploitation). And the second one is the crowding distance(for exploration).

In 2005, B. V. Babu et al. used the multi-objective differential evolution algorithm to optimize various entities like productivity, selectivity and yield of and adiabatic styrene reactor.

In 2006, M. Janga Reddy and D. Nagesh Kumar used multi-objective differential evolution to solve the reservoir system optimization.

In 2012, Tapas Si, Samanta Hazra, N. D. Jana used a variant of DE called DEGL algorithm (DE with global and local neighbourhood mutation) to train an ANN classifier with satisfactory results.

In 2014, Xu Chen, Wenli Du, Feng Qian proposed ranking-based mutation operator in the MODE algorithm which significantly increased the performance.

In 2018, Beatriz A. Garro classified DNA micro arryas using an ANN classifier which was trained using DE. This application is of high importance in the field of genetics as the data represented by the DNA micro arrays is the crux of an organism's genetics.

Chapter 3

Problem Statement

The Future of transportation is Electric Vehicles as we are facing a very high rise in the prices of Petrol and Diesel due to Covid 19 and lack of these non renewable resources which directly affect the middle and upper middle class on their purses.Thus Electric Vehicle Users increases and we have a clean ecosystem also with this usage of electric vehicles.

We intend to come up with an idea so that electric vehicle charging can be done in smooth and easy way to the nearest charging Station and the time in this process of EV users as well availability of station became easy.The main issue how much energy a particular charging station stores for a particular day or week.For this purpose we are using EV Charging Forecasting.

We are predicting the requirement of electrical energy at the stations from a data set by applying different methods to forecast demand of energy at a particular station.

Chapter 4

Proposed Work

4.1 Electric vehicles Charging Forecasting

4.1.1 Artificial Neural Network

Artificial intelligence is simulation of human neurological behaviour, to enhance speed, precision and effectiveness of human efforts. Basis of artificial intelligence is artificial neurons. Several features like voice analysis, face recognition , forecasting of weather, and forecasting of future of transportation, electric vehicles charging , are available for use to human mankind.

Fundamental unit of artificial neural network is neuron. There are input and output neurons as well as hidden neurons. Various forms of information is received through these input units, and neural network learns patterns from this information and produce an output. There are various concepts of weightage of input, bias , outliers, to increase the efficiency of neural network.Before passing through activation functions, inputs are given some weightage. Several types of artificial neural networks are Modular Neural Networks, Feedforward neural networks, Recurrent Neural Networks, Convolutional Neural Network, Long/Short Term Memory (LSTM).

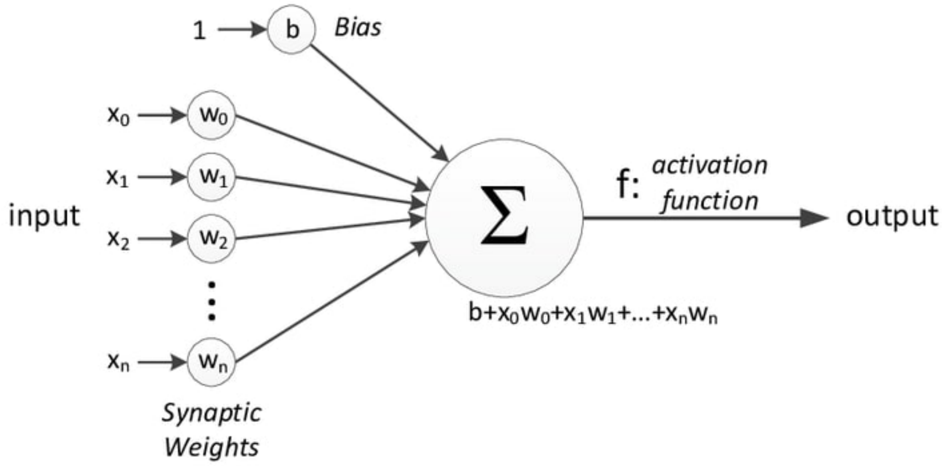

Figure 1: Structure of an artificial neuron

Layers of neurons are interconnected in a neural network, Number of neurons, type of neurons , activation functions of these neurons does vary for different uses. Layers other than first and last are called hidden layers , Activation functions are basically mathematical functions. Some of them are sigmoid, relu, softmax, softsign etc.

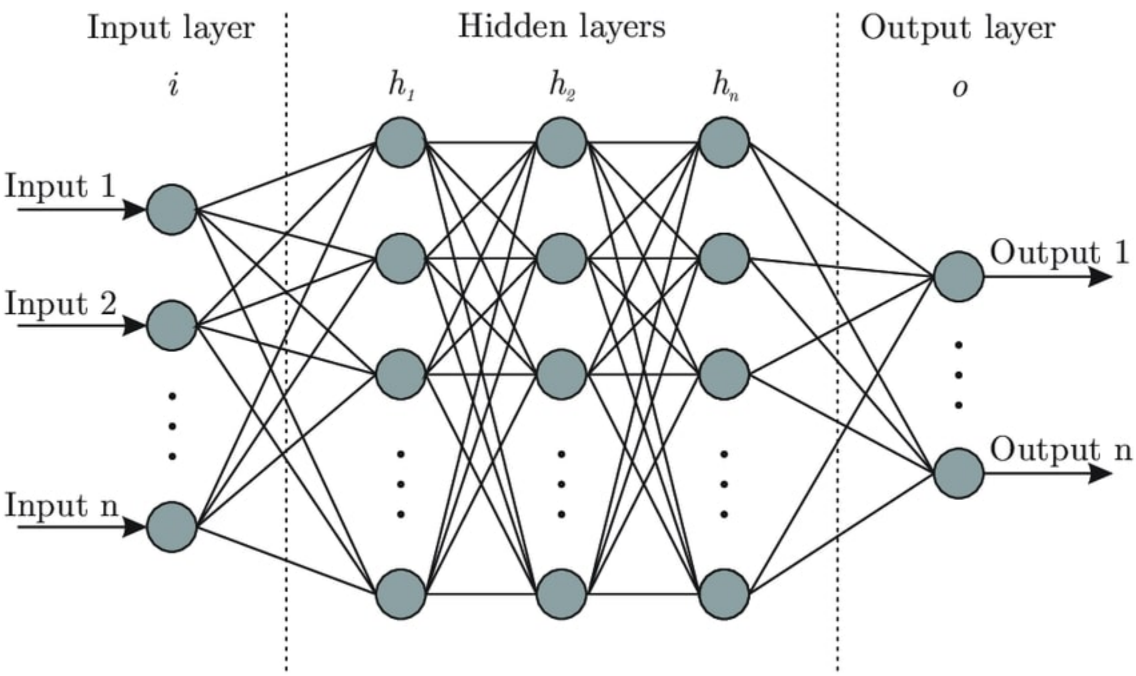

Figure 2: Structure of an artificial neural network

4.1.2 Long/ Short Term Memory

LSTM were first introduced by Hochreiter Schmidhuber (1997), LSTM are like RNN and can long term dependencies . When output have a long-term dependency of input points, then LSTM is required , normal ANN will not remember this dependency. Long-term dependency comes into picture, when working with time-varied data,also in Natural Language Processing. Electric vehicle data is time-varied, with dataset carrying starting and ending point of charging and the total power delivered to vehicle.

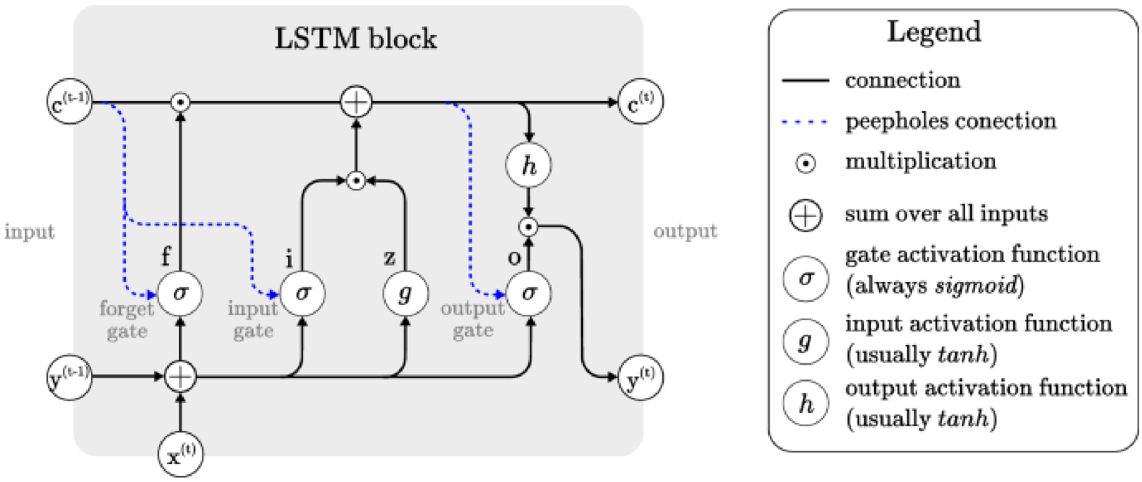

Figure 3: Structure of LSTM neuron

4.1.3 Preprocessing

Raw data must be converted to useful data, Two different models are used for day wise forecasting and hour wise forecasting. so total power delivered to vehicle is averaged per hour as well as per day. Removing outliers is also essential, outliers are sudden peaks and drops in power delivered. Dataset is distributed into training and testing data . window size is also varied for both day wise and hour wise. Scikit learn is also used to normalize data.

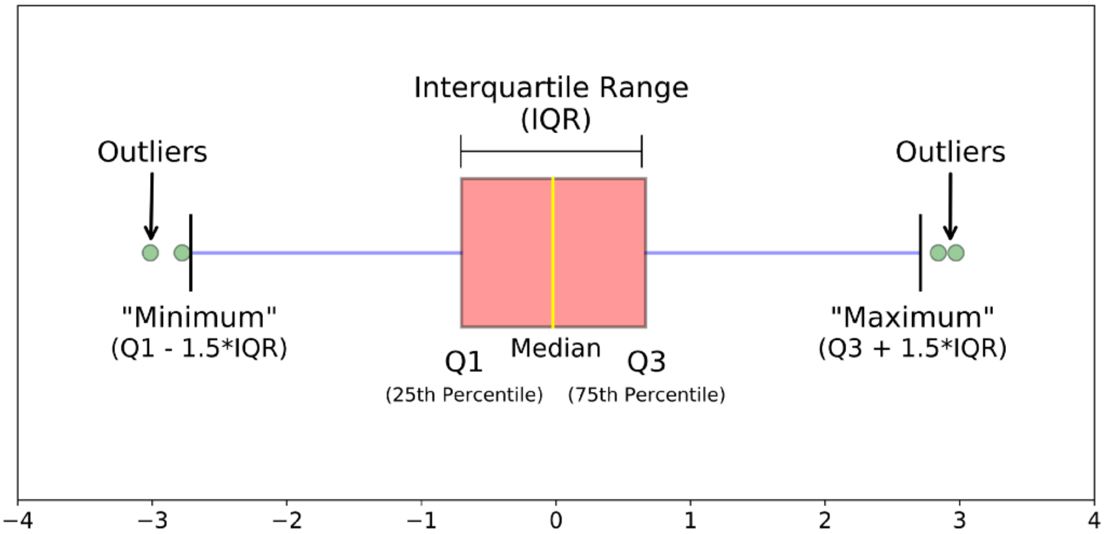

Figure 4: Outliers Calculation

4.1.4 LSTM Model

Models for both hour wise and day wise varies mostly in input shape and number of hidden layers and neurons, Bidirectional layers are used to increase the accuracy. Dropout layers are used to stop overfitting, Hidden layer neurons consist of LSTM neurons as well as Dense neurons.Keras library provides these functionalities to use as higher level functions. Epochs , batch size are varied to check overfitting and underfitting and overall accuracy. r2 score is used to check accuracy .

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
bidirectional_1 (Bidirection (None, 7, 32)             2304
_________________________________________________________________
dropout_2 (Dropout)          (None, 7, 32)             0
_________________________________________________________________
lstm_3 (LSTM)                (None, 32)                8320
_________________________________________________________________
dropout_3 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 33
=================================================================
Total params: 10,657
Trainable params: 10,657
Non-trainable params: 0
```

Figure 5: Model for Day Wise Forecasting

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
bidirectional_2 (Bidirection (None, 24, 32)            2304
_________________________________________________________________
dropout_4 (Dropout)          (None, 24, 32)            0
_________________________________________________________________
lstm_5 (LSTM)                (None, 32)                8320
_________________________________________________________________
dropout_5 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 33
=================================================================
Total params: 10,657
Trainable params: 10,657
Non-trainable params: 0
_________________________________________________________________
```

Figure 6: Model for Hour Wise Forecasting

4.2 Experimental Setup

For experimental analysis, we have used the following hardware and software specifications:

The software specifications of the setup are as follows:

- Keras=2.2.2 It is a python library, based on Theano and Tensorflow frameworks, It permits us to train neural network models in effecient and easier way on top of Theano or Tensorflow like frameworks.
- Pandas Pandas allow us to import and use data, available in many formats, This library allows us to operate on data and convert them into several formats and make changes to them Features like merge,reshape,select, clean are available.ff
- numpy=1.14.2 Numpy library allows us to perform several advanced mathematical operations on data.
- python=3.5.6
- scikit-learn=0.20.0 Several machine learning and statistical analysis, models are available for direct use in this library. Models for classification and regression and clustering are some of them.
- Matplotlib This library is one among the best for data visualization. Effect of model on dataset can also be visualized very easily

The hardware specifications of the setup are as follows:

- Processor : Intel(R) Core(TM) i5-9300HQ CPU @ 2.50 GHz
- GPU : NVIDIA GeForce 1650
- RAM : 8.00 GB DDR4 Memory
- Storage : SSD

4.3 Dataset

For training and testing purpose we used Caltech dataset. This dataset consists of over 30,000 charging sessions This was collected from 2 charging sites in California managed by PowerFlex, a smart electric vehicle charging startup. This dataset is regularly updated on daily basis. This

- Caltech
- JPL

4.4 Results

4.4.1 Graphical Results

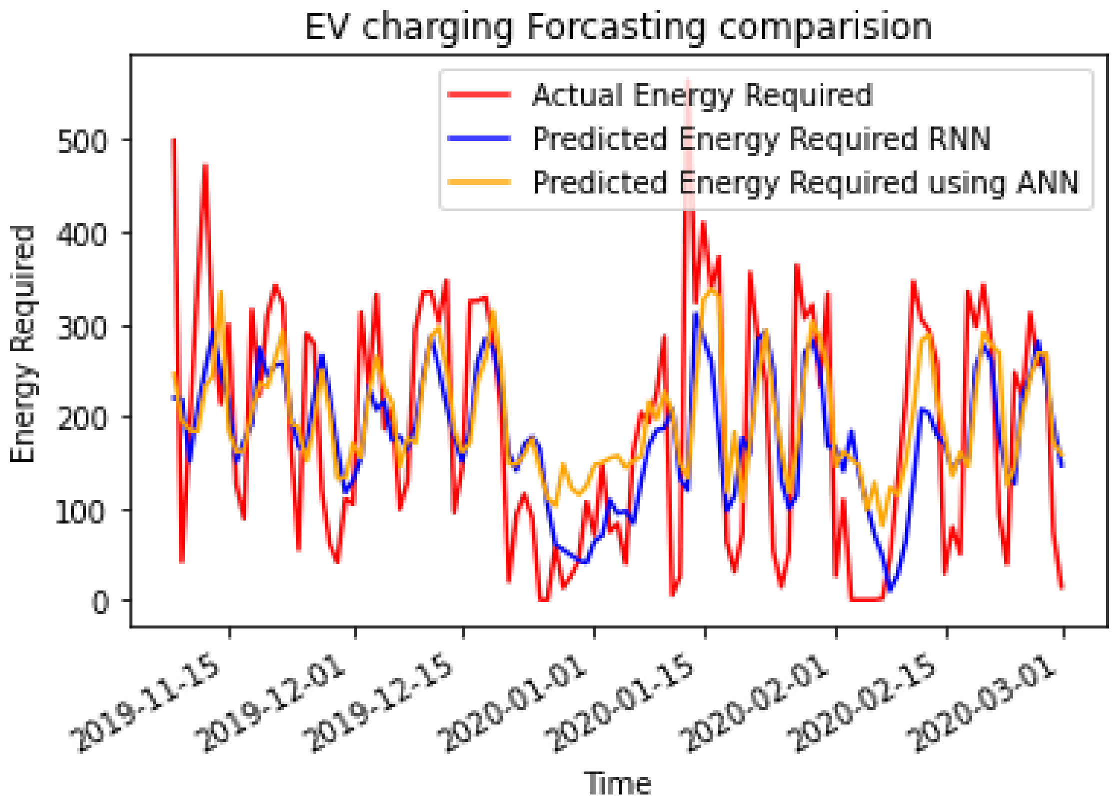

Figure 7: Actual Energy vs Energy Predicted By RNN vs Energy Predicted By ANN on Daily Basis

We trained RNN and ANN model with 80:20 training testing division and obtained following acuracy on our dataset for Daily Basis.

ANN accuracy = 0.35693641155777234

RNN accuracy = 0.29967679575196315

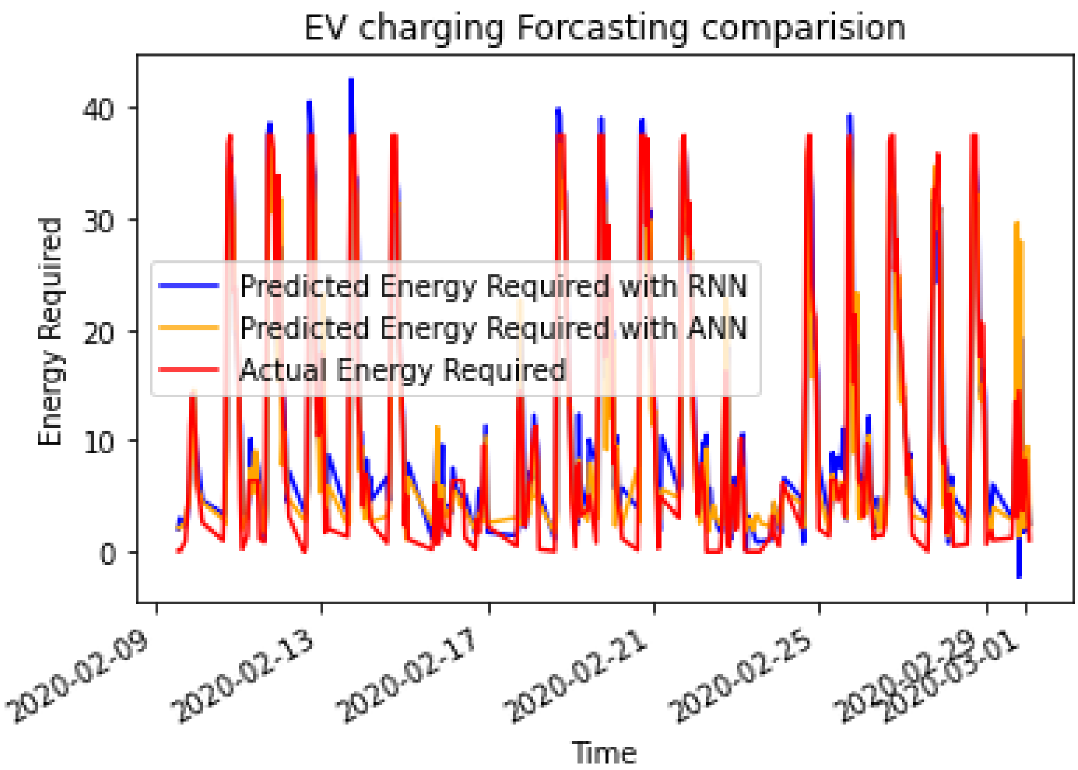

Figure 8: Actual Energy vs Energy Predicted By RNN vs Energy Predicted By ANN on Hourly Basis

We trained RNN and ANN model with 80:20 training testing division and obtained following acuracy on our dataset for Hourly Basis.

ANN accuracy = 0.7934518403188806

RNN accuracy = 0.814473714353031

4.4.2 Dataset visualization

Dataset is of 54 Electric Vehicle charging stations,using a 50 kW dc fast charger. The Caltech ACN parking garage is open for public. Different users use charging station at different time of day, and weekends can also affect data, which results in peek and drops in power usage.

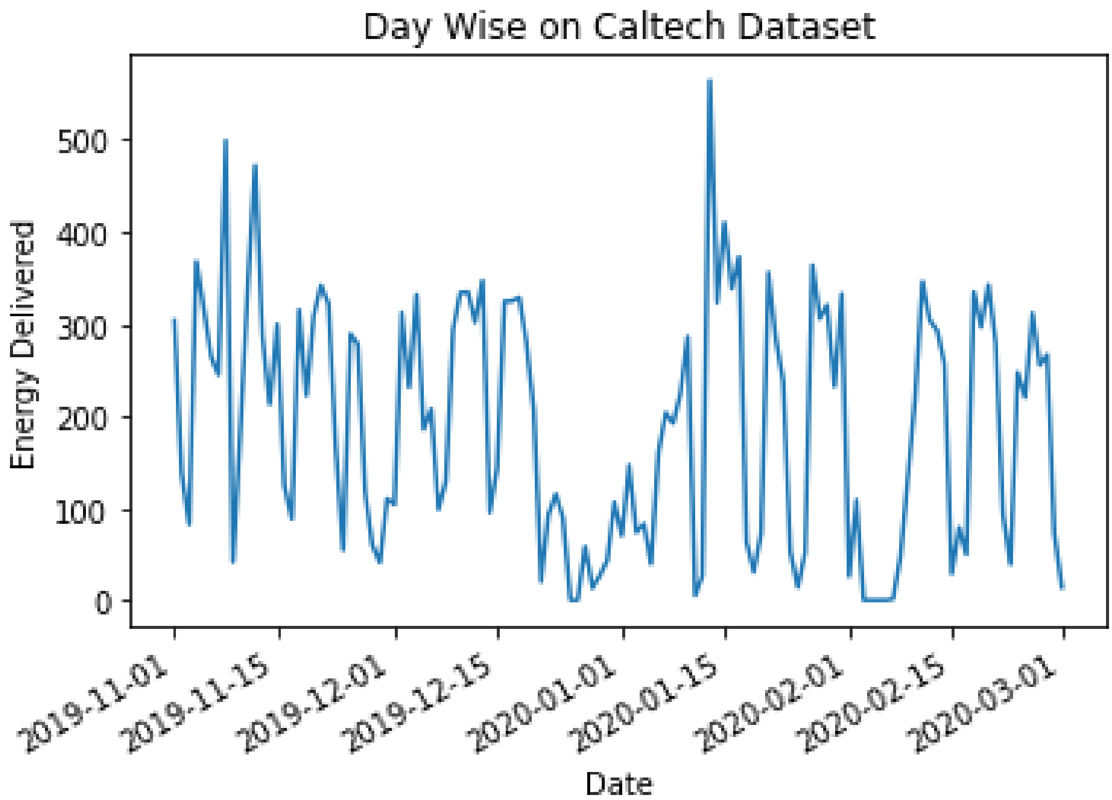

Figure 9: Energy vs Time grouped by Day

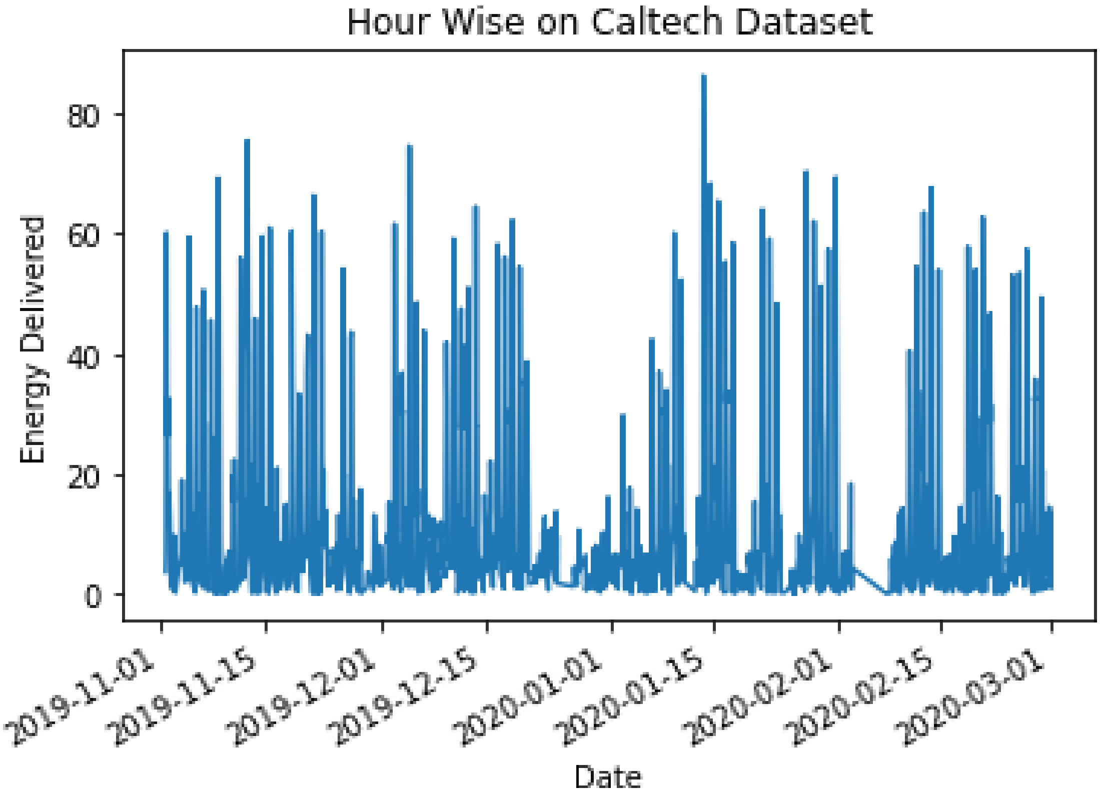

Figure 10: Energy vs Time group by Hour

4.5 Coding

Colab Link :- https://colab.research.google.com/drive/15Lx1puwm23RJoxsqEiM0tmKO8ITyLUtX

Chapter 5

Conclusion and Future Work

5.1 Conclusion

As results shows we can use this model for EV Charging forecasting .But accuracy is not that good so we have to still work on it to make accuracy up to mark.

5.2 Future Work

In this project, accuracy is a great point of concern. To there is many areas where we can improve our system. Few of them are listed below.

- Dataset :- Data set was not large enough and some portion of dataset were missing which affected accuracy of model.
- More Attributes :- Need to find more attribute which will influence the model and ultimately lead to more accuracy.
- Long Term Forecasting :- We can extend this project for long term forecasting i.e. Weekly, Biweekly, Month.

[1] ABOUT THE REFERENCE

[1] Juncheng Zhu, Zhile Yang, Yan Chang, Yuanjun Guo, Kevin Zhu, Jianhua Zhang *A novel LSTM based deep learning approach for multi-time scale electric vehicles charging load prediction*, 2019.