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Master Thesis

Time-of-Use Tariff and Valley-Filling based Scheduling Algorithm for Electric Vehicle Charging

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Course of Study: Information Technology (INFOTECH)

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Commenced: 7 October, 2020

Completed: 6 April, 2021

Acknowledgement

I would like to thank my supervisor and Professor Dr. Marco Aiello for giving me the opportunity to work on this research topic and for guiding me throughout the thesis. Your insightful feedback was invaluable in bringing my work to a higher level. I would also like to express my gratitude to my family and friends for their constant moral support for the entire duration of my Master's studies.

Abstract

The use of electric vehicles has gained momentum in recent times as they prove to be eco-friendly and energy-efficient. EVs offer a long-term solution to reduce the dependence on fossil fuels and greenhouse gas emission. Decreased air pollution due to the elimination of the exhaust pipe in electric cars promotes sustainable mobility. This in turn greatly reduces the negative impact of transportation on the quality of the atmosphere. However, uncoordinated charging of a large fleet of EVs poses serious challenges to the stability and security of the electric grid. Smart electric vehicle charging has recently gained significant attention in the research community due to the need to charge large number of electric vehicles economically. Not only should EV charging be economical, but also be energy-efficient and not tax the electric grid. Since the power demands of a building or residential area are not always constant throughout the day, the surplus power could be utilised by shifting time-flexible consumption such as EV charging to periods of lower demand of power. Ideally, EV charging load could be shifted to fill the overnight electricity demand valley while also considering the electricity tariff. In this thesis, a valley-filling scheduling algorithm is implemented that considers the Time-of-Use tariff to shift EV charging to off-peak hours and low tariff periods. The research also proposes a neural network model to predict future load based on weather attributes such as temperature and humidity. The simulation results demonstrate a good percentage of valley-filling achieved by the algorithm along with reduced tariffs.

Contents

1	Introduction	19
1.1	Problem Statement	19
1.2	Research Questions	20
1.3	Methodology	20
1.4	Assumptions	20
1.5	Thesis Structure	21
2	Background	23
2.1	Peak Shaving and Valley-Filling	23
2.2	Dynamic Pricing	23
2.3	Load Forecasting	25
2.4	Adaptive Charging Network : ACN Caltech	28
3	State of the Art	29
4	Implementation	35
4.1	ACN Simulator	35
4.2	Peak Shaving and Valley-Filling	36
4.3	Load Forecasting	41
5	Evaluation	45
5.1	Setup	45
5.2	Results	48
5.3	Discussion	52
6	Conclusion and Future Work	57

List of Figures

2.1	The repeating module in a standard RNN contains a single layer [Ola]	27
2.2	The repeating module in an LSTM contains four interacting layers. [Ola]	27
3.1	Surplus power that could be utilised for EV charging.	31
3.2	Uncoordinated EV Charging power profile.[JZS17]	31
3.3	Coordinated EV Charging power profile. [JZS17]	32
4.1	Software Design. [LLL+16]	35
4.2	Time-of-Use Tariff.	38
4.3	Load Vs Time-of-Use Tariff for Summer (June - September).	38
4.4	Load Vs Time-of-Use Tariff for Winter (October - May).	38
4.5	Periodicity of daily load.	41
4.6	Temperature Vs Load.	42
4.7	Humidity Vs Load.	43
4.8	Flowchart of the scheduling algorithm.	44
5.1	One week of training data.	46
5.2	Predicted Vs Observed load (Testing dataset)	48
5.3	Last 100 time-steps of Predicted Vs Observed load (Testing dataset).	48
5.4	Training Vs Testing loss.	49
5.5	Predicted Vs Observed load (Validation dataset).	49
5.6	Peak hours on an average day.	51
5.7	Load and aggregate current profile with the scheduling algorithm. (Weekday_16)	51
5.8	Load and aggregate current profile with uncontrolled charging. (Weekday_16)	51
5.9	Load and aggregate current profile with the scheduling algorithm. (Weekday_20)	52
5.10	Load and aggregate current profile with uncontrolled charging. (Weekday_20)	52
5.11	Frequency of EVs charging at Caltech on a daily basis.	53
5.12	Remaining energy demand profile for EV: 2_39_95_444_2019-08-29 17:41:16.869694	54

List of Tables

4.1	Input dataset for the LSTM model.	43
5.1	Input parameters for the LSTM model.	45
5.2	User input parameters for the ACN Simulator	47
5.3	Valley-filling percentage (Weekdays)	50
5.4	Valley-filling percentage (Weekends)	50

List of Listings

4.1 ACN EV charging session data	36
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List of Algorithms

4.1	Calculation of EV laxity	37
4.2	Calculate surplus power for the current hour	39
4.3	Array of time-slots index	39
4.4	Schedule EVs at off-peak hour	40
5.1	Calculation of valley-filling percentage	47

List of Abbreviations

EV	Electric Vehicle
ACN	Adaptive Charging Network
TOU	Time-of-Use
LF	Load Forecasting
LSTM	Long-Short-Term-Memory
RNN	Recurrent Neural Network
CAISO	California Independent System Operator
EVSE	Electric Vehicle Supply Equipment
SCE	Southern California Edison
RMSE	Root Mean Square Error
V2G	Vehicle-to-Grid

1 Introduction

For a long time, we have been relying on fossil fuels as the major source of energy for transportation. But not only are they a non-renewable resource, but also a major contributor to air pollution. Burning of fossil fuels releases toxic particles such as sulphur dioxide and heavy metals into the atmosphere [ene]. Due to the deterioration of the global environment and scarcity of fossil fuels, it has become an urgent challenge to introduce sustainability to the transportation sector [JZS17]. Electric vehicles prove to be eco-friendly and energy-efficient posing it to be a sustainable alternative for the future transportation system. The governments of many countries have introduced preferential policies such as tax exemption, tax deduction, financial subsidies, etc in order to encourage citizens to purchase electric vehicles and contribute to sustainability. [WEH16], [TA16], [iea].

In recent years, there has been a surge in the penetration of electric vehicles. In the year 2017, the sales of new EVs surpassed 1 million units and the global stock of electric passenger cars reached 3.1 million (an increase of 57% compared to 2016) . In 2018, nearly 2 million new EVs were sold and the global stock increased to 5.1 million units (63% more than in 2017) [Com]. Though electric vehicle usage is already having a burgeoning growth, it pertains to serious impacts on the generation, transmission and distribution of electricity. That is why, several scheduling algorithms are being introduced to accommodate the additional EV charging loads for the existing power grid. In order to tackle the peak power demands that arise due to the increasing use of EVs, one of the possible solutions is to reinforce the power grid. But this leads to huge amount of investments in upgrading grid infrastructures and deploying distributed generations. Hence, coordinated charging within a smart grid is a more prudent solution that has been proposed to shift the peak power demands to off-peak hours. [JZS17]

1.1 Problem Statement

The goal of coordinated charging is to allocate the charging loads to fill the conventional load valley of the power grid, thereby utilising the surplus power generated in the off-peak hours of the day and mitigate the demand pressure during peak hours. [JZS17] proposes a valley-filling algorithm that also considers the electric vehicle charging laxity. It schedules EVs taking residential load into consideration. However, it does not include any load pricing scheme in the scheduling algorithm, which is why its economic impact is unknown. Since residential load demand has to be considered to propose a valley-filling scheduling algorithm for EVs, prediction of future load plays a key role as it helps to determine the peak and off-peak hours in advance. Load, having a time-series characteristic, is closely related to weather parameters such as temperature and humidity [KMS+15]. There have been previous works of deep-learning based prediction of load demand based on hourly temperature such as in [KPS19] and [He17]. Due to unavailability of humidity data, it was not considered in the research work of [He17].

For the formulation of an EV scheduling algorithm, relevant charging session data has to be

considered. There are many open-source EV charging session data available online, for example, the Dutch smart EV charging provider ElaadNL, which mainly offers aggregate data from the entire country of Netherlands. But this data proves to be unsuitable for localized statistical analysis when considering just an area of a city. Another data source called My Electric Avenue [CH16] comprises of collected data from residential EV charging to examine its effect on the distribution grid, but it is difficult to publicly access this data due to privacy concerns. The Adaptive Charging Network (ACN) Research Portal is an open-source portal for real-world EV charging session data that has previously been used in [LLL19a], where the focus was on learning the charging session parameters of users via Gaussian mixture models. [GEL17] also uses the ACN data to formulate an online optimal charging algorithm that computes the charging rates for all existing EVs.

1.2 Research Questions

There has been limited research on an economical as well as energy-efficient scheduling algorithm for Electric Vehicle Charging using charging session data from the Adaptive Charging Network (ACN) open-source portal. The research is based on the research questions mentioned below:

- How can electric vehicles be scheduled based on valley-filling strategy?
- How can EV charging be scheduled in an economical way?
- Which machine learning technique can be employed to predict load?

1.3 Methodology

The thesis aims to develop a scheduling algorithm for electric vehicles based on the charging session data available at the ACN portal. The focus of the research is to implement a scheduling algorithm for Electric Vehicle charging that is economical as well as achieves valley-filling. In this thesis, a valley-filling strategy is implemented for scheduling EV charging by considering the surplus residential power. By shifting the EV charging to off-peak hours, peak shaving is achieved. The method of pricing scheme adopted in this research is Time-of-Use tariff. By considering the EV charging laxity, the EVs are deferred to the lower tariff periods, thus making the scheduling algorithm economical. The algorithm was run on the ACN simulator which is an open-source simulator that operates a real-world EV charging system. Long Short Term Memory based load forecasting was implemented considering weather attributes such as temperature and humidity values of the area of study.

1.4 Assumptions

Following are the assumptions which are valid throughout the thesis:

- The type of EV charging considered in this thesis is V1G, which refers to unidirectional controlled charging where the charging rate can be dynamically modified.

- The operating power of the EV charger is taken as 7.4kW for calculations, assuming it to be a single phase power supply with 220 V AC.

1.5 Thesis Structure

Chapter 2 describes the background knowledge required to understand the concept discussed in this work. Chapter 3 deals with the state-of-the-art technologies and existing work related to this thesis. Chapter 4 describes the design of the scheduling algorithm and its implementation represented by pseudocode. It also describes the relationship between weather attributes and load and its method of prediction. Chapter 5 deals with evaluation of the load forecasting neural network model and the scheduling algorithm. It compares the evaluation results of the scheduling algorithm implemented in this thesis with uncontrolled charging. Lastly, Chapter 6 provides the conclusion and lists future work and improvements to this work.

2 Background

The most significant application of coordinated charging of EVs is load filling. It ensures the better utilization of electrical equipment and therefore, the electric power companies can serve power load with lower costs. It has been reported that most EVs are used only 4% of the time for transportation [ZC14]. This gives the EV owners the flexibility to select during which periods they can charge their vehicles, hence making EV charging load an ideal resource to fill the load valley. For accurate load forecasting, it is necessary to identify and reflect factors such as weather attributes that affect load. [KMS+15]

2.1 Peak Shaving and Valley-Filling

Uncoordinated charging of EVs is the charging mode when EVs start charging as soon as it is plugged in and finish charging as soon as their batteries are full or are disconnected from the grid. This would lead to increase of peak loads at rush hours which would further cause the instability of the electric grid [JZS17], as this method does not have any regards to the state of the electric grid. This would lead to further increase in the gap between peak load and valley load of future power grids [HZZS16]. Therefore, coordinated charging would help to extenuate the negative impacts by making use of the surplus power that is available during the off-peak hours, by a valley-filling algorithm. [HZZS16] Specially, charging the EVs overnight helps to fill the valley considerably as the off-peak hours exist during this time. This would greatly alleviate daily cycling of power plants and operational costs of utilities [DFL+09]. From the EV owner's perspective, the EV batteries could be charged overnight so that they disconnect it by morning and go about their day with fully charged batteries. This forms the basis of smart charging control [DFL+09]. Shifting of charging during periods of overproduction forms the basis of demand response. Demand response is one of the approaches used to manage power load by the cooperation between power company and the consumers. It involves the shifting of time-flexible consumption such as household water heaters, charging of EVs, etc to time intervals when overproduction is expected [KBT+17].

2.2 Dynamic Pricing

Each kilowatt of energy consumed costs a certain amount due to the generation, transmission and distribution of electricity that involves running/operational costs and fixed costs. To recover these costs, every consumer of electricity is charged with a certain amount based on kilowatt hour of energy consumed, which is called tariff [KMS+15]. The conventional tariffs that were used predominantly in the past were simple tariff, flat rate tariff, block rate tariff, two part tariff, maximum demand tariff and power factor tariff. But due to the progress of technology and ever since the incorporation of smart grids, these conventional tariffs could no longer prove to be a method of

fair pricing for electricity. With the introduction of distributed generation in the grid system, the old tariff methods could no longer comply with the requirements of smart grids and intelligent electronic devices (IEDs). That's why, smart pricing schemes were initiated to comply with the modern system [KMS+15].

There are three existing time-based pricing schemes:

- **Time-of-Use (TOU) pricing**

TOU uses pre-determined fixed intervals of expected high demand (seasons of the day, hours of the day) derived from the statistical analysis of historical data. This is the oldest and most prevalent existing demand response scheme [HP08]. Time of use pricing is a type of pricing used by the residential energy management which vary depending on the time of day. In this type of pricing, the peak hour electricity consumption costs more than the off-peak hour consumption. This is because during peak hours, the demand of the consumers is at its peak and so during these hours, the peaking power plants supply the additional power which have higher operating costs and higher greenhouse gas emissions [EM10]. The peaking power plants are usually based on less efficient and expensive fuels such as petrol, diesel or natural gas as compared to base load or mid-load plants which derive energy from renewable energy sources [KMS+15]. Therefore it is only vital to reduce the peak hour energy consumption which pertains to reduction of greenhouse gas emissions. To encourage more demand response, the on-peak price can be set higher as compared to the flat rate. However, if the peak TOU rate is too high, there can be more customer participation and again create new system peaks [SZPR10].

- **Critical peak pricing (CPP)**

CPP is similar to TOU but have very high prices during critical peaks. Sometimes, due to system contingencies, it costs the utilities a high wholesale price which turns out to be much greater than the TOU peak price. In order to keep a fair pricing, CPP is declared in advance to rectify this economic inconsistency and for peak shaving. It is declared only when the load forecast is abnormally high and is generally announced a day ahead. CPP plays a significant role in stabilising the electric grid as the CPP peak price is inordinately high and the consumer would be forced to reduce their electric load during this period which would in turn reduce the peak load [KMS+15].

- **Real time Pricing (RTP)**

This type of pricing scheme provides varied prices throughout the day based on the wholesale electricity prices that reflect the cost incurred by the utility for the electricity that is utilized by the consumer. This scheme is of two types- hourly pricing and day ahead pricing. RTP works best when consumers are involved in it as they can be updated with information of lowest electricity price periods. RTP signals along with the smart grid, benefits the consumer as well as the utility through peak shaving and reducing load through Demand-Side Management (DSM) in times of capacity limitation of generation or distribution system, thus increasing the reliability of the system [KMS+15].

Since CPP and RTP are real-time pricing schemes and require instantaneous information from the utility, this thesis implements a valley-filling algorithm based on TOU pricing as it is constant for the year and does not vary instantaneously. It is fetched from the Southern California Edison online portal that has the latest updated TOU pricing scheme for the area of Southern California. [SCE]

2.3 Load Forecasting

Load forecasting is the method used by the power utilities to predict the power needed to meet the demand and supply equilibrium, which is why its accuracy is vital for the operational and managerial loading of a utility company [tec]. The conventional methods of load forecasting treat the load demand alone as time series and predict based on time-series methods without considering the weather attributes such as temperature, humidity, rainfall, etc. These techniques have proved to be inaccurate in the past, which is why the problem formulation and modelling is a challenge that needs dedicated statistical analysis [FKQ+98]. In order to precisely forecast load, the seasonal load change, annual load growth and the latest daily load change have to be considered [HM94]. The branch of machine learning that has been greatly influential in forecasting tasks is neural network technology as it is efficient in modelling the non-linearity in data and approximates complex functions to arbitrary precision. The forecasting techniques are broadly categorised into Statistical based modelling and Artificial intelligence (AI) based modelling.

2.3.1 STATISTICAL BASED MODELLING

In this type of modelling, the forecasting models are represented in the form of a mathematical equation. Some of the mathematical methods of statistical based modelling are multiple regression, exponential smoothing, iterative re-weighted least-squares, etc.

- **Multiple regression**

This LF model uses the weighted least square technique to establish a relationship between load, weather condition, day timing and consumer class, etc, used by Mbamalu and El-Hawary for the analysis of measured load [EM90].

$$Y_t = v_t a_t + e_t$$

Where t= sampling time

Y_t = Measured load

v_t = vector of adapted variable such as weather, temperature, day type etc.

e_t = model error at time t.

This technique was used to predict 24-hour load forecast and compared with other models by Moghram and Rahman [MR89], while [HH97] presents a regression based weather-load model to predict load demand for Irish electricity, which was later modified as adaptable regression model to predict day ahead load.

- **Exponential Smoothing**

This is a forecasting technique that uses the previous load data to predict the future load, in which $Y(t)$ represents the load as a fitting function as represented below.[KMS+15]

$$Y(t) = \beta(t)T * f(t) + e(t)$$

Where $Y(t)$ = load at time t

$f(t)$ = fitting function vector of the process

$\beta(t)$ = coefficient vector

$e(t)$ = white noise

T = transpose operator

This model substantiates to reduce error in demand prediction upto 12% as compared to conventional forecasting models.

- **Iterative re-weighted least-squares**

The iterative re-weighted least-squares is used to identify the order and parameters of the LF model. It only controls a single variable that defines the optimal starting point of the model. Its equation is represented as below: [KMS+15]

$$Y = X\beta + e$$

Where $Y = n \times 1$ observation vector

$X = n \times p$ matrix of known coefficient (previous load data)

$\beta = p \times 1$ vector of unknown parameters

$e = n \times 1$ random error vector.

The unknown β can be found by iterative method presented in [EM90].

2.3.2 ARTIFICIAL INTELLIGENCE BASED MODELLING

Some of the artificial intelligence based forecasting models are Artificial Neural Network (ANN), fuzzy neural network, Long Short Term Memory (LSTM), Recurrent Neural Network (RNN) etc.

- **Artificial Neural Network (ANN)**

Artificial Neural Network (ANN) is a computational model which takes inspiration from animal or human central nervous system. This system is represented by the interconnection of “neurons” that calculates values from inputs feeding information through network. ANN for load forecasting is classified into two groups, one which consists of only one output node to predict next hour, next day peak load and the other group is based on several output nodes to forecast hourly load. [KMS+15]

- **Long Short Term Memory (LSTM)**

Recurrent Neural Network (RNN) comes under the class of neural networks where connections between nodes form a part of a directed graph along a temporal sequence. It is derived from feed forward neural networks and uses its internal memory to process variable length sequences of inputs. But in the long run, RNNs are unable to learn to connect information, which is why LSTM is more widely used for prediction. LSTMs are a special type of RNN that is capable of learning long-term dependencies. They are able to learn information for long periods of time. While recurrent neural networks have repeating module for a single neural network, LSTMs have repeating module for four neural networks. [Ola]

The Recurrent Neural Network models its input sequence (x_1, x_2, \dots, x_n) using the recurrence: $h_t = f(h_{t-1}, x_t)$ where x_t is the input at time t , and h_t is the hidden state which can be considered as a vector representation of all inputs seen up to time t . But for a large sequence of data such as load forecasting, vanishing gradient is bound to occur. LSTM solves the vanishing gradient/ explosion problem which is more common in RNNs by introducing gates into the recurrence function f and computing the hidden state as follows [KMS+15]:

Figure 2.1: The repeating module in a standard RNN contains a single layer [Ola]

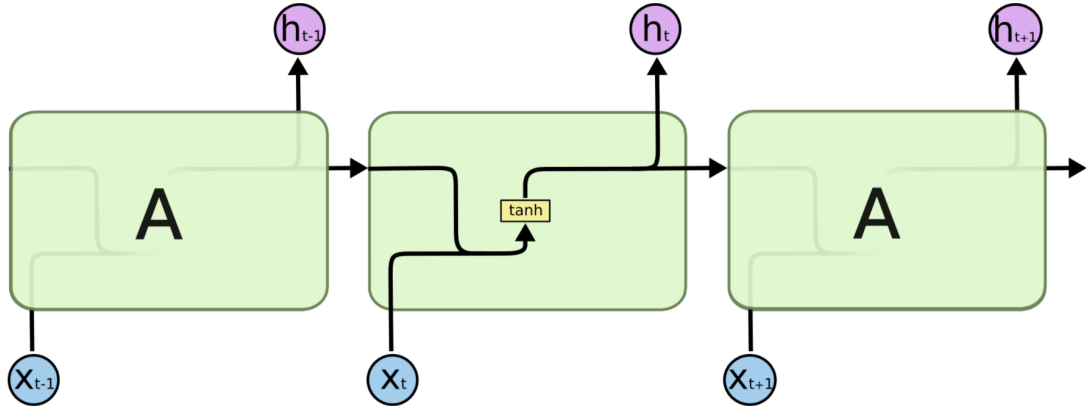
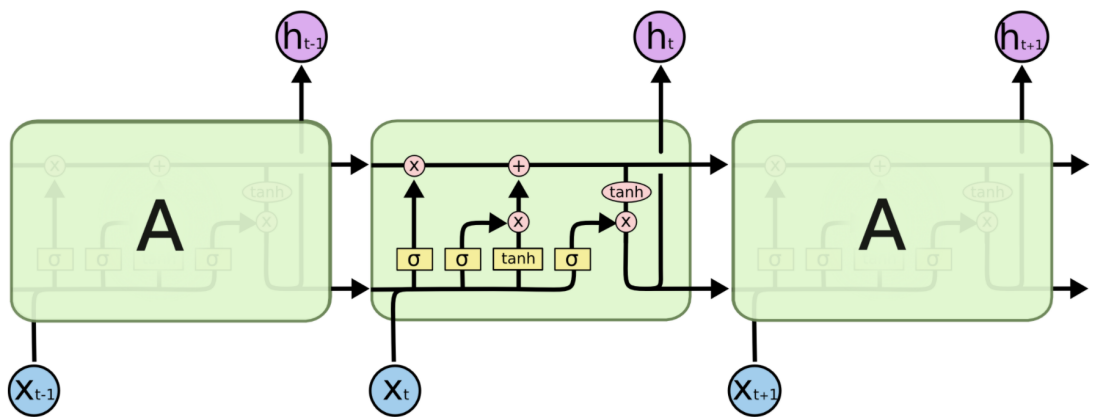


Figure 2.2: The repeating module in an LSTM contains four interacting layers. [Ola]



$$\begin{aligned}
 i_t &= (W_i * [h_{t-1}, x_t] + b_i) \\
 f_t &= (W_f * [h_{t-1}, x_t] + b_f) \\
 C_t &= \tanh(W_C * [h_{t-1}, x_t] + b_C) \\
 o_t &= \sigma(W_o [h_{t-1}, x_t] + b_o) \\
 h_t &= o_t * \tanh(C_t)
 \end{aligned}$$

where i_t , f_t and o_t are the input gate, forget gate and output gate respectively; C_t is cell state and C_t represents candidate cell state; and the W 's and B 's are parameters of the LSTM unit. By feeding the input sequence x_1, x_2, \dots, x_n into the RNN, we get a list of hidden corresponding h_1, h_2, \dots, h_n as the outputs.

[MAM16] manifests the superiority of Long Short Term Memory (LSTM) based sequence to sequence model over standard LSTM based Recurrent Networks in predicting one-minute step load data.

2.4 Adaptive Charging Network : ACN Caltech

Adaptive Charging Network was developed at Caltech to provide a test-bed to develop smart scheduling algorithms that are adaptive in nature [acn]. When a driver plugs into the ACN, the driver provides their estimated departure time and energy request through a mobile app [acn]. From this information provided, the best scheduling algorithm is prepared so that all users receive the requested energy before the mentioned departure time. As new EV's arrive or when users change their input parameters, the ACN should be able to adapt accordingly and provide the optimum scheduling algorithm. The optimal scheduling algorithm refers to delivering the driver's requested energy before the mentioned departure time without exceeding the power limit of the grid which would otherwise not only overload the grid, but also lead to over-subscription of transformers. This would pertain to increased electricity costs [LLL19a]. It has been proved that in this way, the charging demands of most office charging systems can be met with 75% lower infrastructure capacity compared to conventional systems, thus proving the significant role of Adaptive Charging Network in reducing the electric grid load [acn]. The ACN simulator uses ACN-data that is a publicly accessible dataset for EV charging research [LLL19b]. The data available is the details of electric vehicle charging sessions collected over the past three years, at the Caltech university, California. The ACN currently has over 80 EV charging ports in a garage on the Caltech campus which share a power limit of 300 kWh that is enough for 42 conventional ports. The system currently charges an average of 65 EVs a day and over the last 3 years it has delivered over 2.3 million miles worth of charge [acn].

3 State of the Art

[MCH10] Discusses a scheduling algorithm that fills the valley that especially exists overnight through the concept of Nash equilibrium. Each EV chooses its own charging strategy to minimize its individual cost. The cost price discussed in this paper varies according to the total demand, making it a method of dynamic pricing. [MCH10] substantiates a valley-filling strategy when the total demand, comprising of aggregated Plug-in Electric vehicle (PEV) charging load and non-PEV demand, is constant during charging intervals. In [CHD09], the vehicles are assumed to be charged at home and different percentages of penetration of electric vehicles are taken into consideration such as with zero penetration, 10%, 20% and 30%. It studies the impact of uncoordinated charging on the distribution grid and concludes maximum power loss and voltage deviations as a result of this. The optimal charging algorithm in [CHD09] is formulated by keeping the power losses to minimum. [SZPR10] analyses the impact of TOU electricity rate on the distribution load shape in a smart grid with EV penetration. [CTQ14] introduces a valley-filling online algorithm in which the vehicles have a bidirectional communication with the utility that guides the charging rate of the vehicle by updating the valley level. [GTL12] also discusses online and offline algorithms with bidirectional communication with the utility based on real-time electricity price profile. Each EV updates its own charging profile by the guidance of the utility via a control signal. [MCH10] proposes an optimal charging schedule for EVs with homogeneous requirements such as same start and end times of charging, energy requests and maximum charging powers, while [GTL12] describes the usage of dynamic prices for EV charging with the aim of valley-filling. The model proposed in [ZC14] is set up in a microgrid that is equipped with renewable energy such as wind and solar energies as the main source of electricity. The microgrid is also said to be equipped with a Battery Swap Station (BSS) that gives the benefit of replacing the battery with a fully charged one to the users. The charging strategy for BSS is based on time-of-use pricing for the battery parameters to complete charging of batteries within the specified time. [ZC14] mainly concentrates on renewable energy sources and does not take the residential load demand into consideration.

[HZS16] and [XMC16] also propose online pricing schemes for valley-filling. [HZS16] introduces two types of valley-filling pricing mechanisms, non-cooperative and cooperative scenarios. In the non-cooperative one, each EV charges without cooperation with other EVs, while in the cooperative type, all the EVs are controlled by an aggregator. Simulation results in this paper demonstrates that under the proposed pricing mechanisms, cost-minimizing charging schedules of self-interested EVs could also fill the load valley effectively. [LKT+11] introduces a two dimensional dynamic pricing and charging schedule for EV that substantiates to reduce the peak consumption and increase off-peak consumption drastically. [CTL+11] proposes a Time-of-Use based EV charging model. In this paper, the charging cost is further minimised considering the relation between the charging power of the EV battery and its state of charge (SOC).

In this thesis, along with valley filling criteria, the electric vehicle charging laxity is taken into consideration. That is, based on its departure time, if a vehicle has lesser time remaining in the charging session, lesser would its laxity be as in [LLL+16], where, laxity factor is defined as :

$$l_i := \frac{e_i}{(d_i - a_i) * r_i}$$

where, i represents the EV

l_i = laxity factor of the i^{th} EV

e_i = energy demand by the EV

d_i = departure time of the i^{th} EV

a_i = arrival time of the i^{th} EV

r_i = peak charging rate

l_i is in the range of [0,1], where 1 means the EV has to be charged at its peak rate at all time $t = a_i, \dots, d_i - 1$

[JZS17] introduces a valley-filling algorithm that also considers the electric vehicle charging laxity. It schedules EVs taking conventional load into consideration. But it does not include any pricing scheme in the scheduling algorithm. Valley-filling is considered in this thesis by the calculation of a time-slot that depends on the surplus power in the utility as well as the total electric vehicle charge demand per hour. The time slot to charge the EV is calculated and prioritised as mentioned in [JZS17] :

$$Index_{TS} = \frac{P_{sup}}{P_{dem}}$$

Where :

P_{sup} = Surplus power in supply which is calculated as

$$P_{sup} = P_{con}^{max} - P_{con}^k$$

P_{con}^{max} = maximum power demand of the day which is forecasted

P_{con}^k = conventional load at the k^{th} time slot.

P_{dem} = total EV load at the k^{th} time slot.

The k^{th} time-slot that has the highest $Index_{TS}$ is chosen as the ideal time-slot to charge EV. The slots are prioritised based on descending $Index_{TS}$ values. However, there is no electricity pricing scheme adopted in [JZS17]. Figure 3.1 represents the surplus power that could be utilised for EV charging, against the residential load. The uncoordinated and coordinated EV charging power profiles as obtained from [JZS17] are as shown in Figures 3.2 and 3.3.

Load forecasting has been previously investigated by [HM94], which presents a transformation technique with translation and reflection methods. The transformation function was estimated with the previous year's data points and is slightly translated so that the transformed data points fit into the shape of temperature-load relationships in that year. This method proves to reduce the load forecasting errors caused by the weather-load nonlinear characteristic in the transitional seasons. Multivariate regression is the basic forecasting method used here. The peak load is highly influenced by weather factors such as temperature and humidity. The regression model used in the paper [HM94] is

$$P = \beta_0 + \sum_{j=1}^m \beta_j X_j$$

Figure 3.1: Surplus power that could be utilised for EV charging.

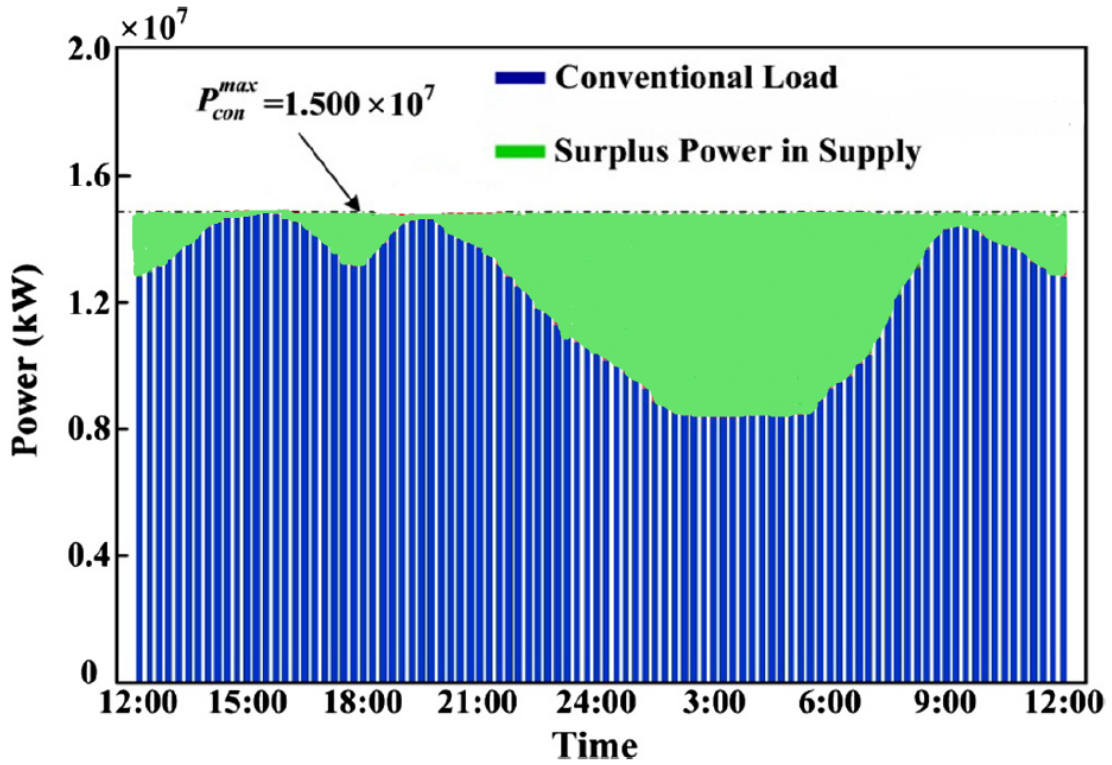


Figure 3.2: Uncoordinated EV Charging power profile.[JZS17]

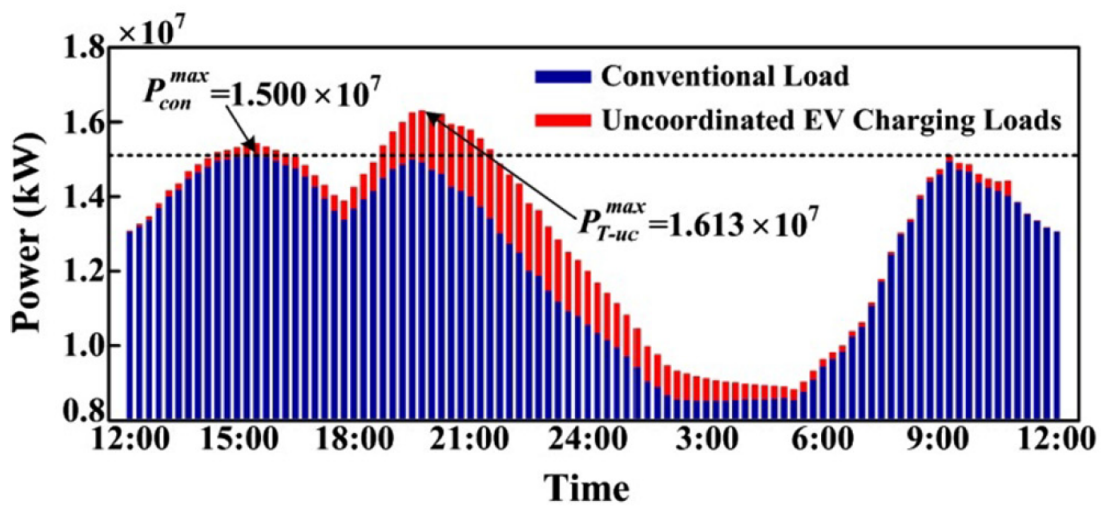
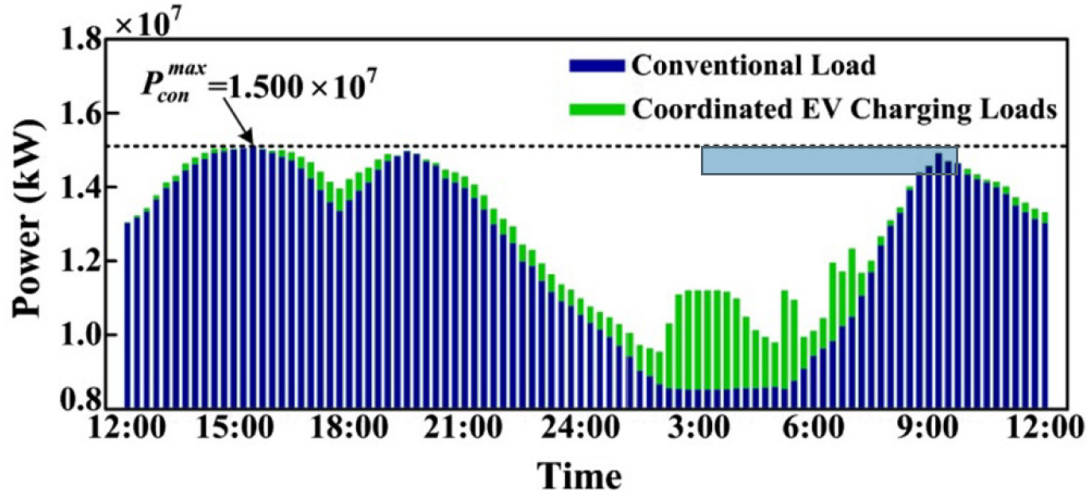


Figure 3.3: Coordinated EV Charging power profile. [JZS17]



where, P is a peak load. X_j is an explanatory variable correlated with P . β_0 and β_j are regression coefficients. The explanatory variables are chosen based on correlation analyses and experiences in utility operators.

[HM94] has also presented a regression based model with transformation technique that predicts daily peak load, while [CWH95] introduces an adaptive auto-regressive moving average model to perform 24 hours and one week ahead load forecast. It adopts the Box-Jenkins transfer function approach that does not adapt the forecasting errors available to update the forecast. It considers only temperature as the weather variable and predicts short term load for 24 hours ahead. Based on a set of historical load and weather data, the model structure as well as its parameters are determined and estimated. The fitted model is then used to forecast the future load one hour to one week ahead. As time elapses, the newly obtained hourly loads are added to the set of load data. The parameters of the model are then re-estimated according to this new batch of data [CWH95]. In conclusion, this paper mainly centralizes on short-term load forecasting. [GNC06] models the nonlinear influencing factors by using support vector machine. The electric load data used in this paper is from Hebei province of China. It substantiates to perform load forecasting better than the neural networks but however, it does not consider the influence of weather parameters in its implementation. [KPS19] and [He17] have implemented deep-learning based load prediction based on daily temperature, but due to unavailability of humidity data, it was not considered in [He17]. In this thesis, the machine learning technique that is used to predict load is multivariate LSTM, in which the multiple variables considered are hourly temperature, humidity values and load values. Since the data in consideration is nearly twelve months of load and weather information that comprises of hourly temperature and humidity values, there is scope for vanishing gradient to occur due to the massive amount of time-series data. Therefore, it is only ideal to use the multivariate LSTM technique of machine learning. The historical load data in this thesis is obtained from California ISO (CAISO) [ISO] and the historical weather information of the region of study, i.e, Pasadena, California is taken from [wun].

The ACN data that is used in this thesis has previously been used in [LLL19a], where the charging session parameters of users are learned via Gaussian mixture models. The scheduling algorithm in this paper is based on driver laxity. It also proposes a scheduling method based on on-site solar energy and shows how 50% of EV charging demand can be met by the same. Though on-site renewable energy proves advantageous, not all buildings are equipped with large PV arrays. In these scenarios, EVs must be charged using the available energy from the electric grid, taking into consideration the energy consumption pattern of the area since the effect of charging a large number of EVs is dependent on the overall utilization of the grid energy.

[GEL17] also uses the ACN data to formulate an offline optimal charging algorithm, in which the EV's arrival times, departure times and energy demands are given in prior. A brief introduction to online charging algorithm is given in this paper that computes the charging rates for all existing EVs assuming that there would be no future arrivals. A uniformly monotone cost is adopted for the online algorithm and proves that it attains same as the offline optimal this way. In this paper [GEL17], a facility operator is considered that decides the optimal charging rates for a collection of EVs $N = \{1, 2, \dots, N\}$ over a finite time horizon $T = \{1, 2, \dots, T\}$. Each EV n is specified by its arrival time a_n , departure time d_n , total energy demand e_n and peak charging rate vector $\bar{r}_n = (\bar{r}_{nt}, t \in T)$. \bar{r}_{nt} depends on time t so that the information of a_n and d_n can be specified as $\bar{r}_{nt} = 0$ for $t < a_n$ or $t > d_n$. However, \bar{r}_{nt} is allowed to be a constant over $t \in [a_n; d_n]$. Given the EV specification, a charging profile of EV n is a vector $r_n = (r_{nt}; t \in T)$ of charging rates such that $0 \leq r_{nt} \leq \bar{r}_{nt}$ for all $t \in T$ and $\sum_{t=1}^T r_{nt} = e_n$

P_t denotes the available charging power at the facility at time t . In the optimal charging problem, the operator tries to minimize a certain linear cost subject to feasibility constraints:

$$\begin{array}{ll}
 \min_{r_n: n \in N} \sum_{n=1}^N \sum_{t=1}^T c_{nt} r_{nt} & \\
 s.t. \sum_{t=1}^T r_{nt} = e_n, n \in N & (1a) \\
 \sum_{n=1}^N r_{nt} \leq P_t, t \in T & (1b) \\
 0 \leq r_{nt} \leq \bar{r}_{nt}, t \in T, n \in N & (1c)
 \end{array}$$

(1a) ensures that the total charging rates at each time interval amount to the total EV energy demand. (1b) guarantees that the total charging rate does not exceed the capacity, and (1c) enforces the rate limits. This is a linear program which can be solved offline by any LP solver. It provides an upper bound to benchmark the performance of any online algorithm [GEL17]. Similarly, in this thesis, the EV is always charged at its peak charging rate, but in case of no feasibility, the charging rate is reduced but ensured that it never goes below zero and is clipped at zero.

There are many other open-source EV charging sessions data available online, for example, the Dutch smart EV charging provider ElaadNL, which mainly offers aggregate data from the entire country of Netherlands unlike the ACN data that provides collective data for a certain area of the city, hence making the ACN data applicable for localized statistical analysis. ElaadNL has been used by [DSSR16] to examine capacity for demand response and to construct statistical models.

Another data source called My Electric Avenue [CH16] comprises of collected data from residential EV charging to examine its effect on the distribution grid, but it is difficult to publicly access this data due to privacy concerns.

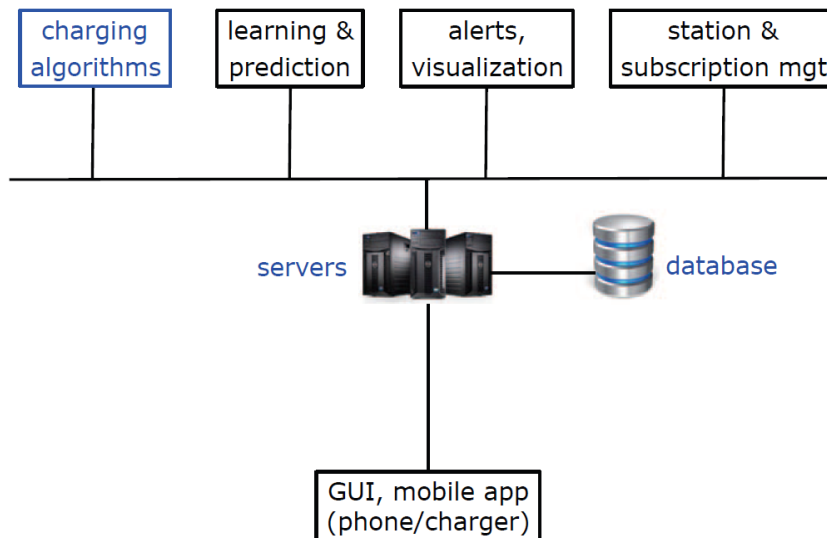
There has been limited research on the valley-filling strategy using Time-of-Use tariff to formulate scheduling algorithms for EV charging. There has not been much research on neural network based load forecasting using temperature and humidity as independent variables, although there have been previous works on statistical based modelling. Research works that have used the ACN database have not considered the potential of using the surplus power at the utility for EV charging and thus filling the load valley of the area.

4 Implementation

4.1 ACN Simulator

The scheduling algorithm implemented in this thesis is run on the ACN (Adaptive Charging Network) simulator. ACN-Sim is a data-driven, open-source simulator that operates a real-world EV charging system [acn]. The ACN consists of 54 level-2 EV chargers which are connected to the EV switch panel at 208V/80A. They are based on an open-source implementation of EVSE (Electric Vehicle Supply Equipment) compliant with the SAE J1772 standard [LLL+16]. The Adaptive Charging Networks are located in the Caltech campus as well as JPL's in California. The JPL site represents workplace charging whereas Caltech campus represents a hybrid between workplace and public use charging [LLL19a]. We have chosen Caltech site in this thesis due to higher incidence of overnight charging in this location. The existing software design is as given in Figure 4.1. It consists of an interface module in the form of a mobile app that interacts with the user to obtain the EV make and model, the energy demand in miles and the departure time. This information, which is stored as database for offline analysis, is used in the scheduling algorithm implemented in this thesis. Listing 4.1 shows the charging session data of an EV on the JSON database.

Figure 4.1: Software Design. [LLL+16]



Listing 4.1: ACN EV charging session data

```
{
  "_id": "5c6a0ab5f9af8b30307054be",
  "clusterID": "0039",
  "connectionTime": "Fri, 01 Feb 2019 20:33:50 GMT",
  "disconnectTime": "Sat, 02 Feb 2019 01:07:42 GMT",
  "doneChargingTime": "Fri, 01 Feb 2019 23:10:31 GMT",
  "kWhDelivered": 16.395,
  "sessionID": "2_39_139_28_2019-02-01 20:33:49.672736",
  "siteID": "0002",
  "spaceID": "CA-303",
  "stationID": "2-39-139-28",
  "timezone": "America/Los_Angeles",
  "userID": "00000734",
  "userInputs": [
    {
      "WhPerMile": 275,
      "kWhRequested": 16.5,
      "milesRequested": 60,
      "minutesAvailable": 258,
      "modifiedAt": "Fri, 01 Feb 2019 20:34:39 GMT",
      "paymentRequired": true,
      "requestedDeparture": "Sat, 02 Feb 2019 00:51:50 GMT",
      "userID": 734
    }
  ]
}
```

4.2 Peak Shaving and Valley-Filling

In order to achieve peak shaving and valley-filling, EV charging is shifted to the off-peak hours, based on the laxity of the EV. The laxity of an EV charging session is defined as :

$$Index_{ev} = \frac{E_{rn}}{T_{rn} * dT * P_n}$$

where,

$Index_{ev}$ = laxity of the n^{th} EV

E_{rn} = Remaining demand of the n^{th} EV.

T_{rn} = Remaining time for the n^{th} EV to be charged as per the user's demand.

dT = length of the time slot, which is taken as 1 hour here.

P_n = The operating power of the charger into which the n^{th} EV has been plugged in. It is considered as 7.4kW assuming it to be a single phase power supply, 230 V AC. [Wik]

active_ests is an in-built ACN simulator parameter that returns a list of active EVs connected to the EVSE. *active_ests* currently connected to an EVSE for charging are sorted in descending order by its value of *index_ev*. Higher the energy demand of the EV and lesser the time remaining for it to charge, greater is its priority to be charged.

Algorithm 4.1 Calculation of EV laxity

input : EVs currently connected to the EVSEs : *active_ests*

output *index_ev*

:

procedure CHARGE_PRIO(*active_ests*)

// Fetch the Session info of all the currently active ests

for *ev* ∈ *active_ests* **do**

$$\text{index}_{\text{ev}} = \frac{(\text{ev.remaining_demand})}{(\text{ev.remaining_time} * 7.4)}$$

//Sort the active ests in descending order based on its *index_ev* value

sorted(*active_ests*, *index_ev*, reverse=True)

end procedure

The TOU price values are fixed based on historical load consumption. For this thesis, it is obtained from the Southern California Edison (SCE) subsidiary which is the primary electricity supply company for Southern California [SCE]. It is evident from Figure 4.2 that the TOU prices during summer months (June - September) is maximum during the peak hours of the day compared to winter months (October - May). It can also be observed that the TOU values during weekends are much lower and are constant throughout the day. Overall, TOU prices throughout the year range from 0.05623\$ to 0.26668\$ per hour. From Figures 4.3 and 4.4, it is evident that the peak hours are not always coinciding with the high TOU tariff periods, especially during winter. Therefore, TOU tariff has a great influence in determining the time-slot index to charge EVs. Lower the TOU price of the hour, higher is the charging priority during that hour. Also, during the off peak hours, there is surplus power available at the utility, which means EV charging could be shifted to these hours. Therefore, the hour to charge EVs is selected based on the surplus power available at the utility, the total EV energy demand of that hour as well as the TOU price for the hour.

An index value which is directly proportional to surplus power and inversely proportional to the energy demand and TOU price is obtained as below :

$$\text{Index}_{\text{TS}i} = \frac{P_{\text{si}}}{P_{\text{di}} * \text{tou}_i}$$

Where, the surplus power is the difference of maximum residential load of the day (obtained from the hourly load database) and the residential load demand at the hour of concern. *i* here ranges from 1 to 24 hours.

Figure 4.2: Time-of-Use Tariff.

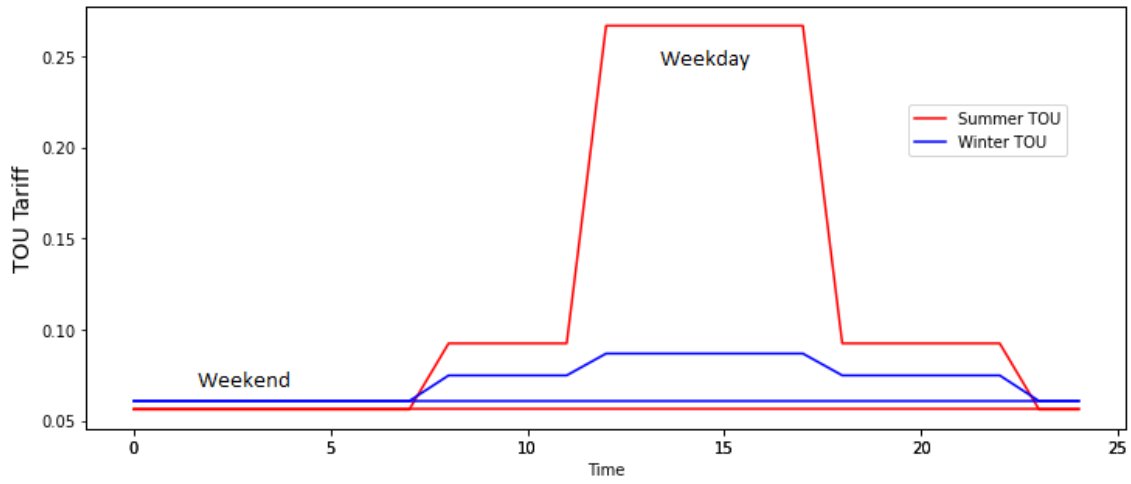


Figure 4.3: Load Vs Time-of-Use Tariff for Summer (June - September).

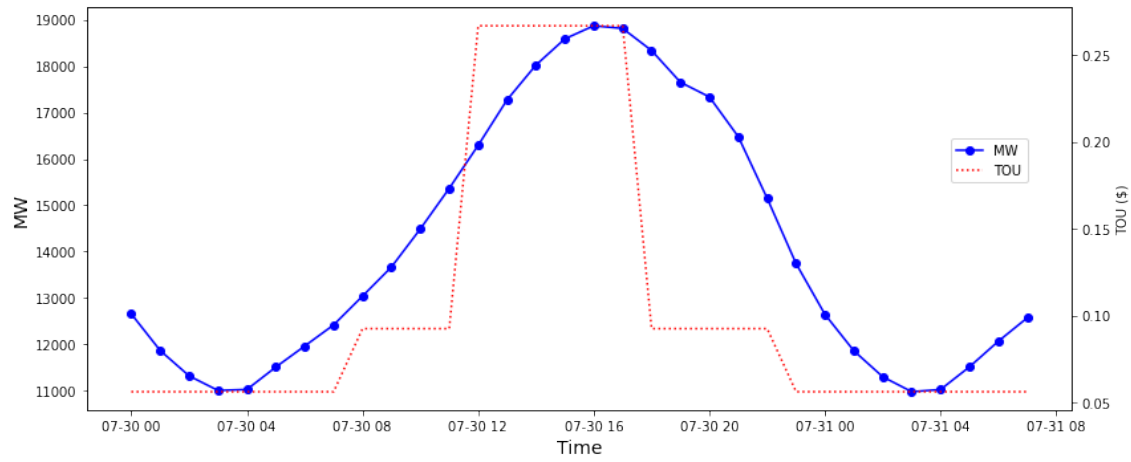
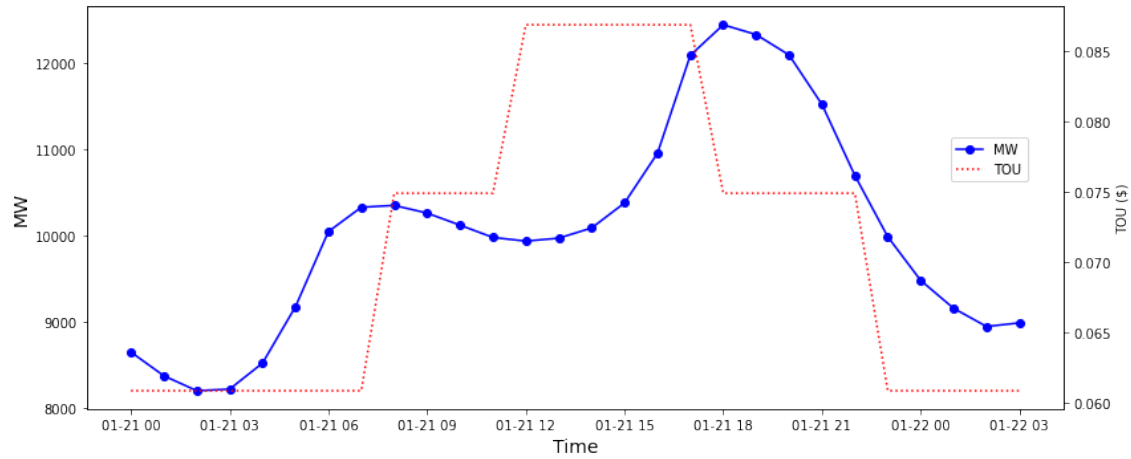


Figure 4.4: Load Vs Time-of-Use Tariff for Winter (October - May).



$$P_{si} = P_{\max} - P_i$$

The *sur_power[]* per hour is saved as an array. *max_power* is the maximum power of the day and *hour_power[]* is the residential load demand of the i^{th} hour.

Algorithm 4.2 Calculate surplus power for the current hour

input : EVs currently connected to the EVSEs : *max_power*, *hour_power*

output *sur_power[]*

:

procedure SURPLUS_POWER(*max_power*, *hour_power*)

// Find the surplus power for the current hour

for $i \in [start, end]$ **do**
 sur_power[i] = (*max_power* - *hour_power*[i])

end procedure

The EV energy demand per hour is calculated as below :

$$P_{di} = \sum_{k=1}^i E_k$$

Where, E_k = EV energy demand per hour. In the Algorithm 4.3 that defines the array of time-slot indices (*Index_TS*) to schedule EV, *ev_demand[]* is the array of total energy demand per hour, *tou[]* is the array of Time-of-Use prices for the day.

Algorithm 4.3 Array of time-slots index

input : *sur_power[]*, *ev_demand*, *tou*

output *max(Index_TS[])*

:

procedure INDEX_POWER(*sur_power*[])

 // Create array for time-slot index

for $i \in [start, end]$ **do**
 Index_TS = $\frac{sur_power[i]}{(ev_demand[i] * tou[i])}$
 i ++

end procedure

The vehicles are scheduled by assigning a specific charging rate as defined by [LLL+16]:

$$\begin{array}{ll}
0 \leq r_i(t) \leq \bar{r}_i & a_i \leq t < a_i + d_i, i \in V \quad (2a) \\
r_i(t) = 0 & t < a_i, t \geq a_i + d_i, i \in V \quad (2b) \\
\sum_{t=a_i}^{d_i-1} r_i(t) \leq e_i & i \in V \quad (2c)
\end{array}$$

(2a) ensures that the charging rates $r_i(t)$ are non-negative and below or equal to the maximum charging rate \bar{r}_i . (2b) makes sure that the EV does not charge before its arrival or after its departure time and (2c) limits the total energy delivered to the EV i to the requested energy demand e_i . The energy delivered may not always reach the user's requested energy due to the EV's battery becoming full or due to congestion in the system. [LLL+16]

The maximum value of $Index_{TS}$ is found out every 3 hours and the corresponding hour is chosen to schedule EV depending on the *remaining_time* of the EV. If the *remaining_time* of the EV is more than 5 hours and if the *current_hour* is not equal to the off-peak hour previously calculated, then its schedule is deferred. Else, it is scheduled immediately. *schedule{}* is a dictionary of EVs in the order to be scheduled, represented by their *station_id*. Each EV that is ready to be scheduled is assigned the *max_pilot_signal*, which is the maximum charging rate that can be assigned to it. If it is not possible to charge at its maximum rate, then it is decremented.

Algorithm 4.4 Schedule EVs at off-peak hour

input : sorted_ests, sur_power[], ev_demand, tou

output schedule[ev.station_id]

:

procedure SCHEDULE_EV(sorted_ests, sur_power[])

// Find the off-peak hour with maximum $Index_{TS}$ every 3 hours

for $ev \in sorted_ests$ **do**

if ($ev.remaining_time \geq five_hours$) & ($current_hour \neq off_peak_hour$) **then**

 pass

else if ($ev.remaining_time < five_hours$) || ($current_hour == off_peak_hour$) **then**

$schedule_ev[ev.station_id] = [max_pilot_signal(ev.station_id)]$

while not is_feasible **do**

$schedule[ev.station_id][0] -= self_decrement$

if $schedule[ev.station_id][0] < 0$ **then**

$schedule[ev.station_id] = [0]$

 break

end procedure

The part of the Algorithm 4.4 below ensures that the charging rate when decremented, never goes below zero, thereby clipping at zero.

```
if schedule[ev.station_id][0] < 0 then
```

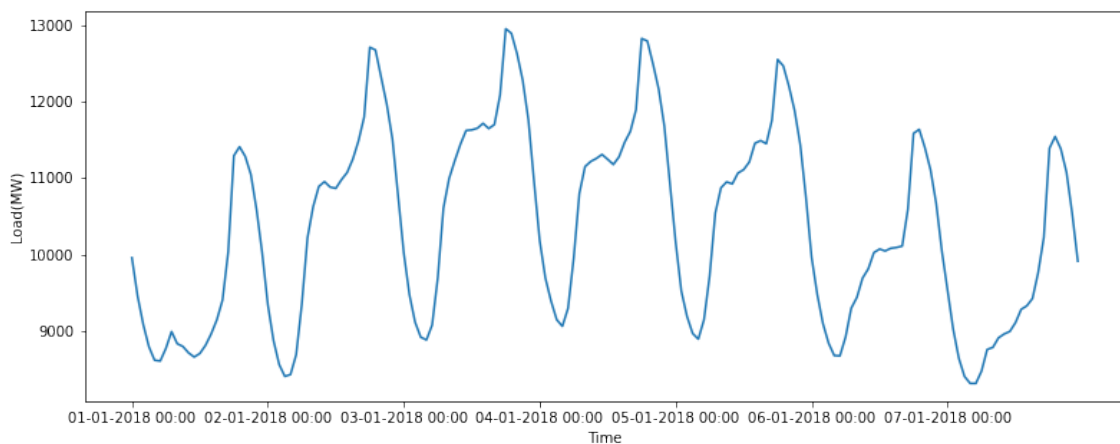
```
    schedule[ev.station_id] = [0]
```

```
break
```

4.3 Load Forecasting

The method of load forecasting implemented in this thesis is Long Short Term Memory (LSTM) neural network. As LSTM models work best with a lot of data as input, it is ideal for predicting load on the basis of a year of training data. Though the training data is a large sequence, LSTM avoids the vanishing gradient/ explosion problem [KMS+15]. From the Figure 4.5, it can be seen that there is a specific trend in the load magnitude throughout the day. The hourly load data is taken from California ISO (CAISO). Load as observed from the figure, is maximum during mid-day and minimum during the wee hours.

Figure 4.5: Periodicity of daily load.



Relationship between Weather Parameters and Load

In order to analyse the relationship between weather parameters and load, a month of historical load and weather data are taken from the area of study - Pasadena, California. From the historical load data of the region, it was observed that the highest peak loads occurred during the month of July. Therefore, for better analysis of their influence on load, the temperature and humidity values of July 2019 was taken. The measure of variance, represented by R^2 , between temperature and load is obtained as 0.7053. Temperature has a linear relationship with load, i.e, higher the temperature, greater is the residential load consumption. The linear equation is as described below:

$$y = 0.0012x + 6.8893$$

$$R^2 = 0.7053$$

4 Implementation

The R^2 value for Humidity-load relation is obtained as 0.5661. Although inconsistent, humidity has a moderately logarithmic relationship with load with a negative slope as given below :

$$y = -76.12 \ln(x) + 795.22$$
$$R^2 = 0.5661$$

Due to the specific trend of daily load and its relationship with temperature and humidity, the LSTM method of neural networks is ideal as it is a type of recurrent neural network that can learn the order dependence between items in a sequence. LSTM networks are capable of automatically learning features from sequence data, support multi-variate data and can output a variable length sequence that can be used further for multi-step forecasting. The LSTM recurrent neural networks are able to model problems with multiple input variables with better efficiency than classical linear methods [Jas]. In this thesis, the sequential data is the hourly temperature and humidity values that form the independent variables with load being the dependent variable. The multi-variate LSTM model implemented is further used to forecast load.

Figure 4.6: Temperature Vs Load.

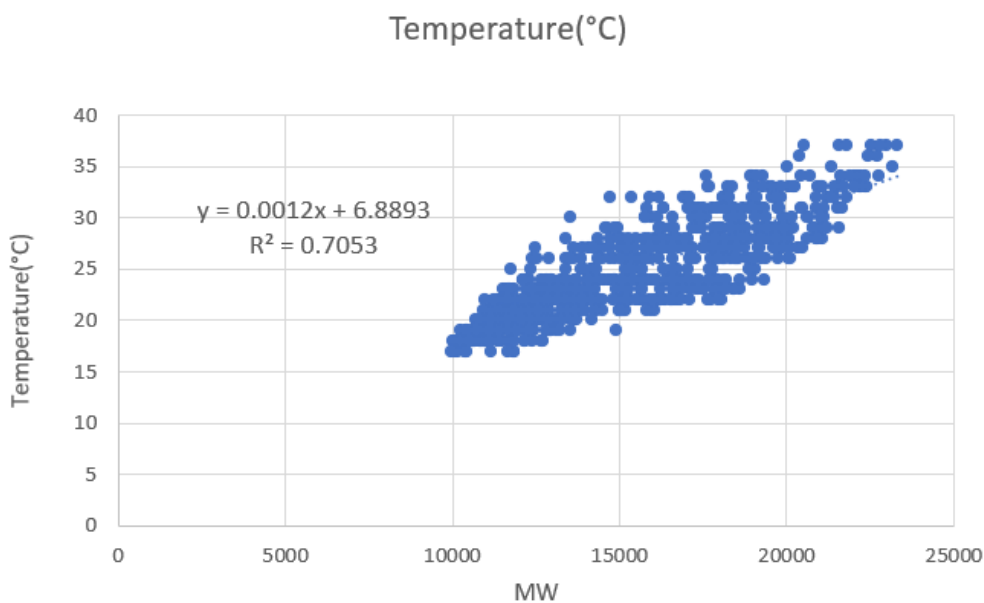
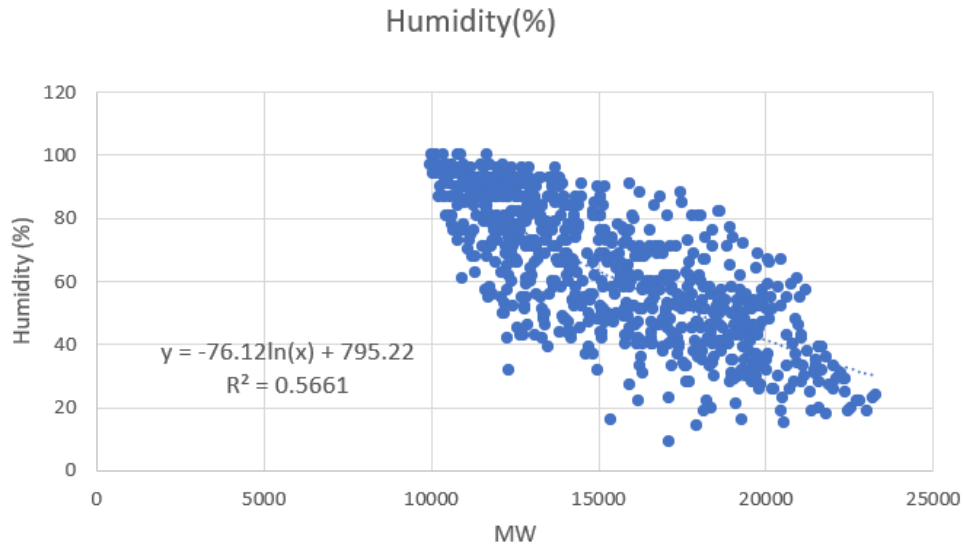


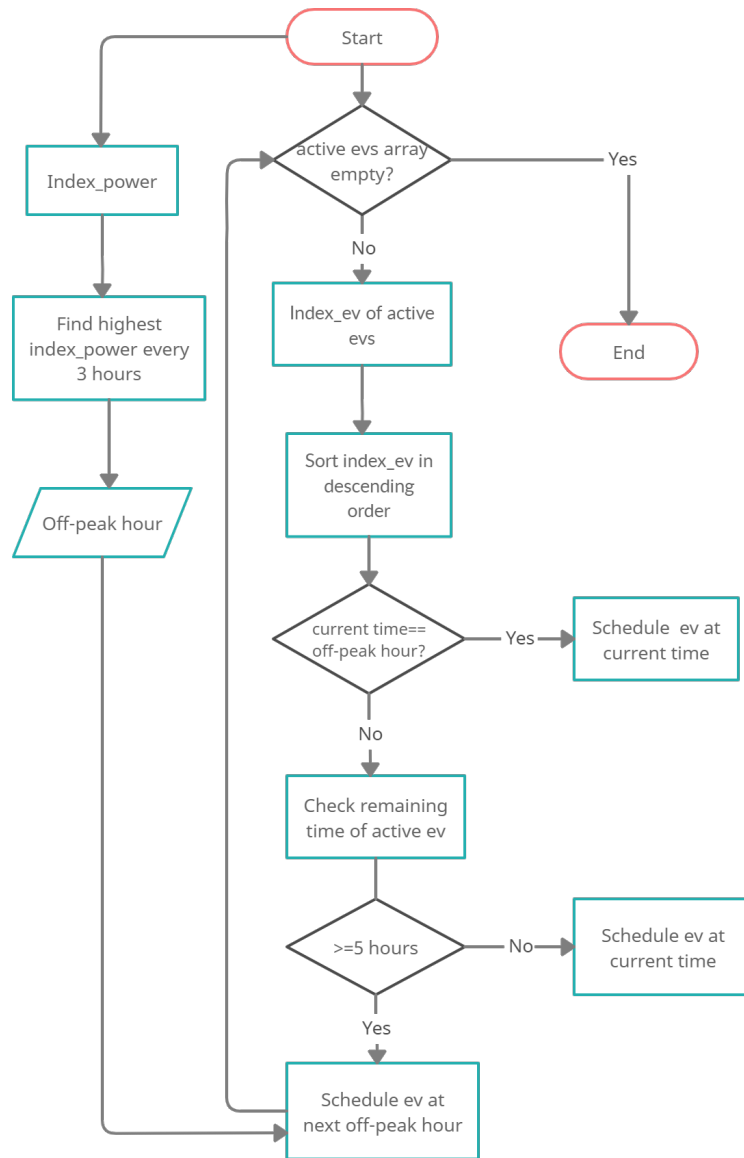
Table 4.1 gives the first few rows of the raw input dataset.

Figure 4.8 gives the overall flowchart of the scheduling algorithm implemented in this thesis.

Figure 4.7: Humidity Vs Load.**Table 4.1:** Input dataset for the LSTM model.

date_time	MW	Humidity(%)	Temperature(°C)
01-01-2018 00:00	9957.145	64	11
01-01-2018 01:00	9457.931	66	9
01-01-2018 02:00	9086.319	69	9
01-01-2018 03:00	8795.616	68	9
01-01-2018 04:00	8619.311	71	9
01-01-2018 05:00	8608.489	73	8

Figure 4.8: Flowchart of the scheduling algorithm.



5 Evaluation

5.1 Setup

- **Weather-based load prediction**

The parameters for the weather-based load prediction are:

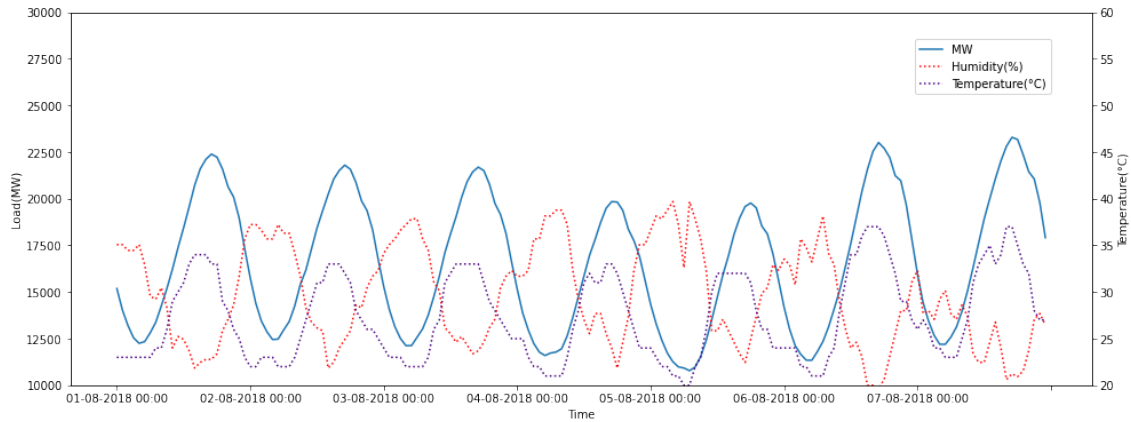
- **Training dataset** : It consists of 300 days of hourly residential load data, temperature and humidity values from the year 2018, from the month of January to October. The historical load data is taken from California ISO (CAISO) [ISO]. The California Independent System Operator (CAISO) is a non-profit Independent System Operator (ISO) that oversees the operation of California’s bulk electric power system. It has provided 3 years of historical data from the energy management system (EMS) to allow the public to analyse periods of coincident load peaks [ISO], thus making it a reliable source of load data. The data is chosen based on the transmission access charge (TAC) area. Since the area of study in this thesis is Pasadena, California, the TAC selected here is Southern California Edison (SCE) which is the primary electricity supply company for Southern California. The hourly temperature and humidity values are obtained from the weather forecast web application [wun].
- **Testing dataset**: It consists of hourly residential load data, temperature and humidity values from the year 2018, from October through mid-December.
- **Validation dataset**: Hourly residential load data, temperature and humidity values from the year 2018, from mid-December to the end of December 2018.

Figure 5.1 represents one week of training data which consists of hourly load, temperature and humidity values.

The overall input parameters for the LSTM model is given in Table 5.1 along with the number of time-steps for each. Here, *samples* represent the total time-steps and *features* represent the independent variables, which are temperature and humidity.

Table 5.1: Input parameters for the LSTM model.

Data	Input parameters [samples, timesteps, features]
Training dataset	[7200, 1, 2]
Test dataset	[1200, 1, 2]
Validation dataset	[336, 1, 2]

Figure 5.1: One week of training data.

Data pre-processing: Data pre-processing is an important step to attain better performance and accuracy of the deep learning algorithm. Since neural networks are sensitive to data scales, input data must be normalized before they are used in the algorithm [KPS19]. In this thesis, the min-max normalization method is used to normalize the input data.

Load forecasting errors : The load forecasting errors are computed based on the Root Mean Square Error (RMSE). It gives a measure of the neural network accuracy in prediction. It mainly compares the predicted value with the observed value. n below represents the number of samples.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Predicted_load_i - Observed_load_i)^2}{n}}$$

- **Peak shaving and Valley-Filling**

In order to evaluate how much of valley-filling is attained through the scheduling algorithm implemented in this thesis, random weekdays and weekends were taken from each month of the year 2019 and comparison was made using the algorithm against uncoordinated charging of EV, i.e, without any method of scheduling. Uncoordinated or uncontrolled charging has already been implemented in the ACN Simulator. [LLL19a]. In this type of charging, the EVs are assigned its maximum charging rate as soon as they are plugged into the EVSE. The user input parameters for the ACN Simulator and their meaning are as given in Table 5.2. $start_dt$ and end_dt are the input datetimes for which the simulation has to be run. The interval between $start_dt$ and end_dt is assumed to be 24 hours. The default value for $max_recompute$ is 1, which means the scheduling algorithm will be called every period-time, the $period$ here being 10 minutes of simulation time.

The valley-filling percentage is calculated by adding the aggregate current $agg_current$ of all the simulation time-steps $sim_time[]$, excluding the peak hours $peak_hour[]$. $count_peak$ is the total current during peak hours (Algorithm 6.1). The peak current of each simulation is obtained from its current profile.

Table 5.2: User input parameters for the ACN Simulator

Simulation Parameters	Values	
<i>timezone</i>	America/Los Angeles	
<i>start_dt</i>	start date	It is the start date for which the simulation has to run.
<i>end_dt</i>	end date	It is the end date for which the simulation has to run.
<i>period</i>	10	It is the length of each time interval in the simulation in minutes.
<i>max_recompute</i>	1	Maximum number of periods between calling the scheduling algorithm even if no events occur. If None, the scheduling algorithm is only called when an event occurs.
<i>voltage</i>	220V	
<i>default_battery_power</i>	32*voltage /1000 (kW)	
<i>site</i>	caltech	
<i>API_KEY</i>	DEMO_TOKEN	The EV charging dataset is accessed by the Caltech ACN-Data API key.

Algorithm 5.1 Calculation of valley-filling percentage**input** :peak_hours[]**output** vfill_pcent

:

procedure VF_PERCENT(*v fill_pcent*)**if** *sim_time*[*i*] > *peak_hour*[0] & *sim_time*[*i*] < *peak_hour*[*n*] **then***count_peak* = *count_peak* + *agg_current*[*i*]

$$vfill_pcent = \frac{(1 - count_peak)}{agg_current} * 100$$

end procedure

To analyse the economic benefits of the scheduling algorithm, the total tariff is calculated by:

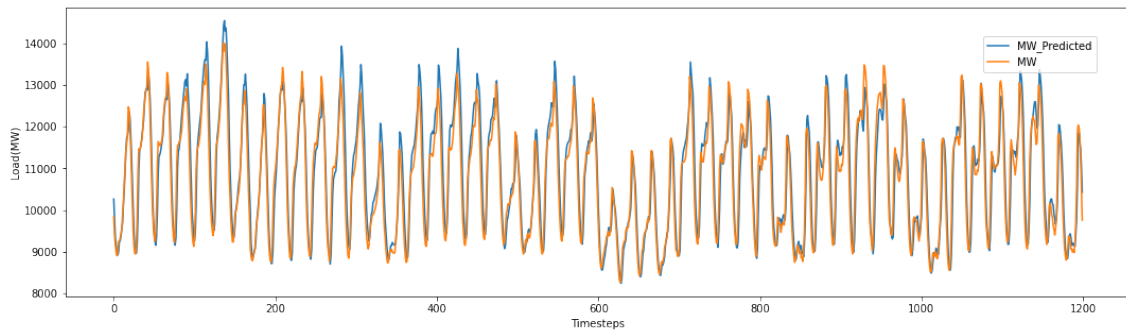
$$Tariff = \sum_{k=1}^{24} TOU[k] * E_k$$

Where, *TOU* is the Time-of-Use price for the k^{th} hour of the day and E_k is the total energy demand of k^{th} hour.

5.2 Results

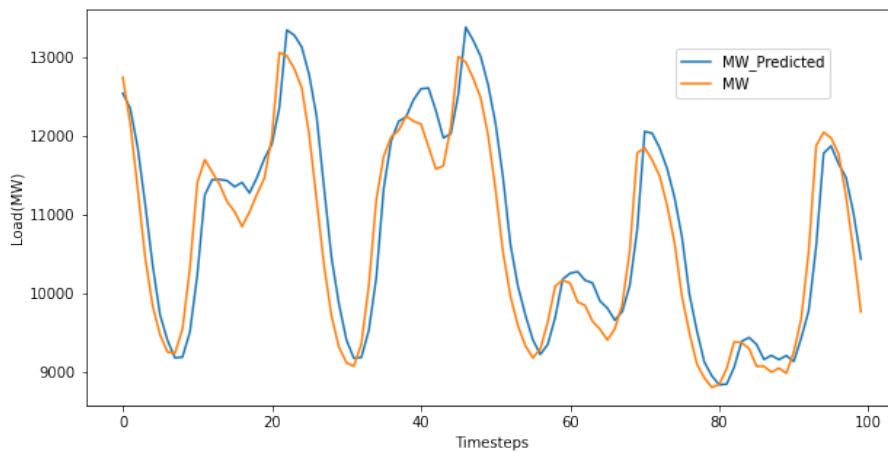
Figure 5.2 gives the predicted test data Vs observed load data based on the training of the LSTM model.

Figure 5.2: Predicted Vs Observed load (Testing dataset)



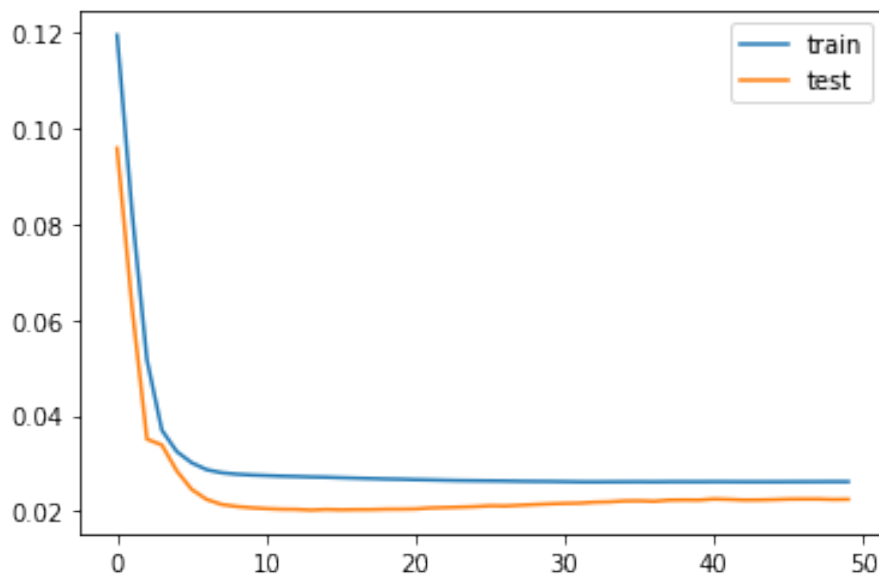
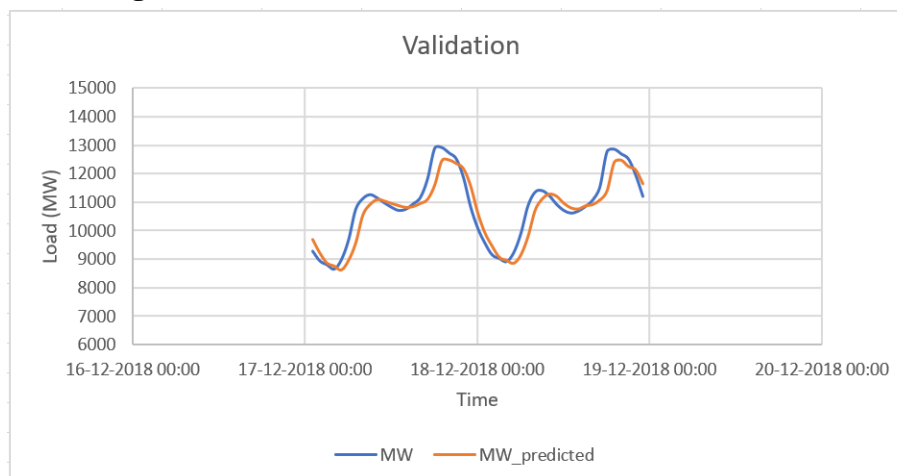
For the purpose of analysis, the last 100 time-steps of training Vs testing values are extracted. It can be observed from Figure 5.3 that the peak and minima load values are fairly predicted by the testing set. In order to evaluate the performance of weather-based load prediction, the hyper-parameters of the LSTM network, units and batch size are tuned to obtain the least root mean square error (rmse). With a batch size of 72 and units of 50, we were able to achieve a test RMSE of 462.581.

Figure 5.3: Last 100 time-steps of Predicted Vs Observed load (Testing dataset).



The training Vs testing loss curve evaluates whether the machine learning model was underfitting, overfitting or good fit [Jas]. A good fit is a case where the performance of the model is good on both the training and testing sets. Since the training and testing losses decrease and stabilize around the same point (Figure 5.4), the LSTM model implemented in this thesis is said to be a good fitting model.

The LSTM model is further used to predict a validation data set of 336 time-steps of load data, with a RMSE value of 467.6425284 (Figure 5.5). It can be seen from the figure that the model has predicted with good accuracy.

Figure 5.4: Training Vs Testing loss.**Figure 5.5:** Predicted Vs Observed load (Validation dataset).

The evaluation of the scheduling algorithm is performed based on its ability to achieve valley-filling, its TOU tariff and peak current. (Tables 5.3 and 5.4)

Figure 5.6 gives the peak hours to avoid EV charging on an average day. They mostly occur during mid-day.

The load vs aggregate current profile with the scheduling algorithm gives an overview of how most of the EV charging has been deferred to the off-peak hours (Figure 5.7). This is an illustration for Weekday_16 from Table 5.3.

The load vs aggregate current profile was also obtained with uncontrolled charging for Weekday_16 to analyse how most of the EV charging has occurred during the peak hours of the day (Summer TOU). (Figure 5.8)

Table 5.3: Valley-filling percentage (Weekdays)

Month	Day	% Valley-filling		Tariff (\$)		Peak Current (A)	
		Scheduling algorithm	Uncontrolled charging	Scheduling algorithm	Uncontrolled charging	Scheduling algorithm	Uncontrolled charging
January	Weekday_1	69.92	31.23	33.15350118	35.838615	389	509.33
	Weekday_2	38.15	29.95	28.91706689	31.03930719	422.27	394.48
February	Weekday_3	53.6	24.82	25.38748316	29.53968447	256	473.06
	Weekday_4	64.85	40.71	35.41694589	38.98917568	404.44	391.11
March	Weekday_5	55.61	30.02	27.38079826	28.53736774	352	356.03
	Weekday_6	68.08	22.67	23.48643622	25.57232347	398.1	406.39
April	Weekday_7	62.25	60.97	24.18700354	25.71504836	206.67	325.89
	Weekday_8	44.27	35.21	23.59655756	25.6489633	288	390.74
May	Weekday_9	62.25	31.38	25.41551435	26.84028839	334.67	314.17
	Weekday_10	31.98	68.9	24.3794564	27.32346992	336	487.55
June	Weekday_11	51.87	41.3	27.69636931	37.14586918	255.08	279.84
	Weekday_12	32.99	21.36	38.01566638	55.57757232	261.54	407.51
July	Weekday_13	65.84	40	38.0517264	50.77659667	288	342.33
	Weekday_14	59.98	28.75	26.47009821	47.7538713	276.49	311.66
August	Weekday_15	67.23	22.51	37.96576612	67.21652697	402.34	536.14
	Weekday_16	59.89	32.38	37.3054142	57.41726826	334.29	384.84
September	Weekday_17	38.82	7.5	33.59734801	58.74413678	352	416
	Weekday_18	61.13	22.61	38.1551064	59.7170684	329.83	384
October	Weekday_19	26.99	38.24	23.95155108	25.0680794	272	288
	Weekday_20	28.08	65.22	23.33470646	25.49887082	320	352
November	Weekday_21	33.08	2.12	15.55921216	16.78611922	224	388.31
	Weekday_22	59.93	19.89	23.17703846	24.7752075	320	469.69
December	Weekday_23	42.72	16.95	24.27208267	26.28524812	313.41	345.41
	Weekday_24	70.67	64.38	7.347739663	6.871575047	64	64

Table 5.4: Valley-filling percentage (Weekends)

Day	% Valley-filling		Tariff (\$)		Peak Current (A)	
	Scheduling algorithm	Uncontrolled charging	Scheduling algorithm	Uncontrolled charging	Scheduling algorithm	Uncontrolled charging
Weekend_1	50.10467201	53.28870671	6.47437668	6.47437668	96	96
Weekend_2	69.79965372	69.79965372	9.92592887	9.92592887	128	128
Weekend_3	63.21707791	64.16310339	7.40183258	7.54956407	64	64
Weekend_4	61.73	58.5	7.28906076	7.28906076	128	128
Weekend_5	69.56581979	69.56581979	10.69035462	10.69035462	96	98.07
Weekend_6	72.97891766	72.97891766	7.67786912	7.67786912	64	89.88
Weekend_7	66.75245401	66.75245401	4.5445086	4.5445086	64	64
Weekend_8	71.05653933	60.17	6.05867004	6.05867004	96	96
Weekend_9	62.14300764	62.14300764	2.93559961	2.93559961	32	32
Weekend_10	14.05674025	14.05674025	3.35209061	3.35209061	160	160
Weekend_11	12.97380586	12.97380586	0.98761575	0.98761575	32	32
Weekend_12	85.01192016	85.01192016	6.02564304	6.02564304	64	64

Figure 5.6: Peak hours on an average day.

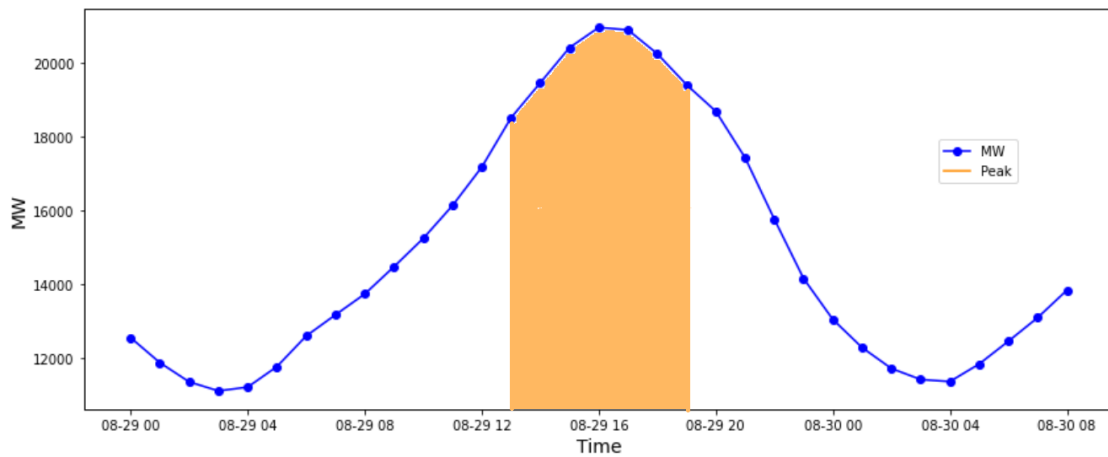


Figure 5.7: Load and aggregate current profile with the scheduling algorithm. (Weekday₁₆)

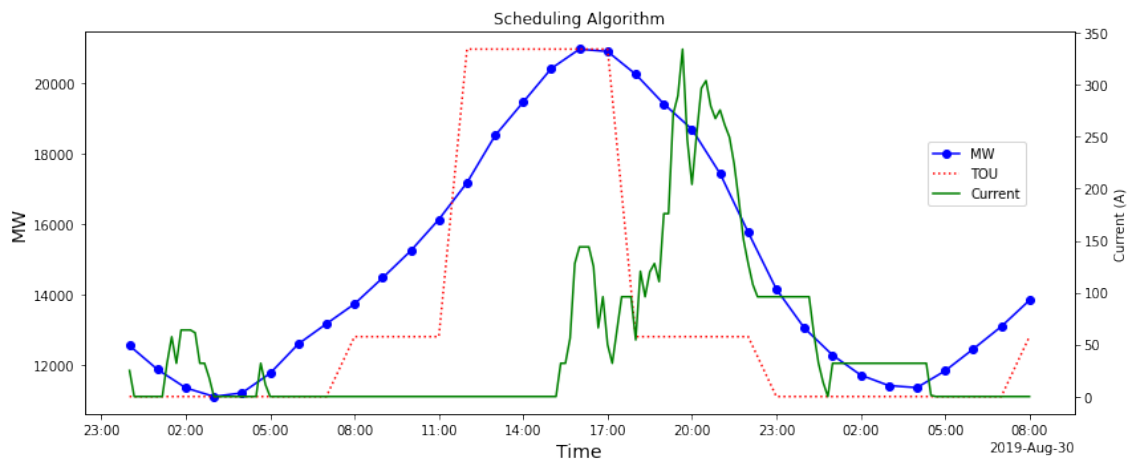
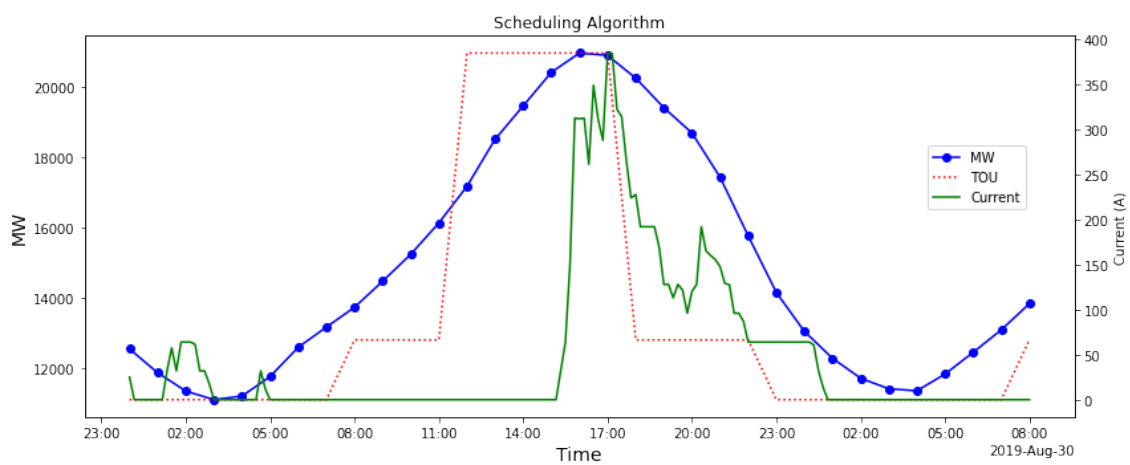
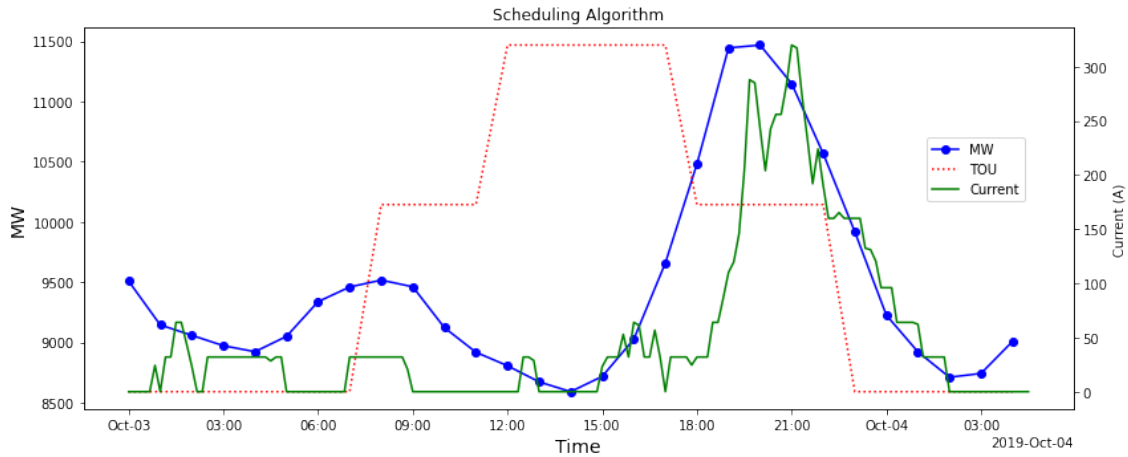


Figure 5.8: Load and aggregate current profile with uncontrolled charging. (Weekday₁₆)



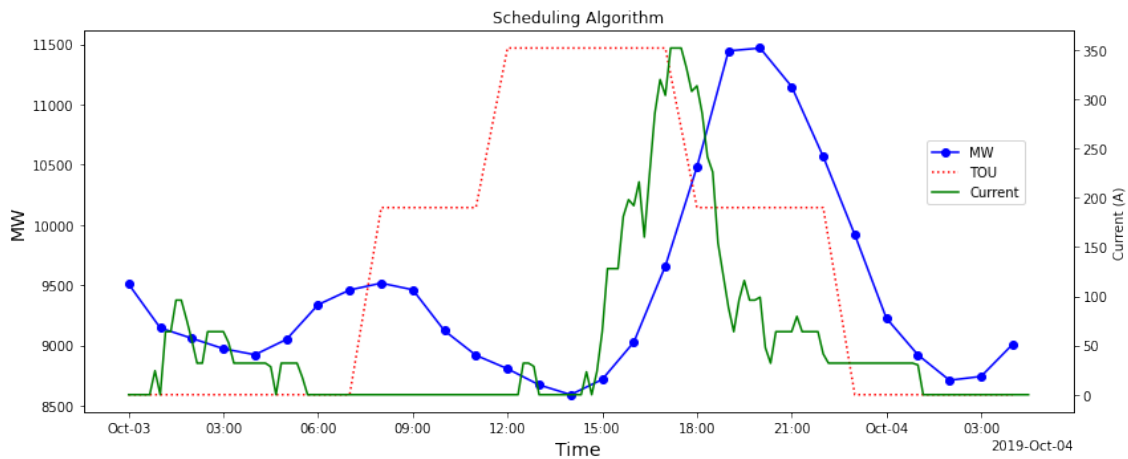
The load vs aggregate current profile with the scheduling algorithm in Figure 5.9 gives an overview of how most of the EV charging has occurred during peak hours but avoided the high tariff period. This is an illustration for Weekday_20 from Table 5.3.

Figure 5.9: Load and aggregate current profile with the scheduling algorithm. (Weekday_20)



The load vs aggregate current profile was also obtained with uncontrolled charging for Weekday_20 to analyse how most of the EV charging has occurred during the off-peak hours of the day but during the high tariff period. (Winter TOU). (Figure 5.10)

Figure 5.10: Load and aggregate current profile with uncontrolled charging. (Weekday_20)



5.3 Discussion

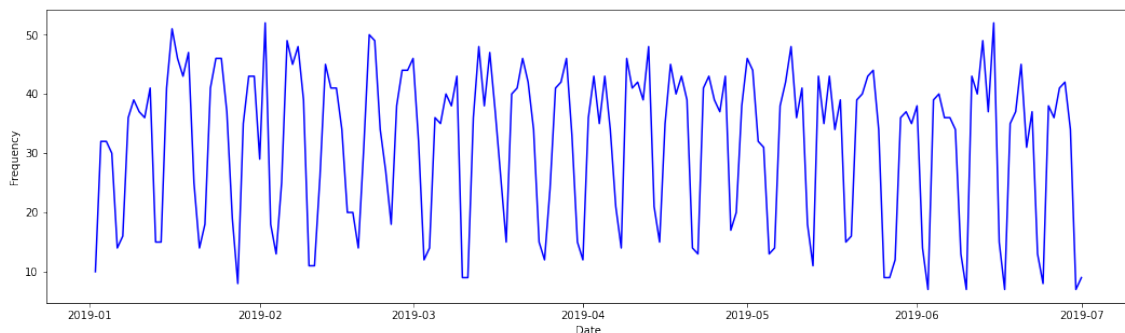
- Weather-based Load Prediction

From the Figure 5.5, it can be observed that the LSTM model for load prediction was successfully able to predict with a low RMSE value of 467.6425284. The peaks and minima were predicted with accuracy, based on the weather parameters - temperature and humidity.

- **Peak shaving and Valley-Filling**

From the Table 5.3, it is observed that the scheduling algorithm implemented in this thesis was able to attain a higher percentage of valley-filling on most days as compared to that of uncontrolled charging. Apart from achieving valley-filling, the tariffs imposed by the Time-of-Use pricing scheme is significantly lower for the scheduling algorithm as compared to uncontrolled charging. For days such as Weekday_17, the tariff imposed by the scheduling algorithm is nearly half the tariff imposed by uncontrolled charging. Apart from achieving valley-filling, the peak current is considerably lower for the algorithm compared to uncontrolled charging, with few exceptions such as Weekday_2 and Weekday_4. However, the peak current never exceeds 500A with the algorithm, in all cases. In uncontrolled charging, the peak current is always high because of the assignment of maximum charging rate to the EV with no concern for feasibility. Whereas, for the algorithm implemented in this thesis, if the maximum charging rate is not feasible, then it is decremented. The peak current is an important factor in determining how large the capacity of the transformers and cables must be in order to support the EV charging system. With respect to valley-filling, there are few exceptions such as in Table 5.3, Weekday_10 and Weekday_20 have a considerably lower percentage of valley-filling attained despite the algorithm. But the peak current and tariffs are low as opposed to uncontrolled charging. From Table 5.4, it is observed that for weekends, the percentage of valley-filling, tariffs and peak currents with the scheduling algorithm are almost as same as that of uncontrolled charging. This is mainly due to the fewer number of vehicles parked on campus during weekends as observed from Figure 5.11. There is a considerable dip in the frequency of EVs parked at Caltech during weekends. Also, the vehicles are parked for only few hours at campus during weekends. Due to this, the charging time of each EV is significantly lesser when compared to weekdays when there is a higher number of EVs parked overnight. The tariffs are equal during weekends with and without the algorithm because of constant TOU tariffs throughout the day.

Figure 5.11: Frequency of EVs charging at Caltech on a daily basis.

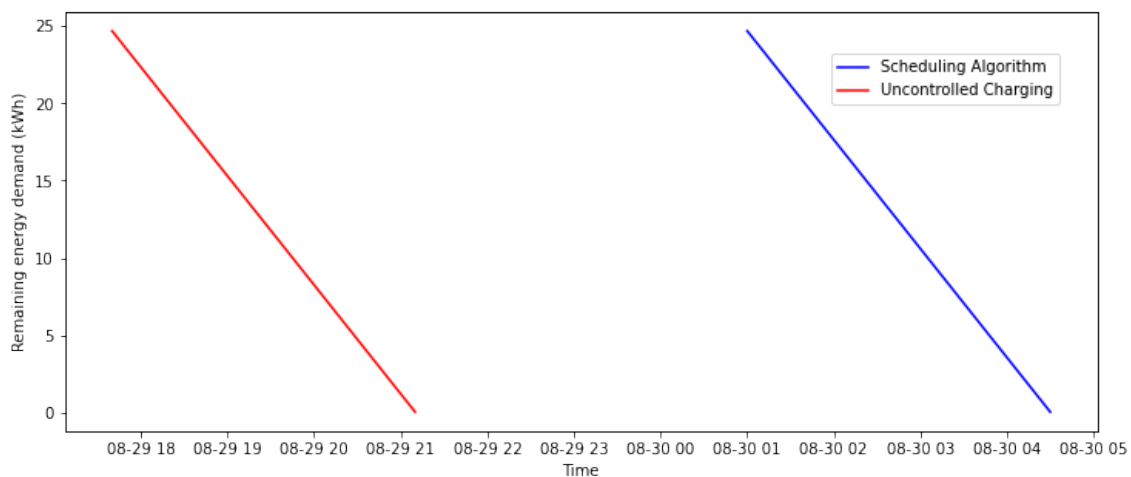


The peak hours of a day, as marked on Figure 5.6, is the period during which the EV charging is deferred so as to avoid aggravating the existing residential peak load and causing instability of the electric grid. [JZS17] The residential load and aggregate current profile with the scheduling algorithm for an average summer weekday is as shown in Figure 5.7 (taken

here for example as 29-08-2019). It can be observed that with the help of the algorithm implemented, most of the EV charging is deferred to the off-peak hours of the day. The area of the curve converging with the higher TOU cost is much lesser for the scheduling algorithm in comparison with uncontrolled charging (Figures 5.7 and 5.8). It can also be observed from the Figure 5.7, how with the scheduling algorithm, not only are the residential peak hours avoided for charging, but also the periods of higher cost imposed by the TOU pricing scheme. The peak current is reached during the off-peak hours with the algorithm but with uncontrolled charging, not only is the peak current reached during the peak hours, but also is it coinciding with the high tariff period. The aggregate current Vs residential load profile in Figure 5.9 shows how the TOU and load curve do not coincide during peak hours especially in winter. It is evident from the Figure 5.9, how most of the EV charging has taken place during peak hours with a low valley-filling percentage of 28.08% despite the algorithm, but the high TOU tariff period was completely avoided. Whereas, in uncontrolled charging (Figure 5.10), though considerable percentage of valley-filling (65.22%) was achieved, the peak current is reached during high tariff period. This further substantiates the significance of including TOU in the scheduling algorithm in order to make it economical.

Also, without the scheduling algorithm (Figure 5.12), it can be noted that the EVs are charged as soon as they are plugged in for charging without deferral, irrespective of the residential peak hours or the TOU peak periods. An EV with the session ID *2_39_95_444_2019-08-29 17:41:16.869694* scheduled on the same day (29-08-2019) is taken for illustration. The session ID manifests that the EV was plugged in at time 17:41:16. Figure 5.12 shows the remaining energy demand profile of charging with and without the scheduling algorithm. The figure proves that for uncontrolled charging, the EV starts charging immediately at 17:41:16 even though the time period falls under peak-hours. Whereas, with the scheduling algorithm, the EV does not start charging until 30-08-2019 1:00:00, which is categorized under off-peak hours.

Figure 5.12: Remaining energy demand profile for EV: *2_39_95_444_2019-08-29 17:41:16.869694*



The method of load forecasting executed in this thesis based on weather parameters is an effective way to predict future load demands. It was able to predict with an rmse value of 486.79.

The scheduling algorithm implemented in this thesis was able to achieve a high percentage of valley-filling on most days, ranging from 26.99% to 85.01%. The peak current with the algorithm

is always maintained below 500A. Due to deferral of EV charging to low tariff periods by the algorithm, it was able to achieve upto 44.57% reduction in tariff compared to that of uncontrolled charging. The algorithm is based on offline database of EV charging sessions, i.e, the algorithm assumes complete knowledge of all EV arrival times, departure times and energy demands in advance. An online adaptive charging algorithm can be implemented based on the one presented in this thesis. In the online adaptive charging algorithm, the charging rates could be assigned to EVs assuming that there will be no future arrivals. In this method, the future EV arrivals need not be known in advance and the algorithm can adapt based on the current EV charging demands.

6 Conclusion and Future Work

The scheduling algorithm implemented in this thesis is based on charging session data such as the EV arrival time, departure time and energy demand. The charging rates are assigned based on EV laxity which determines its deferral to off-peak hours. This algorithm has proven to achieve a significant percentage of valley-filling ranging from 26.99% to 85.01%. By employing the Time-of-Use tariff and scheduling EVs to lower tariff periods, the algorithm was able to achieve upto 44.57% reduction in tariffs compared to that of uncontrolled charging. The algorithm was also capable of maintaining a low peak current for charging. Since the peak current is an important factor in determining how large the capacity of the transformers and cables should be, lower peak current attributes to lower infrastructural cost for EV charging facilities. The ACN Simulator, on which the research was performed, helped to analyse the scheduling algorithm in a real-world EV charging system. Due to the periodicity of load demand and its relation to weather attributes, temperature and humidity, the multi-variate LSTM model manifested to be ideal for load prediction.

Future Work

The scheduling algorithm can be implemented as an online optimal charging algorithm which adapts to the changes of the charging system over time. Such an algorithm would help give an insight into the practical issues present in real charging systems. With an adaptive online charging algorithm, the concept of Vehicle-to-Grid (V2G), in which the Plug-in Hybrid Electric vehicles (PHEV) return the excess electric power to the grid, could be incorporated. The scheduling algorithm could be adapted in a way that allows PHEVs to charge and store energy during periods of overproduction of renewable energy such as solar and wind energy and allow it to return this energy to the grid during low production hours. This could further ensure the sustainability of energy. The load prediction model presented in this thesis could be further enhanced to include the energy produced from renewable resources and study its effect on the peak demands. By analysing the characteristics of solar power such as solar irradiance or the direction of wind for wind energy, load prediction can be further augmented.

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bibliography

Declaration

I hereby declare that the work presented in this thesis is entirely my own and that I did not use any other sources and references than the listed ones. I have marked all direct or indirect statements from other sources contained therein as quotations. Neither this work nor significant parts of it were part of another examination procedure. I have not published this work in whole or in part before. The electronic copy is consistent with all submitted copies.

Stuttgart, 6 April, 2021

Divya Kannan