CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

Efficient Charging and Scheduling of Electric Vehicles through Load Forecasting Models

by

Hassan Khan

A thesis submitted in partial fulfillment for the degree of Master of Science

in the

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Department of Electrical Engineering

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I dedicate this work to my dearest parents for their affectionate love, support and encouragement

CERTIFICATE OF APPROVAL

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Hassan Khan

(MEE173013)

THESIS EXAMINING COMMITTEE

S. No.	Examiner	Name	Organization
(a)	External Examiner	Dr. Ahmed Salman	NUST, Islamabad
(b)	Internal Examiner	Dr. Raza Samar	CUST, Islamabad
(c)	Supervisor	Dr. Amir Qayyum	CUST, Islamabad

Dr. Amir Qayyum
Thesis Supervisor
June, 2020

Dr. Noor Muhammad Khan
Head
Dept. of Electrical Engineering
June, 2020

Dr. Imtiaz Ahmad Taj
Dean
Faculty of Engineering
June, 2020

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(Hassan khan)

Registration No: MEE173013

Abstract

Electric vehicles (EVs) will have major influence on the power grid due to increase in consumption of electricity. An intelligent scheduling scheme is required for EVs charging. Whereas EVs are the main solution for green transport and control environmental challenges. Firstly, it is difficult to find optimal scheduling solution which can minimize the cost of EVs charging. Considering an optimization problem, in which the charging powers of EVs are optimized to reduce the total cost for all EVs charging. However, the scheduling scheme required the information of future base load. Hence charging cost is modeled as linear function of total load in respective interval. Forecasting models are used to predict base load for day ahead, weekly and monthly. The load forecasting model used the temperature information and electric load history of the region. In this thesis linear regression, bagged tree regression and artificial neural network is used to predict the electric load. These forecasting models are compared to find the prediction accuracy. Mean absolute percent error (MAPE) is 1.24%, 3.2%, 5.14% of artificial neural network, bagged tree regression and linear regression respectively for daily forecasted load. MAPE is 1.04%, 3.0%, 5.02% of artificial neural network, bagged tree regression and linear regression respectively for weekly forecasted load. MAPE is 0.94%, 2.01%, 4.53% of artificial neural network, bagged tree regression and linear regression respectively for monthly forecasted load.

Secondly, traffic jam, driver nature and vehicular density on the road effect the energy consumption of EVs. In this thesis scheduling of EVs to charging station is modeled as linear programming problem. The assignment of EVs related charging stations should satisfy all constraint. The results show that the energy consumption is not only proportional to distance between EVs and related charging station but depends on traffic conditions as well.

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Abbreviations

AER	Alberta Energy Regulator
ANN	Artificial Neural Network
ARMA	Autoregressive Moving Average Model
BP	Back-Propagation
BR	Battery Recharging
BS	Battery Swapping
CC	Controlled Charging
CLF	Conventional Load Forecasting
CNN	Convolutional Neural Systems
CS	Charging Station
EV	Electric Vehicle
GDP	Gross Domestic Product
GHG	GreenHouse Gas
GM	Grey Model
HEV	Hybrid Electric Vehicle
IEA	International Energy Agency
ICE	Internal Combustion Engine
LSTM	Long Short Term Memory
RBF	Radial Basis Function
RNN	Recurrent Neural Networks
SOC	State of Charge
USA	United States of America

Symbols

n	Group of EVs $(EV_1, EV_2, ...EV_n)$
m	Group of charging stations$(S_1, S_2, ...S_m)$
Veh_d	Vehicle density between EV_i and S_j
V	Speed of vehicle
V_{ref}	Reference speed of vehicle
T_{rjam}	Traffic condition between EV_i and S_j
Veh_{flow}	Flow of vehicle
T	Time required to reach the station
d	Distance between EV_i location to S_j
E_{cn}	Consumed energy
SOC_f	Final state of charge
SOC_i	Initial state of charge
n_p	Number of charging points
SOC_{min}	Threshold value of SOC
N	Interval set
Q_i	Group of EVs
E_{fin}	Final energy of EV
E_c	Battery capacity of EV
τ	Duration of interval
T_m	Charging period
E_{in}	Initial energy of EV
P_{max}	Maximum charging power
γ_q	Final energy ratio of EV

G	Charging internal matrix
L_{Ti}	Total load
L_{bf}	Forecasted base load
L_c	Charging load
C_i	Cost for EV charging

Chapter 1

Introduction

In this chapter, the overall introduction about the electric vehicles (EVs) along with their advantages over internal combustion engines (ICE) vehicles are presented. Later, the characteristics of charging station (CS) demand, load forecast for charge facilities, and load forecasting models for optimized charging are discussed in detail. Towards the end of the chapter, thesis motivation, thesis objective, and the organization of the thesis are presented.

1.1 Overview

At the conference of Paris climate in December 2015, more than 180 countries have signed the first ever universal environmental vary agreement [1]. In this agreement, a general activity plan is made to put mankind on track and to restrict a dangerous atmospheric deviation to well underneath 2C to cover the levels of pre industrial. This plan needs a critical reduction in emission of greenhouse gas (GHG) by starting 2020. As demonstrated by the International Energy Agency (IEA), the concentration of GHG in the climate for long period must be restricted to around 400 areas for each million of carbon dioxide equivalent [2].

With worldwide energy crisis and increased pollution of the environment, EV has picked up opportunities for advancement lately, in light of the fact that it has various favorable circumstances, for example, low energy utilization, less pollution, etc. [3]. The advancement of EV depends on the establishment of infrastructures, for example, CS as shown in Fig 1.1, which is the most significant component of the misusing market for EV.

FIGURE 1.1: Charging of EVs [3].

On the other hand the developed countries are investing heavily in fully EV in order to minimize the Carbon emissions which cause different diseases and mainly to free themselves from oil reliance in recent automobiles industry. As they spend a lot of money to import oil. Hence the EV will have large impact on the electric power grids due to high consumption of electric power. The whole load profile of electric grid system will be different after the addition of EV charging. An efficient charging and scheduling scheme is required to overcome the impact on power grid after the inclusion of EV. At present, a massive part of discharged GHG originates from the ICE of automobiles. As indicated by [4], automobiles make a contribution of about 16% of the worldwide guy made carbon dioxide discharges. Additionally, the GHG, with the aid of burning fossil fuel, ICE launch dangerous pollutants that may obviously degrade the air of high quality. This dangerous pollution and GHG emissions can be appreciably decreased if the use of the ICE might be avoided. In this regard, EV offers a solution. Every EV is equipped with a battery-driven engine and ICE, therefore, it can essentially diminish its reliance on the environment polluting the combustion engine [5].

In previous years, the renewable energy has become an emerging technology and worldwide acceptance due to lack of fossil fuel, i.e., global warming because of exaggerated carbon emissions, and petroleum [6]. The efficient way to overcome the problem of shortage of fossil fuel and to reduce the pollution of the environment by popularizing the EVs to replace ICE based vehicles. The EVs are charged through electricity [7], which extremely decreases the utilization of oil usage and doesn't produce any harmful gases related to environmental pollution during the complete cycles of life. With the intense growth of the EV industry, it is necessary to bring modifications to the power sector because of the huge capacity of the battery and stochastic charging manners of the EV users.

1.2 Why Electric Vehicle Over Internal Combustion Engine Vehicle?

EVs are becoming a state of art nowadays for its various advantages over conventional vehicle engines. Some of the major advantages of EVs are described below:

- EVs are preferred over ICE vehicles and can possibly significantly reduce the pollution from non-renewable energy sources like fossil fuels. Normally EV utilizes approximately ten kWh for each fifty to sixty miles it drives. As of now, there are roughly 3.2 million EVs on roads around the globe. 750,000 of these are in America. So, around 7,500,000 kWh power is utilized each time the aggregate of EVs in America travels 50-60 miles. As EV adoption keeps on rising, so will the interest on the grid [8].
- Fueling with power offers advantages not accessible in ICE vehicles. Since electric motors react quickly, EVs are especially responsive and have generally excellent torque. EVs are much of the time more digitally related than ICE vehicles, with different EV CS giving the choice to control charging from the application of mobile [9].

- EVs can lessen the emissions that add to the environmental change, improving the health of the public, and reducing the ecological harm when compared to ICE vehicles. Charging the EV on the maintainable power source, for instance, sunlight based or wind lessens these emissions fundamentally more [8, 10]. The difference between the emissions of ICE vehicles and an EV is shown in Fig 1.1.

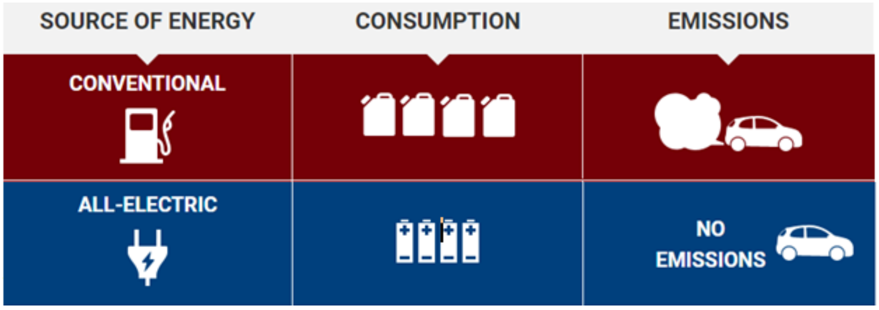

FIGURE 1.2: Emissions of ICE Vehicles and EV [8].

- With progressively strict necessities of the economic improvement and the protection of the environment, EVs, with the benefit of energy protection and decline of outflow, have become essential for new energy resources advancement, such as the consequence of which, the utilization of EVs at large scale has become an certain development. The facilities of charging demand forecast is the foundation of its appropriate development and define the accessibility and effectiveness of financial development. Hence, it is more significant to predict the charging facility demands and afterwards find the number of facilities [8, 11].

- EVs produce very less GHG emissions than gas-fueled vehicles as shown in Fig 1.2. This is true when considering the vehicle's whole life cycle, from removing the resources used to make it to rejecting it toward the finish of its life. With an EV, the greatest environmental effect is delivered during manufacturing. With an ICE vehicle, the best effect is created during the stage of utilization [9, 10].

- Furthermore, EV is a sophisticated mixture of the traditional hybrid electric-powered vehicle (HEV) and EV. Both have an electric powered motor similar

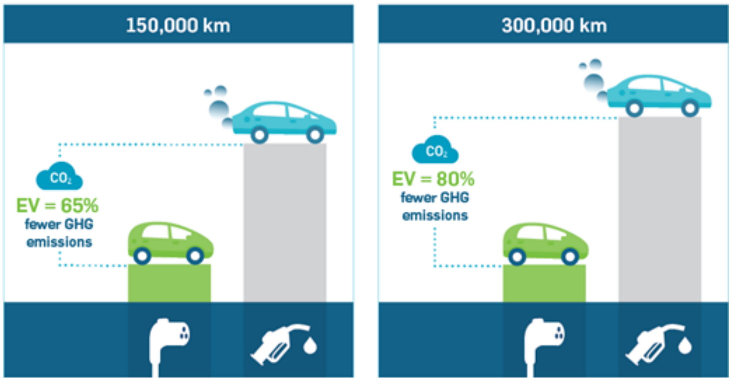

FIGURE 1.3: Emissions of ICE Vehicles and EV.

to the ICE. Model primarily based load forecasting methods encompass statistical models using recursive and traditional mathematical tools [12, 13], and artificial intelligence models including various state-of-the-art machine learning approaches [14, 15]. Traditional forecasting methods are usually straightforward and making use of explainable presentations in the model composition, while artificial intelligence techniques produce grey models in producing the forecasting outcomes. Due to the sturdy adaptive getting to know and generalization ability, artificial neural network(ANN) has come to be a hit in delivering load forecasting responsibilities [16].

1.3 The Characteristics of Charging Station Demand

The charging procedure of EVs has incredible uncertainty, which decreases the charging time frame uncertainty, and the state of charging when the EVs gain contact to the electric grid network [17]. The above mentioned variables create difficulty in charging facilities arrangements. A few characteristics of CS load are the following:

- Different Modes of Charging.
- EV Population.

- Users' behavior habits.

1.3.1 Different Modes of Charging

On the basis of various requests of clients, the approaches for EVs charging are classified into three different kinds, and the various methods of charging decide the various qualities of CS load. Following are the different modes of charging:

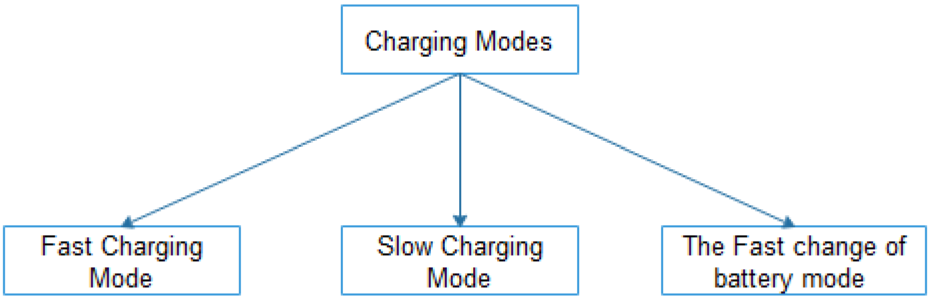

FIGURE 1.4: Charging Modes.

1.3.1.1 Fast Charging Mode

In this mode, the CS is commonly arrange the EV lines unoccupied for emergency charging of EV at corner store. In this mode of EV charging the battery of EV can reach about over 90% in matter of moments with the surprising charging current. Regardless of the way this charging mode really debilitates the framework nature of intensity supply, it can extraordinarily diminish the usage of charging times and convey comfort to customers [18].

1.3.1.2 Slow Charging Mode

The following method of CS is mostly functional at residential locations such homes, office parking and shopping malls, where EV charge with little amount of current to utilize the free time. As indicated by the everyday behaviors of the client, the highest demand of a typical CS usually begins in the time off duty and keeps going to midnight. With the improvement of EV, the development of the typical CS in areas of residential will be a significant primary work [16, 18].

1.3.1.3 The Fast Change of Battery Mode

In following method, the battery of EVs which has use down will be swapped to full charge battery in a definite CS. Following approach is an effective way to increase the shortcoming of the little durability of EV. As the speedy variation in mode of battery, EV can recharge battery at the CS in a brief time. These depleted batteries are charged when they are swapped from EV or at a specific time at the CS the batteries are charged together which are depending on the various requests. Due to the helpful administration, following mode of charge is operational in transports operations in various cities, for example, Beijing, Shanghai, and Guangzhou, etc. [17].

1.3.2 Electric Vehicle Population

The international population of EVs is going on rise with the improvement of the low-cost and advancement of EVs strategy. Consistently, the amount of charging capability determined by the proportion of loads and vehicles, is increasing. To predict the load of an EV, the researchers typically fitted the vehicle tendency sales information or GDP (Gross Domestic Product) development information, and afterward determined the proportion of loads and vehicles by visit out to the distribution of traffic to predict the demand of the charging facilities [19].

1.3.3 Users' Behavior Habits

The variables such as starting point of charge, the time of charge, a location of EV, distance of EV from CS and sorts of EVs are determining the behavior of EV user. The initial SOC is determine by the beginning point of charge; the electric system load is affected by the distinction of charging period, which lastly impacts the charging power; charging power demand is affected by a distance of driving and daily rated charging limit of CS, on which the amount of charging facility has been decided.

1.4 Load Forecast for Charge Facilities

Load forecasting for charging facilities can be divided into the following two types:

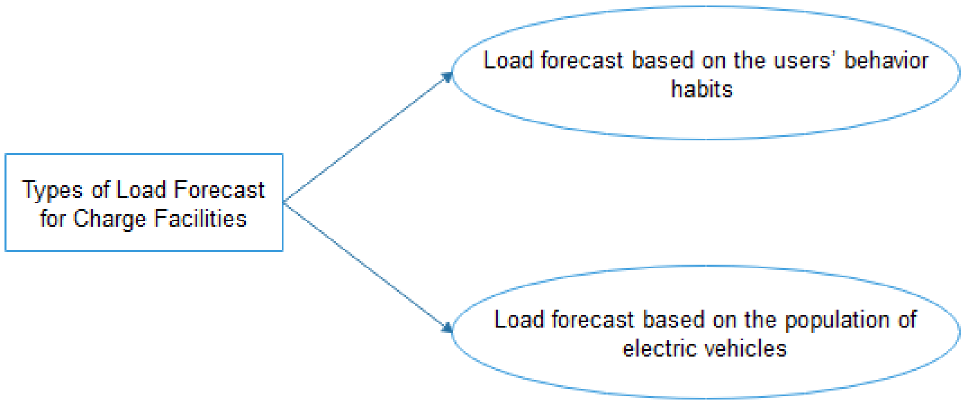

FIGURE 1.5: Different types of Load Forecast for Charge Facilities.

1.4.1 Load Forecasting for Charging Facility Based on Electric Vehicle Users' Behavior Habits

- Firstly, it emphasized the examination of clients' demand for travel.
- Secondly, decide the suitable loads as indicated by the degree of clients' acceptance to the initial SOC so the likelihood delivery of charging necessity can be resolved.
- Lastly, on the basis of the delivery of probability, the proportion of loads and vehicles can be permanent and a load of the CS can be forecast. At present, the gauge model dependent on the clients' movement practices has been full-grown, yet the thought of affecting elements isn't favorable. Most of the study accepted that the clients simply charge their battery once in a

day and haven't considered for multi charging and discontinuous charging in a day. Likewise, the ongoing examines chiefly center around the interest estimate of charge control, scarcely considering the connection between the charge control and the amount of charge office.

1.4.2 Load Forecasting for Charging Facility Based on the Electric Vehicles Population

The strategy depends on the forecast of a population of the EV and, joined with the influencing terms, determined the charging power and limit of charging facilities. At last, with a permanent proportion of piles and cars, the demand for the load can be resolved. Estimate the number of EVs in both short-term and long-term respectively with the elastic coefficient technique.

1.5 Load Forecasting Models for Optimized Charging

The day by day demand of EV CSs are complicated and the algorithms of conventional load forecasting (CLF), for example, regression analysis and linear time series hardly have the capacity to simulate the complex electric load of power. Instead of the CLF techniques, the modern way of load forecasting, machine learning techniques can self-learn and perform nonlinear modeling and adaptation [20]. The following some load forecasting techniques used for optimized charging are presented:

- Back-Propagation (BP) neural network model
- Radial basis function (RBF) neural network model
- Grey model (GM)(1,1) model
- Linear Regression Technique

- Regression Trees Technique
- Artificial Neural Network (ANN)
- Recurrent Neural Networks (RNN), etc.

1.5.1 Back-Propagation Neural Network

For load forecasting in electric power system the BP neural network is used which is an artificial neural network. The BP neural network consists of input layer, hidden layer and output layer as shown in Fig 1.6 which has the ability of self-learning. There are neurons in each layer which has the ability of processing individually. Afterwards a nonlinear or linear function is applied to the weighted sum from the input neurons which resulting to decide the output. The stopping criteria of BP neural network is whether a threshold value is set to bring error below that value or the preset time of learning is accomplished. The performance of following algorithm is determined by the structure of neural network which plays important role in evaluation of algorithm performance [21].

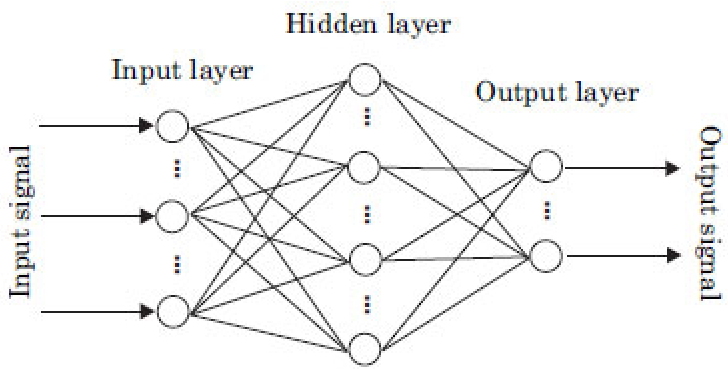

FIGURE 1.6: Structure of BP Neural Network [21].

1.5.2 Radial Basis Function Neural Network

RBF as one significant approach of neural networks, has the capacity to estimate and show finest overall results. The utilization of training time in RBF neural network is extremely decreased as compared with the BP neural network but cause over fitting or under fitting of data. Due to the benefits of the RBF neural network, it has been broadly used in a non-linear time series forecast. RBF neural network consist of three layers forward network as shown in Fig 1.7. The first is the input layer, second is the hidden layer, and the third one is the output layer, which gives the results on the basis of input pattern [22].

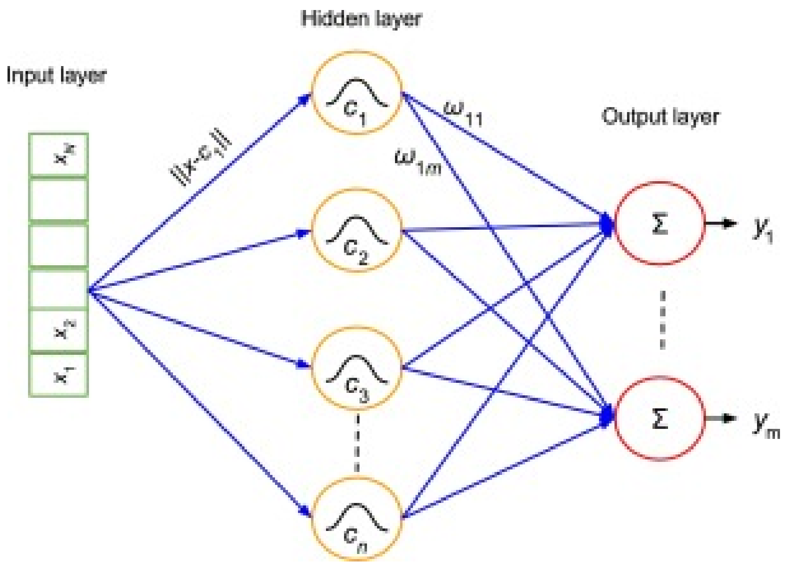

FIGURE 1.7: Structure of RBF Neural Network [22].

1.5.3 Grey(1,1) Model

Grey model which is widely used for the load forecasting in electric power system is based on grey system theories. GM (1,1) is one of the famous or widely used model among grey models, which contain first-order differential equations as system variables. The ultimate advantage of the GM (1,1) model is to effort on system forecasting with poor, partial, or undefined messages. The utilization of training time in grey model is extremely decreased as compared with the BP neural network but cause over fitting or under fitting of data.Most of the study accepted that the clients simply charge their battery once in a day and haven't considered for multi charging and discontinuous charging in a day. Likewise, the ongoing examines chiefly center around the interest estimate of charge control, scarcely considering the connection between the charge control and the amount of charge office. The GM (1,1) model has more preferences over those traditional forecast methods since it doesn't have to know whether the forecast factors obey normal distribution, and furthermore doesn't need an excessive amount of measurement test [23].

1.5.4 Artificial Neural Network

An ANN is a mathematical model that is utilized to simulate the functionalities and structure of neural networks. The strategy depends on the forecast of a population of the EV and, joined with the influencing terms, determined the charging power and limit of charging facilities. The major block of each ANN is artificial neuron, which is a basic mathematical model. ANN has three fundamental standards, i.e., Summation, multiplication, and initiation. Towards the beginning of artificial neuron the inputs are weighted what implies that each input information value is multiplied with single individual weight. A little change in input data results in changed output. Each connection between layers have own significance and define the strength of every neuron's effect on another neuron. In the middle of artificial neuron, there is an aggregate function that sum all the input weights and bias. Lastly the artificial neuron, the sum of previously weighted inputs and bias goes through the activation function which is also known as transfer function or propagation function.. While the functioning principles and basic guidelines of ANN looks like nothing special, the main purpose and calculation command of these models come to life when we start to interconnect them into ANN (Fig 1.8) [24].

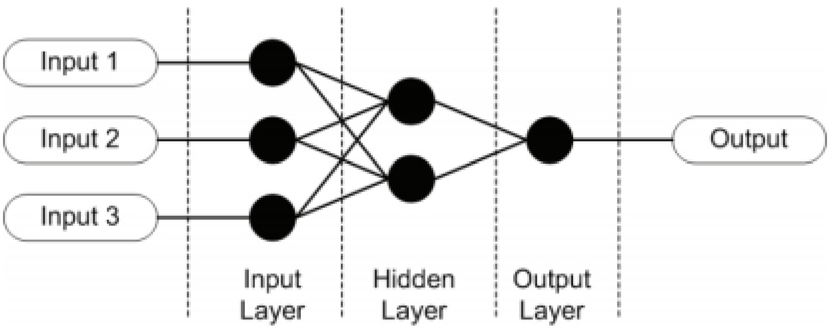

FIGURE 1.8: Structure of simple ANN [24].

1.5.5 Linear Regression Technique

The regression technique is a statistical technique that is used to define the relationships among different variables .The models are achieved by multiple regress the data information space and fitting a simple forecast model inside each divided part. The easiest scenario to analyze is about a variable Y mentioned to as the dependent or the target variable, might be identified with one variable X, called an independent variable, or basically a regressor. If there is a linear connection between X and Y, then the following equation can be used for a line:

$$\gamma = \beta 1 + \beta 2X \tag{1.1}$$

where $\beta 1$ denotes the intercept term and $\beta 2$ represents the slope coefficient. In simplest terms, the main determination of regression is to try to discover the finest fit line or equation that states the correlation between Y and X. Linear regression is a basic method to supervised learning. The dependence of Y on X1, X2, . . . XP is linear to be assumed. The actual function of regression is never linear as shown in Fig 1.9. while it may appears overly basic, linear regression is very valuable both conceptually and practically [25].

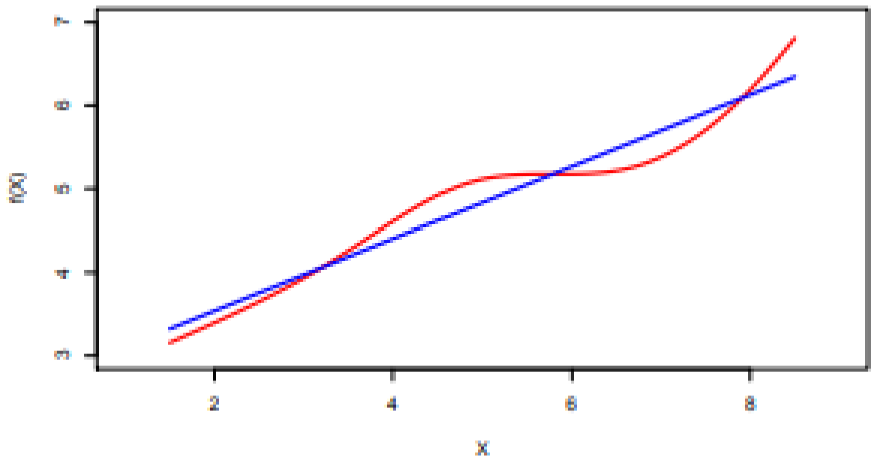

FIGURE 1.9: Linear and Non-Linear function [25].

1.5.6 Regression Tree Technique

Regression trees is one of machine learning strategies for developing forecast models from the information. The models are achieved by recursively splitting the data information space and fitting a simple forecast model inside each divided part. Accordingly, the splitting can be graphically represented as a decision tree as shown in Fig 1.10. In a regression tree strategy, the Y variable takes ordered values and a regression model is fitted to every node to provide the forecasted values of Y [26].

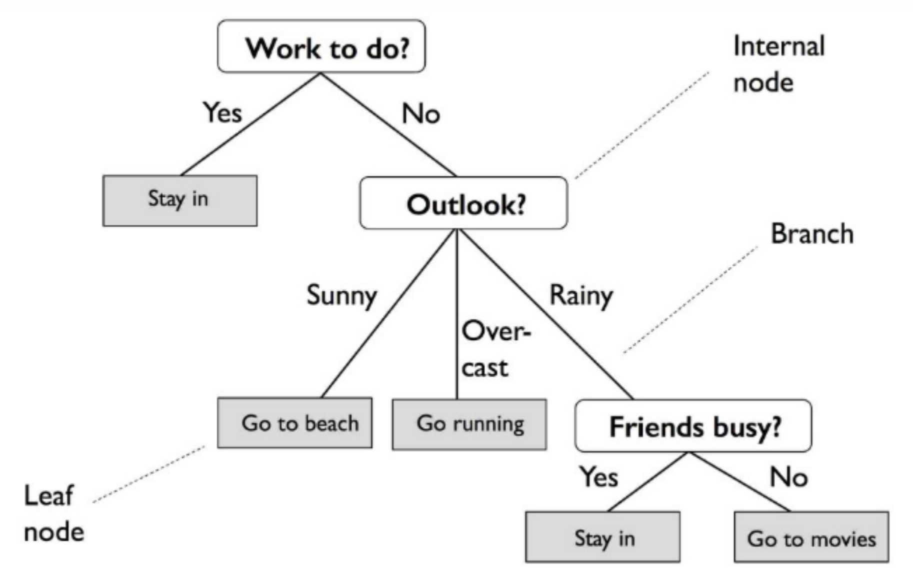

Figure 1.10: Structure of Regression Trees [26].

1.5.7 Recurrent Neural Network

RNN is a kind of neural network in which the output from a recent step is feds input to the present step. In conventional neural networks, every input and output is independent of each other, yet in scenarios like when it is necessary to estimate the next word of the sentence, the recent words are needed and hence there is a need to remember the previous words. Hence, RNN came into existence, which solved this issue with the addition of a hidden layer as shown in Fig 1.11. The basic and most significant element of RNN is a hidden layer, which remembers some data about a sequence. RNN has a memory that remembers all data about what has been determined. It utilizes similar parameters for each input as it performs the same task on every input or hidden layer to produce the output. This decreases the complexity of parameters, in contrast to other neural systems [27].

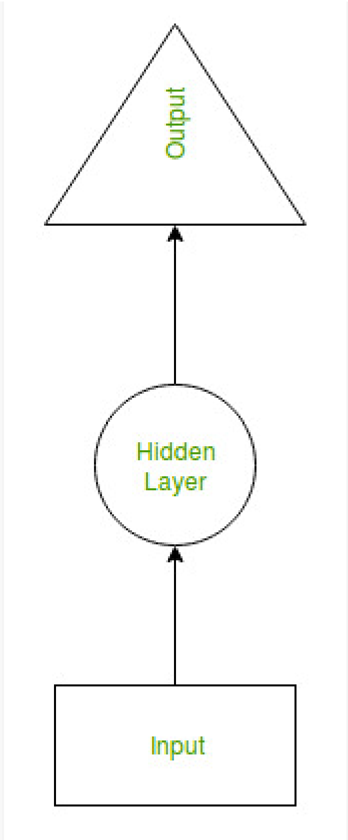

FIGURE 1.11: Structure of RNN [27].

1.6 Thesis Motivation

The motivation of this work came from various research papers in which many researchers managed the charging of EVs. In various countries, EVs are preferred over ICE vehicles and can significantly reduce pollution from non-renewable energy sources like fossil fuels. EVs can diminish the emissions that add to environmental change and smog, improving the public health and decreasing ecological harm when compared to ICE vehicles. Charging your EV on the sustainable power source, for example, sunlight based or wind reduces these emissions significantly more. Due to its various advantages over conventional vehicle engines as discussed earlier, the EVs have been a topic of interest for the researchers over the last three/four decades.

1.7 Thesis Objective

This thesis is aimed to optimize the charging management of EVs. In this regard, optimization algorithms are used for the optimal assignment of EVs to CSs and minimizing the entire cost of all EVs which perform charging. Moreover, the load forecasting is done through three techniques such as linear regression, tree regression, and neural network. The advantages and disadvantages of these load forecasting techniques have been discussed in detail. A comparative study is conducted between these three forecasted models on the basis of mean square error. The model with the least mean square error is chosen to minimize the cost of EV charging.

Furthermore, the objective function is made for a small geographic area with a finite number of EVs and CSs. The objective function is modeled as linear with the parameters such as constraints of vehicles, CSs and the traffic situation on the roads. With the suggested solution EVs keep the state of charge (SOC) of battery to its maximum level while reaching the assigned CS.

1.8 Thesis Organization

Organization of the complete thesis is in the following order;

Chapter 1: Introduction

In this chapter, the overall introduction about the EVs along with their advantages over ICE vehicles are presented. Later, the characteristics of CS demand, load forecast for charge facilities, and load forecasting models for optimized charging are discussed in detail. Towards the end of the chapter, thesis motivation, thesis objective, and the organization of the thesis are presented.

Chapter 2: Literature Review and Problem Formulation

This chapter presents a literature survey on the topics of various techniques of EV charging load forecasting, schemes of charging management, limitations and challanges in the charging of EVs, and classification of EV charging schemes. The literature survey is the accompanied by a critical gap analysis of the research where the research gap is identified. This gap analysis then proceeds towards problem formulation. At the end of the chapter, research methodology and thesis contributions are presented.

Chapter 3: Load Forecasting Models

In this chapter, different load forecasting approaches and the significance of load forecasting for EVs charging scheduling are presented. Furthermore, load forecasting models are also discussed in detail.

Chapter 4: Mathematical Modeling for EV Charging Scheduling

This chapter presents the mathematical modeling for optimal EVs charging scheduling. The modeling for optimizing energy consumption for EVs before charging and problem constraint are presented. Furthermore, the modeling for optimizing the charging cost during all day is also discussed in this chapter.

Chapter 5: Simulations and Results

In this chapter, results are presented for an optimal scheduling model for charging of EVs is used which goals to minimize the total cost by optimizing the charging power of EVs. A detailed comparison of performance of these forecasting models is offered. On the basis of these results, the goal of optimum scheduling for EVs charging is achieved. Afterwards results for the second phase of this thesis is presented which aims to reach the respective CS with less energy consumption by considering the disturb conditions of traffic.

Chapter 6: Conclusion and Future Work

In this chapter, a brief conclusion of the thesis is presented. Moreover, some future work is suggested for the researchers interested to work in the area of charging management of EVs.

Chapter 2

Literature Review and Problem Formulation

In this chapter, a literature survey is presented on the topics of various techniques of EV charging load forecasting, schemes of charging management, limitations and challenges in the charging of EVs, and classification of EV charging schemes. The literature survey is the accompanied by a critical gap analysis of the research where the research gap is identified. This gap analysis then proceeds towards problem formulation. At the end of the chapter, research methodology and thesis contributions are presented.

2.1 Background

Since the transformation of industry, the load of electricity is a fundamental concern for managing the regular functioning of the current society. Forecasting of load can be split in to three types; i.e., time interval [22], long term oriented forecast load (1 year to 10 years), medium term oriented forecast load (1 month to 12 months ahead), and a short term oriented forecast load (1 hour to 7 days ahead). The strategy depends on the forecast of a population of the EV and, joined with the influencing terms, determined the charging power and limit of charging facilities. At last, with a permanent proportion of piles and cars, the demand for the load can be resolved. Estimate the number of EVs in both short-term and long-term respectively with the elastic coefficient technique.

In previous few years, the broad acceptance of sustainable power source has become an emerging pathway because of absence of fossil fuel; i.e., global warming because of exaggerated carbon emissions, and petroleum [7]. The efficient way to overcome the problem of shortage of fossil fuel and to reduce the pollution of the environment by popularizing the EVs to alter traditional vehicles based on ICE. Electricity is used to powered the EVs [6], which extremely lessen the use of petroleum assets and does not produce any gases related to environmental pollution during the complete life cycles. Before the twenty-first century, because of the robust adaptive, generalization capability of ANN, and self-studying, it had grown to be a hot research matter for adopting the ANN techniques in forecasting of load. The electrification of the transportation zone is visible as an effective approach to reducing GHG emissions from the burning of fossil fuel. Other environmental worries including city air high-quality and related health effects have also brought about coverage makers and stakeholders to opt for the popularization of EVs [23] in changing conventional ICE based automobiles.

EVs may be considered as zero-emissions automobile all through its operation whilst power from renewable assets is used to rate them. However, the speedy improvement of the EV industry is introducing new challenges to the existing energy device shape as a result of their huge battery potential [25] and tremendously stochastic individual charging conduct.

Traditional forecasting methods are usually straightforward and making use of explainable presentations in the model composition, while artificial intelligence techniques produce grey models in producing the forecasting outcomes.

Due to the sturdy adaptive getting to know and generalization ability, ANN has come to be a hit in delivering load forecasting responsibilities [14].

2.2 Studies Related to Various Techniques of Electric Vehicles Charging Load Forecasting

Different techniques have been used by different researchers which are as follows:

2.2.1 Time Series Input of Historical Data Technique

In the properties of load-based time measurement extension, the underlying research on load estimating issue relies on the time series expectation strategy proposed by the author [25] in 1976.
The technique has fewer input requirements for the load estimating model, which just considers the time series input of historical information and doesn't consider other multi-faceted impacting parameters that influence the load.

2.2.2 Recurrent Neural Network

In [26], to set up a short term load forecasting model, RNN was utilized. However, the traditional RNN would affect the gradient evaporating issue and the long short term memory (LSTM) model is a powerful way to deal with the issue.

2.2.3 Load Peak Model

In [27], the load peak model was provided that considered external parameters, for example, climate and humidity. In previous years, spring peak loads on the Vepco framework show an unpredictable development pattern as appeared in Fig 2.1. Following approach is an effective way to increase the shortcoming of the little durability of EV. As the speedy variation in mode of battery, EV can recharge battery at the CS in a brief time.These depleted batteries are charged when they are swapped from EV or at a specific time at the CS the batteries are charged together which are depending on the various requests. At present, the gauge model dependent on the clients' movement practices has been full-grown, yet the thought of affecting elements isn't favorable.

The international population of EVs is going on rise with the improvement of the low-cost and advancement of EVs strategy. This irregularity in the peak load development was principally brought by varieties in the summer climate. With the climate changeability filtered out, it was discovered that the Vepco summer peak load for the most recent decade has pursued the smooth exponential development.

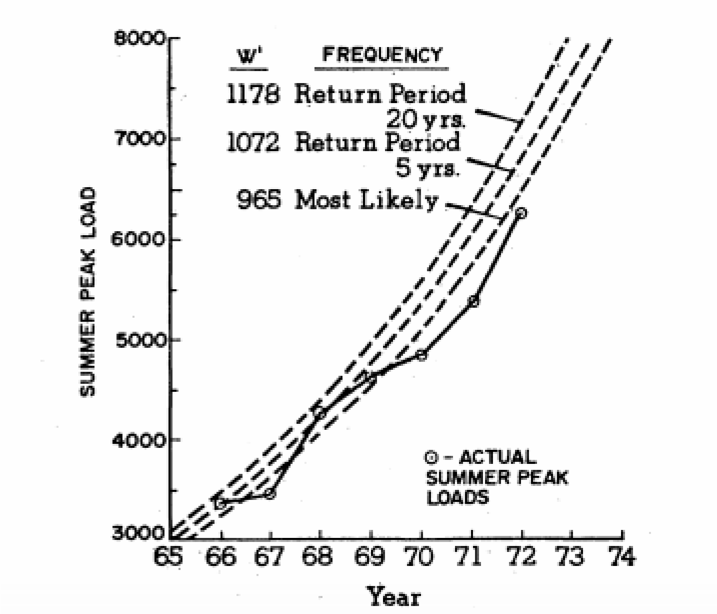

FIGURE 2.1: Load Peak Model [27].

2.2.4 Autoregressive Moving Average Model

In [27], the ARMA expectation technique was proposed and the authors of [19] built up the ARIMA to accomplish the load forecasting.

2.2.5 Random Forest Approach

Due to the various sorts of load and complexity of impacting factors, the choice of input factors and the strategy in building the load forecasting models become significant. Many wise forecast strategies were proposed using progressively relevant data. The study in [28] utilized an arbitrary forecast way to build a load estimating model and the inputs are refined by master feature choice utilizing fuzzy rules.

2.2.6 Tuning Fuzzy System and Artificial Neural Network Technique

The study in [29] was used tuning the fuzzy framework and ANN technique for demonstrating the medium voltage load. Existing methodologies have demonstrated the applicability for the time arrangement based mathematical models and computational knowledge models in solving the load estimating issue. However, new members, for example, renewable generation and EVs have seen complicated qualities and high uncertainty, which challenge the traditional methodologies.

2.2.7 Long Short Term Memory and Convolutional Neural Systems

The study in [30] developed an LSTM system to estimate the load of particular homes. Authors joined the energy utilization of a home with the attitude of a home resident, changed the attitude patterns of energy purchaser into an arrangement of input features to the network, on account of which the accuracy of the load estimating was bettered. Some different investigations [31, 32] additionally utilized LSTM to forecast the load.

In [33], utilized the CNN for one-stage short term EVs charging load estimating, where aggressive forecasting precision could be acquired.

2.2.8 Spatial-Temporal Model

EVs have risen around the world. So the huge power limit of their battery gives an unprecedented challenge to the current power system. Precise and proficient load forecasting for EV charging is basic for the maintenance and operation of various charging stations.

In [34] introduced a Spatial-Temporal model to assess the effect of large scale arrangement of EVs on urban distribution systems.

In [35], proposed an approach for modeling and examining the load in a distribution system considering EV battery charging, and received Monte Carlo simulation in situation generations.

2.2.9 Stochastic Model

In [36], proposed a Monte Carlo model based on simulation to estimate the charging load of the EVs in China. In any case, these traditional strategies are hard for evaluating the outside variables that influence the charging load of EVs, and it is not possible to set up a deterministic model.

2.3 A Survey of Charging Management Schemes for Electric Vehicles

Despite the fact that the different technical aspects of battery charging discussed in previous studies based on EV's fueling adaptability, which is necessary at the present phase of EV proliferation.The variables such as starting point of charge, the time of charge, a location of EV, distance of EV from CS and sorts of EVs are determining the behavior of EV user.

EVs have been officially characterized by the government of United States of America (USA) as a vehicle that, It has an electric motor notwithstanding a conventional consuming motor.

- It has an electric engine also to a traditional burning engine.
- Draws motive power from a battery with a limit of 4 kWh.
- It can be again charged from an outer power source.

2.3.1 Charging of Battery by Using Different Modes

The operations of EV can be divided into two different modes named as charge depleting mode and charge sustaining mode. In charge depleting mode, EV disables its inner burning motor and draws the propulsion energy, until it arrives at SOC threshold, where SOC is an amount that estimates the level of resting charge in the battery. The limit of SOC shows the minimal energy that should be stored in the battery consistently. After arriving at the minimum SOC, EV changes to work in charge sustaining mode and the burning engines give the energy to drive the vehicle just as to manage the charge of the battery above however close to the minimal SOC.

EVs can exceedingly diminish fossil fuel utilization and GHG emissions by keeping away from the charge sustaining mode. For the better efficiency of fuel, a third mode, called charge blended, has been upheld [36, 37]. In charge blended mode, electric engine and inner ignition engine are ideally and powerfully utilized during a drive cycle, so they can work longer utilizing the most productive setting, while accomplishes a large decrease in GHG emissions.

By avoiding the charge sustaining and charge blended modes, the GHG emissions can be reduced and along these lines, we may speculate that a bigger battery limit is better. However, the researchers in [38] have indicated that the expense and energy effectiveness brought by a bigger battery capacity arrives at an asymptotic worth, and hence, a limitless large capacity isn't essential.

Depending upon the kinds of the vehicles, [39] has demonstrated that the capacity of the battery should be about 11.6 kWh for a traveler vehicle to cover a distance of 40 miles at a speed of around 25-30 mph, without utilizing interior ignition engine. This is a sensible battery size in light of the fact that an ordinary USA traveler vehicle travels an average of under 30 miles every day [40].

Despite the actual capacity of the battery, as trips are carried out and batteries are discharged, then the SOC drops. Because of the restricted capacity of the battery, the battery should be regularly recharged to keep up its SOC inside an ideal range, which is characterized by the minimal SOC and full battery capacity. Commonly, it is required to keep a high SOC toward the start of a trip to limit the total energy cost just as to accomplish a more extended alberta energy regulator (AER), a high SOC brings about quicker battery degradation [41].

2.3.2 Restoring Methods of Vehicle's State of Charge

In [42, 43], restoring techniques of Vehicle's SOC was presented in two different ways, i.e., battery swapping (BS), and battery recharging (BR). In BS technique, EV driver trades the drained battery for a completely charged one at a CS.

This methodology possesses zero waiting time for the charging of battery and enables the service provider to receive the rewards from lower energy costs for charging during off-peak hours.

This negligible time required in restoring the SOC is the greatest advantage in contrast with the second technique, i.e., BR that needs the drivers to connect their EVs to electric outlets for the charging. In spite of the advantage of zero waiting time, BS has yet to become popular because of three significant difficulties, in particular, large upfront cost for framework deployment, restricted AER for every battery, and troubles in guaranteeing similar performance among every single replaceable battery.

2.4 Problems and Challenges in the Charging of Electric Vehicles

At the same time, when multiple EVs are charged, the extra electric load can cause various issues to the grid, as far as extreme voltage variations, warm overloads, raised losses of power, expanded aging of transformers and lines, and so on [44]. With progressively strict necessities of the economic improvement and the protection of the environment, EVs, with the benefit of energy protection and decline of outflow, have become essential for new energy resources advancement, such as the consequence of which, the utilization of EVs at large scale has become an certain development. These issues and challenges can be comprehensively arranged into three groups as under:

2.4.1 Degradation of Power Quality

This kind of issue influence the quality of power, which is estimated regarding power factor, harmonics, voltage deviation, a shift in frequency, and so on [45]. All in all, a low quality won't quickly disturb the electrical grid, however, it is a pointer for an upcoming major problem, if no corrective move is made. Despite the fact that there is no interruption, a lower control quality may, in any case, influence the operation of electricity loads. For instance, the lower voltage can make breakdowns home apparatuses.

2.4.2 Electrical Network Instability

This kind of issue destabilizes and disturbs the electrical systems, prompting power blackouts, etc. At the point when it occurs, some portions of the electrical system will lose the supply of power. Practically, preventing system interruption is one of the most significant tasks for the operators of the grid [45].

2.4.3 Deterioration of Operation Efficiency

This sort of issue doesn't affect the functionality of the grid yet its productivity. Losses of higher transmission lead to less income and benefit. Reliable warm overload speed up equipment aging hence, require a high investment of money for the replacement of hardware [45].

According to the above problems, it is required to guarantee the quality of power, the stability of the network, and the operational effectiveness of the electrical network. All issues should be removed so as to help to expand the popularity of EV.

In May 2016, there are more than 1.5 million electric traveler vehicles overall [46], however, this figure most likely speaks to under 1% of total traveler internationally. As indicated by [47], the light-obligation penetration level of EV is relied upon to reach over 50% by 2050.

Simply, the vast majority of the electrical grid issues are caused by the charging of EV, a consequence of an imbalance between the power supply and interest (load). In order to guarantee the stability of the grid, the request for power should be nearly matched with the power supply. Basically, this matching is very hard to accomplish in a changing situation like EV charging, where load is not predictable and can change significantly between various hours in a day. This issue is more complicated by the introduction of renewable power sources, for example, solar and wind power into the network [48].

2.5 Classification of EVs Charging Schemes

As in Fig. 8, schemes of EVs charging can be divided into controlled and uncontrolled (UC) charging [49]. In previous studies, controlled and uncontrolled charging is known as coordinated and uncoordinated charging schemes, respectively. The controlled charging is further divided into three charging schemes as shown in Fig 2.2.

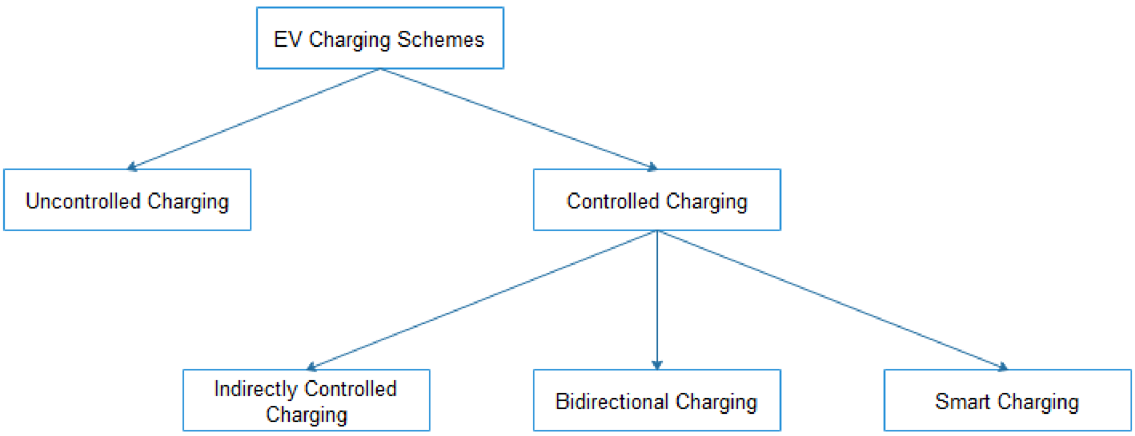

FIGURE 2.2: Schemes of EV Charging.

2.5.1 Uncontrolled Charging

In UC charging scheme [49], the batteries begin to charge quickly when batteries are connected, or after client specified delay. UC charging is sensible in a situation where the operator of grid doesn't have the important data to control the charging profiles. Although UN charging is very easy because it directly display the grid to volatility and arbitrariness in the charging load, which are significantly reliant on the behavior of the driver.

2.5.2 Controlled Charging

In the controlled charging (CC) scheme, the operator manages the moments of charging and parameters in order to prevent grid from encountering unsatisfactory quality of power and suffering from disruptive destabilization, simultaneously of fulfilling driver's charging requests. CC can be more split into different schemes, i.e., indirectly CC, bidirectional charging, and smart charging.
In the indirectly CC scheme, it doesn't directly control the parameter of charging, for example, the capacity of charger, time of charging, charging span, etc. But, smart charging directly controls the different parameters of charging.
Smart charging schemes doesn't need to be charged constantly when it is connected, because it doesn't draw energy from the grid when the outlet power is set to be zero. Thus, this scheme can correctly transform every EV battery into a flexible load [49].
In a bidirectional charging scheme, every EV has a mobile energy source and flexible load despite the fact there is no difference in different aspects when contrasted to the smart charging. Advantages of using the EV batteries as the energy sources were considered in [50, 51].
Just, with the bidirectional flow of power, battery of EV can help in balancing out grid by returning back energy in order to fill the gap of demand, when there is an enormous electrical load.
The research in [52]- [53] was concentrated on researching and analyzing the effect

of joining EVs population on the electrical grid due to the lack of control.

The study in [54, 55] was concentrated only on the CC, but the comprehensive simulation exposed from the surveying UC charging techniques is a beneficial reference, even in guiding the evaluation needs for future CC techniques.

With an expanded flexibility in control, [56, 57] has indicated that the smart charging can support an appreciably higher EV penetration, contrasted with UC charging.

2.6 Research Gap and Problem Formulation

In the previous literature, different scheduling schemes have been recommended for EV charging. However, the present work in which the techniques used are basically centralized algorithms to optimize the charging power to reduce cost, which might not be applicable for the systems of EV charging with a large EV population. The total load profile of the electric structure would be transformed after the introduction of EV charging. A power grid would be affected significantly after the introduction of a large number of EVs. It is hard to find the optimal solution of scheduling which can reduce the overall cost of charging, especially in the existence of a immense EV population. It is very difficult to model an optimal scheme meanwhile it needs the information about EVs such as future base loads, charging period, and time of arrival.

For a practical solution, a load forecasting model with the least mean square is required to achieve an optimal solution which results in the reduction of cost. With the change in recent systems of power grid, various factors such as weather, prices of real time electricity, holidays and even the growth in cities and human being activities, have several effects on load demand. Old load forecasting approaches are incapable to give different forecasting models with appropriate predictive accuracy. In this regard, precise load forecasting is a significant measure of the optimal scheduling of EV charging.

This work is an attempt to fill this gap by proposing a solution for a small geographic area, which objective is to reduce the overall cost for charging all the EVs within the 24 hours of time. To solve efficiently the problem, the scheduling issue is a convex optimization issue with linear constraints. The objective function is based on the forecasted base-load. For load forecasting, three models are formulated e.g. neural linear regression, tree regression, and neural network. To obtain the best possible result the model with least mean square is chosen, To obtain the total minimal cost, first, optimal scheduling system defines the optimal charging powers for all the EVs for entire intervals by resolving a particular scheduling optimization problem.

With the optimization of the cost of EVs charging there is a need of an energy-efficient model for EVs to reach the CS which is nearest or where EV reach with less loss of energy under the disturbed condition of traffic.

This thesis provide the second foremost objective for EVs is to reach the suggested CS while consuming less amount of energy in disturbed condition of traffic by considering the system parameters such as SOC of battery, distance from different charging station, traffic conditions and EV location as the EV current position is dense area or highway.

2.7 Research Methodology

The complete thesis is comprised into the following two phases:

- Charging phase.
- Scheduling phase.

2.7.1 First Phase of Thesis (Charging Phase)

- As depicted in Fig 2.3, in the first phase of thesis, an indirectly control approach is considered for the optimal solution of scheduling. By controlling the cost of EVs charging, the scheduling is optimized.

- The objective function is modeled as linear function of the total load to minimize the cost.
- Total load represents the baseload without EVs and load of charging which represents a load of EV charging in such interval.
- The baseload is forecasted by three different approaches such as tree regression, linear regression, and neural network. For the simulation of linear regression, neural network, and tree regression, MATLAB is used.
- As the optimization problem is a convex problem, for that purpose CVX tool is downloaded from their website. This is then unpacked and used in the command window of MATLAB.

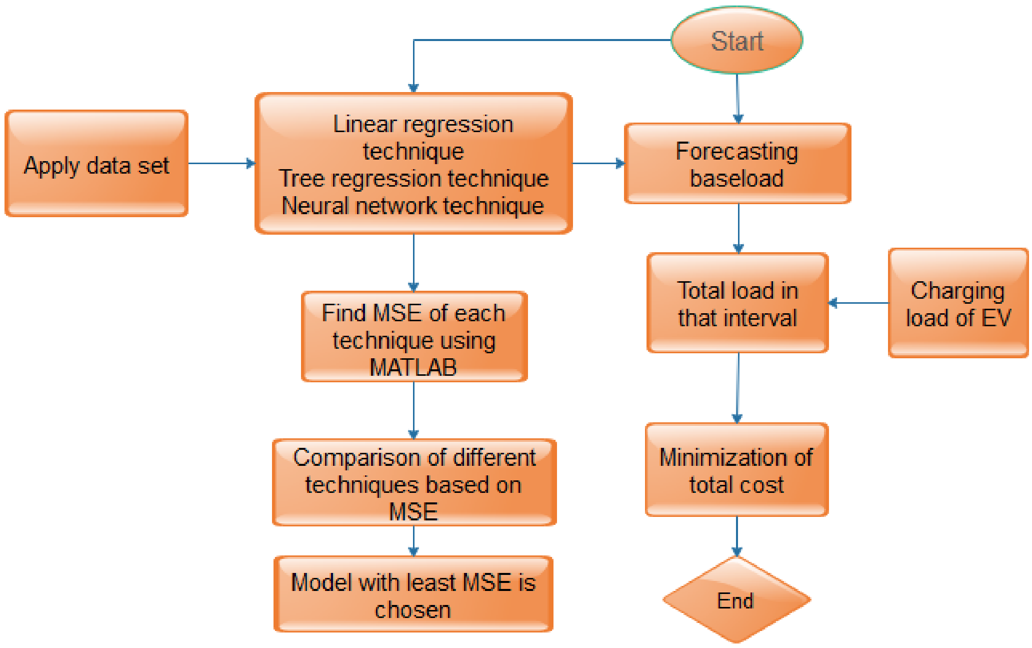

FIGURE 2.3: Flow chart of Cost Minimization.

- A comparative study is conducted between these three forecasted models. The model with the least mean square error is considered most to minimize the cost of EV charging.

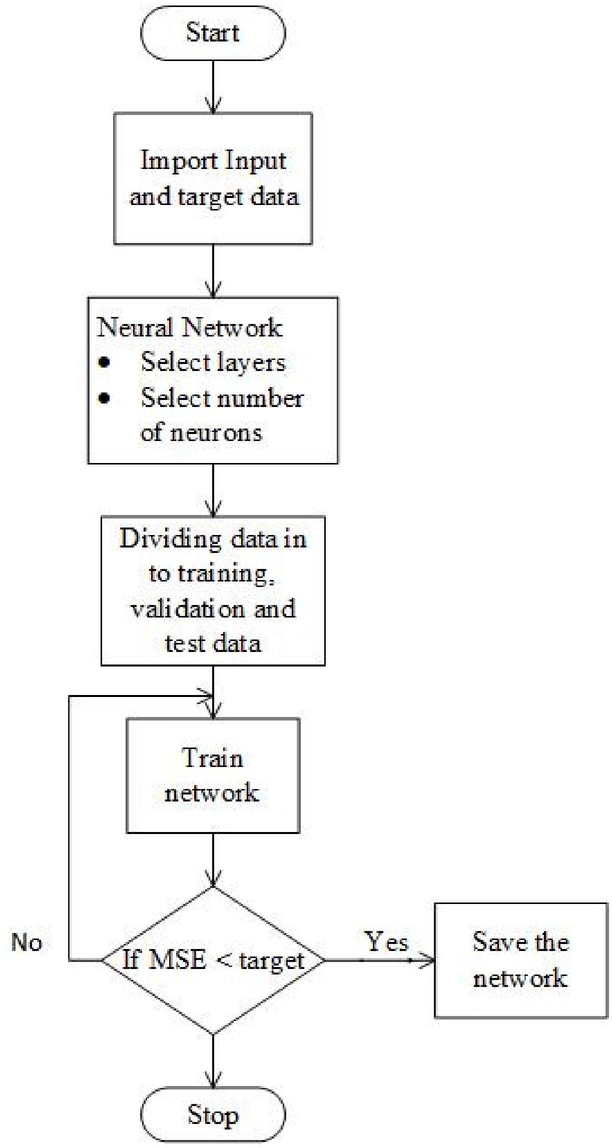

FIGURE 2.4: Flow chart of Neural Network.

2.7.2 Second Phase of Thesis (Scheduling Phase)

- In the second phase as shown in Fig 2.4, an optimization algorithm is proposed for the optimal assignment of EVs to CSs. This methodology delivers a solution to reduce the consumption of energy by the EVs while reaching CSs.

- Afterward, formulating the objective function a small geographic area is considered with a limited number of EVs and CSs.

- A geographic area is divided into two kinds of areas such as an area with heavy traffic and low traffic area. This problem is solved by linear programming, for which linear toolbox is used present in MATLAB.

- The objective function is modeled as linear with the following parameters such as constraints of different vehicles, CSs and the situation of traffic on the roads. With the suggested solution EVs keep the SOC of battery to its maximum level while reaching the assigned charging station.

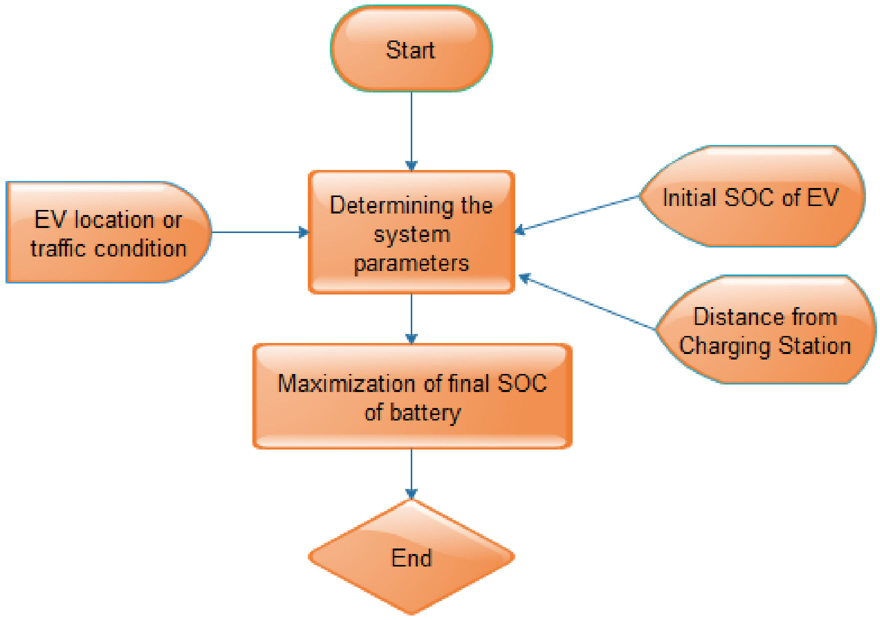

FIGURE 2.5: Flow chart of Energy Efficient Scheduling.

2.8 Research Contributions

In recent future, there is expectation of large number increase in sales and development of EVs that's the main reason of importance and challenge is about the improvement in the development of the charging infrastructures as well as the charging methods and their management during charging process.
To mitigate the influence of uncontrolled method of charging on power grid, an indirectly controlled method of charging is proposed. Indirectly controlled charging approach controls the system parameters such as charging power of EVs, energy

price and charging cost which may affect the charging process. Aim of indirectly controlled charging method is to see the user's perspective as well as grid perspective for its stability.

The major hurdle for EV driver is where and when they should charge their vehicle by satisfying all constraints. It's not always important that the nearest charging station is suitable some other factors also affects such as traffic conditions and number charging point at respective charging station.

In order to consider these assumptions we proceed to model the problem with optimal solution which have linear equations and problem constraints. Afterwards we define some system parameters which are given in list of symbols. Our aim is to maximize the objective function by considering these system parameters.

There is need of a smart scheduling system which can optimally schedule the charging pattern of EVs. As a result load profile of electrical system flattened efficiently. Hence the aim of minimizing the operational cost could be achieved. This is very important step towards smart grid implementation.The major contributions of the following thesis are listed below.

1. Three different techniques namely; tree regression, linear regression, and neural network are applied to load forecasting. The advantages and disadvantages of these load forecasting techniques are discussed in detail. These techniques are also compared with each other on the basis of mean square error.

2. An optimization solution of charging management is recommended to EVs. The given issue is modeled by using the linear programming with the ultimate goal to reach the CS by satisfying all constraints.

3. The scheduling optimization problem for EVs charging is analyzed. Moreover, a solution is proposed in order to optimize the charging power of EVs by minimizing the entire cost of all EVs which perform charging.

Chapter 3

Load Forecasting Models

In this chapter, different load forecasting approaches and the significance of load forecasting for EVs charging scheduling are presented. Furthermore, load forecasting models are also discussed in detail.

3.1 Load Forecasting Approaches

Buying and producing electric power and infrastructure advancement plays vital role in making important decision. These decisions are become easy with the help of forecasting electric load. The focus of forecasting load is to estimate the future load demand. This requires the precise prediction of the magnitude of electric power load for the different phases of the planning perspective. Forecasting of load demand is considered as one of the serious aspects for cost of operation of power systems. As control operation could save the maximum amount of savings which is achieved by precise load forecasting. Due to forecasting errors (either positive or negative) results in increased operating cost.
The goal of most research target towards the estimating EVs charging demand pattern. This grouped the EVs charging configuration into charging load estimation and charging pattern identification. The several categories of approaches and models are comprised in the literature. On the basis of time perspective, load

forecasting can be generally distributed into three groups which base on duration of time which are following:

- Short term load forecast (1 hour to 1 week)
- Medium term load forecast (1 month to 1 year)
- Long term load forecast (1 year to 10 years)

3.2 Significance of Load Forecasting for Electric Vehicles Charging Scheduling

The world especially developed countries are shifting rapidly from fossil fuels automobiles to EVs. There is expectation of increase in number of EVs all over the world. A reliable mechanism of EV charging will be necessary for its effective integration into the power system, which is necessary for stability and reliability of power system. Uncontrolled method of EVs charging causes huge deviation in electrical grid which affects the power quality of power system. As a result high energy consumption, high load peaks and degradation of power quality is occurring. Scheduling and forecasting are mainly used to control and minimize the impact of these following mentioned factors.

In forecasting approaches, error avoidance and network stability are crucially reliant on the forecasting of the everyday load demand. The precision of the EV charging forecast is necessary for development and management. The performance of a very precise forecasting model will support the improvement of EV charging and inspire productions to encourage the usage of EVs.The stability of the power grid and guarantee the balance between the electricity supply and demand is achieved by appropriate scheduling of EV charging.

3.3 Selection of Data Set

The data is used in load forecasting as input, the data are survey data and metering data. The data set is taken from ISO intended for the years 2004 to 2008. The data set which is used in following thesis consist of historical load data hourly based and information regarding weather conditions. There is high correlation between the weather and load demand in area. The demand of electricity increases when there is drop of temp below 10 degree in order to fulfill the heating requirements. Whereas, the demand of electricity increases when there is increase of temp beyond 23 degree in order to fulfill the cooling requirements. The weather conditions comprise of dry bulb and dew point temperature. Whereas the historical data include average load of previous day, load of previous day of same hour and load of previous week of same day and same hour. Other input data for load forecasting is hour of such day and day of that week.
To create the load forecast model, following 3 steps are used which is given below.

- Create a matrix for load prediction which is based on historical data such as weather condition and electrical load.
- Design a load forecasting model such as linear regression, bagged tree regression and neural network.
- Produce forecast load of coming day, week or month on the basis of historical data.

The data set is split into following sets which are given below.

- Training Set (from 2004 to 2007)
- Test set (data of 2008)

Training set is used for constructing the model to approximate the parameters of system. The performance of models is validating on data from test. Afterwards models are built on data from training data set for forecasting the load.

The models are verified by data of test set ensure the performance of following load forecasting models used. After forecasting the load, compare the actual load with forecasted load to find the forecasting error of models used in following thesis. In order to validate the performance of forecasted model mean square error (MSE), mean absolute percent error (MAPE) and daily peak error in forecasted load has been checked.

The models for load forecasting used in following thesis are given below. This would be discussed in detail one by one. The section is ended by giving the methods that is used for load forecasting.

- Linear regression model
- Bagged tree regression model
- Artificial Neural network

3.4 Linear Regression Model

In following section, a detailed explanation about the linear regression algorithm is given. Linear regression modeling approach is used for understanding the relationship between a continuous dependent variable 'y' and one or more independent variable $x_1, x_2, \ldots..x_n$.

The aim in linear regression approach is to recognize a function that describes a close correlation between these variables so that the values of the dependent variable can be estimated by series of independent variables.

In linear regression technique for load forecasting, the independent variable for load is found as weather condition such as dry bulb and dew point temperature with historical data of load. These values have direct effect on electrical load. The load forecasting model by using linear regression approach is stated in the form as.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ...\beta_k x_k + e \tag{3.1}$$

where y represents the load, x_i represents the affecting features, β_i represents the parameters of regression with respect to x_i, and e represents the error value in above relation. The mean of error value is zero with constant variance.
Meanwhile, β_i parameter are unknown, by observing y and x_i they should be predicted. Let b_i (i=0,1,2,.....k) be predicted in form of β_i (i=0,1,2,...k). Therefore the predicted value of y is given below:

$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2 + ...b_k x_k \tag{3.2}$$

On average the difference between the forecasted values of load $\hat{y}$ and real value of load y would tend to zero. So it is assumed that the value of error term in Equation (3.1) has an expected or average value of zero if the PDF for the dependent variable y at different level of the independent variable are normal distributed like bell shaped. Therefore we eliminate the error value in calculating forecasted parameters. Afterwards, to minimize the sum of squared residual values is estimated by least square estimation to obtain the parameter b_i which are given below.

$$\underline{B} = [b_0 \quad b_1 \quad b_2....b_k]^T = (\underline{X}^T \underline{X})^- 1 \underline{X}^T \underline{Y} \tag{3.3}$$

In above expression X and Y are the column vector and matrix:

$$\underline{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \text{ AND } \underline{X} = \begin{bmatrix} 1 & x_1 1 & x_1 2 & \dots & x_1 k \\ 1 & x_2 1 & x_2 2 & \dots & x_2 k \\ \vdots & \dots & \dots & \dots & \vdots \\ 1 & x_n 1 & x_n 2 & \dots & x_n k \end{bmatrix}$$

The following model is ready to use for forecasting the load values after these parameters are calculated. Afterwards, by considering that all the values of independent variable are estimated correctly hence the standard error will be less. For obtaining standard error the equation is given below.

$$s = \sqrt{\frac{SSE}{n - (k+1)}} \tag{3.4}$$

$$SSE = \sum (y_i(t) - \hat{y}_i(t))^2 \tag{3.5}$$

where $y_i(t)$ is observed value and $\hat{y}(t)$ is estimated value.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i(t) - \hat{y}_i(t))^2}{\sum_{i=1}^{n} (y_i(t) - \overline{y_i}(t))^2} \tag{3.6}$$

where $y_i(t)$ is the average value of $y(t)$.

3.5 Bagged Regression Tree Model

A regression tree is a non-parameter statistical classification and regression approach which is also known as automatic classifier. This technique is planned for improvement in stability and accuracy of machine learning algorithms. This approach is used to increase the predictive performance of base model e.g. decision trees or those approaches that do flexible selection and fitting in linear model.
Bagged regression tree model is a kind of aggregated bootstrap in which the output from a recent step is feds input to the present step. In conventional neural networks, every input and output is independent of each other, yet in scenarios like when it is necessary to estimate the next word of the sentence, the recent words are needed and hence there is a need to remember the previous words.
By creating the linear combination of fitting model and merging with several predictors instead of using a single fit model. For a learning phase sample consist of n number of historical cases $(x_1, y_1), (x_2, y_2), \ldots .(x_n, y_n)$ where x is the independent variable with m-dimensional vector, and y is the parallel response variable having numerical value, hence regression tree is tree kind of structure.
The tree is made up by dividing the recurring splits of subsets into two more successor subsets on the basis of sample input variable. Each split is an review about the input variable which points to left and right successor subsets on the basis of 'yes' or 'no' respectively. Since tree regression approach only deals with the discrete values, the function is discretized into vectors of input and output

variable in the domain.

Meanwhile for output function, bagged regression tree model is used. On the basis of this regression tree a model is built, which have set of regression trees each having different set of instructions for execution of non-linear regression.

The mechanism starts with the structure of 20 such trees with a least leaf size of 40. The larger size of leaf gives smaller tree size. Which manage the over fitting of data and performance. Afterwards analyzing the model parameters, model is finalized with the collection of 20 trees and leaf size of 15 having all the features. Fig 3.1 is the regression tree of load forecasted model.

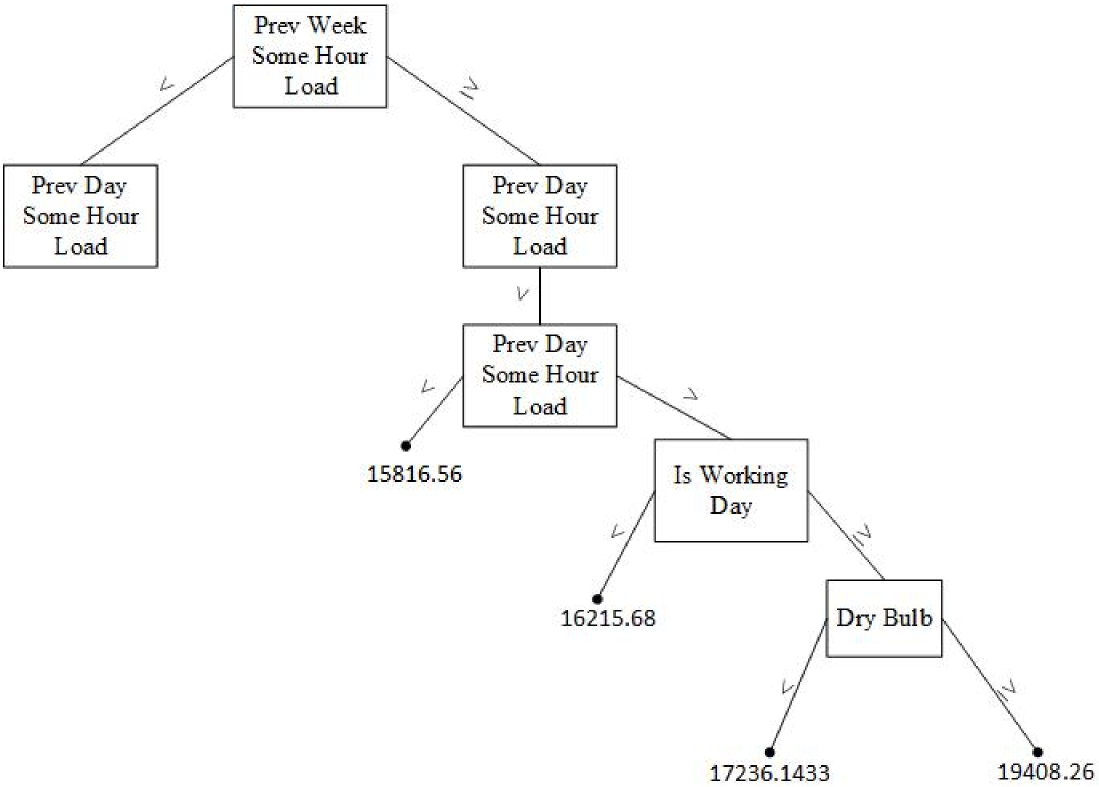

Figure 3.1: Bagged Tree Regression.

The model also defines the relative feature (input) of significance which gives the most predictive power for the predictors. In Fig 3.2 relative significance of the features is given. As it's clearly seen that the 'IsWorkingDay' and 'drybulbtemperature' features have most significance among all features.

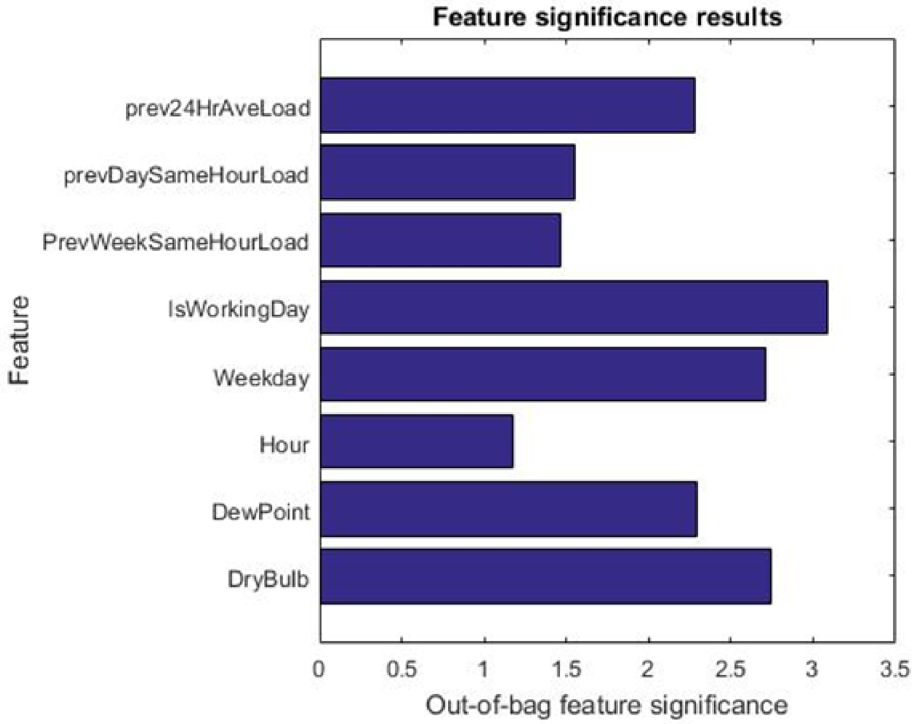

Figure 3.2: Significance of Features.

3.6 Artificial Neural Network

ANN have very large number of applications due to their ability of learning. ANN has the ability to overcome the dependence on a functional form of a load forecasting model. There are several types of neural network multi-layer perceptron, self-organizing networks etc. There is an input layer, a hidden layer and an output layer in ANN. There are different input features in input layer, hidden layer have many neurons. Input are multiplied by weights (ω_i) which are added to threshold (θ) to make an inner product number. The key benefit is that most of forecasting approaches regarding neural network do not need a load model. Though, in training phase neural networks usually takes a lot of time. Artificial neural network is fully connected feed forwarding neural network. Where input and hidden layers are connected to output unit which is linear functions through weights. Afterwards linear equations are solved for these output weights. For the optimization of output weights, a back propagation method is used for each iteration on training data samples. The transfer function for output layer is a Levenburg-Marquardt fitness function that use weighted sum of input layer and the bias as shown Fig 3.3. In proposed ANN architecture, sigmoid activation function is used in order to compute the output of hidden layer whereas linear function is used in order to compute the output of input layer.

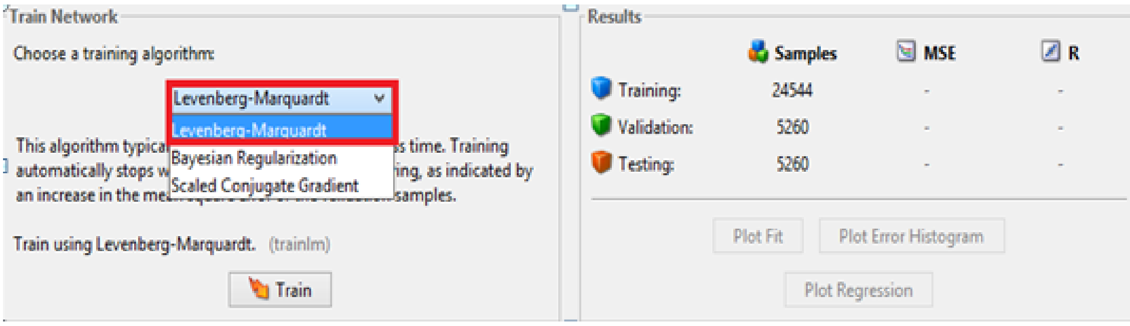

FIGURE 3.3: Choosing a Training Algorithm.

For load forecasting Equation (3.7) is used.

$$Output = \sum_{j=1}^{m}(\frac{2v_j}{1+e^{-}2^{(}\sum_{i=1}^{n} w_i j x_i) - T_j} - T_o ut \tag{3.7}$$

Where vj (j=1, 2, m) and Tout represents the weight and bias value of the output layer neuron respectively. The weights and bias of each neuron are modified through iterative training of input data with a goal to find lesser forecast error. The load forecasting model is initializes with 20 neurons in hidden layer with 8 input features. The training period became shorter due to use of Levenburg-Marquardt fitness function. The whole dataset is divided into 3 sets; a 70% training set, 15% validation set and 15% is the remaining test samples as shown in Fig 3.2.

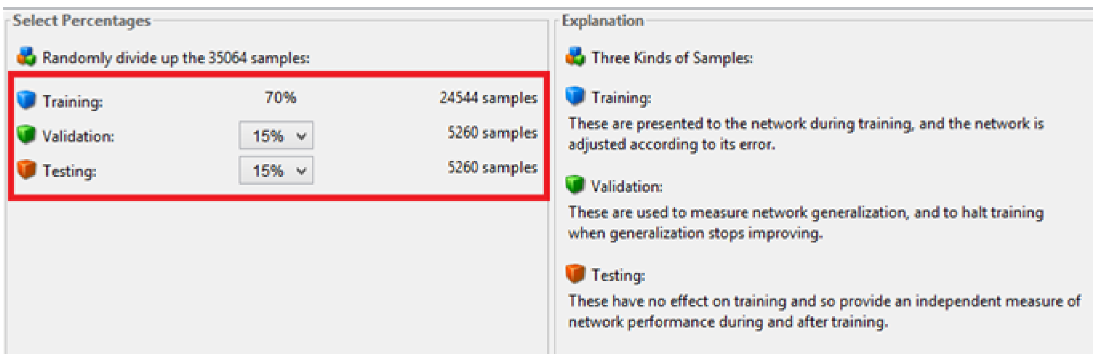

FIGURE 3.4: Distribution of Data Set.

In Fig 3.4 Neural network is presented, which is used for load forecasting in following thesis with 8 input features, 20 neurons and an output layer in hidden layer. (Fig 3.4)

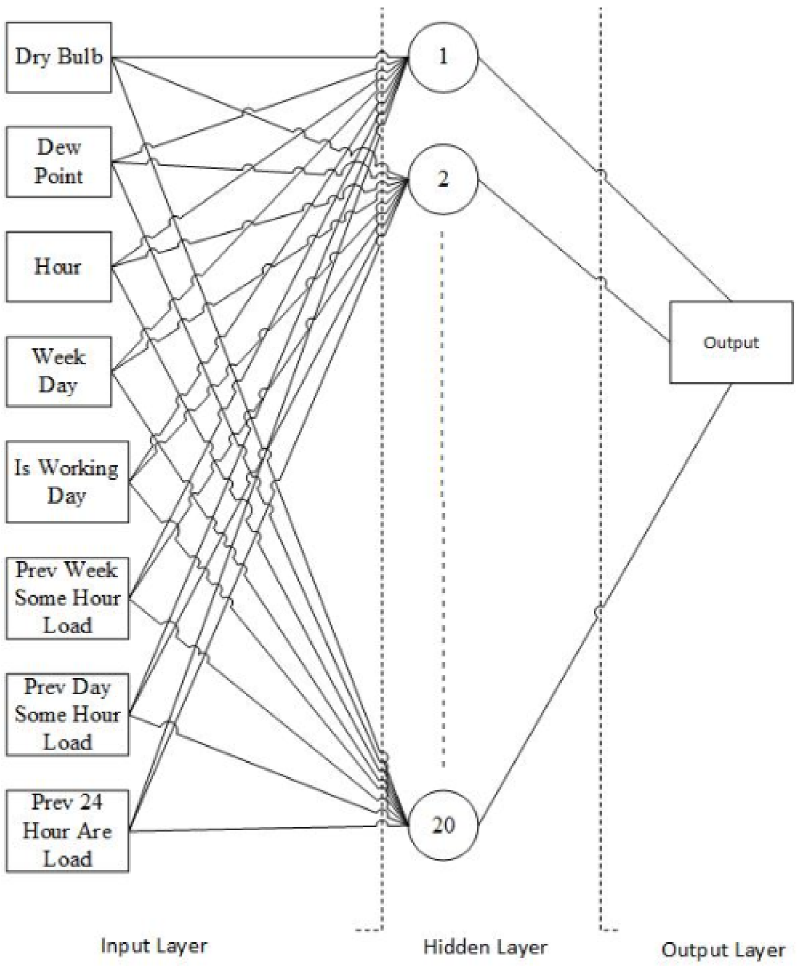

Figure 3.5: Neural Network.

Though, ANN is the best technique for load forecasting due to the reason of self-learning abilities. Whereas ANN implementation is complex and it requires large historical data for training and for least mean square error.

Chapter 4

Mathematical Modeling for Electric Vehicle Charging and Scheduling

This chapter is devoted to the mathematical modeling for optimal EVs charging scheduling. The modeling for optimizing energy consumption for EVs before charging and problem constraint are presented. Furthermore, the modeling for optimizing the charging cost during all day is also discussed in this chapter.

4.1 Mathematical Modeling for Optimal Electric Vehicles Charging and Scheduling

In recent future, there is expectation of large number increase in sales and development of EVs that's the main reason of importance and challenge is about the improvement in the development of the charging infrastructures as well as the charging methods and their management during charging process.
To mitigate the influence of uncontrolled method of charging on power grid, an indirectly controlled method of charging is proposed. Indirectly controlled charging approach controls the system parameters such as charging power of EVs, energy

price and charging cost which may affect the charging process. Aim of indirectly controlled charging method is to see the user's perspective as well as grid perspective for its stability.

The major hurdle for EV driver is where and when they should charge their vehicle by satisfying all constraints. It's not always important that the nearest charging station is suitable some other factors also affects such as traffic conditions and number charging point at respective charging station.

There is need of a smart scheduling system which can optimally schedule the charging pattern of EVs. As a result load profile of electrical system flattened efficiently. Hence the aim of minimizing the operational cost could be achieved. This is very important step towards smart grid implementation.

In following thesis there are two methods are adopted for optimal EVs charging scheduling to achieve the respective goal. These approaches are given below.

- Optimized energy consumption for EVs while reaching respective charging station.
- Optimized charging cost of all EVs during all day.

4.2 Modeling for Optimized Electric Vehicles Scheduling

In order to solve the problem with linear programming we consider some assumptions which are given below:

- There is limited number of EVs and limited number of charging stations.
- All these EVs are of same features.
- All CS have same features.
- Each CS assign to EV is according to number of charging points availability.

In order to consider these assumptions we proceed to model the problem with optimal solution which have linear equations and problem constraints. Afterwards we define some system parameters which are given in list of symbols. Our aim is to maximize the objective function by considering these system parameters.
The relationship between vehicle speed and traffic density is proposed by Greenshield in [58]. In presented relationship there is proportionality between vehicle speed and traffic density. The following relationship is presented in Equation (4.1) given below.

$$V = V_r ef(1 - \frac{Veh_d}{T_r jam}) \tag{4.1}$$

As there is number of vehicles and CS are more than one, therefore EVi and Sj are considered for vehicles and CS respectively. So Equation (4.2) represents the following condition.

$$V(i,j) = V_r ef(i,j)(1 - \frac{Veh_d(i,j)}{T_r jam(i,j)}) \tag{4.2}$$

As traffic density is proportional to flow of vehicles. Such relationship is represented by Equation (4.3).

$$Veh_d(i,j) = \frac{Veh_f low(i,j)}{V(i,j)} \tag{4.3}$$

The time required for EV to reach the CS can be calculated by Eq. 4.4.

$$T(i,j) = \frac{d(i,j)}{V(i,j)} \tag{4.4}$$

The expression for vehicle density is given by Equation (4.5), which is obtained by combining Equation (4.3) and (4.4).

$$K(i,j) = \frac{Veh_f low(i,j)T(i,j)}{d(i,j)} \tag{4.5}$$

Equation (4.6) describing the relationship between vehicle speed, flow of vehicle, time, distance from CS and traffic density. Which is obtained by manipulating Equation (4.2) and (4.5).

$$V(i,j) = Vref(i,j)(1 - \frac{Veh_f low(i,j)T(i,j)}{d(i,j)T_r jam(i,j)} \tag{4.6}$$

Equation (4.7) represents the expression under normal conditions the energy consumption of EVs is directly proportional to distance of EV from CS $d(i,j)$, battery capacity $C(i)$ and battery autonomy $A(i)$.

$$E_c n(i,j) = \frac{C(i)d(i,j)}{A(i)} \tag{4.7}$$

As presented in [59], final SOC is calculated according to initial SOC and energy consumption while reaching the CS by keeping in view the speed variation due to traffic conditions. Equation (4.8) represents our scenario, where $d_c(i,j)$ represents the disturbed conditions of traffic.

$$SOC_f(i,j) = SOC_i(i,j) - E_c n(i,j)Y(i,j) \tag{4.8}$$

With,

$$Y(i,j) = V_r ef(i,j)(1 - \frac{Veh_f low(i,j)T(i,j)}{d(i,j)T_r jam(i,j)}) \tag{4.9}$$

Afterwards our objective is to find that value of SOC_f when EV reaches the CS it should be highest possible level. In simple words our goals are presented below.

- Reduce the energy needs of EV
- Keep the battery above the threshold level $SOC_m in$
- Reduction of charging time
- Prevent waiting time in CS

- Cost reduction of charging which is not that much affected from this objective function.

Finally the aim to reach the CS ensure to maximize the objective function Y which represents by Equation (4.10)

$$Y = \sum_{i=1}^{n} \sum_{j=1}^{m} SOC_f(i,j)x(i,j) \tag{4.10}$$

4.3 Problem Constraints

The system has several constraints which is represented by following linear equation and given below.

- For i=1,2,. . . .n

$$\sum_{j=1}^{m} x(i,j) = 1 \tag{4.11}$$

  Eq. 4.11 explained that each EV_i should be assigned to one CS_j at given time.

- For j=1,2,. . . m

$$\sum_{i=1}^{n} x(i,j) \leq n_i j \tag{4.12}$$

  Above constraint explained that the each CS S_j should not entertain more than n_j EVs at same time. Whereas n_j represents the charging point in CS.

- Equation (4.13) represents the final SOC of EV should not go down from threshold which is SOC_min.

$$SOC_f(i,j) \geq SOC_min \tag{4.13}$$

  where, SOC_min is the threshold value of SOC which is 30kwh

Afterwards, a communication framework is presented in Fig. 4.1.

FIGURE 4.1: Communication Framework for Scheduling .

4.4 Modeling for Optimizing Charging Cost during all Day

The following method of CS is mostly functional at residential locations such homes, office parking and shopping malls, where EV charge with little amount of current to utilize the free time. As indicated by the everyday behaviors of the client, the highest demand of a typical CS usually begins in the time off duty and keeps going to midnight.

After examine the battery charging during a day, it is evenly distributed into group of intervals which is represented by N. The size of such interval is represented by τ. The charging power of EVs in defined interval will remain same. In following thesis we split the day equally into 24 intervals with each interval of 1 hour. Fig. 4.2 represents the division of interval and charging period of mth EV.

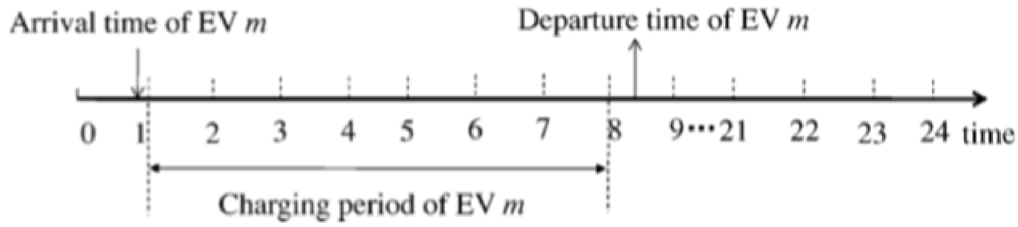

FIGURE 4.2: EVs Charging Duration.

The group of EVs which perform charging during respective interval is represented by M. This group consists of those numbers of vehicles which require charging. The charging power of EVs is represented by $x_m i$ where m represents those EVs which perform charging and i represent the interval. During the charging of EVs this condition $x_m i \geq 0$ must be satisfied to confirm that battery does not discharge that time.

The entrance time of EVs in charging station is the time when EV starts charging. On the other hand the departure time is the time when EV stops charging. The charging period of EVs in N interval is represented by T_m, that time required for EV to be charged. The initial energy of EVs battery is represented by $E_i n$, this is the condition of EVs battery before charging starts. Whereas final energy of EVs battery is represented by $E_f in$, this is condition of EVs battery after charging completes. The final energy of EVs battery should not exceed the battery capacity of EV. Equation (4.14) represents the final energy ratio.

$$\gamma_q = \frac{E_f in}{E_c} \tag{4.14}$$

The CS detects the entrance time, initial battery energy and capacity of EV battery before EV starts charging. Afterwards the departure time and final ratio of energy is provided to user before the charging starts. Period of charging is determined by the difference of entrance time and departure time. A charging-interval matrix is present which describe the relationship between the charging events and intervals. The charging-interval matrix is represented by G which is defined as:

$$G_q i = \begin{cases} 1 & \text{if interval i falls wihin the charging period} \\ 0 & \text{otherwise} \end{cases} \tag{4.15}$$

In the following thesis the model is used for scheduling the charging of EVs is for small geographic area. For real time pricing two assumptions are made which are given below:

- Power loses are very small hence negligible
- In transmission lines there is no congestion

These assumptions are made to keep the electricity price constant disregarding of spatial variations. Therefore electricity price kept same for charging time interval irrespective of CS location. So the optimization of EV charging is only temporal based. The price of electricity is modeled as linear function of load which is given below:

$$f(L_t) = k_0 + k_1 L_t \tag{4.16}$$

In above relation k_0 is the intercept and k_1 is the slope. These both values are non-negative and should be real number and L_t is the total load. The total load in $i^t h$ interval comprises two parts.

- L_b is the base load which is total load in respective interval without EV charging.
- L_c is the charging load which is the load of EVs charging in respective interval.

The base load L_b is assumed to be constant in respective interval. Whereas charging load of EVs is given by Equation (4.17).

$$L_c = \sum_{q \in Q} x_q i g_q i \tag{4.17}$$

The charging load is considered to be positive if the load from grid to the EVs batteries is greater in respective interval. Hence the total load is given by Equation (4.18).

$$L_T i = L_b f + L_c \tag{4.18}$$

As the assumption is total base load and charging power in respective interval is constant, therefore total load in respective interval is constant. In following thesis, charging cost in respective interval is represented by C_i, which refers to the total amount that EV users pay for charging in respective interval. The charging cost in respective interval is based on price model which is linear function of load and is given by Equation (4.19).

$$C_i = \int_{L_b}^{L_T i} (k_0 + k_1 L_T) dL_T = (k_0 L_T i + \frac{k_1}{2}(L_T i)^2) - (k_0 L_b f + \frac{k_1}{2}(L_b f)^2) \tag{4.19}$$

In order to find optimal schedule system for EVs charging during respective interval which is 24hrs. Following assumptions are made which is given below:

- Entrance and departure time of each EV in respective interval is known.
- Initial and final energy of each EV in respective interval is known.
- Base load of each interval during all day is known.
- There is central controller required which gather these information afterwards perform optimization for EV charging scheduling.

The total cost is calculated by adding charging cost in each interval over N intervals. Equation (4.20) is used to represents the total cost during all day.

$$C_T = \sum_{i \in N} C_i = \sum_{i \in N} ((k_0 L_T i + \frac{k_1}{2}(L_T i)^2) - (k_0 L_b f + \frac{k_1}{2}(L_b f)^2)) \tag{4.20}$$

The scheduling optimization problem is defined as to minimize the total cost of EVs charging during N intervals in a day. This respective problem is solved by optimizing the total load and charging power EVs subject to the correlation between total load in respective interval and charging power of single EV, the instantaneous energy constraint, the final energy constraint, and the lower limit and upper limit of charging power. Mathematically the optimization problem is states as given below:

$$\sum_{i \in N} ((k_0 L_T i + \frac{k_1}{2}(L_T i)^2) - (k_0 L_b f + \frac{k_1}{2}(L_b f)^2)) \tag{4.21}$$

$$L_T i = L_b + \sum_{q \in Q} x_q i g_q i, \qquad \forall \quad i \in N \tag{4.22}$$

$$0 \leq E_i n + \sum_{k \in H} \tau x_q k g_q k \leq E_c, \qquad \forall \quad q \in Q \tag{4.23}$$

$$E_i n + \sum_{i \in N} \tau x_q i g_q i \geq \gamma_q E_c, \qquad \forall \quad \gamma \in Q \tag{4.24}$$

$$0 \leq x_q i \leq P_m ax, \qquad \forall \quad q \in Q, \qquad \forall \quad i \in N \tag{4.25}$$

Equation (4.21) represent the objective function which has to be minimized the total cost of EVs charging. Afterwards Equation (4.22) represents the correlation between total load and charging power of single EV, Equation (4.23) represents the instantaneous energy constraint which is the required limit at the end of interval that should not be 0 or not greater than battery capacity of EV, and Equation (4.24) represents the final energy constraint which is the minimum requirement of EV charging which is given by Equation (4.26).

$$E_f in = E_i n + \sum_{i \in N} q_i g_q i \tag{4.26}$$

Equation (4.25) represents the lower limit 0 and upper limit $P_m ax$ of the charging power of the EVs in respective interval. In the following optimization problem, the objective function is convex with subject to linear constraints.

Chapter 5

Simulations and Results

In this chapter, results are presented for an optimal scheduling model for charging of EVs is used which goals to minimize the total cost by optimizing the charging power of EVs. The following optimizing depends on future base load which is forecasted by using three different models. A detailed comparison of performance of these forecasting models is offered. On the basis of these results, the goal of optimum scheduling for EVs charging is achieved. Afterwards results for the second phase of this thesis is presented which aims to reach the respective CS with less energy consumption by considering the disturb conditions of traffic.

5.1 Load Forecasting Results

There are following three models are used for forecasting such as ANN, bagged tree regression and linear regression which is used in optimizing the EVs charging scheduling by minimizing the cost. In following section the load forecasting results are divided into three parts which are following:

- Load forecast for day ahead.
- Load forecast for coming week.
- Load forecast for coming month.

There are three parameters are used to check the performance of forecasting models and validate the prediction accuracy. The parameters are mean average error (MAE), mean average percent error (MAPE) and Daily Peak MAPE.

5.1.1 Load Forecast for Day Ahead

Comparison of forecasted load with actual base load for day ahead is presented in this section. Fig. 5.1 represents the predicted load and actual base load by using linear regression technique.

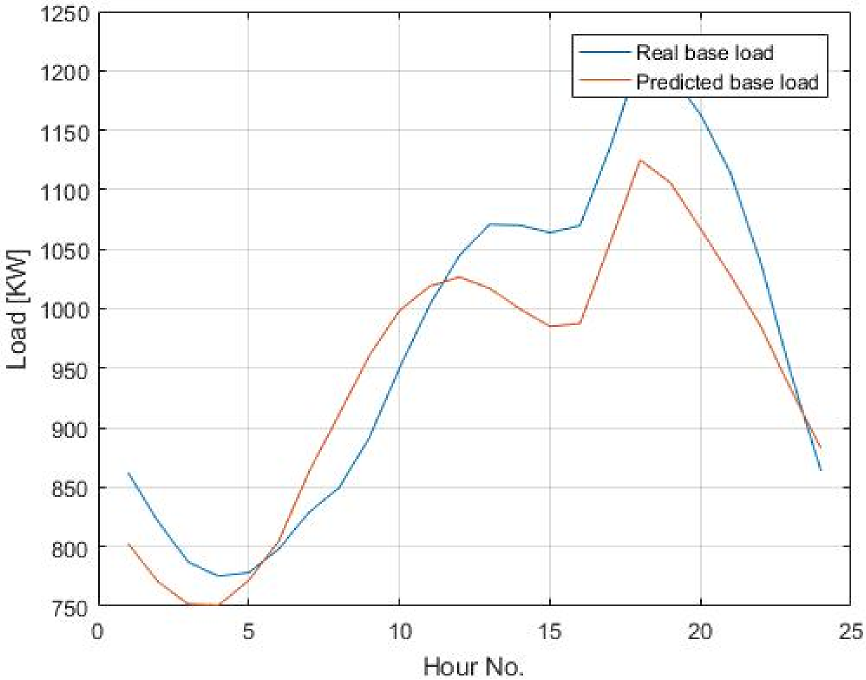

FIGURE 5.1: Daily Load using Linear Regression.

Fig. 5.2 represents the predicted load and actual base load by using bagged tree regression technique.

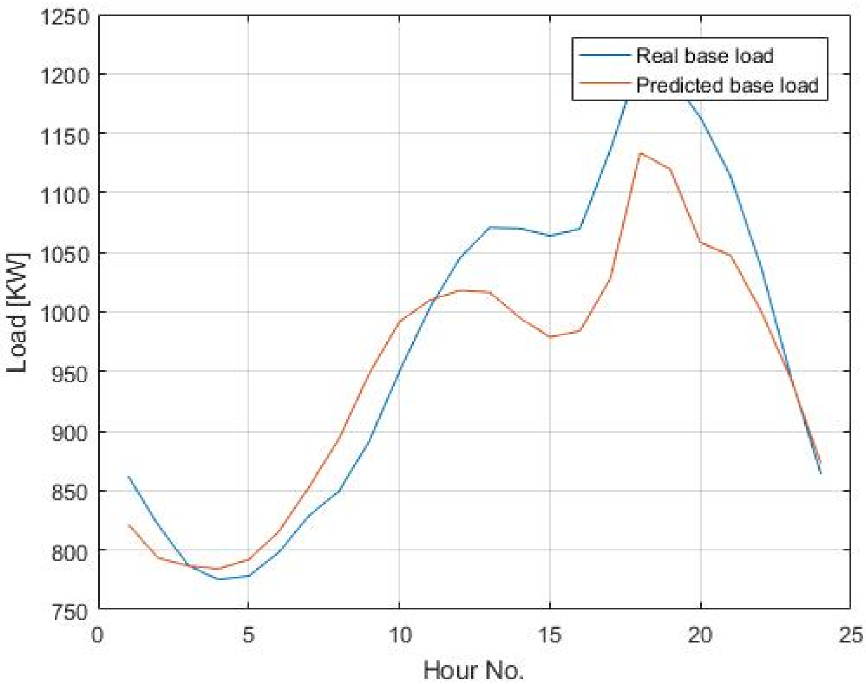

FIGURE 5.2: Daily Load using Tree Regression.

Fig. 5.3 represents the predicted load and actual base load by using ANN technique.

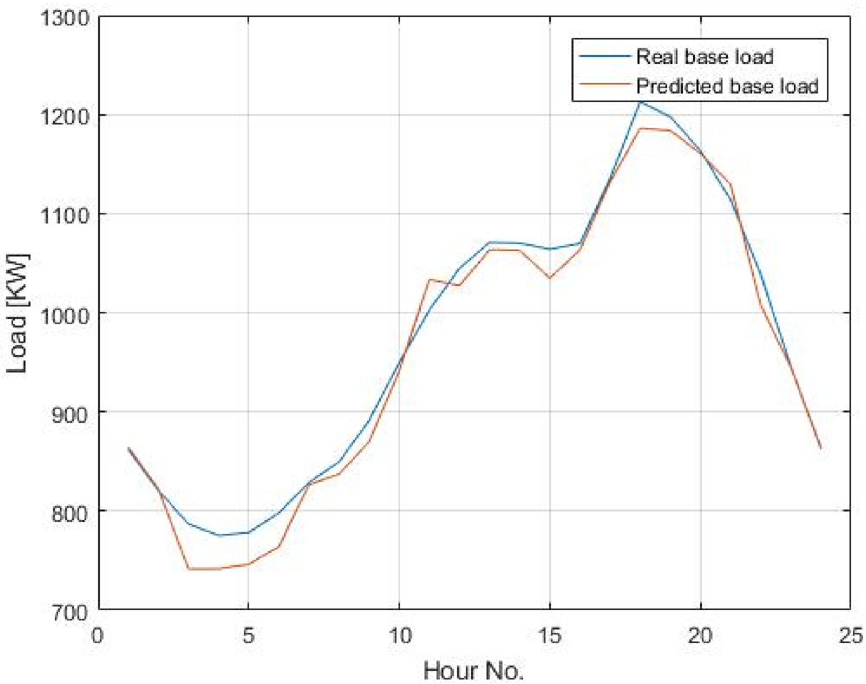

FIGURE 5.3: Daily Load using ANN.

TABLE 5.1: Daily Prediction Error.

Forecasting Models	**MAE (Kwh)**	**MAPE (%)**	**Daily Peak MAPE(%)**
Neural Network	16.09	1.24	1.55
Tree Regression	45.55	3.2	5.11
Linear Regression	51.81	5.14	7.23

The outcomes of errors for day ahead load forecast are present in Table 5.1.

5.1.2 Load Forecast for Coming Week

Comparison of forecasted load with actual base load for coming week is presented in this section. Fig. 5.4 represents the predicted load and actual base load by using linear regression technique.

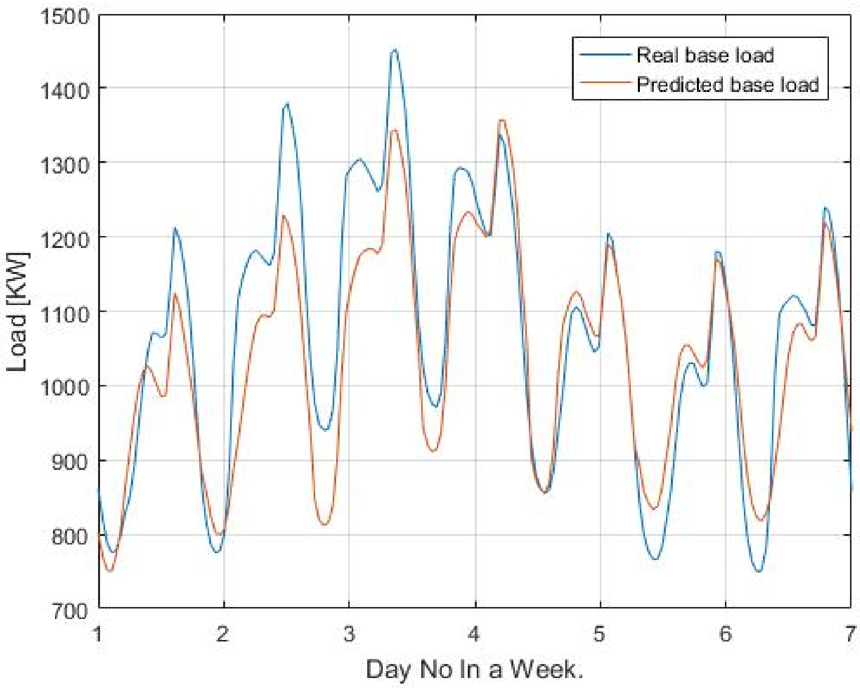

FIGURE 5.4: Weekly Load using Linear Regreesion.

Fig. 5.5 represents the predicted load and actual base load by using bagged tree regression technique.

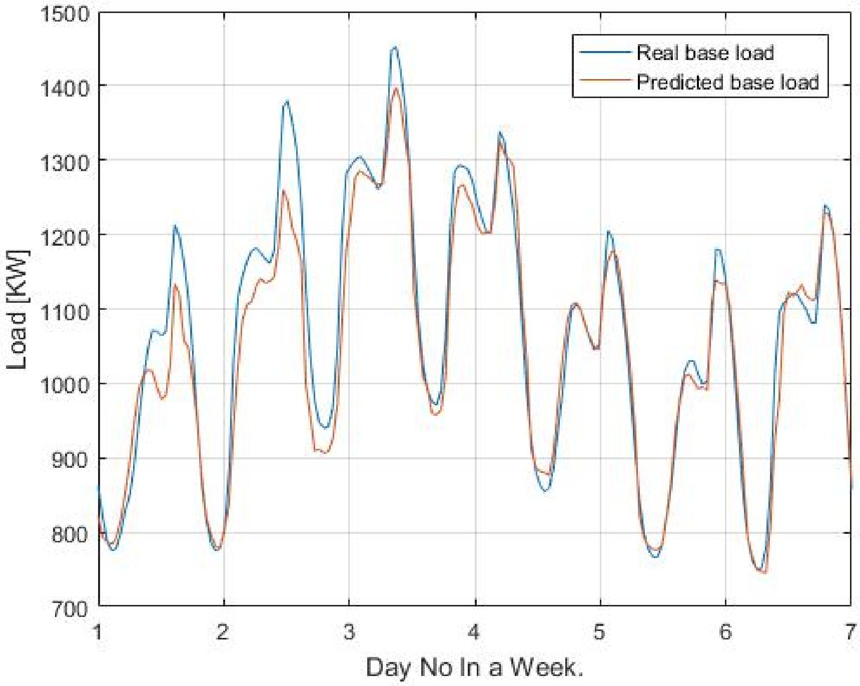

FIGURE 5.5: Weekly Load using Tree Regression.

Fig. 5.6 represents the predicted load and actual base load by using ANN technique.

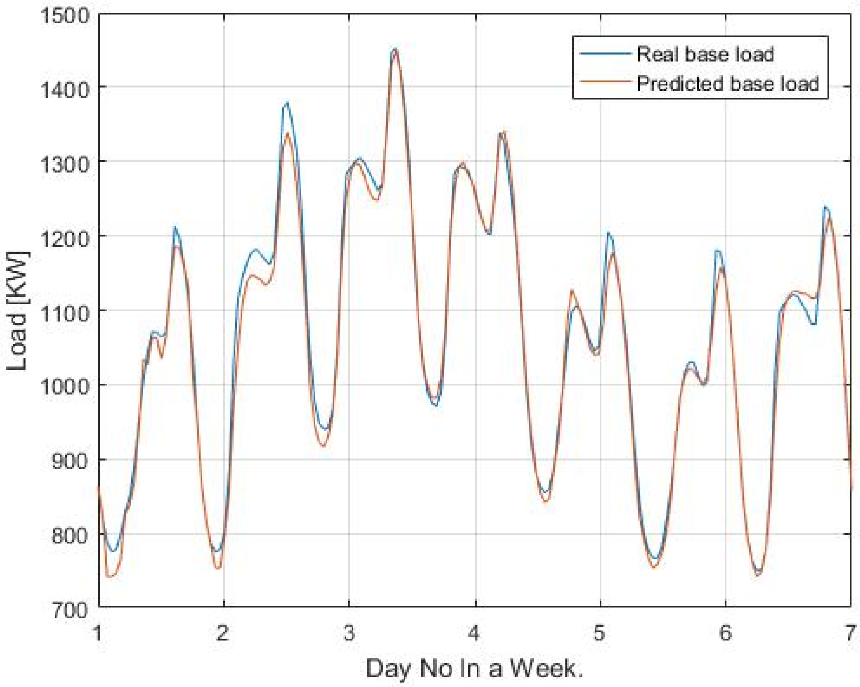

FIGURE 5.6: Weekly Load using ANN.

Table 5.2: Weekly Prediction Error.

Forecasting Models	MAE (Kwh)	MAPE (%)	Daily Peak MAPE(%)
Neural Network	7.82	1.04	1.18
Tree Regression	33.14	3	3.78
Linear Regression	49.08	5.02	5.38

The outcomes of errors of load forecast for coming week are present in Table 5.2.

5.1.3 Load Forecast for Coming Month

Comparison of forecasted load with actual base load for coming month is presented in this section. Fig. 5.7 represents the predicted load and actual base load by using linear regression technique.

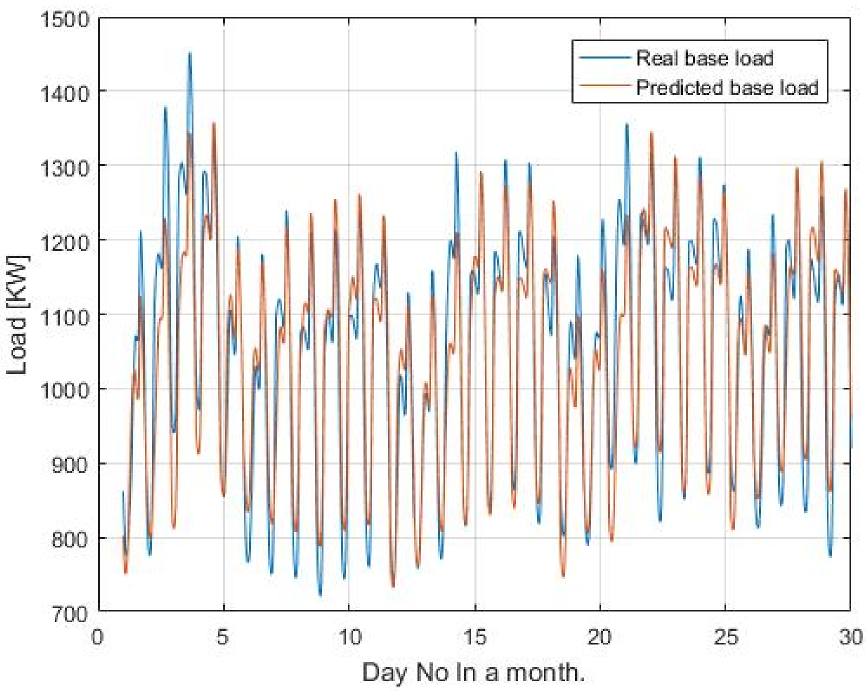

Figure 5.7: Monthly Load using Linear Regression.

Fig. 5.8 represents the predicted load and actual base load by using bagged tree regression technique.

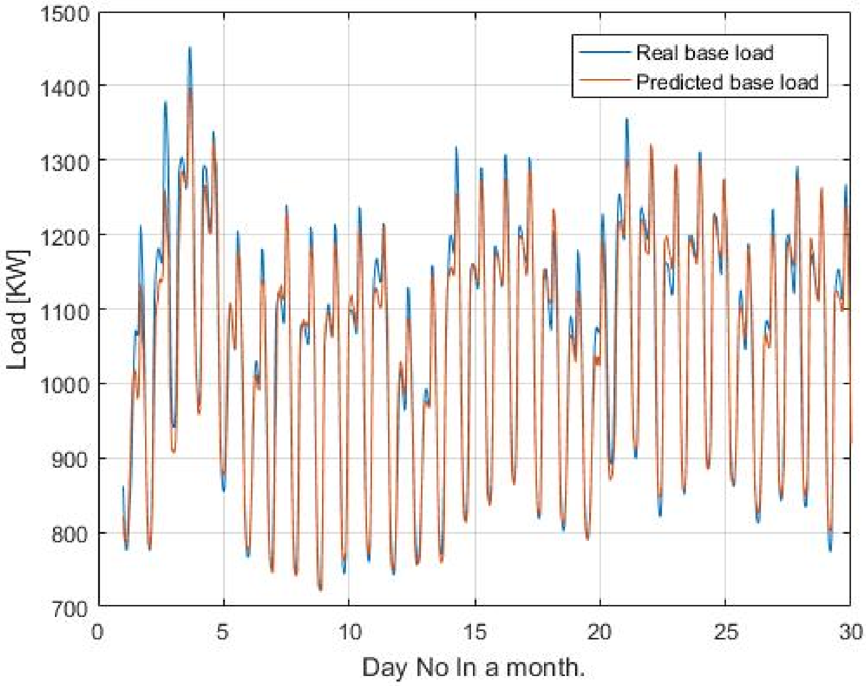

FIGURE 5.8: Monthly Load using Tree Regression.

Fig. 5.9 represents the predicted load and actual base load by using ANN technique.

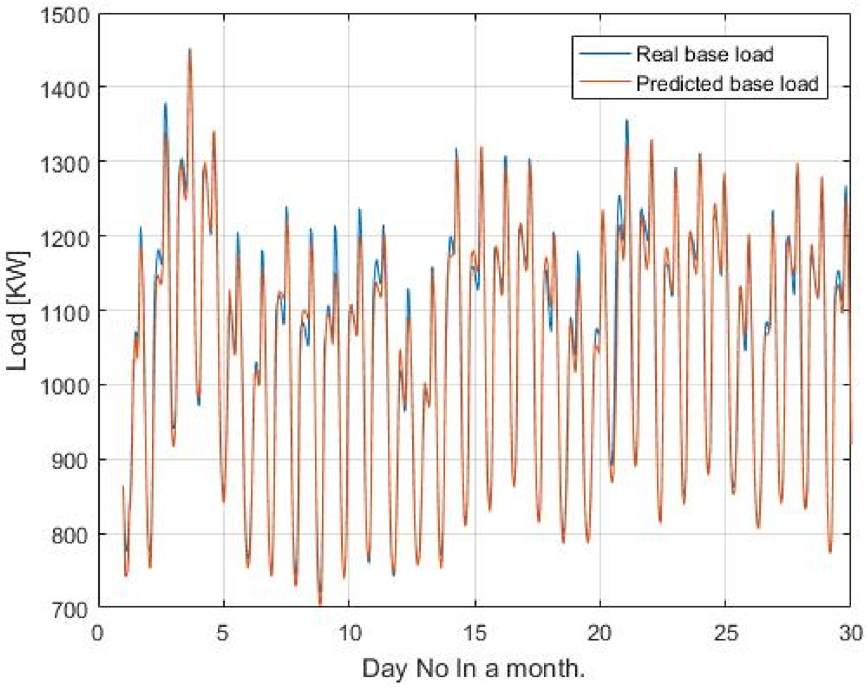

FIGURE 5.9: Monthly Load using ANN.

TABLE 5.3: Monthly Prediction Error.

Forecasting Models	**MAE (Kwh)**	**MAPE (%)**	**Daily Peak MAPE(%)**
Neural Network	5.03	0.94	1.09
Tree Regression	21.6	2.01	2.34
Linear Regression	47.13	4.53	3.33

The outcomes of errors of load forecast for coming month are present in Table 5.3. Afterwards, analyzing the results obtained from these forecasting models it can be assume that ANN gives better result than rest of two forecasting model. ANN forecasting took time because there is training phase but converges in less time than bagged tree regression due to statistical approach of ANN model. Cost reduction after applying the algorithm is presented in Fig. 5.10.

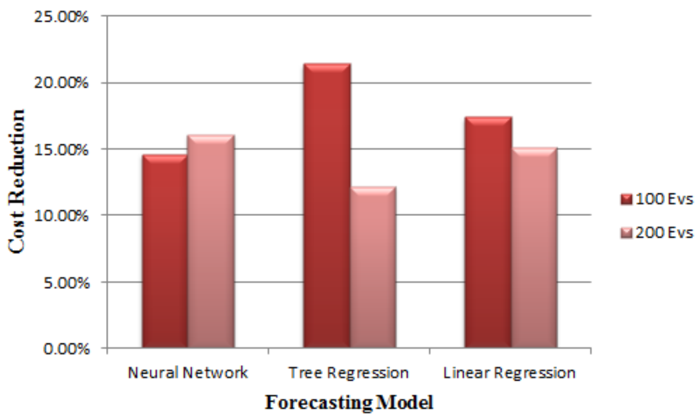

FIGURE 5.10: Cost Reduction.

5.2 Error Distribution of Forecasting Models

The distributions of forecasted errors are presented in Fig. 5.11 - Fig. 5.13 for linear regression, bagged tree regression and ANN respectively.

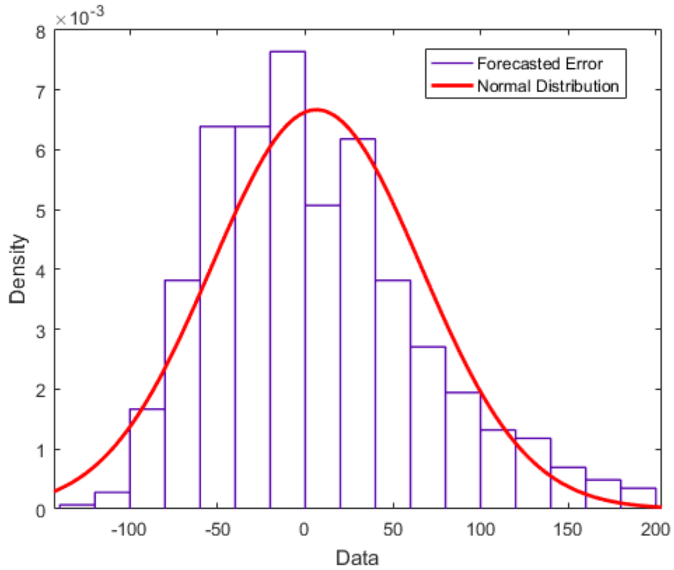

FIGURE 5.11: Error Distribution using Linear Regression.

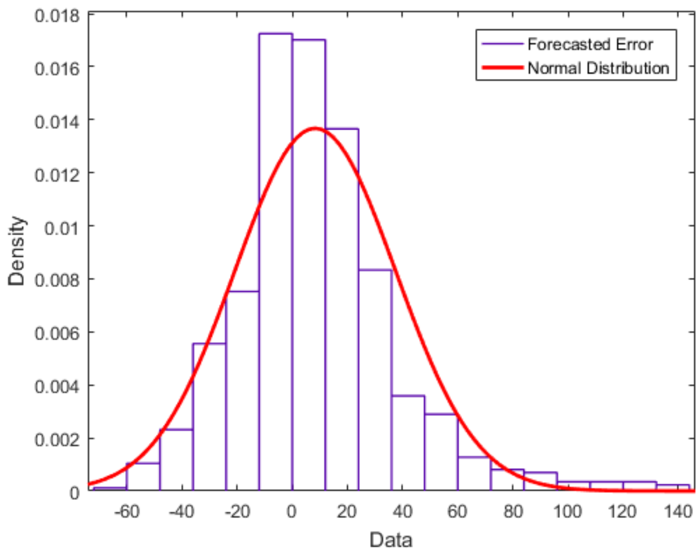

FIGURE 5.12: Error Distribution using Tree Regression.

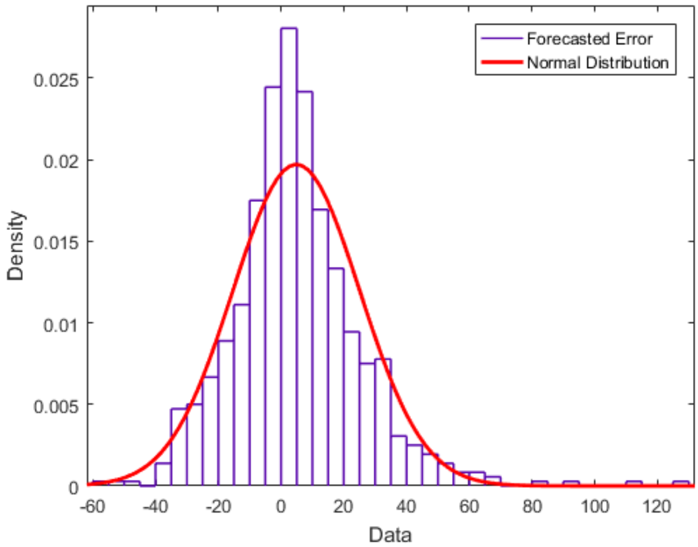

FIGURE 5.13: Error Distribution using ANN.

The most satisfactory error distributions are observed for ANN as compared to rest of two forecasting models. Performance of bagged tree regression is moderate as seen in error distribution plot. Whereas, the error distribution is more flattened and asymmetrical for linear regression.

5.3 Result for Cost Optimization for Electric Vehicles Charging Scheduling

The EV charging is examined for 24 hours during a day. The 24 hours are equally divided into 1 hour interval. The base load and forecasted load is discussed in above section in detail. The unit for electricity price is dollar ($)/Kwh.

5.3.1 System Parameters

Ford car is considered for the study. The system parameters are given below.

Battery capacity = 33 Kwh

Charging Power = 6.6 Kw

No of vehicles = 100,200

Charging period = 4-12 hours

Initial energy of EVs = 0-80

On the basis of load forecasting results in previous section are used for EV charging scheduling. A detailed comparison is presented between actual and predicted load by using three different forecasting models.
Fig. 5.14 represents a comparison of charging load (EVs load only) for 100 and 200 no of vehicles. The charging load in each interval is observed. Whereas decreases in EV charge demand is seen between 15-20 hour intervals. Hence this time is utilized for shifting the charging load to these intervals.

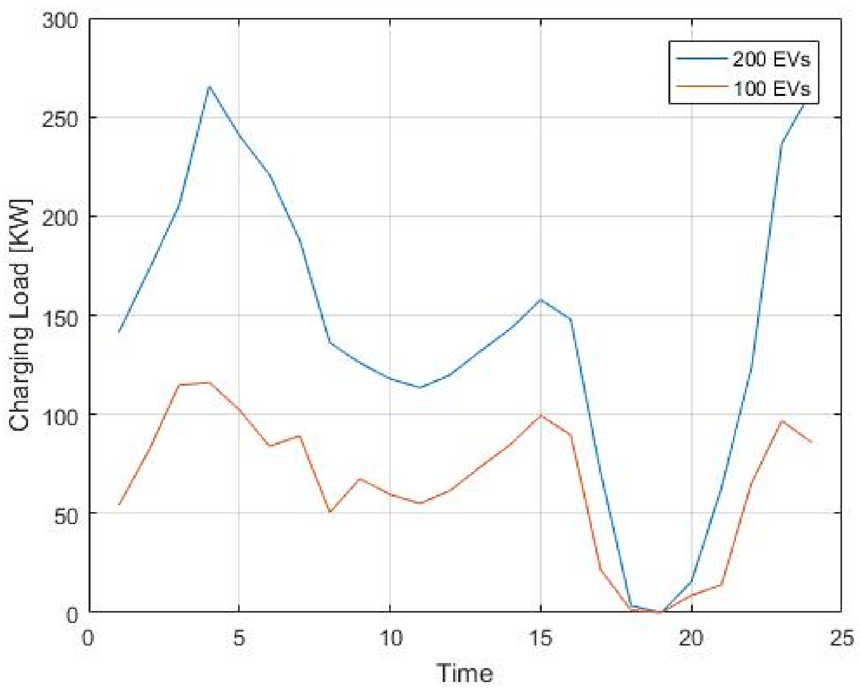

FIGURE 5.14: Variation of Charging Load.

The optimization of EVs charging requires precise information about base load and arrival of cars. The arrival of EVs uniformly distributed over entire interval seems to be impractical.
Therefore, arrival of EVs is considered to be poisson process which is near to practical scenario. The forecasted base load is selected among linear regression, bagged tree regression and artificial neural network. The comparison between actual base

load and predicted base load. The values obtained from artificial neural network is selected due to least mean absolute percent error among rest of forecasting models. We compare three charging scenarios: 1) The scenario in which the arrival of EVs are uniformly distributed over the interval: 2) The charging scenario in which the arrival of EVs is modeled as poisson process to meet the real scenario: 3) The charging scenario for EVs in which there is equal allocation of charging power is allotted on the basis of following criteria.

- Price for EV charging is considered from previous day in an interval.
- The charging power in i^{th} interval for EVs remains constant.

Fig. 5.15 shows the comparison of charging power of EV3 and EV7. An equal allocation of charging is achieved by solving the optimizing problem.

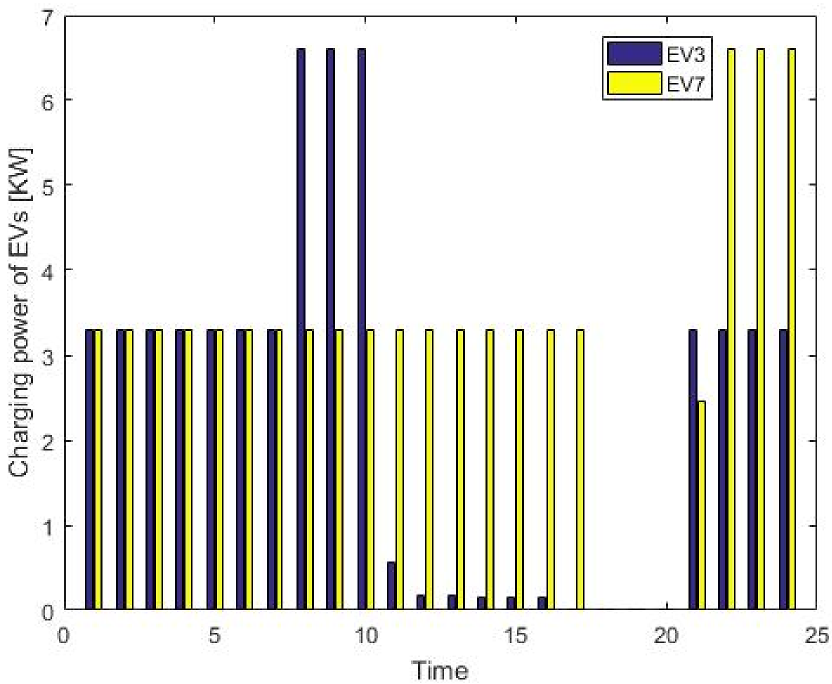

FIGURE 5.15: Variation of Charging Power of EV3 and EV7.

Table 5.4: A Comparison of Optimal Cost.

Forecasting Models	No of Veh	Optimum Price	Total Charged Energy (Kwh)
Neural Network	100	245.827	1729.48
	200	483.042	3242.21
Tree Regression	100	226.297	1577
	200	505.194	3404.59
Linear Regression	100	237.631	1655.24
	200	488.77	3253.79

Afterwards, solution of optimizing problem gives the min base price and max base price 0.112932 and 0.174356 respectively. Table 5.4 presents the detail comparison of minimum cost by using three models for predicting load.

5.4 Result for Electric Vehicles Scheduling to a Charging Station

In order to analyze the approach that used in this thesis for assigning charging stations to EVs with less amount of energy consumption Fig. 5.16 is considered with 5 charging stations and 10 EVs in area with less amount of traffic and high density traffic. Each CS has 2 charging points. The group of EVs which perform charging during respective interval is represented by M. This group consists of those numbers of vehicles which require charging. The charging power of EVs is represented by x_{mi} where m represents those EVs which perform charging and i represent the interval. During the charging of EVs this condition $x_{mi} \geq 0$ must be satisfied to confirm that battery does not discharge that time.

The entrance time of EVs in charging station is represented by t_m^{ent}, this is the time when EV starts charging. On the other hand EVs departure time is represented by t_m^{dep}, this is time when EV stops charging. The charging period of EVs in N interval is represented by T_m, that time required for EV to be charged. The initial energy of EVs battery is represented by E_{in}, this is the condition of EVs battery before charging starts. Whereas final energy of EVs battery is represented by E_fin, this is condition of EVs battery after charging completes.

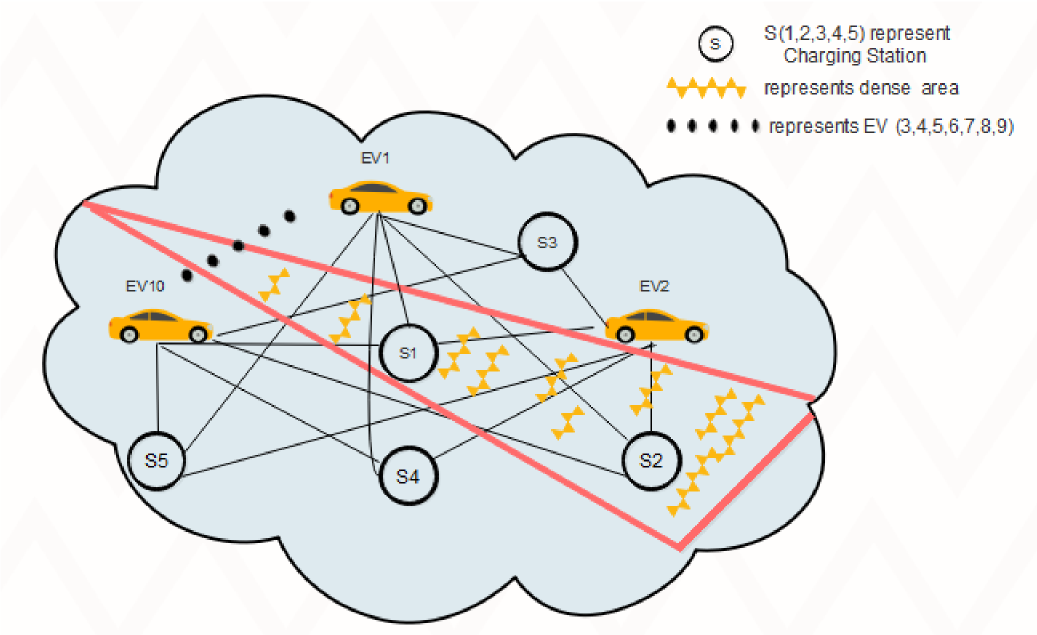

FIGURE 5.16: A Geographic Area with EVs and CS.

There are two conditions to be considered which are following:

- Reference speed for EV is 40 Km/h, vehicle flow is 400 veh/h, and traffic density between EV and CS is 60. These conditions are considered for CS1-CS2.
- Reference speed for EV is 60 Km/h, vehicle flow is 300 veh/h, and traffic density between EV and CS is 40. These conditions are considered for CS3-CS5.

The initial SOC of battery and distance of EVs from each charging station is presented in Table B.1. The obtained results of energy consumption and final SOC for EV1 without traffic and with disturbed traffic condition as well is given in Table 5.6.

Fig. 5.17 shows the results for EV1 travelled distance to CS's. It has been observed that the shortest distance for EV1 is CS1 but CS2 is assigned to EV1 by satisfying

Table 5.5: Consumed Energy and Final SOC for EV1.

Result of EV1/Si	**S1**	**S2**	**S3**	**S4**	**S5**
Ecn[Kwh] without	0.347368421	0.607894737	0.868421053	0.781578947	0.521052632
Ecn[Kwh] with	9.263157895	1.157894737	26.31315789	21.10263158	5.471052632
SOCf without	59.65263158	59.39210526	59.13157895	59.21842105	59.47894737
SOCf with	50.73684211	58.84210526	33.68684211	38.89736842	54.52894737

all the constraints. Energy consumption and final SOC of all EVs are presented in Appendix B.

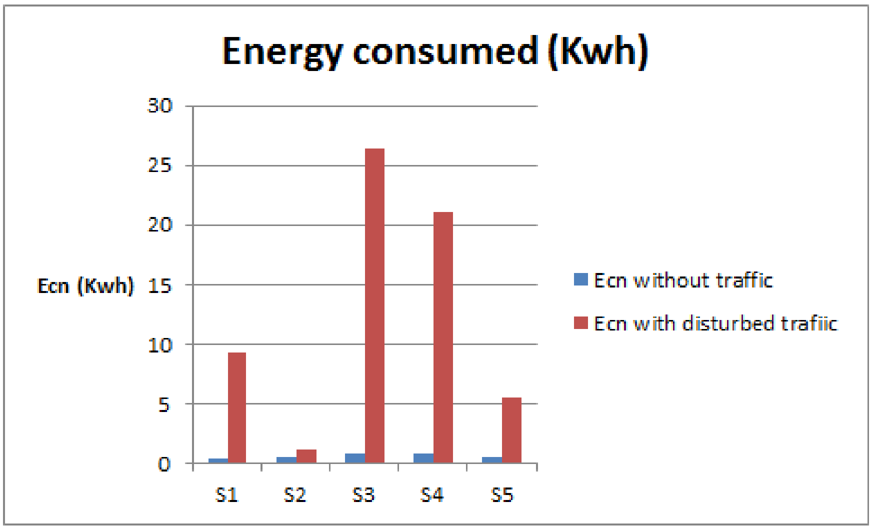

Figure 5.17: Energy Consumption of EV1 with respect to CS's.

Whereas Table B.3 presents the optimal solution of EVs assignment to CS. Afterwards following goals are achieved which are given below:

- All EVs are assigned to CS.
- The number of EVs are not exceeded in all CS.
- All EVs reached to assign CS with maximum SOC.

Chapter 6

Conclusion and Future Work

In this thesis, an optimization problem is addressed for EV charging and assignment management of EVs to the CS among set of CS's in selected geographic area. In first phase a scheduling problem is considered for EV charging in which the charging powers of EVs are optimized to minimize the total cost in 24 hrs interval. However, optimal scheduling scheme for EVs charging required the base load of a day in advance. For load forecasting three models is used e.g. linear regression, bagged tree regression and ANN. The comparison of these techniques is presented in detail. In second phase, the assignment problem of EVs to CS's is modeled as linear programming with some constraints to satisfy.

6.1 Conclusion

After evaluating the results achieved through simulations of both EVs charging and assignment management, this whole work is concluded in the subparagraph as follows;

In first phase thesis the numbers of EVs is varying from 100 to 200 and then compare total cost, charging power of EVs and base load by using above mentioned forecasting techniques. Afterwards, by analyzing the results of load forecasting models the prediction is highly depended on consistent historical load and temperature data. The ANN model is compared with linear regression and bagged tree regression model. Hence ANN model is founded to give more accurate with less mean absolute error for daily, weekly and monthly forecasting load. On the basis of load forecasting cost of electricity has been modeled as linear function of forecasted load. The optimal scheduling scheme is scalable but shows resistance towards random arrival of EVs which may lead for future work. Through which the performance of optimal scheduling become closer to practical example.

In second phase of thesis the assignment problem of EVs to CS has been considered which has been solved by linear programming in order to satisfy all the constraints. Hence satisfying all the constraints all EVs should reach the CS by consuming less amount of energy or after reaching the CS its battery final SOC has been at highest possible level. For the optimal assignment of EVs to CS two cases has been considered: under normal condition of traffic and disturb condition of traffic. Under normal condition vehicle density, traffic jam, and driver behavior has been neglected on the other hand under disturb condition these all parameters has been took into account. A comparative study has been carried out between these two cases and presented in Table B.2. After analyzing the results presented in Table B.2 the final SOC under normal condition is greater than the disturbed condition and energy consumption of EVs while reaching the CS in normal condition is less than the disturbed condition.

6.2 Future Work

The work presented in this thesis provides a foundation for several future works. As three different models have been used for load forecasting, in future a hybrid of these three models could be used to suppress the error more and achieve accuracy. Afterwards minimizing cost for EV charging considers an interval with fixed number of EVs; in future the system could be designed for random arrival of EVs by modification in optimization model.

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Appendix A

A Comparison of Daily Load Forecasting Models and Energy Evolution of Electric Vehicles during Journey

A comparison of daily load is presented in Table A.1 which is obtained by linear regression, bagged tree regression and ANN. The energy evolution of EV1-EV5 is presented in Fig. A.1 .

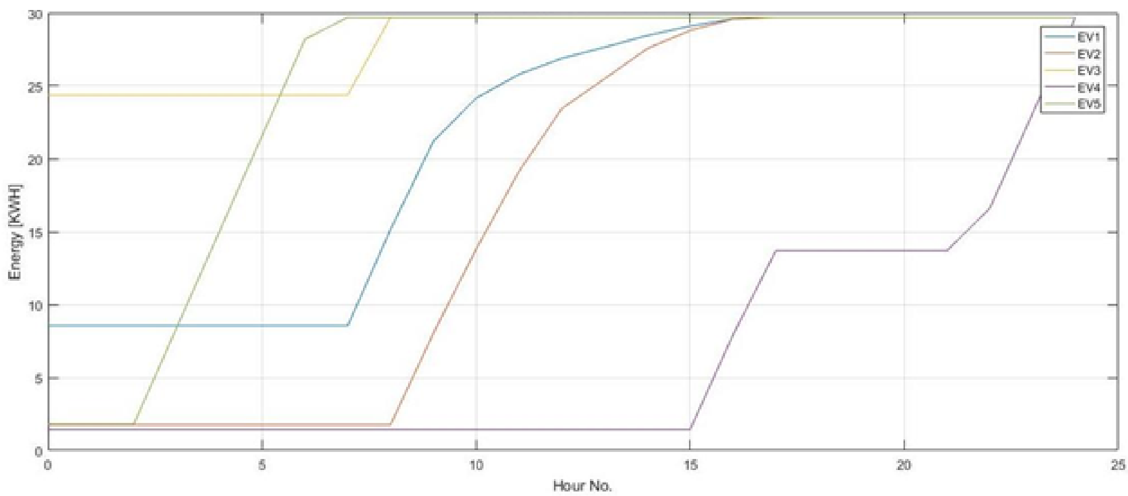

FIGURE A.1: Energy Evolution of EV1-EV5.

Table A.1: Load Comparison between Forecasted Load and Actual Load.

LR	**TR**	**NN**	**Actual Load**
12037	12325	12966	12930
11554	11899	12333	12311
11274	11802	11127	11805
11262	11765	11128	11629
11574	11880	11196	11674
12074	12234	11461	11972
12943	12792	12400	12433
13668	13404	12559	12744
14405	14221	13049	13370
14972	14874	14122	14246
15283	15147	15503	15042
15399	15271	15411	15672
15258	15248	15952	16064
14999	14928	15943	16053
14776	14682	15522	15960
14811	14761	15952	16047
15828	15413	16979	17033
16875	17007	17790	18190
16589	16794	17755	17964
16010	15873	17408	17450
15416	15711	16942	16708
14779	15020	15114	15580
13984	14161	14178	14186
13242	13091	12946	12960

Appendix B

Detail about Electric Vehicle with Respect to Distance and System Parameters

Initial SOC and distance of EVs from all CS is presented in Table B.1. Energy consumption and final SOC under normal condition and disturbed condition is presented in Table B.2 and Fig. B.1. Final assignment of EVs to respected CS is presented in Table B.3.

Table B.1: Initial SOC with respective CS Distances.

SOCi(EVi)/Sj	Distance wrt S1	Distance wrt S2	Distance wrt S3	Distance wrt S4	Distance wrt S5
EV1: SOCi=60	2	3.5	5	4.5	3
EV2: SOCi=58	1	2	2.5	4	5.3
EV3: SOCi=51	5	4	3	6	2
EV4: SOCi=48	2	4	5	5.4	3
EV5: SOCi=54	2	6	3	5	4
EV6: SOCi=52	2.5	1	5	4	6.5
EV7: SOCi=56	4	2.5	6	5.2	7
EV8: SOCi=45	4.2	5	4	2	6.5
EV9: SOCi=49.5	5.7	2	6	4	6.7
EV10: SOCi=55	1	2	3.5	4.5	3

Table B.2: Energy Consumption and Final SOC of each EVs.

Electric Vehicle	**Parameters o EVi**	**S1**	**S2**	**S3**	**S4**	**S5**
EV1	Ecn without	0.34	0.60	0.86	0.78	0.52
	SOCf without	59.65	59.39	59.13	59.21	59.47
	Ecn with	9.26	1.15	26.31	21.10	5.47
	SOCf with	50.73	58.84	33.68	38.89	54.52
EV2	Ecn without	0.17	0.34	0.43	0.69	0.92
	SOCf without	57.82	57.65	57.56	57.30	57.07
	Ecn with	16.21	9.26	0.26	15.89	29.43
	SOCf with	41.78	48.73	57.73	42.10	28.56
EV3	Ecn without	0.86	0.69	0.52	1.04	0.34
	SOCf without	50.13	50.30	50.47	49.95	50.65
	Ecn with	11.57	4.63	5.47	36.73	3.95
	SOCf with	39.42	46.36	45.52	14.26	47.05
EV4	Ecn without	0.34	0.69	0.86	0.93	0.52
	SOCf without	47.65	47.30	47.13	47.06	47.47
	Ecn with	9.26	4.63	26.31	30.48	5.47
	SOCf with	38.73	43.36	21.68	17.51	42.52
EV5	Ecn without	0.34	1.04	0.52	0.86	0.69
	SOCf without	53.65	52.95	53.47	53.13	53.30
	Ecn with	9.26	18.52	5.47	26.31	15.89
	SOCf with	44.73	35.47	48.52	27.68	38.10
EV6	Ecn without	0.43	0.17	0.86	0.69	1.12
	SOCf without	51.56	51.82	51.13	51.30	50.87
	Ecn with	5.78	16.21	26.31	15.89	41.94
	SOCf with	46.21	35.78	25.68	36.10	10.05
EV7	Ecn without	0.69	0.43	1.04	0.90	1.21
	SOCf without	55.30	55.56	54.95	55.09	54.78
	Ecn with	4.63	5.78	36.73	28.39	47.15
	SOCf with	51.36	50.21	19.26	27.60	8.84
EV8	Ecn without	0.72	0.86	0.69	0.34	1.12
	SOCf without	44.27	44.13	44.30	44.65	43.87
	Ecn with	6.02	11.57	15.89	4.95	41.94
	SOCf with	38.97	33.42	19.26	40.05	3.05
EV9	Ecn without	0.99	0.34	1.04	0.69	1.16
	SOCf without	48.51	49.15	48.45	48.80	48.33
	Ecn with	16.44	9.26	36.73	7.89	44.02
	SOCf with	33.05	40.23	12.76	41.60	5.47
EV10	Ecn without	0.17	0.34	0.60	0.78	0.52
	SOCf without	54.82	54.65	54.39	54.21	54.47
	Ecn with	16.21	9.26	10.68	21.10	5.47
	SOCf with	38.7895	45.7368	44.31842105	33.89736842	49.52894737

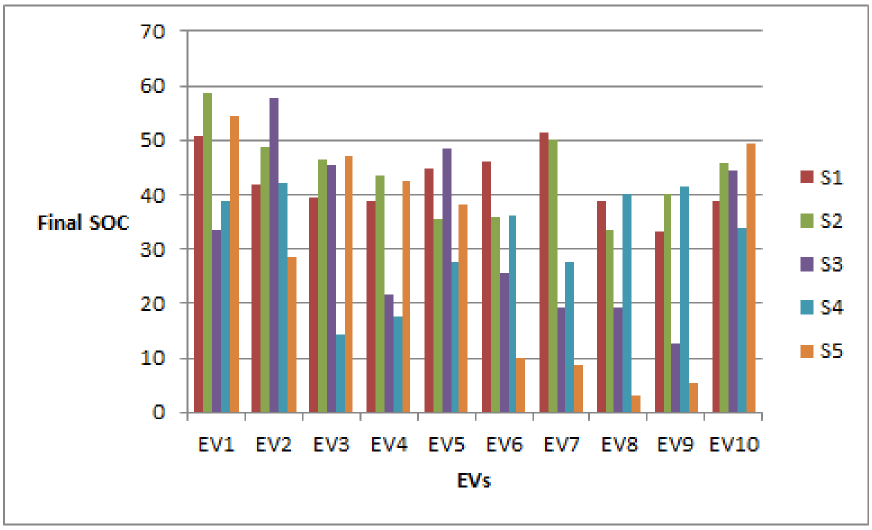

FIGURE B.1: Final SOC of all EVs.

TABLE B.3: Assignment of EVs to CS

EVi/Si	**S1**	**S2**	**S3**	**S4**	**S5**
EV1/SOCf	50.73	58.846	33.68	38.89	54.52
EV2/SOCf	41.78	48.73	57.73	42.10	28.56
EV3/SOCf	39.42	46.36	45.52	14.26	47.05
EV4/SOCf	38.73	43.36	21.68	17.51	42.52
EV5/SOCf	44.73	35.47	48.52	27.68	38.10
EV6/SOCf	46.21	35.78	25.68	36.10	10.05
EV7/SOCf	51.36	50.21	19.26	27.60	8.84
EV8/SOCf	38.97	33.42	19.26	40.05	3.05
EV9/SOCf	33.05	40.23	12.76	41.60	5.47
EV10/SOCf	38.78	45.73	44.31	33.89	49.52
Assignments of EV's	EV6,EV7	EV1, EV4	EV2 , EV5	EV8 , EV9	EV3 , EV10