Impact of PEV Charging Loads on Distribution System Operations and Optimal Siting and Sizing of PEV Charging Stations

by

Shubhalakshmi Shetty

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Smart grid has emerged as a promising paradigm to promote and deliver a clean, modern and efficient electricity grid to all customers, and it allows Local Distribution Companies (LDC) to integrate renewable sources more reliably, efficiently, safely and economically. Smart grid realizes Plug-in Electric Vehicles (PEVs) as a potential solution to reduce green house gas (GHG) emissions. However, large scale penetration of PEVs can significantly impact distribution system operations.

This thesis first presents an extensive study of PEV characteristics such as, owner driving behavior, mobility trends of the system as a whole, battery capacity, State of Charge (SOC), different charging levels and energy required for charging the battery. The US National Household Travel Survey (NHTS) 2009 data set is explored to model the PEV load characteristics by representing customers' charging behavior in close to reality. This includes the study of the number of trips covered each day, during weekdays and weekends, over different seasons, the miles traveled, and the home arrival and departure times. Using the developed PEV load profiles, distribution system impact analysis and optimal operational studies are carried out to examine how the LDC can accommodate such loads.

The NHTS data set is also used to develop probability density functions (pdfs) of certain mobility patterns such as initial SOC and starting time of charging. Using these pdfs, a Stochastic Distribution Optimal Power Flow (SDOPF) model with various objectives such as minimization of feeder loss, minimization of energy drawn and minimization of PEV charging cost, subject to feeder operational constraints is presented. Various scenarios of uncontrolled and smart charging are studied. In the uncontrolled charging case, the worst case scenarios are discussed. The smart charging scenarios provides with the optimal charging schedules which result in flattening the load profile.

This thesis further presents an approach to optimally siting and sizing of Electric Vehicle Charging Stations (EVCS). Various aspects in identifying the optimal location of EVCS, from both the LDC's and customers' perspectives are discussed. A new approach to modeling the initial SOC of PEVs considering the travel distance from home to EVCS in relation to the feeder sections' electrical parameters is presented. A heuristic approach to determine the optimal siting and sizing of EVCS considering minimum feeder loss, peak demand and customer charging cost is proposed.

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Dedication

I dedicate this work to my parents and my sisters.

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Nomenclature

Sets

i, j Distribution system buses, i, j=1,2,..,N

t, k Hours, t=1,2,..,24

Indices

Δ_t Time interval, 1 hour

b Index for electric vehicle charging station (EVCS) bus

N Number of buses

s Scenarios for initial SOC

SS Substation

Parameters

C_B Capacity of a battery

$D_{i,b}$ Distance from bus i to EVCS bus b

E Energy required to recharge a PEV

$f(t)$ Pdf of starting time of charging of PEV

FC Total fuel cost, $

$G_{i,j}$ Conductance of feeder branch, p.u.

Nev_i Number of electric vehicle at bus i

Np Maximum number of PEVs owned by a resident

P^{max} Maximum substation capacity limit for active power, p.u.

P^{min} Minimum substation capacity limit for active power, p.u.

Pd Active power load, p.u.

Pev Power drawn by PEV during charging, p.u.

Pev_{max} Maximum energy drawn by PEV, kWh

Q^{max} Maximum substation capacity limit for reactive power, p.u.

Q^{min} Minimum substation capacity limit for reactive power, p.u.

Qc^{max} Maximum reactive power support limit, p.u.

Qc^{min} Minimum reactive power support limit, p.u.

Qd Reactive power load, p.u.

SOC State of Charge of a battery

SOC_f Final SOC

$SOCi_s$ Initial SOC in scenario s

$SOCi_s^1$ Revised initial SOC

V^{max} Maximum bus voltage limit, p.u.

V^{min} Minimum bus voltage limit, p.u.

x PEV penetration, p.u.

$Y_{i,j}$ Magnitude of admittance matrix element, p.u.

η Battery charging efficiency

ρ Energy price, \$/MWh

λ Average residential load per hour, kW

$\phi(s)$ Probability density function (pdf) of initial State of Charge (SOC)

ρ_{fuel} Fuel cost per mile, \$/mile

Variables

J_C Objective function-Minimization of customer PEV charging cost

J_E Objective function-Minimization of energy drawn

J_L Objective function-Minimization of loss

$Pev_{i,t,s}$ Energy drawn by PEV at bus i, at hour t and in scenario s, kWh

Pg Active power supplied through substation, p.u.

Qc Reactive power supplied by reactor support, p.u.

Qg Reactive power supplied through substation, p.u.

V Bus voltage, p.u.

δ Bus voltage angle, rad

Θ Phase angle associated with Y-matrix, rad

Chapter 1

Introduction

1.1 Motivation

Plug-in electric vehicles (PEVs) have come to the limelight in recent years for their contribution to reduction of greenhouse gas (GHG) emissions and freeing the countries' economies from dependence on foreign fuel. In Canada, the conventional transportation sector is contributing around 23% of total GHG emission [4] as shown in Figure 1.1, and accounts for 27% of the total energy demand. According to a research carried out by National Renewable Energy Laboratory, USA, a 42% reduction in national average CO_2 emission is expected by replacing conventional internal combustion engine (ICE) based vehicles by PEVs.

In 2014, the US market share of electric vehicles was 3.47%. The number of electric vehicles sold in 2014 increased to 570,000 from 480,000 in 2012, which was about 19% increase in market share within two years [5]. In Ontario, the number of light vehicles is expected to grow from 7.1 million in 2009 to 8.6 million by 2025 [6]. Assuming 8 hours of continuous uniform charging, an average load per PHEV30 (Plug-in Hybrid Electric Vehicle) of 1.2 kW, 50% of PEV penetration, the total average load would be about 5.1 MW. It is obvious that, in case of PHEV60, the average load would increase twice, considering the same size engine as a PHEV30.

Large-scale penetration of PEVs is expected to significantly influence peak demand, feeder loss, and voltage fluctuations in the distribution system. The impacts on the power system depend on PEV driving characteristics and their charging/discharging profiles [7]. This includes factors such as when and where the PEVs are charging, and this could create

Figure 1.1: Canada's Emissions Breakdown 2013, by Economic Sector

regional or local network constraints for a Local Distribution Company (LDC). Also, substation transformers can be overloaded when charging is not controlled [8]. Therefore, there is a need to develop PEV mobility characteristics and hence investigate the effects of PEV charging on the distribution system. To this effect, analysis is necessary to examine the impacts on the feeder operations considering various types of PEVs with different battery capacities and uncontrolled charging scenarios. Since, PEVs are associated with uncertainties, probability distribution of PEV charging characteristics need also be developed to capture the stochastic nature of PEV mobility characteristics and consequent impacts on the distribution system.

While examining the impacts of PEVs in uncontrolled and smart charging scenarios, the main challenge involves taking care of the uncertainties. The charging profile of PEVs and consequently the PEV charging demand depends on the driving behavior, charging level and charging time, which are uncertain and varies from one customer to another. In the process of understanding customer driving behavior patterns, detailed studies need be carried out.

In [9], it is shown that in the case of uncontrolled charging only 10% of penetration is acceptable to the distribution system, while with smart charging upto 40% penetration is acceptable. Therefore there is a need to examine smart charging schedules to reduce the worst impacts and hence maximize the benefits of PEVs.

PEVs are being adopted and encouraged by governments as a solution to long-term energy crisis, reduction of GHG emissions and enhancing the standard of living. To achieve the best outcomes, research work to develop appropriate models for PEV charging demand and frameworks for analysis of PEV impacts on the distribution system, considering all possible combinations of uncertainties is needed. Developing strategies for smart charging to minimize distribution system impacts and maximize the customer benefits are also called for.

With high penetration of PEVs envisaged in the future years, the PEV support facilities are also being developed and one of these developments are fast charging stations. As in case of the conventional vehicles which can be recharged within few minutes by filling the gasoline fuel, the customers would be very satisfied if the same situation can be developed in the case of PEVs. Many energy storage manufacturers are dedicated to deliver more efficient and fast chargers. Once these chargers are developed, one of the major challenges is to identify the appropriate location. Improper siting of electric vehicle charging stations (EVCS) may have negative impacts on the operation of distribution system, voltage profile and convenience of PEV owners. In the recent years, the optimal siting and sizing of EVCS has drawn attention of many researchers. In [10], the effect of fast charging facilities installed at many sites is investigated. The results show that when the EVCS location is not optimal, it results in high system loss and poor voltage profile. The customers' convenience, the cost of PEV charging incurred by them and the LDC system loss, will directly influence the siting and sizing of EVCS.

1.2 Literature Review

In [11], the impacts of PEV charging on power generation, fuel rate and electricity price are explored by assuming a PEV population of 7.5 million in the US. The results show that uncontrolled charging has significant impact on the utilities. Therefore it is very important to propose and adopt smart charging for efficient utilization of resources. In [12], four scenarios *i.e.*, uncontrolled domestic charging, uncontrolled off-peak domestic charging, uncontrolled public charging and smart domestic charging are introduced to model the load demand in a distribution system due to PEV charging. Mathematical models considering the stochastic nature of PEVs are proposed to examine the impacts on the distribution system. The uncontrolled domestic charging for the system under study, could result in an increase in the daily peak demand of the system by up to 18% and 36% in the case of 10% and 20% PEV penetrations, respectively.

In [13], PHEV load modeling and load flow analysis is performed to determine the impact on system power losses and voltage deviations. Assuming a 30% PHEV penetrations by 2030, the impact on transformer overloading, peak demand and voltage drop are studied. In [14], the National Household Travel Survey (NHTS) 2009 data is explored to develop the probability of light duty PEVs to be parked for the purpose of charging. Electric energy and power consumption is determined by considering uncontrolled charging of the vehicle at any time of the day the vehicle is parked at home, and uncontrolled opportunistic charging at any location. The results show that uncontrolled charging increases the peak demand of the system significantly.

In [15], probability density functions (pdfs) to estimate the PEV charging load are proposed. The starting time of charging is modeled in two ways, *i.e* one group of vehicles start charging immediately as soon as they arrive home, the other group considers a delay before charging and pdf of the starting time of charging assumes a Poisson distribution. In [16], the PHEV charging load model is formulated by assuming a normal pdf with 6 PM as the mean of the starting time of charging with a standard deviation of one hour. The impact of time of use (TOU) price on the customers charging behavior and hence the impact on the demand response is studied. The analysis illustrates that with proper design of TOU rates, the peak demand, even with PHEV charging loads can be reduced.

In [17], modeling of PHEV charging loads applying queuing theory is presented, where PHEVs with different types and battery capacities are modeled, for both residential charging and at the EVCS. The authors proposed a probabilistic power flow model to handle the uncertainties associated with PHEV charging. In [18], PEV charging uncertainties are modeled using Monte Carlo simulation. Pdfs for home arrival time, departure time, and daily traveled distance by PEVs are presented and the impact on the distribution transformer load is analyzed.

Smart charging of PEVs is introduced in [19] to minimize the system losses, total energy drawn and the total cost of PEV charging. The analysis assumes all PEVs to be PHEV30 with battery capacity of 8.14 kWh and the penetration level of PEVs is varied from 0% to 100%. The state of charge (SOC) is assumed to vary between 20% to 90%. The impact on the current and voltage profile of a unbalanced distribution system is presented using deterministic analysis. The continuation of this work is presented in [20]. Uncertainties such as, SOC of the PEVs and starting time of charging are taken into consideration using Monte Carlo simulation to determine the impacts of PEV charging on feeder loss, peak demand and energy cost. In smart charging scenarios, the optimal schedules are determined only between 7 PM -7 AM.

The impacts of PEV penetration on the Dutch distribution network are examined using a stochastic modeling approach based on Monte Carlo simulation in [21]. Using parameters such as, geographic area information, vehicle properties and PEV penetrations over different years, the stochastic model generates suitable PEV charging schedules. The simulation considers various penetration levels for the future years. The results are compared for uncontrolled and controlled charging scenarios, and it is noted that, with controlled charging the average power losses can be brought down to 32% from 39% as in the case of uncontrolled charging. With uncontrolled charging, there is a 30% probability of MV/LV transformers being overloaded in 2030, whereas, with smart charging, 13% of MV/LV transformers are expected to be overloaded. Several other research works reported, have proposed smart charging strategies of PEVs including [22], [23],[24], [25].

In [26], the effects of PEV charging loads on the distribution system are compared considering deterministic and stochastic analysis. The stochastic method is based on the Roulette wheel selection concept and Monte Carlo simulation. A significant difference in the results of the two methods are observed, and it is noted that the deterministic method fails under uncertain conditions. A stochastic formulation of distributed energy resource (DER) customer adoption model considering uncertainties in PEV driving schedules is introduced in [27]. The significant influence on DER investments and total energy costs due to adoption of PEVs are presented.

In [28], a novel mathematical model is introduced for optimal siting and sizing of EVCS by considering environmental factors, service radius of EVCS and minimization of overall cost. The proposed model results in various combinations of optimal sizes and locations of EVCS. In [29], the optimal siting and sizing of EVCS is presented, considering minimization of integrated cost of investment and operation of EVCS. Various transportation factors are taken into consideration and graph theory is applied to establish a network model. The work extended in [30] by considering slow and fast charging modes. The different types of PEVs with different levels of penetration are studied, and their charging demand is predicted for the future year. Depending on the types of vehicles and their charging demand, slow chargers at the parking lot stations and fast chargers at the public EVCS are planned with minimum investment and operation cost.

In [31], the optimal siting and sizing of EVCS is studied, considering the minimization of customers' loss (travel cost and travel time) on the way to the EVCS. The weighted Voronoi diagram is formed to locate and subdivide the service area of the EVCS. The size of the EVCS is determined based on the predicted charging demand of PEVs.

1.3 Research Objectives

The main objectives and contributions of this thesis are as follows:

- Carry out comprehensive studies considering the PEV driving characteristics using the NHTS data, including details on all electric range (AER), different types, penetration levels, battery technology, driving behavior, SOC, starting time of charging, charging level and the amount of energy required to recharge the PEVs. Perform statistical analysis on home arrival pattern of vehicles and miles driven per day on weekdays and weekends for three different seasons of the year (Fall, Winter and Summer).

- Estimate the SOC of the PEVs before charging, the duration of charging and energy required to charge and hence develop a bus-wise PEV charging load profile that would appear on the distribution feeder system. Thereafter perform load flow analysis to examine the impacts of uncontrolled PEV charging loads on distribution system losses, bus voltages and total cost. Furthermore, optimal operations studies for the distribution system are carried out with the developed PEV load model considering minimization of feeder loss and minimization of energy drawn from the substation.

- Perform stochastic load flow analysis considering three scenarios of uncontrolled charging of PEVs to examine the impacts on the distribution grid. Develop a stochastic optimal operations model considering smart charging and minimization of expected energy drawn, minimization of expected total loss and minimization of expected cost of PEV charging and hence study the impacts of PEV charging loads on residential load profile, distribution system losses, bus voltage profiles and total cost.

- Propose a heuristic approach to obtain the optimal siting of EVCS considering the benefits of both the LDC and the customers, and optimal sizing of EVCS that is capable of supplying power to PEVs in all scenarios. The selected EVCS location minimizes the distribution feeder losses and customer cost of traveling.

1.4 Outline of the Thesis

The rest of the thesis is structured as follows: Chapter 2 presents the background topics related to this work. This chapter presents types of Electric Vehicles (EVs), PEV charging characteristics, battery capacities and charging levels. Also, a brief introduction to power distribution systems and the General Algebraic Modeling System (GAMS) optimization solver is given. Chapter 3 presents the statistical analysis of transportation patterns using the NHTS data to develop the PEV charging load profile. Using these information, load flow analysis to examine the impact of PEV charging, on a distribution system operations, using deterministic analysis is presented. This chapter further develops pdfs of uncertainties associated with PEV charging, proposes a stochastic Distribution Optimal Power Flow (DOPF) model to investigate the impacts of PEV charging loads on the distribution system operations including peak demand, energy drawn, system loss, and customer charging cost, and the results for uncontrolled and controlled charging are discussed. Smart charging strategies are proposed which result in minimizing the impacts of PEV charging from both the LDC's and customers' perspectives. In Chapter 4, the optimal siting and sizing of EVCS is introduced. A heuristic approach to obtain the optimal siting of EVCS is presented. In Chapter 5, the summary and future work of this thesis is discussed.

Chapter 2

Background

This chapter presents a background review of the major concepts relevant to the research work carried out in this thesis. Section 2.1 describes the types of EVs, PEV charging characteristics, details on the battery capacities of different types of PEVs and charging levels. This section also presents mathematical formulations to estimate the battery capacity, SOC and the amount of energy required to recharge. Section 2.2 presents a brief overview of the power distribution system. This is followed by Section 2.3 which describes optimization problems and solution methods. Finally, the chapter is summarized in Section 2.4.

2.1 Electric Vehicles

There are different types of EVs available today. Their classifications are based on whether the EVs are operating on electricity alone, using a combination of ICE and electricity, or have plug-in facilities, etc. The different types of EVs are discussed below [32], [33].

1. Battery Electric Vehicle (BEV)

   A BEV runs completely on a battery and electric drive train, and the traditional ICE is not used. The batteries can be charged by plugging into an external source of electricity. BEVs are featured with regenerative braking that recaptures the vehicle's kinetic energy, which would otherwise be lost in the conventional mechanical braking. The present day BEVs have a range between 140 km to 180 km, once fully charged. The charging of batteries may take place overnight when Level 1 (120 V) outlet is used, or in a few hours or few mins when Level 2 or Level 3 charging are considered, respectively. Higher battery capacity BEVs provide higher range of miles per complete charge, but also draws more power from the grid. These vehicles help in reducing CO_2 emissions and hence are highly encouraged by governments. The fast charging stations (400 V) for BEVs are installed at many sites.

2. Hybrid Electric Vehicle (HEV)

   It is the most common type of EV. Hybrid vehicles can be driven by two or more sources of power. Most hybrid vehicles operate using a combination of ICE powered by fossil fuel, and a battery. In some cases these systems can run independently. In the parallel hybrid type EV, both ICE and electric motors supply power to the wheel. However, in series hybrid type, ICE is used only to recharge the battery by powering the electric motor. The electric motor is mechanically connected to the wheels to drive. HEVs cannot be plugged in to recharge from the grid. The battery is recharged only through the regenerative braking process. These vehicles are designed as energy storage systems where the energy lost in braking is captured by the vehicle, using an electric motor which functions as a generator, and stored in a battery. It is noted that the fuel efficiency in HEVs are increased by 25% when compared to conventional light duty vehicles.

3. Plug-in Hybrid Electric Vehicle (PHEV)

   PHEVs are similar to HEVs, driven by two sources of power that generated by a battery or the ICE power. These vehicles can be plugged in to the outlets to draw power from the grid. Moreover, like HEVs, these vehicles can be recharged through the regenerative braking process. Usually, PHEVs run on battery power till the SOC of the battery depletes to low levels and is then driven using ICEs. PHEVs are designed for different battery capacities and most of the vehicles have an AER (all electric range) limit. AER is the maximum miles range the battery can support per complete charge cycle. PHEVs provide significantly higher range of miles compared to the BEVs. Since, PHEVs can be recharged from the power outlet at home or at any EVCS, the customer saves fuel. Most of the cars travel in the range of 25-30 miles per day, hence these vehicles can run on one complete charge till the end of the trip and does not have to be refueled in between. PEVs refer to any electric vehicles which can be plugged in to the wall socket or outlet to recharge the battery.

Table 2.1: Specific energy requirements per mile drive [2]

Vehicle Type	Energy required (kWh/mile)
Compact Sedan	0.26
Mid-size Sedan	0.30
Mid-size SUV	0.38
Full-size SUV	0.46

2.1.1 PEV Charging Characteristics

PEV charging requirements vary significantly based on the type of vehicle, battery and battery capacity. Vehicles starting with full battery charge can travel using electric power alone in charge-deplete mode till the SOC drops to about 20-30%, and once this threshold level is reached, vehicles can be supported by ICE in case of PHEVs to drive in charge-sustaining mode to maintain the SOC close to the threshold level. As the battery capacity increases, the AER range increases, also the charging time increases. The total power consumed by a PHEV entirely depends on the battery type, battery capacity and the charging level.

The charging rate is based on the charge strategies adopted- constant current (CI) or constant voltage (CV). A battery pack may be charged using any of the strategies depending on the battery technology. In most of the cases a combination of these can be used. For instance, Lithium-Ion batteries are commonly charged using a combination of both CI/CV [34]. The process can be explained as, at the beginning a constant current is applied, meanwhile the voltage reaches its upper limit. Once the voltage reaches the upper limit, it must be maintained constant in order to avoid any damage to the battery. During the period of constant voltage, the battery charges to the full SOC level and the charge current starts decreasing gradually. When the current drops to the minimum threshold limit, the charging cutoff occurs.

2.1.2 Battery Capacity

Different types of vehicles have different features with different battery capacities. Using the data from Electric Power Research Institute (EPRI), Pacific Northwest National Laboratory (PNNL) presents in [2] the information on energy requirements per mile drive by various types of PEVs, and it is shown in Table 2.1.

The battery capacity is determined using the energy required per mile drive. Vehicles with different levels of AER have different battery capacities. AERs are total ranges in

Table 2.2: Battery capacity of different types of vehicles [2]

Vehicle	PHEV30	PHEV40	PHEV60
Compact Sedan	7.8	10.4	15.6
Mid-size sedan	9	12	18
Mid-size SUV	11.4	15.2	22.8
Full-size SUV	13.8	18.4	27.6

miles that a vehicle can drive only on electric power. Once the vehicle crosses this range, the ICE drives the vehicle until the vehicle is recharged at a charging station. Here, the battery capacity is estimated using (2.1) by assuming different levels of AER, as shown in Table 2.2 .

$$C_B = \text{ AER(mile)*Energy consumption per mile (kWh/mile)} \tag{2.1}$$

These battery capacity values are used to determine the energy required to recharge the battery fully. The percentage of energy stored in a battery at any particular time is measured as SOC of the battery at that particular time. To determine SOC, miles driven by the vehicle, AER and the battery capacity of the vehicle are need to be considered.

The SOC of a vehicle when arriving home after the last trip is calculated as,

$$SOC = \begin{cases} (1-(D/AER)), & D \leqslant AER \\ 0, & D \geqslant AER \end{cases} \tag{2.2}$$

Where $D = \gamma d$; γ is the percentage of distance driven in electric mode and d is the total distance driven. It is assumed that vehicle works in electric mode till the SOC depletes to zero and then it works as a conventional vehicle. When the miles driven crosses more than AER then the SOC drops to zero.

The energy required to charge the PEV battery to the full capacity is calculated as,

$$\eta E = (1 - SOC)C_B \tag{2.3}$$

It is assumed that the vehicle charges till its SOC reaches 100%. The energy required to charge the battery depends on the size of the battery. Since in reality, the efficiency of the battery charging need not be 100%, here the efficiency η is assumed to be 85%. E is the actual energy that needs to be supplied from the substation to charge the battery fully.

In this work, Level 2 and Level 3 charging are assumed for the residential EVs and public EVCS respectively. This assumption is based on [35], where an experiment is conducted on two Chevrolet Volts and two Nissan Leafs with Level 1 (120 V) and Level 2 (240 V) charging, and the results are tracked for the period June-November 2013. The results obtained are in favor of Level 2 charging with 5.6% more efficiency compared to Level 1 charging. Also, the Level 2 charging efficiency is better than Level 1 charging under different temperatures. Level 3 charging is considered for fast charging options at public charging stations.

2.2 Power Distribution System

The principal function of a power distribution system is to supply electricity to the end-use customers to meet their energy demand at voltage levels below that of transmission systems. The electric power from the transmission system is stepped down to a lower voltage level close to the customer, and the sub-transmission system transfers this power to distribution substations close to the demand center. This power is then distributed on a primary distribution feeder after transforming to a lower voltage level. In North America, the distribution systems operate at different voltage levels including, 34.5 kV, 23.9 kV, 14.4 kV, 13.2 kV, 12.47 kV, 4.16 kV, and others [36].

The primary types of distribution system are radial, loop, or network. The combination of these three types of systems can be used as per requirement. The radial distribution system is the simplest and least expensive type and is used frequently. This system is designed such that only one power source distributes power to the customers in the entire system. Even though the complexity in design and maintenance is reduced in radial system, the reliability is very low since the failure of the main power source causes power outage to the entire network.

In loop system, the loop will be connected to an alternative power source and the power can be transferred from either of the sources. The main advantage of this system is that, the failure of one source does not interrupt the power flow to the end-use customers since the alternative can support the power supply. Any circuit breaker (CB) can be disconnected for maintenance without power outage. This system is highly reliable and expandable. Whenever any fault is found in the line, the utility only has to do switching around it to restore the power supply. This system comes with more complexity and the cost is higher compared to the radial bus system. Since this system uses more switches or CBs, the protection complexity increases too. But these disadvantages can be traded off with the high reliability of the system.

Network systems are interlocking loop systems. They are the most complicated and the most expensive systems. In this system, many power sources can be used to distribute electricity to a given customer. The purpose of this design is to obtain high reliability. The power outage can be almost nullified in this system since many alternative sources will be prepared to supply power in case of any fault in one line. So this system is mainly used in high load density areas [37].

The distribution system usually faces few challenges such as high power loss, voltage instability, voltage collapse and transformer overloading. The proper planning of distribution system design plays a major role in avoiding these issues. Distribution line losses can be classified into the following two types: technical losses and non-technical losses. Technical losses are the result of any loss in components dependent on the resistance and current in the conductor, line voltage levels, peak demand, or conductor and core losses etc. Non-technical losses can occur due to meter inaccuracies, theft or billing errors etc. The overall technical loss is found to be 5.4% in 2012 [38]. Voltage instability can occur at high density load demand when the reactive power support is not enough. Reactor support needs to be used at every node to maintain the voltage reliability.

2.3 Optimization Models

There are various types of optimization problems. In this thesis, linear programming (LP) and non-linear programming (NLP) optimization problems are solved using MINOS solver in GAMS.

Linear programming is applied to obtain the optimal solution to a problem with linear relationships. These problems comprise a linear objective function subject to linear equality and linear inequality constraints. The general mathematical representation of LP problems is given as:

$$\begin{aligned} \text{Max} \quad \text{or} \quad \text{Min} \quad C^T x \\ \text{s.t} \quad ax \leqslant b \\ l \leqslant x \leqslant u \end{aligned} \tag{2.4}$$

In (2.4), x is a n-dimensional variable vector to be determined, also called decision variable, c and b are the known vector coefficients with n and m-dimensions, a is a mxn-dimensional known matrix of coefficients, l and u represents the lower and upper bounds, respectively. It is important to ensure few conditions are met before solving LP problems. They are as follows [39] :

- The problem has only linear objective function. All decision variables are only added or subtracted, and should be of power one.
- There is only one objective function to solve and it is either minimization or maximization.
- Only linear constraints are allowed and they can only be in the type of $\leqslant$. $\geqslant$, or $=$.

The most effective and widely used method to solve LP problems is the Simplex method. Simplex method forms polyhedron and polytope regions with feasible solution unbounded and bounded respectively. Basically, it starts with an extreme point in the feasible region and then performs a sequence of iterations by moving along the direction to its neighboring vertex to obtain optimal solution to the given objective function. In this method, since the objective function is linear and the feasible region is convex, there exists only one local optimum value and it is the global optimum value [39]. The interior-point-method (IPM) is superior to Simplex method by delivering same or better performance. The IPM requires fewer iterations compared to the Simplex method and hence it is preferred for larger problems and when prior information is not available [39].

Non-linear programming is used to achieve the optimal solution for a problem which consists of atleast one nonlinear objective function or constraints. The general mathematical representation of NLP problems is given as:

$$\begin{aligned} \text{Max} \quad \text{or} \quad \text{Min} \quad f(x) \\ \text{s.t} \quad g_i(x) \leqslant 0 \quad \text{for all} \quad i = 1, ..m \\ h_j(x) = 0 \quad \text{for all} \quad j = 1, ..n \\ x \in X \end{aligned} \tag{2.5}$$

In GAMS/MINOS, the problems with nonlinear objective functions are solved using reduced gradient technique and quasi-Newton technique. The problems with nonlinear constraints are solved using Lagrangian algorithm. This method performs a sequence of iterations to obtain linearized version of nonlinear constraints. Reduced-gradient algorithms performs searching along edges of the curves which are near feasible set. This method eliminates a subset of the variable by using the equality constraints, and hence the original problem is reduced to a bound-constrained problem in the variable's remaining region [40]. In this thesis, the DOPF model considering PEV charging demand and stochastic scenarios are solved using MINOS NLP minimization method.

2.4 Summary

In this chapter the overview of PEVs including their types, charging characteristics, battery capacity and charging levels were presented. The mathematical formulations to estimate the battery capacity, SOC and the amount of energy required were demonstrated. In the next section, the power distribution system in general was described, including the types of distribution system, some of the aspects of power loss and voltage reliability. In the last section, optimization problems, solution methods and the GAMS tools to solve these problems were discussed.

Chapter 3

Distribution System Operations Framework to Study the Impact of PEV Charging Loads

In this chapter, an extensive study of PEV driving behavior is carried out, considering parameters such as purpose of trips, miles driven per day, initial SOC, home arrival and departure time, percentage of different types of vehicles, different levels of penetrations, battery capacity, and levels of charging. Statistical analysis of the information is carried out to extract useful behavioral patterns of PEV customers. Using these information, PEV charging load models are thereafter formulated considering seasonal variations. Furthermore, an appropriate mathematical model is developed to examine the impacts on distribution system operations such as feeder loss, peak demand, voltage profile and customer cost. The model considers both uncontrolled and controlled charging scenarios.

The rest of the chapter is structured as follows: Section 3.1 presents the statistical analysis of transportation patterns and PEV mobility characteristics. Section 3.2 presents mathematical models of optimal operation of distribution system including deterministic studies and stochastic studies. Also, this section describes various scenarios of uncontrolled and smart charging of PEVs. Results and analysis are discussed in section 3.3. The chapter is summarized in section 3.4.

3.1 Statistical Analysis of PEV Mobility Data

3.1.1 Studying NHTS 2009[1]

NHTS data center[1] provides a large bank of information on the number of different types of vehicles, vehicle home arrival and departure times, trip purpose, miles driven per day, weekdays and weekend driving behavior, and others. NHTS provides information on travel and transportation patterns including data for 150,147 houses in the United States. In this work, two files are extracted from NHTS 2009 Data Center, they are: DAYV2PUB.csv and VEHV2PUB.csv. These files are explored to derive the PEV mobility characteristics as discussed here.

3.1.1.1 DAYV2PUB.csv

This excel file contains vehicles' data of 1,041,000 trips. In this work only five attributes, namely, house identification number (HOUSEID), type of vehicle (VEHTYPE), trip end time or home arrival time (ENDTIME), travel day of week (TRAVDAY), travel date (TDAYDATE) are considered. Two main characteristics are derived from this file; home arrival time and percentage of different vehicle types. The travel day and travel date information is used to separate the data into winter, summer, fall as well as weekdays and weekend travel patterns.

3.1.1.2 VEHV2PUB.csv

This excel file contains data of 309,164 vehicles. Again here, only five attributes are extracted from this file; HOUSEID, VEHTYPE, TRAVDAY, TDAYDATE and BESTMILE. BESTMILE is the best estimation of the annual miles traveled by each vehicle. To find the daily traveled mile, BESTMILE is divided by 365.

Three different seasons are considered in a year; Fall, Winter and Summer. As the travel pattern is different on different days of different seasons, the two excel files are subdivided into 6 files; Fall Weekdays, Fall Weekend, Winter Weekdays, Winter Weekend, Summer Weekdays and Summer Weekend. Figure 3.1 - 3.3, shows the plot of last home arrival time on a typical weekday in the three seasons. Figure 3.4 shows the home arrival patterns on a typical weekend in winter. It is observed that there are significant differences in home arrival patterns across different seasons, and weekdays and weekends. In general, during weekdays, a majority of the vehicles arrive home in the evening between 17:00 to 20:00

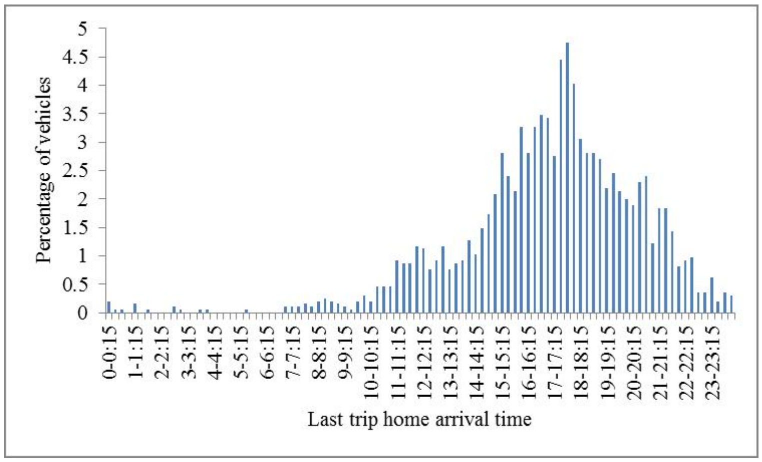

Figure 3.1: Last home arrival time of vehicles on a typical weekday in Fall

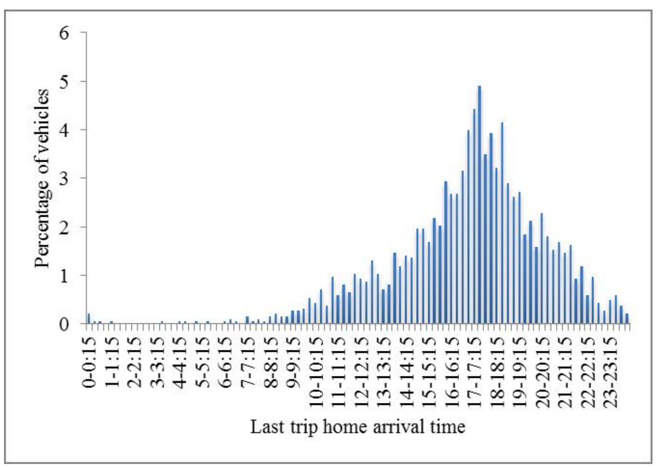

Figure 3.2: Last home arrival time of vehicles on a typical weekday in Winter

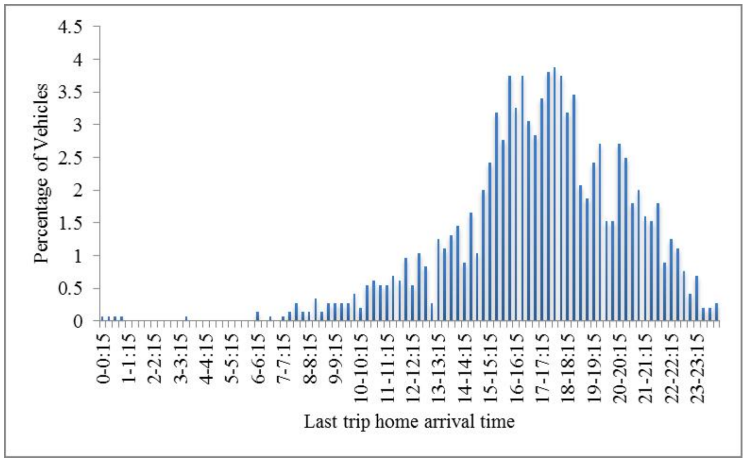

Figure 3.3: Last home arrival time of vehicles on a typical weekday in Summer

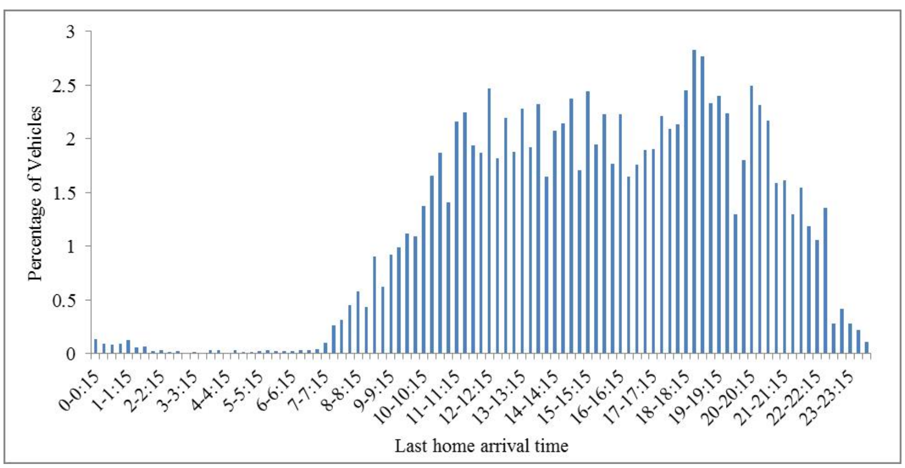

Figure 3.4: Last home arrival time of vehicles on a typical weekend in Winter

hours after work. It is clear that weekend home arrival patterns may have many variations as compared to weekdays since people leave and return home as per their convenience. Here, the last trip home arrival time is assumed to be the starting time of charging. The vehicles are plugged in for charging immediately after they arrive home.

The number of different types of vehicles is estimated using the DAYV2PUB.csv file. As different types of vehicles have different features and different battery capacities, the energy required to charge the battery fully, in each case, is different. The most common PEV in use currently is the compact sedan as shown in Figure 3.7.

The daily miles driven characteristics is derived using the VEHV2PUB.csv file. Figure 3.6 shows the percentage of vehicles versus miles driven by the end of the trip on a typical weekday of summer. Most of the vehicles travel a maximum of 30 miles per day and the peak is in the range of 15-25 miles. In winter, the peak miles driven is noted to be in the range of 15-20 miles. It is very important to determine the miles driven by the vehicles to calculate the SOC of their batteries.

From the available information, miles driven details are used to develop pdf of miles driven per day. The miles driven data best fits the Weibull distribution (Figure 3.5) with a shape parameter value of 1.5311 and scale parameter value of 35.044. The pdf of the latest home arrival time best fits a log logistic three-parameter distribution with $\alpha = 3.1629E{+}8$, $\beta = 5.8529E + 8$ and $\gamma = -5.8529E + 8$ as shown in (3.11). The last home arrival time is assumed as the starting time of charging without considering any delay.

It is assumed that all PEVs are mid-size SUVs PHEV40 with a battery capacity of 15.2 kWh [41]. Each PEV can charge up to a maximum of 4.8 kW per hour considering Level 2 charging [20]. The PEV battery charging efficiency is assumed to be 85% . Hence, approximately 3 to 4 hours are required to charge the battery to the full capacity. It is further assumed that the PEV works in electric mode till the SOC depletes to zero and then it works as a conventional vehicle. When the miles traveled exceeds AER limit, the SOC level falls to zero.

3.2 Optimal Operation of Distribution System

3.2.1 Deterministic Studies

The objective functions considered are:

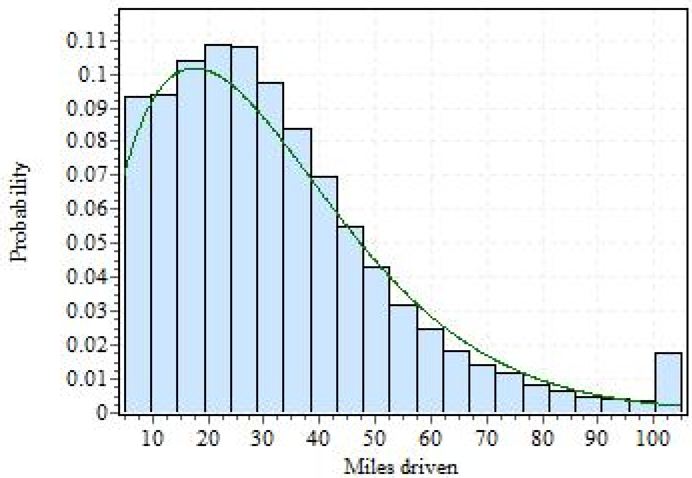

Figure 3.5: Probability density function of miles driven

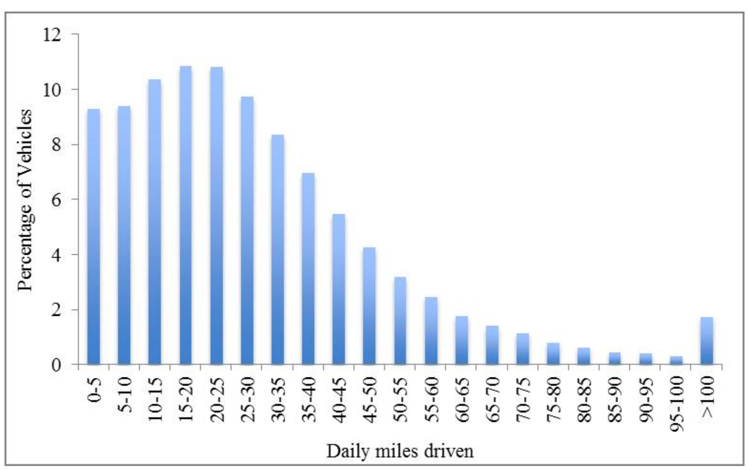

Figure 3.6: Daily miles driven by vehicles on a typical weekday in Summer

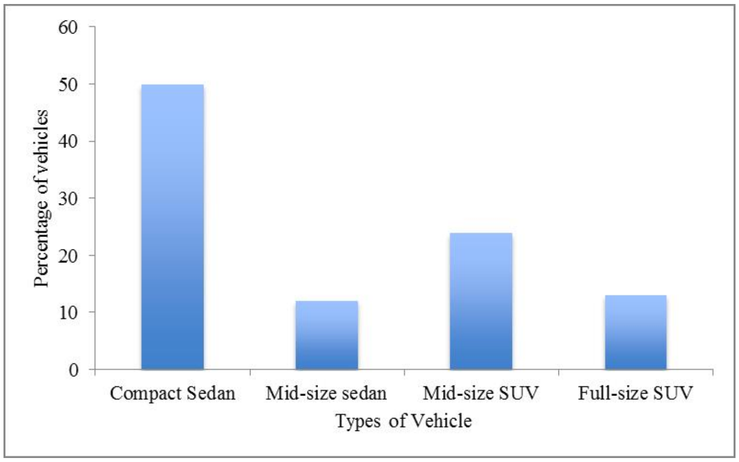

Figure 3.7: Distribution of types of vehicles on the road

- Minimization of Total Loss: This objective represents the typical operating objective of the LDC, and is given as follows:

$$J_L = 1/2 \sum_{t=1}^{24} \sum_{i=1}^{N} \sum_{j=1}^{N} G_{i,j}[V_{i,t}^2 + V_{j,t}^2 - 2V_{i,t}V_{j,t}\cos(\delta_{j,t} - \delta_{i,t})] \tag{3.1}$$

- Minimization of Total Energy Drawn: This represents another possible operating criterion from the perspective of the LDC, and is given as follows:

$$J_E = \sum_{t=1}^{24} \sum_{i=1}^{N} Pg_{i,t}\Delta_t, \quad \text{where} \quad i = SS \tag{3.2}$$

Subject to,

Demand Supply Balance: These are the traditional power flow equations and take into account the nodal active and reactive power balance.

$$Pg_{i,t} - Pd_{i,t} - Pev_{i,t} = \sum_{j=1}^{N} V_{i,t}V_{j,t}Y_{i,j}\cos(\Theta_{i,j} + \delta_{j,t} - \delta_{i,t}) \tag{3.3}$$

$$Qg_{i,t} - Qd_{i,t} + Qc_{i,t} = \sum_{j=1}^{N} V_{i,t}V_{j,t}Y_{i,j}\sin(\Theta_{i,j} + \delta_{j,t} - \delta_{i,t}) \tag{3.4}$$

Operational Constraints:

$$V_i^{min} \leqslant V_{i,t} \leqslant V_i^{max} \tag{3.5}$$

$$P_i^{min} \leqslant Pg_{i,t} \leqslant P_i^{max} \tag{3.6}$$

$$Q_i^{min} \leqslant Qg_{i,t} \leqslant Q_i^{max} \tag{3.7}$$

$$Qc_i^{min} \leqslant Qc_{i,t} \leqslant Qc_i^{max} \tag{3.8}$$

3.2.2 Stochastic Studies

- Uncontrolled Charging
  In uncontrolled charging, only the customers decide the charging schedule. Hence, it is assumed that the PEVs are plugged in for charging as soon as they arrive home. Three scenarios are considered to investigate the impact of uncontrolled charging on the distribution grid.

  1. S1: Off-peak Period Charging
     In this scenario, it is assumed that customers charge their PEVs during three specific hours in the off-peak price period, charging can start at the beginning of the off-peak price period (hour 21 or at hours 22 and 23) and can continue latest up to hour 2, as the maximum charging duration of a vehicle is 4 hours. A uniform pdf of the starting time of charging, $f_1(t_1)$, is formulated as follows:

     $$f_1(t_1) = \begin{cases} 0.33, & \forall t_1 \in t, t_1 = 21, 22, 23 \\ 0, & \forall t, t \notin t_1 \end{cases} \tag{3.9}$$

  2. S2: Starting Time of Charging is Hour 17
     In this scenario, the customers plug in their PEVs at hour 17, assuming that they charge their vehicles right after arriving home after the day's work. Accordingly, the probability distribution of start time of charging, $f_2(t_2)$, is as follows:

     $$f_2(t_2) = \begin{cases} 1, & \forall t_2 \in t, t_2 = 17 \\ 0, & \forall t, t \notin t_2 \end{cases} \tag{3.10}$$

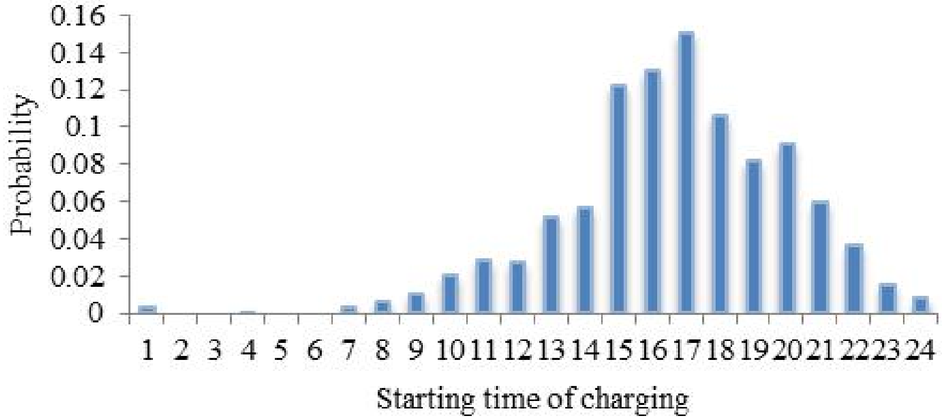

Figure 3.8: Pdf of starting time of charging in Scenario S3

3. S3: Starting Time of Charging as per NHTS 2009
In this scenario, the probability distribution of starting time of PEV charging is developed using NHTS 2009 data [1]. The last home arrival time of the day is assumed as the time when PEVs are plugged in to recharge. A log logistic [3P] distribution is employed to represent the probability distribution of starting time of charging as shown in Figure 3.8. The pdf, $f_3(t_3)$, is represented by:

$$f_3(t_3) = \frac{\alpha}{\beta}(\frac{t-\gamma}{\beta})^{\alpha-1}(1+(\frac{t-\gamma}{\beta})^{\alpha})^{-2} \quad \forall t_3 \in t, t = 1, .., 24 \tag{3.11}$$

To appropriately estimate the impact of PEV charging on the grid, it is necessary to consider all scenarios of SOCi when the vehicle arrives home and plugs in to charge. Using (8), the SOCi for the corresponding miles driven is determined. The pdf of SOCi is developed using the pdf of miles driven and is shown in Figure 3.9. Since the cumulative probability of driving 45 miles or more is high, and PHEV40 is being considered, the battery will be fully depleted and hence the probability that SOCi will be zero, will also be high. On weekdays, most of the vehicles make trips only to work, hence covering only up to 20-25 miles; thus yielding SOCi probability between 0.5 – 0.7. From Figure 3.8 and 3.9, the probability of charging the PEVs at each hour with different SOCi values and the time required to charge, are determined. As the battery capacity and features change with different types of vehicles, the energy required to charge the battery also varies.

The probability of impact of PEV charging loads with SOC s, at any time $t(1 \leqslant t \leqslant$

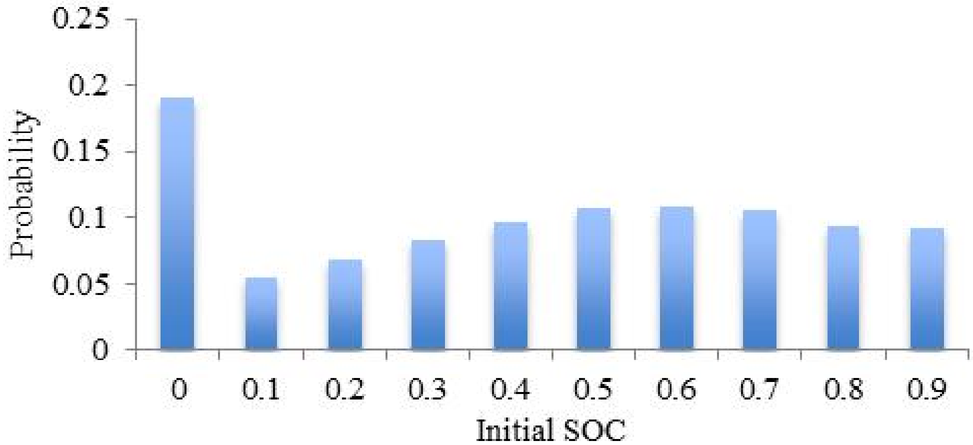

Figure 3.9: Probability density function of initial SOC

24), when it started charging at time $k(1 \leqslant k \leqslant 24, k \leqslant t)$ is given by $P(s,t)$. As per the assumption, it takes 3 to 4 hours to charge a PEV completely from 0% to 100%. Hence, another assumption is used, i.e. the SOC increases by three levels every hour, for example, if SOCi is 20%, it reaches up to 50% in the next hour. Using these assumptions, and the pdf of starting time of charging, and of SOCi, $P(s,t)$ can be mathematically expressed as:

$$P(s,t) = \sum_{k=1}^{t} f(k)\phi s - 3(t-k) \tag{3.12}$$

- Smart Charging
  While in uncontrolled charging the probability distribution of the starting time of charging depends on the customer driving behavior, in smart charging, such a probability distribution is not considered, instead a specific charging window is allowed. The starting time of charging is then optimally determined by the LDC, based on the objective function considered. It is assumed that customers can charge their PEVs only between hours 19 to 24 and 1 to 7, i.e., between 7 PM to 7 AM, and the LDC decides the optimal charging schedule within this window. The pdf of SOCi is taken into account to calculate the expected energy required to charge fully. The uncontrolled and smart charging scenarios are summarized in Table 3.1.

- Stochastic Distribution Operations Model The generic stochastic distribution operations model is described below, which is used for both uncontrolled and smart

Table 3.1: Uncontrolled and controlled charging scenarios

	Uncontrolled			Smart Charging		
	S1	S2	S3	S4	S5	S6
Objective function	None			$E[J_L]$	$E[J_E]$	$E[J_C]$
Voltage limits	No			Yes		
Peak demand limit	No			Yes		
Charging Period	$f_1(t_1)$	$f_2(t_2)$	$f_3(t_3)$	7 PM - 7 AM		
Charging Price	HOEP	HOEP	HOEP	HOEP	HOEP	HOEP/TOU

charging scenarios, with appropriate modifications. The objective functions considered are:

Minimization of Expected Loss: This objective represents the typical operating objective of the LDC, and is given as follows:

$$E[J_L] = 1/2 \sum_{t=1}^{24} \sum_{s} \phi(s) \sum_{i=1}^{N} \sum_{j=1}^{N} G_{i,j}[V_{i,t,s}^2 + V_{j,t,s}^2 - 2V_{i,t,s}V_{j,t,s} \cos(\delta_{j,t,s} - \delta_{i,t,s})] \quad (3.13)$$

Minimization of Expected Energy Drawn: This represents another possible operating criterion from the perspective of the LDC, and is given as follows:

$$E[J_E] = \sum_{t=1}^{24} \sum_{i=1}^{N} \sum_{s} \phi(s) Pg_{i,t,s} \quad (3.14)$$

Minimization of Expected Cost of PEV Charging: This represents a typical objective of customers, assuming their rational behavior, which the LDC considers as its operating objective, and is given as follows:

$$E[J_C] = \sum_{t=1}^{24} \sum_{i=1}^{N} \sum_{s} \phi(s) Pev_{i,t,s} \rho_t \quad (3.15)$$

The energy price ρ represents the tariff structure applied to PEV customers. The proposed stochastic distribution operations model is solved subject to the following operational constraints:

Demand Supply Balance Equations: These are the traditional power flow equations and take into account the nodal active and reactive power balance.

$$Pg_{i,t,s} - Pd_{i,t} - Pev_{i,t,s} = \sum_{j=1}^{N} V_{i,t,s} V_{j,t,s} Y_{i,j} \cos(\theta_{i,j} + \delta_{j,t,s} - \delta_{i,t,s}) \quad \forall i, j \tag{3.16}$$

$$Qg_{i,t,s} - Qd_{i,t} + Qc_{i,t,s} = -\sum_{j=1}^{N} V_{i,t,s} V_{j,t,s} Y_{i,j} \sin(\theta_{i,j} + \delta_{j,t,s} - \delta_{i,t,s}) \quad \forall i, j \tag{3.17}$$

Note that the active power equation (3.16) includes the PEV charging load at every bus i, time t, and scenario s. It is assumed that no reactive power is drawn during PEV charging.

PEV Charging Constraints: It is assumed that PEVs can be discharged to an SOC of 0% while arriving home. The probability distributions of SOCi and the starting time of charging are considered in order to model the stochastic nature of the PEV charging load. The energy drawn by PEVs depends on the SOC of the battery before plugging in. Hence, the total energy drawn by PEVs at bus i over the charging period is given by,

$$\sum_{t} \eta Pev_{i,t,s} = (SOC_f - SOCi_s) C_{max} Nev_i \tag{3.18}$$

The constraint on maximum power drawn by PEVs is as follows:

$$Pev_{i,t,s} \leqslant Pev_{max} Nev_i \tag{3.19}$$

Other Constraints: Some other constraints considered, include bus voltage limits, limits on capacitor support, and substation capacity limits.

3.3 Results and Analysis

3.3.1 Test System Description

The 33-bus radial distribution system [3] is used in this work (Figure 3.10) with assumed PEV penetration levels of 30%, 50% and 70%. Bus 1 is the only substation bus in the

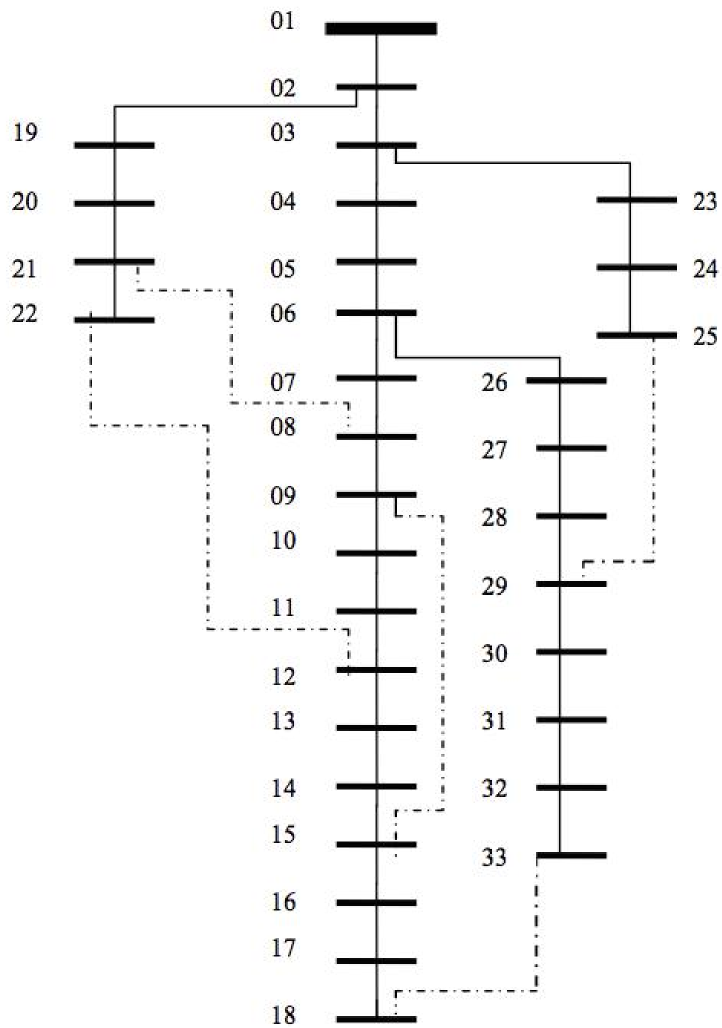

Figure 3.10: 33-bus radial distribution system [3]

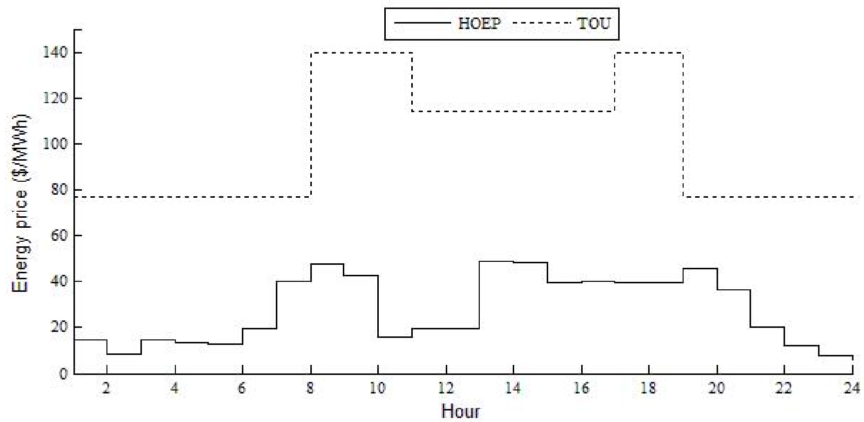

Figure 3.11: HOEP and TOU rate (HOEP as per March 4, 2015)

network and serves as a slack bus. The number of PEVs at each bus is mathematically represented as [20],

$$Nev_i = floor(xfloor(\frac{PD_i}{\lambda})Np) \quad \forall i = 2, 3, .., 33. \tag{3.20}$$

In (3.20), x is the PEV penetration in p.u., PD_i is the active power load at a bus (kW) [3], Np is the maximum number of PEVs owned by a resident, and λ is the average residential load per hour (kW). It is assumed that $Np = 1$, $x = 0.5$ p.u. (in case of 50% penetration), and $\lambda = 2.08$ kW.

For the given residential base load, the total number of PEVs in the system is found to be 877, and the number of PEVs at each node is calculated using (3.20).

Two different tariff structures are considered for the studies, Hourly Ontario Energy Price (HOEP) and time of use (TOU). The HOEP data is obtained from the Independent Electricity System Operator (IESO) public data resource, for March 4th, 2015. The TOU tariff rates considered, are as per Ontario's winter rate i.e., 0.077$/kWh off peak, 0.14 $kWh on peak, 0.114 $/kWh mid peak. Observe from Figure 3.11, that the HOEP rate is significantly lower than the TOU rate.

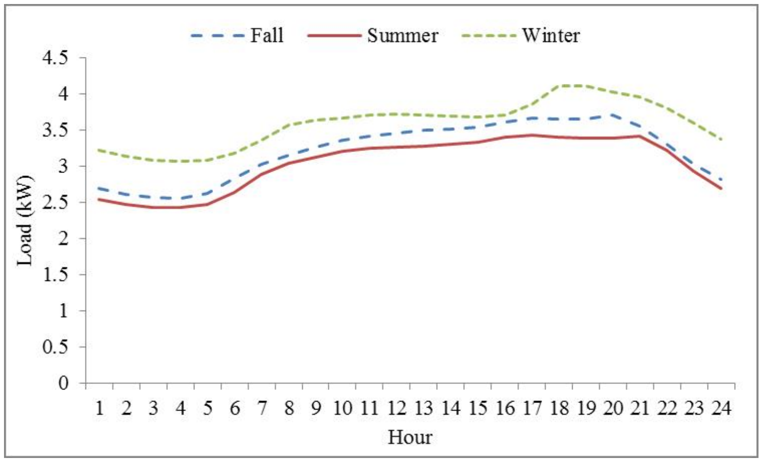

Figure 3.12: An average hourly household load profile over 24 hours

3.3.2 Deterministic Studies

3.3.2.1 Impact on Load Profile with Different Levels of PEV Penetration

The average household load profile is generated using real-time data from a house and is used as a reference load profile to obtain the distribution system load profile with PEV penetrations. Figure 3.12 shows the 24 hour daily load profile for three different seasons. The household load profile at each bus is generated depending on number of residential houses and PEVs at each bus. Reactive power of any residential load at any bus is calculated by assuming a power factor of 0.9 p.u. The extra power from charging PEVs is added only to the active power demand, assuming that no reactive power is drawn during PEV charging.

Different levels of PEV penetration are considered for all three seasons, for weekdays and weekends. Using (2.2), (2.3), and (3.20), Table 2.2 and Figure 3.7, the extra load due to PEV charging is estimated. In this calculation, the percentage of different types of vehicles and their battery capacities are taken into account. Figures 3.13 to 3.15 highlights the impacts of PEV charging on the base load profile with 50% PEV penetrations for three seasons.

It is observed that the peak demand occurs between 4 - 7 PM, as per Figure 3.1, 3.2 and 3.3, the highest percentage of vehicles arrive home during this time of the day after daily work. Note that, the charging schedule is according to the customer behavior captured in the NHTS 2009 report, which is uncontrolled. Peak demand reaches 8.4 MW load with

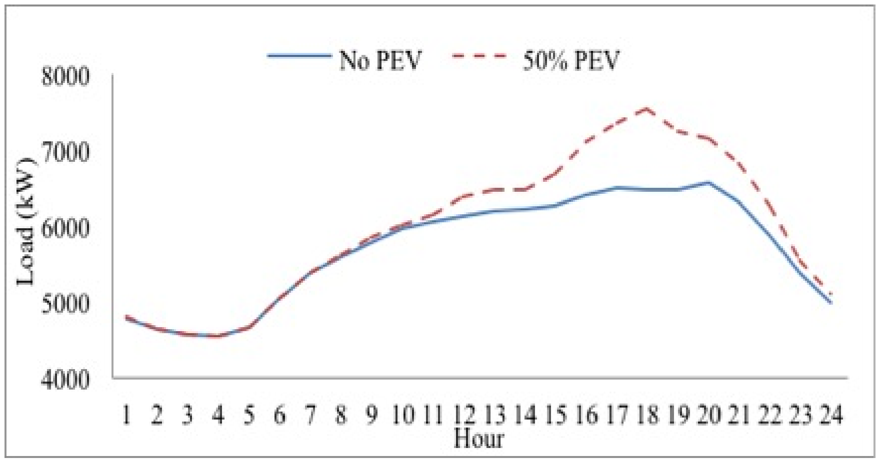

Figure 3.13: Impact of PEV charging on load profile for a typical Fall day

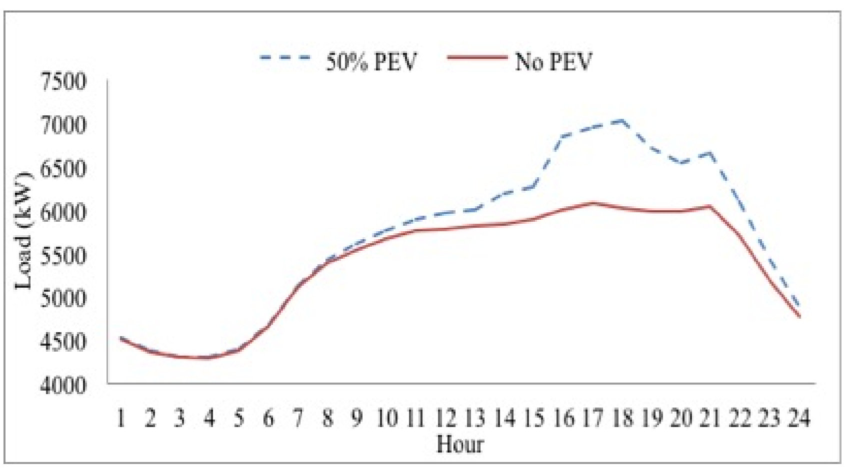

Figure 3.14: Impact of PEV charging on load profile for a typical Summer day

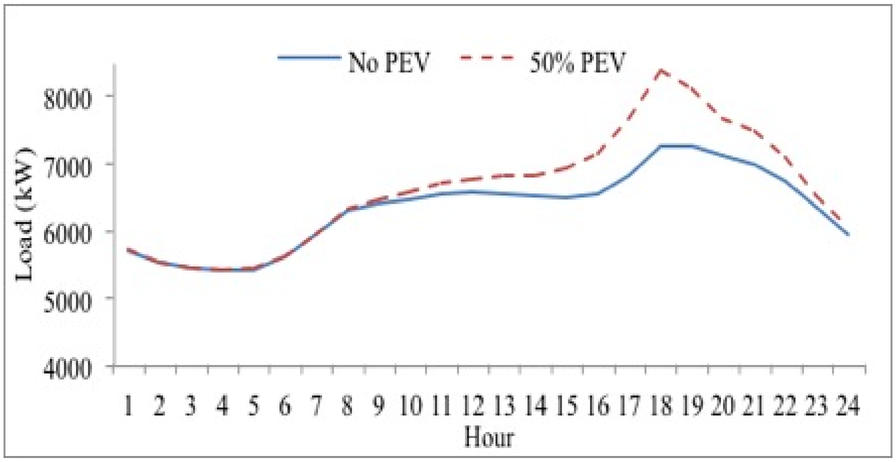

Figure 3.15: Impact of PEV charging on load profile for a typical Winter day

50% of PEV penetrations in Winter days. The impact of PEV charging during peak hours results in approximately 16% increase in demand during Winter days. It is noted that, there is not much significant difference in the demand between 11 PM - 6 AM. In addition, it should be noted that the base load is low during these hours, hence this results in a huge difference between peak load and average load.

3.3.2.2 CASE 1: Uncontrolled Charging

The Distribution Load Flow (DLF) model is solved using MINOS solver. This is an uncontrolled charging scenario, where customers are allowed to plug in vehicles to charge upon completion of the last trip for the day. The percentage of different types of PEVs charging are based on the Figure 3.7. The battery capacity varies for different types of vehicles according to the Table 2.2. The impact of PEV charging loads on the voltage profile and feeder loss, when there is no control by an LDC is investigated in this case.

The impact on the voltage profile at peak hour 6 PM on a typical Summer day is shown in Figure 3.16. It is noticed that the voltage drop is high at the remote buses, bus 18 and bus 33. The voltage drops to approximately 0.88 p.u from 0.9 p.u in the case of PEV loads in summer days with 50% of PEV penetrations. In winter days the voltage drop is noticed to be 0.8 p.u. To maintain system reliability, regulation of voltage is necessary to avoid system failure due to voltage collapse. It is evident that smart-charging will have to be embraced by PEV owners to experience the benefits of PEVs.

The impact on the feeder loss with different penetration levels of PEVs is demonstrated

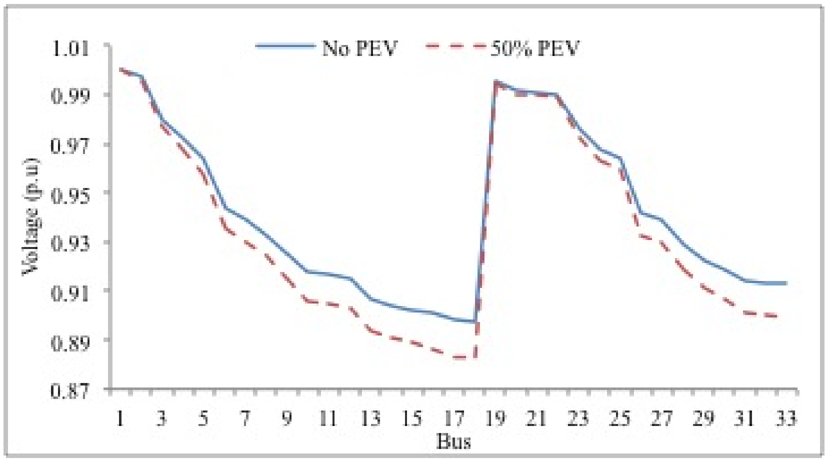

Figure 3.16: System bus voltage at peak hour (6 PM) on a typical Summer day, uncontrolled charging DLF

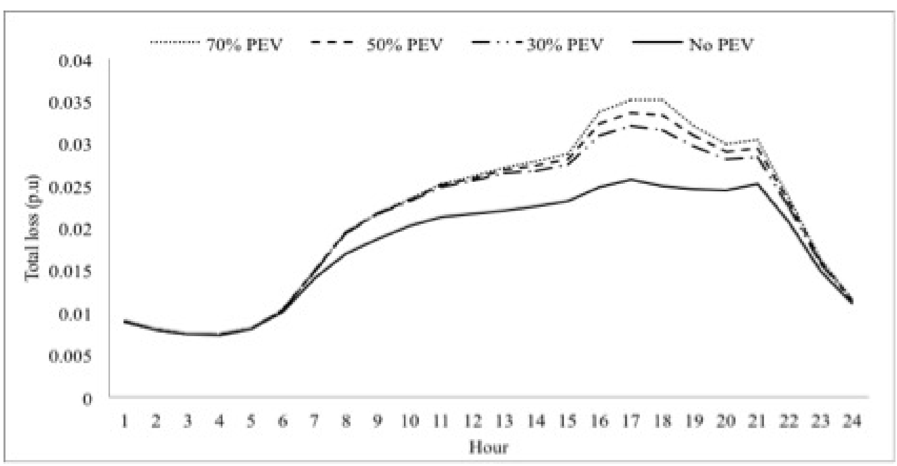

Figure 3.17: Impact on total loss with different penetration levels during a typical summer day, uncontrolled charging DLF

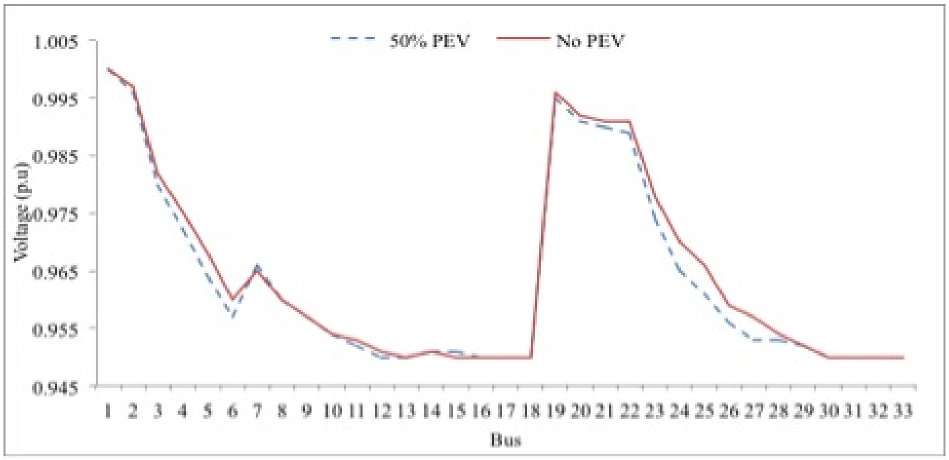

Figure 3.18: System bus voltage at peak hour (6 PM) on a typical Summer day, uncontrolled charging DOPF

Table 3.2: Summary of DLF and DOPF results with 50% PEV

DLF/DOPF results	Summer		Fall		Winter	
	DLF	DOPF	DLF	DOPF	DLF	DOPF
Energy drawn from the grid (MWh)	149.7	145.5	159.0	154.6	179.2	174.2
Total loss (MWh)	14.1	9.9	16.11	11.66	20.4	15.48
Total cost ($/day)	3,867	3,867	4,090	4,090	4,467	4,467

in Figure 3.17. The total feeder loss increases by approximately 36% with 70% of PEV penetration. The increase in total loss between 11 PM- 6 AM is almost negligible since not many PEVs charge during these hours.

3.3.2.3 CASE 2: Uncontrolled Charging with LDC Operational Constraints

The proposed DOPF model is solved using MINOS solver. In this case, two objective functions are modeled one by one to analyze the PEV charging impacts. The results obtained with minimization of loss is more efficient and shown in this section. This is an uncontrolled charging mode where customers are allowed to plug in vehicles to charge upon completion of the last trip for the day. In this DOPF model, the LDC tries to minimize feeder loss and improve bus voltage profiles. Reactive power support is provided at each bus to improve the voltage profile.

It is noted that the voltage is maintained within the limit of 0.95p.u to 1.05p.u. At

Table 3.3: Summary of DLF and DOPF results with 50% PEV in Summer with scaled load

DLF/DOPF results	Summer	
	DLF	DOPF
Energy drawn from the grid (MWh)	101.9	101.21
Total loss (MWh)	5.004	4.252
Total cost ($/day)	2,834	2,834

the remote buses, bus 18 and bus 33, the voltage drops to 0.95 p.u. The difference in bus voltage profiles with 50% PEV and without PEV is not significant when the voltage limit constraints are considered. A very small variations in the voltage profile are noticed between Summer and Winter.

The DLF and DOPF results with 50% of PEV penetration are summarized for three seasons in Table 3.2. The values for energy drawn from the grid and feeder loss lead to the inference that, appropriate control strategy from the LDC minimizes negative impacts due to PEV charging. The loss decreases by about 30% when an LDC tries to minimize loss. The impacts worsen in Winter compared to Summer and Fall. The total estimated cost includes base load and PEV charging load. It is noted that, the customer cost remains the same in DLF and DOPF model since the base load and PEV charging loads are not controlled by the LDC. These costs form the aggregate electricity charge of the residents in the system under study.

In all the further work in this thesis, only Summer load is considered for the analysis and this base load is scaled down as per the system load [3]. The DOPF and DLF results for the scaled summer load in deterministic analysis is summarized in Table 3.3.

3.3.3 Stochastic Studies

3.3.3.1 Uncontrolled Charging

1. Scenario S1
   It is assumed that customers are concerned only about the electricity price and their charging cost. Hence, they start charging their vehicles during the off-peak price period. There are no limits on the voltage and peak power drawn. The impacts of this scenario are shown in Figure 3.19 and 3.20. It is observed that if the customers start charging their vehicles only during these 3 hours, the peak demand is significantly high during the off-peak price period (hours 21,22 and 23), thus overloading the

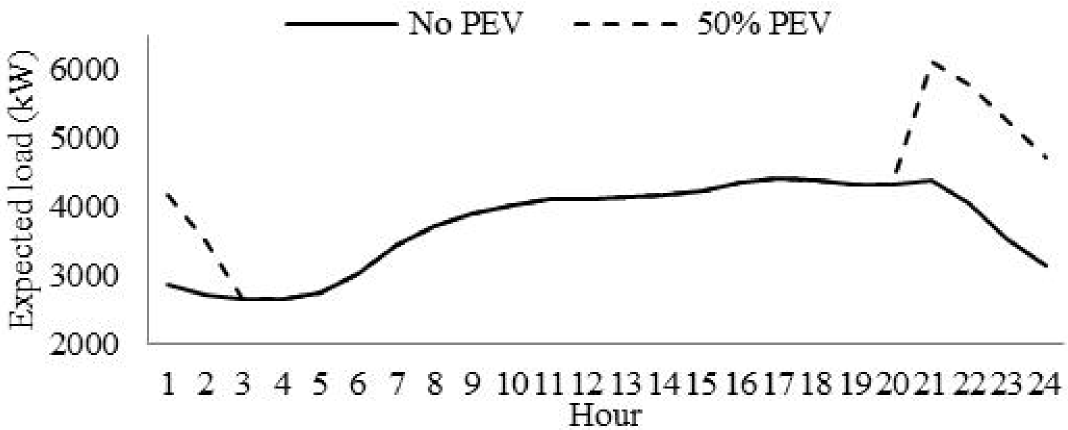

Figure 3.19: Expected load profile in Scenario S1

transformer. The voltage at the remote buses-18 and 33 drops to 0.85 p.u., which is not desirable.

2. Scenario S2
   In this scenario, the starting time of charging is fixed for hour 17. (5 PM). The PEV load impacts can be seen for the next four hours if the battery is completely discharged before plugging in for charging as shown in Figure 3.21. The expected voltage profile at 5 PM is presented in Figure 3.22. Compared to scenario S1, the peak demand is higher in S2, because the charging period is limited to four hours only. This scenario demonstrates the worst possible charging behavior of PEV owners. The voltage drop is expected to be as low as 0.82 p.u., at the remote buses.

3. Scenario S3
   In this scenario, the charging period is distributed throughout the day, and so is the PEV charging load. The expected load and the voltage profile are shown in Figure 3.23 and 3.24 respectively. Even though the load profile presents a less severe impact on the distribution system than the previous two scenarios, since the PEV charging is not optimally scheduled, it has significant adverse impacts during the peak demand hours. In all the above uncontrolled scenarios, the impact of PEV charging loads was studied using traditional power flow analysis only. Consequently, bus voltage limits were not taken into account and significant voltage drops were noted at the remote buses. Hence, for reliable system operation, controlled charging schedules, obeying system operational constraints are called for. The expected values

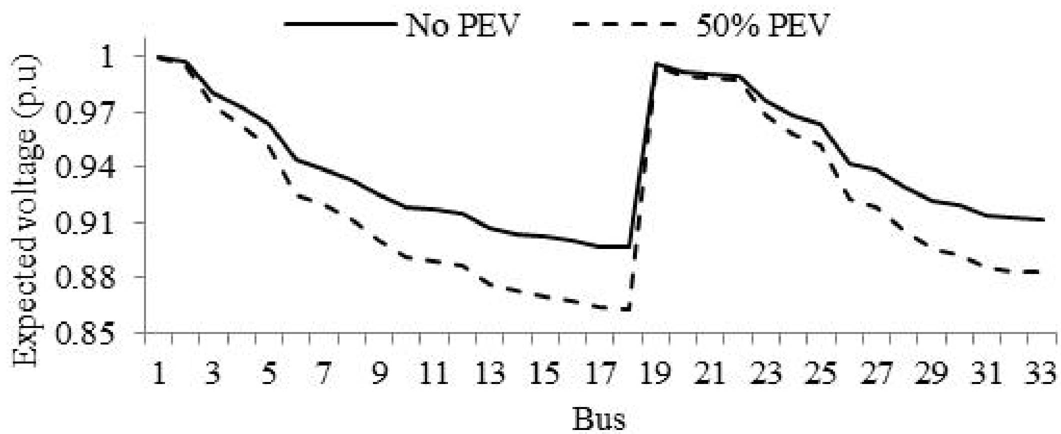

Figure 3.20: Expected voltage profile at 9 PM (S1)

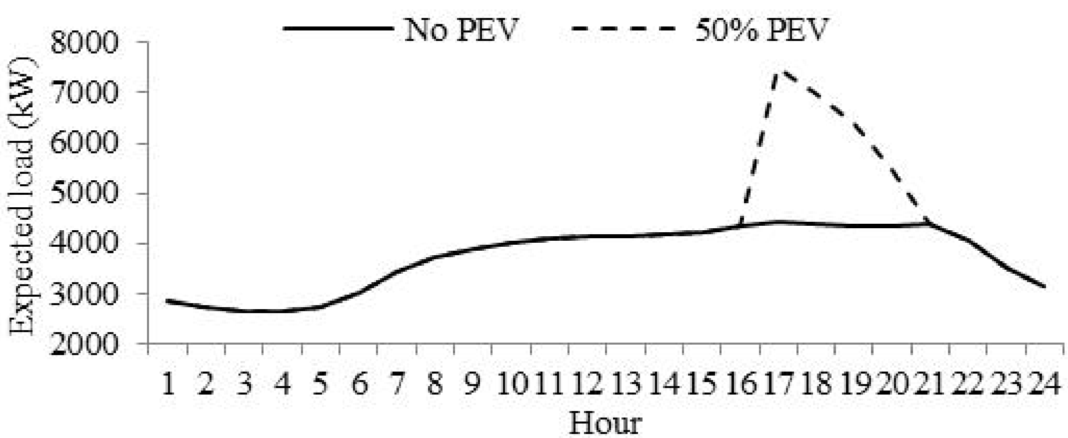

Figure 3.21: Expected load profile in Scenario S2

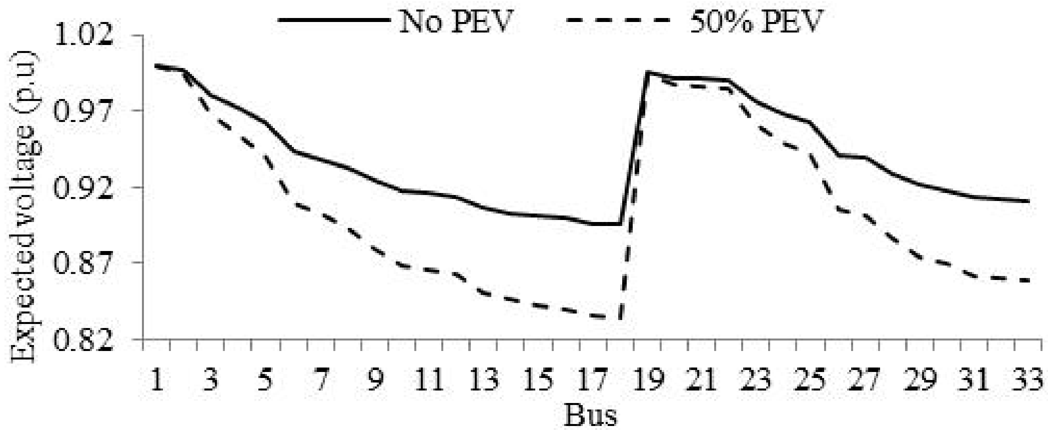

Figure 3.22: Expected voltage profile at 5 PM (S2)

Table 3.4: Uncontrolled charging scenarios

Cases	S1	S2	S3
Expected feeder loss, MWh	5.13	5.53	5.05
Expected energy drawn, MWh	103.2	103.6	103.1
Expected cost of PEV charging, $/day	104	360	265

of decision variables for uncontrolled charging scenarios are summarized in Table 3.4. As evident from Table 3.4, the most significant difference between the scenarios is with respect to the expected cost of charging, the lowest being for S1 where off-peak price charging occurs while the most expensive being for S2 where charging occurs during the peak price hours; and S2 also accounts for the highest loss and energy drawn.

3.3.3.2 Smart Charging

In this case, the charging is constrained between the hours 7 PM to 7 AM, when customers are most likely to be at home. Figure 3.25 to 3.27 and Table 3.5 presents the results for the scenarios in smart charging; Figure 3.25 demonstrates that scenario S4 results in a fairly flat load profile. The expected values of feeder loss, energy drawn and cost of charging, in scenarios S4 and S5 are almost the same. Note that scenarios S4 and S5 are developed using HOEP rates. In S6, it is noted that new

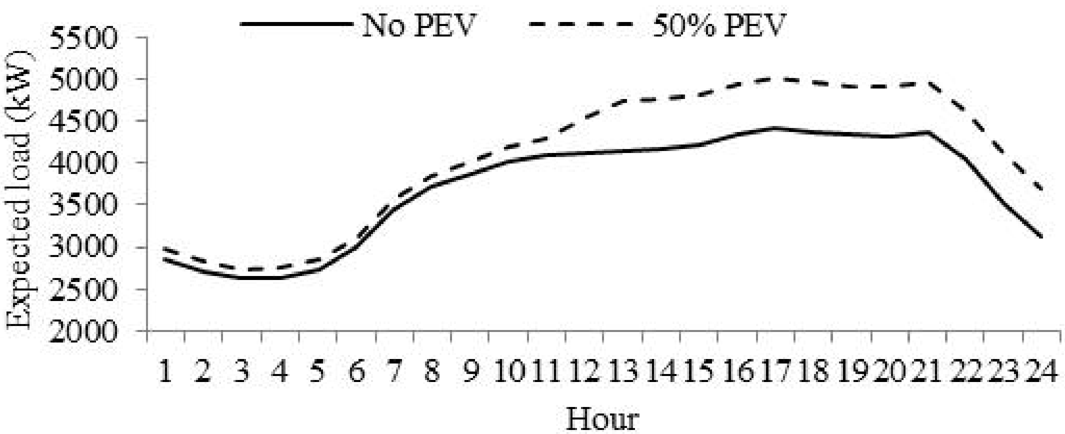

Figure 3.23: Expected load profile in Scenario S3

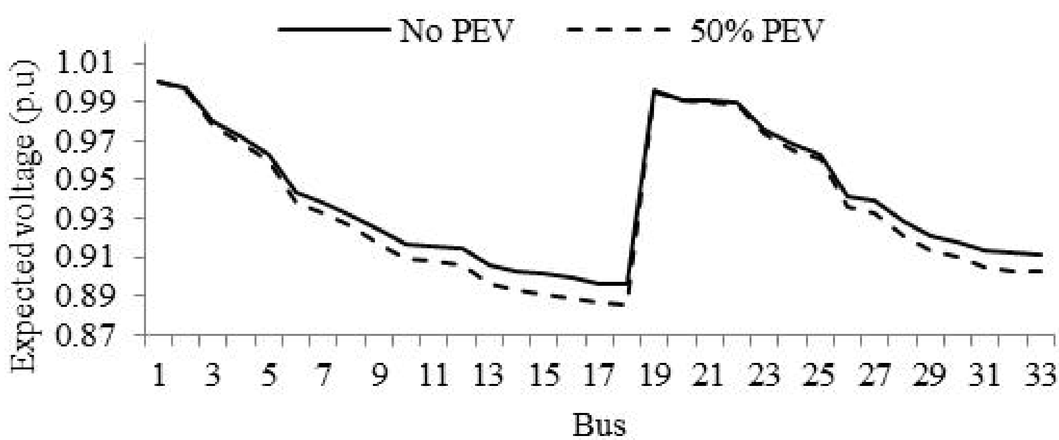

Figure 3.24: Expected voltage profile at 5 PM (S3)

Table 3.5: Smart charging scenarios

Cases	S4	S5	S6 (TOU)	S6 (HOEP)
Expected feeder loss, MWh	4.02	4.02	10.77	9.82
Expected energy drawn, MWh	102.7	102.7	108.83	107.88
Expected cost of charging, $/day	113	113	690	77

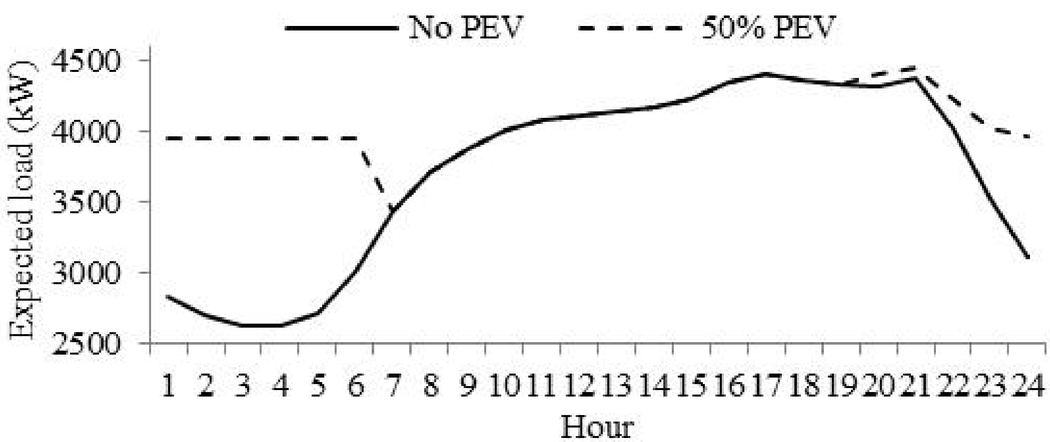

Figure 3.25: Expected load profile in Scenario S4

peaks are created during late night hours for both HOEP and TOU rates (Figure 3.27) when smart charging is introduced, and is not desirable. These results illustrate the effects on the distribution system operation and it is clear that the most preferred objective function from the utility's perspective is either loss minimization or energy minimization, since these reduces the feeder losses and total energy drawn, while maintaining the total cost of PEV charging at a reasonable value. Whereas, cost minimization is more suitable from a customer's perspective as it reduces the charging cost from $113 to $77 per day, for HOEP rates, but with adverse impact on feeder loss and total energy drawn from the grid. The optimal charging schedule obtained in scenario S4 or S5 can be considered as the best charging schedule.Figure 3.28 shows the probability of PEV charging hours in the case of optimal scheduling in S4.

3.3.3.3 Scenario S7: Analysis of S6 considering peak demand limit

It is noted that, in case of S6, since LDC tries to minimize the customer cost of PEV charging, the LDC pays high feeder loss and energy drawn. In this section, a peak demand

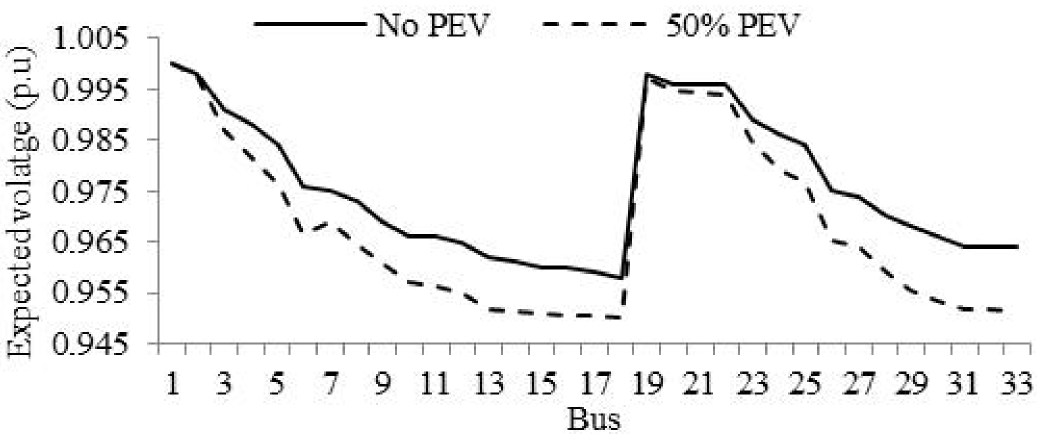

Figure 3.26: Expected voltage profile at 4 AM (S5)

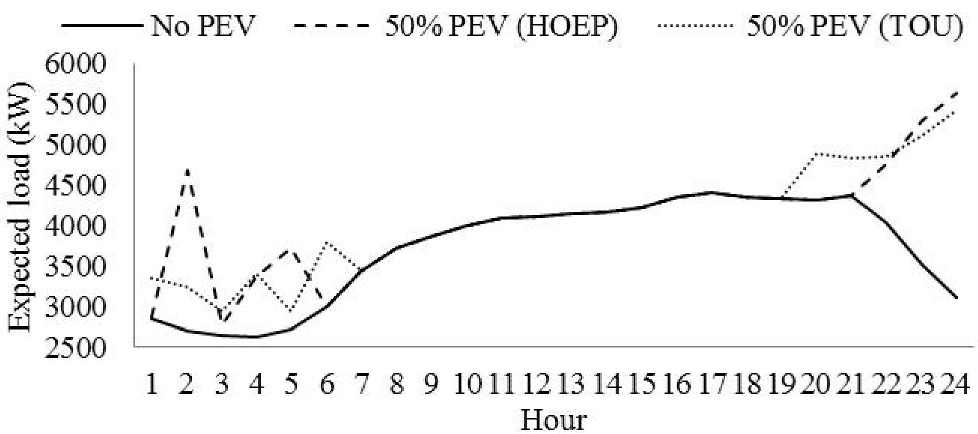

Figure 3.27: Expected load profile in Scenario S6

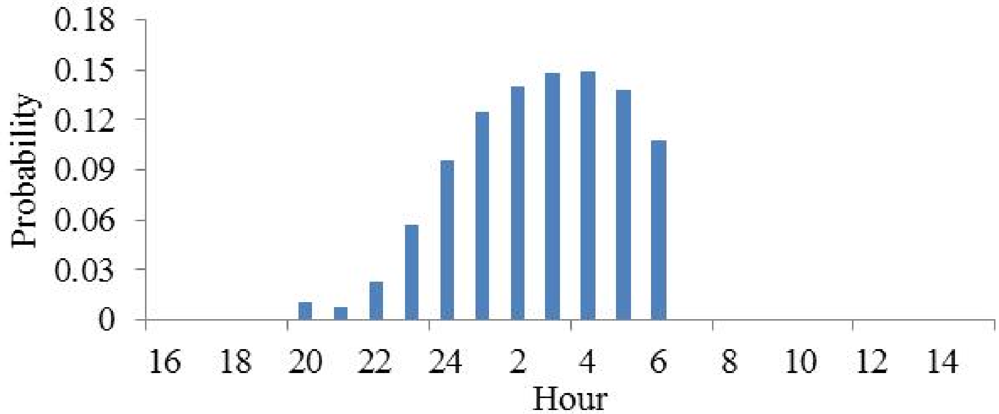

Figure 3.28: Probability of PEV charging time for optimal charging schedule in Scenario S4

limit is considered to maintain the peak demand of PEV charging. The peak demand is expected to be in the range of the base load peak demand. The analysis is carried out by considering minimization of cost with peak demand limit. The results are shown in Figure 3.29 and Figure 3.30. It is noted that with peak demand limit, the LDC tries shift PEV charging hours in such a way that the peak demand is minimized and maintained within the limit. The charging hours are more shifted to the midnight when the base load is low and also the electricity price is relatively low. By adding peak demand limit, even with minimization of PEV charging cost the smart schedules can be obtained.

3.4 Summary

This chapter presented a detailed study of PEV driving characteristics and charging behavior was carried out, and deterministic analysis was performed to investigate the uncontrolled charging impact on the distribution system. In stochastic analysis a SDOPF model with various objectives and operational constraints incorporating PEV charging loads within a 33-bus balanced distribution system was presented. The various possible uncertainties of PEV charging and their impacts on the distribution system were taken into consideration to develop a stochastic optimization model. Uncontrolled and controlled charging effects on the distribution system were compared. It was noted that uncontrolled charging had the worst impacts on the system with large amount of energy drawn and

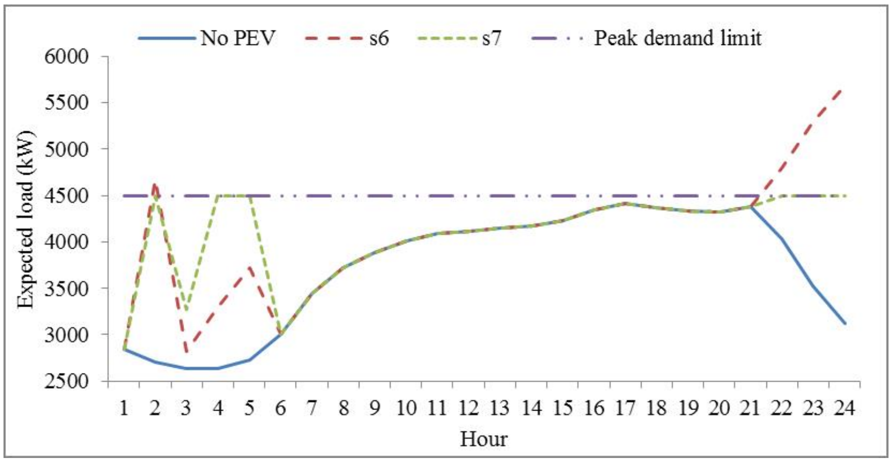

Figure 3.29: Expected load profile with peak demand limit (S7 HOEP)

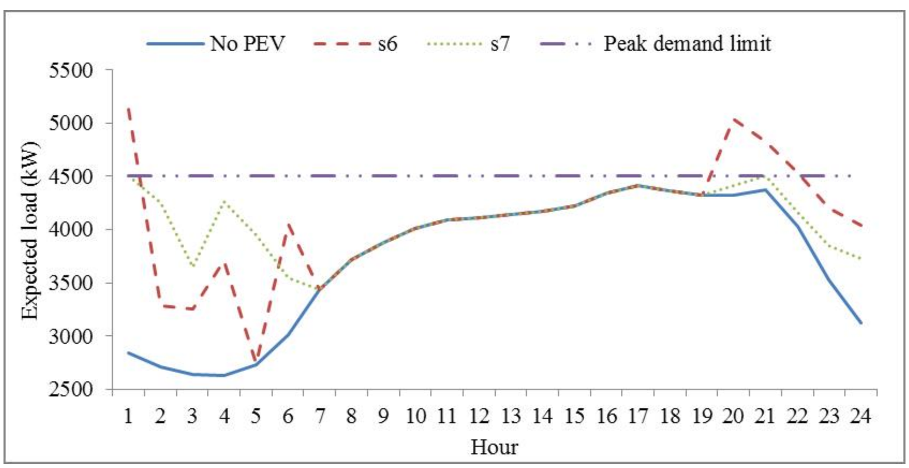

Figure 3.30: Expected load profile with peak demand limit (S7 TOU)

hence the loss. Also, it did not meet the operational constraints of the grid. Smart charging resulted in a reasonable amount of energy drawn, feeder losses and low energy costs. The case of smart charging with cost minimization from the customer's perspective was not a very viable option for the LDC as it increases energy drawn and the feeder losses. Hence, a peak demand limit was added to the constraints to control the peak demand with cost minimization. The most favorable options in smart charging are energy or loss minimization objectives wherein charging schedules were proposed which resulted in flattening the load profile.

Chapter 4

Optimal Siting and Sizing of Electric Vehicle Charging Station

In this chapter, the PEV mobility characteristics developed in the previous chapter are used to optimally locate an EVCS in the distribution system. A mathematical model and a heuristic algorithm are developed to determine the optimal siting and sizing of EVCS. This model can be generalized to any test system provided the PEV driving characteristics and feeder lengths are known. In Section 4.1, the mathematical model for optimal siting of EVCS is presented along with the proposed heuristic approach. The results are demonstrated in Section 4.2. In Section 4.3, the optimal sizing of EVCS is discussed. The chapter is summarized in Section 4.5.

4.1 Optimal Siting of EVCS

4.1.1 The Approach

In the previous chapter, it was assumed that PEVs charge only at home and the PEV charging loads are added to the residential load. However, often, PEV owners may encounter situations where charging facilities are required away from home. To this effect, public charging station facilities or EVCS are being developed to overcome such issues. It is essential to determine the siting and sizing of EVCS in an optimal manner. In this work, one EVCS is planned within the 33-bus distribution system. It is assumed that the roads are in parallel with the distribution feeders. Hence, the distribution system considered here, also represents the road map of the local area.

In the case of optimal planning, many factors need to be considered. The major concern is customer convenience. Other factors such as infrastructure and maintenance cost are not taken into account here. To reduce the total cost of PEV charging and the time to reach the EVCS, the shortest route along the feeders is considered. The distance between each feeder bus is estimated using the resistivity and resistance data of the feeder system. The feeder size is considered to be 500 AWG and hence the resistivity of 0.206 [42]. A distance matrix D[i,b] is created by assuming that the vehicles travel to the EVCS from their home and therefore, the distance is estimated from respective home buses to the EVCS bus.

4.1.2 Mathematical Model

SOCi of the PEVs

Whether a PEV is using battery power or gas to travel to the EVCS from its home location, the initial SOC of the vehicle depends on the SOC when it arrives home after the last trip and the distance to the EVCS from home. This is determined using the following mathematical equations.

$$\Delta SOC_{i,b} = D_{i,b}/AER \tag{4.1}$$

In (4.1), $\Delta SOC_{i,b}$ is the depletion of SOC of the PEV after traveling from bus i to b, with a distance of $D_{i,b}$, where bus b is the charging station. If $\Delta SOC_{i,b}$ is smaller than $SOCi_s$, the vehicle uses electric power. Else, the vehicle would travel using electric power till the SOC of the vehicle depletes to zero, and for rest of the distance gasoline fuel is used. The remaining distance $\Delta D_{i,b,s}$ for scenario s, that need to be covered by fuel energy is calculated as follows:

$$\Delta D_{i,b,s} = \begin{cases} (\Delta SOC_{i,b} - SOCi_s).AER, & \Delta SOC_{i,b} > SOCi_s \\ 0, & \Delta SOC_{i,b} < SOCi_s \end{cases} \tag{4.2}$$

The total cost of a customer for using PEVs is the sum of PEV recharging cost and the fuel cost to travel to the EVCS. The fuel cost to travel from bus i to bus b EVCS is given by,

$$E[FC_{i,b,t,s}] = \Delta D_{i,b,s} \rho_{fuel} Nev_i f(t) \phi(s) \tag{4.3}$$

In (4.3), $E[FC_{i,b,t,s}]$ is the expected fuel cost to travel from bus i to EVCS bus b at time t with the SOC scenario s, ρ_{fuel} is the fuel charge per mile. The new initial SOC at the EVCS is given by,

$$SOCi_s^1 = \begin{cases} (SOCi_s - \Delta SOC_{i,b}), & \Delta SOC_{i,b} < SOCi_s \\ 0, & \Delta SOC_{i,b} > SOCi_s \end{cases} \tag{4.4}$$

The total energy drawn by PEVs over the charging period is modified as follows:

$$\sum_t \eta Pev_{i,t,s} = (SOC_f - SOCi_s^1)C_{max}Nev_i \tag{4.5}$$

The sum of all the PEV loads across all buses is the PEV charging load at the EVCS since it is assumed that all vehicles are charging only at the EVCS.

$$TPev_{t,s} = \sum_{i=1}^{N} Pev_{i,t,s} \tag{4.6}$$

The power flow model is modified as follows:

$$Pg_{i,t,s} - Pd_{i,t} - TPev_{t,s} = \sum_{j=1}^{N} V_{i,t,s}V_{j,t,s}Y_{i,j}\cos(\theta_{i,j} + \delta_{j,t,s} - \delta_{i,t,s}) \quad \forall i = b \tag{4.7}$$

$$Pg_{i,t,s} - Pd_{i,t} = \sum_{j=1}^{N} V_{i,t,s}V_{j,t,s}Y_{i,j}\cos(\theta_{i,j} + \delta_{j,t,s} - \delta_{i,t,s}) \quad \forall i \neq b \tag{4.8}$$

$$Qg_{i,t,s} - Qd_{i,t} = -\sum_{j=1}^{N} V_{i,t,s}V_{j,t,s}Y_{i,j}\sin(\theta_{i,j} + \delta_{j,t,s} - \delta_{i,t,s}) \quad \forall i \tag{4.9}$$

This distribution load flow model is executed to obtain the expected feeder loss and expected customer cost as follows:

$$E[L_b] = 1/2\sum_{t=1}^{24}\sum_{s}\phi(s)\sum_{i=1}^{N}\sum_{j=1}^{N} G_{i,j}[V_{i,t,s}^2 + V_{j,t,s}^2 - 2V_{i,t,s}V_{j,t,s}\cos(\delta_{j,t,s} - \delta_{i,t,s})] \tag{4.10}$$

$$E[C_b] = \sum_{t=1}^{24} \sum_{s} (\phi(s) TPev_{t,s} \rho_t + E[FC_{i,b,t,s}]) \tag{4.11}$$

4.2 Heuristic Approach

This section presents the actual execution of the proposed model and the heuristic approach to determine the optimal siting of EVCS (Figure 4.1). The statistical and probability analysis inferences from the previous chapter are used in this approach. The initial SOC of a PEV changes by certain percentage depending on the distance from source to destination as discussed in the previous section (4.1) and (4.4). A distance matrix $D[i, b]$ is created using feeder resistance and resistivity as explained earlier. Using (4.1)-(4.4), the revised initial SOC values are generated and the probability distribution of revised initial SOC is developed. To determine the optimal location of EVCS, the impacts are studied considering EVCS at every bus in the distribution system, starting at bus 2 (since bus 1 is a slack bus). The proposed stochastic distribution power flow given by (4.7)-(4.9) is executed to determine the expected values of feeder loss, customer cost, energy consumption and voltage profile. The bus with EVCS, for which the expected values are minimum is chosen as the optimal EVCS site.

4.3 Results and Analysis

The impact on SOCi with various buses as the EVCS is investigated. Figure 4.2 shows the results when the EVCS is assumed to be at one of the remote buses *i.e.* bus 18. The probability distribution of the initial SOC of the vehicle before charging varies significantly when compared to the home charging scenario.

The probability of SOC of the vehicle depleting to zero, increases by 75% when the EVCS is placed at bus 18. This is because of the extra distance traveled to reach the EVCS. This certainly increases the customer cost and feeder loss, but this trade off is necessary when there is a requirement of public EVCS. Again, the increase in customer cost and feeder loss depends on where the charging station is installed. With the optimal siting of the EVCS, significant reduction in these values can be achieved.

To determine the optimal location of the EVCS within the test distribution system, the impact of PEV charging on the expected customer cost, feeder loss and voltage drop is

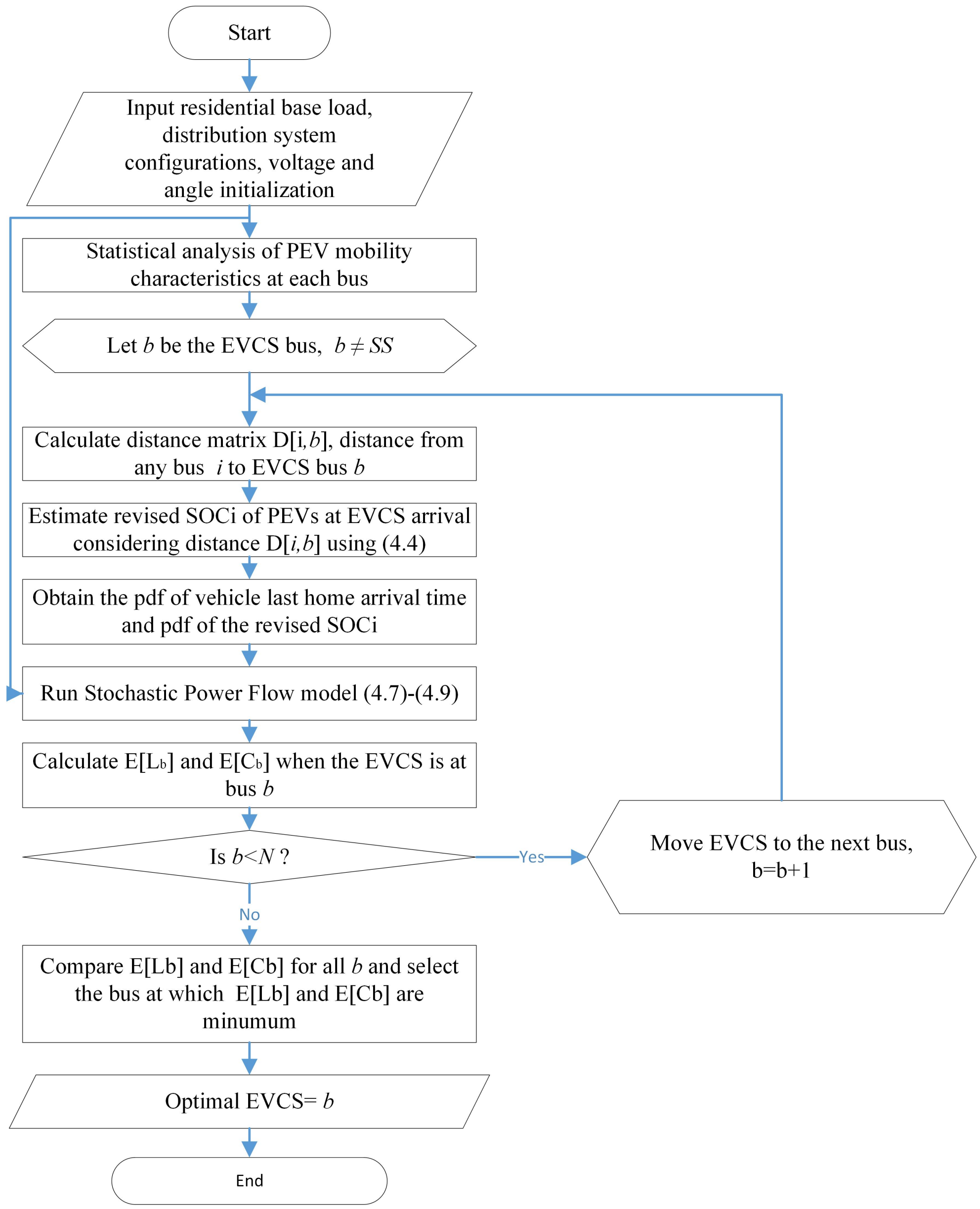

Figure 4.1: Flowchart of the proposed approach to optimal siting of EVCS

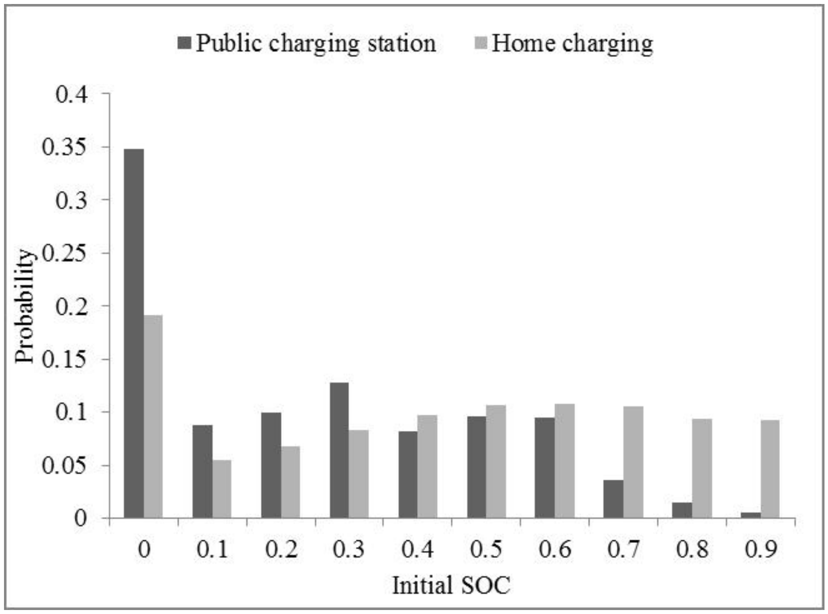

Figure 4.2: Pdf of SOCi of PEVs arriving at the EVCS vis-a-vis home charging facility

measured by moving the EVCS from one to bus to the other (Bus 2 to Bus 33) as shown in Figure 4.1. The bus with lowest feeder loss and customer cost is chosen as the optimal EVCS bus. The trade-off between overall expected cost of customers and the feeder loss is demonstrated in Figure 4.3.

From Figure 4.3 it is clear that, the expected customer cost is relatively low when the EVCS is located at any of the buses-2,3,4,6,7,19,23 or 26, with bus 6 as EVCS accounting for the lowest expected customer cost. Since these buses are located in such a way that, if any of these buses is fixed as the EVCS, then the distance from all other buses to this bus is short, hence resulting in low costs. In the test system, bus 18 and bus 33 are the remote buses, and hence if the EVCS is placed at these buses, large expected cost and feeder loss is incurred. Feeder loss is relatively low for EVCS installed at any of the buses-2,3,4,5,6,7,19 or 23, with bus 2 or bus 19 as EVCS resulting in the lowest feeder loss. Feeder loss is less when the EVCS load is near the substation. But, the issue here is, the buses near the substation are very far from all the other buses, hence it is not very convenient from the customers' perspective.

To finalize the siting of EVCS, the expected load profile of the system for various feasible buses as the EVCS site are compared. Figure 4.4 illustrates the variations in the expected load profile with different buses as EVCS. It is seen that the load profiles overlap

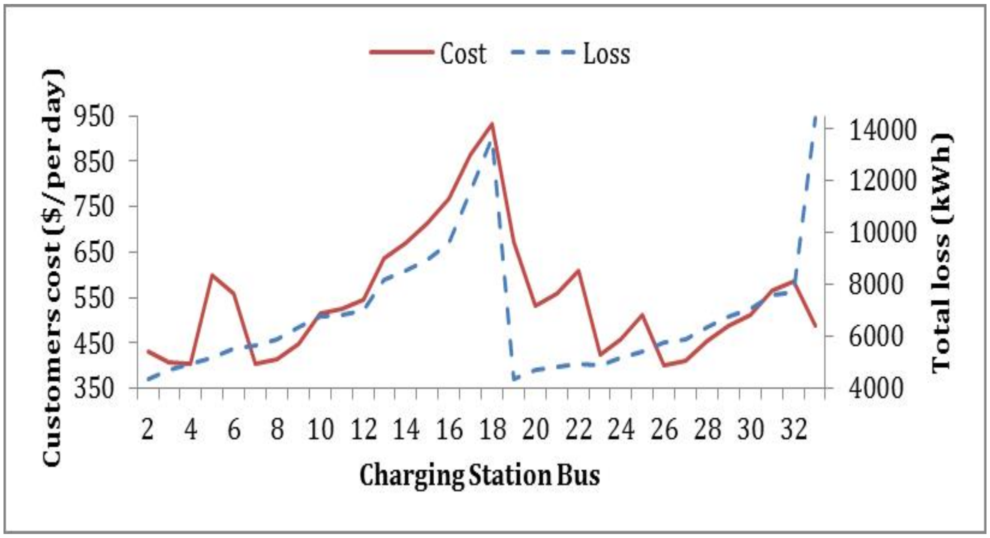

Figure 4.3: Total expected loss and expected cost with EVCS at different buses

with the next nearest bus profiles, such as bus 6 load profile almost overlaps with bus 7 load profile, bus 2 with bus 3, bus 4 and bus 26, and bus 19 with bus 23. It is observed that with the EVCS installed at bus 6 or bus 7, the charging profile is better and results in low peak demand compared to other cases. This also depends on the distance to reach the EVCS and hence the charging time shifts accordingly. The peak demand should be maintained within limit in order to save energy. Hence, the EVCS may be at either bus 6 or bus 7, of which bus 6 is selected for its low expected feeder loss and expected customer cost. Hence, the optimal EVCS location would be at bus 6.

Since only one bus is considered as the EVCS, the PEV charging loads are concentrated at bus 6. In order to achieve a reliable and stable distribution system, the voltage drop should be maintained within the limit. Figure 4.5 shows the voltage deviations over all the buses in the system when EVCS is at bus 6. Since this is an uncontrolled scenario, the voltage drop is considerably high with the worst voltage being 0.8743 p.u., at the remote bus 18.

4.4 Optimal Sizing of EVCS

Determining the optimal sizing of EVCS is very crucial to reduce the overall infrastructure cost, maintenance cost and to meet the feeder operational constraints. The number of

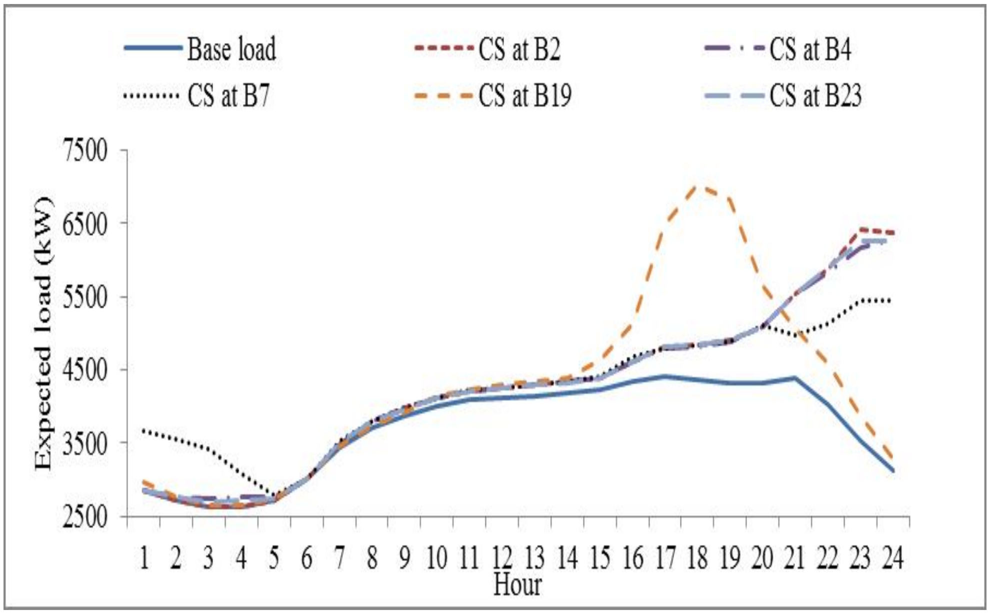

Figure 4.4: Expected load profile with EVCS installed at various buses

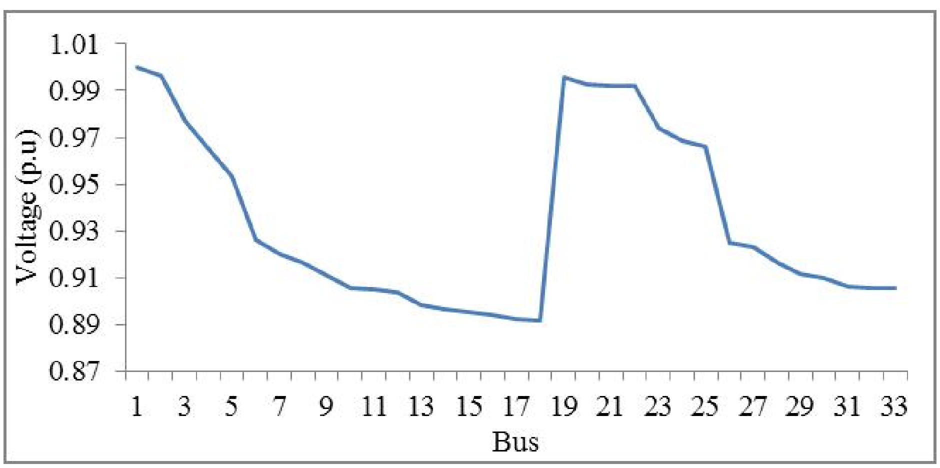

Figure 4.5: Expected voltage profile with EVCS at bus 6

chargers in the charging station should suffice all the PEVs. In the previous work, for home charging, Level 2 charging is assumed with maximum charging capacity of 4.8 kW, which would take approximately 3-4 hours to fully charge the 15.2 kWh battery, which is not realistic in the case of charging at the EVCS. In charging stations, it is recommended to consider fast charging for customers' convenience. Recently, many industries around the globe are focusing on fast charging of EVs and competitive products have been launched.

In references [43], [44], and [45], quick charging stations are proposed with various charging capacities. In [44], analyses of the need of fast charging station and design of a Level 3 three-phase off-board charging station with a power capacity of 10 kVA is presented. In [45], a DC fast charging station with 200 kW battery bank at a charging rate of 5C is proposed, which is enough to meet the overall PEV charging demand up to 1.1 MW. In [46], a detailed description of the range of charging capacities, various charging trades and standards are discussed. From the extensive study of these research works, Level 3 charging (200/600 V DC, 400 A) [47] with a charging capacity of 240 kW is assumed for the system under study.

There are 877 electric vehicles in the system, each with maximum battery capacity of 15.2 kWh, resulting in a total maximum energy demand of around 14 MWh. Since in reality, the probability of customers charging their vehicles during the evening time after their office work is high, it is required to plan the EVCS in such a way that it should be capable of supplying power during the peak hour as well. From the load flow analysis, it is found that at peak customer charging hour the demand can reach up to 3 MWh. So, to suffice this requirement, it is decided to install 16 chargers, each of capacity 240 kW at the EVCS at bus 6, so that it can supply up to 3.8 MW per hour.

4.5 Summary

In this chapter, an attempt was made to achieve optimal siting and sizing of the EVCS. Using the statistical analysis of PEV stochastic mobility characteristics, the charging demand and initial SOC was estimated. The revised initial SOC due to EVCS adoption was modeled. The model was modified to incorporate the changes in initial SOC, and PEV charging demand. A heuristic approach to find the optimal siting was introduced. The site with minimum feeder loss and minimum customer cost was selected to be as feasible locations. The charging load profile and the voltage profile at these selected locations were compared to choose the optimal site for EVCS. The optimal sizing of EVCS was presented.

Chapter 5

Conclusions and Future Work

5.1 Summary and Conclusions

Chapter 1 presented the primary motivations of this work. The need to develop PEV charging characteristics was discussed. The necessity of modeling the stochastic nature of PEV charging loads and developing appropriate models to investigate the impacts of PEV charging on the distribution system was highlighted. The chapter presented a literature review of related works, and the research objectives of this thesis were outlined.

In Chapter 2, the background of models and tools related to this work was presented briefly. The types of EVs, and their charging characteristics and battery capacities were discussed along with the mathematical formulations to estimate the SOC and energy required to recharge the battery. This chapter also presented a background to power distribution systems in general. The optimization problem solving methods and tools to solve were discussed.

In Chapter 3, a statistical analysis of PEV driving behavior was presented. An extensive study of the NHTS to model PEV charging loads for different seasons of the year was carried out. Using these uncontrolled PEV charging loads, a deterministic analysis was performed to investigate the impact on distribution system operations considering various types PEVs with different battery capacities and penetration levels. Further in this chapter, statistical analysis was carried out to capture the various uncertainties associated with PEV driving and their charging characteristics. Several scenarios in uncontrolled and controlled mode of charging were presented and a stochastic DOPF model was proposed considering various combinations of uncertainties associated with PEV charging. The PEV charging impact on distribution system operations and customer PEV charging cost was analyzed in various scenarios. A 33-bus radial, balanced, distribution system was considered for the studies. Smart charging strategies were further proposed with smart charging schedules resulting in flattening the load profile.

Chapter 4 proposed an approach to optimal siting and sizing of PEV charging stations within a distribution system. Modeling of the initial SOC considering the distance to the EVCS was presented and compared with initial SOC with home charging. The model was modified to incorporate the changes in initial SOC, and PEV charging demand. A heuristic approach to find the optimal siting was presented. The approach considers customer driving distance from home to the EVCS, cost incurred, feeder loss and the PEV charging load profile as the major decision factors in determining the optimal siting of EVCS. Sites resulting in minimum feeder loss and customer cost, was considered as few possible locations, and further, at these buses the PEV charging load profile and the bus voltage profile were compared to choose the optimal site for EVCS. The optimal sizing of EVCS was determined, which suffices the energy demand of all PEVs.

5.2 Contributions

The major contributions of this work are as follows:

- An extensive study of NHTS 2009 report was carried out to develop realistic PEV charging characteristics considering the driving patterns, home arrival time and miles driven in various seasons of the year and weekdays and weekends. Probability distribution functions of uncertain parameters associated with PEV mobility are also developed to model PEV charging loads.

- Deterministic studies pertaining to the impacts of PEV charging on distribution system operations were carried out considering various types PEVs with different battery capacities and penetration levels.

- A SDOPF model considering all possible combinations of uncertainties associated with PEV charging was proposed to study the impacts on feeder loss, peak demand and customer cost of PEV charging. Different uncontrolled and controlled charging scenarios are constructed and these provide information to the LDC to best prepare for the various scenarios of PEV charging. Smart charging schedules were proposed which result in flattening the load profile, and minimizing feeder loss. Also, a SDOPF model with minimization of customer PEV charging cost with peak demand constraints which results in reducing the peak demand and hence the feeder loss, was proposed.

- An approach to determine optimal siting and sizing of EVCS was proposed considering customer convenience, travel distance to EVCS, feeder loss, PEV charging load profile and bus voltage profile at EVCS as the major decision factors. The proposed heuristic approach considers stochastic nature of PEV charging.

5.3 Future Work

This research work could be extended further, and following are some of the ideas for future work:

- In this work, the case study is carried out considering a balanced distribution system, whereas, this work could be extended considering unbalanced distribution system.
- The impact of PEV charging loads on distribution system operations is investigated. However, using the NHTS, vehicle to grid (V2G) energy injections could be modeled and the impact on distribution system operations considering both V2G and grid to vehicle loads could be explored.
- In the approach of determining the optimal siting and sizing of EVCS, multiple objective functions such as, the minimization of infrastructure and maintenance cost of EVCS facilities, customer charging cost of PEVs and feeder loss could be considered.

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