Distribution System Planning in Smart Grids to Accommodate Distributed Energy Resources and Electric Vehicles

by

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A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Doctor of Philosophy
in
Electrical and Computer Engineering

Waterloo, Ontario, Canada, 2017

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Abstract

Major changes in planning paradigms have taken place in power systems in recent years because of deregulation of the power industry, environmental policy changes, advancements in technology, and the transformation of the grid to intelligent systems, referred to as the smart grid. These changes will continue to drive the distribution systems planning function to evolve in the coming years. It is therefore important to develop effective planning strategies to identify the qualities, capabilities, and attributes that are necessary for the future distribution grid.

Demand response (DR), distributed generation (DG), energy storage systems (ESS), and plug-in electric vehicles (PEV) are expected to be a part of the solution of these distribution system planning challenges. However, very little of the present research on distribution system planning have considered these options simultaneously. Moreover, traditional planning options such as substation expansion, new feeder connections and capacitor placements should also be simultaneously considered. Such a coordinated planning can help evaluate the alternatives to provide maximum benefits to the network owner and customers.

With the increase in gas prices driven by a foreseeable fossil fuel depletion in the future, development in the automotive sector, and environmental concerns, penetration of PEVs has been increasing in recent times. The charging load of PEVs will definitely impact the distribution grid. To mitigate these effects, the local distribution companies (LDCs) need to adopt the right actions and policies, and develop associated infrastructure.

In the current context of smart grids, the LDCs need to control PEV charging demand while also considering customer preferences, which can lead to benefits such as deferment of the decisions on reinforcement and other investments, and maximize the use of existing infrastructure. In addition, LDCs need to establish rate structures that incentivize the use of smart charging and increase the adoption and use of PEVs, which can benefit both the LDCs and the customer.

This research focuses on developing models to investigate and address the problem of distribution system planning in the presence of PEV charging loads. First, a comprehensive long-term distribution planning framework from the perspective of LDCs is proposed considering DG, substations, capacitors, and feeders. Apart from considering the usual demand profile, the proposed framework considers uncontrolled and controlled (smart) PEV charging demand, as well as DR options. Based on a back-propagation algorithm combined with cost-benefit analysis, a novel approach is proposed to determine the optimal upgrade plan, allocation, and sizing of the selected components in

distribution systems, to minimize the total capital and operating cost. A new iterative method is proposed which involves post-processing the plan decisions to guarantee acceptable adequacy levels for each year of the planning horizon.

Second, a generic and novel framework is proposed to assess the Distribution System Loading Margin (DSLM) to accommodate uncontrolled and smart PEV charging loads without the need for any additional investments or upgrades in the distribution system. The model determines what percentage of the fleet can be served by uncontrolled charging and smart charging, respectively. Monte Carlo simulation has been carried out to simulate the uncertainty of demand, drivers' behaviour, market share of PEV class, and charging level. The maximum allowable penetration of uncontrolled and smart charging loads are determined based on the current available market data pertaining to PEV type and charging level, considering different charging scenarios.

Finally, a PEV smart charging approach is proposed where the charging loads are incentivized by the LDC for every unit of energy controlled. A novel framework is proposed to determine the optimal participation of PEVs in the smart charging program and optimal incentives paid by the LDC to PEV customers, such that both parties are economically benefited. The proposed framework models the relationship between customers' participation and incentives offered by the LDC. The relationship between the expected investment deferral and hence the economic benefits from smart charging participation are considered as well. Monte Carlo simulation is carried out to simulate the uncertainty of demand, electricity market price, drivers' behaviour, PEV market share, and charging level.

Acknowledgements

First of all, I shall praise and thank Allah almighty for helping me through this difficult but very inspiring work and for providing me with the ideas and patience necessary for the successful completion of this thesis.

Then, I would like to express my sincere gratitude and appreciation to Professor Kankar Bhattacharya, for the invaluable guidance, continual support and encouragement which he provided throughout my graduate studies at the University of Waterloo. Prof. Bhattacharya's commitment with high quality research is an inspiration for pursuing excellence and success not only in academic endeavors but in every other aspect of life.

I would like to thank Prof. Ramadan El-Shatshat, Prof. Catherine Gebotys, and Prof. Tarek Hegazy for being in my Advisory Committee. Their careful reading and comments have significantly improved the quality of this thesis. I am also very thankful to Prof. Udaya Annakkage, from University of Manitoba, for serving as the external thesis examiner and for his insightful comments and observations. I would like also to thank Prof. Martin Ross for chairing my thesis examination committee.

Special thanks to Umm Al-Qura University, Makkah, Saudi Arabia, for the scholarship to pursue my graduate studies. I also would like to thank the Ministry of Education, Saudi Arabia, and the Saudi Arabian Cultural Bureau in Canada for their support.

I am truly indebted to my parents, my grand parents, my brothers, and my sisters for their endless support, encouragement, and prayers. I also extend my deepest appreciation to my dear brother Omar for his sincerity, friendship and encouragements during my academic journey.

I cannot express enough gratitude to my wife, Nada, for her constant support. Without her encouragements, this thesis would not be completed. For sure, my beautiful kids, Munirah, Noora, and Saleh have made me pursue my research more deeply, with their unconditional love, which helped me overcome the tough times that one faces at some points during research work.

Finally, I would like to thank all my friends at the University of Waterloo, who helped me through the course of my studies, discussed new ideas about my research, and made my life at Waterloo enjoyable.

Thank you all!

Dedication

To my father, my stepmother, my mother (May Allah be merciful to her), and my grand parents (May Allah be merciful to them)

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List of Abbreviations

AER	All Electric Range
BEV	Battery Electric Vehicle
DG	Distributed Generation
DOD	Depth of Discharge
DR	Demand Response
DSM	Demand-Side Management
FOR	Forced Outage Rate
HEV	Hybrid Electric Vehicles
LDC	Local Distribution Company
LOLE	Loss of Load Expectation
LOLP	Loss of Load Probability
OPF	Optimal Power Flow
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
RTS	Reliability Test System
SOC	State of Charge
TOU	Time of Use

Chapter 1

Introduction

1.1 Motivation

In the last decade, a major change in paradigm has taken place in power system planning because of deregulation of the power industry, policy changes driven by concerns on environmental emissions, advancement in technology including renewable energy generation, two-way communication between customer and utility, and the consequent transformation of the grid to a self-healing and intelligent system, referred to as smart grids. These changes have a significant bearing on the electrical distribution systems with increasing penetration of demand response (DR), distributed generation (DG), energy storage systems (ESS), and plug-in electric vehicles (PEV), together, known to as distributed energy resources (DERs), and proposed as part of the solution to today's energy and environmental challenges. Since DERs are mainly targeted at the distribution system level, design and planning issues at this level are key features for the development of the future distribution system.

DGs are expected to play an important role in the distribution system because of their numerous benefits. They can help in the deferral of system upgrades, such as large power plants and new transmission lines; and can also increase market competition, in generation, leading to better services and lower energy prices. DGs also help improve the reliability of the distribution system, improve voltage profiles, and reduce line losses and network congestion [1]. Moreover, renewable based DGs can bring about a reduction in fuel consumption and greenhouse gases. However, improper integration of DGs in the distribution system may lead to negative impacts such as poor voltage profiles, increased network losses and overloading of lines.

In recent years, penetration of DGs into distribution systems has been increasing around the world. For instance, in the United States, demand growth combined with plant retirements is projected to require as much as 1.7 million GWh of additional electrical energy by 2020, almost twice the growth of the last twenty years. Over the next decade, the DG market in USA, in terms of installed capacity, is estimated to be 5 to 6 GW per year. Worldwide forecasts show that energy consumption is expected to rise by 41 per cent from 2012 to 2035, largely due to demand growth in developing countries. The projected embedded and renewable DG capacity increase associated with the global market is conservatively estimated at 20 GW per year over the next decade [2].

In Canada, widespread integration of DG in the form of wind and solar energy has been initiated in recent years. As of 2014, Canada had over 5,130 wind turbines operating on 225 wind farms for a total installed capacity of 9,694 MW, compared with only 60 wind turbines, 8 wind farms and 23 MW in 1997. Since 2004, the average annual growth rate of installed capacity of solar thermal power in Canada has been 13.8%, and that of solar photovoltaic power during 2008-2014 period was marked by significant growth, reaching a capacity of 1,843 MW in 2014 [3]. Changes in provincial and federal policies, together with new technological developments suggest that wind and solar will very likely play an increasingly important role in the future.

Due to environmental concerns and fossil fuel resource depletion, the penetration of PEVs in the transportation sector is expected to increase in the future. Many countries have set PEV penetration goals to reduce emissions and achieve energy independence. As of 2015, over than one million electric cars has been sold around the world, compared with only a few hundreds in 2005 [4]. The Electric Vehicles Initiative (EVI) sets a global target of 20 million PEVs by 2020. The Paris Declaration on Electro-Mobility and Climate Change and Call to Action sets a global target of 100 million PEVs by 2030. In Ontario, Canada, the government has set a PEV goal of 5 % of all vehicle sale by 2020 and 12% by 2030 [5]. Electrifying the transportation sector will have a potential impact on distribution systems such as increased system peak load, increased losses, deterioration in voltage profile and change in load pattern. Given that distribution networks are not inherently designed to accommodate PEV charging loads, local distribution companies (LDCs) are required to accurately assess and quantify the maximum PEV penetration that distribution systems can accommodate and their impacts, to decide on the right actions and policies and develop associated infrastructure.

The transition toward the smart grid has been taking place in power systems, which has a significant impact on distribution grids. A smart distribution grid involves the use of information and communication technology, system automation technologies, demand-side management (DSM), integration of renewable energy sources (RES) based DG and

Distributed Generation, and accommodation of electric vehicle loads. Customers play an important role in smart grids by introducing flexibility in electricity usage, in particular PEV charging loads. Therefore, new modelling strategies, and optimization techniques need be adopted in order to evaluate and incorporate these technologies in the planning process.

So far, planning of distribution systems considering all these resources, namely, DGs, capacitors, feeders and transformers, and including PEV charging loads (both uncontrolled and smart) and DR mechanisms, has not been reported in the literature. Distribution system planning should therefore be carried out in such a way that the resultant plan provides a reliable and cost effective service to customers while satisfying constraints. Considering all these resources is an important requirement of the planning process that can impact the outcomes significantly. As a result, it is important to develop and implement effective planning strategies that properly addresses these issues.

There is also a need to assess and determine the maximum allowable PEV penetration that can be accommodated by a distribution system and what percentage of the fleet can be served by uncontrolled charging and smart charging, respectively, without the need for any additional investments or upgrades. To this effect, there is a need to develop an approach to estimate the uncontrolled charging load profile using vehicle mobility data and considering different charging scenarios and the uncertainties associated with drivers' behaviour (arrival time and mileage driven), PEV market share, and share of charging level.

In the context of smart grids, the LDCs can control PEV charging demand while also considering customer preferences; such smart charging has benefits by way of deferment of the decisions on reinforcement and other investments, and maximizing the use of existing distribution infrastructure. To encourage PEV owners adopt smart charging, the LDC can offer appropriate programs and/or incentives to PEV customers. However, an LDC managed smart charging program involves a business relationship between the two parties. Assuming rational behaviour of PEV customers, their participation in smart charging programs will depend on the incentive amount, higher the incentive, more PEV customers are likely to adopt smart charging, while from the LDC's viewpoint, high incentives result in increased financial burden to itself. Adoption of smart charging is beneficial to the LDC in the short-run, because of the flattening of the overall system load profile to reduce its demand charges; and in the long-run, when deferral costs of capacity additions are taken into account.

Therefore, there is a need to develop a generic framework to determine these inter-relationships between the LDC and PEV customers, while considering their own perspectives of system operations and economic returns from such a program. There is also a need to determine the optimal participation of PEV customers that would result in the optimal benefits to both parties; and what optimal incentive would drive such an optimal participation.

1.2 Literature Review

Distribution system planning problems have been extensively researched over the years. However, these problems have undergone a change in paradigm over the past decade because of the structural transition that utilities and LDCs have gone through, advancement in tools available to researchers, changes to distribution systems, advancement in technology, and changes in policy. Therefore, distribution system planning is becoming a very complex problem. In this section, a review of the problems addressed and mathematical modeling approaches to distribution system planning is classified into three major groups as follows:

- Traditional distribution system planning
- Distribution system planning in the presence of DG
- Planning for PEVs in distribution system

1.2.1 Traditional Distribution System Planning

A comprehensive review on distribution system planning is presented in [6] wherein the planning models have been classified based on their solution techniques into optimization models and heuristic algorithms. The optimization based planning models have been further classified, based on the duration of the plan, into single-stage models and multi-stage models.

Single-stage optimization models are considered static models where the load growth is forecasted for the terminal year of the plan horizon. Such models are classified into different categories based on the particular problem addressed:

- Individual Feeders Models: The objective of this class of models is the optimal design of individual feeders, which includes configuration, length, and capacity, [7, 8].

- System Feeder Models: In this class, the objective is to determine the optimal feeders routing such that the load points are served at minimum cost [9–11].

- Comprehensive Models: Substation and feeder plan decisions are optimized simultaneously in this class of models. In [12] an iterative two-stage model is used wherein, in the first stage, substation installation decisions are determined which are then used as an input to the second stage to determine the optimal feeders configurations. On the other hand, in [13], plan decisions involving new substation and feeder installation are optimized simultaneously.

Multi-stage optimization models are those where the distribution system plan is determined for the entire duration of the plan horizon. Such problems are solved either by treating the planning problem as a series of single-stage models or extending a single-stage model by adding binary and discrete selection variables and inter-temporal constraints. In the first case, each stage represents a step ahead of time, treating its output plan decisions as input to the proceeding stage. The optimal solution of each stage does not guarantee that the overall plan is optimal, since the stage does not consider the proceeding stage's input parameters. In the second case, the plan decisions for all years in the planning horizon are determined simultaneously.

Due to the large size of real distribution systems, practical life distribution planning problems can be computationally unmanageable or infeasible as the number of variables and constraints can be considerably large and very complex to solve. To overcome this problem, heuristic methods and algorithms have been proposed to simplify the planning problem into manageable and feasible ones by relaxing some constraints [14], dividing the planning problem into solvable phases or sub-problems [14–17], or transforming the dynamic optimization problem into a static one. However, there is no guarantee that the optimal solution of the simplified problem is an optimal solution for the main problem.

Driven by economic considerations, changes in policies and regulations, advancement in technology, and environmental concerns, the traditional planning strategies need be re-adjusted to include non-traditional options for capacity investment to address these issues. DG is one of the attractive alternative capacity options for distribution system planning.

1.2.2 Distribution System Planning in the Presence of DGs

In recent years, the integration of DG units in distribution systems has become increasingly important and the optimal DG allocation problem has attracted the interest of many researchers. Several strategies and models have been proposed to address the optimal DG sizing and siting problem. This section presents a modest attempt to survey the research literature related to DG allocation problems.

Various analytical models have been proposed for the DG allocation problem. The 2/3 rule, often used in capacitor planning studies, is proposed in [18] to allocate DG units in radial distribution systems with a uniformly distributed load. Although the model is simple and easy to implement, it is only applicable to radial systems with uniformly distributed loads. In [19], an analytical model is proposed to determine the optimal DG location in radial and networked systems by minimizing the power loss of the system.

Linear programming models have also been proposed to solve the DG allocation problem. A linear programming model in [20] is proposed to determine the optimal allocation of DG units, seeking to maximize the DG capacity. In [21], a model for planning and operation of non-firm output of DG units is proposed. Non-firm generation is the output of a DG unit that is greater than the granted allowable generation under the connection agreement between LDCs and perspective DG owners depending on the network constraint. The model aims to minimize the generators cost of non-firm access through coordinated operation.

The well-known ac optimal power flow (OPF) model is considered a powerful analysis tool in power systems. A number of models have been proposed to address the DG allocation problem using the nonlinear ac power flow. In [22], a deterministic planning model for optimal allocation of wind DG units is proposed, seeking to minimize the annual energy loss. A probabilistic model for generation and load are combined and incorporated in the deterministic planning model. The optimization model is a mixed integer non-linear programming (MINLP) model. A multi-period ac OPF model is proposed in [23] to determine the optimal DG accommodation while minimizing the system energy losses under smart grid operation. Smart control schemes such as coordinated voltage control and adaptive power factor control are considered in the proposed model.

An MINLP optimization model for determining the optimal location and number of DG units in hybrid electricity markets is proposed in [24]. Minimization of total fuel cost of conventional and DG sources and the line losses in the network comprise the objective function. The sensitivity of the results to the variation in the demand has been examined.

In the literature, heuristic techniques have also been proposed to address this problem. A genetic algorithm (GA) and e-constrained method is proposed in [25] to solve the multi-objective DG allocation problem. The cost of network expansion, cost of power losses, cost of unserved energy and cost of energy required to serve customers, comprise the multi-objective function.

In [26], a multi-objective mixed integer programming model is solved using GA to maximize the LDCs benefits and hence to optimally size and site DG units within the distribution network. The deferral of investment upgrades, reduction of the cost of energy losses, and reliability improvements comprise the objective function. A GA is used to solve the DG allocation problem in [27]. The proposed model considers a multi-objective function with different load models to examine the effect of these models on the location and size of DG.

All the previous mentioned publications have only focused on DG allocation problems without considering other distribution system components, such as expansion or addition of substations and feeders. The DG allocation and traditional planning are dependent on each other and should be considered in the planning process simultaneously which will provide maximum benefits to LDCs and customers.

In [28], a comprehensive optimization model combined with planners experience is proposed to optimally allocate DG units and also determine other traditional planning options such as expanding an existing substation, adding new feeders, or/and purchasing power from neighboring LDCs via an existing intertie. The objective function aims to minimize investment and operating costs of the planning alternatives, and cost of system losses. However, this model only considers the system peak load and dispatchable DG units in the planning problem. Additionally, by considering only a peak load scenario, technical issues, such as poor voltage profile, increased network losses, or overloading the lines, might appear in other load scenarios. Moreover, reliability of the system is not considered in the planning model.

Wong et al. [29], propose a comprehensive multi-year optimization framework for distribution planning including DG units in a deregulated environment. The objective function aims to minimize the economic cost (including investment and operation cost of expanding an existing substation, adding new feeders, adding an intertie, or/and building DG units, and CO2 emissions tax. However, this model does not consider the reactive power and its associated constraints in the planning problem. Another drawback is the inaccuracy of representing the reserve of the system by a fixed percent of the peak load.

A multi-objective optimization model is proposed in [30] for distribution system expansion planning which is solved using GA. The model considers topology changes such as the installation of new switches or reconfiguring the system with existing switches, new DG units installation, rewiring of specific lines, and addition of new load points as alternatives for expansion. The uncertainties related to DG power output and load response growth are considered through the use of multiple scenarios. The costs of reliability, losses, power imported from transmission, and network investments comprise the multi-objective function. However, the model does not consider substation expansion as an expansion alternative.

In [31], an MINLP problem is proposed for multi-year distribution system planning considering DG units (natural gas generators). The objective function aims to minimize the investment costs, the operation and maintenance costs, and the cost of power losses. A GA approach is used to determine the optimal DG locations and transformer installation decisions and their installation time as a first stage and then fed into an OPF model for finding their optimum capacities. However, the DG penetration limit is assumed to be a percentage of the total load. This assumption is inaccurate since it does not consider minimum load conditions which might violate some technical limits such as maximum reverse power flow limit and equipment rating limit. Moreover, feeder expansion capacity is not considered in the proposed model. Another drawback is the inaccuracy of representing the reserve of the system by a fixed percent of the peak load and ignoring system reliability.

An optimization model for allocating different renewable DG systems is proposed in [32]. The reactive power capability of renewable DGs and the uncertainty related to the load and intermittent generation are considered in the proposed model. The optimization model is an MINLP and solved using particle swarm and ordinal optimization, minimizing the total cost. However, the model does not consider planning over years. Moreover, substation and feeder capacity expansion are not considered as an alternative option in the proposed model.

A multi-objective optimization approach for long-term distribution system planning is proposed in [33]. The model considers DG allocation, network reconfiguration, and feeder upgrades as alternatives for expansion. The proposed model is formulated as an MINLP and solved using non-dominated sorting GA. Economic and environmental objectives are considered in the proposed model through the cost of line upgrades, energy losses, switching operations, DG capital, operation and maintenance costs, and emissions. However, substation upgrade is not considered in the planning model and representing the DG units output as in terms of a fixed capacity factor of the total installed capacity is not accurate. Moreover, reliability of the system is not considered in the planning model.

In [34, 35], a multistage optimization model for distribution system planning model is proposed. The model considers expansion of existing substations, installing new ones, allocating DG units, feeder addition, load transfer between feeders; and replacement of conductors. The costs of substation and feeder installations, costs of maintenance and operation of the network and DG units comprise the objective function. However, load variation impact and reliability enhancement are not considered in this work.

When system upgrades are essentially driven by the continuously increasing demand, capacitors can play a vital role in deferring the need for upgrades. They can improve voltage profiles, reduce feeder losses and network congestion by reducing the reactive power flows on the feeders. Coordination of capacitor and DG placement can therefore maximize the savings from loss reduction in distribution networks. Although, in the literature, there are several studies that consider the coordination of capacitors and DG placements [36–38], very few researchers have considered the comprehensive range of options such as capacitors, DGs, feeders and substations [39].

It is therefore important to investigate optimal DG placement with simultaneous placement of capacitors. Moreover, traditional planning options, such as substation and feeder addition or expansion should also be simultaneously considered which can provide maximum benefits to LDCs and customers.

1.2.3 Planning for PEVs in Distribution System

It is evident that the impact of PEV charging on the distribution grid will be significant as PEV penetration increases in the coming years. There is a large and growing body of literature that have been devoted to integrate PEVs into power system problems. The research topics mainly include impacts on distribution system operation [40–44], smart charging and discharging strategies [45–49], the interaction between PEV charging load and renewable resources [50–53]. In [54], a survey of PEV industry trends and impacts on distribution systems are presented.

A. Distribution System Planning in the Presence of PEVs

It is noted that most of the works have focussed on the impact of PEV charging loads on distribution system operations while only a few on planning [55–58]. In [55], a multi-objective planning model is presented to allocate PEV fast charging stations, substation, and feeders. While in [56], a multi-objective optimization model is proposed which considers the optimal PEV penetration, DG units and feeder upgrades in a distribution system.

In [57], a model for estimating the energy consumption of PEVs in the distribution network is presented. This model is utilized to optimally allocate DG units to mitigate the impact of high PEV penetration using a GA. While in [58], a model is presented to optimally allocate renewable DGs in the presense of PEV charging loads while minimizing the cost of capacity adequacy, network loss, and the cost of DGs' investment, operating, and maintenance. However, these models only focus on the DG allocation problem without considering other distribution system components, i.e., expansion or addition of substations and feeders.

B. Assessment of Distribution System to Accommodate PEVs

While most of the reported approaches have focussed on the impact of PEV charging loads on distribution system operations, a few studies have focused on assessing and determining whether the existing generation capacity would be sufficient for supplying the PEV charging loads. In [59,60], an optimization model is proposed for the transmission level to determine the maximum allowable penetration of PEVs in Ontario by 2025, without requiring the development of new infrastructure, considering overnight charging only. However, it is more important to assess and determine the maximum allowable PEV penetration that can be accommodated by a distribution system without the need for any additional investments or upgrades rather than assessing the system overall generation capacity.

In the context of distribution systems, an optimization model is proposed in [61] to determine the maximum penetration level of PEVs. The impact of three charging scenarios namely, uncontrolled charging, loss optimal, and price optimal, are considered to assess PEV accommodation in distribution systems. However, the uncertainty of different parameters such as drivers' behaviour, mileage driven, and demand have not been considered. In addition, PEV charging loads are expected to be a mix of controlled (smart) and uncontrolled charging, which is not considered [61].

So far, the assessment of Distribution System Loading Margin (DSLM) to accommodate PEV charging loads under a number of possible charging scenarios while considering both uncontrolled and smart charging, has not been reported in the literature.

C. Planning for PEV Smart Charging in Distribution Systems

The transition towards the smart grid has been taking place in power systems, which has a significant impact on distribution grids. A smart distribution grid involves the use of information and communication technology, system automation technologies, DSM, integration of RES and DG, and accommodation of PEV charging loads.

In the current context of smart grids, the LDCs can control PEV charging demand while also considering customer preferences. By planning for PEVs, LDCs can defer the decisions on reinforcement and other investments, and maximize the use of existing infrastructure. In addition, LDCs can establish rate structures that incentivize the use of smart charging and increase the adoption and use of PEVs. Therefore, electrifying the transport sector can benefit both the LDCs and the customer.

There is a growing body of literature on smart charging strategies of PEVs and their role in DR programs [42, 50–53, 62–69]. Studies have focused on PEV smart charging for frequency regulation [62, 63], load shaping [64], alleviating transformer overloads [65, 66], feeder congestion management [42, 67], distribution system reliability [70], and interaction between RES and PEV charging loads [50–53, 63, 68]. While other studies have examined the potential economic benefits of smart charging strategies [63, 69].

A number of studies have focused on incentive design to encourage PEV customers to participate in DR programs [71–75]. In [71], a smart charging algorithm is proposed where PEVs can inject power to the grid for frequency regulation or absorb power by utilizing renewable energy. In addition, an economic analysis is performed to evaluate the benefits of the proposed model. An incentive scheme is proposed in [72] for PEV battery exchange stations to participate in DR programs to reduce the peak to average ratio. In [73], an incentive mechanism is proposed to allow an LDC to schedule PEV charging on a day-to-day basis. An energy pricing scheme is proposed in [74] to control the PEV charging loads, where the longer a PEV customer is willing to defer its charging, the larger is its reduction in energy price. Real-time control of PEV charging loads is proposed in [75] by generating an incentive signal to PEV users in order to minimize the cost of electricity supply.

Utility managed smart charging programs involve a business relationship between the LDC or aggregator and the PEV customers. None of the reported works have considered this relationship in smart charging programs vis-a-vis the promotional incentives offered by the LDC. The optimal penetration of smart charging, arising from such inter-relationships and incentive mechanisms, from a long-term perspective, have not been investigated.

In addition to the need to determine optimal penetration of smart charging into distribution systems, there is also a need to examine the participation rate of customers in LDC smart charging programs.

1.3 Research Objectives

The main objectives of this research can be summarized as follows:

- Develop a comprehensive, multi-year, distribution planning framework that simultaneously determines the optimal sizing, placement and investment timelines of various resources for LDCs such as DGs, substations, capacitors and feeders, as well as ensuring an adequate and reliable distribution system in the long-term. In addition, the work considers PEV uncontrolled and smart charging loads as well as DR as a plan option to mitigate the growing impact of PEV charging loads.

- Develop a generic framework to assess the DSLM to accommodate PEV charging loads considering uncontrolled and smart charging without the need of any additional investments. In addition, using vehicle mobility data, develop an approach to estimate the uncontrolled PEV charging load profile while considering different charging scenarios, as well as the uncertainties associated with drivers' behaviour (arrival time and mileage driven), PEV market share, and share of charging level.

- Develop a generic framework to simultaneously determine the optimal participation of PEV customers in the smart charging program and the optimal incentives to be offered by the LDC, taking into consideration LDC-customer interactions and the distribution system operational aspects. The framework builds upon two aspects, the relationship between the incentives offered by the LDC and the participation of PEV customers; and the relationship between the participation of PEV customers and the long-term economic benefit of capacity deferral accrued from smart charging.

1.4 Thesis Outline

The remainder of this thesis is organized as follows:

Chapter 2 reviews the background of distribution systems, distribution system planning models, impact of DG on distribution systems, DG planning models, and PEV characteristics and their impacts on distribution system.

Chapter 3 presents the proposed distribution system planning model, the heuristic back-propagation approach, PEV charging load modelling, and results.

Chapter 4 presents a novel framework to assess the DSLM to accommodate PEV charging loads considering uncontrolled and smart charging under different charging scenarios, vehicle types, and charging levels.

Chapter 5 presents a generic and novel framework to assess the optimal participation of PEV smart charging and the optimal incentive paid to customers under different vehicle types, and charging levels.

In Chapter 6, summary and conclusions, main contributions, and directions for future research work.

Chapter 2

Background

2.1 Distribution Systems

The power system can mainly be divided into generation, transmission, sub-transmission and distribution. Traditionally, the generation systems task is to produce electricity, the transmission system is responsible for the delivery of power from generating stations to the sub-transmission system, at voltage levels of 230 kV or higher. Then, the sub-transmission system transmits the power at voltage levels between 69 kV - 138 kV to the distribution systems. Finally, the distribution systems deliver electricity to the customers at voltages typically under 34.5 kV [76]. Figure 2.1 illustrates a typical electricity supply system. The primary distribution system comprises of distribution substations and feeders. In the distribution substations, the voltage is stepped down from the sub-transmission system to between 34.5 kV and 4.16 kV. The main feeders in the primary distribution system branch out from the substation and then as lateral feeders to serve local areas. In secondary distribution system, the voltage is reduced to the customers level via distribution transformers, generally at 120/240 V and 480 V (Figure 2.2).

2.2 Distribution System Planning

Distribution system design and planning seeks the best expansion plan to provide reliable and economic services to meet the customers load demand in the long-term horizon considering the predicted load growth. In the recent years, distribution systems are

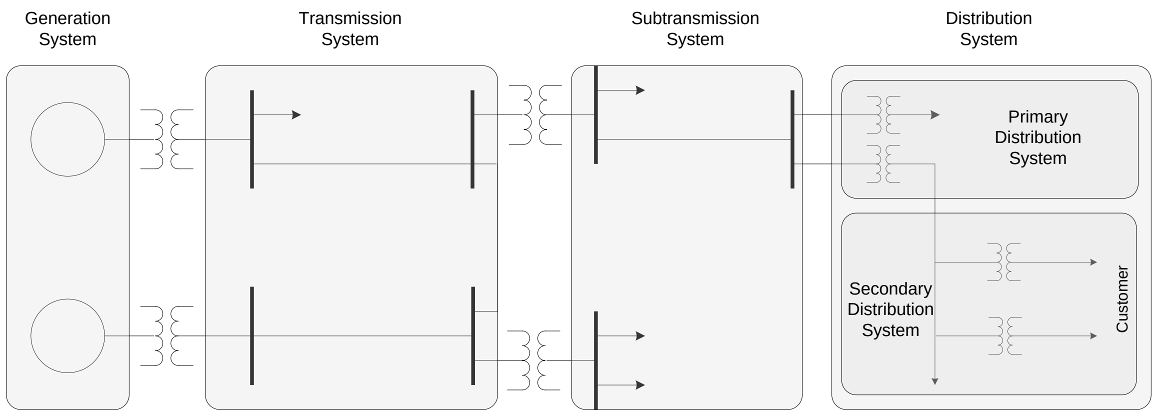


Fig. 2.1. Basic power system structure

undergoing a change in paradigm because of the transformation of the grid to a smart grid which is expected to drive distribution system planning in the coming years. In classical planning, the load growth typically is met by adding a new substation or upgrading the existing substation capacity along with their feeders. Today, with rapid penetration of DR, and DG, particularly intermittent sources such as wind and solar, ESS, and PEVs, it is important to develop effective planning strategies for the evolution of a smart distribution grid.

2.2.1 Traditional Distribution System Planning

Distribution system planning is essential to assure that the distribution network is capable to serve the growing electricity demand economically and reliably. In traditional planning, the load growth is typically met by adding a new substation or upgrading the existing substation capacity along with their feeders. Distribution system planners endeavor to determine the best expansion strategies to provide reliable and economic services to the customer. In the earlier years, the research focused on traditional planning problems such as the placement of substations and routing of feeders to minimize costs and losses to the LDC. Generally, traditional distribution system planning decisions can be classified according to the distribution system component, as follows:

- Substation: their selection can be based on multiple factors such as load growth, load density, and land availability; the planning problem determines the optimal new

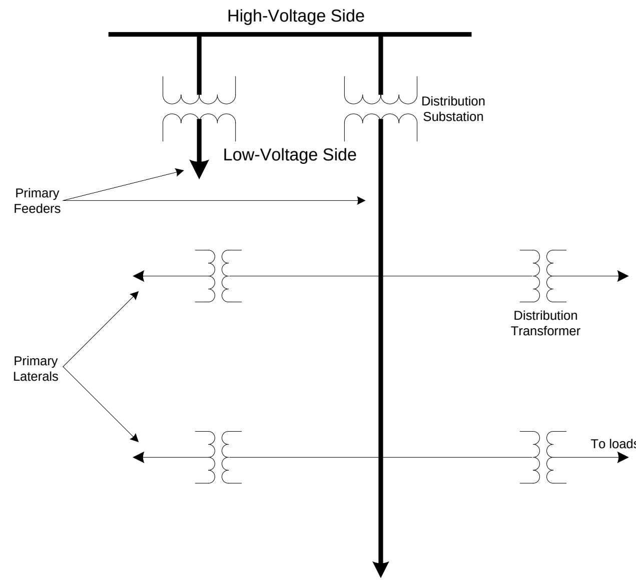


Fig. 2.2. Typical configuration of a radial distribution system

substation location and capacity, optimal expansion capacity for existing substation, or optimal mix of transformers.

- Feeders: the planning problem determines their optimal routing, optimal upgrade capacity, or optimal individual feeder design. These decisions are required in combination with a new substation installation, the expansion of existing one, or independently if there is sufficient capacity in the existing substation. The design of the feeder must comply with the system operational constraints.

- Optimal load allocation: this includes load shedding or/and load transfer between substations.

These plan decisions are affected and constrained by different factors, such as:

- Capacity constraints: includes substation transformers capacities, and feeders thermal limits

- Operating constraints: such as demand supply balance, power flow, and voltage limits.

- Budget constraints: this constraint imposes a limit on how much capacity the LDC can invest in, over the plan period by imposing a limit on capital expenditure.

Distribution system design and planning involves four major activities which starts with load forecasting, and are discussed below with reference to Figure 2.3.

- Load Forecast: A detailed spatial future demand is forecasted. The inputs to this task includes population growth, load density, historical data, city plans, alternative energy sources, etc.
- Performance Check: Using the outcomes from the first step, performance analysis is carried out considering the LDCs policies and obligations to customers and involves tests for service continuity, voltage drop, maximum peak load capacity, reliability, power losses, etc. These analyses requires the use of tools such as load flow, voltage drop calculation, short circuit and fault calculation, etc. Based on the performance results, the planner determines whether the existing system is capable of handling the forecasted demand.
- Substation Planning: It starts with the identification of all possible alternatives ranging from improving an existing substation to build a new substation. Size of the substation, number of transformers, and their siting are determined for each alternative. After that, an evaluation of all the alternatives is carried out in order to find the best alternative that meets all the technical constraints at minimum cost.
- Feeder Planning: Once the substation decision is obtained, feeder planning involves feeder route selection, optimal number of feeders, and conductor sizing followed by calculating the total cost of the candidate plan and determining whether the plan total cost is within the budget. If it is accepted, then the final plan is obtained. If not, the planner has to select the second best alternative and repeat the same procedure. The total cost must contain all components such as equipment and site costs, maintenance and operation costs, cost of loss, and taxes.

2.2.2 Distribution System Planning in the Presence of DGs

Till now, there is no universal agreement regarding the definition of a DG. The general definition for DG commonly used in the literature is:

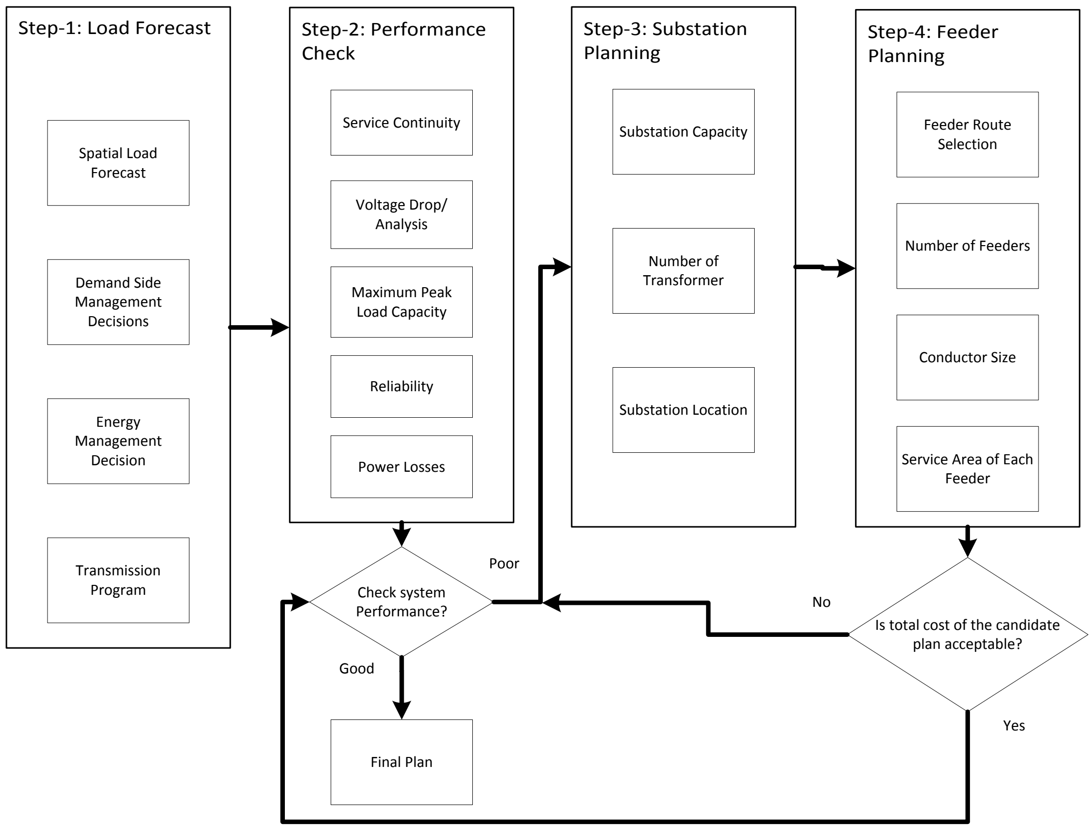


Fig. 2.3. Traditional distribution planning framework

Electric power generation within distribution networks or on the customer side of the network [1].

DGs can be classified based on their size [1]. The DG unit capacity ranges from 1 kW solar PV cells to 1 MW engine generators to 1000 MW offshore wind farms [77]. Typically, the classification is as follows:

- Micro DG: 1 W - 5 kW
- Small DG: 5 kW - 5 MW
- Medium DG: 5 MW - 50 MW
- Large DG: 50 MW - 300 MW

DGs have multifarious benefits on the distribution network when installed properly. DG units based on renewables can reduce environmental emissions. DG units can also have a beneficial impact on power quality and reliability such as improved voltage profile, reduced line losses and network congestion [78]. These can also help in the deferral of new transmission lines and large power plants, reduce system operating costs with increased penetration of renewable energy and increased overall efficiency. DGs also have the potential to increase competition in generation which can lead to better service and lower energy price.

Distribution systems were not planned originally to accommodate DG units, therefore these sources have to be carefully sited with appropriately sized. Improper integration of DG sources may have negative impacts on distribution systems such as line overloading, increased power loss, overvoltage, and increased short circuit current levels. In addition, the nature of renewable DGs and the uncertainty related to their output adds more complexity and challenges to the planning problem.

Over the last decade, the integration of DG units in distribution systems has become increasingly important. Therefore, the optimal DG allocation problem has attracted the interest of many research efforts. Several strategies and models have been proposed to address the DG allocation problem. Generally DG planning can be considered a single or multi-objective planning problem; the more commonly used objectives, decision variables, and related constraints are listed in Table 2.1 [78]:

TABLE 2.1 Objectives, decision variables, and constraints for DG planning problems

Objective function	Decision variables	Constraints
System loss minimization	DG Location	Discrete size of DG units
Voltage limit loadability maximization	DG Size	Short-circuit level limit
Cost minimization	Type of DG technology	Limited buses for DG installation
Voltage deviations minimization	Number of DG units	Power generation limits
DG penetration maximization		Budget limit
Profit maximization		DG with constant power factor
Benefit/cost ratio maximization		DG penetration limit
System average interruption duration index (SAIDI) minimization		Total harmonic voltage distortion limit
		Maximum number of DG units
		Reliability constraints, e.g., max SAIDI

2.2.3 Supply Adequacy of Distribution Systems

Power system reliability can be defined as the ability of a generation system to adequately and securely supply electrical energy to its end-customers. Power system reliability analysis involves system adequacy and security. Adequacy generally refers to ensuring sufficient supply capacity in the system to meet the demand considering long-term load growth, generator outage rates and maintenance schedules. Security is the ability of the system to respond to short-term disturbances such as the unexpected loss of a major generating plant. Generally, adequacy assessment is carried out considering system steady-state conditions, whereas security evaluation considers the system dynamics during disturbances [79]. In this thesis, reliability assessment of the distribution system is limited to adequacy assessment; hence, the terms reliability and adequacy are used interchangeably.

At the planning stage, it is necessary to determine the amount of supply capacity that need to be installed to satisfy the predicted electricity demand. The main criteria for supply adequacy assessment for power systems is presented below [79, 80].

A. Deterministic Techniques

Deterministic techniques for adequacy assessment were first developed and used by many power utilities to determine the required generating capacity. These techniques seek the optimal installed supply capacity considering a fixed percentage reserve such as a fixed reserve equal to the largest generating unit, a fixed percentage of the total installed capacity or the peak load, or a mix of these. The main drawback of these techniques is that they are unable to respond to the actual stochastic nature of power systems that result from customer demand fluctuations or component failures [79].

B. Probabilistic Techniques

The probabilistic criteria considers the stochastic nature of power systems that result from customer demand fluctuations or component failures to evaluate the system risk state [81]. Two main probabilistic approaches exist for evaluating the reliability of power systems; analytical and simulation based, often known as Monte Carlo simulation (MCS). The analytical approach uses a mathematical model to represent system elements and their outage rates to evaluate system reliability indices. The MCS technique, on the other hand, estimates reliability indices by simulating the actual process and random behavior of the system. Each category of methods have their advantages and disadvantages, so the appropriate method is chosen based primarily on the type of evaluation desired and the nature of the problem.

Evaluating the adequacy of a distribution system is achieved by examining its main components; the supply side and the load model. The two models are then combined to evaluate and obtain the reliability indices (Figure 2.4).

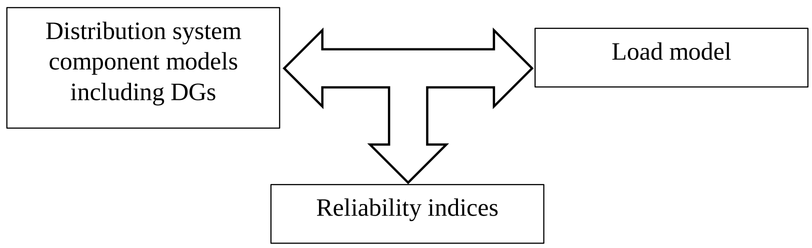


Fig. 2.4. Framework for adequacy assessment in distribution system

1. Supply Side (DGs and Substation) Model in Probabilistic Methods

   A DG or substation transformer is represented by a two-state model (fully rated state or failed state) [79]. The forced outage rate (FOR) is the probability of finding the DG or the substation transformer in an outage state and is measured by their unavailability (U). Usually, FOR is calculated based on the historical outage data of these components, if the failure rate and the repair rate are known, FOR can be calculated as follows.

   $$FOR = U = \frac{\sum T_{down}}{\sum T_{up} + \sum T_{down}} = \frac{\lambda}{\lambda + \mu} \tag{2.1}$$

   The basic outage characteristic used in the probabilistic techniques is a Capacity Outage Probability Table (COPT). The COPT is represented by an array of capacity levels with their associated probabilities of not serving the load.

2. Load Model in Probabilistic Methods

   The load model is a representation of the systems energy demand over a specific period of time [79]. A variety of load models have been utilized for evaluating the adequacy of the supply side capacity. The simplest load model considers the peak load of the system as, fixed, for the entire study period. The hourly peak load variation curve, or the load duration curve is frequently used to represent the actual load model. It is created by arranging the individual hourly peak loads in descending order.

3. Reliability Evaluation Indices

   Power system reliability is usually assessed by indices that measure the reliability and adequacy. These indices include Loss of Load Probability (LOLP), and Loss of Load Expectation (LOLE) [80].

   LOLP: is the probability that the load will exceed the available generation.

   LOLE: is the expected average number of hours during which the load is expected to exceed the existing generating capacity, as given below:

$$LOLE = \sum_{k}^{n} t_k p_k \qquad (L > C) \tag{2.2}$$

   where

   n : number of capacity outage states in the COPT

   p_k : probability of capacity outage

   t_k : time duration for which the loss of load will occur due to capacity outage

   L : load level

   C : capacity outage states in COPT

2.2.4 Demand Response

Demand response is one of the various options within the broad scope of demand side management. It is the determination of programs to manage the customer load demands and achieve least-cost system operation [82]. DR programs are classified into two broad types, incentive-based programs and time-based programs.

Incentive-based programs

In these types, customers provide load reductions when needed and receive incentives or direct payments. Generally, there are five subtypes of incentive-based programs, as follow:

- *Direct load control:* Operating and managing end-use devices, such as air-conditioning, pool pumps, or PEV charging. This type is considered one of the most common used programs. Typically, residential and small commercial customers are targeted in this type of program.

- *Demand buyback:* Customers choose to curtail upon request for event. Commercial and industrial customers are targeted in this type of programs.

- *Demand bidding:* Customers bid load reduction into utility or market on advance basis. This type is considered a variation of demand buyback program.

- *Interruptible rate:* discounted rate or credits for large industrial or commercial users that are willing to curtail operations. This type of programs is attractive to customers that have the ability to temporarily reduce, shut down, or shift their loads.

- *Ancillary-services market:* Customers, in this program, receive payment for agreeing to fast response to reduce load when requests.

Time-Based Programs

In these types, electricity prices are set for a specific time period on a forward basis. To apply time-based programs, there is a need for an advanced meters to records reads in time steps. Generally, there are three subtypes of time-based programs, as follow:

- *Time-of-use pricing:* Prices set for a specific time period on a forward basis. Based on the expected average real-time prices, TOU prices are set for each part of the day.

- *Critical peak pricing:* Established time-of-use prices in effect except for critical peak load days or hours, on which a critical peak price is in effect.

- *Real-time pricing:* In this type, electricity prices vary based on the market. The prices are changing every hour based on the real-time system conditions.

2.3 Plug-in Electric Vehicles (PEVs)

Fossil fuel depletion and environmental concerns, are factors leading to electrifying the transportation sector through PEVs. The PEV, as defined by IEEE, has a battery storage system of 4 kWh or more, a means of recharging the battery from an external source, and the ability to drive at least 10 miles in all electric mode [83]. These vehicles will have a significant impact on the existing power systems.

Electric vehicles can be classified into three main classes [84]:

- Battery Electric Vehicles (BEV)

  BEVs use batteries to store the energy that will be transformed into mechanical power by electric motor(s) only, without the use of internal combustion engine (ICE). The battery is the only source of energy which as recharged from the grid.

- Hybrid Electric Vehicles (HEV)

  In HEVs, propulsion is the result of two energy sources where it combined actions of electric motor, battery and ICE. The battery is recharged by utilizing vehicle's kinetic energy lost while braking.

- Plug-in Hybrid Electric Vehicles (PHEV)

  PHEVs are essentially a combination of BEV and HEV, having the all-electric capability of a BEV in urban areas and a smaller onboard ICE for extended range capability as an HEV. PHEVs utilizes the battery energy during a trip until the battery gets depleted and then it switches to the ICE as the main energy source. The battery can be recharged from the grid.

It is to be noted that PEV is a general term for vehicles that is recharged from the electricity grid which includes BEV and PHEV. In this thesis, only BEV and PHEV are considered since their batteries are recharged from the grid which will have a potential impact to the electricity grid.

2.3.1 PEV Load Characteristics

The impact of PEVs, represented by a significant new load in the distribution network, should be considered in the planning process. The main parameters that defines PEV load is discussed below [54]:

- Driving patterns:

  Driving patterns or the behavior of PEV owners is an important factor that determines where, and how many PEVs will be charged.

- Charging characteristics:

  Charging characteristics determines the amount of load added to the base load and the total duration of the charge. The battery capacity, the state-of-charge (SOC), charging level, miles driven and charging efficiency are the main parameters that define PEV charging characteristics.

- Time of charge:

  Another important parameter to consider is when vehicles will be recharged. The timing of charge should consider the season of the year, type of day, i.e., weekdays, weekend, or holiday, and the time of the day.

- Penetration level of PEVs:

  The penetration level is an important factor that may have a significant impact on the distribution system demand. Based on realistic statistics, customers acceptance, government and vehicle manufacturer trends, policies and regulations, the market share and the penetration level of PEVs need be determined for the studied area.

2.4 Charging level

The SAE J1772 standards defines two residential charging levels (Level-1 and Level-2) with a third ac level and a dc level for PEVs [54], as presented in Table 2.2.

TABLE 2.2 PEV Charging Level Characteristics

Type	Power Level
Level 1: 120 VAC	1.2 - 2.0 kW
Level 2 (low): 208-240 VAC	2.8 - 3.8 kW
Level 2: (high): 208-240 VAC	6 - 15 kW
Level 3: 208-240 VAC	>15 kW-96kW
Level 3: DC Charging: 600VDC	>15kW-240kW

2.5 Concluding Remarks

In this chapter, three topics have been briefly discussed: distribution systems, distributed system planning, and PEVs. In the first section, a brief background of distribution system is presented. In the second section, traditional distribution system planning, and distribution system planning in the presence of DERs and DGs are discussed. This section also includes a discussion on supply adequacy of distribution systems and demand response. Thereafter, a discussion on PEV types, mode of operations and PEV load characteristics is presented.

Chapter 3

Distribution System Planning to Accommodate Distributed Energy Resources and PEVs[1]

3.1 Introduction

With deregulation of the power industry, environmental policy changes, advancements in technology, and the transformation to smart grid, the distribution planning paradigm has gone through significant changes in recent years. Concurrently, with increase in gas prices, driven by a foreseeable fossil fuel depletion in the future, developments in the automotive sector, and environmental concerns, penetration of PEVs has been increasing. These changes will continue to drive the distribution planning problem to evolve in the coming years.

This chapter presents a comprehensive long-term distribution planning framework from the perspective of LDCs considering DG, substations, capacitors, and feeders.

[1]This chapter has been published in: A. Bin Humayd, and K. Bhattacharya. "Distribution system planning to accommodate distributed energy resources and PEVs." Electric Power Systems Research, 145 (2017),1-11.
Earlier versions of the work has been published in: A. Bin Humayd, and K. Bhattacharya. "Comprehensive multi-year distribution system planning using back-propagation approach." IET Generation, Transmission and Distribution, 7(12), 1415-1425.
A. Bin Humayd, and K. Bhattacharya. "Impact of PEV penetration on distribution system planning considering time-of-use electricity prices." IEEE PES General Meeting, 2014, National Harbor, MD (Washington, DC Metro Area).

Apart from considering the usual demand profile, the proposed framework considers uncontrolled and controlled (smart) PEV charging demand, as well as DR options. Based on a back-propagation algorithm combined with cost-benefit analysis, a novel approach is proposed to determine the optimal upgrade plan, allocation, and sizing of the selected components in distribution systems, to minimize the total capital and operating cost. A new iterative method is proposed which involves post-processing the plan decisions to guarantee acceptable adequacy levels for each year of the planning horizon. The performance of the proposed framework is examined considering several case studies on the 33-bus and 69-bus test systems.

The structure of the chapter is as follows. The nomenclature used in this chapter is presented in Section-2.7. In Section-2.9, the mathematical model of the proposed multi-year planning problem is presented and this is followed by a description of the proposed solution approach in Section-2.10. In Section-2.11, the two test systems considered for analysis are described and the results are presented in Section-2.12. Conclusions are drawn in Section-4.6.

3.2 Nomenclature

Indices

b	Index for load block, $b = 1, 2, ..B$
i, j	Index for buses, $i = 1, 2, ..N$
N	Total number of system buses
SS	Subset of substation buses ($SS \in i$)
t	Index for year, $t = 1, 2, ..T$

Parameters

BL	Budget limit, \$
C^{C}	Capital cost of capacitor, \$/p.u.
$C^{DG.F}$	Capital cost of DG unit, \$/p.u.
$C^{DG.O}$	Operating cost of DG units, \$/ p.u.
C^{DR}	Payment toward responsive demand, \$/ p.u.

$C^{Fdr.F}, C^{Fdr.V}$	Fixed and variable component of capital cost of feeder, \$ and \$/ p.u.
$C^{SS.F}, C^{SS.V}$	Fixed and variable component of capital cost of substation, \$ and \$/ p.u.
C^{UN}	Cost of unserved energy, \$/ p.u.
CBL	Capacitor budget limit,\$
DG^{CapMax}	Maximum allowable DG capacity, p.u.
DG^{NMax}	Maximum number of installed DG units
E	Energy needed to charge a PEV, p.u.
$Ge_{i,j}$	Geographic cost factor of feeder i-j, \$
Hr_b	Hours per day in load block b
$Le_{i,j}$	Length of feeder between i and j, km
M	Big number used in MIP modelling
NH_i	Total number of houses at bus i
$P^{PEV_{Cap}}$	Maximum allowable power drawn by PEV during charging, p.u.
$P_{i,j,b}^{Fdr}, Q_{i,j,b}^{Fdr}$	Active and reactive power flow from i to j, p.u.
$P_{i,b}^{PEV_{UNC}}$	Power drawn by PEV in uncontrolled mode, p.u.
$Pd_{i,b}, Qd_{i,b}$	Active and reactive power demand, p.u.
$PEV^{\%_{pen}}$	The percentage of PEV penetration
$Q^{C_{Max}}$	Maximum capacitor size, p.u.
$S_{i,j}^{Fdr_{Cap}}$	Existing feeder capacity, p.u.
$S^{SS_{Cap}}, P^{SS_{Cap}}$	Existing substation capacity, p.u.
V^{Min}, V^{Max}	Minimum and maximum allowble voltage, p.u.
$Y_{i,j}$	Magnitude of admittance matrix element, p.u.
γ	Capacity reserve margin with respect to Base Case peak load
$\theta_{i,j}$	Angle of bus admittance matrix element, rad
ρ_b	Electricity market price, \$/ p.u.
α_0	Share of demand that is available for DR, p.u.

Variables

$P_i^{DG_{Cap}}$	Capacity of DG unit, p.u.
$P_{i,b}^{DG}$	Power generated from DG unit, p.u.
$P_{i,b}^{DR}$	Power contributed by DR participants, p.u.
$P_{i,j,b}^{Fdr}, Q_{i,j,b}^{Fdr}$	Active and reactive power flow from i to j, p.u.
$P_{i,b}^{PEV_S}$	Power drawn by PEV in smart mode, p.u.
$P_{i,b}, Q_{i,b}$	Real and reactive power imported by LDC via substation, p.u.
$P_{i,b}^{UN}$	Unserved power at bus i and load block b, p.u.

$Q_i^{C_{Cap}}$	Capacity of shunt capacitor, p.u.
$Q_{i,b}^{C}$	Reactive power injected by capacitor i, p.u.
$S_{i,j}^{NFdr}$	Capacity added to feeder i - j, p.u.
$S_{ss}^{NSS}, P_{ss}^{NSS}$	Capacity added to substation, p.u.
$S_{ss,b}$	Apparent power imported via substation, p.u.
$S_{i,b}^{UN}$	Unserved apparent power, p.u.
$V_{i,b}$	Voltage magnitude at bus i and load block b, p.u.
z_i^{DG}	Binary decision on DG investment, (0/1)
$z_{i,j}^{Fdr}$	Binary decision on feeder upgrade, (0/1)
z_{ss}^{SS}	Binary decision on substation upgrade, (0/1)
$\theta_{i,j,b}^{Fdr}$	Power angle of the flow from i to j, rad
$\theta_{ss,b}^{SS}$	Power angle of the power imported by substation, rad
$\delta_{i,b}$	Voltage phase angle at bus i and load block b, rad

3.3 Proposed Framework For Distribution System Planning

Fig. 2.5 presents the overall schematic of the proposed framework for multi-year distribution system planning which comprises two main levels. The proposed approach is based on a back-propagation algorithm starting from the terminal year and arriving at the first year. The proposed approach uses a bi-level procedure as described next. In Level-1 (ADEQ-OPTSELECT), the determination of the optimal size and location of distribution system upgrades that are required to be in place, at the plan terminal year, as well as, an appropriate reserve margin (γ). While in Level-2 (ADEQ-OPTPERIOD), determination of the optimal period of commissioning, for the upgrades selected in Level-1.

A back-propagation of model solution, starting from the plan terminal and ending at the first year, is proposed. Within this framework, Two mathematical models are proposed, namely Smart-DSPLAN and Smart-DSPLAN2, in level-1 and 2 respectively. In addition, Benefit-to-Cost Ratio (BCR) and a novel adequacy check are introduced that involves post-processing the plan decisions at both the levels to ensure that plan is beneficial and the target plan adequacy level is satisfied for each year.

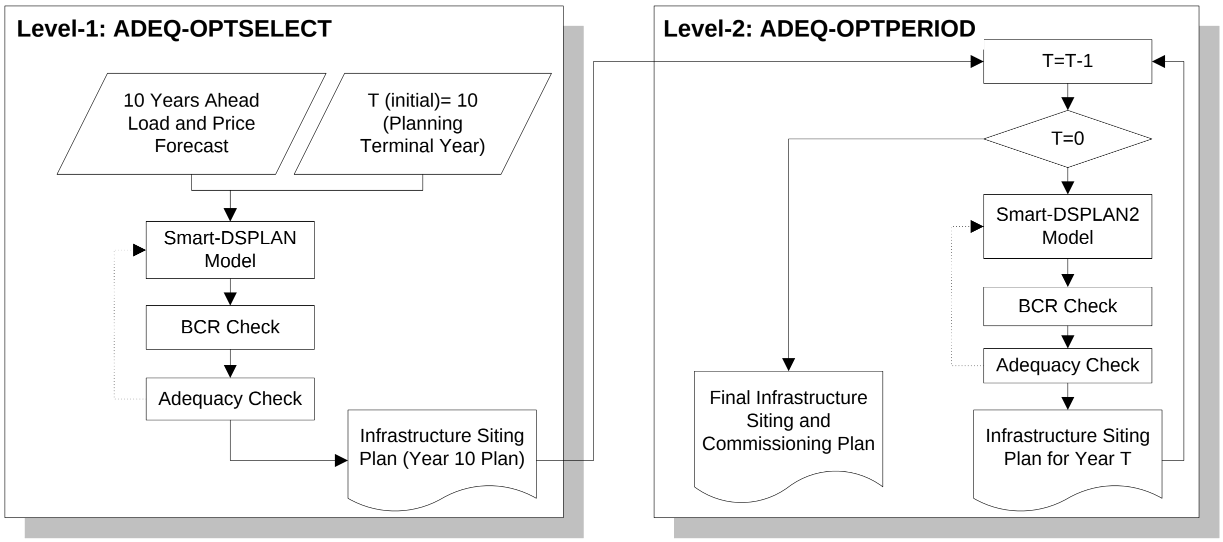


Fig. 3.1. Proposed framework

3.4 Smart Distribution System Planning Model

3.4.1 Smart-DSPLAN

The first proposed generic mathematical model for long-term distribution planning, considering the comprehensive set of decisions and issues discussed earlier, is referred to as, Smart-DSPLAN, and is presented below.

Objective Function

The objective function (J) aims to minimize the annualized cost of capital and operation of the LDC.

$$
\begin{aligned}
J = &\sum_{i \in N} \Big(C^{DG.F} P_i^{DG_{Cap}} + \sum_{b \in B} (C^{DG.O} P_{i,b}^{DG} Hr_b) \Big) \\
&+ \sum_{i \in SS} \Big(C^{SS.F} z_i^{SS} + C^{SS.V} S_i^{NSS} + \sum_{b \in B} (\rho_b P_{i,b} Hr_b) \Big) \\
&+ \sum_{i,j \in N : \exists (i,j)} \Big(C^{Fdr.F} Ge_{i,j} Le_{i,j} z_{i,j}^{Fdr} + C^{Fdr.V} S_{i,j}^{NFdr} \Big) \\
&+ \sum_{i \in N} \Big(C^C Q_i^{C_{Cap}} \Big) + \sum_{i \in N, b \in B} \Big(C^{DR} P_{i,b}^{DR} Hr_b \Big)
\end{aligned} \tag{3.1}
$$

The first line of (2.3) includes the capital and operating cost of the candidate DG units. The second line includes the engineering, procurement, and construction (EPC) cost and the variable component of the capital cost to upgrade the substation, and payment toward purchased power by the LDC. The third line represents the EPC cost, and the variable component of the capital cost to upgrade the feeders, the last line denotes the capital cost of candidate capacitors, and the payment made by the LDC to DR customers. The associated operational and planning constraints are discussed next.

Power Flow Equations

The injected power at a bus is the power from the substation and DG units, net of the load, uncontrolled and smart PEV charging loads, and DR; and is governed by the traditional ac power flow equations:

$$
P_{i,b} + P_{i,b}^{DG} - P_{i,b}^{PEV_S} - Pd_{i,b} + P_{i,b}^{DR} = \sum_{j \in N} V_{i,b} V_{j,b} Y_{i,j} cos(\theta_{i,j} + \delta_{j,b} - \delta_{i,b}) \qquad \forall i, b \tag{3.2}
$$

$$
Q_{i,b} + Q_{i,b}^{C} - Qd_{i,b} = - \sum_{j \in N} V_{i,b} V_{j,b} Y_{i,j} sin(\theta_{i,j} + \delta_{j,b} - \delta_{i,b}) \qquad \forall i, b \tag{3.3}
$$

Feeder Capacity Limits

Power flow through any distribution feeder must comply with the thermal capacity of the feeder. This limit also takes into consideration the new investments in feeder upgrades.

$$
\begin{aligned}
-V_{i,b}^2 Y_{i,j} cos\theta_{i,j} + V_{i,b} V_{j,b} Y_{i,j} cos(\theta_{i,j} + \delta_{j,b} - \delta_{i,b}) \leq \\
(S_{i,j}^{Fdr_{Cap}} + S_{i,j}^{NFdr}) \cos\theta_{i,j,b}^{Fdr} \qquad \forall (i,j) \in N : \exists (i,j), \forall b
\end{aligned} \tag{3.4}
$$

$$V_{i,b}^2 Y_{i,j} sin\theta_{i,j} - V_{i,b} V_{j,b} Y_{i,j} sin(\theta_{i,j} + \delta_{j,b} - \delta_{i,b}) \leq \\ (S_{i,j}^{Fdr_{Cap}} + S_{i,j}^{NFdr}) \sin\theta_{i,j,b}^{Fdr} \qquad \forall (i,j) \in N : \exists (i,j), \forall b \tag{3.5}$$

$$S_{i,j,b}^{NFdr} \leq M z_{i,j}^{Fdr} \qquad \forall (i,j) \in N : \exists (i,j), \forall b \tag{3.6}$$

In (2.8), M is a sufficiently large number often called the "big M", which renders the constraint (2.8) nonbinding. When $z_{i,j}^{Fdr} = 0$, $S_{i,j}^{NFdr}$ is zero while when $z_{i,j}^{Fdr} \neq 0$, the large value of M allows sufficient room for selection of new feeder capacity, and the value of M ensures that (2.8) is satisfied. The binary variables $z_{i,j}^{Fdr}$ act as a "switch" on the continuous constraints, appearing with a large number greater than or equal to the maximum allowable feeder upgrade capacity.

Substation Capacity Limits

These constraints ensure that the total power delivered by the substation transformer is within the substation capacity limit. These limits take into consideration new investments in substation upgrades.

$$Q_{ss,b} \leq (S^{SS_{Cap}} + S_{ss}^{NSS}) sin(\theta_{ss,b}^{SS}) \qquad \forall b \tag{3.7}$$

$$P_{ss,b} \leq (S^{SS_{Cap}} + S_{ss}^{NSS}) cos(\theta_{ss,b}^{SS}) \qquad \forall b \tag{3.8}$$

$$S_{ss}^{NSS} \leq M z_{ss}^{SS} \tag{3.9}$$

DG Capacity Limits

The power generated by a DG unit is limited by the DG capacity (2.12). The installed capacity of DG is limited by the maximum allowable DG size (2.13). Constraint (2.14) limits the number of allowable DG units. The maximum DG penetration is limited by the minimum load (including PEV charging load) plus 60% of maximum substation rating in order to limit the maximum reverse power flow over the transformer, as given in (2.15) [85].

$$P_{i,b}^{DG} \leq P_i^{DG_{Cap}} \qquad \forall i, b \tag{3.10}$$

$$P_i^{DG_{Cap}} \leq DG^{CapMax} z_i^{DG} \qquad \forall i \tag{3.11}$$

$$\sum_{i \in N} z_i^{DG} \leq DG^{NMax} \tag{3.12}$$

$$\sum_{i \in N} P_{i,b}^{DG} \leq \sum_{i \in N} (Pd_{i,b} + P_{i,b}^{PEV}) + 0.6P_{i,b} \qquad \forall b \tag{3.13}$$

Capacitor Limits

These constraints ensure that the installed capacitor size is limited by a specified maximum allowable capacitor size (2.16). The reactive power injected by a capacitor must be less than the installed capacity (2.17).

$$Q_i^{C_{Cap}} \leq Q^{C_{Max}} \qquad \forall i \tag{3.14}$$

$$Q_{i,b}^{C} \leq Q_i^{C_{Cap}} \qquad \forall i, b \tag{3.15}$$

PEV Smart Charging Constraints

These constraints determine the optimal PEV charging schedule by ensuring that the total energy required by PEVs is equal to their daily energy needed to charge the battery (E); and the power drawn by PEVs is within the charging level. It is to be noted that E is calculated based on the average mileage driven by a vehicle as determined from the National Household Travel Survey data (NHTS) [86].

$$\sum_{b \in B} P_{i,b}^{PEV} = NH_i \cdot E \cdot PEV^{\%_{Pen}} \qquad \forall i \tag{3.16}$$

$$P_{i,b}^{PEV} \leq NH_i \cdot P^{PEV_{Cap}} \cdot PEV^{\%_{Pen}} \qquad \forall i, h \tag{3.17}$$

Capacity Adequacy Limit

This constraint ensures the installation of enough capacity in the system so that supply can be maintained during peak hours in case of resource failure.

$$(S^{SS_{Cap}} + S_{ss}^{NSS}) cos(\theta_{ss,peak}^{SS}) + \sum_{i \in N} P_i^{DG_{Cap}} \geq (1 + \gamma) \sum_{i \in N} (Pd_{i,peak}) \tag{3.18}$$

DR Constraints

These constraints impose a limit on the DR at each time block and bus in the system.

$$P_{i,b}^{DR} \leq \alpha_0 Pd_{i,b} \qquad\qquad \forall i, b \tag{3.19}$$

Voltage Limits

These constraints ensure that the voltage magnitude at a bus is within the allowable limits.

$$V^{Min} \leq V_{i,b} \leq V^{Max} \qquad\qquad \forall i, b \tag{3.20}$$

Budget Limit-General

This constraint imposes a limit on the capital spending and consequently how much capacity the LDC can invest. The first term of (2.23) is the capital cost of DG units, the second term is the EPC cost and the variable component of the capital cost to upgrade the substation. The third term is the EPC cost and the variable component of the capital cost to upgrade the feeders. The capital cost of capacitors is presented in the last term. All these costs together, must be within the budget limit, BL.

$$\begin{aligned} &\sum_{i \in N} \left(C^{DG.F} P_i^{DG_{Cap}} \right) + \sum_{i \in SS} \left(C^{SS.F} z_i^{SS} + C^{SS.V} S_i^{NSS} \right) \\ &+ \sum_{i,j \in N : \exists (i,j)} \left(C^{Fdr.F} Ge_{i,j} Le_{i,j} z_{i,j}^{Fdr} + C^{Fdr.V} S_{i,j}^{NFdr} \right) + \sum_{i \in N} \left(C^C Q_i^{C_{Cap}} \right) \leq BL \end{aligned} \tag{3.21}$$

Budget Limit on Capacitor Banks

This constraint imposes a limit on spending that the LDC can make on new capacitor banks.

$$\sum_{i \in N} C^C Q_i^{C_{Cap}} \leq CBL \tag{3.22}$$

In it to be noted that the capital cost of capacitor banks are relatively smaller compared to that of DG units, and if a separate budget limit for capacitors is not imposed, the planning model will tend to over-select the number of capacitors, at the cost of DG units, which is undesirable. To alleviate this problem, a separate budget is therefore allocated to capacitor banks, without any loss of generality.

3.4.2 Smart-DSPLAN2

The second proposed mathematical model, referred to as, Smart-DSPLAN2, is presented below.

The objective function ($J2$) aims to minimize the annualized cost of capital and operation of the LDC.

$$\begin{aligned} J2 = & \sum_{i \in N} \Big(C^{DG.F} P_i^{DG_{Cap}} + \sum_{b \in B} (C^{DG.O} P_{i,b}^{DG} Hr_b) \Big) \\ & + \sum_{i \in SS} \Big(C^{SS.F} + C^{SS.V} S_i^{NSS} + \sum_{b \in B} (\rho_b P_{i,b} Hr_b) \Big) \\ & + \sum_{i,j \in N: \exists (i,j)} \Big(C^{Fdr.F} Ge_{i,j} Le_{i,j} + C^{Fdr.V} S_{i,j}^{NFdr} \Big) \\ & + \sum_{i \in N} \Big(C^C Q_i^{C_{Cap}} \Big) + \sum_{i \in N, b \in B} \Big(C^{DR} P_{i,b}^{DR} Hr_b \Big) \\ & + \sum_{i \in N, b \in B} \big(C^{UN} P_{i,b}^{UN} Hr_b \Big) \end{aligned} \tag{3.23}$$

The associated operational and planning constraints are same as Smart-DSPLAN constraints with some differences as follows:

- Constraints (2.8), (2.11), (2.13), (2.14), (2.16), (2.20), (2.23), and (2.24) are excluded.
- Constraints 2.4, is modified to include unserved power variable as follows:

$$P_{i,b} + P_{i,b}^{DG} - P_{i,b}^{PEV_S} - P_{i,b}^{PEV_{UNC}} - Pd_{i,b} + P_{i,b}^{DR} = f(V_{i,b}, \delta_{i,b}) \qquad \forall i, b \tag{3.24}$$

- The upgrades capacities are now considered as a fixed decisions.

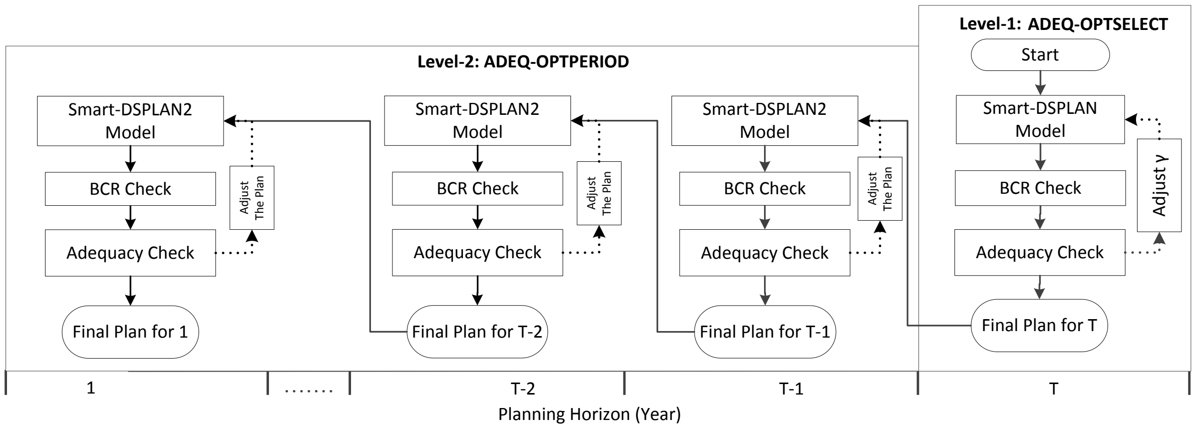


Fig. 3.2. Architecture of the proposed approach to solution of planning problem

3.5 Proposed Approach To Solution of Planning Problem

The proposed approach to determine the optimal upgrade plan combines a bi-level procedure as follows:

Level-1 (ADEQ-OPTSELECT): determines an appropriate reserve margin (γ) and selects the optimal size and location of distribution system upgrades that are required to be in place, at the plan terminal year.

Level-2 (ADEQ-OPTPERIOD): determines the optimal period of commissioning, for the upgrades selected in Level-1.

A back-propagation of model solution, starting from the plan terminal year T and ending at the first year, is proposed. Within this framework, a novel adequacy check is introduced that involves post-processing the plan decisions at both the levels to ensure that the target plan adequacy level is satisfied for each year (Fig.2.6). The details of the proposed framework are discussed next.

3.5.1 Level-1: ADEQ-OPTSELECT

In this stage the optimal plan decisions for the plan terminal year are determined. The step-by-step procedure is discussed as follows.

1. Start with an initial value of reserve margin γ and consider all LDC components as candidates for upgrade set {L}.

2. Execute Smart-DSPLAN model, considering set {L}, to determine the optimal planning decisions, set {H}, which provides continuous values of capacities.

3. Standardize the upgrade capacities of {H} and consider them as fixed decisions in the Smart-DSPLAN. Also, now include an unserved power variable in the demand-supply balance (2.4) with an associated high cost of unserved power in the objective function (2.3). The modified version is now referred to as Smart-DSPLAN2.

4. Execute Smart-DSPLAN2 to calculate the Benefit-Cost-Ratio (BCR) of each upgrade in set {H} by uninstalling an upgrade, one at a time, from {H}, and calculate the marginal benefit of each upgrade. The marginal benefit for an upgrade is obtained from the difference in the objective function (1) before and after removing the element. The BCR for an upgrade is calculated by dividing the marginal benefit by the total cost of the upgrade as follow:

$$BCR_{i,Type} = \frac{MB_{i,Type}}{TC_{i,Type}} \tag{3.25}$$

   Where $MB_{i,Type}$ is the marginal benefit obtained from the difference in the objective function (J) before and after removing a specific upgrade; $TC_{i,Type}$ is the total cost of installing an upgrade; and $Type$ is the type of upgrade (substation, DG, capacitor or feeder)

5. Select all upgrades with BCR>1, and form a set {H1}, also construct a set {R} with rejected upgrades having BCR<1 and solve Smart-DSPLAN2 with set H1 to check if the above selected upgrades satisfy the system constraints and there is no unserved power.

6. If YES, go to next step. If NO, modify set {L} with all buses except those in set {R}. If the selected upgrades from {H1} do not satisfy system constraints, and all upgrades from set {L} have been tested for BCR>1, then choose upgrades with the highest BCR from the rejected set {R}. If otherwise, go to Step 2.

7. Develop a capacity outage probability distribution table. Calculate the Loss of Load Expectation (LOLE) [79] for the obtained plan {H1} and check if LOLE is less than the specified value.

8. If YES, the final solution is obtained. If NO, revise γ as: $\gamma = \gamma + \triangle\gamma$, which means the reserve margin, and hence supply capacity (DG and substation), is appropriately increased to meet the Capacity Adequacy Limit in (17), and go to Step 2.

It is to be noted that the choice of the starting value of γ has no significant impact on the distribution plan. If the initial choice of this margin is too far off, the number of iterations required for convergence will be more. But since this is a long-term planning problem, solved 10 years in advance, computational time is not a critical issue, and a few additional iterations will not affect the plan. Moreover, there is no unique starting value of γ that is universally appropriate for all distribution planning problems. This is because the LOLE depends on a number of factors such as the magnitude and the duration of each load block and the number of load blocks considered, the FOR, and the capacity of the generation units. Any knowledgeable guess by the distribution system planner is sufficient; in this work, a value of $\gamma = 0.15$, which is the reserve margin in year-0 is used; and γ is increased in steps of 0.01 p.u. per iteration.

The final plan for year T is now passed on to Level-2 wherein through the back propagation process, the optimal year of commissioning of the plan upgrades are obtained.

3.5.2 Level-2: ADEQ-OPTPERIOD

The ADEQ-OPTPERIOD starts from year (T-1), and propagates back to the first year of the plan horizon to find the optimal set of upgrades for each year of the plan.

Two essential verification tests are used at this level to determine the optimal set of upgrades for each year. The first test, BCR, is used to reject the non-beneficial upgrades from that year and earlier. While the second, is the adequacy check which ensures that the selected upgrades meet a specified adequacy level.

In each year of the plan, BCR and LOLE are calculated starting from year (T-1). Based on the BCR check, any upgrade with a BCR of less than unity will be a possible candidate for rejection. If the selected upgrade does not satisfy the system constraints and the adequacy level, the rejected upgrades will be re-selected one by one based on their BCR, until the system constraints are satisfied, and the adequacy level is met. The step-by-step procedure of Level-2 is discussed as follows:

1. Set initial value t = T - 1.

2. Solve Smart-DSPLAN2 for year t and calculate BCR for all upgrades.

3. Reject upgrades with BCR<1 from {H1} and form rejected set {R2}. It is to be noted that the upgrades that are rejected, are only for year t and earlier, implying that these upgrades are made in year t + 1.

4. Check if selected upgrades in {H1} satisfy the system constraints. If YES, go to Step-5. If NO, re-select the upgrade with the highest BCR from {R2} and perform step-4 again.

5. Develop a capacity outage probability distribution table and calculate the Loss of Load Expectation (LOLE) for the obtained plan H1 and check if LOLE is less than the specified value. If NO, re-select the upgrade with the highest BCR from {R2} and perform step-5 again.

6. Modify set {H1} with all upgrades that are selected for year t.

7. Update t = t - 1. If t $\neq$ 0, go to Step-2. ELSE, the final plan is obtained.

3.6 Test System

The first test system under study comprises 33 buses in radial configuration [87]. The main substation at bus-1 has two transformers of 15 MVA each, and one of 16 MVA. The total system peak demand is 37 MW in year-0.

The second test system is the IEEE 69-bus radial distribution feeder comprising one main branch and seven laterals [88]. The main substation at bus-1 has two transformers of 1.5 MVA each, and one of 2.2 MVA. The total system peak demand is about 3.8 MW in year-0. The network parameters and the load data are given in the Appendix. The system demand has been scaled to suit the problem case requirements and supplemented with the additional technical details of feeder, and substation limits, and DG options. For both systems, the demand is assumed to grow at 3% annually, all the substation transformers are assumed to have a force outage rate (FOR) of 0.02 [89], and the feeder segments are assumed to be 1 km long, Ge = 0.4 [29]. Table 2.3 provides the capital costs of the resources available for planning. Details of various other parameters used for the studies are taken from [29] and [90]. Assuming a fuel consumption of 300 m^3/hr and a gas price of 0.14 $/L, the operating cost of the DG units are obtained to be 42 $/MWh [91], and have a FOR of 0.05 [89]. A budgetary limit of $10 million is imposed. The targeted LOLE is assumed to be 2.8 hrs/year and the unserved energy cost is 1000 $/MWh [92]. The load profile is represented by load duration curves which are constructed by re-arranging the chronological load curve in descending order of magnitude. It determines the number of hours per day when the load is greater than any particular amount [82]. Electricity price or the price at which the LDC imports power through the substation are specified in terms of seven load blocks, as shown in Table 2.4, using load scaling factors (LSF). The average Hourly Ontario Energy Price (HOEP) in 2012 is considered in this study to be the expected electricity price for the plan period [93]. Note that the planning problem addressed in this chapter is from the perspective of an LDC, and hence the issues of electricity market prices, bidding, and risk management, are not considered. The price at which the LDC purchases power from the external grid is assumed to be known *a priori*, and the LDC does not participate in the wholesale electricity market to purchase this power, but has a standing power purchase contract.

TABLE 3.1 Capital Cost of Utility Resources

Element	**Fixed Cost**	**Variable Cost ($/MVA)**
Feeder	150000$/km	1000
Substation	$200,000	50000
Gas Turbine DG	-	825000
Capacitor	-	50000

TABLE 3.2 Electricity Market Price

Load Block (b)	1	2	3	4	5	6	7
Number of Hours	5	4	4	4	3	3	1
LSF	0.4	0.5	0.6	0.7	0.8	0.9	1
ρ **($/MWh)**	10	15	22	32	48	70	103

In the present work, it is assumed that the DG units are dispatchable, and are natural-gas based; therefore siting or sizing of DG units is not constrained by the availability of resources and can be optimally determined from the model as per system requirements. In this work, the DG units are assumed to operate at unity power factor, as per [94] and [56], however, the proposed algorithm is generic and computationally fast to handle DG reactive power support capability. The Smart-DSPLAN is a mixed-integer non-linear programming model, solved using the COINBONMIN solver; while Smart-DSPLAN2 is a non-linear programming model, solved using the SNOPT solver, and are coded in GAMS.

3.7 Case Studies

3.7.1 Case-1: Base Case; 33 Bus System

In this case, the PEV charging load and DR are not considered, accordingly (17), (18) and (20), and the associated variables are excluded from the Smart-DSPLAN model. The results are divided into two parts; the first part determines the optimal upgrade plan for the terminal year. Using this output, the year of commissioning of selected upgrades is obtained in the second part.

ADEQ-OPTSELECT

The proposed schematic discussed in Section-2.10.1 is used to determine the optimal γ simultaneously with the optimal size and location of LDC component upgrades in the plan terminal year (T). Table 2.5 presents the outcome of the iterative process to arrive at the optimal value of γ.

TABLE 3.3 Reserve Margin, Added Capacity and LOLE

γ	**Added Capacity (MVA)**	**LOLE (hr/yr)**	**Target LOLE (hrs/yr)**	**Adequacy Level Met?**
0.15	21.4	3.47	2.8	No
0.2	24.1	3.17	2.8	No
0.21	24.7	2.29	2.8	Yes

After three iterations, it is found that with $\gamma = 0.21$, LOLE is obtained as 2.29 hrs/year which meets the targeted adequacy level. The step-by-step outcome of the ADEQ-OPTSELECT process for $\gamma = 0.21$ is thereafter presented in Table 2.6. In the first iteration, set {H} of selected upgrades comprises the upgrade of 1 substation, 5 DG units, 6 capacitors and 5 feeders. The BCRs for each selected upgrade is calculated and found to be greater than unity except for DG at bus 32, which is hence rejected. In the second iteration, a new set {H} is obtained. After calculating BCRs for each selected upgrade, all of them are found to have a BCR > 1, and hence, the optimal plan for the terminal year is obtained, denoted by set {H1}.

ADEQ-OPTPERIOD

At this level, the final selected upgrades from ADEQ-OPTSELECT, *i.e.*, set {H1}, are considered again. The LOLE for the upgraded system and BCR corresponding to each

TABLE 3.4 Step-by step Outcome of ADEQ-OPTSELECT with γ=0.21

Itr.	Set H of upgrades	Size, MW	BCR	Set H1	Rejected set R
1	Substation	15.4	5.56	Substation	
	DG #13	2.2	1.1	DG #13	
	DG #24	0.7	1.4	DG #24	
	DG #29	3.5	1.2	DG #29	
	DG #31	2.3	1.1	DG #31	
	DG #32	0.7	0.8	-	DG #32
	Capacitor #18	0.1	10.22	Capacitor #18	
	Capacitor #19	0.3	15.09	Capacitor #19	
	Capacitor #20	0.3	15.12	Capacitor #20	
	Capacitor #21	0.3	15	Capacitor #21	
	Capacitor #31	0.3	110.81	Capacitor #31	
	Capacitor #32	0.2	106.02	Capacitor #32	
	Feeder 1-2	6.2	303.73	Feeder 1-2	
	Feeder 2-22	1.5	76.04	Feeder 2-22	
	Feeder 3-4	1.1	44.15	Feeder 3-4	
	Feeder 26-27	0.7	43.33	Feeder 26-27	
	Feeder 28-29	0.6	55.66	Feeder 28-29	
2	Substation	15.9	6.3	Substation	
	DG #17	0.7	1.3	DG #17	
	DG #21	0.4	1.2	DG #21	
	DG #24	0.7	1.4	DG #24	
	DG #29	3.8	1.3	DG #29	
	DG #31	3.2	1.2	DG #31	
	Capacitor #13	0.1	2.68	Capacitor #13	
	Capacitor #14	0.1	2.67	Capacitor #14	
	Capacitor #15	0.1	2.71	Capacitor #15	
	Capacitor #16	0.1	2.74	Capacitor #16	None
	Capacitor #17	0.3	26.65	Capacitor #17	
	Capacitor #30	0.3	126.86	Capacitor #30	
	Capacitor #31	0.3	126.99	Capacitor #31	
	Capacitor #32	0.2	125.23	Capacitor #32	
	Feeder 1-2	6.4	350.08	Feeder 1-2	
	Feeder 2-22	1.5	76.04	Feeder 2-22	
	Feeder 3-4	1.1	48.55	Feeder 3-4	
	Feeder 26-27	0.2	8.6	Feeder 26-27	
	Feeder 28-29	0.2	19.08	Feeder 28-29	

component of {H1} are determined starting from year (T-1), and the optimal upgrade plan for each year is obtained. In the present case study, first, the BCR is calculated for year 9, considering the selected upgrades {H1} from Table 2.6. It is found that three feeders have

BCR <1 and hence these are possible candidates for rejection and the updated plan for year 9 is checked using Smart-DSPLAN2. It is found that the system is feasible and there is no unserved power resulting from these rejected upgrades. The LOLE considering the updated plan for year 9 is 1.57 hrs/yr and meets the targeted adequacy level. Therefore, the three feeders are removed from year 9 and earlier years, and installed at year 10. Table 2.7 presents the optimal period of commissioning of each upgrade as obtained from ADEQ-OPTPERIOD.

In Table 2.8, the step-by-step procedure of ADEQ-OPTPERIOD, considering a sample year, year 6 is presented. The revised set {H1} at the beginning of year 6 is as follows: {Substation, DG #29, #31, all Capacitors, Feeder 1-2, 2-22}. After calculating BCR for all these upgrades, it is found that DG #29 and #31 have $BCR < 1$. When Smart-DSPLAN2 is executed without these upgrades, the system encounters unserved energy. As explained in the step-by-step procedure of ADEQ-OPTPERIOD, DG #29 having the highest BCR amongst the rejected upgrades, is re-introduced at the end of iteration-1. Following the same procedure, upgrade of DG #31 is rejected in iteration-2, but system LOLE is found to be higher than the targeted adequacy level and hence DG #31 is re-introduced. In iteration-3, with no rejected upgrades LOLE is calculated and it is found that the plan meets the targeted adequacy level for year-6.

TABLE 3.5 Case-1 Results of ADEQ-OPTPERIOD

Year	**Upgrades size (MW) and site (Bus)**	**LOLE (hr/yr)**
10	(1.1) Fdr 3-4, (0.2) Fdr 26-27, and (0.2) Fdr 28-29	2.29
9	(0.7) DG #17, and (0.7) DG #24	1.57
8	(0.4) DG #21	1.55
7	-	1.52
6	(3.2) DG #31	1.46
5	(1.5) Fdr 2-22	1.9
4	(6.4) Fdr 1-2	1.39
3	-	1.39
2	-	1.18
1	(15.9) Substation, (3.8) DG # 29, Capacitors: (0.1) #13, (0.1) #14, (0.1) #15, (0.1) #16, (0.3) #17, (0.3) #30, (0.3) #31, and (0.2) #32	0.48

3.7.2 Case-2: PEV Penetration; 33-Bus Test System

The impact of PEV charging load on distribution system planning is examined in this section. Two case studies are performed, smart charging and uncontrolled charging, to

TABLE 3.6 ADEQ-OPTPERIOD step-by-step procedure for year 6

Iteration of ADEQ-OPTPERIOD	Rejected upgrades	Unserved power	Re-Introduce Upgrade?	LOLE
1	DG #29 DG #31	Yes	DG #29	-
2	DG #31	No	DG #31	3.96
3		No		1.09

evaluate their impact on the plan. It is assumed that the entire load is residential and by the plan terminal year there would be one PEV every two houses; *i.e.* 50% PEV penetration. The number of PEVs connected at a bus is calculated based on a typical average hourly load of a house, 2.08 kW [47]. The SAE J1772 standards defines two residential charging levels (Level-1 and Level-2) with a third ac level and a dc level for PEVs [54], as presented in Table 2.9. In our work we have considered Level-2 (low) charging with a charging efficiency of 85%. PHEV60 is considered in this case study, with a battery capacity of 15.9 kWh [95].

TABLE 3.7 PEV Charging Level Characteristics

Type	Power Level
Level 1: 120 VAC	1.2 - 2.0 kW
Level 2 (low): 208-240 VAC	2.8 - 3.8 kW
Level 2: (high): 208-240 VAC	6 - 15 kW
Level 3: 208-240 VAC	>15 kW-96kW
Level 3: DC Charging: 600VDC	>15kW-240kW

For this case there is a need for a real and detailed travel dataset, for example the NHTS [86], which is used herein to estimate the PEV driving pattern parameters such as daily mileage driven and the probability of latest home arrival time. The PEV charging load profile is developed considering the start of charging time, the energy required at each load bus, and the charging duration.

Case-2a: Smart Charging

In this case, the LDC is assumed to have a control on PEV charging schedules. Accordingly, the DR related variable and constraint (20) are excluded from the Smart-DSPLAN model. The approach presented in Section-III is executed and results from ADEQ-OPTSELECT are obtained. It is seen that the targeted adequacy level is

TABLE 3.8 Case-2a Results of ADEQ-OPTPERIOD

Year	Upgrades size (MW) and site (Bus)	PEV Loading in MW
10	(0.4) Fdr 22-23	22.21
9	(0.4) DG #24 and (1.9) #29	15.02
8	(0.4) DG #21	10.16
7	(2.5) DG #14	6.87
6	-	4.64
5	(1.8) Fdr 2-22	3.14
4	(5.5) Fdr 1-2	2.12
3	-	1.44
2	-	0.97
1	(20.9) Substation, (4.6) DG #30, Capacitors: (0.3) #28, (0.3) #29, (0.3) #30, (0.3) #31, and (0.3) #32	0.66

Note: PEV loading occurs during the base load (load block = 1) at each year of the plan

now met with a higher value of $\gamma = 0.31$, as against $\gamma = 0.21$ without PEVs; this is attributed to the increased system demand from PEV charging. The optimal plan outcome of this level comprises one substation upgrade, five DG units, five capacitors and three feeder upgrades; and one iteration is needed to arrive at the final plan.

At level-2 (ADEQ-OPTPERIOD), PEV penetration over the plan period is assumed to increase exponentially; starting at approximately 1.5% in year 1 and touching 50% in the plan terminal year. The plan outcome of this level (Table 2.10) shows that the optimal charging of PEVs occurs during the base load (load block = 1) because of the prevailing low market price shown in Table 2.4.

Case-2b: Uncontrolled Charging

In this case, the impact of uncontrolled PEV charging on the required distribution system upgrades is evaluated. The PEV smart charging related constraints (17), (18) and associated variables are now excluded from the Smart-DSPLAN model, while the DR variables and constraint (2.21) is now included. A high DR cost of 1000 \$/MWh is assumed, and a budgetary limit of \$15 million is imposed for this case study. The DR option is included in order to negotiate a distribution plan when budgetary constraints are imposed on the planner. In the second level (ADEQ-OPTPERIOD), the maximum forecasted DR penetration is assumed to be 1% in year 1, which increases exponentially; rising to 20% in the plan terminal year.

The PEV charging load is simulated in two ways to mimic the behaviour of PEV customers. The first group is assumed to start charging immediately after arriving home while the second group's behavior is modelled considering a Poisson distribution to mimic those drivers' behavior who arrive at on-peak electricity price hours and wait until the onset of off-peak price to plug-in their vehicles. The charging delay (λ) is assumed considering Ontario's Time-of-Use (TOU) electricity price; for vehicles arriving during off-peak hours (7 PM - 7 AM), $\lambda = 0.1$ hours, while for on-peak arrivals, λ is the wait time between their arrival and onset of off-peak TOU price. The energy required by a PEV is calculated based on its mileage driven. The charging duration is calculated from the power drawn at a given charging level, the charging efficiency, and the energy required. The resulting uncontrolled PEV charging profile is then combined with the base demand to form the total demand profile as shown in Fig. 2.7.

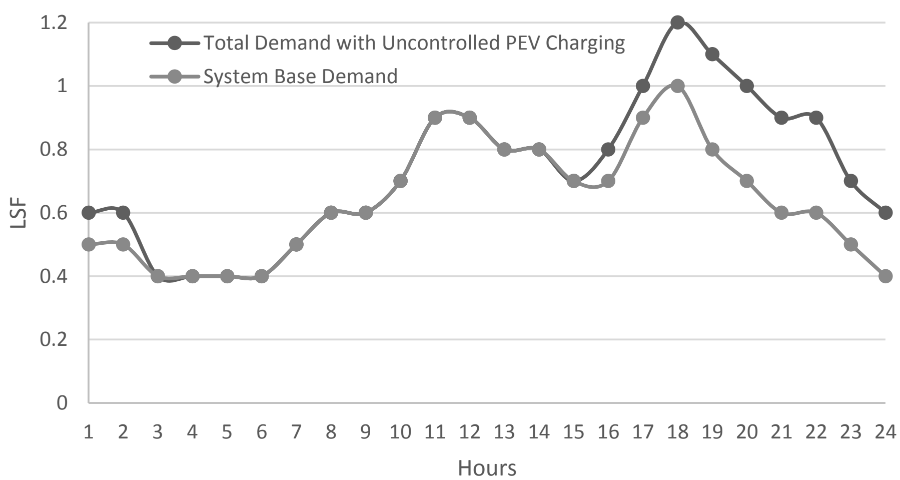


Fig. 3.3. System demand without and with uncontrolled PEV charging

The proposed approach presented in Section-2.10 is executed and results from ADEQ-OPTSELECT are obtained, the targeted adequacy level is met with $\gamma = 0.54$. It is noted that the optimal γ is higher compared to the Base Case and smart charging scenarios because of the significant increase in demand during peak periods (Fig. 2.7). The plan outcome of ADEQ-OPTSELECT comprises one substation upgrade, five DG units, six capacitors, 11 feeder upgrades and the optimal DR; and one iteration is needed to arrive at the final plan. It is noted that DR is allocated in load blocks 8 and 9 which have the highest LSF and only at the remote buses. The outcome of ADEQ-OPTPERIOD presented in Table 2.11 shows that there is a need for DR capacity starting from year 7 until the plan terminal year because of the increasing penetration of PEVs.

TABLE 3.9 Case-2b: Results of ADEQ-OPTPERIOD

Year	**Upgrades size (MW) and site (Bus)**	**DR Capacity (MW)**
10	(1.2) Fdr 2-3, (2.8) Fdr 3-4, (1.6) Fdr 4-5, (1.7) Fdr 26-27, and (1.1) Fdr 27-28	1.21
9	(0.1) Capacitor #21, and (2.9) DG #29	0.266
8	(0.9) DG #32	0.191
7	(11.5) Fdr 1-2, (0.6) Fdr 1-18, (3.2) Fdr 22-23, (1.6) Fdr 23-24, (2) Fdr 28-29 and (1.7) DG #28	0.137
6	-	0
5	(5) Fdr 2-22	0
4	(5) DG #12	0
3	-	0
2	-	0
1	Capacitors: (0.2) #28, (0.3) #29, (0.3) #30, (0.3) #31, and (0.3) #32, (5) DG #30, and (23.3) Substation	0

3.7.3 Summary of 33-Bus System Studies

A comparison of the distribution system plan outcomes obtained from the Base Case, smart PEV charging and uncontrolled PEV charging cases are presented in Table 2.12. It is noted that the present worth of the plan cost in the PEV smart charging case is slightly higher than the Base Case, while much higher for uncontrolled charging. The results also reveal that the impact of PEV penetration are much damped in terms of added cost and added capacity when smart charging is considered as compared to uncontrolled charging. The proposed model can be utilized by LDCs to determine the allowable PEV penetration limits for a given distribution system infrastructure, expected impacts on system operation, the capital spending, and the required upgrades in the distribution network in case of PEV smart charging (best case scenario) and uncontrolled charging (worst case scenario).

In Fig. 2.8, the variation of LOLE with γ and the optimal value of γ, for the three considered case studies are presented. It is noted that the optimal value of γ is reached

TABLE 3.10 LDC Plan Comparison for 33-Bus Case Studies

	Case-1	**Case-2a**	**Case-2b**
Present Worth of Total Cost (M$)	8.64	9.59	14.92
Added Capacity (MVA)	24.7	30.7	38.8
Reserve Margin, γ	0.21	0.31	0.54

when γ is below the dashed line, the Target Adequacy Level. It is noted that γ increases from 0.21 in the Base Case to 0.54 with uncontrolled PEV charging, indicating a high reserve requirement because of the significant increase in charging demand during peak periods due to high PEV arrival rates. However, when PEV smart charging is considered, optimal γ is 0.31 and the burden on the system planner is much lower with reduced peak demand compared to Case-2b (Uncontrolled Charging) because the charging demand is mostly scheduled to off-peak periods.

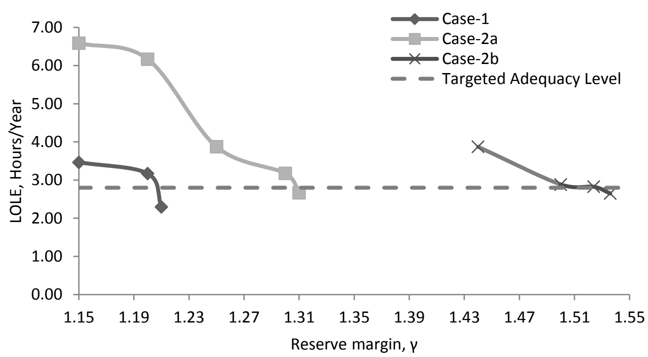


Fig. 3.4. LOLE for different reserve margins, , with and without PEVs

3.7.4 Case-3: Base Case; 69 Bus Test System

It is to be noted that only Base Case studies are carried out for this test system. The results reveals that the targeted adequacy level is met with $\gamma = 0.17$; the selected upgrades from ADEQ-OPTSELECT comprises one substation, two DG units, two capacitors and two feeders. Two iterations are needed to arrive to the optimal plan for the terminal year. The final plan, after executing ADEQ-OPTPERIOD, are presented in Table 2.13.

TABLE 3.11 Case-3 Results of ADEQ-OPTPERIOD

Year	Upgrades size (MW) and site (Bus)
10	-
9	-
8	(0.5) Fdr 1-2 and (0.5) Fdr 2-3
7	-
6	(0.4) DG #64
5	-
4	-
3	-
2	(0.6) DG #61
1	Capacitors: (0.1) #61 and (0.2) #62, and (1.3) Substation

3.7.5 Computational Aspects

The Smart-DSPLAN is an MINLP model which is solved using the COINBONMIN solver which uses the branch and bound, branch and cut, and outer approximation algorithms. The Smart-DSPLAN2 is an NLP model solved using the SNOPT solver which uses a sequential quadratic programming algorithm that obtains search directions from a sequence of quadratic programming sub-problems. The considered test system is programmed and executed on a Dell PowerEdge R810 server, in GAMS environment, Windows 64-bit operating system, with 4 Intel-Xeon 1.87 GHz processors and 64 GB of RAM.

The model and solver statistics are given in Table-2.14. It can be seen that Smart-DSPLAN requires more CPU time per iteration as compared to Smart-DSPLAN2 in all case studies, because of the presence of binary variables in Smart-DSPLAN. In addition, the 69-bus test system requires more time per iteration compared to the 33-bus test system due to the increased number of buses and hence the number of variables and constraints. Moreover, the total CPU time varies across the case studies as it depends on the number of iterations to arrive at the optimal solution, and the required CPU time per iteration.

3.8 Conclusions

In this chapter, a comprehensive framework for multi-year distribution system planning was presented. The proposed framework aimed to determine the optimal upgrade plan,

TABLE 3.12 Model Statistics

Case Study	Model	Single Variables	Discrete Variables	CPU time, per Iteration, s	Total CPU time, s
Case-1	Smart-DSPLAN	1,840	98	770	10,783
	Smart-DSPLAN2	2,535	0	0.22	5
Case-2a	Smart-DSPLAN	2,071	98	721	11,534
	Smart-DSPLAN2	2,535	0	0.25	4
Case-2b	Smart-DSPLAN	2,597	98	496	6,950
	Smart-DSPLAN2	3,259	0	1.75	35
Case-3	Smart-DSPLAN	3,800	206	1,061	6,363
	Smart-DSPLAN2	5,258	0	11	284

siting and sizing of DGs, substations, capacitors and feeders in distribution systems, considering the penetration of PEVs in an uncontrolled as well as smart charging environment, and DR options. Two criteria, BCR and adequacy analysis, were incorporated within the proposed framework, to determine the optimal distribution system plan. The uncontrolled PEV charging load model considered driver behaviour, arrival time, mileage, and other information to develop a charging load profile for inclusion in the planning problem. Similarly, a novel set of PEV operational constraints were included in the planning model, to capture PEV smart charging effects. The proposed planning framework was applied to two test systems. Four case studies were considered to investigate the impact of PEV smart and uncontrolled charging loads as well as DR options on the distribution plan.

The studies revealed that it is important for planners to take into consideration the effects of PEV penetration while deriving their plan outcomes, particularly, when the share of uncontrolled PEV charging is high. It was noted that the present worth of the plan cost in the PEV uncontrolled charging case was much higher than that in the Base Case (No PEV), while the impact of PEV penetration was much damped in terms of added cost and added capacity when smart charging was considered. Compared to the Base Case, with uncontrolled PEV charging loads, there was a 77% and 63% increase in the present worth of the plan cost and in the added capacity (in MW), respectively. The reason behind this significant increase was that the system peak demand coincided with the uncontrolled charging demand due to the coincident home arrival rates during peak hours. On the other hand, it was noted that there was a 11% and 24% increase in the present worth of plan cost and in the added capacity (in MW) when smart charging was used. There was a decrease in peak demand compared to uncontrolled charging because of smart charging which scheduled the charging demand to off-peak periods.

The proposed framework can be used by LDCs to quantify the impacts, and determine the required upgrades in the distribution networks; and can be readily applied to any radial distribution system. It is also noted that although the present work considered distribution systems connected to the grid, the proposed framework is easily extendable to isolated/islanded distribution systems or microgrids, without any loss of generality.

Chapter 4

A Novel Framework for Evaluating Maximum PEV Penetration into Distribution Systems[1]

4.1 Introduction

In Chapter-3, a comprehensive distribution planning model was developed to address the current change in distribution systems. The proposed model simultaneously determines optimal sizing, placement and investment timelines of various resource alternatives for LDCs such as DG sources, substations, capacitors and feeders. In addition, the impact of PEV uncontrolled and smart charging loads on the planning problem was evaluated.

This chapter presents a novel framework to determine the appropriate level of PEV uncontrolled and smart charging penetration that distribution systems can accommodate without requiring any capacity reinforcement. Monte Carlo Simulation has been used to simulate the uncertainty of typical demand, drivers behaviour, PEV market share, and charging level share. Moreover, the maximum allowable penetration of uncontrolled and

[1]This chapter has been accepted for publication in:
A. Bin Humayd, and K. Bhattacharya. "A Novel Framework for Evaluating Maximum PEV Penetration into Distribution Systems." IEEE Transactions on Smart Grid. (in print).
Earlier versions of the work have been published in:
A. Bin Humayd, and K. Bhattacharya. "Assessment of distribution system margins to accommodate the penetration of plug-in electric vehicles." IEEE Transportation Electrification Conference and Expo (ITEC), 2015, Dearborn, MI, USA.

smart charging loads are determined based on the current available market data pertaining to PEV type and charging level, considering different charging scenarios. The proposed framework is examined and compared across a number of scenarios.

The structure of the chapter is as follows. The nomenclature used in this chapter is presented in Section-3.2. In Section-3.3, a description of the proposed framework is presented. This is followed by a description of case studies and assumptions in Section-3.4. In Section-3.5, the proposed framework is applied and the results are presented to demonstrate the effectiveness of the proposed model. Conclusions are drawn in Section-3.6.

4.2 Nomenclature

Indices

c	Index for PEV class
g	Index for PEV groups classified by their State of Charge (SOC)
h	Index for hours
i, j	Index for buses, $i = 1, 2, N$
N	Total number of buses
s	Scenarios of uncertainty
SS	Subset of substation buses ($SS \in i$)

Parameters

AER_c	Driving range of a PEV of class c in electric mode, km
B_c^{Cap}	Battery capacity of a PEV of class c, p.u.
D_c^{km}	Mileage driven by a PEV of class c, km
DOD	Depth of discharge of a PEV, p.u.
$E_{c,g}$	Energy needed to charge a PEV battery of class c and SOC classification group g, kWh
N_i^V	Number of vehicles at bus i
P^{ChL}	Power drawn by a PEV at a given charging level, p.u.
$P_{i,h}^D, Q_{i,h}^D$	Real and reactive power demand at bus i and hour h, p.u.
$P_{i,h}^{PEV_{Unc}}$	Maximum allowable uncontrolled charging demand at bus i and hour h, p.u.

$S_{i,j}^{Fdr_{Cap}}$	Existing capacity of feeder i-j, p.u.
$S^{SS_{Cap}}$	Substation capacity, p.u.
SOC_c	State of charge of a PEV of class c, p.u.
SOC^{min}	Minimum allowable SOC for a PEV, p.u.
T_c^{Ch}	Charging duration of a PEV of class c, hours
V^{Min}, V^{Max}	Lower and upper limits of voltage magnitude, p.u.
$X_{c,g}^{E}$	Share of total fleet of class c and group g that require $E_{c,g}$ amount of energy, p.u.
$X_h^{PEV_{home}}$	Share of total fleet that are at home at hour h, p.u.
X_h^{UnP}	Uncontrolled charging demand at hour h, share of total fleet, p.u.
Xc_c	Share of PEVs of class c in the total fleet, p.u.
$Y_{i,j}$	Magnitude of bus admittance matrix element i-j, p.u.
$\alpha_{h,s}^{Unc}$	Share of total fleet that can be accommodated without violating the Distribution System Loading Margin (DSLM) at hour h in scenario s, p.u.
α_s^{min}	Minimum value of $\alpha_{h,s}^{Unc}$ over all operating hours
η	Charging efficiency
$\theta_{i,j}$	Angle of bus admittance matrix element i-j, rad

Variables

$P_{i,j,h}^{Fdr}, Q_{i,j,h}^{Fdr}$	Real and reactive power flow from i to j at hour h, p.u.
$P_{ss,h}, Q_{ss,h}$	Real and reactive power imported by LDC via substation at hour h, p.u.
$P_{i,h}^{PEV}$	Power drawn by PEV fleet at bus i and hour h, p.u.
$P_{c,g,i,h}^{PEVc}$	Power drawn by PEV of class c at bus i and hour h, p.u.
$S_{i,j,h}^{Fdr}$	Complex power flow from i to j at hour h, p.u.
$S_{ss,h}$	Complex power imported via substation at hour h, p.u.
$V_{i,h}$	Voltage magnitude at bus i and hour h, p.u.
X_h	DSLM, at hour h, share of total fleet, p.u.
$X_{i,h}^{PEV}$	Bus loading margin at hour h and bus i, share of total fleet, p.u.
$\alpha^{Smt_{Sys}}$	Share of total fleet that can be charged in smart charging mode without violating system constraints, p.u.
α_i^{Smt}	Share of fleet at bus i that can be charged in smart charging mode without violating system constraints, p.u.
$\delta_{i,h}$	Voltage phase angle at bus i and hour h, rad

4.3 Proposed Framework For Assessment of Distribution System Loading Margin

Fig. 3.1 presents the overall schematic of the proposed framework to assess the DSLM which comprises three main stages.

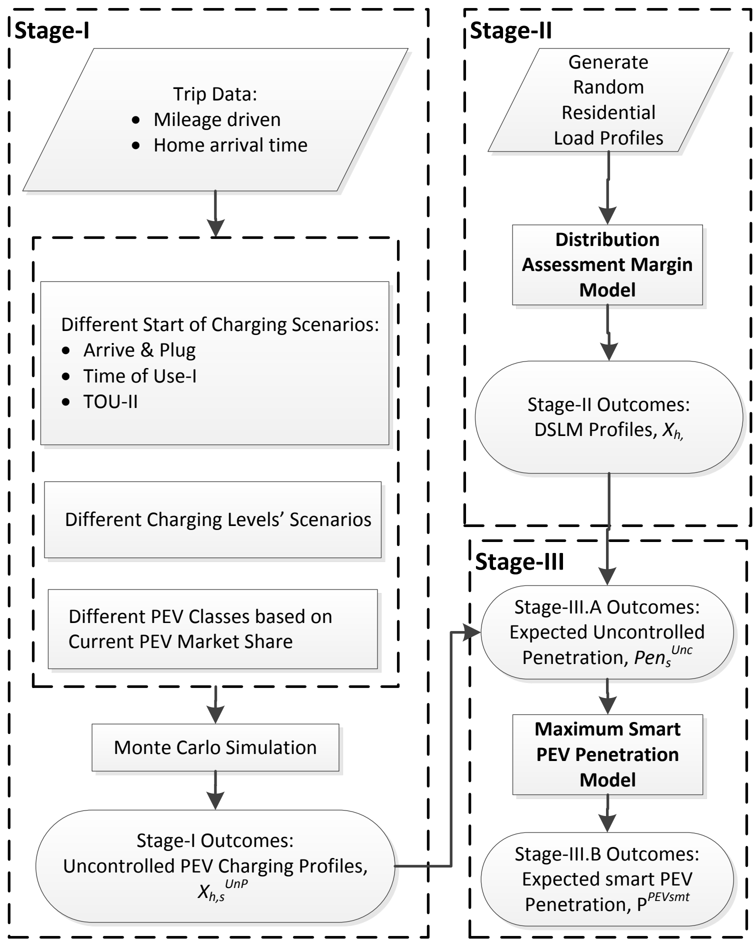


Fig. 4.1. Proposed framework for assessment of DSLM

In Stage-I, a large number of uncontrolled PEV charging profiles considering different charging scenarios, charging levels, and PEV types are constructed. At this stage, there is a need for a real and detailed travel dataset such as mileage driven, home arrival and departure times, and vehicle types, which can be used to simulate the driver behaviour and hence develop the charging profiles. Stage-II starts with generating a large number of random residential load profiles which are then fed to an optimization model to determine the hourly DSLM profiles. The outcomes of Stage-I and Stage-II are then fed to Stage-III to determine the expected allowable uncontrolled and smart charging PEV penetration.

Monte Carlo simulation is carried out considering a range of vehicles daily mileage driven and hence a multitude of scenarios of state of charges (SOC) of PEVs are generated. Monte Carlo simulation is also carried out to simulate the start time of charging for three different charging strategies. It is to be noted that for PEV charging patterns, to date, no real data is available. The simulations carried out in this work are extensive and takes into account realistic probability distributions from National Household Travel Survey (NHTS) data, and the PEV charging patterns developed in this chapter are based on the use of the battery technologies available in todays market.

4.3.1 Stage-I: Uncontrolled PEV Charging Load Modeling

This stage focusses on developing the PEV charging profile using vehicle type, charging level information and the charging scenarios. A number of daily PEV charging scenarios at each bus is estimated assuming that the whole fleet comprises PEVs. After that, the hourly PEV load is transformed to per unit as a fraction of the total fleet, X_h^{UnP}, which is used later in stage-III. The uncontrolled charging profile is constructed based on three main steps as follows:

Simulation of Driving Pattern Parameters

Using the NHTS data, the probability density function (pdf) of the daily mileage and home arrival times are determined. The cumulative distribution function of the two parameters are then obtained, which are used for Monte Carlo simulations to generate random trip mileage and home arrival times, to be used in Step-2 and 3.

Determine Charging Duration

The charging duration, T_c^{Ch}, for each vehicle in the fleet is estimated in this step, from the power drawn at a given charging level (P^{ChL}), the charging efficiency (η), the SOC of the vehicle, and the battery capacity, B_c^{Cap}, as follows:

$$T_c^{Ch} = \frac{(1 - SOC_c)B_c^{Cap}}{P^{ChL}\,\eta} \tag{4.1}$$

the SOC is calculated from the mileage driven (D_c^{km}), generated using the pdf of the daily mileage, the driving range in the electrical mode (AER_c), the SOC^{min} and DOD of the vehicle, as given below:

$$SOC_c = \begin{cases} SOC^{min} + (1 - \frac{D_c^{km}}{AER_c})DOD & D_c^{km} \leq AER_c \\ SOC^{min} & D_c^{km} > AER_c \end{cases} \tag{4.2}$$

There are several organizations that assess the emission level of car engines, fuel economy and driving range based on a series of tests, for example, the Environmental Protection Agency (EPA) in the US and the New European Driving Cycle (NEDC) in Europe. The driving range in the electrical mode (AER_c), used in this chapter, is based on the EPA since their fuel economy tests have been correlated with US national average values for many real-world driving conditions, including stop-and-go traffic, cold weather, air conditioning use, and high speed and aggressive driving [96, 97]. In [98], a study is reported that analyzes fuel economy of PEVs and the factors influencing it. It is reported in the study that EPA ratings are used as a real-world electric driving range, or 0.75 of the NEDC value, if no EPA range is available.

The PEVs considered in this chapter are from eleven commonly found makes, based on their sales, and covers 95% of the total number of PEVs sold in the US between 2010 to September 2015 [99]. These PEVs are grouped into four major classes, plug-in hybrid electric vehicle-I (PHEV), PHEV-II, battery electric vehicle-I (BEV) and BEV-II, with their parametric details provided in Table-3.1.

The charging level is another important factor that affects the charging duration and the power drawn from the grid. The SAE J1772 standard [100] defines two residential charging levels (Level-1 and Level-2) for PEVs and the same have been used in several studies [44,54]. In this study too, these charging levels are used; the PEV owners survey [101] reports that 65% customers have Level-1 access while 35% have the potential to install Level-2 charging. Furthermore, to investigate the effect of different charging levels, three different scenarios of mix of charging levels are formulated, as listed in Table-3.2.

TABLE 4.1
PEV CLASSES CONSIDERED FOR STUDIES

	Market Share	**Battery Capacity Range (kWh)**	**AER (km)**	**Weighted Average Battery Size (kWh)**	**Weighted Average AER (km)**	**Vehicls' Type**
PHEV-I	26.05%	4.4-7.6	18-32	5.76	24.03	Ford C-MAX Energi, Ford Fusion Energi, Toyota Prius Plug-in
PHEV-II	23.83%	18.4	85	18.40	85	Chevrolet Volt
BEV-I	34.22%	14-24	100-135	21.89	124.03	BMW i3, Chevrolet Spark, Fiat 500E, Ford Focus Electric, Nissan LEAF, Smart fortwo
BEV-II	15.90%	85	426	85.00	426	Tesla Model S

Scenarios of Starting Time of Charging

The behaviour of PEV drivers has a direct impact on the starting time of charging and hence the charging profile, which plays a significant role in determining the maximum allowable PEV penetration in distribution grids. Previous researchers have considered various scenarios to simulate the starting time of charging. In [40–42, 44, 61], the authors assumed that PEV drivers will start charging immediately after arriving home after their last trip while in [59, 60], overnight charging [8 PM - 8 AM] have been considered. To date, no real data are available with respect to starting time of charging and PEV charging profiles and therefore there is a need for rational assumptions.

In this work, the starting time of charging is modelled considering three realistic scenarios to mimic the behaviour of PEV customers and hence assess the impact of the charging load, arising there from, on the distribution.

- *Arrive and Plug*: In this scenario, it is assumed that PEV owners start charging their vehicles immediately after arriving home after their last trip, regardless of the electricity price or network limitations; the charging takes place at a constant rate until the battery is full.

- *TOU-I*: In this scenario, all PEV drivers are assumed to respond to TOU electricity price. Therefore, PEVs arriving at on-peak electricity price hours wait until the onset of the off-peak price to plug-in their vehicles. This scenario is considered the worst case scenario since all PEVs arriving home at peak hours, simultaneously start charging their vehicles at the onset of the off-peak period.

TABLE 4.2
Charging Level Scenarios Considered For Studies

Charging Scenario	Percentage (%)	
	Level-1	Level-2
Scenario-1	100	0
Scenario-2	0	100
Scenario-3	65	35

- *TOU-II*: The starting time of charging, in this scenario, is modelled considering a Poisson distribution with λ equals to the charging delay which is assumed considering Ontarios TOU electricity price. For vehicles arriving during off-peak hours (7 PM - 7 AM), $\lambda = 0.1$ hours, while for on-peak arrivals, λ is the wait time between their arrival and onset of off-peak TOU price.

After determining the charging duration and the starting time of charging of each vehicle in the fleet, the uncontrolled charging profile is constructed. For example, if the charging duration of a vehicle is 5 hours considering Level-1 charging, and the starting time of charging is 3 pm, the charging demand will take place from 3 pm to 8 pm with an amplitude of 1.44 kW (Level-1 charging power).

4.3.2 Stage-II: Distribution System Loading Margin Assessment

A Monte Carlo simulation of the peak day's demand is carried out to arrive at a large number of hourly load profiles $P^{D}_{i,h}$ and $Q^{D}_{i,h}$, which are then fed into an optimization model to determine the hourly DSLM. The randomness of the hourly loads are simulated considering Gaussian distributions with specified hourly averages and standard deviations.

Objective Function

The objective function (J_1) seeks to maximize the aggregate hourly DSLM which essentially maximizes the PEV charging load at every bus and hour, $P^{PEV}_{i,h}$, and is given as:

$$J_1 = \sum_{h} X_h \tag{4.3}$$

The associated operational constraints are as follows.

Power Flow Equations

The injected power at a bus i and hour h is the power from the substation, net of the load, and potential PEV charging loads; and is governed by the traditional power flow equations:

$$P_{i,h} - P_{i,h}^{PEV} - P_{i,h}^{D} = \sum_{j \in N} V_{i,h} V_{j,h} Y_{i,j} cos(\theta_{i,j} + \delta_{j,h} - \delta_{i,h}) \quad \forall i \in N, \forall h \tag{4.4}$$

$$Q_{i,h} - Q_{i,h}^{D} = -\sum_{j \in N} V_{i,h} V_{j,h} Y_{i,j} sin(\theta_{i,j} + \delta_{j,h} - \delta_{i,h}) \quad \forall i \in N, \forall h \tag{4.5}$$

PEV Accommodation Constraints

These constraints ensure that all buses have a loadability margin at least equal to DSLM, X_h, which is governed by the charging load that can be accommodated at a bus i, the bus loading margin, $X_{i,h}^{PEV}$, and is proportional to the number of vehicles at that bus, N_i^V.

$$P_{i,h}^{PEV} = X_{i,h}^{PEV} N_i^V P^{ChL} \quad \forall i \in N, \forall h \tag{4.6}$$

$$X_h \leq X_{i,h}^{PEV} \quad \forall i \in N, \forall h \tag{4.7}$$

In addition, constraint (3.6) ensures that the power drawn by PEVs during an hour and at bus i is as per the charging level, P^{ChL}. Since the bus loading margins ($X_{i,h}^{PEV}$) should be greater than or at least equal to X_h, as per (3.7), the model effectively ensures that all bus loading margins are maximized as well, and the lowest of the bus loadings margins is at least equal to the DSLM (X_h).

Feeder Capacity Limits

Power flow through any distribution feeder must comply with the thermal capacity limit of the feeder.

$$P_{i,j,h}^{Fdr} = -V_{i,h}^2 Y_{i,j} cos\theta_{i,j} + V_{i,h} V_{j,h} Y_{i,j} cos(\theta_{i,j} + \delta_{j,h} - \delta_{i,h}) \quad \forall (i,j) \in N : \exists (i,j), \forall h \tag{4.8}$$

$$Q_{i,j,h}^{Fdr} = V_{i,h}^2 Y_{i,j} sin\theta_{i,j} - V_{i,h} V_{j,h} Y_{i,j} sin(\theta_{i,j} + \delta_{j,h} - \delta_{i,h}) \quad \forall (i,j) \in N : \exists (i,j), \forall h \tag{4.9}$$

$$S_{i,j,h}^{Fdr} \quad \leq \quad S_{i,j}^{Fdr_{Cap}} \qquad\qquad \forall (i,j) \quad \in \quad N \quad : \quad \exists (i,j), \forall h \tag{4.10}$$

Substation Capacity Limits

This constraint ensures that the total power transferred over the substation transformers is within substation capacity limit, $S^{SS_{Cap}}$.

$$S_{ss,h} \leq S^{SS_{Cap}} \quad \forall i \in SS, \forall h \tag{4.11}$$

Voltage Limits

This constraint ensures that the voltage magnitude at a bus is within the minimum and maximum allowable voltage limits.

$$V^{Min} \leq V_{i,h} \leq V^{Max} \quad \forall i \in N, \forall h \tag{4.12}$$

4.3.3 Stage-III: Assessment of Allowable PEV Penetration

The expected allowable penetration of uncontrolled and maximum allowable penetration of smart charging PEVs are determined, in this stage, using the outcomes of Stages-I and II. It starts with determining the expected maximum allowable uncontrolled PEV charging load profile, which is fed to an optimization model to determine the maximum allowable PEV smart charging load.

Expected Allowable Uncontrolled PEV Penetration

The expected value of the allowable uncontrolled penetration, $E[\alpha_s^{min}]$, is defined at this stage. First, the percentage of the fleet that can be accommodated without violating the hourly DSLM, $\alpha_{h,s}^{Unc}$, for each scenario s of the Monte Carlo simulation and hour h, is calculated as follows:

$$\alpha_{h,s}^{Unc} = \frac{X_{h,s}}{X_{h,s}^{UnP}} \qquad \forall s, h \tag{4.13}$$

Where, $X_{h,s}$ denotes DSLM, and $X_{h,s}^{UnP}$ the uncontrolled charging demand at hour h, for given loading scenarios. For example, if $X_{h,s}$, for hour h, and scenario s, equals 0.2 it means that the system can accommodate up to 20% of the total fleet at that hour.

Similarly, $X_{h,s}^{UnP}$ equals to 0.4 means that 40% of the total fleet is ready to charge in uncontrolled mode at hour h. Accordingly, the value of $\alpha_{h,s}^{Unc}$ will be 0.5, *i.e.*, 50% of the uncontrolled charging fleet can be accommodated by the system at hour h. Then the maximum allowable uncontrolled PEV penetration for scenario s, α_s^{min}, is the minimum of all values of $\alpha_{h,s}^{Unc}$, as follows:

$$\alpha_s^{min} = min \ \left(\alpha_{1,s}^{Unc}, \alpha_{2,s}^{Unc}, ...\alpha_{24,s}^{Unc}\right) \qquad \forall s \tag{4.14}$$

The expected value of α_s^{min}, *i.e.*, $E[\alpha_s^{min}]$, is obtained when the desired level of accuracy is attained in the Monte Carlo simulation. The expected value of $X_{h,s}^{UnP}$, $E[X_{h,s}^{UnP}]$ is also simultaneously obtained after the convergence of the Monte Carlo simulations. The expected allowable uncontrolled PEV charging profile is thereafter obtained as follows:

$$E[P_{i,h}^{PEV_{Unc}}] = E[\alpha_s^{min}]E[X_{h,s}^{UnP}]N_i^V P^{ChL} \qquad \forall i, h \tag{4.15}$$

Maximum Allowable Smart PEV Penetration

An optimization model is proposed, considering the expected allowable uncontrolled PEV charging profile obtained earlier ($E[P_{i,h}^{PEV_{Unc}}]$) as a fixed load profile, to determine the maximum allowable smart PEV penetration, $\alpha^{Smt_{Sys}}$. Since the smart charging PEVs are assumed to be controlled by the LDC, and the LDC seeks to understand the maximum allowable loadability, the charging schedules are optimally allocated over the day to maximize the number of PEVs charging.

The proposed mathematical model for evaluating the maximum allowable penetration of smart charging PEVs in the distribution grid is presented here. The objective function (J_2) aims to maximize the system penetration of PEV smart charging, $\alpha^{Smt_{Sys}}$.

$$J_2 = \alpha^{Smt_{Sys}} \tag{4.16}$$

The operational constraints, presented in Section 3.3.2, are now modified to include the expected uncontrolled PEV charging profile, $E[P_{i,h}^{PEV_{Unc}}]$, obtained from Section 3.3.3, in the active power balance constraint as follows:

$$P_{i,h} - \sum_{c,g} P_{c,g,i,h}^{PEVc} - P_{i,h}^{D} - E[P_{i,h}^{PEV_{Unc}}] = f(V_{i,h}, \delta_{i,h}) \qquad \forall i \in N, \forall h \tag{4.17}$$

In addition, the PEV accommodation constraints (3.6) and (3.7) are now replaced by constraints (3.18)-(3.22) to ensure that the total energy required by each class c of PEV is equal to the daily charging energy drawn from the grid (3.18) and that the power drawn by PEVs during an hour must be within the charging level (3.19). It is to be noted that the range of SOC and hence the energy required by each PEV class has been divided into a number of discrete intervals, g, and $E_{c,g}$ denotes the energy required by a PEV of class c, in range g, with $X^{E}_{c,g}$ denoting the percent of fleet that require $E_{c,g}$. Constraint (3.20) ensures that the penetration of smart charging PEVs at a bus i is greater or at least equal to the system smart charging penetration. While (3.21) ensures that the percentage of PEV charging at hour h and bus i does not exceed the percentage of PEVs being home at hour h, $X_h^{PEV_{home}}$.

$$\sum_{h} P^{PEVc}_{c,g,i,h} \;=\; \alpha_i^{Smt} X c_c E_{c,g} X^{E}_{c,g} N_i^{V}/\eta \qquad \forall i \;\in\; N, \forall c, \forall g \tag{4.18}$$

$$\sum_{c,g} P^{PEVc}_{c,g,i,h} \leq N_i^{V} P^{ChL} X_h^{PEV} \quad \forall i \in N, \forall h \tag{4.19}$$

$$\alpha^{Smt_{Sys}} \leq \alpha_i^{Smt} \quad \forall i \in N \tag{4.20}$$

$$X_h^{PEV} \leq X_h^{PEV_{home}} \quad \forall h \tag{4.21}$$

$$0 \leq X_h^{PEV} \leq 1 \quad \forall h \tag{4.22}$$

Where X_h^{PEV} is the same as $X_{i,h}^{PEV}$ used in Section-3.3.2 except that the values are same for all buses.

4.4 Case Studies And Assumptions

4.4.1 Descriptions of Case Studies

The main focus of this work is to evaluate the DSLM to accommodate PEVs under uncontrolled and smart charging. The work is carried out considering the impact of different parameters such as charging level, electricity price, and driver behaviour. To achieve this target, nine case studies have been constructed as shown in Table-3.3.

TABLE 4.3
DESCRIPTION OF CASE STUDIES

	Charging Level Scenario (refer to Table-3.2)	Charging Scenario
Case-1a	Scenario-1	Arrive & Plug
Case-1b		TOU-I
Case-1c		TOU-II
Case-2a	Scenario-2	Arrive & Plug
Case-2b		TOU-I
Case-2c		TOU-II
Case-3a	Scenario-3	Arrive & Plug
Case-3b		TOU-I
Case-3c		TOU-II

4.4.2 Assumptions

In order to evaluate the PEV penetration and the maximum accommodation by the system, the following assumptions are made:

- The distribution system under study comprises 33 buses in radial configuration (Fig.3.2) [87]. The main substation is at bus-0 with a capacity of 6 MVA, and the total system peak demand is 4.54 MVA. The network parameters and the load data are given in the Appendix.

- The IEEE RTS [102] peak day load profile is used. Only the peak day demand is considered in this study to determine the expected allowable PEV penetration, since assessing the same for average or non-peak loads can result in degraded performance during peak load periods. The randomness of bus-wise and hourly loads are simulated based on Gaussian distributions with a standard deviation of 0.15 p.u. Fig. 3.3 and 3.4 presents the original and Monte Carlo generated load profiles for some buses for a peak day.

- NHTS 2009 data [86] has been considered with a sample size of 150,147 usable households, and 309,164 vehicles. The data reflects daily trips over a 24-hour period, and were reportedly collected for different type of vehicles, trips, purposes, trip lengths. Although NHTS pertains to conventional vehicles, the same dataset has been used because of lack of PEV data, to obtain the probability distribution function (pdf) of the daily mileage driven and home arrival times of the PEVs.

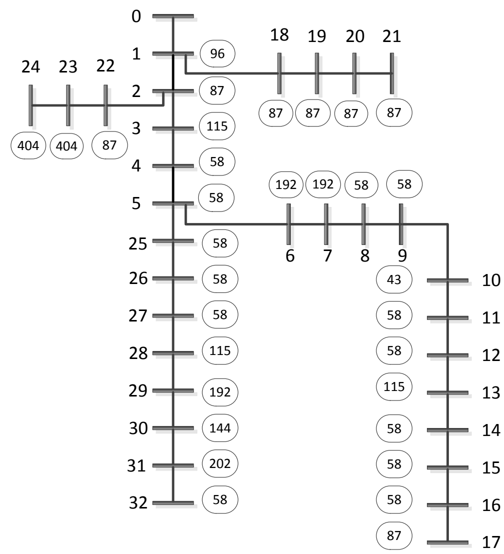


Fig. 4.2. Test system configuration and number of vehicles at each bus, shown inside the circles

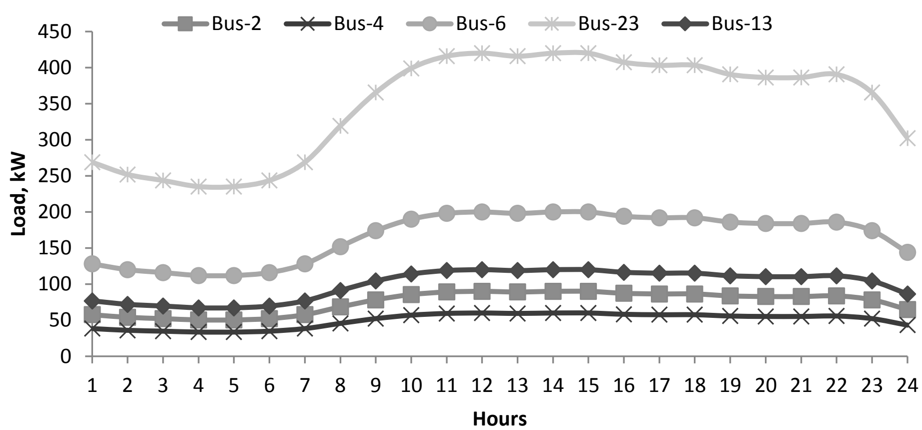


Fig. 4.3. RTS peak day load profile at some buses

Thereafter, Monte Carlo simulations are carried out to generate random trip mileage and home arrival times to build the uncontrolled charging profiles at each bus. In addition, for the optimization model in Stage-3 (Section-3.3.3), parameters such as $E_{c,g}$, $X^{E}_{c,g}$, and $X_h^{PEV_{home}}$ are obtained from the NHTS data set.

- The randomness of PEV market share and charging level mix are simulated based on Gaussian distributions with a standard deviations of 0.05 p.u.

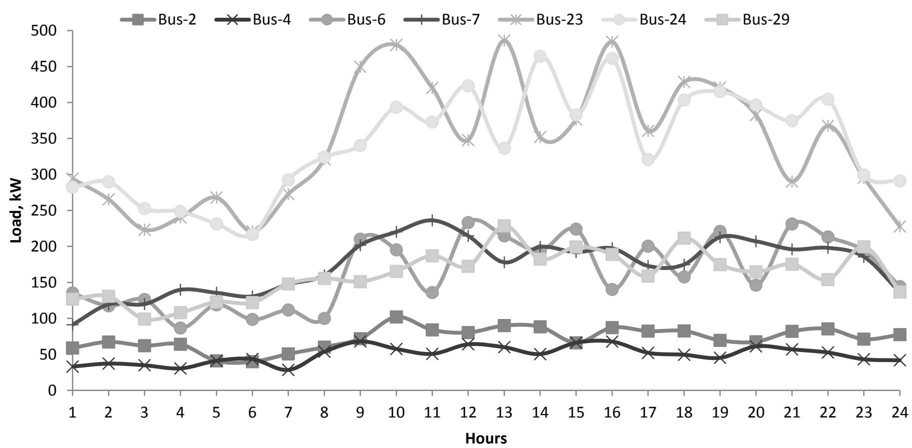


Fig. 4.4. Monte Carlo generated load profile at some buses for a given scenario

- A 24 hour time horizon is assumed, with one hour time intervals. However, the proposed model can accommodate smaller time steps if required, but at the cost of increased computational burden.

- The charging efficiency is assumed to be 90% [44, 46, 52].

- With respect to the number of vehicles at each bus, N_i^V, it is assumed that the entire load is residential and there are two vehicles per house and PEV charging occurs only at home. The number of houses at a bus is calculated assuming that the peak load of a house is 2.08 kW. For example, given that bus-23 peak load is 420 kW, as given in [87], the number of houses is 420 kW/2.08 kW$\approx$ 202 houses, and accordingly the number of vehicles at bus-23 is 404. In Fig. 3.2. the numbers inside the circles denotes the number of vehicles at each bus (N_i^V).

- Given the battery life-cycle considerations, it is assumed that $DOD = 0.7$ p.u., and $SOC^{min} = 0.2$ p.u. [60].

- The percentage of PEV charging is limited by the percentage of PEVs being home at an hour, $X_h^{PEV_{home}}$, as determined from the NHTS data, Fig. 3.5.

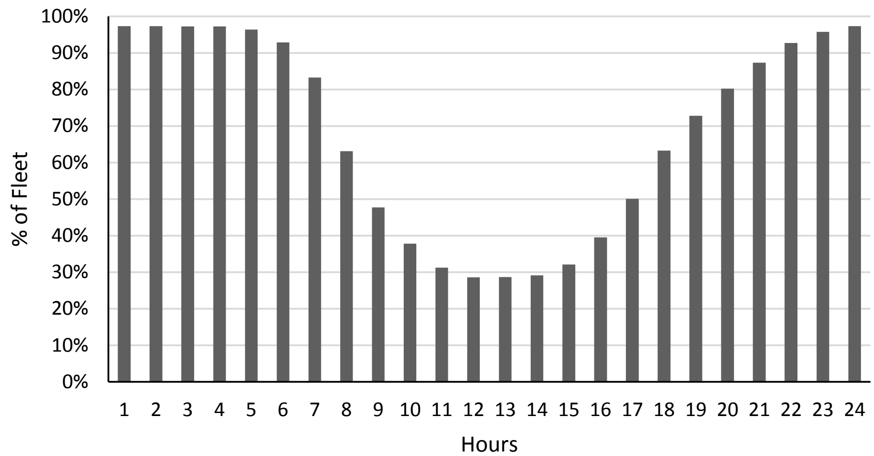


Fig. 4.5. Probability of vehicle being at home

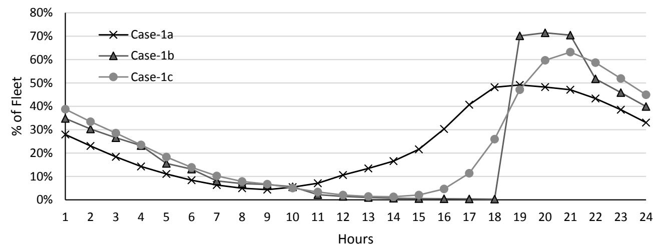
4.5 Results And Discussions

4.5.1 Uncontrolled Charging Profiles

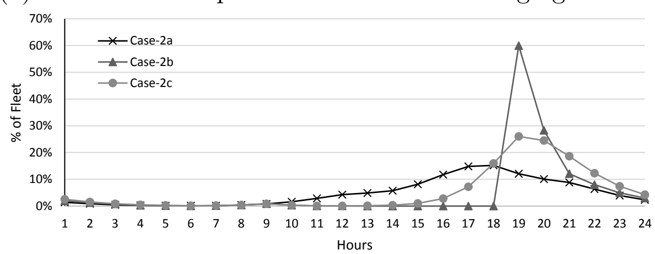
The uncontrolled charging profiles developed from Stage-I, for the considered case studies are presented in Fig. 3.6 wherein the differences among the various profiles are distinct. As can be seen, the charging load in the *Arrive & Plug* charging scenarios, *i.e.*, Cases 1a, 2a, and 3a, are more distributed over a period of time, based on the home arrival rate profile, and has a window of peak load appearing between hours 16 to 21.

On the other hand, the peak time window for *TOU-I* and *TOU-II* scenarios is narrower since all PEV owners react to the same price signal. In addition, most PEVs start charging simultaneously at the beginning of the off-peak price period (hour 19).

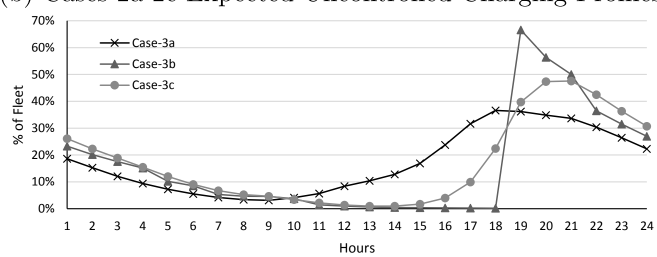
Level-2 charging, Cases 2a to 2c, are considered to be of a higher charging level than Level-1, and, therefore, has faster charging times, the peak charging hours are shifted to earlier hours compared to Level-1 charging profiles (1a - 1c). In addition, the charging demands are less distributed over the day and tend to have lower simultaneous charging due to shorter charging duration. Moreover, it is noted that overnight Level-1 charging demand is higher than Level-2 demand. This is due to the fact that lower charging level increases the charging duration.



(a) Cases 1a-1c Expected Uncontrolled Charging Profiles



(b) Cases 2a-2c Expected Uncontrolled Charging Profiles

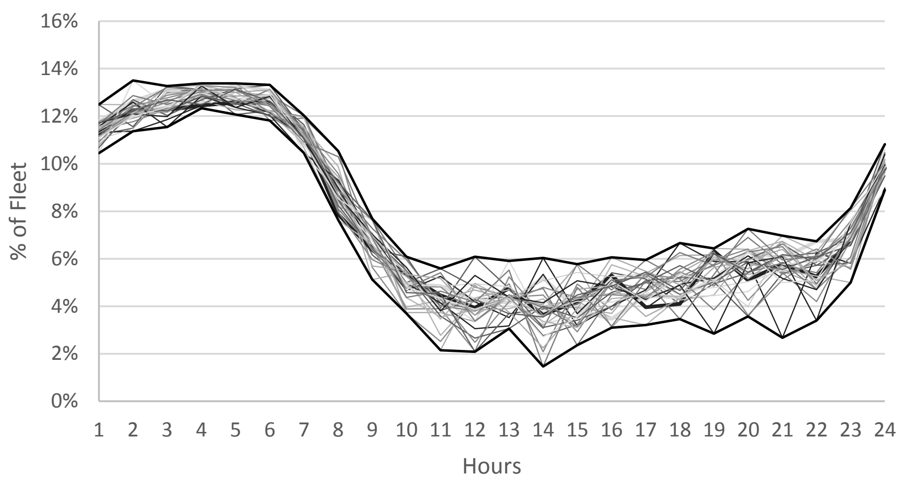


(c) Cases 3a-3c Expected Uncontrolled Charging Profiles

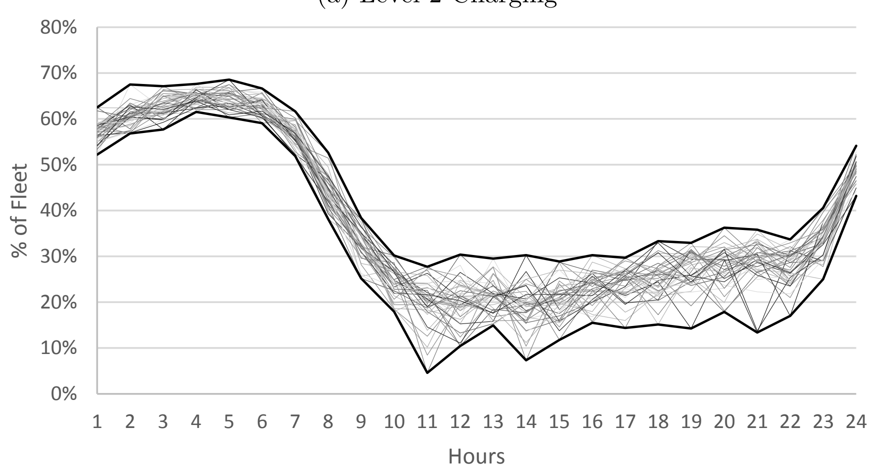
Fig. 4.6. Uncontrolled charging profiles for the proposed case studies

4.5.2 Distribution System Loading Margin

Fig. 3.7 presents the DSLM profiles considering charging Level-1 and Level-2 respectively, for different loading scenarios, presented as a percentage of the fleet that can be charged. It can be seen from Fig. 3.7, that simultaneous PEV charging is high between midnight and 7 AM which can be attributed to the decreased system demand. Between 11 AM and 3 PM the maximum and minimum percentages of PEVs charging simultaneously are approximately 30% and 4% for Level-1 charging, while 6% and 2% for Level-2 charging. It is noted that the percentages of simultaneous charging considering Level-1 are much higher than those for Level-2. This is due to the fact that lower charging levels have a low level of power drawn from the grid which enables more simultaneous charging PEVs.



(a) Level-2 Charging



(b) Level-1 Charging

Fig. 4.7. DSLM profiles obtained from Stage-II

4.5.3 Maximum Allowable Penetration Level

In this section, the expected allowable penetration of uncontrolled and smart charging PEVs are determined, using the outcomes of Stages-I and II. As discussed earlier in Section-3.3.3, first, the maximum allowable uncontrolled PEV penetration is determined, using Eq. 3.14 for each scenario and its expected value is arrived at after convergence of the Monte Carlo process. Table-3.4 presents the obtained values of $E[\alpha_s^{min}]$, for the different cases considered. Fig. 3.8 shows the convergence to the expected value, obtained by the proposed framework, in Case-3a.

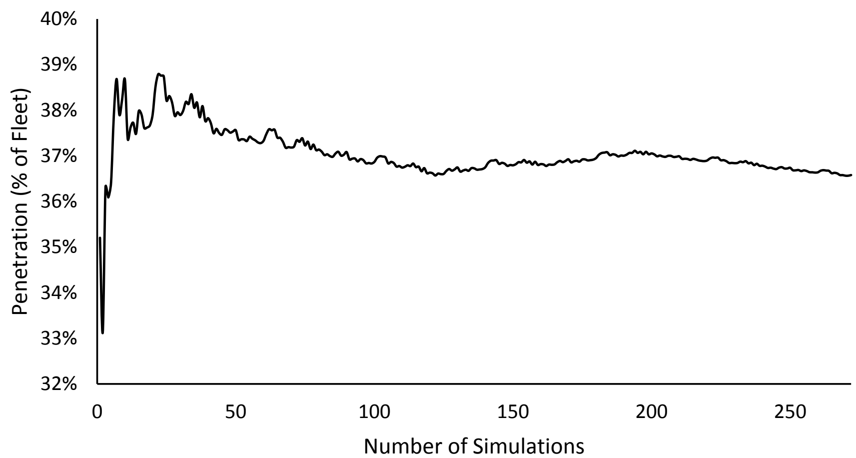


Fig. 4.8. Case-3a stopping criteria

It can be seen from Table-3.4 that the *Arrive & Plug* charging cases (Cases- 1a, 2a and 3a) allow higher levels of penetration compared to the other charging cases. Since all PEVs react on the price signal in *TOU-I* cases, resulting in a large number of PEVs simultaneously charging at the start of the off-peak price period, the maximum allowable penetration level in these cases (Cases 1b, 2b and 3b) are lower than those of the *Arrive & Plug* cases. The same applies to *TOU-II* cases (1c, 2c and 3c), although the difference is somewhat smaller.

With regard to the charging level, it is noted from Table-3.4 that for Level-1 (Cases 1a to 1c), the maximum allowable uncontrolled penetration is greater as compared to Level-2 (Cases 2a to 2c). This is because of the fact that a lower charging level increases the charging time which consequently allows more PEVs to charge simultaneously.

In addition, the new expected peak load hours and consequently the bottleneck hours are determined by comparing the base load and the uncontrolled PEV charging load profiles, and are presented in Table-3.5. It is to be noted that the bottleneck hours vary for different cases. In the TOU cases, most PEVs start charging at the beginning of the off-peak price period (hour 19) and hence the bottlenecks are concentrated at hours 19, 20 and 21; while for the *Arrive & Plug* cases, the bottleneck hours are spread out since the charging is spread out over a period based on PEV arrival rates; high probability of bottleneck at hour 18 is noted, which coincides with the high arrival rate at this hour.

The expected allowable uncontrolled profile is determined using (3.15), which is then used in the proposed optimization model of Section 3.3.3 to determine the maximum allowable smart PEV penetration, $\alpha^{Smt_{Sys}}$, and is given in Table-3.4. Since the smart charging PEVs are assumed to be controlled by the LDC, their charging schedules are optimally allocated over the day to maximize the number of PEVs charging. Hence the PEV penetration for various cases, considering smart charging, are much higher than that for uncontrolled charging.

TABLE 4.4
MAXIMUM ALOWABLE PENETRATION LEVEL

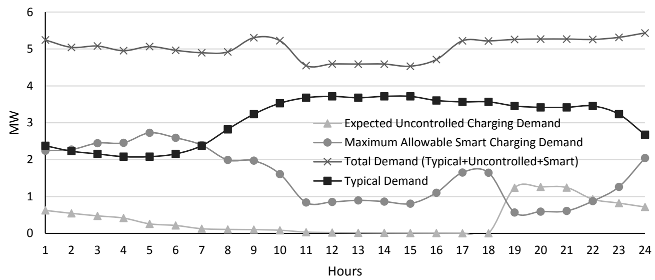
	$E[\alpha_s^{min}]$ **(% of Fleet)**	$\alpha^{Smt_{Sys}}$ **(% of Fleet)**
Case-1a	46.5	108.4
Case-1b	33.3	122.3
Case-1c	43	113.6
Case-2a	28.1	123
Case-2b	8.5	142.6
Case-2c	19.6	131
Case-3a	36.6	119
Case-3b	17.8	141
Case-3c	31	126

TABLE 4.5
BOTTLENECK HOURS FOR THE PROPOSED CASE STUDIES

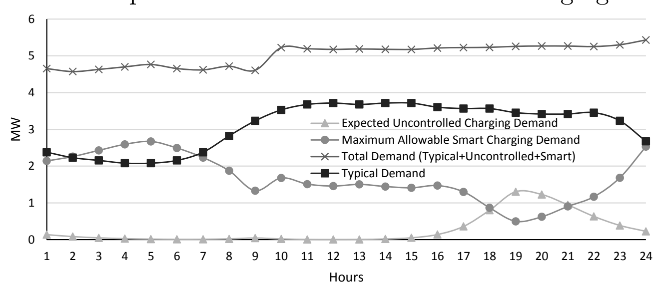
	Bottleneck Hours Probability							
	15	**16**	**17**	**18**	**19**	**20**	**21**	**22**
Case-1a	0.01	0.02	0.11	0.36	0.21	0.15	0.06	0.09
Case-1b					0.38	0.39	0.23	
Case-1c					0.03	0.41	0.26	0.31
Case-2a	0.04	0.13	0.34	0.41	0.05	0.00	0.04	
Case-2b					1.00			
Case-2c				0.02	0.54	0.39	0.05	
Case-3a	0.02	0.05	0.19	0.46	0.14	0.09	0.05	
Case-3b					0.95	0.04	0.01	
Case-3c				0.01	0.30	0.48	0.16	0.05

Fig.3.9 presents the resultant expected allowable uncontrolled charging, smart charging, typical, and total load (Base+Uncontrolled+Smart) profiles for three specific cases. It can be seen, in all cases, that the peak demand from the uncontrolled charging profiles are concentrated between hour 17 to 22 due to customers' arrival rate and TOU prices while

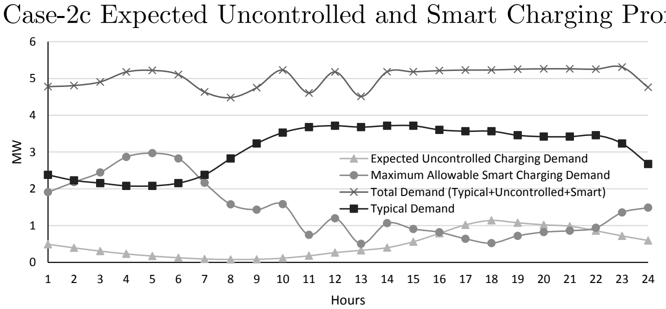
smart charging demands are mostly distributed between midnight and 7 AM which can be attributed to the decreased system demand. It is to be noted that the smart charging demand profile coordinates with the uncontrolled profile and reduces charging during peak hours when uncontrolled charging is high.



(a) Case-1b Expected Uncontrolled and Smart Charging Profiles



(b) Case-2c Expected Uncontrolled and Smart Charging Profiles



(c) Case-3a Expected Uncontrolled and Smart Charging Profiles

Fig. 4.9. Expected Allowable Uncontrolled and Smart Charging Profiles

It is to be noted that current TOU electricity prices were designed to reduce the system peak load and flatten the load profile, and bring about many benefits to the system. However, TOU prices can adversely impact the loadability of the distribution system and hence the uncontrolled PEV penetration. Therefore, further research should be undertaken to investigate the optimal TOU pricing scheme considering the penetration of PEV loads.

Furthermore, the charging level is clearly a major factor that affects the uncontrolled PEV charging load profile. From a customers' perspective, a higher charging level is preferable because it requires shorter time to charge the vehicle. It is also worth noting that there is enough margin for the whole fleet for smart charging. Unlike typical loads, PEVs are considered more flexible and elastic, and can be controlled by LDCs with the right incentives, which could be beneficial for LDCs without affecting customers convenience.

It should be pointed out that with increased PEV penetration into the grid, and with shorter charging durations, there will be increased charging demand appearing on the grid. This will indeed impact the system operational aspects and therefore unit ramping capabilities, frequency regulation, etc.. While some researchers have considered the problem of frequency regulation using grid-to-vehicle charging operation [103, 104], some others have examined these aspects considering the vehicle-to-grid operation mode [105–107]. However, since the framework proposed in this chapter seeks to assess distribution system margins in accommodating PEVs in the long-run, the very short-term system operational dynamics are not considered.

4.5.4 Effect of Charging Level

To study the impact of charging level on the penetration of uncontrolled and smart charging loads, three more combinations of charging levels are studied, for the *Arrive and Plug* scenario, namely 75%-25%, 50%-50%, and 25%-75% of Level-1 and 2 respectively, as shown in Fig. 3.10. It can be seen that as the share of Level-2 charging increases, the penetration of uncontrolled charging PEVs reduce. This is due to the fact that more Level-2 charging reduces the charging time and also involves more power being drawn from the grid, consequently reducing the maximum allowable uncontrolled penetration. On the other hand, smart charging penetration increases with the increase in share of Level-2 charging since the reduction in energy drawn by the uncontrolled fleet will lead to more room for smart charging.

4.5.5 Effect of Reactive Compensation Devices

When reactive devices are considered in the distribution system, the system will be able to accommodate an increased level of penetration of PEVs. Inclusion of reactive power compensation devices will improve the voltage profile and reduce losses. In order to examine this, a case study with similar assumptions of Case-3a, with two capacitors of 100 kVAR and 300 kVAR at buses 12 and 29, respectively, are considered. The location of the

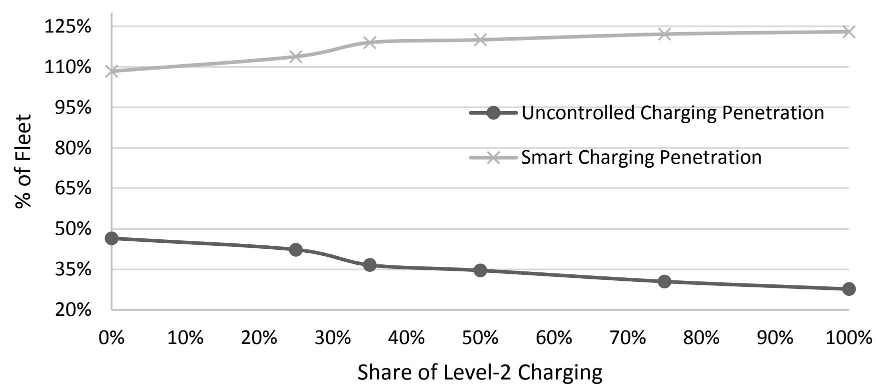


Fig. 4.10. Impact of charging level to the penetration of PEVs

capacitors has been chosen based on reference [108] which uses the same test system. It is noted in Table-3.6 that the maximum allowable uncontrolled ($E[\alpha_s^{min}$) and smart charging penetrations ($\alpha^{Smt_{Sys}}$) are 45% and 139.2%, respectively, which means an increase in both uncontrolled and smart charging penetration by approximately 9% and 20%, respectively.

Table generated by Excel2LaTeX from sheet 'Sheet1'

TABLE 4.6
EFFECT OF REACTIVE COMPENSATION DEVICES ON CASE-3A

	$E[\alpha_s^{min}]$ (% of Fleet)	$\alpha^{Smt_{Sys}}$ (% of Fleet)
Case-3a	36.6	119
Case-3a (considering reactive devices of reference [108])	45.03	139.2

4.5.6 Validation of Results

To examine the validity of the assessment, load flow runs are carried out considering the obtained uncontrolled and smart charging penetrations for Case-3a, namely 36.6% and 119% respectively, as a fixed loads. From Fig. 3.11, it can be seen that bus voltages at hour-14 are all within the allowable limits. Voltages at buses-15, 16, and 17 are close to the lower limit of 0.95 p.u. due to their location at the end of the feeder.

Furthermore, the penetration of the smart charging fleet is increased slightly to 119.1%. It can be seen that the voltages at buses 12-17 violated the allowable voltage limits due to the marginally increased penetration. These results validate the fact that the margin determined from the proposed framework are the critical limits which the planners need to take into account in their planning studies.

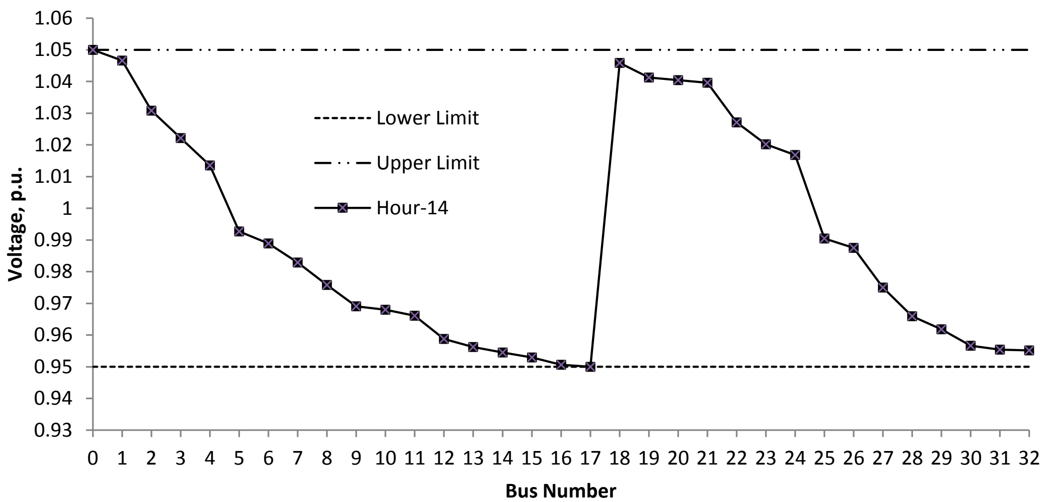


Fig. 4.11. Case-3a voltage profile for the system buses at hour-14

4.5.7 Computational Aspects

The OPF models, in Stage-II and Stage-III, are solved using the SNOPT solver [109] which is suitable for non-linear programming (NLP) problems. The considered test system is programmed and executed on a Dell PowerEdge R810 server, in GAMS environment [110], Windows 64-bit operating system, with 4 Intel-Xeon 1.87 GHz processors and 64 GB of RAM.

The model and solver statistics are given in Table-3.7. The OPF model in Stage-II requires 2.153 seconds per iteration, while in Stage-III it requires about 401 seconds. Note that the OPF in Stage-II is executed up to 350 times (until convergence of Monte Carlo simulation) while the Stage-III OPF is executed once. Therefore, the total time required to perform one case study is $(2.153 \times 350 + 401)$ seconds, i.e., 19 minutes; which is reasonable, for an essentially offline, long-term assessment study. Therefore, the proposed approach is scalable to large real distribution systems.

TABLE 4.7
Model Statistics

	Stage-II Distribution Assessment Margin Model	Stage-III Maximum Smart PEV Penetration Model
Model Type	NLP	NLP
Solver Used	SNOPT	SNOPT
Single Equations	6,217	20,097
Single Variables	5,521	207,538
CPU time, s	2.153	401.016

4.6 Conclusions

This chapter presented a novel framework to assess and determine the level of uncontrolled and smart PEV penetration that a distribution system can accommodate without any additional investments or upgrades. The model incorporated PEV driver habits, various vehicle types and charging levels in order to capture the charging pattern of PEV owners. In addition, Monte Carlo simulations were used to take various uncertainties into account. Various case studies were presented to demonstrate the performance of the proposed model, which can be used by LDCs to quantify the impacts, decide on the right actions and policies, and the required upgrades in their distribution networks.

This chapter fills the gap between current distribution system status and ongoing research on future grid by developing a generic framework that can be used to assess the DSLM to accommodate PEV charging loads.

Chapter 5

Design of Optimal Incentives for Smart Charging Considering Utility-Customer Interactions and Distribution Systems Impact[1]

5.1 Introduction

Electrifying the transportation sector will impact the distribution networks with increased peak load, increased losses, deterioration in voltage profile and change in load pattern. To mitigate these effects, the LDCs need to adopt the right actions and policies, and develop associated infrastructure. In the context of smart grids, the LDCs can control PEV charging demand while also considering customer preferences, which can lead to benefits such as deferment of the decisions on reinforcement and other investments, and maximize the use of existing infrastructure. In addition, LDCs can establish rate structures that incentivize the use of smart charging and increase the adoption and use of PEVs. Therefore, electrifying the transport sector can benefit both the LDCs and the customer.

To encourage PEV owners adopt smart charging, the LDC can offer appropriate programs and/or incentives to PEV customers. However, an LDC managed smart

[1]This chapter has been submitted for publication in:
A. Bin Humayd, and K. Bhattacharya. ”Design of Optimal Incentives for Smart Charging Considering Utility-Customer Interactions and Distribution Systems Impact.” IEEE Transactions on Smart Grid. (in review).

charging program involves a business relationship between the two parties. Assuming rational behaviour of PEV customers, their participation in smart charging programs will depend on the incentive amount, higher the incentive, more PEV customers are likely to adopt smart charging. On the other hand, from the LDC's viewpoint, high incentives result in increased financial burden to itself, and adoption of smart charging will only be beneficial in the short-run, by virtue of its flattening the overall system load profile to reduce its demand charges; and in the long-run, when deferral costs of capacity additions are taken into account.

Denoting X^S as the share of PEV fleet that arrive at peak hours and participate in the smart charging program, it can be assumed that there exists a relationship between the incentives offered by the LDC and X^S. Also, a relationship exists between X^S and the peak load reduction achieved by the LDC through smart charging, in the short-run; and the resulting economic benefit of capacity deferral accrued there from in the long-run.

None of the reported works have considered these inter-relationships in smart charging programs, *i.e.*, between X^S and the incentives offered by the LDC; or between X^S and the resulting economic benefits of capacity deferral. The optimal participation of PEV customers in smart charging programs, arising from such inter-relationships and the optimal incentive mechanisms, from a long-term perspective, have not been investigated. Therefore, there is a need to develop a generic framework to determine these inter-relationships between the LDC and PEV customers, while considering their own perspectives of system operations and economic returns from such a program. There is also a need to determine the optimal participation of PEV customers that would result in the optimal benefits to both parties; and what optimal incentive would drive such an optimal participation.

In this chapter, a PEV smart charging approach is proposed where the charging loads are controlled and incentivized by the LDC for every unit of energy controlled. A novel framework is proposed to determine the optimal participation of PEVs in the smart charging program and optimal incentives paid by the LDC to PEV customers, such that both parties are economically benefited. The proposed framework models the relationship between customers' participation and incentives offered by the LDC. The relationship between the expected investment deferral and hence the economic benefits from smart charging participation are considered as well. Monte Carlo simulation is used to simulate the uncertainty of demand, electricity market price, drivers' behaviour, PEV market share, and charging level share.

The structure of the chapter is as follows. The nomenclature used in this chapter is presented in Section-4.2. In Section-4.3, a description of the proposed framework and the associated mathematical models are presented. This is followed by a description of the case studies and assumptions in Section-4.4. In Section-4.5, the proposed framework is applied to a distribution system and the results are presented to demonstrate the effectiveness of the proposed model. Conclusions are drawn in Section-4.6.

5.2 Nomenclature

Indices

ct	Index for charging level type, charging level 1 and 2
g	Index for PEV groups classified by their charging duration, $g = 1, 2, ...G$
h, k	Index for hours, $h, k = 1, 2, ..24$
i, j	Index for buses, $i = 1, 2, ..N$
N	Total number of buses
s	Scenarios of uncertainty
SS	Subset of substation buses ($SS \in i$)

Parameters

C^{Peak}	Peak demand charge, \$/MW
C^{Sm}	Cost of smart charging device and communication, \$/unit
C_h^{TOU}	Time-of-Use electricity price, \$/MWh
ChD_g	Charging duration, hours
$E_{g,ct}$	Energy required to charge group g of PEVs at charging level ct
N_i^{PEV}	Number of PEVs at bus i
P_{ct}^{ChL}	Power drawn by a PEV at charging level ct, p.u.
$P_{i,h}^D, Q_{i,h}^D$	Real and reactive power demand at bus i and hour h, p.u.
V^{Min}, V^{Max}	Lower and upper limits of voltage magnitude, p.u.
$X_{i,k}^A$	Share of PEV fleet that arrive at hour k and require ChD_g charging duration
X_i^P	Share of PEV fleet that arrive during on-peak period, p.u.
$X_{i,g,ct}^{ChD}$	Share of PEV fleet that uses charging level ct and require charging duration of ChD_g, p.u.
ρ_h	Hourly market price, \$/MWh

η	Charging efficiency
$\theta_{i,j}$	Angle of bus admittance matrix element i-j, rad

Variables

$P^{Fdr}_{i,j,h}, Q^{Fdr}_{i,j,h}$	Real and reactive power flow from i to j at hour h, p.u.
P^{Peak}	Daily peak load imported by substation, p.u.
$P^{S}_{i,h}$	Total power drawn by PEV fleet in smart mode at bus i and hour h, p.u.
$P^{Sm}_{i,g,h,ct}$	Power drawn by PEV fleet in smart mode of group g, using charging level ct, at bus i and hour h, p.u.
$P^{U}_{i,h}$	Total power drawn by PEV fleet in uncontrolled mode at bus i and hour h, p.u.
$P^{UncOf}_{i,h,ch}, P^{UncP}_{i,h,ch}$	Off-peak and on-peak power drawn by PEV fleet in uncontrolled mode using charging level ct, at bus i and hour h, p.u.
P^{SS}_{h}, Q^{SS}_{h}	Real and reactive power imported by LDC via substation at hour h, p.u.
$V_{i,h}$	Voltage magnitude at bus i and hour h, p.u.
X^{S}	Share of PEV fleet that arrive at peak hours and participate in smart charging program, p.u.
$\delta_{i,h}$	Voltage phase angle at bus i and hour h, rad

5.3 Proposed Framework

In this chapter, it is assumed that the PEV owners can either adopt uncontrolled charging or participate in a smart charging program by transferring the control access of their vehicle to the LDC to regulate their charging and receive incentives. The optimal participation of smart charging customers, resulting from such an incentive-driven program, and the optimal incentives that would not cause financial loss to the LDC, are determined simultaneously.

Fig. 4.1 presents the overall schematic of the proposed framework which comprises three models, the Cost of Capacity Saving Model (CCSM), the Customer Participation Model (CPM), and Optimal Incentives for Smart Charging Model (OISCM). In CCSM, a new mathematical model is proposed that quantifies the peak demand reduction accrued due to the participation of PEV customers in smart charging program and hence a relationship is determined between smart charging participation and the cost of capacity savings, achieved thereby, by the LDC. While in CPM, a model is proposed to determine the relationship between customers' participation in smart charging programs vis-a-vis the promotional incentives offered by the LDC. In the third model, OISCM, a model is proposed to determine the optimal incentives that the LDC should offer to PEV smart charging customers, that will in-turn induce the optimal smart charging participation (X^S). The outcomes from the first two models are fed into the third model. Monte Carlo simulation is used to generate a large number of residential load profiles and PEV charging profiles, considering different charging levels, PEV types, and electricity market prices.

5.3.1 Cost of Capacity Saving Model (CCSM)

With continuous increase in the system demand from increasing penetration of PEVs, there will be need for reinforcements, or even new investments in the distribution system in the long-run. However, adequate participation of PEV owners in smart charging programs will help alleviate the peak demand growth and defer the need for upgrades. In this section, a new mathematical model is presented that quantifies the peak demand reduction accrued due to the participation of PEV customers in smart charging and hence a relationship is determined between smart charging participation and the cost of capacity savings, achieved thereby, by the LDC.

Objective Function

The objective function (J_1) seeks to minimize the LDC's operations costs, and is given as follows:

$$J1 = \sum_{h=1}^{24} \rho_h P_h^{SS} + \sum_h P^{Peak} C^{Peak} \quad - \sum_i \sum_h C_h^{TOU} (P_{i,h}^D + P_{i,h}^U + P_{i,h}^S) \tag{5.1}$$

where the first term of (4.1) is the cost of purchased power from the grid at market price, the second term represents the peak demand charge, and the last term denotes the revenue earned by the LDC from sell of energy to customers at time-of-use (TOU) price which includes the uncontrolled and smart charging PEV energy sold, as well. Note that since TOU price is in force in Ontario, Canada, the same is considered in this work;

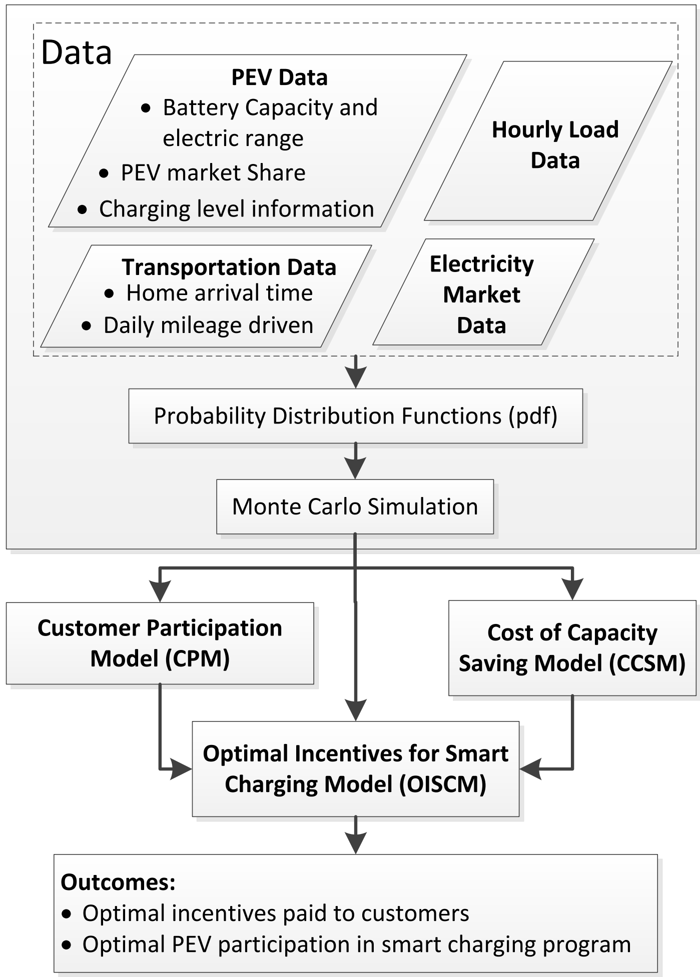


Fig. 5.1. Framework for LDC-PEV customer interaction based smart charging

however, C_h^{TOU} is generic and can represent any other price structure as well. The associated operational constraints are as follows.

Power Flow Equations

The injected power at bus i and hour h is the power drawn from the substation, net of the load, the uncontrolled, and smart PEV charging loads; and is governed by the ac power flow equations:

$$P_{i,h}^{SS} - P_{i,h}^{U} - P_{i,h}^{S} - P_{i,h}^{D} = \sum_{j \in N} V_{i,h} V_{j,h} Y_{i,j} cos(\theta_{i,j} + \delta_{j,h} - \delta_{i,h}) \qquad \forall i \in N, \forall h \quad (5.2)$$

$$Q_{i,h}^{SS} - Q_{i,h}^{D} = -\sum_{j \in N} V_{i,h} V_{j,h} Y_{i,j} sin(\theta_{i,j} + \delta_{j,h} - \delta_{i,h}) \qquad \forall i \in N, \forall h \quad (5.3)$$

Note that (4.3) does not considers any reactive component in the PEV charging.

PEV Uncontrolled Charging Constraints

It is to be noted that X^S is considered as a portion of peak arrivals, X^P. While the share of customers not participating in smart charging program (uncontrolled charging) includes off-peak arrivals, $X^A - X^P$, and peak arrivals not participating in smart charging program, $X^P - X^S$, as follows:

$$X^A = \begin{cases} X^P, & \begin{cases} X^S, & Smart \\ X^P - X^S, & Uncontrolled \end{cases} \\ X^A - X^P, & Uncontrolled \end{cases} \quad (5.4)$$

where X^A is the total share of arrivals. The uncontrolled charging load at any given hour over the off-peak period (7 PM to 7 AM) [111], is denoted by the relation given below, and comprises all accumulated charging loads from $h, h-1, h-2, ..., h-(ChD_g+1)$, which means all charging loads from previous hours that have not completed their charging cycle. Note that the charging duration, ChD_g, are integer values that are equal to the order of its index g, *i.e.* $ChD_1 = 1, ChD_2 = 2, ..ChD_G = G$.

$$P_{i,h,ct}^{UncOff} = \sum_{g} \sum_{\substack{h-ChD_g+1 \le k \le h \\ k \in h^{OffPeak}}} X_{i,k}^{A} X_{i,g,ct}^{ChD} N_i^{PEV} P_{ct}^{ChL} \qquad \forall i, \forall ct, \forall h \quad (5.5)$$

For example, the uncontrolled charging load at $h = 5$ comprises:

Vehicles start charging at:	$k = h = 5$
Need charging duration of:	$g = 1, 2, 3..., G$
Vehicles start charging at:	$k = h - 1 = 4$
Need charging duration of:	$g = 2, 3, 4..., G$
:	:
Vehicles start charging at:	$k = h - G + 1$
Need charging duration of:	$g = G$

On the other hand, the uncontrolled charging arising from $(1 - X^S)$ fraction of the PEVs arriving home during on-peak hours and opting for uncontrolled charging, is given as follows:

$$P_{i,h,ct}^{UncOn} = \sum_{g} \sum_{\substack{h-ChD_g+1 \le k \le h \\ k \in h^{OnPeak}}} X_{i,k}^{A} X_{i,g,ct}^{ChD} N_i^{PEV} P_{ct}^{ChL} (1 - X^S) \qquad \forall i, \forall ct, \forall h \quad (5.6)$$

It is to be noted from (4.6) that only on-peak arrivals are candidates for smart charging. The total uncontrolled charging demand is hence obtained as follows:

$$P_{i,h}^{U} = \sum_{ct} P_{i,h,ct}^{UncOf} + P_{i,h,ct}^{UncOn} \qquad \forall i, \forall h \qquad (5.7)$$

PEV Smart Charging Constraints

These constraints ensure that the total charging energy required by each PEV group g using smart charging is equal to the daily energy needed to charge the battery. In addition, these constraints ensure that the smart charging window is from the time of their home arrival till 10 AM next day.

$$\sum_{h \in h^{OffPeak}} P_{i,g,h,ct}^{Sm} = X_i^P X_{i,g,ct}^{ChD} N_i^{PEV} E_{g,ct} X^S \qquad \forall i, \forall g, \forall ct \quad (5.8)$$

where

$$X_i^P = \sum_{h \in h^{OnPeak}} X_{i,h}^{A} \qquad (5.9)$$

Moreover, the power drawn by PEVs during any hour must be within the charging level, as follows:

$$P_{i,g,h,ct}^{Sm} \leq X_i^P X_{i,g,ct}^{ChD} N_i^{PEV} P_{ct}^{ChL} X^S \qquad \forall i, h, g, ct \quad (5.10)$$

Accordingly, the total smart charging demand is obtained as follows:

$$P_{i,h}^{S} = \sum_{ct,g} P_{i,g,h,ct}^{Sm} \qquad \forall i, \forall h \quad (5.11)$$

Peak Load Constraints

LDCs are charged for their monthly peak demand [112] and hence it is important that the PEV charging loads do not increase the system peak demand beyond acceptable limits. The following constraint, in conjunction with (4.1), ensures that the peak demand is minimized:

$$P_{i,h}^{SS} \leq P^{Peak} \qquad \forall i \in SS, \forall h \quad (5.12)$$

Voltage Limits

These constraints ensure that the voltage magnitudes at all buses are within the minimum and maximum allowable limits.

$$V^{Min} \leq V_{i,h} \leq V^{Max} \qquad \forall i \in N, \forall h \quad (5.13)$$

Step-by-Step Procedure

The step-by-step procedure of quantifying the expected economic benefit to the LDC from deferral of capacity investments accrued from smart charging participation by PEV owners is as follows:.

1. Set the share of PEV smart charging $X^S = 10\%$.
2. Randomly generate the market price profile (ρ_h), system load profiles, and PEV uncontrolled charging loads for each bus in the system.

3. Execute the proposed CCSM to determine the Peak Reduction Ratio (PRR), denoted by (λ), which is the ratio of system peak demand with smart charging to that with no smart charging.

4. Calculate the expected value of λ, denoted by $E[\lambda]$, for multiple simulations.

5. Calculate the expected deferral of investment costs, in years, ($E[\Delta N]$) due to smart charging participation by PEV owners, as follows [113]:

$$E[\Delta N] = \frac{\log \frac{1}{E[\lambda]}}{\log(1+\tau)} \tag{5.14}$$

   where τ is the annual growth rate of the system load.

6. Calculate the expected benefit accrued to the LDC from the capacity deferral using the following:

$$E[B] = C^{Inv}\left(1 - \left(\frac{1+i}{1+d}\right)^{E[\Delta N]}\right) \tag{5.15}$$

   where C^{Inv} denotes the transformer capital cost (\$), i and d are inflation and discount rates, respectively.

7. Repeat steps 1- 6 and tabulate $E[B]$ for various levels of smart charging participation by PEV owners.

8. Stop if $X^S = 100\%$ and estimate the relationship between X^S and $E[B]$ using the data obtained, as follows:

$$E[B] = f^{CS}(X^S) \tag{5.16}$$

5.3.2 Customer Participation Model (CPM)

A PEV smart charging program need develop a business model between the LDC and PEV customers as they are both impacted by this relationship. To date, there is no real data or PEV customer surveys that examine the relationship between customers' participation in smart charging programs vis-a-vis the promotional incentives offered by the LDC.

In this work, customer participation is modelled as a function of the incentive provided by the LDC. A two-part incentive structure comprising a fixed component (α^{Rebate}) and a variable component (α^{Inc}), is proposed, as follows:

- α^{Inc}: PEV customers are paid for the amount of charging energy shifted through smart charging control (\$/kWh).

- α^{Rebate}: PEV customers are paid a portion of the fixed cost of the smart charging device to be installed (\$).

The expected annual economic benefit ($E[AEB]$) for PEV customers can be estimated from the reduction in the annual energy cost based on the incentive paid by the LDC, α^{Inc}, and the rebate received for smart charging device, α^{Rebate}, and can be expressed as follows:

$$E[AEB] = E[E^{PEV}]\alpha^{Inc} - (C^{Sm} - \alpha^{Rebate}) \tag{5.17}$$

where $E[E^{PEV}]$ is the expected annual PEV charging energy and C^{Sm} is the annualized cost of smart charging device. It is assumed that X^S is proportional to E[AEB], normalized with respect to its PEV charging cost in 100% uncontrolled mode, as given below:

$$X^S = \frac{E[AEB]}{E[C^{Chg}]} \tag{5.18}$$

Therefore, from (4.18) it is noted that if the incentives are very low, or null, E[AEB] will be very low or negative, and X^S = zero; while if E[AEB] covers the entire annual charging cost ($E[C^{Chg}]$), *i.e.*, E[AEB] = $E[C^{Chg}]$, the participation is 100%.

5.3.3 Optimal Incentives for Smart Charging Model (OISCM)

In this section, a novel mathematical model is proposed to determine the optimal incentives (α^{Inc} and α^{Rebate}), that the LDC should offer to PEV smart charging customers, that will in-turn induce the optimal smart charging participation (X^S).

Objective Function

The objective function (J_2) considered for minimization, is a comprehensive representation of the LDC's cost of system operation, promotion and adoption of PEV smart charging infrastructure, as well as the long-term economic benefit from capacity deferral accrued from such policy implementation, and is given as follows:

$$\begin{aligned}
J2 = &\sum_{h=1}^{24} \rho_h P_h^{SS} \qquad ⓐ\\
&+ \sum_i X^S N_i^{PEV} \alpha^{Rebate} \qquad ⓑ\\
&+ \sum_i \sum_h \alpha^{Inc} P_{i,h}^S \qquad ⓒ\\
&+ \sum_h P^{Peak} C^{Peak} \qquad ⓓ\\
&- \sum_i \sum_h C_h^{TOU} (P_{i,h}^D + P_{i,h}^U + P_{i,h}^S) \qquad ⓔ\\
&- f^{CS}(X^S) \qquad ⓕ
\end{aligned} \tag{5.19}$$

where

a	Purchased power from grid at market price.
b	Rebate paid to customers for adopting smart charging devices
c	Incentives paid to customers participating in smart charging program
d	Peak demand charge incurred by LDC ($\$/kW$)
e	Revenue from customers for energy sold at TOU price
f	Cost of capacity saving, obtained from Section-4.3.1, and given by (4.16).

Customers' Participation Rate Constraint

Applying (4.17) in (4.18), the customers' participation in smart charging (X^S) can be modelled as follows:

$$X^S = A\alpha^{Inc} + B\alpha^{Rebate} + C \tag{5.20}$$

The objective function (4.19), constraints (4.2)-(4.3), (4.5)-(4.13) and (4.20) comprises the OISCM, which is a non-linear programming (NLP) model. A Monte Carlo simulation of the load profile, considering a range of PEV data (such as charging duration, starting time of charging), and electricity market price, is carried out to arrive at a large number of input profiles, which are then fed into the OISCM to determine the expected smart charging participation ($E[X^S]$) and the expected incentives.

5.4 Test System and Assumptions

The distribution system under study comprises 33 buses in radial configuration [87]. The total system peak demand is 4.54 MVA. The network parameters and the load data are given in the Appendix. Three case studies with different PEV market penetrations, namely 25%, 50%, and 75%, have been considered. In order to evaluate the optimal PEV smart charging participation and the optimal incentives paid to customers, the following assumptions are made:

- The IEEE RTS [102] base load profile is used; the randomness of bus-wise and hourly loads are simulated using Gaussian distributions with a standard deviation of 0.15 p.u. around the nominal.
- Daily trip data was extracted from the US National Household Travel Survey (NHTS) 2009 [86] of a sample size of 150,147 households, and 309,164 vehicles, for different type of vehicles, and trips, to obtain the probability distribution function (pdf) of daily mileage driven and home arrival times of the PEVs (Fig.4.2 and 4.3). Thereafter, Monte Carlo simulations are carried out to generate random trip mileage and home arrival times.

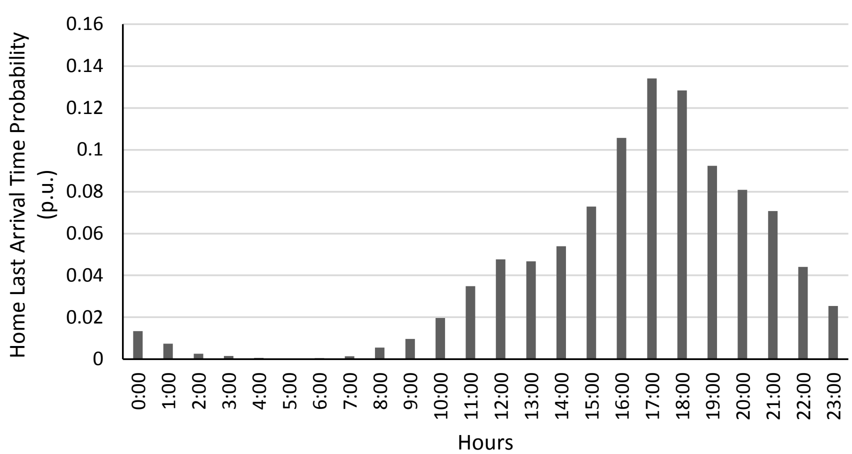


Fig. 5.2. Probability distribution function for home last arrival time

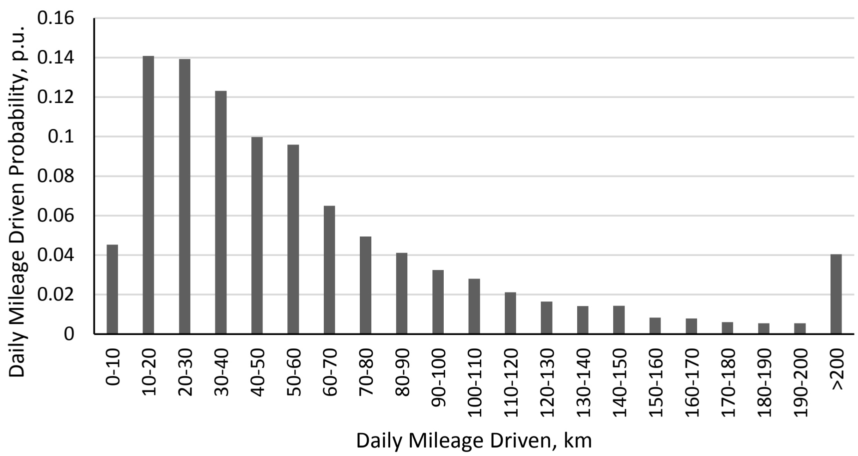


Fig. 5.3. Probability distribution function for daily mileage driven

- Eleven common makes of PEVs are considered, which covers 95% of the total market of PEVs in USA, and these are grouped into four classes (Table 3.1).
- Two residential charging levels are considered (Level-1 and Level-2) which have been used in several studies, with shares of 65% and 35%, respectively [101].
- The market shares of the PEV classes are uncertain, and so is the mix of the charging level. Monte Carlo simulations are carried out considering Gaussian distributions with a standard deviation of 0.05 p.u.
- The charging efficiency is 90%.
- The entire load is residential, there are two vehicles per house and PEV charging occurs only at home. The number of houses at a bus is calculated assuming the house peak load to be 2.08 kW. Therefore, the number of bus at each bus is known.
- Given the battery life-cycle considerations, it is assumed that the maximum allowable depth of discharge is 70%. [60].
- The daily market price profiles for 2015 of Hourly Ontario Energy Price (HOEP), and Ontario TOU electricity price are considered for the simulations. The uncertainty in HOEP is simulated using Gaussian distribution with standard deviation of 0.15 p.u.
- The cost of a smart charging device, C^{Sm}, is assumed to be \$150 [114]; the annualized cost considering a life of five years and 10% discount rate is obtained to be \$40.

Furthermore, C^{Peak} is assumed to be 6.55\$/kW which is the provincial transmission service charge in Ontario. For calculating the deferrals, (4.14)- (4.15), annual growth rate (τ) = 1.5%; and inflation rate (i) = 1.5% are assumed.

5.5 Results And Discussions

5.5.1 Cost of Capacity Saving Function

Table-4.2 presents the impact on the expected PRR ($E[\lambda]$), expected capacity deferral in years (ΔN), and the equivalent economic benefits ($E[B]$) accrued to the system, with increasing X^S for varying degrees of market penetration of PEVs, obtained using the CCSM. Since the peak load increases as X^S increases in the three cases, the deferred substation capacity upgrades will also increase; and are assumed to be 3, 4, and 5 MW, and the associated deferred investment costs are \$350,000, \$400,000, and \$450,00, respectively.

The expected PRR ($E[\lambda]$) and the expected economic benefit due to investment deferral E[B] are presented in Fig. 4.4 and Fig. 4.5, respectively. As seen from Fig. 4.4 and Table-4.2, the PRR decreases with the increase in X^S, attains a minimum, and then increases, with further increase in X^S because a new peak is now created at off-peak periods with high participation of PEVs in smart charging. This trend is observed for all the three cases, but in Case 3, the expected PRR attains the lowest value amongst the three, and the trend is more pronounced, because of the high market penetration of PEVs.

As seen from Table-4.2 and Fig. 4.5, the capacity deferral and hence the expected benefit accrued are proportional to X^S. A linear curve fit function of E[B] versus X^S is also presented in Fig. 4.5, which is used in the OISCM.

5.5.2 Customer Participation Rate

The CPM discussed earlier, is solved to determine the PEV customers participation in the smart charging program as a function of the incentive (α^{Inc}) and rebate (α^{Rebate}) paid by the LDC. As discussed in Section-II.B, the first step is to determine E[AEB] as per (14) and $E[C^{Chg}]$ in uncontrolled mode. This is done by generating a number of scenarios on daily mileage driven and where the start time of charging is based on arrive and plug, and using the pdfs obtained earlier.

In Table-4.3, it is noted that $E[C^{Chg}]$ increases with increase in battery capacity and Level-2 charging leads to higher energy cost as compared to Level-1 for the same PEV

TABLE 5.2
EXPECTED PRR, CAPACITY DEFERRAL, AND BENEFIT FOR THE CONSIDERED CASE STUDIES

	Case-1 (25% PEV Market Penetration)				Case-2 (50% PEV Market Penetration)				Case-3 (75% PEV Market Penetration)			
X^S (p.u.)	$E[\lambda]$ (p.u.)	ΔN (Years)	E[B] ($)	Annualized E[B] ($)	$E[\lambda]$ (p.u.)	ΔN (Years)	E[B] ($)	Annualized E[B] ($)	$E[\lambda]$ (p.u.)	ΔN (Years)	E[B] ($)	Annualized E[B] ($)
0	1	0	0	0	1	0	0	0	1	0	0	0
0.1	0.982	1.2	29143	7492	0.968	2.2	58088	14934	0.961	2.7	77737	19986
0.2	0.965	2.4	55158	14181	0.937	4.3	106572	27399	0.923	5.4	143156	36804
0.3	0.948	3.6	78309	20133	0.911	6.2	143540	36903	0.890	7.8	192734	49551
0.4	0.936	4.4	95002	24424	0.893	7.6	167296	43011	0.868	9.5	222093	57098
0.5	0.925	5.2	108730	27954	0.880	8.6	183426	47157	0.853	10.7	240227	61761
0.6	0.917	5.8	119161	30635	0.871	9.3	193447	49734	0.843	11.4	250854	64493
0.7	0.911	6.3	126147	32431	0.866	9.7	199442	51275	0.839	11.8	255739	65749
0.8	0.906	6.6	131275	33750	0.863	9.9	202203	51985	0.840	11.7	255178	65604
0.9	0.904	6.8	134427	34560	0.864	9.8	201368	51770	0.849	11.0	244600	62885
1	0.902	6.9	136134	34999	0.870	9.4	195114	50162	0.869	9.4	220282	56633

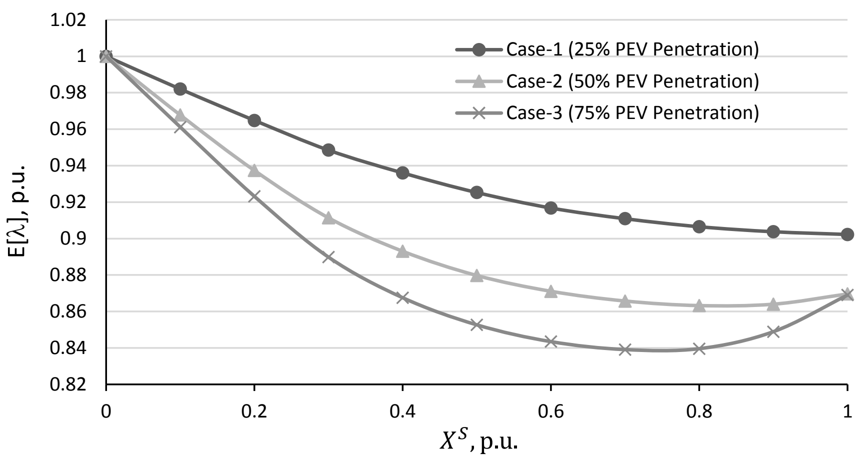


Fig. 5.4. Expected PRR ($E[\lambda]$) versus smart charging participation

class. This is due to the shorter charging duration, compared to Level-1 users, and high arrival rate during on-peak period which means a significant portion of charging occurs during on-peak TOU price. On the other hand, Level-1 users need longer charging duration and hence a major portion of their charging occurs during off-peak periods. The weighted average values for the considered PEV classes are obtained as shown in the last row of Table-4.3, which are then used to calculate the parameters of the customer participation function (4.18). The estimated customers' participation function can be written as follows:

$$X^S = 8.7895\alpha^{Inc} + 0.0038\alpha^{Rebate} - 0.1489 \tag{5.21}$$

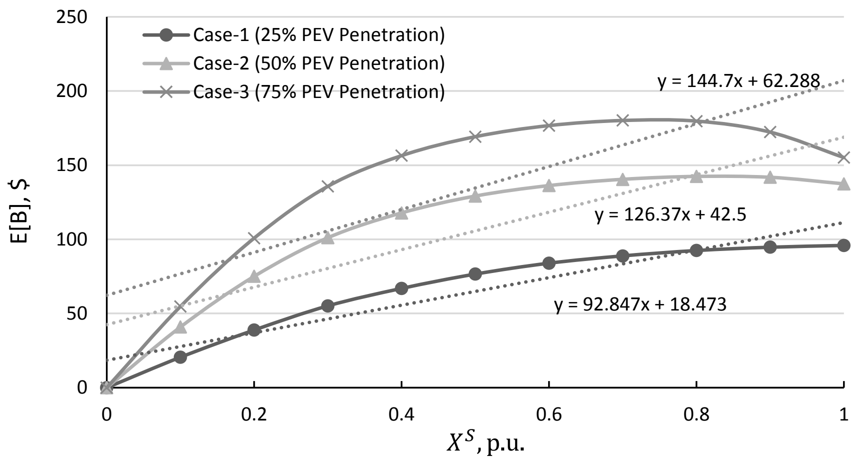


Fig. 5.5. Expected benefit versus smart charging participation

Fig. 4.6 presents the variation in customer participation with changes in incentive and rebate, as obtained in (4.21). It is noted that α^{Inc} has a more pronounced effect on X^S as compared to α^{Rebate}.

TABLE 5.3
Expected Annual Energy, Energy Cost, and Average Cost for the Considered PEV Classes

	$E[C^{Chg}]$ ($)	$E[E^{PEV}]$ (kWh)	Expected Annual Average Cost $/kWh
PHEV-I (Level-1)	162	1,388	0.117
PHEV-I (Level-2)	171	1,383	0.124
PHEV-II (Level-1)	293	2,710	0.108
PHEV-II (Level-2)	340	2,757	0.123
BEV-I (Level-1)	271	2,496	0.109
BEV-I (Level-2)	303	2,513	0.121
BEV-II (Level-1)	296	2,743	0.108
BEV-II (Level-2)	391	3,348	0.117
Weighted Average Values	**266**	**2,338**	**0.114**

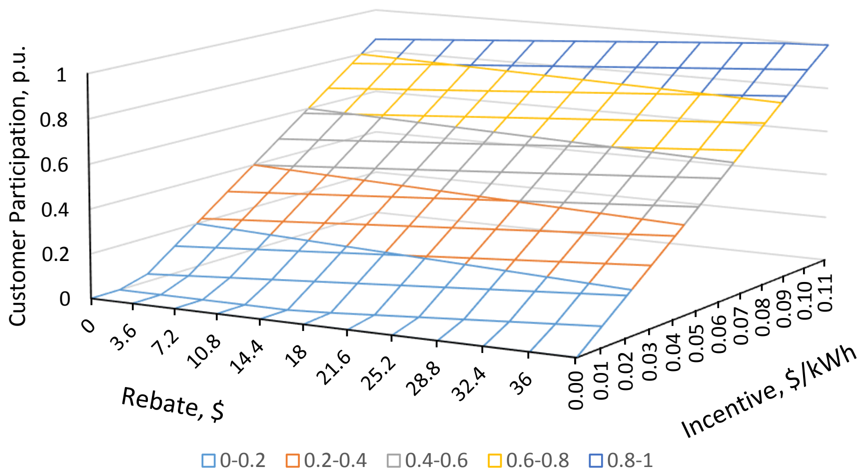


Fig. 5.6. Customer participation with respect to incentive and rebate

5.5.3 Optimal Share of PEV Smart Charging

The optimal value of α^{Inc}, α^{Rebate}, and X^S of PEV customers are now determined using the proposed OISCM which includes the outcomes from CCSM and CPM, discussed earlier. The expected values of these variables are arrived at, after convergence of the Monte Carlo process, as presented in Table-4.4 for the different cases considered. Fig. 4.7 shows the convergence to the expected value, obtained from the proposed framework, in Case-3.

It can be seen from Table-4.4 that there is no significant difference in terms of α^{Inc}, α^{Rebate}, and X^S for the different cases of market penetrations of PEVs. However, there will be a proportionate increase in the absolute number of PEVs participating in the smart charging program as market penetration of PEVs increase. The optimal incentives obtained are 3, 2.9, and 2.9 cents per kWh, which implies about 33% savings in annual PEV charging cost since they will be credited for every kWh controlled and PEV load will be shifted to the off-peak period and hence charged at off-peak prices.

Fig. 4.8 presents the resultant profiles for the considered PEV market penetration cases. It can be seen that there is a proportional increase in the demand of uncontrolled and smart charging with the increase in the market penetration of PEVs.

TABLE 5.4
Optimal Smart Charging Share, Incentives, and Rebate for the Considered Case Studies

	Optimal Smart Charging Share (X^S), %	Optimal number of PEVs	Optimal Incentive, cents	Optimal Rebate, $
Case-1 (25% PEV Pen.)	14	104	3	22
Case-2 (50% PEV Pen.)	13	193	2.9	23
Case-3 (75% PEV Pen.)	12.9	287	2.9	22

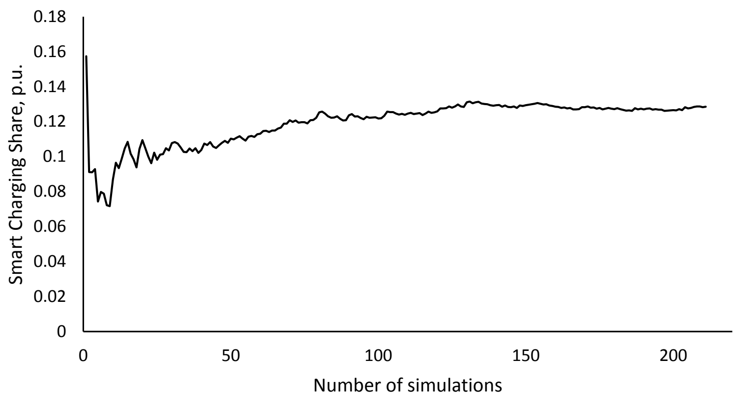
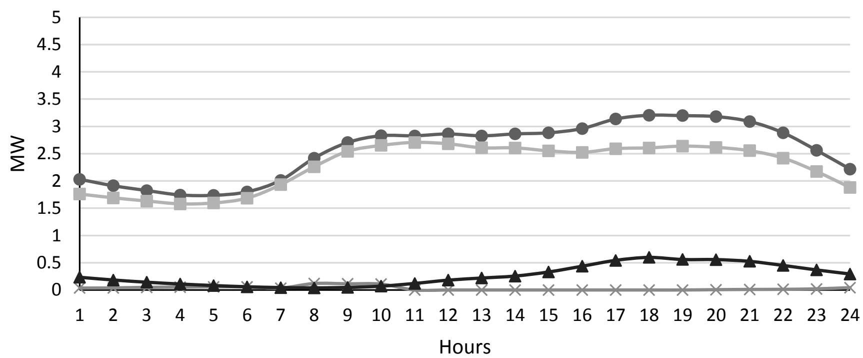


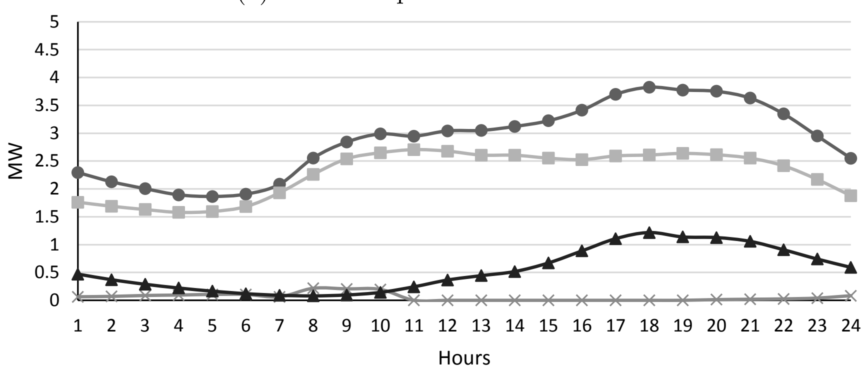
Fig. 5.7. Convergence of OISCM Model for Case-3

5.6 Conclusions

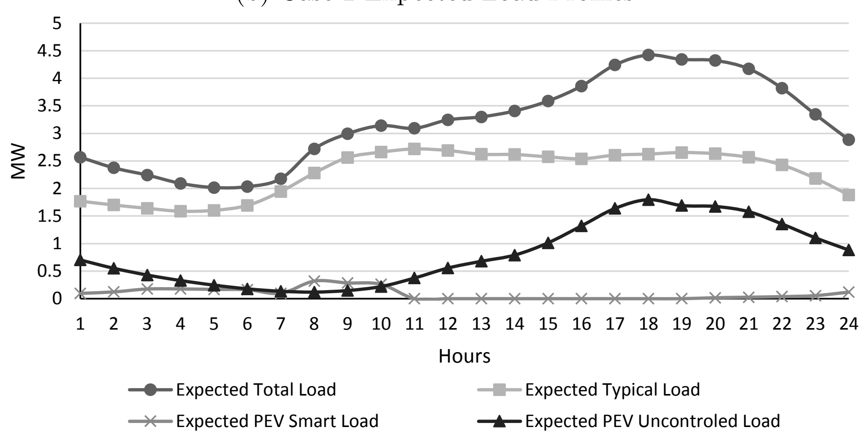
This chapter presented a novel smart charging control algorithm to mitigate the additional PEV charging load. The proposed algorithm presented the PEV owners with the option to either adopt uncontrolled charging or participate in a smart charging program by transferring control access of their vehicle to the LDC to regulate their charging load and receive incentives. The optimal participation of smart charging customers, resulting from such an incentive-driven program, and the optimal incentives that would not cause financial loss to the LDC, were determined simultaneously. The model incorporated vehicle driver habits, various vehicle types and charging levels in order to capture the charging pattern of PEV owners. In addition, Monte Carlo simulations were used to consider various uncertainties. Three case studies were presented to demonstrate the performance of the proposed model, which can be used by LDCs to assess and quantify the optimal participation of smart charging customers and decide on the right incentives to be paid to them.



(a) Case-1 Expected Load Profiles



(b) Case-2 Expected Load Profiles



(c) Case-3 Expected Load Profiles

Fig. 5.8. Expected typical, uncontrolled, smart, and aggregated load profiles for the considered case studies

Chapter 6

Conclusions

6.1 Summary and Conclusions

In summary, the goal of this research was to develop models to investigate and address the problem of distribution system planning in the presence of PEV charging loads. The motivations for this research, and review of associated literature, which laid out the main research objectives, were presented in Chapter 1.

In Chapter 2, the relevant topics related to the research have been discussed. A background to distribution systems was discussed, followed by traditional distribution system planning, and distribution system planning in the presence of DERs and DGs. This section also included a discussion on supply adequacy of distribution systems and DR. Thereafter, a discussion on PEV types, and PEV load characteristics was presented.

In Chapter 3, a comprehensive framework for multi-year distribution system planning was presented. The proposed framework aimed to determine the optimal upgrade plan, siting and sizing of DGs, substations, capacitors and feeders in distribution systems, considering the penetration of PEVs in an uncontrolled as well as smart charging environment, and DR options. Two criteria, BCR and adequacy analysis, were incorporated within the proposed framework, to determine the optimal distribution system plan. The uncontrolled PEV charging load model considered driver behaviour, arrival time, mileage, and other information to develop a charging load profile for inclusion in the planning problem. A novel set of PEV operational constraints were included in the planning model, to capture PEV smart charging decisions. The proposed planning framework was applied to two test systems. Four case studies were considered to investigate the impact of PEV smart and uncontrolled charging loads as well as DR options on the distribution plan.

Chapter 4 presented a novel framework to assess and determine the level of uncontrolled and smart PEV penetration that a distribution system can accommodate without any additional investments or upgrades. The model incorporated vehicle driver habits, various vehicle types and charging levels in order to capture the charging pattern of PEV owners. In addition, Monte Carlo simulation was carried out to take various uncertainties into account. Various case studies were presented to demonstrate the performance of the proposed model, which can be used by LDCs to quantify the impacts, decide on the right actions and policies, and the required upgrades in their distribution networks.

In Chapter 5, a novel smart charging control algorithm to mitigate the effect of additional PEV charging load was proposed. The proposed algorithm presented the PEV owners with the option to either adopt uncontrolled charging or participate in a smart charging program by transferring control access of their vehicle to the LDC to regulate their charging load and receive incentives. The optimal participation of smart charging customers, resulting from such an incentive-driven program, and the optimal incentives that would not cause financial loss to the LDC, were determined simultaneously. The model incorporated vehicle driver habits, various vehicle types and charging levels in order to capture the charging pattern of PEV owners. In addition, Monte Carlo simulations were used to consider various uncertainties. Three case studies were presented to demonstrate the performance of the proposed model, which can be used by LDCs to assess and quantify the optimal participation of smart charging customers and decide on the right incentives to be paid to them.

The following conclusions can be drawn from the thesis:

- The studies revealed that it was important for planners to take into consideration the effects of PEV penetration while deriving their plan outcomes, particularly, when the share of uncontrolled PEV charging is high. It was noted that the present worth of the plan cost in the PEV uncontrolled charging case was much higher than that in the Base Case (No PEV), while the impact of PEV penetration was much damped in terms of added cost and added capacity when smart charging was considered. Compared to the Base Case, with uncontrolled PEV charging loads, there was a 77% and 63% increase in the present worth of the plan cost and in the added capacity (in MW), respectively. The reason behind this significant increase was that the system peak demand coincided with the uncontrolled charging demand due to the coincident home arrival rates of vehicles during peak hours. On the other hand, it was noted that there was only a 11% and 24% increase in the present worth of plan cost and in the added capacity (in MW), respectively, when smart charging was used. There was a decrease in peak demand compared to uncontrolled charging because of smart charging which scheduled the charging demand to off-peak periods. In addition, different optimal size and site of DG units were obtained, when PEV charging loads were considered.

- Current TOU electricity prices were designed to reduce the system peak load and flatten the load profile, and bring about many benefits to the system. However, the research results reveal that in the presence of PEV charging loads, TOU prices can adversely impact the loadability of the distribution system and hence the uncontrolled PEV penetration.

- It is noted that the charging level is clearly a major factor that affects the uncontrolled PEV charging load profile. From a customers' perspective, a higher charging level is preferable because it requires shorter time to charge the vehicle. It is also worth noting that there is enough margin for the whole fleet for smart charging. Unlike typical loads, PEVs are considered more flexible and elastic, and can be controlled by LDCs with the right incentives, which could be beneficial for LDCs without affecting customers convenience.

- LDCs need to monitor PEV sales and upcoming PEV technologies to prepare effective plans for required infrastructure, smart charging programs, incentives, and appropriate electricity tariff. In addition, an effective interaction between PEV companies and LDCs should be established to help forecasting future PEV penetration, PEV technologies and allocating and offering new PEV owners with proper incentives to participate in smart charging programs.

6.2 Contributions

The main contributions of this research can be summarized as follows:

- A novel, comprehensive, multi-year planning framework was developed that simultaneously determine the optimal sizing, placement and investment timelines of various resource alternatives for LDCs such as DG sources, DR option, substations, capacitors, and feeders. A novel set of PEV operational constraints in the distribution planning model was developed, to capture the impact of PEV smart charging loads. In addition, a model for estimating the uncontrolled PEV charging load profiles considering real transportation data including driver behaviour, arrival time, mileage, and other information was developed and included in the distribution planning problem.

- A novel adequacy check module was developed in the planning process to ensure that a desired level of reserve margin was maintained in the distribution system.
- A generic and novel framework to assess the DSLM was developed to accommodate PEV charging loads, *i.e.* how much additional PEV uncontrolled and smart charging load the distribution system can accommodate, without requiring any capacity reinforcement. Vehicle mobility data was used in a novel manner to develop the uncontrolled PEV charging load profile considering the uncertainties associated with drivers' behaviour (arrival time and mileage driven), PEV market share, and share of charging level. In addition, different charging scenarios have been considered to assess the impact of TOU electricity price on the starting time of charging.
- A generic and novel framework was proposed to determine the optimal incentives for smart charging considering LDC-customer interactions. The framework builds upon two aspects, the relationship between the incentives offered by the LDC and the participation of PEV customers (X^S); and the relationship between X^S and the long-term economic benefit of capacity deferral accrued from smart charging. Mathematical models were developed to represent these inter-relationships, for the first time. The proposed framework included a new mathematical model along with a step-by-step approach to determine the economic benefits to the LDC from deferral of capacity investments. In addition, a two-part incentive structure was proposed for the first time, for PEV customers to adopt smart charging, and the relation of PEV participation with this incentive structure was modelled. Finally, a new mathematical model is developed to simultaneously determine the optimal participation of PEV customers in the smart charging program and the optimal incentives to be offered by the LDC, taking into consideration the distribution system operational aspects.

6.3 Future Work

Further research can be conducted based on the work presented in this thesis. Some ideas are presented below:

- The issues of power pricing, bidding, and risk management are not considered in this thesis. The price at which the LDC purchases power from the external grid is assumed to be known a priori, the LDC does not participate in the wholesale electricity market to purchase this power, but has a standing power purchase contract. These issues are very interesting and considering the retail market competition aspects can be taken up as a future work.
- In Chapter 3, dispatchable DG (natural gas turbine) units were considered for the studies. The impact of renewable based DG units, such as wind and solar, considering Ontario FIT program on the planning decisions need be examined.
- The utilization of V2G and ancillary services such as frequency regulation through smart charging program are not considered in the proposed framework, in Chapter 5. It may be useful to examine such services which will effect the benefit to the LDC and hence the incentives and smart charging share.
- It was assumed in this thesis that PEV charging occurred only at home; while charging at work, parking lots, and fast charging stations were not considered, which could be possible avenues of future work.
- In the presence of PEV charging loads, current TOU electricity prices can adversely impact the loadability of the distribution system and hence the uncontrolled PEV penetration. Therefore, further research should be undertaken to investigate the optimal TOU pricing scheme or different pricing schemes considering the penetration of PEV loads.

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APPENDICES

Appendix A

Distribution System Data

TABLE A.1 Data for 33-Bus system: Feeder Parameters

Line i-j	R (ohms)	X (ohms)
1.2	0.0922	0.0477
2.3	0.493	0.2511
3.4	0.366	0.1864
4.5	0.3811	0.1941
5.6	0.819	0.707
6.7	0.1872	0.6188
7.8	0.7114	0.2351
8.9	1.03	0.74
9.1	1.044	0.74
10.11	0.1966	0.065
11.12	0.3744	0.1238
12.13	1.468	1.155
13.14	0.5416	0.7129
14.15	0.591	0.526
15.16	0.7463	0.545
16.17	1.289	1.721
17.18	0.732	0.574
2.19	0.164	0.1565
19.2	1.5042	1.3554
20.21	0.4095	0.4784
21.22	0.7089	0.9373
3.23	0.4512	0.3083
23.24	0.898	0.7091
24.25	0.896	0.7011
6.26	0.203	0.1034
26.27	0.2842	0.1447
27.28	1.059	0.9337
28.29	0.8042	0.7006
29.3	0.5075	0.2585
30.31	0.9744	0.963
31.32	0.3105	0.3619
32.33	0.341	0.5302

TABLE A.2 Data for 33-Bus system: Load

Bus i	P (kW)	Q (kVAR)
2	100	60
3	90	40
4	120	80
5	60	30
6	60	20
7	200	100
8	200	100
9	60	20
10	60	20
11	45	30
12	60	35
13	60	35
14	120	80
15	60	10
16	60	20
17	60	20
18	90	40
19	90	40
20	90	40
21	90	40
22	90	40
23	90	50
24	420	200
25	420	200
26	60	25
27	60	25
28	60	20
29	120	70
30	200	600
31	150	70
32	210	100
33	60	40

TABLE A.3 Data for 69-Bus system: Feeder Parameters

Line i-j	R (ohms)	X (ohms)
1.2	0.0005	0.0012
2.3	0.0005	0.0012
3.4	0.0015	0.0036
4.5	0.0251	0.0294
5.6	0.366	0.1864
6.7	0.3811	0.1941
7.8	0.0922	0.047
8.9	0.0493	0.0251
9.1	0.819	0.2707
10.11	0.1872	0.0691
11.12	0.7114	0.2351
12.13	1.03	0.34
13.14	1.044	0.345
14.15	1.058	0.3496
15.16	0.1966	0.065
16.17	0.3744	0.1238
17.18	0.0047	0.0016
18.19	0.3276	0.1083
19.2	0.2106	0.069
20.21	0.3416	0.1129
21.22	0.014	0.0046
22.23	0.1591	0.0526
23.24	0.3463	0.1145
24.25	0.7488	0.2745
25.26	0.3089	0.1021
26.27	0.1732	0.0572
3.28	0.0044	0.0108
28.29	0.064	0.1565
29.3	0.3978	0.1315
30.31	0.0702	0.0232
31.32	0.351	0.116
32.33	0.839	0.2816
33.34	1.708	0.5646

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TABLE A.3 Data for 69-Bus system: Feeder Parameters

Line i-j	R (ohms)	X (ohms)
34.35	1.474	0.4673
3.36	0.0044	0.0108
36.37	0.064	0.1565
37.38	0.1053	0.123
38.39	0.0304	0.0355
39.4	0.0018	0.0021
40.41	0.7283	0.8509
41.42	0.31	0.3623
42.43	0.041	0.0478
43.44	0.0092	0.0116
44.45	0.1089	0.1373
45.46	0.0009	0.0012
4.47	0.0034	0.0084
47.48	0.0851	0.2083
48.49	0.2898	0.7091
49.5	0.0822	0.2011
8.51	0.0928	0.0473
51.52	0.3319	0.1114
9.53	0.174	0.0886
53.54	0.203	0.1034
54.55	0.2842	0.1447
55.56	0.2813	0.1433
56.57	1.59	0.5337
57.58	0.7837	0.263
58.59	0.3042	0.1006
59.6	0.3861	0.1172
60.61	0.5075	0.2585
61.62	0.0974	0.0496
62.63	0.145	0.0738
63.64	0.7105	0.3619
64.65	1.041	0.5302
11.66	0.2012	0.0611
66.67	0.0047	0.0014
12.68	0.7394	0.2444

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TABLE A.3 Data for 69-Bus system: Feeder Parameters

Line i-j	R (ohms)	X (ohms)
68.69	0.0047	0.0016

TABLE A.4 Data for 69-Bus system: Load

Bus i	P (kW)	Q (kVAR)	Bus i	P (kW)	Q (kVAR)
2	0	0	36	26	18.55
3	0	0	37	26	18.55
4	0	0	38	0	0
5	0	0	39	24	17
6	2.6	2.2	40	24	17
7	40.4	30	41	1.2	1
8	75	54	42	0	0
9	30	22	43	6	4.3
10	28	19	44	0	0
11	145	104	45	39.22	26.3
12	145	104	46	39.22	26.3
13	8	5.5	47	0	0
14	8	5.5	48	79	56.4
15	0	0	49	384.7	274.5
16	45.5	30	50	384	274.5
17	60	35	51	40.5	28.3
18	60	35	52	3.6	2.7
19	0	0	53	4.35	3.5
20	1	0.6	54	26.4	19
21	114	81	55	24	17.2
22	5.3	3.5	56	0	0
23	0	0	57	0	0
24	28	20	58	0	0
25	0	0	59	100	72
26	14	10	60	0	0
27	14	10	61	1244	888
28	26	18.6	62	32	23
29	26	18.6	63	0	0
30	0	0	64	227	162
31	0	0	65	59	42
32	0	0	66	18	13
33	14	10	67	18	13
34	19.5	14	68	28	20
35	6	4	69	28	20