Planning Model for Implementing Electric Vehicle Charging Infrastructure in Distribution System

by

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AUTHOR'S DECLARATION

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

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Abstract

Plug-in electric vehicles (PEVs) are growing in popularity in developed countries in an attempt to overcome the problems of pollution, depleting natural oil and fossil fuel reserves and rising petrol costs. In addition, automotive industries are facing increasing community pressure and governmental regulations to reduce emissions and adopt cleaner, more sustainable technologies such as PEVs. However, accepting this new technology depends primarily on the economic aspects for individuals and the development of adequate PEV technologies. The reliability and dependability of the new vehicles (PEVs) are considered the main public concerns due to range anxiety. The limited driving range of PEVs makes public charging a requirement for long-distance trips, and therefore, the availability of convenient and fast charging infrastructure is a crucial factor in bolstering the adoption of PEVs. The goal of the work presented in this thesis was to address the challenges associated with implementing electric vehicle fast charging stations (FCSs) in distribution system.

Installing electric vehicle charging infrastructure without planning (free entry) can cause some complications that affect the FCS network performance negatively. First, the number of charging stations with the free entry can be less or more than the required charging facilities, which leads to either waste resources by overestimating the number of PEVs or disturb the drivers' convenience by underestimate the number of PEVs. In addition, it is likely that high traffic areas are selected to locate charging stations; accordingly, other areas could have a lack of charging facilities, which will have a negative impact on the ability of PEVs to travel in the whole transportation network. Moreover, concentrating charging stations in specific areas can increase both the risk of local overloads and the business competition from technical and economic perspectives respectively. Technically, electrical utilities require that the extra load of adopting PEV demand on the power system be managed. Utilities strive for the implementation of FCSs to follow existing electrical standards in order to maintain a reliable and robust electrical system. Economically, the low PEV penetration level at the early adoption stage makes high competition market less attractive for investors; however, regulated market can manage the distance between charging stations in order to enhance the potential profit of the market.

As a means of facilitating the deployment of FCSs, this thesis presents a comprehensive planning model for implementing plug-in electric vehicle charging infrastructure. The plan consists of four main steps: estimating number of PEVs as well as the number of required charging facilities in the network; selecting the strategic points in transportation network to be FCS target locations; investigating the maximum capability of distribution system current structure to accommodate PEV loads; and developing an economical staging model for installing PEV charging stations. The

development of the comprehensive planning begins with estimating the PEV market share. This objective is achieved using a forecasting model for PEV market sales that includes the parameters influencing PEV market sales. After estimating the PEV market size, a new charging station allocation approach is developed based on a Trip Success Ratio (TSR) to enhance PEV drivers' convenience. The proposed allocation approach improves PEV drivers' accessibility to charging stations by choosing target locations in transportation network that increase the possibility of completing PEVs trips successfully. This model takes into consideration variations in driving behaviors, battery capacities, States of Charge (SOC), and trip classes.

The estimation of PEV penetration level and the target locations of charging stations obtained from the previous two steps are utilized to investigate the capability of existing distribution systems to serve PEV demand. The Optimal Power Flow (OPF) model is utilized to determine the maximum PEV penetration level that the existing electrical system can serve with minimum system enhancement, which makes it suitable for practical implementation even at the early adoption rates. After that, the determination of charging station size, number of chargers and charger installation time are addressed in order to meet the forecasted public PEV demand with the minimum associated cost. This part of the work led to the development of an optimization methodology for determining the optimal economical staging plan for installing FCSs. The proposed staging plan utilizes the forecasted PEV sales to produce the public PEV charging demand by considering the traffic flow in the transportation network, and the public PEV charging demand is distributed between the FCSs based on the traffic flow ratio considering distribution system margins of PEV penetration level. Then, the least-cost fast chargers that satisfy the quality of service requirements in terms of waiting and processing times are selected to match the public PEV demand. The proposed planning model is capable to provide an extensive economic assessment of FCS projects by including PEV demand, price markup, and different market structure models. The presented staging plan model is also capable to give investors the opportunity to make a proper trade-off between overall annual cost and the convenience of PEV charging, as well as the proper pricing for public charging services.

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Nomenclature

Acronyms

AADT	Annual Average Daily Traffic
AER	All – Electric Range
AFV	Alternative fuel vehicle
ARMA	Autoregressive moving average
BARON	Branch-And-Reduce Optimization Navigator
BC	Battery Capacity
BCR	Benefit to cost ratio
BEV	Battery Electric Vehicle
BMS	Battery management system
CSSR	Charging station service range
DS	Distribution System
EDF	Empirical Distribution Function
EPRI	Electric Power Research Institute
EREV	Extended range electric vehicle
EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
FCFS	First-come first-served
FCLMs	Flow–Capturing Location Models
FCS	Fast charging station
FCV	Fuel Cell vehicle
FRLMs	Flow–Refueling Location Models
GHG	Greenhouse gas
GIS	Geographic Information System
HEV	Hybrid Electric Vehicle
ICEV	Internal combustion
LDC	Load Duration Curve
MCLP	Maximum Covering Location Problem
MCS	Monte Carlo simulation
MIP	Mixed Integer Program
MLRM	Multiple Logistic regression model
NHTS	National Household Travel Survey

NPV	Net Present Value
OD	Origin–Destination
OPF	Optimal Power Flow
pdf	Probability distribution function
PEV	Plug – in electric vehicle
PHEV	Plug – in hybrid electric vehicle
RER	Remaining Electric Range
ROI	Return of Investment
SAE	Society of Automotive Engineers
SOC	State of Charge (based on AER)
TEF	Tractive Effort Factor
TN	Transportation network
TOU	time-of-use rate
TSR	Trip Success Ratio
V2G	Vehicle to grid
VTD	Virtual Travel Distance

Indices

N_b	Index of the electrical buses in the distribution system
N_{CS}	Index of fast charging station candidate locations
N_T	Index of transportation nodes
n	Index of scenarios
pn	index of the number of charger posts inside the charging station
rd	Index of the roads
ut	index of the charger unit type and capacity (e.g. 50kW, 100kW) inside the charging station
bt	Index of battery capacities in the market
c	Index of class of trip
i,j,g	Indices of load points
k	Index of year
q	Index of battery types

Parameter

AADT_{rd}	The annual average daily trips on road (rd) in (veh. /day).
$\mathrm{ADT}_{(pn,k)}$	The average daily traffic flow of all vehicles at step (k) captured by an FCS post (pn)
$\mathrm{Capacity}_{rd}$	The road capacity based on the annual average daily trips on road (rd) in (veh.).
$\mathrm{Cost}_{(k)}$	The annualized cost of the FCS project at step (k)
$\mathrm{Gas}_{\mathrm{k}}$	The annual average gas price in $/L in year k
M_{k}	The set of ICEV models comparable with the PEV models in year k
PEV^{FCS}	The number of PEVs requiring fast charging service
$\mathrm{w}_{\mathrm{mk}}^{\mathrm{PEV}}$	The relative weight of the PEV model (m) to the comparable ICEV in year (k)
$\beta_{\mathrm{n}}^{\mathrm{PEV}}$	The regression coefficients for the explanatory variables
$\varepsilon_{\mathrm{k}}^{\mathrm{PEV}}$	The error term for PEV sales
$\lambda_{(pn,k)}$	The mean arrival rate of vehicles to the FCS post number (pn) at step (k) in (veh./hr.)
$AADT_{g}^{FCS}$	The average number of PEVs served daily by FCS
BC_{q}	The battery capacities in kWh of PEVs available in the market
$D_{j,k}$	The matrix of the shortest paths between any transportation node (j) and node (k) in the transportation network
$I_{(i,j)}^{max}$	The maximum current flowing between bus(i) and bus(j)
$I_{(j,g)}^{max}$	The maximum current flowing between charging station(g) and bus(j)
K_{rd}^{30}	The ratio of traffic volume at the 30th peak hour on road (rd).
$Max\ P\ FCS_{(k)}$	The maximum power limit provided by the distribution system for an FCS in year (k)
$Max\ Units_{(k)}$	The maximum number of charger posts allowable inside an FCS in step (k)
$P_{(i,t)}^{D}$	The basic electrical power demand at DS bus(i) at time (t)
$P_{(i,t)}^{ss}, Q_{(i,t)}^{ss}$	Active and reactive power provided by the substation at DS bus(i) at time (t)
$P_{(i,t)}^{Load}, Q_{(i,t)}^{Load}$	Active and reactive power load at DS bus(i) at time (t)
P^{FCS}	Charging power and duration for fast charging mode (level 3)
P^{H}	Charging power and duration for home charging mode (level 1, 2)

$QL_{(pn,k)}$	The queue length for PEVs using post number (pn) at step (k)
$TEF_{(c)}$	The average tractive effort factor of a PEV conducting a trip in Class “c” (kWh/km)
$U_{g,t}$	Number of PEVs arrived at Fast charging station in DS node (g) in time (t)
$U_{i,t}$	Number of PEVs connected to DS node (i) in time (t)
$UnitCap_{(ut)}$	FCS charger unit of type (ut) rating power capacity (kW)
$UnitCost_{(ut)}$	FCS charger unit of type (ut) installation cost in ($)
$UnitST_{(ut)}$	FCS charger unit of type (ut) service time in (min.) to charge 16 kWh battery
$VTD_{(c)}$	The virtual travel distance in km of a trip in Class “c”
V_{min}, V_{max}	Minimum and maximum voltage limits, respectively
$YBus_{(i,j)}$	The bus admittance matrix (Y bus matrix) of the distribution system
$tq_{(pn,k)}$	The time PEVs spend in the queue to start charging at post number (pn) at step (k)
$ts_{(pn,k)}$	The time PEVs spend during charging at post number (pn) at step (k)
$tw_{(pn,k)}$	The total time PEVs spend in the entire FCS system using post number (pn) at step (k)
$\alpha_{(k)}$	The PEV penetration level (α) at step (k)
$\lambda_{k,g}^{RH}$	The number of PEVs arrive to charging station (g) at rush hour in (veh.) at step (k)
$\mu_{(pn,k)}$	The mean service rate of a post number (pn) at step (k) in (minutes)
μ_1, σ_1	The estimated mean and standard deviation of actual trip data pdf
μ_2, σ_2	The estimated mean and standard deviation of state of charge pdf
$\rho_{(pn,k)}$	The occupation rate of charging post number (pn) at step (k)
$Area$	The area in km^2 of the network under study
B_k	The annual benefit at the end of stage (k) for the FCS project
BPV	The benefit present value of the FCS project at time (k)
Charge	The average public charging event (16 kWh) conducted by FCS
C_k	The annual cost at the end of stage (k) for the FCS project
CPV	The cost present value of the FCS project at time (k)
CSSR	The station service diameter in km, which is obtained from the TSR model
$d_{i,j}$	The distance between transportation nodes in the network
HWL	The length of the highway under study in km
$ICEV_{eff}$	ICEV efficiency in (liter/km)
NV	The total number of vehicles in the system based on the number of houses
TEF, PEV_{eff}	PEV efficiency in (km/kW)
r	Interest rate

t_i	The transportation demand according to location (i)
X_j^{cs}	The x-coordinate of Charging Station (j)
Y_j^{cs}	The y-coordinate of Charging Station (j)
γ	The PEV public charging share
DGR	The annual growth rate of the basic electrical demand
Max Tq	The maximum allowable time that PEVs spend in the queue to start charging
Max Tw	The maximum allowable time that PEVs spend in the entire FCS system
α	PEV penetration level

Functions

f_1	The probability distribution function of the actual trip data
F_1	The cumulative distribution function of the actual trip data
F_2^{-1}	the inverse of the cumulative density function of SOC at the beginning of a trip in Class "c"
F_n	The CDF (step function) for the Empirical Distribution Function

Variables

CS_g	Flag variable equals 1 if charging station connected to bus (g); 0 otherwise
$I_{(i,j,t)}$	the current flowing between bus(i) and bus(j) at time (t)
$I_{(j,g,t)}$	the current flowing between bus(j) and charging station(g) at time (t)
$SOC_{(c)}$	The random PEV battery state of charge at the beginning of a trip in Class "c"
SOC_R	The distributed random variable representing the charge level
SOC_{prev}	The random initial state of charge used to generate the SOC level
$SS_{(i)}$	the apparent power of substation (i)
$V_{(i,t)}, V_{(j,t)}$	Voltage magnitude of bus (i) and bus (j) at time (t)
$a_{(g,rd)}$	Decision variable to assign road (rd) to charging station (g).
$p_{i,t}^H$, $p_{i,t}^{FCS}$	Nodal charging powers of home charging and fast charging facilities at DS node (i) in time (t)
$y_{(ut,pn,k)}$	Decision variable equaling 1 if the unit type (ut) of the post number (pn) in step (k) is installed, and 0 otherwise

$\theta_{(i,j)}, \delta_{(i,t)}$	Phase angle deviation of branch (i,j) in time(t) and the voltage angle at bus (i) in time (t);
CS_j	The decision variable equaling '1' if a station is located at node (j) and '0' otherwise
z	Normally distributed random variable between zero and one

Chapter 1
Introduction and Objectives

High oil prices and energy demand are major challenges facing transportation sectors, as reliance on fossil fuels as the main source of energy has negative affected those sectors. Environmentally, the transportation sector overall produces a large percentage of emitted carbon dioxide, causing greenhouse gas (GHG) emissions to increase greatly. According to the U.S. Greenhouse Gas Inventory Report 2011 [1], 30% of carbon dioxide emissions in the US come from the transportation sector. In Canada, 35% of energy demand is represented by the transportation sector, and it is the second-highest source of GHG emissions, at 23% [2]. Therefore, meeting future transportation energy demands by finding alternative energy sources has gained much attention.

Shifting the high energy demands of transportation to the electrical system will raise some concerns. The future electrical system must be prepared to serve PEVs as a new type of load in the system. These loads have the ability to move, so the connection times and places of PEV loads have high degrees of uncertainty; hence, electrical systems have to be protected and mitigated from any technical impacts that PEV charging may cause. Moreover, the reliability and dependability of these new vehicles (PEVs) are considered as the main public concerns due to their limited driving range, whereas accepting this new technology depends primarily on the economic aspects for individuals as well as for the development of adequate PEV technologies. It is normally expected that PEVs will be recharged nightly at home [3], but the limited driving range of PEVs makes public charging a requirement for long-distance trips.

Charging PEVs at home depends mainly on users' behaviors, so if there is no control over home charging for PEVs, zonal peak demands and local overloads will arise in the form of new distribution system problems [3]. Electric system infrastructure is designed to meet the highest expected demand, which occurs only at certain times of the day [4]. Such demand concentrations can cause significant stress on local power distribution systems, if this demand occurs at all time. The additional load imposed by high PEV penetration is expected to have severe consequences, such as feeders' thermal limit violations, phase imbalances, transformer degradation, and fuse blowouts if not managed effectively [4]. However, providing alternatives to home charging will definitely assist local distribution utilities in managing the additional load from PEVs.

The availability of public charging infrastructure is a crucial factor in increasing the adoption of PEVs, because long-distance trips cannot be achieved with PEVs' limited Electric Range (ER). Therefore, providing a public charging service as a complement to home charging will be an essential need. Electrical Fast Charging Stations (FCSs) will eventually be dispersed in the network, but inefficient planning for implementing charging infrastructure will hold back PEV adoption. Hence, the siting and sizing of the charging stations, as well as the time for construction, should be properly planned in order to utilize FCSs effectively.

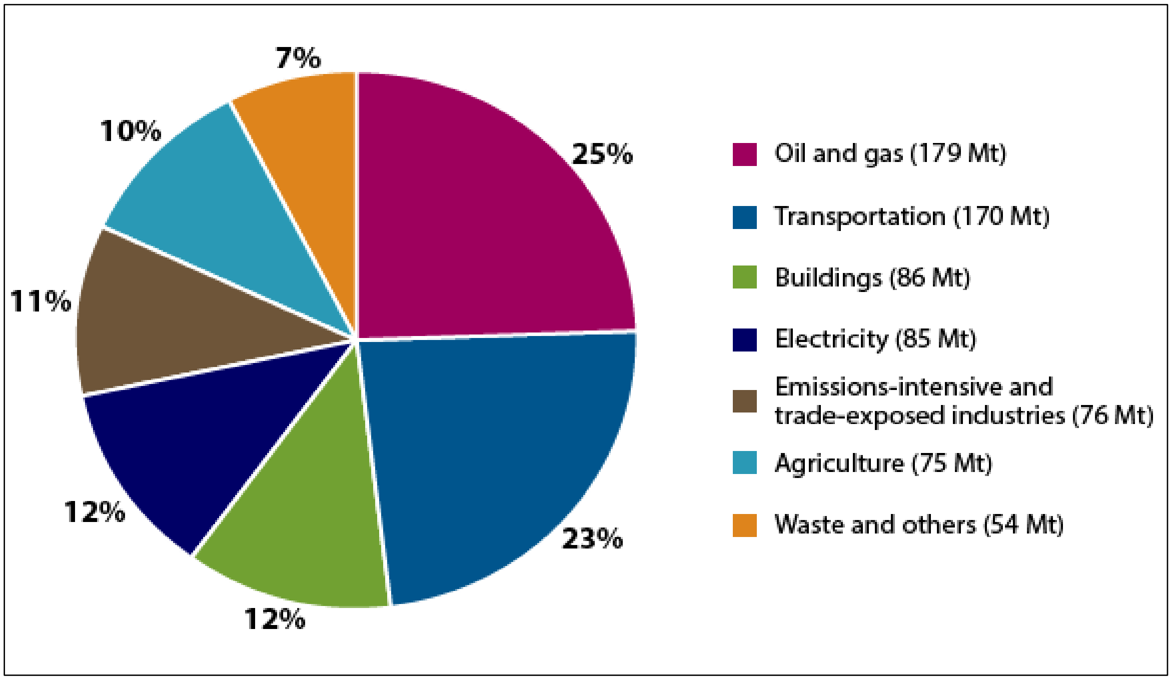

Figure 1-1 Distribution of greenhouse gas emissions by economic sector, Canada, 2013 [2]

The planning approach for implementing charging infrastructure should be done with a view to meet users' and suppliers' needs. PEV users require access to FCSs whenever they need them, accompanied with a high quality of service. Therefore, a lack of charging facilities due to siting FCSs inappropriately or not at all will have a negative impact on drivers' convenience. The planning model should also enhance PEV drivers' accessibility to charging points by optimally choosing those points from candidate sites in order to cover the planning network. Moreover, investing in premature technology is considered high-risk. Investors desire a profitable business that promises maximum profits and a secure investment, so providing a public charging service has to be evaluated with the consideration of all uncertainties and parameters affecting that business. Forecasting the future demand for PEVs will enhance investment security and give decision-makers and investors the ability to evaluate their investments over the long run, as well as providing electrical utilities data on the expected PEV demand that must be covered in their upgrade plans.

The key parameters influencing the implementation of FCS networks are: 1) the extent of PEV sales in the future; 2) the required locations for installing FCSs; 3) the proper capacity of the FCSs; and 4) the times to install FCS posts over the planning horizon to match the PEV pubic charging demand. Therefore, the work presented in this thesis focuses primarily on those key parameters. The work can be described as consisting of four phases, with the first phase addressing forecasting PEV market sales and its correlation with public charging facility availability. The second phase deals with the allocation of public charging stations (FCSs) considering the impact of their locations on enhancing the ratio of successfully-completed PEV trips. In the third phase, the ability of distribution systems to serve the extra PEV demand is addressed considering the influence of shifting PEV demands. The fourth and last phase deals with the best staging plan for implementing the FCS posts over time considering quality of service as well as the economic benefit associated with FCSs. Those four phases are described in detail in the next section.

1.1 Research Objectives

As mentioned in the previous section, the key factors in planning the implementation of Fast Charging Stations (FCSs) can be summarized in the following points:

1- Forecasting PEV market sales and the main parameters that influence the PEV market size, including the availability of public charging facilities.

2- Determining the Optimal Locations of public charging facilities to cover the transportation network and to enhance the ability of PEVs to complete their trips successfully.

3- Evaluating the capability of distribution systems to serve PEV demands with no major upgrades, and the influence of using public charging facilities in managing PEV demands.

4- The best times to install public charging facilities to gradually match PEV demand considering the quality of charging service in terms of waiting and charging times, as well as the economic benefit associated with the installed facilities.

The research was therefore based on four main objectives related to those four parameters, as shown in Fig. 1.2 and outlined below.

1.1.1 Objective 1: Forecast PEV market sales and the forecast parameters

For this objective, the task was to estimate the key parameters that influence the market sales of Plug-in Electric Vehicles (PEVs) by developing a model that describes the correlation between the PEV market sales as a response variable and number of explanatory variables such as gas prices, electricity rates, available charging infrastructure, vehicle prices, and government incentives. Limited information on PEV sales is one of the major challenges that the estimation's task faces. For many early adopters, power outlets at home are likely the primary charging facilities in the near term, but many emerging technologies and business models that are under development may also reshape PEV market sales and people's recharging behavior in the longer term. The model should determine the key parameters among the various factors that jointly influence the dynamics of PEV sales. The model should also identify the correlations between each of the considered factors and PEV market sales in order to evaluate the significance of their influences on PEV sales. A number of scenarios were considered with respect to the different parameters influencing the PEV market sales in order to examine these parameters relative significance.

1.1.2 Objective 2: FCS allocation in the transportation network

For the second objective, the research focused on the development of an allocation model for plug-in electric vehicle charging stations from a new perspective, which is PEV drivers' convenience. The model should choose, from the available candidate sites, the charging station set that optimally enhances the ratio of trips completed successfully. A PEV trip can be completed successfully if the electrical energy remaining in the PEV's battery is sufficient to allow the PEV to reach its destination; otherwise, the PEV battery has to be recharged on route in order to complete the trip. Optimal FCS location selection can guarantee a certain level of convenience for PEV drivers. The proposed model includes consideration of the uncertainty and the variability associated with vehicle usage, as well as of battery capacity.

1.1.3 Objective 3: Evaluating the capability of distribution systems to serve PEV demand

For this objective, the models and the methodologies developed in the previous two objectives are utilized in order to evaluate the impact of the extra PEV load on electrical network performance in terms of voltage violation, power losses, and line loading. The additional PEV demand is assumed to be fed by the network as a normal charging load at home or fast charging load at public charging stations. Therefore, modelling the PEV charging demand for normal and fast charging levels is the first step in the evaluation. By adding this extra PEV loading to the selected target locations (Objective 2), the model can determine the maximum PEV penetration level (α) that the existing distribution network would be able to serve without violating its technical constraints. The model was also used to evaluate the influence of using public charging facilities in managing PEV demands as well as on distribution system performance.

1.1.4 Objective 4: Economical staging plan for implementing FCS posts

This objective is the development of an optimization methodology for determining the optimal economical staging plan for FCS post as a last step of implementation model. The PEV penetration level (Objective 1) and the target FCS locations (Objective 2) are utilized to produce public charging demand (the demand) using the traffic flow in the transportation network. Then, the maximum ability of distribution system to serve PEV demand (Objective 3) is considered as "the supply". The solution should matching the demand and the supply by determining at which times the FCS posts should be installed, along with their power capacities, in order to obtain the minimum overall cost of the FCS project. Then, the lowest-cost FCS posts that satisfy the quality of service requirements in terms of waiting and queueing times are selected. The model was also used to evaluate the profitability of FCS projects considering different charging prices.

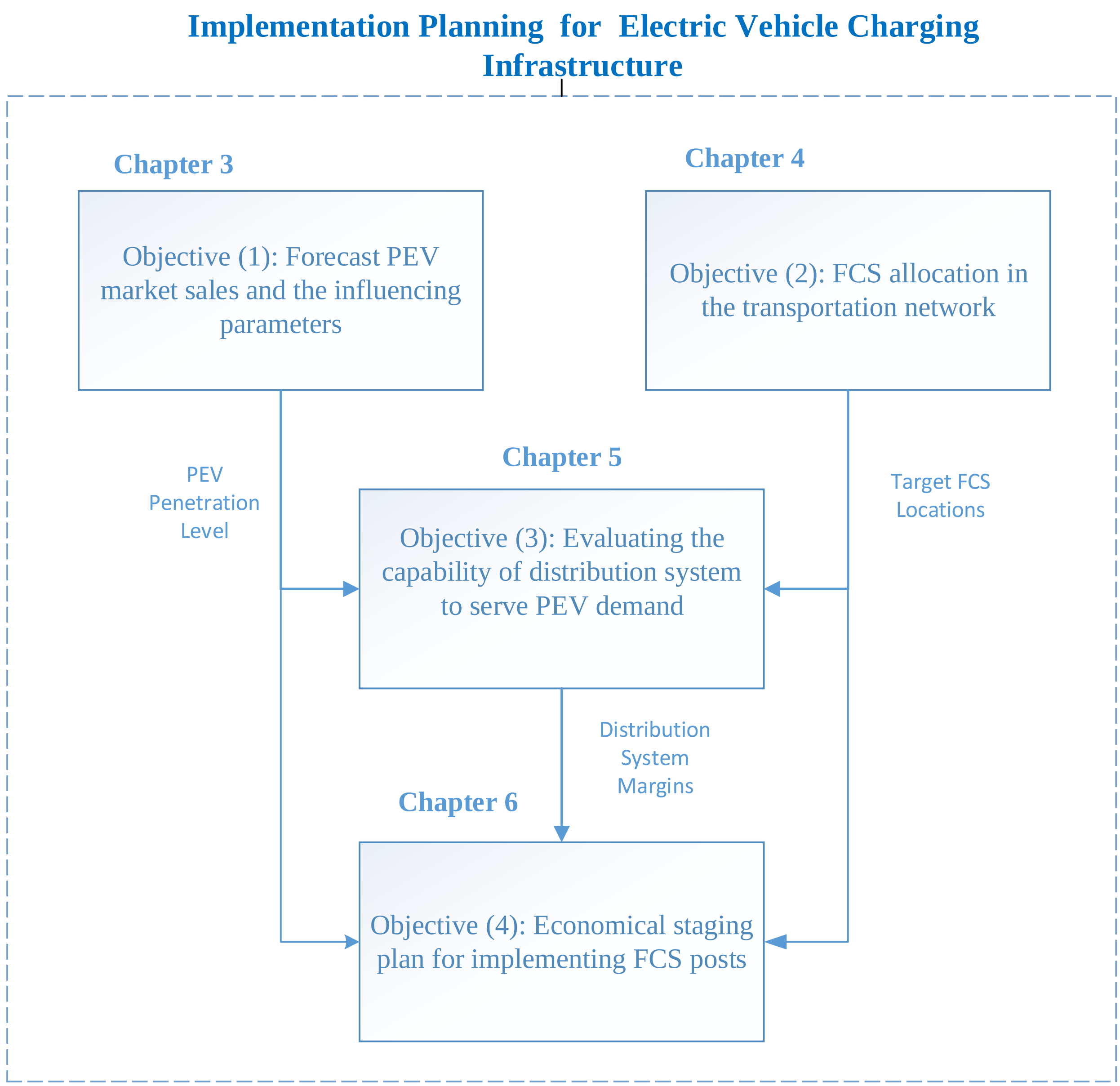

Figure 1-2 Research objectives

1.2 Thesis Outline

The reminder of the thesis is organized as shown in Fig. 1.2, and the details of each chapter are as follows:

Chapter 2 provides a brief review of the background topics and the associated literature pertinent to this research.

Chapter 3 presents the proposed approach for forecasting PEV sales as well as its key influencing parameters, along with related simulation results.

Chapter 4 explains the Trip Success Ratio model for allocating FCSs in the transportation network, along with related case studies on both in-city and highway networks.

Chapter 5 introduces the evaluation approach to modeling PEV charging demand in order to determine the capability of distribution systems to serve that extra demand, as well as demonstrating the impact of using FCSs in managing PEV demand.

Chapter 6 describes the proposed economical staging plan for implementing FCS posts in order to optimally match PEV demand with the lowest cost FCS system.

Chapter 7 summarizes the research and its contributions, and offers suggestions for future work.

Chapter 2

Background and Literature Review

This chapter provides an introduction to and background information on Electric Vehicles (EVs) considering their types, battery technologies, and charging technologies, followed by a discussion of previous research. Finally, the drawbacks with respect to forecasting PEV market sales, siting and sizing charging stations, and the economics of using charging stations are highlighted in the chapter assessment.

2.1 Electric Vehicles (EVs)

Electrical system infrastructure has been built to meet the maximum expected demand, which occurs at most at 5% of the year overall [3]. However, electrical systems should deliver energy for other sectors and utilize their infrastructure, especially during off-peak times. That, as mentioned earlier, makes the electrical energy sector the best alternative for feeding the transportation sector. GHG emissions and oil prices are the biggest reasons to electrify the transportation sector. According to the Oregon Department of Energy, Oregonians drive over 60 billion kilometers per year, with more than 70% of these kilometers being driven in private cars [6]. Hence, electrifying private vehicles will be a cornerstone for energy-switching. Electric vehicles are not a new invention; they go back to the 1830s when the first electric vehicle, with no rechargeable battery, was driven [5]. Electricity was one of the preferred methods for motor vehicle propulsion; however, electric vehicles have not achieved the vast success of internal combustion (IC) vehicles, which normally have much longer ranges and are easy to refuel. Lately, due to the environmental impact of petroleum-based vehicles along with the price of oil, EVs have received increased attention over the traditional IC-engine vehicles. Therefore, different types of EV have been developed in conjunction with the development of batteries, electronics, and control technologies.

2.1.1 Electric Vehicles Types

The term “electric vehicle” refers to any vehicle that uses an electric motor for propulsion [5]. Electric trains, electric boats, and electric cars are examples of electric vehicles. In this research, the term “electric vehicle” will refer only to electric cars or automobiles that have an electric motor and are powered fully or partially by electricity. There are many types of electric vehicles; however, five of them, until now, have been the most popular types in research: Hybrid Electric Vehicles (HEVs), Fuel Cell Vehicles (FCVs), Plug-in Hybrid Electric Vehicles (PHEVs), Battery Electric Vehicles (BEVs), and Extended Range Electric Vehicles (EREVs). Because EV innovation has gained more attention recently, the possibility of having new types rather than just these five is expected in the near future.

2.1.1.1 Hybrid Electric Vehicle (HEV)

Hybrid Electric Vehicle refers to vehicles powered by a combination of an IC engine and an electric motor. The combination makes the HEV more energy-efficient than IC-powered vehicles, with almost half the fuel consumption. Moreover, CO2 emissions are decreased significantly due to the regenerative braking system. The design could even have more than two power sources, with a large number of variations [5]. HEVs operate exactly like IC-engine vehicles, but with higher fuel economy thanks to the electric motor.

2.1.1.2 Battery Electric Vehicle (BEV)

Battery Electric Vehicle refers to vehicles using electric motors powered only by chemical energy stored in battery packs. The concept of the BEV is very simple in that it uses electric motors and controllers for propulsion. The energy stored in rechargeable batteries is used as the fuel supply for the electric motor, and the controller regulates the vehicle's speed by controlling the power supplied to the motor. Due to being fully dependent on a limited battery capacity, BEVs have a shorter driving range than conventional cars [5].

2.1.1.3 Plug-in Hybrid Electric Vehicle (PHEV)

Plug-in Hybrid Electric Vehicle refers to vehicles that use both gas and electricity. PHEVs can be perceived as an intermediate technology between HEVs and BEVs. A PHEV is a form of HEV with larger batteries to allow the vehicle to be driven farther, and it has the ability to charge its batteries directly from the electrical network. Having two different power sources gives PHEVs a high degree of energy resilience [5].

2.1.1.4 Fuel Cell Vehicle (FCV)

Fuel Cell Vehicle refers to vehicles powered by fuel cells. The basic principle of the FCV is similar to the BEV, but the chemical driving force comes from combining a fuel, usually hydrogen, with oxygen, rather than batteries. Hydrogen is most frequently derived from methane or other fossil fuels; however, hydrogen is not technically an energy source, but is instead considered an energy carrier [5].

2.1.1.5 Extended Range Electric Vehicle (EREV)

Extended Range Electric Vehicle refers to vehicles powered by batteries, similar to BEVs, along with a small generator. The small onboard generator is used to recharge the batteries and extend the range of the vehicle in order to improve on the limited range of BEVs. The generator can be fed by various fuels: gasoline, diesel, ethanol, or even fuel cells [5].

In order to investigate the impact of charging PEVs as a new load on the distribution system, only Plug-in Electric Vehicles (PEVs) that have direct access to the electrical grid will be considered in this research. Charging points for these PEVs will be required in the distribution network, but different technical impacts can result due to FCS implementation, and so planning the distribution system and controlling these new loads deserves more attention. Battery sizes, charging times, and the movable nature of these loads should be considered in the planning process for these new types of loads. This type of load is mainly a battery type; therefore, a review of battery technologies is conducted to summarize the different properties of these technologies.

2.1.2 Battery Technologies

Electric vehicles have several components that comprise the electrical structure of the vehicle, regardless of the vehicle type. Battery packs, battery chargers, power converters, controllers, and electric motors are the key parts of any EV's structure. The diversity in the major components of the vehicles affects EV performance and leads to different consequences of charging PEVs [4]. In addition, some similar types of EV have different electrical setups. For instance, PHEVs have two electrical structure types associated with them, parallel and series, and each type has its pros and cons [4]. The diversity of PEV structures is accompanied by different battery technologies, which means taking into consideration how these technologies work, the required specifications for using them, and their different properties.

In BEVs, the battery is the only energy source, and it is the component with the highest cost, weight, and volume. The battery should have a large energy capacity to meet the vehicle's demand. In PHEVs, there is more than one energy source onboard the vehicle: a battery and some form of fossil fuel. In order to be more efficient, the volume and weight of PHEV batteries should be kept low. Although battery technology is advanced, applying it to automotive applications is considered a crucial challenge. A highway trip of EV requires that the battery contain a large amount of energy and can deliver high power for acceleration. For instance, a typical family car would need a battery capacity of about 50kWh to provide a one-way range of 350 km. The lead-acid battery is the traditional vehicle battery; however, a 50kWh lead-acid battery weighs 1.5 metric tons. The low energy density is the biggest obstacle limiting lead-acid batteries in driving applications. Table 2.1 shows a summary of the energy and power that can be delivered by different battery technologies [7].

Among all battery technologies, lead-acid is the most mature one, with a low initial cost; however, the limited lifecycle is the largest drawback. NiMH batteries have a high specific energy and are appropriate for HEVs. NiMH batteries are also used in PHEVs and BEVs; however, self-discharge is a drawback when the vehicle is not being used [7]. Lithium-ion (Li-ion) batteries have very high power and energy density. Li-ion battery technology is considered to be the next generation in PEV battery technology [4], but faces a challenge in scaling up the size of the batteries while lowering costs [7]. The ZEBRA battery requires a high temperature of around 300°C to operate, but the energy density is high. It needs an energy supply for heating when it is not in use.

Table 2-1 Energy and Power Densities for Different Battery Technologies [7]

	Lead-Acid	NiCad	NiMH	Li-ion	ZEBRA
Energy Density (Wh./kg)	30-35	50-60	60-70	60-150	125
Power Density (W/kg)	80-300	200-500	200-1500	80-2000	150

2.1.3 Charging Technologies

The Society of Automotive Engineers (SAE) describes charging technologies for electric vehicles in their publication *Surface Vehicle Recommended Practice* J1772 [8]. EV charging technologies are classified into three types: Level 1, Level 2, and Level 3. In Level 1 and Level 2 charging, the battery and converter are located onboard the vehicle, and the conversion from AC to DC occurs *on-board* in the converter. Power and data are delivered through the inlet, which is coupled to an *off-board* connector. PEVs are connected to the power grid via EV Supply Equipment (EVSE), which is located *off-board*. Level 1 charging uses single-phase 120V with a maximum rated current of 15-20A, and the supplied power is limited to about 1.9kW. No additional infrastructure is necessary for home or business usage [9]. Level 2 charging uses 240V single-phase, and the current is rated to 16-32 A. The vehicle charges faster with Level 2 charging than with Level 1 charging, and most PEV makers recommend Level 2 charging as the main charging method for PEVs [9]. Typically, the onboard charging system (for Level 1 and Level 2 charging) is fed by AC power. The PEV charger converts the AC power to DC *on-board*, so there is a limitation on the power due to the weight, size, and cost constraints of the converter [9]. Level 3 commercial fast charging can be installed in highway rest areas and city recharging points. The off-board charging system is controlled by a battery management system (BMS) in order to deliver the DC power to the vehicle. The charger type is supplied with a voltage ranging from 3-phase 230VAC to 600VAC, and the fast charging rate is limited to 250kW [10]

The diversity in battery sizes and charging power levels means that the charging time for PEVs can range from a few minutes to many hours. Table 2.2 shows the usage, expected power level, and charging time based on a 16 kWh battery size for different charging systems.

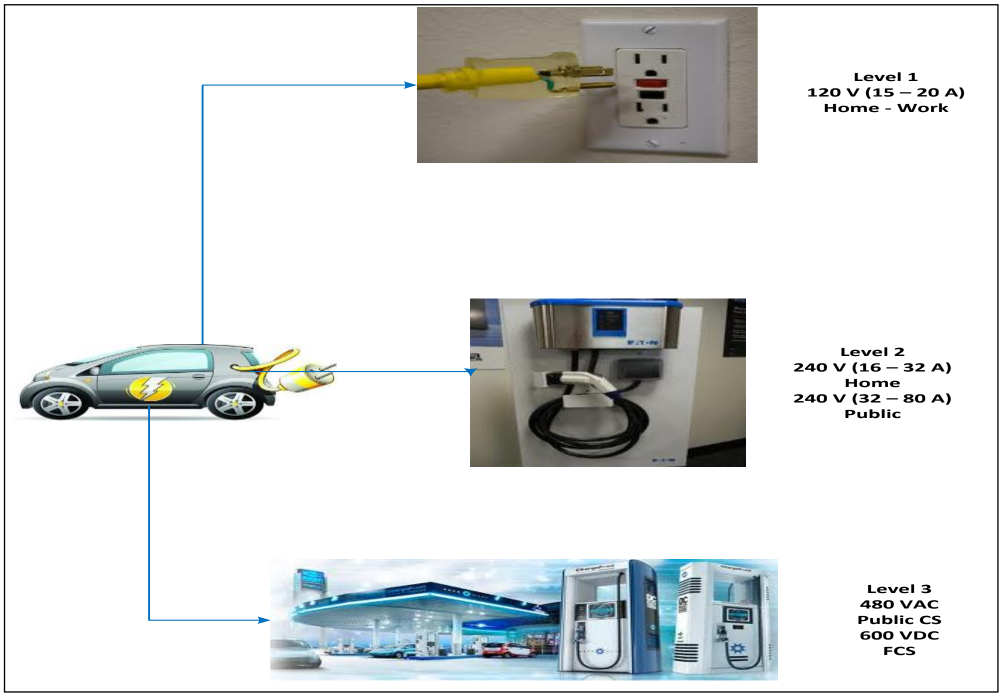

Figure 2-1 PEV Charging System Power Levels

Table 2-2 Charging Power Levels Based on [7 – 9]

Power level types	Converter location	Usage	Expected power level	Charging time (16kWh)
Level 1 120VAC	Onboard Single-phase	Home and Office	1.44 kW (15A) 1.92 kW (20A)	11 hours 8 hours
Level 2 208VAC 240VAC	Onboard Single-phase	Residential Outlet	3 kW (16A) 6 kW (32A)	5.5 hours 2.75 hours
		Commercial outlet	15.5 kW (80A)	1 hour
Level 3 480VAC 600VDC	Off-board three-phase	Commercial Fast Charging Station (FCS)	50 kW 100 kW 250 kW	20 min 10 min 4 min

2.2 Forecast PEV market sales

The charging load of PEVs is influenced by many factors: number of PEVs, trip purpose, PEV density, arrival time, arrival rate, State of Charge (SOC) level based on electric range, battery capacity, charging time, and travel patterns [11]. For many early adopters, power outlets at home are likely the primary charging facilities in the short term, but many emerging technologies and business models that are under rapid development may also reshape PEV market sales and people's recharging behavior in the longer term. One of the key parameters that should be considered in estimating the extra demand of PEVs is the number of PEVs that will be consuming electrical energy from the distribution system in the future. Forecasting the future demand for PEVs will provide electrical utilities an estimation of extra loading that they should consider in their planning of distribution systems. In addition, forecasting PEV demand will enhance investment security, and it gives decision-makers and investors the ability to evaluate their investments over the long run.

In the face of the many challenges, forecast information for PEV sales and recharging demand is urgently needed to assess the long-term impacts of PEVs on the distribution system, which could be dramatically more significant than the current impact, which has been virtually unnoticeable. Several existing studies have addressed these issues. One of those studies, conducted by the Pacific Northwest National Laboratory (PNNL) [12], scrutinized PEV market penetration scenarios based on information obtained from the literature and interviews with industry representatives and technical experts. Three scenarios (hybrid technology-based assessment, R&D goals achieved, and the supply-constrained scenario) were presented for the period 2013 – 2045, and the annual market penetration rates for PEVs were forecast for that period. The results showed that PEV market penetration was expected to reach 9.7%, 9.9%, and 26.9% by 2023 in USA market, and 11.9%, 29.8%, and 72.7% by 2045 for the three scenarios, respectively. An Electric Power Research Institute (EPRI) report [13] estimated new vehicle market shares of conventional, hybrid, and plug-in electric vehicles using choice-based market modeling of customer preferences, and the results showed that PEVs will have market shares of 20%, 62%, and 80% by 2050 in the low-, medium-, and high-penetration scenarios respectively. An Oak Ridge National Laboratory (ORNL) study [14] forecast that the market for PEVs in the US will be approximately 1 million by 2015, which agrees with President Obama's expectations [14]. The ORNL's Market Acceptance of Advanced Automotive Technologies Model and UMTRI's Virtual Automotive Marketplace Model were utilized in [14] to assess a list of policy options in terms of their potential for improving PEV sales in the next two decades. In a Morgan Stanley report [15], proprietary information was used to forecast sales of hybrid electric vehicles and PEVs, and its prediction was that market demand will reach 250,000 by 2015 and 1 million by 2020. In [16], Gallagher et al. used a Multiple Linear regression model to estimate how hybrid electric vehicle sales respond to various types of incentives. Their results showed that: “a one thousand dollar tax waiver is associated with a 45% increase in hybrid vehicle sales, whereas a one thousand dollar income tax credit is associated with a 3% increase in hybrid vehicle sales.” A related recent study in [17] used a sales forecasting model that was based on information about consumer preferences between hybrid electric vehicles and internal combustion engine vehicles, which was extracted from hybrid electric vehicle historical data. A Multiple Logistic regression model was utilized in the study, and it considered some explanatory variables extracted from hybrid vehicle historical sales data with the assumption that PEV market sales would follow the pattern of HEV market sales. Since they used hybrid electric vehicle data, the correlation between charging infrastructure availability and PEV market sales was not addressed. According to [18], battery range is customers’ biggest concern, followed by cost, so considering charging infrastructure availability in forecasting PEV market sales will lead to a better estimation, since we forecast PEV sales rather than HEVs.

2.3 Siting and sizing charging facilities

One problem in siting and sizing public charging stations lies in connecting two different systems together: the electric distribution system and the transportation system. Each system has its own requirements and restrictions for choosing the best siting and sizing of charging infrastructure, and focusing on one system’s requirements and ignoring the other’s will lead to favoring places for one system, which might cause some concerns and difficulties for the other. For instance, if the problem of siting and sizing charging stations is solved based only on the electrical system’s requirements, and the diversity of travel patterns and traffic flow aspects are not considered, that may lead to locating charging stations at sites favorable for electrical utilities but not easy for drivers to access due to not including traffic flow aspects. As a result, the solution will not be sufficient to serve the demand of PEVs that move in the transportation network. On the other hand, locating charging stations based only on traffic flow might result in difficulty for the distribution system to supply a concentrated PEV demand in those locations due to local overload problem. Therefore, both systems have to be considered in order to obtain the best solution for siting and sizing charging stations. Figure 2.3 shows the interconnection between the distribution and transportation systems, using the Geographic Information System (GIS) [19].

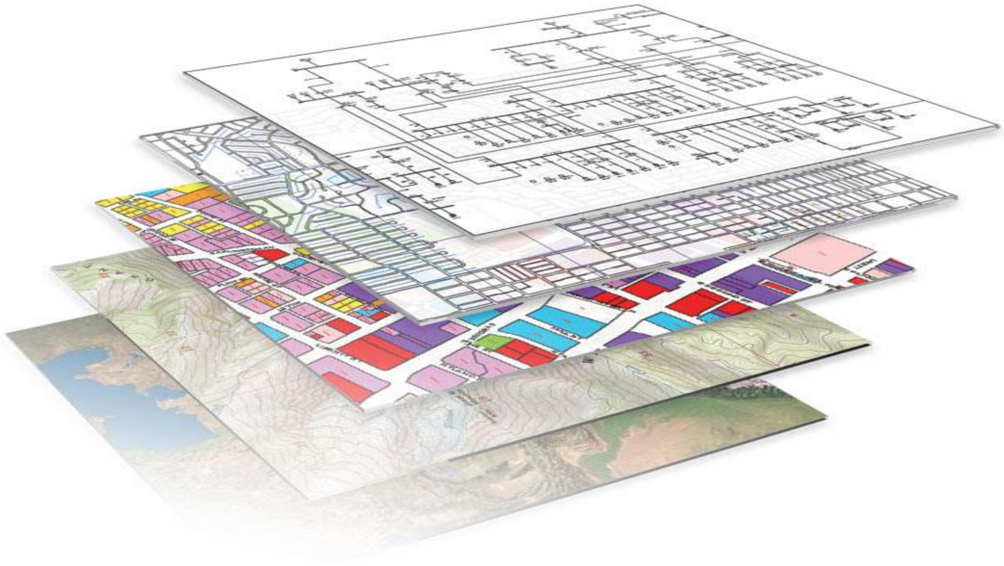

Figure 2-2 Geographic Information System Layers [19]

Recently, more attention has been paid to the optimal siting and sizing of PEV charging stations. The placement and sizing of refueling and recharging stations has also been investigated recently in electrical as well as transportation publications, and the next two subsections present a review of the previous work to solve that problem on both the electrical and transportation systems.

2.3.1 Previous work in transportation field

In recent transportation research on siting refueling stations [20 – 23], Flow–Refueling Location Models (FRLMs) have been developed to site Alternative Fuel Vehicle (AFV) stations for vehicles that need refueling during trips. FRLMs are an extended form of Flow–Capturing Location Models (FCLMs), which have been used for siting convenience stores [24]. FRLM formulation is obtained by adding vehicle travel range as a constraint. All trips from the same Origin–Destination (OD) pair have been assigned to one path in [20] or for several detours in [21], but ignoring travelers' habits and behaviors will lead to inappropriate locations for FCSs, especially in-city. Because the suitability of their model depends on the availability of trip destination data, the lack of PEV trip data will make their model inapplicable for in-city PEV – FCS locating.

The diversity of various vehicles' ranges has not been considered in previous models [20 – 23]. In addition, they considered only fixed battery capacities and did not consider varying SOC levels during trips. The detours and alternative paths are assumed based only on a single scenario; however, considering different vehicle ranges – using different SOC levels and battery capacities – will accordingly change those detours and alternative paths. As a result, the number of electric vehicle FCSs planned in the system will be inadequate in an in-city network due to discounting the diversity of PEV Remaining Electric Ranges (RERs).

2.3.2 Previous work in electrical field

Electrifying the transportation sector is projected to enhance energy efficiency. The key concern is with regard to the sufficiency and viability of the power infrastructure with large-scale PEV integration [25]. The diversity of travelers' habits, behaviors, trip distances, and the ability of charging station networks to cover the demand sufficiently are not well demonstrated in the previous electrical research on siting and sizing charging stations, although a number of studies have considered aspects related to the site selection of charging stations and the overall planning of FCS networks [25 – 33].

The diversity of travel patterns and traffic flow aspects are not considered in [25 – 31], which may lead to locating charging stations at sites favorable for electrical utilities but not easy for drivers to access due to not including traffic flow aspects. In [32], the traffic flow and charging requirements are included as constraints in the model, but the diversity of trip mileages and the variety of PEV electric ranges are not considered. A study in [33] was done to look at charging station placement from a new perspective of FCS accessibility; however, the authors assumed that charging station service ranges are equal to the average of the electrical ranges available in the market. This assumption is questionable due to the high diversity in the ranges of PEVs (80 – 300 km), which is not addressed in the model. In the model, if most PEV ranges are not considered in relation to average battery capacity, the variations in ranges will have a real impact on the percentage of incomplete PEV trips due to insufficient energy in the PEVs batteries.

A few studies have focused on the problem of siting and sizing PEV charging stations to match the expected PEV demand [34 – 38]. A two-step screening method considering the environmental factors and the service radius of PEV charging stations is proposed in [34] to determine the optimal placement and sizing of PEV charging stations. In [35], a hierarchical clustering analysis is developed to identify the Battery Electric Vehicle (BEV) recharging demand clusters, and then the charging demands of these clusters are met by formulating a BEV charging station allocation model, but charging station capacity was not considered in the model. Similarly, in [36], a maximal covering model was developed in order to site only a fixed number of charging stations in central urban areas. In [37], a multi-objective planning strategy model maximizes the traffic flow to charging facilities and minimizes the investment and operational cost of the distribution system; however, the estimation of PEV demand is not addressed well in the model, and they considered only a fixed penetration level of PEVs. Their proposed model will choose the minimum number of FCSs that have high levels of traffic flows, but that number of FCSs may not be adequate to match PEV demand, which can lead to traffic network problems if the charging facilities have insufficient sizing. In [38], the fast charging station siting and sizing are obtained using a developed P-center method using a Mixed Integer Program (MIP). The fast charging demand is considered in this study as an urgent demand, and the investment budget for matching this demand is fixed, which may lead to insufficient sizing when the budget is exceeded. It is important to consider the economic assessment and investment availability in studying the optimal deployment of fast charging stations, however, considering them should not limit the number of FCSs or their sizes in order to obtain a better solution.

2.4 Economics of implementing public charging stations

Many research efforts have been dedicated to the problem of PEV integration considering both alleviating the negative impacts of large-scale penetration of PEVs and covering the potential benefits obtained by integrating electric vehicles into the grid (V2G). The main research areas are in investigating the operational influences on the distribution network of using PEVs [39 – 42], the integration of PEVs with renewable energy generation [43 – 45], and coordinated charging and discharging strategies [46 – 48]. However, only a few studies have investigated the implementation planning of PEV public charging stations from economic aspects.

In literature, only a few papers have considered the implementation of fast charging stations from an economic perspective. The authors of [49] investigated the technical-economic factors for combining gas stations and PEVs fast chargers. The daily PEV demand in the study is assumed as being similar to gas station demand, which leads to overestimating the PEV load in the early adoption stage. The economic evaluation results are questionable due to ignoring fast charging service prices and ignoring the variety of charging unit capacities. A remarkable study has been done in [50], where the authors analyzed the economics of PEV fast charging infrastructure in Germany using a Return on Investment (ROI) model. The results of the study showed how the key parameters – PEV demand and markup price – influence the profitability of FCSs; however, the PEV demand is estimated in the study based on gasoline station data without considering the effect of having home and work charging (Levels 1 and 2 respectively) as substitutes. Hence, it leads to inaccurate estimations that will influence the economic evaluation negatively. In [51], a non-cooperative Stackelberg game is proposed to determine the optimal charging price that leads to the Stackelberg social equilibrium point. The Smart Grid (SG) is considered the leader, setting the charging price, and PEVs are the followers that choose their charging strategies. The study did not consider the infrastructure cost of both the SG and the FCS network in its model, which is required in the economic assessment. It is assumed in the study that electrical utilities own the charging stations, which is not generally the case in the FCS market. In [52], an FCS profit optimization model based on the fast charging service price is developed. The model uses the Net Present Value (NPV) approach to determine the economic viability and the fast charging price. The PEV demand profile is not clearly mentioned in the study, and the electricity cost is assumed to be at the medium voltage tariff, which is not applicable for different FCS locations.

2.5 Chapter assessment and major research gaps

This chapter began by giving a brief review of EVs, and it then covered the classification of EVs, the recent battery technologies being applied for EVs, and the different PEV charging technologies. Anxiety over the limited driving range of EVs and long charging times are major obstacles that decrease public acceptance of EVs; however, spreading out public charging stations (for Level 3) will assist EV penetration. Therefore, the implementation planning of public charging stations has to be developed while also looking at the consequences to the reliability of the distribution network of using only the home-charging alternative.

The literature review included in this chapter reveals that a number of studies have been conducted in the area of forecasting PEV market sales (see Section 2.2). Despite the amount of research completed, major drawbacks are still unresolved and have provided the impetus for the work presented in this thesis. With respect to the PEV market sales methodologies described in the literature, these drawbacks can be summarized as follows:

- The absence of PEV charging data presents a problem. The work presented in the area of estimating PEV charging demand must be enhanced using additional data that reflects charging characteristics and driver behaviors, but this information will not be available prior to significant PEV penetration.
- Most of the forecasting models have used hybrid vehicle historical sales data with the assumption that PEV market sales would follow the HEV market sales pattern. Since they used hybrid electric vehicle data, the correlation between charging infrastructure availability and PEV market sales has not been addressed. However, the forecasting model for PEVs has to include the availability of public charging infrastructure due to its necessity for enhancing PEV adoption.

It is also clear from the discussion in section 2.3 that the research published in the area of siting and sizing charging stations has some limitations, and that it has overlooked significant aspects that can increase the accuracy of the results. According to the authors' best knowledge, most of the previous electrical and transportation research has not considered certain items, and these limitations can be summarized in the following:

- The diversity in drivers' habits and behaviors has not been adequately addressed. Drivers can make a variety of daily trips according to their habits and behaviors. Hence, the energy remaining in drivers' vehicles during the course of a day is influenced by the drivers' routines.
- The randomness of PEV electric ranges (travel distances) has not been addressed well, as the variety of battery types and capacities can influence the range of PEVs. In addition, the energy efficiency of different PEV driving modes (In-city and Highway) can influence travel range as well, so including these variations will lead to outcomes that are more realistic.
- The diversity in trip purposes and mileages has not been considered as thoroughly as might have been possible. Trips in a day can have different mileages: short trips (within city), long trips (highway trips), or a combination of both, and hence, considering trip mileages should be done from an event base rather than a lumped sum of all daily trips.
- Quantifying the quality of charging station service has not been addressed. There are no measurements in the previous work showing that the planned charging infrastructure can meet PEV drivers' needs. Instead, most of the previous work has focused on the impact of charging stations on the power grid, and hence, most of the proposed plans lack consideration of drivers' convenience.
- There is a lack of evaluation and assessment of the additional electrical system requirements during the early PEV adoption stages with low PEV penetration levels. With only a few exceptions, the ability of existing electrical systems to feed the additional PEV charging station load in the early adoption stages is not investigated thoroughly in the previous work in this area.

The economic evaluation methodologies for implementing public charging infrastructure presented in the literature are characterized by the following drawbacks:

- The availability of public charging infrastructure is an essential need for PEV drivers; hence, any huge investment in premature technologies will raise concerns about the benefit of this investment. Therefore, evaluating public charging projects from an economic aspect during the early stages of adoption is crucial.
- Implementing public charging stations without considering the gradual adoption rate of PEVs negatively impacts the economics of using charging stations, especially for early adoption rates. Matching the PEV demand can be achieved in stages to obtain a minimum cost for implementation, since electric chargers can be installed as separate units.

- Dealing with a PEV load as similar to a normal electric load ignores the benefit of PEVs' ability to wait to be served. PEV charging is a service, so quality of service in terms of waiting and charging times should be considered in economic evaluations in addition to the charging price.

The above issues motivated the research presented in this thesis. The next four chapters describe the work conducted to address these gaps and develop useful methodologies that can benefit both utility operators and customers. Specifically, Chapter 3 focuses on the development of a PEV market sales forecasting approach, and Chapter 4 introduces a new method of allocating public charging stations with respect to driver accessibility. Chapter 5 introduces a new approach to model PEV charging demand in order to determine the capability of distribution systems to serve that extra demand, as well as demonstrating the impact of using FCSs in managing PEV demand. Chapter 6 presents an economical staging planning approach for the accommodation of PEV penetration levels.

Chapter 3
Forecast PEV Market Sales

Although plug-in electric vehicles have been identified by many as part of a solution to problems in the transportation sector, electric power systems must be prepared to deal with the challenges and opportunities that come with the new charging load. Many research efforts have been dedicated to the problem of PEV integration considering both alleviating the negative impacts of large-scale penetration of PEVs and fully covering the potential benefits obtained by integrating electric vehicles into the grid [39 – 48]. However, many of those efforts are based, with insufficient justification, on two simplifying assumptions: the number of PEVs on the road and their charging load curve. These assumptions have critical implications: the number of PEVs is a direct multiplier of the magnitude of the impact, and the PEV load curve affects the cost of serving the PEV charging load. Moreover, these two assumptions are also interdependent: on the one hand, the charging load for a small number of PEVs may be buried in the fluctuation of the baseline load (i.e., the electricity load other than the PEV charging load), whereas a large number of PEVs could overwhelm the generation capacity during peak load hours. On the other hand, PEV sales will also be affected by the availability of charging infrastructure, including smarter electric rates and meters, which also influence the PEV charging load curve.

The proposed approach addresses the drawbacks mentioned in Chapter 2 by taking into account the following:

- The assumption that PEV market sales would follow the pattern of HEV market sales as a similar technology
- The relationship between charging infrastructure availability and PEV market sales; i.e., the forecasting model for PEVs has to include the availability of public charging infrastructure due to its necessity for enhancing PEV adoption.
- The proper estimation of PEV charging: Estimating PEV charging was enhanced using additional Travel Survey data for North America [53] that reflect transportation demand characteristics and driver behaviors.

The next two sections describe the problem and explain the modeling. The problem formulation, sample case studies, and concluding remarks are presented in the last three sections of this chapter.

3.1 Problem description

The forecast model proposed in this chapter includes some explanatory variables such incentive and fuel cost saving that extracted from hybrid vehicle historical sales data with the assumption that PEV market sales would follow the pattern of HEV market sales as a similar technology to PEVs. However, the forecasting model is developed by introducing of the availability of charging infrastructure as a new feature regarding PEVs. The scope of the proposed model is Canada-wide, with additional focus on its top three PEV sales provinces between 2016 and 2025. PEVs include both plug-in hybrid electric vehicles (such as the Chevrolet Volt) and pure electric vehicles (such as the Nissan Leaf).

Our approach for PEV sales forecasting is based on the observation that PEVs and HEVs share some key features, such as being more fuel-efficient and having a higher price tag than conventional internal combustion engine vehicles (ICEVs), to varying extents. First, a Multiple Logistic regression model is used to extract the relationship between HEV sales and several independent factors from historical data. Then, a new explanatory variable is introduced in the Multiple Logistic regression model to evaluate the relationship between PEV sales and the availability of charging infrastructure. Finally, a similar model is used to forecast PEV sales from the estimated trajectories of the corresponding key independent factors for PEVs.

3.2 PEV Sales Forecasting Model

In this section, our proposed PEV sales forecast model is described, including the key factors that influence PEV market sales and PEV penetration levels (α). By fitting a logistic equation to the observed data, the Multiple Logistic regression model is obtained to describe the relationship between PEV market sales as a response variable and several explanatory variables. Compared to several existing studies addressing the same issue [12 – 17], our proposed model introduces fast charging station availability as a new explanatory variable in the Multiple Logistic regression model, and we consider both BEV and PHEV historical sales data as observed data in our model. Table 3.1 shows a summary of key previous studies and their methodologies, and Figure 3.1 shows the comparison of previous studies presented in [17].

A Multiple Linear regression model has been used previously to predict the change on a dependent variable based on some independent variables such as in [54], in which yearly data are utilized to describe electricity demand with regard to several economic indicators. The logarithmic function is used in the proposed model to satisfy the homogeneity of the variance condition of the Multiple Logistic regression model, as stated in [17].

The following Multiple Logistic regression model is utilized:

$$\log y_k^{PEV} = \beta_0^{PEV} + \beta_1^{PEV} \log x_{k,1}^{PEV} + \beta_2^{PEV} \log x_{k,2}^{PEV} + \cdots + \beta_n^{PEV} \log x_{k,n}^{PEV} + \varepsilon_k^{PEV}, \forall \ \text{k} = 1, 2, \ldots, \text{K} \tag{3.1}$$

where

$\mathbf{y_k^{PEV}}$ the response variable, representing PEV market sales in year (k)

$\mathbf{x_{k,n}^{PEV}}$ the explanatory variables identified as responsible for PEV sales

$\boldsymbol{\beta_n^{PEV}}$ the regression coefficients for the explanatory variables, where β_0^{PEV} is the intercept

$\boldsymbol{\varepsilon_k^{PEV}}$ the error term

Table 3-1 Summary of key studies in forecasting PEV market sales [12 – 17]

	Study	Proposed Model	PEV Demand Forecast
1	EPRI (2007)	Choice-based Market Modeling of Customer Preference	Forecast period (2010 – 2050) PEV Rates (2050) $\begin{cases} Low & 20\% \\ Mid & 62\% \\ High & 80\% \end{cases}$
2	PNNL (2008)	Information from the literature and interviews with industry representatives and technical experts using three scenarios: **S1**: Hybrid technology-based assessment **S2**: R&D Goals **S3**: Supply-constrained	Forecast period (2013 – 2045) PEV Rates (2023) $\begin{cases} S1 & 9.7\% \\ S2 & 9.9\% \\ S3 & 26.9\% \end{cases}$ PEV Rates (2045) $\begin{cases} S1 & 11.9\% \\ S2 & 29.8\% \\ S3 & 72.7\% \end{cases}$
3	Morgan Stanley (2008)	Forecast HEV and PEV sales using demographic and ownership data	Forecast period (2010 – 2020) PEVs Rate (2015) 250,000 PEVs PEVs Rate (2020) 1 Million PEVs
4	Duan et al. (2014)	Forecast PEV sales using Multiple Linear Regression Model on HEV sales data (1999 – 2009)	Forecast period (2012 – 2020) PEV Rates (2015) $\begin{cases} Low & 0.25\ M\ PEVs \\ Mid & 0.38\ M\ PEVs \\ High & 0.50\ M\ PEVs \end{cases}$ PEV Rates (2020) $\begin{cases} Low & 0.50\ M\ PEVs \\ Mid & 1.00\ M\ PEVs \\ High & 1.80\ M\ PEVs \end{cases}$

Electric Power Research Institute (EPRI)

Pacific Northwest National Laboratory (PNNL)

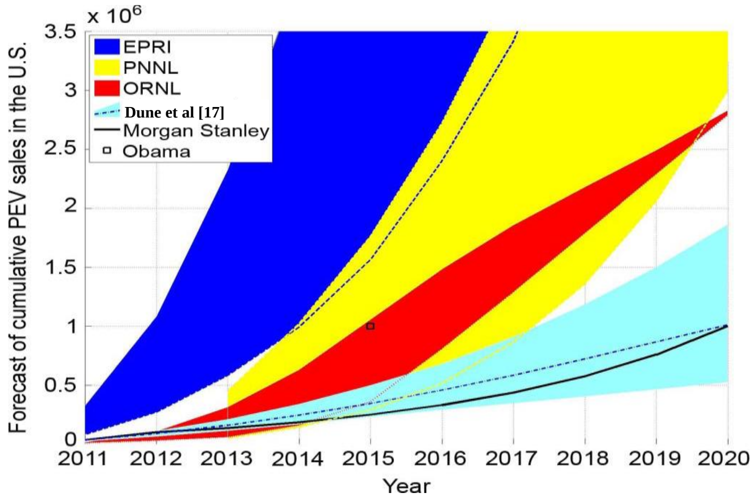

Figure 3-1 PEV Cumulative Sales Forecast for the U.S. (Adapted from [17])

3.3 Explanatory Variables of PEV Market Sales

Several factors may potentially influence PEV sales and accordingly PEV penetration levels (α), including fuel efficiency, gasoline price, vehicle price, average mileage traveled, electricity price, tax incentives, charging infrastructure availability, manufacturing capacity, etc. In our regression model (3.1), fuel cost savings, vehicle price, tax incentives, and number of PEV models are considered as the four key factors recognized in the literature as the most significance factors on the response variable, HEV market sales [12 – 17]. Since we are studying PEV market sales, we introduced a new factor, public charging infrastructure availability, to the Multiple Logistic regression model as a fifth explanatory variable in order to estimate the relationship between PEV sales and public charging availability. The five explanatory variables that yield the best regression results are explained as follows.

3.3.1 Fuel cost savings

$x_{k,1}^{PEV}$ is the average fuel cost savings in year (k) over a comparable internal combustion-engine vehicle (ICEV). This variable is computed using the following equation:

$$x_{k,1}^{PEV} = \sum_{m \in M_k} Gas_k TD_k \left(\frac{1}{EF_{mk}^{ICEV}} - \frac{1}{EF_{mk}^{PEV}} \right), \quad (3.2)$$

where

$\mathbf{M_k}$ the set of ICEV models that are considered comparable with the PEV models available in the market in year k

$\mathbf{Gas_k}$ the average annual gas price in \$/L in year k

$\mathbf{TD_k}$ the average annual vehicle travel distance in km in year k

$\mathbf{EF_{mk}^{ICEV}}$ the fuel efficiency of the ICEV that is comparable to the PEV model m in km/L
$\mathbf{EF_{mk}^{PEV}}$ the fuel efficiency of the PEV model m in km/L

The annual average fuel cost savings between the considered PEV models and comparable ICEV models were obtained from Eq. (3.2). The annual average fuel cost savings is influenced by the annual gas price, the average annual vehicle travel distance, and fuel efficiency of PEV models compared to the ICEV models. The historical and projection data for these influence parameters can be obtained from the Canadian Energy Board [55], and the top three selling PEV models in Canada (Chevy Volt™, Tesla Model S™, and Nissan Leaf™) are compared in this work to the ICEV models Toyota Camry™, Lexus ES 350™, and Toyota Corolla™ [56] respectively.

3.3.2 Average price difference

The average price difference ($\mathrm{x}_{\mathrm{k},2}^{\mathrm{PEV}}$) between PEVs and their comparable ICEVs (in $) in year k is investigated. The maturity of ICEV technology compared to PEV technology makes the ICEV price data (historical and forecasted) easy to access; however, different parameters can affect the price of PEVs, such as battery technologies, media coverage of PEVs, manufacturing capacity, etc. The price difference between ICEVs and PEVs is assumed in the proposed model to be similar to that in [57].

3.3.3 Average government incentives

$x_{\mathrm{k},3}^{PEV}$ is the average incentives for PEVs provided by governments in $ in year k. This variable also represents the effect of various other government policies, which cannot all be reflected in a simple regression model. In our proposed model, provincial incentive programs for both PEV purchases and Charging Station (FCS) installation are considered. The former is directly applied for PEV sales; however, the latter indirectly affects PEV purchase decisions. The incentive program data are available in [58 – 60] for different Canadian provinces.

3.3.4 Number of PEV models available in the market

$x_{\mathrm{k},4}^{PEV}$ is the number of PEV models available in the market in year k, including both PHEVs and BEVs. The data for these models are available in [61]. This variable takes into account the supply side constraints on PEV sales. In the early adoption of Toyota Prius [62], Chevrolet Volt [63], and Nissan Leaf [64], the bottleneck in vehicle sales was due to manufacturing capacity, materials supply, and other logistical constraints faced by vehicle manufacturers, rather than consumer demand [17].

3.3.5 Public charging infrastructure availability

$x_{k,5}^{PEV}$ is the public charging station availability (in percentage) relative to gas stations in year k. This explanatory variable, newly introduced to the Multiple Logistic regression model for forecasting PEV market sales, helps in taking into account the anxiety over limited driving range in the decision to purchase a PEV. The availability of public charging facilities is a key factor in enhancing PEV driving range. Since we are estimating PEV sales rather than HEV sales, as has some previous work in the same area, this variable has to be considered in the regression model in order to describe its influence on the response variable, PEV sales.

To predict PEV sales, we need to obtain not only estimates of these five explanatory variables, but also estimates of the regression coefficients that reflect the influences of the explanatory variables on PEV sales. Due to the limited observable data for PEV sales (2008 –2015), we can only support our estimation of the regression coefficients for the first four explanatory variables by using HEV sales as a similar technology. However, for the fifth explanatory variable, public charging station availability, the available data for PEV sales (2008 –2015) is the best that we can obtain currently, but when more PEV sales data are available, that will enhance the accuracy of our estimates for the fifth coefficient.

3.4 PEV sales forecast sample results (2016 – 2025)

In this section, four case studies are presented for the period 2016 – 2025. The first case study was conducted Canada-wide, and we considered the incentive programs provided by different Canadian provinces. The other three case studies covered the three top Canadian provinces in PEV sales, British Columbia (BC), Ontario (ON), and Quebec (QC) [65]. Jointly they are associated with 97% of all PEV sales in Canada for the period 2008 –2015 [65]. The results of the case studies are presented in high, medium, and low projections in order to be consistent with Canadian Energy Board projections [55].

3.4.1 PEV sales forecast Canada-wide (2016 – 2025)

This case study shows the forecast data for PEV sales in Canada for the period 2016 – 2025 using the proposed Multiple Logistic Regression Model (MLRM). For the fuel cost savings estimation, we considered the average annual travel distance Canada-wide. As well, since each Canadian province has its own incentive programs, we considered the average value of three different provinces' (BC, ON, and QC) incentive programs. The coefficients of the PEV sales regression model are summarized in Table 3.2. As expected, x_1^{PEV} (fuel savings), x_3^{PEV} (incentive program), x_4^{PEV} (number of vehicle models), and x_5^{PEV} (charging infrastructure availability) all have positive influences on the sales, whereas x_2^{PEV} (average price difference) has a negative influence. As shown in Table 3.2, there is an inverse correlation between the average price difference between PEVs and their comparable ICEVs. Therefore, when there is a significant price difference between new PEV models and comparable new ICEV models, that difference will negatively influence potential PEV drivers' purchase decisions.

Figure 3.2 shows the PEV sales forecast for Canada for 2016 – 2025, and the results are shown in both the annual cumulative number of PEV sales and the penetration levels (α_{CAN}). For validation, we compare only penetration level results (α_{CAN}) to the ones presented in [17], since we cannot compare the cumulative PEV sales due to different geographical areas with different populations.

Table 3-2 PEV sales regression coefficients (Canada-wide)

Coefficient	estimate	Std. error	t ratio	p-value	Adjusted R^2
β_0^{PEV}	3.3065	1.096	3.0169	0.0021	0.765
β_1^{PEV}	0.41165	0.121	3.4021	0.0006	0.731
β_2^{PEV}	-0.1826	0.056	-3.2607	0.0012	0.778
β_3^{PEV}	0.1986	0.061	3.2557	0.0015	0.803
β_4^{PEV}	0.076	0.022	3.4545	0.0005	0.822
β_5^{PEV}	0.5182	0.113	4.5858	<0.0001	0.834

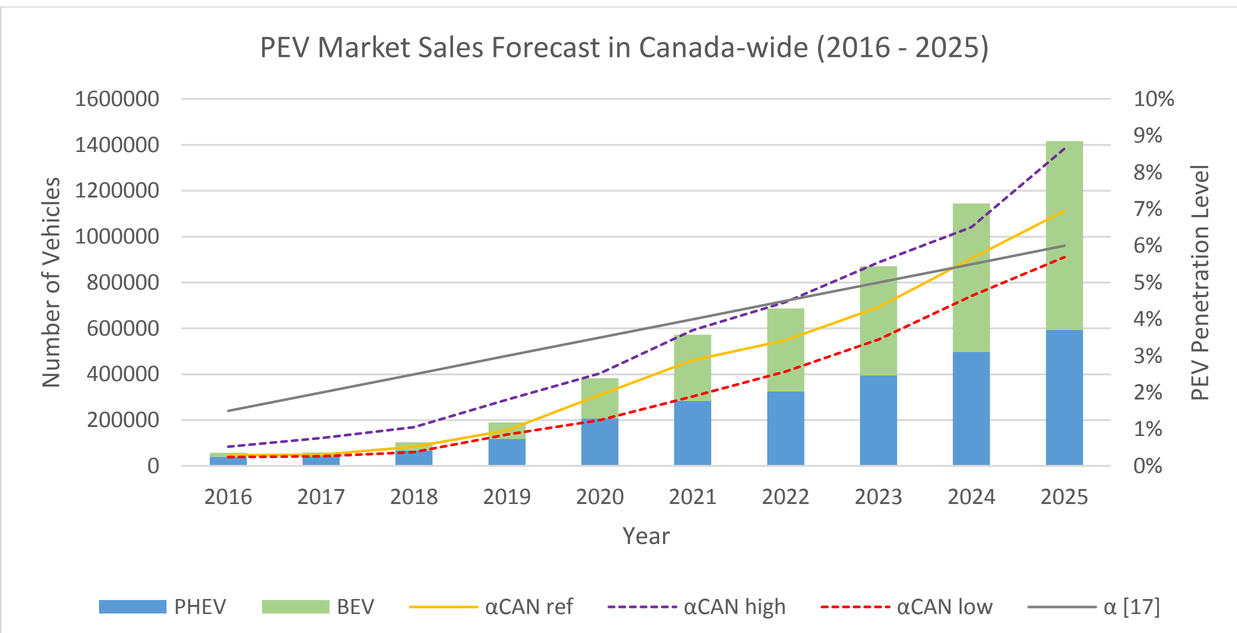

Figure 3-2 PEV Cumulative Sales Forecast for Canada (2016 – 2025)

The results for the reference scenario (α_{CAN}) show that the PEV penetration level is expected to reach 5% by 2024 and that total PEV sales will exceed 1,400,000 by 2025. The penetration level of PEVs in Canada (α_{CAN}) is less optimistic than the one proposed in [17] for the early stages of adoption; however, α_{CAN} will take over during the last couple of years of forecasting based on the reference scenario, and the last four years based on the high case. One important observation is that the number of PEV sales in 2020 will be almost double those in 2019, consistent with the fact that most charging stations permitted or planned are going to be in service by 2020, according to Mogile Tech data [66].

3.4.2 PEV sales forecast for British Columbia (2016 – 2025)

British Columbia (BC) is the westernmost province in Canada. British Columbia is also a component of the Pacific Northwest and the Cascadia bioregion, along with the US states of Oregon and Washington. The largest city is Vancouver, the third-largest metropolitan area in Canada, the largest in Western Canada, and the second-largest in the Pacific Northwest. In October 2013, British Columbia had an estimated population of 4,606,371 [55]. The proposed MLRM has been applied for the historical data for BC, and the results are shown in Table 3.3.

Table 3-3 PEV sales regression coefficients (British Columbia)

Coefficient	estimate	Std. error	t ratio	p-value	Adjusted R^2
β_0^{PEV}	-1.2505	0.296	-4.22	0.0002	0.802
β_1^{PEV}	0.7718	0.191	4.04	0.0006	0.834
β_2^{PEV}	-0.4097	0.126	-3.25	0.0012	0.784
β_3^{PEV}	0.1551	0.051	3.04	0.0025	0.858
β_4^{PEV}	0.1301	0.042	3.10	0.0019	0.832
β_5^{PEV}	0.4352	0.106	4.11	0.0004	0.761

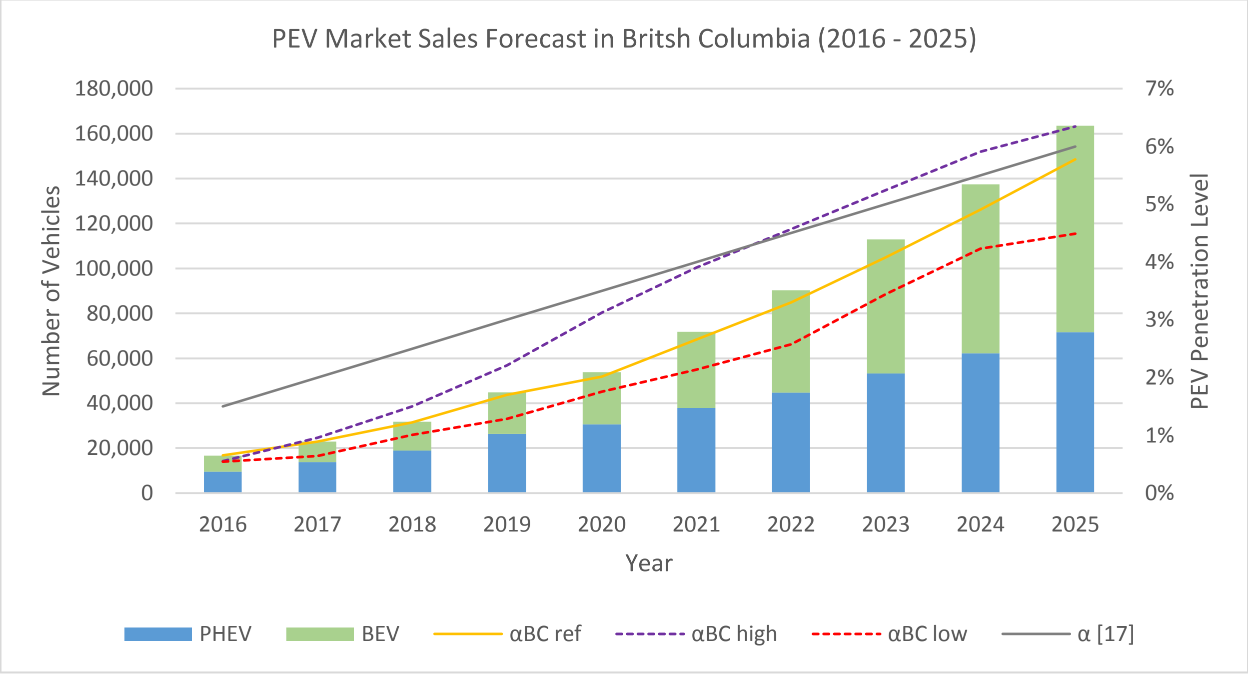

Figure 3-3 PEV Cumulative Sales Forecast for British Columbia (2016 – 2025)

The observed data for PEV sales in BC (2008 –2015) show that PEV sales are usually high in the first three months of each year, and then decline. That is correlated with the fact that the incentive programs are usually stopped after the first three months of the year due to limits in the BC government's budget. Therefore, customers will often delay their purchases until the next year in order to be eligible for the incentives. PEV sales in BC started very strong between 2008 and 2011; however, when the number of hopeful buyers exceeds the budget limits of the BC incentive program, and the procedure for getting the incentive is based on a first-come, first-serve basis, this negatively influences sales. The BC government then reduced the incentive to 5,000 dollars in order to approve more applications, and that decision also negatively affected BC PEV sales.

As shown in Figure 3.3, the PEV sales forecast for BC is less optimistic compared to the Canada-wide case. The forecasted sales are expected to exceed 5% of all vehicles by 2025, which could not be achieved without the fact that BC has one of the strongest charging station infrastructures in Canada, with a ratio of 1 public charging station to 3 gas stations in 2013 [66].

3.4.3 PEV sales forecast for Ontario (2016 – 2025)

Ontario is one of Canada's ten provinces, and is located in the east-central part of the country. It is Canada's most populous province by a large margin, accounting for nearly 40 percent of all Canadians, and is the second-largest province in total area. It is home to the nation's capital city, Ottawa, and the nation's most populous city, Toronto [55]. The large population of Ontario makes it a target for Canadian clean energy projects [55], and the Ontario government has a vision of having 1 in 20 vehicles electrically powered by 2020 [67]. The government of Ontario will be required to take adequate steps for the preparation and development of a province-wide strategy for energy and infrastructure (Ontario Ministry of Transportation, 2010a) [67]. In 2010, the Ontario government announced an incentive program for PEVs of up to 8,500 dollars towards the purchase of a new PEV and up to 1,000 dollars to install a home charging facility, but still, lack of public charging station infrastructure is one of the biggest obstacles facing public PEV acceptance in Ontario. Table 3.4 shows the PEV sales coefficients for Ontario.

Table 3-4 PEV sales regression coefficients (Ontario)

Coefficient	estimate	Std. error	t ratio	p-value	Adjusted R^2
β_0^{PEV}	-5.641	1.467	-3.85	0.0002	0.769
β_1^{PEV}	0.4772	0.127	3.76	0.0006	0.854
β_2^{PEV}	-0.0176	0.006	-2.93	0.0093	0.832
β_3^{PEV}	1.0622	0.266	3.98	0.0005	0.812
β_4^{PEV}	0.2315	0.064	3.62	0.0009	0.809
β_5^{PEV}	0.7853	0.208	3.78	0.0006	0.874

Figure 3.4 shows the results of applying the MLRM on the observed data for Ontario, and the forecast data show that Ontario's vision of having 5% of all vehicles electrified is achievable by 2023 in the high scenario and by 2024 in the reference scenario. However, the vision will not be achieved by 2025 based on the low scenario. In order to guarantee that the vision is achieved on time, the Ontario government should take further steps in supporting public charging station infrastructure.

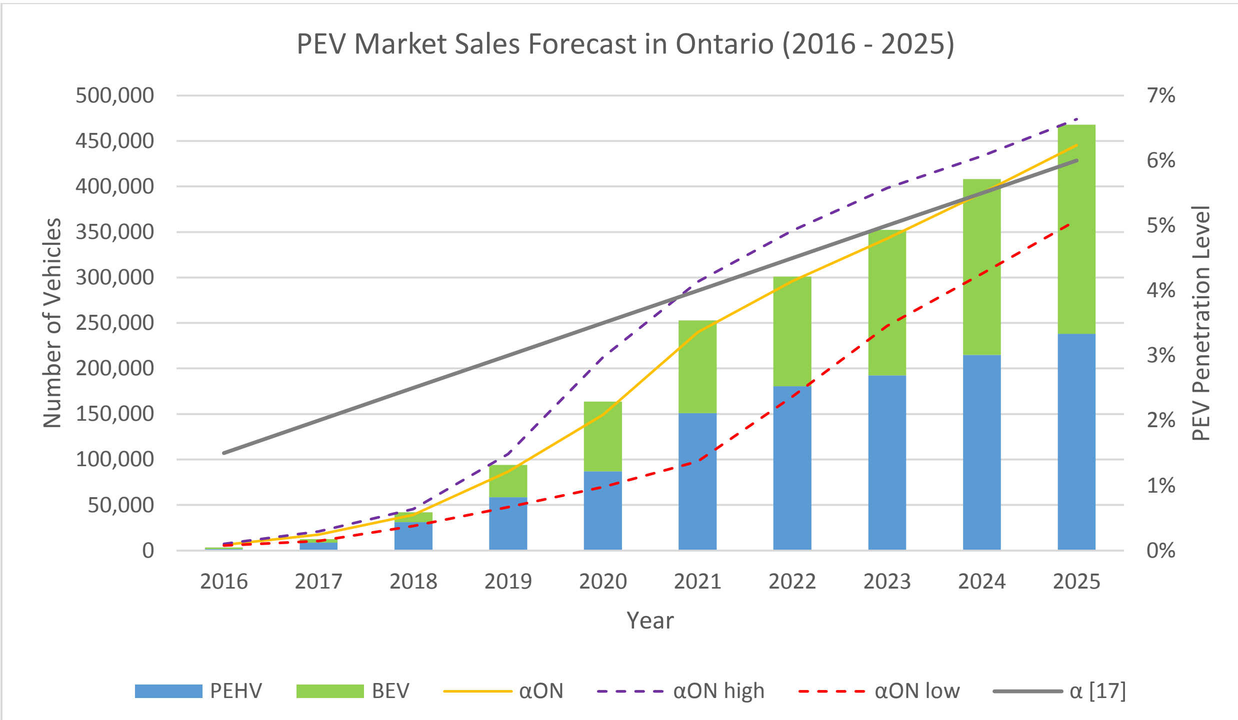

Figure 3-4 PEV Cumulative Sales Forecast for Ontario (2016 – 2025)

3.4.4 PEV sales forecast for Quebec (2016 – 2025)

Quebec (QC) is a province in east-central Canada, and it is Canada's largest province by area. In addition, it is Canada's second most populous province after Ontario. Approximately half of Quebec residents live in the Greater Montreal Area, including the Island of Montreal [55]. The proposed MLRM has been applied to the observed data for Quebec, and the results show that the QC PEV sales forecast is the most optimistic one. The government of QC has taken several steps in supporting charging station infrastructure, and it supports switching to PEVs through different incentive programs that reach 8,250 dollars per purchase, based on the battery capacity of the PEV. The ratio of charging stations to gas stations is expected to jump to 1:6 by 2025 [66]. One important point resulting from the observed data is that the government should focus on standardized the charging station ports to make them more convenient for different cars' owners to access the charging network. The challenge in the current charging station network is that Tesla owners must use Tesla chargers, Nissan Leaf owners must use their own charging facilities, and so on. When the charging station network is standardized, it will be easier for any PEV driver to recharge their vehicle across the province. However, this is still a problem with most charging station networks worldwide.

Table 3-5 PEV sales regression coefficients (Quebec)

Coefficient	estimate	Std. error	t ratio	p-value	Adjusted R^2
β_0^{PEV}	82.623	19.467	4.24	<0.0001	0.805
β_1^{PEV}	0.7965	0.175	4.55	<0.0001	0.823
β_2^{PEV}	-0.3135	0.086	-3.65	0.0009	0.783
β_3^{PEV}	21.732	5.934	3.66	0.0008	0.835
β_4^{PEV}	0.3516	0.078	4.51	<0.0001	0.811
β_5^{PEV}	0.5183	0.121	4.28	0.0006	0.856

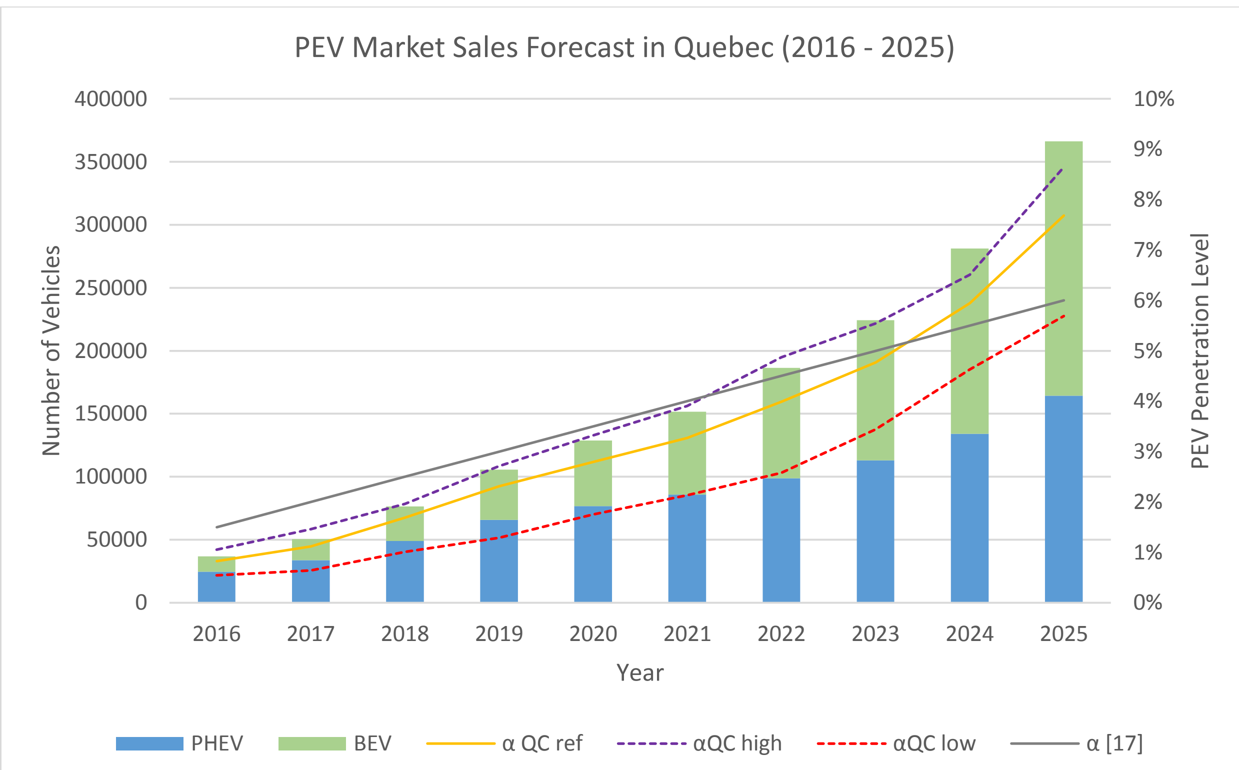

Figure 3-5 PEV Cumulative Sales Forecast for Quebec (2016 – 2025)

3.5 Discussions

In this section, a sensitivity analysis is presented to consider different steps that governments can take to update their plans for achieving their green transportation goals. First, a summary of the correlations between the response variable and each explanatory variable for each province as well as Canada-wide is shown in Table 3.6. It is observed from the table that PEV sales have the strongest correlation with the available charging infrastructure variable (x_5^{PEV}) in ON, QC, and Canada-wide; however, the (x_3^{PEV}) incentive program variable has the strongest correlation with PEV sales in BC. Therefore, the ON and QC governments should pay more attention to their charging infrastructure plans in order to achieve their green transportation goals, whereas the BC government should consider more incentive programs for PEVs in order to enhance PEV sales.

Table 3-6 Correlations between response variable and each explanatory variable

		$\log y^{PEV}$	$\log x_1^{PEV}$	$\log x_2^{PEV}$	$\log x_3^{PEV}$	$\log x_4^{PEV}$	$\log x_5^{PEV}$
Canada	$\log y^{PEV}$	1	0.347	0.425	0.493	0.436	0.674
BC	$\log y^{PEV}$	1	0.362	0.571	0.681	0.569	0.467
ON	$\log y^{PEV}$	1	0.531	0.363	0.416	0.494	0.795
QC	$\log y^{PEV}$	1	0.549	0.536	0.641	0.719	0.743

To investigate the influence of charging infrastructure availability on market sales, the Ontario PEV sales forecast case is considered. The forecast data for available charging infrastructure have been increased by 10, 30, 50, and 70% respectively. Table 3.7 shows the positive influence on PEV sales in Ontario of increasing the public charging availability parameter. In Figure 3.6, the enhanced PEV sales are shown, and the penetration level is shown in Figure 3.7.

Table 3-7 the influence of increasing charging infrastructure parameter on PEV sales

Charging infrastructure availability enhancement	10%	30%	50%	70%
PEV sales growth	7.80%	22.90%	37.50%	51.70%

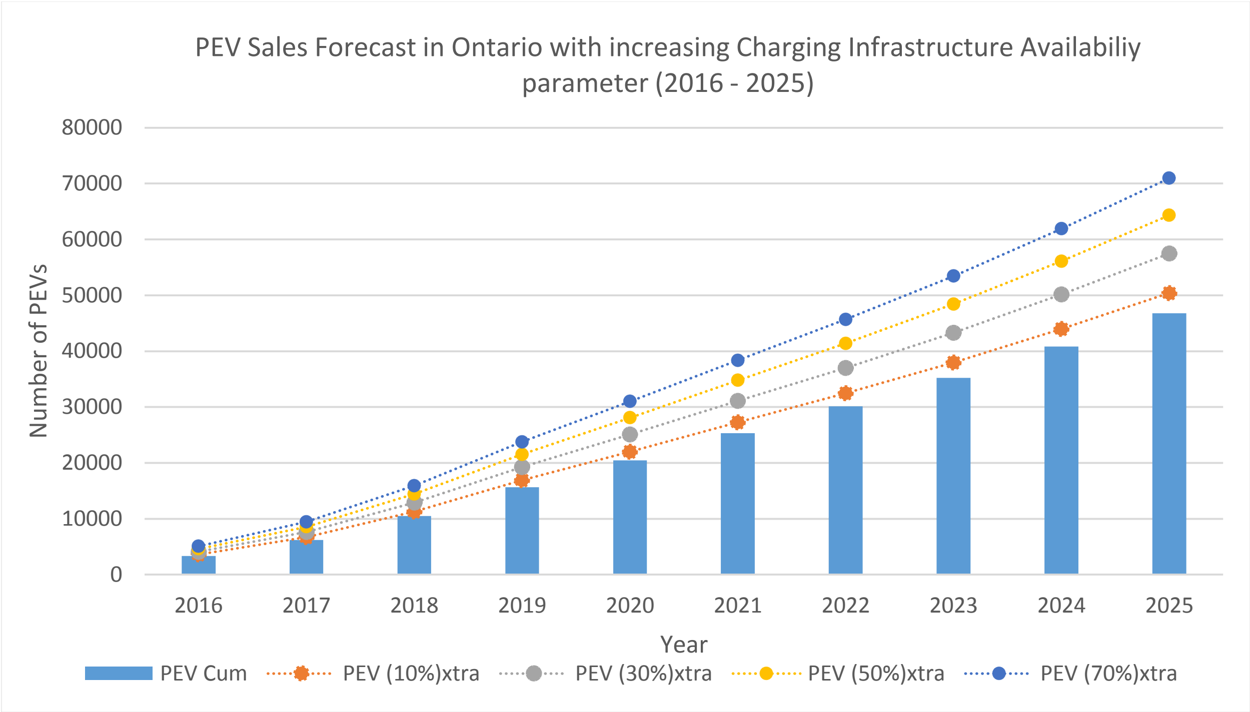

Figure 3-6 The correlation between PEV Sales Forecast in Ontario and charging infrastructure availability

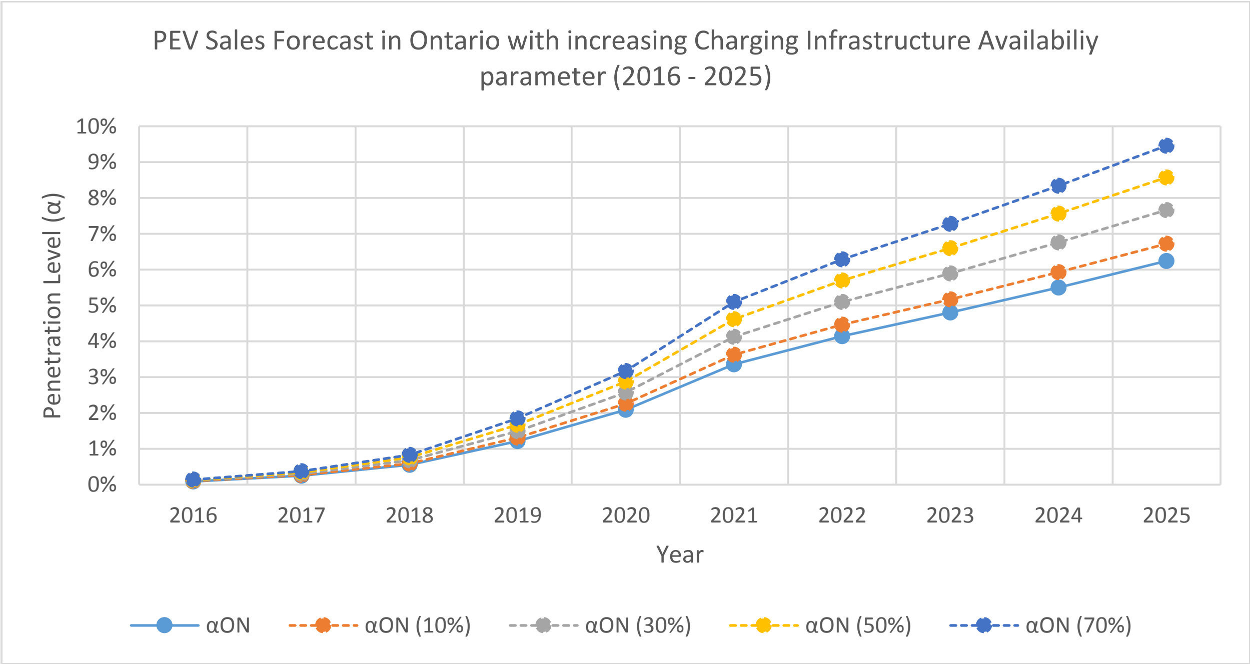

Figure 3-7 The correlation between PEV penetration level in Ontario and charging infrastructure availability

It is observed from the results that the government of Ontario should not only focus on incentive programs for PEVs, but also they should pay more attention to their charging infrastructure, which has a significant influence on PEV market sales.

In 2013, the ratios of PEVs to charging stations for Canada, BC, ON, and QC were 4:1, 1:1, 7:1, and 5:1 respectively, according to Mogile Tech data [66]. However, these ratios are expected to be 3:1, 1.5:1, 5:1, and 3:1 by 2025 respectively. These ratios are very useful indicators to evaluate the important of charging station availability on the one hand, and to evaluate the economic benefit of investing in charging infrastructure on the other. Hence, Ontario is the best market for investing in charging infrastructure in the next decade, while BC is considered the least attractive market to invest in in the next decade due to the high ratio of charging stations there to the number of PEVs.

3.6 Chapter assessment

In this chapter, a modified Multiple Logistic regression model has been presented. A new explanatory variable, charging station availability, is introduced into the model in order to investigate the correlation between that variable and PEV market sales forecasts. For the sake of validation, the proposed model has been compared to a model [17] previously presented in the literature. Due to the different demographic information in the observed data, in order to have a fair comparison, the comparison was made for penetration levels rather than for cumulative numbers of PEV sales. In comparison to [17], our forecast results show less optimistic patterns in most cases, especially at the beginning of the forecast period. The sensitivity analysis and observations discussed in the chapter have been highlighted to support governments in achieving their green transportation goals. For example, according to the model, enhancing the public charging infrastructure in Ontario influenced PEV market sales positively, which should be considered by the government in order to achieve their goals. The Ministry of Transportation in Ontario has taken a step to deal with the lack of public charging stations by announcing a program called Electric Vehicle Chargers Ontario (EVCO) at the end of December 2015. The EVCO program supports public charging infrastructure with a value up to 20 million dollars. The program will support around 200 charging stations Level 3 and around 300 charging stations Level 2 to be installed by March 2017.

The PEV market sales forecast and the parameters affecting PEV adoption are the keys to estimate the PEV penetration level as an important input for PEV charging station implementation plan. The PEV penetration level will be utilize as well as the FCS target locations (next chapter) to produce the PEV demand by using traffic flows. The PEV demand is a main input in both Chapter 5 and 6

Chapter 4
Fast Charging Station Optimal Location

This chapter proposes an optimization model for allocating plug-in electric vehicle charging stations from a new perspective, which is PEV drivers' convenience. The main purpose of the study is to optimally choose from the available candidate sites the charging station set that best enhances PEV drivers' convenience. The proposed allocation model addresses the drawbacks mentioned in Chapter 2 by taking into account the following:

- Including the diversity in drivers' habits and behaviors. Drivers can make a variety of daily trips according to their habits and behaviors; hence, the remaining energy in drivers' vehicles during the course of a day is influenced by the drivers' routines.
- Including the randomness of PEVs' remaining energy range (RER), as battery types and capacities can influence the electric range of PEVs. In addition, the energy efficiency of different PEV driving modes (in-city and highway) can influence the electric range as well, so including these variations will lead to outcomes that are more realistic.
- Developing a Trip Success Ratio (TSR) Model based on a Monte Carlo Simulation (MCS) in order to quantify the quality of charging station infrastructure service from a driver convenience perspective. There are no measurements in the previous work showing that the planned charging infrastructure can meet PEV drivers' needs. Instead, most of the previous work has focused on the impact of charging station locations on the power grid, and hence most of the proposed plans lack consideration of drivers' convenience.

4.1 Problem description

A PEV trip can be completed successfully if the electrical energy remaining in the PEV's battery is sufficient to allow the PEV to reach the destination; otherwise, the PEV battery has to be recharged on route in order to complete that trip successfully. If the energy remaining in the PEV's battery is insufficient to reach the destination or the nearest FCS, the PEV fails to complete its trip. Since it is hard to predict the remaining electric range of PEVs and the trip lengths due to the high degree of uncertainty, the FCSs should be allocated optimally to make the distances between FCSs short enough to increase the number of trips reaching their destinations successfully. Choosing a proper distance between FCSs depends on modeling both the uncertainties in the remaining electric energy in PEV batteries and the trip (driver) behaviors. Most of the previous research on locating charging infrastructure simply assumed arbitrary distances between FCSs. As a result, this might negatively influence the drivers' convenience by overestimating the distance between stations, or may waste some resources by underestimated that distance. Moreover, locating FCSs based on maximum flow capturing will concentrate PEV demand in some buses; hence, that will stress the distribution system from one side and impact the driver convenience negatively from the other side.

The work presented in this chapter includes an allocation model that selects optimal FCS locations to guarantee a certain level of PEV driver convenience based on the level of successful trips. The proposed allocation approach consists of two stages, in which the first stage introduces a Trip Success Ratio (TSR) model that provides a measure for quantifying the ability of a charging station network to serve PEV demand successfully. The TSR model includes two sub-models to demonstrate the randomness of PEV trip behaviors and the randomness of the electrical energy available in PEVs' batteries at the beginning of trips. The second stage selects the best FCS locations that maximizing the transportation network covering. The convenience level of FCS network has an inverse relation with distance between charging stations. Shorter distance between charging stations means more trips reach destination successfully which enhances the drivers' convenience level. The selected convenience level of an FCS network in serving PEV drivers is guaranteed by utilizing a specific service range obtained from the first stage to locate charging stations.

4.2 Trip Success Ratio Model

This section presents the Trip Success Ratio (TSR) model. This proposed model evaluates the charging station network based on two components: the service range of charging stations and the trips completed successfully by PEVs. Instead of modelling the transportation network as OD pairs that has different detours and alternative paths [20 – 23], the transportation network is divided into smaller parts, and each of these parts should be covered by at least one FCS. Hence, the FCS locating problem will be modeled as a coverage problem rather than a flow-capturing problem. The division process is based on the Charging Station Service Range (CSSR) where CSSR is the distance between FCSs. CSSR will be a major factor that influences the percentage of PEV trips completed successfully. When the CSSR is small, it means that more FCSs will be installed in the transportation network; therefore, the ability of PEVs with a smaller battery capacity to complete their trips will be increased. However, the distance between FCSs should be far enough to utilize resources efficiently. The TSR model investigates the relationship between different CSSRs and different TSR levels.

Two other factors influence the TSR level of PEV trips besides the distance between FCSs. The first factor is PEV daily trip distances, and the second is the amount of energy in the PEV's battery at the start of each trip. Hence, the TSR model consists of two sub-models in order to demonstrate the uncertainty of PEV travel patterns and PEVs' remaining electrical energy. As a result, the TSR model will be capable of evaluating and estimating the required CSSRs. The TSR model will be utilized in the allocation model for FCSs.

4.2.1 Travel Pattern model

The travel pattern model will utilize the travel survey data for general transportation in North America [53] to generate Virtual Travel Distance (VTD) trips using a Monte Carlo Simulation (MCS). The travel survey data for general transportation include trips by different means (regular cars, trucks, etc.), and the model considers only trips conducted by privately owned vehicles. In order to obtain the virtual trip distance, the model classifies the actual trips into two classes: short trips (less than 20 mile) and long trips (more than 20 mile) to represent in-city and inter-city trips, and each class of trips is categorized by different time – intervals based on trips' starting times. Figure (4.1) shows the pdf of trip mileage and the percentage of in – city (short) and inter – city (long) trips, and Figure (4.2) shows the pdf of trips based on the starting time of trips.

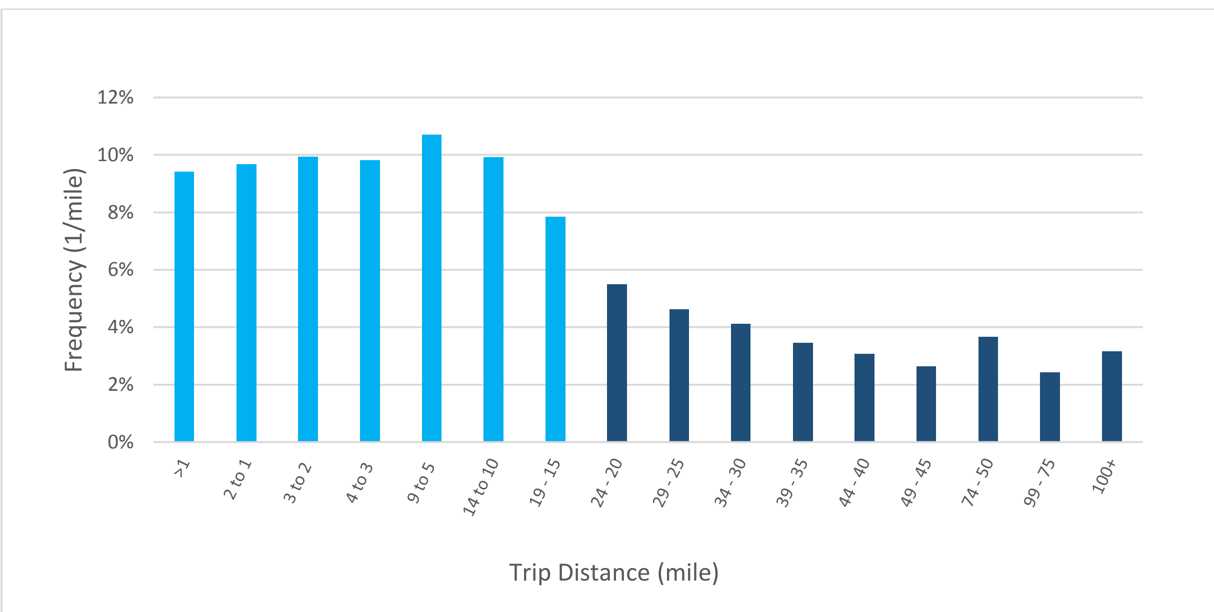

Figure 4-1 The Probability distribution function of trip mileage (NHTS 2009)

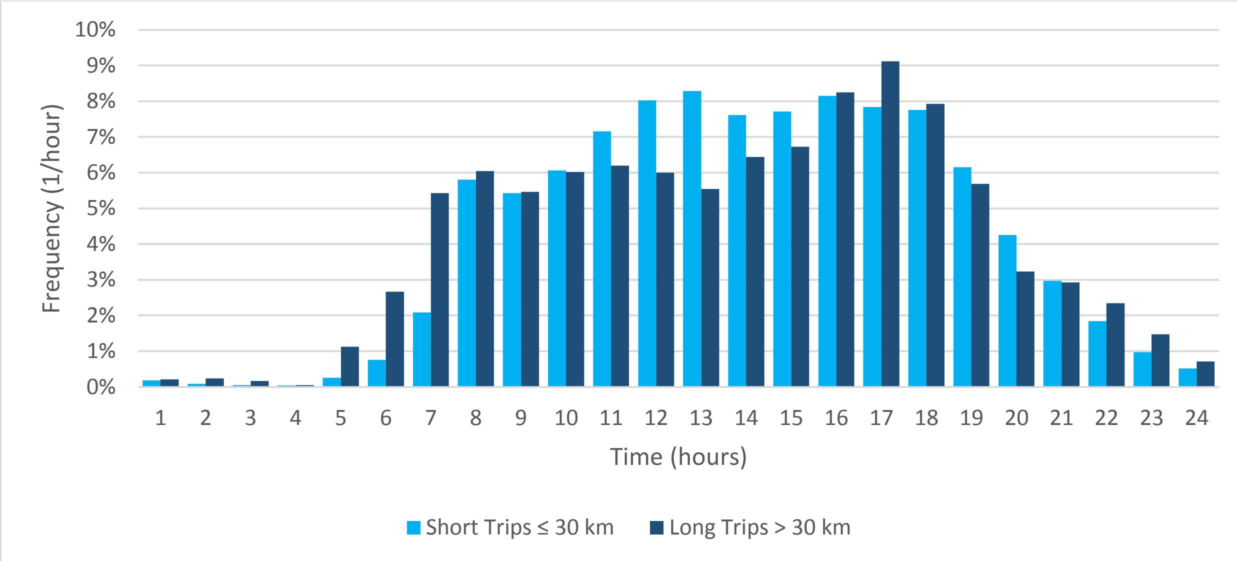

Figure 4-2 Daily Trip classification (starting time and mileage)

The actual data for each class have been fitted to the closest Probability Distribution Function (pdf) by using the Maximum Likelihood method to estimate the PDF parameters. Then, the highest-likelihood PDF and its parameters are chosen to represent each class. Finally, using Equations (4.1 – 4.3), the cumulative distribution function is calculated to obtain the VTD trips for each class.

$$f_1(td) = \frac{1}{td\sigma\sqrt{2\pi}} e^{-\frac{(\ln(td)-\mu)^2}{2\sigma^2}} \tag{4.1}$$

$$F_1(x|\mu_1,\sigma_1) = \frac{1}{\sigma_1\sqrt{2\pi}} \int_0^x \frac{e^{-\frac{(\ln(td)-\mu_1)^2}{2\sigma_1^2}}}{t}\, dtd \tag{4.2}$$

$$VTD_{(c)} = F_{1\,(c)}^{-1}(z) \tag{4.3}$$

where

f_1 the probability distribution function of the actual trip data

F_1 the cumulative distribution function of the actual trip data

μ_1, σ_1 the estimated mean and standard deviation of the PDF of the actual trip data

$VTD_{(c)}$ the virtual travel distance in km of a trip in Class “c”

$F_{(c)}^{-1}$ the inverse of the cumulative density function, which describes the probability of a trip in class “c” to be less than a certain distance

z a normally distributed random variable between zero and one

td the trip distance in km

National Household Travel Survey data [53] contains different trips' purposes: Earn a living, School, Church, Family, Personal Business, Social, Recreational and other. Hence, including these purposes when virtual trips are produced should represent the traveler's habits. Different trip purposes shares are presented in Figure (4.3). In addition, each trip purpose has modeled similarly by two pdfs (mileage and starting time). For example, the two pdfs of Earn a living purpose are shown in Figures (4.4, and 4.5). Similarly, the other trip purposes are modeled and all of them are utilized when virtual trips are generated to estimate the SOC means and standard deviations; which will be explained later in the Remaining Electric Range (RER) model.

The outcomes of the travel pattern model are the virtual trip distances conducted by PEVs. Using the travel survey data for private gas-powered vehicles to mimic the mechanical energy of PEVs will lead to accurate estimation than monitoring PEVs due to the high maturity level of the gas station network compared to the FCS network currently reported in [21, 31]. Therefore, the travel pattern model that utilizes the data of the private gas-powered vehicles are applicable in representing the virtual trip distances conducted by PEVs.

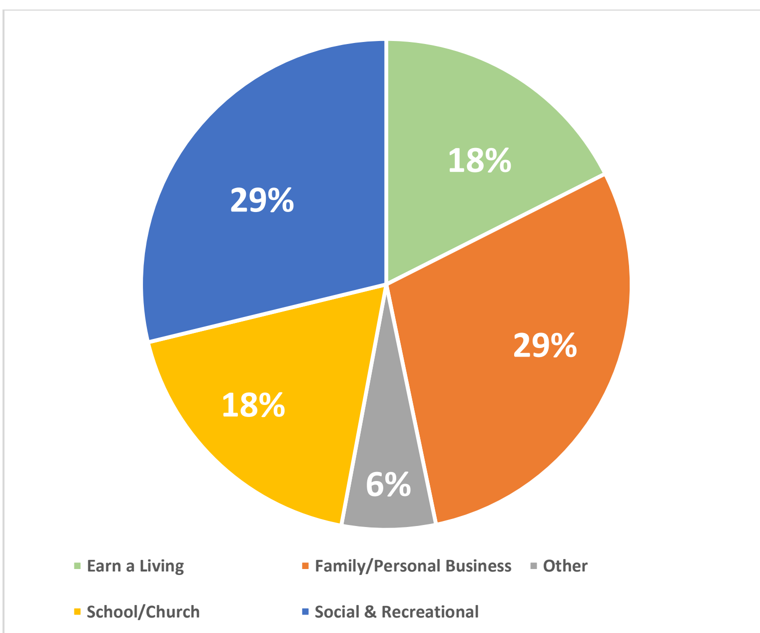

Figure 4-3. The probability of trips based on trip purpose (NHTS 2009)

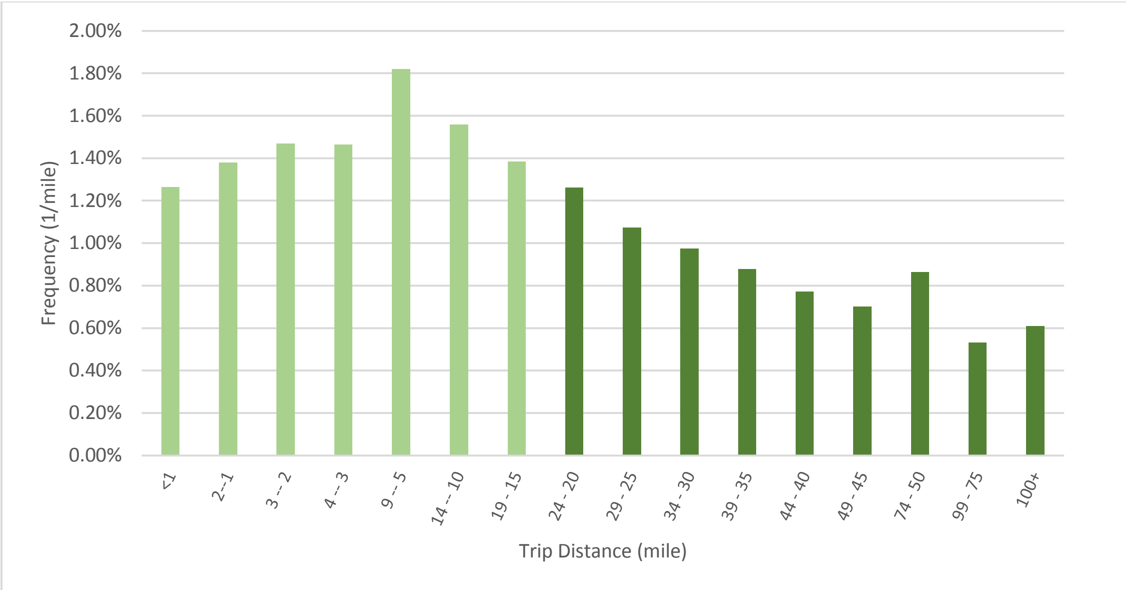

Figure 4-4 The probability of Earn a Living trips based on trip mileage (NHTS 2009)

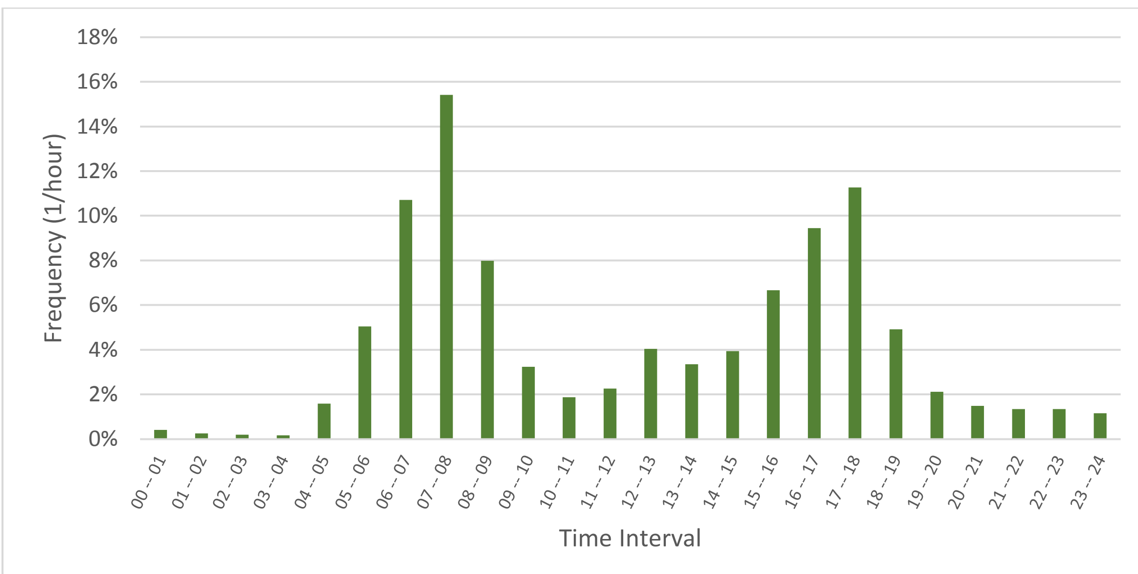

Figure 4-5 The probability of Earn a Living trips based on trip starting time (NHTS 2009)

4.2.2 Remaining electric range model

Three components influence the Remaining Electric Range (RER) of PEVs: Battery Capacity (BC), State of Charge (SOC), and average Tractive Effort Factor (TEF). The RER is estimated with consideration of the diversity of BCs in the PEV market sales, different SOC levels at the beginning of each trip, and different TEFs (kWh/km). The latter factor is mainly based on the driving modes (In-city or Highway), so city driving requires higher energy consumption per kilometer (kWh/km). The RER model can be demonstrated using Equations (4.4 – 4.8)

$$RER_{(c)} = \frac{BC \times SOC_{(c)}}{TEF_{(c)}} \tag{4.4}$$

where

$RER_{(c)}$ the remaining electric range in km for a trip in Class "c"
BC the battery capacity of a PEV in kWh
$SOC_{(c)}$ the state of charge of a usable range of PEV battery in (%) at the beginning of a trip in Class "c"
$TEF_{(c)}$ the average tractive effort factor of a PEV conducting a trip in Class "c" (kWh/km)

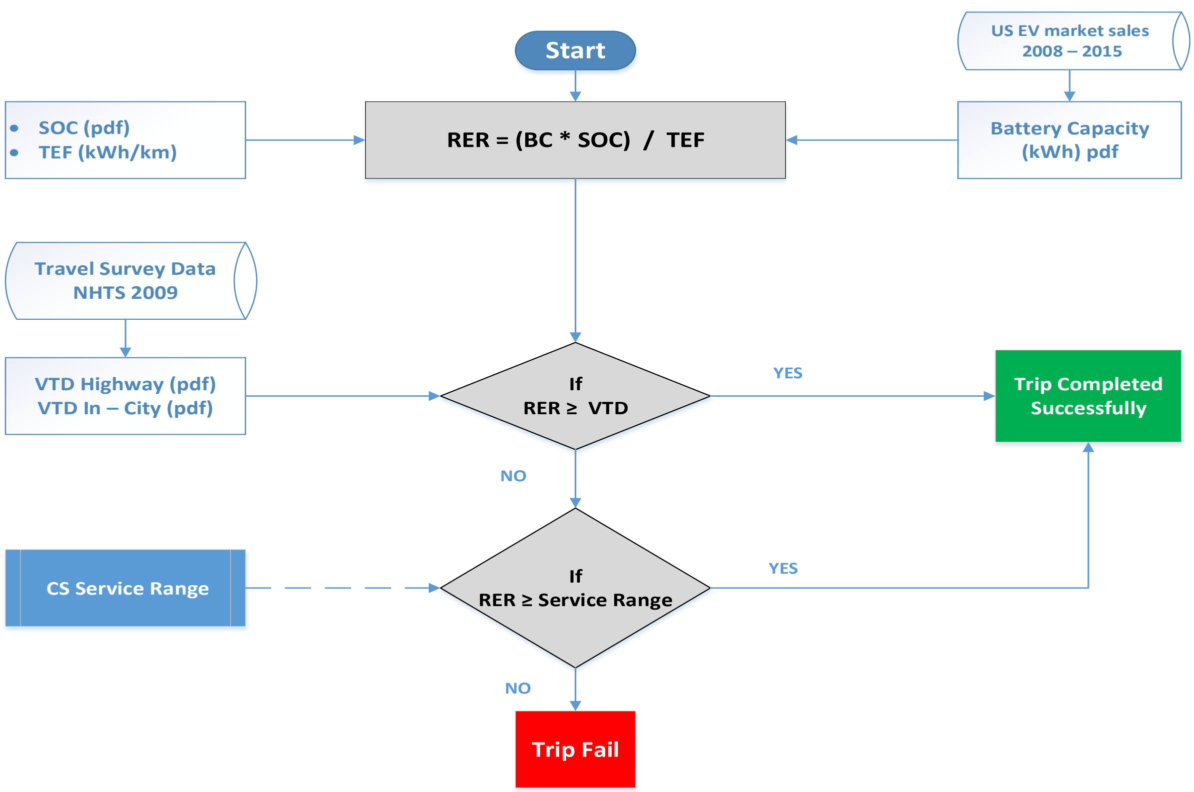

Figure 4-6 The Proposed Trip Success Ratio Model

The diversity of PEV battery capacities in the market can be considered by using previous market sales of PEVs and their battery capacities. As a result, the BC in the model will represent the share of each battery capacity according to sales of PEVs. The Empirical Distribution Function (EDF) is utilized to consider the randomness of the battery capacities based on market sales, as shown in Equation (4.5).

$$F_n(bt) = \begin{cases} 0 & , \ for\ bt < BC_1 \\ n_q/n & , \ for\ BC_q \le bt < BC_{q+1} \ , q = 1, 2, \ldots, n-1 \\ 1 & , \ for\ bt \ge BC_n \end{cases} \tag{4.5}$$

where

F_n	the CDF (step function) for the Empirical Distribution Function
n	the number of samples considered from the market sales data
q	the number of battery types considered from the market sales data
BC_q	the battery capacities in kWh of PEVs available in the market
bt	the observed random sample of battery capacities in the market

The SOC of a PEV's battery can take any value in the range of 30 – 100% at the beginning of In-city trips [18]. However, it is most likely that PEVs will not have a low level (30 – 50%) of SOC at the beginning of highway trips due to the drivers' anxiety of energy shortage; especially when public charging facilities are limited. Furthermore, it is most likely that highway-driven PEVs will not have a very high level of SOC (90 – 100%) due to the consumption of energy to reach the highway. Therefore, the SOC for highway trips is concentrated mostly in the range of 50 – 90%.

Considering these assumptions, the SOC can be represented differently for the two trip classes. The diversity of SOC levels can be modeled efficiently if there are data available for the class of the trip and the SOC levels at the beginning of each trip. However, this information will not be available prior to a significant PEV penetration level. Hence, the lack of available data about SOC levels at the beginning of each trip leads to utilizing Monte Carlo simulation (MCS) in order to generate random readings for SOC levels (up to 1 million experiments (computer run of MCS) to cover the randomness of SOC levels) for both trip classes.

The SOC level at the beginning of any trip has a significant influence on the range that the vehicle can travel to, so modeling the randomness of SOC efficiently will lead to outcomes that are more realistic. The work presented in this section proposes a method to enhance the estimation of SOC levels at the beginning of trips by creating virtual daily trips (daily routines) that mimic the sequence of trips that conventional cars made daily, which are recorded in NHTS data [53].

The estimation method of SOC levels is illustrated in Figure 4.7, and it has the following assumptions and procedures.

<u>Assumptions</u>

- The first trip of the daily routine start from home
- The SOC level (SOCprev) at the beginning of the day (before the first trip) is 100%

- The battery will be recharged automatically up to 80% when it is empty during the daily routine using public charging facility

<u>Procedures</u>

STEP	Procedure
1	Generate randomly a number of sequence trips (TR) during a day (using the pdf in Figure 4-8)
2	Assign randomly a starting time for trip (tr) using the pdf in Figure 4-2
3	Assign randomly a purpose for trip (tr) based on the hourly probability of each purpose pdf
4	Assign randomly a travel distance for trip (tr) based on trip mileage pdf for the assign purpose
5	Calculate SOC_R after trip (tr) using equation (6)
6	Record SOC_R as a new data point (in %), then SOCprev = SOC_R
7	tr = tr+1
8	if tr < TR, go to STEP 2
9	iter = iter +1
10	if iter < Iter_max, go to STEP 1
11	End

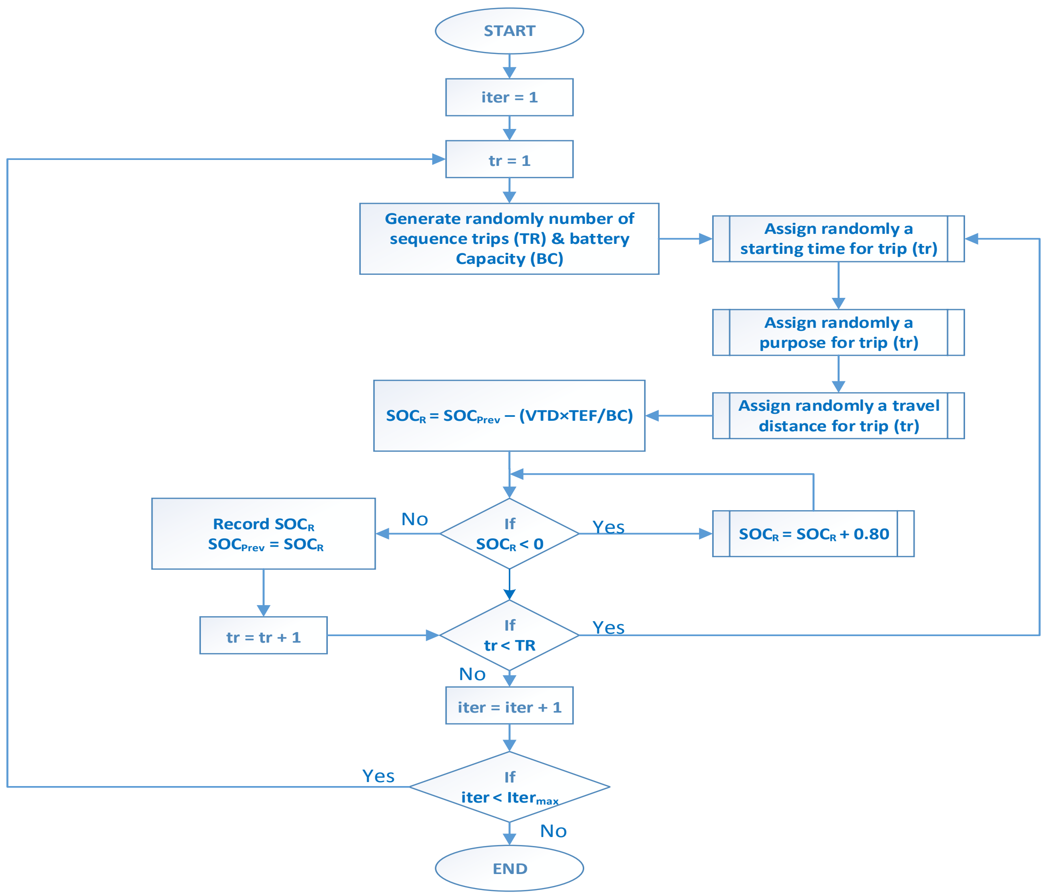

Figure 4-7 SOC estimation method flow chart

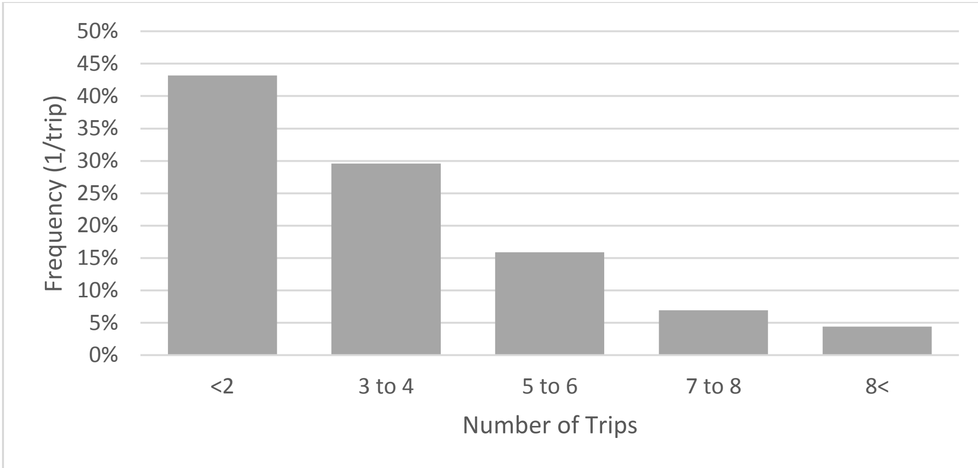

Figure 4-8 Probability of daily trips per vehicle NHTS[53]

Finally, we use MCS to run the previous routine for both classes (in – city, Highway) and recording SOC_R readings for each case. MCS runs over 1 million iterations in order to cover long range of varieties at each class.

$$SOC_R = SOC_{prev} - \frac{VTD \times TEF}{BC} \tag{4.6}$$

$$f_2(soc_R, \mu_2, \sigma_2) = \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{(soc_R-\mu_2)^2}{2\sigma_2^2}} \tag{4.7}$$

$$SOC_{(c)} = F_2^{-1}(z) \tag{4.8}$$

where

SOC_R	the distributed random variable representing the charge level
SOC_{prev}	the random initial state of charge used to generate the SOC level
$SOC_{(c)}$	the random PEV battery state of charge at the beginning of a trip in Class "c"
F_2^{-1}	the inverse of the cumulative density function, which describes the probability of an SOC at the beginning of a trip in Class "c" to be less than a given level
μ_2, σ_2	the estimated mean and standard deviation of the PDF of the state of charge

Equation (4.6) is repeated over daily time intervals in order to reach the condition for stopping the Monte Carlo simulation. After that, we apply the maximum likelihood method on the SOC readings in order to estimate the parameters of the closest PDF. Then, the SOC level for each trip class can be represented using Equations (4.7 – 4.8). It is assumed that in-city driving consumes more energy per km compared to highway driving; therefore, different TEFs are considered in order to represent the diversity in driving behaviors [69].

The results of the Trip Success Ratio (TSR) model provide the degree of convenience that different CSSRs have for PEV drivers by including the estimated Remaining Electric Range (RER) at the beginning of each trip, the diversity of battery capacities (BC), the randomness of SOC levels, and different driving behaviors (TEF).

4.2.3 Trip Success Ratio model results

Sample results for the TSR model (described in the previous section) are presented in this section. As described in Fig.4.6, the virtual PEV travel distances from the travel pattern model are compared to the electric energy remaining estimated by the RER model. If a PEV's RER is large enough to cover the PEV's VTD, the trip is considered to have been completed successfully. If not, the PEV's RER is compared to the distance to the nearest charging station, and the trip is considered as being completed successfully if the PEV's RER can cover the distance to the FCS; otherwise, the trip is considered as a failed trip. MCS is utilized to obtain the TSR for different CSSRs. The CSSR increases in predefined steps (i.e., 10 km), and the outcomes of the MCS show the relationship between the TSR and different CSSRs.

The data for the f_1 PDFs utilized by the travel pattern model are from the National Household Travel Survey (NHTS 2009) [53]. Table 4.1 shows the parameters of the best-fit PDFs obtained from the travel pattern model. Table 4.1 also shows the best-fit f_2 PDFs and their parameters for the data generated from Equations (4.6 – 4.8).

Table 4-1 fitted pdf parameters of different TSR inputs

Input	Fitted pdf	Parameters	
$VTD_{(city)}$	Lognormal distribution	$\mu_1 = 1.8285$	$\sigma_1 = 1.0626$
$VTD_{(HW)}$	Weibull distribution	$\alpha = 1.8254$	$\beta = 100.15$
$SOC_{(city)}$	Normal distribution	$\mu_2 = 0.56436$	$\sigma_2 = 0.18512$
$SOC_{(HW)}$	Normal distribution	$\mu_3 = 0.6495$	$\sigma_3 = 0.17585$

where:

μ_1 and σ_1 are the mean and standard deviations respectively for the lognormal distributions;
a and b are the shape and the scale for the Weibull distribution respectively;
μ_2 and σ_2 are the mean and standard deviations respectively for the normal distribution.

The average tractive effort factors are assumed to be similar to [70]: TEF $_{(city)}$ = 0.2 kWh/km and TEF $_{(HW)}$ = 0.125 kWh/km. The battery capacities are assumed according to the market sales data for the US (2008 – 2015) [71], and four capacities are considered with their market shares, as shown in Table 4.2.

Table 4-2 PEV battery capacities and their market share [71]

PEV's Battery Capacity	US Market Share (2008 – 2015)
16 kWh	20%
24 kWh	50%
32 kWh	20%
54 kWh	10%

The relationships between the TSR and the different CSSRs for the in-city and highway cases are shown in Fig.4.9 and Fig.4.10 respectively.

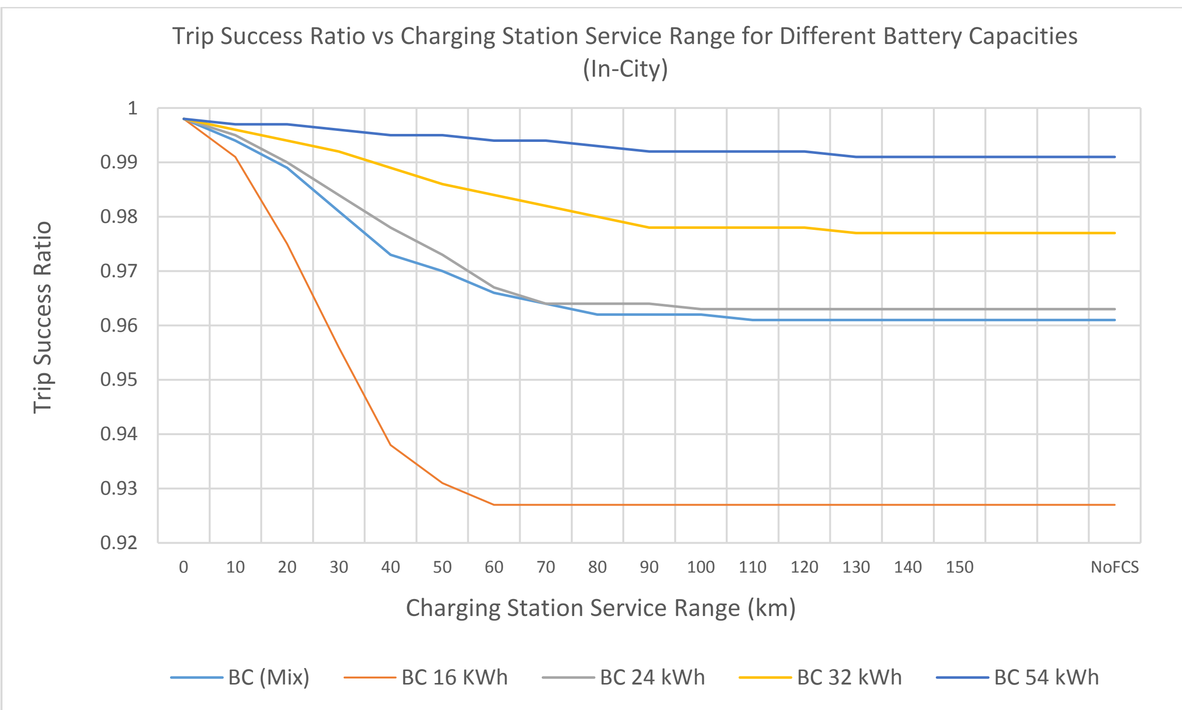

Figure 4-9 The relationships between the Trip Success Ratio and Charging Station Service Range for different battery capacities (In-city)

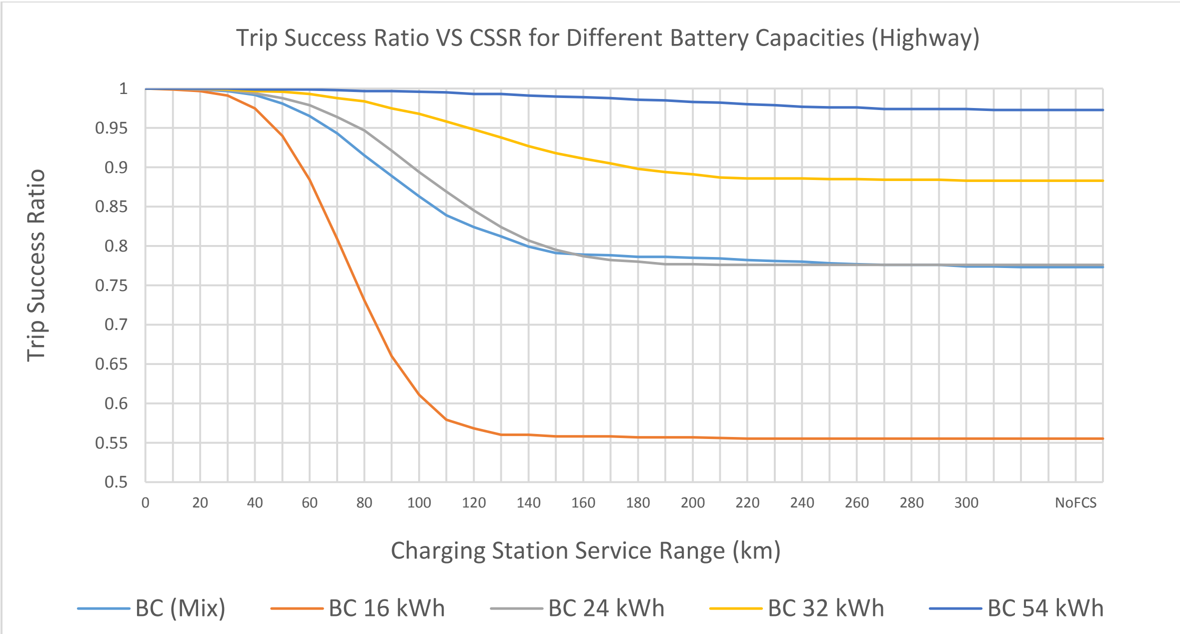

Figure 4-10 The relationships between the Trip Success Ratio and Charging Station Service Range for different battery capacities (Highway)

It was observed from the sample results that at least 92% of all in-city trips could be completed successfully in the absence of an FCS network for all battery capacities. The reason behind this is that in-city trips distances are short and so PEV RERs can cover these trips easily. However, at least 78% of all highway trips can be completed successfully in the absence of an FCS network for 24, 32, and 54 kWh battery capacities, while almost 45% of PEVs with a 16 kWh battery capacity cannot complete their highway trips in the absence of an FCS network. According to the NHTS (2009) [53], 80% of daily trips are considered in-city trips, and only 20% of daily trips are considered highway trips. As a result, another important observation can be obtained from the sample results, and that is related to the number of failed trips. Therefore, even if the TSR level in-city is higher than the TSR level for Highway that does not mean the corresponding number of failed trips is lower. For instance, if there are 5000 PEVs in the system and each one conduct the average daily trips (i.e., three trips/day according to [53]), there will be about 3,000 highway trips and 12,000 in-city trips daily. Hence, if the highway TSR increases **3%** (from 95% to 98%), that will decrease the number of failed trips from 150 trips to only 60. However, increasing the TSR level in-city by **3%** will decrease the failed trips by 360, which is about four times that of the highway ones. Therefore, the TSR level in the two cases has different representations in terms of trip numbers.

Furthermore, Figures (4.9 – 4.10) show the relationships of each battery capacity, as well as the mixed case, which have the ability to cover PEV drivers' daily needs. For example, based on the mixed battery capacity scenario, decreasing the distance between the charging stations on highways by an average of 15 km will increase the level of trips completed successfully by one percent. However, based on the 16 kWh battery capacity scenario, a distance reduction of only 2 km will enhance the highway charging station network trip success level by one percent. Therefore, the 16 kWh battery capacity is not efficient for the highway driving mode due to its severe dependence on the charging network.

4.3 FCS Optimal Location model

In this section, a formulation of the proposed FCS allocation problem is presented. The problem is modeled as the Maximum Covering Location Problem (MCLP), with a cutoff impedance (distance between the demand node to the nearest supply facility) equaling the CSSR obtained from the TSR model. The selected convenience level identifies the proper CSSR that should be used in this section. The optimization model is formulated as a mixed-integer non-linear problem (MINLP) with maximization of FCS coverage as the objective function, subject to several constraints.

Objective function:

$$Max \sum_{i=1}^{N_T} t_i w_i \tag{4.9}$$

Subject to:

$$d_{i,j} = \left(\left|x_i^{cs} - x_j^{cs}\right| + \left|y_i^{cs} - y_j^{cs}\right|\right) \qquad \forall\, i \neq j \tag{4.10}$$

$$M_{i,j} = \begin{cases} 1 & if\ (d_{i,j} \leq CSSR) \\ 0 & if\ (d_{i,j} > CSSR) \end{cases} \tag{4.11}$$

$$\sum_{j=1\, \in M: d_{i,j} \leq CSSR}^{N_T} CS_j\ M_{i,j} \geq w_i \qquad \forall\, i \in N_T, \forall j \in M \tag{4.12}$$

$$CS_i * CS_j \leq (1 - M_{i,j}) \qquad \forall\, i \neq j \tag{4.13}$$

$$w_i\ ,\ CS_j \in \{0,1\} \tag{4.14}$$

$$\sum_{i=1}^{N_T} CS_i < \frac{Area}{\frac{\pi}{2} \times CSSR^2} \tag{4.15}$$

$$\sum_{i=1}^{N_T} CS_i > \frac{Area}{2\pi \times CSSR^2} \tag{4.16}$$

where

N_T the number of transportation nodes in the network

t_i the transportation demand according to location (i)

w_i a binary decision variable that equals '1' if the transportation demand at location (i) is covered, and '0' otherwise

CS_j the decision variable equaling '1' if a station is located at node (j) and '0' otherwise

$d_{i,j}$ the Manhattan distance metric between transportation nodes in the network

CSSR the station service diameter in km, which is obtained from the TSR model

X_j^{cs} the x-coordinate of Charging Station (j)

Y_j^{cs} the y-coordinate of Charging Station (j)

Area the area in km^2 of the network under study

i, j set to be transportation node indices where j ∈ NT when (the distance between i and j) ≤ CSSR

M the set of nodes near to charging station node (i) when (the distance between i and j) ≤ CSSR

In this formulation, the objective is to maximize the number of PEV drivers served or "covered" within the desired service distance (CSSR). Equation (4.12) allows w_i to equal 1 only when at least one facility is established at a site in the set N_T. The number of facilities allocated is restricted to upper and lower boundaries with the constraints in (4.15 – 4.16). The solution to this problem specifies not only the largest population that can be covered but also the number of FCSs that can achieve this maximal coverage. The upper and lower boundary constraints are used to ensure that the whole area under study is covered by FCSs; therefore, the service ranges of the CSs (CSSRs) divide the area under study in order to obtain the lowest number of FCSs that can cover the area (see Equation 4.15). However, the upper boundary constraint, Equation (4.16), is used in order to not overdesign the charging station network, thereby wasting resources.

If the network under study is a highway, the length of the highway in km is used instead of the area, as shown in (4.17 – 4.19), to obtain the distance, the upper and lower boundaries for FCSs respectively.

$$d_{i,j} = \left(\sqrt{(x_i^{cs} - x_j^{cs})^2} + \sqrt{(y_i^{cs} - y_j^{cs})^2}\right) \qquad \forall\, i \neq j \tag{4.17}$$

$$\sum_{j=1}^{N_T} CS_j < \frac{HWL}{CSSR} \tag{4.18}$$

$$\sum_{j=1}^{N_T} CS_j > \frac{HWL}{2\,CSSR} \tag{4.19}$$

where

HWL the length of the highway under study in km

The non-linearity of the problem results from Equation (4.13), and therefore, the Branch-And-Reduce Optimization Navigator (BARON) model is utilized to solve mixed-integer nonlinear programs (MINLP) using the GAMS platform. While traditional NLP and MINLP algorithms are guaranteed to converge only under certain convexity assumptions, BARON implements deterministic global optimization algorithms of the branch-and-bound type that are guaranteed to provide the global optima solution, and no starting point is required [72]. Since the lower and upper boundaries are provided in the problem formulation, BARON guarantees that the global optimal solution is achievable [72].

To investigate the feasibility and robustness of the proposed optimization model, the problem is reformulated as a Mixed Integer Problem (MIP) by considering only the shortest paths between the transportation nodes. Hence, constraint (4.13) is replaced by the following:

$$CS_i + CS_j \leq 1 \qquad \forall\, i \neq j \quad \text{and} \quad \forall\, j \in D_{i,j} \tag{4.19}$$

where

$D_{i,j}$ the matrix of the shortest paths between any transportation node (i) and node (j) in the transportation network

Although this formulation, MIP, guarantees the global optimal solution, it requires the provision of a starting point in order to obtain that solution [33]. According to [33], the problem should be solved iteratively by using each of the charging station candidate nodes (CSCN) as a starting point, and then choosing the best among the CSCN to be the global optimal solution for our problem. However, BARON does not require any starting point to reach an optimal solution, and the optimality of the solution obtained by BARON is assured by comparing the best of all global optimal solutions obtained by the iterative MIP proposed in [27] with the optimal BARON solution.

4.4 FCS Optimal Location sample results

In this section, three case studies are considered to validate the proposed model. The first case study is adopted from [27] in order to validate the feasibility and robustness of our model. The second case study is adopted from [37] to investigate the differences between our proposed model and the flow-capturing one. Different CSSRs have been considered in the second study to illustrate several TSR levels. Finally, to demonstrate the ability of our proposed model to deal with different network topologies and driving modes (in-city and highway), we present a case study considering a real highway network (Highway 401 in Ontario, Canada) with candidate FCSs located at rest stops on the OnRoute™ network on Highway 401.

4.4.1 In city network case study

This case study is presented to demonstrate the robustness of our proposed optimization model based on maximum covering location problem (MCLP) to locate charging stations using different Charging Station Service Ranges (CSSRs). Our model is compared to models presented in [27] where the virtual in-city area is 100 km^2 and there are 10 candidate FCSs located randomly in the network. The installation cost is assigned randomly (0 – 1) to the candidate FCSs, and the transportation demand (t_i) is set to be 1. The CSSRs are (80 – 24 km), similar to [27]. The CSSRs in this case study are similar to [27] rather than utilizing the TSR model to focus on the performance of our optimization model. Figure 4.11 shows the selected FCSs based on a CSSR = 40 km.

Five FCSs can cover the area, and the FCS set is {2, 6, 7, 9, and 10}, with a total output equaling 2.231. The total outputs in [27] equals (2.215 and 2.235) in MIP and Greedy methods prospectively, and therefore the outcome of our proposed model is consistent with [27].

Table 4-3 Comparison between MCLP model and MIP and Greedy methods proposed in [27]

CSSR (km)	Obj_{MIP}	Obj_{Greedy}	Obj_{MCLP}
80	0.5473	0.5712	0.545
72	0.7824	0.8204	0.656
64	0.9375	0.9784	0.869
56	1.3774	1.4339	1.277
48	1.8374	1.8724	1.783
40	**2.2146**	**2.2358**	**2.231**
32	3.1412	3.1746	3.112
24	4.0834	4.0834	4.082

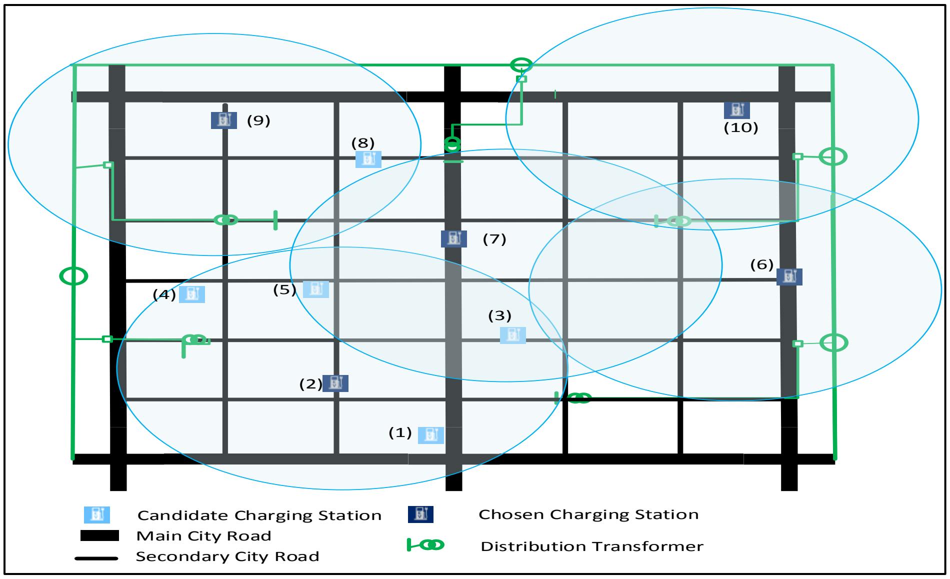

Figure 4-11 Selected Charging Stations (In-city Network, CSSR = 40 km)

4.4.2 In city network (20 – node transportation 23 – node distribution) case study

The 20-node transportation network and the 23-node distribution system data are available in [37]. The voltage level of this radial distribution system is 15.0kV. There are two candidate substations and 35 candidate feeders to be considered. Each node in the 20-node transportation network represents an intersection between links and roads. The coupled transportation – distribution network is illustrated in Fig. 4-12. In this case study, three scenarios are presented to demonstrate first the significance of MCLP model to locate FCSs to satisfy PEV drivers' convenience, second the tradeoff between using different CSSRs and the total construction cost of FCS network, and third the effect of different TEFs, as different traffic and weather conditions, on TSR levels.

<u>Scenario 1</u>

The same transportation network topology and traffic volume data presented in [37] is used. A 25 km CSSR is utilized to allocate FCSs in the network with corresponding TSR level of 0.985 (as shown in Fig.4-9). In order to satisfy at least 98.5% of trips in the coupled network, five FCSs have to be installed. Figure 4.12 shows the selected FCSs (in blue) using our proposed model. The best set is {6, 7, 11, 17, and 20}, while the selected FCSs (in silver) using the maximum flow-capturing method proposed in [37] are {6, 12, and 13}. It is notable that the number of FCSs in our optimal set is greater by two stations compared to [37]; however, the charging stations installation cost is increased by only 35% compared to [37]. Conversely, the success level of the charging station set obtained in [37] is analyzed using our TSR model. The FCS {6, 12, and 13} do not cover some parts of the coupled network. For instance, the paths between node 1 and node 17 and between node 4 and node 20 are not covered, and the extra distance for detouring via nodes 12 and 13 makes the TSR level about 0.965. More than 700,000 failed trips will be saved annually by using our proposed model with a 0.99 TSR level, and therefore the PEV drivers' convenience is a significant advantage in our proposed model. We have to emphasize here that achieving this drivers' convenience comes with a cost; 35% increase in FCS installation cost in the case studied here.

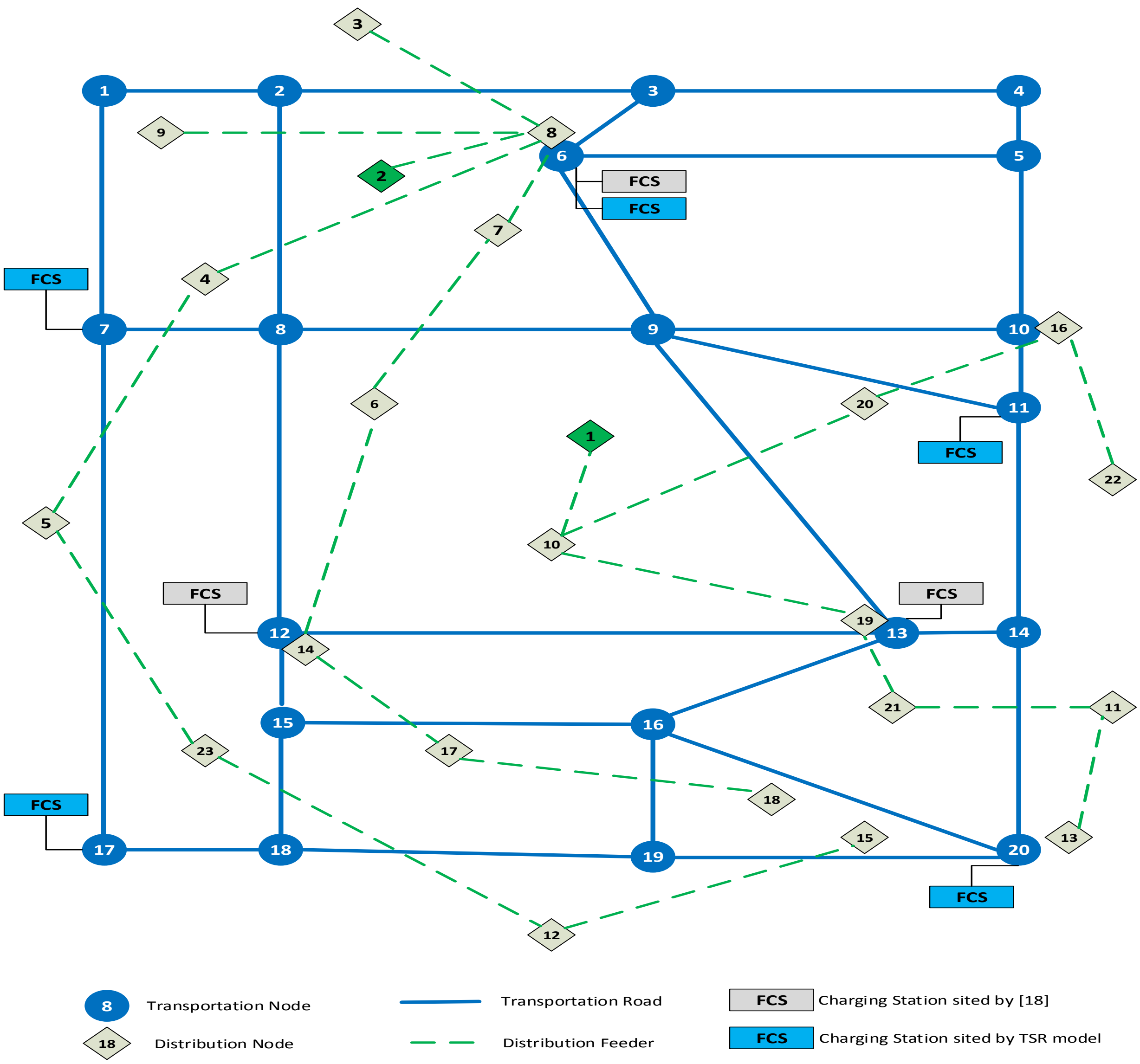

Figure 4-12 The 20-node transportation 23-bus DS, and the selected charging stations, based on a CSSR = 25 km

Scenario 2

In this scenario, the tradeoff between trip success levels and FCS construction costs is demonstrated, and the same problem is solved over using different CSSRs (5 – 70 km). When the distance between charging stations (CSSR) is short, more charging stations are required to be installed in order to cover the network; hence, the possibility of trips to reach their destinations successfully (TSR) is high and vice versa. Figure 4-13 shows the relationship between the FCS construction cost and different CSSRs as well as the required number of FCSs.

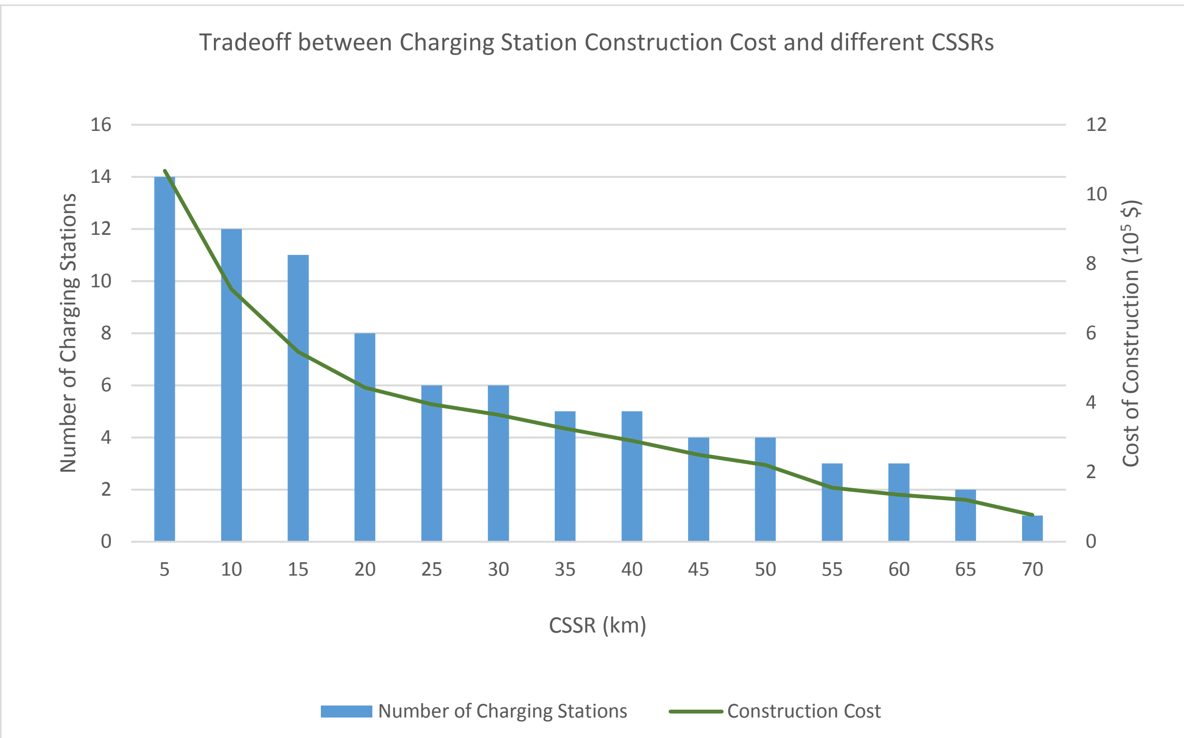

Figure 4-13 The relationship between charging station construction costs and different CSSRs

In order to consider the tradeoff between the PEV drivers' convenience and the FCS construction cost, the annual number of saved trips from being failed is estimated for each CSSRs. The annual number of saved trips curve has been added to Figure 4-14, and it shows that (CSSR = 20 km) is the most cost-effective service range in this transportation network. However, limited cost-effectiveness is obtained when using (CSSR ≥ 55 km) since the number of saved trips regarding charging stations is very low compared to the number of saved trips regarding PEVs' Electric Range (no FCS).

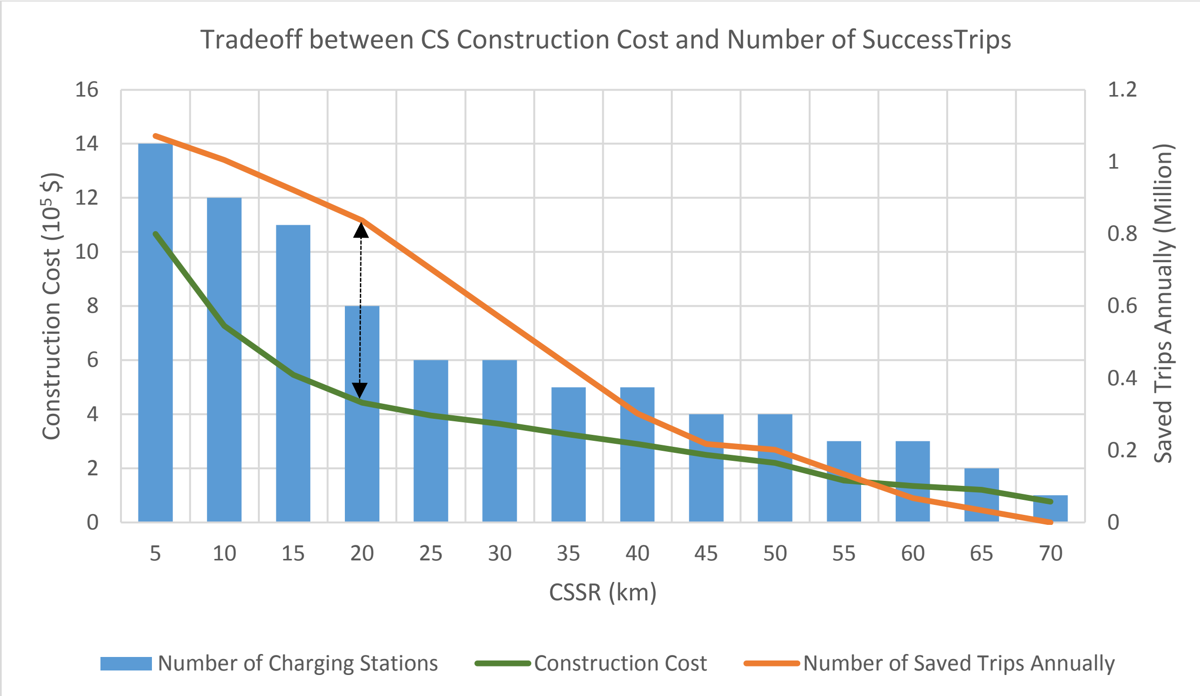

Figure 4-14 The relationship between charging station construction costs and number of success trips

Scenario 3

In this scenario, the effects of considering different traffic conditions (heavy and light) and weather conditions (summer/winter and fall/spring) on the trip success ratios are investigated. Changing the weather conditions will influence PEV drivers to use AC in the summer season and Heater in the winter season, and that will affect the efficiency of PEV in terms kWh/km. In addition, more energy is consumed when driving in heavy traffic condition compare to light traffic condition due to different speeds and accelerations. As a result, modeling the weather and traffic changes effect can be achieved by changing the Tractive Effort Factor (TEF) to represent the extra loading of (AC/heater) as well as driving condition. According to the experimental investigation of the energy efficiency of an EV in different driving conditions [70], the lower TEF limit (no AC/no heater, light traffic) is (TEF_{low} = 0.14 kWh/km). Where the upper TEF limit of TEF (AC/Heater, heavy traffic) is (TEF_{high} = 0.27 kWh/km). The upper and lower boundaries are utilized by TSR model in order to obtain a sensitivity analysis for the mixed-battery curve (TEF_{mid} = 0.20 kWh/km) presented in Figure 4-9. The effect of considering different traffic and weather conditions is shown in Figure 4.15.

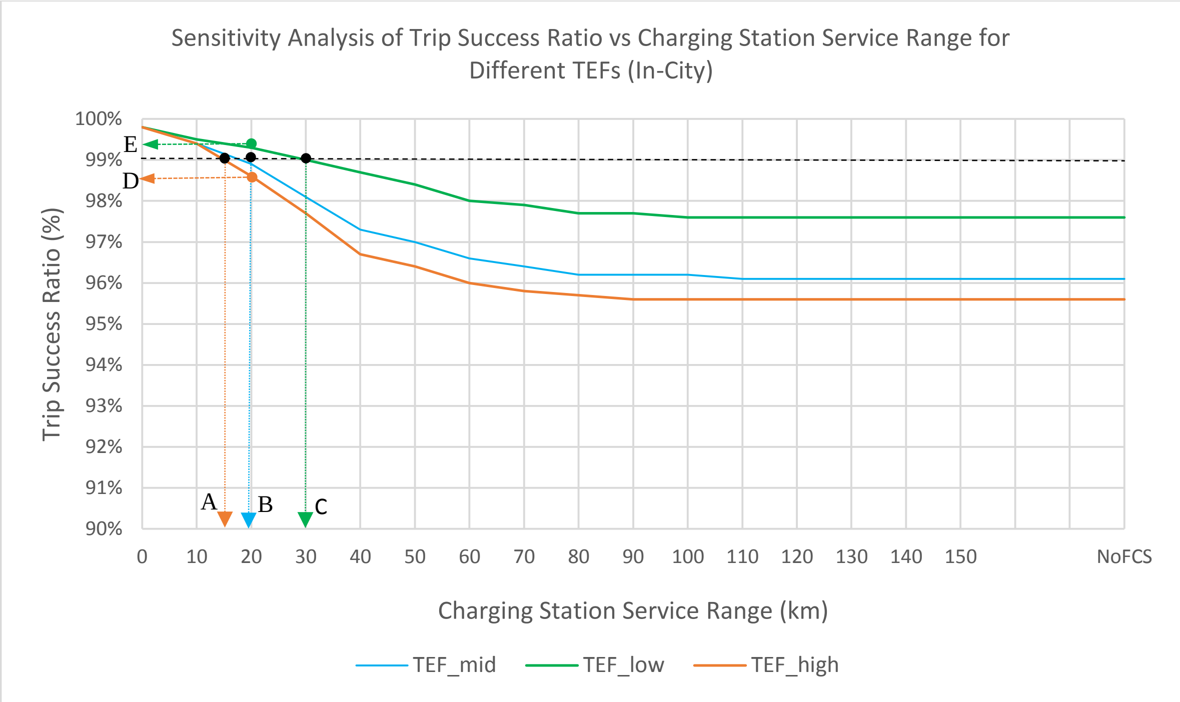

Figure 4-15 The sensitivity analysis of Trip Success Ratio and CSSR for different TEFs (in - City)

Figure 4.15 shows that in order to have at least 99% TSR level, CSSR should be (A = 15 km, B = 20 km, and C = 30 km) for (TEF_{high}, TEF_{mid}, and TEF_{low}) respectively. The corresponding construction cost according to Figure 4.13 is (A = 5.46×10^5 \$, B = 4.43×10^5 \$, and C = 3.65×10^5 \$). However, the lower and upper boundaries for TSR levels when (CSSR = 20 km) is used are (D = 98.6% and E = 99.3%), so the range of variation in TSR level due to the weather and traffic conditions is limited to ±0.4%. The corresponding number of (success/ failed) trips annually according to Figure 4-14 is limited to ±175,000 trips/ year.

4.4.3 Ontario 401 Highway case study

King's Highway 401, also known as Ontario's 401 Highway, is a 400-series highway in the Canadian province of Ontario. It stretches 817.9 km (508.2 mi) from Windsor to the Quebec border. The part of Highway 401 that passes through Toronto is one of the busiest highway segments in the world [73]. In order to maximize coverage of the highway, the proposed model has been applied only for a 0.90 TSR level due to the long distances between the candidate locations. The OnRoute™ gas station network [73] is used for the candidate locations for installing FCSs along the highway. Figure 4.16 shows the highway and the candidate locations [73]. The installation cost is assumed based on the land price of the candidate locations adopted from [74], and the footprint of each station is assumed to be 0.8 hectares. Table 4-4 shows the candidate FCS locations and cost according to [73 – 74].

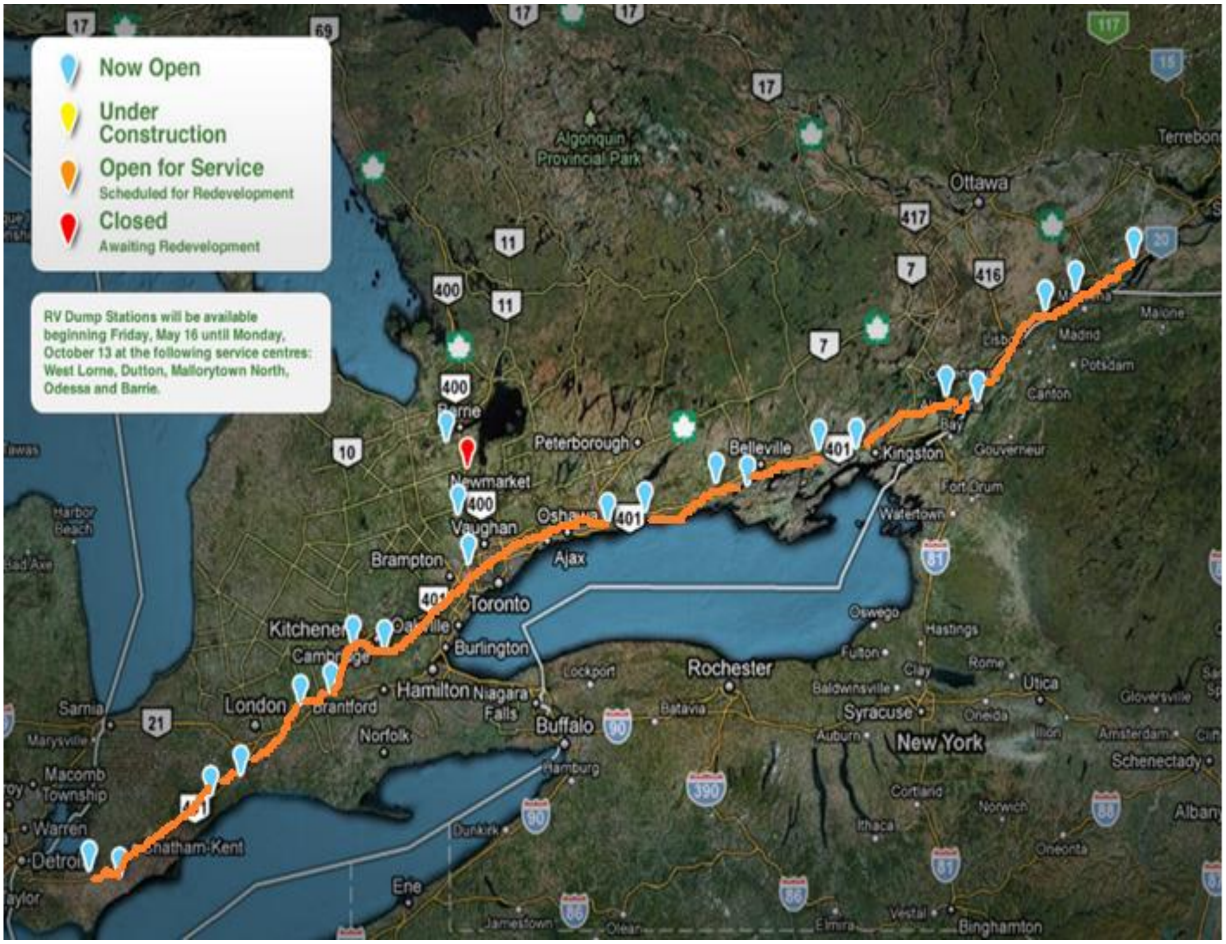

Figure 4-16 Candidate Charging Stations (Ontario Highway 401, OnRoute™) [73]

Table 4-4 Ontario 401 Highway candidate FCS locations and cost [73– 74]

FCS	L (km)	Renting Cost ($/hectare)	FCS	L (km)	Renting Cost ($/hectare)
Tilbury	53	30,000	**Trenton**	530	50,000
West Lorne	136	21,000	**Napanee**	590	8,000
Dutton	147	18,000	**Odessa**	610	9,000
Ingersoll	226	32,000	**Mallory town (N)**	670	16,000
Woodstock	236	34,000	**Mallory town (S)**	690	18,000
Cambridge	275	16,000	**Morris burg**	750	23,000
Maple	365	17,000	**Ingleside**	780	24,000
Newcastle	455	22,000	**Bainsville**	813	20,000
Port Hope	470	25,000			

The results of applying our proposed model show that a minimum of 11 FCSs are required to cover Ontario's Highway 401, with a total land renting cost of about 256,000 dollars per year. The FCSs are proposed to be installed at: Tilbury, West Lorne, Ingersoll, Cambridge, Maple, Newcastle, Trenton, Odessa, Mallorytown (N), Morrisburg, and Bainsville. The average distance between the FCSs is 69.09km, and the proposed FCS network assures a 0.90 TSR level. However, the current network (which is based on the existing location of OnRoute™ gas station network) cannot achieve the 0.95 TSR level since there are four segments longer than 70 km: 1) Tilbury – West Lorne, 2) Dutton – Ingersoll, 3) Cambridge – Maple, and 4) Maple – Newcastle. Therefore, to achieve a 0.95 TSR level, additional candidate FCSs have to be considered along these segments.

4.5 Conclusions and discussion

The results obtained from the TSR model, have shown the ability of each battery capacity to fulfill its daily trips with different FCS allocations. It is observed that PEVs with a battery capacity of 16kWh showed huge dependence on the charging station network for highway trips. However, about 97% of all highway trips are completed successfully in the absence of FCSs if all PEVs' batteries are 54kWh and above. Another important observation from the TSR model results is that PEV battery capacities influence FCS service range, and therefore, considering the data from PEV market sales in selecting optimum FCS sites leads to more realistic and accurate outcomes.

The proposed model has been applied to different scenarios for two types of network: In-city and Highway. The results show clearly the robustness of the proposed model, and the outcomes of the model demonstrate the significance and the advantage of the proposed model when compared to the models reported in the literature. It is also observed that the number of FCSs in-city is very sensitive to the charging station service range (CSSR) due to the quadratic relationship between service range and the covered area. In the highway scenario, the CSSR should be shorter in distance than the segments between any two neighboring FCSs; otherwise, the TSR level should be reduced in order to get an appropriate CSSR.

4.6 Chapter assessment

In this chapter, a new PEV charging station allocation model has been presented. The model consists of two parts. In the first part, the relationship between charging station service range and the probability of PEVs completing trips successfully is discussed. The model utilizes an MCS to generate virtual trip distances and PEVs' remaining electric ranges. It takes into consideration the variations in driving habits, the battery capacities, the states of charge, and the trip classes. Consideration of the variations in these factors is assumed to present a more realistic and accurate model for estimating the trip success ratio for each charging station service range as compared to the literature.

In the second part, different CSSRs are utilized in the allocation optimization problem in order to locate the charging stations in the optimal locations in order to assure that the TSR of PEVs is above a certain threshold. Instead of using a single service range or Origin-Destination (OD) pair path, the model locates the FCSs using different CSSRs by applying a maximum coverage location problem (MCLP). The results obtained show the differences in quality of service based on their TSR levels. Therefore, the proposed model is capable to measure how successful the FCS network is in meeting PEV demand in order to make the optimum decisions based on the available resources. Moreover, the proposed model considers PEV accessibility in the location problem by using TSR levels, so the model outcomes are influenced by drivers' needs rather than electrical utilities' requirements.

The traffic volume data in addition to the forecasted penetration level of PEVs (Chapter 3) will produce the estimated charging demand of PEVs in the next chapter. This demand will be distributed over the transportation network at the selected optimal locations presented in this chapter. The target locations will be utilized in the next chapter as candidate locations for the decoupled network (transportation network and distribution system) in order to transfer PEV demand from the transportation network to the distribution system.

Chapter 5
Technical Evaluation for Accommodating PEV Load in Distribution System

Accommodating a penetration of PEV charging has been dealt with in the literature only with regard to either normal charging (Level 1 and Level 2), as in [39, 40, 43 – 45], or fast charging (Level 3), as in [35, 37, 41]. However, considering both normal and fast charging levels when investigating the accommodation of PEVs, was not discussed in a great depth. Obvious gaps exist between the solutions proposed in the literature and the status of the current grid, which can be summarized as follows:

- The absence of PEV public charging data (Level 3) presents a problem. The work presented in the area of estimating PEV charging demand must be enhanced using additional data that reflect charging characteristics and driver behaviors, but this information will not be available prior to significant PEV penetration levels and constructing charging station network.
- There is a lack of evaluation and assessment of the additional electrical system requirements on low PEV penetration levels. With only a few exceptions, the ability of existing electrical systems to feed the additional PEV charging station load in the early adoption stage has not been investigated thoroughly in the previous work in this area.
- Using public charging infrastructure is an essential need for PEV drivers; hence, the impact of using public charging infrastructure on distribution system Load Duration Curves (LDCs) has to be investigated in order to evaluate the ability of current distribution systems to serve the additional PEV loads.

The presented work in this chapter was thus undertaken with the goal of filling these gaps through the proposal of a technical evaluation algorithm based on Optimal Power Flow (OPF) as a means of assessing the ability of current distribution systems to serve PEV penetration levels in the early adoption stage. The results of this work are therefore expected to provide an alternative for upgrading the distribution system during the transitional period between the current status of the grid and a significant penetration of PEVs. The additional load from PEVs will be matched only with the required public charging infrastructure capacity.

5.1 Problem description

One of the major questions faced by electric utilities currently is whether the existing distribution network infrastructure would be able to serve a mass introduction of PEVs. In addition, if the existing distribution networks are not capable to do that, what are the necessary network requirements and reinforcement? PEVs have indeterminate penetration in electric grids due to uncertainties in charging and discharging patterns. This uncertainty, together with variations in driving habits, makes it difficult to evaluate accurately the impacts on local distribution networks. The uncoordinated and random charging activities of PEVs could significantly stress the distribution system, causing:

- Degraded system efficiency
- Severe voltage fluctuations and violations
- Increased probability of outages due to network local overloads

Furthermore, the charging levels of different PEVs would disrupt the distribution grid to some extent. Therefore, the planners should evaluate the maximum possible penetration of PEVs in order to maintain seamless operation of the present network without violating its technical constraints.

In this chapter, the proposed technical evaluation algorithm is described, including modeling PEV loads at residential and public locations. The input for the proposed algorithm comprises the normal load model, the PEV uncoordinated residential charging model, and the PEV public charging model. The output of the proposed algorithm consists of the size of candidate FCSs for the selected locations (Chapter 4) as well as the target PEV penetration and its public share of charging. The proposed technical evaluation is intended to demonstrate the impact of charging some of the PEV from public charging networks rather than considering only residential charging option and the effect of this new trend on the system electric demand. It is also intended to investigate how much PEV public charging percentages (shares) using FCSs can affect the ability of the existing distribution system to serve and adopt PEV demand without any technical violations.

5.2 PEV and Normal Load Modeling

This section presents the electrical system technical evaluation model. The proposed evaluation model considers the impact of the extra loading of PEVs on electrical network performance in terms of voltage violation, power losses, and line loading. The additional PEV demand is assumed to be connected to the network as normal charging loads at home and fast charging loads at public charging stations. The aim of the technical evaluation model is first to determine the maximum PEV penetration level (α) that the existing distribution network would be able to serve without violating its technical constraints. The second aim of the study is to investigate the impact of FCSs charging load profile on the system total load, considering different public charging percentage (γ shares). The proposed method applies Optimal Power Flow (OPF) analysis with the objective function of maximizing the PEV penetration level that the system can supply. This method also considers different public charging percentage (γ shares) in order to manage the peak demand of the distribution system when supplying the PEV charging demand. Managing the peak demand can be achieved by varying the charging shares of PEVs with respect to charging from home (i.e., charging from public FCS before arriving home) , which leads to shifting the time and place of the PEV load. As a result, either the PEV peak demand is reduced, or the ability (the margin) of the distribution system to accommodate more PEVs is increased.

5.2.1 Typical Distribution system load modeling

Three types of system loads are assumed: residential, commercial, and industrial. A multi-state model represents the data for each load type. The year is divided into 12 months, each of which is modeled based on two types of days: weekday and weekend. The probability of each load state for the 576 time segments representing the year is calculated based on historical data. For this work, six states were chosen to represent each type of load, and the values of the states are calculated based on the IEEE-RTS [75].

5.2.2 PEV load modeling

The travel patterns should be taken into account in order to estimate the power consumption of PEVs. Three levels of charging standards that are applicable in North America have been introduced by EPRI in [8] and were shown in Table 2.2. It is important to mention here that charging level has a direct impact on the charging time length. This study considers the first two charging levels for modeling PEV home charging, and it considers more weight for Level 2; at 80% and 20% for Level 1 since Level 2 charger is expected to be the most common charger used in North America [9]. However, the Level 3 charger is considered for public charging stations, since charging in public requires less charging time length (about 30 minutes) in order to be acceptable to PEV drivers.

5.2.3 Number of PEVs and charging characteristics

Number of vehicles per household is another factor that should be considered when modeling PEV demand; hence, the total PEV demand is proportional to the number of vehicles in the system. There are about 1.86 vehicles per household in North America, according to the National Household Travel Survey (NHTS) [53]. The PEV load is a mobile load, so the place and time of connecting this load can be changed. However, start-charging time, the time at which vehicles are plugged-in, influences the network performance.

The home arrival after last trip statistics in North America are illustrated in Fig. 5.1 based on NHTS data [53].

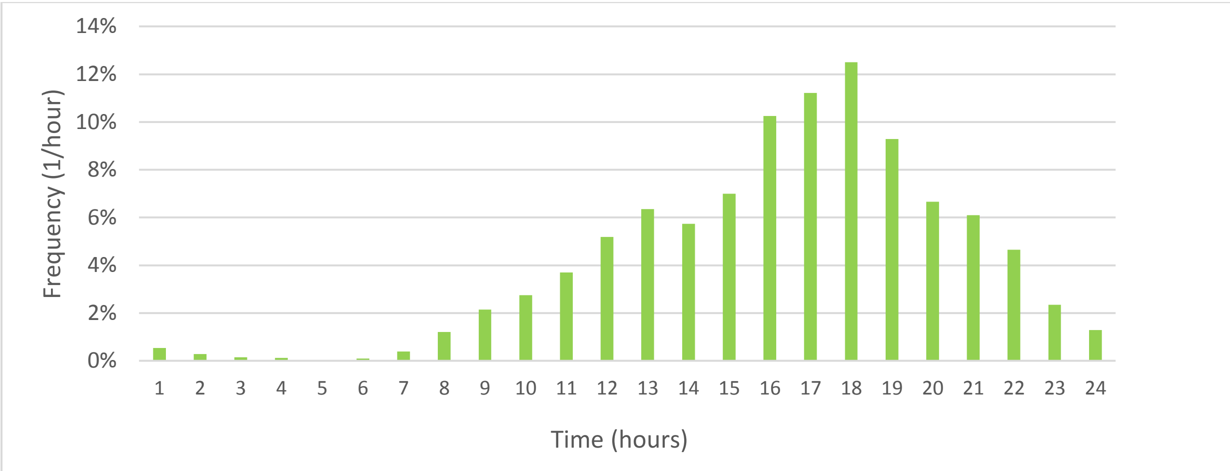

Figure 5-1 Home Arrival Time Distribution in North America (NHTS 2009)

It is recognized that more vehicles arrive probably between 4 pm – 7 pm, and this interval meets the peak electricity demands, which happen around 6 pm – 8 pm. Therefore, this should be taken into consideration in the evaluation process. On the other hand, PEVs will be charged at public charging stations if the daily trip distances are longer than their electric driving ranges. As a result, the percentage of PEVs requiring access to public charging stations (γ) to complete their daily trips can be estimated from the average daily travel distance data [53]. In Fig. 5.2, we assume that γ is equal to different values (0.1, 0.2, and 0.3) which represent different ratios of long daily trips to all daily trips (>70 mile).

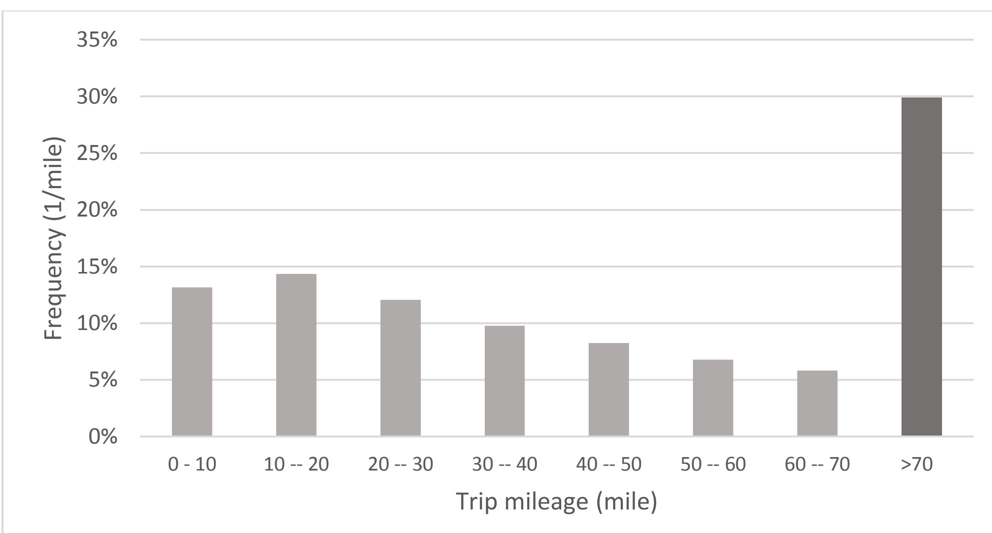

Figure 5-2 The Daily Travel Distance Distribution in North America (NHTS 2009)

In order to model the PEV demand, three parameters have to be determined: connection place, connection time, and energy required from the grid. The latter can be estimated using the daily travel distance data from (NHTS 2009) [53] and assuming each 100 km requires 17 kWh [70]; however, the connection time is related to the probability of PEV plugged at home and the probability of PEV arrived to charging stations. Since PEV charging is uncoordinated, PEVs can be able to start charging at home from the time when they arrived, yet the connection time is relative to the daily travel distance and the power of home charging facilities (Level 1 and 2). As a result, PEVs connection time at home will vary from one hour to several hours according to PEV drivers' daily routines. Thus, the probability of PEVs' connection time at home can be estimated according to home arriving time distribution (Fig. 5-1) and the daily travel distance distribution (Fig. 5-2) where the power of home charging is assumed 20% at level 1 and 80% at level 2. The probability of PEV connected at home as well as the distribution system load profile are shown in Fig. 5-3

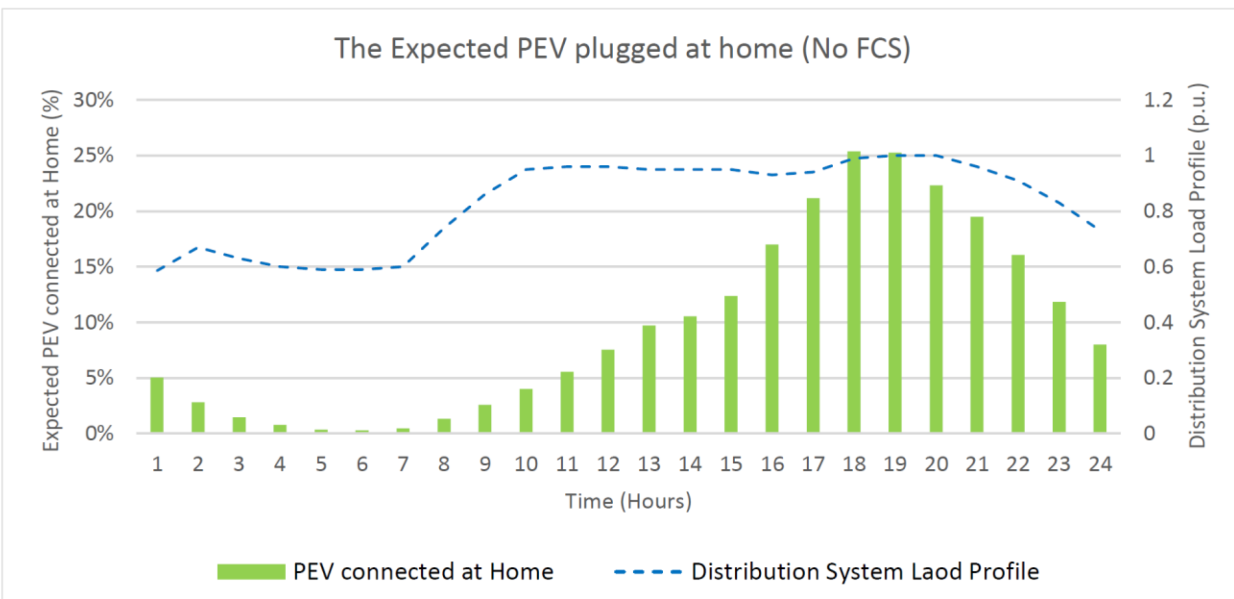

Figure 5-3. The Expected of PEV plugged at home (NHTS 2009)

5.2.4 Traffic flow modeling

Classic electrical distribution system planning considers electrical demands as unmovable demands; however, the mobility of PEV loads makes considering PEV movements essential. Hence, the transportation network has to be examined in order to address traffic flows and driving patterns. From the traffic-flow-capturing model perspective, there are three parameters that should be addressed: charging station road assignment; annual average daily trips (AADT) to each charging station; and annual average trips conducted by PEVs at rush hour (λ^{RH}) to each charging station.

The road assignment follows the shortest path technique, so each transportation node is assigned to the nearest charging stations. We assume in this chapter that candidate charging stations are located based on the Trip Success Ratio model proposed in Chapter 4. After that, the AADT for each road or link between any two transportation nodes is calculated using the relationship between the traffic flow volume at peak hour and the AADT. In road planning, each road has a defined capacity that can be selected based on the 30th peak hour of traffic volume and the AADT [75]. Hence, if the road capacity is known, then the road AADT can be obtained from the relationship in Figure 5.4 using Eq. (5.1). Another way of obtaining the AADT is by monitoring and measuring traffic flow volumes [88]. Several major roads and highways in Ontario Canada are monitored, and the measurements are available in [88]. Finally, the annual average trips conducted by PEVs at rush hour (λ^{RH}) can be calculated using the K^{30} relationship with Peak Hour Factor (PHF) and the PEV penetration level (Eq. 5.2).

$$AADT_{rd} = \frac{Capacity_{\,rd}}{K_{rd}^{30}} \qquad \forall\, road\ in\ the\ transportation\ network \tag{5.1}$$

$$\lambda_g^{RH} = \sum_{rd} a_{(g,rd)} \times \alpha \times \gamma \times PHF \times AADT_{rd} \qquad \forall\, g \tag{5.2}$$

where

rd	the road index
AADT_{rd}	the annual average daily trips on road (rd) in (veh. /day).
Capacity_{rd}	the annual average daily trips on road (rd) in (veh.).
K_{rd}^{30}	the ratio of traffic volume at the 30th peak hour on road (rd).
λ_g^{RH}	the number of PEVs arrive to charging station (g) in the rush hour in (veh.).
$a_{(g,rd)}$	a flag parameter to assign road (rd) to charging station (g).
α	the PEV penetration level (%)
γ	the PEV public charging share (%)
PHF	Peak Hour Factor to the annual average daily traffic (%)

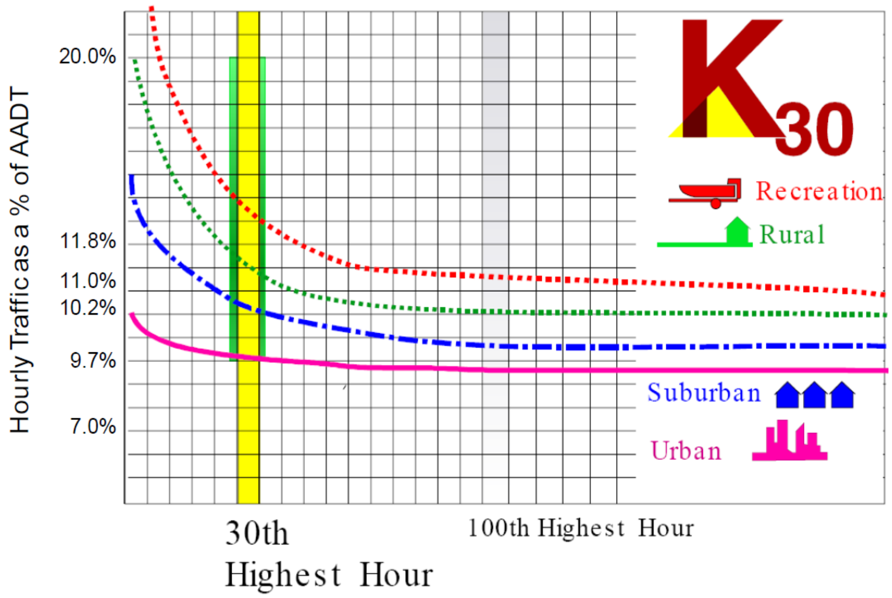

Figure 5-4 The Relation between Peak – Hour and AADT volume; Source: FDOT, Project Traffic Forecasting Handbook 2002 [76]

The AADT and λ^{RH} are key parameters for planning the implementation of charging stations. The traffic volume at rush hour is considered as the peak demand for the charging station, and λ^{RH} plays the main role in selecting the capacity of charging posts. Therefore, the probability of PEV arriving to a charging station will follow the traffic volume profile in the transportation network as shown in Fig. 5-5.

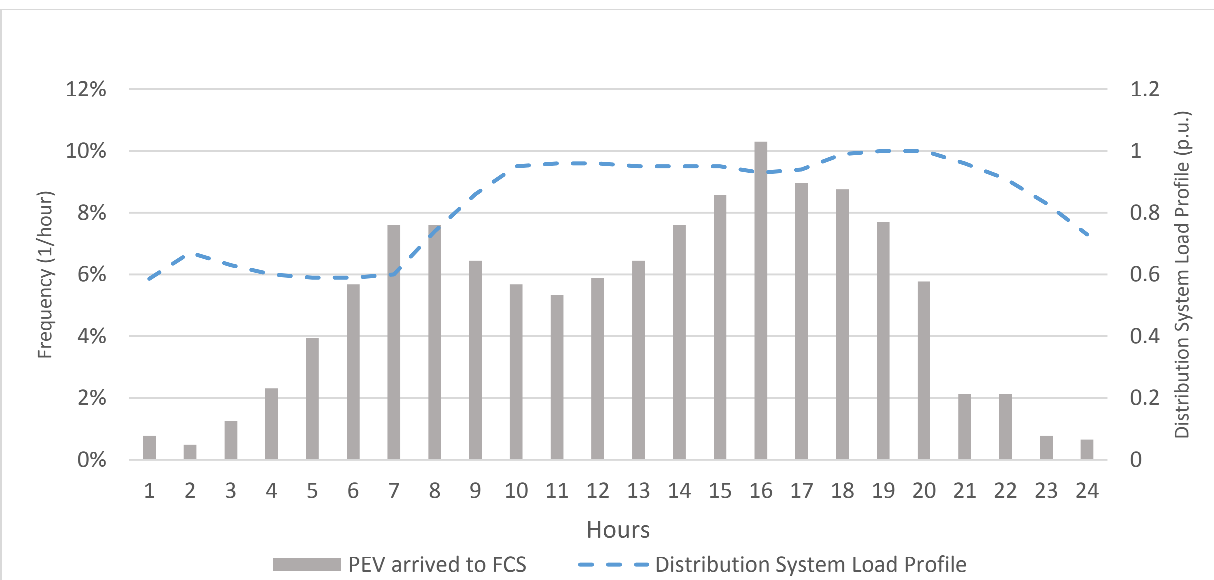

Figure 5-5: The expected PEVs arrived hourly to FCS

Therefore, the nodal charging power for home charging and fast charging facilities can be illustrated as follows:

$$p_{i,t}^{H} = \alpha NV \times (1-\gamma) \times \frac{U_{i,t}}{\sum_{t=1}^{T}\sum_{i=1}^{Nb} U_{i,t}} P^{H} \tag{5.3}$$

$$p_{i,t}^{FCS} = \alpha NV \times \gamma \times \frac{U_{g,t}}{\sum_{t=1}^{T}\sum_{g=1}^{N_{FCS}} U_{g,t}} P^{FCS} \tag{5.4}$$

where

α	the PEV penetration level that can be fed by the existing electrical network (%)
NV	the total number of vehicles in the system based on the number of homes (number)
γ	the share of PEVs that required public charging facilities to complete their daily trips (%)
N_{FCS}	the total number of buses that have charging stations in the distribution system (number)
$U_{i,t}$	the expected number of PEVs at DS node (i) in time (t) (number)
$U_{g,t}$	the expected number of PEVs arriving at fast charging station in DS node (g) in time (t)
P^{H}	the charging power for home charging mode (Levels 1, 2) (kW)
P^{FCS}	the charging power for fast charging mode (Level 3) (kW)

As shown in Equations (5.3 – 5.4), PEV demand involves two terms: normal and fast charging demand for residential and public charging loads respectively. The expected number of PEVs arriving at FCS and their arrival times are considered based on the transportation traffic volume data and their AADT and λ^{RH} parameters. The peak traffic volumes in the transportation network happen in the morning period (7 – 9 am) and the evening period (3 – 5 pm), which are prior to the electricity demand peak as shown in Fig. 5-5. Therefore, using fast charging station as complement to home charging will manage the PEV demand by shifting a share of the PEV demand away from home to different public places as well as time of connection.

5.3 Technical evaluation formulation

The proposed technical model obtains the ability of the distribution system to accommodate several PEV penetration levels (α) without any reinforcement. The penetration level (α) will be increased until the maximum ability of the distribution system is reached without any major upgrades, as shown in Figure 5.6.

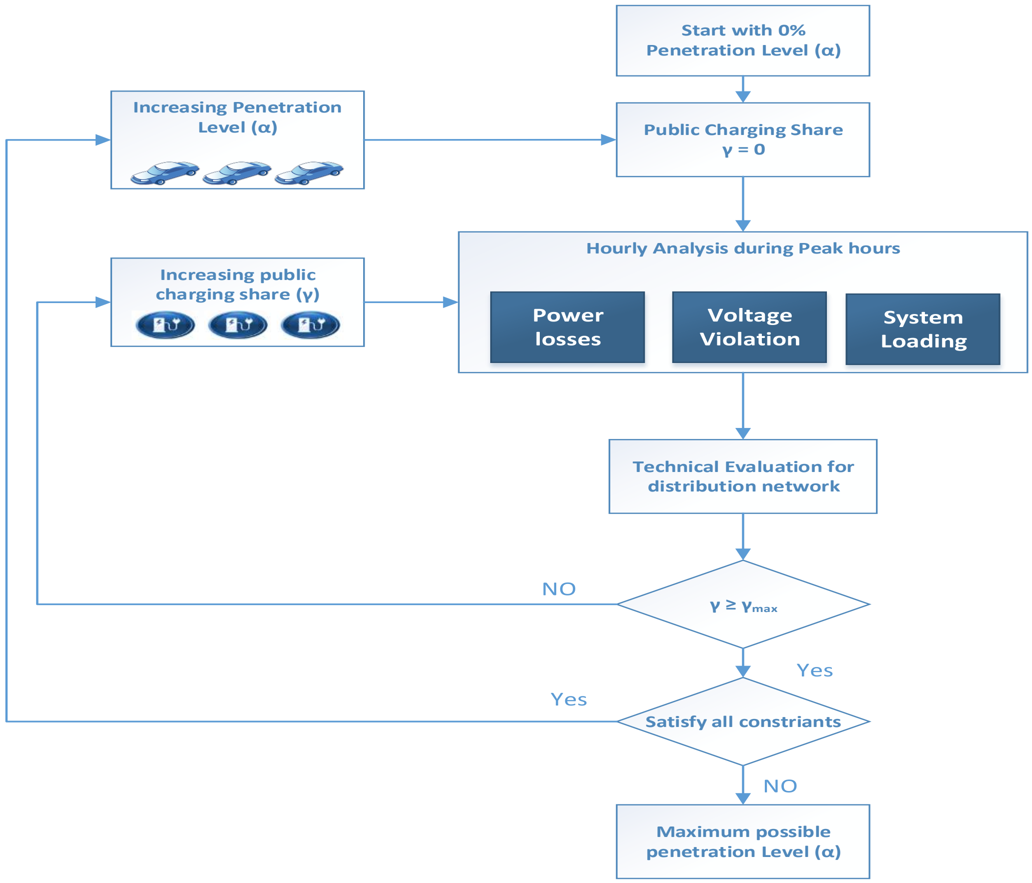

Figure 5-6: Technical Evaluation Model for Accommodate PEV Demand

The OPF analysis is applied here, and the objective function is the PEV penetration level.

<u>Objective Function:</u>

$$\text{Max}(\alpha) \tag{5.5}$$

<u>Subject to</u>

Power flow constraints

$$P^{ss}_{(i,t)} - P^{Load}_{(i,t)} = \sum_{j=1}^{N_b} V_{(i,t)} V_{(j,t)} YBus_{(i,j)} \cos\left(\theta_{(i,j)} + \delta_{(j,t)} - \delta_{(i,t)}\right) \qquad \forall\, i, t \tag{5.6}$$

$$Q^{ss}_{(i,t)} - Q^{Load}_{(i,t)} = -\sum_{j=1}^{N_b} V_{(i,t)} V_{(j,t)} YBus_{(i,j)} \sin\left(\theta_{(i,j)} + \delta_{(j,t)} - \delta_{(i,t)}\right) \qquad \forall\, i, t \tag{5.7}$$

Capacity constraints

$${P^{ss}_{(i,t)}}^2 + {Q^{ss}_{(i,t)}}^2 \leq SS^2_{(i)} \qquad \forall\ i, t \tag{5.8}$$

$$0 \leq I_{(i,j,t)} \leq I^{max}_{(i,j)} \qquad \forall\, i, j, t \tag{5.9}$$

$$0 \leq I_{(j,g,t)}\, CS_g \leq I_{(j,g)}^{max} \quad \forall\, j, g, t \tag{5.10}$$

PEV demand constraint

$$P_{(i,t)}^{Load} = \left[(1 + DGR)^k \times P_{(i,t)}^{D}\right] + \left[p_{i,t}^{H}\right] + \left[p_{i,t}^{FCS}\right] \quad \forall\, i, t \tag{5.11}$$

Voltage limit constraint

$$V_{min} \leq V_{(i,t)} \leq V_{max} \quad \forall\, i, t \tag{5.12}$$

Where

$P_{(i,t)}^{ss}, Q_{(i,t)}^{ss}$	the active and reactive power provided by the substation at DS bus (i) at time (t) in (p.u.)
$P_{(i,t)}^{Load}, Q_{(i,t)}^{Load}$	the active and reactive power load at DS bus (i) at time (t) in (p.u.)
$V_{(i,t)}, V_{(j,t)}$	the voltage magnitude of bus (i) and bus (j) at time (t) in (p.u.)
$YBus_{(i,j)}$	the bus admittance matrix (Y bus matrix) of the distribution system in (p.u.)
$\theta_{(i,j)}, \delta_{(i,t)}$	the phase angle deviation of branch (i,j) at time (t) and the voltage angle at bus (i) at time (t) respectively in (radian)
N_b	the total number of electrical nodes in the distribution system (number)
$P_{(i,t)}^{D}$	the basic electrical power demand at DS bus (i) at time (t) in (p.u.)
DGR	the annual growth rate of the basic electrical demand (%)
$SS_{(i)}$	the apparent power of substation (i) in (p.u.)
$I_{(i,j,t)}$	the current flowing between bus (i) and bus (j) at time (t) in (p.u.)
$I_{(i,j)}^{max}$	the maximum current flowing between bus (i) and bus (j) in (p.u.)
$I_{(j,g,t)}$	the current flowing between bus (j) and charging station (g) at time (t) in (p.u.)
$I_{(j,g)}^{max}$	the maximum current flowing between charging station (g) and bus (j) in (p.u.)
V_{min}, V_{max}	the minimum and maximum voltage limits, respectively in (p.u.)
CS_g	a decision variable equals 1 if a charging station is connected to bus (g), and 0 otherwise
$p_{i,t}^{H}$, $p_{i,t}^{FCS}$	Nodal charging power of home charging and fast charging facilities at DS node (i) at time (t) in (p.u.)

5.4 Sample Results and Discussion

In this section, different case studies are presented to demonstrate the distribution system evaluation model. Two coupled distribution and transportation network examples are used, similar to [37]. The distribution systems data are adopted from existing systems in North America, and they are similar to the systems presented in [77]. The technical evaluation model is utilized for each case to obtain the capability of each distribution system to serve PEV demand in terms of penetration level (α) as well as the impact of different public charging shares on the distribution system loading profiles.

5.4.1 Coupled 23 – bus distribution system and 20 – node transportation network

The 23-node distribution system has a capacity of 12 MVA and a peak load of 8 MW. The main substations at bus 1 and bus 2 are used to feed an urban area with voltage 15 KV, and the maximum feeders' capacities are 400 A. The 20-node transportation network is similar to [37], and the topology of the system is illustrated in Fig. 5-7. The detailed data about line parameters and the transformers are available in [77], and the detailed data about roads capacities and traffic flows are available in [36].

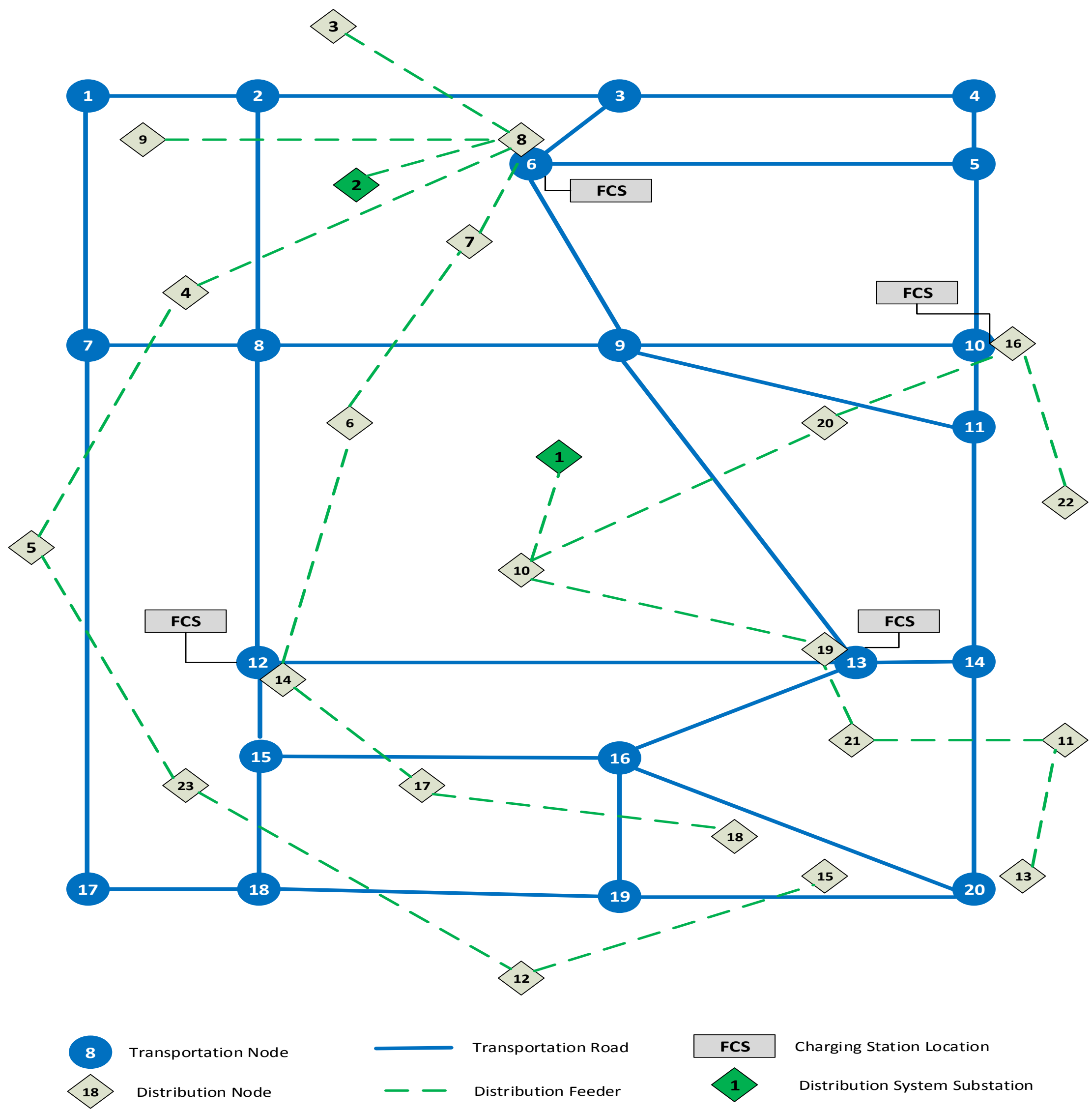

Figure 5-7 Graphical topology of the coupled 23 – node distribution and 20 – node transportation system

There are 2700 households in this urban area, and the number of vehicles per household is set to 1.86, in accordance with the U.S. national household travel survey [53]. The average charging frequency is set to 0.65 times per day, similar to [37], and the annual load growth is set to 3%. The voltage threshold is set to ±8%. Furthermore, the shortest path algorithm proposed in [78] is employed to assign traffic flows to transportation nodes. The K30 factor is assumed to be 10.2%, according to the suburban area in Fig. 5-4 [76], and the traffic volumes at rush hour (λ^{RH}), and AADT volumes are assumed similar to [76].

In this section, we proposed two scenarios: 1) The maximum PEV penetration level for the 23-node distribution system for different PEV public charging shares (γ), and 2) The reduction of the distribution system peak demand (including PEV demand) using predefined public shares (γ = 0.1, 0.2, and 0.3).

Scenario 1:

In Scenario 1, the relation between the maximum PEV penetration level and the public charging share (γ) is investigated. The aim of this scenario is to determine the maximum PEV penetration level that distribution system can supply according to different (γ) ratios starting from no FCSs to a fully connected PEV load to FCS (γ equals 0 – 100 %). In order to include the effect of substation and FCS feeders' thermal limits, different number of charging stations are used as shown in Fig. 5-8.

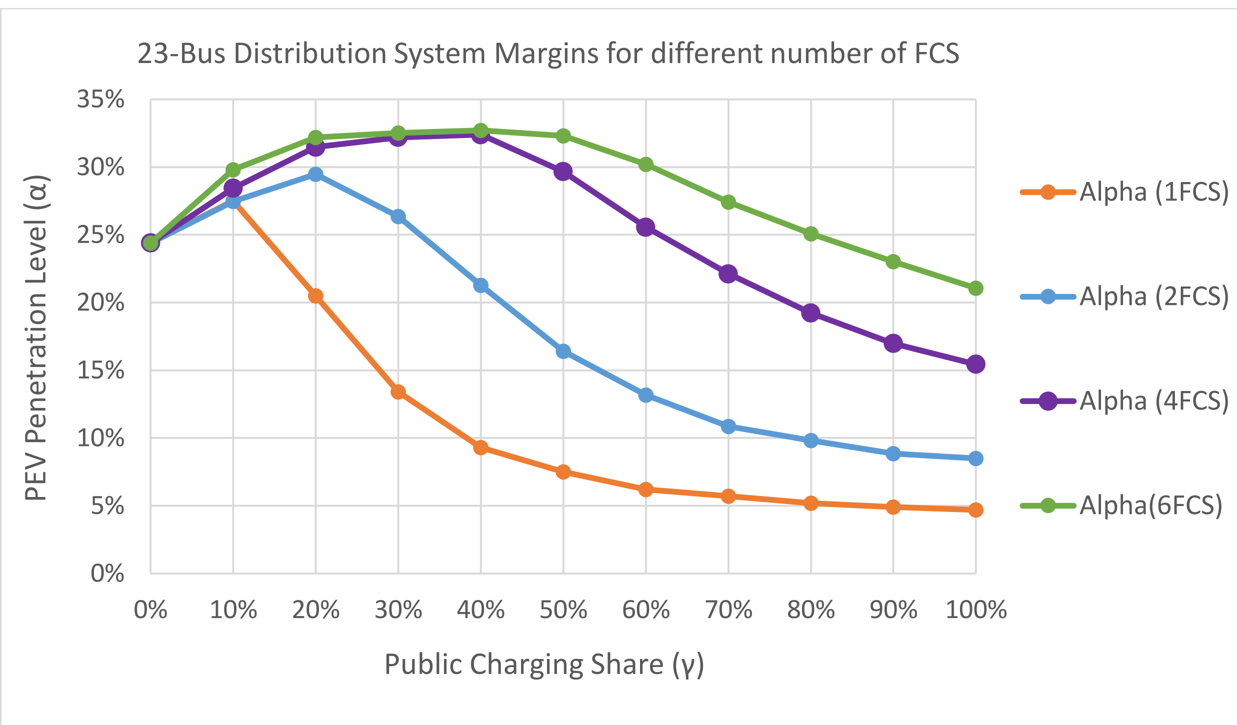

Figure 5-8 The PEV penetration level margins of the coupled 23- bus distribution and 20- node transportation system

The 23-bus electric distribution system that is coupled to the 20-node transportation system has a maximum ability to supply **24.36%** PEV penetration level using only home charging (Level 1 and 2) when public charging share (γ) equals zero. It is important to mention here that the 100% PEV penetration level means 1.86 vehicles per household [53] for each of the 2,700 households in the urban area under study. However, the ability of the distribution system can be improved by shifting some of the PEV loads to the public FCS locations. Changing the percentage of the PEV charged from the FCS (charging shares (γ)) may result in shifting the peak load of PEV away from the system peak load as shown in Fig. 5-5. This peak shifting will allow for more PEV penetration. The improvement of PEV penetration level is proportional to both the maximum ability of FCS to supply PEV demand and the FCS feeders' thermal limits; therefore, using more FCSs will enhance the maximum PEV penetration level since the total FCS ability to supply PEV demand is increased.

The PEV penetration levels are improved to **28.79%**, **31.95%**, and **32.23%** according to **2**, **4**, and **6** FCSs respectively with (γ equals 0.3) as shown in Figure 5-8. When the public charging shares exceed 0.4, the feeders' thermal capacities for both FCS and substation limit the ability of FCS to supply PEV loads; hence, the maximum penetration level start to decline. When the maximum PEV penetration level is less than **24.36% (**γ = 0), there is a negative impact of increasing public charging shares (γ) due to FCS feeders limits. In this scenario, the benefit of 1, 2, 4, and 6 FCSs are limited to (γ) equals 0.1, 0.3, 0.6, and 0.8 respectively.

Scenario 2:

The objective of this scenario is to demonstrate the influence of using FCS to supply part of PEV loads on the total distribution system peak demand. In this scenario, the penetration level is fixed at the base case **(24.36%),** and the public charging share is increased in predefined values (γ = 0.1, 0.2, and 0.3) to investigate the total system peak demand reduction. Four FCS locations are selected in this scenario as shown in Fig. 5-7. The distribution system load profiles for typical load case, at 24.36% PEV penetration level, with γ = 0.1 case, γ =0.2 case, and γ =0.3 case are illustrated in Figure 9.

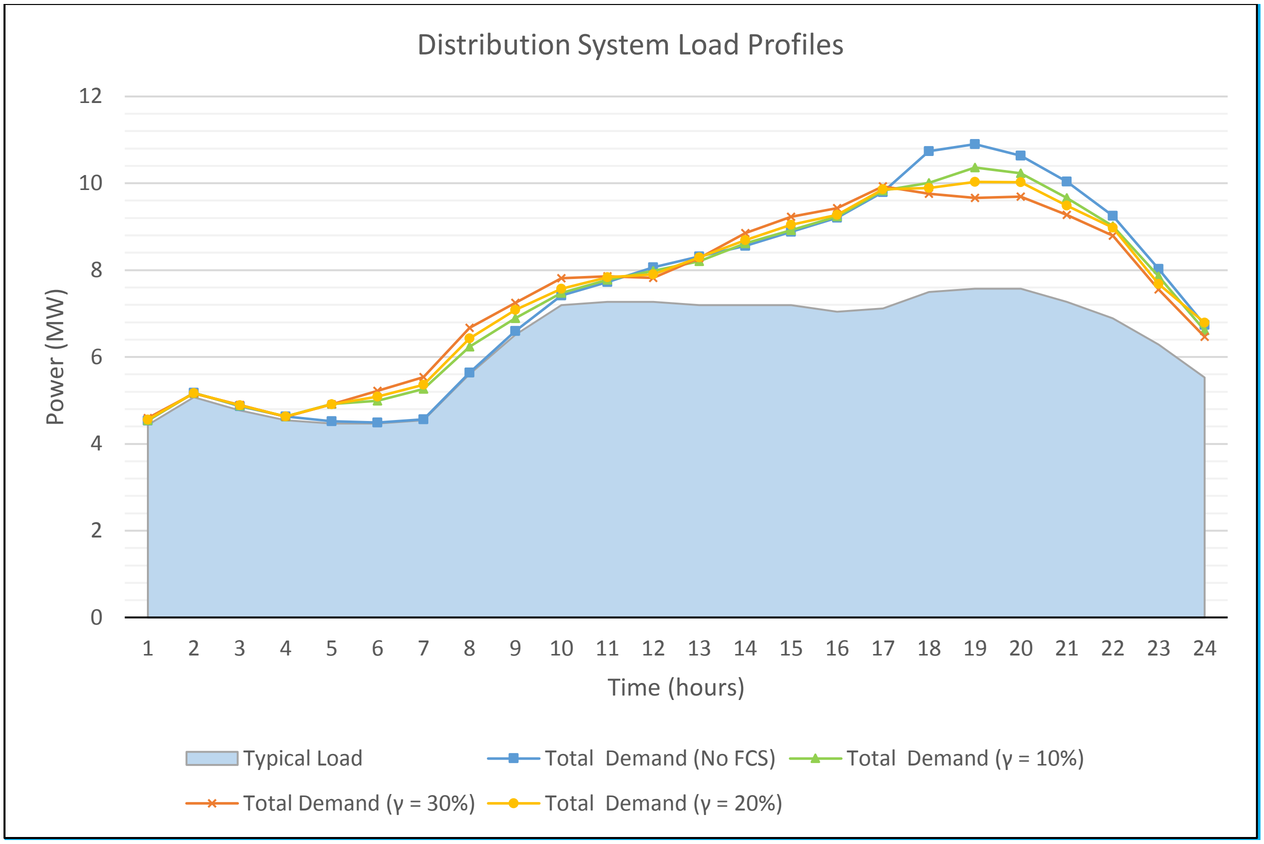

Figure 5-9 The peak demands of the coupled 23- bus distribution and 20- node transportation system

The distribution peak demand was increased due to the extra loading of uncoordinated PEV charging, and using only residential charging option (No FCS) made the peak PEV demand occurring in consistent with the peak typical load with the total system peak equals **10.9 MW**. However, increasing the FCS share of supplying PEVs was reducing the total system peak demand to **10.36 MW, 10.03 MW,** and **9.93 MW** according to **0.1, 0.2,** and **0.3** public share of PEV demand. The **970 kW** reduction at the latter case (γ = 0.3) is resultant from first the PEV demand peak reduction as shown in Figure 5-10 and second from shifting of the peak hour from **7 pm** at typical load to **5 pm** at (γ = 0.3) case as was shown in Fig. 5-9.

The movability of PEV loads makes the extra demand of charging PEVs more flexible to be managed not only by the time of use but also by the place of charge. Therefore, PEV load profile can be adjusted to not stress the distribution system during typical load peak (system load is mainly residential load) by connecting some PEV load to public FCS. It is interested to notice here that the PEV load connected to public FCS is affected by the traffic volume profile, Fig. 5-5, which has different peak time from the electric distribution system peak load time.

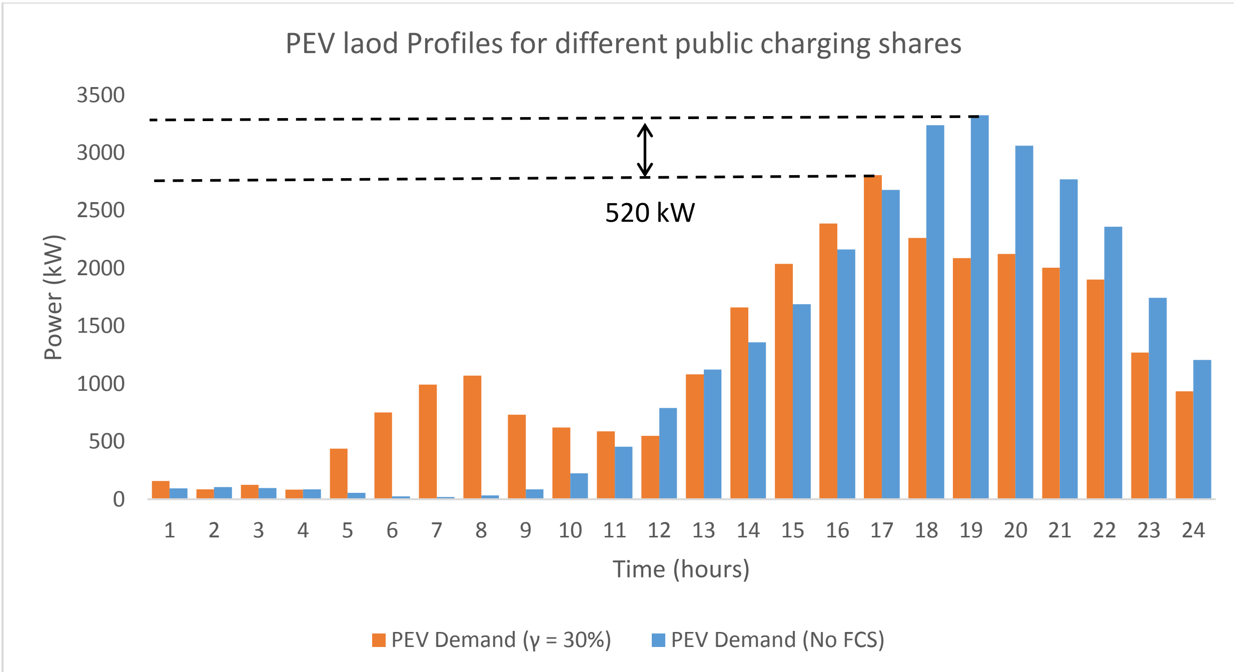

Figure 5-10 PEV load profiles of the coupled 23- bus distribution and 20- node transportation system

The relationship between the public charging share (γ) and the allowable demand of public connection of PEV makes charging behaviors of PEV drivers and the public charging price major factors in shaping PEV electric demand when a significant PEV penetration level is achieved in the future. Hence, including public charging station implementation in distribution system planning will be essential.

To illustrate the effect of PEV penetration level on the distribution system voltage profile, the voltage profile of the 23-node distribution system under study is shown in Fig. 5.11. Public charging stations are connected to buses 8, 14, 16 and 19. The maximum voltage deviation due public charging share (γ = 0.30) reaches 8% at Bus 18, which is the end load point for two FCSs at (Bus 8 and Bus14). The voltage deviation at Bus 19 reaches 4% when public charging share is equal to (γ = 0.1); however, increasing the public load to (γ = 0.30) makes the voltage deviation reaches 6.25%.

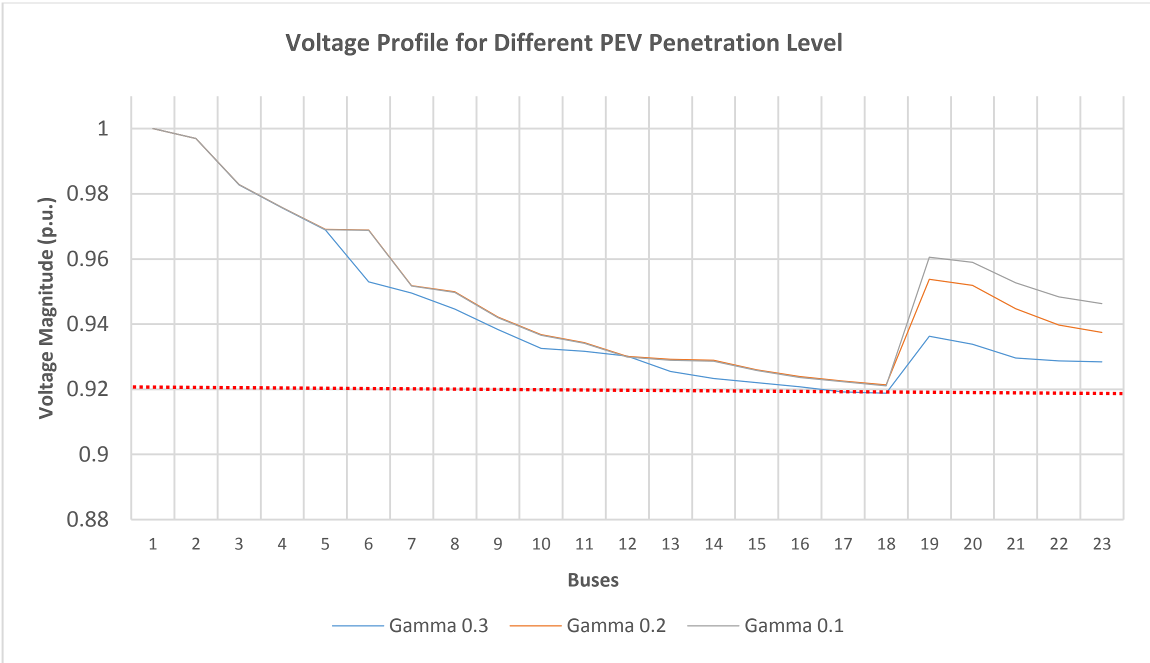

Figure 5-11 The Voltage profile of the coupled 23 – node distribution and 20 – node transportation system

5.4.2 Coupled 54 – bus distribution system and 25 – node transportation network

The 54-bus distribution system has a peak load of 21.5 MVA. It is a 15.0-kV radial distribution system feeding 50 load nodes, and four main substations are used to feed an urban area, with a maximum feeder capacity of 400A. The 25-node transportation network is similar to [37], and the topology of the test system is illustrated in Fig. 5.12. Detailed data about line parameters and the transformers are available in [79], and detailed data about road capacities and traffic flows are available in [80]. It is assumed that there will be 12,500 households in this urban area, and the number of vehicles per household is set to 1.86, according to the U.S. national household travel survey [53]. The percentage of PEVs which are charged at public stations (γ) is set to three different scenarios (0.1, 0.2, and 0.3). The average charging frequency is set to 0.65 times per day, similar to [37], and the annual load growth is set to 3%. The voltage threshold is set to ±8%. Furthermore, the shortest path algorithm proposed in [78] is employed to assign traffic flows to transportation nodes. The K_{30} factor is assumed to be 10.2% according to the suburban area in Fig. 5-4 in order to estimate traffic volumes at rush hour (λ_{RH}), and AADT volumes are assumed as similar to [76]. The PEV accommodation rate of the 54-bus distribution system is set in predefined steps to (5 – 30%), and output results are obtained using our proposed OPF model. The overall system losses and peak demands for different (α, γ) ratios are shown in Fig. 5.13 and Fig. 5.14 respectively. The system overall losses increased by 23% and the peak system demand increased by 38% when the PEV penetration level was set to (α = %30). Shifting some of PEV charging load to public CFS (share (γ = 0.3)) reduces the increase in the overall system losses to 16% (was 23% at $\gamma = 0$) and the peak system demand to only 20% (was 38% at $\gamma = 0$).

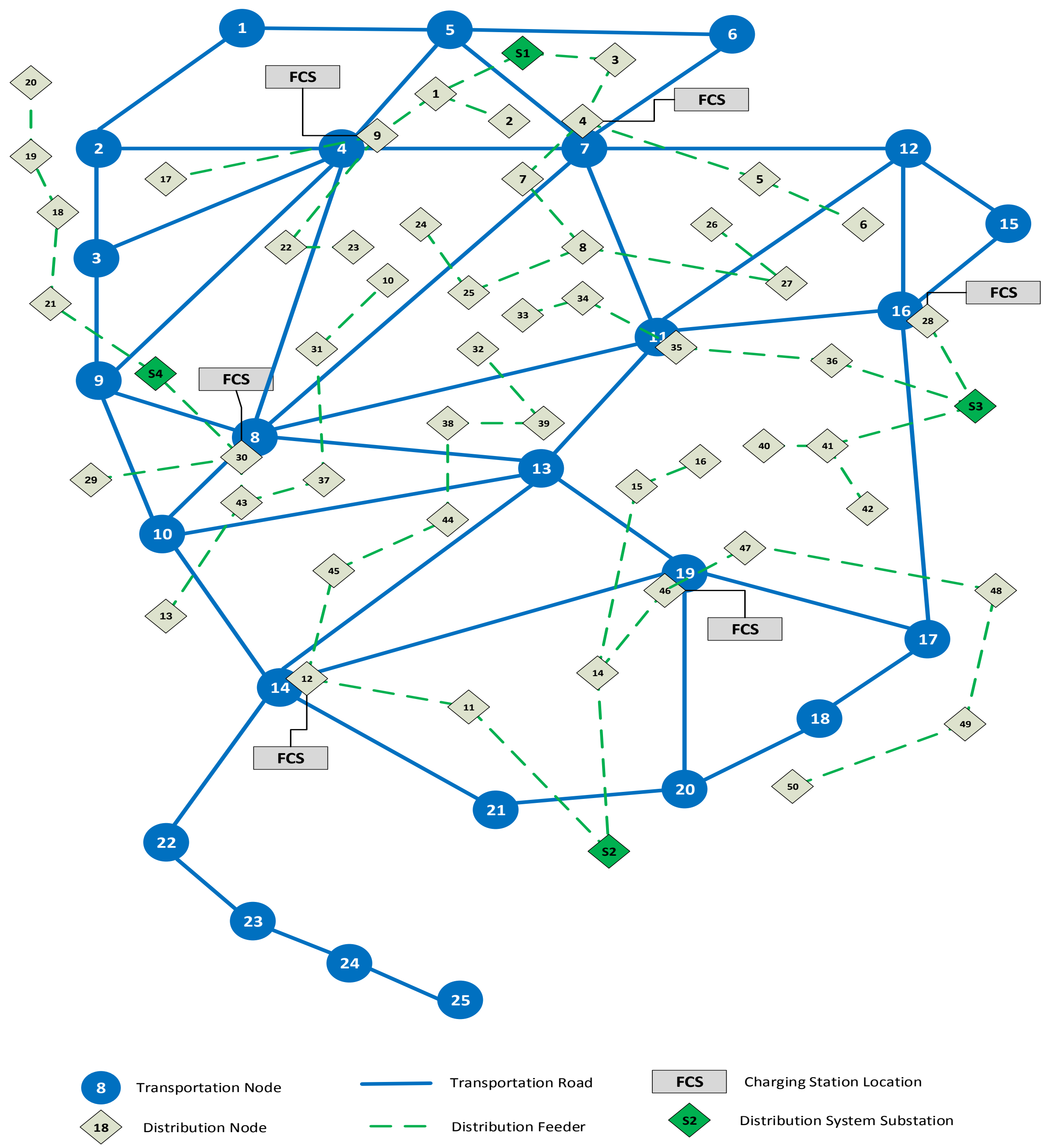

Figure 5-12 Graphical topology of the coupled 54 – Bus distribution and 25 – node transportation system

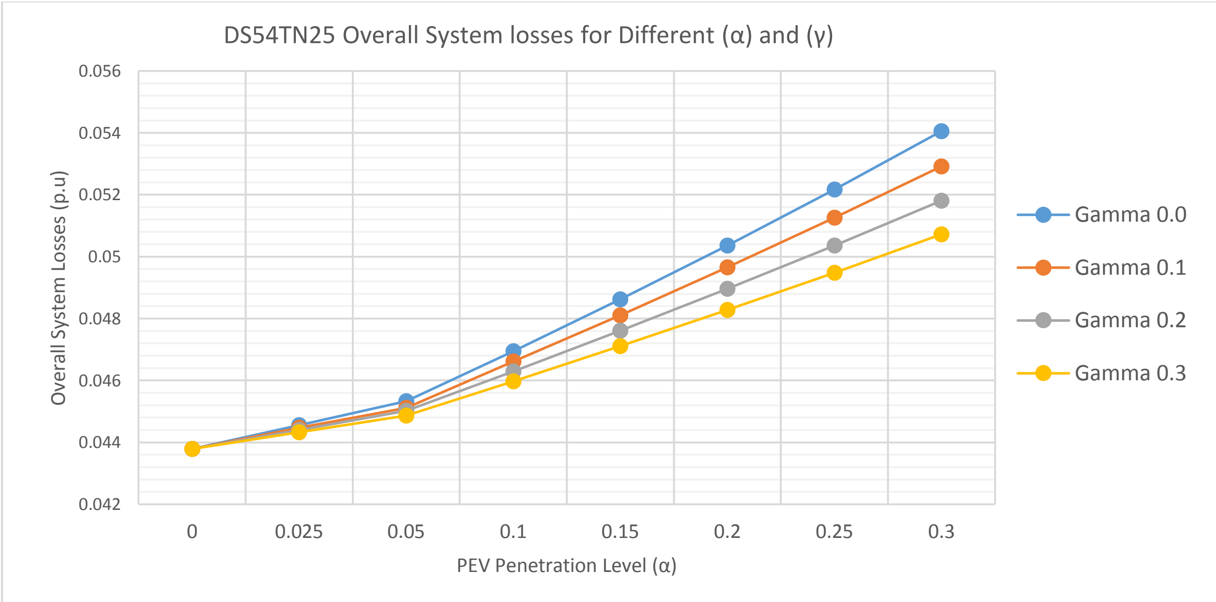

Figure 5-13 The overall losses of the coupled 54 – Bus distribution and 25 – node transportation system

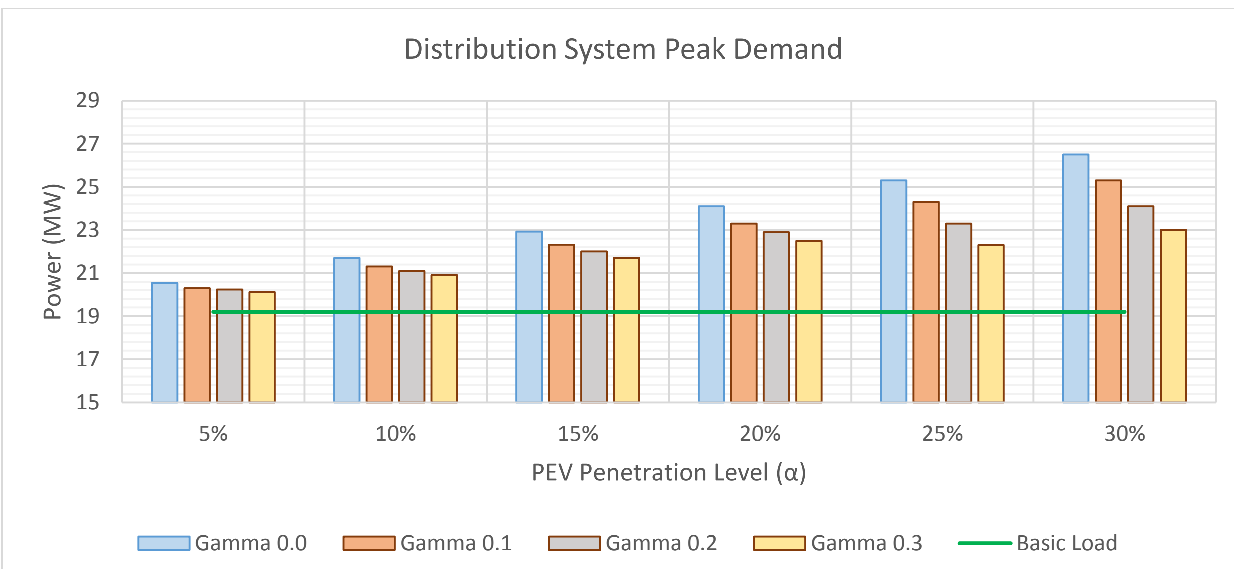

Figure 5-14 The Peak demands of the coupled 54 – Bus distribution and 25 – node transportation system

The 3.5 MW reduction in peak demand when α equals 30% indicates the importance of using FCSs to managing the PEV charging profile with a high PEV penetration level. Providing a public charging service with a reasonable charging price and quality of service in terms of queue waiting time and service time will have a major impact in shaping PEV demand when a significant PEV penetration level is achieved in the future. The effect of using different public charging shares (γ) on the PEV charging demand is shown in Fig. 5.15.

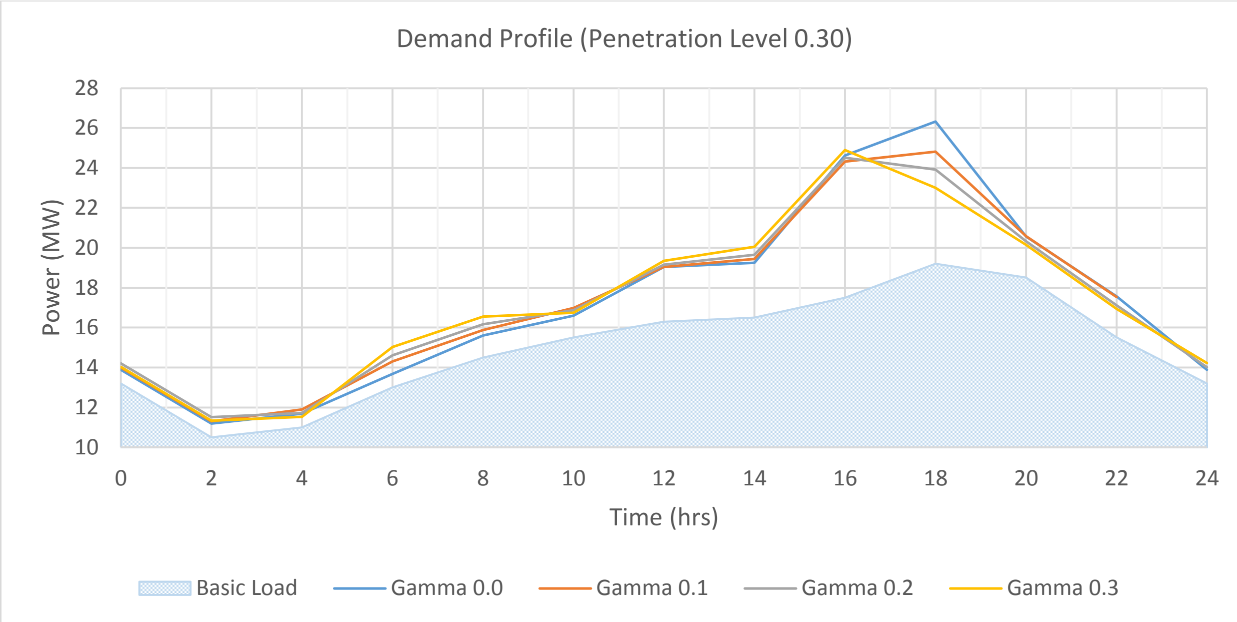

Figure 5-15 The PEV demand profiles of the coupled 54 – Bus distribution and 25 – node transportation system

According to Fig. 5.16, the deviation occurred at Bus 46 and all the following end load points reaches almost 6% due public charging share of (γ = 0.10); however, the maximum voltage deviation is occurred when the public charging share is increased to (γ = 0.30). The voltage profile at Bus 28 is not affected by different public charging shares (γ = 0.10 – 0.30) since the charging station is connected to substation (S3)

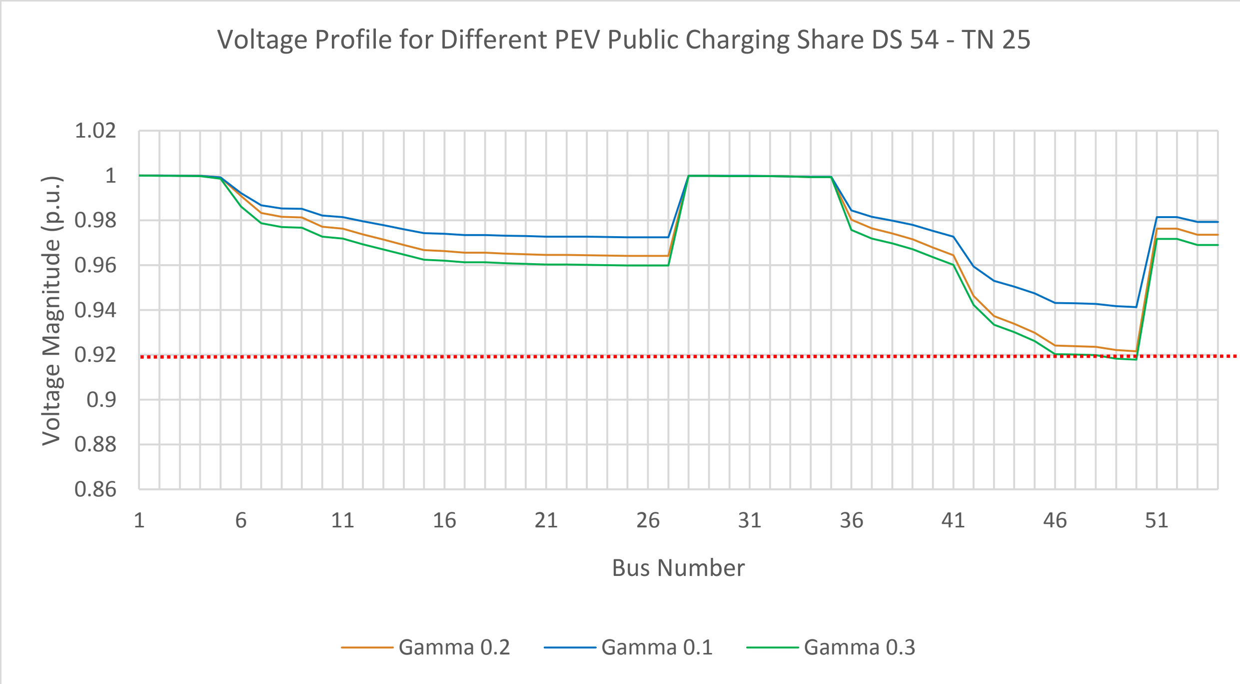

Figure 5-16 The voltage profile of the coupled 54 – Bus distribution and 25 – node transportation system

5.5 Chapter assessment

The proposed technical evaluation model, which can minimize the overall annual peak demand and energy losses, has been developed for planning the implementation of public fast charging systems. In the proposed model, the ability of distribution systems to adapt to PEV demand with the existing infrastructure is fully explored. The OPF model is applied to address the technical evaluation of distribution systems performance. The managing of system peak demands and losses is achieved by charging some PEV from public FCSs. The proposed model was applied for different distribution system and transportation network topologies. The simulation results demonstrate the robust performance of the proposed model to respond to the dynamics of public charging stations in a timely manner. The findings also reveal the effectiveness of the proposed model in providing higher PEV charging success by manipulating public charging shares. The advantages of the proposed model can thus be summarized as utilizing current distribution system infrastructure to provide charging service with minimum system enhancement, all of which make it suitable for practical implementation for early adoption rates.

We considered only the peak public charging demand during the rush hour in the technical evaluation since we were looking at the maximum ability of distribution system to serve PEVs. However, the average public charging demand according to the annual average daily traffic (AADT) is considered in the next chapter in order to obtain the number and capacity of chargers for each target FCSs selected in (Chapter 4). The PEV level margins of distribution system obtained in this Chapter 5 are going to be a strong constraint in the economic model in Chapter 6, so the maximum power of each selected locations will not be exceed.

Chapter 6
Economical Staging Plan for Implementing Fast charging Stations

This chapter proposes an economical staging plan method that optimally matches Plug-in Electric Vehicle (PEV) charging demand with the installation plan for Fast Charging Stations (FCSs) in the distribution system. The growth of public PEV demand is optimally matched in the long run with the installed FCS capacity by using an economical staging plan model. By including the waiting and service times for charging service, the proposed planning model considers not only the economic assessment of the FCS plan but also the quality of charging service that should be met by the FCSs.

Electrical Fast Charging Stations will eventually be dispersed in the network, but inefficient planning for charging infrastructure implementation will hold back PEV adoption, and so the implementation of charging stations should be properly planned. The planning approach for implementing charging infrastructure should be executed with a view to meeting users' and suppliers' needs. PEV users require access to charging stations whenever they need them, accompanied with a high quality of service. Therefore, a lack of charging facilities due to implementing them inappropriately or not at all will have a negative impact on drivers' convenience. On the other hand, providing fast charging services will be attractive for investors when a significant PEV penetration level is achieved. Electrical FCSs will eventually replace gas stations, but investing in premature technology is considered high-risk. Investors desire to have secure investments in profitable businesses that promise maximum profits, and so FCSs have to be evaluated with the consideration of all uncertainties and parameters affecting the potential business, especially in the early adoption period. Therefore, in the implementation planning for charging stations, the planning model should provide enhanced PEV driver convenience as well as security for investors in both the short and long term by optimally matching the PEV charging demand with the installation of FCS infrastructure.

6.1 Problem description

The limited driving range of PEVs is currently considered the second-highest concern in making a purchasing decision on a new PEV, according to [18]. Enhancing the electric vehicle charging infrastructure will lead to facilitating long-range driving for electric vehicles, and thus could serve as a means to mitigate range anxiety, with PEV users having the opportunity to access public charging infrastructure at times and places where they are running low on charge. As a result, a significant improvement in the PEV penetration level can conceivably be achieved, which will make participating in PEV charging station projects more attractive for investors as discussed in Chapter 3.

Since electric vehicle technology is in the early stages of adoption, the business model for PEV public charging infrastructure should be investigated with respect to all parameters affecting the profit feasibility of this business, such as PEV penetration levels and the structure of energy cost from electrical utility providers. PEV penetration level is considered a key parameter in estimating the expected demand for charging stations. The size of the charging stations and the number of chargers should be chosen to meet the expected demand of PEVs during rush hours with the minimum associated cost. The capital cost of installing fast charging units, as well as the electricity cost, provides insights into investment decisions. As well, issues with regard to PEV demand, price markup and different market structure models should be scrutinized in order to obtain the required number of charging units to be installed as well as their installation time.

In order to obtain the required number of chargers per FCS, the peak demand of PEVs during rush hours must be estimated. Moreover, the profitability of FCS projects is associated with PEV demand as well as the price of fast charging service. The FCS project is feasible from an economic perspective if there is sufficient PEV demand that using fast charging services with an acceptable price (less than the gasoline price as an upper limit), which will return the cost of the FCS project during its lifetime.

From the above discussion, the implementation plan for FCSs should consider two areas. The first is with regard to matching the PEV demand with the minimum associated cost of an FCS project. It should include the following:

- Estimate PEV penetration levels in the long and short run (input from Chapter 3)
- Estimate PEV demand during rush hours using the available traffic volume data for conventional cars (input from Chapter 5)
- Determine the minimum number and size of fast chargers that will meet the expected PEV demand during rush hours
- Determine the installation time for FCS chargers that will optimally match PEV demand growth in the short and long run

In the second part, an economic evaluation should be considered to investigate FCS project profit feasibility based on expected PEV demand and an acceptable fast charging service price. The economic evaluation should include the following:

- The installation cost of FCS chargers (from the first part)
- Different costs of energy based on electrical utilities’ tariff structures (flat rate, and time of use [TOU])
- The annual utilization rate of FCS chargers

- The acceptable price for a fast charging service to make the project profitable

6.2 Economical Staging Plan Modeling

This section presents the economical staging plan model. The proposed plan determines when the FCS units should be installed, along with their power capacities, in order to obtain the minimum overall cost of the FCS project. The proposed plan first estimates the public PEV charging demand by considering the traffic flow in the transportation network. The public PEV charging demand is distributed between the FCSs based on the traffic flow ratio. Then, the least-cost FCS units that satisfy the quality of service limits in terms of waiting and queueing times are selected to match the public PEV demand.

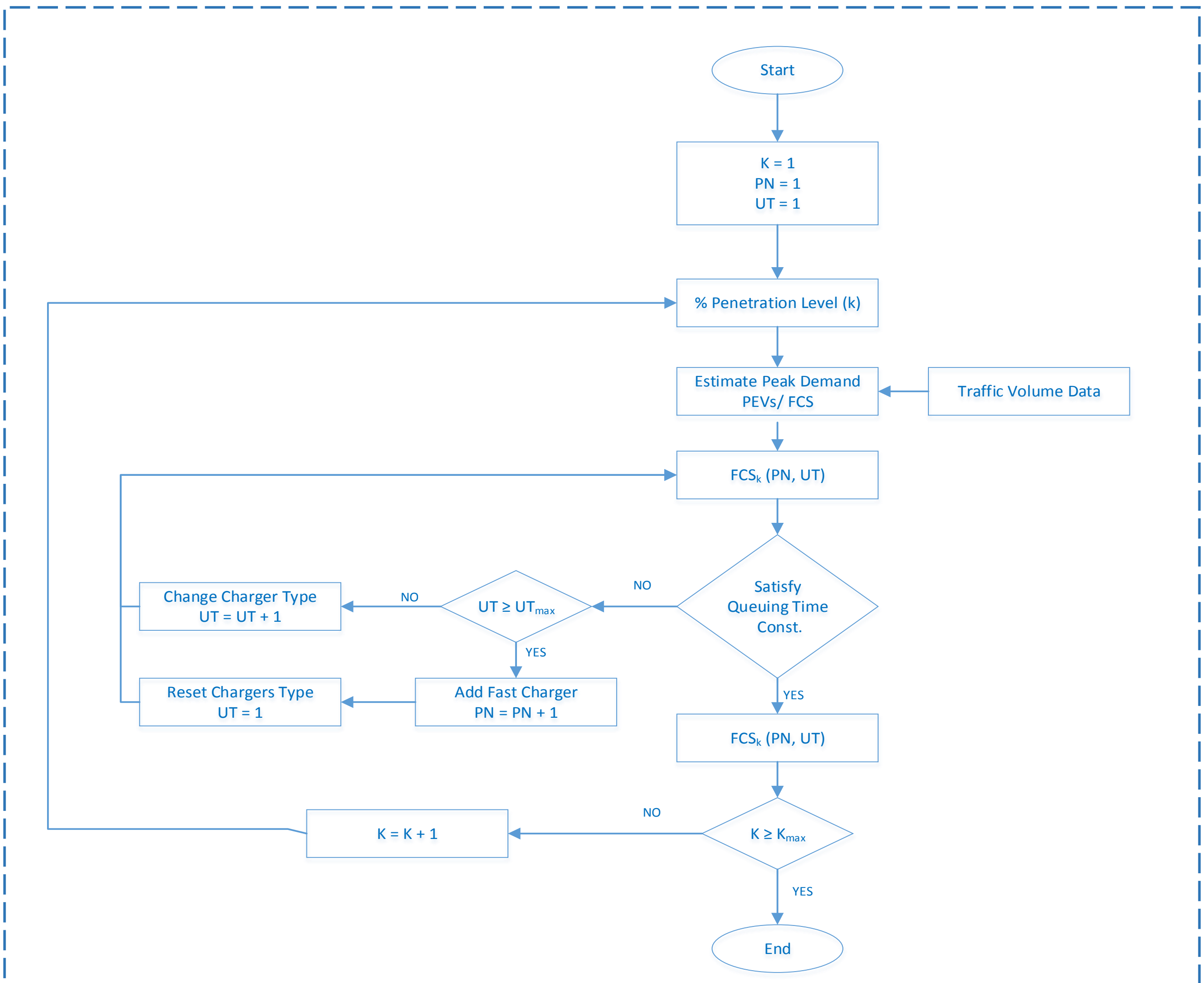

Figure 6-1 Economical Staging Plan Model

It is assumed that a negative exponential distribution could model the PEV arrival times, and that the service time for FCSs follows a Poisson process [81]. Furthermore, there are several fast charging facilities in each FCS, and the PEVs are served based on a first-come first-served (FCFS) rule. Thus, the staging plan problem for FCSs can be modeled as a nonlinear integer programming (NLIP) model according to the *M/M/s* queuing theory.

In order to obtain the minimum cost plan for an FCS network, the economical staging model involves several input parameters, as shown in the following.

6.2.1 Investment cost

There are currently various types and capacities of fast charging station units in the market. According to Aerovironment™ [82], there are four different standard FCS units, with capacities of 50, 100, 125, and 250 kW. Table 6.1 shows the FCS unit specifications and the best educated guesses for their cost figures.

Table 6-1 Fast charging station specifications and investment costs [82]

Parameters	FCS50	FCS100	FCS125	FCS250
Lifetime (years)	10	10	10	10
Voltage Limit (V)	400	800	1,000	2,000
Amperage Limit (A)	125	125	125	125
Output Power (kW)	50	100	125	250
Charging duration of 20kWh Battery (min)	24	12	10	5
Max PEV/Day	60	120	144	288
Material Cost ($)	50,000	110,000	150,000	220,000
Installation Cost ($)	35,000	50,000	50,000	65,000
Distribution Transformer Cost ($)	10,000	15,000	17,500	35,000
Total Capital Cost ($)	**95,000**	**175,000**	**217,500**	**320,000**
Annual Operation Cost ($)	2,500	4,500	5,500	10,000
Total Operation Cost ($)	**25,000**	**45,000**	**55,000**	**100,000**
Total Investment Cost over 10 years ($)	120,000	220,000	272,500	420,000
Annual Levelized Cost (r = 6%) ($)	16,305	29,898	37,032	57,078

For the calculation of contribution margins, one must distinguish the total and levelized investment costs. While total cost refers to total capital cost and total operation cost, levelized investment cost distributes the total cost over the project's lifetime. Equations (6.1 – 6.2) are utilized to calculate the annual levelized cost, with (r) being the interest rate and (k) the lifetime of the project.

$$Annual\ Levelized\ Cost = Total\ Investment\ Cost\ \times Annuity\ Factor \qquad (6.1)$$

$$Annuity\ Factor = \frac{(1+r)^k \times\ r}{(1+r)^k - 1} \qquad (6.2)$$

With interest fixed at 6% and a project lifetime of 10 years, an annuity factor of 0.1359 is obtained. This implies a yearly cost of 13.59% of total cost. A fast charging unit (50 kW) with a total cost of $120,000 would thus require a levelized cost of $16,305 per year.

Using high speed charging units will enhance the quality of service that an FCS can provide, especially at rush hour; however, for the same demand, when using faster charging units the utilization rate of the FCS will be impacted negatively due to the ability to serve more cars during the day. Thus, the profitability of an FCS has a positive correlation with the utilization of its units. Contrariwise, there is a negative relationship between FCS unit cost and service time, as shown in Fig. 6.2.

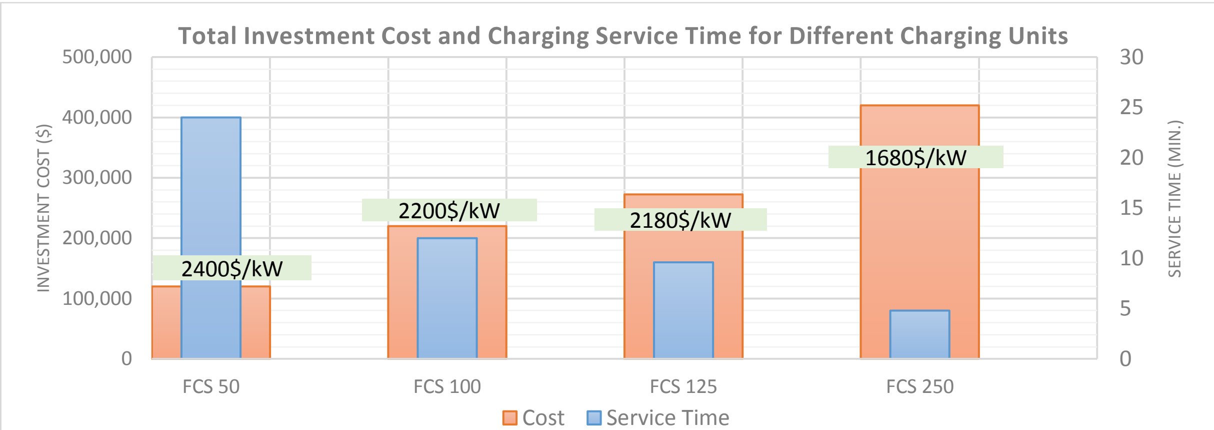

Figure 6-2 The relationship between the investment cost and the service time of FCS units based on a 20kWh charging event

Each charging unit has an hourly capability for serving PEVs. If the number of PEVs arriving at a charging station is greater than its capability, there will be PEVs waiting to be served, and therefore, if the actual queueing time is longer than the assumed queuing time, the system is not meeting requirements.

6.2.2 PEV market penetration

The number of PEVs is another parameter that should be considered when modeling an economical staging plan. FCS profit feasibility is associated with total PEV demand, which is proportional to the number of vehicles in the system. As discussed in Chapter 5, there are about 1.86 vehicles per household in North America according to National Household Travel Survey (NHTS) [53]. PEVs will be charged at public charging stations if the daily trip distances are longer than the PEVs' driving ranges. The percentage of PEVs that require access to public charging stations (γ) to complete their daily trips can be estimated from the average daily travel distance data [53]. According to the discussion in Chapter 5, we assume that γ is equal to different values (0.1, 0.2, and 0.3) which represent different ratios of daily highway trips to all daily trips. As a result, the estimated number of PEVs requiring fast charging service can be obtained by equation (6.3):

$$\mathrm{PEV}^{FCS} = \alpha NV \times \gamma \times \frac{U_{g,t}}{\sum_{t=1}^{T}\sum_{g=1}^{N_{FCS}} U_{g,t}} \tag{6.3}$$

For the short run, the forecast model for PEVs presented in Chapter 3 is used to obtain (α); however, for the long run, The PEV penetration level is set to (5 – 30%) in predefined steps (stages) to cover the variety of PEV accommodation rates that will become available in the system in the future.

6.2.3 FCS average and peak demand

In order to choose the number and type of chargers for an FCS, the average daily number of PEVs serviced by the FCS as well as the peak number of PEVs arriving at the FCS has to be estimated. As discussed in Chapter 5, traffic volume data have to be involved in order to address FCS average and peak demands. The charging stations' road assignments, the annual average daily trips (AADT) to each charging station, and the annual average trips conducted by PEVs at rush hour (λ^{RH}) to each charging station are estimated using equations (5.1 – 5.2), as proposed in Chapter 5. The road assignment follows the shortest path technique, so each transportation node is assigned to the nearest charging station.

The λ^{RH} and AADT are key parameters for the economical staging plan for charging stations. On the one hand, the traffic volume at rush hour is considered as the peak demand for the charging station, and λ^{RH} plays the main role in selecting the number and type of fast chargers with regard to predefined waiting time thresholds. Hence, a higher number of PEVs served during rush hour influences the design and size of an FCS project, along with increasing its total investment cost. On the other hand, the average demand of PEVs is the main indicator for the profit feasibility of an FCS project. The project's revenue is directly associated with the average number of PEVs served daily, so profit feasibility is increased with a higher number of PEVs served. The average number of PEVs served daily by an FCS (AADT^{FCS}) can be estimated using Equations (6.4 – 6.5):

$$U_{(g,t)} = \sum_{rd} a_{(g,rd)} \times \alpha \times \gamma \times AADT_{(rd,t)} \qquad \forall\, g, t \tag{6.4}$$

$$AADT_{g}^{FCS} = \sum_{t=1}^{24} U_{(g,t)} \qquad \forall\, g \tag{6.5}$$

6.2.4 Electricity prices and tariffs

FCS project owners should have clear foresight of electricity purchase prices from the electricity provider. The electricity purchase price is considered a main factor in the project running cost. The willingness of the customer to pay a markup for fast charging should be investigated, where the markup is considered as a margin over total electricity cost, including taxes and fees. Two different types of tariff are investigated: a) a flat rate; and b) a time-of-use rate (TOU). Local utilities have the option of charging different rates throughout the day, and these rates are divided into three separate bands, known as **off-**

peak, **mid-peak** and **on-peak**. These different bands and rates are set by local utilities that provide electricity to FCS projects. If the local utility is not utilizing time-of-use billing, FCS projects are charged the same rate regardless of when they consume their electricity. The flat rate has two price tiers, and the price that FCS owners pay depends on how much electricity they use. In the summer, the higher price is used when they consume more than a given amount of kWh of electricity in a month. In the winter months, the higher electricity price is charged for consumption above a higher threshold of kWh. For example, Ontario's Hydro One charges customers the following TOU rates: off – peak rate of 8.3 cents/kWh; mid – peak rate of 12.8 cents/kWh; and on – peak rate of 17.5 cents/kWh. However, Hydro One charges a flat rate in some places where the TOU is not applicable. The flat rate has two price tiers: 9.9 cents/kWh, and 11.6 cents/kWh. The price you pay depends on how much electricity you use. In the summer, the higher price is used when you consume more than 600kWh of electricity in a given month, and in the winter months, the higher electricity price is charged for consumption above 1,000 kWh.

6.3 Economical Staging Plan Formulation

The Economical Staging Plan Model has two phases. The first phase presents a staging model that is used to match the growth of PEV demand with the installed charging station capacity. This can be achieved by selecting the FCS charger types that satisfy the queueing and waiting time limits with the minimum associated cost. Not only the number and type of chargers are obtained in this phase, but the staging model also determines the year of installation for each charging unit. The least-cost implementation plan obtained in Phase One is utilized in the economic evaluation phase to determine the profit feasibility of the project. In the second phase, the FCS project is economically evaluated to obtain the break-even fast charging price in order to have a feasible business.

6.3.1 The staging plan model

The staging plan problem is formulated as an NLIP model according to the *M/M/s* queuing theory, and the objective of the model is to minimize the total investment cost, as follows:

Objective Function:

$$\mathrm{Min}(TCost) = \sum_{k=1}^{K} \left[\frac{(1+r)^{k-1}}{r(1+r)^{k}} \sum_{ut=1}^{UT} \sum_{pn=1}^{PN} y_{(pn,ut,k)} \times Cost_{(ut,k)} \right] \tag{6.6}$$

Subject to

There are three categorizes of constraint in the planning model:

1) Capacity constraints (Eq. 6.7 – 6.10): these are used to ensure that only one type is assigned to each FCS charger in order to ensure that the installed chargers remain ON to the end of the planning period, and to ensure that the power capacity limits and number of allowable chargers are not violated.

Capacity constraints

$$\sum_{ut=1}^{UT} y_{(pn,ut,k)} \leq 1 \qquad \forall\ pn, k \qquad (6.7)$$

$$y_{(pn,ut,k-1)} \leq y_{(pn,ut,k)} \qquad \forall\ k\ \in \{2,3, \dots, \mathrm{K}\} \qquad (6.8)$$

$$\sum_{pn=1}^{PN} \sum_{ut=1}^{UT} y_{(pn,ut,k)} \leq \mathrm{MaxUnits}_{(k)} \qquad \forall\ k \qquad (6.9)$$

$$\sum_{pn=1}^{PN} \sum_{ut=1}^{UT} y_{(pn,ut,k)} \times UnitCap_{(ut)} \qquad \leq \mathrm{Max\ P\ FCS}_{(k)} \qquad \forall\, k \qquad (6.10)$$

2) Traffic flow constraints (Eq. 6.11 – 6.12): these constraints are very important to ensure that the FCS queueing system is stable, so that the average inflow time is less than the processing time in order to serve charging events within the time limits.

Traffic flow constraints

$$\lambda_{(pn,k)}^{RH} \leq \sum_{ut=1}^{UT} y_{(pn,ut,k)} \times UnitST_{(ut)} \qquad \forall\, pn, k \qquad (6.11)$$

$$ADT_{(g,k)} = \sum_{rd} a_{(rd,g)} \times AADT_{(rd,k)} \qquad \forall\, g, k \qquad (6.12)$$

3) Queue system constraints (Eq. 6.13 – 6.21): these are used to obtain the queueing system parameters, such as service time, occupation rate, queueing time, waiting time, and queue length. The last two constraints are used to ensure that maximum waiting and queueing time limits are not exceeded.

Queueing System constraints

$$\mu_{(pn,ut,k)} = \frac{Charge}{UnitCap_{(pn,ut,k)}} \qquad \forall\, pn, ut, k \qquad (6.13)$$

$$\rho_{(k)} = \sum_{pn=1}^{PN} \frac{1}{\lambda_{(pn,k)}} \times \sum_{ut=1}^{UT} \frac{1}{y_{(pn,ut,k)} \mu_{(pn,ut,k)}} \qquad \forall\, k \qquad (6.14)$$

$$0 < \rho_{(k)} < 1 \qquad \forall\, k \qquad (6.15)$$

$$\mathrm{tq}_{(pn,k)} = \frac{(\sum_{ut=1}^{UT} y_{(ut,pn,k)} \times \mu_{(pn,k)} \times \rho_{(pn,k)})}{1 - \rho_{(pn,k)}} \qquad \forall\, pn, k \qquad (6.16)$$

$$\mathrm{ts}_{(pn,k)} = \mu_{(pn,k)} \qquad \forall\, pn, k \qquad (6.17)$$

$$\mathrm{tw}_{(pn,k)} = \mathrm{tq}_{(pn,k)} + \mathrm{ts}_{(pn,k)} \qquad \forall\, pn, k \qquad (6.18)$$

$$\mathrm{QL}_{(pn,k)} = \mathrm{tq}_{(pn,k)} + \left(\lambda_{(pn,k)} \times \mu_{(pn,k)} \right) \qquad \forall\, un, k \qquad (6.19)$$

<u>Queue Time and Waiting Time limits constraints</u>

$$\mathrm{tq}_{(pn,k)} \leq \mathrm{MaxTq} \qquad \forall\, un, k \qquad (6.20)$$

$$\mathrm{tw}_{(pn,k)} \leq \mathrm{MaxTw} \qquad \forall\, un, k \qquad (6.21)$$

Where:

$\alpha_{(k)}$	the PEV penetration level (α) at step (k)
k	an index representing the number of steps using in increasing PEV penetration level α
PN	an index representing the number of charger posts inside the charging station
UT	an index representing the charger unit type and capacity (e.g. 50kW, 100kW) inside the charging station
$y_{(ut,pn,k)}$	a decision variable equaling 1 if the unit type (ut) of the post number (pn) in step (k) is installed, and 0 otherwise
r	the interest rate value
$\mathrm{Cost}_{(k)}$	the average annualized cost of the FCS unit at step (k)
$\mathrm{ADT}_{(pn,k)}$	the average daily traffic flow of all vehicles at step (k) captured by an FCS post (pn)
Charge	the average public charging event (16 kWh) conducted by FCS
$UnitCost_{(ut)}$	the FCS charger unit of type (ut) installation cost in ($)
$UnitCap_{(ut)}$	the FCS charger unit of type (ut) rating power capacity (kW)
$UnitST_{(ut)}$	the FCS charger unit of type (ut) service time in (min.) to charge 16 kWh battery
$Max\ Units_{(k)}$	the maximum number of charger posts allowable inside an FCS in step (k)
$Max\ P\ FCS_{(k)}$	the maximum electrical power limit provided by the distribution system for an FCS in step (k) obtained from (Chapter 5)
$\lambda_{(pn,k)}$	the mean arrival rate of vehicles to the FCS post number (pn) at step (k) in (veh/hr)
λ_k^{RH}	the maximum arrival rate of vehicles to the FCS during rush hour at step (k) in (veh/hr)
$\mathrm{AADT}_{(k)}$	the annual average daily traffic flow of all vehicles at step (k) assigned to the FCS
$\mu_{(pn,k)}$	the mean service rate of a post number (pn) at step (k) in (minutes)

$\rho_{(pn,k)}$	the occupation rate of charging post number (pn) at step (k)
$tq_{(pn,k)}$	the average time that PEVs spend in the queue to start charging at post number (pn) at step (k)
$ts_{(pn,k)}$	the average time that PEVs spend during charging at post number (pn) at step (k)
$tw_{(pn,k)}$	the total time that PEVs spend in the entire FCS system using post number (pn) at (k)
$QL_{(pn,k)}$	the average queue length of PEVs using post number (pn) at step (k)
Max Tq	the predefined maximum allowable time for PEVs to spend in the queue to start charging
Max Tw	the predefined maximum allowable time for PEVs to spend in the entire FCS system

The proposed economical staging plan model utilizes the (AADT, λ^{RH}) parameters from the traffic flow data and then chooses the least-investment-cost staging plan for installing FCS chargers. The output of the planning model is the design for each FCS in terms of number of charging posts (pn), capacity of each charging post (ut), and when the charging posts are installed (k). The annual levelized cost of FCSs should be used in order to have a fair comparison that is independent of the time of installation, and then the total cost is represented by the Present Value.

6.3.2 Economic evaluation model

The Benefit to Cost Ratio (BCR) method is utilized to choose the best fast charging price. This price should recoup the total investment cost of the staging plan that satisfies all technical aspects with the most beneficial outcomes from an economic point of view. The charging service price is assumed to be in the range of the home charging price and the average gasoline price. However, to represent the gasoline price in ($/kW), Equation (6.22) is used, as follows:

$$GasPr\ \left(\frac{\$}{kW}\right) = Gas\ \left(\frac{\$}{l}\right) * ICEV_{eff}\left(\frac{l}{km}\right) * PEV_{eff}\left(\frac{km}{kW}\right) \tag{6.22}$$

where:

$ICEV_{eff}$ and PEV_{eff} are the efficiencies of ICEV and PEV motors in (liter/km) and (km/kW), respectively.

The benefit-cost ratio is defined as the ratio of the discounted benefits to the discounted cost at the same point in time. The benefit-cost ratio method is not as straightforward as the net present value method. While this method is often used in the evaluation of public projects, the results may be misleading if proper care is not exercised in its application on different proposals [83].

In view of Equations (6.23 – 6.24), the criterion for accepting an independent project on the basis of the benefit-cost ratio is whether or not the benefit-cost ratio is greater than or equal to one, as shown in Equation (6.25).

$$BPV = \sum_{k=0}^{K} B_k(P|F,r,k) = \sum_{k=0}^{K} B_k(1+r)^{-k} \tag{6.23}$$

$$CPV = \sum_{k=0}^{K} C_k(P|F,r,k) = \sum_{k=0}^{K} C_k(1+r)^{-k} \tag{6.24}$$

$$\frac{BPV}{CPV} \geq 1 \tag{6.25}$$

Where

B_k	the annual benefit for the FCS project at the end of stage (k)
C_k	the annual cost for the FCS project at the end of stage (k)
BPV	the benefit present value of the FCS project at time (k)
CPV	the cost present value of the FCS project at time (k)

The annual cost of the FCS project at time (k) is obtained from the estimated cost of electricity as well as the levelized annual cost. However, the annual benefit of the FCS project at time (k) is calculated based on the fast charging price and the average amount of energy consumed by PEVs using FCS chargers.

The main objectives achieved in the economical staging plan model are as follows:

- The number of fast chargers that matches PEV demand growth in terms of capacity and installation time
- The impact of PEV demand growth on both the cost and benefit of the FCS project
- The break-even price of fast charging service that makes FCS project profitability feasible

6.4 Sample Results and Discussion

In this section, different case studies are presented to demonstrate the economical staging plan model. The first part shows the cost analysis of fast chargers with different numbers of PEVs serviced daily. In the second part, the two coupled distribution and transportation network examples discussed in Chapter 5 are used to investigate the short and long term planning. The short term plan is obtained by utilizing the economical staging plan model and the penetration level (α) forecasted in Chapter 3, while the long term plan is achieved using the predefined penetration level (α) assumed to be (5% - 30%). Each case study has two scenarios, single charger capacity (50kW) and multiple charger capacities (50, 100, 250kW). All these scenarios are investigated thoroughly and the economical evaluations for all case studies are illustrated in the next section.

6.4.1 The cost analysis of Fast Charging units

In this section, we investigate the cost analysis of fast charging units according to the average number of PEVs serviced daily. The cost of charging has two major components: total investment cost, and electricity cost. In addition to the up-front costs presented in Table 6.1, DC fast chargers have operating costs as follows:

- Variable costs include electricity per a typical charge and a transaction fee. These costs can be passed directly onto the customer.
- Fixed annual costs, which include:
    - Utility demand charges (if applicable), the bulk of which are demand charges
    - The charging station network management system fees, which provides remote data collection monitoring, payment processing, and call center
    - General maintenance

These costs need to be repaid according to the number of customers per year.

First, different electricity prices and tariffs are investigated to obtain the markup-charging price that gives a unity benefit to cost ration (BCR). Three electricity tariffs are included in this analysis: flat rate, time of use (TOU), and demand charge. It is assumed in this analysis the typical charge is 16kWh, the transaction fee is $0.91, the utility demand charge is $1000, and the management system and general maintenance fees are $260 annually, according to ChargePoint™ [84]. We include in this analysis only the fast charging unit with a 50kW capacity, and Figure 6.3 shows the markup-charging price per kWh that gives unity BCRs for different electricity tariffs along with different numbers of PEV serviced daily.

Next, we investigate the charging price feasibility for different fast charging units along with different numbers of PEV serviced daily. The feasible charging price is assumed to be $0.099/kWh as the lower boundary and $0.92/kWh as the upper boundary. The upper boundary is calculated according to Equation 6.22, with assumptions of average gas price of $1.1/liter [55], average ICEV fuel efficiency of 17L/100km [70], and average PEV energy efficiency of 5 km/kWh [70]. Figure 6.4 illustrates the acceptable region (the green area) of the charging price of different fast charging units along with their daily average utilization rates by PEVs.

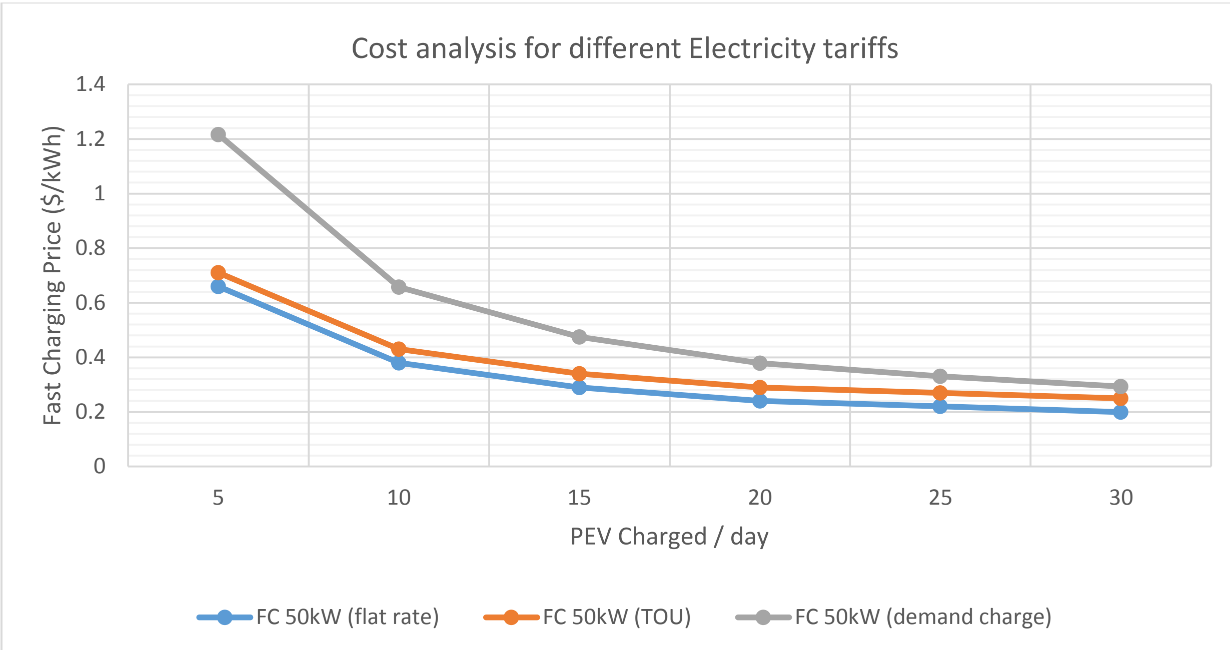

Figure 6-3 The impact of different electricity tariffs on the markup-charging price with different utilization rates

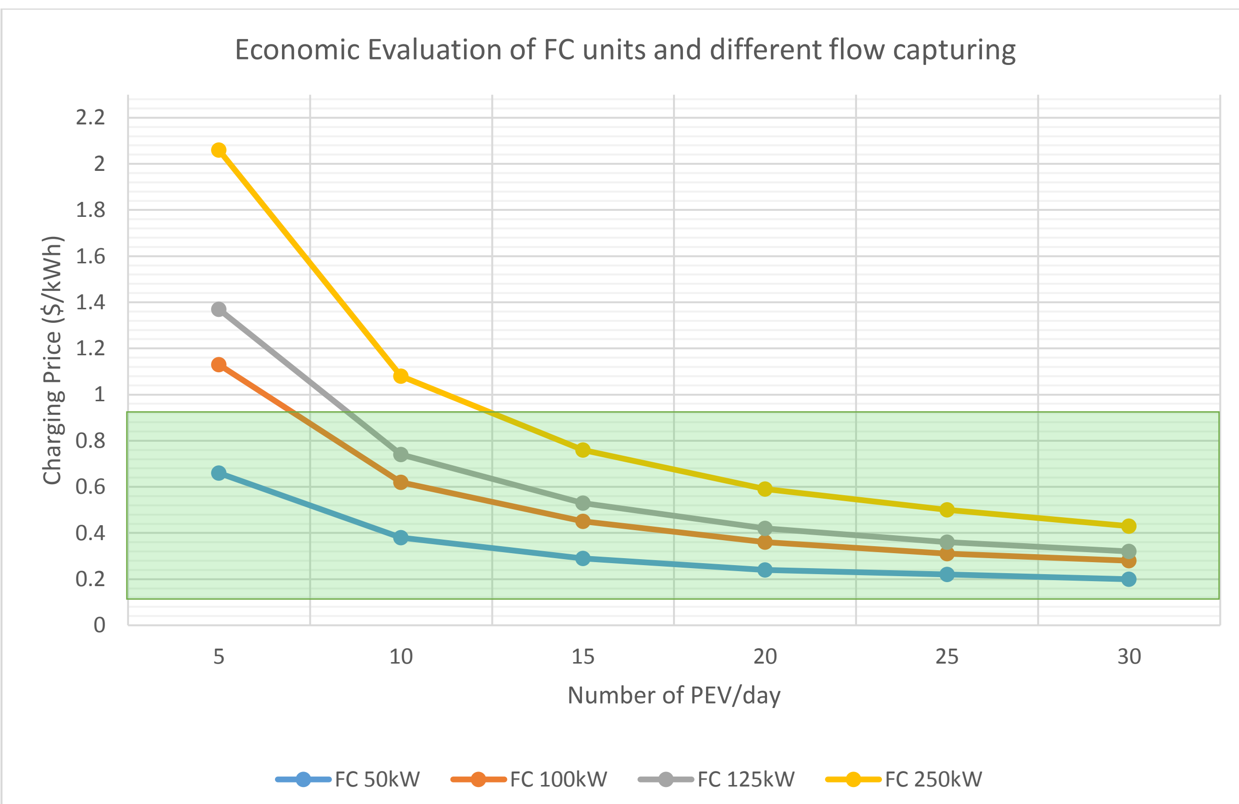

Figure 6-4 The markup-charging price feasibility for different fast charging units according to their utilization rates using flat rate

The results obtained from the cost analysis are summarized as follows.

- The utility demand charge has a huge negative impact on the charging price, especially during low adoption rates for PEVs. During low PEV penetration levels, obtaining a unity BCR is not feasible unless the average gas price exceeds $1.3/liter.

- The TOU price increases the energy cost by about 25% in the winter and 18% in the summer compared to a flat rate pricing benchmark. This occurs because most of the traffic flow capturing occurs during the mid-peak and on-peak periods; however, if fast charging stations have their own TOU schedules; it will encourage FCS businesses especially for early adoption rates.

- When PEV penetration level is low (less than 5%), only one capacity (50kW) fast charger can achieve a unity BCR, whereas having higher-capacity charging units is feasible with higher penetration levels. So, having different DC chargers, i.e., fast charger, super-fast charger, and ultra-fast charger, with different markup-charging prices ($0.20/kWh, $0.30/kWh, and $0.40/kWh), is feasible in the near future.

6.4.2 Coupled 23 – bus distribution system and 20 – node transportation network

In this section, we estimate first the average traffic volume and the peak traffic volume during rush hour for the 20-node transportation network [37], and then we obtain number of chargers, capacity of chargers and the time of installation using the proposed economical staging model. After that, we calculate the benefit to cost ratio of the obtained structure. The topology of the test system is illustrated in Figure 5.7. (Page 68), and the detailed data about road capacities and traffic flows are available in Appendix C. The percentage of PEVs which are charged at public stations (γ) is set to a medium value of 0.15, and the average charging frequency is set to 0.65 times per day, similar to [37]. Furthermore, the locations of the FCSs are selected based on the TSR model proposed in Chapter 4, and the shortest path algorithm proposed in [78] is employed to assign traffic flows to transportation nodes. There are four FCSs selected to cover the 20 – node transportation network, located at (DS-Bus 8, TN-node 6), (DS-Bus 16, TN-node 10), (DS-Bus 14, TN-node 12), and (DS-Bus 19, TN-node 13). The K_{30} factor is assumed to be 10.2% according to the suburban area in Fig. 5.4 in order to estimate traffic volumes at rush hour (λ_{RH}), and AADT volumes are assumed as similar to [76]. In this study case, three scenarios are presented, as follows.

<u>Short-Run Planning (Single Charger Capacity)</u>

In the first scenario, the economical staging plan model is applied to the forecasted PEV penetration level proposed in Chapter 3 (low adoption rate) for the short run plan. Only one fast charger capacity (50kW) is included in this scenario due to the low adoption rate of PEVs. The planning horizon is for 10 years (2016 – 2025), and we assume that the 20 – node network will have the penetration level of Ontario, as proposed in Chapter 3 and shown in Figure 3.4.

The estimation of PEVs at rush hour (λ^{RH}) and the AADT for each selected FCS location are shown in Table 6.2, and we assume the queue waiting time limit to be 20 minutes and the service time limit to be 40 minutes as 4 times to gas station average time spent [87].

Table 6-2 The traffic volume data for the coupled 23 – Bus and 20 – node system for low adoption rates

Year	Penetration Level (α)	FCS (DS Bus-8 , TN node-6)		FCS (DS Bus-16, TN node-10)	
		Rush Hour (λ^{RH}) (# vehicles)	(AADT) (veh./day)	Rush Hour (λ^{RH}) (# vehicles)	(AADT) (veh./day)
2016	0.00089	1	0.338	1	0.198
2017	0.00247	1	0.934	1	0.546
2018	0.00548	1	2.075	1	1.214
2019	0.01214	1	4.597	1	2.690
2020	0.02090	2	7.913	1	4.630
2021	0.03360	3	12.718	2	7.442
2022	0.04146	4	15.695	2	9.183
2023	0.04799	4	18.167	3	10.630
2024	0.05500	5	20.822	3	12.183
2025	0.06238	5	23.614	3	13.817
Year	Penetration Level (α)	FCS (DS Bus-14, TN node-12)		FCS (DS Bus-19, TN node-13)	
		Rush Hour (λ^{RH}) (# vehicles)	(AADT) (veh./day)	Rush Hour (λ^{RH}) (# vehicles)	(AADT) (veh./day)
2016	0.00089	1	0.180	1	0.178
2017	0.00247	1	0.498	1	0.492
2018	0.00548	1	1.106	1	1.094
2019	0.01214	1	2.450	1	2.423
2020	0.02090	1	4.218	1	4.171
2021	0.03360	2	6.779	2	6.704
2022	0.04146	2	8.365	2	8.273
2023	0.04799	2	9.683	2	9.576
2024	0.05500	3	11.098	3	10.976
2025	0.06238	3	12.587	3	12.447

The economical staging plan model is applied in order to obtain the staging plan that optimally matches the estimated traffic volume data. The Benefit to Cost Ratio (BCR) is then calculated for different charging prices: 50 cents/kWh, 75 cents/kWh, and 125 cents/kWh. Two of the markup-charging prices are within the feasible region discussed in the previous section, and the 125 cents/kWh price exceeds the acceptable region; however, it is included in order to show the break-even price for low adoption rates of PEVs. We assume in this scenario that the electricity tariff will be the same as Ontario's winter flat rate as in [85], and the exchange rate as in [86]. Table 6.3 shows the fast charging units required to match the traffic volume data for the 23 – bus 20 – node system for the short run plan (2016 – 2025), as well as the BCR for each station over the planning horizon. BCRs of less than one are shown in red.

Table 6-3 The economical staging plan for the coupled 23 – Bus and 20 – node system for low adoption rates

Year	FCS (DS Bus-8 , TN node-6)				FCS (DS Bus-16, TN node-10)			
	Stage Plan	FC price (50c/kW)	FC price (75c/kW)	FC price (125c/kW)	Stage Plan	FC price (50c/kW)	FC price (75c/kW)	FC price (125c/kW)
2016	1×50kW	0.019	0.028	0.047	1×50kW	0.013	0.020	0.033
2017	1×50kW	0.052	0.077	0.129	1×50kW	0.036	0.054	0.090
2018	1×50kW	0.115	0.172	0.286	1×50kW	0.080	0.121	0.201
2019	1×50kW	0.254	0.381	0.634	1×50kW	0.178	0.267	0.445
2020	1×50kW	0.437	0.655	1.092	1×50kW	0.307	0.460	0.767
2021	1×50kW	0.702	1.053	1.755	1×50kW	0.493	0.739	1.232
2022	2×50kW	0.471	0.706	1.177	1×50kW	0.608	0.912	1.521
2023	2×50kW	0.545	0.818	1.363	1×50kW	0.704	1.056	1.760
2024	2×50kW	0.625	0.937	1.562	1×50kW	0.807	1.210	2.017
2025	2×50kW	0.708	1.063	1.771	1×50kW	0.915	1.373	2.288
	BCR	**0.403**	**0.605**	**1.008**	**BCR**	**0.414**	**0.621**	**0.905**
Year	FCS (DS Bus-14, TN node-12)				FCS (DS Bus-19, TN node-13)			
	Stage Plan	(50c/kW)	(75c/kW)	(125c/kW)	Stage Plan	(50c/kW)	(75c/kW)	(125c/kW)
2016	1×50kW	0.012	0.018	0.030	1×50kW	0.012	0.018	0.030
2017	1×50kW	0.033	0.049	0.082	1×50kW	0.033	0.049	0.081
2018	1×50kW	0.073	0.110	0.183	1×50kW	0.072	0.109	0.181
2019	1×50kW	0.162	0.243	0.406	1×50kW	0.161	0.241	0.401
2020	1×50kW	0.279	0.419	0.698	1×50kW	0.276	0.414	0.691
2021	1×50kW	0.449	0.674	1.123	1×50kW	0.444	0.666	1.110
2022	1×50kW	0.554	0.831	1.385	1×50kW	0.548	0.822	1.370
2023	1×50kW	0.641	0.962	1.603	1×50kW	0.634	0.951	1.586
2024	1×50kW	0.735	1.103	1.838	1×50kW	0.727	1.090	1.817
2025	1×50kW	0.834	1.251	2.084	1×50kW	0.824	1.237	2.061
	BCR	**0.330**	**0.566**	**0.943**	**BCR**	**0.326**	**0.489**	**0.815**

The economical staging plan model results show that it is infeasible to make a profit from FCS projects during low adoption rates of PEVs and low traffic volume for the coupled 23 – bus 20 – node system. As a result, to support green transportation, more incentive programs are required from governments to support fast charging station projects during the early stages of adoption.

Long-Run Planning (Single Charger Capacity)

In the second scenario, for the long run plan, the economical staging plan model is applied to predefined PEV penetration levels (5 – 30%) as high adoption rates. Only one fast charger capacity (50kW) is included in this scenario. The planning horizon for each stage is 10 years, so we assume that the network will take the estimated PEV rush hour (λ^{RH}) and AADT for the selected FCS locations, as shown in Table 6.4, and similarly we assume the queue waiting time to be 20 minutes and the service time to be 40 minutes.

Table 6-4 The traffic volume data for the coupled 23-bus distribution and 20-node transportation network (Fig. 5-7)

Penetration Level (α)	FCS (DS Bus-8 , TN node-6)		FCS (DS Bus-16, TN node-10)	
	Rush Hour (λ^{RH}) (# vehicles)	(AADT) (veh./day)	Rush Hour (λ^{RH}) (# vehicles)	(AADT) (veh./day)
0.05	4	18.93	3	11.08
0.10	8	37.86	5	22.15
0.15	12	56.78	7	33.23
0.20	16	75.71	9	44.30
0.25	19	94.64	12	55.38
0.30	23	113.57	14	66.45
Penetration Level (α)	**FCS (DS Bus-14, TN node-12)**		**FCS (DS Bus-19, TN node-13)**	
	Rush Hour (λ^{RH}) (# vehicles)	(AADT) (veh./day)	Rush Hour (λ^{RH}) (# vehicles)	(AADT) (veh./day)
0.05	3	10.09	2	9.98
0.10	5	20.18	4	19.95
0.15	7	30.27	6	29.93
0.20	9	40.35	8	39.91
0.25	11	50.44	10	49.89
0.30	13	60.53	12	59.86

The proposed model is applied to obtain the staging plan that optimally matches the estimated traffic volume data, and then BCR is calculated for different markup-charging prices: 50 c/kWh, 65 c/kWh, 75 c/kWh. All the markup-charging prices are within the feasible region discussed previously. Similarly, we assume in this scenario that the electricity tariff will be the same as Ontario's winter flat rate. Table 6.5 shows the fast charging units required to match the traffic volume data for the long run at each penetration level, as well as the BCR for each station over the planning horizon. BCRs of less than one are shown in red.

The results obtained from the second scenario show that all locations could achieve a profit from FCS projects when the PEV penetration level is 10% and above, with a feasible markup-charging price of 75 cent/kWh. While locations with high traffic volumes could achieve a profit with a PEV penetration level as low as 5% such as FCS (DS-bus 16, TN-node 10), and FCS (DS-bus 14, TN-node 12) could achieve a profit with a similar markup price. Most locations could achieve a profit with a markup price of 65 cent/kWh when the penetration level reached 15%; however, when the PEV penetration level hits 20%, participating in FCS projects is now attractive for investors due to the low markup-charging price; e.g., 50 cents/kWh, which would make a profit certain.

Table 6-5 The economical staging plan for the coupled 23 – bus and 20 – node system for high adoption rates (single-charger)

α	FCS (DS Bus-8 , TN node-6)				FCS (DS Bus-16, TN node-10)			
%	Stage Plan	BCR (50c/kW)	BCR (65c/kW)	BCR (75c/kW)	Stage Plan	BCR (50c/kW)	BCR (65c/kW)	BCR (75c/kW)
5	2×50kW	0.522	0.679	0.783	1×50kW	0.734	0.954	1.100
10	3×50kW	0.836	1.086	1.254	2×50kW	0.917	1.192	1.375
15	4×50kW	0.940	1.222	1.410	3×50kW	0.917	1.192	1.375
20	6×50kW	1.045	1.358	1.567	3×50kW	1.223	1.589	1.834
25	7×50kW	1.119	1.455	1.679	4×50kW	1.146	1.490	1.719
30	8×50kW	1.175	1.528	1.763	5×50kW	1.100	1.430	1.651
α	FCS (DS Bus-14, TN node-12)				FCS (DS Bus-19, TN node-13)			
%	Stage Plan	BCR (50c/kW)	BCR (65c/kW)	BCR (75c/kW)	Stage Plan	BCR (50c/kW)	BCR (65c/kW)	BCR (75c/kW)
5	1×50kW	0.668	0.869	1.002	1×50kW	0.661	0.859	0.991
10	2×50kW	0.724	0.941	1.086	2×50kW	0.716	0.931	1.074
15	3×50kW	0.780	1.013	1.169	2×50kW	1.156	1.503	1.735
20	3×50kW	1.114	1.448	1.671	3×50kW	1.101	1.432	1.652
25	4×50kW	1.044	1.357	1.566	4×50kW	1.033	1.342	1.549
30	5×50kW	1.002	1.303	1.504	4×50kW	1.239	1.611	1.859

Long Run Planning (Multiple Charger Capacities)

The third scenario is similar to the second one, but different charging unit capacities are included (50 kW, 100 kW, and 250 kW). With high adoption rates, the traffic volume at rush hour requires more charging units to satisfy the waiting time constraint. However, the charging service time can be reduced by using faster charging units; as a result, the waiting time is also reduced with a lower number of charging units that have higher capacities. The proposed staging plan model selects the least-cost combination of fast chargers that match the traffic volume and satisfy the queueing time constraints. Consequently, the quality of service is enhanced with faster charging units, and the profit margin is also improved due to reducing the total investment cost for chargers. The proposed economical staging plan model is applied to the same traffic volume data in Table 6.4, and the results are shown in Table 6.6.

The results show that using multiple charging capacities reduces the number of chargers required as well as the capital investment cost, so the benefit to cost ratio is increased when the penetration level exceeds 10%. Figure 6.5 shows a comparison of benefit to cost ratios for the FCS (DS-Bus 8, TN-Node 6) using single– and multiple charger types. In the long term, using multiple charging capacities is more cost-effective, as well as maintaining a high quality of service.

Table 6-6 The economical staging plan for the coupled 23 – Bus and 20 – node system for high adoption rates (multiple-charger types)

α	FCS (DS Bus-8 , TN node-6)				FCS (DS Bus-16, TN node-10)			
%	Stage Plan	BCR (50c/kW)	BCR (65c/kW)	BCR (75c/kW)	Stage Plan	BCR (50c/kW)	BCR (65c/kW)	BCR (75c/kW)
5	1×250kW	0.298	0.388	0.448	1×100kW	0.400	0.520	0.600
10	1×250kW	0.716	0.931	1.074	1×100kW	1.000	1.300	1.500
15	1×250kW	1.074	1.397	1.611	1×100kW	1.500	1.950	2.250
20	1×100kW+1×250kW	1.175	1.528	1.763	2×100kW	1.000	1.300	1.500
25	1×100kW+1×250kW	1.469	1.909	2.203	2×100kW	1.250	1.625	1.875
30	50kW+100kW+250kW	1.484	1.930	2.226	2×100kW	1.500	1.950	2.250
α	FCS (DS Bus-14, TN node-12)				FCS (DS Bus-19, TN node-13)			
%	Stage Plan	BCR (50c/kW)	BCR (65c/kW)	BCR (75c/kW)	Stage Plan	BCR (50c/kW)	BCR (65c/kW)	BCR (75c/kW)
5	1×100kW	0.364	0.474	0.547	1×100kW	0.360	0.469	0.541
10	1×100kW	0.790	1.026	1.184	1×100kW	0.781	1.015	1.171
15	1×100kW	1.275	1.658	1.913	1×100kW	1.261	1.640	1.892
20	2×100kW	0.911	1.184	1.367	1×50kW+1×100kW	1.166	1.516	1.749
25	2×100kW	1.139	1.480	1.708	1×50kW+1×100kW	1.458	1.895	2.186
30	2×100kW	1.367	1.777	2.050	2×50kW+1×100kW	1.293	1.681	1.939

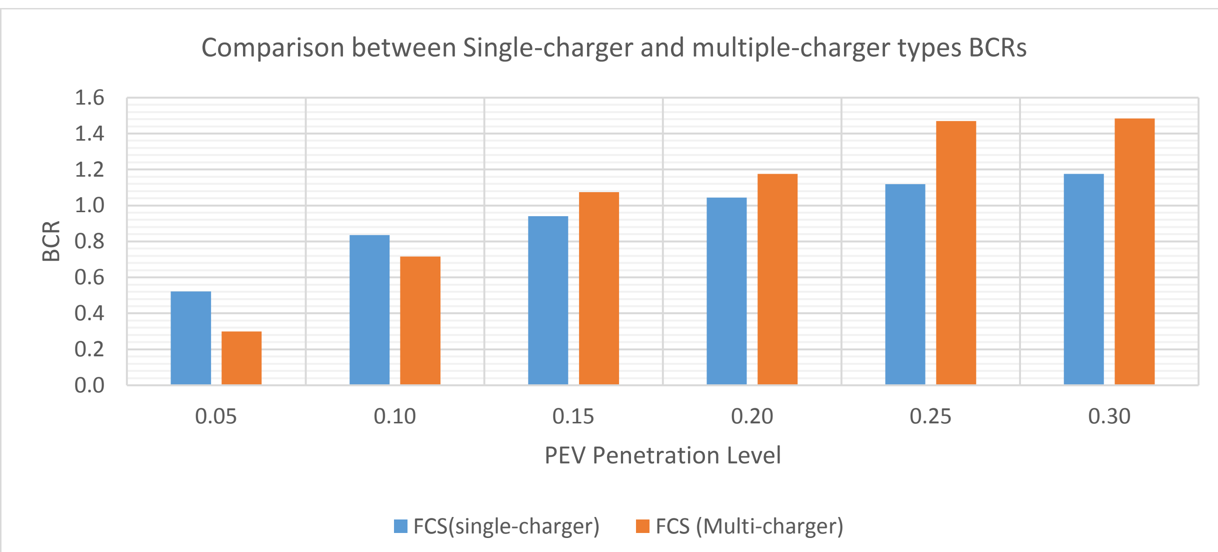

Figure 6-5 Comparison between Single – charging capacity and Multiple – charging capacities BCRs

For the validation of our model, the results in terms of traffic volume captured and the total investment cost of FCS networks are compared with the results in [37], where α equals 20%. Since the same locations for FCSs are used, the vehicle/year traffic volume is almost the same (3.7×10^7); however, there is a huge reduction in total FCS investment cost, of 35%, when the staging plan is used.

6.4.3 Coupled 54 – bus distribution system and 23 – node transportation network

This case study has a higher traffic volume compared to the coupled 20 – node transportation network due to TN-node 4, TN-node 14, and TN-node 19 being located next to highways. The 25-node transportation network is similar to [37], and the topology of the test system is illustrated in Fig. 5.12. Detailed data about road capacities and traffic flows are available in [80] and is shown in Appendix C. It is assumed that there will be 12,500 households in this urban area, and the number of vehicles per household is set to 1.86 according to the U.S. national household travel survey [53]. The percentage of PEVs to be charged at public stations (γ), is set to (0.15) as a medium value. The average charging frequency is set to 0.65 times per day, similar to [37]. Furthermore, the FCS locations are selected based on the TSR model proposed in Chapter 4, and the shortest path algorithm proposed in [78] is employed to assign traffic flows to transportation nodes. The K_{30} factor is assumed to be 10.2% according to the suburban area in Fig. 5.4. In order to estimate traffic volumes at rush hour, (λ_{RH}), and AADT volumes are assumed as similar to [76]. Six FCSs are selected to cover the 25 – node transportation network, which are located at (DS-Bus 4, TN-node 7), (DS-Bus 9, TN-node 4), (DS-Bus 12, TN-node 14), (DS-Bus 28, TN-node 16), (DS-Bus 30, TN-node 8), and (DS-Bus 46, TN-node 19). This case study is designed to consider a high traffic volume network, and it includes three scenarios as presented in the following sections.

Short-Run Planning (Single Charger Capacity)

In the first scenario, the economical staging plan model is applied to the forecasted PEV penetration level proposed in Chapter 3 (low adoption rate) for the short-run plan. Only one fast charger capacity (50 kW) is included in this scenario due to the low adoption rate of PEVs. The planning horizon is for 10 years (2016 – 2025), and we assume that the 25 – node network will have the penetration level of Ontario, as proposed in Chapter 3 and showed in Figure 3.4. The estimations of PEVs at rush hour (λ^{RH}) and the AADT for each selected FCS location are shown in Table 6.7. In this scenario, we assume the queueing time to be 20 minutes and the service time to be 40 minutes, similar to the previous case studies.

Table 6-7 The traffic volume data for the coupled 54 – Bus and 25 – node system for low adoption rates

Year	Penetration Level (α)	FCS (DS Bus-4 , TN node-7)		FCS (DS Bus-9, TN node-4)	
		Rush Hour (λ^{RH})	(AADT)	Rush Hour (λ^{RH})	(AADT)
2016	0.00089	1	0.15	1	0.38
2017	0.00247	1	0.42	1	1.05
2018	0.00548	1	0.94	1	2.33
2019	0.01214	1	2.07	2	5.15
2020	0.02090	2	3.57	3	8.87
2021	0.03360	2	5.73	5	14.25
2022	0.04146	3	7.07	6	17.59
2023	0.04799	3	8.19	7	20.36
2024	0.05500	3	9.38	8	23.34
2025	0.06238	4	10.64	8	26.47
Year	Penetration Level (α)	FCS (DS Bus-12, TN node-14)		FCS (DS Bus-28, TN node-16)	
		Rush Hour (λ^{RH})	(AADT)	Rush Hour (λ^{RH})	(AADT)
2016	0.00089	1	0.87	1	0.15
2017	0.00247	1	2.41	1	0.42
2018	0.00548	2	5.37	1	0.94
2019	0.01214	4	11.89	1	2.09
2020	0.02090	7	20.46	2	3.59
2021	0.03360	10	32.89	2	5.78
2022	0.04146	13	40.59	3	7.13
2023	0.04799	15	46.98	3	8.25
2024	0.05500	17	53.84	3	9.46
2025	0.06238	19	61.06	4	10.73
Year	Penetration Level (α)	FCS (DS Bus-30, TN node-8)		FCS (DS Bus-46, TN node-19)	
		Rush Hour (λ^{RH})	(AADT)	Rush Hour (λ^{RH})	(AADT)
2016	0.00089	1	0.17	1	0.42
2017	0.00247	1	0.46	1	1.16
2018	0.00548	1	1.03	1	2.58
2019	0.01214	1	2.27	2	5.72
2020	0.02090	2	3.91	3	9.84
2021	0.03360	2	6.29	5	15.81
2022	0.04146	3	7.76	6	19.51
2023	0.04799	3	8.99	7	22.58
2024	0.05500	4	10.30	8	25.89
2025	0.06238	4	11.68	9	29.36

The proposed economical staging plan model is applied in order to obtain the staging plan that optimally matches the estimated traffic volume data. The Benefit to Cost Ratio is then calculated for different markup-charging prices: 50c/kWh, 75c/kWh, and 125c/kWh. We assume in this scenario that the electricity tariff will be the same as Ontario's winter flat rate. Table 6.8 shows the fast charging units required to match the traffic volume data for the 54 – bus 25 – node system for the short-run plan (2016 – 2025) as well as the BCR for each station over the planning horizon. BCRs of less than one are shown in red in Table 6.8.

Table 6-8: The proposed economical staging plan for the coupled 54 – Bus and 25 – node system for low adoption rates (Single-charger)

Year	FCS (DS Bus-4 , TN node-7)				FCS (DS Bus-9, TN node-4)			
	Stage Plan	FC price (50c/kW)	FC price (75c/kW)	FC price (125c/kW)	Stage Plan	FC price (50c/kW)	FC price (75c/kW)	FC price (125c/kW)
2016	1×50kW	0.020	0.030	0.050	1×50kW	0.042	0.063	0.105
2017	1×50kW	0.056	0.084	0.139	1×50kW	0.115	0.173	0.289
2018	1×50kW	0.124	0.186	0.310	1×50kW	0.257	0.385	0.642
2019	1×50kW	0.274	0.412	0.686	1×50kW	0.569	0.853	1.422
2020	1×50kW	0.472	0.709	1.181	1×50kW	0.979	1.469	2.448
2021	1×50kW	0.759	1.139	1.898	2×50kW	0.901	1.351	2.251
2022	1×50kW	0.937	1.406	2.343	2×50kW	1.111	1.667	2.778
2023	1×50kW	1.085	1.627	2.712	3×50kW	0.852	1.278	2.131
2024	1×50kW	1.243	1.865	3.108	3×50kW	0.977	1.465	2.442
2025	2×50kW	0.767	1.151	1.918	3×50kW	1.108	1.662	2.770
	BCR	**0.524**	**0.787**	**1.311**	**BCR**	**0.753**	**1.130**	**1.883**
Year	FCS (DS Bus-12, TN node-14)				FCS (DS Bus-28, TN node-16)			
	Stage Plan	(50c/kW)	(75c/kW)	(125c/kW)	Stage Plan	(50c/kW)	(75c/kW)	(125c/kW)
2016	1×50kW	0.096	0.144	0.240	1×50kW	0.012	0.018	0.030
2017	1×50kW	0.265	0.398	0.664	1×50kW	0.033	0.049	0.082
2018	1×50kW	0.590	0.885	1.475	1×50kW	0.073	0.110	0.183
2019	2×50kW	0.654	0.980	1.634	1×50kW	0.162	0.243	0.405
2020	3×50kW	0.750	1.125	1.875	1×50kW	0.279	0.418	0.696
2021	4×50kW	0.904	1.356	2.260	1×50kW	0.448	0.672	1.119
2022	5×50kW	0.893	1.339	2.231	1×50kW	0.553	0.829	1.381
2023	5×50kW	1.033	1.550	2.583	1×50kW	0.640	0.959	1.599
2024	6×50kW	0.987	1.480	2.467	1×50kW	0.733	1.100	1.833
2025	7×50kW	0.959	1.439	2.398	2×50kW	0.453	0.679	1.131
	BCR	**0.713**	**1.070**	**1.783**	**BCR**	**0.309**	**0.464**	**0.773**
Year	FCS (DS Bus-30, TN node-8)				FCS (DS Bus-46, TN node-19)			
	Stage Plan	(50c/kW)	(75c/kW)	(125c/kW)	Stage Plan	(50c/kW)	(75c/kW)	(125c/kW)
2016	1×50kW	0.018	0.028	0.046	1×50kW	0.046	0.070	0.116
2017	1×50kW	0.051	0.076	0.127	1×50kW	0.128	0.192	0.320
2018	1×50kW	0.113	0.170	0.283	1×50kW	0.285	0.427	0.712
2019	1×50kW	0.251	0.377	0.628	1×50kW	0.631	0.946	1.577
2020	1×50kW	0.432	0.648	1.080	1×50kW	1.086	1.629	2.715
2021	1×50kW	0.695	1.042	1.736	2×50kW	0.999	1.498	2.497
2022	1×50kW	0.857	1.286	2.143	2×50kW	1.233	1.849	3.082
2023	1×50kW	0.992	1.488	2.480	3×50kW	0.945	1.418	2.363
2024	2×50kW	0.585	0.878	1.463	3×50kW	1.084	1.625	2.709
2025	2×50kW	0.664	0.995	1.659	3×50kW	1.229	1.843	3.072
	BCR	**0.445**	**0.667**	**1.112**	**BCR**	**0.835**	**1.253**	**2.089**

The economical staging plan model results show that there are three feasible locations of FCS (TN-node 4, TN-node 14, and TN-node 19) to make profits from FCS projects during a low adoption of PEVs but with high traffic volume of the coupled 54 – bus 25 – node system. According to our analysis, choosing locations of FCS next to highways is the best strategy to deal with FCS projects during the early stage of adoption. Therefore, inter-city locations have a higher priority for installing FCSs than in-city, not only from a technical point of view but also from an economic perspective.

Short-run Planning (Multiple Charging Capacities)

In this scenario, different charging unit capacities are included (50kW, 100kW, and 250kW) in order to lower the investment cost. The proposed staging plan model selects the least-cost combination of fast chargers that match the traffic volume and satisfy the queueing time constraints. Consequently, the quality of service is enhanced with faster charging units, and the profit margin is also improved due to reducing the total investment cost for chargers. The proposed economical staging plan model is applied to the same traffic volume data in Table 6.7, and the results are shown in Table 6.9.

The results show that using multi – charging capacities reduces the number of chargers required, as well as the capital investment cost at the location (DS-Bus 12, TN-node 14), so the benefit to cost ratio is increased after the year 2020, when the penetration level exceeds 2%. The improvement in FCS14's BCR is around 12%, whereas the rest of the locations have the same staging plan as in the previous scenario. Therefore, from an economic perspective, the importance of having multiple charging capacities is associated with higher penetration levels. Figure 6.6 shows a comparison of benefit to cost ratios for the FCS (DS-Bus 12, TN-Node 14) using a single – charging capacity and multi – charging capacity. In the short run, having multiple charging capacities has a limited positive impact on cost-effectiveness, but it has a major positive impact on the quality of charging service.

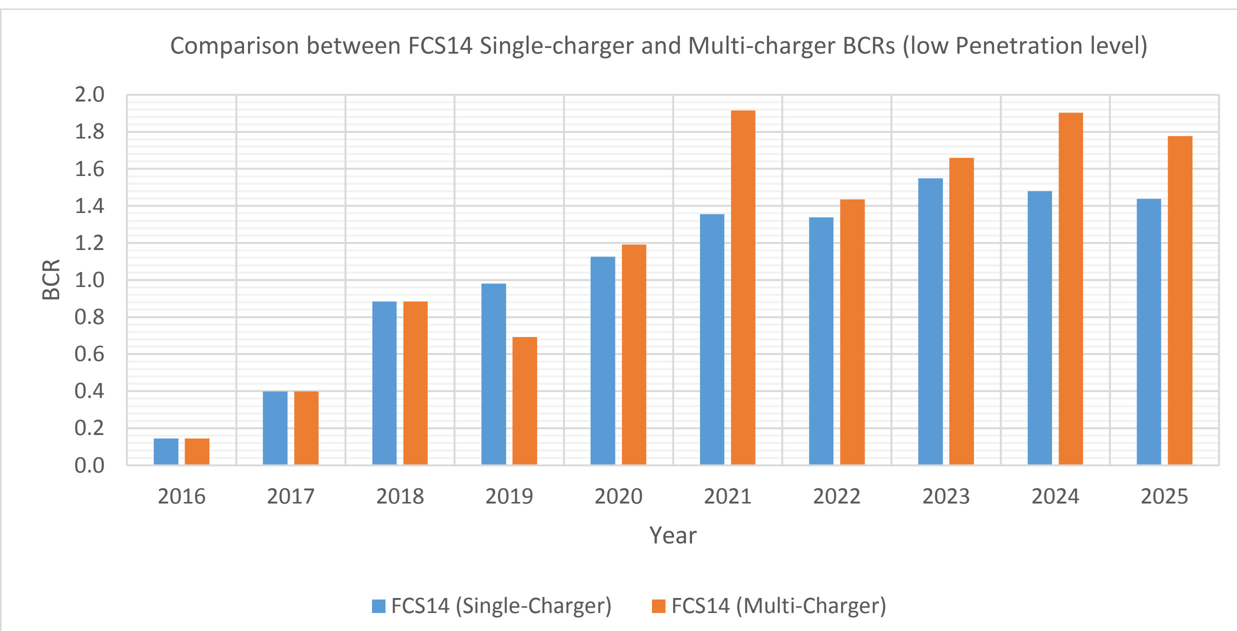

Figure 6-6 Comparison between FCS 14 BCRs of Single – charging capacity and Multiple – charging capacities

Table 6-9: The proposed economical staging plan for the coupled 54 – bus and 25 – node system for low adoption rates (Multiple-charging Capacities)

Year	FCS (DS Bus-4 , TN node-7)				FCS (DS Bus-9, TN node-4)			
	Stage Plan	FC price (50c/kW)	FC price (75c/kW)	FC price (125c/kW)	Stage Plan	FC price (50c/kW)	FC price (75c/kW)	FC price (125c/kW)
2016	1×50kW	0.020	0.030	0.050	1×50kW	0.042	0.063	0.105
2017	1×50kW	0.056	0.084	0.139	1×50kW	0.115	0.173	0.289
2018	1×50kW	0.124	0.186	0.310	1×50kW	0.257	0.385	0.642
2019	1×50kW	0.274	0.412	0.686	1×50kW	0.569	0.853	1.422
2020	1×50kW	0.472	0.709	1.181	1×50kW	0.979	1.469	2.448
2021	1×50kW	0.759	1.139	1.898	2×50kW	0.901	1.351	2.251
2022	1×50kW	0.937	1.406	2.343	2×50kW	1.111	1.667	2.778
2023	1×50kW	1.085	1.627	2.712	3×50kW	0.852	1.278	2.131
2024	1×50kW	1.243	1.865	3.108	3×50kW	0.977	1.465	2.442
2025	2×50kW	0.767	1.151	1.918	3×50kW	1.108	1.662	2.770
	BCR	**0.524**	**0.787**	**1.311**	**BCR**	**0.753**	**1.130**	**1.883**
Year	FCS (DS Bus-12, TN node-14)				FCS (DS Bus-28, TN node-16)			
	Stage Plan	(50c/kW)	(75c/kW)	(125c/kW)	Stage Plan	(50c/kW)	(75c/kW)	(125c/kW)
2016	1×50kW	0.096	0.144	0.240	1×50kW	0.012	0.018	0.030
2017	1×50kW	0.265	0.398	0.664	1×50kW	0.033	0.049	0.082
2018	1×50kW	0.590	0.885	1.475	1×50kW	0.073	0.110	0.183
2019	1×50kW + 1×100kW	0.461	0.692	1.153	1×50kW	0.162	0.243	0.405
2020	1×50kW + 1×100kW	0.794	1.191	1.985	1×50kW	0.279	0.418	0.696
2021	1×50kW + 1×100kW	1.276	1.914	3.190	1×50kW	0.448	0.672	1.119
2022	1×50kW + 2×100kW	0.956	1.434	2.390	1×50kW	0.553	0.829	1.381
2023	1×50kW + 2×100kW	1.107	1.660	2.767	1×50kW	0.640	0.959	1.599
2024	1×50kW + 2×100kW	1.268	1.903	3.171	1×50kW	0.733	1.100	1.833
2025	2×50kW + 2×100kW	1.185	1.777	2.962	2×50kW	0.453	0.679	1.131
	BCR	**0.799**	**1.199**	**1.999**	**BCR**	**0.309**	**0.464**	**0.773**
Year	FCS (DS Bus-30, TN node-8)				FCS (DS Bus-46, TN node-19)			
	Stage Plan	(50c/kW)	(75c/kW)	(125c/kW)	Stage Plan	(50c/kW)	(75c/kW)	(125c/kW)
2016	1×50kW	0.018	0.028	0.046	1×50kW	0.046	0.070	0.116
2017	1×50kW	0.051	0.076	0.127	1×50kW	0.128	0.192	0.320
2018	1×50kW	0.113	0.170	0.283	1×50kW	0.285	0.427	0.712
2019	1×50kW	0.251	0.377	0.628	1×50kW	0.631	0.946	1.577
2020	1×50kW	0.432	0.648	1.080	1×50kW	1.086	1.629	2.715
2021	1×50kW	0.695	1.042	1.736	2×50kW	0.999	1.498	2.497
2022	1×50kW	0.857	1.286	2.143	2×50kW	1.233	1.849	3.082
2023	1×50kW	0.992	1.488	2.480	3×50kW	0.945	1.418	2.363
2024	2×50kW	0.585	0.878	1.463	3×50kW	1.084	1.625	2.709
2025	2×50kW	0.664	0.995	1.659	3×50kW	1.229	1.843	3.072
	BCR	**0.445**	**0.667**	**1.112**	**BCR**	**0.835**	**1.253**	**2.089**

Long-run Planning (Multiple Charging Capacities)

The third scenario is the long-run planning with multi – charger capacities. Different charging unit capacities are included (50kW, 100kW, and 250kW) similar to the previous scenario. The traffic volume at rush hour requires more charging units to satisfy the waiting time constraint during high adoption rates. However, the charging service time can be reduced by using faster charging units; as a result, the waiting time is also reduced with a lower number of charging units but with higher capacities. The least-cost combination of fast chargers that match the traffic volume and satisfy the queueing time constraints are selected by using the proposed staging plan model. Accordingly, the quality of service is enhanced with faster charging units, and the profit margin is also improved due to reducing the total investment cost for chargers.

The proposed economical staging plan model is applied to the traffic volume data in Table 6.10, and the results are shown in Table 6.11.

Table 6-10 The traffic volume data for the coupled 54 – bus and 25 – node system (high adoption rates)

Penetration Level (α)	FCS (DS Bus-4 , TN node-7)		FCS (DS Bus-9, TN node-4)	
	Rush Hour (λ^{RH})	(AADT)	Rush Hour (λ^{RH})	(AADT)
0.05	3	8.53	7	21.21
0.10	6	17.06	13	42.43
0.15	8	25.59	20	63.64
0.20	11	34.12	26	84.85
0.25	13	42.65	32	106.06
0.30	16	51.18	39	127.28
Penetration Level (α)	FCS (DS Bus-12, TN node-14)		FCS (DS Bus-28, TN node-16)	
	Rush Hour (λ^{RH})	(AADT)	Rush Hour (λ^{RH})	(AADT)
0.05	15	48.95	3	8.60
0.10	30	97.89	6	17.20
0.15	45	146.84	8	25.79
0.20	59	195.78	11	34.39
0.25	74	244.73	13	42.99
0.30	89	293.67	16	51.59
Penetration Level (α)	FCS (DS Bus-30, TN node-8)		FCS (DS Bus-46, TN node-19)	
	Rush Hour (λ^{RH})	(AADT)	Rush Hour (λ^{RH})	(AADT)
0.05	3	9.36	8	23.53
0.10	6	18.73	15	47.06
0.15	9	28.09	22	70.59
0.20	12	37.45	29	94.12
0.25	15	46.81	36	117.65
0.30	17	56.18	43	141.18

Table 6-11 The proposed economical staging plan for the coupled 54 – bus and 25 – node system for high adoption rates (Multiple charging capacities)

α	FCS (DS Bus-4 , TN node-7)				FCS (DS Bus-9, TN node-4)			
%	Stage Plan	FC price (50c/kW)	FC price (65c/kW)	FC price (75c/kW)	Stage Plan	FC price (50c/kW)	FC price (65c/kW)	FC price (75c/kW)
5	1×100kW	0.616	0.801	0.924	1×250kW	0.669	0.870	1.003
10	1×100kW	1.335	1.736	2.003	1×250kW	1.472	1.913	2.208
15	2×100kW	1.078	1.402	1.618	1×100kW+1×250kW	1.580	2.055	2.371
20	2×100kW	1.541	2.003	2.311	2×100kW+1×250kW	1.699	2.208	2.548
25	2×100kW	1.926	2.504	2.889	1×50kW+2×100kW+1×250kW	2.007	2.609	3.010
30	1×50kW+2×100kW	1.816	2.361	2.724	1×50kW+3×100kW+1×250kW	2.107	2.739	3.161
α	FCS (DS Bus-12, TN node-14)				FCS (DS Bus-28, TN node-16)			
%	Stage Plan	(50c/kW)	(65c/kW)	(75c/kW)	Stage Plan	(50c/kW)	(65c/kW)	(75c/kW)
5	1×250kW	1.537	1.999	2.306	1×100kW	0.363	0.472	0.545
10	2×250kW	1.691	2.198	2.537	1×100kW	0.787	1.024	1.181
15	3×250kW	1.845	2.398	2.767	2×100kW	0.591	0.768	0.886
20	4×250kW	1.999	2.598	2.998	2×100kW	0.848	1.102	1.272
25	5×250kW	2.152	2.798	3.228	2×100kW	1.136	1.476	1.703
30	6×250kW	2.306	2.998	3.459	1×50kW+2×100kW	1.142	1.485	1.713
α	FCS (DS Bus-30, TN node-8)				FCS (DS Bus-46, TN node-19)			
%	Stage Plan	(50c/kW)	(65c/kW)	(75c/kW)	Stage Plan	(50c/kW)	(65c/kW)	(75c/kW)
5	1×100kW	0.564	0.733	0.845	1×250kW	0.742	0.965	1.113
10	1×100kW	1.240	1.612	1.860	1×250kW	1.632	2.122	2.449
15	2×100kW	1.015	1.319	1.522	1×100kW+1×250kW	1.753	2.279	2.630
20	2×100kW	1.466	1.905	2.198	2×100kW+1×250kW	1.450	1.884	2.174
25	1×50kW+2×100kW	1.550	2.015	2.325	3×100kW+1×250kW	1.443	1.876	2.164
30	1×50kW+2×100kW	1.993	2.591	2.990	4×100kW+1×250kW	1.438	1.870	2.158

The results show that a high penetration level as well as a high traffic volume network are key factors for decision-making for investing in the FCS business. In addition, using multi – charging capacities at locations with a high traffic volume, e.g. highways, is cost-effective in the long run. For example, using 6×250kW chargers in FCS14 at a 30% penetration level, rather than 30×50kW chargers, will reduce around one million dollars from the total investment cost. Accordingly, the BCR will have a huge improvement of up to 42% due to reducing the number of chargers required. Figure 6.7 shows a comparison of benefit to cost ratios for the FCS (DS-Bus 12, TN-Node 14) using multiple charging capacities (Table 6.11) and single charging capacity (Appendix C).

As shown in Table 6.11, our results in terms of traffic volume and the cost of the FCS network are compared for validation purposes with the work in [37], where α equals 20%. The traffic volume captured by our proposed model is almost 9.4×10^7 vehicles/year, compared to 7.3×10^7 vehicles/year in [37], since we used six FCSs rather than five FCSs, as was done in [37]. However, there is a 20% reduction in FCS total investment cost when the staging plan is used, even when using one more FCS.

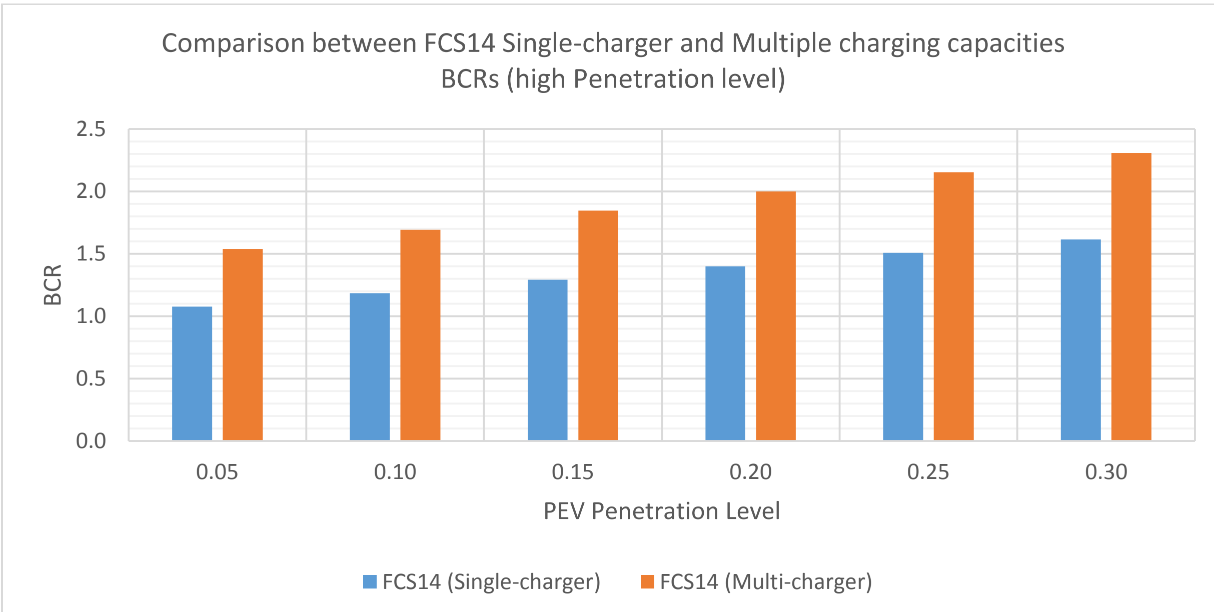

Figure 6-7 Comparison between FCS 14 BCRs of Single and Multiple – charging capacities (high penetration level)

6.5 Chapter assessment

The economical staging plan model to minimize the overall annual cost of investment is developed for planning the implementation of public fast charging systems. The proposed model optimally selects the size of the charging stations and the number of chargers to meet the expected demand of PEVs during rush hours with the minimum associated cost. The capital cost of installing fast charging units, as well as electricity costs, provides insights into investment decisions. The model not only calculates the required numbers of charging units to be installed in the system, but also computes the installation times of the FCS by including PEV demand, price markup and different market structure models.

The economical staging plan model is applied for two coupled distribution and transportation systems and the results are presented and discussed thoroughly in order to demonstrate the feasibility of the developed model and verify the effectiveness of the algorithm as compared to previous work in this area. The presented approach gives investors the opportunity to make a proper trade-off between overall annual cost and the convenience of PEV charging, as well as the proper pricing for public charging services.

Chapter 7
Concluding Remarks

7.1 Summary and Conclusion

The goal of the research in this thesis is to develop a planning model for implementing and constructing electric vehicle charging stations in the distribution system. The research has four main parts: forecasting PEV sales and their correlation with charging station availability; Optimal Location for electric vehicle charging stations; technical evaluation for accommodating PEV loads in the distribution system; and an economical staging model for implementing PEV charging stations.

In Chapter 3, an approach for estimating the key factors that influence the market sales of PEVs was developed using a modified Multiple Logistic regression model (MLRM). The model attempts to describe the correlation between a response variable and number of explanatory variables by fitting a logistic equation to the observed data. The proposed model was utilized to determine the key factors among the numerous factors that jointly influence the dynamics of PEV sales, such as gas prices, electricity rates, available charging infrastructure, vehicle prices, and government incentives. Using historical sales data, the model was able to identify the correlations between the considered factors and PEV market sales in order to evaluate the key factors that influence PEV sales. Electric vehicle charging station availability was introduced to the MLRM as a new explanatory variable, and the proposed model indicated a strong correlation between charging station availability and PEV market sales. A case study of different Canadian provinces was conducted in order to forecast PEV market sales for the period 2016 – 2025.

In Chapter 4, a new PEV charging station allocation model has been presented. The model consists of two parts. In the first part, we investigate the relationship between charging station service range and the probabilities of PEVs completing trips successfully. The proposed trip success ratio model was developed to utilize an MCS to generate virtual trip distances and PEV's remaining electric ranges. It takes into consideration the variations in the driving habits, the battery capacities, the states of charge, and the trip classes. Studying the variations in the above factors allowed us to develop more realistic and accurate model for estimating the trip success ratio for each charging station service range as compared to the literature.

In the second part, different CSSRs were utilized in the allocation optimization problem to optimally locate charging stations in order to include PEV drivers' convenience based on different TSR levels. Instead of using a single service range or Origin-Destination (OD) pair path, we apply the MCLP model to locate the FCSs using different CSSRs. The results showed the differences in quality of service based on their TSR levels, and therefore, the proposed model was able to measure how successful the FCS network is in meeting PEV demand in order to make optimum decisions based on the available resources. Moreover, by using TSR levels, the proposed model considers PEV accessibility in the location problem, so the model outcomes are influenced by drivers' needs rather than only by electric utilities' requirements.

The technical evaluation model was presented in Chapter 5. The proposed model was developed for the planning of public fast charging systems, and it was capable to minimize the overall annual peak demand and energy losses. The ability of distribution systems to absorb PEV demand with the existing infrastructure was fully explored. The optimal power flow (OPF) model was applied to address the technical evaluation of distribution systems. Managing peak system demands and reducing system losses were achieved by shifting some of the charging demand of PEV to FCSs (FCS share). The proposed model was applied for different distribution system and transportation network topologies. The simulation results demonstrated the robust performance of the proposed model to respond to the dynamics of public charging stations in a timely manner. The findings also revealed the effectiveness of the proposed model in providing higher PEV charging success through using different public charging shares. The advantages of the proposed model can thus be summarized as enabling the current distribution system infrastructure to provide charging services with minimum system enhancement, which makes the proposed model suitable for practical implementation even for early adoption rates.

In Chapter 6, using the economical staging plan model, the growth of the public PEV demand was optimally matched with the installed FCS capacity. The proposed model was able to select the size of the charging stations and the number of chargers that would meet the expected demand of PEVs during rush hours with a minimum associated cost. The model was also able to decide when the charging units should be installed. By including PEV demand, price markup, and different market structure models, the proposed planning model was able to provide an extensive economic assessment of FCS projects. Moreover, the quality of FCS service was also considered in the proposed model by including the waiting and service times for charging. Two comprehensive case studies on coupled transportation and electrical networks (23-Bus distribution, 20-node transportation, and 54-Bus distribution, 25-node transportation) are discussed. The results of the two coupled distribution and transportation systems were presented in order to demonstrate the feasibility of the developed model and verify the effectiveness of the algorithm as compared to previous work in this area. The presented approach was able to give investors the opportunity to make a proper trade-off between overall annual cost and the convenience of PEV charging, as well as the proper pricing for public charging services.

7.2 Contributions

The main contribution of this thesis is the development of a planning model to implement electric vehicle charging stations in the distribution network. Associated with this main contribution, several other contributions are also needed to build the model, highlighted as follows:

- The development of a PEV forecasting model that includes the availability of public charging infrastructure as a new explanatory variable. Public charging availability has a strong correlation with PEV sales, so adding this new variable leads to more realistic forecasting approach due to the necessity of public charging facilities to overcome limited PEV driving ranges.
- The development of a Trip Success Ratio (TSR) model based on Monte Carlo Simulation (MCS) to quantify the quality of charging station infrastructure from a driver convenience perspective. The proposed TSR model is used to allocate public charging stations with the consideration of the randomness in the followings: battery capacities, charging activities, driving behaviors, and trip ranges.
- Evaluating a charging station network's ability to meet PEV drivers' convenience using Trip Success Ratio (TSR) as a measure of service quality, since most of the previous work has focused only on power grid requirements.
- By considering home charging and public charging demands with different shares, we were able to evaluate the distribution system's capability to absorb PEV demand with the existing infrastructure.
- The development of an economical staging plan model to match the traffic flow demand of PEVs by deciding the capacities and times of installation of fast chargers. The proposed model considers the quality of charging service in terms of waiting and service times based on a queueing system method.

7.3 Direction for Future Work

In continuation of this work, the following subjects are suggested for future studies:

- Investigating the integration of energy storage systems with the PEV charging system from technical and economic perspectives. The objective of this research is to determine the optimal size of energy storage systems that will provide ancillary active and reactive support services for distribution systems. In this work, the economical staging plan model from Chapter 6 will be modified to include the economic benefit of an energy storage system and its influence on annual investment costs and charging prices.

- Developing dynamic real-time electricity pricing based on smart meters. The objective of this research is to introduce a new TOU pricing system for charging stations that is different from residential TOU pricing in order to manage PEV charging characteristics. Using the customary TOU pricing makes the distribution system unable to control shifts in times and places of charging demand. When public charging prices can compete with residential charging prices, PEV drivers' behaviors will be influenced and charging demand characteristics will be managed. The distribution system will benefit from PEV batteries being movable, as this is a means of managing the demands on the system.
- Developing an integrated power distribution planning approach for distribution systems that includes PEV charging systems, and renewable energy resources. The objective of this research is to develop a comprehensive planning model that is able to minimize the overall annual cost of investment and energy losses and maximizing the traffic flow of PEV charging systems, as well as maximizing the integration of renewable resources. Therefore, the comprehensive planning model should consider power distribution plans, PEV charging system implementation plans, and renewable energy resources implementation plans.

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Appendix A

Table A- 1 Available Electric Vehicles in Canada models and specifications [65]

Model	Make	Type	AVG. RANGE ON ELECTRIC	AVG. COST PER 100KM	AVG. EMISSIONS PER 100KM	ACCELERATION (0-100KM/H)	TIME TO CHARGE	MSRP
i3	BMW	BEV	130 km	$ 2.16	4.9 KG	7.2 sec	3.5 hours	45,300
i8	BMW	PHEV	24 km	$ 7.26	17.0 KG	4.4 sec	2.25 hours	150,000
ELR	CADILLAC	PHEV	60 km	$ 4.74	11.3 KG	9.0 sec	5 hours	80,050
VOLT	CHEVROLET	PHEV	85 km	$ 2.99	6.9 KG	8.4 sec	4.5 hours	39,590
C-MAX	FORD	PHEV	32 km	$ 5.02	11.9 KG	7.9 sec	2.25 hours	37,233
Focus EV	FORD	BEV	122 km	$ 2.57	4.21 KG	11.5 sec	5 hours	27,998
LEAF	Nissan	BEV	172 km	$ 2.36	5.3 KG	9.9 sec	5 hours	37,398
Panamera	Porsche	PHEV	25 km	$8.23	19.3 KG	5.2 sec	2.5 hours	106,600
Model S	Tesla	BEV	435 km	$2.88	6.6 KG	4.4 sec	14.75 hrs.	107,900
Model X	Tesla	BEV	413 km	$2.95	10.8 KG	24.9 sec	12 hours	132,000

Appendix B

Table B- 1 Traffic Data for 20 Node transportation system [36]

Link	Travel Time	Capacity	Link	Travel Time	Capacity	Link	Travel Time	Capacity
1–2	1.2	34.22	8–2	1.8	9.82	11–14	0.6	9.65
1–7	1.2	46.81	8–9	1.5	20	14–13	1.2	4.42
2–1	1.2	25.82	8–7	1.8	9.82	14–11	0.6	9.65
2–3	0.6	28.25	8–12	1.2	9.75	14–20	1.2	10.01
2–8	1.8	9.04	7–1	1.2	46.81	20–14	1.2	6.05
3–2	0.6	46.85	7–8	1.8	9.82	20–19	1.8	10.12
3–4	1.2	13.86	7–17	0.9	51.8	20–16	1.5	10.15
3–6	1.5	10.52	17–7	0.9	51.8	19–20	1.8	10.12
4–3	1.2	9.9	17–18	1.2	10.18	19–16	0.6	10.46
4–5	0.6	21.62	12–8	1.2	9.75	19–18	0.9	9.77
5–4	0.6	9.8	12–13	1.5	10.26	16–13	1.2	20.63
5–6	1	10.1	12–15	1.2	9.85	16–20	1.5	10.15
5–10	1.5	10.09	13–9	1.8	27.02	16–19	0.6	10.46
6–3	1.5	20	13–12	1.5	10.26	16–15	1.2	10
6–5	1	10.1	13–14	1.2	9.64	15–12	1.2	9.85
6–9	0.9	27.83	13–16	1.2	20.63	15–16	1.2	10
9–6	0.9	27.83	10–5	1.5	10.09	15–18	0.6	10.16
9–8	1.5	20	10–9	1.5	10.27	18–17	1.2	11.38
9–13	1.8	27.02	10–11	0.6	10.46	18–19	0.9	9.77
9–10	1.5	10.27	11–9	2.1	9.99	18–15	0.6	10.16
9–11	2.1	9.99	11–10	0.6	10.46			

Table B- 2 Traffic data for 25 - node transportation network

Link	Travel Time	Capacity	Link	Travel Time	Capacity
1–2	1.2	67.2	10–13	1.8	67.2
1–5	1.2	37.5	10–14	1.5	336.2
2–3	1.2	201.7	11–12	1.8	134.5
2–4	0.6	134.5	11–13	1.2	67.2
3–4	1.8	67.2	12–15	1.8	37.5
3–9	0.6	67.2	12–16	0.9	67.2
4–5	1.2	67.2	13–14	0.9	37.5
4–7	1.5	37.5	13–19	1.2	67.2
4–8	1.2	134.5	14–19	1.2	67.2
4–9	0.6	34	14–21	1.5	336.2
5–6	0.6	34	14–22	1.2	336.2
5–7	1	37.5	15–16	1.8	37.5
6–7	1.5	34	16–17	1.5	67.2
7–8	1.5	34	17–18	1.2	201.7
7–11	1	134.5	17–19	1.2	201.7

7–12	0.9	67.2	18–20	1.5	269
8–9	0.9	34	19–20	1.5	67.2
8–10	1.5	134.5	20–21	0.6	269
8–11	1.8	34	22–23	2.1	269
8–13	1.5	37.5	23–24	0.6	269
9–10	2.1	134.5	24–25	0.6	37.5

Table B- 3 AADT for GTA (2006 - 2031) [88]

		2006				2031			
		AADT	DHV	%CV	CV	PM Vol*	Auto AADT	CV AADT	AADT
Niagara to GTA Study Area									
Hwy 403 Hamilton	Hwy 24 to Hwy 52	40,800	9.4%	15.6%	6,365	5,003	52,328	12,000	64,300
	Hamilton 52 to Hwy 6 (Fiddlers Green)	57,800	10.2%	20.0%	11,560	6,528	61,600	21,700	83,300
	Hwy 6 W to Hwy 6 E (York Blvd.)	113,100	10.2%	20.0%	22,620	11,062	104,000	42,500	146,500
	Hwy 6 to QEW (Waterdown Road)	140,400	9.4%	9.0%	12,636	10,858	134,680	23,700	158,400
QEW Halton	Hwy 403/QEW to Guelph Line (Brant St.)	182,000	9.4%	25.0%	45,500	15,969	159,000	85,600	244,600
	Guelph Line to Burloak Dr. (Walkers Ln)	175,800	9.4%	10.0%	17,580	15,321	161,100	33,100	194,200
	Burloak Dr. to Third Line (Bronte Rd.)	171,300	9.4%	9.0%	15,417	18,563	195,650	29,000	224,600
	Third Line to Hwy 403 (Trafalgar Rd.)	175,600	10.6%	10.5%	18,438	18,831	175,420	34,700	210,100
QEW Niagara	Fort Erie to Hwy 420 (McLeod Rd.)	35,000	10.2%	16.5%	5,775	5,353	50,935	10,900	61,800
	Hwy 420 to Hwy 405 (Mountain Rd.)	90,000	9.8%	7.4%	6,660	7,425	83,340	12,600	95,900
	Garden City Skyway Bridge	82,500	12.0%	12.3%	10,148	9,731	79,807	19,100	98,900
	GC Skyway to Hwy 406 (Ontario St.)	90,600	9.8%	10.7%	9,694	10,185	102,695	18,200	120,900
	Hwy 406 to Niagara Bdy (Casablanca)	91,000	9.8%	15.2%	13,832	11,442	114,480	26,000	140,500
	Niagara Bndy to Eastport (Burlington St)	143,100	10.0%	15.1%	21,608	14,931	146,028	40,700	186,700
Hwy 406	QEW to Hwy 58 (Glendale Ave.)	54,200	10.2%	3.0%	1,626	6,761	65,960	3,000	69,000
	Hwy 58 to RR 20 (N. of RR 20)	29,500	10.2%	5.9%	1,741	4,161	40,463	3,200	43,700
	RR 20 to East Main (Port Robinson Rd.)	21,100	10.2%	6.0%	1,266	3,771	36,660	2,300	39,000
Hwy 405	QEW to Queenston-Lewiston Bridge	13,300	9.8%	22.0%	2,926	2,470	24,180	5,500	29,700
Hwy 3	Fort Erie to Hwy 130 (Ridge Rd.)	11,700	9.8%	6.9%	807.3	1,957	19,551	1,500	21,100
	Hwy 130 to Chambers Corners (Townline)	5,000	10.1%	16.5%	825	827	8,350	1,600	9,900
Hwy 6	Hwy 403 to Hwy 5 (Dundas St.)	44,900	10.0%	12.8%	5,747	5,247	51,448	10,900	62,300
	Hwy 5 to Campbellville Rd	31,400	9.4%	12.4%	3,894	4,040	42,048	7,400	49,400
	Campbellville Rd to Hwy 401	24,900	10.0%	14.2%	3,536	2,073	21,364	6,600	28,000
407 ETR NGTA	QEW to Dundas St					10,228	54,288	3,600	57,900
	Dundas St to Bronte Rd					12,374	57,584	4,100	61,700
	Bronte Rd to Hwy 403					10,383	47,350	4,300	51,600
GTA-West Study Area									
407 ETR GTAWest	Hwy 403 to Hwy 401					7,453	43,562	4,200	47,800
	Hwy 401 to Hwy 410					11,626	77,605	8,000	85,600
	Hwy 410 to Hwy 427					18,272	138,900	12,500	151,400
	Hwy 427 to Hwy 400					19,948	146,167	15,800	162,000
Hwy 400	Hwy 9 to King Road (Aurora Rd.)	89,100	9.8%	12.0%	10,692	17,382	175,120	20,100	195,200
	King Road to Hwy 407 (Langstaff Rd.)	135,400	10.1%	7.3%	9,884	15,964	157,590	18,600	176,200
	Hwy 407 to Hwy 401 (Finch Ave.)	194,500	10.2%	8.0%	15,560	19,144	186,760	29,200	216,000
Hwy 401	Hwy 24 to Hwy 6	126,100	10.0%	21.3%	26,859	13,120	125,133	50,500	175,600
	Hwy 6 to Hwy 25 (Milton WL)	104,400	10.0%	25.5%	26,622	12,700	118,455	50,000	168,500
	Hwy 25 to Hwy 407 (Trafalgar Rd.)	129,300	9.4%	16.8%	21,722	16,571	171,392	40,800	212,200
	Hwy 407 to Hwy 410 (Mavis Rd.)	167,500	9.4%	13.8%	23,115	17,565	183,606	43,500	227,100
	Hwy 410 to Hwy 427 (Renforth Ave.)	351,200	9.4%	9.0%	31,608	24,448	319,592	59,400	379,000
	Hwy 427 to Hwy 400	408,000	10.2%	9.5%	38,760	30,740	369,240	72,900	442,100
Hwy 410	Hwy 401 to Hwy 407 (Courtney Park Dr.)	170,600	10.2%	10.0%	17,060	16,046	155,700	32,100	187,800
	Hwy 407 to Hwy 7 (Clark Blvd.)	135,400	10.6%	7.0%	9,478	16,293	152,520	17,800	170,300
	North of Hwy 7 (Williams Parkway)	111,000	10.2%	4.2%	4,662	4,841	106,338	8,800	115,100
Hwy 427	Hwy 401 to Hwy 409 (Dixon Rd.)	186,300	9.4%	8.5%	15,836	14,091	170,465	29,700	200,200
	Hwy 409 to Hwy 407 (Rexdale Blvd.)	123,400	10.6%	8.5%	10,489	17,782	166,530	19,800	186,300
Hwy 403 Mississauga	Hwy 407 to Hurontario St	165,700	10.2%	10.0%	16,570	16,452	159,300	31,200	190,500
	Hurontario St to Hwy 401 (Eglinton Ave.)	180,100	10.2%	15.0%	27,015	16,452	157,250	50,900	208,100
Hwy 6	Hwy 401 to Guelph Limits	27,100	10.6%	17.4%	4,715	3,332	30,562	8,800	39,400
	Guelph Limits to Hwy 7	39,200	10.6%	10.0%	3,920	4,632	43,200	7,400	50,600
Hwy 7	Hwy 6 to Hwy 25 (Wellington Rd. 27)	7600	9.4%	10.3%	782.8	1,375	14,352	1,400	15,800
	Hwy 25 to WC Blvd (Trafalgar Rd.)	18,200	9.4%	8.6%	1,565	2,318	24,678	2,900	27,600

Table B- 4 Lane Deficiencies along Highway 401 Corridor [88]

Highway	Location	Existing Lanes	Planned Lanes	Required Lanes	Lane Deficiency
401	Guelph to Highway 25	6	8	10	2
	Highway 25 to Highway 407	6	10+HOV	14	2
	Highway 407 to Highway 410*	8	12+HOV	14	-
	West of Highway 427	12	12	14	2
	West of Highway 400	14	14	16	2

Appendix C

Table C - 1 The economical staging plan for the coupled 54 – bus and 25 – node system for high adoption rates (Single charging capacity)

α	FCS (DS Bus-4 , TN node-7)				FCS (DS Bus-9, TN node-4)			
%	Stage Plan	FC price (50c/kW)	FC price (65c/kW)	FC price (75c/kW)	Stage Plan	FC price (50c/kW)	FC price (65c/kW)	FC price (75c/kW)
5	1×50kW	1.130	1.469	1.695	3×50kW	0.781	1.015	1.171
10	2×50kW	1.224	1.591	1.836	5×50kW	1.030	1.339	1.546
15	3×50kW	1.318	1.714	1.978	7×50kW	1.204	1.566	1.807
20	4×50kW	1.413	1.836	2.119	9×50kW	1.353	1.759	2.030
25	5×50kW	1.413	1.836	2.119	11×50kW	1.490	1.937	2.235
30	6×50kW	1.413	1.836	2.119	13×50kW	1.621	2.108	2.432
α	FCS (DS Bus-12, TN node-14)				FCS (DS Bus-28, TN node-16)			
%	Stage Plan	(50c/kW)	(65c/kW)	(75c/kW)	Stage Plan	(50c/kW)	(65c/kW)	(75c/kW)
5	5×50kW	1.076	1.399	1.615	1×50kW	0.666	0.866	1.000
10	10×50kW	1.184	1.539	1.776	2×50kW	0.722	0.938	1.083
15	15×50kW	1.292	1.679	1.937	3×50kW	0.722	0.938	1.083
20	20×50kW	1.399	1.819	2.099	4×50kW	0.777	1.011	1.166
25	25×50kW	1.507	1.959	2.260	5×50kW	0.833	1.083	1.249
30	30×50kW	1.615	2.099	2.422	6×50kW	0.888	1.155	1.333
α	FCS (DS Bus-30, TN node-8)				FCS (DS Bus-46, TN node-19)			
%	Stage Plan	(50c/kW)	(65c/kW)	(75c/kW)	Stage Plan	(50c/kW)	(65c/kW)	(75c/kW)
5	1×50kW	1.034	1.344	1.550	3×50kW	0.866	1.126	1.299
10	2×50kW	1.137	1.478	1.705	5×50kW	1.143	1.486	1.714
15	3×50kW	1.240	1.612	1.860	8×50kW	1.169	1.520	1.753
20	4×50kW	1.344	1.747	2.015	10×50kW	1.039	1.351	1.559
25	5×50kW	1.447	1.881	2.171	12×50kW	1.082	1.407	1.624
30	6×50kW	1.550	2.015	2.326	15×50kW	1.113	1.447	1.670