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UNIVERSITÉ DE MONTRÉAL

MANAGING STRESS OF ELECTRIC VEHICLES ON SMART GRIDS

SAEEDEH BARGHI-NIA

DÉPARTEMENT DE GÉNIE ÉLECTRIQUE

ÉCOLE POLYTECHNIQUE DE MONTRÉAL

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Ce mémoire intitule :

MANAGING STRESS OF ELECTRIC VEHICLES ON THE SMART GRIDS

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a été dûment accepté par le jury d'examen constitué de :

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DEDICATION

This thesis work is dedicated to my husband, Ebrahim, who has been a constant source of support and encouragement during the challenges of graduate school and life. A very special thank you for your practical and emotional support as I added the roles of wife and then mother, to the competing demands of business, work, study and personal development. I am truly thankful for having you in my life.

This work is dedicated to my son, Danial who has made me stronger, better and more fulfilled than I could have ever imagined. I love you to the moon and back.

This work is also dedicated to my parents, my mother, and my late father, both of whom gave me the foundation of something they had never enjoyed – education. Ever since then, I have been able to appreciate the value of reading and lifelong learning., who have always loved me unconditionally and whose good examples have taught me to work hard for the things that I aspire to achieve.

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I would also like to thank my thesis committee members, Prof. Roland P. Malhamé and Prof. Catherine Morency, for their contributions to this work that each has given me superb scientific guidance, many insightful suggestions and demonstrated a sincere interest in my work. I feel extremely lucky and humbled to have had the opportunity to learn from such an impressive and supportive committee.

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RÉSUMÉ

Chaque jour, les attentes des consommateurs d'énergie augmentent en termes de fiabilité du réseau et d'impact environnemental de l'énergie. Au-delà d'avoir d'assurance que tous leurs appareils électroniques seront fournis, les consommateurs veulent bénéficier des technologies qui peuvent les responsabiliser et leur permettre de maîtriser leur énergie. Pour répondre à ces attentes croissantes, la façon dont l'énergie est produite, distribuée et consommée doit évoluer. La solution implique à la fois une demande plus intelligente et un approvisionnement plus intelligent.

L'un des plus grands défis de la feuille de route pour le réseau intelligent est la responsabilité (et l'obligation, dans de nombreux cas) de combiner les sources d'énergie existantes avec l'énergie alternative afin de réduire l'impact sur l'environnement et de sécuriser l'énergie. La nature variable de la plupart des énergies renouvelables, ainsi que l'émergence de nouvelles charges importantes comme les véhicules électriques (VE), peuvent compliquer les équilibres de charge sur les lignes, conduisant à une instabilité de la tension et même à des défaillances.

VEs offrent une solution efficace et concrète pour réduire l'empreinte carbone du transport, mais ils représentent également un nouveau type de demande pour les services publics. Comme les maisons, les entreprises et toute autre source d'énergie électrique, les VEs doivent être gérés de manière efficace et responsable par les services publics sur le réseau. De plus, parce qu'ils ont le potentiel à la fois de consommer et de produire de l'énergie, les VEs deviennent une partie inextricable de la gestion de la demande.

La possibilité d'un déploiement à grande échelle de VEs pose d'importants obstacles aux services d'électricité selon la façon et le moment de la facturation des VEs. Ce nouveau mode de transport et l'infrastructure nécessiteront des solutions de gestion de l'énergie fiables et sûres. Il est nécessaire de veiller à ce que les VEs et l'infrastructure de recharge soient sûrs, pratiques, économiques et écoénergétiques pour les conducteurs et les opérateurs de services publics. De plus, les gestionnaires de réseau doivent s'assurer qu'ils sont capables de gérer les impacts de la recharge des VE sur le réseau et qu'ils peuvent intégrer la consommation de ces nouvelles charges dans la demande de charge des services publics sans problème. Certainement, les VEs peuvent créer des avantages pour les services publics si leur intégration est correctement effectuée. Ce projet présente une étude approfondie et se concentre sur la gestion du stress accru des VE sur les réseaux de distribution. C'est un problème hautement stochastique et la méthode appliquée dans ce travail est

basée sur des modèles stochastiques. Le modèle stochastique proposé est appliqué à un distributeur urbain d'une grande entreprise d'électricité canadienne. Deux scénarios de recharge de VE, de charge incontrôlée et contrôlée, sont simulés et analysés.

ABSTRACT

Every day, the expectations of energy consumers increase in terms of grid reliability and energy's environmental impact. Beyond having the assurance that all of their electronic devices will be supplied, consumers want to benefit from the technologies that can empower them and put them in control of their energy. To address these growing expectations, the way energy is produced, distributed, and consumed must evolve. The solution involves both smarter demand and smarter supply.

One of the biggest challenges on the roadmap to the smart grid is the responsibility (and obligation, in many cases) to combine established power sources with alternative energy in order to lower the impact on the environment and to secure additional energy for the future. The variable nature of most renewable generation, as well as the emergence of significant new loads like Electric Vehicles (EVs), can complicate load balances on lines, leading to voltage instability and even failures.

EVs offer an effective and concrete solution for reducing the carbon footprint of transportation, but they also represent a new type of demand for utilities. Like homes, businesses, and any other electric power source, EVs must be effectively and responsibly managed by utilities on the grid. Moreover, because they have the potential to both consume and produce energy, EVs are becoming an inextricable part of Demand Management.

The possibility of large-scale deployment of EVs raises significant obstacles for electric utilities depending on how and when EVs are charged. This new mode of transportation and the infrastructure will require reliable and safe energy management solutions. It is necessary to ensure that the EVs and the charging infrastructure are safe, convenient, economical, and energy efficient for drivers and utility/system operators. Additionally, system operators must ensure that they are able to manage the impacts of EVs charging on the grid and also that they can integrate the consumption of these new loads into utility load demand without issue. Certainly, EVs can create benefits for utilities if their integration is properly done. This project presents an extensive study and is concentrated on the managing of the increased stress of EVs charging on the distribution networks. This is a highly stochastic problem and the applied method in this work is based on stochastic models. The proposed stochastic model is applied to an urban distribution feeder of a

large Canadian power utility. Two EV charging scenarios, uncontrolled and controlled charging, are simulated and analyzed.

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LIST OF SYMBOLS AND ABBREVIATIONS

AMI	Advanced Metering Infrastructure
BEV	Battery EV
CC	Coordinated Charging
CCCV	Constant Current/Constant Voltage
CPPS	Cyber-Physical Power System
DG	Distributed Generation
DOD	Depth of Discharge
DS	Distribution System
DSO	Distribution System Operator
EV	Electric Vehicle
GFCI	Ground Fault Circuit Interrupter
GV	Gridable Vehicle
G2V	Grid-to-Vehicle
ICE	Internal Combustion Engine
LCC	Life Cycle Cost
MCS	Monte Carlo Simulation
MSRP	Manufacturer's Suggested Retail Price
PHEV	Plug-in Hybrid Electric Vehicle
PEV	Plug-in Electric Vehicles
SOC	State of Charge
UC	Uncoordinated Charging
V2G	Vehicle-to-Grid

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CHAPTER 1 INTRODUCTION

Electric power systems and especially distribution systems (DS) have started to change drastically. One of the basic functions for modernization of the grid, i.e. a smart grid, is allowing for the integration of all energy generation and storage options, including plug-in electric vehicles (PEV) or in general electric vehicles (EVs). One of the major changes is a transformation of the transportation sector with the use of electricity and introduction of EVs. EVs are linking energy consumers and producers via the smart grid. According to the European Federation for Transport and Environment (T&E) and also US energy Information administration (eia), transportation is responsible for more than 30% of CO2 emissions [1].

EVs represent a challenging new element of energy demand, and they must be properly integrated to bring balance and efficiency to the power system. EVs are soon expected to grow in popularity as a low emission mode of transportation as compared to conventional vehicles. They reduce dependence on imported petroleum and potentially provide consumers a lower cost alternative to gasoline [2]- [3].

EVs offer an effective and concrete solution for reducing the carbon footprint of transportation, but they also represent a new type of demand for utilities. EVs must be effectively and responsibly managed by utilities on the grid, like any other electric power source. Moreover, because they have the potential to both consume and produce energy, EVs are becoming an inextricable part of Demand Management [4].

1.1 Choice of Phenomenon/Problem Studied

Plug-in hybrid electric vehicles (PHEVs) are a new and upcoming technology in the transportation and power sector. As defined by the IEEE, these vehicles have a battery storage system of 4 kWh or more, a means of recharging the battery from an external source and the ability to drive at least 10 miles in the all-electric mode [2]. PHEVs essentially work with a combination of two power sources, i.e., batteries and gasoline. They are an extended version of current hybrid EVs including a battery with larger autonomy and able to connect to the grid to be charged. Compared to hybrid EVs, the advantages of PHEVs are fuel flexibility and a larger electric-only

driving range. PHEVs might be a fast and temporary solution until more advanced EVs technologies become mature [3].

Figure 1.1 schematically shows the general differences between conventional, hybrid, plug-in hybrid and all electric vehicles:

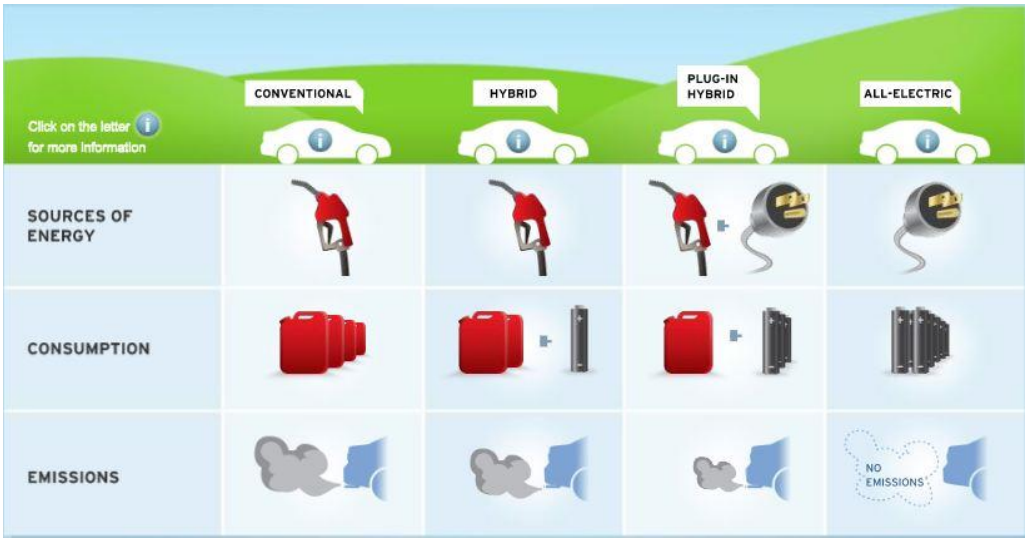


Figure 1.1: Conventional, Hybrid, Plug-in Hybrid and All Electric Vehicles [5]

However, this great change will pose new challenges and opportunities for electric distribution companies. Actually, because of their potentially massive number, EVs will not only constitute a potentially significant proportion of the DS load, but they will even have to be considered as part of the distribution grid of the future [6].

The EV penetration level determines the total number of EVs, i.e. the total number of EV batteries that need to be charged in the DS. The penetration level refers to the ratio of EVs to the total vehicles in a given area [7]. As an increasing number of EVs enter the market, the effects of adding large numbers of power electronic devices to the grid become more and more predominant. So, penetration level of EVs will certainly have a drastic impact on the distribution grid [8].

The number and variety of EVs batteries connecting to the electrical DS is expected to grow rapidly, presenting a potential burden on local power companies. In order to adequately prepare for the increase in load demand and provide support through technical standards and trade regulations, utilities and government organizations must be able to predict the EVs battery charging loads under various scenarios and evaluate the ability of existing power systems to accommodate them [7].

According to the IEEE Standard, PEVs or PHEVs can be considered both as load and source/storage to provide power back to the grid to balance energy supply. PEVs are considered as a load when they are stationary and energy is drawn from the grid to charge their batteries. Proper dimensioning of the utilities distribution networks with PEV adoption forecast is important to avoid unexpected peaks of energy consumption when charging PEVs [9].

As PEVs are developed, distribution system operators (DSOs) become responsible for realizing the required network upgrades to supply the PEV charging points. In addition, similarly to distributed generation (DG), DSOs have little control on the location of future PEV charging points or stations, and no direct control over periods and frequency of PEV charging. As a consequence, the network expansion planning problem will become more complicated due to a high degree of uncertainty [3].

The impacts that these aspects of PHEVs will have on distribution networks have been measured and calculated by multiple authors in different locations using many different tools that range from analytical techniques to simulations. While much work has already been completed in this area, there is still much to do.

Previous works on the topic have focused on economic models, economic incentives [10] and load/charging profiles [11]-[12] for these new vehicles, but little work has been done to assess the impact of EVs on the DS itself. As these new vehicles will constitute a significant new load on the power grid while commanding significant changes to the infrastructures, it is necessary to develop tools that will allow assessing their impact on DS, mostly regarding the management of daily load consumption profiles. Then, strategies must be explored in order to make easier the transition towards today's situation and a high penetration level of EVs in DS, which is expected to occur over the next decade [13]. Taking advantage of the smart grid communication facilities and/or of the inherent energy storage ability of batteries present in EVs are all options to consider in order to maximize the benefits that EVs can provide to society [8].

The main goal of this project is to establish a methodology for modeling and analyzing the load demand in a DS due to EV battery charging in order to assess the impact of this new stress on DS. This is done by considering high penetration rates of EVs in the power system and by proposing strategies to mitigate the new problems and turn them into opportunities.

1.2 Literature Review

The impact of charging of PHEVs on a typical distribution feeder in Blacksburg, VA is analyzed in [14]. The network consists of five homes and two PHEVs, which are Chevy Volts. Two charging strategies are considered: charging of all PHEVs at 6 P.M. and charging of all PHEVs at off-peak hours. The first case represents the worst case and results in a transformer load increase by 68% in winter and 52% in summer. The second case results in a transformer load increase by 58% in winter and 52% in summer. Since none of these scenarios results in transformer overloading, the cases are reexamined using quick charging with a higher voltage outlet in order to charge the PHEVs in less time. This results in a transformer overload only when the quick charging starts at 6 P.M. The final investigated scenario involves five PHEVs per distribution transformer. As this obviously overloads the transformer, two new charging methodologies are suggested: PHEV stagger charge and household load control. Stagger charge staggers the charging time of PHEVs while household load control allows consumers the choice to shed some non-essential loads in order to recharge their PHEV more quickly. The conclusion of this paper is that the addition of PHEVs creates a new load for the distribution grid, but this load should be manageable through advanced and smart techniques such as the advanced metering infrastructure (AMI). Despite this conclusion, the authors suggest further research into large fleets and their effect on the distribution grid. The strength of this paper is: it uses a very simple system for its analysis: five homes, two PHEVs and one 25 kVA feeder. It builds PHEV load curves based on battery charge and discharge characteristics, then it proposes and tests multiple charging scenarios and it incorporates smart charging techniques. These are all important traits that any PHEV study should include. The paper lays a strong base for future studies of PHEVs on the DS.

The impact on the Belgium distribution grid through the analysis of current Belgium traffic and driving patterns is discussed in [15]. The important section of this paper analyzes the load flow analysis when PHEVs are added in a distribution grid. Three different cases of uncontrolled charging are examined: i) charging between midnight and 2 A.M., ii) charging between 6 and 8 P.M. and iii) charging during the day. These charging profiles are tested on a 34-node IEEE test feeder across low and high load scenarios in both summer and winter with four different penetration levels of PHEVs: 0%, 10%, 50%, and 100% The paper concludes that the integration of PHEVs deeply affects the power losses and voltage deviations in the distribution grid and that these

changes cannot be ignored, especially in a small country like Belgium. The impacts of PHEVs on the distribution grid must be measured and quantified in order to preserve the reliability of the electric grid.

A quadratic and dynamic programming model is developed in [16] for assessing the impacts of PHEVs on the distribution grid of Belgium when PHEVs are charging at home. Both deterministic and stochastic methods are used in this paper. The input variables in both cases are the daily/hourly load profiles. The load profiles are static in the deterministic case. In the stochastic case, the load profiles are transformed into probability density functions and are used to generate 2000 different loading scenarios that are optimized and compared. Both give similar results, but the quadratic programming is more accurate as it works over a continuous solution space while the dynamic programming method works over a discrete solution space. In order to determine impacts on the distribution grid, the simulation is running for two different scenarios: uncoordinated charging and coordinated ‘‘smart’’ charging. The losses for the distribution grid during uncoordinated charging are not negligible, while coordinated charging has not such impacts on the DS. The paper concludes that PHEV charging must be coordinated via operators and other multi-agent-systems in order to maintain the integrity of the distribution grid while reducing power loss and voltage drop.

The electrical power required for charging a fleet of PHEVs in Belgium has been determined in [12]. A stochastic model based on the driving behavior of Western European drivers, determines the availability of the PHEVs for grid charging. Three scenarios are defined to generate charging profiles based on the driving profiles. The first two scenarios, defined as uncoordinated charging (UC), are based on a continuation of the current tariff schemes available to residential users, i.e. a single electricity tariff or a double electricity tariff including day and night tariffs. In the third scenario, coordinated charging (CC) is proposed. When CC is applied, the time of charging is shifted to a more appropriate moment of the night where total electrical load is minimal. The charging of a fleet of PHEVs, as expected for Belgium in 2030, will impact the electricity producers. If charging were to be uncoordinated, peak power would rise substantially while base power would increase only a little. The grid would need upgrades for the higher power levels and new peak power plants would need to be built. Demand side management can minimize the impact of charging and may curtail some of the costs of UC. For CC there will be less need for grid modifications because peak power increases only 30MW. The proposed CC method offers the PHEV user many advantages: low electricity cost under the constraint of maximum electrical

driving share while at the same time offering electricity producers, transmitters and distributors advantages too: no extra peak demand, more base load and less variable load. Smart meter technology can be used for implementing CC.

An evaluation of the loading of PHEVs on DS of Hydro-Quebec is studied in [11]. The distribution network itself is designed to accommodate cold load pickup during long winter outages. The calculated PHEV load is 2400 kWh per year per vehicle, the same load as a water heater. Based on the number of cars in Quebec, at 25% penetration, this would be a 2.4 TWh load per year for all PHEVs, less than 1.3% of Hydro-Quebec's generation capacity. The model presented is deterministic and takes into account thermal loading, voltage regulation and transformer loss of life based on a full array of PHEV characteristics (battery type, charger efficiency, battery state of charge (SOC), and charging profiles). The deterministic model is run in order to identify asset sensitivities to new loads. For instance, the model predicts that transformers' life will be maintained while service transformers and three-phase primary lines are the most vulnerable assets to the higher loads caused by PHEVs. The model also shows that the key factor affecting the distribution grid is the charging profile (voltage and power level).

A basic framework for analyzing the impact of PHEVs on local DS is developed in [17]. In order to issue consistent results, the model is applied to multiple utility distribution circuits. The model calculates thermal loading, voltage regulation, transformers' loss of life, unbalance, power losses and harmonic distortion levels for multiple scenarios in both deterministic and stochastic methods. Using OpenDSS, the paper concludes that the distribution grid tends to increase as the penetration of PHEVs increases. This paper also examines what time scale should be considered when evaluating the impact of PHEVs on the distribution grid. As this paper studies only through year 2010, it must be considered that both short and long term analysis must be completed. Short-term analysis will allow utilities to prepare for immediate impacts while longer-range studies will allow utilities to adjust and accommodate future usages and loads.

A study of the necessary energy requirements for conversion of U.S. light duty vehicles into PHEVs while also studying the effect it could have on emissions as well as the impact that this change will have on the grid is undertaken in [18]. While this paper draws many conclusions regarding energy requirements and emissions across the 12 NERC regions, these conclusions are not discussed here as they are out of the scope of this masters' thesis. Regarding PHEVs' impact

on the DS, this study suggests that supplying 73% of the energy requirements of the U.S. light duty fleet of vehicles would add an additional load of 910 billion kWh to the electrical grid. This would force the grid to operate at nearly full capacity at all hours of every day. This effectively flattens the current peak and valley load that is on the grid and could have a huge impact on reliability while also forcing up wholesale electricity prices (due to demand) and encouraging the development of a new generation of technologies that are less expensive. This would also most likely mean the eventual use of planned outages in order to perform plant maintenance. Smart charging and vehicle-to-grid (V2G) technology are suggested as possible solutions to these issues.

A detailed analysis of the economical benefits of PHEVs is examined in [10]. A typical PHEV is assumed to be driven 33 miles per day and is charged using electricity from the grid. Analysis is performed using life cycle cost (LCC) analysis for consumers and electricity cost for utilities. While admitting that more economic analysis needs to be done, this paper concludes that there are economical benefits for both consumers and utilities with regards to off-peak charging of PHEVs.

The effects of PHEV penetration on generation expansion are studied in [19]. This paper uses the National Energy Modeling System (NEMS) tool and suggests examining four different charging profiles, all at high PHEV penetration levels. These charging profiles include uniform charging, home-based charging, off-peak (9 P.M. to 11 A.M.), and V2G charging. The authors also assume that all PHEV batteries are capable of driving 20 miles and the average consumer drives 33 miles per day. One interesting assumption made is that only 75% of PHEVs can be charged electronically at any given time due to possible infrastructure restrictions (i.e. charging stations not in place, etc.). All simulations are run across the entire U.S. The paper concludes that while all charging methodologies produce a need for new sources of power generation while the V2G charging plan causes the smallest capacity expansion and the smallest infrastructure cost.

A detailed discussion on the impacts of PHEVs on the power grid is developed in [20]. This study suggests that there may be three main impacts from PHEV integration into the power grid: i) an increase in transformer temperatures due to increased load, ii) reduced wear-and-tear on the transformer bushings due to flattened load and iii) increased harmonics due to PHEV power electronics. While the first two impacts may be able to offset each other (reduced wear-and-tear will compensate financially for decreased lifetime due to the increased load), there is concern that power harmonics could have a major impact on transformers. The remainder of the paper develops

a mathematical model for examining these impacts and concludes that the impacts will be widely varied in different parts of the power grid.

In [21], it has been mentioned that the main sources of today's carbon emissions are from the electricity and transportation infrastructures. An objective of a cyber-physical power system (CPPS)[1] is to integrate renewable energy sources and gridable vehicles (GVs) to minimize operation cost and maximize emission reduction. A cyber-physical energy system consists of renewable energy, GVs and conventional thermal units. PEVs can be used as loads, sources and energy storages in a CPPS. A smart grid is a large CPPS and takes into account all the conventional and green distributed energy resources, dynamic data from sensors and smart operations needed (e.g. charging/discharging, control, etc.) from/to the grid in order to reduce both operation cost and carbon emission. If a large number of PEVs are connected to a smart grid randomly, peak load might be very high. The use of conventional thermal power plants to sustain electrified transportation will be economically expensive and environmentally unfriendly. Intelligent scheduling and control of energy system elements have great potential for evolving a sustainable, integrated electricity and transportation infrastructure. Three cases listed below were studied to illustrate the effect of PEVs in an integrated electricity and transportation infrastructure:

Case 1: Random Model: PEVs are charged/discharged randomly;

Case 2: Intelligent Dynamic Load-Leveling Model: PEVs are charged from conventional generation using load-leveling[2] optimization;

Case 3: Smart Grid Model: PEVs are charged from the grid with renewable energy sources at off-peak hours and discharged to the grid at peak hours.

The smart grid model is thus a promising approach for sustainable integrated electricity and transportation infrastructure whereas the random mode is not practical. Excess load from PEVs is

[1] Cyber-Physical Power Systems (CPPS) consist of significant cyber components that manage the physical electric power infrastructure under distributed control of power electronics devices. This represents a departure from more centralized SCADA-type control.

[2] A method for reducing the large fluctuations that occur in electricity demand, for example by storing excess electricity during periods of low demand for use during periods of high demand.

intelligently distributed to off-peak hours using optimization in the intelligent dynamic load-leveling model.

A methodology for modeling and analyzing the load demand in a DS due to EV battery charging has been presented in [7]. The method is stochastically formulated in order to consider the stochastic nature of the start time of individual battery charging and the initial battery SOC. The EV load demand can be dictated to some extent by the electricity tariff structure. Three types of typical electricity tariff structures are considered: fixed electricity rate, time-of-use electricity rate, and real-time electricity rate. The fixed electricity rate refers to the tariff in which energy charge per kWh remains constant regardless of the time of use. Time-of-use electricity price divides the tariff into two main blocks: off-peak and on-peak price. The real-time price, i.e., the electricity rate per kWh varies by time of day and month of year.

Four EV charging scenarios have been developed in this paper, comprising uncontrolled domestic charging, uncontrolled domestic off-peak charging, smart domestic charging and uncontrolled public charging. Since not all EVs in the DS start charging simultaneously, it is assumed that the time of switching on an individual charger is a random variable, with a probability density function, which is determined by the electricity tariff structure and the pattern of vehicle usage. The initial SOC of the EV battery (residual capacity since last charge) is also assumed to be a random function of the total distance it travels since it was last charged. The distribution of initial SOC can be assumed therefore to have a probability density function. The value of SOC varies from zero to the full capacity of the battery.

The electricity tariff structure, vehicle traffic patterns (usage) and battery types are global variables: the structure of electricity tariff and vehicle traffic patterns determine the start time of EVs battery charging load; the traffic patterns (daily mileages) determine the residual battery capacity since last charge, i.e., the initial SOC before recharging; while the battery types determine the charging characteristics. The smart charging method that optimizes the start time and the number of batteries starting charging at each time interval is the most beneficial to both the distribution network operator and EV customers. However, starting charging simultaneously during the peak load time will impose a new peak to the power system. In addition, EV can introduce a new peak or near peak load in early off-peak period.

A comprehensive approach has been proposed in [3] for evaluating the impact of different levels of PEV penetration on distribution network investment and incremental energy losses. A large-scale distribution network planning model has been used for the calculation of the required network investment with different future levels of PEV penetration. Each distribution area is defined by its size and location. The total population, the location and demand of consumers are also known. The base case distribution network in each distribution area considers that no PEV is connected yet. Three scenarios, representing PEV penetration levels of 35%, 51%, and 62%, have been modeled. These penetration levels would be achieved by 2020, 2030 and 2050, respectively. In addition, two different modes of PEV charging are considered: normal and fast. A behavior pattern of charging and driving hours is also assumed for PEVs. For each PEV penetration scenario, the operation of the electric distribution network is analyzed at peak and off-peak hours. The number of connected PEVs and modes of charging are different for peak and off-peak hours. The large-scale planning distribution model computes quasi-optimal reinforcements to the base case network in case they are needed to connect and to supply the load required by PEVs. This model also computes incremental energy losses with respect to the base case due to PEV charging. In addition to the number and type of PEV in each scenario, it is needed to define their connection and charging patterns at peak and off-peak hours. In this paper, it is assumed that 85% of the PEVs are charging at off-peak hours and most of them in a slow or normal charge mode. At peak hours, it is assumed that 40% of the PEVs are connected, 90% are charging, some of them in a fast charging mode and 10% are injecting power into the grid. This approximation is based on EPRI's studies [20]. The possibility of V2G has been also considered. Under this mode, a percentage of the total PEVs are modeled as injecting energy into the grid at peak hours when electricity prices are higher assuming that time-of-use tariffs are implemented. The considered rated power for this operation mode goes from 3 to 10 kW.

1.3 Project Objective

The main goal of this project is to establish a methodology for modeling and analyzing the load demand in a DS due to EV battery charging in order to assess the impact of this new stress on DS. It is done by considering high penetration rates of EVs in the power system and by proposing strategies to mitigate the new problems and turn them into opportunities.

The questions to be answered fall in three categories:

1) EVs as electric loads

- How much consumption represents the load of EVs?
- What are the expected charging periods?
- Are there optimal charging strategies?

2) Distribution Networks

- Are existing networks capable to feed the expected consumption?
- Will distribution energy losses increase significantly by adding EVs as a load?

3) Generation and System Operation

- How much should we increase the installed capacity?
- Could EVs provide storage capability and ancillary services to improve system operation?

1.4 Methodology

The modeling required to integrate EVs as loads within the distribution grid is of great importance, since the validity of the results are only as good as the models that are used [14]. The models presented in this project, are based on the physical behavior of EV batteries (EV charging model [16]), but in order to treat the diversity that is naturally present in large populations of EVs, we build in details our statistical distributions that are representative of these populations, considering the diversity in battery types, random SOC of the batteries, type of charge (level I, II or III), etc. [23].

There is also the need to develop statistical mobility models for EVs, based on typical driving patterns (origin, destination, distance traveled in a day, etc.). This allows determining the DS from which the EVs draw their electricity (mobile load) [2], as well as the temporal load profiles

associated to EVs [11]. Socio-economical data are also required in order to forecast the penetration rate of EVs in different geographic territories. All data above are of course related to power system data, which also exhibit time-dependent probabilistic fluctuations. The fusion of these two layers of probabilistic events (temporal fluctuation of load and temporal fluctuation of vehicles' location) represents a major modeling challenge, and it forms the core of the originality of this work.

CHAPTER 2 INVENTORY OF EVS AND CHARGING OPTIONS

It is universally accepted that gasoline engines cannot be the long-term solution for transportation and that EVs combined with green generation sources is the only sustainable way to address this issue. Indeed, environmental concerns will unavoidably lead to an electrification of the transportation sector. Hence it is just a matter of time before EVs become the most popular means of transportation. The barrier that slows down their penetration is the high cost of the batteries, but despite this fact, EVs already provide consumers with a lower energy and operating cost than gasoline engines, and therefore offer a way to reduce dependence on petroleum. The purpose of this chapter is to introduce most kinds of EVs that have been commercialized and entered in the Canadian market, as well as charging options and charging profiles. However, the information on EVs shown in this chapter does not represent a rule to be followed. It collects the common specifications observed in the EV industry. Actually, it can be a survey to use in researches regarding EVs and their impacts on the power systems (smart grids), environment, etc.

2.1 Electric Transportation

Petroleum products presently power Internal Combustion Engines (ICEs) to provide 95% of the world's motorized movement of people and freight. The use of petroleum products to fuel ICEs providing land transportation is likely to decline during the next several decades and be replaced chiefly by electric traction. There are two strong reasons for moving away from the use of oil products as the main fuel for transportation: reduced availability of oil and avoidance of climate change [23]-[25].

Late in 2010 the first mass-produced EVs hit dealer showrooms, bringing car buyers a new, electric option. Electric cars offer performance, safety and versatility and can be charged from the electric grid, providing convenient, low-cost and at-home charging. Displacing gasoline with electricity also lowers emissions and decreases petroleum use. On a typical day half of all drivers log 40 km or less, so EVs, if widely adopted, could reduce petroleum fuel consumption by 70- 90% [26].

The market for EVs in North America is growing as Canadians and Americans look for cleaner and more efficient vehicles. Research confirms that consumers in North America are willing to pay

more for an EV if the environmental benefits are significant. In Canada, it is expected that these benefits can be achieved because the majority of electricity in Canada is generated from renewable and low-emission sources [24].

This chapter contains valuable information regarding the commercial EVs, their components, types, electrical specifications and charging methods. The information was taken from manufacturers technical web sites.

2.2 Electricity as an Alternative Fuel for Land Transportation

Electricity and electric motors figure strongly in comparison to oil and ICEs. Electric traction has numerous advantages in addition to causing less local and global pollution and obviating dependence on oil. These advantages include the following [24]:

- **Efficiency**

Electric motors convert up to 90% of applied energy to traction. Gasoline engines normally convert no more than 30% of applied energy and diesel engines convert up to 40%.

- **Torque**

Electric motors provide maximum output (torque) at zero or near-zero revolutions, i.e. when it is most required. An ICE's maximum torque is typically delivered at several hundreds or thousands of revolutions per minute, requiring gearing to move a stationary vehicle. Electric motors' high torque at low speeds contributes to their superior performance in stop-start conditions and during acceleration from low speeds (electric-drive systems can require simple gearing to provide high speeds).

- **Regenerative braking**

Electric motors can capture kinetic energy during deceleration, storing it as electrical energy and thereby reducing energy consumption and mechanical brake wear.

- **Power per unit weight or unit volume**

For a given power output, electric motors are much smaller than ICEs, even without the ICEs' required emission control systems. Electric motors' higher power/weight ratios mean less energy is required to move traction systems and more room is available within the vehicles.

- **Simplicity**

Electric motors typically have one or a few moving parts. ICEs usually have hundreds of moving parts. In principle, EVs are thus more reliable and cheaper to maintain (from a mechanical point of view).

- **Silence**

Electric motors are almost silent in operation. ICEs harness controlled explosions of fuel and air mixes. They are intrinsically noisy, adding to urban stresses.

- **Storage of grid energy in vehicles (V2G)**

The storage devices in EVs, in principle, can be used as storage for the electric grid, potentially reducing requirements for peak generation.

- **Flexibility as to ultimate energy source**

EVs that use externally supplied electricity (e.g. Battery EVs (BEVs), PHEVs) are indifferent as to how the electricity is generated. Nothing has to change inside the vehicle if the fuel for electricity generation changes. Such EVs are thus readily compatible with a transition to renewable generation. ICEs, by contrast, usually need substantial modification to accommodate change of the energy source(s) for which they were designed.

2.3 Types of Vehicles

There are three key types of EVs: Hybrid EVs (HEV), PHEV, and BEV [26].

HEVs contain a small electric battery to supplement the standard ICE. They use a dual-fuel system. Both the electric motor and the ICE are able to drive the wheels. The battery is recharged both by the gasoline engine and regenerative braking. Regenerative braking captures kinetic energy to charge batteries when the driver pushes the brakes. This provides increased fuel efficiency. HEVs cannot be recharged from the grid.

PHEVs are dual-fuel vehicles. This means that both the electric motor and the ICE can be used in this type of vehicles. The added feature of a plug-in is the ability to charge from an electric outlet to extend the use of electricity as a fuel. PHEVs have a smaller combustion engine and a larger battery pack compared to HEVs. Batteries can be charged by the gasoline engine, regenerative

braking and by plugging into the grid. This generally allows for more use of the electric motor and less use of the petrol / gasoline engine.

BEVs are all-electric, have no ICE, and are totally dependent on plugging into the electric power grid. They are powered by an electric motor and battery alone. BEVs can travel farther on electricity than PHEVs, but their total range is more limited. BEVs never use gasoline and most models are designed to travel up to 100 miles between charges.

In this work, we consider only the PHEV and BEV types of EVs which are the ones consuming electricity from the power grid. In order to be able to determine the diversity in battery types, we use the information of several types of EVs.

2.4 Challenges and Opportunities for EV Stakeholders

The future widespread adoption of the PEV will present some unique opportunities for consumers, auto manufacturers, and utility operators. However, responses to the different stakeholders' questions and concerns must be found for the EV to truly take off. Effective energy management solutions will be needed to make the EV an alternative to traditional combustion-engine-powered vehicles. Purchasing an EV is a major decision for many consumers. Industry partnerships, public programs, and consumer education from electric utilities, vehicle manufacturers, and energy professionals will be essential to ensuring that drivers have access to the information, equipment, and trained professionals they need to enjoy their EVs safely, cost-effectively, and conveniently [1].

- **Safety**

Safety is perhaps the biggest question in consumers' minds. Consumers need to be informed about how to charge their vehicles at home safely, avoiding electrical hazards and other dangers like falls caused by stray power cords. With emerging standards, charging equipment will meet tough safety requirements developed and tested to avoid these dangers.

- **Cost**

Cost is another concern in the minds of consumers, who may wonder about the impact of EV charging on their home energy bill, the cost of any necessary equipment upgrades, and who is responsible for financing these upgrades. Away-from-home charging is another issue. How much

will it cost? How will consumers pay? There are utilities in US actively working on promoting an incentive to own an EV by offering an EV rate.

- **Convenience**

Convenience is not to be underestimated as a major factor in consumers' EV purchasing decisions. "Range anxiety" has long been cited as a stumbling block to EV adoption. Consumers need to know how far they can go on a charge, where to recharge (At home? At work? In public places like shopping centers?), and how long it will take.

Once consumers overcome these barriers to EV adoption, they can begin to reap the benefits of cleaner, quieter, cheaper transportation without sacrificing safety or convenience.

2.5 Selected Electric Vehicles & their Comparisons

Because most EVs have batteries with at least slightly different charging profiles and because it is very unlikely that consumers in any area own one single type of EV from a single company, we must consider the distribution of different types of vehicles and batteries in fleets of EVs. This is extremely important as manufacturers compete with each other based on battery life, charging time and charge duration. The determination of the right mix of vehicles must also be based on socio-economic data in a given geographical area [27].

Most car manufacturers are currently working on the development of the electric car. Some models are already being marketed and in circulation and a wide range of models will be available during the next few years. There are more than 28,000 electric cars on the road in Canada and among them, there are 21 different models [28].

In this project, we are using the information of 21 EVs, i.e. 13 PHEVs and 8 BEVs models. The 13 selected PHEVs are: Audi E-Tron, BMW e330, BMW i8, BMW X5 40e, Chevrolet Volt, Chrysler Pacific PHEV, Ford C-Max Energi, Ford Fusion Energi, Hyundai Sonata PHEV, Mercedes Benz S 550e, Porsche Cayenne S E-Hybrid, Porsche Panamera S E-Hybrid, and Volvo XC90 Twin Engine. The 8 selected BEVs are: BMW i3, Chevrolet Bolt, Ford Focus Electric, Kia Soul EV, Mitsubishi i-MiEV, Nissan Leaf, Tesla Model S and Tesla Model X.

In Figure 2.1, the selected EVs are shown and ordered based on their battery capacities.



Figure 2.1: Selected EVs in our case studies [28]

Tables 2.1 and 2.2 show the most relevant information about those EVs. They were taken from manufacturers' web sites and may certainly change rapidly over time:

Table 2.1: Performance Comparison of the Introduced EVs

Name	Category	Electric Motor Power	Engine Power (hp)	Top Speed	Acceleration (0-100 kM/h)	Starting Price (MRSP)[3]
Audi E-Tron	PHEV	75 kW	204 hp	220 km/h	7.6 s	45,900.00 CAD
BMW 330e	PHEV	65 kW	247 hp	225 km/h	5.4 s	52,100.00 CAD
BMW i3	BEV	125 kW	170 hp	150 km/h	7.2 s	47,300.00 CAD
BMW i8	PHEV	98 kW	362 hp	250 km/h	4.4 s	150,000.00 CAD
BMW X5 40e	PHEV	83 kW	308 hp	210 km/h	6.8 s	74,000.00 CAD
Chevrolet Bolt	BEV	150 kW	200 hp	145 km/h	7 s	42,895.00 CAD
Chevrolet Volt	PHEV	111 kW	149 hp	160 km/h	8.4 s	39,590.00 CAD
Chrysler Pacific PHEV	PHEV	---	248 hp	---	---	56,495.00 CAD
Ford C-Max Energi	PHEV	68 kW	141 hp	164 km/h	7.9s	39,729.00 CAD
Ford Focus Electric	BEV	107 kW	143 hp	135 km/h	8.6 s	31,998.00 CAD
Ford Fusion Energi	PHEV	68 kW	141 hp	136 km/h	7.9 s	36,399.00 CAD
Hyundai Sonata PHEV	PHEV	50 kW	202 hp	N/A	N/A	43,999.00 CAD
Kia Soul EV	BEV	81 kW	109 hp	145 km/h	11.5 s	35,395.00 CAD
Mercedes Benz S550e	PHEV	85 kW	436 hp	210 km/h	5.2 s	102,600.00 CAD
Mitsubishi i-MiEV	BEV	47 kW	66 hp	130 km/h	11.5 s	27,998.00 CAD
Nissan Leaf	BEV	80 kW	107 hp	150 km/h	9.9 s	37,398.00 CAD
Porsche Cayenne S E-Hybrid	PHEV	71 kW	333 hp	243 km/h	5.9 s	89,400.00 CAD
Porsche Panamera S E-Hybrid	PHEV	71 kW	416 hp	268 km/h	5.2 s	106,600.00 CAD
Tesla Model S	BEV	283 kW	417 hp	249 km/h	4.4 s	95,300.00 CAD
Tesla Model X	BEV	386 kW	762 hp	249 km/h	6.2 s	132,000.00 CAD
Volvo XC90 Twin Engine PHEV	PHEV	65 kW	400 hp	230 km/h	5.6 s	73,400.00 CAD

[3] MSRP: Manufacturer's Suggested Retail Price

Table 2.2: Electric Specification Comparison of the Introduced EVs

Name	Category	Battery Capacity	Time to Charge[4]	Electric Range	Total Range
Audi E-Tron	PHEV	8.4 kWh	2.5 hrs	26 km	665 km
BMW 330e	PHEV	7 kWh	2 hrs	22 km	358 km
BMW i3	BEV	33 kWh	6.25 hrs	160 km	240 km
BMW i8	PHEV	7 kWh	2.0 hrs	24 km	509 km
BMW X5 40e	PHEV	9 kWh	3 hrs	28 km	695 km
Chevrolet Bolt	BEV	60 kWh	9.5 hrs	383 km	383 km
Chevrolet Volt	PHEV	18 kWh	4.5 hrs	85 km	675 km
Chrysler Pacific PHEV	PHEV	16 kWh	2 hrs	53 km	911 km
Ford C-Max Energi	PHEV	8 kWh	2.25 hrs	32 km	856 km
Ford Focus Electric	BEV	21 kWh	4 hrs	122 km	122 km
Ford Fusion Energi	PHEV	7.2 kWh	2.5 hrs	34 km	884 km
Hyundai Sonata PHEV	PHEV	9.8 kWh	2.7 hrs	43 km	925 km
Kia Soul EV	BEV	27 kWh	4.5 hrs	149 km	149 km
Mercedes Benz S550e	PHEV	8 kWh	2 hrs	22 km	724 km
Mitsubishi i-MiEV	BEV	16 kWh	5 hrs	100 km	100 km
Nissan Leaf	BEV	30 kWh	5 hrs	172 km	172 km
Porsche Cayenne S E-Hybrid	PHEV	11 kWh	3 hrs	22 km	772 km
Porsche Panamera S E-Hybrid	PHEV	9 kWh	2.5 hrs	25 km	850 km
Tesla Model S	BEV	90 kWh	12 hrs	435 km	435 km
Tesla Model X	BEV	90 kWh	12 hrs	413 km	413 km
Volvo XC90 Twin Engine PHEV	PHEV	9.2 kWh	2.5 hrs	22 km	563 km

[4] *Time to charge* is the average time to charge the battery with the available Level 2 (240V charger), which uses a voltage similar to household appliances, like ovens and dryers.

Emission and cost to drive comparison of the introduced EVs are shown in Appendix A.

2.6 Charging Options

Driving patterns produce an impact on the distribution grid simply by defining where PEVs will be when they are charged. A typical daily drive for any person starts at home, goes to work, maybe to lunch, back home, then possibly out for a small trip to the store. This means that at any moment during the day, a PHEV can be in the garage, in an employer's parking lot, in a restaurant/store parking lot, or on the road. This suggests studying where PEVs will be when charging. The main locations for charging and some of their characteristics are provided below.

- **Charging at home**

Home is the most economical location for charging an EV. Typically, vehicles spend most of the night at home, making it an ideal place and time frame to charge.

- **Charging at work**

EV users will likely be concerned about having enough charge to get back home. They will want to charge their vehicles at work, especially those who are near the limit of the vehicle's range.

- **Charging at public places**

EV owners will appreciate the convenience of charging at public places to ensure enough range is available to complete all their errands. Retail store and restaurant owners have an opportunity to attract customers by providing charging stations.

According to Hydro-Quebec, the main charging site for EV owners will be at home. At night, vehicles are parked there for a number of hours.



Figure 2.2: Charging options in Quebec [5]

At the current time, it is expected that more than 80% of EV charging will be done at home. Therefore, in the model presented in this project, we assume that the vehicles can charge only when they are at home.

2.7 Charging Characteristics

Charging characteristics are simply the loading characteristics of EVs in different locations. Charging characteristics typically incorporate the type of circuit, the voltage drawn, the load added on the power system and the duration of the charge [2]. It is important to include these characteristics in our investigations in order to build accurate models of EVs.

2.7.1 Electrical Ratings

In North America, there are three charging levels or modes, defined according to their output (see Table 2.3) [29]. Two levels are defined by SAE J1772 [30]. Level 1 corresponds to a voltage of 120V AC and Level 2 to a voltage of 208 or 240V AC. At present, only the CHAdeMO-JEVS[5] is used for charging at a higher rate [29].

Table 2.3: Comparison of Charging Levels/Modes

Characteristic	Level 1	Level 2	CHAdeMO
Voltage	120 V	208 or 240 V	Up to 500 V
Type of Current	AC	AC	DC
Typical Output	1.4 kW	3.6 or 7.2 kW	50 kW
Maximum Output	1.9 kW	19.2 kW	50 kW
Charge Time	12 hrs[6]	2.5-5 hrs	20 min[7]
Connector	J1772	J1772	CHAdeMO

[5] A standard for fast charge stations promoted by a Japanese association. “CHArge de MOve” (charge for moving). In Japanese, CHAdeMO evokes the phrase.

[6] Charge time for a fully discharged 16 kWh battery, at the typical output (120 V).

[7] 80% of full charge, i.e., 12 kWh. The CHAdeMO standard does not allow full recharging.

Typical charging parameters that are usable in a North American residence are provided in Table 2.4:

Table 2.4: Typical Charging Parameters in North America

Station Type	Outlet Voltage	Cable Current	Station Output
Level 1	120 V	12 A	1.4 kW
Level 2	240 V	15-A Station (2 pole 20-A breaker)	3.6 kW
Level 2	240 V	30-A Station (2 pole 40-A breaker)	7.2 kW

Hydro-Quebec and its partners have begun rolling out a network of public charging stations to help improve the autonomy of EVs. CAA-Quebec is a partner in this initiative. EV drivers enjoy greater freedom with the ability to charge their vehicles during their travels.

The ideal place to recharge the vehicle, however, is at home. Installation of home charging stations is now possible because all EVs sold in North America come equipped with an SAE J1772 receptacle. This coupling system allows for vehicle recharging using 120V or 240V household alternating current.

- **Level 1 (120V) charging stations**

Level 1 charging station connects to any standard 120V outlet; 89% of households in Quebec already have access to a standard outlet (level 1 charge) at their parking spaces [29]-[31]. So, Quebec is already well positioned to meet residential charging demand. The charging station looks like a large pistol attached to a cable. It takes 6 to 8 hours to fully charge a PHEV, and 11 to 16 hours for a BEV. The electrical demand is comparable to that of a 1.5 kW air conditioner [29].

- **Level 2 (240V) charging stations**

Charging time can be cut in half with a Level 2 station. This requires a dedicated 240V circuit permanently connected to the household electrical distribution panel [29]-[31].

With a 3.6 kW charging station (the type most often used at present), charging a PHEV takes between 3 and 4 hours, while charging a BEV takes from 6 to 8 hours. The electrical demand with this system is about the same as for a 40-gallon water heater.

- **Installing a level 2 charging station**

EV owners can buy a wall-mount or freestanding (pedestal-mount) Level 2 charging station from a dealership, a certified electrician or a hardware store. Most can be installed either inside or outside. The job of connecting the charging station to the household electrical panel, however, must be done by a qualified electrician [31].

- **Safety in EV charge station**

There is some safety precautions about using such a powerful electrical connection. All charging stations are equipped with a ground fault circuit interrupter (GFCI), which reduces the risk of electric shock [29]. Also, electricity will not flow through the plug's connector pins unless the plug is correctly inserted into the receptacle on the vehicle. The coupling connector is equipped with weather-tight seals, and a retention component keeps it from disconnecting if someone or something accidentally pulls on the cable [29]-[31].

Since we chose to consider only home charging, and since all EVs sold in North America equipped with a SAE J1772 receptacle can be charged either at 120V or 240V, data in Table 2.6 can all be used when considering realistic charging conditions.

2.8 State of Charge of EV Battery

The SOC corresponds to the remaining charge of the battery divided by its maximum charge. It is a direct measure of the remaining stored energy. The SOC is affected by battery operating conditions such as load current and temperature [32].

2.9 Depth of Discharge

The depth of discharge (DOD) is the percentage of battery capacity (rated capacity) to which a battery is discharged. The withdrawal of at least 80% of battery (rated) capacity is referred to as deep discharge. It should be noticed that the initially fully charged battery is discharged until 20% SOC is reached. After reaching 20% SOC, the battery is operated in the charge sustaining cycle [32].

2.10 Charging Stages of EV Battery

Lithium-ion is the top technology for EV batteries due to a combination of performance capability, safety, life and cost. Currently, several battery-charging strategies have been proposed with the development of EVs. Among them, the constant current/constant voltage (CCCV) charging technique is the mostly popular type. In the CCCV charging process, the battery is charged at CC until the battery voltage reaches its upper cutoff voltage. Then the battery switches to a CV charging process until the current reaches a predetermined small value (3% of the rated current) [33].

The charging stages of Lithium-ion batteries are illustrated in Figure 2.3 [34]:

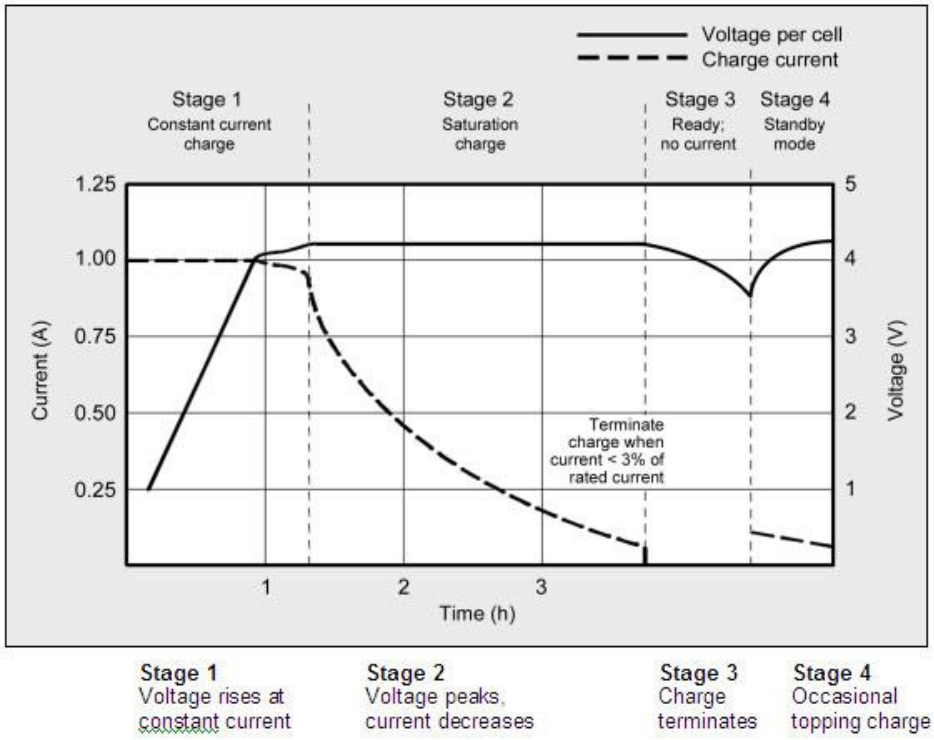


Figure 2.3: Charging stages of Lithium-ion batteries [34]

Battery charge profile of EVs can be determined based on the charge current model of Lithium-ion batteries in Figure 2.3.

2.11 EV Battery Charging Profile

A generic trapezoidal charging model for EV batteries is used all along this project. Details of the selected battery charge profile is explained in chapter 4.

CHAPTER 3 DRIVING PATTERNS & MOBILITY INFORMATION

As already mentioned in the previous chapter, driving patterns have an impact on the electric network by defining where PEVs will be when they are charged. So, it is necessary to study where PEVs are located when charging. The truth of the matter is that the final destination of most driving patterns is highly stochastic, but the average mileage driven during any given day has been determined to be roughly 26 miles (~ 42km) per day [2]. Thus, the majority of papers calculated the daily driven distance by using this statistic. In order to handle the randomness of the locations of the PEVs, multiple studies simply place the PEVs randomly across radial distribution networks.

There is a need to develop statistical mobility models for PEVs, based on typical driving patterns (origin, destination, distance traveled in a day, etc.). This allows determining the distribution networks from which the PEVs draw their electricity (mobile load) [2], as well as the temporal load profiles associated to EVs [11]. Socio-economical data are also required in order to forecast the penetration rate of EVs in different geographic territories.

We are interested in using stochastic models of driving. In other words, instead of using average and expected values for the number of miles driven per day, we will use stochastic models across multiple simulations in order to get a more realistic picture and analysis of this situation.

All data above are of course related to power system data, which also exhibit time-dependent probabilistic fluctuations. So, there would be the combination of these two layers of probabilistic events (electric load data and vehicles mobility data) that demonstrates our major modeling challenge.

3.1 Studied Network

The sector under investigation is supplied by a large 120/12 kV urban substation located in the Montreal area, Canada. The substation supplies 16 distribution feeders and more than 18,200 customers. The simulations realized in the project targeted one particular distribution feeder supplying 3621 clients through 43 transformers.

The map of this area (distribution substation of DeLorimier in Montreal) which has been prepared by HydroQuebec, is shown in Figure 3.1:

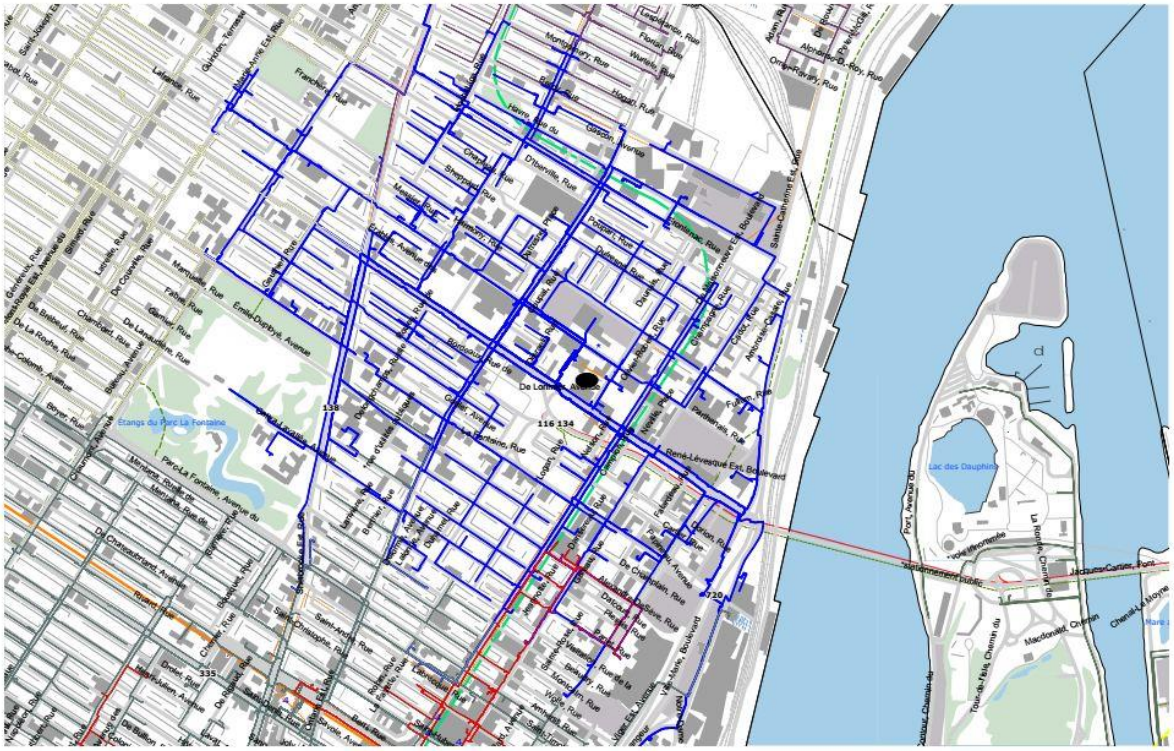


Figure 3.1: Area covered by the Delorimier substation in Montreal

Appendix B shows another layout of the studied area.

3.2 Source of Mobility Data

The main source of the mobility data used in this project is the Origine-Destination survey, conducted in Montreal in 2008, and aimed at providing a quite accurate picture of most important displacements habits of people, namely: origin, destination, trip purpose, transportation mode, and departure/arrival hours [37]. In this survey, some socio-economical variables were also collected, for instance the annual income of families, ages of people at a given address, etc. Figure 3.2 shows the sampling realized in the selected case study area.

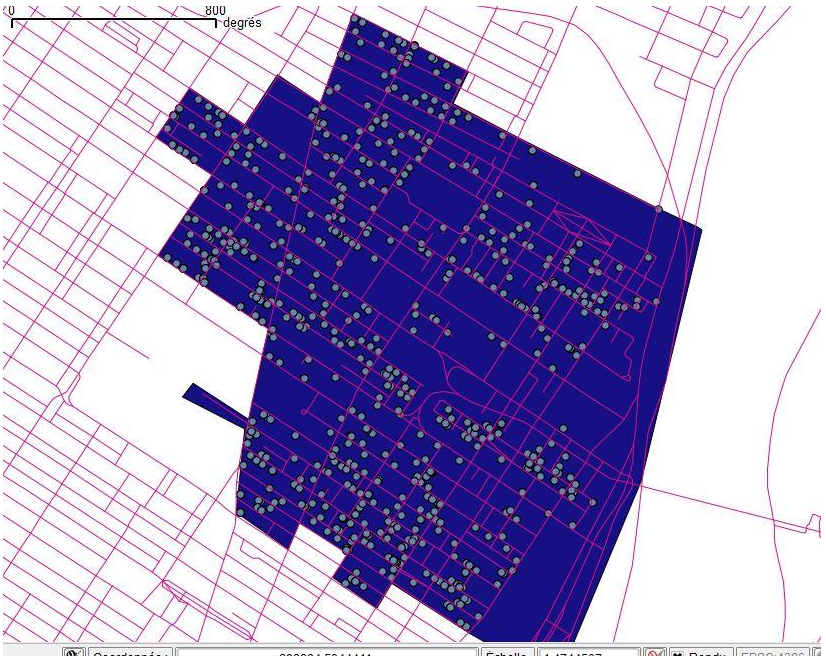


Figure 3.2: Sampling used for the mobility survey in the area supplied by the considered substation

3.3 Statistical Data of the Selected Area

We computed the main information about the residents of this area by their transportation data. The main information is in excel file format and the required information are extracted via Matlab code. They are explained completely here.

- **Distribution of houses in the area**

The number of houses in this area is 21879. The number of residents per house is presented in Table 3.1 and the income level of residents is presented in Table 3.2.

Table 3.1: Number of Houses with Different Number of Residents

No. of Residents Per House	One	Two	Three	Four	Five	Six and More
No. of Houses	12019	6967	1625	950	219	99
% No. of Houses	54.94%	31.84%	7.43%	4.34%	1%	0.45%

Table 3.2: Number of Houses with Different Income Levels

Household Income	< $20k	$20k-$40k	$40k-$60k	$60k-$80k	$80k-$100k	> $100k	unknown
No. of Houses	4832	5309	3145	1854	1076	1021	4643
% No. of Houses	22.08%	24.27%	14.37%	8.47%	4.92%	4.67%	21.22%

- **Distribution of population in the area**

The number of residents in this area is 37767. Table 3.3 presents the number of people in different categories, like gender and driving license holders. The number of people with different ages is shown in Table 3.4 and the number of people with different occupation is presented in Table 3.5.

Table 3.3: Number of Population in Different Categories

	Female	Male	Driving License Holders
No. of People	16440	21326	22403
% No. of People	43.53%	56.47%	59.32%

Table 3.4: Number of People with Different Ages

Age Ranges (Years Old)	0-4	5-9	10-14	15-19	20-24	25-34
No. of People	1117	973	1057	1243	4145	9367
% No. of People	2.96%	2.58%	2.79%	3.29%	10.98%	24.80%

Age Ranges (Years Old)	35-44	45-54	55-64	65-74	>= 75
No. of People	6623	5156	3581	2239	2266
% No. of People	17.54%	13.65%	9.48%	5.94%	5.99%

Table 3.5: Number of People with Different Occupations

Occupation	Full Time Job	Part Time Job	Students or Pupils	Retired	Other	at Home	Children (4+)
No. of People	17818	2468	7097	5564	1572	2177	1071
% No. of People	47.18%	6.53%	18.79%	14.73%	4.16%	5.77%	2.84%

Children 4+ is considered for children who are before educational process.

- **Distribution of vehicles in the area**

The number of vehicles in this area is 11575. Table 3.6 presents the number of houses with different number of vehicles.

Table 3.6: Number of Houses with Different Number of Vehicles

No. of Vehicles	0	One	Two	Three	Four	Five +
No. of Houses	12154	8323	1172	119	60	51
% No. of Houses	%55.55	%38.04	%5.36	%0.54	%0.28	%0.23

- **Distribution of trips and trip distances and trip times in the area**

The number of total trips made by the population living in this area, is 80867.

The number of trips by using vehicles in this area is 23953 or 29.62%. This includes the car driver plus car passenger trips.

Based on this survey, we could generate various statistical distributions for the mobility patterns, as shown in Figures 3.3, 3.4, 3.5 and 3.6 [27].

Distribution of the daily trip distances in this area are shown in Figures 3.3 and 3.4. Figure 3.4 indicates the lognormal probability density function (pdf) of the trip distances that is held by car owners in this area.

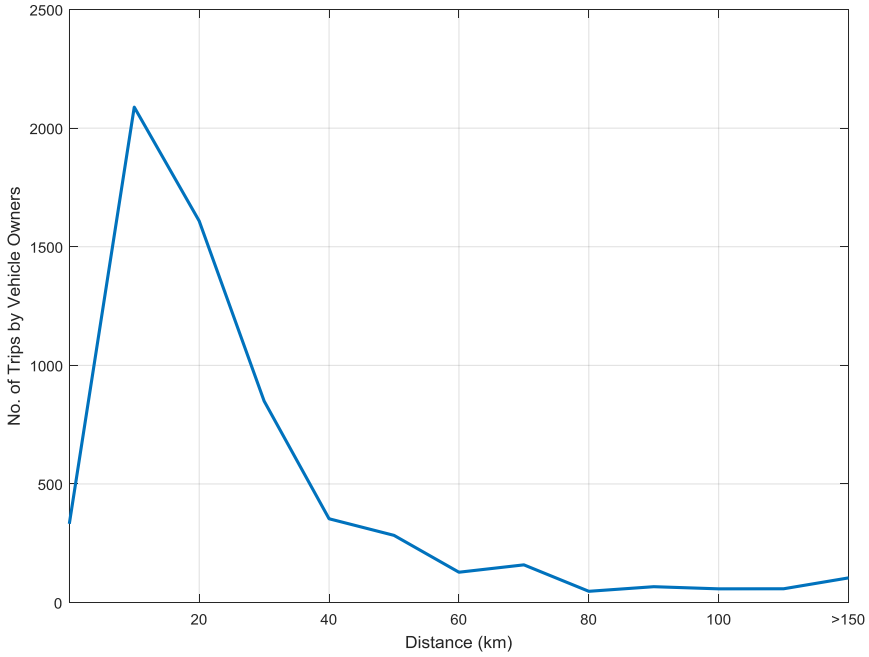


Figure 3.3: Distribution of daily trip distances by vehicle owners

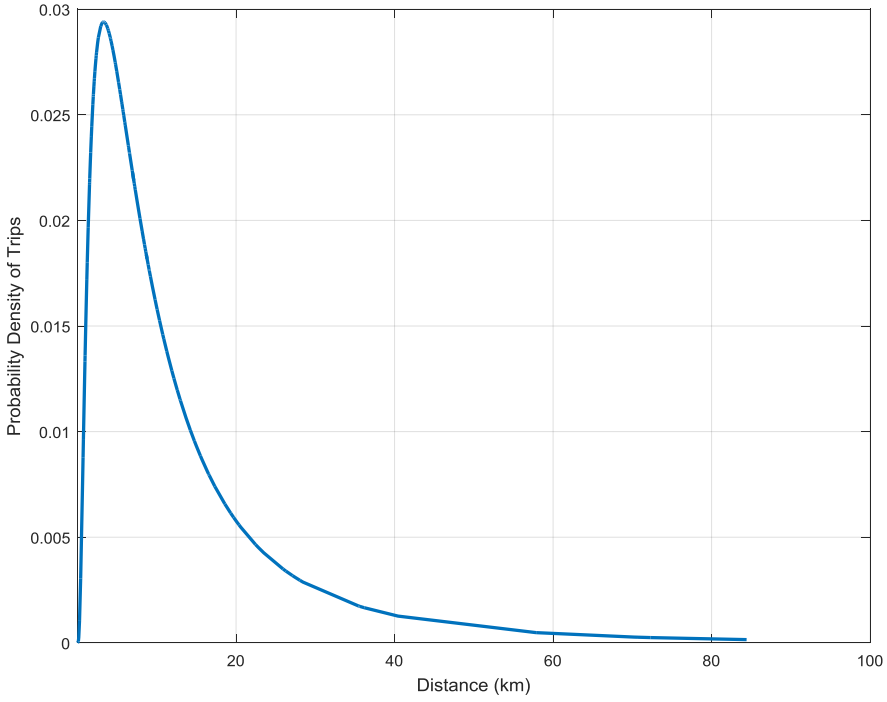


Figure 3.4: Probability density function of vehicle daily trip distance

Figure 3.5 shows the distribution of departure time from home in the hourly interval.

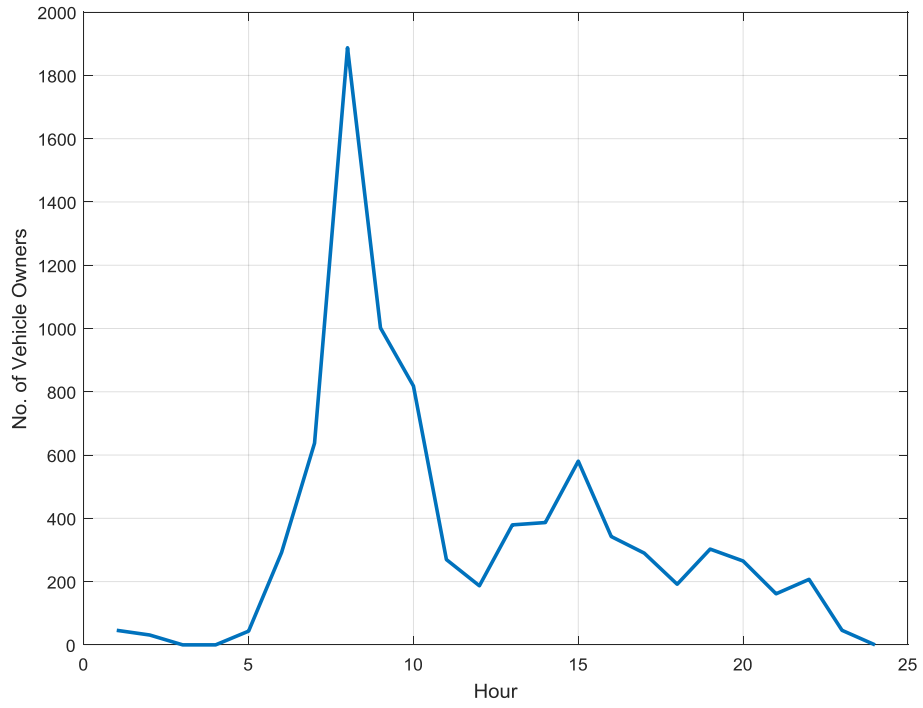


Figure 3.5: Statistical distribution of vehicles departure time from home

Because there is no information about the arrival time to home, we used the information of the departure time to return home. The distribution of trip's departure time to return home in this area is shown in Figure 3.6 and are considered as their arrival time to home in this project.

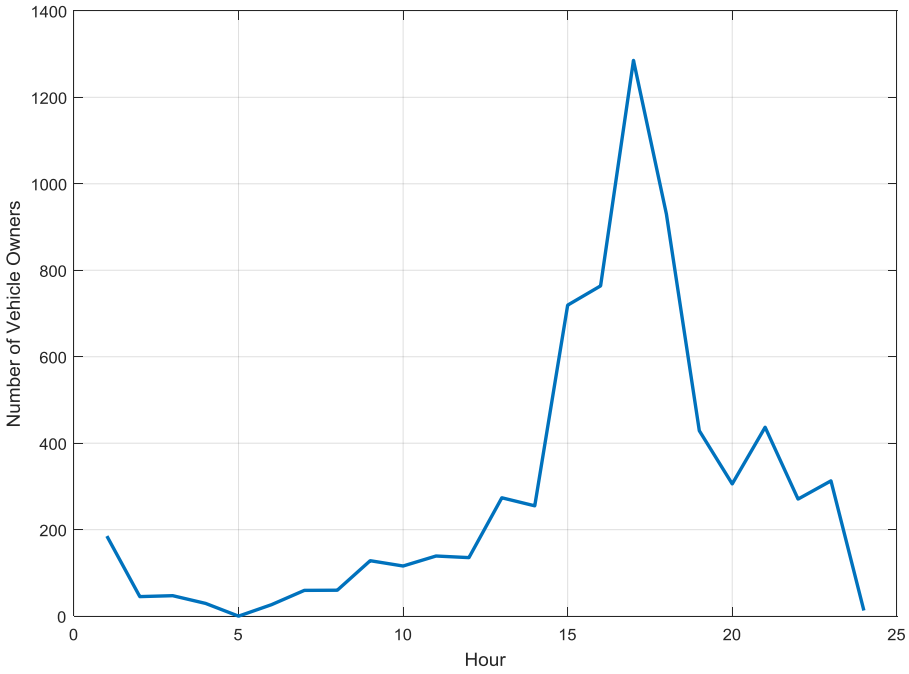


Figure 3.6: Statistical distribution of vehicles arrival time to home

CHAPTER 4 METHODOLOGY

As the quantity and variety of EV batteries connected to the electrical DS is growing, it becomes necessary to take into account the associated increase in load demand on existing power systems [10]. The impacts of EVs on the distribution grid must be measured and quantified under various scenarios and one must evaluate the ability of existing power systems to accommodate them in order to preserve the reliability of the electric grid [12]. Given the stochastic aspect of this problem, we chose to use a Monte Carlo Simulation (MCS) in order to achieve this goal. The details of the application of MCS in the project are as follows.

4.1 Electrical Data

As mentioned in chapter 3, the studied network is supplied by a large 120/12 kV urban substation in Montreal. The simulations realized in the project targeted one particular distribution feeder supplying 3621 clients with 1889 vehicles through 43 transformers. The complete information of the selected feeder is presented in Appendix A.

We opted to model a single feeder in order to develop the initial modeling methodology. Doing this provides a realistic framework to test different scenarios of EV penetration and EV trips, according to the statistical distributions introduced below [27].

4.2 Mobility Models

Driving patterns have an impact on the load profile of the distribution grid simply by defining where EVs are physically located and whether they are being recharged at a given time instant [27].

Although the exact location of EVs at a given time is highly stochastic, one can consider the statistical distribution of the driving distances in a given geographical area. This distribution is later used in MCS in order to generate realistic load profiles associated to the presence of EVs in the DS.

4.3 Distribution of EV Models in the Selected Area

The size of EV batteries has obviously an important impact on the electrical demand over time, as well as their charging profile. In order to take this into account in the model, we considered the distribution of different types of vehicles and batteries over the territory of our case study. The

methodology used to define the ownership distribution of the 21 selected types of EVs mentioned before is based on the income level and on the distance traveled by car owners (see Figure 4.1). It must be noticed that income level is household income and we may have more than a car for a household based on the analyzed information.

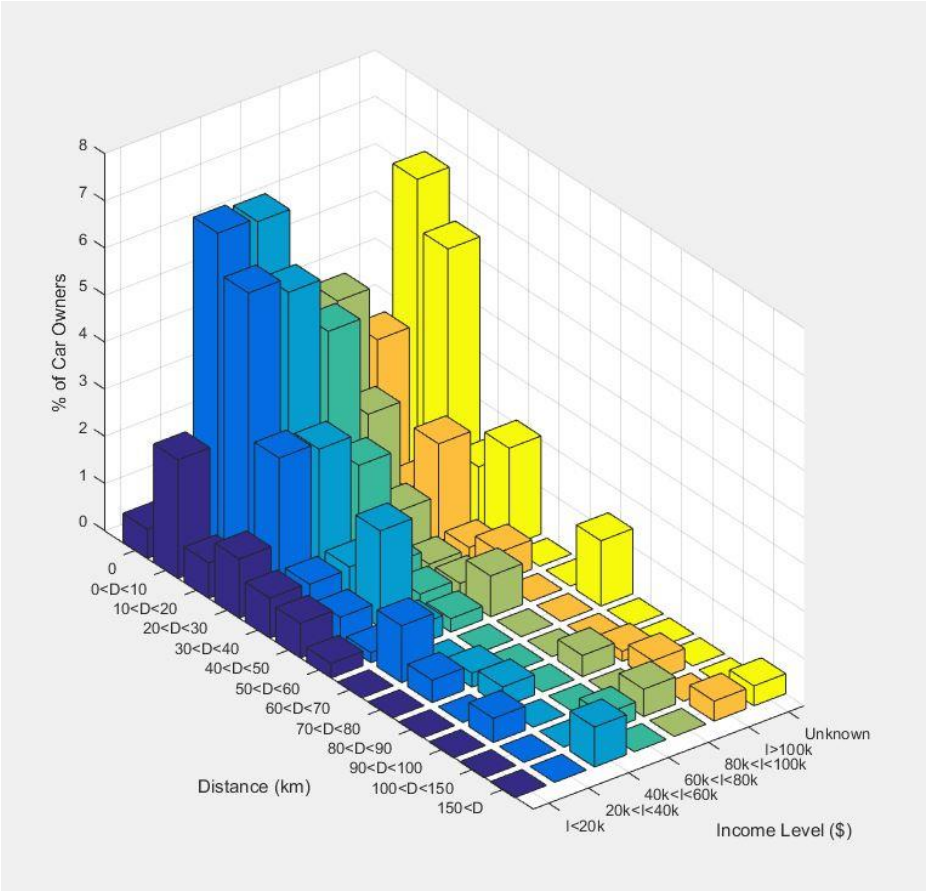


Figure 4.1: Income level of car owners & their daily traveled distance

With this information in hand, we could establish probabilities for a given car owner in the studied area to own a given type of EV, according to its electric range and selling price. In order to do so, we had to consider simultaneously the EV data (EV types, prices and maximum electric range) and the mobility and socio-economical data (income level, number of vehicles per house and distribution of traveled distance by car owners), under the following reasonable assumptions;

1) The lowest price of EVs at this time is around $27k, so we assumed that the minimum income level for a car owner to purchase an EV should be at least of $20-40 k per year.

2) The maximum price that a given car owner can afford for purchasing an EV is equal to the average of upper and lower limit of the income level category the owner belongs to (i.e. $50k is the maximum price that somebody in the $40-60 k salary category could afford to pay).

3) The electric range of the selected EV must be more than the daily traveled distance by the car owner.

4) The selected EVs in each group have the equal weights to be purchased.

Figure 4.2, shows the selected EVs in the ascending order of their prices and then their corresponding electric ranges.

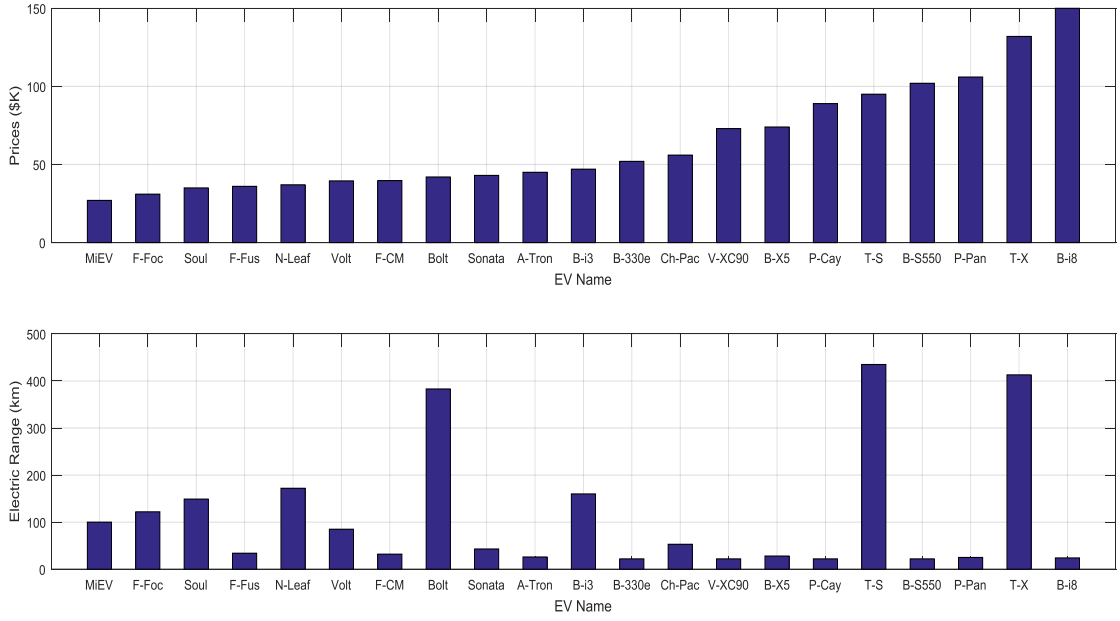


Figure 4.2: EVs prices in ascending order and their corresponding electric range

Based on the above reasoning, Table 4.1, shows the percentage of the overall car owners able to purchase a given type of EV, assuming that they are equally accessible from retailers. For example, 25.82% of car owners in this area are able to purchase Mitsubishi i-MiEV. As a result of this exercise, we find that *86 %* of car owners in this area would be able to buy an EV.

Table 4.1: Distribution of EVs in the Selected Area based on the Assumptions

No.	Name	Category	Battery Capacity	Electric Range	Price (CAD)	% of Car Owners
1	Mitsubishi i-MiEV	BEV	16 kWh	100 km	27,998.00	25.82
2	Nissan Leaf	BEV	30 kWh	172 km	37,398.00	6.72
3	Ford Focus Electric	BEV	21 kWh	122 km	31,998.00	6.41
4	Kia Soul EV	BEV	27 kWh	149 km	35,395.00	6.41
5	Chevrolet Volt	PHEV	18 kWh	85 km	39,590.00	6.14
6	Ford Fusion Energi	PHEV	7.2 kWh	34 km	36,399.00	4.64
7	Ford C-Max Energi	PHEV	8 kWh	32 km	39,729.00	4.64
8	Chevrolet Bolt	BEV	60 kWh	383 km	42,895.00	3.65
9	BMW i3	BEV	33 kWh	160 km	47,300.00	3.65
10	Chrysler Pacific PHEV	PHEV	16 kWh	53 km	56,495.00	2.85
11	Hyundai Sonata PHEV	PHEV	9.8 kWh	35 km	43,999.00	2.71
12	Audi E-Tron	PHEV	8.4 kWh	26 km	45,900.00	1.84
13	BMW 330e	PHEV	7 kWh	22 km	52,100.00	1.84
14	Tesla Model S	BEV	90 kWh	435 km	95,300.00	1.55
15	Tesla Model X	BEV	90 kWh	413 km	132,000.00	1.55
16	Volvo XC90	PHEV	9.2 kWh	22 km	73,400.00	1.25
17	BMW X5 40e	PHEV	9 kWh	28 km	74,000.00	1.25
18	Porsche Cayenne S E	PHEV	11 kWh	22 km	89,400.00	0.77
19	Mercedes Benz S550e	PHEV	8 kWh	22 km	102,600.00	0.77
20	Porsche Panamera S E	PHEV	9 kWh	25 km	106,600.00	0.77
21	BMW i8	PHEV	7 kWh	24 km	150,000.00	0.77

Based on the above reasoning, Figure 4.3, shows the percentage of the overall car owners in the area who are able to purchase a given type of EV, and also the percentage of EVs contribution in the area.

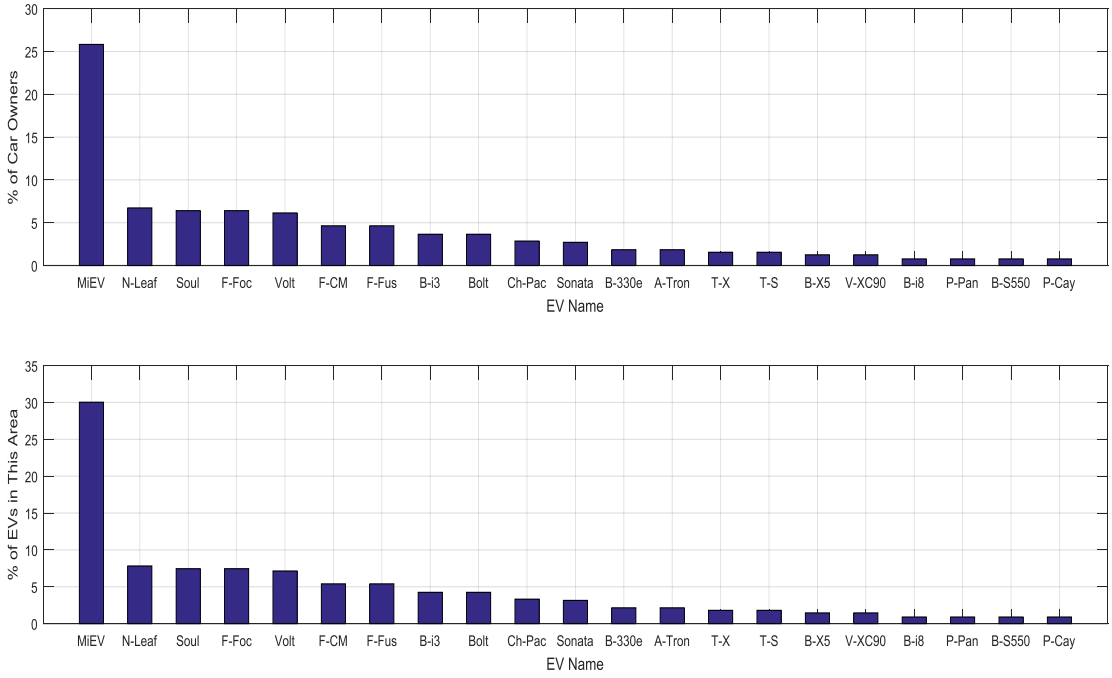


Figure 4.3: EVs contribution in the studied area based on the assumptions

4.4 EV Characteristics

The characteristics of EVs required to assess their impact in the DS are classified in the following categories:

- EV penetration rate
- EV type/range
- EV charge profile and power level
- Customer charge behavior (Mobility Model)
- Battery SOC based on distance driven
- Charge efficiency

In order to analyze the electrical impact of a population of EVs on the DS, we can divide the analysis in a deterministic part and in a stochastic part.

4.5 Deterministic Variables

The deterministic part comprises all aspects that are technical and allows defining the power consumption of EV batteries. This includes the individual charging profile, the SOC of the battery at the moment of charging, as well as the efficiency and type of battery charger used. Details about the models and assumptions used in this work are provided in separate sections below.

4.5.1 EV Penetration Rate

First, as the main factor of the analysis, we consider the penetration rate of EVs in the case study. According to the study in North America, EVs could reach a maximum of 50% market share by 2030 [12]. On the other hand, we found that 86% of car owners are able to buy an EV. So, by considering the same socio-economical conditions than that of the population of the selected feeder during the future years as well as the same EV specifications (electric range, price, etc.), we start with 10% penetration rate in the simulations and progressively increase this number to 86%.

4.5.2 Min/Max of SOC and Charger Efficiency

It should be noticed that the fully charged battery is discharged until 20% SOC is reached before it needs to be recharged [35]. Actually, the minimum SOC is the least amount of energy that can be left in a battery without letting it take any damage. Minimum SOC is limited by the maximum DOD. Under normal conditions, optimum DOD should not be discharged above 80% of the rated battery size. So, typically, the minimum SOC would be around 0.2. As already mentioned, the usage of at least 80% of battery rated capacity is known as deep discharge. Lithium-ion batteries do not need to be fully charged. In fact, it is better not to fully charge them, because high voltages stress the battery [34]. The recommended maximum SOC is 85%, which is the SOC as shown in section 2.9, when the cell voltage limit is reached. When the maximum SOC is reached, the EV charging is complete. So, the Min/Max SOC in this project are respectively 0.2 and 0.85 and then it is assumed that the SOC of each battery must be between a maximum and minimum level of SOC.

The charging efficiency is directly related to the losses occurring in charging process. In this work, this efficiency is considered to be 90% at all times [16].

4.5.3 Base Load Profile

We have chosen the load profile of the selected feeder such that it corresponds to two cold days of January 2013, which was also in this case the annual peak load on the feeder. The temperature during those two days fluctuated between -15°C and -35°C. It is considered as the base case in our analysis. Figure 4.4 shows the load profile as well as the temperature of that chosen date.

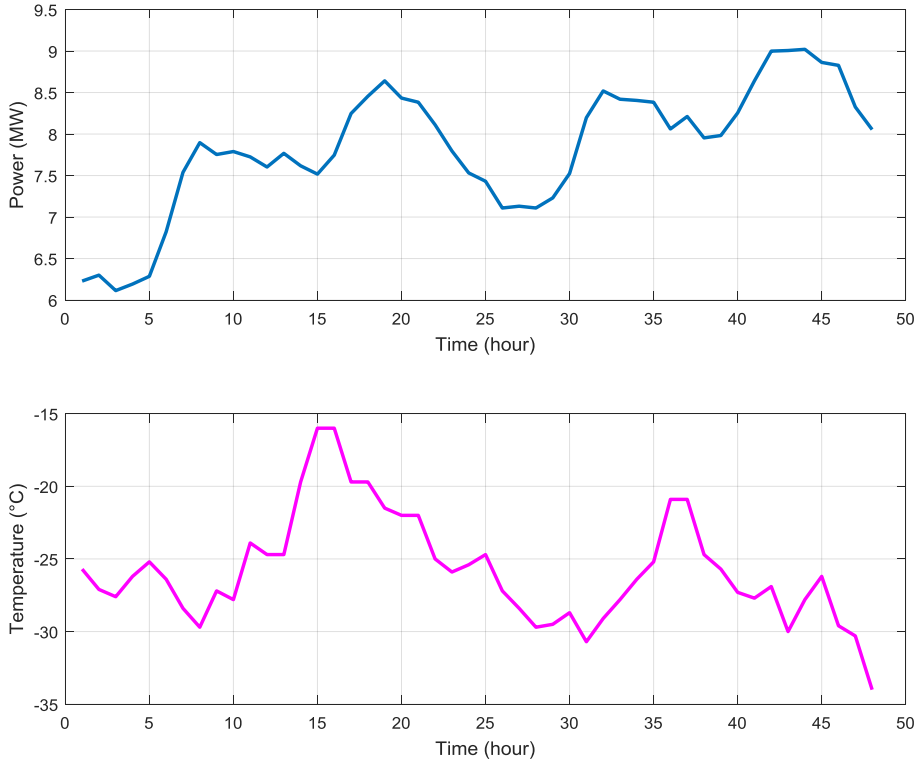


Figure 4.4: Base load profile and temperature as a sample in the selected feeder

4.6 Stochastic Variables

The stochastic variables considered in this work are listed below:

- Travel distance
- Departure/ arrival times
- Initial SOC of EV battery
- Distribution of three types of the charging rates or charging levels

Details about their treatment in the MCS are described in details in the next section.

4.7 Formulation of the Problem and Developed Program

A MATLAB code that can handle all the above inputs and constraints has been developed. It uses MCS in order to simulate the electrical impact of EVs on the chosen distribution feeder. It is assumed that EVs battery charging is done at home. This code is completely described in this section. The code receives in input the results of the "Mobility Analysis" and "EV Selection", as explained above, as well as other inputs/constraints introduced related to the deterministic variables introduced earlier. Then the code performs EV Charging Load study by MCS.

The data from the "Mobility Analysis" section include trip distance categories, as shown in Figure 4.1 (y axis), statistical distributions of departure and arrival time, and the total number of vehicles considered in the case study area, based on the number of clients and percentage of clients with one, two, or more vehicles per house.

The results from "EV Selection" are EVs' electrical range, battery energy and their contribution percentage according to the results shown in Table 4.1.

The output of this code is the calculated load profile of EVs (in kW or MW), which is added to the base load profile in order to analyze the measured stress on the distribution grid.

The steps described in the forthcoming sections are done for each trail of MCS:

4.7.1 First step

The first step is the random selection of EVs among 21 models. Based on the results of previous section, we performed a random draw of the number of EVs of each model in the geographic area. This number is weighted by the percentage of penetration of EVs in the population. For example, in 10% EV penetration rate, we draw a random sample from 21 types of EVs based on their contribution percentage in the area resulted in Table 4.1 for the number of 10% of the number of vehicles in this area.

4.7.2 Second step

The second step consists of introducing the required information from the mobility data:

- Distribution of trip distances (Figure 3.4)
- Distribution of departure/arrival time (Figures 3.5 and 3.6)

Now, stochastic parameters in the MCS and for each selected EV are defined as follows.

- **Random selection of travel distance for each EV**

According to the travel distance probability shown in Figure 3.4, we can randomly draw the distance that each EV will drive on each day of the analysis. Travel distance is a random variable subjected to the log-normal distribution. As shown in Figure 4.1, the daily travel distance of vehicle owners are categorized into 13 groups, from zero (no travel) to >150 km. The algorithm, first randomly draws the distance category based on their probability. Then, if the chosen category is not the first one, i.e. no travel, then we can generate a random travel distance which would be in the categories limits. For example, if the random drawn of travel distance category is 4, i.e. the distance is in the limit of 20 and 30 km, then it draws a random value in the mentioned limits.

- **Random selection of initial SOC for each EV**

The initial SOC of the EV battery (residual capacity since last charge) is also assumed to be a random function of the total distance that has been traveled since it was last charged. It is assumed that the SOC of each EV battery must be between a minimum and maximum level. For each selected EV, a random SOC value in accordance to its Min/Max values is drawn as the initial SOC. The algorithm uses a function that results the pseudorandom integer value drawn from the discrete uniform distribution on SOC_{min}: SOC_{max}.

- **Random selection of charging level**

We assumed that the three charging levels mentioned before (Table 2.6) are present in proportions of 50% (level 1: 120 V, 12 A, 1.4 kW), 35% (level 2: 240 V, 15 A, 3.6 kW) and 15% (level 2: 240 V, 30 A, 7.2 kW) respectively, randomly distributed in each home considered in this study.

- **Random selection of departure and arrival times**

The random values for departure and arrival times are drawn based on their distribution in Figures 3.5 and 3.6.

4.7.3 Third step

The third step verifies if there is a need for charging EV batteries. As mentioned earlier, we consider the load data of two sample days and then our simulations are done based on these two days. Time evolution scheme of the algorithm is hourly. In this step, the algorithm modifies the SOC based on the travel distance and takes it into account as next day's initial SOC and then initiates the battery charging (if needed).

Furthermore, we assume that the SOC of an EV drops linearly with the travel distance [30]:

$$\left(SOC = SOC_{initial} - \frac{d}{R} \middle| 0 < d < R\right) \tag{4.1}$$

where $SOC_{initial}$ represents the initial SOC of an EV battery in percentage, d is the daily distance traveled by a vehicle and R is the maximum electric range of the EV.

EV charge is initiated if any of the following two conditions occurs:

- The travel distance is greater than the max electrical autonomy, so, complete charging is required;
- The SOC in (4.1) is less than or equal the SOC_{min} and then, there is no possibility to drive the desired distance with the existing SOC.

A generic trapezoidal charging model for EV batteries is used all along this project, as illustrated in Figure 4.5 [35]-[36]. It presents a typical charging profile of Lithium-ion EV batteries.

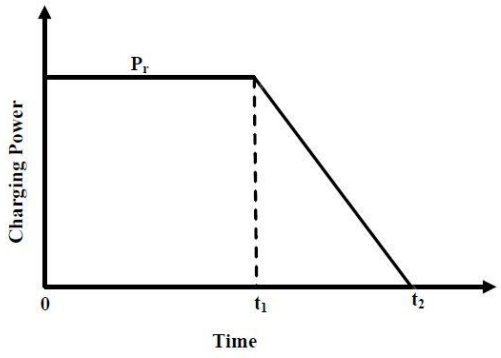


Figure 4.5: Generic charging profile of Lithium-ion EV batteries

It is reproduced by a piece-wise linear simplification of the actual test data. The model profile can be mathematically expressed as:

$$\begin{cases} P_r & 0 < t \le t_1 \\ P_r \dfrac{(t_2 - t)}{(t_2 - t_1)} & t_1 < t \le t_2 \end{cases} \tag{4.2}$$

where P_r is the charge level magnitude (kW) and t_1 and t_2 are the times that determine the switching between constant current (CC) charge and constant voltage (CV) charge as the battery approaches full charge. The area of this trapezoid is equal to the required energy (E_R) for charging the battery. In other words, (E_R) in the charging profile would be:

$$E_R = \frac{1}{2} \times P_r \times (t_1 + t_2) \tag{4.3}$$

As shown in Figure 2.3, we assume that time difference between t_1 and t_2 to switch the charging process from CC to CV is around one hour. Therefore, the charging time (t_2) would be:

$$t_2 = 0.5 + \frac{E_R}{P_r} \tag{4.4}$$

On the other side, the required energy to charge the battery is a function of battery energy, $SOC_{initial}$, SOC_{max}, charger efficiency and charge level.

$$E_R = ((SOC_{max} - SOC)/100) \times E_B \times (1 + (1 - \tau)) \tag{4.5}$$

where E_R represents the required energy to charge the battery and, SOC_{max}, E_B, and τ are respectively the maximum SOC, battery energy and charger efficiency.

So, by having the calculated required energy to charge the battery and also, the power of charge level, we can obtain the charging time.

4.7.4 Fourth step

Finally, in the fourth step, we consider two following charging scenarios:

Uncontrolled charging

In this case, customers charge their EVs as soon as they plug in upon their arrival at home. Based on Figure 3.6, we see that they mostly arrive between 3 and 8 pm. It is assumed that most of the charging in the area occurs immediately at the time EV owners arrive at home.

Therefore, charging start and end times are:

$$\begin{cases} T_{Start} = T_{Arrival} \\ T_{End} = T_{Start} + t_2 \end{cases} \quad (4.6)$$

where T_{Start}, $T_{Arrival}$, T_{End} and t_2 represent respectively the charging start time, the arrival time at home, the charging end time and the charging time, as introduced in (4.4).

For each MCS iteration, the contribution of battery charging power for each EV (according to (4.3)) during the period of $[T_{Start}, T_{End}]$ is added to the base load demand.

Controlled charging

Charging start time is controlled by the EV customer or the utility. The charge is performed during off-peak hours.

The goal of the controlled charging is to obtain the daily optimal scheduling of EV demand to flatten the loading profile of the grid. The loading profile corresponds to the addition of a considered load demand and a total EV hourly demand. To level the load profile of the whole system and avoid the deviation of the load between consecutive hours, it is necessary to develop an optimal schedule of EV charging to fill the gaps of the load profile during periods of lower load demands and avoid charging EVs during peak load hours. To achieve this, charging start time is controlled by the EV owner or the utility. The charge is performed during off-peak hours.

Here, we define the range for off-peak hours. For instance, (4.7) defines a sample of that range:

$$t_{off-peak} = \left[t_l, t_h\right] \quad (4.7)$$

Now, charging start and end times can be defined as:

$$\begin{cases} if \quad T_{Arrival} \geq t_l \quad \& \quad (T_{Arrival} + t_2) \leq t_h \\ or \quad T_{Arrival} \leq t_h \quad \& \quad (T_{Arrival} + t_2) \leq t_h + 1 \end{cases} \Rightarrow \begin{cases} T_{Start} = T_{Arrival} \\ T_{End} = T_{Start} + t_2 \end{cases}$$

$$else\ if \quad t_l \leq T_{Depart} \leq t_h \Rightarrow \begin{cases} T_{End} = T_{Depart} - 1 \\ T_{Start} = T_{End} - t_2 \end{cases} \quad (4.8)$$

$$otherwise \quad \begin{cases} T_{Start} = t_1 \\ T_{End} = T_{Start} + t_2 \end{cases}$$

It means, if EV owners arrival time to home and then EV's charging time immediately after arrival are in the off-peak time interval, so, charging start and end time would be arrival time and arrival time plus immediate charging time respectively.

If EV owners' departure time from home is in the off-peak time interval, so, charging end time would be one hour before departure time and then start time would be charging time less than end time.

Otherwise, the lowest time in the off-peak time interval would be considered as the charging start time and then charging end time would be charging start time plus the EV battery's charging time.

At the end, battery charging load for each EV in the range of $[T_{Start}, T_{End}]$ is added to the feeder's base load.

4.8 Simulation Results

Different EV penetration scenarios into low-voltage residential network have been considered in this project, to address the impact of EVs on distribution network. EV users' behavior constraints that are based on real-world driving mobility in Montreal are considered in the algorithm.

In this section, we present the simulation results based on the hypotheses introduced in the previous sections. The impact of EV battery charging on the load profile of the network is analyzed and compared to the base case with no EVs in the system. The chosen base case is that of two cold days of January 2013, corresponding to the annual peak load (Figure 4.4). In this project, it is assumed that EVs battery charging is done at home.

EVs charging schemes have been developed and can be classified into two categories: uncontrolled charging schemes that the EVs charging starts just when EV owners arrive home and plug-in at home and, controlled charging schemes that the charging process is time-delayed to avoid peak demand periods.

First, it is assumed that the EV penetration rate is 10% (low penetration). Figures 4.6, 4.7, 4.8 and 4.9 show the distributions of random selection of EV types, SOC and charging levels, trip distances,

and departure/arrival times by considering 10% of EV penetration level among the 100 MCS observations. In Figure 4.6, EVs are sorted based on their prices.

In Figures 4.7 and 4.8, the value zero shows that the random value chosen for charge level and/or travel distance is zero, e.g. no trip is performed on this day. The SOC of the battery of each EV must be within the limits of $[SOC_{min}, SOC_{max}]$ in every MCS observation.

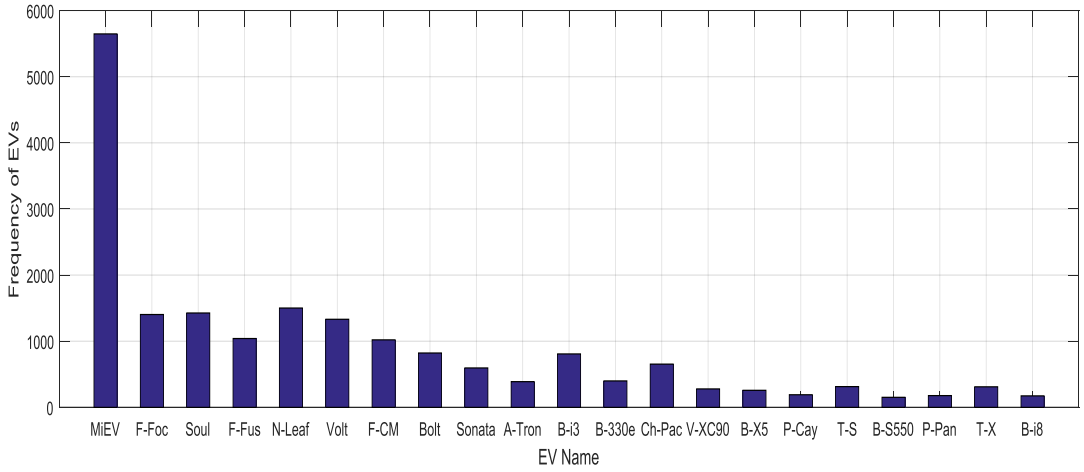


Figure 4.6: Distribution of random selection of EV types with 10% EV penetration rate

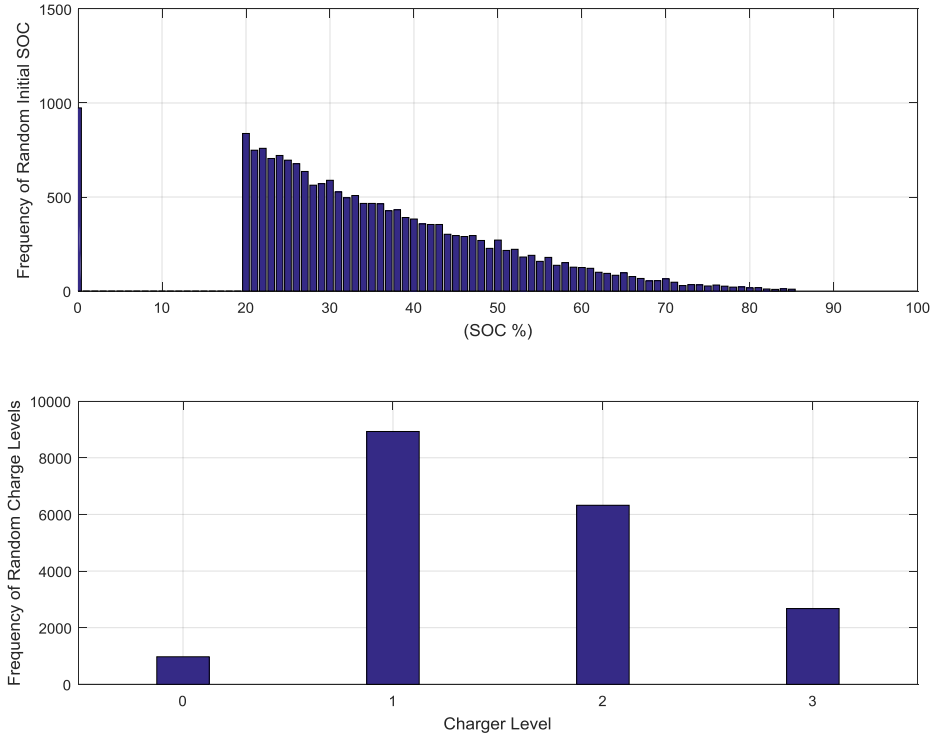


Figure 4.7: Distribution of random selection of SOC / charging level with 10% EV penetration rate

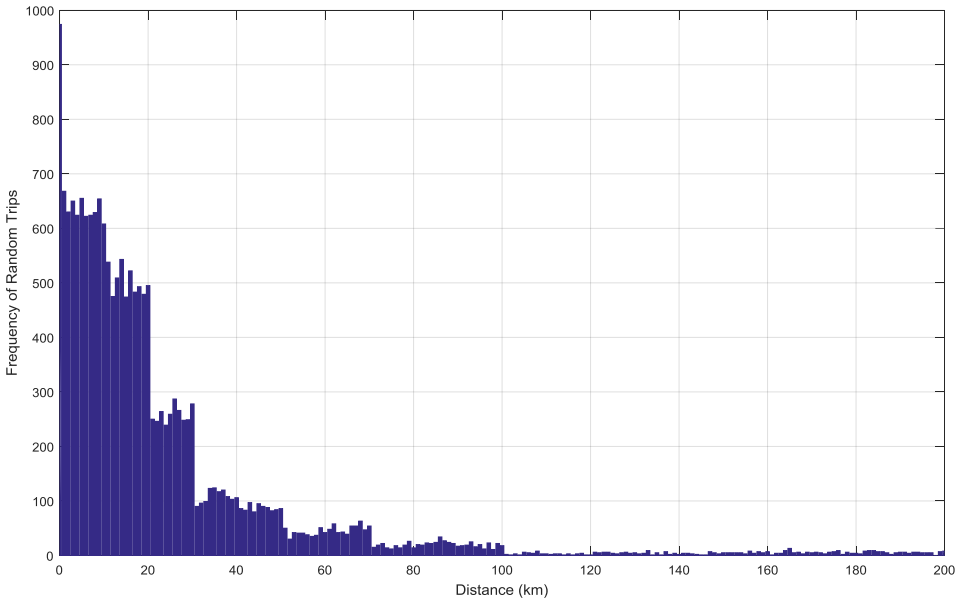


Figure 4.8: Distribution of random selection of trip distances with 10% EV penetration rate

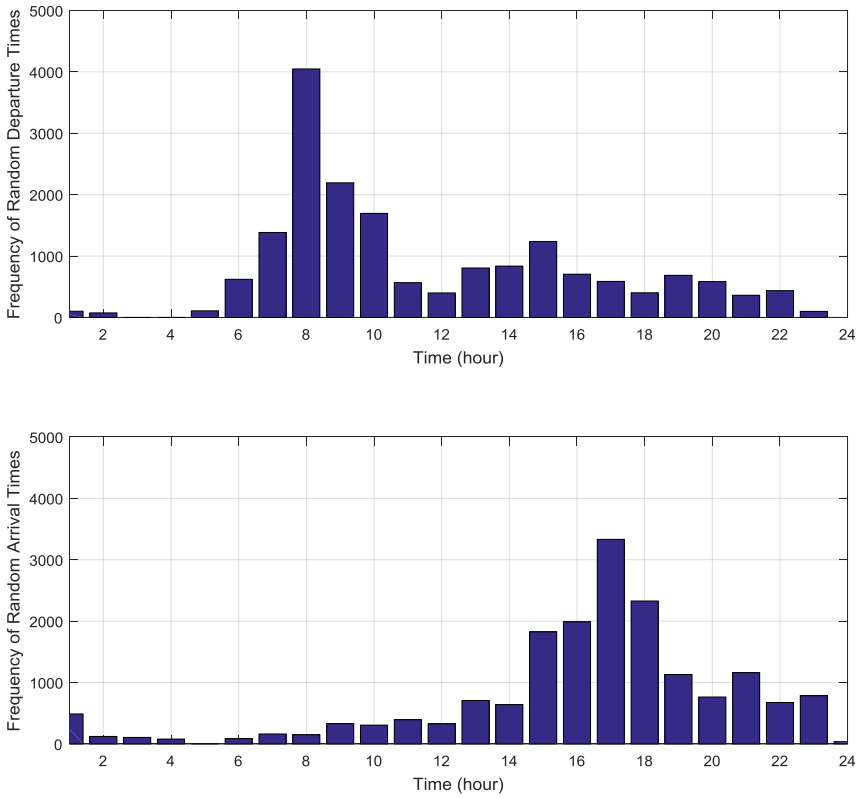


Figure 4.9: Distribution of random selection of departure / arrival time with 10% EV penetration rate

Figure 4.10 shows the average loading profile of the feeder by considering 10% EV penetration rate and 100 MCS observations, for the controlled and uncontrolled charging scenarios.

Figures 4.11 and 4.12 show the min, max and average deviation in load profile for 100 MCS trials in controlled and uncontrolled charging with 10% EV penetration.

As shown in Figures 4.10 to 4.12, there is not so much difference in the load profile with 10% penetration rate.

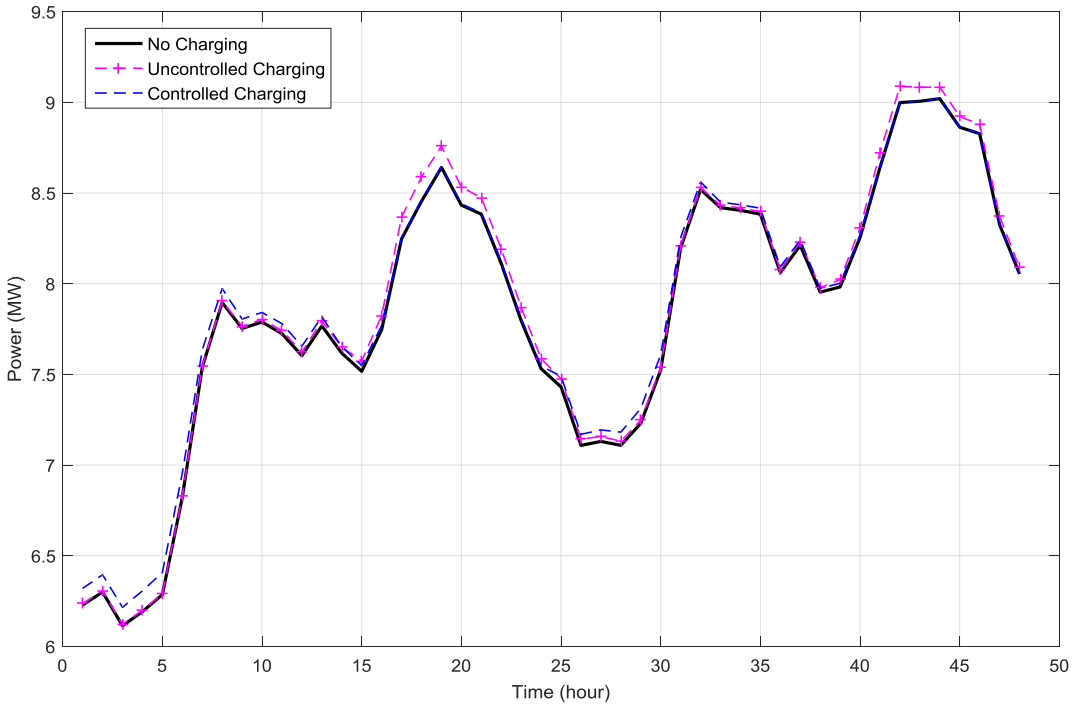


Figure 4.10: Load profile with 10% EV penetration rate and with uncontrolled/controlled charging

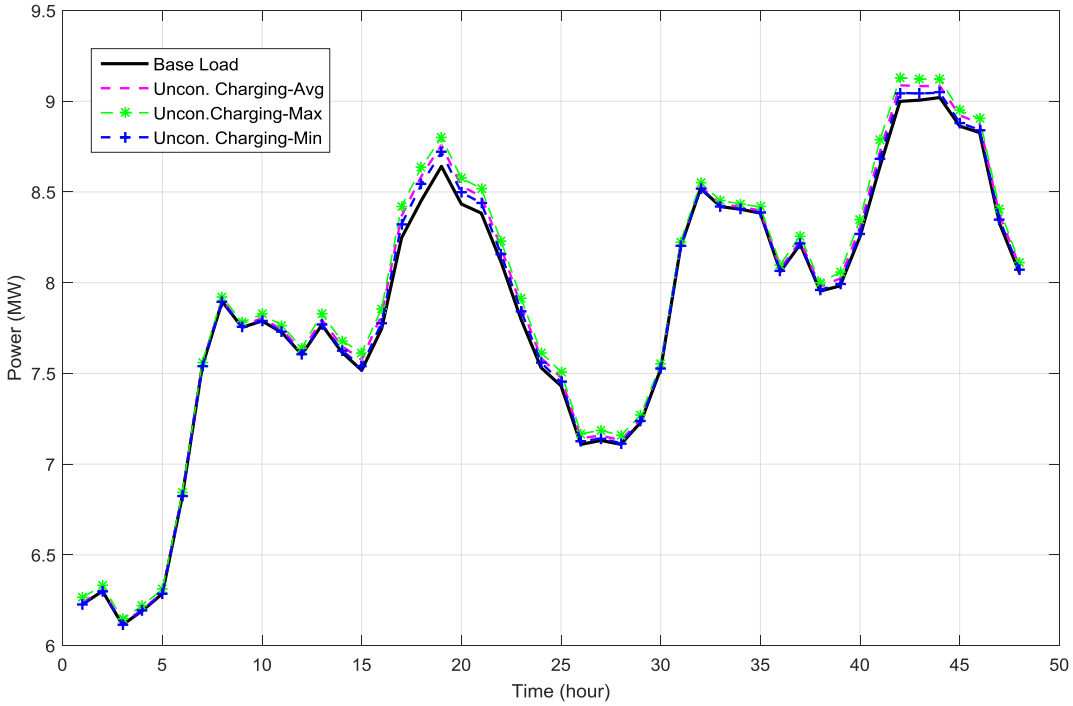


Figure 4.11: Uncontrolled charging deviation with 10% EV penetration rate

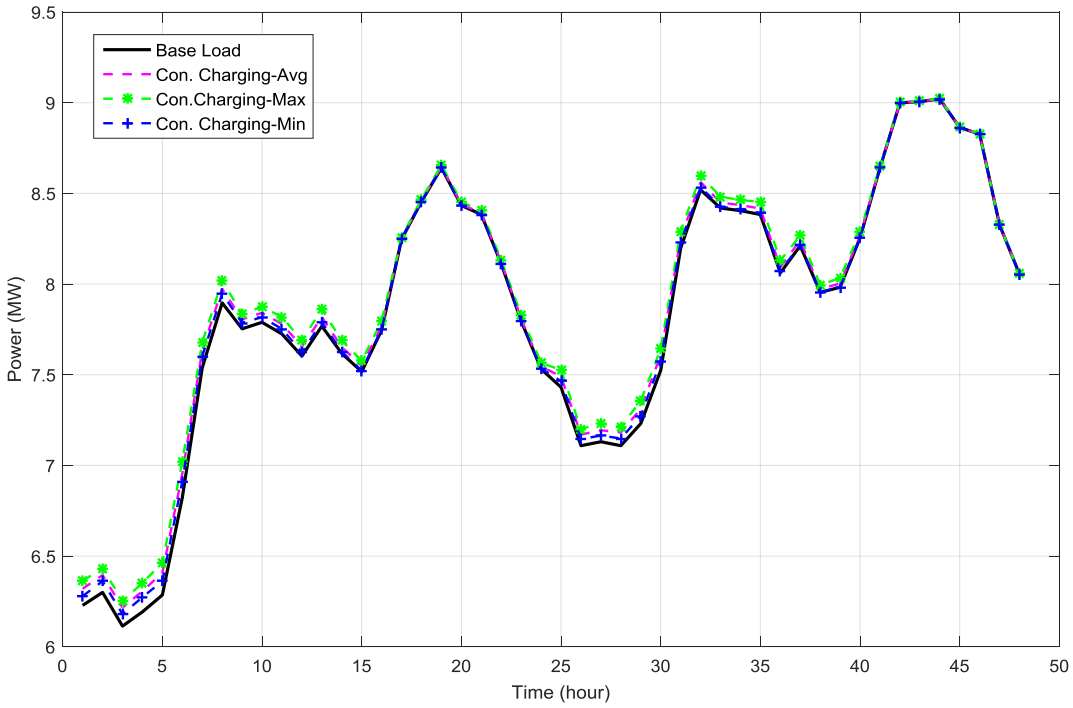


Figure 4.12: Controlled charging deviation with 10% EV penetration rate

Now, we increase the EV penetration rate to the high penetration rate in the studied area or 86%, which is the maximum rate of car owners in this area who are able to buy an EV. By considering the same scenarios, Figures 4.13 to 4.16 show the distributions of random selection of EV types, SOC and charging levels, trip distances, departure/arrival times among the 100 MCS observations, with 86% EV penetration level.

Figure 4.17 shows the average loading profile of the feeder by considering 86% EV penetration rate and 100 MCS observations, for the controlled and uncontrolled charging scenarios.

Figures 4.18 and 4.19 show the min, max and average deviations in load profile for 100 MCS trials in controlled and uncontrolled charging with 86% EV penetration.

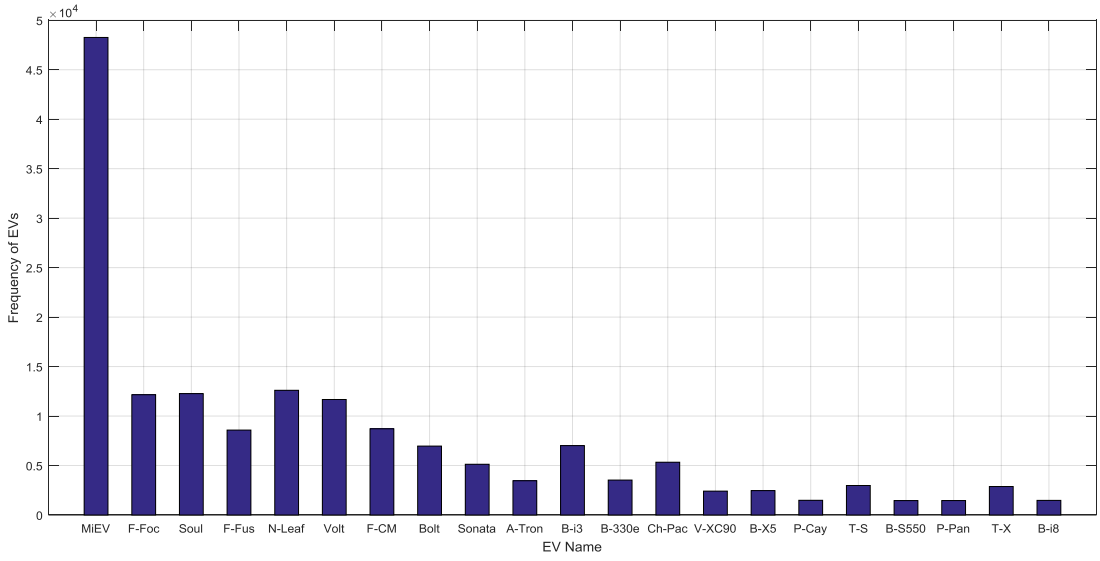


Figure 4.13: Distribution of random selection of EV types with 86% EV penetration rate

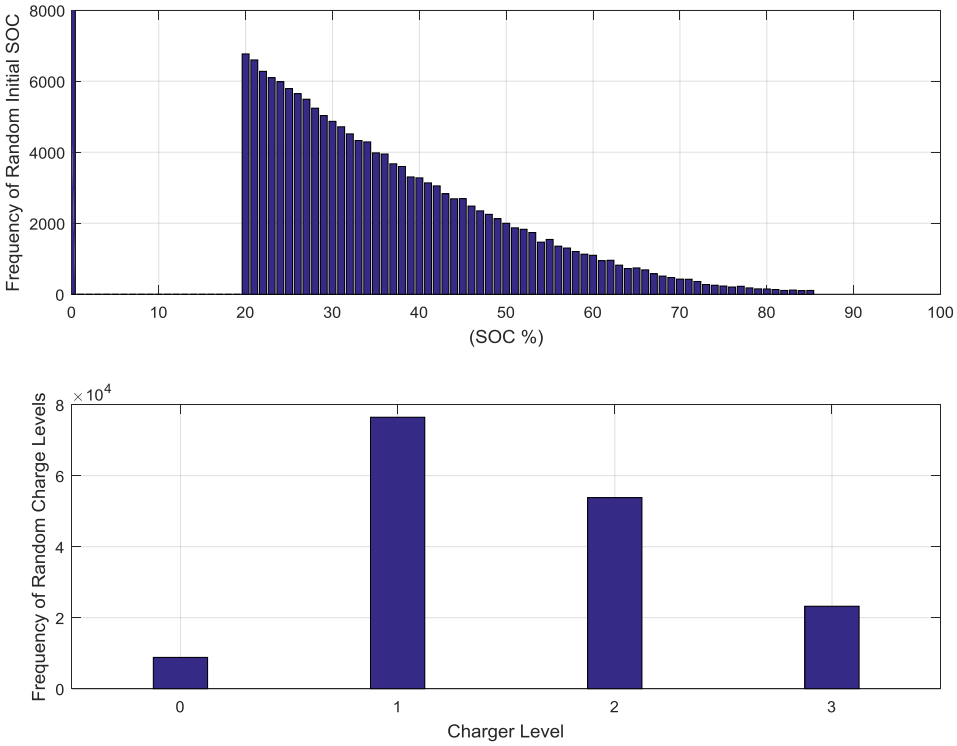


Figure 4.14: Distribution of random selection of SOC / charging level with 86% EV penetration rate

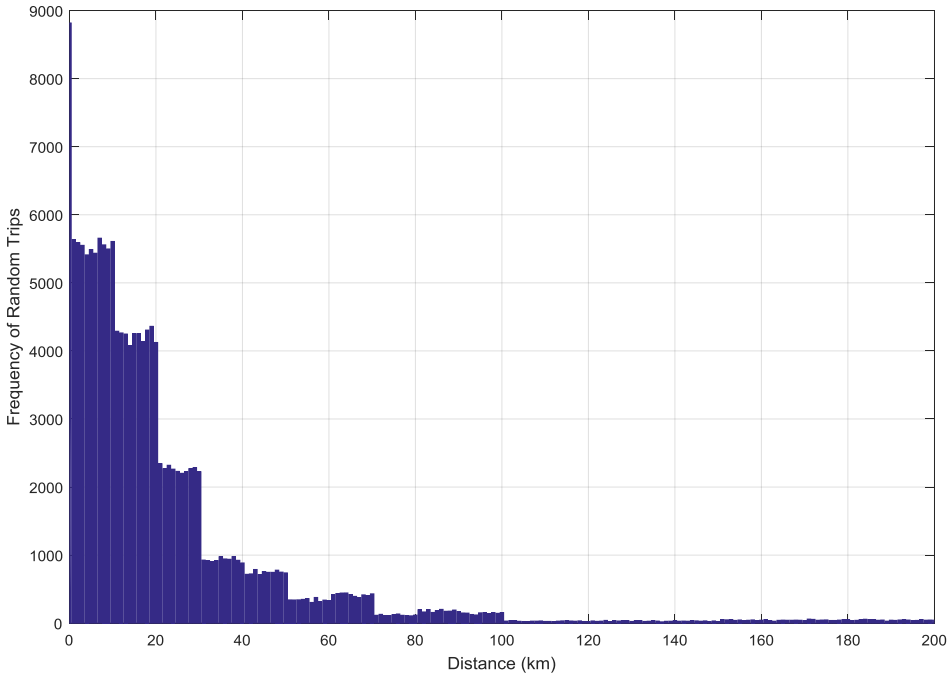


Figure 4.15: Distribution of random selection of trip distances with 86% EV penetration rate

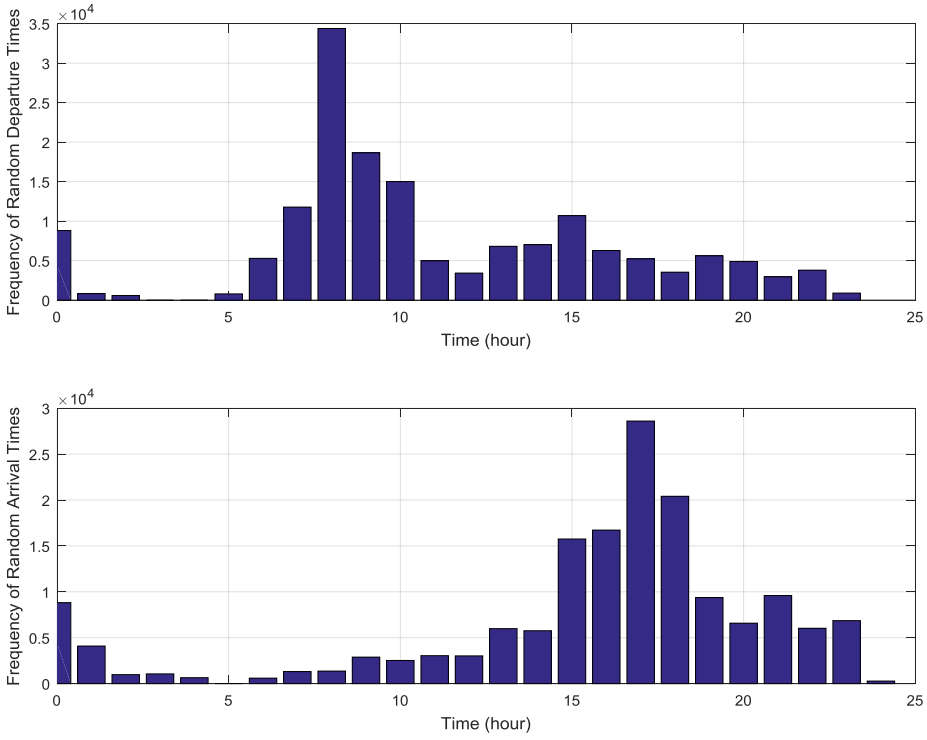


Figure 4.16: Distribution of random selection of departure / arrival time with 86% EV penetration rate

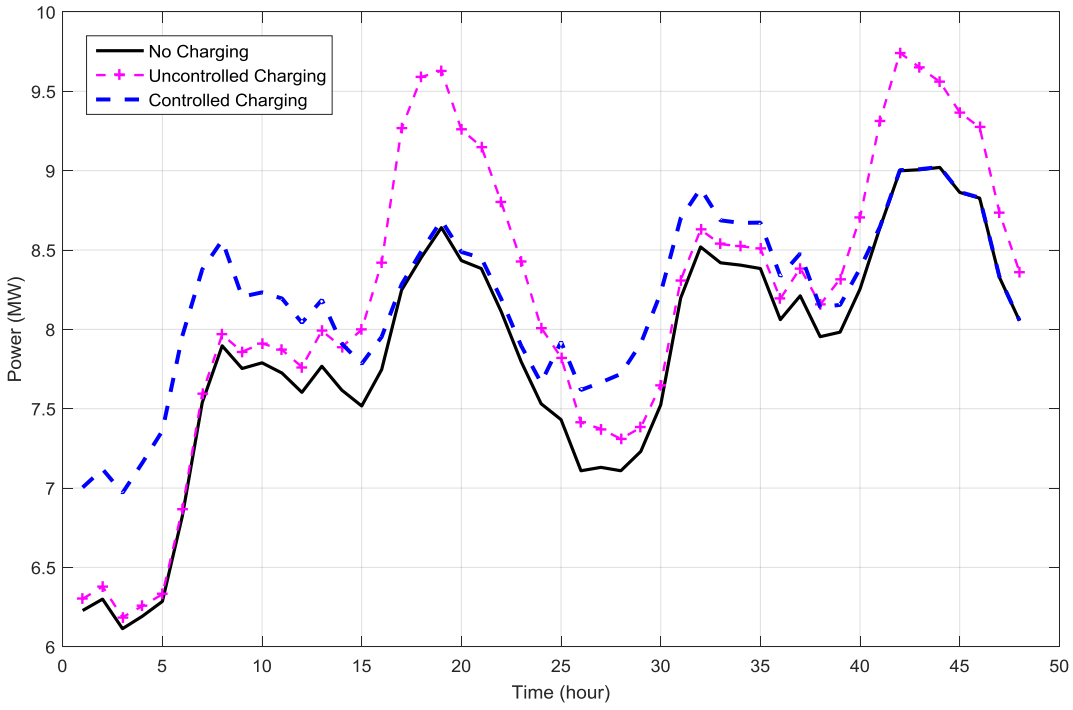


Figure 4.17: Load profile with 86% EV penetration rate and with uncontrolled/controlled charging

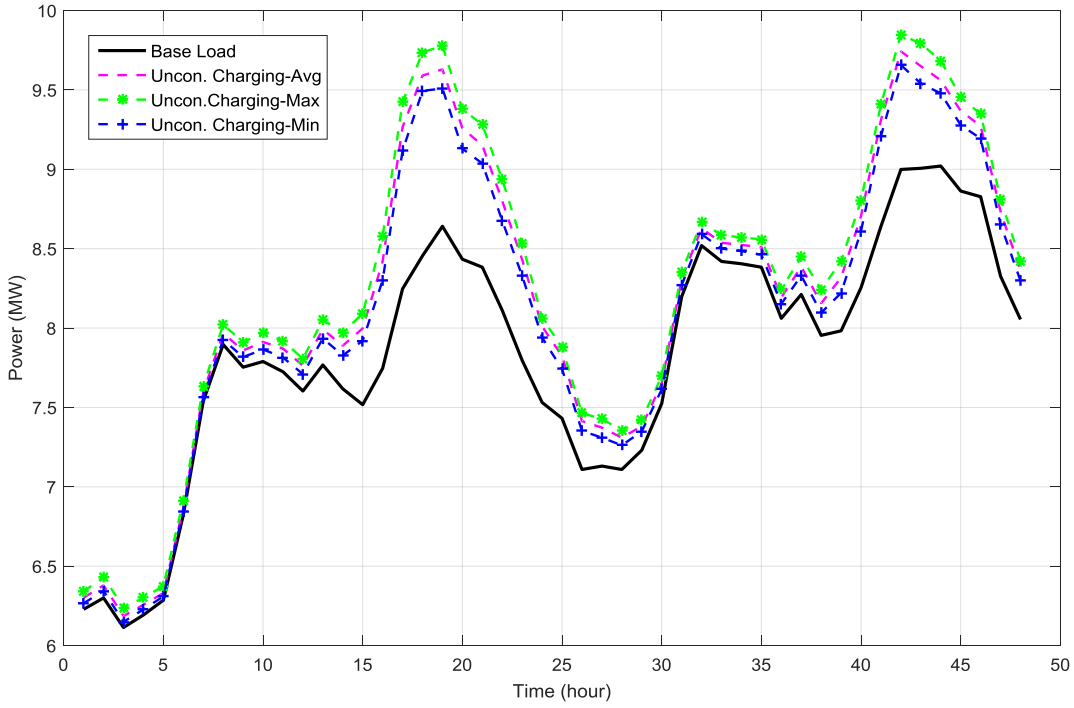


Figure 4.18: Uncontrolled charging deviation with 86% EV penetration

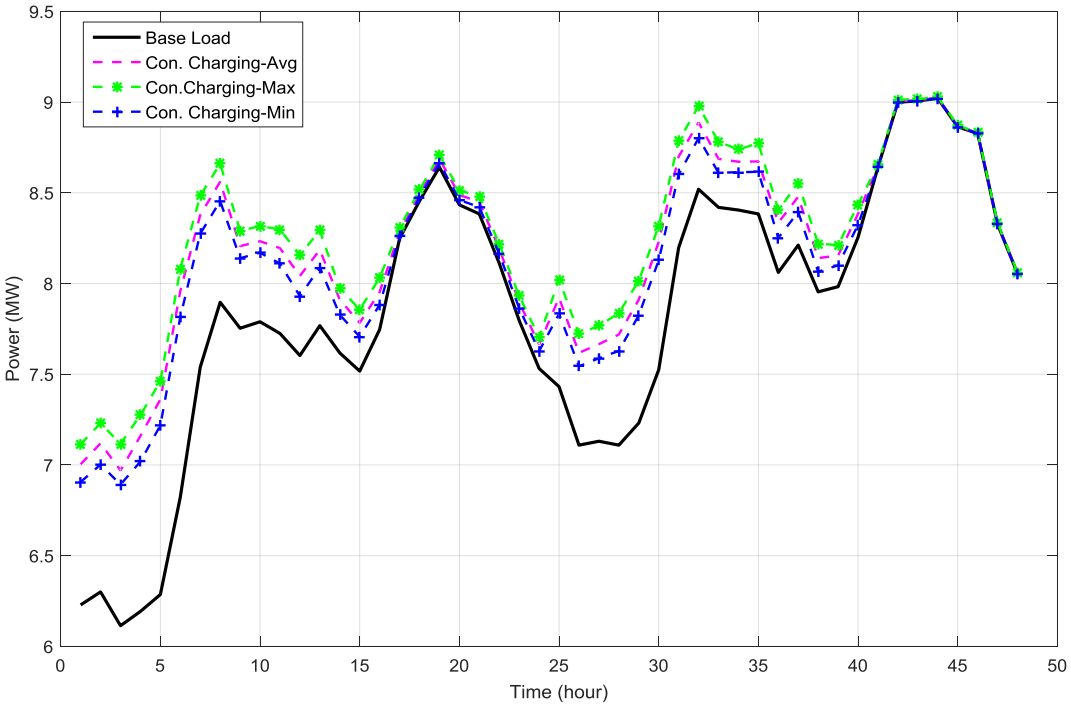


Figure 4.19: Controlled charging deviation with 86% EV penetration rate

For the uncontrolled charging strategy, EVs are charged as soon as the EV is plugged-in at home. Based on the vehicle user behavior study, it is considered that EVs are connected to the network, and consequently charged, during the following periods.

Normally, 68% of EV owners arrive at home between 16:00 and 23:00, and with uncontrolled charging, they are supposed to be plugged into the electricity network immediately. This period of time occurs during the peak load demand on the substation transformer. So, simultaneous battery charging during peak load periods generates a new peak in the power system, which would likely lead to transformer and power cable overload in the DS. The capacity of the DS might need to be reviewed and reinforced.

Table 4.2 presents a sample of increased percentage in the peak load among different penetration rate scenarios, which in the case of 86% EV penetration level, leads to about 1 MW increase, i.e. more than 10% of the base load profile.

Table 4.2: Increase in Daily Peak Load under Different Scenarios

EV Penetration Rate	**10%**	**30%**	**50%**	**86%**
Uncontrolled charging- Peak increase-1st day (%)	1.27	3.95	6.60	11.45
Uncontrolled charging- Peak increase-2nd day (%)	0.72	2.76	4.55	8.14
Controlled charging- Peak increase- 1st day (%)	0.12	0.18	0.31	0.51
Controlled charging- Peak increase- 2nd day (%)	0.004	0.011	0.02	0.03

It can be observed that the electricity demand for the high EV penetration level is spread throughout the night so that no overload takes place. Controlled charging increases the off-peak load and can introduce a new peak or near peak load in early off-peak period, but this can easily be handled by the capacity margin available in these periods. In addition, they can be used as Grid to Vehicle (G2V) providers, offering the service of valley filling. Such a controlled action also improves the DS load factor, i.e. fixed costs are spread over more kWh of output. Not surprisingly, controlled charge of EV charging should be implemented in order to avoid costly DS upgrade.

CHAPTER 5 CONCLUSION AND RECOMMENDATIONS

EVs are emerging as a key solution to one of the biggest challenges in the future of energy, i.e. the impact of transportation on our environment. The smart grid will be one of the keys to a cleaner transportation future; and could handle widespread adoption of EVs by consumers and the construction of the charging stations that these plug-in cars will require. Despite an uncertain energy future, there is one thing we must know that transportation will be a major target for future energy savings. EVs offer a promising alternative for tomorrow's transportation sector due to zero gas, no particle emission, extremely quiet operation, and a readily-available fuel (electricity).

5.1 Summary of the Work and Methodology

Figure 5.1 summarize the outline structure of the model to integrate the EVs as loads in the distribution system.

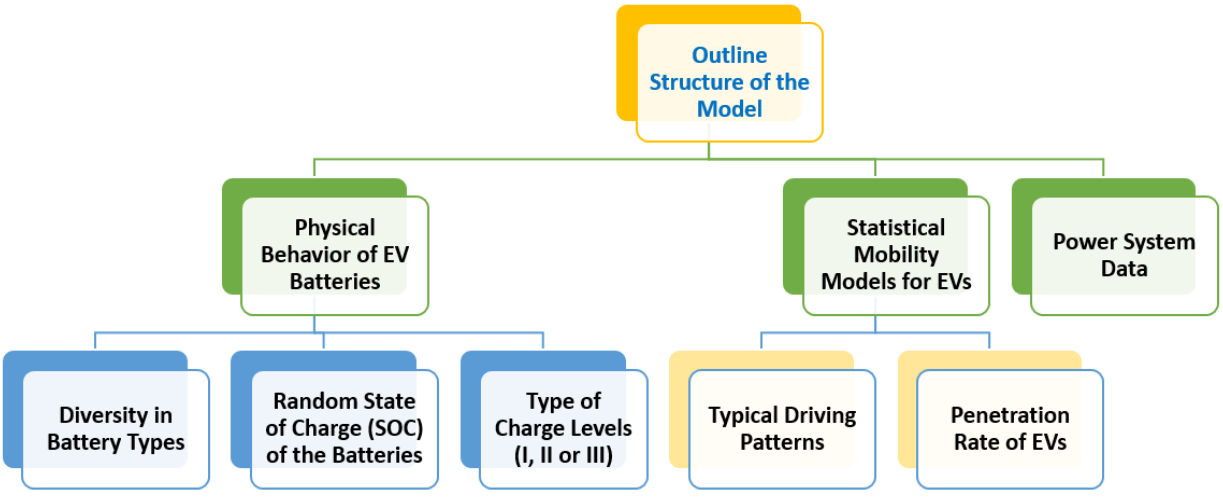


Figure 5.1: Outline structure of the EV integration model in the DS

The summary of the methodology is listed here:

- Different EV penetration scenarios into low-voltage residential network have been considered in this project, to address the impact of EVs on distribution network.
- EV users' behavior constraints that are based on real-world driving mobility in Montreal are considered in the algorithm.

- The impact of EV battery charging on the load profile of the network is analyzed and compared to the base case with no EVs in the system.
- The chosen base case is that of two cold days of January 2013, corresponding to the annual peak load.
- In this project, it is assumed that EVs battery charging is done at home.
- EVs charging schemes have been developed and can be classified into two categories.
- Uncontrolled charging schemes that the EVs charging starts just when EV owners arrive home and plug-in at home.
- Controlled charging schemes that the charging process is time-delayed to avoid peak demand periods.

5.2 Discussion on the Results

This study investigated the impact of the increased stress of deploying a large number of EVs on a typical urban distribution power grid infrastructure, which supplies most of the energy required for operating the EVs. The major contribution of this project was to take into account the stochastic nature of the problem. It was shown that EVs represent a new moving load and a challenging new element of energy demand in power distribution networks. These moving demands have significant influence on power networks if the large scale of EV demand is not accommodated in a suitable way.

The results show that in the uncontrolled scenario, the EV charging challenge lies in the fact that a high electrical power is required. EVs charge when the owner arrives at his/her home which is mostly at the same time during the periods of maximum demand or peak hours. However, potential problems such as sudden peak demand or sudden overloading can happen. The electrical network could collapse if this situation is not controlled.

Uncontrolled charging creates an important impact on the power system load profile (more than 10% of the peak load in the studied area as shown in the results of this project). As more vehicles plug into the network via EV recharging stations, urban grids will need to be upgraded to handle the additional power.

Knowing where EV load will occur, having the data and tools to analyze their impacts and

providing incentives for network-friendly charging patterns will all be key elements both consumers and utilities for taking advantage of the full potential of EVs.

5.3 Managing the Stress of EVs in the System

Actions are therefore required in order to manage this increased stress in the system and plan the transition path towards the grid of today and the grid+transportation scheme of tomorrow. We can jump from challenge to opportunity. Currently, there are major differences in demand at different times of the day; "peak" hours where a high power capacity is required and "valley" hours where capacity is at a minimum. Technology can be implemented to make the demand curve "uniform" when charging EV batteries with "smart" systems.

Controlled or smart chargers are one opportunity where utilities and consumers are equally benefiting. The above problems from uncontrolled charging could be shaped or flattened by using a smart charging schedule for the EVs' batteries. A smart charger in a home makes sure that an EV is charged during off-peak hours when the energy demand on the grid is low. However, if users charge their EV batteries during off-peak hours, utilities can respond to demand using cleaner or more sustainable sources of power like wind farms, hydroelectric power for instance. Furthermore, slow charging at night could help to reduce fluctuations in demand. Surprisingly, nuclear-dependent countries like France often face nighttime overproduction. Nighttime EV charging could help absorb this excess supply, which would otherwise be wasted.

The charger's parameters can also be set by the user to charge only during the expected time, cost, or even the CO_2 content of the charge while at the same time reducing the power drawn from the grid. Additionally, utilities can send signals to chargers to incentivize charging when (renewable) energy is abundant and costs less. By encouraging EV drivers to charge during off-peak hours, it is likely that the existing utility infrastructure will be able to absorb widespread adoption of EVs. However, utilities may need to invest in equipment like smart metering, local transformers, etc.

5.4 Recommendations and Next Step Researches

Like most energy efficiency solutions just over the horizon, the rise of the EV will require innovative, safe, reliable, and cost-effective energy management solutions. Demand-response

management will be another major requirement that utilities will need to meet. From a technical standpoint, widespread EV charging will increase energy demand, putting the grid under substantial stress. The optimization of EV charging is a demand-response strategy that must be incorporated into demand-side management (DSM) and implemented by an EV aggregator to improve the flexibility of the distribution network. For electric utilities, the smart grid, with its advanced energy management capabilities, is a crucial step on the pathway to managing the EV interface with the grid. The smart-grid-enabled EV landscape will include fully-connected vehicles on a smart grid where power consumption is optimized and users can give or sell power back to the grid (for backup or peak power for example) when not needed. Tomorrow's intelligent grid-enabled vehicles will also feature mobile applications to monitor the engine, charging status, traffic, trip planning, and other driver activities.

New regulations will be needed to encourage utilities to innovate; standards are needed so that manufacturers can build safe, interoperable EV equipment; and infrastructure is needed to make using EVs convenient and cost-effective. Regulators and manufacturers are today joining forces to design more energy-efficient, less-polluting vehicles and inventing ways to link them to smarter energy infrastructures. Regardless of how we ultimately address tomorrow's energy challenges, more efficient transportation is a must, and smarter energy management will be the key to reaping all of the potential environmental and economic benefits new, greener forms of transportation can offer. By getting all stakeholders to work together, our energy-hungry motor-vehicle-driven lifestyle can be transformed into a cleaner, quieter, cheaper mobility landscape in which the EV will play a key role.

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APPENDIX A –EMISSION COMPARISON OF SELECTED EVS

Table A.1: Emission and Cost to Drive Comparison of the Introduced EVs [28]

Name	By Province	Electric Vehicle	
		Emission- CO2(kg)/100 km	Cost- $/100km
Audi E-Tron	Quebec	11.7 kg	$5.54
	Average in Canada	13.6 kg	$5.79
BMW 330e	Quebec	14.4 kg	$6.95
	Average in Canada	16.2 kg	$7.06
BMW i3	Quebec	0.2 kg	$1.51
	Average in Canada	4.9 kg	$2.16
BMW i8	Quebec	15.2 kg	$7.01
	Average in Canada	17.0 kg	$7.26
BMW X5 40e	Quebec	18.0 kg	$8.38
	Average in Canada	20.4 kg	$8.71
Chevrolet Bolt	Quebec	0.2kg	$1.50
	Average in Canada	5.1kg	$1.90
Chevrolet Volt	Quebec	2.1kg	$2.36
	Average in Canada	6.9kg	$2.99
Chrysler Pacific PHEV	Quebec	8.3kg	$4.79
	Average in Canada	11.3kg	$5.02
Ford C-Max Energi	Quebec	9.8kg	$4.75
	Average in Canada	11.9kg	$5.02
Ford Focus Electric	Quebec	0.2kg	$1.80
	Average in Canada	5.9kg	$2.57
Ford Fusion Energi	Quebec	9.8kg	$4.75
	Average in Canada	11.7kg	$5.00
Hyundai Sonata PHEV	Quebec	8.0kg	$4.18
	Average in Canada	10.6kg	$4.53

Kia Soul EV	Quebec	0.2kg	$1.79
	Average in Canada	5.9kg	$2.56
Mercedes Benz S550e	Quebec	16.4kg	$7.66
	Average in Canada	18.8kg	$7.81
Mitsubishi i-MiEV	Quebec	0.2kg	$1.68
	Average in Canada	4.21kg	$2.39
Nissan Leaf	Quebec	0.2kg	$1.66
	Average in Canada	5.3kg	$2.36
Porsche Cayenne S E-Hybrid	Quebec	17.3kg	$8.24
	Average in Canada	20.2kg	$8.63
Porsche Panamera S E-Hybrid	Quebec	16.9kg	$7.91
	Average in Canada	19.3kg	$8.23
Tesla Model S	Quebec	0.2kg	$2.02
	Average in Canada	6.6kg	$2.88
Tesla Model X	Quebec	0.2kg	$2.07
	Average in Canada	10.8kg	$2.95
Volvo XC90 Twin Engine PHEV	Quebec	17.3kg	$7.90
	Average in Canada	19.1kg	$8.15

APPENDIX B – LAYOUT OF THE STUDIED AREA

Beside Figure 3.1that showsa area deserved by the Delorimier substation in Montreal, Appendix B, shows another layout of the studied area.

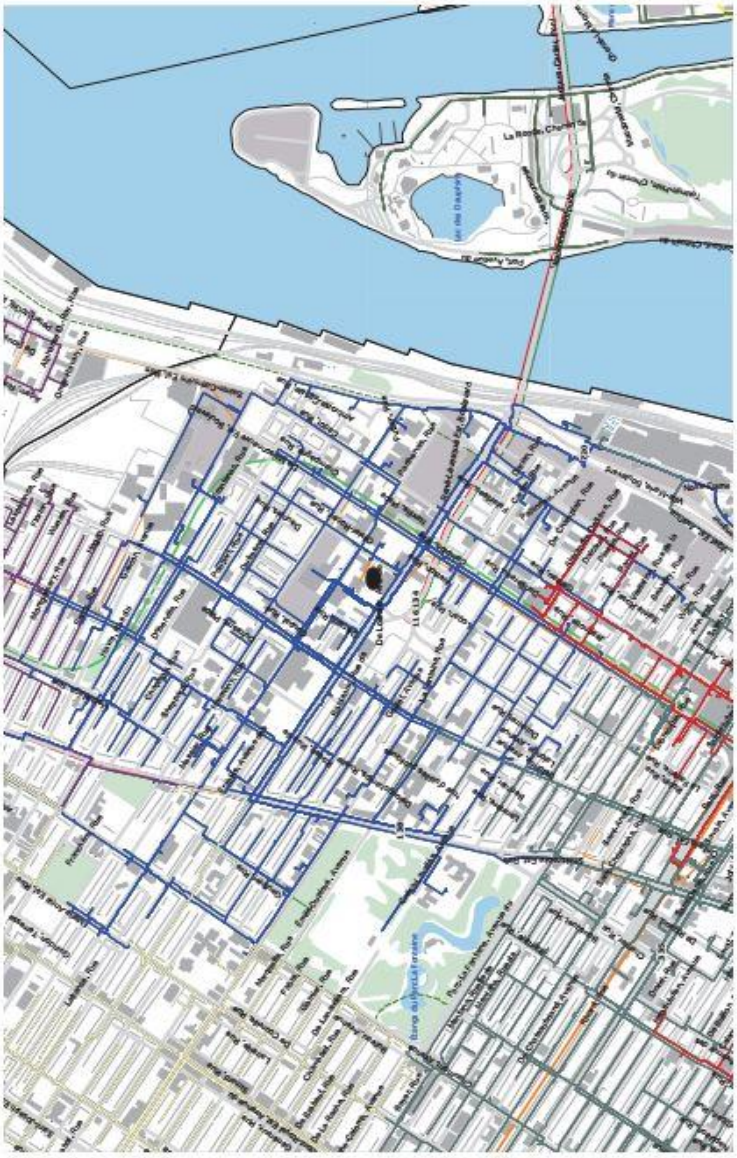


Fig. B.1: The layout of the studied area

APPENDIX C – ELECTRICAL DATA OF THE SELECTED FEEDER

The simulations realized in the project targeted one particular distribution feeder, Line 4 in the Delorimier distribution substation. The information about this feeder has been provided by Hydro-Quebec. This feeder is supplying 3584 clients through 45 transformers as shown in the table C.1.

Table C.1: Transformers in the Selected Feeder

No.	Code	Description (in French)	No. of Transformers	No. of Supplied Clients
1	TR	Transformateur Aérien Monophasé	24	2258
2	TA	Transformateur Chambre Annexe	1	82
3	TB	Transformateur sur Socle Triphasé	2	2
4	TT	Transformateur Aérien Triphasé	2	127
5	TX	Transformateur Submersible Triphasé	3	213
6	TY	Transformateur Submersible Monophasé	13	902