Minimization of Net-Load Variance Using Smart EV Charging Algorithm

by

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B.Sc.EEE., BRAC University, 2017

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

Master of Science in Engineering

In the Graduate Academic Unit of Electrical and Computer Engineering

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This thesis is accepted by the
Dean of Graduate Studies

THE UNIVERSITY OF NEW BRUNSWICK

October, 2023

ABSTRACT

Electric vehicles (EVs) are developing faster than ever. With the increasing number of EVs and their uncoordinated charging, the additional electric load significantly impacts the distribution grid for low penetration levels. If the EV penetration level reaches a high degree for a specific regional grid, the EV load will cause more significant risks. to the grid.

In this research, using localized statistical information and the Dichotomous Search Method, a charging algorithm considering the charging priority is proposed to minimize the net-load variance and the negative impacts of EV load on a medium voltage distribution. The charging priority of EVs is defined according to the State of Charge (SoC), the charging time required of individual EVs, and the power generated by the local grid. Each EV is assigned a specific period to charge. This motivates minimizing the demand peak and the valley filling by shifting the EV load.

DEDICATION

I dedicate this thesis to five beloved people who mean so much to me. First and foremost, my parents, Mushiur and Luna, who have always loved me unconditionally and whose good examples have taught me to work hard for the things that I aspire to achieve. They both taught me and my sister to be kind, strong, and courageous.

Next, my sister Afra has always supported me regarding all my decisions in my life. The past year has been hard for our family, and Afra took care of it and she still is, all by herself in my absence. I am proud of the woman she has become. I am also grateful to her for taking care of my cat Toto.

Lastly, my grandmothers and aunt for their endless love and blessings. I know their blessings were always with me, and they helped me pass through the tough times of the global pandemic, online classes, and depressing cold weather.

ACKNOWLEDGEMENTS

I would like to thank my co-supervisors, Dr. Bo Cao and Dr. J. Cardenas Barrera. Dr. Bo has supervised me from the beginning of my research. I started my research when the pandemic started and it was tough coming up with research ideas and obtaining data. Bo has guided me to figure out and focus on which track to choose for my research. Dr. Cardenas joined in as my co-supervisor in early 2023 and I am grateful for his invaluable advice, and continuous support in helping me with the edits of my thesis.

I would like to thank Professor Dr. Liuchen Chang, who allowed me to come to the University of New Brunswick to study for my master's degree and allowed me to be part of the Emera Research Centre for Smart Grid Technologies. I am grateful to him for allowing me to visit my family right in the middle of my degree and be by their side during the most challenging time my family has faced so far. I would also like to thank Dr. Yevgen Biletskiy for his brief guidance in my research.

I would like to express a special acknowledgment and appreciation to Rashed who was my first lab mate and has been a constant source of support and encouragement during the challenges of graduate school.

Lastly, I would like to thank and praise Allah SWT for helping me through this work and for providing me with the patience and health necessary to complete my master's degree.

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List of Symbols and Abbreviations

Symbols:

ϵ	Adjusting value for Dichotomous Search Method
λ	Tolerance
μ_{soc}	Mean of SoC
μ_t	Population Mean of Home Arrival Time
σ_{soc}	Standard Deviation of SoC
σ_t	Home Arrival Time
$\sum X$	Sum of a EV Population
$dn^k p$	Distance Driven by EV
E_{charge}	Charging Energy of EV
EV_{slot}	Number of EV per Slot
$f(soc\|\mu_{soc}, \sigma_{soc})$	Probability Density Function of SoC
$f(t\|\mu_t, \sigma_t)$	Probability Density Function of Home Arrival Time
P_{con}	Constant Load for Time-slot Allocation of EV
P_{grid}	Total Load of Distribution Grid
P_{uc}	Uncontrolled Load of EV
S_a	Arrival SoC
S_n	Nominal SoC of EV Battery
$SoC_{cut-off}$	Threshold for EV Priority Determination
T_{charge}	Charging Duration of EV
A	Average Energy Consumption
a, b	Constants
C	EV Battery Capacity
k	Slot Number
L	Length of Charging Interval
n	EV Number
N	Total Number of EVs
P	EV Charging Power
soc	State of Charge
t	Charging Time of an EV

Abbreviations:

BCB	Battery Charging Behavior
BEV	Battery Electric Vehicle
BLPC	Barbados Light Power Company
BSS	Battery Swapping Station
CAN	Controller-Area Network
DSM	Dichotomous Search Method
DSO	Distribution System Operator
EV	Electric Vehicle
EVCS	Electrical Vehicle Charging Station
G2V	Grid to Vehicle
ICE	Internal Combustion Engine
LDC	Local Distribution Company
LV	Low Voltage
MV	Medium Voltage
OBD-II	On-Board Diagnostic
PDF	Probability Density Function
PEV	Plug-in Vehicle
RTP	Real-Time Pricing
PV	Photovoltaic
RES	Renewable Energy Source
RTP	Real-Time Pricing
SoC	Battery State of Charge
SoD	Battery State of Discharge
ToU	Time-of-Use
UNB	University of New Brunswick
V2B	Vehicle to Building
V2G	Vehicle to Grid
V2H	Vehicle to Home
WC	Wireless Charging

Chapter 1

Introduction

1.1 General

Greenhouse gas (GHGs) emissions, global warming, and climate change are receiving significant attention worldwide [3]. Countries aim to diminish fossil fuel use, which is the main reason behind these issues. Most fossil fuel consumption is in the electricity generation and transportation sectors [4]. In Canada, almost 35% of the total energy demand is from the transport sector, and it is the second largest source of GHG emissions [5]. Governments worldwide are moving toward a green energy economy and taking multiple measures to act against climate change. A primary objective of the measures is supporting electric mobility, which involves utilizing alternative natural resources as energy carriers. This situation is particularly important for the transport sector of the economy; therefore, it increases the transport sector's impact on electric systems. This leads to EVs, an emerging alternative to combustion engines, because of their low emissions and high energy efficiency. The roll-out of EVs occurring in parallel with the decarbonization of the power sector brings uncontested environmental benefits in terms of CO2 emission reduction and air quality improvement in urban areas.

To increase EV adoption, many countries have made preferential policies [6]. For instance, the Ontario Green Energy Act (GEA) of 2009 proposed to reduce the province's impact on GHG emissions and create significant employment opportunities in a green economy [7]. Hence, the Government of Ontario chalked out a path to move toward a green energy economy through increased penetration of EVs as well as Renewable Energy Sources (RES) [8], which present significant potential for solving environmental and economic problems. Furthermore, in Ontario, customers are eligible for up to $10,000 in rebates when purchasing certain EVs [9]; this has accelerated EV sales and is expected to continue to increase rapidly over the next several years.

1.2 Motivation

The present EV market is expanding and is expected to grow with advances in new technologies, particularly in high-energy and power-density batteries. As EV adoption grows, utilities and other power generators grapple with managing the load needed to charge those vehicles and how to forecast when—and where—that electricity will be required. Therefore, there is a need to develop algorithms to control the charging of a large number of EVs.

As EVs bring both challenges and opportunities for power systems, one challenge caused by high EV penetration is the potential increase of peak power demand if charging operations occur in conjunction with current demand peaks. This leads to a large load variance in the power system. Load variance is a part of the power system, and it means that power needs to be generated to achieve the load demand. Variation in loading has specific undesirable effects, the most palpable of which are an increase in power generation cost, difficulty in controlling the system, requirement of additional equipment, and increased loss in machines. Load variance mainly occurs in the case of uncontrolled or dumb charging, where EVs are plugged into the grid randomly in time and space mainly due to uncertainty, together with various driving habits. This charging mode operates regardless of the status of the utility grid and triggers extreme surges in demand specifically when a large number of EVs are plugged in during rush hours. Also, it may threaten the stability and quality of power service of the power grid. [10] According to a survey released by an investigation agency [11], more than 85% of EVs are plugged into the power grid at home after a day's work. EV loads also present a risk to the grid at the distribution level, where major slumps of load peaks can result in severe voltage drops [12] and increase power losses [13]. These EVs will probably bring a huge burden on the power grid during peak hours, leading to a large load variance. Therefore, uncoordinated charging may lead to elevated load peaks early in the evening, whereas there is surplus electricity in the off-peak periods late at night. Hence, minimizing the load variance is needed to decrease system losses, and generally, avoid severe voltage drops. For verification and to see the changes after adding the uncontrolled EV charging load to a grid, an isolated 21-Bus power system of Barbados Light Power Company (BLPC) is taken as a reference grid. Figure 1.1 shows a typical example of adding the uncontrolled charging load of 10,000 EVs to the grid load. It can be seen the original load peak increases by 9.378% after adding the EV charging load.

Among the opportunities, the possibility of using EVs as flexible loads can provide balancing services to grids with large shares of intermittent or fluctuating renewable energy generation [14, 15]. Furthermore, EV load demand can be altered by adjusting the charging pattern known as peak shifting. This can be done using smart charging strategies. Potential problems such as sudden peak demand or sudden overloading can also be shaped or flattened by using a smart charging schedule for the EV's batteries [16]. Moreover, the optimal scheduling of EV battery charging could allow high EV penetration without requiring any upgrades to the existing electricity infrastructure [17]. Hence, to fully exploit the potential of EVs as flexible loads,

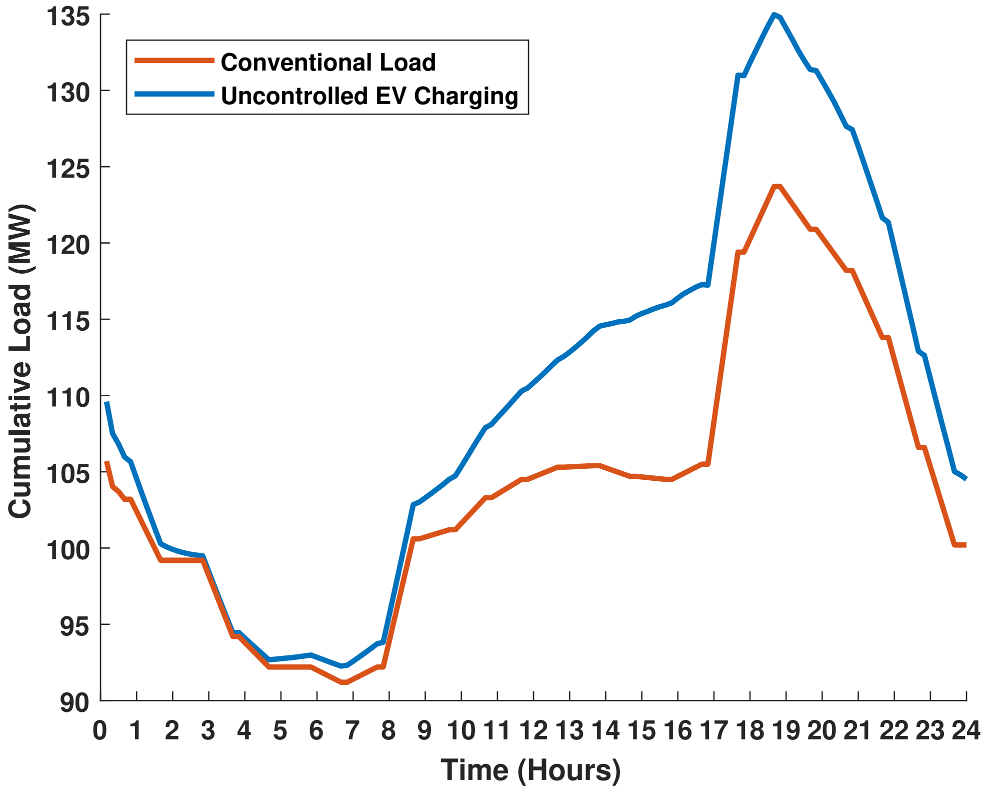


Figure 1.1: Conventional Load Over Day in MW

smart charging strategies need to be implemented.

This research aims to flatten the net-load curve of MV distribution systems associated with a large number of EVs, by reducing the peak load, filling the valley, and thus minimizing the overall load variance. The smart charging algorithm is designed based on the charging priority of the EV, which is defined based on the arrival State of Charge (SoC) value and charging time allocation of the EV. A major focus of this research draws on the centralized charging strategy, in which the EV aggregators can control the EV charging directly. Subsequently, the effectiveness of the proposed method is evaluated and its impact on the power system voltage stability profile is investigated.

1.3 Background

1.3.1 EV Charging Technology

EV charging technologies can be classified into three main categories: conductive charging, wireless (i.e., contactless) charging (WC), and battery swapping. Conductive charging is the simplest and the most widely used charging method. For conductive charging, there is physical contact (i.e., cable) between the power supply and the battery. EV battery chargers for conductive charging have a significant responsibility in the advancement of EVs because the EV adoption and social acceptance depend on effortless access to charging stations or street chargers. Several topologies were presented for single-phase and three-phase EV chargers [18, 19]. It consists of AC/DC converter, power factor correction elements, and DC/DC converter. Charger systems are classified as on-board (i.e., inside the vehicle for slow charging) and off-board (i.e., the outside of the car for fast charging). Moreover, there are three charging levels for conductive charging:

- Level 1: This is the slowest and simplest charging way because no additional infrastructure is needed, and any wall outlet can be used. A standard 120 V/15 A wall outlet in North America is used for Level 1 chargers. It is available only as an onboard charger. Although its cost is less than other charging levels, the EV needs a long time to charge fully. Due to its low power rating, this charging level has the lowest impact on distribution systems.

- Level 2: This charging level uses 208 V or 240 V at currents up to 80 A and 19.2 kW charging power. EV owners prefer Level 2 to Level 1 because of its shorter charging time. Some EVs, such as Nissan Leaf, have an onboard charger of this charging level.

- Level 3: This is for fast charging and operates as a commercial refueling station (i.e., less than 1 hour charging time) similar to the conventional gas station, which can be installed on city main roads and highways. It is supplied from a three-phase circuit with 480V or higher voltages. It is available only as an off-board charger because the charging power is high and may exceed 100 kW. Level 3 charging is not suitable for home charging. Also, it has a high installation cost. Public chargers are expected to use Level 2 or Level 3 for fast charging in shopping centers, parking lots, restaurants, hotels, theaters, etc. High charging power represents an advantage from a charging time point of view. Still, it may generate a peak demand and overload the distribution network equipment in addition to high installation costs.

Most EV owners are expected to charge overnight at home, according to the Electric Power Research Institute (EPRI) [20]; therefore, mostly Level 2 chargers will be the primary option compared to the other charging levels.

WC enables EV charging without physical contact or cable between the power supply and the battery. Advancement of WC will reduce the required onboard battery capacity, which will decrease the EV's price and mass and will result in a reduction of EV energy. WC may become a future alternative to traditional conductive charging. Current WC is designed for unidirectional power flow from the grid to the vehicle. Still, future development of this technology is to enable EVs to discharge power to the grid wirelessly to provide electrical services. The advantages of this technology are electrical safety, no cable requirement, and user convenience. However, the challenges of this technology are the high infrastructure cost compared to conductive charging and low power transfer efficiency between coils [21].

On the other hand, Battery Swapping Station (BSS) is a charging station at which the empty EV battery will be replaced by a fully charged battery in a few minutes [22]. Battery swapping may be used with electric buses that have a high-capacity battery which will take a long time to be charged by traditional conductive charging. This technology requires a large stock of batteries owned by the BSS or a third party and rented to the EV owner. However, this technology includes battery standardization, high infrastructure cost, and large space for BSS.

Among all the technologies, conductive charging is the most suitable and simple one for home charging. In this research work, the conductive unidirectional charging with a Level 2 charger is considered.

1.3.2 EV Charging Methods

Conductive charging can be classified as unidirectional or bidirectional chargers [23]. Unidirectional charging has simple charging hardware and allows power flow from the grid to EV only (i.e., uncontrolled charging and controlled charging), whereas, bidirectional charging allows power flow from the EV to the grid (V2G, V2B, and V2H). It can inject power from the EV battery into the grid, building, or home. This research focuses on unidirectional charging. The most common methods of unidirectional charging are uncontrolled and controlled charging.

- Uncontrolled Charging: This is the simplest method to charge EVs and the most commonly used way. The EV is plugged in for charging at the maximum power rating of the EV charger until the EV battery is fully charged (i.e., SoC is 100%). Several studies concluded that uncontrolled charging of EVs may result in severe negative impacts on distribution networks, such as an increase in peak load demand, overloading of transformers and cables and reduce their life, increase in voltage drop, increase in system unbalance due to single-phase chargers, increase in power losses, and harmonic distortion [24, 25]. Moreover, this charging limits EV's acceptable penetration level because EV owners charge their vehicles when arriving home from work, which usually coincides with peak hours. This charging method is also known as dumb, uncoordinated, and unregulated.

- Controlled Charging: This method controls the charging time and charging power of EV depending on some distribution network parameters such as total power demand, transformer loading, voltage stability, power losses, etc., or to minimize the charging cost. In this technique, EV acts as a controllable load. Various studies proposed controlled charging algorithms for increasing EV owner benefits by setting cost reduction and maximizing utility benefits by reducing distribution network stress and losses, enhancing power quality, and shifting the EV load to off-peak hours, which result in valley filling [26, 27]. This charging method is also known as coordinated charging and smart charging.

1.4 Literature Review

A significant challenge for integrating EVs with the electrical grid is balancing supply and demand. Uncontrolled EV charging at high penetration levels is expected to introduce various undesirable negative impacts on the power system, including increased system peak load, net-load variance, voltage instability, and decrease in load factor. Moreover, such charging practices can create complications for the grid with increased stress on the distribution transformer and line congestion. Hence, coordinated EV charging is needed to mitigate such problems.

1.4.1 Deterministic Control Approaches

While the global, or system-wide, negative impacts on the bulk power system are likely only at high EV penetration levels [28], local impacts on the distribution system are expected to be more significant even at moderate penetration levels. However, it was found that with adequate management, the negative impacts of EVs can be reduced, and the penetration depth of electric vehicles can be increased [29]. Several strategies have been introduced to control EV charging to prevent negative impacts on the grid. These can be classified into centralized and decentralized charging control strategies.

In centralized scheduling and control, the control algorithm of EV is executed centrally after collecting all the information regarding the EV status and owners' preferences as well as other system data, such as market prices and system constraints and loading. The central controller can be an aggregator or a system operator. The EV aggregator combines the conventional load of the grid with the charging demand of EVs to manage the charging load of EVs for an established objective [30]. There are various objective functions for centralized charging strategies in previous studies; it minimizes power losses to achieve an optimal charging strategy of EVs [30, 31]. The other two optimal objective functions include minimizing the total load variance [32], [33], and maximizing the load factor [34]. Minimizing the total load variance for practical systems will reduce power losses approximately. In addition, maximizing the load factor is equivalent to minimizing load variance. Compared with reducing power losses, minimizing load variance is a better choice for mathematical modeling because it is independent of the system topology. Maximizing the load factor is the best method in case of the computation time [35]. Three approaches were studied in [36]: dumb charging, dual tariff policy, and smart charging. Voltage profiles and line congestion levels were evaluated for peak load hour and grid technical limits checking. In addition, network issues were evaluated for a typical daily load profile. Smart charging with hierarchical, centralized control showed the best performance, showing that voltage is the limiting factor for higher EV integration. On the other hand, similar to the centralized strategies, the decentralized strategies have gotten increasing attention since they can be operated conveniently. Each EV owner should decide "when and how much charge" according to the electricity price system. The price mechanism is designed by the aggregator for minimizing overall generating costs [37]. It should be noted that the EV owner has to be intelligent enough to get the optimal charging strategy for minimizing the charging cost [37]. The decentralized charging approaches only can motivate EV owners to charge in the load valley periods but can't control the charging profile of EVs. It may raise a potential security concern on the power grid [38]. By comparison, in the centralized charging strategies, the EV aggregator makes decisions about EV charging power and time, which can provide the optimal solution for the power grid [35]. Therefore, the research focuses on a centralized charging scheme as the aggregator is exclusively responsible for ensuring a coordinated process for EV charging, keeping in view the benefits of both the parties, i.e., the network operator and the charging customers.

1.4.2 Smart Charging Strategy

Various coordinated charging schemes of EVs have been proposed to reduce the overloading conditions of the grid. The EV load is distributed over the tenure of the daily load profile, and it is preferred to charge the EVs in off-peak periods to minimize the load variance. With grid-to-vehicle (G2V) techniques, EVs act as a variable or an interruptible load. Recent research also considers using EVs as a generation source to provide power back to the grid for peak load periods. Thus decreasing grid congestion [39]. This vehicle-to-grid (V2G) mechanism requires smart EV chargers with bidirectional power flow characteristics [40]. Nevertheless, the V2G strategy depletes the EV battery as the V2G implementation requires frequent charging and discharging processes which can cause extra deterioration to the EV batteries [41]. Furthermore, time-based demand response schemes like Real-Time Price (RTP) and Time-of-Use (ToU) are also proposed to minimize the load variance. RTP is a dynamic rate designed to reflect the balance of supply and demand, whereas ToU is defined as a long-term pricing method that gives different prices based on the time of day [42]. Both time-based demand response schemes allow the possibility of good planning for customers and reduced peak demand. However, RTP is complicated to implement and requires accurate communication and metering, whereas ToU has a limited reflection on the supply/demand [43]. This downside of the coordinated charging schemes, which has created a strong social barrier between EV users and their charging demand, can be avoided by implementing an intelligent charging control.

The literature focuses on several smart charging schemes to minimize net-load variance. In [44], a controlled charging scenario is calculated using an optimization approach to flatten the total load profile. Spatial heterogeneity is incorporated into the modeling of vehicle use, electricity demand, and network structure. The authors have observed that controlled charging has a significant benefit as it can reduce expansion requirements for electricity generation capacities and investment into the distribution network. Even though the work [44] was able to demonstrate the possibility of optimizing EV charging at the generation level without increasing distribution constraint violations, it was not applicable as they relied on the forecasts of conventional vehicle use instead of using real, local data. On the other hand, [45] used a quadratic program to design a coordinated charging scheme to minimize load variance. Grid impacts using coordinated charging with load balancing by PV inverters and EV chargers were simulated in a Belgian LV network, reducing grid losses. However, a requirement for infrastructure upgrade limits the application of the design due to high costs [46]. Moreover, both [44] and [45] did not change the penetration level, thus refraining from observing the impact of smart charging in a wide range of penetrations.

In [47], a scheme of internet of smart charging points with PV integration (ISCP-

PV) for V2G scheduling is proposed in an edge computing model to reduce the peak-valley difference of net load, as well as to improve computational efficiency, preserve the privacy of PEV users and support the self-consumption of the PV output by the PEV charging. The authors simulated the grid impact of smart charging in a campus grid and compared it with uncoordinated charging. The proposed scheme could conduct peak-shaving and valley-filling of the total net load compared to uncoordinated charging. Furthermore, in [48], smart charging using fuzzy logic control was designed with electricity price signal and SoC as inputs and the charging power as an output. According to the controller design, the EV charging power changes based on the electricity price. Simulation results show that smart charging reduced the maximum power demand and improved the voltage profile compared to uncontrolled charging. However, both the papers, [47] and [48], considered the uncertainty of EV mobility parameters and did not vary the penetration level.

A probabilistic load flow analysis is performed in [49] by modeling the variability of electric vehicle mobility, household load, PV system generation, and the adoption of the PV system and EVs. The optimization formulation of the smart charging scheme is in a quadratic programming form, also referred to as a convex problem, and solved with the interior-point-convex algorithm. The objective of the smart charging scheme was to reduce the net-load variance. However, the reduction did not occur significantly when the penetration increased because there was more unconsumed PV power when the number of houses with PV was higher. A large amount of unconsumed PV power leads to high net-load variability, and it is not possible to reduce the usage of PV, which is a significant drawback of this design. Moreover, in the paper [50], genetic algorithms in the optimization model are used to develop a controlled EV charging strategy to optimize the peak-valley difference of the grid when considering the regional wind and PV power output. Simulations of the model successfully stabilized the power fluctuations caused by the regional wind and PV output. However, the limitation of using genetic algorithms is that they are employed based on the optimal size and location of the wind power-based charging stations for the electric buses. Hence, during the construction of renewable energy-based charging stations, urban environmental conditions are also taken into consideration.

Most simulations of smart charging algorithms have proven that increased peak loads after adding EV load to the grid could be reduced. Still, the benefits of the methods were not simulated on an actual MV distribution system. Also, they focus on a single penetration level, and some used forecasted EV data instead of real data. Moreover, most smart charging studies discussed here concentrate solely on EV charging with PV generation to minimize the net load variance. The proposed research intends to work with real data and evaluate the grid impact of smart charging to reduce the net-load variability in MV distribution systems without residential PV generation.

1.5 Objectives

The main objectives of this research work are:

1. To develop an intelligent EV charging algorithm to create alternative power system resources to minimize the load variance in power grids.

    - Smart charging scheme with the objective of peak shaving and valley filling in the load profile.
    - Algorithm focuses on the centralized charging strategy, in which the EV aggregators can control the EV charging directly.
    - EV charging without Renewable Energy Source (RES) generation.

2. To develop an aggregated EV usage profile model using regional statistical information.

- Allow greater EV penetration for a specific regional grid reducing risks on the grid.
- Meeting the charging demand of EV users.

3. To analyze the impact of EV charging on the load bus voltage in an MV distribution network.

1.6 Thesis Organization

The remainder of the thesis is organized as follows:

Chapter 2 presents a brief review of the critical parameters of the EV, such as SoC and plug-in time, which are considered to design the smart charging algorithm, including the charging characteristics of the EV battery and the user behaviour.

Chapter 3 presents a charging priority analysis-based methodology, assumptions, and input data for modeling an EV aggregator's 24-hour charging demand profile. The proposed mathematical algorithm formulation, which includes the PDF, DSM, and Monte Carlo approach, is provided in this section.

Chapter 4 shows the impact of EV load models on distribution systems and the change in voltage stability for uncontrolled and controlled charging examined and compared. The load and voltage profiles are obtained using MATLAB and CYME.

Chapter 5 summarizes the research presented in the thesis, highlights the main contributions, and suggests directions for future research work.

Chapter 2

Determination of Critical Parameters

2.1 General

From the Local Distribution Company's (LDCs) perspective, meeting the increased demand for charging the EVs while satisfying the distribution system operating constraints is a major challenge. Moreover, reducing the system losses is also considered a significant challenge. On the other hand, the EV charging demand depends on the customers' convenience, and the EV arrival time at a charging station varies. Therefore, integrating EV customer behavior to estimate EV charging demand is a critical issue that needs to be investigated. Furthermore, the charging demand at an Electrical Vehicle Charging Station (EVCS) is affected by different factors, such as the number of EVs arriving in an hour, the number of EVs being charged simultaneously, the SOC of the EV battery, charging levels, battery capacity, charging duration, etc. Some of these parameters are independent processes, such as the arrival rate, and some are dependent on the EV type, such as battery capacity or battery charging behavior (BCB); while some others are dependent on the EV driving patterns, such as the SOC of the EV battery and the charging duration. These factors are divided into specific categories.

2.2 EV Usage

2.2.1 State of Charge (SoC)

The state of charge measures the amount of energy available in a battery at a specific point in time expressed as a percentage: for example, a SOC of 50% implies the battery is half-charged. The SOC provides the user with information on how much longer the battery can perform before it needs to be charged or replaced and helps in describing the actual energy level available at the battery. Understanding the state of charge is important because understanding the remaining capacity of a battery can help make a control strategy.

In this research, the SoC data from an actual EV was collected by sending controller-area network (CAN) requests through the vehicle's onboard diagnostic (OBD-II) port. The EV is a 2019 Nissan Leaf owned by our research group at UNB.
To collect battery SoC data from the vehicle, a Raspberry Pi and vehicle OBD-II scanner was used. The SoC obtained from the EV is the arrival SoC, which is the remaining SoC after the vehicle has traveled all day. Appendix A shows the SoC data that was collected. However, to calculate the power required to charge the EV to 100%, the difference between the maximum SoC and arrival SoC is calculated using Equation 2.1. The difference of SoC calculated is considered as the State of Discharge (SoD). The SoC and SoD is evaluated per unit (p.u.).

$$SoD = S_n - S_a \tag{2.1}$$

where S_n is the maximum SoC of the EV battery, which is considered 1 p.u. (100%)

in this research and S_a is the arrival SoC.

As only one EV was used to collect raw SoC data, the distance of local vehicles was also considered to calculate the SoD for a more realistic approach.

$$SoD = S_n - \frac{\alpha d}{d_R} \tag{2.2}$$

where, d is the daily distance driven by a vehicle, α is the number of days the EV has traveled since the last charge (usually 1 day), and d_R is the maximum daily distance of the EV, which is considered to be 60 km as per New Brunswick Analysis 2016 Census Topic: Journey to Work [51].

2.2.2 EV Plug-in Time

The time of connecting the EVs for charging is still being determined. Hence, it is unknown how many EVs may be charging simultaneously and the probability that the EV charging time interferes with the peak demand time of the distribution networks. Some studies assume the charging start time of EVs, and other studies do surveys in a geographical area or a city to know the home arrival time of vehicles and model it as continuous probability distribution.

In this research, the home arrival time of EVs is taken from a traffic study done in Fredericton, NB, even though the EV loads are tested on the BLPC grid. As it was difficult to retrieve surveys or data on Barbados' driving patterns, hence, it is assumed that the driving pattern of Barbados and Fredericton is the same. The Capital City Traffic Study [1] was a comprehensive transportation planning study of Fredericton's street network completed in 2000. The final document identified priority areas of traffic congestion and has guided transportation planning and infrastructure investment in Fredericton for the past ten years. The Study Area includes all streets and intersections within the City's boundaries, as well as the significant streets incoming from the surrounding areas. According to [1], the transportation network in Fredericton features many core feeder routes passing through the center of the City, where most are provincially designated highways that at one time served as key elements of the provincial roadway network and now also serve as urban arterial or collectors for local transportation needs and commuter traffic. The hourly volume plot of commuter traffic for an average feeder route is shown in Figure 2.1, selected from the travel study to consider the EV home arrival times for the research. The plot explains the number of vehicles on the road traveling inbound and outbound to the city at specific times.

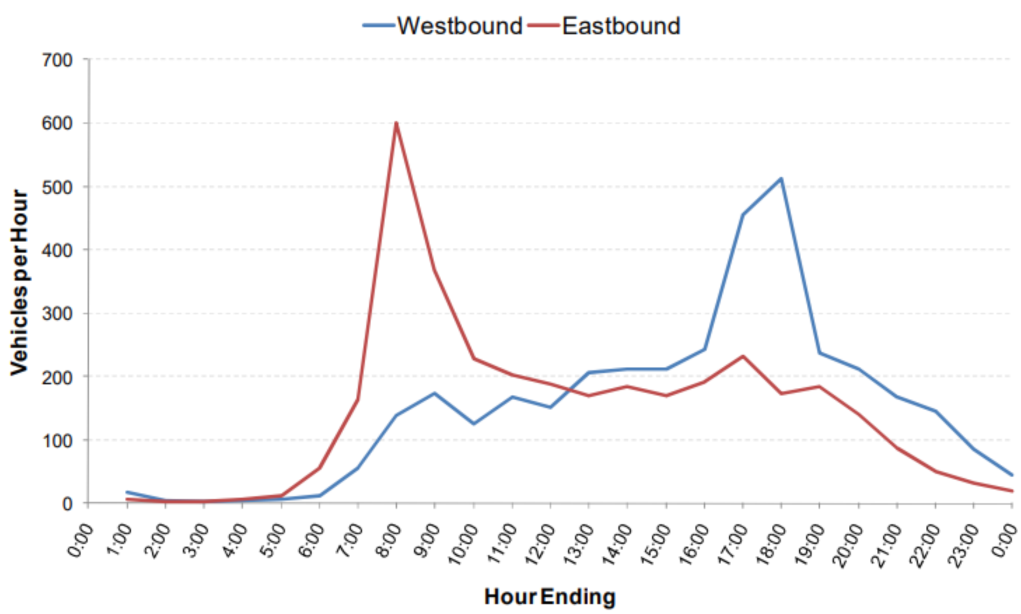


Figure 2.1: Average Traffic Distribution Curve of streets in Fredericton, NB [1]

2.3 Charging Characteristics of EV Batteries

The most commonly used and environment-friendly EV is the Battery Electric Vehicle (BEV), which entirely depends on a rechargeable battery. BEV contains only an electric motor, powered by a battery, and does not contain Internal Combustion Engine (ICE). The electric driving range depends on battery capacity. The main advantage of BEV is that it produces no emissions locally, which is crucial in big cities.

Lithium ion has been the top contending technology for BEV batteries due to a combination of performance capability, safety, life, and cost. Lithium-ion is selected as it has a much longer lifetime and is capable of more charging cycles, which has been mainly applied to EV batteries currently [52]. The Nissan Leaf, a BEV based on lithium-ion batteries with a battery capacity of 40 kWh, is used as a standard model for the research work. For household cars, Level 2 chargers are generally applied as mentioned and explained earlier, and the characteristics of Nissan Leaf are provided in Table 2.1.

Table 2.1: EV Characteristics

EV Model	Nissan Leaf
Range (km)	240
Battery Energy (kWh)	40
Battery Power (kW)	110
Battery Voltage (V)	403.2 volts/360 volts nominal
Charger Power (kW)	6.6

A complete charging curve of the Nissan Leaf 40 kWh battery has been obtained using real and calculated charging data, as shown in Figures 2.2 and 2.3, respectively. The real data is the collected SoC from the Nissan Leaf, and the calculated data is the SoC calculated using the EV battery. EV battery charging profiles are essential for electric energy distribution network operation, load forecasting, utility grid expansion, and planning. A typical EV charging profile includes its start time, initial battery SoC, charging power, and (total) charging time. For the real charging profile shown in Figure 2.2, EV battery data were collected from the UNB Nissan Leaf as explained in subsection 2.1.1. Data from the car was collected every 10 minutes for most of the charge but started collecting every 5 minutes after around 90% to get a better view of the power decrease as the SoC approaches 100%. Appendix B shows the data collected from the Nissan Leaf. Figure 2.2 shows a constant charging power of 5.6 kW during the continuous charging rate. As the SoC level reaches 90%, the charging rate decreases, and the power drops.

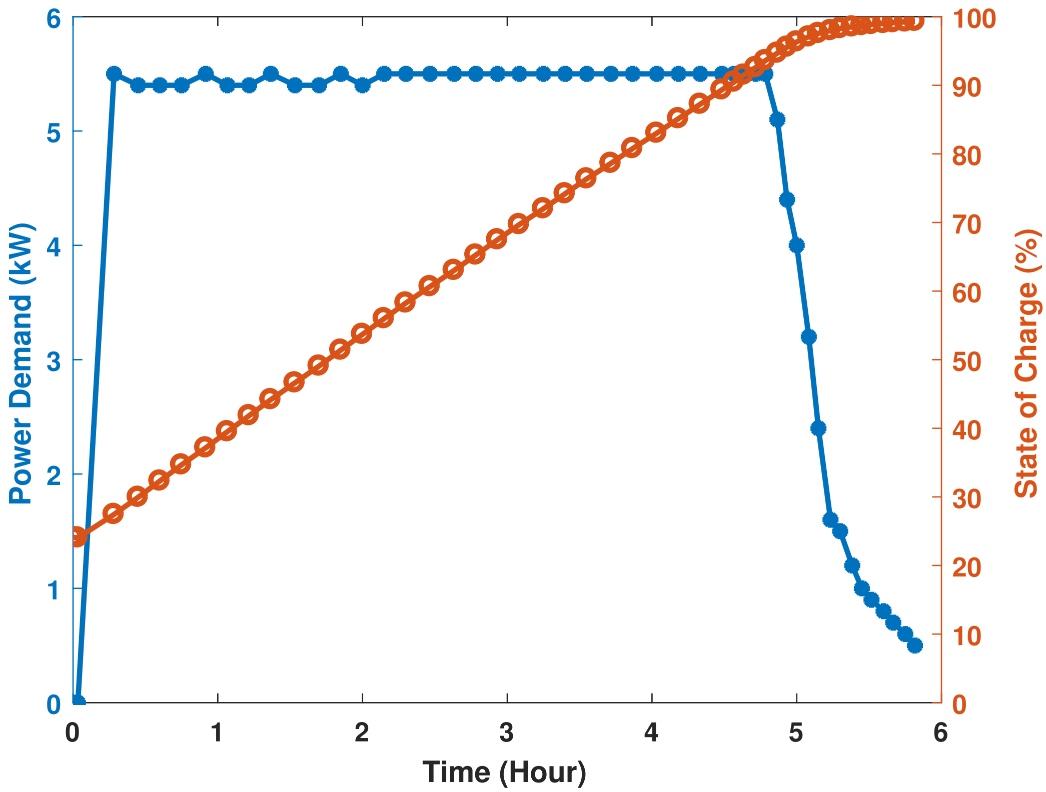


Figure 2.2: Charging Profile of EV Battery (40 kWh) using data from UNB Nissan Leaf

The profile depicted in Figure 2.3 is obtained using data from the EV battery. For the calculation, the C-Rate is initially calculated as shown in Equation 2.3, where C-Rate is expressed as C_r and t is the charging time. The C-Rate measures the rate or current at which the battery is charged or discharged relative to its maximum capacity. The higher the C-Rate, the faster the charging/discharging. The battery's capacity is generally rated and labeled at the 1C Rate (1C current). This means a fully charged battery with a total of 10Ah should be able to provide 10 Amps for one hour. A back-calculation was carried out for the UNB Nissan Leaf to find the C-Rate using the battery pack specifications in Table 2.2.

Table 2.2: EV Battery Pack Specifications

Number of Modules	24
Number of cells	192 (2 in parallel, 96 in series)
Rated Voltage	350 V
Nominal Voltage	3.65 V
Rated Capacity	56.3 Ah
Capacity	40 KWh
Charging Time	8 Hour

$$Cr = \frac{1}{t} \tag{2.3}$$

$$Cr = 0.125C \tag{2.4}$$

A constant charging power of 6.6kW is shown during the constant charging rate in Figure 2.3. Furthermore, at SoC level 100%, the charging rate decreases, and the charging power decreases.

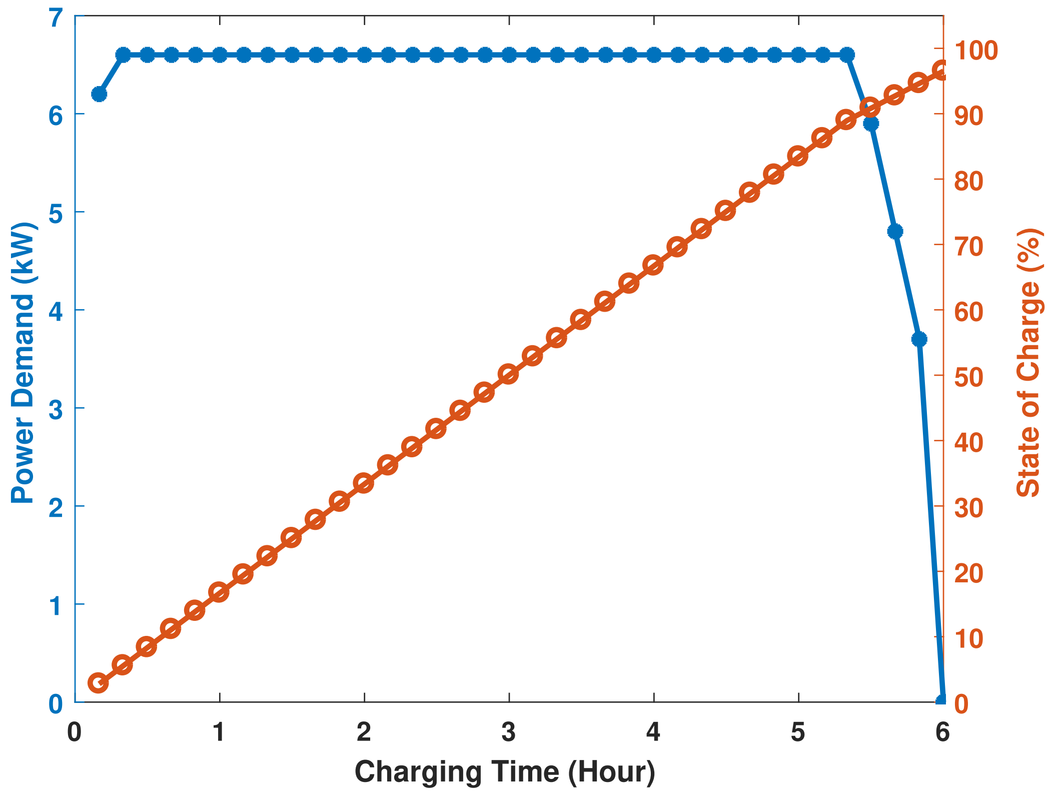


Figure 2.3: Charging Profile of EV Battery (40 kWh) using data calculated from EV Battery

2.4 EV User Behaviour

The EV market is expanding, and there is a significant need for charging infrastructure. To ensure that the infrastructure satisfies the needs and interests of EV drivers and site hosts alike, it is important to understand the driver's demand, how much they use the EV, and how they would use the infrastructure. This information is beneficial to charger operators or aggregators to help design and manage appropriate facilities.

EV drivers tend to recharge daily or once every two days, typically overnight at home, and overall, about 70-80% of charging occurs at home or at a workplace parking lot. Hence, considering home charging, SoC profiles were obtained using the SoC data collected from the UNB Nissan Leaf. The charging profiles show the home arrival

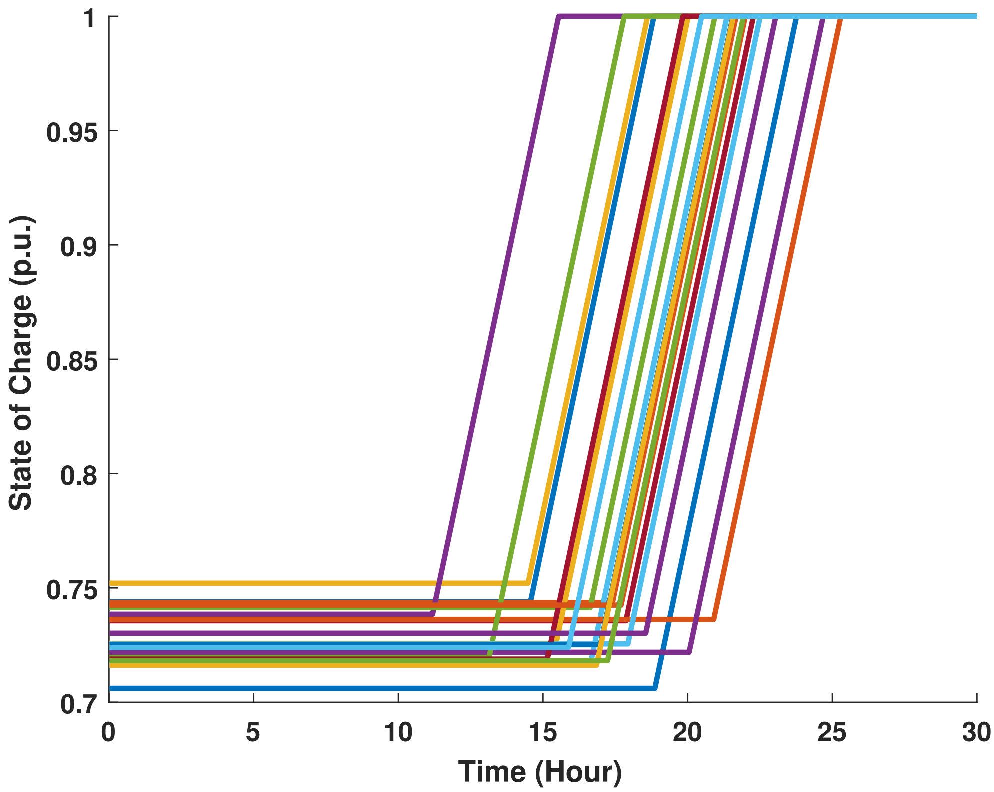


Figure 2.4: SoC Profile for Single EV User

SoC and home arrival time, both taken randomly from collected data and start charging till they reach 100%. The charging rate at which the SoC is increasing is calculated as explained in Section 2.2. Both profiles for single users and multiple users are shown in Figure 2.4 and Figure 2.5 respectively. In multiple user profiles, data for 20 different EV users were simulated and it can be seen that the starting SoC has a wide range from 50% to 98%. However for a single user, as shown in Figure 2.4, the range is really small as the travel routine for one user is pretty much the same every day. SoC charging data was collected for 20 different days for the single user.

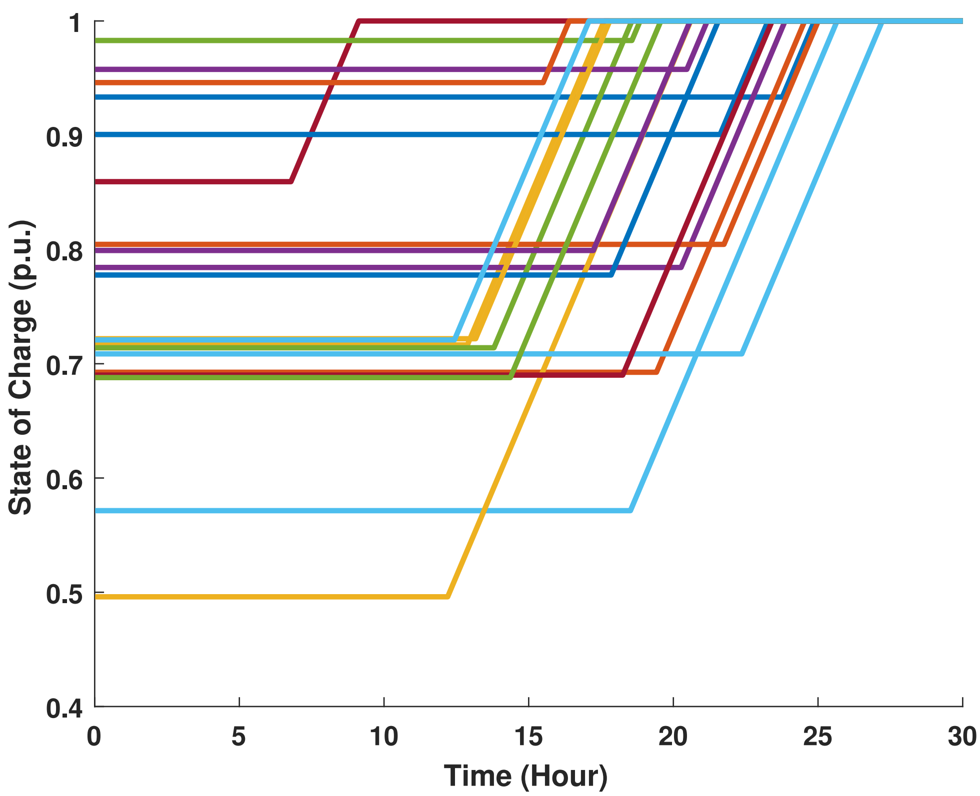


Figure 2.5: SoC Profile for Multiple EV Users

2.5 Operating Process of EV Aggregator

It is expected that EVs will dominate the private cars market in the coming years. This transition will cause a substantial change in the aggregated electric load profiles, with serious repercussions on the distribution networks. To ensure the ongoing reliable operation of electricity distribution networks, control mechanisms must be implemented to manage EV charging. A distribution system operator (DSO) would have to handle a potentially massive number of EVs to achieve this using a centralized control architecture. An aggregator agent for electric vehicles is a commercial middleman between a system operator and a plug-in EV. From the system operator's perspective, the aggregator is seen as a large source of generation or load, which could provide ancillary services such as spinning and regulating reserve. The aggregator which is the centralized controller usually results in the optimal utilization of the system resources but needs a mature communication infrastructure [53].

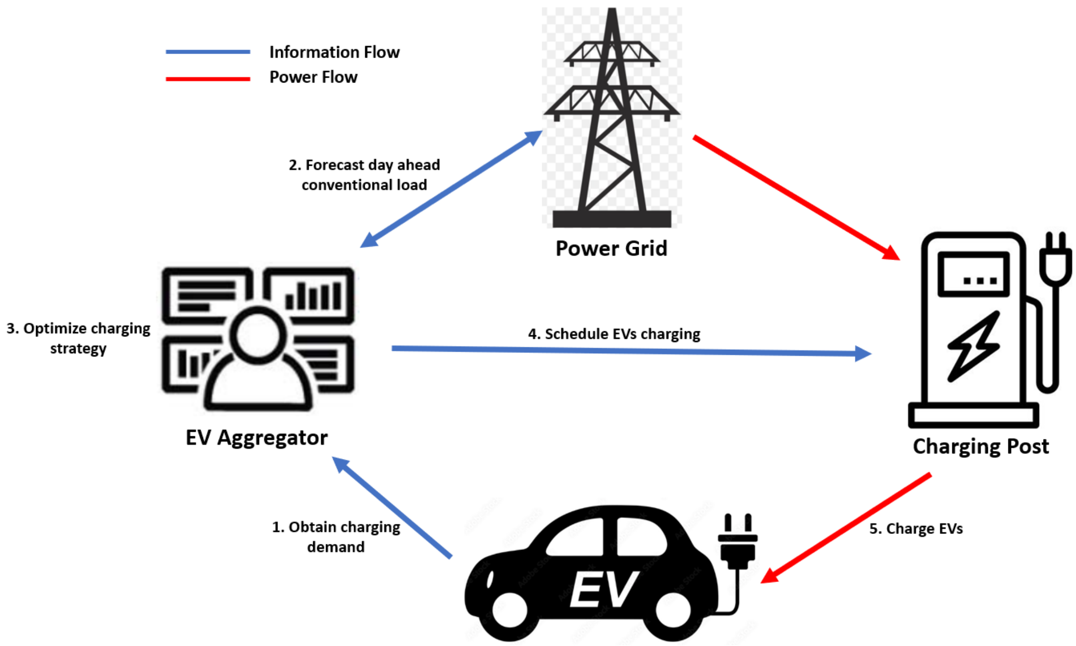


Figure 2.6: Process of EVs charging in centralized charging scheme

Figure 2.6 describes the operating process of the EV aggregator in a centralized charging approach. The aggregator is the most important part of this system. It can be seen that the aggregator communicates with EVs, charging stations, and the power grid. The operating process is as follows:

- Firstly, the aggregator collects the charging demand data on where and when EVs will charge;
- Secondly, the day ahead conventional load curve is forecasted by the historical data obtained from the grid;
- Then, the aggregator can optimize the charging strategy on the basis of the predicted conventional load curve and the charging demand of EVs;
- Next, the aggregator transfers the charging instructions to charging posts;

- Finally, the charging posts will charge EVs according to the charging instructions.

2.6 Summary

This chapter presents the required parameters for the EV smart charging algorithm in this research. A brief background on the parameters, like SoC, EV plug-in time, and battery characteristics is presented as well as how these data were collected. This is followed by the usage behavior of the EV users and finally the aggregator's operating process. These parameters are used to design the EV smart charging algorithm shown in the next chapter.

Chapter 3

Methodology

3.1 General

The problem being faced by the power grid is whether the existing distribution network infrastructure would be able to effectively accommodate the widespread adoption of EV. And if not, how to control the charging behavior of EVs to make the power grid effective is the key point we should concentrate on.

Uncoordinated charging may lead to elevated load peaks early in the evening; meanwhile, it may waste the surplus electricity in the off-peak periods late at night (Fig. 3.1). Thus, a set of mechanisms is needed to shift the charging load from red to green in Figure 3.1.

3.2 Input Data and Assumptions

The target is to control the EVs charge with high power demand in the valley of the conventional power load profile during the day. As illustrated in Figure 3.1, the blue graph is the conventional power load profile of the BLPC grid. The basic period is set to be 24 hours or 1440 min. To avoid the emergence that EVs charge across a

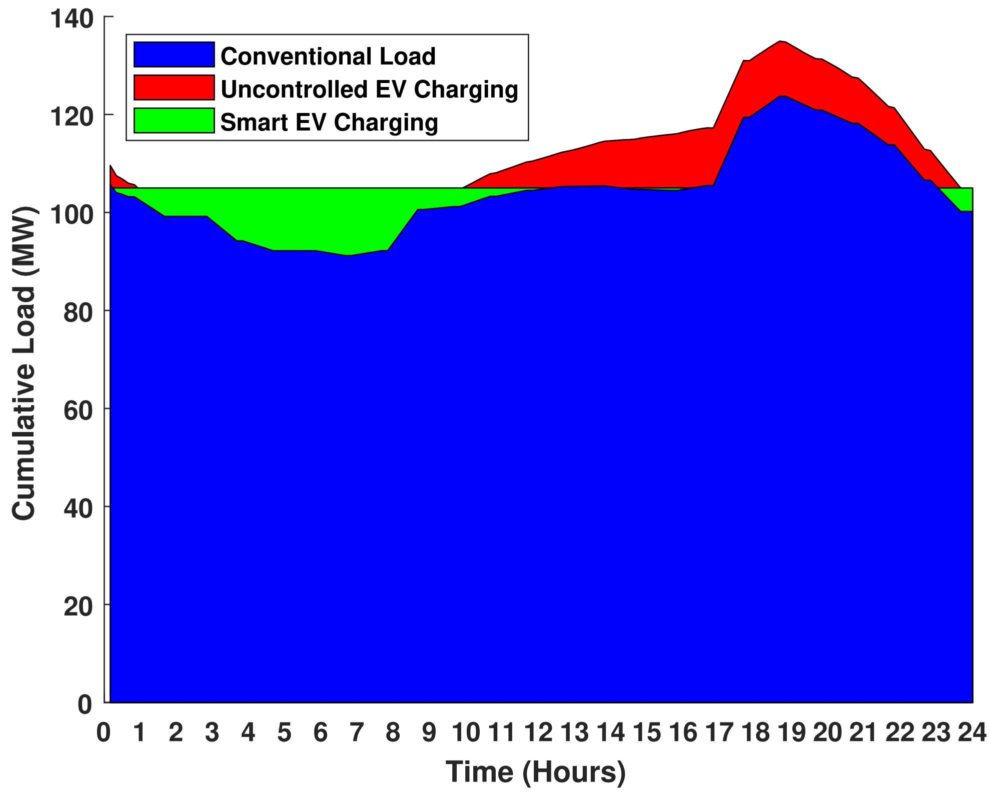


Figure 3.1: Total grid load after adding EV uncoordinated and smart charging load

period in the evening, the starting time of the basic period is chosen as 12:00 AM of the current day, and the ending time is chosen as 12:00 AM of the next day. A basic period is divided into 144 time slots, and each time slot lasts 10 min. The symbol k indicates the serial number of the time slots for each EV. The scheduled charging power (P), which ranges from 2.5kW to 19.3kW for the Level 2 charger, is taken to be 6.6kW for the study and it remains unchanged during each time slot. For each slot, random numbers of EVs will be charged. All the EVs charged in one day add up to the total number of 10,000 EVs. The objective is to control the EV charge with high power demand in the valley of the conventional power load profile during the day and charge up to 10,000 EVs. The symbol n indicates the total number of EVs plugged into the power grid per slot.

As mentioned in Section 2, the main variables considered in the optimization problem to minimize load variance in the distribution grid using EV are SoC and home arrival time data. General home arrival time and patterns of SoC are extracted from long-term SoC data of UNB Nissan Leaf 2019 to create a probabilistic model that reflects the most likely behavior of the EV load profile. This probabilistic model is obtained using the Probability Density Function (PDF), which is a function whose value at any given sample (or point) in the sample space (the set of possible values taken by the random variable) can be interpreted as providing a relative likelihood that the value of the random variable would be close to that sample [54]. Moreover, the average trip duration of a car in NB is assumed to be around 20 minutes, hence, considering the traffic distribution curve shifted for a period of 30 minutes, the arrival-time distribution curve and data for a day are obtained. Lastly, the real medium voltage network of BLPC is used as the test network to integrate loads of EV.

3.2.1 Initial State-of-Charge

To create a probabilistic model that reflects the most likely behavior of the EV load profile, the general values and pattern of the SoC of any EV, which is extracted from long-term SoC data of a Nissan Leaf, is relatively more convincible. A probability density function of SoC generated from real UNB Nissan Leaf data is selected. A log-normal distribution is a continuous probability distribution of a random variable in which the logarithm is usually normally distributed. For the algorithm, the SoC has to be randomly chosen. Hence, the log-normal distribution is used as it helps in modeling natural phenomena, such as making sure the pattern of arrival SoC and behavior for a particular user is roughly constant every day but different from other EV users. The SoC is randomly sampled from the PDF of log-normal distribution with the distribution parameters mean (μ) and standard deviation (σ) as shown in Equation 3.1, and then allocated to each EV charging behavior through the Monte

Carlo method [52]. The Monte Carlo algorithm is a computerized stochastic simulation approach, which is based on the statistical theory of probability and can describe the characteristics of things and physical experimental processes more realistically [55].

The log-normal distribution of a SoC with expected mean value μ_{soc} and standard deviation σ_{soc} is defined as:

$$f(soc|\mu_{soc}, \sigma_{soc}) = \frac{exp\left[\dfrac{-(In(soc) - \mu_{soc})^2}{2\sigma_{soc}^2}\right]}{soc\sigma\sqrt{2\pi}}, \quad 0 < soc < 1 \tag{3.1}$$

where, $f(soc|\mu_{soc}, \sigma_{soc})$ is the PDF of the SoC. The mean $\boldsymbol{m}$ and variance $\boldsymbol{v}$ of a log-normal random variable are functions of the log-normal distribution parameters μ_{soc} and σ_{soc}:

$$\mu_{soc} = log\left[\frac{m^2}{\sqrt{v + m^2}}\right] \tag{3.2}$$

$$\sigma_{soc} = \sqrt{log\left[\frac{v}{m^2 + 1}\right]} \tag{3.3}$$

Figure 3.2 plots the PDF curve of the Log-normal Distribution of SoC after arriving at the charging station.

3.2.2 Home Arrival Time

As explained in Subsection 2.2.2, Fredericton's driving pattern is considered even though the EV loads are tested on BLPC grid load. Figure 3.3 shows the total number of cars arriving per 30 min of a day in Fredericton, taken from the Capital

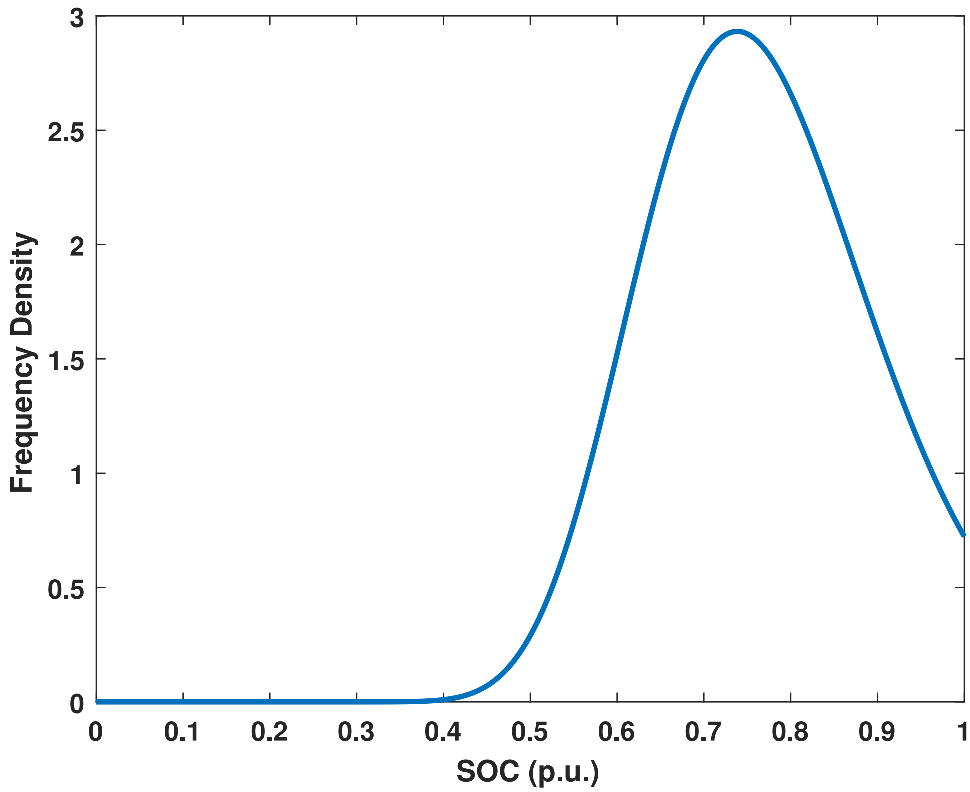


Figure 3.2: PDF of Log-normal Distribution of Initial SoC

City Traffic Study [1]. In general, commuters arrive at work at 7:00–9:00 and return home between 16:00 and 19:00. The location of the arriving cars in Figure 3.3 is unknown. Still, considering Fredericton's daily life, it seems logical to assume that the arrivals from 16:00 to 19:00 represent the arrival time at home. From the figure, it can be seen that the EV plug-in after around 20:00 starts to decrease. This is because not only the arriving cars after 20:00 are fewer in comparison to the rest but also because the interest of the analysis is on the peak electricity consumption caused by the concurrence of domestic consumption and EV charging. The peak in the consumption in the BLPC grid is around 20:00, as shown in blue in Figure 3.1. The sum of the shares in Figure 3.3 adds up to 10,000 EVs which is the maximum number of EVs allowed by the algorithm to charge.

Since all EVs in the distribution system do not start charging simultaneously, it is assumed that the time of switching on an individual charger is a random variable,

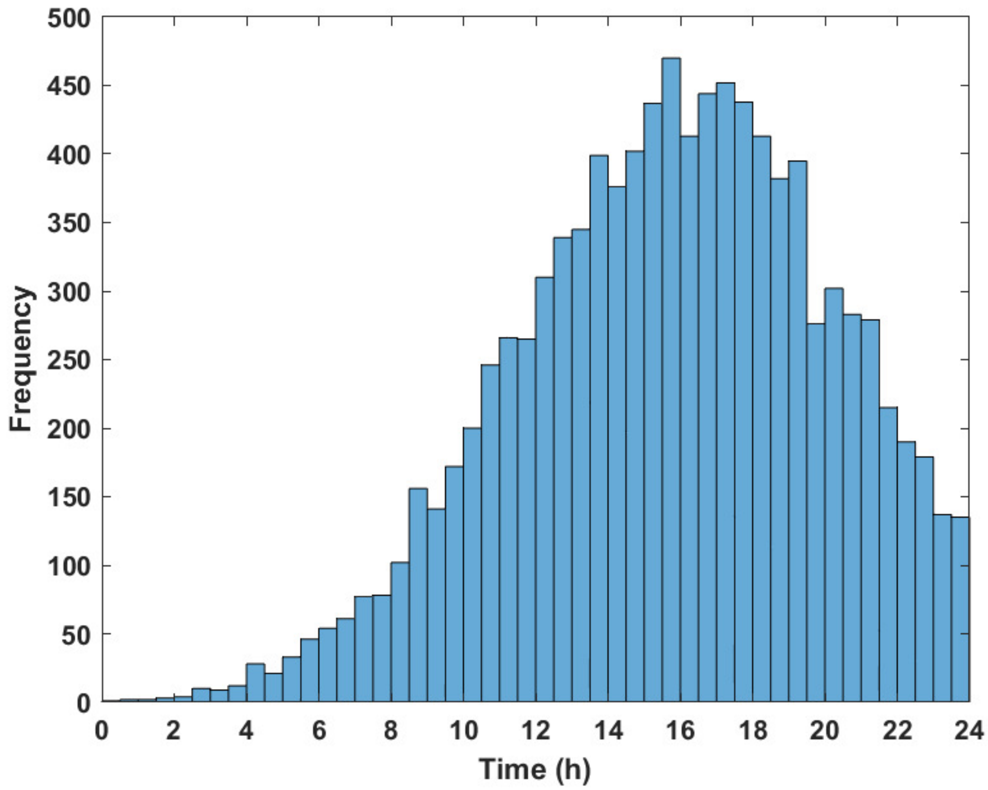


Figure 3.3: Frequency of arriving cars per 30 minutes of a day in Fredericton

with a probability density function of the normal distribution as shown in Equation 3.4, which is determined by the pattern of vehicle usage [56].

$$f(t|\mu_t, \sigma_t) = \frac{exp\left[\dfrac{-(t-\mu_t)^2}{2\sigma_t^2}\right]}{\sigma_t\sqrt{2\pi}} \tag{3.4}$$

The normal distribution, also known as Gaussian, Gauss, or Laplace–Gauss distribution, is a continuous probability distribution for a real-valued random variable. The usual justification for using the normal distribution for modeling is the Central Limit Theorem, which roughly states that the sum of independent samples from any distribution with finite mean and variance converges to the normal distribution as the sample size goes to infinity. The parameter μ_t is the population mean which is the mean or average of all values in the given population and is calculated by the sum of all values in the population denoted by the summation of X divided by the total number of values in people which is characterized by N, as shown in Equation 3.5:

$$\mu_t = \frac{\sum X}{N} \tag{3.5}$$

The parameter σ_t is its standard deviation, which measures the variation or dispersion of a set of values. Equation 3.6 shows how the σ can be calculated:

$$\sigma_t = \sqrt{\frac{\sum (X - \mu_t)^2}{N}} \tag{3.6}$$

The mean (μ) home arrival time for Fredericton, NB, is calculated to be 16.25 Hours, and the standard deviation (σ) is 4.78 Hours. Accordingly, using Equation 3.4, a PDF of the Normal Distribution of Charging Start Time of EV users can be plotted, which is shown in Figure 3.4.

3.2.3 Daily Driving Distance

Using the log-normal random value of home arrival SoC for each EV, the daily driving distance of each EV can be estimated using the Equation 3.7.

$$dn^k = \frac{(1 - SOCn^k)C}{A} \tag{3.7}$$

The C is the battery capacity of the Nissan Leaf, and A is the Average Energy Consumption in kWh/km. The average energy consumption (A) is evaluated as a ratio in kWh/km between the battery capacity and the average range distance of 60 km. This mileage is calculated to verify the mobility pattern of the EV users with

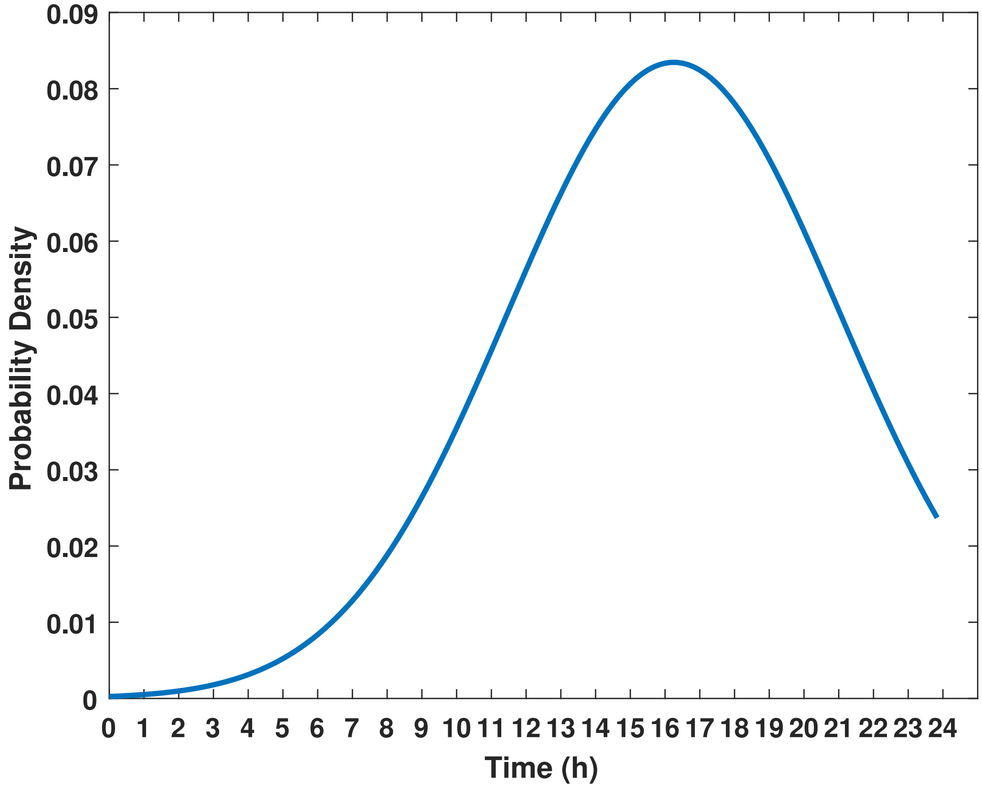


Figure 3.4: PDF of Normal Distribution of Charging Start Time

the general pattern related to the mobility behavior of the standard vehicles in NB. The real driving behavior of car owners is obtained from Statistics Canada for NB [2]. The survey is based on around 550,000 interviews conducted in NB over the last ten years. The data set, as shown in Figure 3.5, describes the traveling of the interviewed people during the day that the interview was conducted. To illustrate the behavior of the privately owned four-wheeled vehicles, the data set is sorted for people operating a vehicle and not just a passenger, for which the daily distance driven is considered. The analysis represents the daily distance driven per privately owned car or van, not per person, which would be a lower number.

After comparing the collected survey data with the calculated mileage data for verification, it was seen that the data calculated fell within the average travel range,

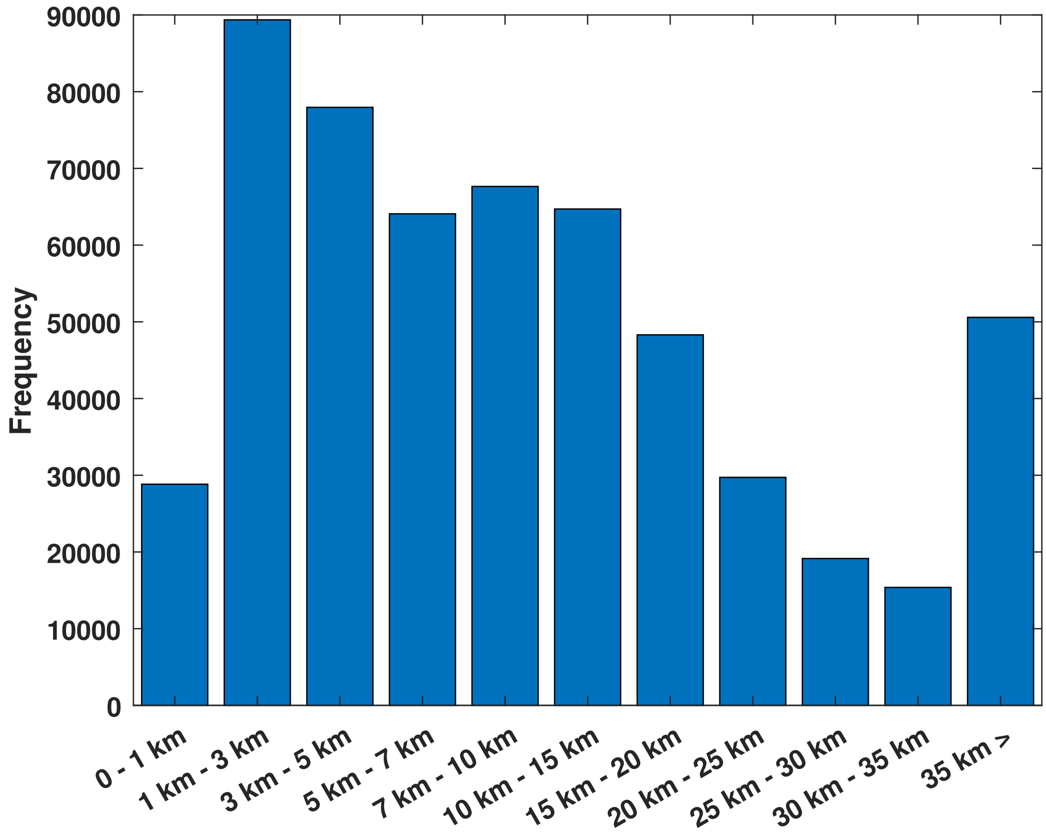


Figure 3.5: Average Travel Distance [2]

confirming the random SoC assigned for each car satisfies the assumption of being real SoC. Furthermore, the Statistics Canada Travel Survey analysis showed that most car owners drive between 40 to 60 km and drive less during the weekends than on the weekdays, with an average of 30 km [57]. On top of that, the use of the car is more distributed during the day hours, and therefore, a more distributed EV charging power contribution is expected during the weekends. Consequently, since the research is interested in the impact of EV penetration on the grid, the EV charging pattern during the weekends is assumed to be the same as on the weekdays. This is also possible, considering that the overall consumption is lower on Saturday and Sunday than on weekdays.

3.2.4 Charging Energy and Duration

Required charging energy (E_{charge}) for an EV to reach full charge is determined by initial SoC and battery capacity C (kWh) as shown in Equation 3.8. Around 80% of the energy stored in the EV battery can be used to drive the wheels [52], which is the set value for the battery's charging efficiency.

$$(E_{charge})_n^k = \frac{C(1 - SoC_n^k)}{0.8} \tag{3.8}$$

Hence, considering the energy conversion efficiency, the required charging duration (T_{charge}) to refill the battery to the full capacity can be calculated by Equation 3.9. P is the charging rate 6.6 kW of a Nissan Leaf with 40 kWh of battery capacity [58].

$$(T_{charge})_n^k = \frac{(E_{charge})_n^k}{P} \tag{3.9}$$

The charging energy and duration to reach full charge, calculated using Equation 3.8 and Equation 3.9 respectively, are randomly assigned to each EV by performing the Monte Carlo simulation. The selected number of simulations is the total number of EVs (N) charging in a day, which is assigned based on (n) the number of EVs arriving at the charging station every 10 min and allowed to be charged in each slot(k). The value (N) corresponds to the number of vehicles in NB. It should be noted that most future EV users could require between 6 to 12 kWh per day [59].

3.3 Priority Determination

The priority determination for charging EVs is based on each EV battery's SoC. The cut-off SoC is a threshold given based on the total EV being charged per slot (EV_{slot}). The term (EV_{slot}) defines the total number of EVs allowed to charge every

10 mins. Two different priority levels are defined, high and low. Low priority is defined as SoC less than the cut-off SoC, and high priority to those greater than and equal to the cut-off. Equation 3.10 shows how numbers of EVs for each slot can be calculated, where (N) is the total number of EVs charged in a day and k is the total number of slots.

$$EV_{slot} = \frac{N}{k} \tag{3.10}$$

The cut-off SoC value has to change as the value for EV_{slot} changes because the algorithm is designed to shift the correct number of the surplus load caused by EVs occurring during the peak period to the off-peak hours. This is done by controlling EV charging in the valley of the conventional power load profile during the day. To shift the right amount of load, the right amount of EVs has to charge for a particular time slot, and the cut-off SoC helps determine every EV's importance. As the total number of EVs allowed to charge per slot is being changed, the value of the cut-off SoC is also changed, and after a few iterations, a linear relation can be determined between the $SoC_{cut-off}$ and (EV_{slot}).

Equation 3.11 shows the linear relationship. The variables, a and b, are constants and will change depending on the SoC distribution parameters and the total number of EVs charged daily. For 10,000 EVs charging in a day the value of a is found to be 0.005 and the value of b is 0.2541 as seen in Figure 3.6.

$$SoC_{cut-off} = \frac{EV_{slot}}{a} + b, \quad a, b > 0 \tag{3.11}$$

After finding the perfect cut-off SoC value, the charging priority of every EV in each slot is defined. The flow chart in Figure 3.7 shows the process of setting the priorities of the EV.

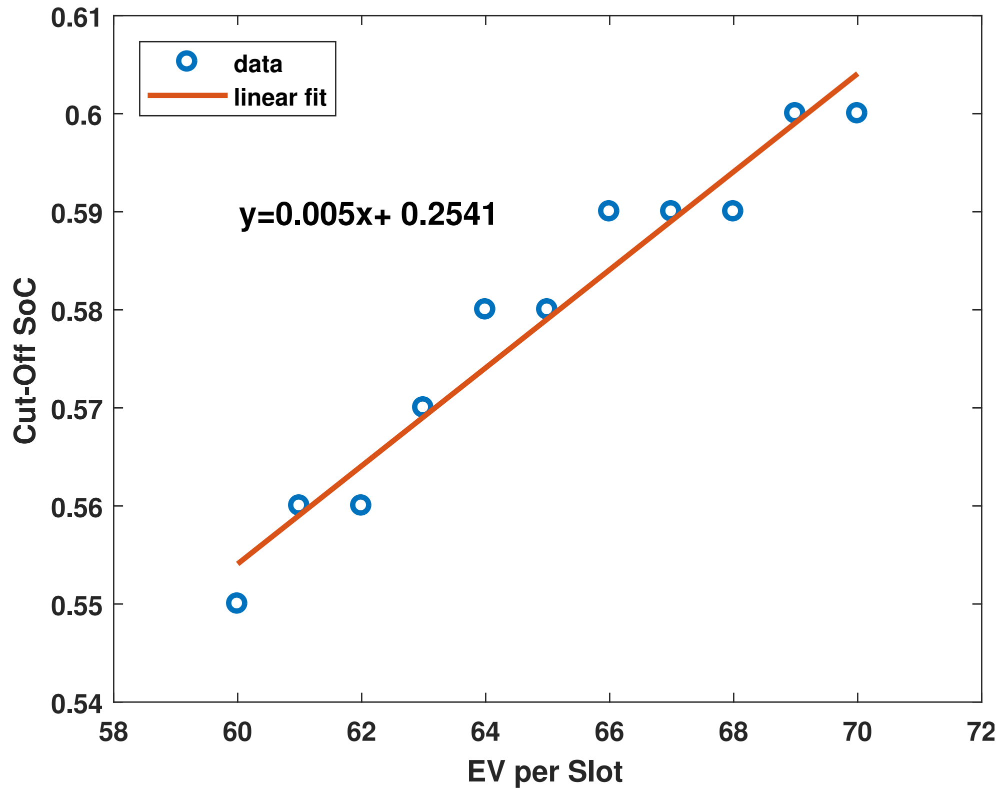


Figure 3.6: Finding Cut-Off SoC

3.4 Time-slot Allocation

After the charging priority is determined, the sequence of the time slots to schedule the charging of EVs is defined. The time-slot allocation to allocate EV charging for each slot concerning the power grid profile is done based on a constant load (P_{con}) that the power grid can supply. This constant load is calculated using the Dichotomous Search Method (DSM) as shown in Equation 3.13, where P_{grid} and P_{uc} are the total load of the distribution grid and the EV uncontrolled load respectively for each slot. The DSM is a search algorithm that operates by selecting between two distinct alternatives (dichotomies) at each step. It is a specific type of divide-and-conquer algorithm. It computes the midpoint between two intervals which are P_{grid} and P_{uc} for the algorithm:

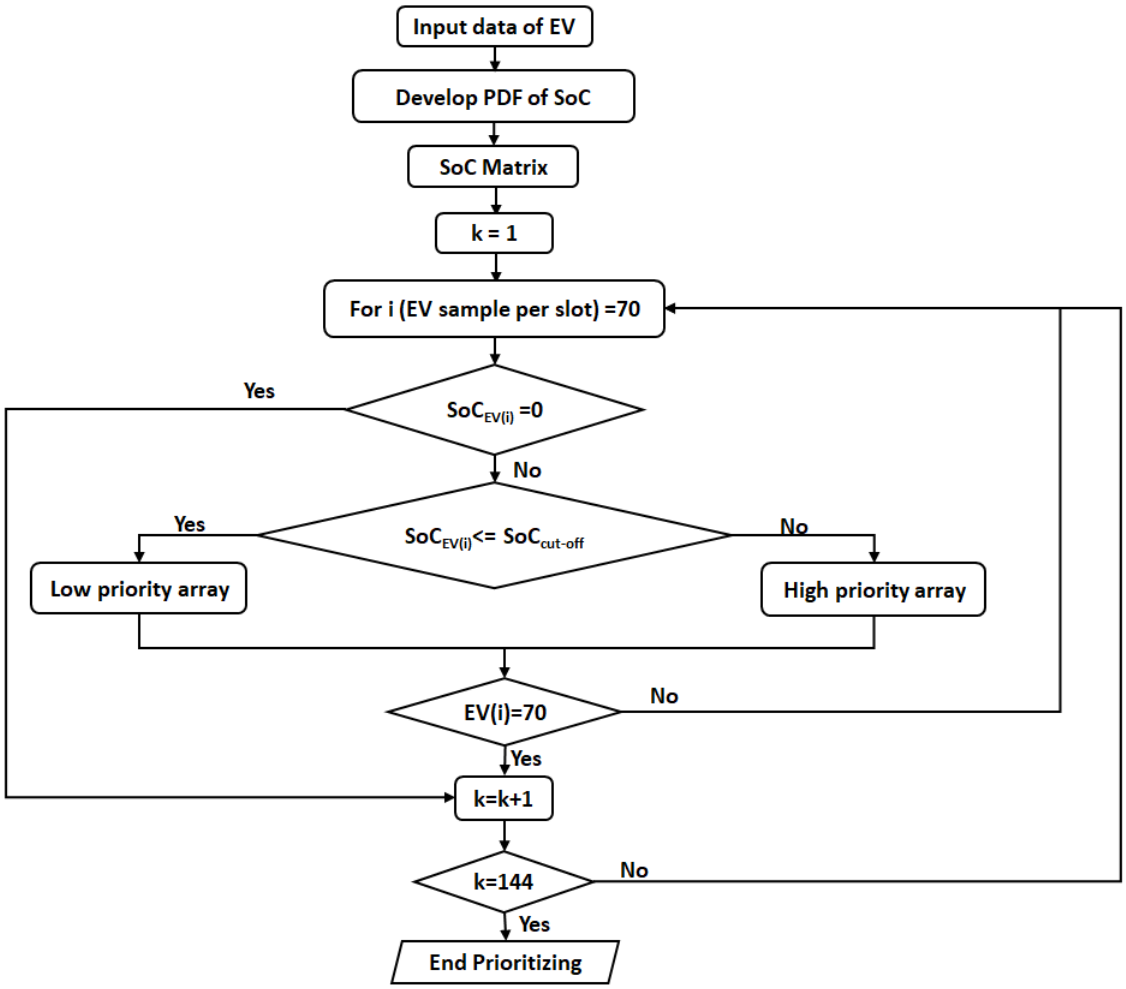


Figure 3.7: Flow Chart of EV Priority Determination

$$m = \frac{P_{grid} + P_{uc}}{2} \tag{3.12}$$

and then moves slightly to either side of the midpoint to compute two test points:

$$P_{con}(x, y) = \frac{P_{grid} + P_{uc}}{2} \pm \epsilon \tag{3.13}$$

where ϵ is a very small number. The objective is to place the two test points as close together as possible. The procedure continues until it gets within some small interval containing the optimal solution.

$$[P_{con^x}]^k = \frac{P^k_{grid} + P^k_{uc}}{2} - \epsilon = P^k_{grid} + \frac{L^k}{2} - \epsilon, \tag{3.14}$$

$$[P_{con^y}]^k = \frac{P^k_{grid} + P^k_{uc}}{2} + \epsilon = P^k_{grid} + \frac{L^k}{2} + \epsilon, \tag{3.15}$$

The new interval can be determined by:

$$P^{k+1}_{grid}, P^{k+1}_{uc} = \begin{cases} [P_{con^x}, P^k_{uc}], & iff([P_{con^y}]^k) > f([P_{con^y}]^k) \\ [P^k_{grid}, P_{con^y}], & iff([P_{con^y}]^k) \leq f([P_{con^y}]^k) \end{cases} \tag{3.16}$$

The length of the obtained interval can be found using Equation 3.17:

.

$$L^{k+1} = \frac{L^k}{2} + \epsilon \tag{3.17}$$

This procedure will continue until:

$$L^k < 2\lambda, \tag{3.18}$$

where, $\lambda > 0$ is a tolerance.

The target is to find the minimum average value of P_{con}, then for each slot, compare it with the conventional load along with added EV load to see whether the total of the conventional and EV load exceeds P_{con} or falls below. As P_{con} is close to the average load of the grid, it falls somewhere between the load profile and helps to find the valley of the grid load. For a particular slot, if P_{con} is greater than the grid load, it defines that there is room for extra load, so the EVs with low priority are assigned to charge for that slot as they require more time and power to charge. And if P_{con} is less than the grid load, it means that additional load may lead to rising in peak, so the EVs with high priority are assigned to charge for that slot as they have high SoC, so they don't require much time and power to charge. The definition of the time-slot allocation is drawn to see if the EV charging demand is beyond the power supply for each time slot. The setting of the EVs for each slot is a dynamic process because the value of the grid and the EV loads change with the period. Figure 3.8 shows the flow chart for assigning each EV particular time slots to charge.

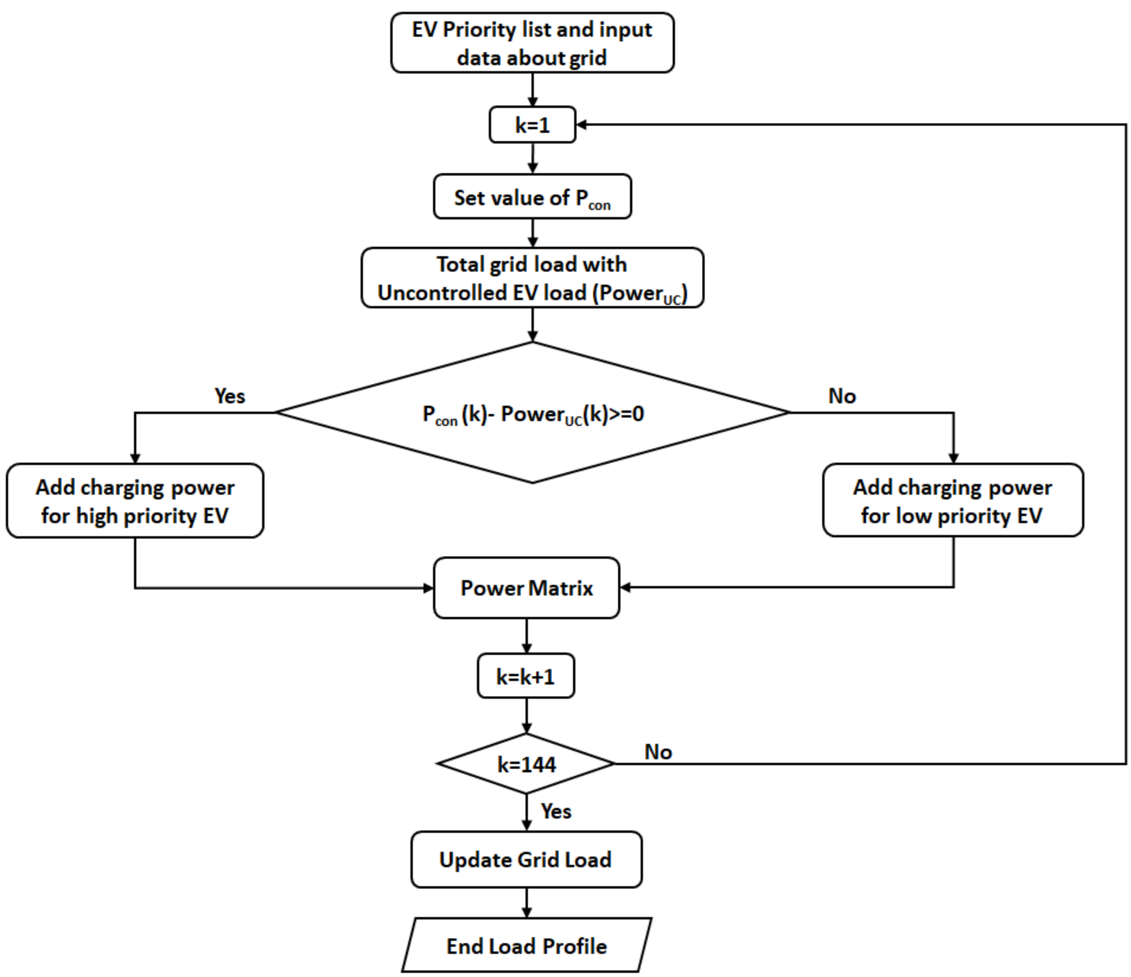


Figure 3.8: Flow Chart of EV Time-Slot Allocation

In Figure 3.9, the blue plot and the red plot represent the total grid load after adding

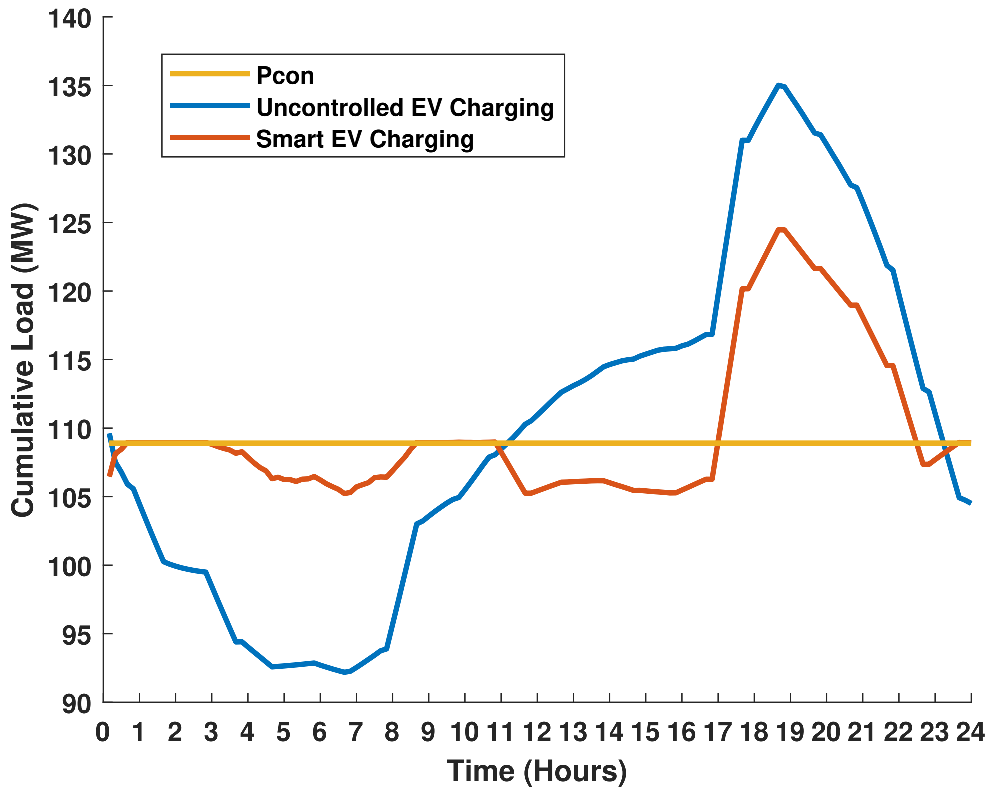


Figure 3.9: EV Charging Load Profile using both Uncontrolled Charging and Smart Charging Algorithm

EV uncontrolled charging and smart charging load respectively. The horizontal line is the average value of P_{con} set for the particular condition. Moreover, in Figure 3.10, the EV load profile for both uncontrolled and smart charging is presented which shows the difference in EV load distribution using both charging strategies.

In Figure 3.10, the blue plot shows how the EV load is arranged based on the smart charging strategy. EVs with low charging demand are allowed to charge during peak hours. As explained earlier, since the EVs with low charging power demand do not require much power to charge, they are allowed to charge during peak hours and EVs with high charging power demand require more power hence they are charged during off-peak hours. It can be seen in Figure 3.10, using the smart charging strategy most EVs are charged during nighttime when the power demand is minimum and the rest are charged during the evening which is the peak time. Therefore, the total charging load is not allowed to go above the P_{con} as shown in Figure 3.9, hence not increasing the existing peak of the grid load.

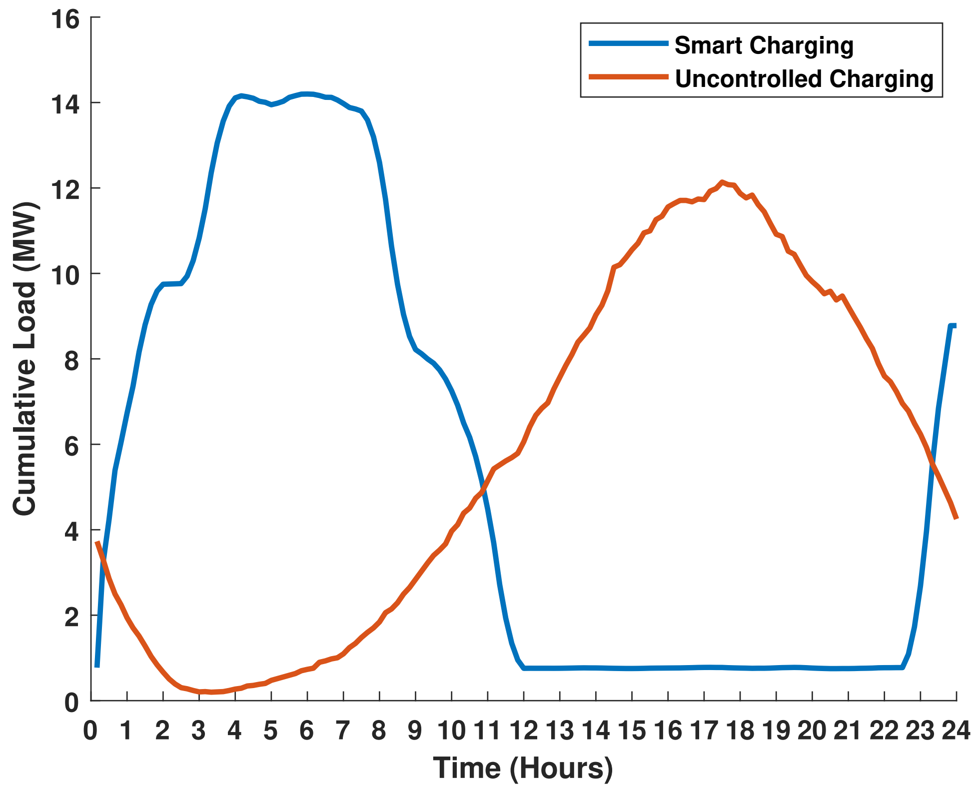


Figure 3.10: EV Charging Load Profile using both Uncontrolled Charging and Smart Charging Algorithm

3.5 Summary

In this chapter, a mathematical algorithm formation for a smart charging strategy for EVs is presented. The objective is to control the EV charge with high power demand in the valley of the conventional power load profile during the day and allow up to 10,000 EVs to be charged. Initially, for both the initial SoC and home arrival time, a PDF is generated from the collected data, and the charging energy and required charging duration to refill the battery to its full capacity are calculated. These data are then randomly sampled and assigned to individual EV charging behavior through the Monte Carlo simulation.

Secondly, the priority determination of individual EVs for charging is done based on the battery SoC level when the EV arrives at the EVCS. The EVs are assigned to any one of the two different priority levels defined by comparing the battery SoC with the cut-off SoC. The term high priority means EV whose SoC is greater than and equal to the cut-off SoC and low priority means EV SoC SoC less than the cut-off.

After the charging priority, the sequence of the time slots to schedule the charging strategy of EVs is defined. The time-slot allocation to allocate EV charging for each slot concerning the power grid profile is done based on a constant load named P_{con} that the power grid can supply and it is calculated using the DSM. The idea is to find the minimum average value of P_{con}, then for each slot, compare it with the total grid load along with added EV load to see whether the total of the conventional and EV load exceeds P_{con} or falls below. Once the EVs are assigned their designated slots, it can be seen that the EVs that require high charging power are allowed to charge during the off-peak time as they require much power and time to charge. However, during the peak period, only the EVs with low charging power demand are allowed to charge as they will not increase the existing peak of the grid from what is already present.

Chapter 4

Results and Discussion

4.1 General

This chapter compares load and voltage profile results for different EV numbers obtained using the proposed smart charging algorithm. Moreover, the effectiveness of the proposed charging scheme is also assessed by comparing its result with uncontrolled EV charging behavior.

4.2 Grid Load Profile

To account for broadening the analysis of the proposed model and different behaviors of the EV load profile, the charging loads for EVs in various scenarios are investigated in this section.

4.2.1 Distribution System Topology

The analysis presented in this research considers an isolated 21-Bus power system of Barbados Light Power Company (BLPC) located on Barbados Island. Figure 4.1 shows the single-line diagram of the power system with S_{base}=30 MVA. The power system has a maximum load of around 150 MW and serves 130,000 customers in

Barbados. It consists of 16 conventional generators of 230 MW in 3 different buses (Bus 1, Bus 16, and Bus10) and 8 PV systems providing around 60-70 MW. It is assumed that an EVCS is arbitrarily located at load Bus-18, named SW2-11, and Bus-10 called MS2-11. The two load bus data employed for the system are provided in Table 4.1.

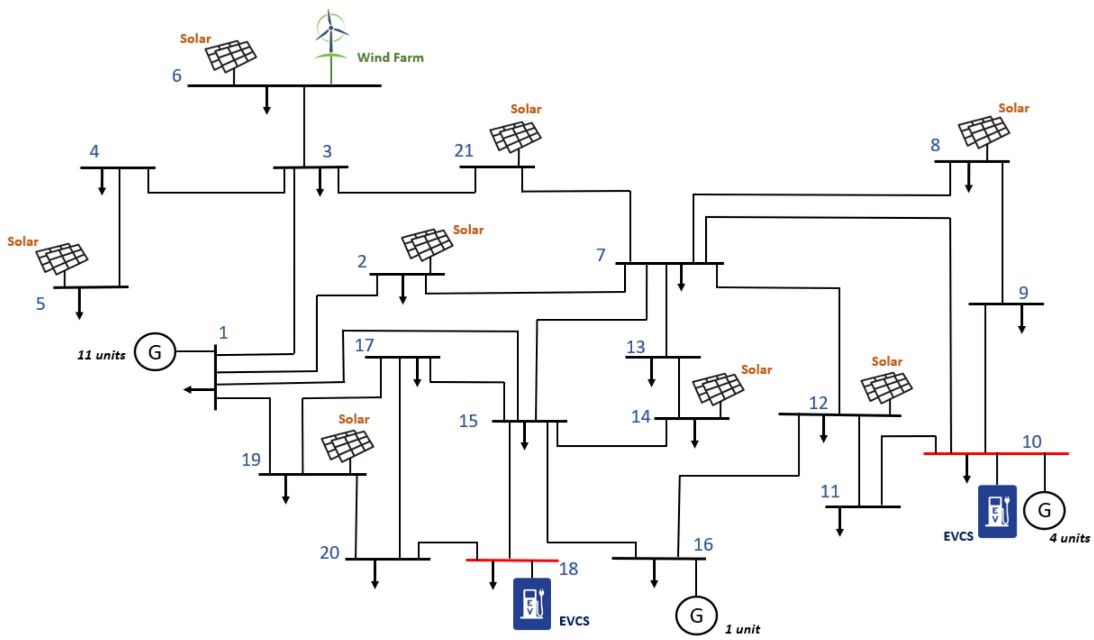


Figure 4.1: Single Line Diagram of the 21-Bus power system of BLPC

Bus	Base Voltage (kVLL)	Voltage (kVLL)	Voltage (p.u.)	P_Gen (MW)	Q_Gen (MVAR)	P_Load (MW)	Q_Load (MVAR)
18	11.0	10.6	0.96	0.00	0.00	5.56	2.46
10	11.0	11.0	1.0	37.70	8.77	5.52	2.44

Table 4.1: Data for the 2 Load Buses in BLPC Power System

4.2.2 Effect of High Penetration of EVs on Grid

It is easy to understand that the number of EVs involved will influence the performance of smart charging. The larger the number of EVs is, the more demand is for electric power. The results of the proposed smart charging method at various levels of EV penetration are depicted in Figures 4.4-4.7.

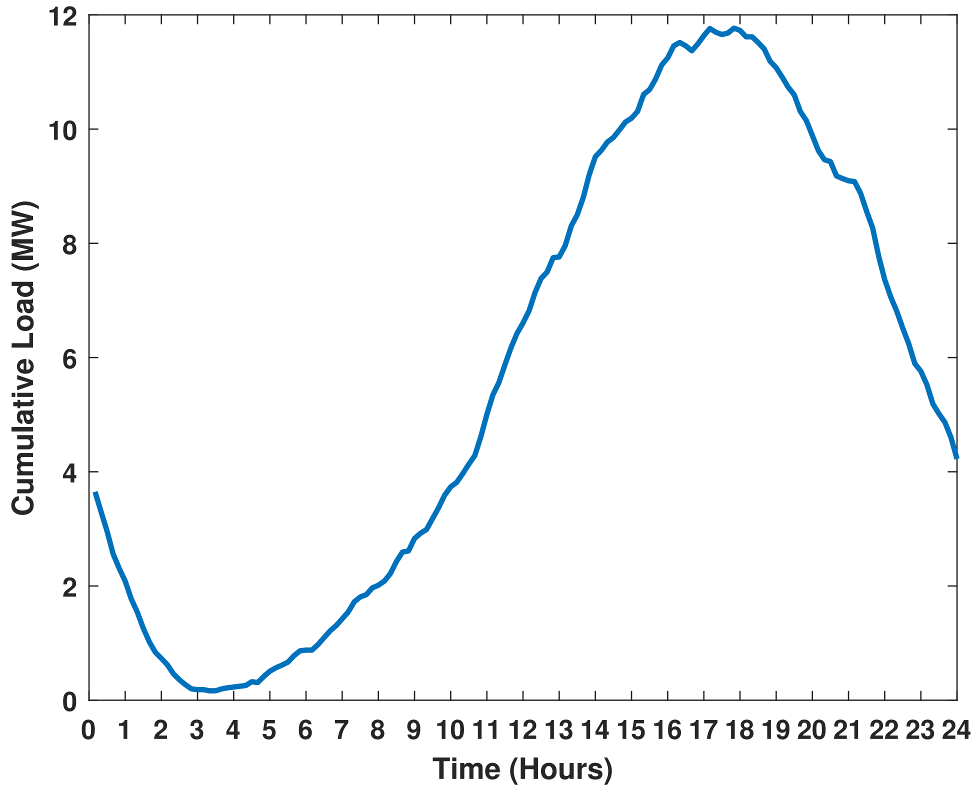


Figure 4.2: Uncontrolled Charging Load Over Day in MW [n=10,000]

The EVs' charging behavior data is simulated to test the proposed methods' effectiveness. Historical data for residential loads are considered to see significant changes on the grid load profile after adding the charging load of 10,000 EVs. Initially, the uncontrolled charging strategy of EV was designed, and the EV load profile is obtained as shown in Figure 4.2. In Figure 4.3, the blue area represents the distribution load of the grid, and the red area defines the total load after adding the uncontrolled EV load to the grid.

Figure 4.3 proves the point we have mentioned earlier that the uncoordinated charging strategy may lead to elevated load peaks early in the evening; significant peaks

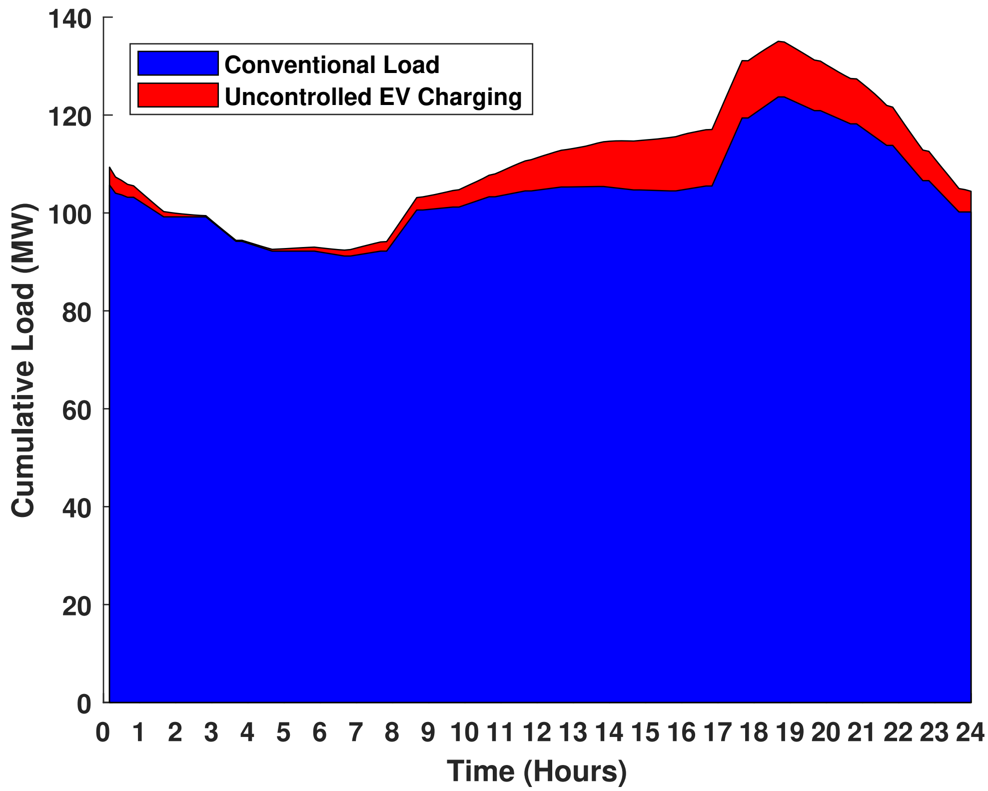


Figure 4.3: Cumulative Load Over Day in MW with Uncontrolled EV Load [n=10,000]

are observed around 4-6 p.m., generally the time period when typical electricity peaks already exist. Meanwhile, it may waste the surplus electricity in the off-peak period late at night. The data on EVs charging is acquired based on simulating the behavior of EVs travel. It leads to a new peak if high number of EVs concentrate on charging during a period. The peak load of 4-6 PM is managed to be reduced, but the load in the other hours does not lead to issues in the grid, mainly because of the low electricity demand at night. So, this additional load has to be appropriately managed to mitigate grid issues. Thus, it is reliable to utilize the proposed algorithm to schedule EV charging in the evening as the strategy is not to allow the grid peak to rise but instead increase the valley, which is done by smart charging.

After using the smart charging algorithm, the green part in Figure 4.4 presents the

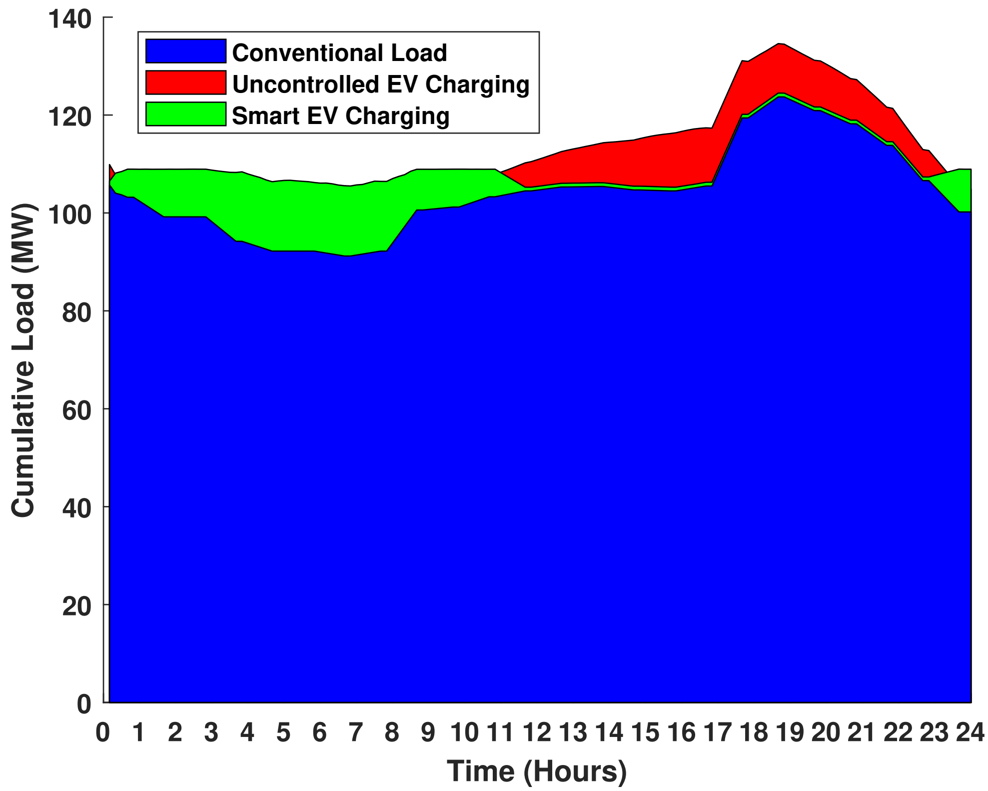


Figure 4.4: Comparison between Uncoordinated and Smart Charging[n=10,000]

updated grid load. In the proposed smart charging algorithm, EVs are allowed to charge based on their priority and are assigned time slots with the help of P_{con}. The high EV loads are assigned to the part where the grid load is less than P_{con}, and the low EV loads are to the peaks. The simulation result shows a significant impact compared to the outputs of controlled and uncontrolled charging. The proposed algorithm allocates EV charging power with high priority during off-peak time. It increases the valley load so that peak load increase can be avoided, allowing the grid to have a more steady load profile.

4.2.3 Effect of 500 EVs on Grid

It is observed that the uncoordinated charging of lower EV penetration does not have a significant impact on the grid, hence they are tested on bus loads. In 4.5, with an EV population of n=500, it can be seen that the highest load attributed to uncoordinated charging of EVs occurs between 16:00 and 22:00. This increases the total consumption of load during this particular period by a total of 47.8 MW as shown by the red-shaded area of the figure. In other words, the value of 47.8 MW is the total of the red-shaded area for the time period of 16:00 to 22:00. By comparison, the optimized P_{con}=6,105 kW by using the proposed method, and it signifies the grid only needs to supply 43.21 MW power overnight as shown by the green-shaded area, to meet EV charging demand.

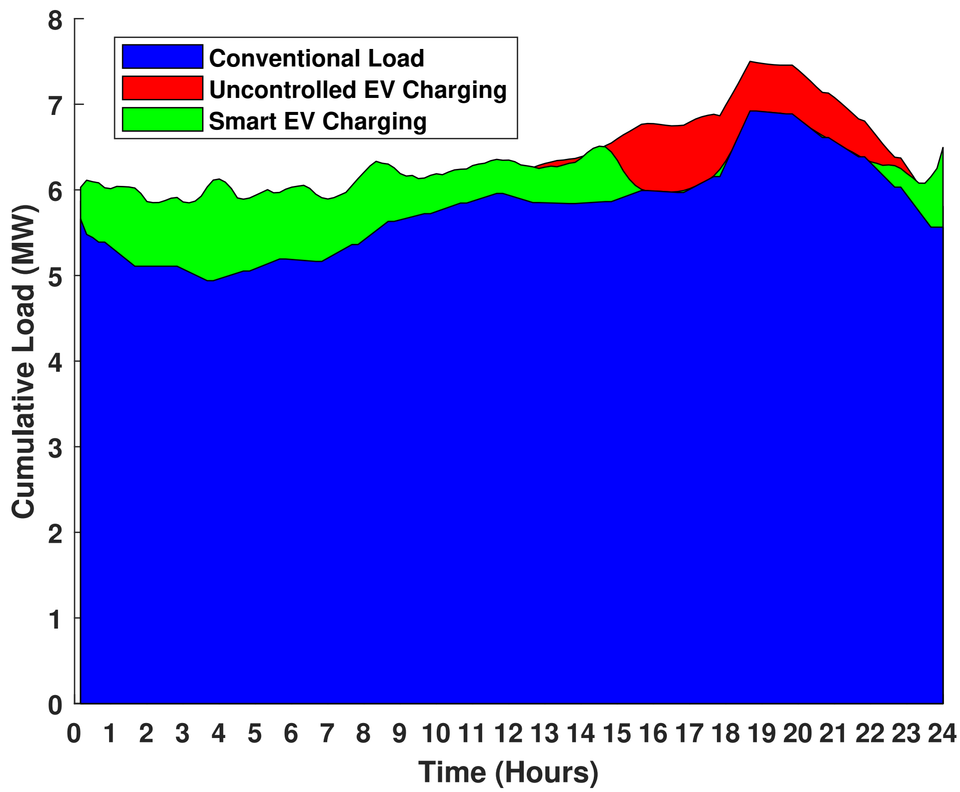


Figure 4.5: Scheduling results of 500 EVs involved

4.2.4 Effect of 1000 EVs on Grid

In Figure 4.6, for n=1000, EV's uncoordinated charging affects the bus load of the power system significantly, and the most significant total load consumption between 15:00 and 23:00 is 79.62 MW. In contrast, the optimized P_{con} is set to be 6,626 kW using the proposed method. Hence, to minimize the load variance, the grid needs to supply 75.50 MW of power overnight to meet the electricity and EV load demand.

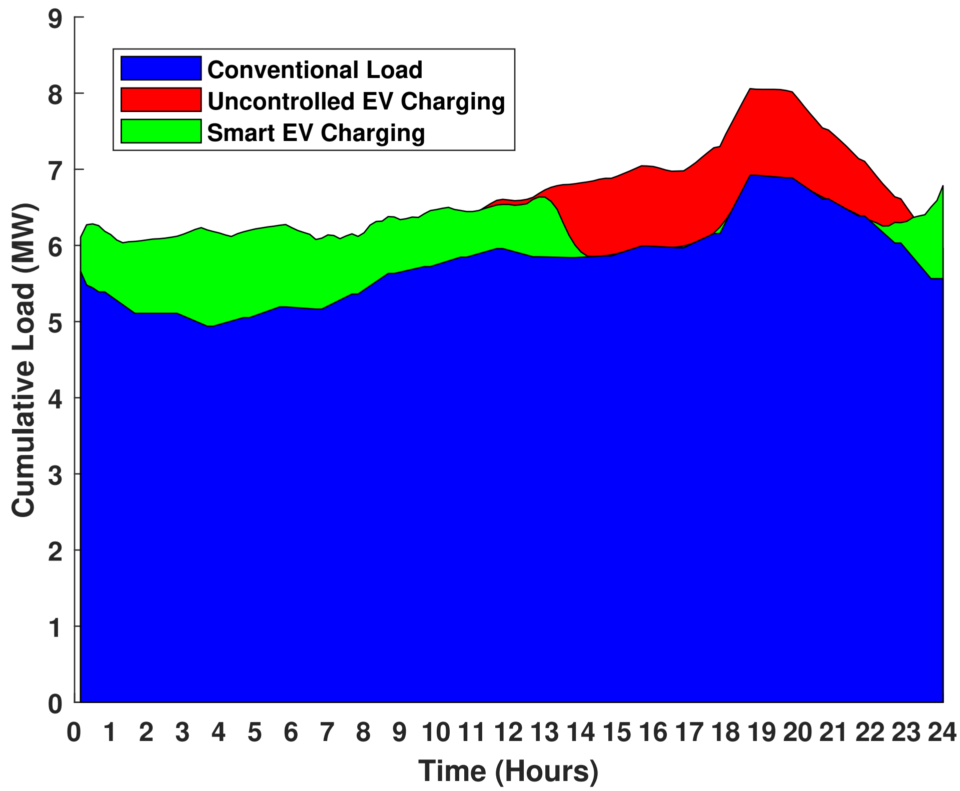


Figure 4.6: Scheduling results of 1000 EVs involved

4.2.5 Effect of 1250 EVs on Grid

In 4.7, for n=1250, the total load consumption between 14:00 and 23:00 is 101.94 MW using uncontrolled charging. Using the proposed method, the optimized P_{con} equals 7,125 kW. It can be shown that this proposed algorithm can reduce the impact of uncoordinated charging on the bus load significantly and make full use of the power in the valley of the conventional load curve by shifting 86.96 MW from the peak load to the valley.

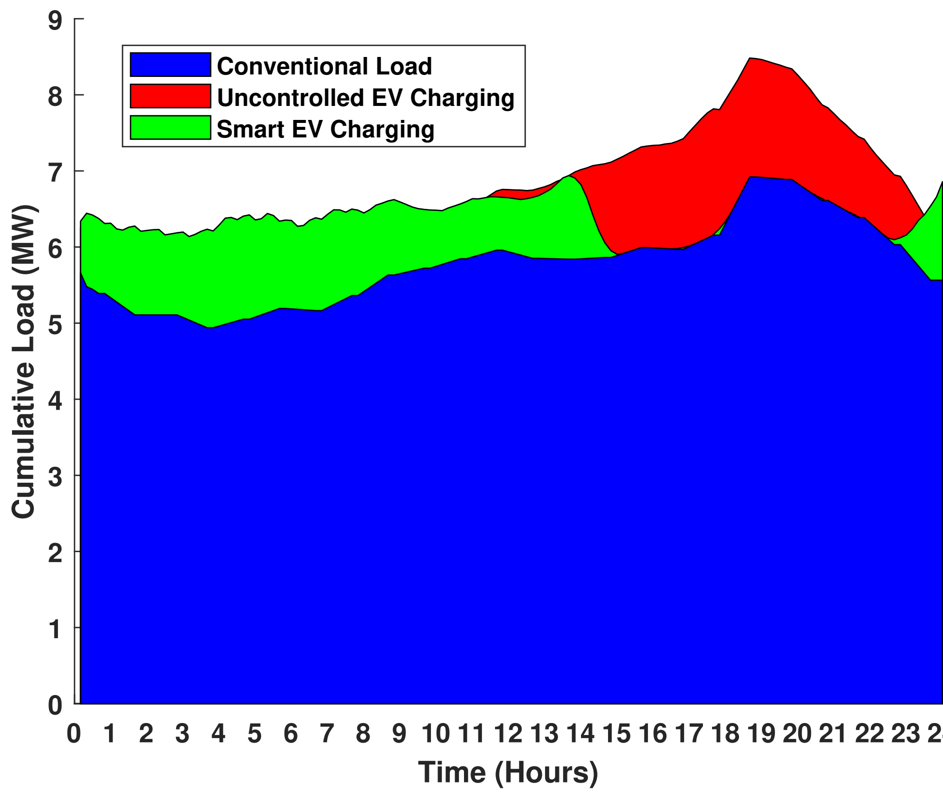


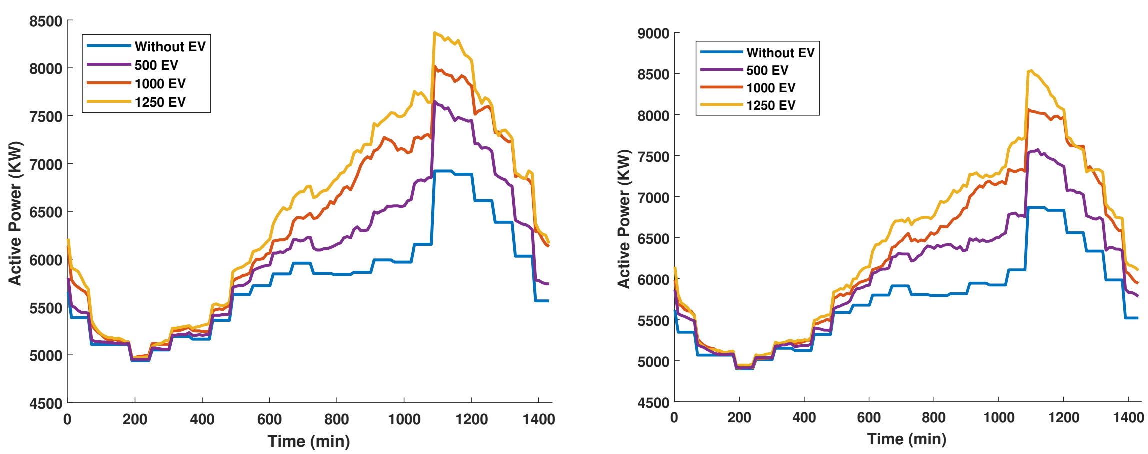
Figure 4.7: Scheduling results of 1250 EVs involved

4.3 Case Study

4.3.1 Load Profile

After adding controlled and uncontrolled charging, the grid load profile is obtained for the BLPC distribution grid. Initially, the database for the grid load is modified by adding the EV loads using MATLAB; then, the database is imported in CYME, which shows the modified load profile and voltage profile for bus MS2-11 and bus SW2-11.

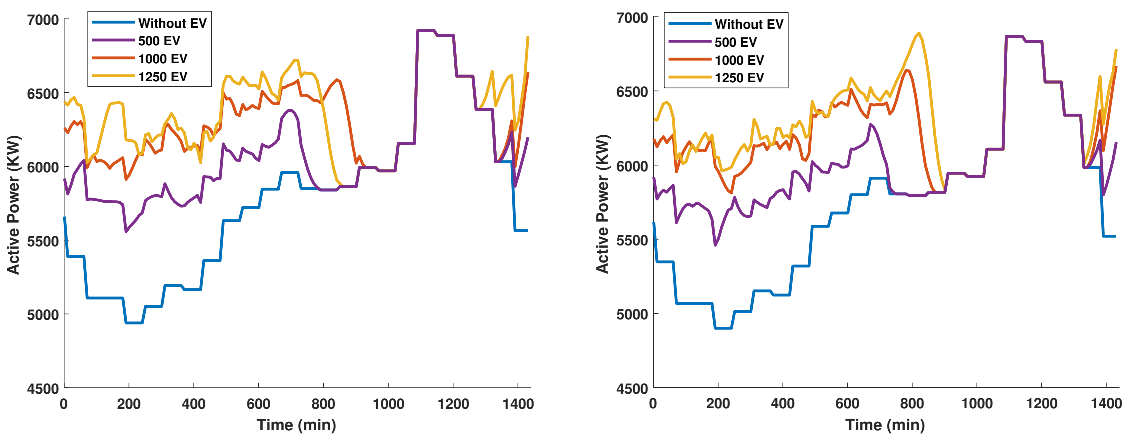
Figure 4.8(a) and Figure 4.8(b) show the simulation results of the daily load of EVs for bus MS2-11 and bus SW2-11, respectively. As expected, it can be seen in Figure 4.8 that the more EVs there are, the higher the peak load. The EV charging load is mainly concentrated around 18:00, which is rush hour, as owners generally begin to charge EVs after arriving home. The simulation results are consistent with the behavior of EV owners. Undoubtedly, if a massive number of EVs are charging autonomously, this will increase the difference between the peak and off-peak system load and the burden on the grid.



(a) Bus MS_LD (b) Bus SW_LD

Figure 4.8: Load Profile of different numbers of EVs under uncontrolled charging mode

In Figures 4.9, using the controlled charging, the EV charging load is mainly concentrated in nighttime off-peak load periods from 0:00 to 12:00. It can be seen that the proposed algorithm reduces the impact of uncoordinated charging on the power grid significantly and make full use of the power in the valley of the conventional load curve. This is more economical for EV owners because of the lower electricity price [60].



(a) Bus MS_LD (b) Bus SW_LD

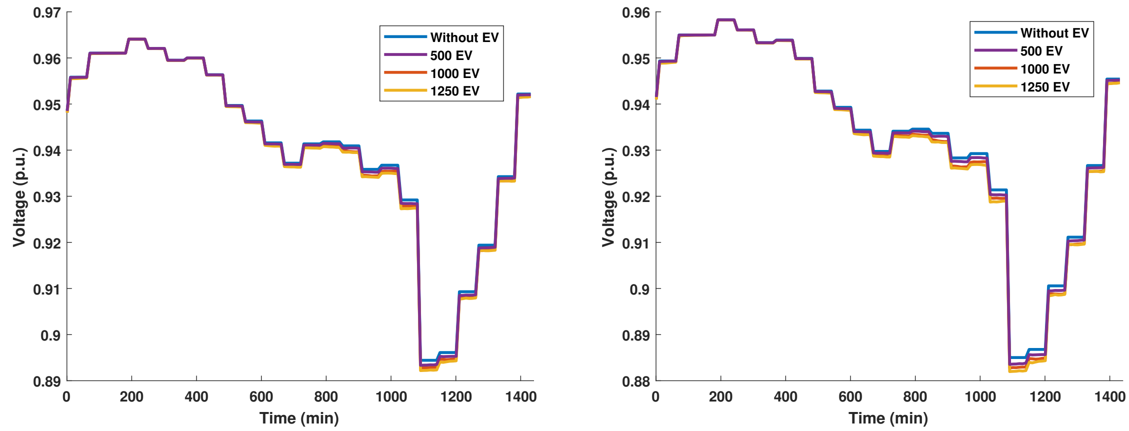
Figure 4.9: Load Profile of different numbers of EVs under controlled charging mode

4.3.2 Voltage Profile

Voltage stability is one aspect of the grid stability indices that is defined as the ability to maintain steady nominal voltage values at all buses after a disturbance. However, the threat to voltage stability is one of the most crucial adverse impacts of the EV charging station. Voltage instability represents a challenging issue and can result in system disruptions. The reason for that is the operation at high load demand and near the stability limit. The grid voltage stability is crucially affected by the characteristics of the load, and the EVs' load characteristics are different from the conventional loads (i.e., residential, industrial, and commercial) characteristics [61]. Due to the charging of EVs, there is a sudden increase in load which results in voltage instability. In other words, when the number of EVs has increased, the total load demand increases, and the voltage steadily decreases. As the proposed controlled charging scheme targets minimizing the net-load variance, it also aims to maintain the voltage stability.

The voltage profiles for uncontrolled and controlled charging are also obtained for two different buses from the BLPC grid, MS_LD, and SW_LD, respectively. The profiles obtained are for 500, 1000, and 1250 EVs. In the uncontrolled charging case shown in Figure 4.10, as the EV load increases the existing peak of the grid load, the voltage for that specific part shows drops in the profile. As the EVs' load is limited, the effect on the grid's voltage is not significant for low EV penetration. Nevertheless, the voltage steadily decreases as the load increases (high penetration of EVs). In the case of very high penetration, voltage boundaries are violated from the high-base-load bus. This is because the mass integration of EVs leads to a rapid load demand increase and, consequently, causes a high voltage drop.

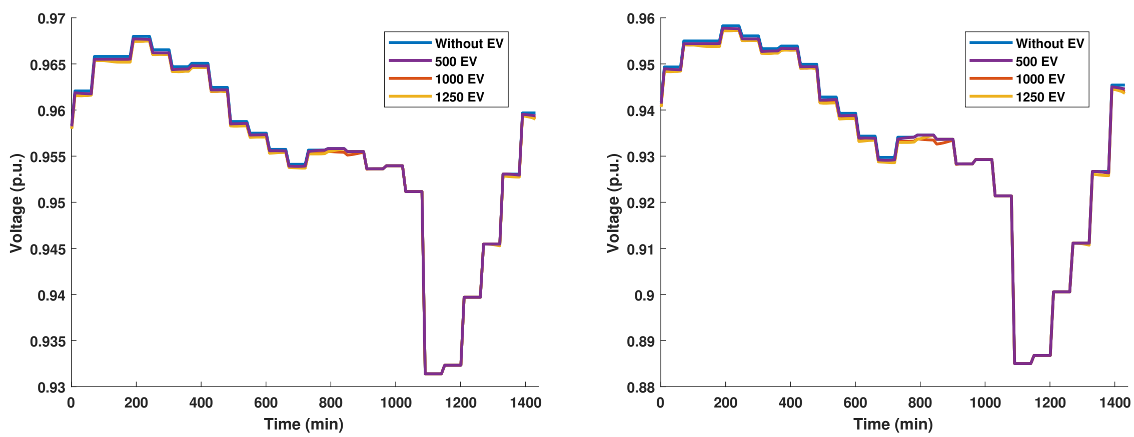
In the case of smart charging, EV penetration does not affect the grid's voltage



(a) Bus MS_LD (b) Bus SW_LD

Figure 4.10: Voltage Profile of different numbers of EVs under uncontrolled charging mode

boundaries, as shown in Figure 4.11. Charging during the night hours, when the load is limited, does not lead to a high load demand because of the EVs. As the algorithm tries to fill up the valley and decrease the existing peak in the grid, minor drops are seen in some parts of the voltage profile.



(a) Bus MS_LD (b) Bus SW_LD

Figure 4.11: Voltage Profile of different numbers of EVs under Controlled charging mode

4.4 Summary

This chapter presents the comparative studies and results obtained using the proposed smart EV charging algorithm as well as the uncontrolled charging strategy. Charging load profiles for EVs in different scenarios are obtained and investigated; starting from 500 up to 10,000 EVs are charged to see the effectiveness on the grid load. The effect of EV loads using both uncontrolled and proposed controlled methods is assessed with the help of an isolated 21-Bus power system of BLPC. Two different buses from the BLPC power system are chosen for EVCS. The load profiles and voltage profiles are obtained for different EV penetration for each bus using CYME.

Chapter 5

Conclusion

5.1 Summary

A smart charging algorithm is designed taking in account of charging priority to minimize the net-load variance and test on an MV distribution. Initially, a Monte Carlo algorithm is used to create an uncontrolled EV charging algorithm. From the results obtained, it has been reviewed that the uncoordinated charging of many EVs will threaten the stability of the power grid. These risks include elevated load peaks, increasing net-load variance, and dropped voltage. The smart charging algorithm has been proposed to minimize the net-load variance, which uses dynamic charging priority. This research focused on the centralized charging strategy, in which the EV aggregators can control the EV charging directly. The charging priority level of EVs is defined according to the arrival State of Charge (SoC) value. Then, each EV is assigned a specific period to charge. This motivates minimizing the demand peak and valley filling by shifting the EV load and eliminating a new peak that arises when many EVs are concentrated on charging. This is also referred to as load variance minimization. The performance of the proposed strategy was evaluated on an isolated 21-Bus power system of BLPC. Furthermore, load flow analysis has investigated the impact of charging many EVs using the proposed scheduling method on the power system voltage stability. The conclusions derived from the research work presented in this thesis can be summarized as follows:

- The proposed charging strategy can coordinate the charging behaviors of EV owners and achieves perfect peak-shaving and valley-filling effects under different scenarios.
- The smart charging algorithm, which has as its primary objective to reduce the net-load variability improves the MV distribution system performance by decreasing the voltage deviation, shaving the peak load, and lowering the total losses.
- Real and local data are used to design the proposed algorithm, such as the SoC, home arrival time, and the distance traveled by local vehicles.
- The proposed algorithm can charge higher levels of EV penetration in the power grid's load valley.

5.2 Contribution

The main contributions of the research presented in this thesis are as follows:

- With the increasing interest and growing deployment of EVs, there is a need to develop algorithms to control the charging of many EVs. This study proposes a new smart EV charging method for minimizing net-load variance with high EV penetration. The algorithm is also developed to fill the valley of the grid load curve and meet the charging demand of EVs without disrupting the EV user's behavior.

- In the case of high penetration of EVs, voltage boundaries may be violated, affecting the power network security. This study analyzed the impact of EV penetration on voltage stability with and without the proposed smart charging algorithm and used data collected from BLPC. The results indicate that the voltage levels are better retained within the accepted minimum-maximum range in the case of the Smart Charging Strategy. Hence, a new smart charging strategy can mitigate voltage problems and allow higher levels of EV penetration.

- Several authors have studied solutions to appropriately manage and alleviate the impacts of EV load on power systems. Although the studies demonstrate their effectiveness on the grid, they are primarily based on assumed information on the EV load. Most works use the SoC data from surveys, which could not be very realistic. However, this study presents EV charging metrics based on local and real information.

5.3 Future Works

Based on the research presented in this thesis, some further research avenues can be identified, as follows:

- The Priority model-based EV charging load models were developed for the charging stations only. These models could be extended to account for charging facilities such as parking lots, offices, and shopping centers with different charging levels. Furthermore, only Level 2 chargers are considered in this research.

- Data for only one particular type of EV (i.e., Nissan Leaf, 40 kWh) and Level 2 chargers are used in this research. Hence, more kinds of EV models with a broader range of battery capacity and Level 3 chargers should be considered.

- It is challenging to get information on EV charging since it is unpredictable when and where EVs charge. So, it is necessary to develop a software system to acquire the data fed back from the EVs. And also, an incentive mechanism is needed to let the EVs upload the charging information to the software system. After that, EV aggregators can focus on optimizing the charging strategy.

- The EV customers may be interested in partial charging instead of full charging at the charging station. Moreover, a priority service may be possible at the charging station so the customer can opt for immediate charging by paying a high price instead of waiting. Including these features can significantly affect the charging schedules at the charging station, which can be studied.

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Appendix A

Date	Arrival SoC (%)	Date	Arrival SoC (%)	Date	Arrival SoC (%)
9/5/2020	70.8001	1/27/2021	77.6001	3/11/2021	44.6001
9/10/2020	97.3001	1/28/2021	68.1001	4/12/2021	74.769
9/11/2020	87.8001	1/29/2021	92.3096	4/13/2021	88.2796
9/16/2020	85.1001	1/30/2021	87.0233	4/14/2021	79.2527
9/19/2020	70.0001	1/31/2021	81.6435	4/15/2021	74.0359
9/21/2020	78.8001	2/1/2021	76.6843	4/16/2021	56.3613
9/21/2020	65.9001	2/3/2021	84.3016	4/17/2021	52.2483
9/22/2020	64.9001	2/4/2021	79.316	4/18/2021	90.5333
9/23/2020	61.7997	2/5/2021	77.8031	4/19/2021	77.5554
9/24/2020	93.5254	2/6/2021	76.7782	4/20/2021	52.1024
9/25/2020	95.6001	2/7/2021	74.0782	4/21/2021	89.8173
9/26/2020	87.4368	2/8/2021	63.7479	4/22/2021	86.3955
9/27/2020	95.6905	2/9/2021	93.2439	4/23/2021	39.6642
9/29/2020	92.4577	2/10/2021	67.6707	5/24/2021	48.4405
9/30/2020	93.1001	2/11/2021	63.0191	5/25/2021	61.8736
10/1/2020	95.9001	2/12/2021	89.3645	5/26/2021	73.2283
10/2/2020	91.9001	2/13/2021	81.5286	5/27/2021	72.2257
10/3/2020	90.7001	2/14/2021	72.1993	5/28/2021	41.4165
9/27/2020	89.6001	2/17/2021	89.272	5/29/2021	40.419
1/13/2021	93.0173	2/18/2021	87.918	5/30/2021	43.2001
1/14/2021	79.9636	2/19/2021	83.0416	5/31/2021	40.9001
1/15/2021	79.4001	2/20/2021	88.7196	6/1/2021	50.7201
1/16/2021	54.1001	2/21/2021	83.6434	6/2/2021	48.6939
1/17/2021	52.4001	3/2/2021	77.7371	6/3/2021	45.7166
1/18/2021	40.3001	3/5/2021	66.6001	6/4/2021	74.9705
1/19/2021	81.7001	3/6/2021	59.3453	6/5/2021	45.6906
1/20/2021	78.8001	3/7/2021	56.1472	7/6/2021	82.6001
1/20/2021	40.9001	3/8/2021	57.5001	7/7/2021	76.8001
1/21/2021	77.2001	3/9/2021	53.6001	7/8/2021	51.1765
1/23/2021	65.7001	3/10/2021	49.3864	7/9/2021	46.8001
1/24/2021	48.4001	3/11/2021	44.6001	7/10/2021	84.2001

Appendix B

SoC(%)	Power Demand (kW)	SoC(%)	Power Demand (kW)
24.0932	0	78.6311	5500
24.0327	0	80.7804	5500
27.4476	5500	83.0241	5500
29.9496	5400	85.1393	5500
32.3204	5400	87.2434	5500
34.6736	5400	89.343	5500
37.153	5500	90.4695	5500
39.5108	5400	91.4833	5500
41.8453	5400	92.5932	5500
44.1822	5500	93.5978	5500
46.6318	5400	94.6888	5100
49.0755	5400	95.564	4400
51.4016	5500	96.3297	4000
53.7	5400	97.0644	3200
55.9887	5500	97.5627	2400
58.276	5500	97.9836	1600
60.6552	5500	98.2676	1500
63.0237	5500	98.5224	1200
65.2667	5500	98.7121	1000
67.4887	5500	98.8741	900
69.7022	5500	99.0208	800
72.0085	5500	99.1333	700
74.1953	5500	99.2398	600
76.3696	5500	99.3272	500

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