Interactions of Connected Electric Vehicles with Modern Power Grids in Smart Cities

by

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Abstract

In a smart city, it is vital to provide a clean and green environment by curbing air pollution and greenhouse gas emissions (GHGs) from transportation. As a recent action from many governments aiming to minimize transportation's pollution upon the climate, new plans have been announced to ban cars with gas engines throughout the world. Therefore, it is anticipated that the presence of electric vehicles (EVs) will grow very fast globally. Consequently, the necessity to establish electric vehicle supply equipment (EVSE) in the smart city through public charging stations is growing incrementally year by year. However, the EV charging process via EVSE which is primarily connected to the power grid will put high pressure upon the centralized power grid, especially during peak demand periods. Increasing the power production of power grid will increase the environmental impact. Therefore, it is fundamental for the smart city to be equipped with a modern power grid to cope with the traditional power grid's drawbacks.

In this thesis, we conduct an in-depth analysis of the problem of EVs' interaction with the modern power grid in a smart city to manage and control EV charging and discharging processes. We also present various approaches and mechanisms toward identifying and investigating these challenges and requirements to manage the power demand. We propose novel solutions, namely Decentralized-EVSE (D-EVSE), for EVs' charging and discharging processes based on Renewable Energy Sources (RESs) and an energy storage system. We present two algorithms to manage the interaction between EVs and D-EVSE while maximizing EV drivers' satisfaction in terms of reducing the waiting time for charging or discharging services and minimizing the stress placed on D-EVSE. We propose an optimization model based on Game Theory (GT) to manage the interaction between EVs and D-EVSE. We name this the decentralized-GT (D-GT) model. This model aims to find the optimal solution for EVs and D-EVSE based on the concept of win-win. We design a decentralized profit maximization algorithm to help D-EVSE take profit from the electricity price variation during the day when selling or buying electricity respectively to EVs or from the grid or EVs as discharging processes. We implement different scenarios to these models and show through analytical and simulation results that our proposed models help to minimize the D-EVSE stress level, increase the D-EVSE sustainability, maximize the D-EVSE profit, as well as maximize EV drivers' satisfaction and reduce EVs' waiting time.

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Dedication

To my father, who has always been behind me in every step of my life. To my mother, for her absolute and endless love.

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List of Acronyms

BEV Battery Electric Vehicles
C-ESS Centralized Energy Storage System
D-ESS Decentralized Energy Storage System
D-EVSE Decentralized Electric Vehicle Supply Equipment
D-GT Decentralized Game-Theoretic
DoD Depth of Discharge
DPMA Decentralized Profit Maximization Algorithm
DR Demand-Response
E-Bus Electric Bus
EMS Energy Management System
ESS Energy Storage System
EV Electric Vehicles
EVSE Electric Vehicle Supply Equipment
FCEV Fuel Cell Electric Vehicles
G2V Grid-To-Vehicle
GHG Greenhouse Gas Emissions
GPS Global Positioning System
GT Game Theory
HEV Hybrid Electric Vehicles
G2V Grid-To-Vehicle
GHG Greenhouse Gas Emissions
GPS Global Positioning System
GT Game Theory
HEV Hybrid Electric Vehicles
Hwy Highway
loT Internet of Thinks
MF Mean Filed
MGMS Micro-Grid Management System
PEV Plug-ln Electric Vehicles

PHEV Plug-in Hybrid Electric Vehicles
PV Photovoltaics
RES Renewable Energy Sources
SDP Stochastic Dynamic Programming
SoC State of Charge
SoH State of Health
ToU Time of Use
TTL Time to live
V2B Vehicle-To-Building
V2G Vehicle-To-Grid
V2H Vehicle-To-Home
V2V Vehicle-To-Vehicle
ZEVIP Zero Emission Vehicle Infrastructure Program

List of Symbols

Ar^i	Arrival time for Electric Vehicle's (EV) number (i)
β	Weather and driver behaviour
B^i_j	EV's ability check to reach the Public charging station (D-EVSE) number (j)
b^i_{Max}	Maximum battery capacities of EV number(i)
$C^{G^{co}}_j$	Power cost (power grid) [cent/kWh] at the D-EVSE number (j)
$C^{G^{pr}}_j$	Power sealing price [cent/kWh] at the D-EVSE number (j) (power grid price)
C^i_j	Discharging power price for EV number(i) at the D-EVSE number (j)
d^i_0	Minimum Deep of Discharge (DoD) of EV number (i)
D-EVSE$_j$	Decentralized Electric Vehicle Supply Equipment number (j)
d^i_j	Distance between EV number (i) and D-EVSE number (j)
D^i_{rate}	EV consumption rate of EV number (i)
δSoC^i	Difference between the initial state of charge (SoC) and required SoC
ESS_j	Current battery level in the energy storage system (ESS) for the D-EVSE number (j)
ESS^{EV}_j	Total cumulative amount of purchased power from EVs in the D-EVSE number (j)
ESS^G_j	Total cumulative amount of purchased power from the power grid in the D-EVSE number (j)
$ESS^{G_{req}}_j$	Amount of purchased power from the power grid in the D-EVSE number (j)
$ESS^{\max}$	Maximum power capacity of ESS
$ESS^{\min}$	Minimum capacity power of ESS
ESS^{RES}_j	Amount of produced power from solar energy in the D-EVSE number (j)
ESS^0_j	Minimum Deep of Discharge (DoD) of D-EVSE number (j)

EV^i	Electric Vehicle number (i)
F_j	D-EVSE's profit in the D-EVSE number (j)
i	EV Number
I_j^G	Incentive price [cent/kWh] from the power grid to the D-EVSE number (j)
j	D-EVSE Number
J	Set of D-EVSEs
λ_j^u	Average of EV arrival rates in unscheduled arrival
μ_u	Average of EV admission rates (charging and discharging processes) in unscheduled procedure
N	Set of EVs
P_j^{ch}	Total amount of power reserved for EVs in D-EVSE number (j)
P_j^{co}	Power cost (Renewable Energy Sources (RESs)) [cent/kWh] of the D-EVSE number (j)
P_j^{dis}	Total amount of power discharged form EVs in D-EVSE number (j)
P_j^{pr}	Power price (Renewable Energy Sources (RESs)) [cent/kWh] of the D-EVSE number (j)
P_j^{PV}	Total amount of photovoltaic power in D-EVSE number (j)
Pr_{dis}^i	Discharging power cost of EV number (i)
R_{ch}	Charging power rate
R_{dis}	Discharging power rate
SoC_j	Current battery status in the D-EVSE number (j)
$SoC_{\max}$	Maximum SoC level of EV
$SoC_{\min}$	Minimum required SoC level of EV
SoC_j^{ch}	Total cumulative amount of requested power form EVs in the D-EVSE number (j)
SoC_j^{dis}	Total cumulative amount of accepted power form EVs in the D-EVSE number (j)
SoC^i	Current battery level (SoC) of EV number (i)
SoC_{Av}^i	Amount of offered power (available) by EV number(i)
SoC_{ch}^i	Amount of requested power (charging) by EV number(i)
SoC_{dis}^i	Amount of accepted power of EV number (i)
SoC_{ini}^i	Initial power (SoC) for EV number(i)

SoC_j^i	Amount of required power of EV number (i) to reach D-EVSE number(j)
SoC_{req}^i	Required power (SoC) for EV number (i) to reach final destination
SoC_j^{sold}	Total cumulative amount of sold power in the D-EVSE number (j)
Sp^i	Speed of EV number (i)
t	time slots
T	Set of time slots
t_{dis}^i	Discharging time of EV number (i)
t_{ch}^i	Charging time of EV number (i)
t_2^i	Departure time of EV number (i)
$Trip^i$	Travel distance of EV number (i)
ε	Indicates the level of the charging station (level 2 or level 3)
X_j	Charging price [cent/kWh] of the D-EVSE number (j)
W_j^{time}	Waiting time of the D-EVSE number (j) for EV charging and discharging processes

Chapter 1

Introduction

1.1 Background

The smart city is a comprehensive concept that has different definitions among practitioners and academia. The smart city is defined in [1] as "...a place where traditional networks and services are made more flexible, efficient, and sustainable with the use of information, digital, and telecommunication technologies to improve the city's operations for the benefit of its inhabitants. Smart cities are greener, safer, faster, and friendlier." Consequently, smart cities are an abundant abstraction that is used as an encompassing label for cities.

The authors of [1] present the following nine components of a smart city: smart infrastructure, smart buildings, smart transportation, smart grid, smart health care, smart technology, smart governance, smart education, and smart citizens. However, not all smart cities are the same, as they each have specific requirements based on their citizens' needs and abilities. In general, the most common components of a smart city lie in smart infrastructure, smart buildings, smart transportation, and smart grid. Specifically, the smart grid is one of the most important goals of the smart city. The smart grid will provide better living conditions by increasing the power consumers' trust and satisfaction and decreasing greenhouse gas emissions (GHGs) to the environment [2].

The smart grid that is based on centralized power generation architecture has many strengths and weaknesses. Centralized power generation is based on an enormous central power plant that uses a non-renewable power generator [3]. In highly populated urban areas, therefore, the electricity demand on the existing power grid increases year by year. In response, the power grid will increase its ability to meet the power demand by allowing the power plant station to generate more power. By increasing the power generated by the power plant, however, air pollution and GHGs will increase accordingly, and that is not a good solution for the smart city. A better solution is distributed power generation architecture [4, 5] that is based on renewable energy sources (RESs) [4, 6] and built in close proximity to the power consumers. The strengths of the distributed power generation architecture based on RESs include increasing the reliability [7] and resilience [8] of the power grid and also lowering the GHGs with high power efficiency.

In smart cities, the communication networks become more and more complex With population growth; thus, the smart city needs an intelligent framework. The most promising emerging technology and framework for smart cities is the Internet of Things (IoT). As vast networks become more and more intelligent, the IoT has become the fundamental backbone of smart city innovations. The IoT has enabled the integration of different heterogeneous systems. Thus, smart cities will become achievable [9]. The IoT in a smart grid will assist smart cities by managing all smart grid entities such as non-renewable and renewable energy generators, grid operators, stakeholders, system reliability, system transparency, resilience, stability, and end-user. The IoT also allows the smart city to better utilize existing power generators and ease the integration of RESs. Power consumers can monitor and control their usage according to their needs and Time-of-Use (TOU) pricing in real-time. Notably, managing and controlling the power production and demand are the most crucial steps to minimize the impact of GHGs on the environment. Consequently, as a modern power grid structure, the smart grid must be reliable, efficient, resilient, secure, safe, clean, and green [10].

The electrification of transportation brings many advantages such as minimizing the effect of transportation's pollution upon the climate. As an action from many governments to achieve the electrification of transportation, recently new plans have been announced to ban cars with gas engines throughout the world. For example, the UK, Sweden, France, Germany, and Australia plan to ban such vehicles by 2035 [11–13]. As these plans unfold, EVs' presence will grow very fast globally, especially in countries such as Canada, where citizens are encouraged by several types of financial incentives to buy EVs [14]. These steps allow smart cities to curb carbon emissions as well as GHGs. However, the electrification of transportation is also leading to crucial challenging issues that need to be solved.

With the growth in the electric vehicle (EV) market due to its zero air pollution and reduction of GHG emissions, the power demand in smart cities will increase accordingly. By 2030, the number of EVs will be more than 100 million globally [15]. Consequently, the necessity of initiating electric vehicle supply equipment (EVSE) in the smart city in the form of public charging stations is growing incrementally year by year. The EVSE will offer and fulfill the EVs' charging demand. EVSEs are essential to support EV charging and discharging processes. The most significant challenges include uncontrolled EV charging as well as EV charging during peak times. Consequently, having a system to manage and balance the EVs' charging demand is an essential tool that will protect the smart grid from being overloaded or jeopardized. Therefore, the EVs' charging process must be well-planned and conducted wisely and intelligently to meet the smart grid operational standards [16–18].

1.2 Motivation

The Government of Canada is planning to increase the sales of EVs to be more than 30% by 2025 and 100% by 2040 under the Zero Emission Vehicle Infrastructure Program (ZEVIP). The ZEVIP has invested more than C$600 million to minimize GHGs. Twenty-five per cent of GHGs are from the transportation sector [19]. Also, the City of Ottawa has set a target of 100% to eliminate GHG emissions [20]. However, integrating a massive number of EVs in the City of Ottawa will stress the existing power grid, and it may cause, in some cases, an overloading of regional transformers or frequency and voltage fluctuations.

Therefore, with the anticipated use of EVs, the EV charging demands will add an extra load to the existing power grid. Consequently, there is a necessity to use RES as green and clean power generators. Thus, the smart grid plays an essential role in urban areas toward energy efficiency and sustainability [21–23]. This solution of RES will help the smart city eliminate GHG emissions. As well, public charging stations will be provided to fulfill the EV drivers' power demand needs. Furthermore, Canada's incentive program, named ZEVIP, is financially supporting approximately 50% of the total project by creating EVSEs as public charging stations [19] in public places; at workplaces; for light, medium, and heavy-duty vehicle fleets; and on-street parking.

On the other hand, EVs have the potential to provide a good opportunity for power storage by supporting the power grid as vehicle-to-grid (V2G) service [24, 25]. EVs also provide many advantages to EV owners such as minimizing their travel expenses and providing revenue by selling their surplus power. Therefore, EVSEs as a public charging station based on RES and equipped by energy storage systems (ESSs) is a promising solution [22,23]. The RESs are classified as a discontinuous and unpredictable means of power production. Subsequently, an ESS is an essential technology that stores the most beneficial generated power by RESs. Thus, we promote the option to switch from EVSE based on power grid to decentralized-EVSE (D-EVSE) based on RESs and ESSs with the RESs used as a primary power source.

Based on these circumstances, communication and coordination among the D-EVSEs are necessary while controlling the EVs' charging demand. We found that the studies in the literature have not addressed these issues or investigated the potential of integrating these equipment types.

Based on these circumstances, communication and coordination among the D-EVSEs types of equipment while controlling the EVs' charging demand have become a necessity. We found that the literature studies did not address these issues or investigated the effectiveness of this integration on these equipment types on the other, which seems promising.

1.3 Objectives

The objective of this thesis can be summarized as follows:

1. To carry out a critical investigation and review of the power consumption management schemes and mechanisms that have been used in the smart grid for EVSEs.

2. To propose a novel solution for EVSE that allows the EVSE to avoid being overloaded or jeopardized.

3. To develop different schemes to coordinate and manage the EV charging and discharging processes.

4. To formulate and test different approaches to maximize the EV driver's satisfaction, minimize the EVSE stress level, and minimize the waiting time for the EV charging and discharging process in smart cities.

5. To propose a novel scheme that helps the EVSE find the optimal solution for both EV and EVSE while considering how to optimize the EV charging and discharging

processes, maximize the EV driver's satisfaction, and increase the EVSE's sustainability.

6. To develop and propose a novel framework to help the EVSE maximize its profits and preserve its sustainability.

1.4 Thesis Contributions

In this thesis, we investigate the interactions of EVs with a modern power grid in smart cities. The primary considerations are managing and controlling the EV charging and discharging processes while considering the proposed D-EVSEs, which means each D-EVSE has its own renewable power generation sources. D-EVSEs as public charging stations are also connected to the existing power grid in case of bad weather. The main contributions of this thesis are as follows:

1. We proposed D-EVSEs architecture with RESs aiming to maximize the EV driver's satisfaction and minimize the D-EVSE's stress level in a smart city. The proposed algorithm is tested through simulations of random scenarios. We presented a compression result between the proposed and random algorithms.

2. We propose two algorithms for the D-EVSE model to select the best D-EVSE while considering the waiting time for the charging and discharging processes. We also take into account the EV driver's satisfaction, and the D-EVSE's stress level. We consider a realistic scenario to validate and compare the proposed schemes with three other algorithms.

3. We proposed a decentralized GT (D-GT) model aiming to optimize the EVs' interaction with the D-EVSE by taking into account EVs' driver satisfaction and D-EVSEs' stability. The D-GT model is used to find the optimal solution for EV charging or discharging processes that fulfill the predefined constraints. We consider random and realistic scenarios to validate the proposed schemes.

4. We proposed a Decentralized Profit Maximization Algorithm (DPMA) as an optimization model. DPMA is designed to maximize D-EVSEs' profit. D-EVSEs profit

from the electricity price variation during the day when selling or buying electricity respectively to EVs or from the grid or EVs as discharging processes. We also acknowledge a power connection to the central power grid when necessary. Five EV arrival rate scenarios are considered to investigate the efficiency of our proposed model.

1.5 Thesis Outline

The remainder of the thesis is organized as follows:

Chapter 2 presents state-of-the-art knowledge in the field of EV and EVSE in smart cities. This chapter also provides an overview of the architecture applications and the approaches used with these technologies. The most relevant issues and challenges in the micro-grid system are highlighted as a new smart grid structure. In Chapter 3, we propose a decentralized energy storage system model based on renewable energy sources. In Chapter 4, we describe a decentralized management system for the charging and discharging model. Chapter 5 presents the optimization model based on a decentralized game-theoretic scheme for D-EVSE. In Chapter 6, we propose a profit maximization model for the D-EVSE. Finally, conclusions and future directions are presented in Chapter 7.

1.6 List of Publications

- **Journal Papers**

  1. Turki G. Alghamdi and Dhaou Said and Hussein Mouftah, “Decentralized Electric Vehicle Supply Stations (D-EVSSs): A Realistic Scenario for Smart Cities,” in IEEE Access, vol. 7, pp. 63016-63026, 2019. DOI: 10.1109/ACCESS.2019.2916917.
  2. Turki G. Alghamdi and Dhaou Said and Hussein Mouftah, “Decentralized Game-Theoretic Scheme for D-EVSE Based on Renewable Energy in Smart Cities: A Realistic Scenario,” in IEEE Access, vol. 8, pp. 48274-48284, 2020. DOI: 10.1109/ACCESS.2020.2974477.
  3. Turki G. Alghamdi and Dhaou Said and Hussein Mouftah, “Profit Maximization for EVSEs-based Renewable Energy Sources in Smart Cities with Different

Arrival Rate Scenarios," in IEEE Access, vol. 9, pp. 58740-58754, 2021. DOI: 10.1109/ACCESS.2021.3070485.

- **Conference Papers**

  1. Turki G. Alghamdi and Dhaou Said and Hussein Mouftah, "Decentralized Energy Storage System for EVs Charging and Discharging in Smart Cities Context," in ICC 2019, Ad Hoc and Sensor Networks (AHSN) Symposium, pp. AHSN-7.4.1 - AHSN-7.4.5, Shanghai, China, May 2019.
  2. Turki G. Alghamdi and Dhaou Said and Hussein Mouftah, "Decentralized Game-Theoretic (D-GT) Approach for D-EVSE based on Renewable Energy in Smart Cities," in ICC 2020, Ad Hoc and Sensor Networks (AHSN) Symposium, pp. AHSN-8.2.1- AHSN-8.2.7, Dublin, Ireland, June 2020.
  3. Turki G. Alghamdi and Dhaou Said and Hussein Mouftah, "Profit Maximization for EVSEs based on Solar Energy in Smart Cities," in proceeding IEEE IWCMC 2021 Conference, Wireless Sensor Networks Track, pp. WA-10.3.1 - WA-10.3.6, Harbin, China, June - July 2021.

Chapter 2

State of the Art

2.1 Introduction

In the smart city, transport electrification is the primary technology with significant potential to reduce GHG emissions and air pollution from fossil fuel vehicles. With advancements, transport electrification will achieve the environmental objectives and deploy the RESs as primary power sources [26]. In this chapter, an analysis is conducted of the state-of-the-art interaction between EV and EVSE as a public charging station. We present exist techniques to control the interactions and avoid stressing and overloading the power grid. The related work presented in this chapter is a general overview of the work done in this area. In Section 2.2, we present the electric vehicle characteristics. In Section 2.3, we review the state-of-the-art technology used in electric vehicle supply equipment infrastructures, power management schemes, and power sources for EVs. The electric vehicle supply equipment consideration-based techniques are presented in Section 2.3. Finally, in Section 2.4, we summarize the chapter.

2.2 Characteristics of Electric Vehicles

At present, EVs are characterized into the following types: hybrid electric vehicles (HEVs), plug-in electric vehicles (PEVs), plug-in hybrid electric vehicles (PHEVs), fuel cell electric vehicles (FCEVs), and battery electric vehicles (BEVs) [27].

The HEV has a gasoline engine (combustion engine), an electric motor, and a small battery for electric storage. The gasoline engine and regenerative braking produce the power and charge the battery. HEVs use the electric motor until the battery has reached its threshold. Once the HEV has switched to the gasoline engine, then the regenerative braking begins to charge the battery. However, there is no plug-in (grid connection) to charge from the power grid.

The PHEV has a gasoline engine (combustion engine) and an electric motor. PHEVs have larger battery storage with a plug-in (grid connection) to charge from the power grid. PHEVs can drive a significant distance using their large battery [28]. Like HEVs, PHEVs use the electric motor until the battery has reached its threshold and then switch to the gasoline engine. PHEVs then use the electric motor once the battery has recharged from the grid.

The FCEV or fuel cell electric vehicle uses a fuel cell generator. FCEVs are powered by combining oxygen and hydrogen to start the electric motor. At present, FCEVs are still in the development phase, and their fuelling stations are very limited [28].

BEVs, PEVs, and EVs all use an electric motor system. EVs have significant battery storage with a plug-in (grid connection). The batteries charge from the power grid using the plug-in connecter [29,30].

Table 2.1 shows the driving range and battery size for PHEVs and EVs. The PHEV battery size ranges between 4 and 22 kWh, whereas the PHEVs' driving range varies from 8 to 80 km. The EV battery size ranges between 24 to 100 kWh, whereas the EVs' driving range varies from 160 to 595 km.

2.2.1 Impact of Electric Vehicles

There are five emerging concepts of grid-connected EV technologies, namely vehicle-to-home (V2H), vehicle-to-building (V2B), vehicle-to-vehicle (V2V), vehicle-to-grid (V2G) [38], and grid-to-vehicle (G2V) [39]. V2H indicates a power exchange between the EV and the home power system where the EV battery could be used as backup energy storage for the home's electric appliances as well as home RESs [40]. V2V indicates a power exchange between EVs. V2G usually indicates demand management between EVs and the smart grid [41,42]. V2B, similar to the concept of V2H, indicates a power exchange

Table 2.1: Example of EVs [31–37]

Company	**Model**	**EV Type**	**Driving Range (Km)**	**Battery Size (kWh)**	**Charging Level**	**Charging Time**
Toyota	Prius	PHEV	8	4		
Buick		PHEV	16	8		
Chevrolet	Volt	EREV	64	16	1 & 2	10 hr& 2.5 hr
Fisker	Karma	PHEV	80	22		
Toyota	Mirai	FCEV	500			
BMW	i3	EV	160	24	1 & 2 & 3	22 hr & 4 hr & 30 m
Honda	Clarity	EV	129	25.5		19 hr & 3 hr& 30 m (80%)
Hyundai	Kona	EV	415	64		
Ford	Focus	EV	123	23	1 & 2	20 hr & 3-4 hr
Chevy	Bolt	EV	384	60	1 & 2	
Toyota	RAV4	EV	190	27		
Nissan	LEAF	EV	364	62	1 & 2 &3	22 hr & 4-8 hr & 30 m
Cooper	Mini E	EV	251	25		
Audi	e-tron	EV		95	2 & 3	
Tesla	Roadster	EV	354	53	1 & 2 & Fast charging & Supercharger	9 hr with 10kW 30 min(80%)
Tesla	Model X	EV	475	100		
Tesla	Model S	EV	550 to 595	100		

between an EV and a building's power system. V2B could be used as energy backup to support the building as required or as energy storage for RESs. G2V refers to power charging from the power grid to the EVs.

V2G schemes have facilitated EVs' processes with the power grid [43, 44]. V2G technology has increased the flexibility of power grid operations. However, the energy trading policy between EVs and the power provider must be clear and guarantee that the EV owner will benefit [45–49]. The authors of [50, 51] reported that V2G could maximize profits for EV owners and power providers. As well, V2G has the ability to minimize GHGs when the optimization technique is used. The authors of [17] proposed a scheme to manage G2V and V2G and maximize their profit. The EV owner has the ability to use a mobile web application to add his information and manage EV's charging request. The proposed scheme uses State of Charge (SoC), departure and arrival times, and charging and discharging processes.

The authors reported that the proposed scheme achieved 7EVs' charging demand requires at minimum a simple controller to manage the EV charging process [52]. The authors of [53] proposed a scheduled EV charging scheme based on V2G services. The proposed scheme uses a binary particle swarm optimization algorithm to optimize the EVs' charging at public parking lots. Two case studies were considered. The first study investigated how to find the best charging price for each EV by using the sell and buy price curve, and the second study allowed all EVs to conduct unlimited transactions to gain more profit. The authors in [54, 55] presented an admission control system for PHEV charging demands. The presented system used two-way communication between the substation as a local distribution system and the EVs. The admission control was installed in the substation as a management system to accept or reject the charging request based on the substation's thresholds. In addition, [55] used a wireless mesh network to deliver the decisions to the EV owner. However, there was no consideration for discharging in either system. Many papers such as [17,28,55] have studied the use of EV's battery as an energy buffer or energy backup for the smart grid. The authors of [24, 25, 56] studied the impact of EVs charging on the power grid. They concluded that EVs' charging demand would drastically increase the demand for power from the power providers [57]. The authors of [58] and [59] investigated the influence of PHEVs and reported that if the EV owner has consumed 3.3 kW, then the household's energy consumption will increase between 17-25The study in [60] investigated the impact of different EVs' charging schemes in Denmark's power system. The proposed model was based on wind energy generation and future power consumption. They concluded that smart charging for EVs significantly reduced the surplus power from wind energy generation.

2.2.2 Summary

As a conclusion for this section, the EV challenge lies on how to mitigate the impact of the new power consumers. Also, how to facilitated the requirements for the EV owners to replace the existing fossil fuel vehicles that will provide a clean environment.

2.3 Electric Vehicle Supply Equipment

Integrating a massive number of EVs in smart cities will require considerable EVSE as public charging stations. Creating EVSE will facilitate the integration of EVs in the smart city. It is necessary to create and deploy EVSE in the smart city to meet the EVs' power demand. The deployment of the EV charging station infrastructure is investigated in [61–64]. EV owners will be most satisfied by charging and/or discharging processes being offered in public places.

2.3.1 Electric Vehicle Supply Equipment Infrastructures

EV wired charging is the fundamental infrastructure and most common technology for the EVs' charging applications. In other words, the EV charging infrastructure can be categorized based on charging location and time, as shown in Table [2.2]. These charging infrastructure categories are divided into four groups [65, 66]. These groups have been standardized to determine which voltage rates are compatible with EV or PHEV as well as the EV or PHEV charging time preference. Table [2] shows the EVSE charging levels. The slow charger is AC Level 1, and this can be used at home. AC Level 2 can be used both at home and also in public or private parking lots. The DC or fast-charger (DC Levels 1 - 3) can be used in public, private, and commercial areas such as EVSE. The charging time in the case of using a fast-charging level is between 15 min to 1 h [67, 68]. The new ultra-fast charger, researched by academia and industry, aims to reach charging speeds comparable to traditional gas refuelling. BMW and Porsche announced that the new EV charger has the ability to charge for 100 km in three minutes. In addition, it can put the batteries' SoC above 80% in 15 minutes [69].

PHEVs' and EVs' charging process takes place at home and usually uses AC Level 1 or Level 2 chargers. The AC Level 1 charger unit is used with a 120 V AC outlet. The EV charging time is between 6 to 8 h. The AC Level 2 charger unit is used with a 240 V AC outlet. The charging time is usually between 3 to 4 h. Most PHEVs and EVs can connect with these units. All EV owners could install EVSE in their houses and use a home energy management system with the onboard battery chargers [73]. However, fast charging takes place at public charging stations with the DC high power terminal. The rated voltage used in the DC charging level ranges from 200 to 600 V. The ultra-fast charging station that has

Table 2.2: EVs' charging levels [31, 33, 70–72]

Charging Level	Rated Voltage	Charging	Maximum Power (kW)	Type
AC Level 1	120V one phase	10–13 h	2	Home/Commercial
AC Level 2	220V one phase	1–4 h	20	Home/Commercial
AC Level 3	220V three phase	~ 1 h	43.5	Home/Commercial
DC Level 1	200–450 V	0.5–1.44 h	36	Commercial
DC Level 2	200–450 V	0.2–0.58 h	96	Commercial
DC Level 3	200–600 V	~ 10 min	200	Commercial

been announced by Porsche will be used at public charging stations with a DC high power terminal. The rated voltage used in the ultra-fast charger ranges from 400 to 800 V in [74] model and from 400 to 920 V in [75] model.

Another EV charging technology is wireless charging. The wireless charging technology allows the energy to be transferred from power transmitters to EVs while the EVs are on the road. Wireless charging for EV efficiency exceeds 90%. WiTricity, Efacec, and other companies are developing a wireless charging technology that allows the power to be transferred wirelessly [76–78]. The authors of [79–82] examined EVs' wireless charging using a dynamic charging strategy that charged the EV while in motion. However, the authors presented some security issues. The authors of [83] proposed another wireless charging model that allows EVs to be charged while in motion. The goal of this study was to minimize the expenses for EV owners. The proposed model minimized the EV owner's expenses and reduced the power generation cost. An electric bus (E-bus) charging model is studied in [84, 85]. [85] proposed a model based on a closed loop between two bus terminuses. The wireless power transmitters were installed in both bus stations and terminuses, and the charging process took place while the E-bus was on the road.

2.3.1.1 Vehicles-to-Grid services and advantages

As we have explained, the V2G technology provides and facilitates the power exchange between EVs and the power grid in the form of power charging or discharging processes. Moreover, there are many advantages of enabling V2G technologies such as using the EVs' batteries as recovery for the power grid during blackouts [86, 87]. These technologies are advantageous to EV owners by supporting the home power system. Similarly, homeowners could use the EV's battery as backup energy storage when they install RES in their homes [88, 89]. The V2G has added more reliability and sustainability to the power system by controlling the energy of the EVs' batteries [89–91].

The authors of [47, 92] illustrated the advantages of a remote-control system that has been used for the PHEV charging process and the resilience of the distribution system to utilize the power grid system. The author of [93] presented V2G services to operate charging and discharging services by interacting with the power grid. The proposed system uses an optimization method to consider battery degradation and find the optimum operation services.

The authors of [94] proposed a model aiming to manage and control charging and discharging processes at EVSE. Two algorithms were proposed in this model: peak load management and guidance algorithm. Peak load management algorithm was used to schedule EVs' charging or discharging process according to the power demand while taking into account the charging time and the EV's location for each EV request. Guidance algorithm was used to guide every EV to the appropriate EVSE to reduce its waiting time before plug-in. The proposed model considered the mobility of vehicles in an urban scenario, and ToU pricing was used. The authors concluded that the peak load management has the ability to use unused EV battery storage as energy storage to support the power grid at all times and especially during peak time. Also, the guidance algorithm minimized the waiting time for each EV before the plug-in phase. Likewise, the authors of [55] used the EVs' batteries to support the power grid and implement the spinning reserve processes. The spinning reserve is comprised of the idle sources that dispatch the power requested to the power grid within 10 minutes of request time.

Figure 2.1 shows the power flow characteristics for EV chargers or dischargers. The power flow characteristics are dependent on the EV and PHEV batteries. Some EV and PHEV batteries are only allowed to conduct G2V operations, and others are allowed to conduct both G2V and V2G operations. Also, the DC/DC in Figure 2.1 [2.3] illustrates the advantages and disadvantages of EVs interacting with the power provider in both cases (Unidirectional battery connecter and Bidirectional battery connecter) [89–91]. V2G will help the power grid to minimize the power peak load and also mitigate the load on the power grid [86, 95, 96]. Table 2.3 illustrates the advantages and disadvantages of EVs interacting with the power provider in both cases (Unidirectional battery connecter and Bidirectional

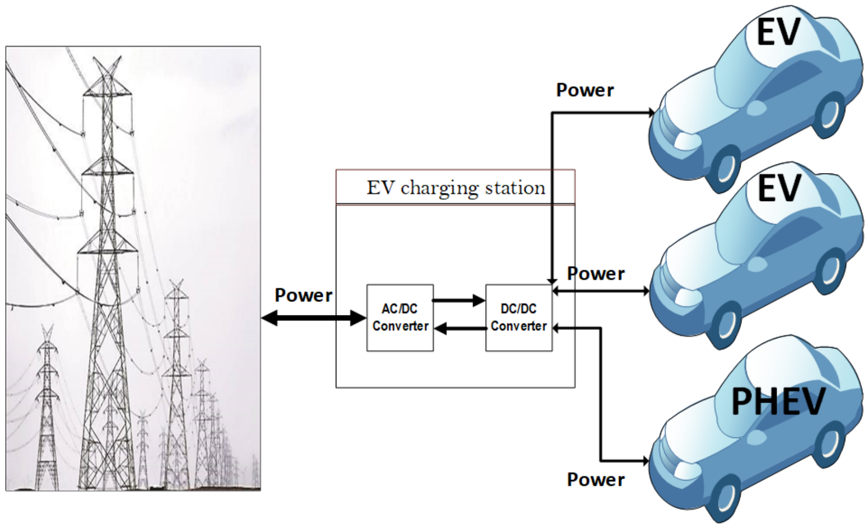

Figure 2.1: Power flow diagram for V2G and G2V [35]

battery connecter) [89–91]. V2G will help the power grid to minimize the power peak load and also mitigate the load on the power grid [86, 95, 96].

Table 2.3: Comparison between G2V-only operation and V2G and G2V operations [97]

	G2V only	**V2G and G2V**
Hardware infrastructures	Unidirectional battery connecter	Bidirectional battery connecter
Power Level	Levels 1, 2, and 3	levels 1 and 2
Cost	Inexpensive	Expensive
Services	Needs power regulator Ability for spinning reserve	Supports interaction power Increases the power stability Needs a frequency regulation Used as a power storage
Advantages	Ability to avoid the power grid overloading Maximizes EVs' profit Low operation cost	Decrease the losses in the power grid Helps the power grid to avoid the overloading Minimizes GHGs
Disadvantages	Restricted service	Decreases battery lifetime Complex infrastructure High operation cost

2.3.2 Electric Vehicle Supply Equipment Power Management Schemes

The authors of [98] present a comparison study between the four charging strategies. These strategies are unmanaged charging, scheduled charging, off-peak charging, and continuous charging. An unmanaged charging scheme refers to PHEV owners using their plugged-in outlet to charge their PHEV batteries at home. The charging stops when the PHEV batteries are fully charged. In the scheduled charging scheme, all PHEVs can schedule charging at a specific time. The off-peak charging scheme takes place overnight. The difference between the scheduled charging scheme and the off-peak charging scheme is that PHEV owners set the scheduled charging time while the power provider sets the off-peak charging time. In the continuous charging scheme, all PHEVs are allowed to charge at any time. The authors of the presented study concluded that the continuous and unmanaged charging schemes overloaded the power grid during peak time, while the charging process using the scheduled and off-peak schemes presented much better results in terms of Increase the power demand at the peak time.

The authors of [99] indicate that the high charging demand of EVs would lead to overloading the transformer and increasing the line losses. The authors suggest that EV charging demand needs to be managed, and efficient approaches need to be developed to safely integrate the charging demand of EVs into the smart grid. On the other hand, the authors of [100–102] noticed that the power demand increased when they used simple charging schemes. In contrast, smart charging schemes can control and manage most of the power demand and balance the overall demand.

The EV smart charging approaches have the ability to achieve many different goals such as managing power demand, minimizing system cost, and minimizing system charging costs in the smart grid [103–105]. The authors of [106] present a comparison study between PHEVs' smart and simple charging. The presented study proved that if the Illinois power grid system was combined with a high wind energy system used for PHEVs smart charging in their system, this would result in savings of almost $200,000/week compared to the PHEVs' simple charging [107]. The authors of [108] proposed a scheme to find the smartest ways to help avoid increased impact on the power grid system. The authors of [109] proposed a prediction system that allows PHEVs to either charge immediately or else delay the charging process until the price drops below the present price threshold. This process reduced the PHEV drivers' expenses when the EV driver avoided charging during a high-price threshold.

The authors of [110] presented a smart charging model to manage the charging process for EVs. The model is based on RES and is also connected to the power grid. The proposed model uses data mining schemes for PHEV consumption based on historical statistics and a global positioning system (GPS) in a mobile device. These technologies were used to identify the EVs' driving characteristics as well as the EVs' battery SoC. The EV's driver used mobile applications to request the charging power. The power provider could access the same mobile applications to set the energy production date. The mobile applications facilitated their interaction; however, the study reported that the driver's responses delayed the communication procedure. The authors of [111] suggest that smart charging should consider the battery's performance and lifetime to increase the lifetime of the EV battery.

2.3.2.1 Smart Grid

The smart grid is an intelligent system that will advance the traditional power grid system and fulfill the new demand with fast response and cooperation [112]. With the smart grid being integral to smart cities, governments of smart cities are motivated to increase the efficiency of energy consumption. Grants or financial incentives are often offered to the researcher to investigate the concept of using energy more efficiently [54]. Figure 2.2 shows the general structure of the smart grid structure with an energy management system (EMS).

Moreover, the smart grid will facilitate better utilization of current power generators and help to integrate RESs. The smart grid will also provide more efficient optimization for the distribution and transmission infrastructure [114]. The smart grid must be reliable, efficient, resilient, secure, safe, and clean. Furthermore, the smart grid must have a sustainable power system. Therefore, smart power generation, power transmission, power distribution, and power consumption are fundamental [10].

A fast-charging model, proposed in [27], allows G2V and V2G operation. Also, this model uses a high-frequency transformer to prevent high voltages in the EV charging procedure. The conclusion is that the proposed model allowed the EV fast-charging system to increase the EV's SoC from 20% to 80% within 30 minutes. A business model is presented in [115] based on a dynamic pricing problem for the EVs using a fast-charging level. The experimental results illustrate the advantage of dynamic pricing over fixed pricing.

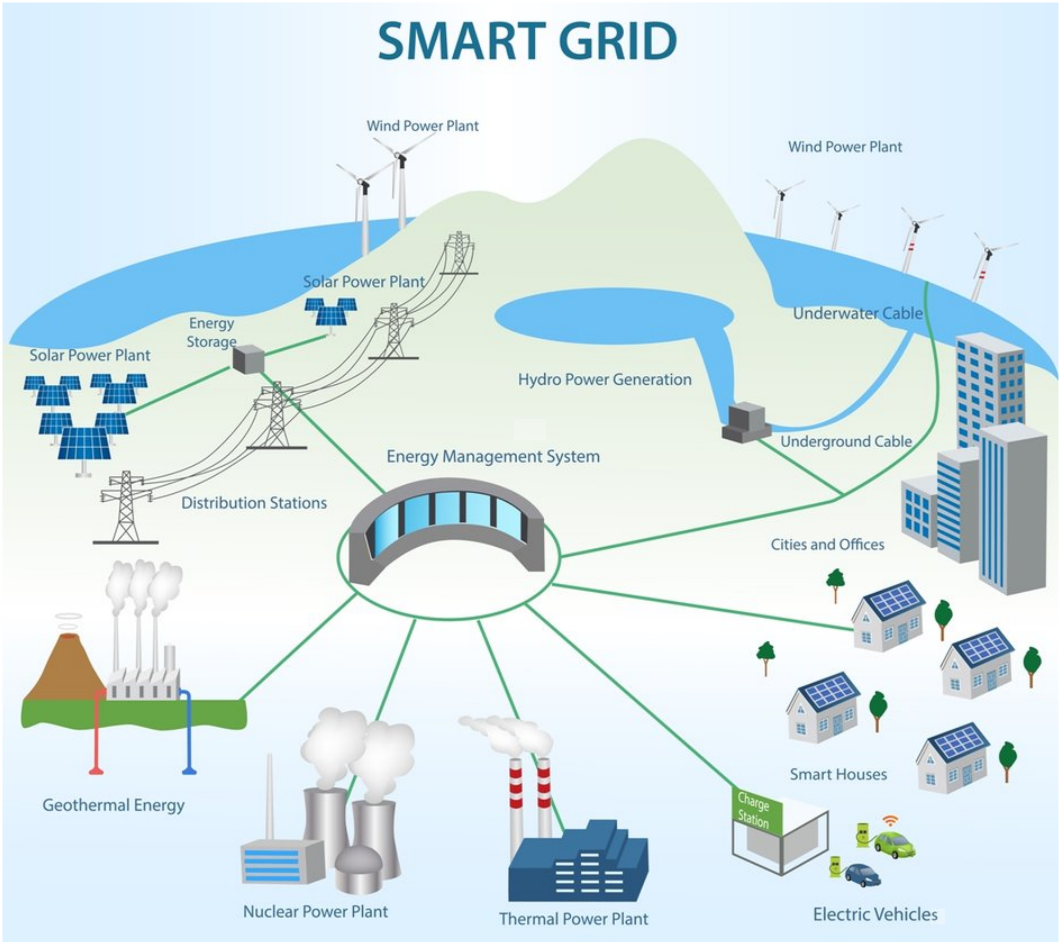

Figure 2.2: Smart grid structure with different RES productions [113]

The authors of [79] proposed deadline scheduling with an admission control model. The proposed model is an online scheduling algorithm aiming to maximize the PHEVs unscheduled arrival for charging processes. The proposed model observed a significant improvement in comparison to the earliest deadline first and the first come, first served algorithms. The author of [116] present a communication-based PHEV load management scheme. The proposed scheme is used to manage the PHEVs' charging demand. Power generation units, transmission, utility header-quarter, and distribution are all connected using WiMAX. The distribution system consists of a smart charging station, residential hoses, and a local substation control centre communicating via 802.11s. In this scheme, the charging process does not start until the PHEVs have received confirmation from the substation. The substation control centre will schedule the charging request based on the utility load to avoid any overloading of the substations.

2.3.2.2 Micro-Grid

The micro-grid structure has many advantages, such as the ability to adopt distributed power sources, increase the reliability of power sources, increase the sustainability of power quality, and increase the safety of a large power grid's operation. The micro-grid energy structure allows the RES to support the power grid directly or indirectly by using the ESS. This structure can be used as a power backup for the power grid whenever a failure or blackout in the power grid occurs. The micro-grid energy structure is composed of renewable energy systems as power source supplements and an ESS as shown in Figure 2.3. This energy structure can be used as backup power for the power grid whenever there is a grid failure or blackout. The micro-grid technology allows the integration of distributed generation and renewable energy power generation technology to be operated as one system [117].

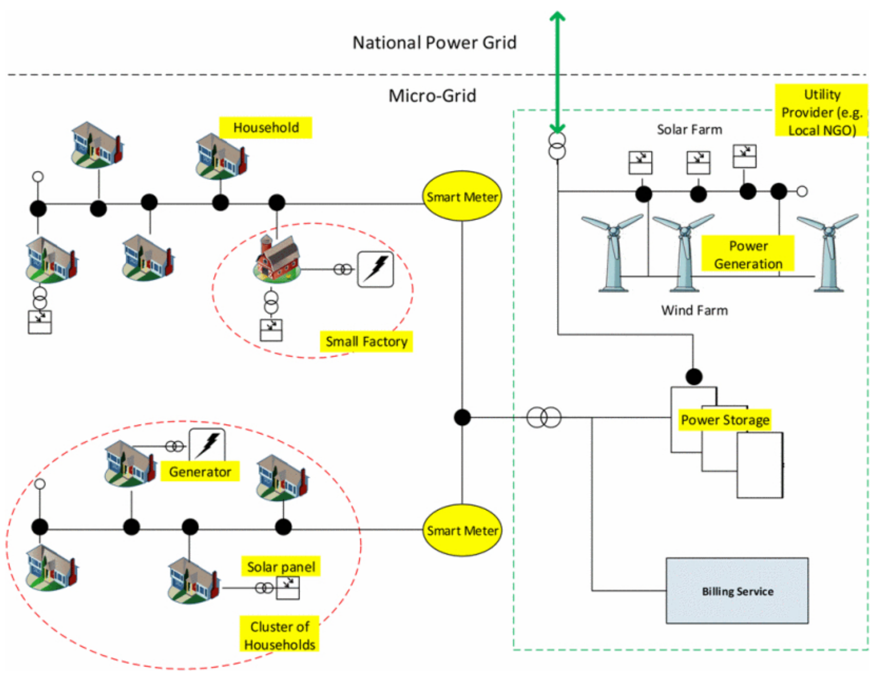

Figure 2.3: Micro-grid structure [118]

Decentralized energy sources have shown better results in emerging systems such as micro-grids. The advantages of decentralized energy systems are that they are well-recognized system, and they enhance reliability. The authors of [119] studied the integration of distributed generation and ESS in decentralized energy sources with CESs. They found that the diversification of using decentralized and centralized energy resources maintained energy and offered energy on a short-term, medium-term, and long-term basis. The authors of [120] proposed a business model that integrates both decentralized energy sources and CESs to guarantee power delivery and increase energy efficiency. Also, the proposed system considered how to increase utility profits with lower risks. The proposed system uses centralized production and distribution of transmission. Moreover, the system is based on two-way communication. The CESs are used due to their high and continuous production capacity.

The authors in [121] proposed a decentralized micro-grid management system framework which showed more functionality than the centralized micro-grid management system in terms of controlling and management. Therefore, the decentralized micro-grid management system presents greater flexibility, reliability, and scalability.

2.3.3 Electric Vehicle Supply Equipment based on Power Sources

In general, a power plant is based on electric power production such as coal-fired power stations, hydroelectric power stations, thermal power stations, nuclear power stations, and solar power stations. Most power plants use a large coal-fired power station, or another means of nonrenewable power production to produce steam which turns and drives turbine generators to produce electricity. However, these station infrastructures need to be managed as well as protected from any vulnerable attacks. The advantages of these plants are as follows: low power cost per unit, economies of scale, low power operation cost, and a well-known structure of production costs. However, the disadvantages of these plants are the environmental impact (high pollution), high cost of maintenance, high transmission failure, high losses, low efficiency, and high expense for unused energy. Fossil energy leads to increased air pollution. In addition, fossil fuel is considered a limited world resource. As a solution, renewable-based energy production will overcome these issues and minimize air-pollution [122]. In general, the reduction of GHG emissions and energy consumption is an important and challenging issue for smart cities. The existing structures of energy systems are no longer able to adapt to dynamic conditions. New communication systems for energy infrastructure networks should be dynamic because static conditions will soon be no longer applicable. Therefore, new infrastructure and communication must be flexible in the smart city to enable the achievement of efficiency and sustainability. The carbon footprint has impacted the global environment with emissions reaching more than 2% of all other emissions in 2007. Furthermore, the global CO2 footprint will be more than 4% in 2020 [123].

2.3.3.1 Power Grid

As a new power consumer to the smart grid, it is clear that uncoordinated charging of EVs will seriously affect the power grid. In [124, 125], the authors studied the impact of PHEV charging based on the distribution of an electric system with the use of utility transformers. The presented system was used to handle the overloading of the power grid within a short period.

The authors of [122] presented a model that combines small power generators and large power stations. The model is based on a decentralized system that uses solar energy and wind power generation. The proposed model uses the vehicle's battery as storage to support the power grid. The distributed renewable power generation works as a group of connected networks to increase the reliability of the power grid and reduce the need for a centralized system.

The authors of [126] demonstrated that the current electricity grid in Ontario, Canada will have the ability to adapt to and control almost 500,000 PHEVs by 2025. Moreover, all PHEVs will be charged from the grid without requiring any new transmission or the investment of power generation to the current infrastructure. The charging demand of these PHEVs will not affect the reliability of the current system. However, this study only considered PHEVs. In the case of using pure EVs, the results would differ.

Coal plants or stations have not been used since 2014. According to the Ontario Power Authority, the integrated power system plan that will be achieved by 2025 is primarily based upon green electricity generation. Furthermore, the Ontario's integrated power system plan has announced that the target value of total generated renewable energy is 15,700 MW by 2025, which is almost 40% of their total load capacity [127].

2.3.3.2 Renewable Energy Source and Energy Storage System

Today, the most common forms of renewable energy production are wind power and solar energy. However, these energy sources are classified as discontinuous and unpredictable. In contrast, other renewable energy sources such as hydro, biomass, tidal, biofuel, waste, wave, landfill, and geothermal are considered a continuous and stable means of energy production. For example, a hydroelectric power station is considered a green power generator. Also, the biomass energy is a "plant material that can be turned into fuel (also known as biofuel when it is made from biological material) to supply heat and electricity" [128]. Biomass generates energy that can be stored for high energy demand [28].

EU plans to use almost 30% of its load from renewable energy by the year 2030 [129]. In addition, the WindEurope energy association has challenged the power companies in Europe to increase wind generation to become 23% of total energy generation by 2030 [122]. In Canada, the government has announced that by 2025, 100% of the electricity used will be from RESs. The federal government of Canada aims to reduce GHG emissions by 40% by 2025 [130]. Germany plans to obtain 50% of its electricity capacity from wind and solar energy by 2030 [28]. The government of Sweden has planned for 100% renewable electricity production by 2040 [131].

The authors of [132,133] proposed an optimization model system with two goals: minimizing the PHEV charging cost and the GHG emissions of PHEVs. The authors reported that the costs and GHG emissions will be minimized if the PHEVs are charged from RES.

The authors of [134] presented a photovoltaics (PV) system built in a parking lot and offering a charging process for EVs. The presented system successfully provided potential energy production for each parking space. Although this would meet most of the charging demands of EVs during the summer season, in the winter season, the charging demands of EVs would not be met. This is one of the disadvantages of using PV during the winter season. The authors of [135] proposed the deployment of a solar model built in car parking lots in the city of Frauenfeld, Switzerland. They concluded that solar energy generation in parking lots could offer between 15% and 40% of the EVs' charging demand. The authors of [106] and [136] presented a model to support the interaction between PHEVs and wind power production using Demand-Response (DR) system. [106] analyzed the economical aspect while [136] investigated the GHG emissions. In [137], a control scheme is considered to show the benefits of V2G technology in the context of RES.

The authors of [28] presented an indirect charging strategy based on a consumer price response. After considering the influence of different charging strategies, the study found that EVs consumed almost 50% of the annual excess renewable energy generation. Overall, EVs have contributed to helping balance the power grid by using RES.

In [138], the authors proposed a model using solar energy production. The model was used to calculate the size of a solar panel that would provide enough power for the PHEV power demands. The authors concluded that on the sunniest days, 20 m^2 of the solar panel could provide enough power to charge an EV for 64 km. However, in the winter season, 78 m^2 of the PV panel was needed to provide the same amount of energy. In the summertime, the surplus solar energy could be sold to the power grid. Table 2.4 shows the monthly average of generated solar energy based on data gathered from Alberta, Canada.

Table 2.4: Average of generated solar energy in each month

Month	**January**	**February**	**March**	**April**
PV-generated energy	5.56	8.31	11.54	13.85
Month	**May**	**June**	**July**	**August**
PV-generated energy	5.90	17.31	17.40	15.53
Month	**September**	**October**	**November**	**December**
PV-generated energy	12.41	8.95	5.86	4.37

Many studies such as [139, 140] have investigated and observed the feasibility of using solar generation as a charging resource for EVs. The authors of [134] presented a renewable energy system based on PV power generation in the state of New Jersey, United States. The solar panels were built on the rooftop of a workplace. The authors studied the impact of providing a charging process for EVs during the day. The study concluded that in the summer season, renewable energy generation was able to generate up to 12.6 kWh. In the winter season, the generation was only able to generate up to 3.78 kWh; however, this was enough for PHEVs' charging processes.

2.3.3.3 Smart Grid

Since there is a necessity to use alternative power sources of energy, solar, wind, tidal, and biomass are being deployed to support the power grid [141]. However, managing and controlling RES is necessary and will require a suitable ESS. It is expected that the attainment of these goals will be very challenging because most of the ESSs are based on the architecture of centralized ESS (C-ESS). Moreover, this architecture is not scalable, not reliable, and a one-point failure. C-ESSs are characterized by high maintenance cost, delayed response to outage issues, and high degradation cost. The greatest challenge of alternative solutions lies in RES.

The power grid occasionally suffers from the discontinuous and unpredictable supply of electricity from RESs [142]. Moreover, RESs may generate more or less energy than the demand based on wind speed and solar radiation [143]. Thus, the ESS solution is to provide a means to store the energy and dispatch it to the power grid. The ESS is used to support the power grid, especially when the demand is very high, and efficiently use the energy that is generated from these RESs [144].

China has set a goal for wind power as well as PV energy. The goal is to achieve between 150 and 180 GW of wind power and more than 20 GW of solar power by 2020. The ESSs will store the energy that comes from RES generation [17, 142]. Also, according to the authors of [145], by 2030 Germany will use ESS to avoid the intermittency of the RES. The ESS can support power grids when the power demand is too high, and it will therefore prevent the power grid from becoming overloaded [17, 142].

Currently, hydro companies use C-ESS architecture to resolve problems related to peak power demand [146]. Currently, the power grid lies in the centralized power grid systems. However, the greatest challenge in the power grid will become the question of how centralized and decentralized systems deal with power as a provider as well as data regarding customer usage.

ESS for RES provides intelligent power storage and efficient handling of resources. In addition, by improving the sustainability of resources, the carbon footprint is decreased. Uncoordinated EV charging will seriously affect the power grid. Thus, it is essential to meet these new demands by using the ESS. EVs can help the power grid by using their battery as storage. ESS must be able to support the power grid when the power grid is in need and, more specifically, when the EVs' charging demand increases.

There are many advantages and disadvantages of using centralized and decentralized ESS. The decentralized energy storage system (D-ESS) tackles these problems and gives more scalability, good battery energy quality (less line loss), and fast reaction to the demand. As a multi-point failure, D-ESS is easy to maintain with a low risk of power outage and a more secure grid [147].

Table 2.5 summarizes the strengths and weaknesses of centralized and decentralized systems.

Table 2.5: Strengths and weaknesses of centralized and decentralized systems [35]

	Strengths	**Weaknesses**
Centralized energy storage system	-Maximize profit for providers and EV drivers - Able to control energy efficiently	-Complexity of the communication infrastructure -Requires a powerful central controller and database storage -Requires full information about EVs -Decisions about the EVs' charging are made by the provider -Ability to handle a large demand -Service delayed due to system overload or cyber attacks
Decentralized energy storage system	-Able to meet the large demands of EVs -Less communication and infrastructure required -Fast and convenient services since decisions are made by EV drivers - Flexible fault tolerance	-Requires efficient decentralized control solutions for charging of EVs -Requires accurate methods to estimate the EVs' demands -The EV users must protect their information from cyber attacks

2.4 Electric Vehicle Supply Equipment Design Considerations

Many studies have considered various aspects of EVSE and EVs such as maximizing the EV arrival rate at the stations and minimizing the EV searching time for charging stations. The authors of [79] proposed deadline scheduling with an admission control model. The deadline scheduling with an admission control model is an online scheduling algorithm aiming to maximize the unscheduled arrival of PHEVs' charging process. The proposed model observed a significant improvement in comparison to the earliest deadline first and the first come, first served algorithms. The authors in [148] presented a system-guidance model to minimize the waiting time for the EV charging process. In this model, the algorithm called SMART-EV-Guidance minimized the directing and searching time for each

EV looking for a charging station.

The authors of [149] presented a two-sided hospital/residents scheme aiming to reduce the complexity of the charging process. However, the proposed architecture does not consider the EV discharging process and EV owner preferences. The authors of [150] proposed a centralized charging controller based on EV owner satisfaction and the power stability requirement in parking lots. The planning for an EV charging station model is studied in [151]. This study presented two optimization models aiming to maximize the number of accepted EVs for charging and minimize the power losses in the distribution network. In [152], a secure framework for exchanging information between EV and smart grid is introduced. The study assumed that each EV has an initial EV SoC and a final destination. The EVs know the charging spots and availability of all EVSE routes.

Paper [153] introduced threshold admission with a greedy scheduling algorithm. The threshold admission with greedy scheduling is an online charging algorithm that allows an unscheduled PHEV's arrival to charge. The PHEV's acceptance or rejection decision is based on the comparison of the potential profit. The presented algorithm was tested under underloaded and overloaded demands and showed significant improvements in comparison to the earliest deadline first and first come, first served algorithms. The authors of [154] proposed a controllable charging model. The proposed model can stop PHEVs and EVs from charging or decrease the charging current for any issue, including battery life or any risk related to the power grid.

The admission control and scheduling algorithm is presented in [155] for EVSE at the workplace. The presented model considered ToU pricing. The objective was to coordinate EV's charging request before departure time. The presented algorithm takes into account how to maximize the charging station's profit by using the ToU pricing. In addition, those who had urgent tasks were given higher priority.

The authors of [156] proposed an EV charging model to minimize energy peak demands. The proposed model considered how to maximize the neighbourhood's charging ability and offer different prices for EVs' charging process. The scheduling process set different constraints such as coordinating realistic EV charging scenarios, EV driver's satisfaction level, and stabilization of the power grid. An admission control system for PHEV charging was presented in [81]. The proposed system installs the admission control at EMS to accept or reject the charging request while taking into account the substation's energy threshold. All of the EVs and PHEVs send a charging request to the EVSE to start charging;

however, no charging begins until the confirmation has been received from the admission control at EMS to ensure that there is no overloading at the substations. All of the systems were monitored at all times to avoid reaching the transformer capacity at the substations.

The authors of [157] proposed a quality-of-service-aware admission control scheme for PHEVs and EVs. The proposed scheme has a blocking probability. The EVs' and PHEVs' charging requests were sent to the EMS of the smart grid, and the blocking probability calculated the maximum charging amount for each of them. The EMS requires information such as arrival rate, service time, battery ratio, and demand intensity for each EV and PHEV to allow the admission control to make a decision. However, these models are based on centralized management.

The authors of [85] proposed a day-ahead reserved wholesale electricity determination algorithm for wireless e-bus charging. The proposed algorithm integrated wirelessly charged electric buses into public transportation and allowed the charging process while the e-bus was on the road. The authors concluded that the proposed algorithm has the ability to reduce operating costs.

The authors of [158] introduced two algorithms: an admission control algorithm and a charging scheduling algorithm. These two algorithms were implemented to investigate the requirements for EVs' charging process, the EV charging station's utility, and the effect of solar energy prediction errors. This investigation aimed to minimize the service delay time and increase the charging station's profits. The presented model performed much better than the first-in, first-out algorithm.

The authors of [159] proposed a model that allows consumers to interact with the central power station for energy trading. The proposed model implements a single leader with multiple followers. The Stackelberg game theory was installed in the central power station to minimize the cost of buying energy and maximize the profits of the EVs as well as the central power station. An optimal distributed load scheduling algorithm is presented in [160]. The presented algorithm is based on a collaborative and non-collaborative game theory system. The presented system allows for the trading of energy between EVs and aggregators. The proposed algorithm aims to maximize the aggregators' profit by using the collaborative game theory. The non-collaborative game theory was used to maximize the customers' profit.

2.5 Summary

This chapter reviews the interaction of electric vehicles (EVs) and electric vehicle supply equipment (EVSE) in the context of the smart city. Power generation and management techniques for EV charging and discharging processes used in the smart grid are also discussed. Much research has been conducted about motivating and accessing the benefits of centralized and decentralized power systems as well as the many services and applications that can be deployed. More specifically, the existing methods of using renewable energy sources (RESs) and energy storage systems (ESS) are discussed. Overall, it is noted that the most proposed schemes in the literature are either centralized power systems or systems which only consider the EV charging process.

Chapter 3

Decentralized Management System Generic-Model

3.1 Introduction

The electrification of transportation as part of the smart city will be a challenging critical issue for DR strategies in the smart grid. Specifically, EVs as a new division in the automobile industry with their zero-emission and low noise [151, 161–163] can stress the power grid by their charging operations. They may cause, in some cases, overloading of regional transformers or frequency and voltage fluctuations. In [154] a study concluded that the number of vehicles in Beijing, China will be more than ten million and the number of PHEVs will be more than three million by 2030. These PHEVs will need to charge every day from the power grid. If each PHEV demands approximately 8 kWh to charge, then the total power demand for all PHEVs will be approximately 24 million kWh every day. This amount of power means that the charging demand for PHEVs will impact the power grid. This estimation was based on PHEV's battery; however, in the case of EV's battery, the power demand will be enormous. In the United States, the number of EVs increased by approximately 22% from 2015 to 2016 [31]. Moreover, the number of EVs on the road in the United States as of the end of December, 2019 was 1.5 million. This number is expected to be more than 18 million by 2030 [164, 165].

Currently, hydro companies use C-ESS architecture to resolve problems related to peak power demand [56, 146]. This architecture is not scalable, not reliable, and one-point failure. Moreover, C-ESS is characterized by high maintenance costs, delayed response to outage issues, and higher cost of degradation. The D-ESS tackles these problems and gives more scalability, better battery energy quality (less line loss), and fast reaction to the demand. Moreover, as a multi-point failure, the D-ESS is easy to maintain with low risk of power outage in the power grid and micro-grid as well as a more secure power grid.

In this work, we assume that D-EVSE is installed as public charging stations and is based on RESs such as PV or wind power. We tackle the problem of EV charging or discharging scheduling when EVs need to identify the best available D-EVSE before the plug-in phase.

Our contributions are as follows: 1) We consider the decentralization of power generation and management in smart cities. 2) We propose a system model to minimize the D-EVSE's stress level. 3) We design a scheduling algorithm which helps the EVs to choose the best D-EVSE and thereby maximize the drivers' satisfaction. 4) Finally, we consider EV driver's preference for charging or discharging participation.

The remainder of this chapter is organized as follows. Section 3.2 presents some related works. Section 3.3 introduces our system model and problem formulation for the EV charge scheduling process. In Section 3.4, performance evaluations are presented. The conclusions are provided in Section 3.5.

3.2 Related Work

Operations of micro-grid and EV charging and discharging in supply stations based on ESSs have resulted in extensive research studies. Authors in [121] proposed a decentralized micro-grid management system framework which showed more control functionality than the centralized micro-grid management system. Therefore, the decentralized micro-grid management system presents greater flexibility, reliability, and scalability. Also, the decentralized micro-grid management system is well-recognized system and enhances the reliability of the system. The authors of [149] presented a two-sided hospital/residents scheme aiming to reduce the complexity of the charging process. However, the proposed architecture did not consider the EV discharging process and EV preferences. The authors of [166] proposed a model to coordinate EV batteries' switching stations. The station was equipped with wind energy production. The proposed model switched the EV batteries by replacing uncharged EV batteries with charged EV batteries to allow the EVs to extend their range. This method provided an excellent opportunity to integrate wind energy into the smart grid as well as EV charging processes.

The authors of [150] proposed a centralized charging controller based on EV satisfaction and the power stability requirement in parking lots. One study [151] presented two optimization objectives: maximizing the number of charged EVs and minimizing the losses in the distribution network. In [50] and [167], several schemes are proposed to aggregate the power and manage the EV charging loads. In [137], a control scheme is considered to show the benefits of V2G technology in the context of RES. The authors of [163] proposed a new metric to describe the EV driver's satisfaction fairness and cost using a centralized charging algorithm. However, these latter two works did not investigate the power grid stress level.

The dynamic pricing scheme proposed in [168] aimed to increase the profit of an EV parking deck. However, in this model, the author did not consider EV driver satisfaction nor the smart grid overload situation. In [161], most issues regarding the cost of EV charging and energy management are considered. However, market-level customer satisfaction is the only parameter in this study. The authors in [169] discussed a travel-aware scheduling scheme while considering the benefits of EVSEs and increasing EV satisfaction. Yet none these works considered the discharging process.

The authors of [56], [24], and [25] studied the impact of the EV charging process on the power grid and concluded that EV charging demand changes the power demand by drastically increasing the demand for power from the power generation providers. The authors of [170] presented a fast-charging station placement with the flexibility to determine the optimal location and capacity of the charging stations. However, there is no mention of the power source nor of how many vehicles were considered in this work.

The author of [171] proposed a profit model aiming to maximize the revenue of EV owners and power suppliers (aggregators). The author considered the two scenarios of real-time and TOU pricing. These two scenarios were used to investigate the satisfaction level of EV drivers based on the influence of the price changing. The investigation concluded that the real-time price showed better performance than the TOU pricing, especially at peak time. The authors of [172] proposed an optimal pricing mechanism. The proposed mechanism aimed to utilize the charging station by increasing the EVs' rate of arrival and maximizing the EV drivers' satisfaction level by providing charging service to the EVs. The optimal pricing mechanism considered two charging services: fast and regular. The power grid supplied the power, and the optimal pricing mechanism chose the optimal price for both services. The authors of [173] established admission and scheduling models based on the power grid and renewable energy sources. The authors studied how EV processes influenced the EV charging station's effectiveness. Yet in all of these works, the power provider is the power grid and the RESs are not considered.

3.3 System Model and Problem Formulation

In this section, we suppose that all D-EVSE operates a set of charging and discharging plug-in sockets within a large city (100*100 km). We also consider that all D-EVSE is equipped by EVSEs and connected to the ESS. The power is stored in a huge battery or ultra-capacitor (see Figure 3.1). Also, the city has two very long bidirectional streets, as shown in Figure 3.2, and the ESSs are powered by RESs (PV and wind turbines). Moreover, we suppose that each EV considered by our model has at least 20% of its maximum battery capacity. The charging and discharging load balancing between D-EVSE in our proposed model is considered by using the D-EVSE's charging or discharging priority.

For each EV, we define the required power to reach the expected destination by Eq. 3.1:

$$SoC^i_{req} = Trip^i \times D^i_{rate} + SoC_{\min} \tag{3.1}$$

Also, the difference between EV initial SoC and EV required SoC is given by Eq. 3.2:

$$\delta SoC^i = SoC^i_{ini} - SoC^i_{req} \tag{3.2}$$

We also suppose that all EVs are randomly distributed on the city streets as shown

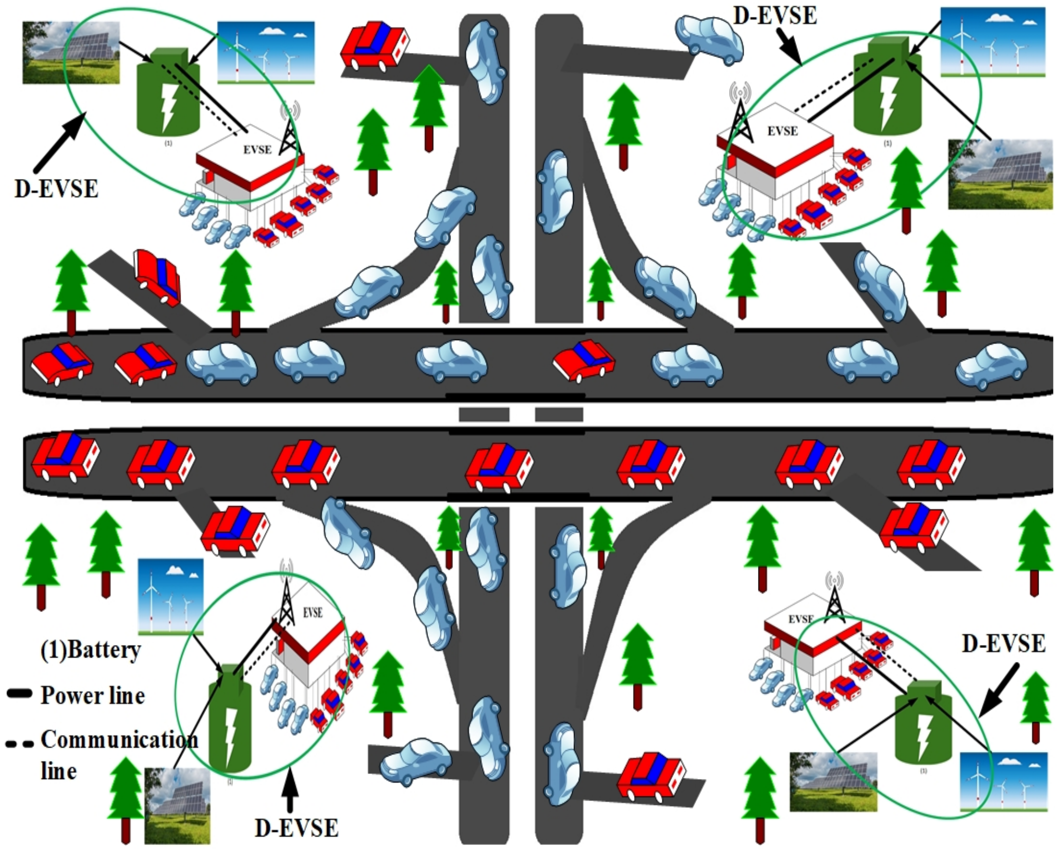

Figure 3.1: D-EVSE System Model

Table 3.1: Distance between EVs and D-EVSEs

	D-EVSE 1	D-EVSE 2	D-EVSE 3	D-EVSE 4
EV_1	$d^{(1,1)}$	$d^{(1,2)}$	$d^{(1,3)}$	$d^{(1,4)}$
EV_2	$d^{(2,1)}$	$d^{(2,2)}$	$d^{(2,3)}$	$d^{(2,4)}$
EV_3	$d^{(3,1)}$	$d^{(3,2)}$	$d^{(3,3)}$	$d^{(3,4)}$
$EV_{(i)}$	$d^{(i,1)}$	$d^{(i,2)}$	$d^{(i,3)}$	$d^{(i,4)}$

in Figure 3.1. As well, all EVs are equipped with a GPS and are randomly assigned (C/D,SoC$_{ini}$ and *speed*). The C/D is used to manage the EV driver's preference for charging or discharging participation. We assume that all EVs and D-EVSE are able to communicate to facilitate the requesting and reservation processes while the EVs are on the city streets.

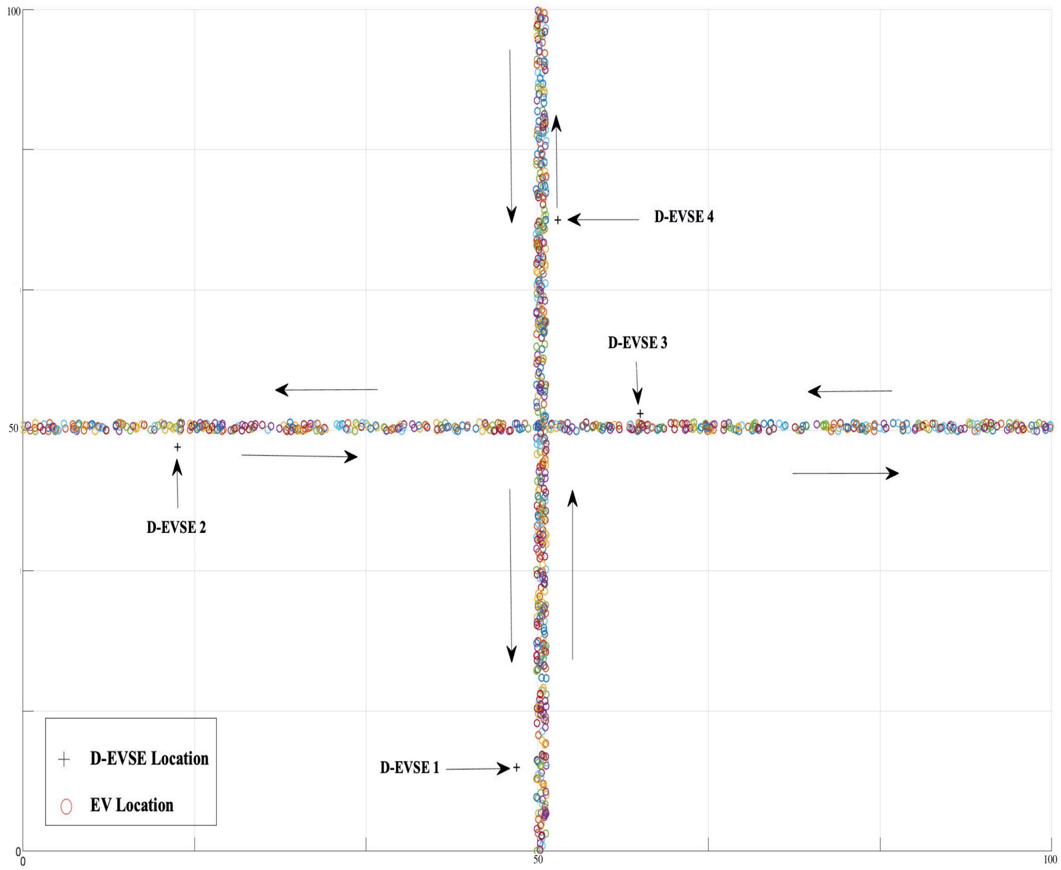

Figure 3.2: Street Overview

The EV arrival time is given by Eq. 3.3:

$$Ar^i = \frac{d_j^i}{Sp^i} + \beta \tag{3.3}$$

As shown in simulation parameters' Table 3.2, we consider three types of cars: Tesla, Nissan Leaf, and BMW i3. We choose the maximum charging level to be 80% from the EV battery's capacity to avoid the non-linear charging behaviour that starts after 80% of the EV battery's charging capacity. However, all EVs can participate in the discharging process if they have more than 20% in their batteries. Each car has its battery capacity as well as its required minimum EV SoC and maximum EV SoC.

In the following, Eq. 3.4 gives the distance between EVs and D-EVSEs.

$$D_{NJ} = \begin{bmatrix} . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & \\ . & . & . & d_{(i,j)} & . & . & . \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \end{bmatrix} \tag{3.4}$$

In our model, EVs can choose to participate or not participate in the charging or discharging service. Each EV can calculate its ability to reach the destination by using Eqs. 3.1 and 3.2. If the δSoC^i is positive, then the EV can participate in the discharging service. If not, then the EV cannot use the discharging service. Thus, when the EV requires power, it can request the charging process. Subsequently, any EVs which want to charge or discharge can send a message to D-EVSE containing the requested SoC (Eq.3.2) the time slot availability, the charging or discharging type, and the D-EVSE priority (to accept charging or discharging). The D-EVSE will reply to the EV with the requested information. The charging time for each EV needing electricity power is given by Eq. 3.5:

$$t_{ch}^{(i,\varepsilon)} = \frac{|\delta SoC^i|}{R_{ch}^{(\varepsilon)}} \tag{3.5}$$

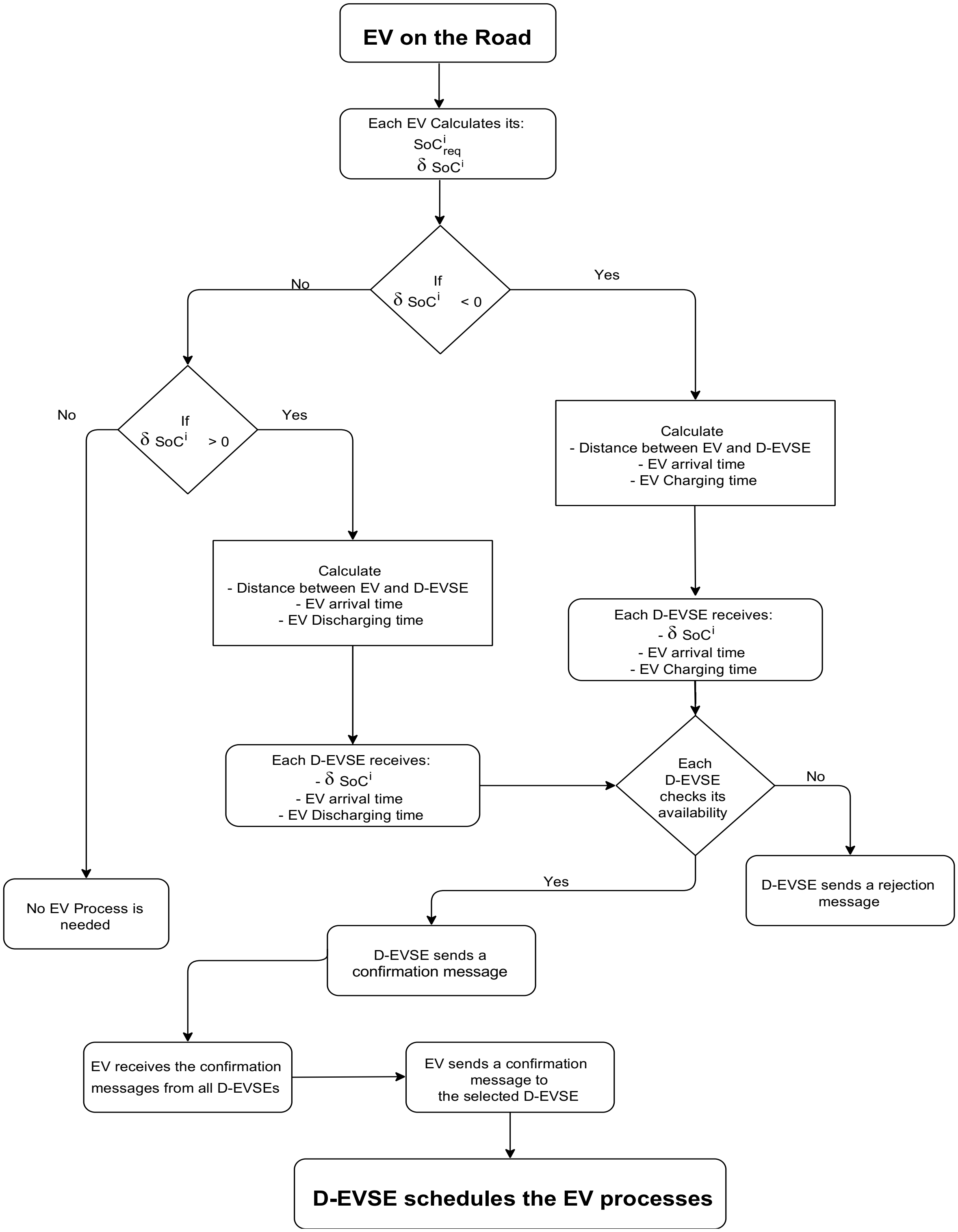

Figure 3.3: EV processes scheduling flowchart

The discharging time for each EV which has agreed to sell its surplus electricity power to reduce the power demand on D-EVSE is given by Eq. 3.6. The discharging process can contribute to a new energy market. However, the EV charging and discharging efficiency depend on the type of the batteries and battery cell design, temperature, and age. Since these are out of our scope, we neglect the EV charging and discharging efficiency, and we assumed that there is no impact on the charging and discharging efficiency.

$$t^{i}_{dis} = \frac{\delta SoC^{i}}{R_{dis}} \tag{3.6}$$

Algorithm 1 Scheduling Algorithm

Input 1 EV [N,C/D, SoC^{i}_{ini}, $Trip^{i}$, Sp^{i}, $t^{(i,\varepsilon)}_{ch}$, t^{i}_{dis}].
Input 2 D-EVSE [Availability].

for each EV($1..N$) **do**
    Calculate SoC^{i}_{req} (Eq. 3.1)
    Calculate δSoC^{i} (Eq. 3.2)
    if $\delta SoC^{i} > 0$ and $EV(C/D) = 2$ **then**
        select D-EVSEs [C/D Priority, Availability] =[1,2]
        Choose the nearest and available D-EVSE
        Schedule: Discharging process
    endif;
    if $\delta SoC^{i} = 0$ **then**
        No charging or discharging for EV
    endif;
    if $\delta SoC^{i} < 0$ and $EV(C/D) = 1$ **then**
        select D-EVSEs [C/D Priority, Availability] =[1,1]
        Choose the nearest and available D-EVSE
        Schedule: charging process
    endif;
endfor.

Additionally, each EV has its decision made based on the information received from D-EVSE. In Algorithm 1, once the EV receives the information from the D-EVSE about time slot availability, charging or discharging type, and priority, then the EV will calculate its arrival time using Eq. 3.3 based on its location as shown in 3.4 and Table 3.1. Also, the EV will calculate the charging or discharging time based on the availability of D-EVSE (see Eqs. 3.5 and 3.6). Afterward, the EV will choose the D-EVSE that best fits its requirements. Finally, a confirmation message will be sent from the D-EVSE to the EV as shown in Figure 3.3. We use Algorithm 1 to test our proposed model.

3.4 Performance Evaluations

In this work, we assume that D-EVSE is installed in public charging stations and is based on PV and wind power production. We investigate the problem of the EV charging and discharging schedule when EVs need to know the best available power supply station before the plug-in phase while taking into account our constraints.

The random algorithm selects the nearest D-EVSE for the EV without taking into account the D-EVSE availability for charging or discharging.

Table 3.2: Simulation Parameters

EV Type	Tesla (36 - 75 kWh) [174] Nissan Leaf (30 kWh) BMW i3 (27 kWh)
Number of EVs N	1000
Initial EV SoC (SoC_{ini}) %	20 - 90%
EV Trip ($Trip$)	Random from 35 - 100 km
EV Speed (Sp)	16 - 65 km/h
Field Size	100*100 km
Number of D-EVSEs J	4
ESS Capacity	10000 kW
Duration of a time slot	10 min
Minimum EV SoC requirement ($SoC_{\min}$)	20%
Level 2 Charging (ε) Fast charging rate (ε) Discharging rate (R_{dis})	7 kW Power 60 kW DC [94] 60 kW DC [94]
Number of sockets	Random from 4 - 10
Tesla Nissan Leaf (D_{rate}) BMW i3	1%/km (0.434 kWh/km) [174] 1%/km (0.483 kWh/km) 1%/km (0.434 kWh/km)

We compare our scheduling algorithm with the random scheduling algorithm. In Scheduling algorithm, the satisfaction level is measured based on the EVs which sent a charging or discharging request and received a charging or discharging confirmation from the D-EVSE. Also, the dissatisfaction level is measured for the EVs which sent a charging or discharging request and received a charging or discharging rejection from the D-EVSE. The EVs which received either a charging or a discharging rejection from the D-EVSE can go to the nearest D-EVSE and try to sell the power to D-EVSE or buy the power from D-EVSE without further investigation if there is any cancellation.

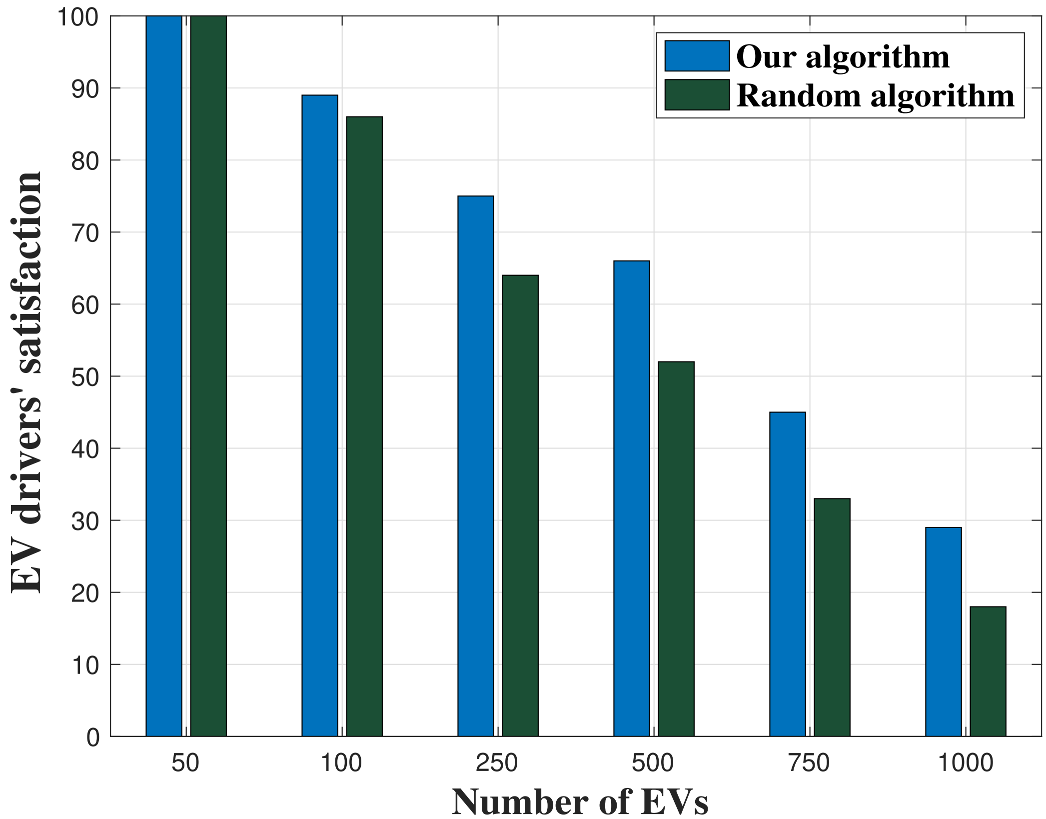

Figure 3.4: EV driver's satisfaction level comparison between random and scheduling algorithms

The EV driver's satisfaction level indicates how satisfied the driver is with the processes that he has requested. In other words, the satisfaction level for each EV driver is kept high. Also, the D-EVSE stress level measures the level of stress placed on the D-EVSE. In other words, the stress level for each D-EVSE is kept low. Figure 3.4 shows only the average satisfaction level for EV drivers in both scheduling algorithm and the random algorithm. As

Table 3.3: EV driver's satisfaction level using random algorithm

Number of EVs	50	100	250	500	750	1000
D-EVSE 1	100%	90%	78%	69%	43%	32%
D-EVSE 2	100%	89%	69%	54%	37%	20%
D-EVSE 3	100%	84%	50%	41%	22%	10%
D-EVSE 4	100%	81%	60%	41%	28 %	16%

shown in Figure 3.4 we compare scheduling algorithm and the random algorithm. Scheduling algorithm is robust and has the ability to maximize the EV driver's satisfaction.

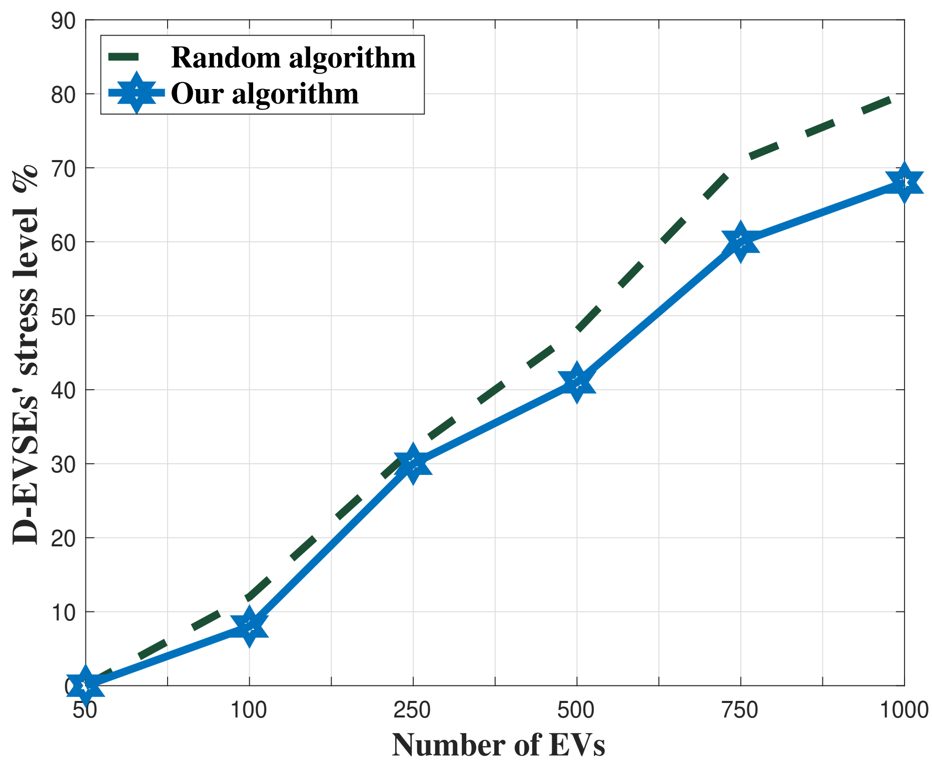

Figure 3.5: D-EVSE's stress level comparison between random and scheduling algorithms

By observing the EV driver's satisfaction in Table 3.3, it is evident that many EV drivers sent a reservation confirmation message to D-EVSE 3. In response, D-EVSE 3 sent a rejection message to the EVs for their reservation request because it was not available. D-EVSE 1 was not as stressed as D-EVSE 3, and D-EVSE 1 received 30% fewer EVs reservation requests than D-EVSE 3. Consequently, scheduling algorithm has the ability to manage most of the charging and discharging requests and maximize the EV driver's satisfaction in all scenarios, as shown in Table 3.4.

Table 3.4: EV drivers' satisfaction using scheduling algorithm

Number of EVs	50	100	250	500	750	1000
D-EVSE 1	100%	89%	80%	66%	48%	30%
D-EVSE 2	100%	89%	78%	67%	47%	28%
D-EVSE 3	100%	88%	72%	67%	45%	27%
D-EVSE 4	100%	90%	71%	64%	43%	29%

Table 3.5: D-EVSEs' stress level using random algorithm

Number of EVs	50	100	250	500	750	1000
D-EVSE 1	1%	14 %	27%	43 %	67 %	70 %
D-EVSE 2	0 %	12 %	30 %	44 %	72 %	78 %
D-EVSE 3	2 %	13 %	42 %	56%	74 %	91 %
D-EVSE 4	0%	9 %	32%	51%	72%	83%

Scheduling algorithm minimized the stress level between D-EVSE, as shown in Figure 3.5. Figure 3.5 shows the average stress levels for all D-EVSE. According to Table 3.5, for the random algorithm, the D-EVSE 3 stress level is the worst-case scenario because there is no consideration for D-EVSE priority, the distance between EVs and D-EVSE, and EVs' charging or discharging request preference when the decision is about to be made. Table 3.6 presents the stress levels among the D-EVSE using scheduling algorithm. As shown in Table 3.7, it is clear that our proposed algorithm minimized the D-EVSE stress level with a savings rate of more than 22% when the number of EVs is between (600 – 1000 EVs) and 21% when the number of EVs is between (251 – 600 EVs). However, when the number of EVs is between (0 – 250 EVs), then the savings rate is 10%. This result proves the robustness of our scheduling algorithm by minimizing the D-EVSE stress level.

To summarize these results, our proposed algorithm is able to manage the D-EVSE stress level while maximizing EV drivers' satisfaction.

Table 3.6: D-EVSE's stress level using scheduling algorithm

Number of EVs	50	100	250	500	750	1000
D-EVSE 1	0%	13 %	24 %	39%	56 %	62 %
D-EVSE 2	1%	8 %	34%	44%	62 %	66 %
D-EVSE 3	1%	6%	32%	42 %	59 %	69 %
D-EVSE 4	1%	7%	28%	40%	60 %	72 %

Table 3.7: Stress level performance between scheduling and random algorithms

Number of EVs	**Scheduling algorithm**	**Random algorithm**	**Savings rate**
50 - 250	**29.5**	**33**	**10.6 %**
251 - 600	**16.5**	**21**	**21 %**
600 - 1000	**21**	**27**	**22.2 %**

3.5 Summary

In this chapter, we proposed a new interaction scheme between EV and D-EVSE located at a public charging station. We present a scheduling algorithm to manage the DEVSEs' stress level and EV preference for the charging or discharging process. Also, we consider the D-EVSE availability and reservation priority as well as the proximity of each EV to the selected D-EVSE. Our scheduling algorithm is tested through simulations while considering EV and D-EVSE constraints. Simulations show that the proposed scheme manages the EVs' charging and discharging process efficiently.

Chapter 4

Decentralized Management for Charging and Discharging Model

4.1 Introduction

Reducing GHG emissions and energy consumption are fundamental and challenging issues for smart cities. However, the existing structures of energy consumption are no longer able to adapt to dynamic conditions. New communication systems which are expected to be used in the smart grid for energy infrastructure devices should be dynamically adaptable because static conditions will soon no longer be applicable. Therefore, new infrastructure and communication must be flexible in the smart city to enable the achievement of efficiency and sustainability. The carbon footprint has impacted the global environment with CO2 emissions reaching more than 9% of all emissions between 2008 and 2017.

Furthermore, the global CO2 footprint is estimated to grow more than 11% by 2020 [175, 176]. For example, the Canadian government has announced that 100% of electricity use will be from RESs by 2025. The Canadian federal government aims to reduce GHG emissions by 40% by 2025 [130].

EV, as part of the electrification of transportation in a smart city, is an important and challenging issue due to its power demand. Although EVs come with zero emissions and low noise [151, 161–163], EVs' charging demand as a new power consumer will add more stress to the power grid and may cause in some cases power outages due to the overloading of regional transformers.

As we have mentioned before, the D-ESS architecture copes with the challenging issues in C-ESS architecture such as one-point failure, high maintenance cost, high cost of degradation, and high delayed response to power outage [56, 146]. The D-ESS provides architecture with advantages such as more scalability, better battery energy quality, and swift reaction to demand with a multi-point failure, easy maintenance, low risk of power outage in the macro-grid, as well as a more secure grid.

In this work, we consider that the D-EVSEs are public charging stations. The D-EVSEs are based on RESs (PV and wind power). We resolve the problem of EV charging or discharging scheduled processes when EVs need to know the best available charing station before the plug-in phase, as well as the EV charging or discharging unscheduled processes when EVs decide to participate in unscheduled processes.

Our contributions are as follows: 1) We design a system model to minimize the D-EVSEs' stress level. 2) We propose a D-EVSE Immediate Scheduling Algorithm (ISA) which helps the EVs to determine and select the best charging station to maximize the drivers' satisfaction. 3) Also, we propose a D-EVSE unscheduling Algorithm to minimize the waiting time for EV charging and discharging processes. 4) Finally, we compare the proposed algorithms with three other algorithms: random algorithm, Dijkstra's shortest path algorithm, and EV smart-guidance algorithm.

The rest of the chapter is organized as follows: Section 4.2 presents some related works. Section 4.3 introduces the D-EVSE system model and problem formulation for the EV charge scheduling process. In Section 4.4, performance evaluations are presented. The conclusions are provided in Section 4.5.

4.2 Related work

The interaction of micro-grid and EVSEs for EV charging and discharging processes has attracted extensive research. A dynamic pricing model proposed in [168] aimed to increase the power supply stations' profit. This model assumed that the power supply stations are connected to the micro-grid directly. Also, the proposed model used EV batteries as an energy storage device. However, in this model, the authors did not consider the EV driver's satisfaction nor smart grid overloading. Likewise, the dynamic pricing protocol proposed in [177] and [56] aimed to minimize the peak EV power demand for the power providers; however, home charging was proposed. Additionally, the ToU pricing was considered in their work to increase the EV satisfaction for charging demand. However, [177] only considered the charging process while [56] considered both the charging and discharging processes. The authors of [178] proposed a simulated annealing algorithm for EV charging in a smart grid based on mathematical optimization to choose the best charging stations. The goal of this work was to minimize the EV driver's cost and reduce the peak demand in these stations. The authors in [169] discussed a travel-aware scheduling scheme while considering the benefits of EVSEs and increasing EV satisfaction. In all previous works described above, a centralized approach has been considered for the power and management system.

The authors of [24] presented two models for EV charging at charging stations. The first model considered the charging waiting times while the second model considered the cut-off priority protocol and a ToU pricing strategy. However, the proposed models assumed that the power came from the power grids. The authors of [94] proposed a model aiming to manage and control charging and discharging processes at EVSEs. Two algorithms were proposed in this model: peak load management and guidance algorithm. peak load management algorithm was used to schedule the EV charging or discharging process according to power demand while taking into account the time and location for each EV's requested process. guidance algorithm was used to guide every EV to the appropriate EVSE to reduce its waiting time before plug-in. The proposed model considered the mobility of vehicles in an urban scenario and ToU pricing. The authors concluded that the peak load management efficiently used unused EV batteries' storage to store energy and thereby support the power grid at all times, especially during peak time. Also, guidance algorithm minimized the waiting times for each EV before the plug-in phase. Yet none of these works considered realistic scenarios.

The authors of [179] presented an EV charging and discharging queuing model at charging stations aiming to manage EV charging and discharging requests in a real-time manner as well as to reduce the EV charging and discharging waiting times. All of the EVs send their charging and discharging requests to the provider through a cloud computing network. A mathematical model was proposed to compute the waiting times for EVs' requests. Two classifications identified each EV as high or low priority and as high or low class. However, this model is used for centralized management, which is not recommended if the system has been shut down or attacked. The authors in [148] presented a system-guidance model to minimize the waiting time for the EV charging process. Also, this model noticed that the algorithm called SMART-EV-Guidance had minimized the directing and searching time for each EV looking for a charging station. Nevertheless, in all of these works, realistic scenarios were not considered.

The authors of [155] proposed an EV charging process model located at a workplace station based on ToU pricing. Two parts are presented in this work: an admission control approach to increase the charging quality process, and a joint searching scheme to maximize the charging station's revenue based on ToU pricing. Likewise, an EV charging process model located at an intelligent parking garage based on real ToU pricing is proposed in [180]. The proposed model used the [155] model and added an adaptive utility-oriented scheduling scheme aiming to optimize the total utility for the charging operator.

The authors of [181] proposed a dynamic charging scheduling scheme in a workplace parking lot aiming to manage and control EV charging processes in a real-time manner. The proposed scheme used the PV power system with the power grid as the primary resources to guarantee the EV charging process at all times. Furthermore, all of the EVs' charging requests are collected in a central controller to obtain the optimal decision for each EV request. However, this work did not consider the discharging processes or identify how to gain the most benefits from the ESS to save the generated energy from the solar panel.

4.3 System model and problem formulation

To develop our detailed problem formulation, we develop our system model on a case study of the city of Ottawa's highways (Hwy) in Ontario, Canada. Also, we selected 12 gas stations in the city of Ottawa in which we propose the D-EVSE model (see Figure 3.1). We consider that all D-EVSEs are equipped by EVSEs, and that all EVSEs operate a set of charging and discharging sockets [24]. The D-EVSEs are powered by PV and wind turbines. The power is stored in a massive battery or ultra-capacitor (ESS) (see Figure 3.1). The city of Ottawa has three highways (Hwy 417, Hwy 416, and Hwy174, as shown in Figures 4.2, 4.3 and 4.4), We selected Hunt Club Road to connect Hwy 417 and Hwy 416 in both directions as shown in Figure 4.5. Moreover, we assumed that each EV considered by the D-EVSE model has at least 20% of its maximum battery capacity.

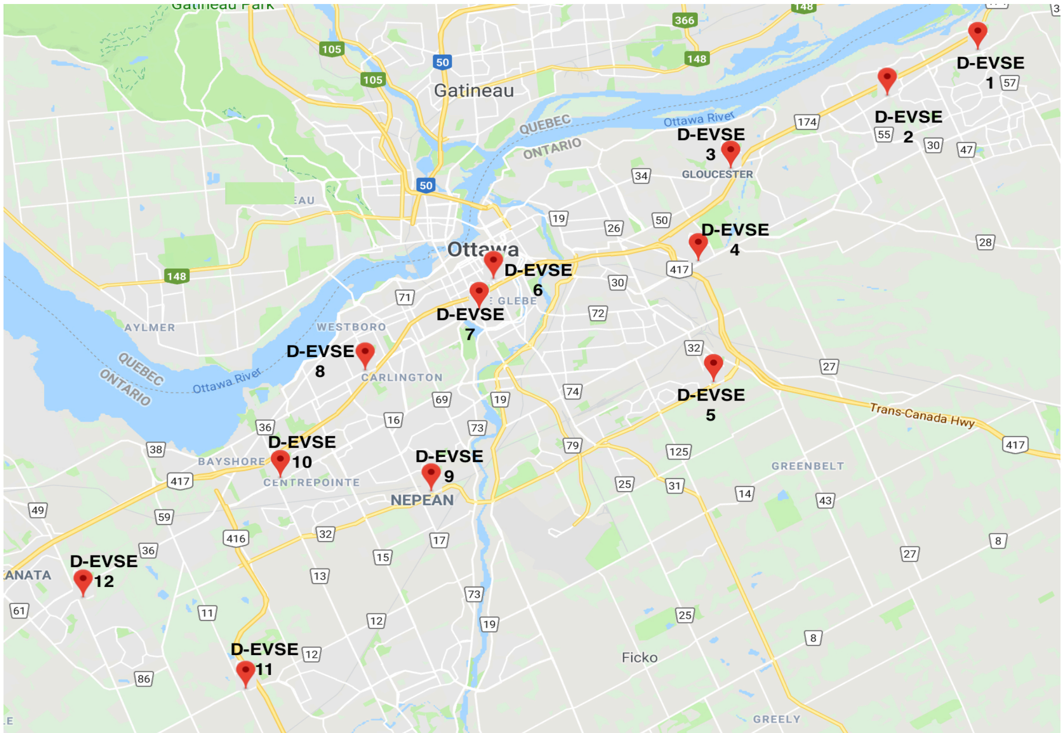

Figure 4.1: Street Map of the realistic scenario

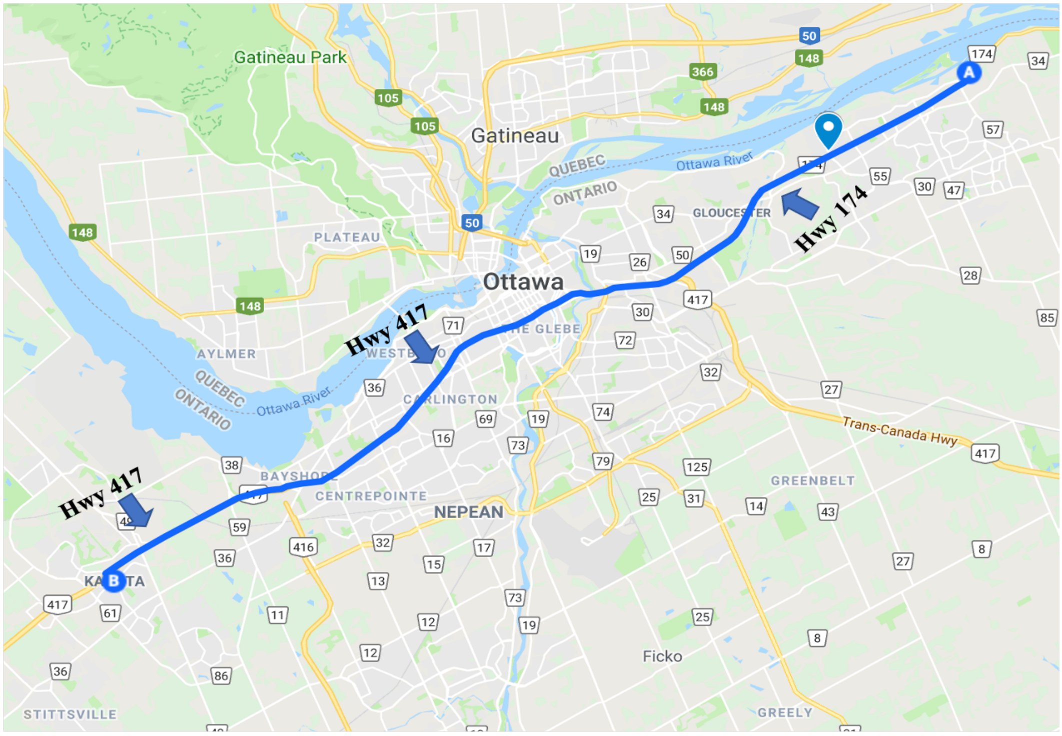

Figure 4.2: Hwy 174 and Hwy 417 in Ottawa, Ontario

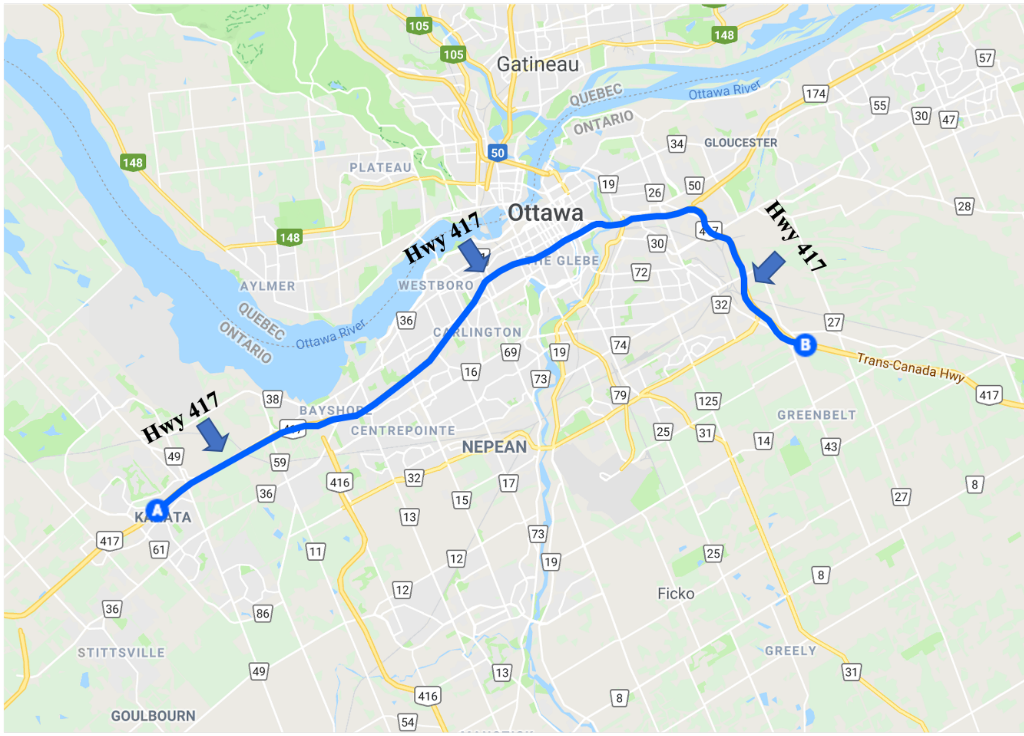

Figure 4.3: Hwy 417 in Ottawa, Ontario

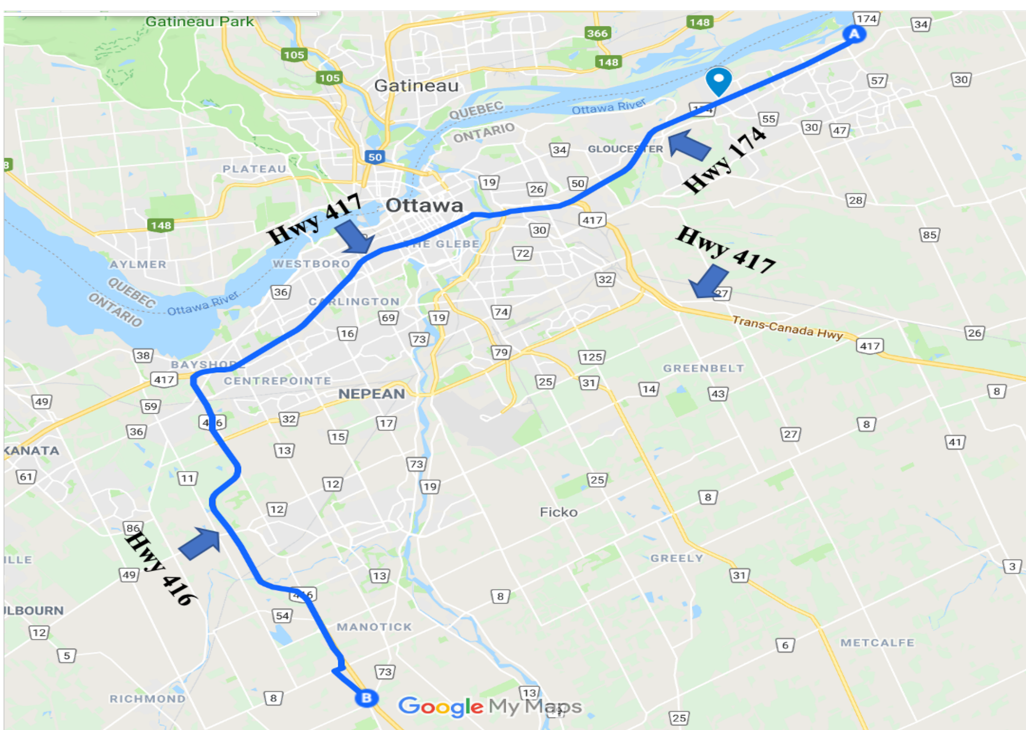

Figure 4.4: Hwy 174, Hwy 417, and Hwy 416 in Ottawa, Ontario

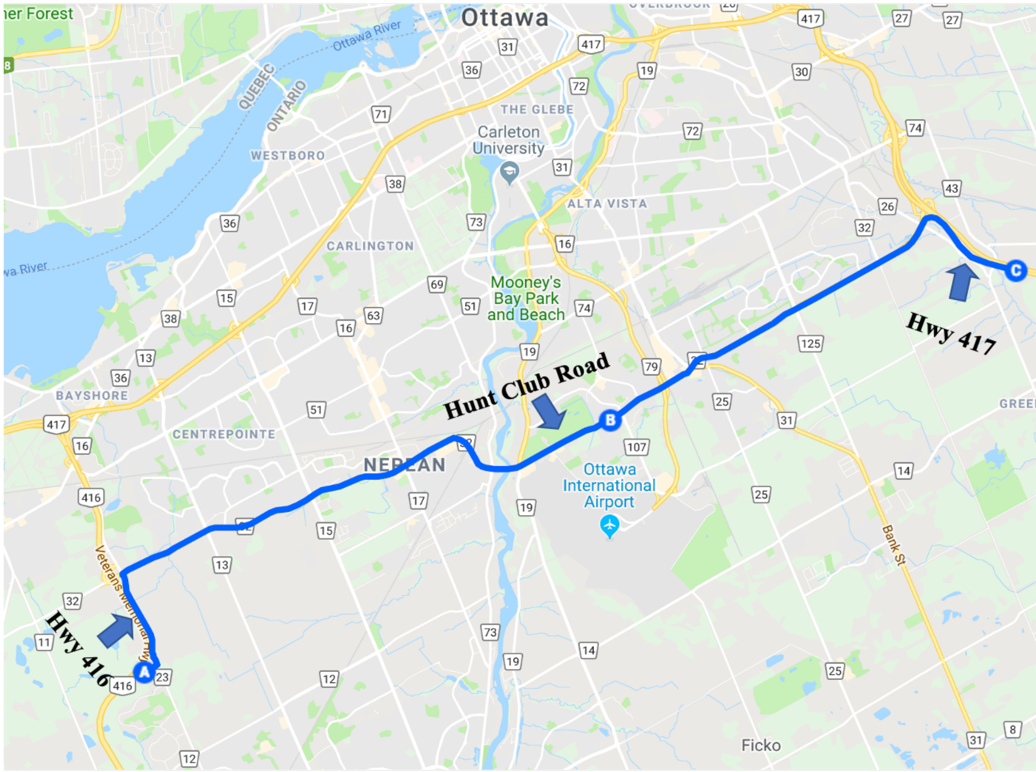

Figure 4.5: Hwy 417 and Hwy 416 via Hunt Club Road in Ottawa, Ontario

Each EV on the Hwy requests the D-EVES' availability that are on its route as well as each D-EVSE's waiting time status. If the EV battery SoC is not enough for its travel commute, then the EV will stop at the D-EVSE once or more than once at different D-EVSEs. For each EV, the required EV battery SoC (SoC^i_{req}) to finish its commute is given by Eq. 3.1:

Each EV creates a table that shows the distance between its location and the different D-EVSEs' locations, as shown in Table 4.1. Then, the EV calculates its ability to reach the D-EVSEs by using Eq. 4.1:

$$B^i_j = [d^i_j \times D^i_{rate}] - [SoC^i_{int} + SoC_{\min}] \tag{4.1}$$

Table 4.1: Distance between EVs and D-EVSEs for the realistic scenario

	D-EVSE $^{(1)}$	D-EVSE $^{(2)}$	D-EVSE $^{(3)}$	D-EVSE $^{(4)}$	D-EVSE $^{(j)}$
EV_1	$d^{(1,1)}$	$d^{(1,2)}$	$d^{(1,3)}$	$d^{(1,4)}$	$d^{(1,j)}$
EV_2	$d^{(2,1)}$	$d^{(2,2)}$	$d^{(2,3)}$	$d^{(2,4)}$	$d^{(2,j)}$
EV_3	$d^{(3,1)}$	$d^{(3,2)}$	$d^{(3,3)}$	$d^{(3,4)}$	$d^{(3,j)}$
EV_4	$d^{(4,1)}$	$d^{(4,2)}$	$d^{(4,3)}$	$d^{(4,4)}$	$d^{(4,j)}$
$EV_{(i)}$	$d^{(i,1)}$	$d^{(i,2)}$	$d^{(i,3)}$	$d^{(i,4)}$	$d^{(i,j)}$

We suppose that all EVs are randomly distributed on the city of Ottawa's streets, as shown in Figure 4.1. Also, we assume that each EV is equipped with GPS. Each EV uses the GPS to measure the distance between its location and the D-EVSE's location. We suppose that all EVs and D-EVSEs can communicate for requesting and reservation processes while the EVs are on the road. Furthermore, we assume that all of the D-EVSEs are communicating with each other.

Table 4.2: EV and its ability to reach the D-EVSEs

	EV^1	EV ^{2}	EV ^{3}	EV ^{4}	EV ^{i}
D-EVSE$_1$	B_1^1	B_2^1	B_3^1	B_4^1	B_j^1
D-EVSE$_j$	B_1^i	B_2^i	B_3^i	B_4^i	B_j^i

Eq. 3.2, calculates the difference between required SoC and initial SoC (δSoC^i). At all times, all EV batteries' SoC must meet the following Eq. 4.2:

$$SoC_{\min} \leq SoC^i \tag{4.2}$$

The D-EVSE requests to be informed of an EV's arrival time and the amount of power needed. Consequently, the EV arrival time (Ar^i) at each D-EVSE is given by Eq. 3.3 and the required power that needs to be charged is given by Eq. 4.3:

$$SoC^i_{ch} = \delta SoC^i + [d^i_j \times D^i_{rate}] \tag{4.3}$$

Then, the EV charging time can be calculated by using Eq. 4.4.

$$t^i_{ch} = \frac{SoC^i_{ch}}{R^{\varepsilon}_{ch}} \tag{4.4}$$

All EVs may choose to participate or not participate in a discharging process as well as the charging process. However, for any EV willing to participate in the discharging process, the result of Eq. 4.5, should be positive. Eventually, the discharging process can lead to a new upcoming energy market.

$$SoC^i_{dis} = SoC^i_{int} - SoC^i_{req} \tag{4.5}$$

If the SoC^i_{dis} is not positive, then the EV cannot participate in the discharging process. Subsequently, any EV which wants to participate in the charging or discharging process will send a request message containing the SoC^i_{ch} or SoC^i_{dis} to D-EVSEs directly asking for the time slot availability and the charging or discharging process. The D-EVSEs will reply to the EV and attach the information requested as well as the current waiting time status. The discharging time for each EV that is able and has agreed to sell its surplus electricity power to help the D-EVSE stabilization is given by Eq. 4.6:

$$t^i_{dis} = \frac{SoC^i_{dis}}{R_{dis}} \tag{4.6}$$

Additionally, each EV has its decision made based on the information received from D-EVSEs. In ISA Algorithm 2, once the EV receives the information from the D-EVSEs which contain the time slot availability, charging, or discharging type, then the EV calculates its arrival time using Eq. 3.3 based on its location and D-EVSEs' location as shown in

Table 4.1. Also, the EV calculates the charging or discharging time based on the availability of D-EVSEs (see Eqs. 4.4 and 4.6). Afterward, the EV selects the optimal D-EVSE that best fits its requirements. Finally, a confirmation message will be sent from the D-EVSE to the EV if the EV has been selected to participate in the immediate process. In this algorithm, the EV's preference is met regarding the EV charging and discharging processes.

Algorithm 2 D-EVSE Immediate Scheduling Algorithm (ISA)

Output 1 EV [N,C/D, SoC^i_{ch}, SoC^i_{dis}, Sp^i, location, $Trip^i$].
Output 1 D-EVSE [Availability: C (charging) & D (discharging)].

```
for each EV_i (1..N) do
    Calculate SoC^i_req (Eq. 3.1)
    Calculate SoC^i_ch (Eq. 4.3)
    Calculate SoC^i_dis (Eq. 4.5)
    if SoC^i_ch > 0 and EV(C/D) = 1  then
        Calculate Ar^i (Eq. 3.3)
        Calculate t^i_ch (Eq. 4.4)
        select [{nearest, available}] D-EVSE
        Schedule: charging process
    endif;
    if SoC^i_dis > 0 and EV(C/D) = 2  then
        Calculate Ar^i (Eq. 3.3)
        Calculate t^i_dis (Eq. 4.6)
        select [{nearest, available}] D-EVSE
        Schedule: Discharging process
    endif;
    if no D-EVSE immediate available  then
        go to algorithm 3
    endif;
endfor.
endif;
```

Each D-EVSE computes its process waiting times using Eq. 4.7 based on the number of EV arrivals rate and processes rate. All of the D-EVSEs are equipped with fast and ultra-fast charging processes charging process as well as discharging process. However, for unscheduling algorithm, only two services are based on level 2 charging and discharging processes. Each EV that chooses to not participate in scheduled charging and discharging processes can participate in the unscheduling process at the selected D-EVSEs by considering the charging and discharging waiting time. Consequently, each EV has access to information about all D-EVSEs' waiting time, as shown in Table 4.3.

$$W_j^{time} = \frac{\lambda_j^u}{\mu_u} \tag{4.7}$$

Table 4.3: Waiting time table for EV processes at each D-EVSE

	D-EVSE $^{(1)}$	D-EVSE $^{(2)}$	D-EVSE $^{(3)}$	D-EVSE $^{(4)}$	D-EVSE $^{(j)}$
EV_1	$W^{(1,1)}$	$W^{(1,2)}$	$W^{(1,3)}$	$W^{(1,4)}$	$W^{(1,j)}$
$EV_{(i)}$	$W^{(i,1)}$	$W^{(i,2)}$	$W^{(i,3)}$	$W^{(i,4)}$	$W^{(i,j)}$

We use the D-EVSE ISA Algorithm 2 and D-EVSE Unscheduling Algorithm 3 to test the D-EVSE system model. The (C/D, SoC_{ch}^i and $speed$) in Algorithm 2 are randomly assigned. The EV C/D in D-EVSE Immediate Scheduling Algorithm is used to manage the EV driver's preference for charging or discharging participation.

Algorithm 3 D-EVSE Unscheduling Algorithm

Output 2 EV [N, SoC_{ch}^i, SoC_{dis}^i, SoC_{req}^i, location, $Trip^i$].
Output 2 D-EVSEs [Availability: C (charging) & D (discharging), W_j^{time}].
for each EV$_i$ (1..N) **do**
  Each D-EVSE Calculate W_j^{time} (Eq. 4.7) //* but NO immediate D-EVSEs available
  select {[nearest, least {W_j^{time}}]} D-EVSEs
  if $SoC_{dis}^i > 0$ **then**
    EV **reserves** plug-in socket for **discharging** process
  else if $SoC_{ch}^i > 0$ **then**
    EV **reserves** plug-in socket for **charging** process
  endif;
endfor.

Figure 4.6 summarizes EV interaction with D-EVSE. There are two states for the EV:

– First: EV is on the road.

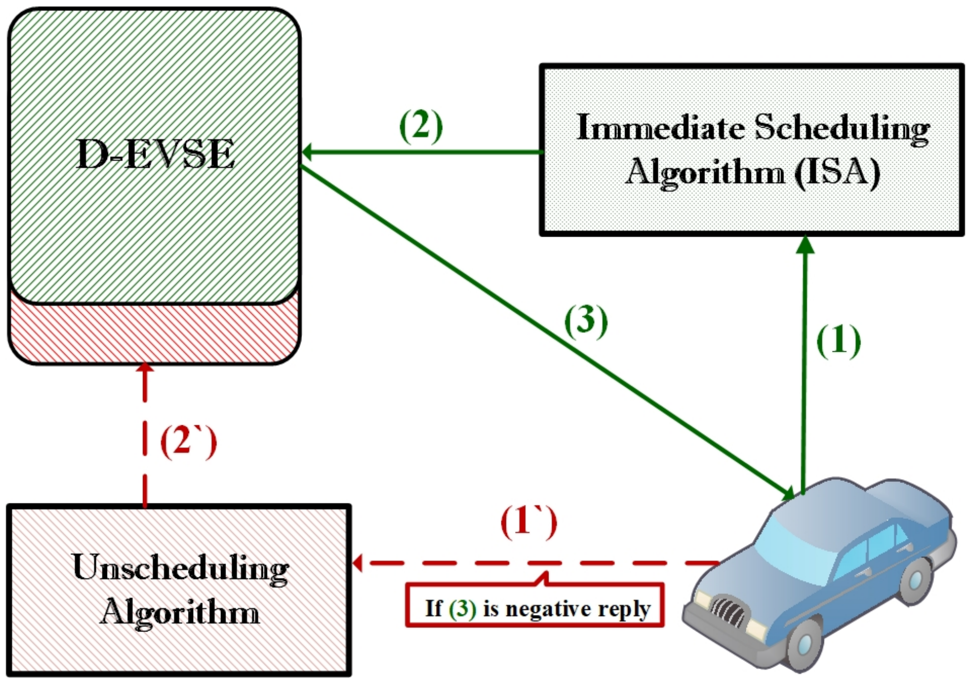

Figure 4.6: Illustrative example of EV interacting with D-EVSE

(1) EV sends a request to D-EVSE scheme.

(2)&(3) D-EVSE scheme uses ISA to reply to EV.

- Second: if the response from the D-EVSE is negative, then EV goes to {nearest D-EVSE, least waiting time}.

(1′) & (2′)D-EVSE uses the unscheduling algorithm to manage EV requests.

4.4 Performance Evaluation

In this section, we discuss the performance of the proposed D-EVSE schemes described by D-EVSE ISA and unscheduling algorithms. We used MATLAB to simulate the D-EVSE proposed models. We considered twelve D-EVSEs in known locations, as shown in Figure 4.1, and we distributed 1000 EVs randomly on the roads, as shown in Figure 4.1. The simulation parameters for the D-EVSE ISA and Unscheduling algorithms are shown in Table 4.4. All EVs have travelling trip (30 - 200 km) and speed (60 - 120 km/h) as well as SoC_{int}^{i} (20 - 90%).

Table 4.4: Simulation Parameters for D-EVSE ISA and Unscheduling algorithms

EV Type	Tesla (75 - 100 kWh) [182] Nissan Leaf (45 kWh) [183] BMW i3 (46 kWh) [184]
Number of EVs (N)	1000
Initial EV SoC (SoC_{ini}) %	20 - 90%
EV stop	0 - 2 times
EV stop durations	0, 15, or 30 mins
EV trip ($Trip^i$)	Random 30 - 200 km
EV speed on Hwy	60 - 120 km/h
Number of D-EVSEs J	12
ESS capacity	10000 kW
Duration of a time slot	10 min
Maximum duration of a time slot (unscheduled arrival)	2 hours
EV SoC requirement ($SoC_{\min}$)	20%
Fast charging rate (ε) Discharging rate	60 kW DC [94]
Max fast charging time Max discharging time	20 min [94]
Ultra-fast charging (ε)	150 kW DC
Max ultra-fast charging time	15 min [69]
Maximum charging level $SoC_{\max}$	80%
Level 2 charging (ε) (*unscheduled*)	7 kW Power
Number of plug-in sockets (*scheduled*)	16 / D-EVSE
Number of plug-in sockets (*unscheduled*)	4 / D-EVSE
λ_j^u	Random {3/1 and 2/1}
μ_u	2/10
Tesla Nissan Leaf BMW i3	1%/km (0.204 kWh/km) [182] 1%/km(0.187 kWh/km) [183] 1%/km (0.187 kWh/km) [184]

As shown in 4.4, we consider three types of vehicles (Tesla, Nissan Leaf, and BMW i3). We choose the maximum charging level ($SoC_{\max}$) to be 80% of the EV battery's capacity because we are trying to avoid the non-linear charging behaviour which starts after 80% of the EV battery's charging capacity. However, all EVs can participate in the discharging process if they have more than 20% in their batteries $SoC_{\min}$. Each vehicle type has its capacity as well as its required $SoC_{\min}$ and $SoC_{\max}$

Moreover, we assume that each D-EVSE has a capacity of approximately 10MW. The D-EVSEs are powered by renewable energy sources such as photovoltaic and wind power. Additionally, each D-EVSE is composed of fast and ultra-fast charging processes as well as the discharging process. Each D-EVSE offers two processes for each EV that needs a process: immediate scheduled process and unscheduled arrival process. Also, each D-EVSE is equipped with 16 plug-in sockets for scheduled processes and 4 plug-in sockets for unscheduled processes. That means that the total number of plug-in sockets is 240 sockets. 192 sockets are for scheduled processes, and the rest of the sockets are for the unscheduled processes in all D-EVSEs.

Another consideration in the unscheduling algorithm is the charging and discharging waiting times. The waiting time is considered only for the second algorithm to encourage EV drivers to participate in scheduled processes. For the same reason, we used level 2 charging sockets for the unscheduled process. Each EV will receive a confirmation including reservation time and the plug-in socket number if the request is for an immediate scheduled process. However, if the request is for an unscheduled process, then the EV will receive the plug-in socket number only at the D-EVSE location.

We assume that the remaining SoC of EV can reach any D-EVSE. We also suppose that the λ_u for all D-EVSEs is flowing by the random distribution between 3/1min and 2/1min. That means that some D-EVSEs' arrival rate is three EVs every minute, while other D-EVSEs' arrival rate is two EVs every minute. We considered that the μ_u is the same in all of the D-EVSEs. The μ_u equals 2/10, which means that two EVs depart every 10 minutes.

We have considered three cases. We present case one, in which we compare the D-EVSE algorithms with the random algorithm, followed by case two, in which we compare the Dijkstra's shortest path algorithm [185] with the D-EVSE algorithms. Finally, we compare the D-EVSE with an EV smart guidance algorithm [148].

In contrast, The random algorithm selects the nearest D-EVES for EV charging and discharging processes and the Dijkstra's shortest path algorithm selects the D-EVES for EV charging and discharging processes based on the shortest path between its current location to the target destination. The EV smart-guidance algorithm selects the nearest D-EVSE for EV charging and discharging processes to minimize the EV charging and discharging waiting time. Also, those algorithms are based on centralized power generation systems.

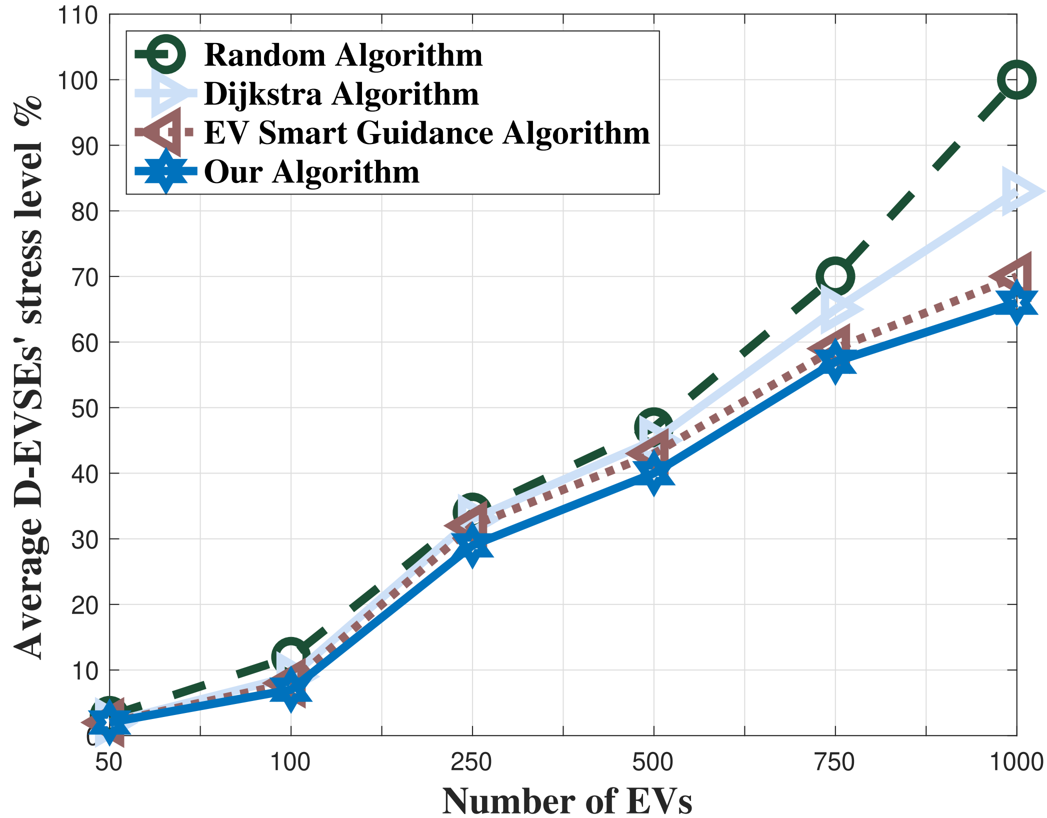

Figure 4.7: Comparison of D-EVSEs' stress level between random, Dijkstra shortest path, EV smart guidance and D-EVSE ISA algorithms

In the D-EVSE scheduling algorithm, the satisfaction level is measured based on the number of EVs that received a charging or discharging confirmation from the D-EVSEs divided by the number of EVs that sent a charging or discharging request. Also, the dissatisfaction level is measured based on the EVs that received a charging or discharging rejection from the D-EVSEs divided by the number of EVs that sent a charging or discharging request. However, the EVs which have received either a charging or discharging rejection from the D-EVSE can go to the nearest D-EVSE to participate in unscheduled processes to either sell the power to D-EVSE or buy the power from D-EVSE. However, the distribution of D-EVSEs within the city would also impact the EV driver's satisfaction level.

The driver's satisfaction level indicates how satisfied the driver is with the processes that he has requested. In other words, the satisfaction level for each EV driver is kept high. Also, the D-EVSE stress level measures how stressed the D-EVSE is. In other words, the stress level for each D-EVSE is kept low. Figure 4.7 shows a comparison of the D-EVSEs' stress level with the D-EVSE algorithm and the other three algorithms. As shown in Figure 4.7, the D-EVSE algorithm minimizes the stress level between D-EVSEs and shows better performance in terms of managing the EV charging and discharging processes. In summary, Figure 4.7 shows the average of all D-EVSEs' stress levels.

Table 4.5: Stress level performance between D-EVSE ISA and Random algorithm

Number of EVs	Random Algorithm	D-EVSE ISA	Savings rate
0 - 250	15%	12.3%	17.8%
251- 500	46%	40%	13%
501 - 750	70%	57%	18%
751-1000	100%	70%	30%

According to Table 4.5, a comparison between the random and D-EVSE ISA algorithms shows that the D-EVSEs' stress levels in the random algorithm, in some cases, are fully stressed. The random algorithm is the worst case in terms of the stress level because there is no consideration for the distance between EVs and D-EVSEs and the EV's charging or discharging request preference when the decision is about to be made. Table 4.5 also presents the stress level using the D-EVSE ISA algorithms and shows that the D-EVSE ISA algorithms have increased the system performance and reliability whenever the number of EVs is increased. For example, when the number of EVs is 250, the savings rate is 17.8%. When the number of EVs is 1000, then the savings rate is 30%. That is a significant improvement.

Table 4.6: Stress level performance between D-EVSE ISA and Dijkstra's algorithm

Number of EVs	Dijkstra's shortest path Algorithm	D-EVSE ISA	Savings rate
0 - 250	14%	12,3%	11.9%
251- 500	45%	40%	11.1%
501 - 750	65%	57%	12.3%
751-1000	83%	70%	15.7%

Table 4.6 compares the D-EVSEs' stress level with the Dijkstra's shortest path algorithm as well as the D-EVSE ISA algorithms. The Dijkstra's shortest path algorithm shows

better performance than the random algorithm in terms of minimizing the stress level between D-EVSEs. However, the D-EVSE ISA algorithms show a savings rate of approximately 15.7% when compared to the Dijkstra's shortest path algorithm performance when the number of EVs is 1000.

Table 4.7: Stress level performance between D-EVSE ISA and EV Smart-guidance algorithm

Number of EVs	EV Smart-guidance Algorithm	D-EVSE ISA	Savings rate
0 - 250	13%	12.3%	5.1%
251- 500	43%	40%	6.9%
501 - 750	61%	57%	6.6%
751-1000	75%	70%	6.7%

The D-EVSEs' stress level using EV smart-guidance and D-EVSE ISA algorithms is shown in Table 4.7.. The EV smart-guidance algorithm shows much better performance in terms of minimizing the stress level between D-EVSEs compared to the Dijkstra's shortest path algorithm and random algorithms. The D-EVSE ISA algorithm shows better performance than the EV smart-guidance algorithm and has achieved a savings rate of approximately 6% in most cases.

Table 4.8: Comparison of the average performance for D-EVSEs' stress level

<table>
<tr><th></th><th>Average D-EVSEs' stress level %</th><th>Savings rate %</th></tr>
<tr><td rowspan="2">Random Algorithm \ D-EVSE ISA</td><td>57.8</td><td rowspan="2">22.4</td></tr>
<tr><td>44.8</td></tr>
<tr><td rowspan="2">Dijkstra's shortest path Algorithm \ D-EVSE ISA</td><td>51.75</td><td rowspan="2">13.4</td></tr>
<tr><td>44.8</td></tr>
<tr><td rowspan="2">EV smart-guidance Algorithm \ D-EVSE ISA</td><td>48</td><td rowspan="2">6.6</td></tr>
<tr><td>44.8</td></tr>
</table>

Table 4.8 presents a comparison of the average stress levels between all of the algorithms. The D-EVSE ISA has minimized the D-EVSE average stress level with a savings rate of more than 22.4% compared to the D-EVSE stress level based on the random algorithm, as shown in Table 4.8. Also, the savings rate was 13.4% when the D-EVSE average

stress level used Dijkstra's shortest path algorithm. However, when the EV smart-guidance algorithm managed the D-EVSE average stress level, the D-EVSE ISA algorithm minimized the D-EVSE average stress level in comparison to the D-EVSE ISA algorithm with a savings rate of 6.6%. This result proves the robustness of D-EVSE ISA in terms of minimizing the D-EVSE stress level.

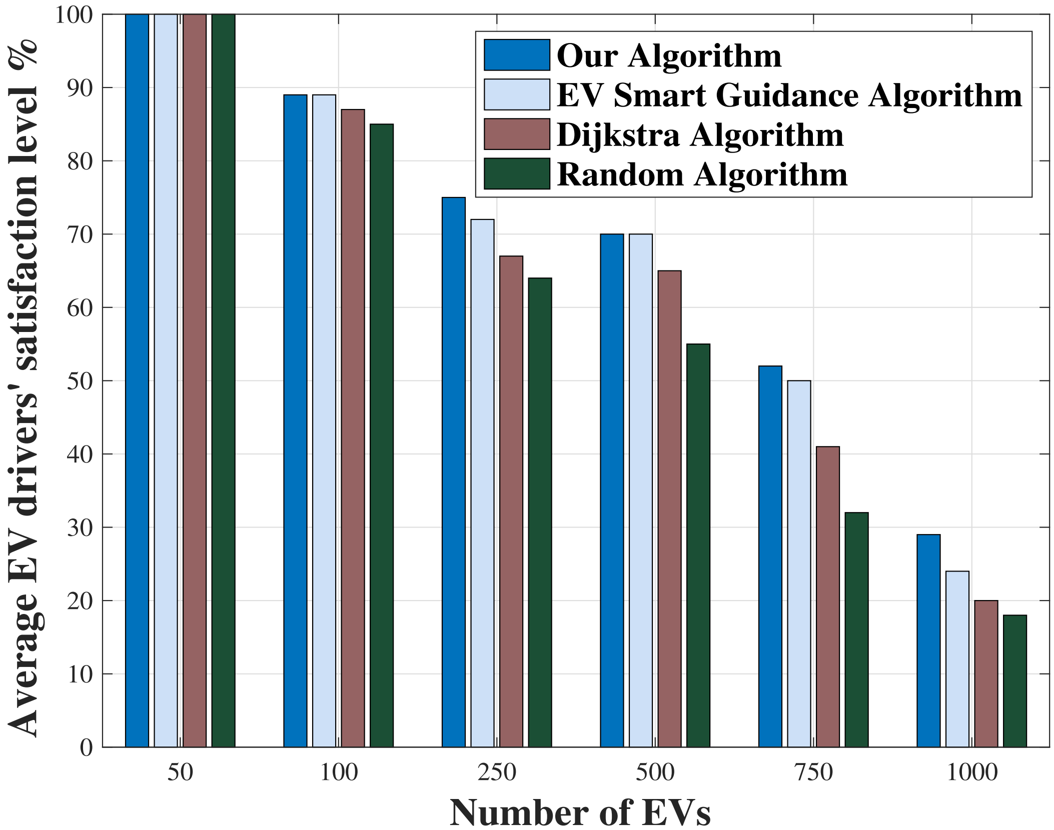

Figure 4.8: Comparison of EV drivers' satisfaction between random, Dijkstra shortest path, EV smart guidance and D-EVSE ISA algorithms

The average level of EV drivers' satisfaction with the D-EVSE ISA in comparison to the other three algorithms is shown in Figure 4.8. Table 4.9 shows the savings rate of the D-EVSE ISA compared to the savings rate of the other three algorithms. The average savings rate in terms of the EV drivers' satisfaction using the random algorithms compared to the D-EVSE ISA is more than 23%, while the average savings rate using the Dijkstra's shortest path algorithm when compared to D-EVSE ISA is more than 14%. Moreover, the EV smart-guidance algorithm is superior to the latter two algorithms. However, when compared to the D-EVSE ISA, the D-EVSE ISA's average savings rate is approximately

5.8%. According to Figure 4.8 and Table 4.9, in a comparison between D-EVSE ISA and the other three algorithms, the D-EVSE ISA is robust and can maximize the EV driver's satisfaction.

Table 4.9: Comparison of average performance for EV drivers' satisfaction level

	Average EV drivers' satisfaction level %	Savings rate %
Random Algorithm \ D-EVSE ISA	52.8	23.3
	40.5	
Dijkstra's shortest path Algorithm \ D-EVSE ISA	47.25	14.3
	40.5	
EV Smart-guidance Algorithm \ D-EVSE ISA	43	5.8
	40.5	

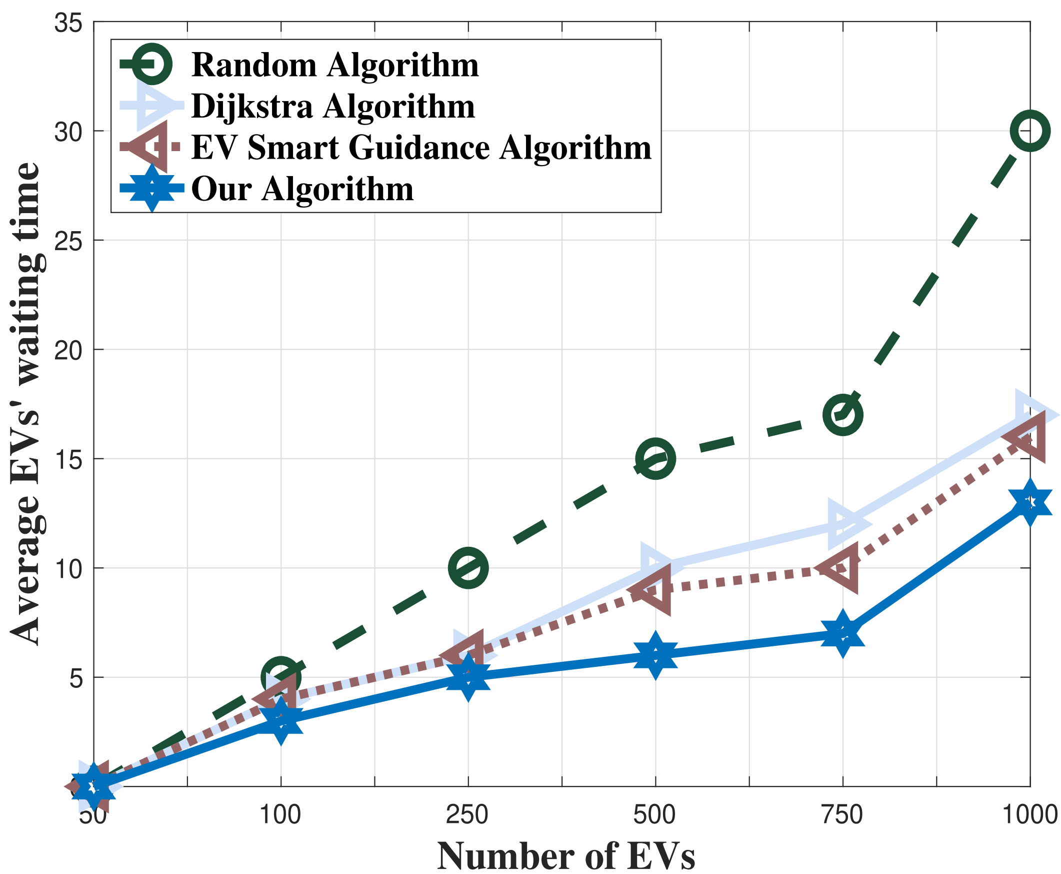

Figure 4.9: Waiting times comparison for EVs by using D-EVSE Unscheduling algorithm

Figure 4.9 shows the waiting time for EV charging and discharging processes by comparing the D-EVSE unscheduling algorithm and the other three algorithms. As shown in Figure 4.9, the D-EVSE unscheduling algorithm minimized the waiting time for EV charging and discharging processes and showed much better performance in terms of managing the EVs' unscheduled arrival processes.

Moreover, Figure 4.9 shows the average waiting time for the EV process in all cases. By observing the EV waiting times in Table 4.10, the D-EVSE ISA savings rate is more than 23.8% compared to the EV smart-guidance algorithm, which is the best savings rate among those three algorithms. In contrast, the worst savings rate is more than 55% with the random algorithm. Consequently, D-EVSE algorithms can manage most of the waiting times accordingly for charging and discharging process requests while minimizing the waiting time for processes in all scenarios, as shown in Table 4.10.

Table 4.10: Comparison of average waiting time for EV charging and discharging processes

	Average Waiting Time (minutes)	Savings rate %
Random Algorithm \	18	55.6
D-EVSE Unscheduling Algorithm	8	
Dijkstra's shortest path Algorithm \	11.5	30.4
D-EVSE Unscheduling Algorithm	8	
EV smart-guidance Algorithm \	10.5	23.8
D-EVSE Unscheduling Algorithm	8	

In summary of these results, D-EVSE scheduled and unscheduling schemes can manage D-EVSE stress levels while maximizing EV drivers' satisfaction as well as minimizing the EV charging and discharging waiting time. Consequently, the D-EVSE algorithms are robust and can manage immediate scheduling and unscheduling algorithms.

4.5 Summary

In this paper, we have proposed a model to manage the interaction between EV and D-EVES. We present two algorithms: ISA and unscheduling algorithm. The ISA is used to minimize the D-EVSE' stress level, maximize the EV drivers' satisfaction, and take into account the EV's preference for the charging or discharging process. Also, we considered the D-EVSE availability to be reserved as well as the distance for each EV to reach the selected charging station. The unscheduling algorithm is used to manage the unscheduled EV arrivals aimed to minimize the EV waiting time for the processes. D-EVSE algorithms are tested through simulations considering realistic scenarios with EV and D-EVSE constraints. We obtained results from different scenarios to investigate the EV drivers' satisfaction as well as the D-EVSE's stress level. We have also proved that the D-EVSE system model far outperforms the random, Dijkstra's shortest path, and EV smart-guidance approaches. Simulations showed that the proposed protocol manages the EVs' charge and discharge processes more effectively.

Chapter 5

Decentralized Game-Theoretic Scheme for D-EVSE

5.1 Introduction

With the growth in the EV market due to its releasing of zero air pollution and reduction of GHG emissions in smart cities, the power demand will increase accordingly. By 2030, the number of EVs will be more than 100 million globally [15]. While this will create a massive power charging demand which must be managed, EVs have the potential to provide power storage by supporting the power grid through the V2G process [24,25]. As well, EVs provide many advantages for EV owners, such as minimizing travel expenses and garnering revenue by selling their surplus power.

In our model, the optimization of EV charging and discharging is modelled based on a Decentralized Game-Theoretic (D-GT). The D-GT approach is proposed to select and determine the optimal solution for both EV processes and the D-EVSE. The optimal solution would increase D-EVSE stability while also maximizing the EVs' satisfaction level. The D-GT is the most crucial aspect of our model, as it allows each EV to manage its charging and discharging process demands based on the concept of win-win while taking into account the defined constraints.

Nowadays, the necessity of adopting RES with the ESS is growing year by year. The RES and ESS will decrease GHG emissions and create a clean, sustainable, and green environment. However, due to discontinuous and unpredictable RES power predictions, the ESS is the essential equipment that will allow the storing of generated power.

In this chapter, we consider that D-EVSE is powered by PV energy production. We propose a solution to resolve the problem of the EV charging or discharging process when EVs need to know the best available plug-in time for both EV and D-EVSE before the plug-in phase.

Our contributions are as follows:

1. We introduce a D-GT model to optimize the EV charging and discharging process demand.
2. We propose a D-GT algorithm to guide EVs for the charging and discharging process.
3. We consider a realistic scenario in the city of Ottawa, Ontario, Canada to test our D-GT algorithm.
4. Finally, our D-GT model takes into account the EVs' satisfaction level as well as the D-EVSEs' stability.

Cooperative game theory is used to help participants (D-EVSEs and EVs - also called players) making collective actions to obtain expected benefits. Cooperatively, EV chooses the optimal solution for both EV and D-EVSE; however, D-EVSE makes the final decision to admit the EV or not. Since each EV aims to maximize its charging or discharging processes, the EV will first select the best offer received from D-EVSEs that meets EV's requirements and defined constraints. When EV receives a confirmation message, EV will schedule the charging or discharging processes; otherwise, the EV will select the second-best offer received from D-EVSEs and so on until EV receives the confirmation message from D-EVSE. However, each D-EVSE aims to maximize the charging and discharging processes by admitting EVs as much as D-EVSE can. Therefore, there is no cooperation between D-EVSEs which means the non-cooperative (competitive) game theory is applied [186, 187].

The structure of this chapter is organized as follows. Section 5.2 peruses some related works. Section 5.3 addresses the proposed system model and problem formulation. In Section 5.4, performance evaluations are presented. The conclusions are provided in Section 5.5.

5.2 Related work

GT operations for EV charging and discharging processes in a charging station have attracted the attention of researchers. In general, GT is classified into three groups, namely cooperative game theory, noncooperative game theory (competitive), and evolutionary game theory.

Many researchers have studied EVs' charging and discharging processes [173, 188–191] based on cooperative GT [192] and [193]. The authors of [194] and [195] addressed different mechanisms based on cooperative game theory for EVs' charging and discharging processes. In addition, the authors of [194] proposed a day-ahead and real-time cooperative EMS. The proposed system considered the power provider to be both a power provider and a power buyer. EVs were also considered in their system. The goal of this system was to maximize the revenue for participants. Likewise, the authors of [195] studied EVs' charging behaviour with the smart grid from an economic perspective. The study aimed to increase the revenue for both EV owners as well as the power provider. The authors of [161] presented two models for EV charging processes based on the GT approach. These two models are a Stochastic Dynamic Programming (SDP) model and a greedy algorithm model. The power providers used renewable energy production with an ESS. For all these works, power management was a centralized approach.

Other recent studies have explored and examined EVs' charging and discharging processes based on noncooperative game theory [196–201]. After investigating the problem of energy management in the decentralized control, the author of [202] proposed a game theory based on the decentralized control strategy for coordinating multiple hybrid energy systems aiming to maximize the preference of each player. However, RESs were not introduced in the study. Furthermore, the proposed system implemented a Nash equilibrium in each controller stage with a learning algorithm. Also, the paper [203] presented a decentralized charging scheme model based on non-cooperative game theory. The presented model coordinated the competitiveness of EVs with aggregators via a population coordinator to manage the interaction.

The authors of [204] introduced a mean filed (MF) game theory scheduling model to manage and schedule for the PHEVs (Gas/Electric) charging process. The goal of this model was to minimize trip time as well as trip distance. The authors of [205] proposed an EV charging model based on two stages of noncooperative game theories. The proposed model considered the ideal and non-ideal actions of many aggregators in the same area. The authors of [206] introduced a decentralized hierarchical EV charging mechanism based on the GT model. The GT model is formulated to combine MF-GT and Stackelberg-GT. The MF-GT was used to minimize the computational cost and communication overhead between power sellers. The Stackelberg-GT was used to define the optimal linear price for the consumer. The model considered the aggregator as a power buyer with the power grid and as a power seller to the EVs. Also, the aggregator was considered to control EV charging processes as well as the charging power prices.

The authors of [207] and [208] studied the implementation of both competitive and cooperative game theories in the same model of EV charging mechanism in a centralized way. The authors of [209] proposed a bi-level optimization model based on AC/DC hybrid multi micro-grids. The structure of hybrid multi micro-grids used distributed power and management mechanisms with two model systems. A bi-level optimization model was considered to coordinate between the utility and supply level with the aim to minimize the operation cost for each level. The difference between the bi-level optimization model and the proposed D-GT optimization model is that the bi-level optimization is based on the distributed power source and management system. In contrast, the D-GT optimization model is based on a decentralized power production and management system. Moreover, the bi-level optimization model used a diesel engine generator as the primary power source. Still, our proposed model used the PV as RES as the primary power source and the power grid source as a backup source.

Other studies have investigated the EVs' charging and discharging processes based on evolutionary game theory. The authors of [210] presented the EMS based on an escort evolutionary game theory. The system's goal was to study the EVs' charging behaviour with aggregators as a power provider. The multi-population approach was considered, and a battery storage system based on RES was used to reduce the EVs' charging during peak demand. The investigation concluded that the peak of EV charging demand and generated power from RESs were changed simultaneously. The paper [211] presented a competitive and evolutionary game theory system for EV charging mechanisms at the EV charging station. The first model was based on the competitive game theory to manage the charging price contest between charging stations. The second system, based on the evolutionary game theory, was implemented to improve the charging decision-maker for all EVs. The goal was to decrease the charging demand at peak time and also to increase the EV charging stations' revenue.

5.3 System model and problem formulation

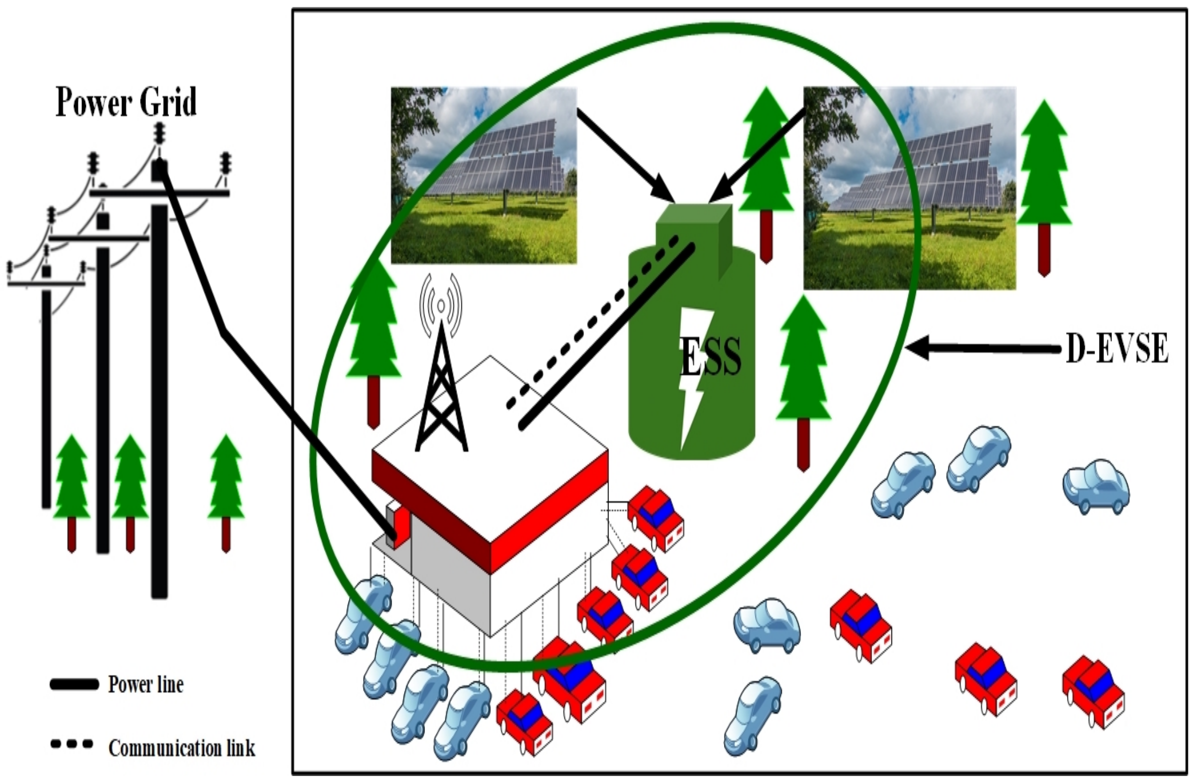

Figure 5.1: Overview of D-GT System model

In this section, we suppose that all D-EVSEs are powered by renewable energy (PV) as the primary power source. Also, we consider the connection to the grid when the solar renewable energy system fails to respond to the demand. The generated power from PV is stored in a massive battery (ESS), as shown in Figure 5.1. Moreover, we assume that all EVs' batteries have at least 20% of their maximum battery capacity at all times as mentioned before.

We present two investigation systems: random and realistic. In both models, we consider that each D-EVSE$_j$ is broadcasting its updated availability schedule as well as the battery storage capacity ESS $(t)_j$ every five minutes. Each EV that is willing to participate in the charging or discharging process will calculate and choose the best available D-EVSE$_j$ and send a reservation request. In return, the D-EVSE will send a confirmation response to the EV. The D-EVSE will use a reservation system based on first come, first served. In the realistic scenario, we have chosen six gas stations located close to the highways in the city of Ottawa, Ontario and replaced them with our proposed D-EVSEs based on the D-GT model, as shown in Figures 4.2, 4.3, 4.4 and 5.2.

Figure 5.2: D-EVSE locations in D-GT model

We propose the following four models, each with two scenarios: (1) charging model, (2) discharging model, (3) ESS capacity variation model, and (4) optimization model based on D-GT. The scenarios are mono D-EVSE and multi D-EVSEs.

5.3.1 Charging model

The only EV processes considered in this model are the charging processes. The purpose of this model is to find a charging process for EVs. We also aim to investigate the interaction behaviour between EVs' charging requests and D-EVSEs as a power provider. In the proposed model, the SoC of i^{th} EV is given by Eq. 5.1:

$$SoC_{\min} \leq SoC_{int}^{i} \leq SoC_{\max} \tag{5.1}$$

The required EV SoC to reach the final destination (SoC_{req}^{i}) for the i^{th} EV is given by Eq. 3.1 and the required SoC to reach the D-EVSE$_j$ [148] for the i^{th} EV is given by Eq. 5.2:

$$SoC_{j}^{i} = d_{j}^{i} \times D_{rate}^{i} \tag{5.2}$$

The amount of charging energy for the i^{th} EV is given by Eq. 5.3:

$$SoC_{ch}^{i} = [SoC_{\max} - SoC_{int}^{i}] + SoC_{j}^{i} \tag{5.3}$$

The charging time (t_{ch}^{i}) for the i^{th} EV is given by Eq. 4.4. The arrival time (Ar^{i}) for the i^{th} EV is given by Eq. 3.3. The arrival and departure time for the i^{th} EV is given by Eq. 5.4:

$$t_{2}^{i} = Ar^{i} + t_{ch}^{i} \tag{5.4}$$

$$Ar^{i} \leq t_{ch}^{i} \leq t_{2}^{i} \tag{5.5}$$

The total amount of energy that is requested by N^j_{ch} EVs is given by Eq. 5.6:

$$SoC^{ch}_j = \sum_{i=1}^{N^{ch}_j} SoC^i_{ch} \tag{5.6}$$

5.3.1.1 For mono D-EVSE

The dynamic variation of the j^{th} ESS battery SoC which depends on its previous status is given by Eq. 5.7:

$$\mathrm{ESS}_j(t) = \mathrm{ESS}_j(t-1) - P^{ch}_j(t) + P^{PV}_j(t) \tag{5.7}$$

Where:

$$P^{ch}_j(t) = SoC^{ch}_j(t) \times b_{Max} \tag{5.8}$$

5.3.1.2 For multi D-EVSEs

The dynamic variation of the total energy storage in the D-EVSEs is given by Eq. 5.9:

$$\begin{aligned} \sum_{j=1}^{J} \mathrm{ESS}_j(t) = \sum_{j=1}^{J} \mathrm{ESS}_j(t-1) \\ - \sum_{j=1}^{J} P^{ch}_j(t) + \sum_{j=1}^{J} P^{PV}_j(t) \end{aligned} \tag{5.9}$$

5.3.2 Discharging model

The only EV processes considered in this model are the discharging processes. The aim of this model is to find a discharging process demand for EV. We also aim to investigate the EVs' discharging interaction behaviour with D-EVSEs. The requirement SoC to reach the final destination (SoC^i_{req}) for the i^{th} EV is given by Eq. 3.1. The requirement SoC (SoC^i_j) to reach the D-EVSE$_j$ for the i^{th} EV is given by Eq. 5.2.

The available amount of power in discharging process for the i^{th} EV is given by Eq. 5.10:

$$SoC^i_{Av} = SoC^i_{int} - [SoC_{\min} + SoC^i_{req}] \tag{5.10}$$

The accepted amount of power in discharging process for the i^{th} EV is given by Eq. 5.11:

$$SoC^i_{dis} = SoC^i_{Av} - d^i_0 \tag{5.11}$$

In this model, d$_0$, which is Deep of Discharge (DoD) for each EV, must meet Eq. 5.12:

$$SoC_{\min} \leq SoC^i_{dis} \tag{5.12}$$

The arrival time (Ar^i) for the i^{th} EV is given by Eq. 3.3. The discharging time for the i^{th} EV is given by Eq. 4.6. The departure time for the i^{th} EV is given by Eq. 5.13:

$$t^i_2 = Ar^i + t^i_{dis} \tag{5.13}$$

$$Ar^i \leq t^i_{dis} \leq t^i_2 \tag{5.14}$$

The total amount of energy that is offered by N^{dis}_j EVs is given by Eq. 5.15:

$$SoC_j^{dis} = \sum_{i=1}^{N_j^{dis}} SoC_{dis}^{i} \tag{5.15}$$

5.3.2.1 For mono D-EVSE

The dynamic variation of the j^{th} ESS battery SoC is given by Eq. 5.17:

$$P_j^{dis}(t) = SoC_j^{dis}(t) \times b_{Max} \tag{5.16}$$

$$\mathrm{ESS}_j(t) = \mathrm{ESS}_j(t-1) + P_j^{PV}(t) + P_j^{dis}(t) \tag{5.17}$$

5.3.2.2 For multi D-EVSEs

The dynamic variation of the total energy storage in the D-EVSEs is given by Eq. 5.18:

$$\begin{aligned} \sum_{j=1}^{J} \mathrm{ESS}_j(t) = \sum_{j=1}^{J} \mathrm{ESS}_j(t-1) \\ + \sum_{j=1}^{J} P_j^{PV}(t) + \sum_{j=1}^{J} P_j^{dis}(t) \end{aligned} \tag{5.18}$$

5.3.3 ESS capacity variation model

Both EV charging and discharging processes are considered in this model. The purpose of this model is to update and monitor the ESS battery status regarding the charging and discharging process demands that are requested or ordered by EVs. In addition to this model, we considered the use of the charging model's Eqs. 5.1 to 5.6 and the discharging model's Eqs. 5.12 to 5.15.

5.3.3.1 For mono D-EVSE

The variation of the charging and discharging D-EVSE batteries is given by Eq.5.19

$$\begin{aligned} \mathrm{ESS}_j(t) = \mathrm{ESS}_j(t-1) - P_j^{ch}(t) \\ + P_j^{PV}(t) + P_j^{dis}(t) \end{aligned} \tag{5.19}$$

5.3.3.2 For multi D-EVSEs

The total variation of the charging and discharging D-EVSE batteries is given by Eq.5.20

$$\begin{aligned} \sum_{j=1}^{J} \mathrm{ESS}(t)_j = \sum_{j=1}^{J} \mathrm{ESS}_j(t-1) \\ - \sum_{j=1}^{J} P_j^{ch}(t) + \sum_{j=1}^{J} P_j^{PV}(t) + \sum_{j=1}^{J} P_j^{dis}(t) \end{aligned} \tag{5.20}$$

5.3.4 D-GT Optimization model for multi D-EVSEs

Each EV aims to increase each D-ESEV's stability and maximize its satisfaction by using a Decentralized GT (D-GT) approach. The purpose of this model is to find an optimal charging or discharging process for each EV while taking into account our defined constraints. As well, we aim to investigate the EVs' charging and discharging interaction behaviour with D-EVSEs. First, we optimize the EV charging model while also considering the use of Eqs. 5.1 to 5.9 in this optimization model. Second, we optimize the EV discharging model while also considering the use of Eqs. 5.12 to 5.18 in this optimization model. Finally, we optimize both the charging and discharging models while also considering the use of Eqs. 5.1 to 5.6, 5.12 to 5.15 and 5.19 to 5.20 in this optimization model.

$$Max \left(\sum_{i=1}^{N_j^{ch}} SoC_{ch}^{i}(t), \sum_{i=1}^{N_j^{dis}} SoC_{dis}^{i}(t) \right) \tag{5.21}$$

$$
st. \left\{ \begin{array}{c} SoC_{\min} \leq SoC^{i}_{ch}(t) \leq SoC_{\max} \\ \\ SoC_{\min} \leq SoC^{i}_{dis}(t) \\ \\ Ar^{i} \leq t^{i}_{ch} \leq t^{i}_{2} \\ \\ Ar^{i} \leq t^{i}_{dis} \leq t^{i}_{2} \\ \\ [\mathrm{ESS}^{\min} + \mathrm{ESS}^{0}_{j}] \leq \mathrm{ESS}_{j}(t) \leq \mathrm{ESS}^{\max} \\ \\ 0 \leq \frac{\mathrm{ESS}^{\min}}{\mathrm{ESS}^{\max}} \leq \frac{\mathrm{ESS}_{j}(t)}{\mathrm{ESS}^{\max}} \leq 1 \end{array} \right\} j = 1 \,..\, J
$$

Both EV charging and discharging processes are considered in this optimization model. The purpose of this model is to determine and select the optimal solution for the EV charging or discharging request that fulfills our constraints. Eq. 5.21 represents the optimal solution considering both EV charging and discharging processes. The defined constraints are applied to help the EV choose the optimal solution. We assume that each EV in the optimization model will interplay with all D-EVSEs for its charging or discharging process requests while aiming to maximize the D-EVSEs' stability and the EVs' satisfaction level. Once the EV selects the proper D-EVSE, then the EV needs to find the best available charging or discharging spot.

We use Algorithm 4 to test our optimization model. The D-GT select algorithm is started once the EV receives the updated information from the D-EVSEs and selects the best D-EVSE that satisfies the predefined constraints. We consider the off-grid mode if the ESS is not empty (e.g. on a sunny day). If the ESS is empty, we switch to the power grid to provide the continuity of EV charging processes.

Algorithm 4 D-GT select Algorithm

Input EV [N_{ch}, N_{dis}, N_j^{ch}, N_j^{dis}, ESS_j(t), P_j^{PV}, $SoC_{\min}$, $SoC_{\max}$, SoC_{ch}^i, SoC_{dis}^i, SoC_{Av}^i, ESS_j, d_0^i, ESS_j^0].

Output D-EVSE [j, $\text{ESS}^{\min}$, ESS_j^0, $\text{ESS}_j(t)$, $\text{ESS}^{\max}$, Availability].

for i = 1 .. N_{ch} **do**
    Calculate SoC_{req}^i according to Eq. (3.1)
    if $SoC_{int}^i \leq SoC_{\min} + SoC_{req}^i$ **then**
        Calculate SoC_j^i according to Eq. (5.2)
        Calculate SoC_{ch}^i according to Eq. (5.3)
        Calculate t_{ch}^i according to Eq. (4.3)
        Calculate Ar^i according to Eq.(5.4)
        select " j " according to Eq. (5.21
        $N_j^{ch} = N_j^{ch} + 1$ **% update D-EVSE state %**
    else
        Charging processes is not available
for h = 1 .. N_{dis} **do**
    Calculate SoC_{req}^iaccording to Eq. (3.1)
    if $SoC_{int}^i > SoC_{req}^i$ $+SoC_{\min}$ **then**
        Calculate SoC_j^i according to Eq. (5.2)
        Calculate SoC_{dic}^i according to Eq. (5.11)
        Calculate Ar^i according to Eq. (5.4)
        Calculate t_{dis}^i according to Eq. (4.6)
        select " j " according to Eq. (5.21)
        $N_j^{dis} = N_j^{dis} + 1$ **% update D-EVSE state %**
    else
        Discharging processes can not be done
    endif;

5.4 Performance Evaluation

In this section, we discuss the performance of the proposed model. Also, we consider two scenarios in our simulation discussion: random and realistic.

Table 5.1: Simulation parameters of D-GT model for random scenario

Number of EVs N	3000 - 8000
SoC_{min} %	20 %
SoC^{i}_{ch} %	20 - 90 %
SoC_{max}%	100%
SoC^{i}_{dic} %	20 - 90 %
ESS^{0} %	0 - 10 %
ESS_{max} %	100 %
d^{i}_{0} %	0 - 20 %
EV Trip $Trip$	Random from 40 - 60 km
EV speed (Sp)	20 - 60 km/h
Number of D-EVSEs J	6
Number of plug-in sockets	6
PV Power $_{everyday}$	25 MW
max ESS Capacity	30 MW
T	36 / Plug-in socket
Duration of a time slot	10 min
$R_{ch}(\varepsilon)$	60 kW DC [94]
R_{dis}	60 kW DC [94]
b_{Max}	24 kW
D_{rate}	1%/km(0.187 kWh/km) [183]
d^{i}_{j}	Random from 10 - 20 km

5.4.1 Random scenario

Table 5.1 shows simulation parameters for the random scenario. We suppose that all D-EVSEs are equipped by level 3 DC. We assume that there are six distributed D-EVSEs, each with a storage capacity of 30 MW. The number of EVs is 3000, 4000, 5000, and 8000. Also, we assume that each EV will make its decision using our proposed model. Moreover, the D-EVSE will send the reservation confirmation based on first come, first served, as mentioned previously. Each D-EVSE will broadcast its availability schedule once every five minutes. Also, all D-EVSEs operate from 6 a.m. until 6 p.m.

The discussion of performance is divided into two parts. The first part discusses the average satisfaction of EVs, and the second part discusses the average of ESS SoC during the daytime (6 a.m. to 6 p.m.). The Monte Carlo technique is used to calculate the average values for both parts..

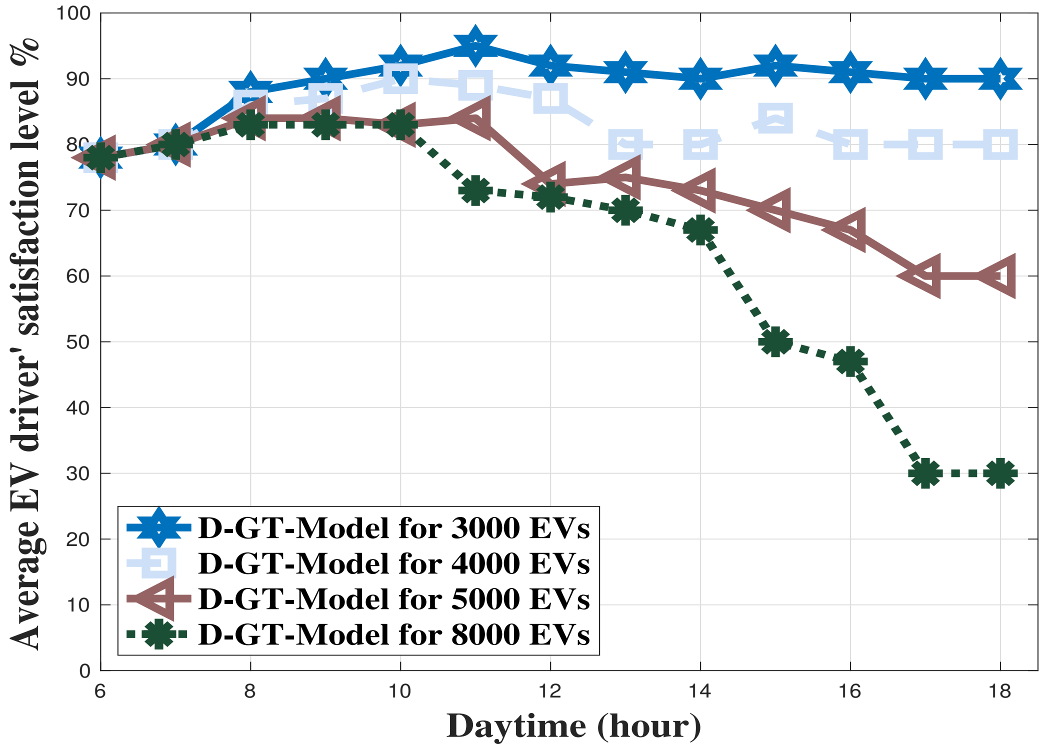

Figure 5.3: Average EV satisfaction level during the operation time for random scenario.

Figure 5.3 shows the results of using the proposed model with different numbers of EVs. We can see that the average EV satisfaction level is usually higher than 78% when the number of EVs is 3000 or 4000. However, when the number of EVs is 8000, the average EV satisfaction level decreases after four hours due to the massive number of EVs and their power demand. According to Table 5.2, we can see that the EV satisfaction level at the beginning and the end of the operation is not the same as the EV satisfaction level during the day due to the renewable energy production.

Table 5.2: Average EV satisfaction for random scenario

Number of EVs	6 a.m.-10 a.m.	10 a.m.-2 p.m.	2 p.m.-6 p.m.
3000	85%	90.5%	89.5%
4000	83.5%	85%	81%
5000	81%	78.5%	66.5%
8000	80.5%	76%	51.5%

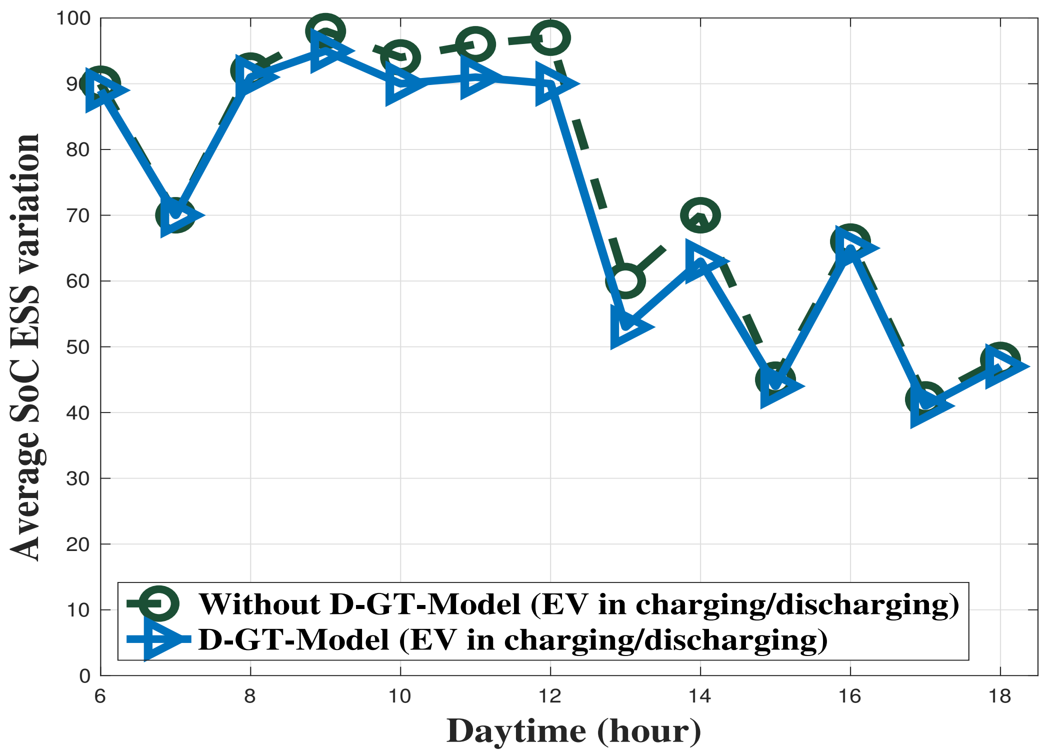

Figure 5.4: Average of the ESSs' SoC level during the operation time for random scenario

Figure 5.4 shows the average of ESS SoC during the operation time (6 a.m. to 6 p.m.) between the proposed model based on D-GT and the EV charging and discharging without using the D-GT model. We can observe that the proposed model shows better performance than the other model during the operation time, more specifically from 8 a.m. to 3 p.m. Table 5.3 presents a clear comparison of the savings rate between both models. As we can see, the savings rate for the proposed model is reasonable from 6 a.m. to 10 a.m.; however, between 10 a.m. to 2 p.m. there is a significant savings rate of almost 26.6%.

As demonstrated in both figures and tables, the D-GT model in the random scenario can manage the interplay between EVs and D-EVS effectively while taking into account the defined constraints.

Table 5.3: ESSs' SoC average level for random scenario

Number of EVs	6 a.m.-10 a.m.	10 a.m.-2 p.m.	2 p.m.-6 p.m.
D-GT model	88.8%	83%	54.2%
Regular model (without D-GT)	87%	77.4%	52%
savings rate	13.85%	26.6%	4.6%

5.4.2 Realistic scenario

Table 5.4 shows simulation parameters for the realistic scenario. We suppose that all D-EVSEs are equipped by level 3 DC. We assume that there are six distributed D-EVSEs, each with a storage capacity around of 30 to 40 MW (Jul 2019) based on real PV date [212]. The number of EVs is 3000, 4000, 5000, and 8000, the same as the number of EVs in the random scenario. Also, we assume that each EV will make its decision using our proposed model.

Table 5.4: Simulation parameters of D-GT model for realistic scenario

EV's Trip $Trip$	Random from 50 - 70 km
EVs' speed (Sp) on Hwy	60 - 120 km/h
Number of D-EVSEs J	6 (see Figure 5.2)
d_j^i	Random from 10 - 30 km
EV's battery size (b_{Max})	$\sim$ 60 kW (Nissan Leaf) $\sim$ 60 kW (Chevrolet Bolt)
D_{rate}	1%/km(0.187 kWh/km) [183] Nissan Leaf [174] 1%/km(0.175 kWh/km) Chevrolet Bolt [213]

In the realistic scenario, the average EV satisfaction level during the operation time (6 a.m. to 6 p.m.) is shown in Figure 5.5. As seen from this figure, the average EV satisfaction level for all cases (3000 to 8000 EVs) from 6 a.m. to 10 a.m. are similar. However, the huge differences in the average EV satisfaction level between 3000, 4000, and 5000 EVs and 8000 EVs grow after 1 p.m. due to the rush hour on highways. Table 5.5 illustrates the average EV satisfaction level for the random scenario for all cases divided into three zones.

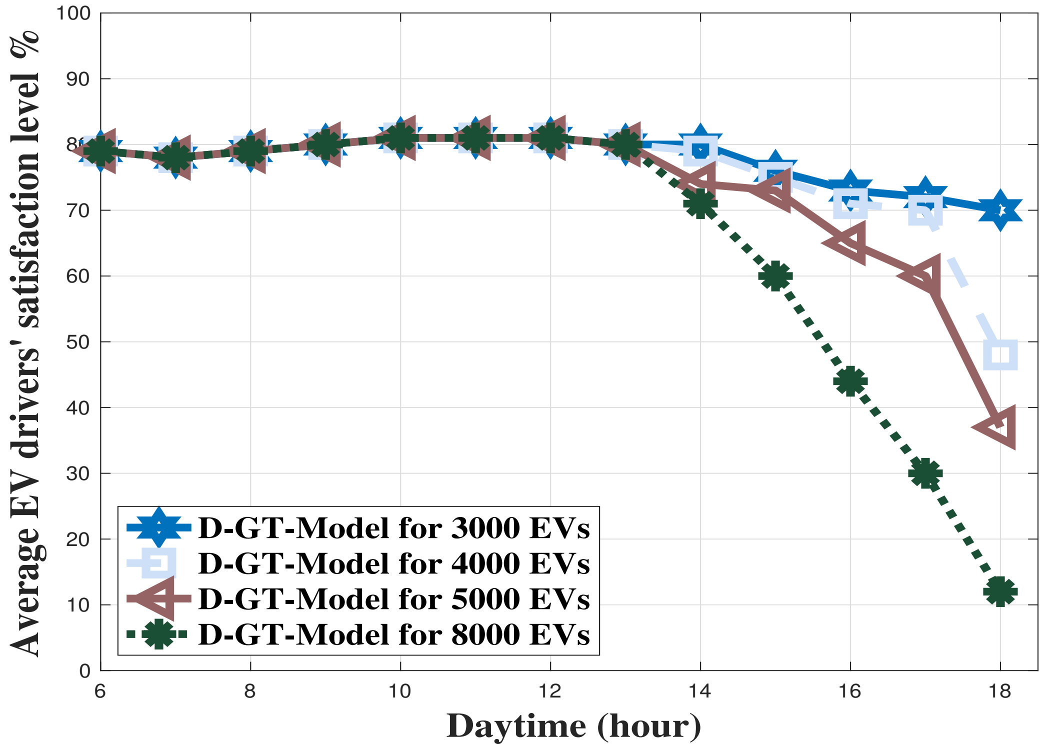

Figure 5.5: Average EV satisfaction level during the operation time for realistic scenario

The D-GT model for 3000 EVs is the most effective result for the entire operation time. Also, the average EV satisfaction level is maintained at over 74%.

Table 5.5: Average EV satisfaction for random scenario

Number of EVs	6 a.m.-10 a.m.	10 a.m.-2 p.m.	2 p.m.-6 p.m.
3000	79.4%	80.6%	74.2%
4000	79.4%	80.4%	68.6%
5000	79.4%	79.4%	61.8%
8000	79.4%	78.8%	43.4%

The average of the ESSs' SoC level during the operation time for a realistic scenario comparison between the D-GT and the regular model is depicted in Figure 5.6 and Table 5.6. The ability of the D-GT optimization model can be seen by looking at the average savings rate from 6 p.m. to 2 p.m., which is 4.6%. Furthermore, the savings rate of more

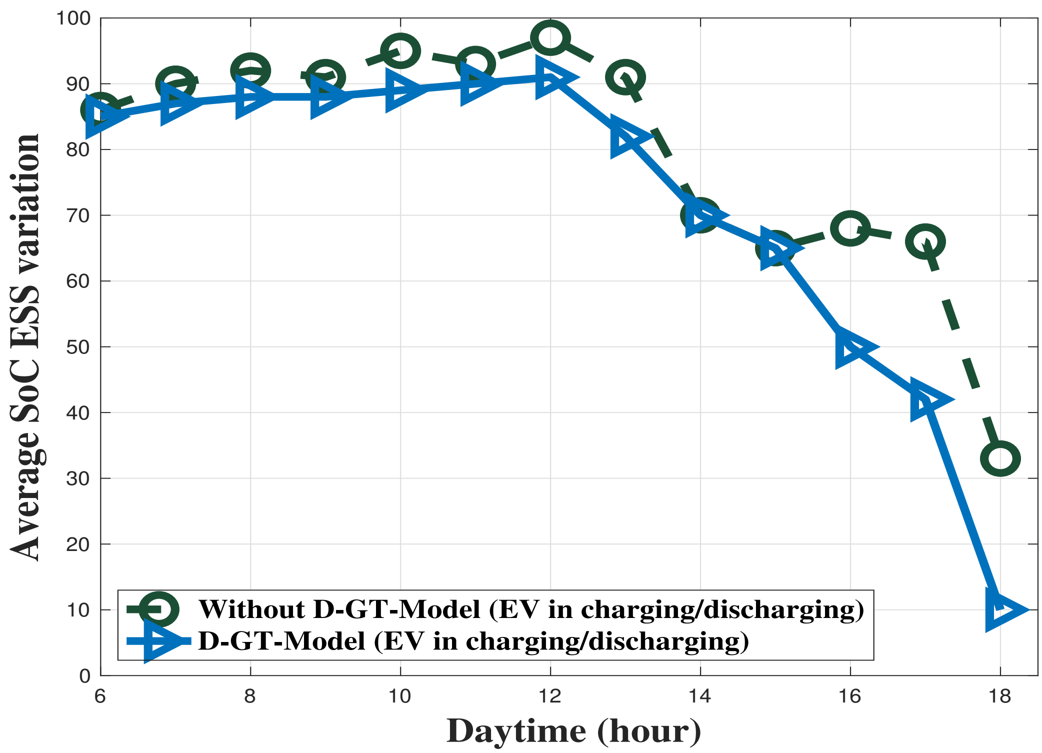

Figure 5.6: Average of the ESSs' SoC level during the operation time for realistic scenario

than 20% is much better from 2 p.m. to 6 p.m., as shown in Figure 5.9 and Table 5.6 .

Table 5.6: ESSs' SoC average level for realistic scenario

Number of EVs	6 a.m.-10 a.m.	10 a.m.-2 p.m.	2 p.m.-6 p.m.
D-GT model	90.8%	89.2 %	60.4%
Regular model (without D-GT)	87. %	84.4 %	47.4%
savings rate	3.75%	5.4%	21.53 %

From the last two figures and tables, it is clear that the performance of the proposed optimization model based on D-GT has proven its robustness in terms of managing the interactions among the EVs and D-EVSEs while taking into account our defined constraints.

5.5 Summary

In this chapter, we discussed the D-EVSE in terms of power generation and management model based on the GT for EVs interacting with D-EVSEs. Renewable energy production (photovoltaic) is chosen to be the main power source for our D-EVSE, and we considered the connection to the grid when the RES is failing to respond to the demand. We proposed a D-GT scheme for the optimization of the EVs' interaction with D-EVSE. Our optimization model considered both the EV's satisfaction as well as the D-EVSEs' stability. The optimal available solution for EV charging or discharging that satisfied the EV's driver and maintained the D-EVSE stability is achieved by using the D-GT algorithm. A realistic scenario in the city of Ottawa is considered as a testbed for our D-GT optimization model. Simulation results showed that the proposed model could manage and control the interactions between EVs and D-EVSEs efficiently.

Two case studies were presented for our D-GT optimization model in terms of managing and facilitating the interaction between D-EVSEs and EVs. The proposed model is based on decentralized power generation and management. Furthermore, the realistic scenario's results showed that the proposed model could manage EV charging and discharging processes more efficiently during the operation time and more specifically from 2 p.m. to 6 p.m.

Chapter 6

Profit Maximization for the D-EVSE

6.1 Introduction

Curbing of air pollutions and GHGs Emissions from transportation and non-renewable power plants in the smart city [214] is vital in providing a clean and green environment. As an action from many governments aiming to minimize the effect of transportation's pollution upon the climate, new plans have been were announced to ban cars with gas engines throughout the world. For example, the UK, Sweden, France, Germany, and Australia plan to ban such vehicles by 2035 [11–13]. As these plans unfold, the presence of EVs will grow very fast globally, especially in countries such as Canada, where citizens are encouraged by several types of financial incentives to buy EVs [14]. Consequently, the necessity of initiating EVSE in the smart city in the form of public charging stations is growing incrementally year by year. The EVSE will offer and fulfill the EVs' charging demand.

However, only allowing EVs charging process via EVSEs, which are primarily connected to the power grid, will put pressure upon the centralized power grid, especially during peak demand periods. For a centralized power grid, increasing the power production using non-renewable energy sources (nuclear and gas) will increase the environmental impacts by increasing the GHGs. Moreover, the massive power demands will affect the power grid's reliability and lead to increased costs of grid maintenance and degradation [215]. Thus, we promote the option to switch from EVSE based on non-renewable energy to decentralize the EVSE based on RESs and an ESS.

D-EVSE is a promising solution and brings more benefits than the EVSE which obtains power only from the power grid. These benefits include increasing the quality of charging power and offering the flexibility of EV charging power based on its ability as well as eliminating power line losses. Moreover, unused generated power will be stored. Overall, the D-EVSE will facilitate the integration of a massive number of EVs in smart cities without causing an additional power load that may jeopardize the power grid's resilience and reliability [215–217].

In this chapter, we propose an optimization model aiming to maximize the D-EVSEs' profits. Each D-EVSE will manage its charging processes and maximize its profits by using the proposed model. Our proposed model also takes into account the D-EVSEs' sustainability while maximizing the D-EVSEs' profits. In the proposed model, we consider that the D-EVSE is primarily powered by solar energy and equipped with ESS to store the generated power. The D-EVSE is not an entirely decentralized EVSE because it has a connection to the power grid. The D-EVSE manages the power grid's interconnection and uses it to request power from the power grid. However, the power requisition will be used only when the D-EVSE does not have enough stored power in the ESS.

In summary, our major contributions of the chapter are presented as follows:

- First, we design a maximization profit model to manage and control EVs' charging and discharging processes.

- Second, we propose a Decentralized Profit Maximization Algorithm (DPMA) based on RESs, power grid, and EV discharging prices to help D-EVSEs take profit from the electricity price variation during the day.

- Third, we consider five EV arrival rates to examine our proposal. Also, we illustrate ToU pricing in our model.

- Fourth, we present the results of the numerical simulation followed by a discussion to prove our proposed solution's effectiveness.

- Finally, we take into account the preservation of the D-EVSEs' sustainability in our proposed algorithm.

The rest of this chapter is organized as follows. Section 6.2 reviews the related works. Section 6.3 defines the proposed system model and problem formulation. In Section 6.4, performance evaluations are addressed. Finally, Section 6.5 concludes this chapter.

6.2 Related work

The challenges of EV charging and discharging processes at EVSE in the smart city have attracted the interest of many researchers from academic and industrial perspectives. The EVSE infrastructure deployment was investigated in [61–64]. A comprehensive survey of the EVs' challenges to the power grid is presented in [218]. The EV charging price is an important aspect for EV drivers and EVSE owners. EV charging price strategies are studied in [172, 219–224]. Other areas have been studied, such as minimizing the waiting time for EV charging [94, 148], discharging processes [225, 226], and reducing EV's charging cost [227]. Another perspective is that the EVSE owners must also benefit [227, 228]. The benefitting of EVSE owners, such as by increasing their profits, will allow EVSE to be diffused in the city. Several studies using many different techniques in [171, 206, 229] have investigated how to increase the profit for the power provider and the EV owner. In general, we have divided the related works of the EVSE charging and discharging benefit management studies into three groups based on the EVSE power source: 1) EVSE based on the power grid, 2) EVSE based on the power grid and PV, and 3) EVSE based on the power grid, the wind turbine, and the PV.

Many studies have investigated EV charging impact and discharging benefit management in EVSE powered from the power grid [190, 203, 230, 231]. The authors of [204] presented A PHEV power management system based on GT aiming to reduce the PHEV charging and battery degradation costs for each PHEV owner. The presented system considered the source of power to be the power grid. The system investigated the PHEV patterns when gas and energy prices were changed; as well, trip distance and trip time were considered. A stochastic model was introduced in [232]. This model implemented the two cases of dynamic pricing and optimal scheduling to examine the presented model. The model studied the price influence on the revenue of the PHEV charging station. The authors concluded that the presented model showed a positive outcome. However, these papers did not study the influence of EV power demands on the power grid.

The EV charging and discharging processes benefitting management in EVSE powered from the power grid and PV are introduced in [173, 233]. An optimization and controlling scheme are presented in [227]. The presented scheme proposed an EVSE for charging and discharging processes. The target of the proposed scheme is to minimize the final operational cost. The EVSE is connected to the power grid and equipped with a PV power production and ESS. In addition, a large building was linked to the EV bidirectional station to purchase energy whenever needed. The power price technique is based on real-time pricing for charging as well as discharging services. However, the EVSE is powered by the power grid and stores the ESS's power when the power grid's price is low. An optimization charging model is presented in [233] for EVSE located in a parking lot. The EVSE is based on the power grid, and the PV is linked to ESS as well as to the power grid. The given model, which aimed to reduce the charging cost, used ToU pricing. The study concluded that the presented model reduced the charging cost and enhanced the EV arrival rate.

The authors of [234] designed EVSE as a charging station for charging and discharging processes; in this case, the EVSE was equipped with RESs. The charging station offered a price for each EV wanting to sell its surplus power. In this study, the EVs' owners were able to accept or decline the offer. The sold power from EVs was injected into the power grid. Likewise, the authors of [234] presented an online pricing approach for EV charging or discharging requests in [235]. This paper used the same mechanism as that which was used in [234]. Both papers allowed the EV owner to choose the extended deadline to reduce the charging cost and aimed to maximize the charging station and EV owners' revenue with a fixed profit pricing strategy. However, the authors of paper [235] did not consider the discharging process in their study. All of these studies used the power grid as the primary power source to the EVSE, and there were no investigations into the EVSE's impacts on the power grid.

Other researchers have examined the benefit of managing EV charging and discharging processes in EVSE powered from the power grid, the wind turbine, and the PV [236, 237]. Two case studies presented in [238] aimed to minimize the power generation cost (wind and grid) and investigate the EV traffic congestion. The wind turbines were connected with the power grid. The EV profits were considered in the study. In this study, all EVs were allowed to schedule charging or discharging services to control the traffic. The conclusion was that the presented model minimized the power generation cost and the delivery cost while avoiding traffic congestion.

The authors of [239] presented a risk-based auction with an adaptive bidding energy trading system. The presented system aimed to maximize the bidding energy trading revenue by using the competitive equilibrium price prediction. The authors of [240] proposed an iterative double auction model to facilitate energy trading between participants using a central controller. The proposed model used a distributed algorithm to maximize the individual utility profits and the profits of participants. These studies considered the power grid to be the primary power source and did not show the power demand's effect on the power grid. A game-theoretic approach based on the decentralized electric vehicle charging schedule was implemented in [215] to minimize the EV charging expenses and increase the power grid performance. The real-time price system was used to increase the power grid's profits and the EV owners' profits. Also, the battery degradation cost and characteristics were both taken into account. The EV charging location was at owner's home with the day-ahead request scheme. Paper [241] proposed a game theoretical-based framework model to facilitate energy trading decisions with the distributed ESSs. All ESSs could decide the maximum amount of trading energy in the utility. However, the proposed model has a trade-off between the profits and costs of energy trading.

Unlike these studies, in this chapter, we consider RESs as the primary power source for the D-EVSEs (as a green energy sources) and include EV charging and discharging processes. We propose a Decentralized Profit Maximization Algorithm (DPMA) to optimize the D-EVSEs' profits and maintaining the stations' sustainability. However, in case of bad weather, a connection to the power grid is used to fulfill the EVs' demands.

6.3 System model and problem formulation

In this section, we consider D-EVSE as a public charging station based on RESs (Solar Energy) and equipped with ESSs, as shown in Figure 6.1.We assume that each D-EVSE has 12 plug-in sockets, and each plug-in socket has 108 time slots [6 (time slots in each hour) *18 (hours) = 108 time slots]. We assume that the D-EVSE uses a fast charging process with 180 kWh as charging rate [242]. The ESS consists of many connected batteries, and each battery has its cable connected to the station. These batteries are considered one big battery managed by D-EVSE. During the daytime, the ESS will be charged from solar energy production. During the nighttime, the D-EVSE will be charged from the power grid if there is not enough power in the ESS.

We suppose that each D-EVSE calculates the total power cost and sets its profit. The D-

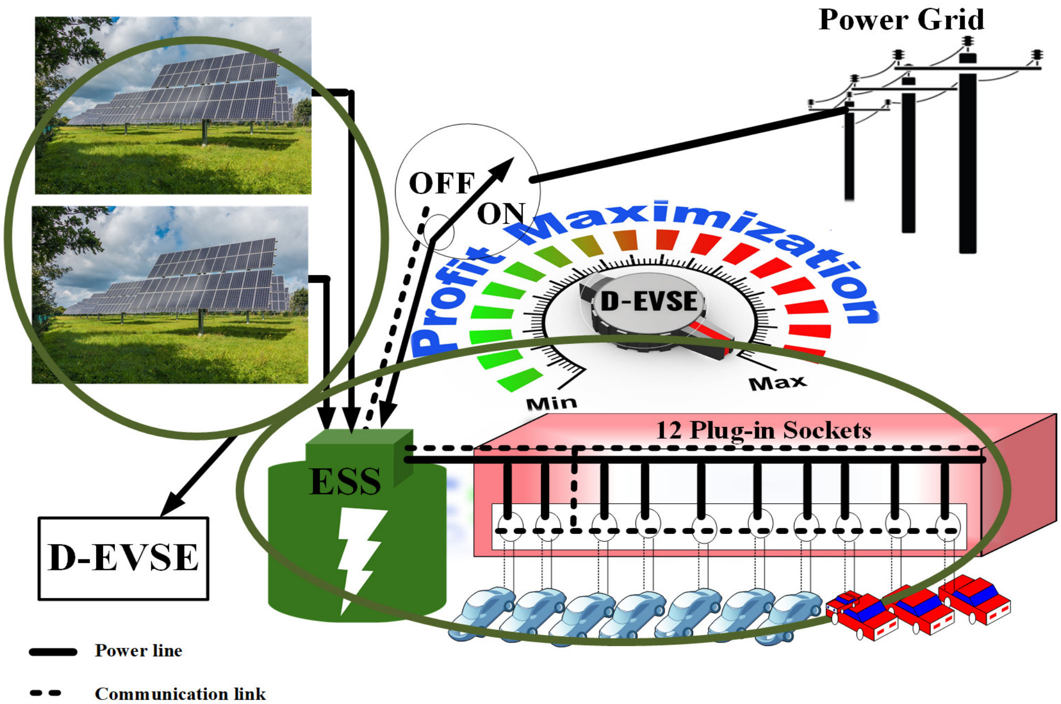

Figure 6.1: Overview of the profit maximization model

EVSE broadcasts the charging price to all EVs on the road. The EV charging price is based primarily on the power source, and the discharging service price is based on the needs of the D-EVSE. The D-EVSE operation time extends from 6 a.m. until 12 a.m.

At the beginning of the day, the D-EVSE gathers the power source information from ESS, and then the price is determined. The symbol X represents the D-EVSE's charging prices. Eq. 6.1 gives the D-EVSE's charging price X_j when the D-EVSE is powered only from the solar energy source:

$$X_j(t) = P_j^{pr}(t) \tag{6.1}$$

If the D-EVSE is powered from the power grid, then the X is given by Eq. 6.2:

$$X_j(t) = C_j^{G^{pr}}(t) \tag{6.2}$$

In the case of purchasing power from EVs as discharging power, the X_j is given by Eq.

6.3:

$$X_j(t) = C_j^i(t) \tag{6.3}$$

$$C_j^i(t) = Pr_{dis}^i(t) + [Pr_{dis}^i(t) * 25\%] \tag{6.4}$$

In our model, we assume that all EVs can reach all D-EVSEs and communicate wirelessly with each other. Each EV on the road calculates its ability to reach the final destination (SoC_{req}^i and δSoC^i) by using Eq. 3.1 and Eq. 3.2:

EV computes the charging time and the amount of charging power by using Eqs. 6.5 and 6.6 respectively:

$$t_{ch}^i(t) = \frac{SoC_{ch}^i(t)}{R_{ch}} \tag{6.5}$$

$$SoC_{ch}^i(t) = |\delta SoC^i(t)| \tag{6.6}$$

The EV discharging time and the amount of discharging power from EV are given by Eqs. 6.7 and 6.8 respectively:

$$t_{dis}^i(t) = \frac{SoC_{dis}^i(t)}{R_{dis}} \tag{6.7}$$

$$SoC_{dis}^i(t) = \delta SoC^i(t) \tag{6.8}$$

Where:

If each D-EVSE has an available plug-in socket for discharging process, then the D-EVSE will admit EV to discharge its surplus power. Eq.6.9 calculates the cumulative total amount of purchased power from EVs.

$$\mathrm{ESS}_j^{EV}(t) = \sum SoC_{dis}^i(t) \tag{6.9}$$

Eq. 6.10 used to calculate the amount of power that will be requested from the power grid.

$$\mathrm{ESS}_j^{G_{req}}(t) = SoC_{ch}^i(t) + ESS^{min} - ESS_j^{RES}(t) - SoC_{dis}^i(t) \tag{6.10}$$

The total amount of the power purchased from the power grid is given by Eq. 6.11:

$$\mathrm{ESS}_j^G(t) = \sum \mathrm{ESS}_j^{G_{req}}(t) \tag{6.11}$$

The total amount of the power in the ESS_j is given by Eq. 6.12:

$$\mathrm{ESS}_j(t) = \mathrm{ESS}_j^{RES}(t) + \mathrm{ESS}_j^{G}(t) + \mathrm{ESS}_j^{EV}(t) \tag{6.12}$$

All power generated from RESs is added into ($ESS_j^{RES}(t)$). At the beginning of the D-EVSE's operations, the P_j^{pr}(t) is based on the total amount of power that comes from RES ($\mathrm{ESS}_j^{RES}(t)$). However, the $\mathrm{ESS}_j^{RES}(t)$ must not reach 20% of its battery capacity. If the D-EVSE requests power from the power grid, then the purchasing power from the power grid is added into $ESS_j^G(t)$. In addition, all power purchased from the EVs as discharging processes is added into $ESS_j^{EV}(t)$.

Each D-EVSE which has sold power will update its sold power tracker $SoC_j^{sold}(t)$ immediately to maintain sustainability as shown in Eq.6.13

$$SoC_j^{sold}(t) = \sum SoC_{ch}^{i}(t) \tag{6.13}$$

The D-EVSE battery status is calculated by using Eq. 6.14.

$$SoC_j(t) = \mathrm{ESS}_j(t) - SoC_j^{sold}(t) \tag{6.14}$$

Each D-EVSE will receive the request messages from EVs, and the D-EVSE will use the proposed model to maximize its profits. The D-EVSE's profits will be calculated based on the source of the sold power to EVs. Therefore, the D-EVSE uses Eq. 6.15 to calculate its profits when the power source is from the RES:

$$F_j(t) = SoC_{ch}^{i}(t) \times [X_j - P_j^{co}(t)] \tag{6.15}$$

If the source of power is from the power grid, then the D-EVSE calculates its profit by using Eq. 6.16:

$$F_j(t) = SoC^i_{ch}(t) \times [X_j - C^{G^{co}}_j(t) + I^G_j(t)] \tag{6.16}$$

The D-EVSE's profit in the case of drawing power from EVs as discharging power is given by Eq. 6.17:

$$F(t) = SoC^i_{ch}(t) \times [X_j - Pr^i_{dis}(t)] \tag{6.17}$$

Eq. 6.18 is our objective function, and it is used to maximize the D-EVSEs profit. Furthermore, our objective function has objective function constraints.

$$Maximize \quad F_j(t) \tag{6.18}$$

Subject to:

$$ESS^{min} \leq ESS^{RES}_j(t) + \mathrm{ESS}^G_j(t) + \mathrm{ESS}^{EV}_j(t) \tag{6.19}$$

$$ESS^{max} \geq ESS^{RES}_j(t) + \mathrm{ESS}^G_j(t) + \mathrm{ESS}^{EV}_j(t) \tag{6.20}$$

$$SoC^i_{ch}(t) \geq 10 \tag{6.21}$$

$$SoC^i_{dis}(t) \geq 10 \tag{6.22}$$

We use Algorithm 5 to test our decentralized profit maximization algorithm (DPMA). The proposed model is initiated once the D-EVSE receives the requested messages from the EVs.

6.4 Performance Evaluation

This section discusses the proposed model's performance described by the Decentralized Profit Maximization Algorithm (DPMA). We used MATLAB 2018b to perform our simulation. We consider 12 D-EVSEs with each D-EVSE having RESs prediction (solar panel).

Algorithm 5 Decentralized Profit Maximization Algorithm (DPMA)

Input D-EVSE [J, SoC^i_{ch} (t), SoC^i_{dis} (t), $\text{ESS}^{\min}$, $SoC_j(t)$]

for j = 1 .. J **do**

  if $SoC_j(t) > \text{ESS}^{\min}$ **then**

    Obtain the power price ($P^{pr}_j(t)$) and cost (P^{co}_j) from Tables 6.3&6.5

    Maximize the profit according to Eqs.6.15&6.18

    update $SoC^{sold}_j(t)$ according to Eq. 6.13

    update $SoC_j(t)$ according to Eq.6.14

  else

    if *there are EVs scheduled for discharging process* **then**

      Obtain the power price ($Pr^i_{dis}(t)$) and cost ($C^{EV}_j(t)$) from Tables 6.3&6.5

      Maximize the profit according to Eqs.6.17&6.18

      update $SoC^{sold}_j(t)$ according to Eq. 6.13

      update $\text{ESS}^{EV}_j(t)$ according to Eq.6.9

      update $SoC_j(t)$ according to Eq.6.14

      end if

    if *the amount of power from EV discharging process is not enough* **then**

      Obtain the amount of power from the power grid according to Eq.6.10

      Based on the time of request:

      Obtain the power price ($C^{G_{pr}}_j$ & power cost ($C^{G^{co}}_j$))from Tables 6.1 & 6.4

      Obtain the incentive price ($I^G_j(t)$=) from Table 6.2

      Maximize the profit according to Eq.s6.16&6.18

      update $SoC^{sold}_j(t)$ according to Eq. 6.13

      update $ESS^G_j(t)$ according to Eq.6.11

      update $SoC^{EV}_j(t)$ according to Eq.6.9

      update $SoC_j(t)$ according to Eq.6.14

    end if

  end if

end for

The RESs prediction is connected with ESS. The ESS storage capacity is 30 MW. We suppose that all D-EVSEs are equipped with a DC fast charger, and each D-EVSE has 12 plug-in sockets for EV charging and EV discharging. Typically, D-EVSEs are not the main customer for the power grid; however, the D-EVSEs would-be customers when there is a bad weather condition. Therefore, EVs are the primary customer for D-EVSEs.

Table 6.1: List of power grid power costs based on ToU pricing

Power grid cost C_j^{Gco} on-peak	0.217 CAN$/ kW
Power grid cost C_j^{Gco} mid-peak	0.15 CAN$/ kW
Power grid cost C_j^{Gco} off-peak	0.105 CAN$/ kW

Table 6.2: Simulation Parameters for the Profit Maximization model

ESS_j^{RES}	Random 11.5 - 19 MW
$ESS^{\max}$	100
$ESS^{\min}$	20
ESS$^{\max}$ capacity [243]	30 MW
Number of D-EVSEs J	12
Operation time	6 a.m. - 12 a.m.
Number of plug-in sockets	12 [242]
Number of time slots (T)	108/h
Charging rate R_{ch}	30 kW/t
Discharging rate R_{dis}	30 kW/t
Duration of a time slot	10 min
Time of incentive price and grid pricing	off-peak (6 a.m. - 7 a.m. and 7 p.m. - 12 a.m.) mid-peak (7 a.m. - 11 a.m. and 5 p.m. - 7 p.m.) on-peak (11 a.m. - 5 p.m.)
Incentive price from grid $I_j^G(t)$	off-peak (0.05 CAN$/kWh) mid-peak (0.03 CAN$/kWh) on-peak (0.015 CAN$/kWh)
Number of EVs N	12000
SoC_{ch}^i	Random 0 - 80 kW
SoC_{dis}^i	Random 0 - 50 kW

Each D-EVSE will broadcast its charging price X_j and charging availability schedule every five minutes. All D-EVDEs will operate from 6 a.m. until 12 a.m. We suppose that each D-EVSE will process the EVs for the charging process using the DPMA to either admit or reject the EV. Moreover, the D-EVSE will be based on a first-come, first-served basis and will send EVs a reservation confirmation. We assume that there are 12000 EVs distributed randomly on the roads. The simulation parameters are shown in Table 6.2.

The time of the incentive's prices and the incentive's prices from the power grid is shown on the simulation parameters' 6.1. The power price from the power grid will be based on the ToU pricing in the city of Ottawa [244] (shown in Table 6.1). The RESs and the EV discharging cost are shown in Table. 6.3.

Table 6.3: List of RESs and EV discharging costs

Renewable energy cost P_j^{co}	0.10 CAN$/ kW
EV discharging power cost $Pr_{dis}^{i}(t)$ on-peak	0.12 CAN$/ kW

In the case of bad weather such as a rainy or cloudy day, or in the case when the ESS_j does not have enough power in its battery, the D-EVSE will rely on the power grid and the price will be based on the ToU pricing. Table 6.4 shows the D-EVSE charging price based on the ToU pricing.

Table 6.4: List of D-EVSE selling price based on ToU pricing

Power grid price $C_j^{G_{pr}}$ on-peak	0.24.95 CAN$/ kW
Power grid price $C_j^{G_{pr}}$ mid-peak	0.17.25 CAN$/ kW
Power grid price $C_j^{G_{pr}}$ off-peak	0.12.025 CAN$/ kW

The RESs' and EV's discharging selling prices are shown in Table 6.5.

Table 6.5: List of RESs' and EV's discharging prices

RES charging price $P_j^{pr}(t)$	0.18 CAN$/ kW
EV discharging power price $C_j^{EV}(t)$ on-peak	0.15 CAN$/ kW

We assume that the proposed model is implemented in the city of Ottawa, Canada, in the summertime. The D-EVSEs' locations in the city of Ottawa are known and fixed. In this study, we consider the following:

- EV charging and discharging processes
- Ottawa's ToU pricing policy in the case of charging from the power grid as shown in Table 6.1
- Additional 15% charging fees D-EVSE$_j^{fees}$ in the case of charging from the power grid as shown in Table 6.4.

In our discussion, we calculate the D-EVSE price diversity and profit for each hour, and we show the average of the D-EVSE price diversity and the D-EVSE profit. We study the following five EV arrival scenario rates in our simulation discussion: our EV arrival rate estimation, Poisson distribution, homogeneous Poisson processes, and two scenarios with non-homogeneous Poisson processes intensity. To keep consistency in our explanation, we chose D-EVSEs 1 to 3 to present the performance of our proposed model. Moreover, D-EVSEs-AVG shows average performance of our proposed model in all D-EVSEs. There is no rational reason behind choosing D-EVSEs 1 to 3 because, in some cases, the D-EVSEs-AVG perform much better than the presented D-EVSEs 1 to 3, which means the other D-EVSEs obtained better performance than the illustrated stations. Each D-EVSE will have a random amount of power from RESs $SoC_{RES}^{ESS_j}$ between 11.5 to 19 MW. Also, each D-EVSE will receive a random number of EVs with their unanticipated power demand $SoC_{ch}^{i}(t)$.

6.4.1 EV arrival rates with Our Arrival Rate Estimation

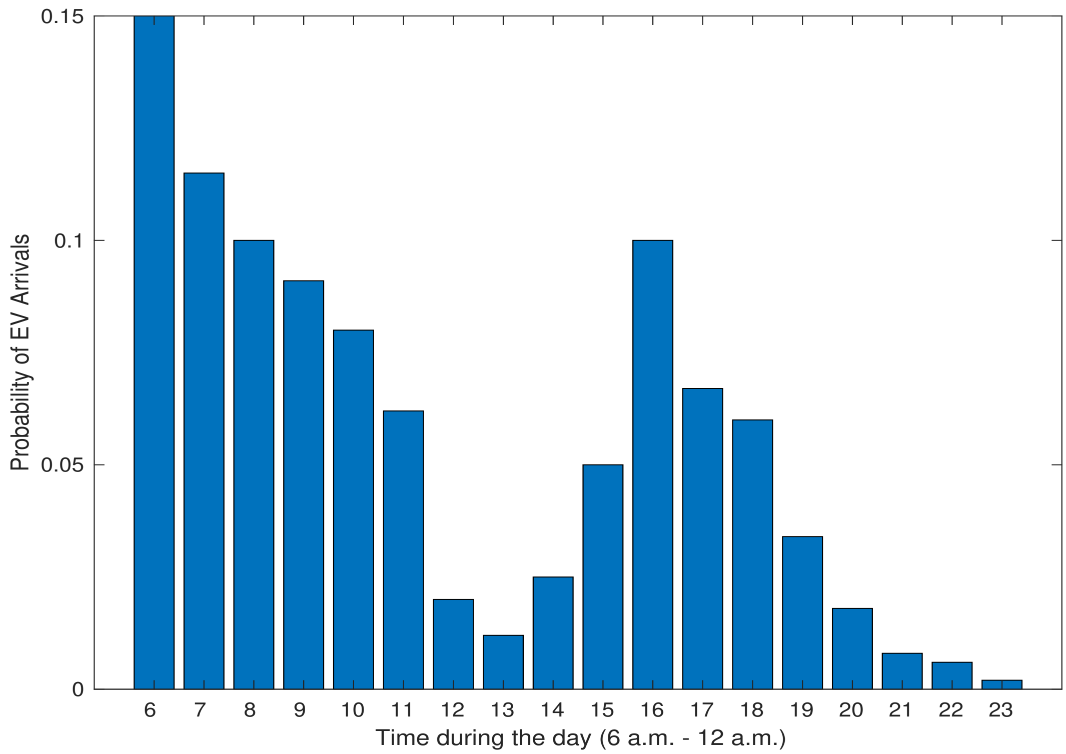

Figure 6.2: EV arrival rates with Our Arrival Rate Estimation

In this scenario, the EV arrival rates in D-EVSEs are based on the probability shown in Figure 6.2. The EV arrival rates are based on our estimation [245].

6.4.1.1 EV charging process only

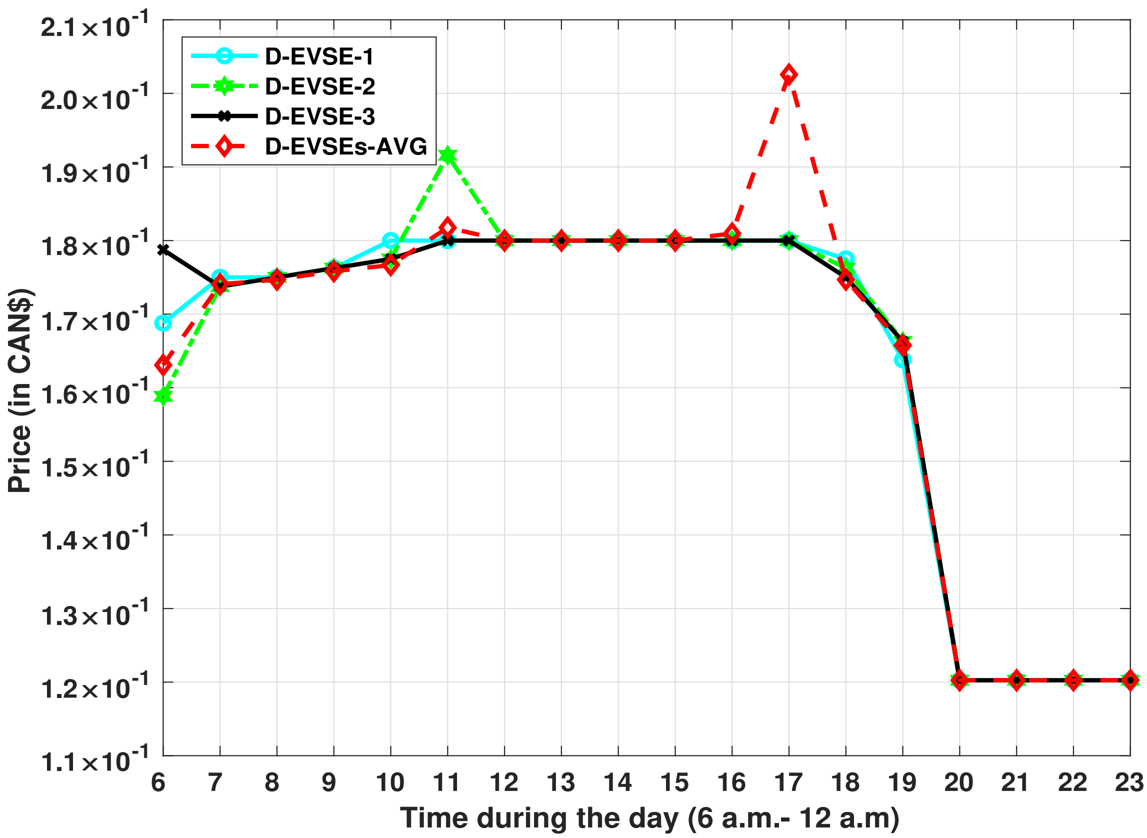

Figure 6.3: Average of the D-EVSEs' diversity price comparison for D-EVSE 1 - 3 with D-EVSEs-AVG of the 12 D-EVSEs with Our Arrival Rate Estimation (EV charging process only)

Figure 6.3 shows the price diversities comparison between D-EVSEs 1 to 3 and the average of all 12 D-EVSEs. The price from (7 a.m. - 10 q.m.) is getting closer to RESs price, which means the RESs power generations are contributing power in the D-EVSEs as depicted in the same Figure During the time from (10 a.m. - 4 p.m.), most D-EVSEs are almost relying on RESs power production, which means that the RESs have mitigated the power grid's power load. However, The red curve as the average of all 12 D-EVSEs (D-EVSEs-AVG) from (4 p.m. - 7 p.m.) shows that the other D-EVSEs are depending on RESs and power grid as well.

Table 6.6: Average D-EVSEs charging price (in CAN$) with Our Arrival Rate Estimation (EV charging process only)

	D-EVSE-1	**D-EVSE- 2**	**D-EVSE-3**	**D-EVSEs-AVG**
6 a.m. - 7 a.m.	1.688×10^{-1}	1.588×10^{-1}	1.788×10^{-1}	1.631×10^{-1}
7 a.m. - 11 a.m.	1.773×10^{-1}	1.788×10^{-1}	1.765×10^{-1}	1.766×10^{-1}
11 a.m. - 5 p.m.	1.800×10^{-1}	1.800×10^{-1}	1.800×10^{-1}	1.838×10^{-1}
5 p.m. - 7 p.m.	1.706×10^{-1}	1.713×10^{-1}	1.706×10^{-1}	1.717×10^{-1}
7 p.m. - 12 a.m.	1.203×10^{-1}	1.203×10^{-1}	1.203×10^{-1}	1.203×10^{-1}

Table 6.6 shows the average price based on the ToU pricing. As shown in Table 6.6, the average price during the mid-peak time (7 a.m. - 11 a.m.) is most likely relying on RESs price, except D-EVSE-3 is almost lean on the power grid price. However, during the on-peak time (11 a.m. - 5 p.m.), the average diversity price is most likely depending on RESs price. Due to a few RESs energy production at (5 p.m. -12 a.m.), the average diversity price relies on the power grid price and, more specifically, after sunset.

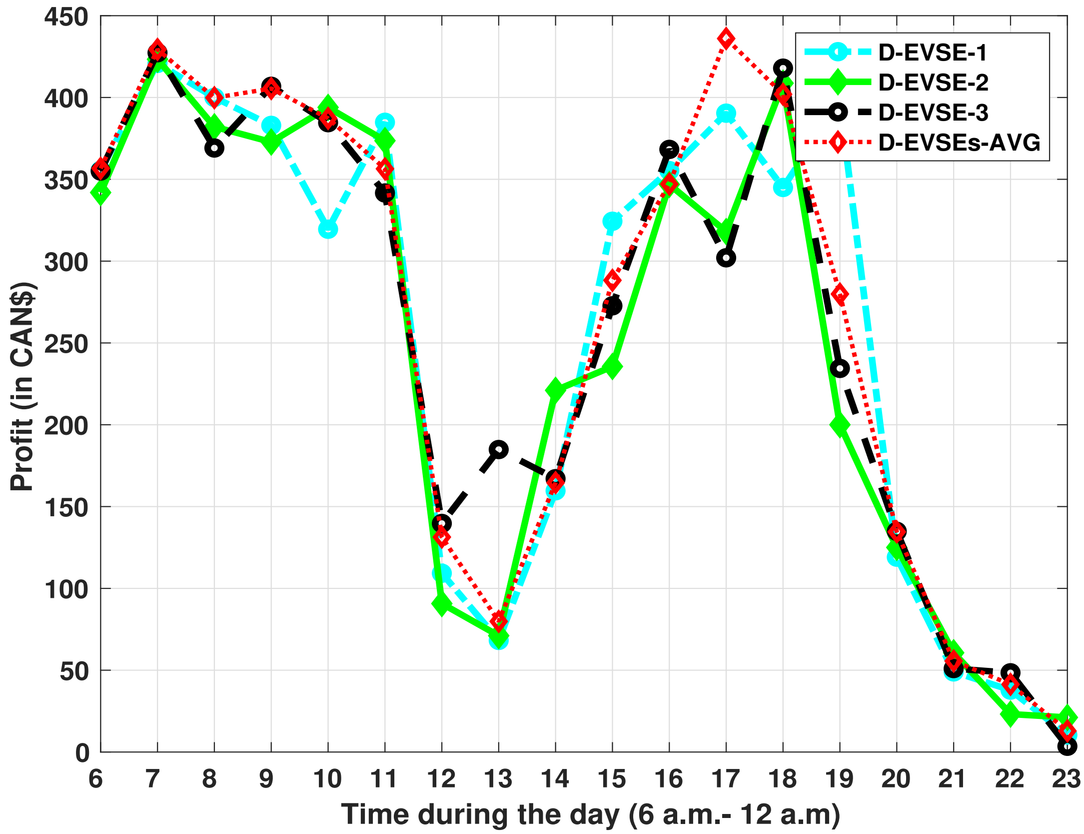

Figure 6.4: Average of the D-EVSEs' profits comparison for D-EVSE 1 - 3 with D-EVSEs-AVG of the 12 D-EVSEs with Our Arrival Rate Estimation (EV charging process only)

Figure 6.4 compare the average of the D-EVSE 1- 3 profits with all 12 D-EVSEs average profits As (D-EVSEs-AVG). Figure 6.4 illustrated that when the EV charging demands is the amount of RESs energy production is high, then the profit is increasing accordingly and more specifically from (1 p.m. - 5 p.m.). The D-EVSE got the most profits can get. However, when the number of EV charging demands is low, and the amount of RESs energy production is high, the D-EVSE gets fair profits such as between (12 p.m. - 2 p.m.). However, the lowest profit is when the D-EVSEs lean on the power grid price and its incentives starting from (6 p.m. - 12 a.m.).

Table 6.7: Average D-EVSEs profit (in CAN$) with Our Arrival Rate Estimation (EV charging process only)

	D-EVSE-1	**D-EVSE- 2**	**D-EVSE-3**	**D-EVSEs-AVG**
6 a.m. -7 a.m.	355.46	341.92	355.05	356.68
7 a.m. - 11 a.m.	1908.18	1945.79	1929.60	1978.37
11 a.m. - 5 p.m.	1407.24	1283.40	1434.60	1447.16
5 p.m. - 7 p.m.	742.14	608.76	652.36	681.89
7 p.m. - 12 a.m.	216.29	230.02	237.81	244.40

As the results illustrated in Table 6.7 presents the total profit compared with all 12 D-EVSEs (D-EVSEs- AVG) during the ToU pricing classification. The D-EVSEs most profit is when the RESs power production is contributing (7 a.m. -11 a.m.) and also during on-peak (11 a.m. - 5 p.m.) as shown in Table 6.7. However, the average profit for presented D-EVSEs between (7 p.m. - 12 a.m.) is around 60 CAN$) in each hour.

Table 6.8: The comparison of the purchased power for D-EVSE 1 - 3 and D-EVSEs-AVG with Our Arrival Rate Estimation (EV charging process only)

	RESs	**Power grid**
D-EVSE-1	79%	21%
D-EVSE-2	78%	22%
D-EVSE-3	76%	24%
D-EVSEs-AVG	68%	32%

Table 6.8 shows the percentage of the RESs and the power grid, and it is clear that the RESs are profitable for the D-EVSEs and have mitigated the power load on the power grid.

6.4.1.2 EV charging and discharging processes

Figure 6.5 compares the price diversities between D-EVSEs 1 to 3 and the average of all 12 D-EVSEs (D-EVSEs-AVG). The price at the beginning of the operation time is almost the same in D-EVSE-1 and D-EVSEs-AVG; however, the D-EVSE-3 is almost completely reliant on the RES's price while D-EVSE-2 is almost dependent on the power grid's price. During the RESs' power production time from (10 a.m. - 4 p.m.), the amount of generated energy from RESs contributes enough power for the stations. It mitigates the power load on the power grid. However, at the time (12 p.m. - 3 p.m.), the D-EVSEs are almost completely reliant on RESs power production and price.

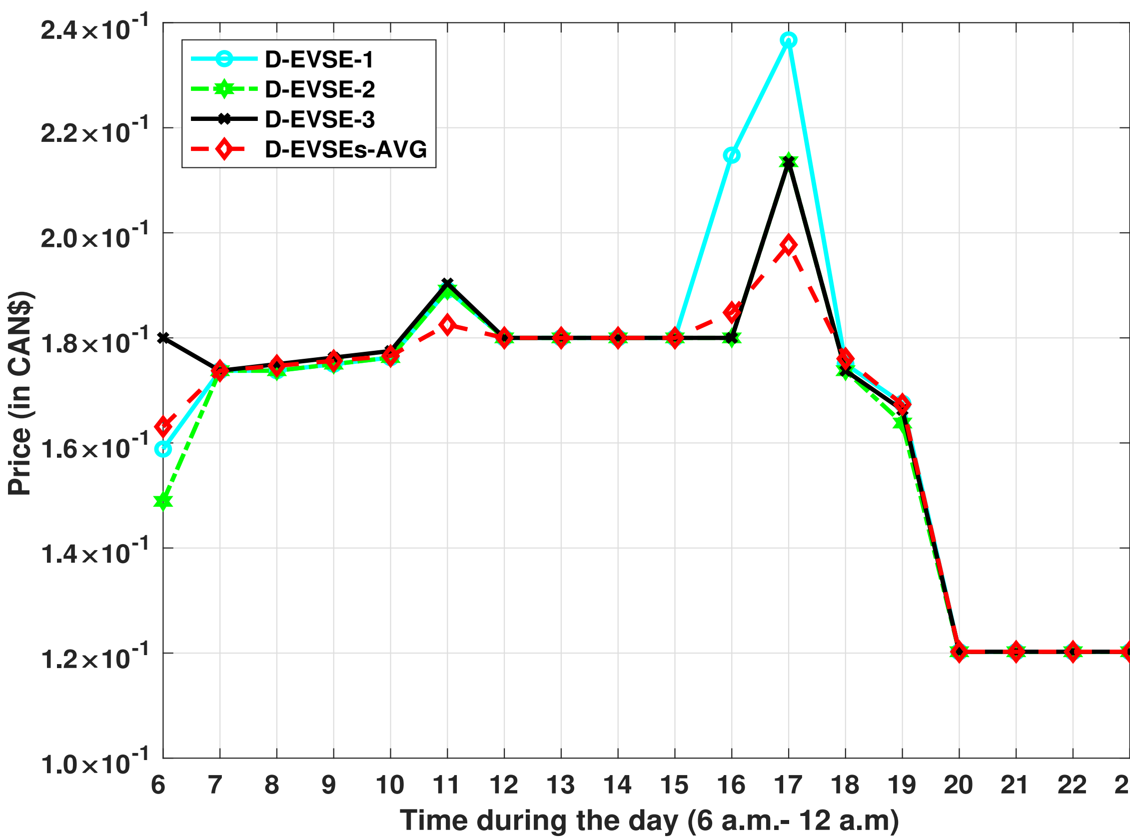

Figure 6.5: Average of the D-EVSEs' diverse charging price comparing D-EVSEs 1 - 3 with D-EVSEs-AVG of the 12 D-EVSEs with Our Arrival Rate Estimation

Table 6.9 shows the average charging price based on the RESs, the power grid, and the

EV discharging power prices. As shown in Table 6.9, the average charging price during the mid-peak time (7 a.m. - 11 a.m.) is between 17.66 to 17.86 cents in CAN$/kW. The RESs power price is 18 cents in CAN$/kW, and the power grid price during mid-peak is 17.25 cents in CAN$/kW as shown in Tables 6.5 and 6.4. This means that all D-EVSEs depend more on the RESs power than on the power grid as depicted in Table 6.9. However, during the on-peak time (11 a.m. - 5 p.m.), the average charging prices rely on RESs' price. From (5 p.m. -7 a.m.) the charging price is between 16.88 to 17.17 cents in CAN$/kW. This means that the EV discharging processes also affect the charging prices because the power grid price is 17.25 cents in CAN$/kW at mid-peak while the EV discharged power price is 15 cents in CAN$/kW as presented in Tables 6.4 and 6.5 respectively. After sunset, the average charging price for all D-EVSEs is dependent on the power grid's price.

Table 6.9: Average D-EVSEs' charging price (in CAN$) with Our Arrival Rate Estimation

	D-EVSE-1	**D-EVSE- 2**	**D-EVSE-3**	**D-EVSEs-AVG**
6 a.m. - 7 a.m.	1.588×10^{-1}	1.489×10^{-1}	1.800×10^{-1}	1.631×10^{-1}
7 a.m. - 11 a.m.	1.776×10^{-1}	1.776×10^{-1}	1.786×10^{-1}	1.766×10^{-1}
11 a.m. - 5 p.m.	1.952×10^{-1}	1.856×10^{-1}	1.856×10^{-1}	1.838×10^{-1}
5 p.m. - 7 p.m.	1.713×10^{-1}	1.688×10^{-1}	1.700×10^{-1}	1.717×10^{-1}
7 p.m. - 12 a.m.	1.203×10^{-1}	1.203×10^{-1}	1.203×10^{-1}	1.203×10^{-1}

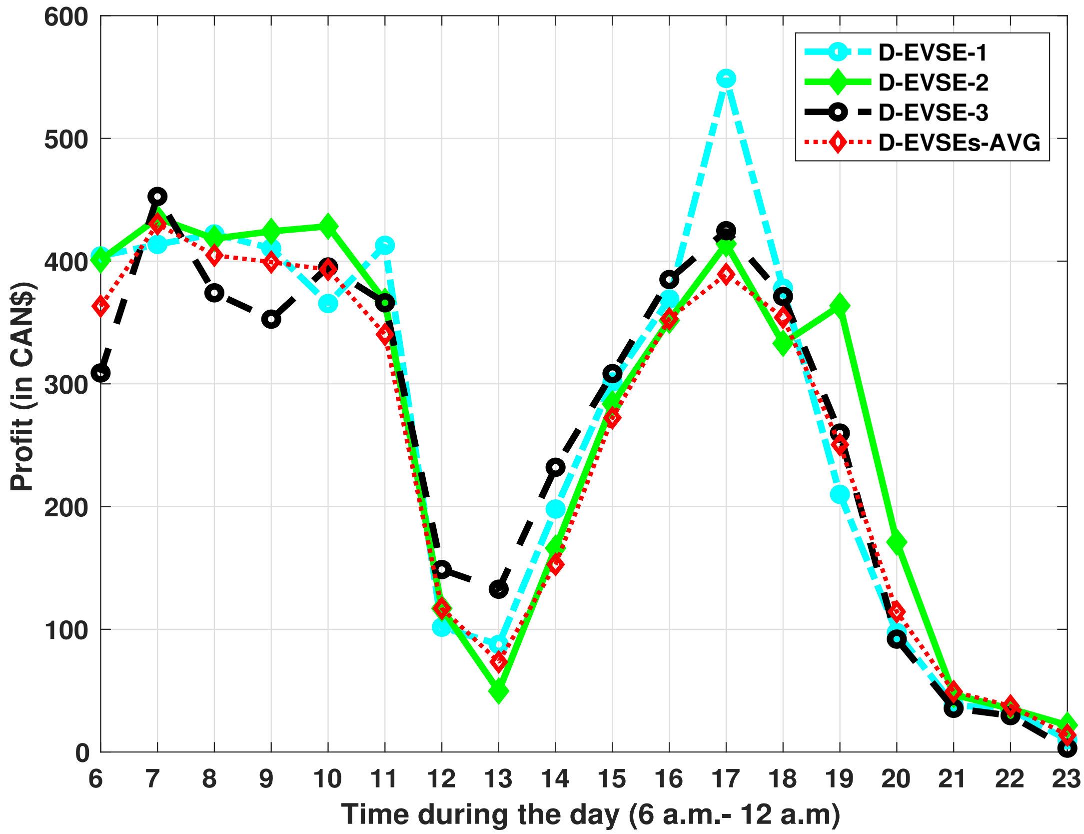

Figure 6.6: Average of the D-EVSEs' profits comparison for D-EVSE 1 - 3 with D-EVSEs-AVG of the 12 D-EVSEs with Our Arrival Rate Estimation

Figure 6.6 compares the average profits of the D-EVSEs 1- 3 with all 12 D-EVSEs' average profits presented as D-EVSEs-AVG. The same figure with Figure 6.6 illustrates that when the EV charging demands are high and the amount of RESs' energy production is high, the profit increases accordingly and more specifically from (8 a.m. - 12 p.m.) and (2 p.m. - 4 p.m.). Therefore, the D-EVSE will get the most profits can get. However, when EV charging demands are low and the amount of RESs energy production is high such as between (12 p.m. - 2 p.m.), then the D-EVSE makes a fair profit. The D-EVSE profit starts decreasing from (6 p.m. - 12 a.m.) due to few EVs. The D-EVSEs rely on the power grid price, which also shows that all D-EVSEs obtained the lowest profit during the day.

Table 6.10: Average D-EVSEs' profit (in CAN$) with Our Arrival Rate Estimation

	D-EVSE-1	D-EVSE- 2	D-EVSE-3	D-EVSEs-AVG
6 a.m. - 7 a.m.	404.2	400.9	308.9	363.3
7 a.m. - 11 a.m.	2024.5	2073.1	1940.9	1967.6
11 a.m. - 5 p.m.	1606.8	1382.3	1631.5	1358.0
5 p.m. - 7 p.m.	587.9	696.6	631.1	604.5
7 p.m. - 12 a.m.	180.3	274.9	160.5	214.9

As the results illustrate in Table 6.10, the total profit is compared with the average profit for all 12 D-EVSEs (D-EVSEs-AVG) during the ToU pricing classification. The D-EVSEs is most profitable when the RESs power production contributes to the power grid during mid-peak (7 a.m. -11 a.m.) and on-peak (11 a.m. -5 p.m.) as shown in Table 6.10. Table 7 also shows that the D-EVSEs-AVG profit is greater than the profit of D-EVSE-3 at the time (6 a.m. - 11 a.m.), which means that the other D-EVSEs are more profitable than D-EVSE-2. However, during the on-peak period, D-EVSE-1 and D-EVSE-3 are far more profitable than D-EVSE-2 and D-EVSEs-AVG.

Table 6.11: Comparison of purchased power for D-EVSEs 1 - 3 and D-EVSEs-AVG with Our Arrival Rate Estimation

	RESs	Power grid	EV Discharging power
D-EVSE- 1	57%	39%	4%
D-EVSE- 2	58%	40%	2%
D-EVSE- 3	72%	26%	2%
D-EVSE- AVG	68%	30%	2%

Table 6.11 shows the percentage of power contributed from RESs as well as the purchasing power from the power grid and EV discharging processes. The table shows that RESs' power contributes more than 57% of the total sold power. This means that the RESs are profitable for the D-EVSEs and have mitigated the power demand on the power grid. Also, the EV discharging processes have contributed 4% of the total sold power for D-EVSE-1 and 2% of the total sold power for the other D-EVSEs. Since this model's objective is to maximize profit, EV charging processes are prioritized.

6.4.2 EV arrival rates with Poisson distribution

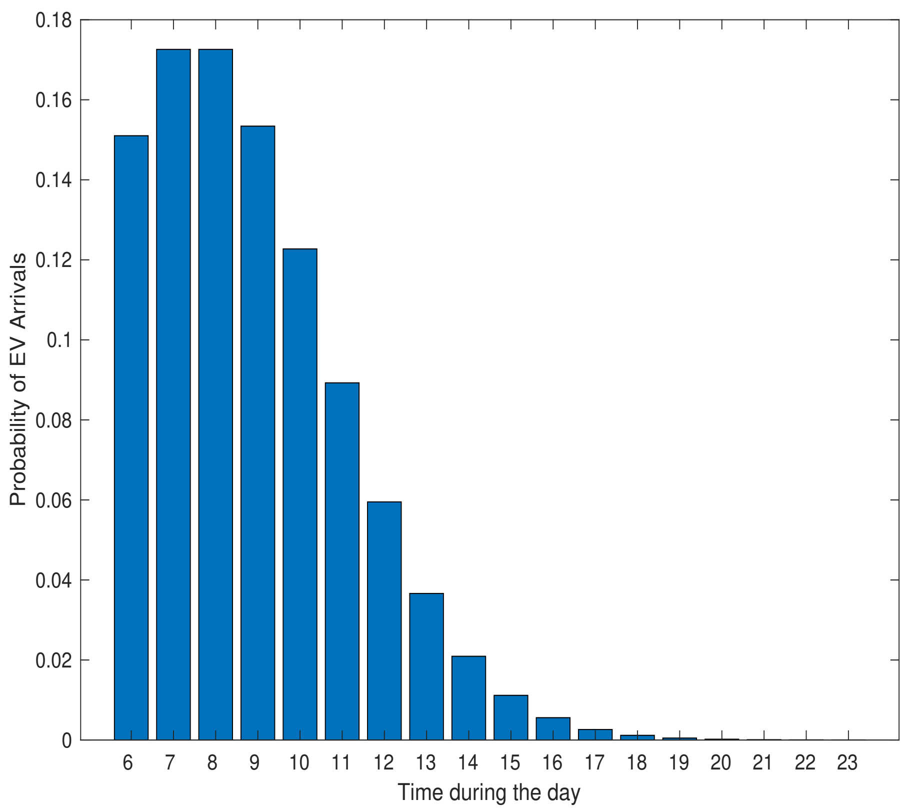

Figure 6.7: EV arrival rates with Poisson distribution

Figure 6.7 shows the probability of EV arrival rates. The EV arrival rate is assumed to be Poisson processes [246, 247] with an arrival rate λ=8.

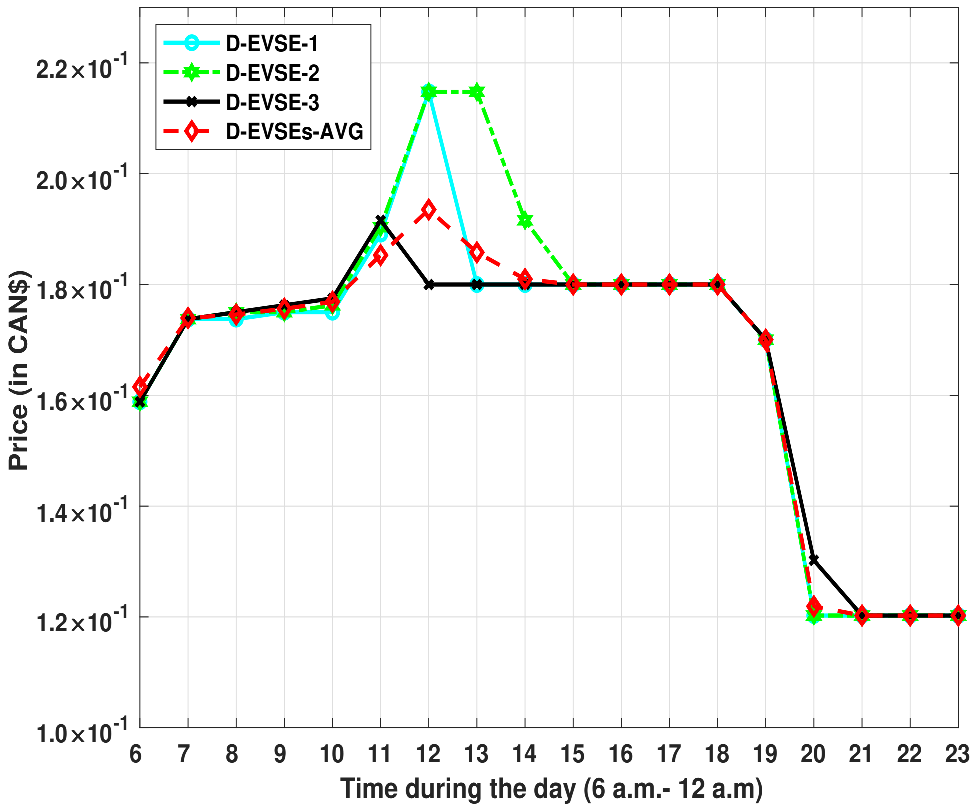

Figure 6.8: Average of the D-EVSEs' diverse charging prices comparing D-EVSEs 1 - 3 with D-EVSEs-AVG of the 12 D-EVSEs with Poisson distribution

At the time between (7 a.m. - 10 a.m.) when there is a very high EV arrival rate with accompanying power demands, the average price for all D-EVSEs relies on the power grid price as shown in Figure 6.8. On the other hand, the same figure demonstrates that the D-EVSE-3 obtains enough power from the RESs from (12 p.m. - 6 p.m.). We can observe that all D-EVSEs are totally reliant on RESs between (3 p.m. - 6 p.m.) due to a low EV arrival rate.

Table 6.12: Average charging price for D-EVSEs (in CAN$) with Poisson distribution

	D-EVSE-1	D-EVSE- 2	D-EVSE-3	D-EVSEs-AVG
6 a.m. - 7 a.m.	1.588×10^{-1}	1.588×10^{-1}	1.588×10^{-1}	1.615×10^{-1}
7 a.m. - 11 a.m.	1.773×10^{-1}	1.781×10^{-1}	1.788×10^{-1}	1.773×10^{-1}
11 a.m. - 5 p.m.	1.858×10^{-1}	1.935×10^{-1}	1.800×10^{-1}	1.834×10^{-1}
5 p.m. - 7 p.m.	1.750×10^{-1}	1.750×10^{-1}	1.750×10^{-1}	1.750×10^{-1}
7 p.m. - 12 a.m.	1.203×10^{-1}	1.203×10^{-1}	1.227×10^{-1}	1.207×10^{-1}

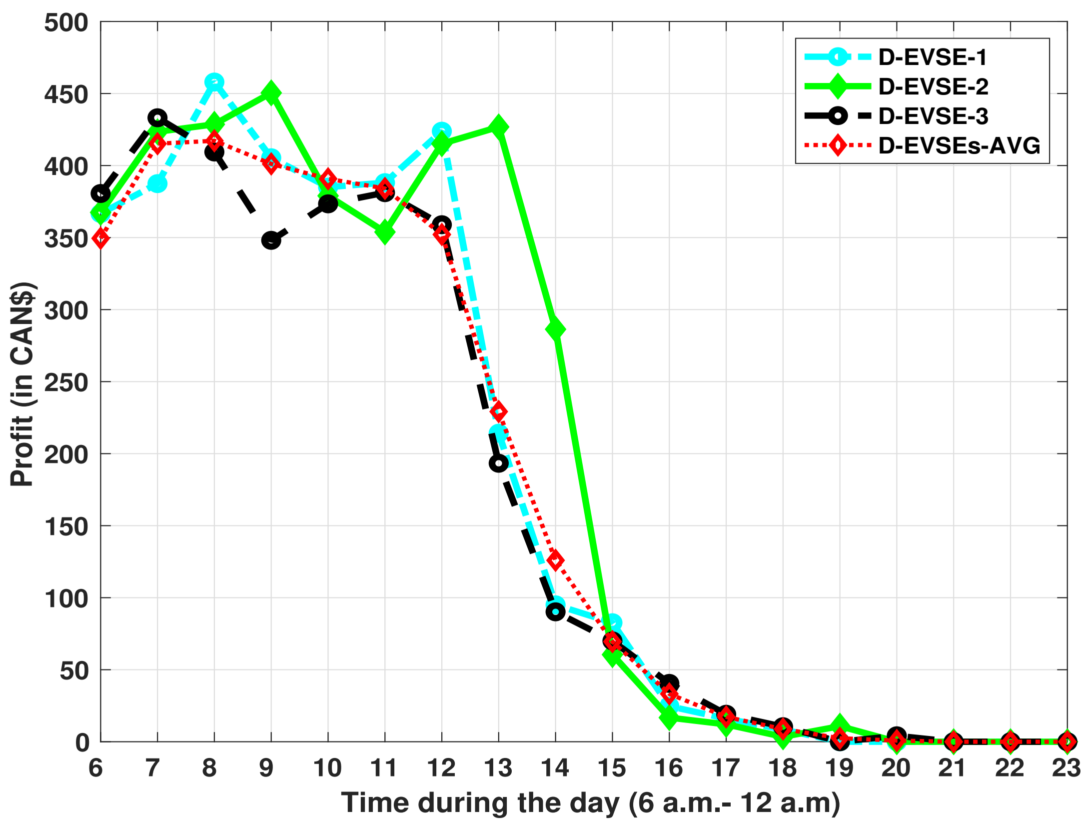

Figure 6.9: Average of the D-EVSEs' profits comparing D-EVSEs 1 - 3 with D-EVSEs-AVG of the 12 D-EVSEs with Poisson distribution

Table. 6.12 illustrates the average charging price for all D-EVSEs. As we can see from this table, the average charging price at the time between (11 a.m. - 5 p.m.) is between 18 to 19.35 cents in CAN$/kW. This means that the power price is based on RESs' price because the power grid price at these times is 24.955 cents in CAN$/kW. In contrast, most D-EVSEs rely on the power grid price from (5 p.m. - 12 a.m.).

Due to a considerable number of EV arrivals between (7 a.m. - 11 a.m.), as shown in Figure 5, the D-EVSEs obtained the highest profit for all D-EVSEs. However, D-EVSE-2 and D-EVSE-1 obtained the highest profit compared to other D-EVSEs except at the beginning of its operation (6 a.m. - 7 a.m.).

Table 6.13: Average D-EVSEs' profit (in CAN$) with Poisson distribution

	D-EVSE-1	**D-EVSE- 2**	**D-EVSE-3**	**D-EVSEs-AVG**
6 a.m. - 7 a.m.	366.7	367.5	380.6	349.5
7 a.m. - 11 a.m.	2024.0	2035.4	1945.2	2008.4
11 a.m. - 5 p.m.	856.4	1217.6	772.0	827.2
5 p.m. - 7 p.m.	8.5	14.2	10.4	11.3
7 p.m. - 12 a.m.	0.0	0.0	4.1	0.8

The average total profit comparing all D-EVSEs is shown in Table 6.13. The D-EVSEs' profit begins to decrease from 1 p.m. to 7 p.m. After 7 p.m. , the profit for each hour is meagre; in some cases, such as for D-EVSE-1 and D-EVSE-2, the profit is zero. As mentioned previously, the profit rate decreases due to the low EV arrival rate with their accompanying power demand.

Table 6.14: Comparison of the purchased power for D-EVSEs 1 - 3 and D-EVSEs-AVG with Poisson distribution

	RESs	**Power grid**	**EV Discharging power**
D-EVSE- 1	68%	29%	3%
D-EVSE- 2	60%	32%	7%
D-EVSE- 3	78%	17%	4%
D-EVSE- AVG	72%	23%	5%

As mentioned previously, D-EVSE-2 and D-EVSE-1 obtained the highest profit compared to other D-EVSEs because of the RESs' power contribution to the D-EVSE-2 and D-EVSE-1 as shown in Table 6.14 and Table 6.12.. Also, the EV discharging processes contributed more than 3%, 4%, 5%, and 7% for D-EVSE-1, D-EVSE-3, D-EVSEs-AVG, and D-EVSE-3, respectively.

6.4.3 EV arrival rates with homogeneous Poisson processes

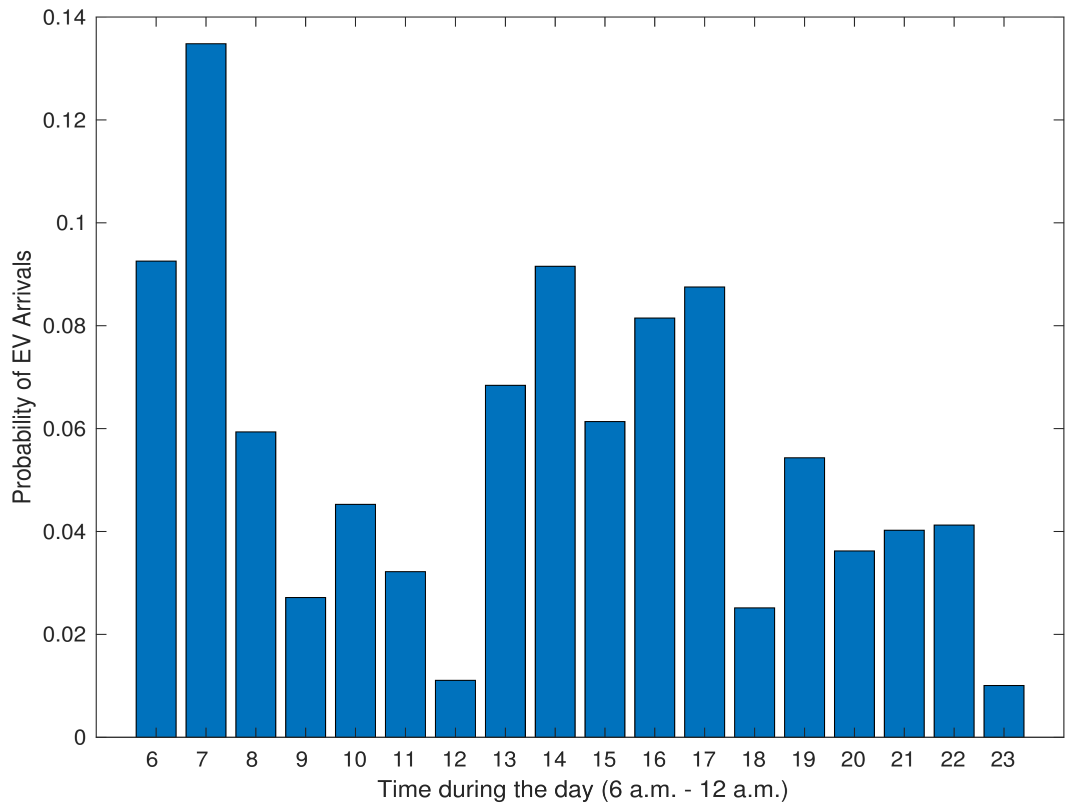

Figure 6.10: EV arrival rates with homogeneous Poisson processes

The EV arrival rates are based on homogeneous Poisson processes [248] [249]. The EV arrival probability rate is shown in Figure 6.10.

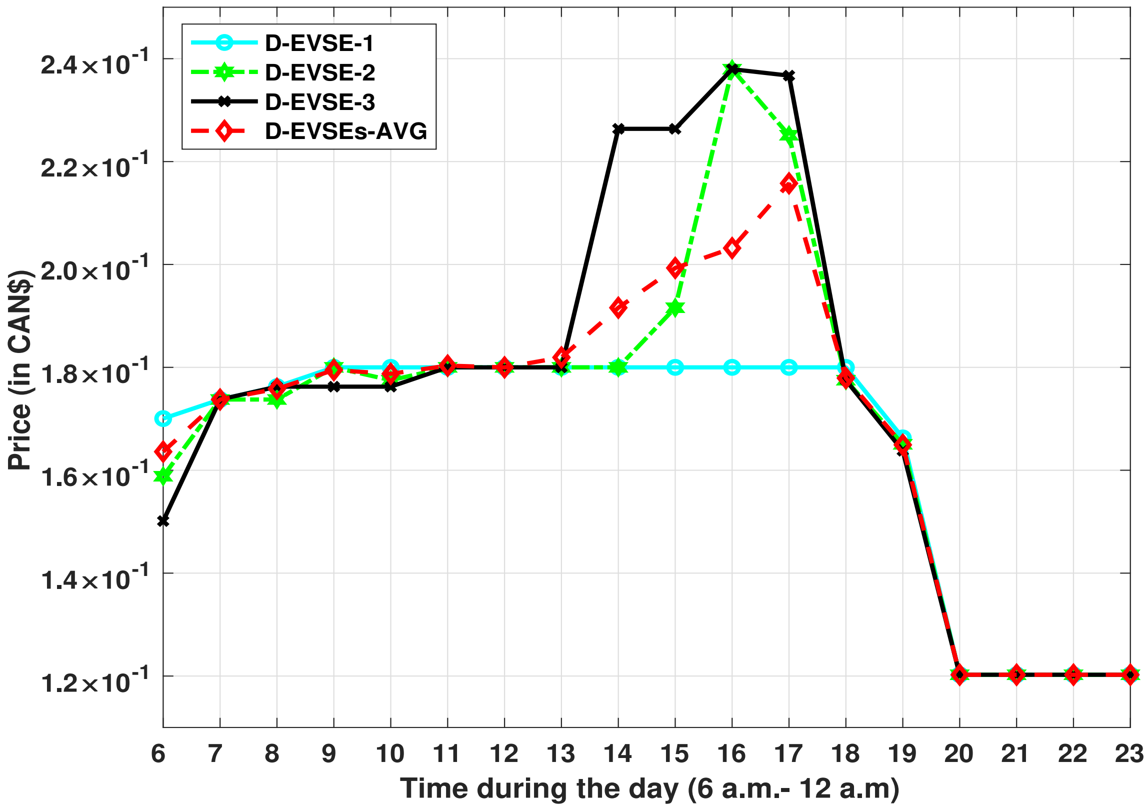

Figure 6.11: Average of the D-EVSEs' diverse charging price comparison for D-EVSEs 1 - 3 with D-EVSEs-AVG of the 12 D-EVSEs with homogeneous Poisson processes

From 9 a.m. to 1 p.m. , the average charging prices for all D-EVSEs is almost completely dependent on RESs' price, as shown in Figure 6.11. However, from 1 p.m. to 6 p.m. , all D-EVSEs (with the exception of D-EVSE-1) show that the power price between RESs' price and power grid price is slightly higher than the RESs' price. All D-EVSEs are reliant on the power grid prices from 6 p.m. to 12 p.m. The red curve (D-EVSEs-AVG) demonstrates that the D-EVSEs-AVG charging price is less than the D-EVSE-3 (black curve) from 1 p.m. to 6 p.m.

Table 6.15: Average D-EVSEs' charging price (in CAN$) with homogeneous Poisson processes

	D-EVSE-1	**D-EVSE- 2**	**D-EVSE-3**	**D-EVSEs-AVG**
6 a.m. - 7 a.m.	1.700×10^{-1}	1.588×10^{-1}	1.501×10^{-1}	1.636×10^{-1}
7 a.m. - 11 a.m.	1.780×10^{-1}	1.770×10^{-1}	1.765×10^{-1}	1.776×10^{-1}
11 a.m. - 5 p.m.	1.800×10^{-1}	1.991×10^{-1}	2.146×10^{-1}	1.953×10^{-1}
5 p.m. - 7 p.m.	1.731×10^{-1}	1.713×10^{-1}	1.706×10^{-1}	1.714×10^{-1}
7 p.m. - 12 a.m.	1.203×10^{-1}	1.203×10^{-1}	1.203×10^{-1}	1.203×10^{-1}

Table 6.15 demonstrates that the charging prices from (6 a.m. - 7 a.m.) for D-EVSE-1 and D-EVSEs-AVG are close to RESs' price while the charging prices for D-EVSE-2 and D-EVSE-3 are shared between the RESs' price and the power grid price. However, from (7 a.m. - 11 a.m.), which is mid-peak, the charging price for all D-EVSEs is close to the RESs' price. By observing Table 6.15, we can see that from 5 p.m. to 7 p.m. , the average charging prices for D-EVSE-2 and D-EVSE-3 as well as D-EVSEs-AVG are less than the charging prices at mid-peak of 17.25 cents in CAN$/kW. This means that these three D-EVSEs accept more EV discharging processes than D-EVSE-1. In contrast, all D-EVSEs from 7 p.m. to 12 a.m. are based on the power grid's price.

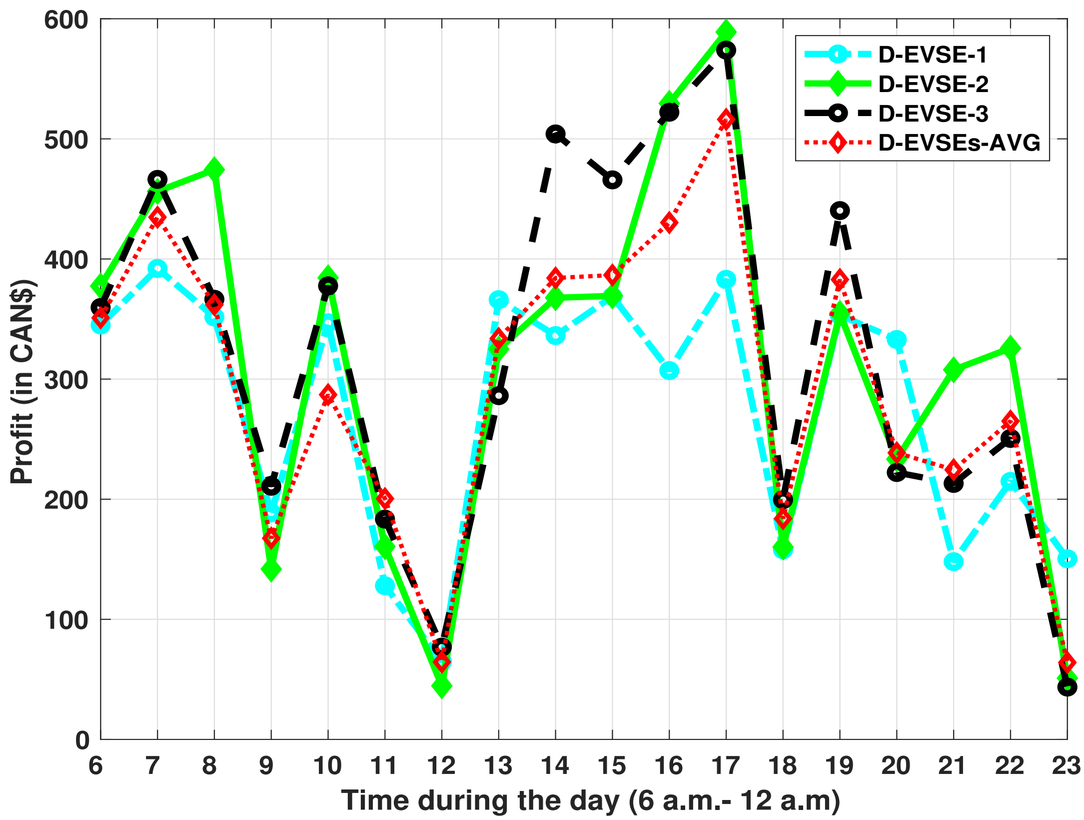

Figure 6.12: Average of the D-EVSEs' profits comparing D-EVSEs 1 - 3 with D-EVSEs-AVG of the 12 D-EVSEs with homogeneous Poisson processes

As shown in Figure 6.12 the D-EVSE-3 and D-EVSE-2 profits (black and green curves) are higher than the other curves. However, the D-EVSEs-AVG gained more profit than D-EVSE-1 except at the end of its operation time from 7 p.m. to 12 a.m.

Table 6.16: Average D-EVSEs' profit (in CAN$) with homogeneous Poisson processes

	D-EVSE-1	D-EVSE- 2	D-EVSE-3	D-EVSEs-AVG
6 a.m. - 7 a.m.	345.0	377.5	359.6	351.0
7 a.m. - 11 a.m.	1407.2	1617.3	1604.5	1451.7
11 a.m. - 5 p.m.	1826.1	2225.0	2429.1	2115.5
5 p.m. - 7 p.m.	511.0	514.8	639.9	566.7
7 p.m. - 12 a.m.	846.3	917.9	729.6	792.2

As shown in Table 6.16, D-EVSE-2, D-EVSE-3, and D-EVSEs-AVG obtained more profit than D-EVSE-1 from 6 a.m. to 7 p.m. while D-EVSE-1 gained more profit than the other D-EVSEs from 7 p.m. to 12 a.m. From 7 a.m. to 5 p.m. , we notice that D-EVSE-2 gained more than 20%, 5%, and 12% profit compared to D-EVSE-1, D-EVSE-2, and D-EVSEs-AVG respectively.

Table 6.17: Comparison of the purchased power for D-EVSEs 1 - 3 and D-EVSEs-AVG with homogeneous Poisson processes

	RESs	Power grid	EV Discharging power
D-EVSE- 1	72%	27%	1%
D-EVSE- 2	51%	47%	2%
D-EVSE- 3	41%	57%	2%
D-EVSE- AVG	57%	41%	2%

Table 6.17 illustrated that D-EVSE-1, D-EVSE-2 and D-EVSEs-AVG obtained 72%, 51% and 57% respectively RESs power more than D-EVSE-3 which obtained 41% RESs

power and the 57% power from the power grid. Also, the EVs' discharging power contributes more than 2% in all D-EVSEs except D-EVSE-1, which is 1%.

6.4.4 EV arrival rates with non-homogeneous Poisson processes intensity - Case (1)

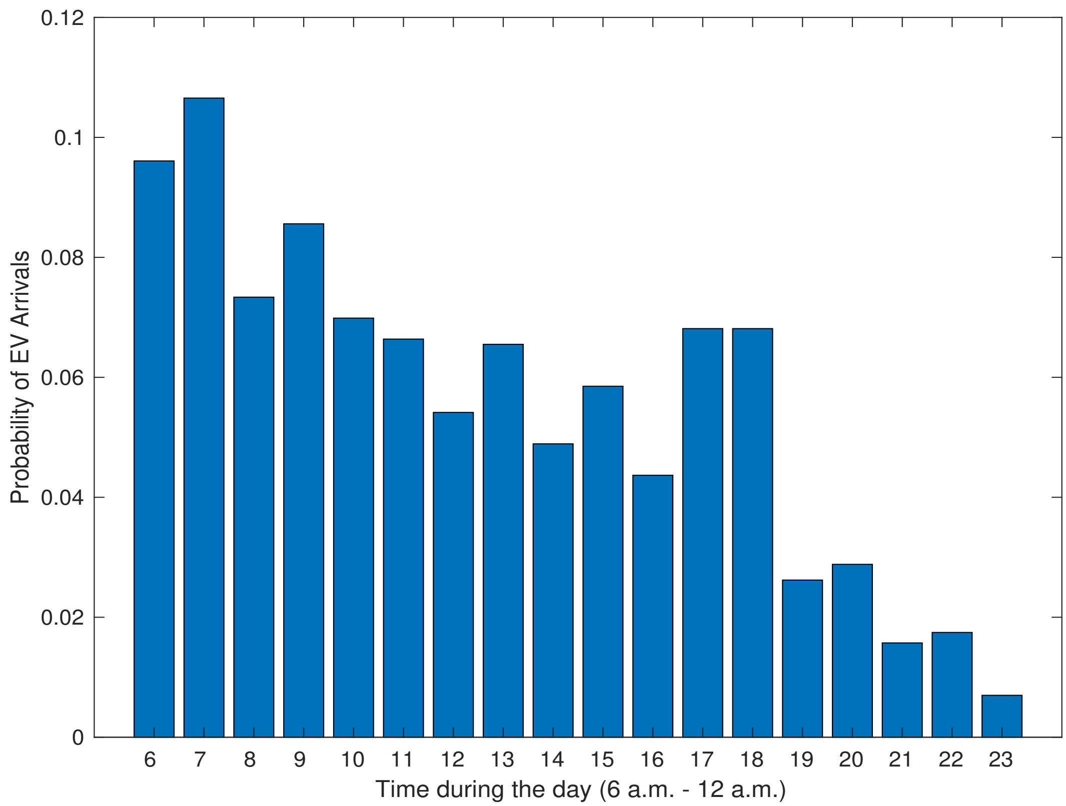

Figure 6.13: EV arrival rates with non-homogeneous Poisson processes - Case (1)

In this subsection, the EV arrival rates are modelled as a non-homogeneous poisson processes intensity [250]. The probability of EV arrival rate is as shown in Figure 6.13.

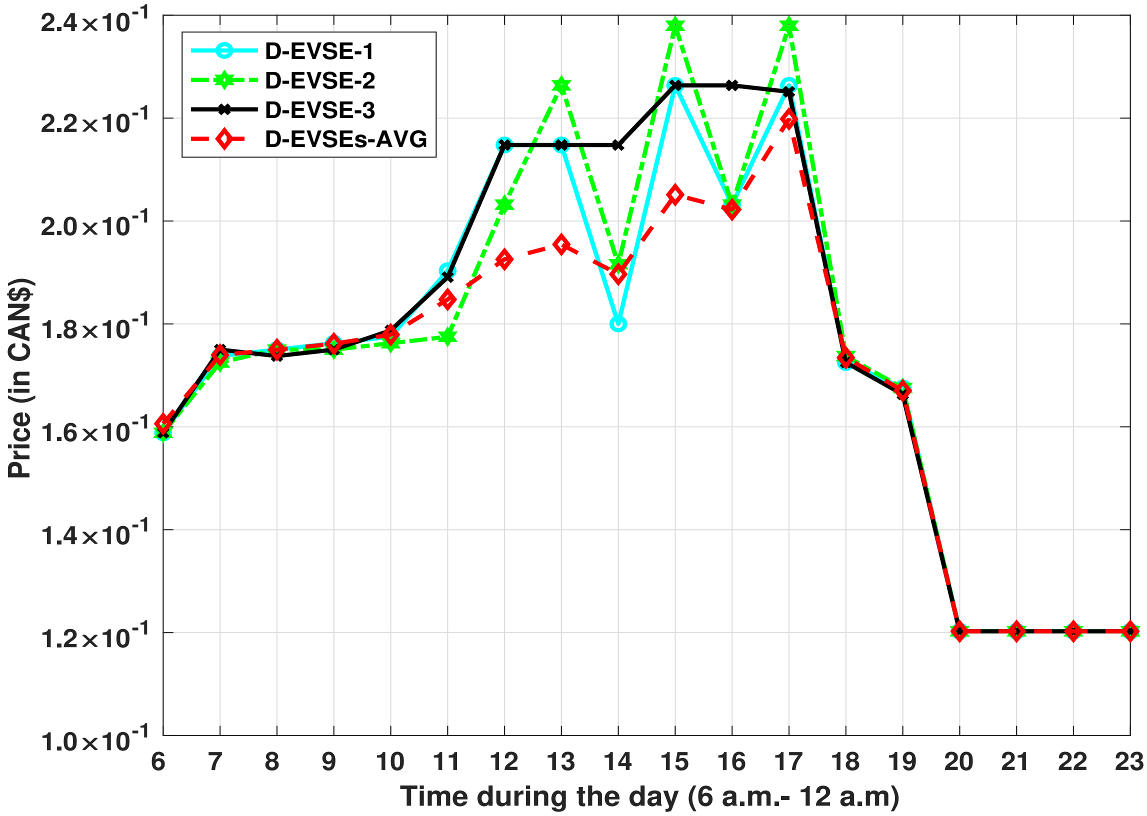

Figure 6.14: Average of the D-EVSEs' diversity charging price comparison for D-EVSE 1 - 3 with D-EVSEs-AVG of the 12 D-EVSEs with non-homogeneous Poisson processes intensity - Case (1)

Figure 6.14 shows that all D-EVSEs share the price between RESs and the power grid from 6 a.m. to 10 a.m. However, from 10 a.m. to 5 p.m. , the average charging price in D-EVSEs-AVG is less than the average charging prices for D-EVSEs (1 to 3). This means that the D-EVSEs-AVG is dependent on the RESs' price. The price of all D-EVSEs decreases and is most likely dependent on the power grid price from 5 p.m. to midnight.

Table 6.18: Average D-EVSEs' charging price (in CAN$) with non-homogeneous Poisson processes intensity - Case (1)

	D-EVSE-1	**D-EVSE- 2**	**D-EVSE-3**	**D-EVSEs-AVG**
6 a.m. - 7 a.m.	1.588×10^{-1}	1.588×10^{-1}	1.588×10^{-1}	1.606×10^{-1}
7 a.m. - 11 a.m.	1.786×10^{-1}	1.753×10^{-1}	1.783×10^{-1}	1.776×10^{-1}
11 a.m. - 5 p.m.	2.109×10^{-1}	2.167×10^{-1}	2.204×10^{-1}	2.008×10^{-1}
5 p.m. - 7 p.m.	1.700×10^{-1}	1.706×10^{-1}	1.694×10^{-1}	1.702×10^{-1}
7 p.m. - 12 a.m.	1.203×10^{-1}	1.203×10^{-1}	1.203×10^{-1}	1.203×10^{-1}

The D-EVSEs-AVG charging price at the time (6 a.m. to 7 a.m.) and (11 a.m. to 5 p.m.) is less than the charging price of D-EVSE-1, D-EVSE-2, and D-EVSE-3. This means that the D-EVSEs-AVG is more reliant on the RESs than the other D-EVSEs as shown in Table 6.18. From (7 a.m. to 11 a.m.), all D-EVSEs are most likely dependent on RESs. As we see in the same table, the EV discharging processes contribute power, and the D-EVSEs' charging prices are less than the power grid's price at the time (5 p.m. to 7 p.m.).

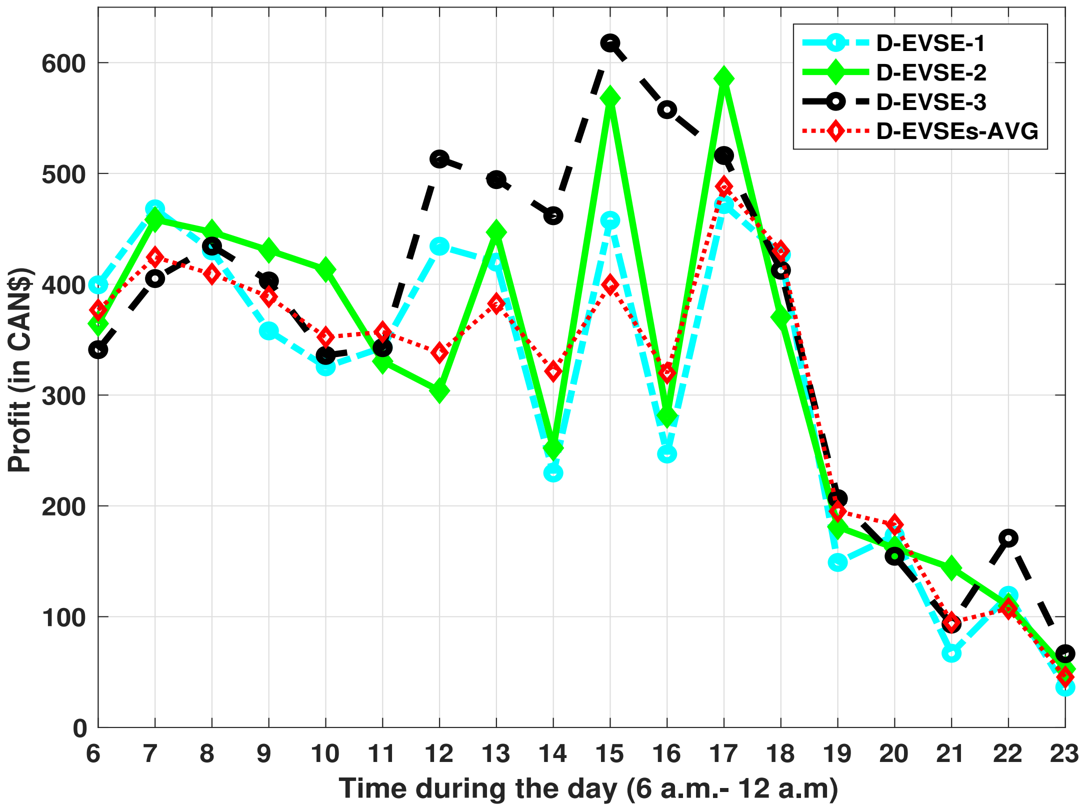

Figure 6.15: Average of the D-EVSEs' profits comparing D-EVSEs 1 - 3 with D-EVSEs-AVG of the 12 D-EVSEs with non-homogeneous Poisson processes intensity - Case (1)

Figure 6.15 shows that the profit obtained by D-EVSE-3 (black curve) is higher than the profit obtained by the other D-EVSEs from 11 a.m. to 4 p.m. In addition, the profit obtained by D-EVSE-2 (green curve) is higher than the profit obtained by the other D-EVSEs from 7 a.m. to 10 a.m. The profit begins dropping at 5 p.m. for all D-EVSEs and especially after 7 p.m. .

Table 6.19: Average D-EVSEs' profit (in CAN$) with non-homogeneous Poisson processes intensity - Case (1)

	D-EVSE-1	**D-EVSE- 2**	**D-EVSE-3**	**D-EVSEs-AVG**
6 a.m. - 7 a.m.	166.40	198.40	223.97	201.29
7 a.m. - 11 a.m.	918.90	782.89	925.70	761.69
11 a.m. - 5 p.m.	949.90	897.33	847.87	776.34
5 p.m. - 7 p.m.	120.17	133.40	176.40	147.30
7 p.m. - 12 a.m.	134.15	131.48	165.73	150.27

Table 6.19 shows that D-EVSE-3 and D-EVSEs-AVG obtained more profit than D-EVSE-1 and D-EVSE-2 at the beginning of the operation time. However, D-EVSE-3 gained more profit than the other D-EVESs at all times except from 11 a.m. to 5 p.m. Between 11 a.m. to 5 p.m. , D-EVSE-1 gained more profit than other D-EVSEs. We notice that D-EVSEs-AVG and D-EVSE-3 obtained higher profit than D-EVSE-1 and D-EVSE-2 from 5 p.m. to 12 a.m.

Table 6.20: Comparison of the purchased power for D-EVSEs 1 - 3 and D-EVSEs-AVG with non-homogeneous Poisson processes intensity - Case (1)

	RESs	**Power grid**	**EV Discharging power**
D-EVSE- 1	55%	40%	5%
D-EVSE- 2	46%	52%	2%
D-EVSE- 3	44%	53%	3%
D-EVSE- AVG	59%	38%	3%

D-EVSEs-AVG and D-EVSE-1 obtained more than 59% and 55% RESs' power respectively while D-EVSE-2 and D-EVSE-3 relied on the power grid and obtained 52% and 53% respectively as demonstrated in Table 6.20. The same table shows that the EVs' discharging power contributed more than 3% to all D-EVSEs with the exception of contributing approximately 2% to D-EVSE-2.

6.4.5 EV arrival rates with non-homogeneous Poisson processes intensity - Case (2)

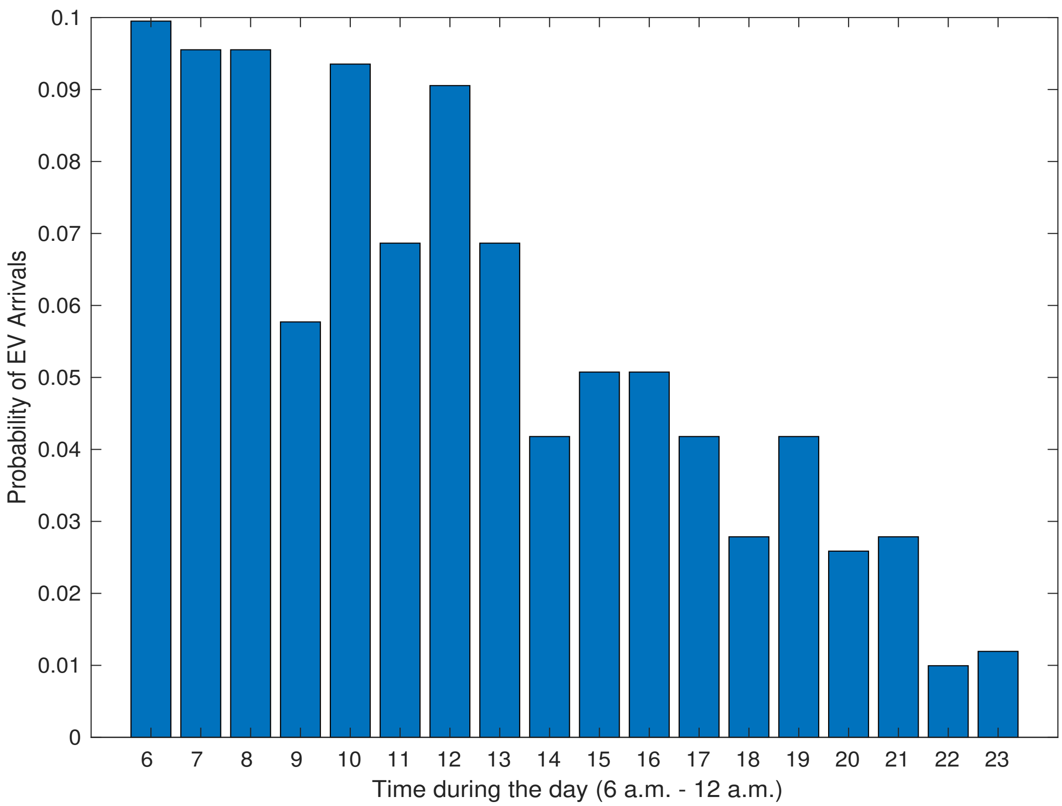

Figure 6.16: EV arrival rates with non-homogeneous Poisson processes - Case (2)

The EV arrival rates are modelled as a non-homogeneous Poisson process with intensity [250]. The probability of EV arrival rates is presented in Figure 6.16.

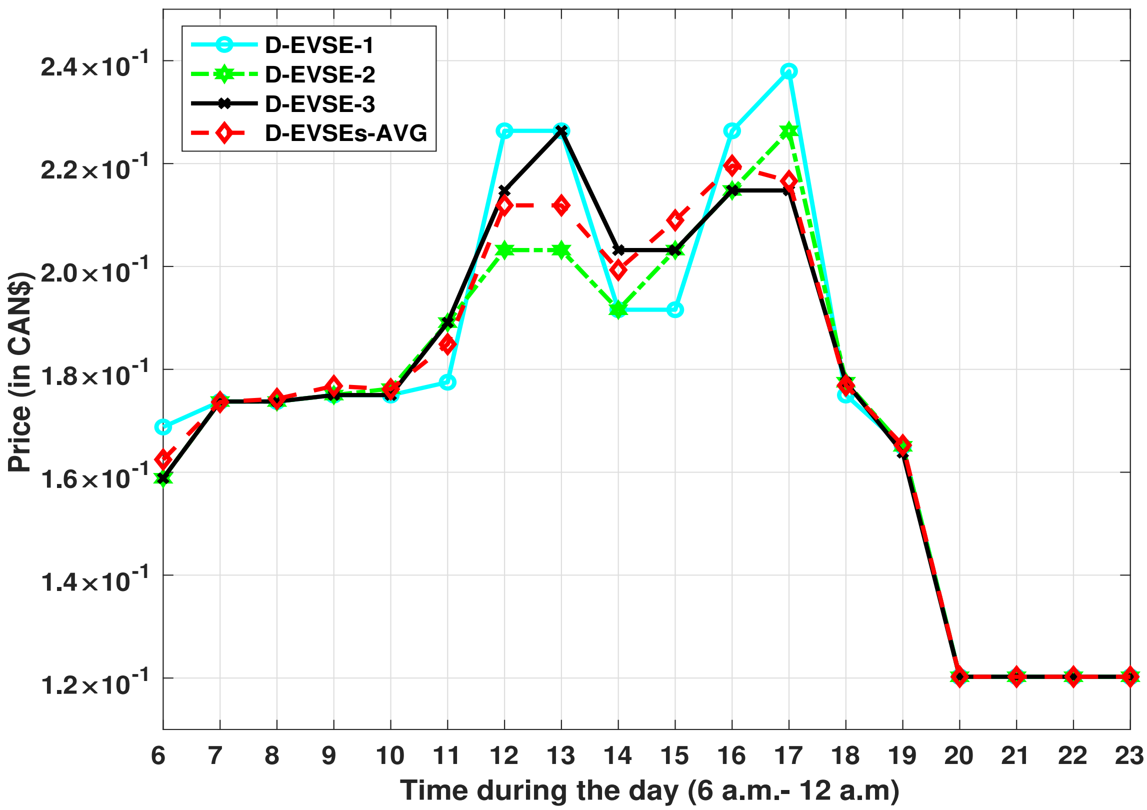

Figure 6.17: Average of the D-EVSEs' diverse charging price comparing D-EVSEs 1 - 3 with D-EVSEs-AVG of the 12 D-EVSEs with non-homogeneous Poisson processes intensity - Case (2)

We can observe in Figure 6.17 that the EV charging price from 7 a.m. to 10 a.m. is similar for all D-EVSEs. The D-EVSE-2 is dependent on RESs' price at the time (12 p.m. to 2 p.m.) while the D-EVSE-1 is most likely dependent on the power grid's price more specifically between (12 p.m. to 1 p.m.). The D-EVSEs-AVG charging price is the highest among the other D-EVSEs at 9 a.m. and 3 p.m. As shown in Figure 6.17, the EV discharging power also influences the EV charging price from 6 p.m. to 7 p.m.

Table 6.21: Average D-EVSEs' charging price (in CAN$) with non-homogeneous Poisson processes intensity - Case (2)

	D-EVSE-1	**D-EVSE- 2**	**D-EVSE-3**	**D-EVSEs-AVG**
6 a.m. - 7 a.m.	1.688×10^{-1}	1.588×10^{-1}	1.588×10^{-1}	1.625×10^{-1}
7 a.m. - 11 a.m.	1.750×10^{-1}	1.776×10^{-1}	1.773×10^{-1}	1.771×10^{-1}
11 a.m. - 5 p.m.	2.167×10^{-1}	2.070×10^{-1}	2.128×10^{-1}	2.114×10^{-1}
5 p.m. - 7 p.m.	1.700×10^{-1}	1.713×10^{-1}	1.706×10^{-1}	1.711×10^{-1}
7 p.m. - 12 a.m.	1.203×10^{-1}	1.203×10^{-1}	1.203×10^{-1}	1.203×10^{-1}

Table 6.21 shows that D-EVSE-2, D-EVSE-3, and D-EVSEs-AVG charging prices are close to RESs' price while D-EVSE-1 is close to the power grid's price from 7 a.m. to 11 a.m. D-EVES-2 charging price is 20.70 cents in CAN$/kW. This means that D-EVES-2 relies on both the RESs' price and the power grid price but more on the RESs' price. Furthermore, all D-EVSEs' prices from 5 p.m. to 7 p.m. indicate that the EV discharged price contributes to all D-EVSEs. The same table also presents that all D-EVSEs' charging prices from 8 p.m. to 12 a.m. are dependent on the power grid price.

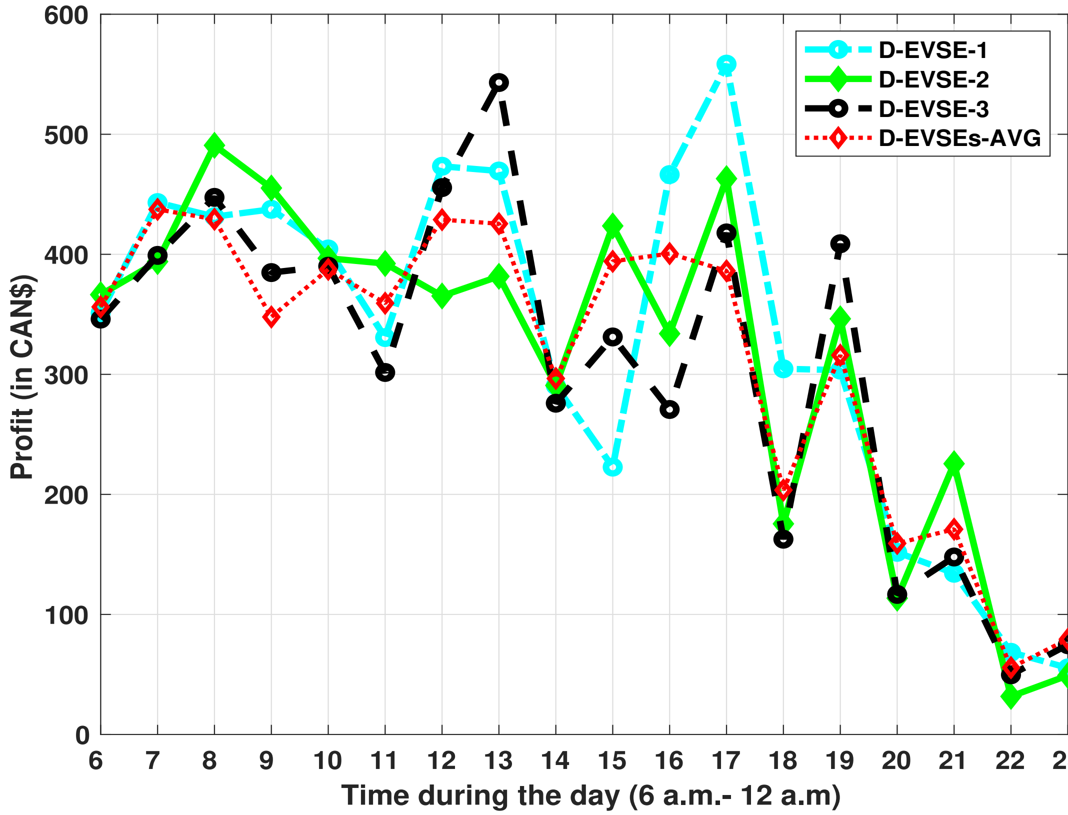

Figure 6.18: Average of the D-EVSEs' profits comparing D-EVSEs 1 - 3 with D-EVSEs-AVG of the 12 D-EVSEs with non-homogeneous Poisson processes intensity - Case (2)

As shown in Figure 6.18, D-EVSE-2 presents the highest profit compared to other D-EVSEs from 8 a.m. to 10 a.m. while the D-EVSEs-AVG is the lowest. D-EVSE-3 obtains the highest profit at 1 p.m. and 7 p.m. and the lowest profit at 11 a.m. , 4 p.m. , and 6 p.m. In contrast, D-EVSE-1 obtained the highest profit compared to other D-EVSEs at 7 a.m. and 12 p.m. and from 4 p.m. to 6 p.m.

Table 6.22: Average D-EVSEs profit (in CAN$) with non-homogeneous Poisson processes intensity - Case (2)

	D-EVSE-1	**D-EVSE- 2**	**D-EVSE-3**	**D-EVSEs-AVG**
6 a.m. - 7 a.m.	351.2	366.4	346.0	356.2
7 a.m. - 11 a.m.	2047.1	2129.0	1923.0	1961.2
11 a.m. - 5 p.m.	2480.8	2258.3	2294.4	2331.9
5 p.m. - 7 p.m.	608.2	521.8	571.5	519.6
7 p.m. - 12 a.m.	410.0	420.0	389.0	465.2

Table 6.22 presents the total average D-EVSEs' profit. D-EVSE-1 and D-EVSE-2 obtain more profit than D-EVSE-3 and D-EVSEs-AVG at the time (7 a.m. – 11 a.m.). From 11 a.m. to 5 p.m. , D-EVSE-1 and D-EVSEs-AVG obtain the highest profit compared to D-EVSE-2 and D-EVSE-3. As we can see from the same table, the least profitable D-EVSE from (7 a.m. - 5 p.m.) is D-EVSE-3, while the most profitable is D-EVSEs-AVG.

Table 6.23: Comparing the purchased power for D-EVSEs 1 - 3 and D-EVSEs-AVG with non-homogeneous Poisson processes intensity - Case (2)

	RESs	**Power grid**	**EV Discharging power**
D-EVSE- 1	49%	48%	3%
D-EVSE- 2	55%	41%	4%
D-EVSE- 3	45%	53%	2%
D-EVSE- AVG	54%	43%	3%

In Table 6.23., the RESs' power contributes more than 49% to all D-EVSEs with the exception of contributing more than 45% to D-EVSE-3. However, D-EVSE-1 is less than

50%, but the purchasing power from the power grid is 48%. D-EVSE-3 obtained 45% from the total sold power and 53% from the power grid. Furthermore, the EVs' discharging power contributes more than 3% to all D-EVSEs, with the exception of contributing 2% to D-EVSE-3.

According to D-EVSEs' profit figures, when EV charging demands are high and the amount of RESs' energy production is high, the profit increases accordingly. As demonstrated in all figures and tables, RESs are profitable and mitigate the power grid's power load. Moreover, RESs make a significant contribution to the D-EVSEs' profit and charging price. Furthermore, the EV discharging power and price contribute to the EV charging price; however, due to this study's aim, which is maximizing the D-EVSE profit, the priority is to reserve the plug-in sockets for charging processes. These results prove that the D-EVSE with our proposed DPMA can maximize its profits more efficiently and manage the EV charging process more effectively. It can also efficiently manage the connection between the D-EVSE and the power grid while taking into account the D-EVSEs' sustainability.

6.5 Summary

In this chapter, we have proposed a Decentralized Profit Maximization Algorithm (DPMA) aiming to optimize the D-EVSEs' profits. Solar energy was the primary power source for the D-EVSE, while D-EVSE has a reciprocal link to the power grid. D-EVSEs manage the reciprocal link for the power grid's requisition between D-EVSE and the power grid. The DPMA helps D-EVSEs maximize their profit from the electricity price variation during the day when selling or buying electricity respectively to EVs or from the grid and EV as discharged power processes. Moreover, renewable energy production reduces the power load on the power grid. For D-EVSEs' charging prices and profits, we presented a comparative study between different D-EVSEs.

The proposed model maximized D-EVSE profits significantly in all different scenarios and showed that the RESs are more profitable than the power grid for D-EVSE. Five EV arrival rate scenarios were considered to investigate the efficiency of our proposed model. Simulation results conducted to validate the proposed algorithm demonstrated its effectiveness while satisfying the defined constraints.

Chapter 7

Conclusion and Future Work

7.1 Concluding Remarks

Recently many governments worldwide have announced their plan to ban cars with gas engines. The aim is to minimize the effect of transportation's pollution upon the climate. In this thesis, the issues of EVs' interaction with the modern power grid in a smart city to manage and control EV charging and discharging processes are investigated in detail. While most proposed literature schemes are either based on centralized power systems or only consider the EVs' charging process, we focus primarily on the power generation sources and management techniques for EV charging and discharging processes. Electric vehicle supply equipment (EVSE) in the smart city must be equipped with renewable energy sources (RESs). The EVSE based on RESs helps to manage the drawbacks of the power grid by minimizing air pollution and greenhouse gas emissions (GHGs). Thus, the EVSE must exhibit robustness by using green and clean energy and managing the power demand more efficiently.

We introduced the concept of using decentralization of power generation and management problems in EVSEs. We propose a novel approach, namely a decentralized-EVSE (D-EVSE) model based on RESs and an energy storage system (ESS), to manage the EV charging and discharging processes. The proposed model is based on a scheduling algorithm aiming to maximize the EV drivers' satisfaction and minimize the D-EVSEs' stress level. We also take into account the D-EVSE availability and the proximity of EV to the selected charging station. The proposed algorithm is tested through simulations of random scenarios. The simulations illustrate that the proposed algorithm manages the EVs' charging and discharging process effectively.

We proposed a new model for D-EVSE based on two algorithms: D-EVSE Immediate Scheduling Algorithm (ISA) and D-EVSE Unscheduling Algorithm. These two algorithms are used to minimize the waiting time for EV charging or discharging processes, minimize the stress level for D-EVSE, and maximize EV drivers' satisfaction and the EV's driver's preference for charging or discharging process. The unscheduling algorithm is used to manage the unscheduled arrivals of EVs and minimize the waiting time for the charging and discharging processes. A realistic scenario was conducted in the City of Ottawa to test and validate the proposed schemes. We investigated and compared our proposed approaches with Dijkstra's shortest path and EV smart-guidance approaches in the simulation. We have proven that the D-EVSE model outperforms the random, Dijkstra's shortest path, and EV smart-guidance approaches. We conclude that the ISA and D-EVSE Unscheduling Algorithm demonstrate the efficiency of the proposed approach while satisfying the defined constraints.

We designed a decentralized power production and management system approach based on Game Theory (GT) for EVs' interplay with D-EVSE. We proposed a decentralized GT (D-GT) model aiming to optimize the EVs' interaction with the D-EVSE and take into account EV driver's satisfaction and D-EVSEs' stability. The D-GT model is used to choose the optimal available solution for EV charging or discharging services that satisfy predefined constraints. Photovoltaic energy is the primary power source for our D-EVSE. Also, we assume that the D-EVSE is connected to the grid when solar renewable energy production fails to respond to the demand. We evaluated the proposed schemes using random and realistic scenarios as a testbed for the proposed models in our simulations. Simulation results indicate that the proposed model can manage and control the interaction between EVs and D-EVSEs efficiently.

Finally, we proposed a Decentralized Profit Maximization Algorithm (DPMA) as an optimization model. DPMA is designed to maximize D-EVSEs' profit. DPMA helps D-EVSEs take profit from the electricity price variation during the day when selling or buying electricity respectively to EVs or from the grid or EVs as discharging processes. The D-EVSE is equipped with solar energy systems. We also acknowledge a power connection to the central power grid when necessary. Moreover, renewable energy production reduces the power load on the power grid. Five EV arrival rate scenarios were considered to investigate the efficiency of our proposed model. For D-EVSEs' charging prices and profits, we conducted a comparative study between different D-EVSEs. The proposed model maximizes D-EVSE profits significantly in all different scenarios and shows that the RESs are more profitable than the power grid for D-EVSE.

7.2 Future Work

Based on the studies and conclusions in this thesis, several areas could be considered for future research. These are summarized as follows:

1. Incorporate different types of processes such as trading energy between EVs and switching EV batteries in the D-EVSE model.
2. Incorporate priority levels for EV charging or discharging demand on the D-GT model and conduct additional investigation.
3. Extend the D-GT model by considering priority levels for EV charging and discharging processes to increase the EV drivers' satisfaction.
4. Incorporate Quality-of-Service, privacy, and security schemes for EV and D-EVSE to investigate the impact of implementing these schemes. The EVs' security issues are challenging in the IoT application since the EVs are vulnerable to an attack or trace tracking or other problems such as privacy. Therefore, Ev's security issues should be solved before integrating large number of EVs in smart cities.
5. Extend the DPMA model by using other RESs such as wind turbines to help the D-EVSE lower the dependency on the power grid.
6. Incorporate battery depth of discharge and battery time as live parameters into the DPMA model.
7. Incorporate different communication technologies to locate the most effective communication techniques that reduce communication latency and mitigate the impact of implementing these schemes.

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Appendix - Confidence Intervals Calculation

There are many different methods to calculate the confidence intervals (CI) of the proposed models. The quantitative technique is one such method.

The n is the number of simulation runs. The simulated metrics such as EV drivers' satisfaction level, D-EVSEs' stress level, EVs' charging and discharging waiting time, and D-EVSEs arrival rates are measured by calculating the mean of a succession of n runs. As well, many simulations are conducted to ensure that there are no correlations in the presented results.

The results of a group of runs that are conducted are gathered to calculate the CI. The confidence level is aimed at 95% with reliability factor (Z_{value})= 1.96.

The average or mean of all runs is represented by R1, R2,..., Rn. Eq. 1 is used to calculate this mean:

$$\bar{R} = \frac{1}{n}\sum_{i=1}^{n} R_i \tag{1}$$

The Variance (V_r^2) is given by Eq. 2. :

$$V_r^2 = \frac{1}{n-1}\sum_{i=1}^{n}(R_i - \bar{R})^2 \tag{2}$$

The standard deviation (σ) is given by Eq. 3:

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(R_i - \bar{R})^2} \tag{3}$$

The sample mean CI is given by 4:

$$CI = \bar{R} \pm Z_{value} * \frac{\sigma}{\sqrt{n}} \tag{4}$$

Where $\bar{R}$ is the sample variance, n is the number of runs (sample size), and Z_{value} is the corresponding value for 95% confidence level.

Eq. 5 and Eq. 6 show the upper and lower values of the 95% CI:

$$U(CI) = \bar{R} + Z_{value} * \frac{\sigma}{\sqrt{n}} \tag{5}$$

$$L(CI) = \bar{R} - Z_{value} * \frac{\sigma}{\sqrt{n}} \tag{6}$$

Through the values in Equations 5 and 6, it is found that the collected results are within the calculated value of CI 95%.