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DESIGN AND DEVELOPMENT OF ADAPTIVE EV CHARGING MANAGEMENT FOR URBAN TRAFFIC ENVIRONMENTS

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Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original. I also declare that this work has not been submitted in whole or in part for consideration for any degree or qualification, to this or any other university. This dissertation is my work and to the best of my knowledge, does not contain content which breaks any law of copyrights, except as specified in the text and acknowledgments.

Name: Mohammad H. A. Al Ja'idi

Signature:

Date: 27 May 2022

Dedications

I want to dedicate this thesis to my parents; Hamad Al Ja'idi and Turkyeh Alkhawaldeh, my beloved wife; Islam Alkhawaldeh, and my children; Yazan, Jana and Daneal. They provided immeasurable support throughut my PhD research journey, and gave me the strength and motivation to reach for the stars and chase my dreams.

I also wanted to give a special thanks to my brothers and sisters, as well as my in-laws who deserve my wholehearted thanks and appreciation.

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I would like to extend my gratitude to my co-supervisors Dr. Xiaomin Chen and Dr. Omprakash Kaiwartya for their invaluable advice, and continuous support during my PhD studies. I would also like to thank Dr. Yousef Al-Gumaei, his knowledge and plentiful experience have encouraged me in the time of my academic research.

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Abstract

Due to the world's shortage of fossil fuels, increasing energy demand, oil prices, environmental concerns such as climate change and air pollution, seeking for alternative energy has emerged as a critical study area. Transportation systems is one of the main contributors to air pollution and consumers of energy. Electric Vehicles (EVs) is considered as a highly desirable solution for a new sustainable transportation for many powerful advantages, such as energy efficient, environmentally friendly and may benefit from increased renewable energy technologies in the future. Despite all the acknowledged advantages and recent developments in terms of reducing the environmental impact, noise reduction and energy efficiency, the electric mobility market is still below the expectations. Among the most challenges that limit the market penetration of EVs as well as achieving a sustainable mobility system are the efficient distribution of adequate Charging Stations (CSs) and also determining the best CSs for EVs in metropolitan environments.

This thesis is concerned in determining the optimal placement of EVCSs and the efficient assignment of EVs to CSs. To accomplish this, we thoroughly examine the interactions between EVs, CSs, and Electrical Grids (EGs). First, a novel energy efficient scheme to find the optimal placement of EVCSs are presented, based on minimizing the energy consumption of EVs to reach CSs. We then propose a comprehensive approach to find the optimal assignment of EVs to CSs based on optimization of EV users' QoE. Finally, we proposed a reinforcement learning-based assignment scheme for EVs to CSs in urban areas, aiming at minimizing the total cost of charging EVs and reduce the overload on EGs. By comparing the obtained results of the proposed approaches with different scenarios and algorithms, it was concluded that the presented approaches in this thesis are effective in solving the problems of EVCS placement and EVs assignment.

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Introduction

1.1 Overview

The increase in energy demand and oil prices are one of the major challenges facing the transportation sector, as reliance on oil as a major source of energy could affect these sectors [1]. Nowadays, vehicles are vital factors of daily life for personal mobility and cargo transportation as evidenced by the constant demand for petroleum. Along with such a demand, rising fuel costs and growing global concerns about the environment due to climate change and air pollution have elicited apprehensions. In 2018, 328 billion vehicle miles were driven on the roads in Great Britain according to the Great Britain transport statistics [2], 78% of transportation is covered by private cars, while the remaining 22% is covered by other type of transportation facilities. knowing that the energy demand in the transportation sector will increase by 54% until 2035 [3]. Environmentally, Internal Combustion Engine Vehicles (ICEVs) are acknowledged to be significant source of Carbon Dioxide (CO_2) emissions, causing Greenhouse Gas (GHG) emissions to dramatically increase. Fig 1.1 shows a global breakdown of GHG emissions by sector.

According to the UN Climate Change Conference (COP26), which was held in Glascow, UK

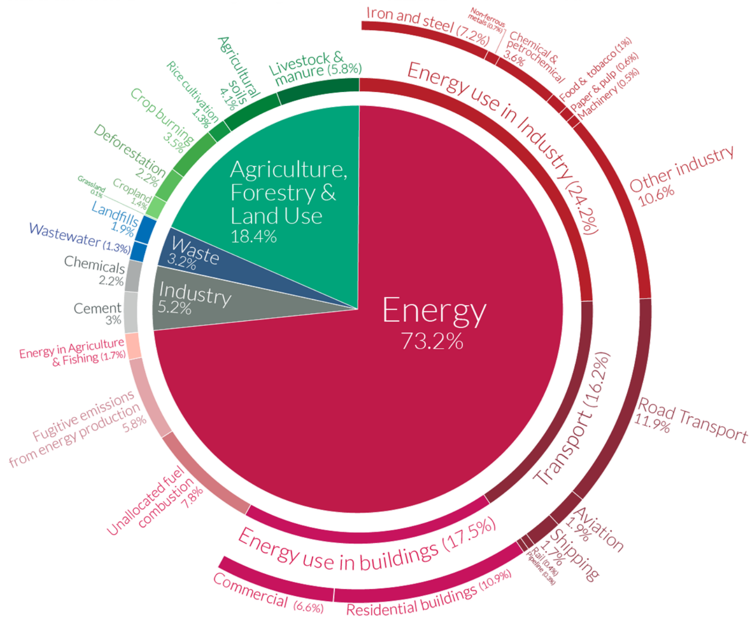

Figure 1.1: A Global Breakdown of GHG Emissions by Sector, 2020 [4]

in 2021, CO_2 emissions may increase by 50% by 2030 [5]. In more developed countries, such as the USA, the transportation sector consumes 30% of the total energy resources, and accounts more than 90% of the demand for petroleum energy [6]. Therefore, some governments have encouraged car manufacturers to find low-emission and environmentally friendly transportation alternatives [7], that are not dependent on fossil fuels.

To find a practical solution for this problem, Electric Vehicles (EVs) have been utilized and developed as promising alternative to ICEVs in order to minimize dependency on fossil fuels and reduce the CO_2, this has resulted in reduction of emissions of GHG and other pollutant [8]. Furthermore, the popularity of EVs is contributed by their outstanding advantages comparing to ICEVs including running cost, low maintenance, and environmentally friendly. Recently, EVs are beginning to compete with ICEVs on both price and performance. Thus, EVs have revealed great interest from the researchers in recent years. In industry field, car manufacturers have spent billions to electrify their products. For example, Toyota Motor Corporation plans to phase out

ICEVs altogether by 2050. Volkswagen AG is targeting 25% of its sales to be electric by 2025 [9]. Furthermore, various factors, such as the technological innovation in electric drivetrain and battery efficiency helped to greatly increase the EVs penetration in recent years in metropolitan areas [10]. The cost of batteries are dropping by about 20% a year, which also gives preference to EVs over ICEVs.

In order to rely on EVs, and use them instead of ICEVs, some countries have taken serious measures, for example, the UK government has announced to end the sales of new diesel and petrol vehicles in the UK by 2030, to be the fastest country in the Group of Seven (G7) to decarbonise vehicles. Diversion of high energy demand for transportation sectors to the systems that use electricity will create additional challenges. The future electricity power distribution system should be ready to deal with EVs as a new form of load in the system. This load has the potential to move, so the connection times and locations of EV loads have high degrees of uncertainty; Therefore, electrical systems have to be mitigated and protected from any practical influences that EV charging may cause [11, 12].

1.2 Motivations

Over the last decades, the development of EVs has risen, and has been regarded as a mean to respond to the transportation sector dependency on nonrenewable energy. However, the adoption rate of EVs mainly depends on the presence of wide range of CSs that should be deployed in optimal locations in urban areas, as the sparsity of current public charging infrastructure remains as a major impediment to the proliferation of EVs [13, 14, 15]. The sparsity of current public charging infrastructure remains as a major impediment to the proliferation of EVs.

For EV users, using charging points at home is an alternative method. However, it takes too much time (6 to 8 hours) for each charging process [16], which is mainly depend on EV user's behavior, so if there is no rules to charge EVs at homes, local overloads and regional peak demands will emerge as new problem of distribution system problems [17]. The infrastructure

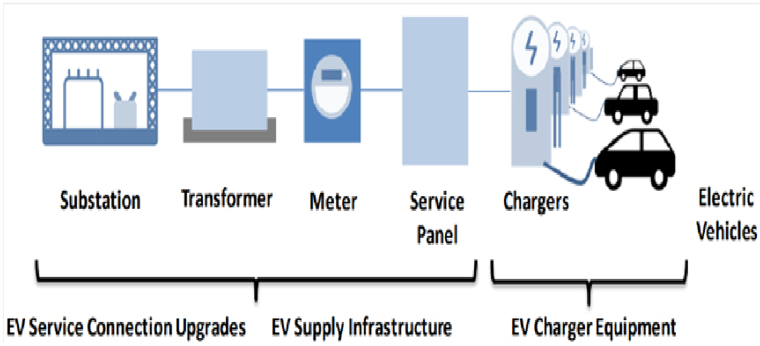

Figure 1.2: Illustration of EV Charging Infrastructure [20]

of the electricity power distribution system is designed inline with the highest expected energy demand, which happens only at specific times over the daytime [18]. Such concentration of demand can rise considerable load on the systems of local power infrastructure, if the demand of the energy happens all the time. The additional stress that forced by high EV spread is anticipated to lead to disastrous effect, such as phase imbalances, feeders' thermal limit breach, fuse blowouts, and transformer degradation if not dealt with effectively [18]. However, looking for alternatives to charge EVs at home will certainly help local distribution facilities in dealing with the extra load caused by EVs. Therefore, high voltage fast CSs are the best way to increase the satisfaction of EV users, as EV batteries can be recharged at least 12 times faster [19]. Many governments are investing in the deployment of public CSs. For example, California and British Columbia have set many goals to build several public CSs in different locations in order to facilitate the journeys of the EV users. Canada has also announced to build many CSs across the province. Fig 1.2 represents illustration of EV charging infrastructure.

Selecting the best CSs among all available CSs is also considered as another challenge to the EV users when they decide to charge their vehicle batteries during their journeys. So, the assignment of EVs to the optimal CSs is considered as an important factor that affects not only the adoption of EVs, but also the total energy consumption and the sustainability of transportation.

The motivation here is to design and develop EV charging management schemes, to address both problems; EVCS placement and assigning EV to the optimal CSs in urban environments.

1.3 Problem Statement

Over the past decade, there was a growing interest and bordering on enthusiasm for EVs. Meeting this projected demand on EVs will require an unprecedented building CSs in urban areas. Therefore, without accessible CSs that can charge EVs in a reasonable period of time, most EV drivers will be unwilling to purchase one, despite all the powerful perks for these vehicles. Moreover, the sparsity of current public CSs remains a major barrier to the diffusion of EVs. Finding the optimal placement of CSs in metropolitan environments[1], and also determining the best choice of CSs for EVs[2], will help in minimizing the time that EV requires to reach CS, the amount of energy the EV consumes to reach the CS, the congestion level on the roads, as well as the waiting time for EVs at CSs.

To address the problem of EVCSs placement and EVs assignment, many approaches have been proposed, considering different parameters and constraints. An approach for optimal CS development has been introduced in [21], focusing on modeling the road network. Running cost, and construction cost have been considered in [22] for optimal EVCS charging management and planning. A new technique has been proposed in [23] to find the most convenient CSs for EVs, taking into account the EVCS's service radius. A multi-objective EVCS planning scheme has been proposed in [24], in which the Electrical Grid (EG) has been represented by a transport network. In [25], a spatial–temporal model was introduced to study the impact of EV charging activities on EG, taking into consideration the origin–destination of EVs in the transport system. A Markov modeling scheme using dataset collected from the utilization of EVs driving pattern has been utilized in [26] to determine optimal EV charging conditions.

The existing studies of EVCSs placement have mainly focused on CSs and electric network [22, 23, 25, 26] or the transportation network [21, 24]. To the best of our knowledge, geographic characteristics associated with the locations of EVs and CSs, particularly, the difference in elevation between the locations of EVs and CSs, as well as the maximum number of vehicles that

[1] Chapter 3 introduces an energy efficient scheme to solve the problem of EVCS placement

[2] Chapter 4 and 5 propose two novel approaches to solve the problem of EVs assignment

should be assigned with each CS have not been considered in the literature in determining the optimal placement of EVCSs. These parameters have a significant impact on the amount of energy that EVs need to reach CSs, and also has an influence on the EV users' satisfaction.

The problem of assigning EVs to CSs has been investigated from different point of views in the literature. The majority of the present research is not user-centered, i.e., they did not mainly take into account the EV users' satisfaction. Moreover, they lack in considering the difference in CSs circumstances, such as the charging rate at CS, the connector technology, number of connectors, and more. Rather, they are transferred to the inverse criteria; they put EV consumers' convenience on the line in order to deliver utility-oriented services like energy cost reduction and CSs' power loss [27, 28]. There are two types of algorithms that are related: dynamic and static routing algorithms [29]. The underlying models in the first type are static; CSs locations and requests for charging from these CSs are given ahead of time to controllers or edge servers, which is going to be used for determining the optimal paths for EVs. In [30, 31, 32], where the roads was designed as a completed un-directed graph, CSs and the Points Of Interests (POIs) are represented by the vertices, and finally the edges of this graph represent the distances between the vertices (CSs and PoIs). On the other hand, there are various works used dynamic routing algorithms for charging EVs. In [32, 33], load balancing algorithms have been improved to reduce the overall queuing time at CSs. However, the presented algorithms did not take into account travel time, i.e., EV can be assigned to a remote CS even under only a light load to optimally distribute the load across all CSs. The authors of [34] assumed there was no queuing at CSs, i.e., all new charging requests would be rejected if the connectors in CSs were busy.

The following are the research problems that will be addressed and discussed in this thesis:

- Placing EVCSs in the best locations in the urban areas, considering the difference in the geographical characteristics, i.e., physical characteristics, of the study area, in terms of the difference in elevation between the location of EVs and CSs. Moreover, the maximum number of EVs that should be assigned with each CS.

- The assignment of EVs to CSs in metropolitan environments, considering the EV drivers' Quality of Experience (QoE). QoE is considered as a crucial factor to increase the EV users' satisfaction with the charging service that can be obtained from a particular CS. In chapter 4, we focus on improving the EV user QoE, taking into account the total time for charging the EV at CS, including the travel time of EVs to reach CSs, which is mainly depend on the distance between the locations of EVs and CSs, and also the congestion level (traffic condition) on the roads, the queuing time at CSs, the time required to charge the EV battery when connected to the charger which is mainly depend on the rated power of the chargers that are installed in CSs. Furthermore, the difference in charging rate at each CS will be taken into consideration, which is mainly affected by the electricity price offered by EGs to the CS owners. The electricity price that offered by EGs to CSs is different due to the load and power loss of these EGs.

1.4 Research Aims and Objectives

In this section, we will introduce the research aims that we are going to achieve in this work, and also the objectives that we will take in in order to fulfill our research aims.

1.4.1 Research Aims

Our work is based on the knowledge that the charging process of EVs is considered as a major challenge that we need to manage, in order to increase the EV users' satisfaction and spread the use of EVs in urban environments. Hence, this thesis intends to design and improve the charging management of EVs for metropolitan traffic environments, based on finding the optimal locations of the EVCSs and also determining the best choice of CSs for charging EVs in these environments, taking in to account the state of the art in this field in terms of the batteries and chargers technologies, and also the recent approaches that have been proposed in the literature.

1.4.2 Research Objectives

In this section, we summary the research objectives as follows, that we are conducting to fulfill the aims of this research:

- Identifying the best sites of public charging infrastructure to cover the transportation network and to improve the ability of EVs to successfully complete their journeys, considering the energy consumption of EVs to reach the locations of CSs.

- To find the optimal assignment of EVs to the available CSs in urban areas, considering the EVs users' QoE in terms of the total time of charging EVs, and the variation in the charging rate between charging stations, EV travelling cost, charging cost at CSs, and the EV's battery SoC.

1.5 Research Contributions

The novel research contributions of this thesis are summarized as follows:

- An energy efficient EVCS placement scheme is proposed. The unique feature of this scheme is an accurate realistic energy consumption model that aims to find the optimal placement of EVCSs taking into account the displacement of EVs towards CSs, as well as the difference in elevation between EV's location and the CS. The problem is modeled as Mixed Integer Linear problem (MILP) problem. A combination of the Genetic Algorithm (GA) technique and the Branch and Bound (B&B) algorithm have been utilized to solve the problem based on actual data of the elevations and coordinates of EVs and candidate CSs taken from Google Maps.

- A novel model for assignment of EVs to CSs in urban areas is proposed in this thesis. The proposed model considers the EV drivers' QoE in terms of the travel time of EVs to reach CS which includes the distance between them and the traffic congestion level on the roads, the queuing time at CSs, also the time needed to charge the EV battery when plugged into charger. Our model takes into account the influence of the urban traffic movement of EVs between adjacent zones on determining the optimal assignment of EVs to CSs in metropolitan areas. An optimization technique for selecting the optimal assignment of EVs to CSs has been introduced in this work. The problem is formulated as Mixed Integer Nonlinear problem (MINLP) problem. The GA technique has been utilized to solve this problem based on real world datasets.

- A RL-technique for assignment of EVs to the optimal CSs in metropolitan environments is proposed in this chapter. The proposed scheme considers the energy consumption cost that is resulted from the movement of EV towards CS (travelling cost), the total expected cost to fully charge EV at CS (total energy cost), and the EV battery's State of Charge (SoC). Q-learning algorithm has been utilized to solve this problem based on maximizing the cumulative reward of the EV during learning process by reducing the total cost of charging EVs. As a results of applying our proposed scheme, we minimize the load on the overwhelmed EGs, by assuming different rewards for the available CSs in the study area. The reward at each CS is determined based on the electricity price offered by electrical grids (EGs) to CSs, these prices vary according to the load and locations of EGs.

1.6 Thesis Outline

The first chapter of this thesis has introduced an overview and background, motivations, the problem statement and the contributions of the proposed research.

- **Chapter 2:** discusses background information on EVs, and charging technologies, then reviews the prior research works on finding the optimal placement of EVCSs in metropolitan environment. It also discusses and analyzes various approaches and techniques that have been introduced to solve the problem of assigning EVs to the best CSs. Besides, The challenges and benefits of the literature relevant to this research are detailed.

- **Chapter 3:** presents an energy efficient strategy to find the best locations of EVCSs in urban areas, that considers a combination of factors including displacement between the EV and CS, elevation difference between their locations and finite capacities of CSs.

- **Chapter 4:** introduces a novel approach to find the optimal assignment of EVs to CSs based on optimizing EV drivers' QoE. Our proposed approach considers the travel time of EV towards CS taking into account the distance between EV and CS, congestion level on the roads, queuing time at the CS and the time required to fully charge the EV battery when connected to any charging slot at a CS. The adjacency between the different zones in a city environment is also considered in order to minimize the potential number of CSs for each EV.
- **Chapter 5:** presents A RL-based Assignment Scheme for EVs to Charging Stations in metropolitan environments, aiming at minimizing the total cost of charging EVs and reduce the overload on EGs. Travelling cost that is resulted from the movement of EV to CS, the charging cost at CS, as well as the EV battery's SoC are considered. The proposed RL-EVAS approach will approximate the solution by finding an optimal optimal policy function in the sense of maximizing the expected value of the total reward over any and all successive steps using Q-learning algorithm, based on the Temporal Difference (TD) learning and Bellman expectation equation.
- **Chapter 6:** concludes the research work and its contributions. In addition, we propose a number of potential study subjects.

1.7 Research Publications

At the time of writing this thesis, the work has resulted in the following publications

1.7.1 Published

1.7.1.1 Conference Papers:

[1] M. Aljaidi, N. Aslam, and O. Kaiwartya, "Optimal Placement and Capacity of Electric Vehicle Charging Stations in Urban Areas: Survey and Open Challenges," in 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT). IEEE, 2019, pp. 238–243.

[2] M. Aljaidi, N. Aslam, X. Chen, O. Kaiwartya, and M. Khalid, "An Energy Efficient Strategy for Assignment of Electric Vehicles to Charging Stations in Urban Environments," in 2020 11th International Conference on Information and Communication Systems (ICICS). IEEE, 2020.

[3] M. Aljaidi, N. Aslam, X. Chen, O. Kaiwartya, and Y. A. Al- Gumaei, "Energy-efficient EV Charging Station Placement for E-Mobility," in IECON 2020 The 46th Annual Conference of the IEEE Industrial Electronics Society. IEEE, 2020, pp. 3672–3678.

[4] M. Aljaidi, N. Aslam, X. Chen, O. Kaiwartya, Y. A. Al- Gumaei, and M. khalid, "A Reinforcement Learning-based Assignment Scheme for EVs to Charging Stations," in 2022 IEEE 95th vehicular technology conference (VTC Spring), 2022. (Accepted)

1.7.2 Under review

1.7.2.1 Journals Papers:

[5] Mohammad Aljaidi, Nauman Aslam, Xiaomin Chen, Omprakash Kaiwartya, Neeraj Kumar, Yousef Ali Al-Gumaei, "QoE-based assignment of EVs to Charging Stations in Metropolitan Environments," IEEE Transactions on Vehicular Technology, 2021. (Under Review)

Chapter 2

Background and Literature Review

2.1 Introduction

This chapter discusses background information on EVs, and charging methods. Then, the latest approaches that have been proposed to solve the problem of finding the optimal placement of EVCSs will be discussed. It also highlights on the recent models that have been introduced to determine the optimal assignment of EVs to the available CSs in metropolitan areas. Various factors, such as the technological innovation in EV battery efficiency, battery capacity, as well as the new technologies for EV chargers play a major role in further spread of EVs in recent years in urban environments [10, 35]. Fig 2.1 shows the expectation of EV sales and distribution over the next 10 years based on Bloomberg New Energy Finance (BNEF).

In the US, EV sales increased by 80% from 2017 to 2018, and it is estimated that by 2030, the number of EVs in US will rise by about 18.7 million based on Institute for Electric Innovation (IEI) and Edison Electric Institute (EEI) [36]. EVs are powered by efficient electric motors powered by electricity from batteries that can be recharged from the CSs [37]. With the increase in EVs, there is an increasing need for public CSs in cities. To fulfil the energy requirements of this number of EVs in the US, approximately 9.6 million CSs are required [38, 36]. Fig 2.2 shows

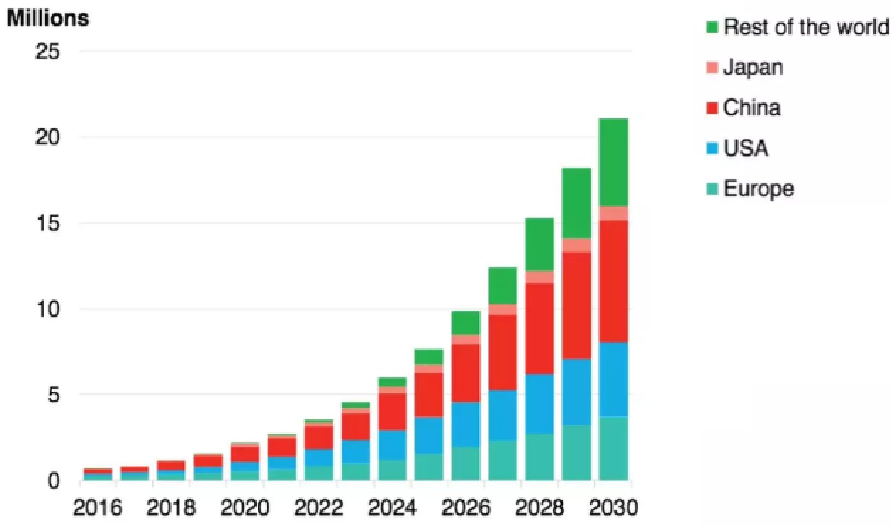

Figure 2.1: EVs Sales Expectation [9]

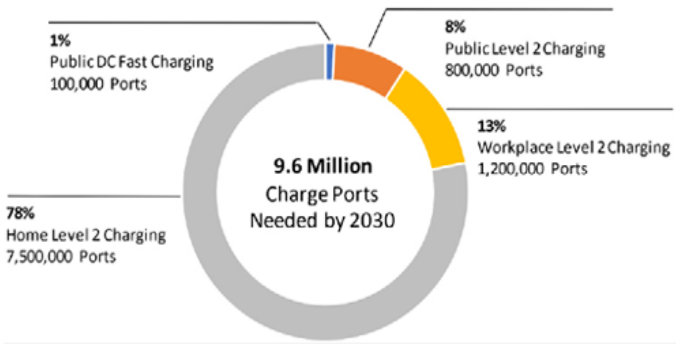

Figure 2.2: EVCS in the US in 2030 Based on EEI/IEI forcast [36]

the EEI/IEI forecast of the number of CSs in 2030 in the US. It should be noted that the development of CSs requires significant expenditures, and therefore this requires a comprehensive study and planning to find the best places for these CSs, especially inside cities. Fig. 2.3 shows the global cumulative CS deployment over the years 2014 – 2020 per the report by IHS Automotive [39].

CSs can be placed at different locations, such as parking lots [40], street parking [41, 42], as well as in driveways and existing gas stations [43]. Depending on the technology of the CS connectors, an EV may take from less than twenty minutes to several hours to be fully recharged

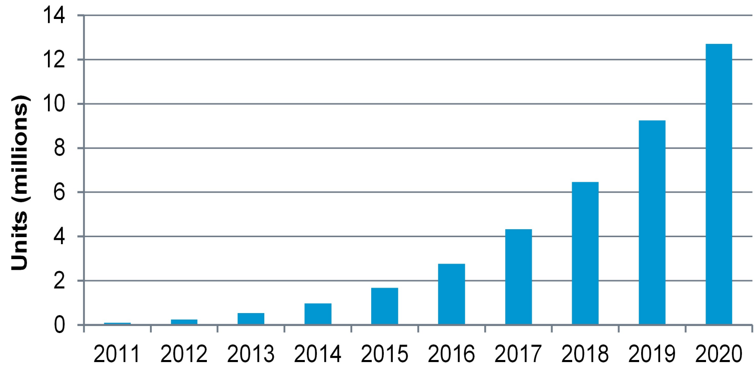

Figure 2.3: The Global Cumulative CSs Deployment Over The Years 2014 – 2020

[44, 45]. The random placement of EVCSs adversely affects the selection of CSs, EV users' convenience, layout of the traffic network and the electric grid load [15]. In the event that CSs are not placed in suitable places and are not properly distributed in urban areas, the fluctuation in power problems and voltages arises [46, 47, 48, 49]. EV charging process increases the demand for the power grid load, which in turn leads to an increase in peak demand, and a decrease in margin reserves [50, 51]. Numerous studies are being conducted across different countries of the world for developing EVCSs. Hence, the deployment of optimally located CSs in cities is the first challenge that essentially needs to be encountered to increase market penetration of EVs and achieving a sustainable mobility system in urban areas.

In addition to solve the problem of finding the best places for CSs insides cities, finding the optimal assignment of EV to CS [52] is considered as another factor that must be taken into account to encourage people to have EVs rather than ICEVs, and also to minimize the impact of EVs on the power grid. In recent years, the research in EVCS placement and EV assignment have received much attention from researchers. Various parameters and constraints have been investigated and analyzed from different perspectives in the literature.

2.2 Electric Vehicles

The term “EV” refers to any vehicle that powered by an electric motor [53]. Electric buses, electric trains, electric boats, and electric cars are examples of EVs. In this work, the term “EV” refers only to electric automobiles or vehicles that are powered by electricity source. The story of EVs began long before ICEVs were introduced. This goes back to the 1830s when the first EVs were powered with non-rechargeable batteries [53]. Electricity is considered as the best source of energy for EVs’ motors. EVs, on the other hand, have not had the same level of success as ICEVs, which they often have substantially longer ranges and are easier to refuel. EVs occupied only a small part of the vehicle market before. EV technologies are relatively new. EVs are now gaining popularity due to many powerful perks, such as zero emission, efficient, no dependency on fossil fuel, relatively silent, and more. Research on EVs has been focused on developing techniques for an efficient charging system, increasing vehicle range and efficiency as well as reducing the price. Therefore, various types of EVs were developed along with the improvement on batteries technologies, control technologies, charger technologies, and electronic equipments.

EVs can be divided into three main types: Hybrid Electric Vehicles (HEVs), Plug-in Hybrid EVs (PHEVs) and All-Electric Vehicles (AEVs) [54, 55]. AEVs are equipped with fully electric motors that are powered by electrical sources. AEVs can be further divided into Battery EVs (BEVs) and Fuel Cell EVs (FCEVs) [56]. Extended Range Electric Vehicles (EREVs) extends the range of driving by adding an Auxiliary Power Unit (APU) which is called Range Extender (REX) based on BEVs [57]. REX supports a short term solution to eliminate the driver’s mileage anxiety [58, 59]. Hence, it was extensively applied in the public transport sector, and it shows a promising future [60, 61]. Fig. 2.4 describes the classification of different types of vehicles. The power flow from the energy source to wheels in EVs is explained in Fig. 2.5.

There are many categories of EVs as mentioned earlier. However, five of the EVs, so far, were the most common categories in research: HEVs, BEVs, PHEVs, FCEVs, and EREVs. Since

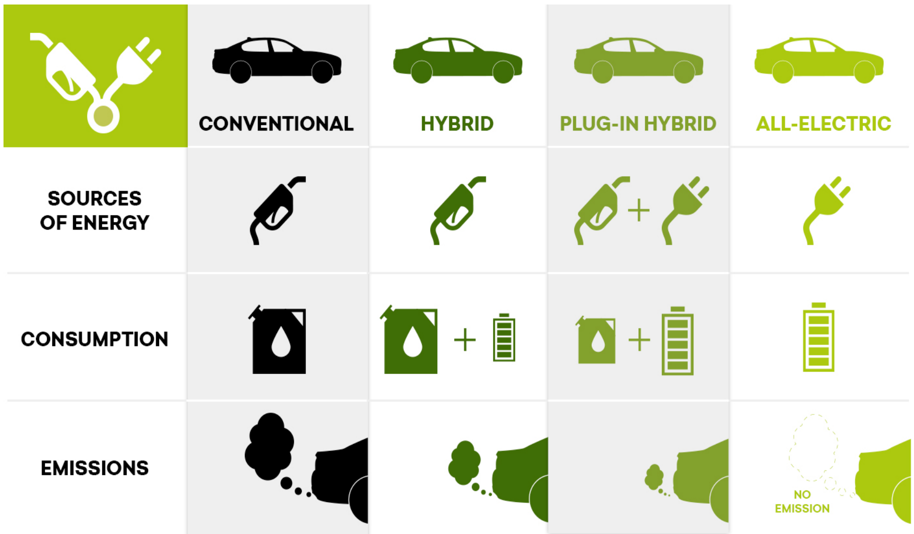

Figure 2.4: Classification of Different Types of Vehicles [62]

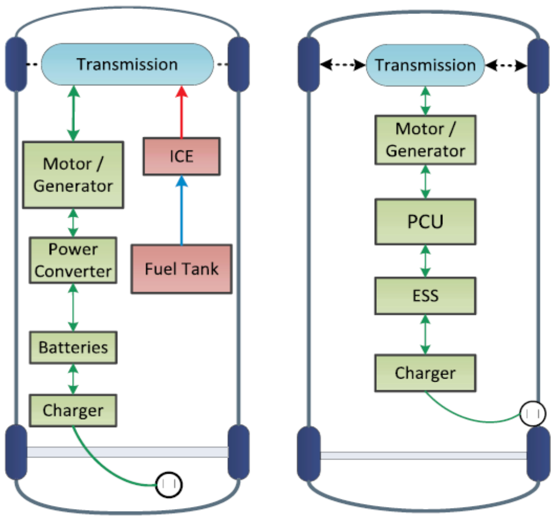

Figure 2.5: Power Flow in different types of EVs (a) PHEV, (b) BEV [56]

the innovation of EVs has gained great attention recently, it is expected that there will be new categories instead of just these categories in the near term.

2.2.1 Hybrid Electric Vehicles

HEVs refer to vehicles that use a combination of an electric motor and internal combustion engine, which make these vehicles more efficient than ICEVs in terms of energy consumption level, with nearly half the power consumption [63]. Furthermore, CO_2 emissions are remarkably reduced because of the regenerative braking technology. The architecture can even contain more energy sources, with a huge number of differences [53]. HEV runs almost like ICEVs, but with higher saving in terms of the energy consumption due to the design of its electric motor. In 2019, HEVs represented above 55% of alternatively powered vehicles sold and more than 6% of new vehicle registrations in the EU [64, 65]. The improved environmental and energetic advantages of HEVs are because of their operating system that incorporates an electric motor and an internal combustion engine to propel the car, and a battery to store the energy produced either by regenerative braking or by internal combustion engine [66]. However, this kind of vehicles generate sporadic high GHG emissions when the internal combustion engine is restarting, because of a combination of various circumstances such as: vehicle speed, driving conditions, ambient temperature, road grade, HEV system design, and driver aggressiveness [67, 68].

2.2.2 Battery Electric Vehicles

BEVs refer to vehicles that use electric motors operated by chemical-energy stored in the cells of the rechargeable battery [69], with no secondary source of energy, such as hydrogen fuel cell, internal combustion engine, etc. BEVs powered by electric motors and motor controllers rather than internal combustion engines for propulsion. They derive all power from the packs of the battery packs and thus have no fuel cell, fuel tank, or internal combustion engine. BEVs include but are not limited to motorcycles, scooters, bicycles, skateboards, watercraft, rail cars, forklifts, trucks, buses, trains, and cars [70]. BEVs do not produce any GHG emissions vehicles, as they only use electric motor [71].

2.2.3 Plug-in Hybrid Electric Vehicles

PHEVs refer to any kind of vehicles, that operated by both internal combustion engine and electric motor for propulsion. PHEV is considered as a hybrid-technology includes BEV and HEV technologies. PHEV has larger battery than HEV, which in turn helps to travel longer distances. PHEV can recharge its battery using electrical network directly. Both different energy resources give PHEV a high level of flexibility in the use of energy [72].

2.2.4 Fuel Cell Vehicles

FCEVs use hydrogen gas to power an electric motor. The basic standard of FCEVs is just like the battery electric vehicles. However, the chemical propulsion force is produced from the fuel mixture, usually oxygen and hydrogen instead of batteries. Most FCEVs are classified as zero GHG emissions vehicles, that emit only heat and water. As compared with ICEVs, hydrogen vehicles concentrate pollutants at the hydrogen production site, where Hydrogen is usually derived from reconstituted natural gas. Like other types of EVs, FCEVs can utilize idle-off mode, which turns off the fuel cell in traffic or stop signs. In specific driving modes, regenerative braking is employed to charge the battery and capture lost energy [73].

2.2.5 Extended Range Electric Vehicles

EREVs refer to vehicles that use batteries for propulsion, the same as BEVs, coupled with a little on-board generator, that is employed to charge the batteries and increase the range of the EV in order to overcome the short range of BEVs. The on-board generator can be supplied by different types of fuels: fuel cells, diesel, gasoline, or even ethanol [53]. As shown in Fig. 2.6, EREVs often powered by a simple chain hybrid powertrain configuration [74].

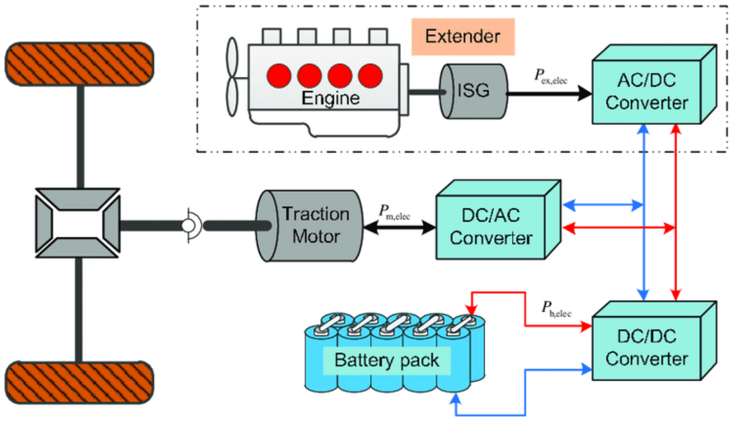

Figure 2.6: EREV powertrain configuration and power flow [74]

2.3 Electric Vehicle Charging Facility

To enhance environmental sustainability, reduce the global fossil fuel consumption. Many countries are going to electrify their transportation systems in the future of their smart city plans, so the number of EVs running in a city will grow dramatically. CSs will be considered as the main source of energy to charge EVs' batteries. EVs users can charge their vehicles' batteries at home. However, charging EVs at home is not a practical solution, as users of EVs must have a home charger installed where they park their vehicles. In addition, to fully recharge EVs takes a long time. Therefore, high voltage fast CSs are the best choice, as EVs' batteries can be fully recharged at least 12 times faster than household charging. To increase EVs users satisfaction, these CSs should be wisely spread in urban areas and also should be placed in optimal locations, so that EVs' users can easily recharge their vehicles' batteries during their trips. Privately and publicly funded projects in CSs infrastructure construction are increasing rapidly. New charging technologies, market tariffs and government policy are accelerating the deployment of public CSs. Moreover, new technologies of rapid chargers play a major and crucial role in increasing charging speed of EVs. Fig. 2.7 shows an example of rapid chargers types in the UK.

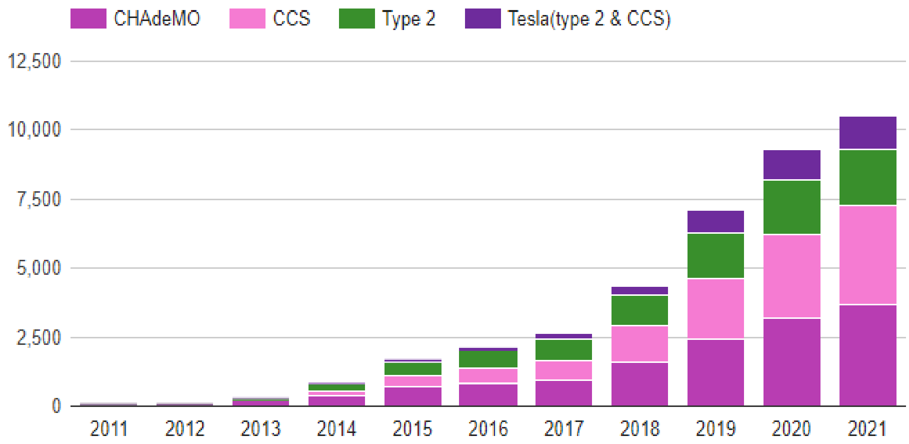

Figure 2.7: Total Rapid Chargers in the UK, Updated: 17 June 2021 [75]

2.3.1 EV Charging Methods

The methods of charging EVs can be categorized into two categories: destination charging technique and on-route charging technique. The first technique includes workplace charging, parking lots charging, and home charging. Moreover, destination charging technique is usually compatible with distributed charging points in public or private areas. The second technique, is usually satisfied by fast CSs and Battery Swap Stations (BSSs), which requires installation of high-power fast chargers in metropolitan environments, where the availability of power infrastructure and transportation may be misaligned [76]. Furthermore, on-route charging enables the adoption of lower weight battery electric buses with smaller batteries, which in turn leads to an increase in battery electric buses energy per mile efficiency and a reduction in replacement costs and maintenance [77]. EVs Wireless charging technique is also considered as an effective on-route charging method that enables EVs' users to charge their vehicles' batteries using special lanes when passing through them, which reduce the waiting time for EVs' users inside CSs. The destination charging technique is the most common one for EVs. However, battery swapping method and fast-charging are still considered as crucial complementary facilities for charging EVs inside cities, increasing flexibility of long-distance driving demand, as well as the driving experience.

Table 2.1: Classification of EV chargers

	Level 1	**Level 2**	**Level 3**
Charger Topology	On-borad	On-borad	Off-borad
Typical Use	Home	Public	DC Fast
Typical Power	2 kW	20 kW	100 kW
Typical Voltage	AC	AC	DC
Charging Time	4-11 h	1-4 h	<20 min
Connector	SAE J1772	SAE J1772	CHAdeMo CCS COMBO 2
Pros	Low-installation cost Low load on electric infrastructure	More efficient than Level 1 in terms of time and energy Different styles	Reduced charge time
Cons	Charging is slow	Installation cost is higher than Level 1 high influence on electric Utility	Very expensive installation cost More load on electric grid

2.3.2 EV Charging Levels

EV charging equipment is mainly classified into three levels, based on charging power and the nature of service: Level 1, Level 2 and Level 3. Different types of EV chargers have different service modes, technical parameters and target customers which initiate different charging behaviours of EVs. The characteristics of different EV charger technologies are compared in Table 2.1.

2.3.2.1 Level 1 Charging

The first level of charging EV is the basic Level 1 charger. A Level 1 charger is simply charging from a standard 120V outlet, which only supports about 4 to 5 miles per hour of charging. This charging level is sufficient for some people, as they do not need to drive long journeys. EV can be left plugged in for several hours to replenish the energy that has been consumed during the day. PHEVs have smaller battery packs than BEVs and might be better candidates for Level 1 charging. It is also worth mentioning that Level 1 charging is mostly limited to Europe; North, Central and South America, because many countries in the world use 220 volts electric supply for their PHEVs [78].

2.3.2.2 Level 2 Charging

Level 2 charging essentially needs in a voltage supply over 200 volts, and will charge EV at a rate between 20 to 97 kM of range per hour, depending on the charger's technology (rated power), and the amount of power EV can accept [78]. This type of chargers is designed to charge EVs with directly plugged in to the Electric Vehicle Supply Equipment (EVSE). It can also be connected to a single-phase AC voltage with utmost output power of 14.4 kW [79].

2.3.2.3 Level 3 Charging (DC Fast Charging)

DC charging is available at a much higher voltage and can charge some PHEVs up to 800 volts. This allows for very quick charging. However, DC fast CSs are very expensive compared to the other types of EV chargers, and the required current is not always readily available, so this type of chargers are not used in residential installations. A single DC fast charger can cost around $50,000 to install and configure. Therefore it is not used for individual residences. EV user can charge some PHEVs to %80 of the battery capacity in a charge for 20-30 minutes [78].

2.3.3 EV Battery Technologies

The main parts of the electrical structure of EVs are battery chargers, power converters, battery packs, electric motors, and controllers. The diversity in the key components affects the performance of EVs and also the charging process of EVs [18]. Some EVs with comparable designs have different electrical configurations. For example, the electrical structure of a PHEV is divided into two types, series and parallel. Each type has its own advantages and disadvantages [18]. A wide range of PHEV architectures is accompanied by a wide range of battery technologies. Thus, the usefulness of these technologies, their varied qualities, and the specifications required for their use must be considered.

In BEV, the battery is the only source of energy and has the largest volume, weight, and cost over all the components of EVs. To match the vehicle's requirement, the battery must have a large

Table 2.2: Power and Energy Density for various Battery Technologies[80]

	Lead-Acid	**Ni-Cad**	**Ni-MH**	**Li-ion**	**ZEBRA**
Power-Density (W/kg)	75-300	220-550	220-1600	875-2050	160
Energy-Density (Wh/kg)	25-35	45-60	60-70	65-160	130

power capacity. As mentioned before, PHEVs have more than one source of energy: electricity and fossil fuel. In order to increase the efficiency, the weight and volume of the batteries for PHEVs must be kept low. Despite the current level of sophistication in battery technology, integrating it to the applications of EVs is considered as a critical challenge. Long-distance EV travel necessitates a battery with sufficient energy and ability to support high propulsion power. For example, for a one-way range of 335 kilometres, a typical family automobile requires a battery capacity of around 48 kWh. Table 2.2 summarises the amount of power and energy density that various battery technologies can offer [80].

Among all current technologies of batteries, a lead acid batteries are considered as the most mature technology, thanks to its low cost. However, the most significant disadvantage is the short life cycle. Nickel Metal Hydride Battery (NiMH) is suitable for HEVs and has a high specific capacity. NiMH is also utilized in both BEVs and PHEVs. However, self discharge is the main challenge of this technology, when the vehicle is not used [80]. Lithium-ion battery has very high energy and power density, and it is considered as the next technology of PHEV battery technology [18]. Increasing battery size while reducing costs is a major obstacle and challenge for companies working in the battery industry [80]. The ZEBRA battery operates at a high temperature of around 300°C. However, the energy density of this type of battery is very high compared to the other types of batteries. One of the disadvantage of this kind of battery, is that it requires an energy source to heat up, when it is not in use.

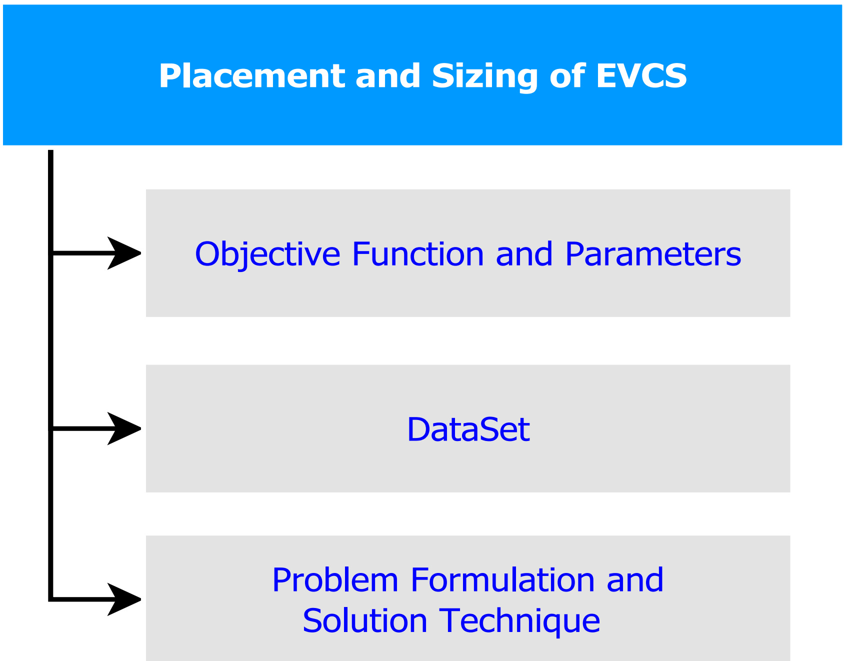

Figure 2.8: Taxonomy of CS Placement

2.4 Placement and sizing of CSs

The problem of finding the optimal placement for EVCSs has been investigated from different perspectives in the literature, i.e., objective functions and the parameters that have been introduced in the previous works, problem formulation, solution techniques, and the data set that have been incorporated with the proposed approaches, Demand Side Management (DSM), etc. Fig. 2.8 shows the proposed taxonomy that have been used in the literature in this area.

2.4.1 Objective Function and parameters

Various objective functions and parameters have been introduced to solve the EVCS placement problem. Time Cost, power loss, user behavior, and energy cost are some of the parameters that have taken into consideration with the proposed objective functions in the literature as indicated in Fig. 2.9. Moreover, several constraints have been used in the previous works. This section investigates the most recent approaches that have been proposed in different research works in order to find the optimal placement and sizing of CSs in urban areas, in terms of the objective functions, parameters, and system constraints that have been proposed.

2.4.1.1 Time Cost

Time cost refers to the travel time of the EV user to arrive CS location, the queuing time (waiting time) and the charging time of EV battery inside CSs. In [81, 82, 83, 84], travel time has been taken into account in order to minimize the trip time of EVs users to reach CSs. Different parameters have been incorporated in order to calculated the travel time, such as the distance that EVs moves from its current position where the charging decision was taken until reaching CSs for charging. Moreover, traffic condition has also been considered, as it has a major influence on the travel time to reach CSs. EV drivers' charging activities to capture the total cost of charging EVs have also been considered in [81]. However, charging time that is required to charge EVs, and also queuing time inside CSs have not been taken into consideration in [82, 83].

Queuing time (waiting time) inside CSs, and additional parameter for balancing the level of service for each individual CS were investigated in [81, 85, 86], in order to minimize the total time of charging EV batteries. Although some parameters that have an influence on reducing the waiting time at CSs were considered in these studies, there are several parameters that were not considered in these studies, such the technology and number of the charging devices inside CSs.

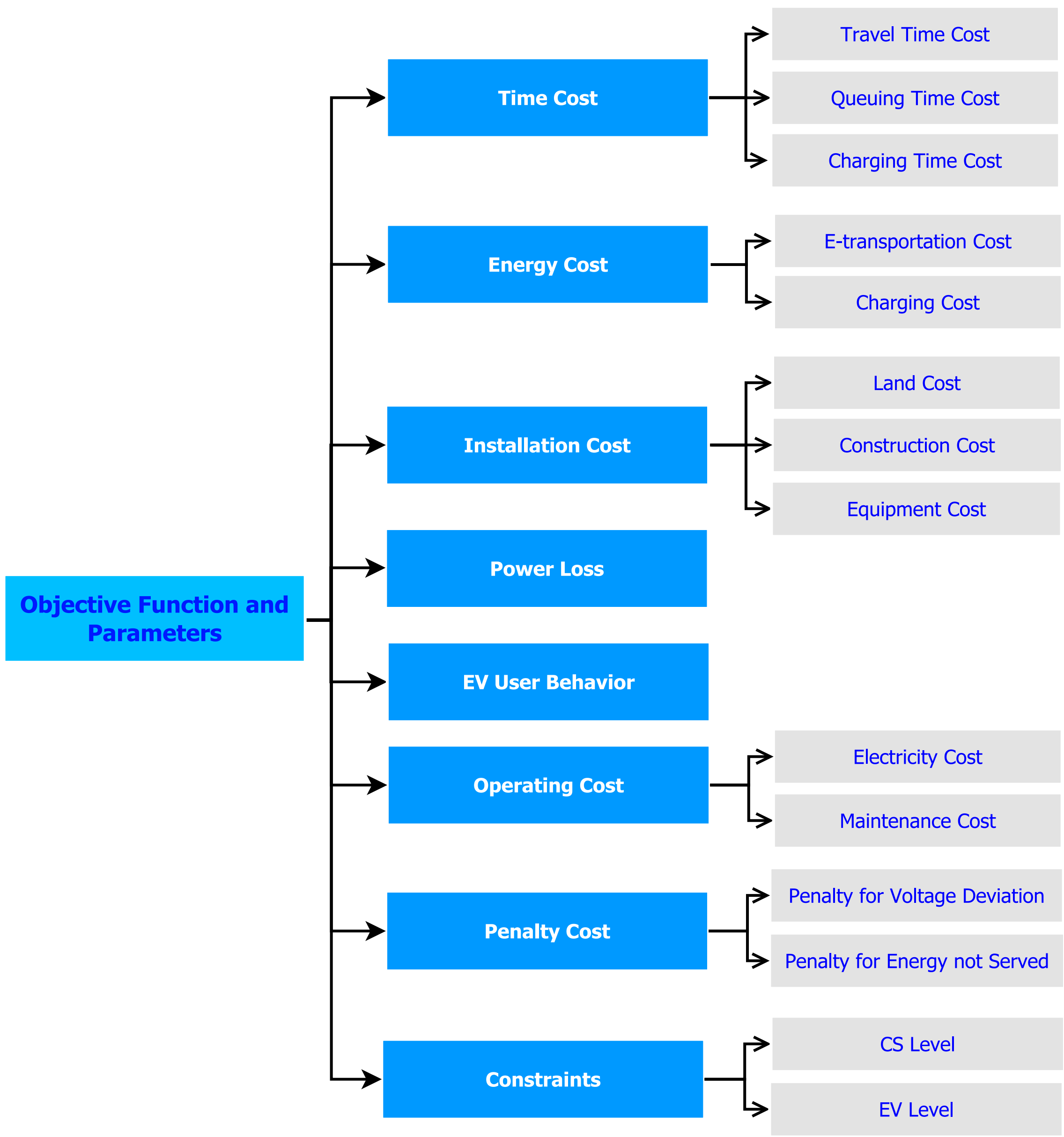

Figure 2.9: The Objective Functions and Parameters used to solve the EVCS Placement Problem

2.4.1.2 Energy Cost

There are many parameters that have an influences on determining the optimal placement of CSs in metropolitan environments in terms of energy cost, such as traveling cost that are resulted from the movement of EVs towards CSs (transportation energy cost), and CSs' geographical factors such as the locations and elevations of CSs. In this section, we will discuss the previous works in terms of the energy cost and show the parameters that have been considered in the literature in order to minimize the energy cost to find the optimal locations of CSs in urban areas.

In [87, 88], transportation energy that is resulted from the movement of EVs to CSs has been investigated. Several parameters have been considered to minimize the travel energy of EVs to reach CSs, such as the distance between the EV users residence and CSs and also between the working places of EV users and CSs, traffic condition on the route towards CSs. Parasitic power losses at the EVs' batteries (heater, light, radio, etc.), and environmental conditions such as weather condition and road service have been also taken into account in [87]. EVs users' behavior in terms of the driving intention and driving style were taken into consideration in [89, 90, 91]. However, the proposed studies did not consider the difference in elevation between the locations of EVs and CSs in their energy consumption models.

2.4.1.3 Installation Cost

Installation cost of CSs has been considered in several works in the literature. In [92, 93, 94, 95], different schemes have been proposed to solve the problem of finding the optimal placement of CSs based on minimizing the installation cost of CSs. Several factors that have a great impact of the installation cost of CSs were investigated, such as the cost of the equipment that are required to be installed at CSs, The price of the land on which the charging stations will be built.

In the literature, the researchers investigated the land cost from two different perspectives, the cost of the area that is required to place charging connectors and also the area that is needed for EVs inside CSs including the waiting area for EVs. In [92], the authors assumed that the area which is required for each charging connector is 25 m^2 as in [96]. In this study, the number and charging rate of charging connectors that are installed at CSs, and also the cost of the feeder that is used to connect CS with EG have been considered as well.

2.4.1.4 Power Loss

Minimizing the power losses for EGs, is one of the most important factors to be taken into account in order to find the optimal placement of CSs. In [97], a new model for EVCS placement has been proposed. In this model, the authors demonstrated an optimized combination of the three types of EV chargers (Level 1, Level 2 and Level 3) for efficiently managing the EV load, minimizing the power loss, and distribution transformer loading. The variation of electricity load that is resulted from installing CSs has been studied to minimize the power losses of EGs [98]. To achieve this, the authors analyzed the load on EG during the day, then they extended the problem to an hourly analysis considering all the day.

In addition to minimize the power losses of EG. Other operating parameters related to CSs, such as voltage stability of CSs, preventing CSs overflows and maximize their Quality of Service (QoS) have been taken into account in [99, 100]. Moreover, EVs users' convenience was also simultaneously considered in both presented approaches.

2.4.1.5 EV User Behavior

The EVs users' charging preference, and driving patterns have been considered as important parameters that affect the decision of selecting the optimal locations if CSs. A methodological framework to consider individual preferences of EV users has been introduced in [101, 102], . In contrast to the most recent studies, the authors of this paper considered the individual preferences of EV users, such as brands, travel distance, and social attractions. Therefore, A consumer behavior of individual EV user based model was applied to predict the CS charging demand using a nested logit model was used in [102]. Moreover, The crowdedness to determine the best locations for CSs was also considered in [101], the authors considered the number of expected

EV users at EVCSs as one of the individual preference factors, as it is possible that EV users would prefer a CS that has more chargers than a closer CS but has fewer chargers available. A nested logit model was also used to analyze the charging preference and behavior of the individual EV user in [103]. This work is an extension of work originally presented in [102]. An optimal placement policy for each EV charging service provider has been obtained using analyzing strategical interactions through a Bayesian game. To derive the optimal placement policy, the authors considered both the electric power network graph and the transportation network graph.

EVs charging strategies has been investigated in [104, 105]. The authors in both studies used different techniques to capture the equilibrated charging behaviors, route-choice of EV users, and characteristics of EV users' daily trips in order to maximize EV users'existing activities. EVs' waiting time at CSs has also been considered, as it is affected by EVs users' charging behavior. Additional factors, such as range anxiety, home and public CS availability, and the energy consumption rate of remaining trips based on the EVs users driving pattern, charging level and travel behavior was analyzed in [106]. A deterministic process for EV charging selection was introduced to simulate the charging selection behavior and preference of EV users as shown in 2.10. The behavior of charging choice for EV users's and range anxiety, have been taken in to account in [107]. In this study, the authors have built a CS location model to solve the problem of finding the optimal locations of CSs, and solved the problem using Tabu search algorithm.

2.4.1.6 Operating Cost

CSs operating cost, such as maintenance cost, adding new equipment cost, etc. are very important parameters that should be investigated with many other factors when selecting the optimal locations of CSs. The main objective of the proposed approaches in [108, 23, 86] is to minimize the operating and investment cost of CSs' owners. The CS operating cost has been determined based on the annual maintenance of voltage transformers, charging devices, and other devices

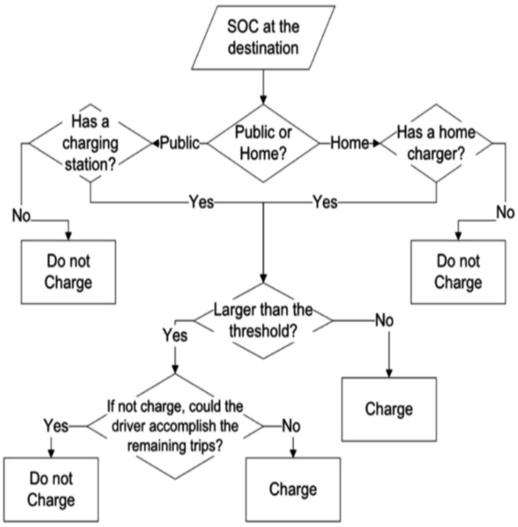

Figure 2.10: Deterministic Process of EV Charging selection behavior [104].

that can be used in EV charging process. Whereas, The investment cost was determined based on the changing the technology of the existing feeder, installing new ones, or finding another electricity supplier.

Maximizing the profits of CSs has been considered in many other studies, rather than minimizing the operating cost of CSs. In [109, 110], a profit-maximizing EVCS placement was proposed. CS operating cost, maintenance services equipment have been considered. The introduced model in [109] permits for congested-station and congested-travel feedback into travelers route options under elastic demand and EV users' CS options, as well as charging rate elasticity for EV charging users. The EVs' QoS requirements according to the operating cost and the EV arrival rate was considered in [110].

2.4.1.7 Penalty Cost

In [111, 112], the objective functions have considered the penalty cost that can be resulted by the penalty for voltage deviation on the buses of the distribution system, this penalty should be paid by the utility per unit voltage deviation and can be calculated based on the voltage and the operating voltage of the investigated buses of the distribution system. Additional penalty has been considered in [111], which is resulted by the energy not served. Moreover, The operating parameters of the distribution networks, such as voltage reliability and profile were taken into account by imposing penalties for violation of the safe limits of these parameters.

In [113], a simple and novel scheme has been introduced to handle the problem of EVCS placement in transport and distribution networks, taking into account the total cost of CSs placement, as well as penalties for breaking grid restrictions. The operational parameters of the distribution grids have been considered by enforcing penalties for violations of the safe limit of these parameters. Additional penalties, i.e., average energy not served and voltage deviation have also been taken into account in the proposed scheme.

A flexible penalty contract for the security issues of voltage to be used as a direct coordination measure was proposed in [114], which was designed to induce the operators of charging stations not to compromise the voltage situations of the distribution network. In this scheme, the distribution network operators noticed hourly the recommended charging power that did not cause voltages below the lower threshold for the charging station operators, and imposed a penalty charge for exceeding the maximum power as an extra to the current electricity tariff, such as the time-of-use rate.

2.4.1.8 Constraints

In [115], the optimal sizing and siting of EVCSs have been determined based on both power grid and transportation constraints. Regarding the power grid constraints, the proposed model considered the voltage amplitude of each distribution network, and the load factor on transmission line. While distribution network constraint, the traffic flow captured by CSs and the service radius constraint, and the user constraint have been considered in the transportation constraints. Different constraints include; user demand, EVCS service range, transportation cost, CSs investment cost, and EV users' convenience have been considered in [116].

While, charging serviceability, power flow, voltage limits, current flowing in each feeder, budget limits are the constraints that have been considered in solving the EVCS placement problem in [117]. CS charging serviceability need to be higher or equal to the minimum power demand of the study area. While the power flow, voltage limits and line current should respect the constraints of the electric network, maximum rated current of the line, and operation safety, respectively. In the implementation part these papers, the authors have incorporated all of these constraints simultaneously in order to ensure that they were all satisfied. In the literature [118, 119, 120, 121], the distribution network operator directly tackled the charging schedules of EVs taking into account the distribution network constraints to follow the reliable and efficient of the distribution network operations. The budget cost of CSs in terms of the type of CSs, and locations has been also taken into account in [122].

2.4.2 Data Set

In [123], parking information from over 30,000 personal-journeys records has been considered in this work to solve the problem of finding the optimal locations of EVCSs in Seattle's downtown, Washington state, USA. Various types of dataset have also been taken into account in this work, such as job locations, trip attributes, population densities, and other variables available in travel surveys. The idea of this paper in to determine the parking slots that received a huge number of EVs to place charging stations in the same area. The models that were developed in this paper are generalizable to different types of datasets available for any region, and can be utilized to make more decisions on CSs locations around the world.

In [124], a method for selecting an optimal EVCS location in expanding charging facilities to activate EV distribution has been proposed. The data of population, number of guest facilities, and work force people which are determined to affect demand for quick charging stations were considered. Machine learning techniques such as the random forest, elastic net, extreme gradient boosting, and support vector machine were applied to examine the influence of the dataset that has been used in predicting the optimal locations of CSs.

In [125], a novel algorithm to plan new CSs, and estimate charging demand has been implemented in this work based on analysis and observation of charging mobile application usage data, which has been developed by the pile usage data of the Beijing's official charging pile network and the EVs public services platform of Beijing.

In [126], a mathematical modeling approach for enabling EV corridors on a real-world transportation network has been proposed for the first time. The methodology that was proposed can be used in line with the GIS-based techniques to help in the decision making process for complex station location difficulties, by introducing quantitative analysis capabilities of numerous possibilities, which requires multiple stakeholder input and expert expertise. Furthermore, the authors have investigated the advantages of proposing new models among possible solutions, such that a solution with more available CSs on the corridor is selected rather than fewer CSs on the corridor.

In [127], an optimal configuration scheme of fast CSs has been proposed, taking into consideration a combination of dataset of traffic road networks, distribution network, and GPS at the same time. The optimal number and sites of CSs have optimized based on analyzing the charging demand of the investigated area for 30 days.

2.4.3 Problem Formulation and Solution Technique

This section shows how the EVCS placement problem has been formulated and solved in the recent literature. In [81], the EVCS placement problem has been formulated as a bi-level optimization problem. Then, the bi-level optimization problem has been converted into a single level optimization problem. Fig. 2.11 shows how the proposed approach has been formulated. An Optimizing eleCtric vEhicle chArging statioN (OCEAN) algorithm was proposed in order to compute the optimal placement of CSs. Due to the scalability issue of the proposed algorithm, the authors furthermore presented a heuristic algorithm with Continuous variables to cope with large scale real world problems. With real world datasets, the experimental results showed that

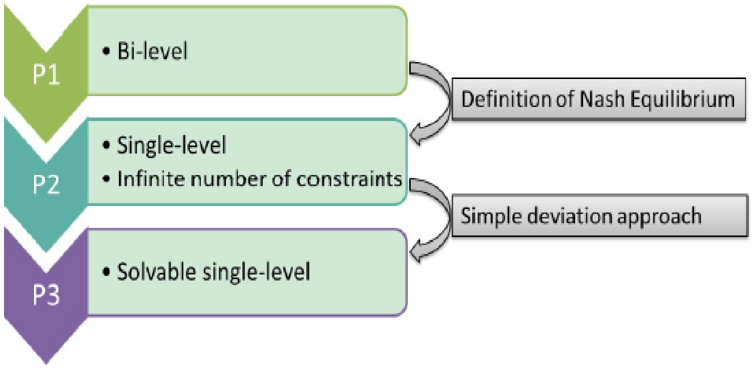

Figure 2.11: Approach Optimization Flow [81]

the proposed approach solves an effective allocation of CSs and outperforms baselines.

In [128], The planning and placement problem of EVCS was formulated as a Mixed-Integer Nonlinear programming (MINLP) from the distributed companies point of view. A co-evolutionary genetic algorithm has utilized to determine the optimal locations of CSs.

In [129], a fuzzy multi-objective function was formulated to find the optimal placement of CSs and Distributed Generations (DGs), considering the objectives of improving desired Distributed Generations, substation power factor, penetration and distribution system performance in terms of voltage profile improvement and loss reduction. The fuzzy multi-objective function was optimized using Grasshopper Optimization Algorithm (GOA) to obtain the optimal locations and sizing of CSs and DGs.

In [130], the EVCS placement problem has been formulated as a multi-variable optimization problem including a number of non-linear objective function and system constraints. To solve the EVCS placement problem, the authors have presented an improved GA adapted to the proposed approach by developing a new heuristic technique to generate initial solutions. Moreover, they have modified the GA's operators (crossover and mutation) to improved the solutions. The results provided by experimentation showed that the proposed algorithm in this paper provided better results compared to the several efficient algorithms in the literature.

In [131], the EVCS placement problem was formulated as five realistic charging objective functions, and then exploited these objectives to build the acceleration algorithms for the MINLP EVCS placement problem. The corresponding algorithms are named Lazy Greedy with Effective Gain (LGEG) and Lazy Greedy with Direct Gain (LGDG), respectively. Both algorithms has been scaled well to the arbitrary size of road networks. Moreover, the authors employed a queuing technique called Erlang-Loss system to determine the optimal Charging placement, which is capable of reducing the gap between the constrained supply of charging resources and growing complexity of charging demands. The experimental results with real data sets shows that, compared with the state-of-the-art methods, the proposed approach revealed better efficiency and effectiveness, and it offered a potent solution to the planning of charging stations for EVs with large-scale datasets in reality.

In [132], an effective charging planning system for EVCSs has been proposed. In this paper, the authors first introduced EVCSs planning problem, and proved the NP-hardness of this problem. Then, they have formulated as Markov Decision Process (MDP). A Deep Reinforcement Learning (DRL) algorithm has been proposed in this work to solve the MDP problem.

In [133], a Deep Q-Network (DQN) Reinforcement Learning (RL)-base model with a supervised-learning based demand model has been implemented for selecting the optimal sites for EVCSs. The authors used a Gradient Boosting model to predict EV charging demand at existing CSs based on POIs and traffic data for selecting areas in the state of New York. The results showed that the proposed model outperformed the other proposed supervised learning models in previous works.

In [134], the Lagrangian Relaxation (LR) approach was used to create and solve a region-based bi-objective mixed integer linear mathematical (MILM) model for CSs locations problem. The total number of connector installed at each CS, and their technologies have been considered in this study. The presented work examined the issue from two different perspectives; social and economic. The aim of this article is to minimize total costs as well as the dissatisfaction of EV drivers.

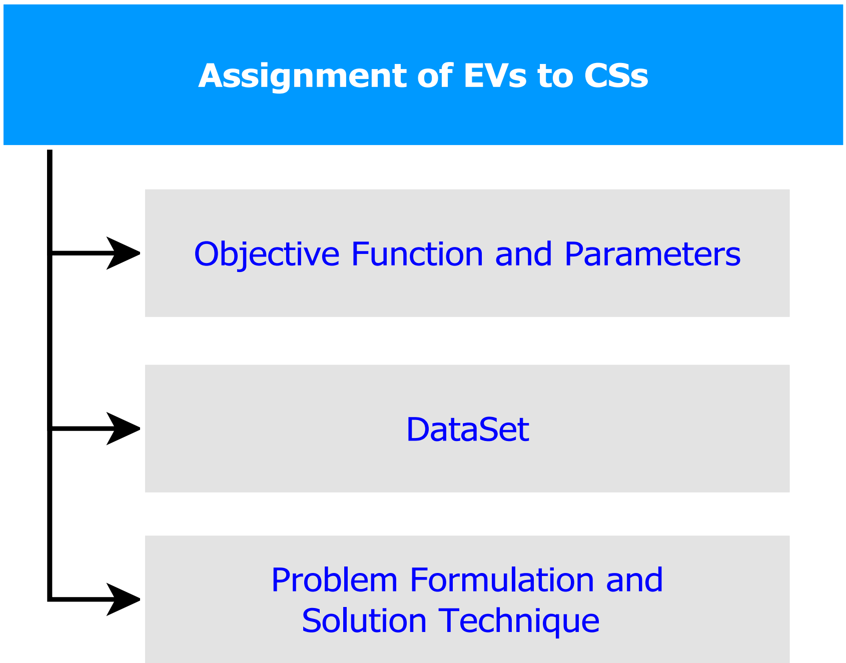

Figure 2.12: Taxonomy of Assignment EVs to CSs

In [135], the authors have studied how the GA that analyzes the open data sources of a city has been utilized to recommend the best sites for EVCSs. This proposal has been used as the basis for a series of experiments that mimic the influence of placing these CSs across the city, to assess the powerful of the results that were proposed by the GA. An agent-based simulation infrastructure was constructed around a fleet simulator in order to achieve this.

2.5 EV assignment

In this section we discuss the recent approaches that have been proposed in the literature to solve the problem of finding the optimal assignment of EVs to CSs in urban environments.

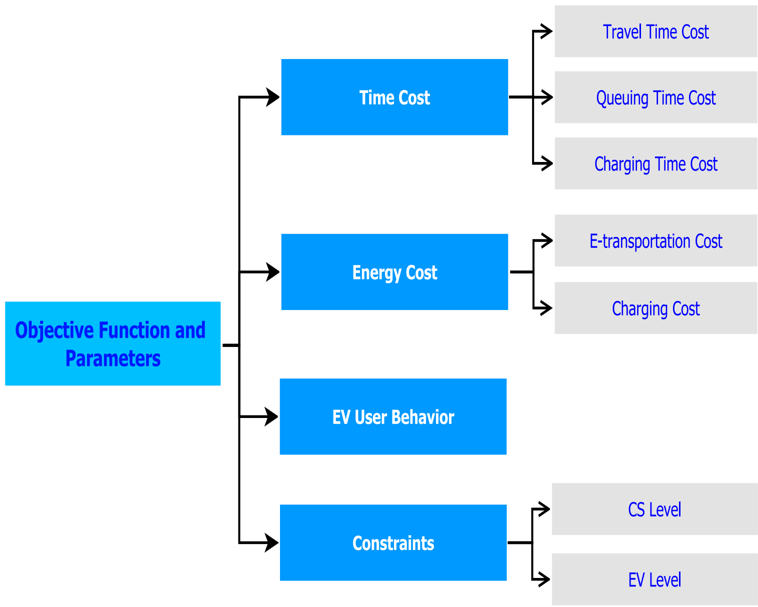

Figure 2.13: The Objective Functions and Parameters used to Solve the EV Assignment Problem

These works will be classified into subsections; objective function and parameters, data Set, and problem formulation and solution technique as shown in Fig. 2.12.

2.5.1 Objective Function and parameters

Different objective functions were introduced in the literature to solve the problem of assigning EVs to the optimal CS in the metropolitan environments. This section investigates the literature in this area according to the objective functions that has been proposed and the parameters that have used to solve the assignment problem. Each objective function will be discussed separately as shown in 2.13:

2.5.1.1 Time Cost

As mentioned earlier, the total charging time of EVs starts from the decision point where EV user heads CSs for charging until leaving CS, which first includes the travel time that an EV needs to reach CS, taking into account several factors that may affect the travel time, such as the distance and the roads traffic conditions. Secondly, the waiting time that EV spends until it finds available connector. Finally, the charging time inside CS.

In [136], a user-oriented EVs control strategy has been investigated, based on the efficient assignment of EVs to CSs. An average travel time that the EV user spend from requesting the charging service until reaching the CS was taken into account in this paper. The travel time towards CS considering the congestion level on streets has also been incorporated in the objective function in [137], to minimize the total charging time of EVs. To facilitate the charging management and design of a dynamic population of EVs in urban areas, a queuing model was used in [136]. The queuing time that EV needs to wait at CS was taken into consideration in [137, 122, 138]. However, in [136], the authors did not consider the impact of the queuing time in the proposed model.

The charging time inside CSs has not been considered in [136, 137, 122, 138]. The charging time at CS mainly depends on the technology of connectors that are used in the CSs. These connectors play a major role on minimizing the charging time at CSs, which in turn minimize the total time of EVs, and also increase the EVs users' satisfaction. In Chapter 4, we demonstrate the impact of this factor on the overall charging time and also on selecting a particular CS rather than the selection the others CSs. The results illustrate how the number of EVs that CSs can serve is directly affected by the technology of the connectors that is used in CSs.

2.5.1.2 Energy Cost

In this section, we will investigate the literature in this area in terms of the energy cost. Some parameters that have been considered to minimize the energy cost will also be discussed. In [28], an innovative EV charging scheme was proposed to minimize the EV charging cost. To address the proposed EV charging scheme effectively, and achieve an optimal and intelligent charging strategy, three charging modes have been considered in the proposed scheme, i.e., battery swapping, slow charging, and quick charging. Battery swapping method has been also been utilized in [139], the goal of this study is to reduce the total EVs energy cost to reach CS for batteries swapping, and also the congestion inside CSs according to the temporary lack in supply of available EV batteries. The total energy cost to fully charged EVs has been taken into account in [137]. In this article, the authors have introduced a Stochastic Decentralized (SD) algorithm to select the best CSs to the EVs that need charging.

2.5.1.3 EV User Behavior

In [140], an integrated approach has been developed, aiming at determining jointly the charging service assignment, and the metropolitan traffic for a population of EVs, that require a battery charging during their journeys. The introduced approach aimed at determining the systematic, i.e., over the long term, behavior of the EV drivers, charging and driving patterns. Charging behavior have been studied and analyzed in detail by the authors in [137]. The goal of analyzing the EVs drivers behavior is to minimize the occurrence of harmful charging misbehaviour of EV drivers, and enforce compliance of EV drivers. To achieve this purpose, they have leveraged on an Internet of Things (IoT) architecture based on a Distributed Ledger Technology (DLT).

In [107], the authors have proposed a new EV to CSs access equilibrium assignment model. The proposed equilibrium model has taken into account EVs users' behavior and choice for charging their vehicles during their daily trips with queue delay modeled as an M/D/C queue approximation as a non-differentiable non-linear program. The model was solved by a developed derivative free Method of Successive Averages (MSA) algorithm that eliminates the need to calculate the derivative in the step size determination or the objective value with the integral, which can be troublesome due to the M/D/C approximation function.

2.5.1.4 Constraints

The authors in the literature have used several constraints in order to fulfil the main object of their approaches. In this section we will discuss these constraints in terms of CSs, EVs, EGs, etc. The authors in [141] have assumed upper and lower boundaries for the SoC of the EV batteries, these constraints prevent violation of the proposed boundaries. Moreover, they have considered some other constraints related to CSs, as they put in place various limitations and constraints to address the upper and lower limits of charging power and levels for CSs. The objective function in [142] has been introduced to solve the assignment problem subject to certain constraints related to the EV battery conditions, i.e., size of the battery and SoC, CSs status, and also traffic conditions. As shown in the results of this paper, the suitable assignment of EVs was when the SoC of its battery remains at its highest possible level with the assigned CS. Keeping the battery SoC at a high level allowed to minimize required charging time and consumed energy.

In [143], the authors assumed that each CS has a number of constraints regarding the power that it provides to its customers. In order to serve EVs, each CS uses an optimization problem to create its own charging schedule, so that the constraints that have been assumed on energy needs of the parked EVs are met, and also no constraints are violated. The same constraints have been incorporated with another objective function for the same authors in [144]. Different constraints on CSs have also been proposed in [145]. In this paper, the authors used certain constraints for each CS independently rather than use the same constraints on all CSs as proposed in the previous works. Various constraints were also applied to respect the service radius of each CS considering the characteristics of each CS, in terms of the maximum number of EVs that can be served by the CS, as well as the CS's location and the availability of connectors inside each CS.

Moreover, additional constraints on the battery swap strategy were taken into consideration in [145] to minimize the load on power grid, power loss, and also to keep the voltage stability on power grids. Constraints on the EVs range have also been considered in [146]. Additional constraints have been applied on the charging time, charging lanes where EVs are charged automatically by traversing the lanes. In this paper, the authors proposed different level on constraints on the EV route choice, which was represented as a source constrained shortest-path sub-problem with charge time.

2.5.2 Data Set

In [147], a data-driven assignment strategy for EV-based taxis has been introduced, where the driving behaviors of EV taxis and load profiles of buildings were characterized by data analysis to make the risk averse decision on EV charging. First, the framework of data driven risk averse EV charging was presented, where a stochastic game model has been proposed. Second, the big data analysis of the statistical information about EV-based taxis and the load profile of buildings were introduced by applying different data process methods. Finally, the performance of the strategy was numerically illustrated by the case study via real Global Positioning System (GPS) information of 490 EV-based taxi, and the smart meter dataset from regional commercial buildings.

2.5.3 Problem Formulation and Solution Technique

In [148], the EV flow assignment problem in transportation network has been formulated as an optimization problem, aiming at minimizing the overall trip time of EV flows to reach CSs, and the queuing time inside CSs. GA, and Flow Distribution Algorithm (FDA) have been utilized to solve the problem based on real world datasets from the eastern Massachusetts highway network, USA. compared to the benchmark of proportional flow distribution, FDA was able to solve the problem with much less overall trip time under all the configurations. Moreover, FDA was also computationally feasible and can find solutions in a few seconds.

In [142], suitable and scheduling assignment of EVs to CSs was approached as an optimization problem. The problem of EVs assignment has been formulated as Linear Programming (LP) problem. In this paper, the authors used calculus algorithm (optimization algorithm) to solve the problem and showed how to assign optimally EVs to CSs. To this end, they represented the system by an optimization model using with LP for decision making and optimal assignment. The objective to reach in this work is to assign EVs to suitable CSs considering the SoC of EVs' batteries.

In [32], a dynamic assignment and charging scheduling the EVs to CSs has been proposed. The task assignment has been formulated as Local Integer Linear Programming (ILP) problem. To solve this problem, the paper proposed a quantized consensus algorithm that the agents autonomously performed to reach a consensus about the assignment of the EVs to CSs. Two various settings of the systems were considered and several consensus algorithms based on the solution of some local ILP problems has been proposed. Moreover, the convergence of the proposed algorithms was proved, and a case study showed the efficiency of the proposed solution.

In [149], EV assignment and relays for EV sharing systems has been introduced. In this work, a novel space-time–battery network approach to determine the optimal EVs assignment and relay decisions was proposed, with extra dimension for tracking each EV battery SoC in the system. the problem has been formulated as MILP problem that minimizes the total routing cost for EVs. To solve the resulting integer program, the authors proposed an efficient algorithm that aimed to exploit an innovative diving heuristic. Numerical results have shown that when EV assignment and relays were optimized in an electric EV sharing system, a comparable EV exploitation rate as in a ICEVs sharing system can also be achieved.

In [150], a comprehensive study has modeled the charging and routing problems of Shared EV (SEV) system as general formulation, taking into account charging station assignment, charging amount, as well as rid matching. Where the global optimization problem. Then the global optimization problem was broken down into four sub problems. The performance of the proposed optimization model has been demonstrated using almost 40,000 trips which were generated from the Shenzhen taxi dataset.

In [151], an interesting EV fleet trip pricing and size problem for one-way car-sharing services by considering the required practical requirements of EV personnel assignment and relocation has been proposed. The problem aims to maximize the profit of the operators of the one-way car-sharing operators by finding the EV trip pricing, fleet size, and strategies of EV personnel assignment and relocation subject to the elastic demand for the one-way car-sharing services. Formulating the problem as MINLP was first built for the problem. By utilizing the structure of the original built model, a Mixed Integer Convex Programming (MICP) model was subsequently developed. An efficient global optimization technique with various outer-approximation approaches was put up to determine the ϵ-optimal or global optimal solution to the problem. A case study based on a one-way car-sharing operator in Singapore was conducted to validate the effectiveness of the proposed model and solution technique and to analyse the degree of demand variance, the influence of demand, payments for personnel on the performance of the one-way car-sharing services, as well as the fixed operating cost of the EVs.

2.6 Summary

This chapter has summarised the most recent technologies related to the EVs and CSs, including the types of EVs and charging facility. Then, a taxonomy of the literature of placement and sizing of CSs, and EV assignment to CSs has been introduced as shown in Fig. 2.8. In the proposed taxonomy, the previous works have been discussed and categorized from different point of views; the objective function and the parameters that have been considered in the presented schemes, problem formulation and solution techniques that have been proposed in the literature in order to solve both problems, and finally the dataset that have been incorporated with the proposed approaches. Objective function and parameters have been investigated in the placement and assignment problems from different perspectives as shown in Figs 2.9 and 2.13, respectively.

Chapter 3

Energy-efficient EV Charging Station Placement for E-Mobility

3.1 Introduction

Despite all the acknowledged advantages and recent developments in terms of reducing the environmental impact, noise reduction and energy efficiency, the electric mobility market is still below the expectations. The efficient distribution of adequate EV charging stations (CSs) in urban environments is among the most important challenges that limit the market penetration of Electric Vehicles (EVs), as well as achieving a sustainable mobility system in cities.

In recent years, more attention has been paid to propose new approaches and models in order to solve the problem of finding the optimal placement of EVCSs in the metropolitan environments. In the recent literature, the most popular and powerful techniques are the optimization approaches that have been presented using different objectives function considering different parameters and constraints in terms of the EVs, CSs, and Electrical Grids (EGs), etc. In [92], a zonal approach has been introduced to determine the optimal location of EVCSs, development cost of EVCS as well as the total expected costs incurred by the grid operator due to EV charging have been considered in the proposed approach. The problem has been formulated as a Mixed Integer Nonlinear Programming (MINLP) problem to minimize the total EV charging costs, and solved using GA. The authors in [96] have also presented a MINLP optimization approach problem for optimal placing and sizing of the fast CSs to minimize the total cost of CSs development. The total cost includes charging facility, electrification cost, land cost, as well as EVs energy loss due to the charging travel and electric grid loss. The EVCS placement problem has been studied with incremental EV penetration rates in [103], a nested Logit model has been employed to analyze and study the charging preference of individual EV user and predict the total charging demand at the CSs. The best locations of EVCSs were selected based on the total charging demand of EVs in the study area. A comprehensive model for optimal sizing and placement of EVCSs that considered grid power loss, transportation loss and build-up costs have been proposed in [152]. Minimizing network losses, sustainable criteria, environmental impact and power system reliability are other objectives in [24]. In [153], a GIS-based fuzzy multiple criteria decision making analysis (MCDA) approach has been employed to find the optimal locations of EVCSs from environmental, urbanity and economic perspectives.

To the best of our knowledge, the existing studies of EVCSs placement did not take into account the amount of energy consumption that EVs need to spend to overcome the slope resistance force towards CSs, i.e., the difference in elevation between the locations of EVs and CSs. In this chapter, the EVCS placement for E-Mobility will be discussed and solutions for this problem will be presented. The objective here is to find the optimal placement of EVCSs in metropolitan environment based on minimizing the total amount of energy consumption of EVs to reach CSs. The model we propose in this work is 3D energy consumption model as we considered not only the displacement of EVs towards CSs, but also the positive slope that EVs need to overcome to reach CSs, i.e., difference in elevation between their locations as mentioned earlier. In order to achieve this, we propose a novel approach to find the best placement for EVCSs that considers a combination of factors including displacement between EV and CS, elevation difference between their locations and finite capacities of CSs, subject to several constraints related to the EVs and CSs. The reason for including these factors in the proposed approach, because they have a significant impact on the amount of energy consumption that EV needs to reach CS, as well as on the satisfaction of the EV driver. The constraints that have been considered in our approach, include the maximum number of EVs that should be assigned to each CS, and also each EV should be assigned to only one CS. These constraints should be incorporated to our optimization problem simultaneously in order to ensure that they are all satisfied. The displacement of EVs towards CSs has been considered before in different approaches [92, 154, 155]. Our proposed approach is unique in incorporating 3D energy consumption model with the displacement of EVs towards CSs, and the difference in elevation between the locations of EVs and CSs.

There are many parameters related to EVs which can be included with our proposed approach, such as the travel time of EVs to CSs, the queuing time inside the charging stations, the charging time that EV drivers need to charge their EV batteries, and also the EV driver's behavior and preferences. Moreover, several parameters related to CSs can also be combined with our approach, such as the installation cost, power loss, land cost, operating cost, penalty cost, maintenance cost as well as the CS constraints. Additional parameters related to the Electrical Grids (EGs) that offer services to CSs, have also significant influence on EVCS placement, such as voltage stability, electricity prices, length of the feeder, etc.

In our proposed approach, we formulated the problem of EVCS placement as a Mixed Integer Linear Programming (MILP) problem, as the objective function of our optimization problem and all constraints are linear. The introduced MINLP optimization approach is working on minimizing the total energy consumption of EVs to reach CSs. A combination of the Genetic Algorithm (GA) technique and the Branch and Bound (B&B) algorithm are used to solve the problem. Despite the high computational complexity of GA and B&B to solve this kind of problems, the combination of both algorithms helped us to get the optimal solution for our problem compared to other techniques that we have tried. In the implementation process of our system we have focused on the optimality rather than just focusing on the computational complexity of using both algorithms, because the system is static and the time elapsed for execution on the machine and environment (discussed in section 3.4.2) we used is not long.

The proposed EVCSs placement technique is experimentally tested considering different case studies. With real world datasets, the results demonstrate the energy centric benefits of the proposed EVCSs placement technique. The contributions of this chapter are listed as follows;

- An energy efficient EVCS placement scheme is proposed that considers key metrics including overall transportation energy cost of EVs to reach CS and the capabilities of EVCSs. The unique feature of this scheme is an accurate and realistic 3D energy consumption model to find the optimal placement of EVCSs taking into account the movement of EVs to CSs, the difference in elevation between the locations of EVs and CSs. The maximum number of EVs that should be assigned to CSs has been considered as a constraint to select CS in our scheme.
- The EVCS placement problem is modeled as a MILP problem. A combination of the GA technique and the B&B algorithm have been utilized to solve the problem based on actual data of the elevations and coordinates of EVs and candidate CSs taken from Google Maps.

The chapter is organized as follows: Section 3.2 describes the energy consumption model. The energy centric EVCS placement will be introduced in Section 3.3. The proposed approach will be evaluated in Section 3.4. Conclusions are given in Section 3.5. The notations used throughout this chapter are listed in Table 3.1. In addition, parameters and variables are described in the text where they are first used.

3.2 Energy Consumption Model

The objective of our proposed 3D energy consumption model, is to find the optimal placement of EVCSs based on minimum amount of energy consumption of EVs to reach CSs. This model will be discussed in detail in Section 3.2.3.

Table 3.1: Notations

Notation	Description
$\mathcal{N}$={1, ..., i, ..., N}	EV set; each EV i has three attributes; EV ID, elevation and the coordinates.
$\mathcal{M}$={1, ..., j, ..., M}	Candidate CS set; each candidate CS j has three attributes; CS's ID, elevation and the coordinates.
$\mathcal{Q}_z$={1, ..., k, ..., Z}	Zone set; each zone k has four attributes; zone ID, EV population, elevation and coordinates of the geographical center of zn_k.
M	The number of candidate CSs locations in the study area.
N	The number of EVs in the study area.
Z	The Number of zones in the study area.
d_{ij}	The displacement between EV i and candidate CS j.
$\hat{e}_{ij}$	The amount of energy consumption that EV i needs to spend horizontally per km to reach CS j (in kWh/km).
e_{ij}	The amount of energy consumption that EV i needs to spend to overcome the slope resistance force per km towards CS j (in kWh/km).
F	The hill climbing force.
$x_{(i,j)}$	Binary decision variable, which equals to 1 if CS j is selected by EV i, otherwise it equals to 0.
$\zeta_{(j)}$	The maximum number of EVs that can be assigned to CS j during peak hour.
M_{EV}	The mass of EV (in kg).
H_{ij}	The difference in elevation between EV i and CS j.
$\mathcal{T}$	The set of CSs that should be installed in the study area (subset of $\mathcal{M}$).
m	The fixed number of CSs to be installed in the study area.

3.2.1 EVs

There are N EVs in the study area. EV i has three attributes:

$(EV_i^{id}, EV_i^{elv}, EV_i^{p})$, where $EV_i^{id}, EV_i^{elv}, EV_i^{p}$ are the EV's ID, the elevation and the coordinates, respectively.

3.2.2 CSs

There are M candidate CSs in the study area. Candidate CS j has three attributes: $(cs_j^{id}, cs_j^{elv}, cs_j^{p})$, where cs_j^{id} is the CS's ID, cs_j^{elv} is its elevation and cs_j^{p} is its coordinates.

3.2.3 EV Energy Consumption

In order to get an accurate value for overall transportation energy consumption, i.e., E_{ij}, for EV i to reach CS j, we need to calculate the amount of energy consumption that EV i needs to spend horizontally per km to reach CS j, as well as the total amount of energy consumption that EV i needs to spend to overcome the slope resistance force per km towards CS j. E_{ij} is calculated as follows:

$$E_{ij} = (\hat{e}_{ij} + e_{ij}) \times d_{ij} \qquad [kWh]. \tag{3.1}$$

where $\hat{e}_{ij}$ is the amount of energy consumption that EV i needs to spend horizontally to reach CS j, e_{ij} is the total amount of energy consumption that EV i needs to spend to overcome the slope resistance force per km towards CS j, and d_{ij} is the displacement between EV i and candidate CS j. As we see in 3.1, the amount of energy is calculated per km, so we need to find the displacement between EV i and CS j, i.e., d_{ij}, to find the overall transportation energy cost of EV i. d_{ij} can be computed using haversine (hav) formula which is used to calculate the shortest distance between two points on a sphere, using their longitudes and latitudes on the surface as shown in Fig. 3.1. A and B represent the locations of EV and candidate charging station, respectively. The haversine is expressed in trignometric function [156], as shown in the

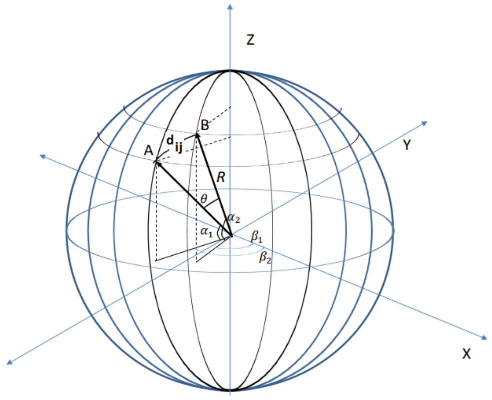

Figure 3.1: Spherical triangle solved by the law of haversines

following equation:

$$hav(\theta) = sin^2\left(\frac{\theta}{2}\right) \tag{3.2}$$

The haversine of the central angle (which is $\frac{d_{ij}}{R}$) [156], can be calculated using the following formula:

$$hav\left(\frac{d_{ij}}{R}\right) = hav\ (\lambda_j - \lambda_i)\ +\ cos\ (\lambda_i)\ cos\ (\lambda_j)\ hav\ (\Phi_j - \Phi_i) \tag{3.3}$$

where R is the Earth radius which is already known to be $6371km$, λ_i, Φ_i are the latitude and longitude of EV i, and λ_j, Φ_j are the latitude and longitude of CS j, respectively.

The haversine function computes only half of a versine of an angle. We solve the distance d_{ij} by applying the inverse of sin function [157], as shown in the following equations:

$$d_{ij} = 2Rsin^{-1} \times \left(\sqrt{hav(\lambda_j - \lambda_i) + cos(\lambda_i)cos(\lambda_j)\ hav(\Phi_j - \Phi_i)}\right) \tag{3.4}$$

$$d_{ij} = 2Rsin^{-1}\ \times \left(\sqrt{sin^2(\frac{\lambda_j - \lambda_i}{2}) + cos(\lambda_i)cos(\lambda_j)sin^2(\frac{\Phi_j - \Phi_i}{2})}\right) \tag{3.5}$$

$\hat{e}_{ij}$ is the amount of energy that EV i needs to spend horizontally per km to reach CS j. In this work, we assume that EV consumes 0.142 kWh/km as given in [92, 158].

e_{ij} is determined using the hill climbing force formula, as the hill climbing force finds the force

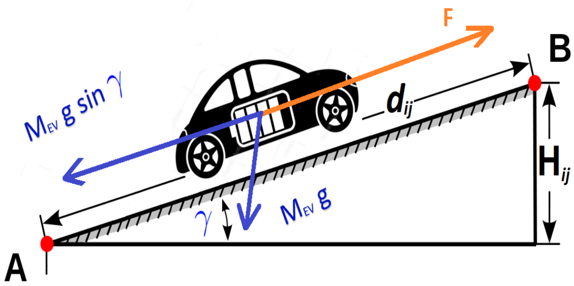

Figure 3.2: An illustration of slope resistance force [160].

that EV i exerts to overcome the slope resistance force to reach CS j. Here we assume that EV moves at constant speed towards CS, which means that the positive slope between the location of EV and CS is also constant, i.e., a straight line as shown in Fig. 3.2, which illustrates the slope resistance force that EV i should overcome to reach candidate CS j. F is calculated as follows:

$$F = M_{EV} \times g \times sin\,\gamma \qquad [N\ or\ kgm/s^2]. \tag{3.6}$$

where F represents the hill climbing force, M_{EV} denotes the mass of EV (kg), g represents the is gravitational force (9.8 m/s^2), and γ is the angle of road slope which is resulted from the difference in elevation between the location of EV i and the location of candidate CS j, which can be calculated as follows:

$$\gamma = sin^{-1}\,(H_{ij}/d_{ij}) \tag{3.7}$$

where H_{ij} is the difference in elevation between EV i and CS j as shown in Fig. 3.2. The value of e_{ij} is calculated using the following equation [159]:

$$e_{ij} = F \times 2.78 \times 10^{-4} \qquad [kWh/km]. \tag{3.8}$$

3.3 Energy Centric EVCS Placement

3.3.1 Problem Formulation

Suppose the candidate CSs set is $\mathcal{M} = \{1, ..., j, ..., M\}$, the EV population set is $\mathcal{N} = \{1, ..., i, ..., N\}$, and the zones set is $Q_z = \{1, ..., k, ..., Z\}$. We assume the location and elevation information for an arbitrary EV i is the same as the geographical center of the zone (zn) where the EV user lives. A zone k has four attributes; zn $_{k}^{id}$, zn $_{k}^{pop}$, zn $_{k}^{elv}$, and zn $_{k}^{cp}$, where zn $_{k}^{id}$ id the zone's ID, zn_{k}^{pop} represents the EV population in zn$_k$, zn_{k}^{elv} is the elevation of zn$_k$ and zn_{k}^{cp} is the coordinates of the geographical center of zn$_k$. The objective function of our optimization problem is to minimize minimize the total energy consumption of EVs to reach CSs considering the proposed parameters, subject to our system constraints as mentioned earlier. The corresponding optimization problem of our proposed scheme can be constructed as:

$$\min_{\mathcal{T},X} \quad \sum_{j\in\mathcal{T},\ \mathcal{T}\subset\mathcal{M}} \sum_{i\in\mathcal{N}} E_{(ij)} \times x_{(ij)} \tag{3.9}$$

$$s.t. \quad \sum_{j\in\mathcal{T}} x_{(ij)} = 1, \qquad \forall i \in \mathcal{N} \tag{3.10}$$

$$\sum_{i=1}^{N} x_{(ij)} \leq \zeta_{(j)}, \qquad \forall j \in \mathcal{T} \tag{3.11}$$

$$x_{(i,j)} \in \{0, 1\}, \qquad \forall i \in \mathcal{N},\ j \in \mathcal{T} \tag{3.12}$$

where the objective function in (3.9), finds the best locations of CSs based on the minimum overall transportation energy cost of EVs to reach the CSs. Each EV is assigned to only one CS as shown in (3.10). $\zeta_{(j)}$ denotes the maximum number of EVs that can be assigned to CS j during peak hour as shown in (3.11). The binary decision variable $x_{(ij)}$ is used to indicate whether EV i is selects candidate CS j or not, as shown in (3.12). The value of $x_{(ij)}$ is 1 if candidate CS j is selected by EV i, otherwise it is set to 0. The fixed number of CSs (m) that should be installed in the study area is less than the total number of candidate locations of CSs in the investigated area (M), i.e., $\mathcal{T}$ is a subset of $\mathcal{M}$.

Here is the associated matrix ($N \times M$) that shows the assignment relationship between EV i and CS j, which finally shows to which CS that EV i is attached subject to the system constraints:

$$\mathbf{X} = \begin{bmatrix} x_{(11)} & x_{(12)} & x_{(13)} & x_{(14)} & \cdots & x_{(1M)} \\ x_{(21)} & x_{(22)} & x_{(23)} & x_{(24)} & \cdots & x_{(2M)} \\ x_{(31)} & x_{(32)} & x_{(33)} & x_{(34)} & \cdots & x_{(3M)} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ x_{(N1)} & x_{(N2)} & x_{(N3)} & x_{(N4)} & \cdots & x_{(NM)} \end{bmatrix}_{\boldsymbol{N \times M}}$$

3.3.2 GA and B&B based Solution

The objective function in (3.9), and the system constraints in (3.10) - (3.12) form a MILP problem, where the decision variable $x_{(ij)}$ has only binary values {0,1}, and all system constraints are linear. To solve this problem, two loops are incorporated. The first loop (outer) works on proposing different possibilities of $\mathcal{T}$, then evaluate each $\mathcal{T}$ in the second loop (inner) based on equations (3.9) - (3.12). The GA works as an outer loop. In each iteration it proposes $\mathcal{T}$ that should be installed in the study area, then the B&B algorithm which works as an inner loop produces the best assignment relationship between EVs and $\mathcal{T}$ in that iteration. The GA updates

$\mathcal{T}$ for the next iteration based on the results of assignment relation that comes from inner loop in the previous iteration. The GA continues to produce $\mathcal{T}$ until it reaches to the maximum number of iterations. Fig. 3.3 shows the flowchart of our proposed approach.

3.4 Case Study

3.4.1 Input Data

The proposed approach has been applied to part of the Newcastle upon Tyne city, UK. The study area has a length of about $10km$ and a width of $5km$. An EV can travel for $7km$ in each 1 kWh [92, 158]. The study area is divided into 7 postcode zones. Table 3.2 shows the zone ID, the EV population in each zone, the elevation and coordinates of each zone's geographical center.

Table 3.2: zones information

Zone ID	**EVs Pop**	**Elevation**	**Coordinates**	
			Latitude	Longitude
$NE1$	240	0.042	54.973794	-1.613159
$NE2$	100	0.053	54.991147	-1.606178
$NE3$	140	0.068	55.004469	-1.619865
$NE4$	190	0.102	54.975669	-1.641450
$NE5$	90	0.075	55.013534	-1.723297
$NE6$	160	0.052	54.976903	-1.578135
$NE7$	80	0.067	54.998767	-1.588819

Fig. 3.4 shows the study area map as well as the distribution of candidate CSs. It is assumed that the total personal vehicles population in the study area is about 100,000, where EVs make up 5% of the total population. We also assume that 20% of EVs need to be charged at the CSs during peak hours, and all EVs' batteries are completely empty when arriving CSs and need to be fully charged. We assume that we have 12 candidate CSs locations a long the main roads in the study area, with around $2km$ of distance between them. In this work we need to place a fixed number of CSs, i.e., m, in the study area.

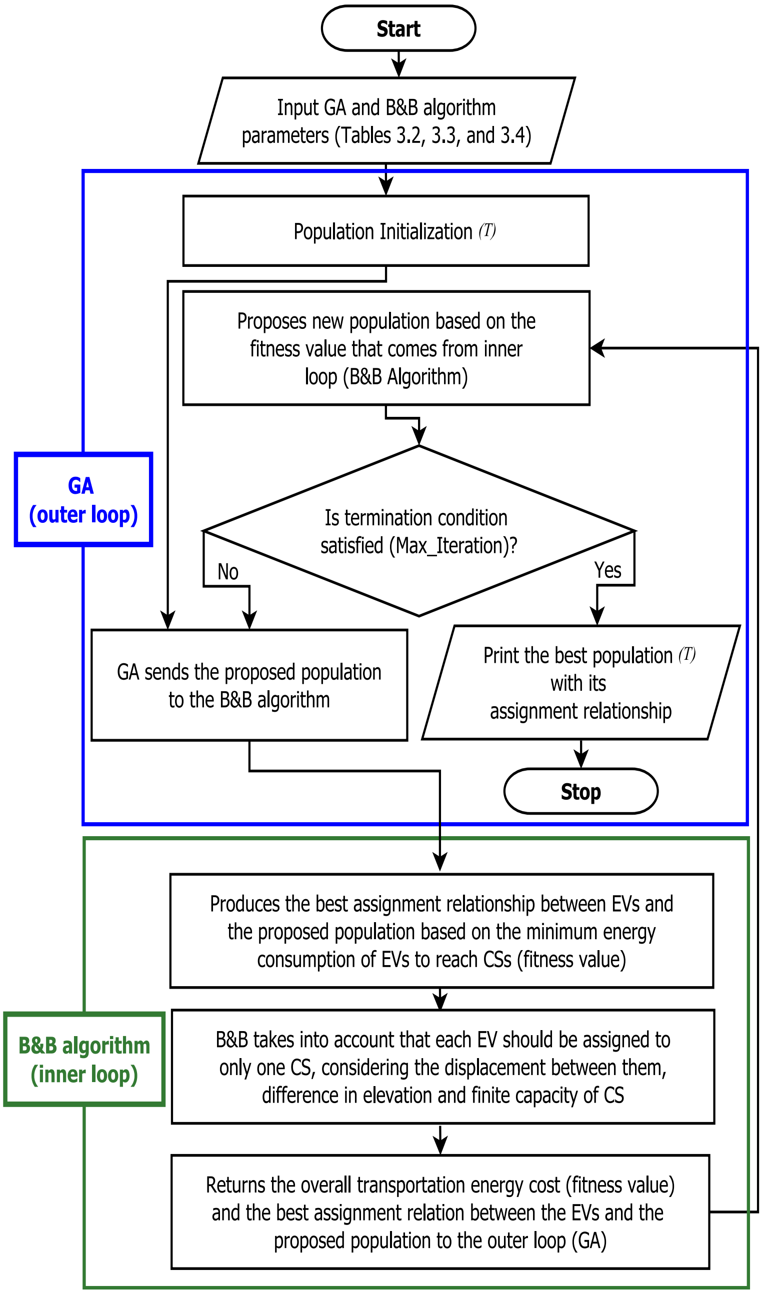

Figure 3.3: Flowchart of proposed approach

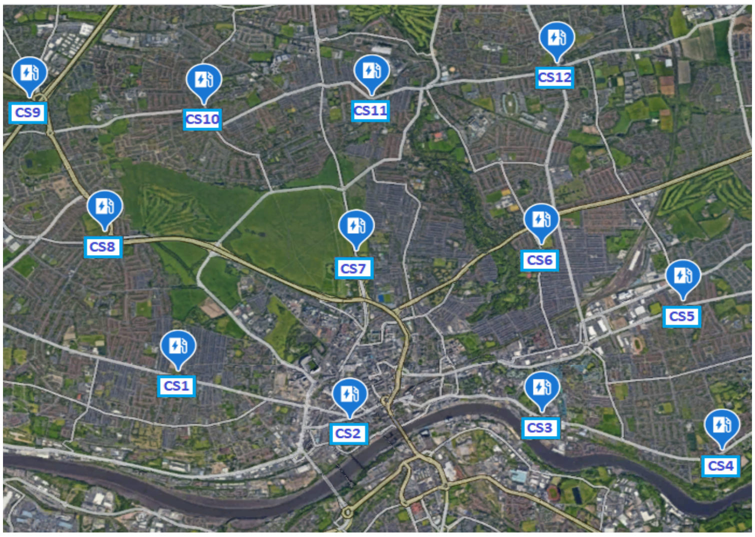

Figure 3.4: The study area map

3.4.2 Base Case Study Results

The proposed approach has been applied to the study area. Fig. 3.5 shows the study area. The geographical center of the zone is represented by black circles, EV population is represented by small blue dots, and the border zones is shown with solid black lines. Table 3.3 shows the candidate CS's ID, the elevation and coordinates. The base case study is based on the information shown in Tables 3.2 and 3.3. Table 3.4 shows the parameter values that have been used in the optimization process. The proposed approach has been performed in MATLAB environment R2019a update 8 (9.6) - academic use platform on HP-PROBOOK laptop with 1.6-GHz (8 CPUs) and 8 GB of RAM.

Fig. 3.6 shows the optimal CSs that have been selected, i.e., CS1, CS2, CS3, CS9, CS11, as well as the EVs that are assigned with each CS. Fig. 3.7(a) and (b) illustrates the total number of EVs that are assigned with each CS, and the total energy consumption of EVs to reach each CS location, respectively. It is obvious that the total energy consumption of EVs to reach CSs in this scenario is not too much as shown in Fig. 3.7(b). The reason behind this is that the difference in elevation between the locations of EVs and CSs is low as shown in Tables 3.2 and 3.3.

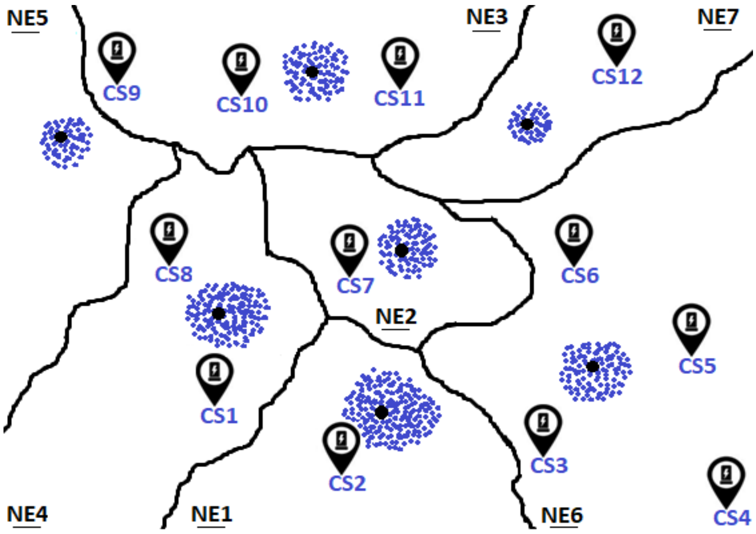

Figure 3.5: The study area illustration

Table 3.3: CSs information

CS's ID	Elevation	Coordinates	
		Latitude	Longitude
CS_1	0.106	54.97448	-1.644712
CS_2	0.035	54.968961	-1.615008
CS_3	0.020	54.969718	-1.581451
CS_4	0.033	54.965464	-1.550075
CS_5	0.029	54.982385	-1.55684
CS_6	0.048	54.988743	-1.581588
CS_7	0.059	54.988027	-1.613854
CS_8	0.107	54.990201	-1.657449
CS_9	0.101	55.005229	-1.670558
CS_{10}	0.082	55.004507	-1.640343
CS_{11}	0.061	55.005568	-1.611165
CS_{12}	0.068	55.009274	-1.578951

Table 3.4: The base case study parameters

Parameter	Value	Unit
N	1000	-
M	12	-
$\hat{e}_{ij}$	0.142	kWh/km [92, 158]
M_{EV}	1600	kg
g	9.8	m/s^2
Z	7	-
m	5	-

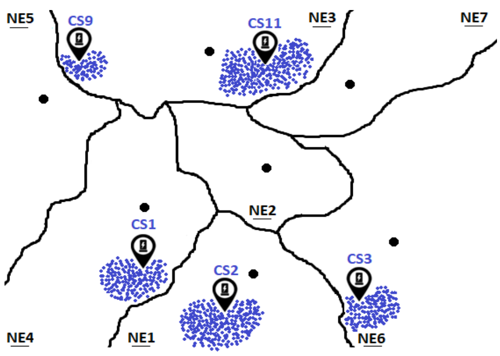

Figure 3.6: The best locations of CSs for the base case study

It can be observed that the EVs in zone NE2 have selected CS2 in a different zone NE1 as shown in Fig. 3.6, rather than CS7 although it is located in the same zone, and it is closer to the location of EVs in NE2. The reason behind this is the difference in positive slope between the locations of EVs and CS7 in NE2.

As shown in Fig. 3.7(a), although the number of EVs that are assigned to CS9 is less than 100 EVs, but the total amount of energy consumption is higher compared to other CSs as shown in Fig. 3.7(b). The main reason for this is the high difference in positive slope and distance between the locations of EVs in NE5 and CS9. On contrary, in zone NE4 EVs assigned to CS1 consume less energy compared to EVs assigned to CS9 although the number of EVs that are assigned to CS1 is more than twice of CS9 as shown in Fig. 3.7(a).

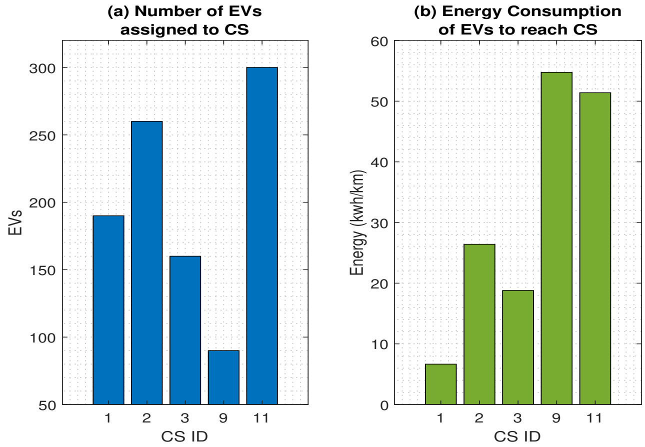

Figure 3.7: Optimization results for the base case study

3.4.3 Other Cases

To evaluate the performance and robustness of our proposed approach in determining the optimal locations of EVCSs in urban environment, more case studies have been investigated in this section. The elevations that are assumed in this section are not the real numbers for Newcastle upon Tyne city. However, they are assumed to verify the proposed scheme.

The three different case studies are given as follows:

- Case A: the elevation of CS9 is doubled and the elevation of the other CSs and zones remain the same as the base case study.
- Case B: the elevation of CS2 is increased by $100m$ and the elevation of the other CSs and zones remain the same as the base case study.
- Case C: the elevation of all CSs in Table 3.3 is doubled, while the elevation of zones remain the same as the base case study, as described in Table 3.2.

Fig. 3.8 shows the locations of optimal EVCSs for Case A and the assignment of EVs to each CS. In this case, after the elevation of CS9 is doubled, all EVs in zone NE5 choose CS10 instead of CS9 as shown in Fig. 3.7, although horizontally CS9 is much closer to the EVs in zone NE5. This is because to reach CS9, EVs need to consume more energy to overcome the elevation increase as shown in Fig. 3.9(b), which makes CS9 not the best choice anymore for EVs in NE5. To achieve an energy efficient, CS10 is chosen instead. Fig. 3.9(a) illustrates the total number of EVs that are assigned with each CS.

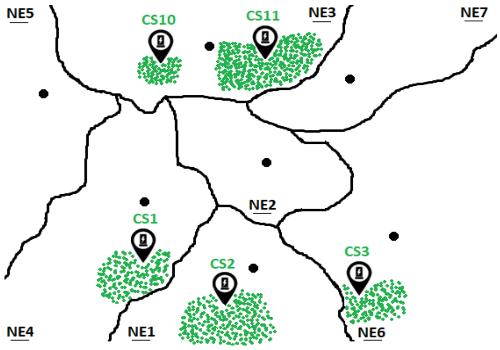

Figure 3.8: The best locations of CSs for Case A

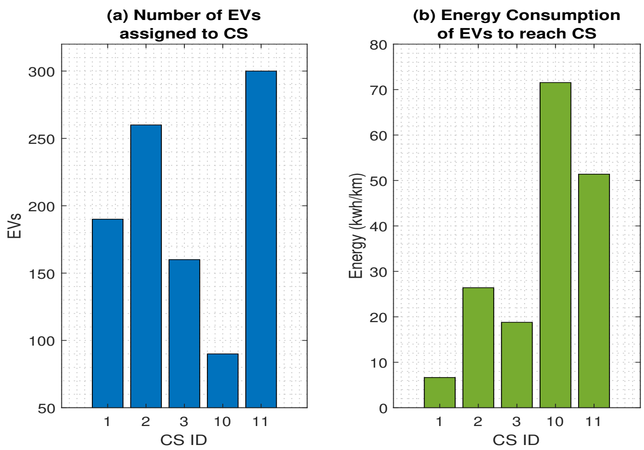

Figure 3.9: Optimization results for Case A

Fig. 3.10 shows the optimal placement of EVCSs, and the assignment of EVs to each CS for Case B. The EVs that have been assigned to CS2 in previous cases, are now associated with CS7 as shown in Fig. 3.10, this is because to reach CS2, EVs need to exert more energy to overcome the elevation increase, which makes CS7 the best choice for EVs in NE1. To achieve an energy efficient, CS7 is chosen instead.

It can be seen from Fig. 3.7(a) and 3.9(a), that the only difference between Case A and the base case study, is that CS10 was chosen instead of CS9, and the EVs assignment to CSs remain the same. However, in Case B, we notice that not only the selection of the optimal CSs is different, but also the assignment of EVs to CS7 is more compared to CS2 in the base case study, and the distribution of EVs to CS3 and CS11 as shown in Fig. 3.7(a) and 3.11(a). Although EVs in zone NE1 choose CS7, but the energy consumption of EVs to reach it is increased more than twice of CS2 as in the base case study as shown in Fig. 3.11(b). This is because the difference in elevation of CS2 and CS7 as shown in Table 3.3.

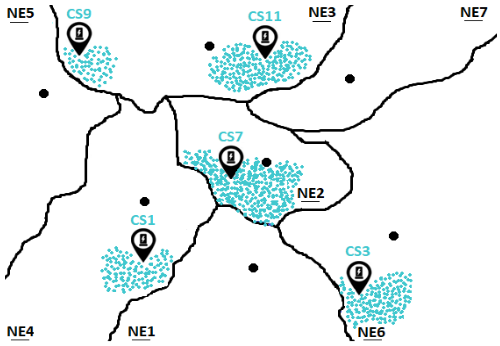

Figure 3.10: The best locations of CSs for Case B

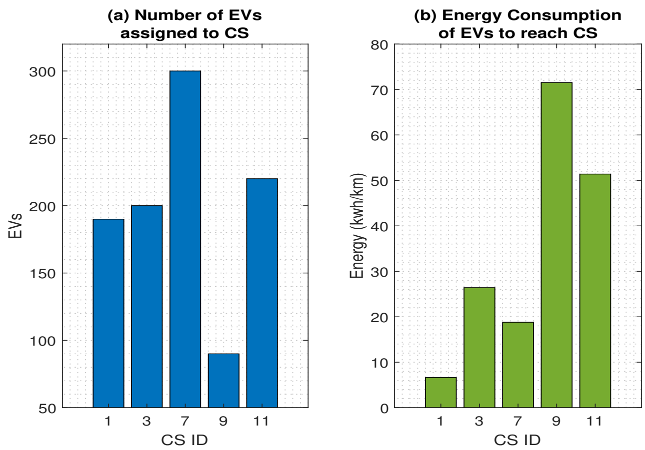

Figure 3.11: Optimization results for Case B

In Case C, when the elevation for all candidate CSs are doubled, CS6 has been selected instead of CS1 as shown in Fig. 3.12. This is because to reach CS1, EVs need to consume more energy to overcome the elevation increase. Due to the high elevation of CSs in zones NE4 as we see in

Table 3.3, the EVs in zone NE4 need to exert more energy to overcome the elevation increase, which makes CS6 the best choice for charging. To achieve an energy efficient placement, CS6 is chosen instead. Another observation in Case C is that over half of the EVs choose CS2 and CS3 as shown in Fig. 3.13(a). The reason for this is the low-elevation of these CSs compared to the other candidate CSs in the study area, as also shown in Table 3.3. It can be seen from Fig. 3.13(b), that the energy consumption is increased in this case. The main reason for this is the elevation of CSs which is increased twice.

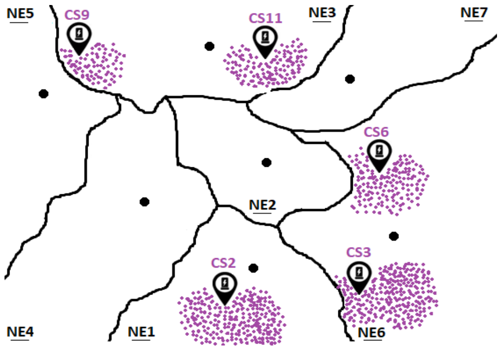

Figure 3.12: The best locations of CSs for Case C

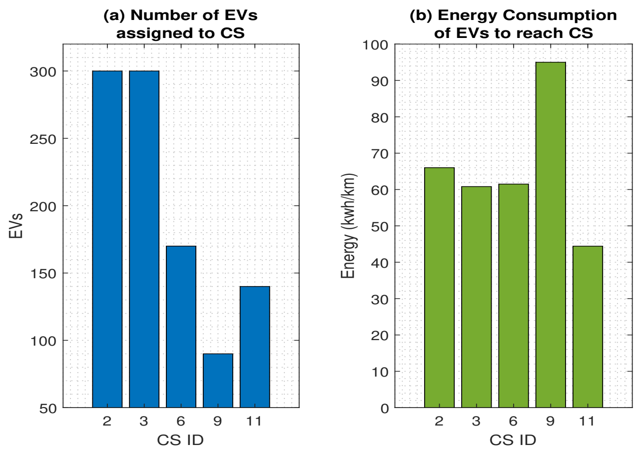

Figure 3.13: Optimization results for Case C

The results obtained for Case A, B and C have shown the effect of elevation on the selection of CSs. Table 3.5 shows the total energy consumption of EVs to reach each CS for each case study.

Table 3.5: Energy Consumption Results

Base Study	Case A	Case B	Case C
158.0093	174.8060	182.5516	327.7532

It is shown in Table 3.5 that the total energy consumption of EVs to reach the CSs in Case A is increased about 11% compared to the base case study. This is due to the fact that the elevation of candidate CS9 is doubled, so the EVs in zone NE5 have selected CS10. The total energy consumption that is associated with the selected CSs in Case B is increased about 15% as shown in Table 3.5, this is because the elevation of CS2 is increased by 100m, while the elevation of the other CSs and zones remain the same as the base case study. In Case C, It is easy to see that the total energy consumption is increased significantly compared to the base case study, this is also because the elevation of all candidate CSs in this case study is increased twice and the elevation of the zones remain the same as the base case study. Therefore, EVs need to consume much more energy to overcome the double elevation.

3.5 Summary

An energy-efficient optimization technique has been proposed in this work to find the optimal placement of EVCSs in urban areas. The problem of EVCS placement has been formulated as a MILP to minimize the total energy consumption of EVs to reach CSs. The displacement between the locations of EVs and CSs, and the difference in the elevation between their locations has been considered in the proposed scheme. The maximum number of EVs that assigned to each CS, and also each EV should be assigned to only one CS are the constraints that should be satisfied in our optimization problem. To evaluate the proposed approach in this chapter, and show the effect of the difference in elevation between the locations of EVs and CSs; different case studies have been investigated, based on different assumptions in elevations for the locations of CSs in the study area. The results have demonstrated the impact of considering the positive slope on the amount of energy consumption that EV i needs to exert to overcome the slope resistance force towards CS j. Based on the comparison between the base case study and the other proposed case studies, it is obvious that the total energy consumption of EVs to reach the CSs in Case A is increased about 11% compared to the base case study. While the total energy consumption for EVs to reach CSs is increased about 15% in Case B and 69% in Case C.

Chapter 4

QoE-based assignment of EVs to Charging Stations in Metropolitan Environments

4.1 Introduction

With the recent advances in battery technology enabling fast charging, public CSs are becoming a viable choice for EVs. However, owning an EV as a private vehicle is still unattractive from a user's point of view for many reasons, such as long charging process and driving range. The shortage of CSs, short driving range, and long charging time are key concerns that affect the EVs users' QoE. Charging EVs in cities is another challenge that limit their use in urban environments. In many cases, EVs drivers need to travel long distances to find the available CSs, which consumes a lot of time and energy, which also negatively affects EV users' QoE in terms of using and charging EVs in metropolitan areas.

Motivated by the above EVs charging problems, we propose QoE oriented assignment for EVs to CSs in cities, in order to improve the EVs users' QoE of finding the optimal CSs for charging their vehicles during their journeys, which in turn enhances EV users' QoE of using EVs instead of ICEVs. In this chapter, we prioritise the EV users' QoE in order to determine the optimal assignment of EVs to CSs in metropolitan environment. So, we focus on the individual EV user satisfaction, in terms of the total time to fully charge an EV. There are several approaches that have been considered in the literature in order to find the optimal assignment of EVs to CSs. To the best of our knowledge, the existing literature in this field did not take into account the EV drivers' QoE in terms of the charging time. Furthermore, they did not consider the efficiency of CSs, which is mainly depend on the number of connectors at CS, and the rated power of these connectors. Our proposed approach is unique in that, as we take into account the influence of of these parameters on the total time of charging EV, and also the constraints that are related to the CSs, and the maximum time that EVs can spend to charge their batteries. We argue that all of these metrics and constraints have significant impact on the decision of assigning EVs to CSs.

The contributions of this work are list as follows;

- A novel model for assignment of EVs to CSs in urban areas is proposed in this chapter. The proposed model considers the EV drivers' QoE in terms of the travel time of EVs to reach CS, the queuing time at CSs, also the time needed to charge the EV battery when plugged into charger. The effect of road congestion level caused by both ICEVs and EVs was considered in this work. The results show the impact of congestion level on the travel times which in turn affects the EV drivers' QoE.
- Our model takes into account the influence of the urban traffic circulation of EVs between adjacent zones on determining the optimal assignment of EVs to CSs in metropolitan areas.
- An optimization technique for selecting the optimal assignment of EVs to CSs has been introduced in this work. The problem is formulated as MINLP problem. The GA technique has been utilized to solve this problem based on real world datasets. The Nonlinear

objective function of the proposed approach is set as minimizing the total charging time of EVs.

The rest of the chapter is organized as follows. The assignment problem formulation and optimization model are presented in Section 4.2, Section 4.3 shows the numerical results of our proposed approach. Section 4.4 draws the summary of this chapter.

4.2 QoE oriented assignment for EVs to Charging Stations

This chapter proposes a novel model to find the optimal assignment of EVs to CSs in metropolitan environment, based on EV users' quality of experience (QoE). Travel time on the road networks including congestion level on the roads and the distance between the locations of EV and CSs, as well as the total expected time inside the CS which mainly depends on queuing time and the time required to fully charge EV battery have been considered in this study. The notations used in this chapter are listed in Table 4.1. In addition, parameters and variables are explained where they are first used.

Fig. 4.1 shows an example of the movement of EVs in two adjacent zones k and j. This example shows the movement of EVs in zone k towards zone j for charging. Here we assume there is only one main road connecting the two zones with only one intersection point, this point represents the port, i.e., t^{kj}, that all EVs in zone k should use to reach CSs in adjacent zone j. It assumes that EVs in the zone k use different roads to reach the port, then they take the same road to reach CS_u^j in zone j. The red arrow shows the direction of EVs movement from zone k to zone j. We assume that the EVs can only be charged in the adjacent zones and also will not select any CS at the same zone (k). Any pair of zones are considered as adjacent if they have a geographical borders with each other. The problem will be modeled and solved as shown in the following sections.

Table 4.1: MAIN NOTATIONS AND THEIR DESCRIPTIONS

Notation	Description
EV_i^k	The EV with global index i in zone k.
$\mathcal{N}$	EV set, in which each EV_i^k has one attribute; p^i, which is the EV_i^k location.
N	The total number of EVs in the study area.
CS_u^j	The CS with global index u in zone j.
$\mathcal{M}$	CS set, in which each CS has one attribute; b^u, which is the CS_u^j position.
M	The number of CSs in the study area.
$\mathcal{Z}$	The set of the zones in the study area.
Z	The number of zones in the study area.
$T_{i,u}^{k,j}$	The total time of charging EV_i^k starting from movement towards CS_u^j until departure.
$\tau_{i,u}^{k,j}$	The travel time of EV_i^k to reach CS_u^j.
ℓ	The linear coefficient of the travel time function.
$d_{i,u}^{k,j}$	The total distance between the current location of EV_i^k and the location of CS_u^j.
$\delta_{i,u}^{k,j}$	The traffic condition, i.e., congestion level on the road which EV_i^k takes to reach CS_u^j per peak hour.
t^{kj}	The port of zone k with an adjacent zone j.
μ_i^k, Ψ_i^k	The latitude and longitude of EV_i^k, respectivelly.
$x_{i,u}^{k,j}$	A binary decision variable shows that EV_i^k selects CS_u^j for charging per peak hour.
$V_{i^k,t^{kj}}$	The number of ICEVs that share the same road with EV_i to reach t^{kj}.
$\zeta_{i^k,t^{kj}}$	The capacity of the road in zone k that EV_i uses to reach t^{kj}.
N^k	The total number of EVs in zone k.
q_u^j	The queuing time at CS_u^j per peak hour.
η_u^j	The number of chargers at CS_u^j.
r_u^j	The maximum number of EVs that can be charged by a charger in CS_u^j per hour.
ρ_u^j	The charging time of EV at CS_u^j.
G_u^j	The number of adjacent zones for CS_u^j.
D_i^k	The number of adjacent zones for EV_i^k.
Γ	The maximum time of charging EV_i^k.
λ_u^j	The maximum number of EVs allowed to be assigned to CS_u^j.
β	The threshold value that shows the difference between the best fitness value of the current generation and the best fitness value in previous iterations.

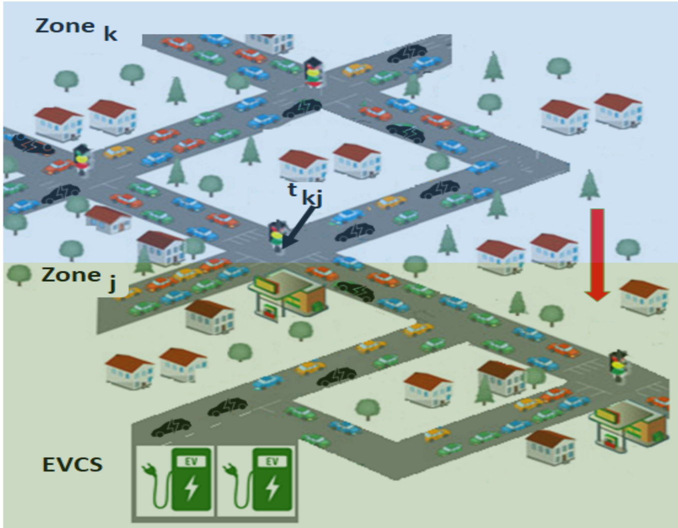

Figure 4.1: An Illustrative example of EVs movement to CSs in adjacent zone

4.2.1 Major Entities in Modeling

In this section, the attributes of EVs, CSs and the zones of the study area will be defined as shown below. Each parameter that has been introduced in our approach will be discussed in the next sections.

4.2.1.1 EVs

Define the EV set as $\mathcal{N} = \{1, ..., i, ..., N\}$. The cardinality of $\mathcal{N}$ is N, i.e., there are N EVs in the investigated area. EV_i^k in $\mathcal{N}$ has one attribute: (p^i), where p^i is the position of EV_i^k.

4.2.1.2 CSs

Define the CS set as $\mathcal{M} = \{1, ..., u, ..., M\}$. The cardinality of $\mathcal{M}$ is M, i.e., there are M CSs in the investigated area. CS_u^j in $\mathcal{M}$ has one attribute; b^u which is the location of the CS_u^j.

4.2.1.3 Zones

Define the Zone set as $\mathcal{Z} = \{1, ..., j, ..., Z\}$. The cardinality of $\mathcal{Z}$ is Z, i.e., there are Z postcode zones in the study area. The model of a postcode zone j is represented by (c^j, pop^j, g^j), in which c^j represents the ICEVs population in zone j, pop^j represents the EV population in zone j, and g^j is the adjacency relation between zone j and other zones in the study area.

4.2.2 Travel Time Estimation

Two important factors should be taken into consideration in terms of travel time: the total distance between the current location of EV_i^k and CS_u^j in the adjacent zone, and the congestion level, i.e., traffic condition on the road. Therefore, the travel time relies on the length and capacity of the road that EV_i^k takes to reach CS_u^j, and also the traffic congestion level on the road. In general, more vehicles on the road lead to higher congestion level. The greater the road capacity, the lower the level of traffic congestion on the roads. The EV travel time (τ) is calculated as follows:

$$\tau_{i,u}^{k,j}(X) = \ell \times d_{i,u}^{k,j} \times \delta_{i,u}^{k,j}(X). \tag{4.1}$$

where $\tau_{i,u}^{k,j}$ represents the travel time of EV_i^k to reach CS_u^j, X is the associated matrix that shows the assignment of EVs to CSs, ℓ is the linear coefficient of the travel time function [161], $d_{i,u}^{k,j}$ denotes the total distance between the current location of EV_i^k and CS_u^j, and $\delta_{i,u}^{k,j}$ is the congestion level on the road that EV_i^k takes to reach CS_u^j. Knowing that the EVs that come from zone k use the same road inside zone j to reach CS_u^j. EVs move under the same route conditions (length, capacity and congestion level) in zone j. Here is the travel time matrix structure (N×M), that shows the travel time for the each EV_i^k with each CS_u^j. Knowing that EVs can charge only in CSs in the adjacent zones. $\tau = 0$, if CS_u^j is not adjacent to the EV_i^k and also if they are in the same zone $(k = j)$:

$$\mathbf{A} = \begin{pmatrix} \tau_{1,1} & \tau_{1,2} & \cdots & \tau_{1,M} \\ \cdot & \cdot & \cdots & \cdot \\ \tau_{N^1,1} & \tau_{N^1,2} & \cdots & \tau_{N^1,M} \\ \tau_{N^1+1,1} & \tau_{N^1+1,2} & \cdots & \tau_{N^1+1,M} \\ \cdot & \cdot & \cdots & \cdot \\ \tau_{N^1+N^2,1} & \tau_{N^1+N^2,2} & \cdots & \tau_{N^1+N^2,M} \\ \tau_{N^1+N^2+1,1} & \tau_{N^1+N^2+1,2} & \cdots & \tau_{N^1+N^2+1,M} \\ \cdot & \cdot & \cdots & \cdot \\ \tau_{N^1+N^2+N^3,1} & \tau_{N^1+N^2+N^3,2} & \cdots & \tau_{N^1+N^2+N^3,M} \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \tau_{\sum_{k=1}^{Z-1} N^k+1,1} & \tau_{\sum_{k=1}^{Z-1} N^k+1,2} & \cdots & \tau_{\sum_{k=1}^{Z-1} N^k+1,M} \\ \cdot & \cdot & \cdots & \cdot \\ \tau_{\sum_{k=1}^{Z} N^k,1} & \tau_{\sum_{k=1}^{Z} N^k,2} & \cdots & \tau_{\sum_{k=1}^{Z} N^k,M} \end{pmatrix}_{N \times M}$$

The distance $d_{i,u}^{k,j}$ between the current location of EV_i^k and CS_u^j is calculated using haversine formula as shown in the previous Chapter in Section 3.2.3. The reason for using the haversine formula, is that it is very accurate to calculate the minimum distances between two points on the surface of a sphere using the latitude and longitude of the two points [160, 162, 157].

The distance between EV_i^k and CS_u^j is calculated in two stages as shown in Eq. (4.2). The first stage from the current location of EV_i^k to the port of adjacent zone j. Then, from the port between the two zones to reach CS_u^j, as illustrated in Fig. 4.1.

$$d_{i,u}^{k,j} = d_{i^k,t^{kj}} + d_{t^{kj},u^j} \tag{4.2}$$

where $d_{i,u}^{k,j}$ denotes the total distance between the location of EV_i^k and CS_u^j, $d_{i^k,t^{kj}}$ represents the distance from the location of EV_i^k to the port with the adjacent zone j, and d_{t^{kj},u^j} is the distance between the port t^{kj} and CS_u^j. Fig. 4.2 shows how the spherical triangle is solved using haversine function, where R is the radius of the Earth, and $d_{i,u}^{k,j}$ is the distance along the surface of the earthly sphere.

The congestion level $\delta_{i,u}^{k,j}$ is resulted from the normal congestion caused by ICEVs, and the congestion caused by the EVs heading for charging. Only normal congestion is taken into account when EV_i^k moves from its location to reach the port with adjacent zones. However, from the port

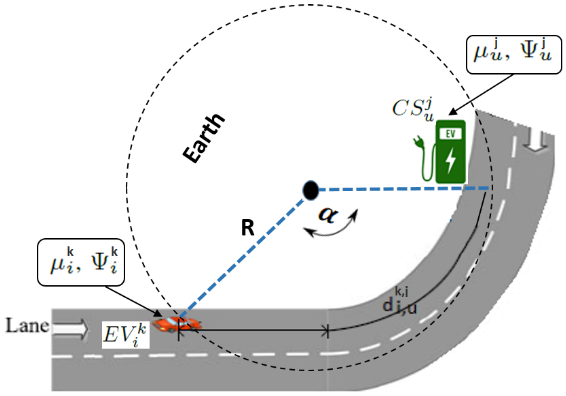

Figure 4.2: Spherical triangle solved by the law of haversines.

to the location of CS_u^j, both congestion are considered, taking into account the capacity of the road in both zones (k and j). Eq. (4.3) shows how the congestion level $\delta_{i,u}^{k,j}$ is calculated:

$$\delta_{i,u}^{k,j}(X) = (V_{i^k,t^{kj}} \;/\; (\zeta_{i^k,t^{kj}} \times \varphi)) + ((V_{t^{kj},u^j} + \sum_{i=1}^{N^k} x_{i,u}^{k,j}) \;/\; (\zeta_{t^{kj},u^j} \times \varphi \times \varepsilon)) \tag{4.3}$$

where $V_{i^k,t^{kj}}$, V_{t^{kj},u^j} represents the number of ICEVs in zone k and zone j that share the same route with EVs, respectively, $\zeta_{i^k,t^{kj}}$, ζ_{t^{kj},u^j} is the capacity of the roads in zones k and j, respectively, N^k represents the number of EVs in zone k that are needed to be charged, $x_{i,u}^{k,j}$ is a binary decision variable which indicates whether EV_i^k selects CS_u^j for charging, and φ, ε represents the proportion of ICEVs and EVs sharing the same roads with EVs per peak hour, respectively.

4.2.3 Queuing Time Estimation

Besides the travel time of the EVs, the queuing time inside CSs also influences the decision of assigning EVs to CSs. The queuing time at any CS depends on the total number of EVs that reach this CS for charging per peak hour, the number of chargers that have been installed in the CS and also the charger technology, which mainly decides the number of EVs that can be

Table 4.2: Classification of EV chargers [163]

EVSE Type	**Power Supply**	**Charger Power**	**Charging Time Battery EV (BEV)**
Level 1 (AC Charging)	120 VAC 12 A to 16 A (Single Phase)	~ 1.44 kW to ~ 1.92 kW	~ 17 Hours
Level 2 (AXC Charging)	208 ~ 240 VAC 15 A ~ 80 A (Single/Split Phase)	~ 3.1 kW ~ 19.2 kW	~ 7 Hours (3.3 kW on-board charger) ~ 3.5 Hours (6.6 kW on-board charger)
Level 3 (Combo Charging System or DC Charging)	200 ~ 920 VDC (Max 500 A) (Poly Phase)	From 120 kW to 350 kW	< 30 Minutes

charged per charger. The queuing time is calculated as follows:

$$q_u^j(X) = \sum_{f=1}^{G_u^j} \sum_{i=1}^{N^k} x_{i,u}^{k,j} / \ (\eta_u^j \times r_u^j \times \varepsilon). \tag{4.4}$$

where q_u^j represents the queuing time at CS_u^j per peak hour, X is the associated matrix that shows the assignment of EVs to CSs, G_u^j represents the set of adjacent zones for CS_u^j, η_u^j denotes the number of chargers at CS_u^j, r_u^j is the maximum number of EVs charged per charger in an hour, and ε denotes the proportion of EVs charge per peak hour. Here is the queuing time vector for CS_u^j, $\overrightarrow{Q} = \{q_1 \ \ q_2 \ \ q_3 \ \ \ldots \ \ q_M\}$.

4.2.4 Charging Time Estimation

In addition to the travel time of the EV to reach CS location, and the queuing time at CS, the charging time of EV battery at a CS is considered as an important factor that affects not only the time that the EV user needs to stay at the CS but also the total number of EVs that CS can serve. The maximum number of EVs charged per charger is the main parameter that has an influence on charging time of EV inside CS. The rated power of the chargers varies in the range of 50 kW to 350 kW, depending on the charger technology and manufacturer [163]. EV chargers can basically be classified into three different charging levels of Electric Vehicle Supply Equipment (EVSE). Table 4.2 lists the differences between the three levels. The charging time for each CS is calculated as follows:

$$\rho_u^j = 60/r_u^j. \tag{4.5}$$

where ρ_u^j is the charging time of a EV at CS_u^j, and r_u^j is the number of EVs that a charger can serve per one hour. $\overrightarrow{P} = \{\rho_1 \;\; \rho_2 \;\; \rho_3 \;\; \dots \;\; \rho_M\}$, is the vector of the charging time at CS_u^j.

Thus, the total time for EV_i^k that have been assigned to CS_u^j is calculated as the sum of the travel time $\tau_{i,u}^{k,j}(X)$ of EV_i^k, where X is the associated matrix that shows the relation between EVs and CSs, the queuing time q_u^j at CS_u^j, and the charging time ρ_u^j inside CS_u^j, as shown in the following equation:

$$T_{i,u}^{k,j}(X) = \tau_{i,u}^{k,j}(X) + q_u^j(X) + \rho_u^j. \tag{4.6}$$

4.2.5 The Objective Function Formulation

To minimize the overall charging time of EVs, we determine the optimal assignment of EVs to CSs in urban environments. The following equation shows the corresponding optimization problem of our proposed approach:

$$\min_X \quad \sum_{i=1}^{N}\sum_{u=1}^{M}(\tau_{i,u}^{k,j}(X) + q_u^j(X) + \rho_u^j) \times x_{i,u}^{k,j} \tag{4.7}$$

$$s.t. \quad \sum_{u=1}^{D_i^k} x_{i,u}^{k,j} = 1, \qquad \forall i \in \mathcal{N} \tag{4.8}$$

$$\sum_{i=1}^{N} x_{i,u}^{k,j} \leq \eta_u^j \times r_u^j, \qquad \forall u \in \mathcal{M} \tag{4.9}$$

$$x_{i,u}^{k,j} \in \{0, 1\}, \qquad \forall i, u \in \mathcal{N},\ \mathcal{M} \tag{4.10}$$

$$(\tau_{i,u}^{k,j}(X) + q_u^j(X) + \rho_u^j) \leq \Gamma, \qquad \forall i, u \in \mathcal{N},\ \mathcal{M} \tag{4.11}$$

where N is the total number of EVs in the study area, M is the total number of CSs, EV_i^k is assigned to only one CS from the set of adjacent zones (D_i^k) as shown in Eq. (4.8). Constraint (4.9) indicates that the total number of EVs assigned to each CS should not exceed the capability of the CS, $x_{i,u}^{k,j}$ is a binary decision variable with values $\{0,1\}$ as shown in Eq. (4.10), to indicate whether CS_u^j in zone j is selected by EV_i^k, $x_{i,u}^{k,j}$ is equal to 1 if the CS_u^j in zone j is selected by EV_i^k, otherwise it is equal to 0. The total time to charge EV_i^k should not exceed a certain threshold value (Γ) which is used as EV drivers' QoE indicator as shown in Eq. (4.11). During the implementation process of the system, we assume that each EV should be fully charged within a certain period of time, i.e., (Γ), in order to limit the maximum time for charging an EV.

The quadratic objective function as shown in Eq. (4.7), and system constraints in Eqs. (4.8)-(4.11) form a MINLP problem, where the values of $x_{i,u}^{k,j}$ are constrained to be integer values $\{0,1\}$, and all constraints are linear terms. Finding the optimal assignment of EVs to CSs represent the solving of this optimization problem. In this work, GA is used to find the optimal assignment of EVs to CSs. Despite the high computational complexity of GA to solve this type of problems, it is considered as one of the most effective techniques that can be used to perform meta-heuristic search in very complex, multimodal landscapes, and large problems, and provide near optimal solutions for fitness or objective functions of optimization problems [164, 165], especially when the approaches using this technique prioritize the accuracy of the results rather than focusing only on the time required for implementation. Algorithm 1 explain the GA steps to determine the optimal assignment of EVs to CSs based on inheritance, mutation, selection and some other techniques. Fig 4.3 shows the flowchart of our proposed approach.

Algorithm 1 GA strategy to determine the optimal assignment of EVs to CSs

Input: $N, M, V_{i^k,t^{kj}}, V_{t^{kj},u}, \ell, \mu_i^k, \Psi_i, \mu_{t^{kj}}, \Psi_{t^{kj}}, \mu_u, \Psi_u,$
$\zeta_{i^k,t^{kj}}, \zeta_{t^{kj},u}, N^k, \varepsilon, \varphi, \eta_u^j, r_u^j, G_u^j, D_i^k, \Gamma, \beta, \lambda_u^j$
Output : X^{opt}

begin:

GA generates an initial population $F^{(1)} = \{X_1^{(1)}, X_2^{(1)}, X_3^{(1)}, ..., X_Y^{(1)}\}$
K = maximum number of GA iterations
Y = size of F
for $i = 1$ to N **do**
    for $u = 1$ to M **do**
        Calculate $d_{i,u}^{k,j}$ using Eqs. (4.2)
    end for
end for
for $u = 1$ to M **do**
    Calculate ρ_u^j using Eq. (4.5)
end for
set iteration ID s = 1
while s < K **do**
    for $n = 1$ to Y **do**
        for $i = 1$ to N **do**
            for $u = 1$ to M **do**
                Calculate $\delta_{i,u}^{k,j}(X_n^{(s)})$ using Eq. (4.3)
                Calculate $\tau_{i,u}^{k,j}(X_n^{(s)})$ using Eq. (4.1)
            end for
        end for
        for $u = 1$ to M **do**
            Calculate $q_u^j(X_n^{(s)})$ using Eq. (4.4)
        end for
        set $l_n = 0$
        for $i = 1$ to N **do**
            for $u = 1$ to M **do**
                $l_n = l_n + T_{i,u}^{k,j}(X_n^{(s)})$, where $T_{i,u}^{k,j}(X_n^{(s)})$ is the total time as shown in Eq. (4.6)
            end for
        end for
    end for
    $\overrightarrow{L} = \{l_1, l_2, l_3, ..., l_Y\}$
    $[b^{(s)}, idx_1] = min(\overrightarrow{L})$. This step calculates the minimum total time of the objective function as shown in Eq. (4.7).
    $R^{(s)} = F_{idx_1}^{(s)}$
    $C = \{b^{(1)}, b^{(2)}, b^{(3)}, ..., b^{(s-1)}\}$
    $[B, idx_2] = min(C)$
    if $b^{(s)} < B$ **then**
        $X^{opt} = R^{(s)}$
    else
        $X^{opt} = R^{(idx_2)}$
    end if
    if $|B - b^{(s)}| \leq \beta$ **then**
        Return X^{opt}
        Break
    end if
    GA selects solutions from $F^{(s)}$, then implements crossover process to create new offspring
    GA applies mutation operator on a random solution
    s = s + 1
    GA updates $F^{(s)}$ subject to the constraints in Eqs. (4.8) - (4.11)
end while
Return X^{opt}

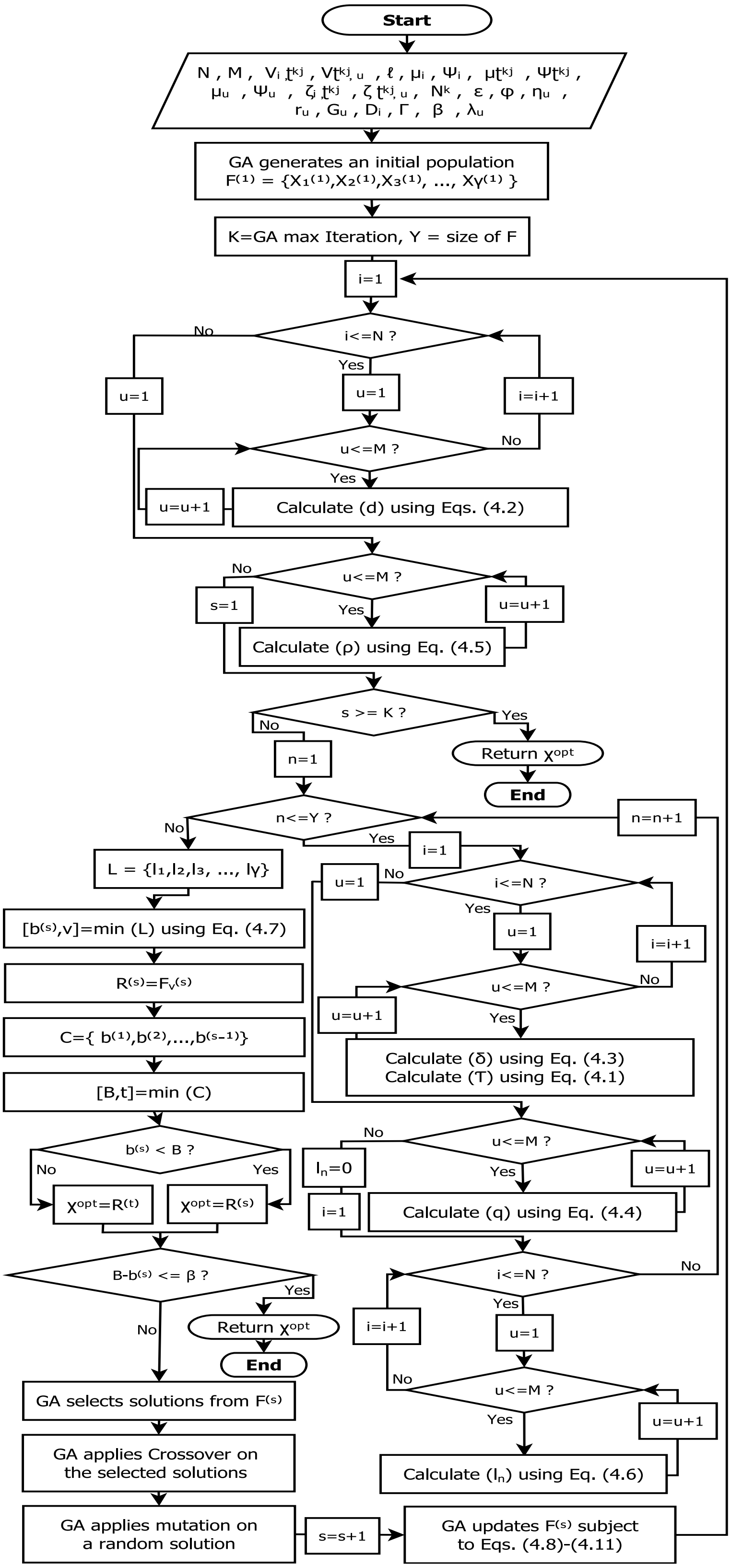

Figure 4.3: Flowchart of the proposed approach

4.2.6 The Objective Function Solution

To implement our optimization algorithm, a centric server is used, where all the required information should be stored on this server. Following is the information that should be stored on this server in advance:

- EV information includes; EV's ID, position, and to which zone its belong.
- CS details includes; CS's ID, location, η_u^j and r_u^j.
- Details of each zone includes; the borders of each zone, coordinates of the ports with adjacent zones, number of EVs, Number of ICEVs, and roads capacity of each zone.
- Study area characteristic includes; number of the zones, adjacency map between zones and the four corners which represents the investigated area.

The assignment of EVs to the optimal CSs is managed by the server which has all the information mentioned before. The implementation process on this server is done once using the objective function of this approach and all system constraints as introduced in Section 4.2.5. Any changes to the study area environment, should be reflected on the information that is saved on the server environment as well, then the algorithm that is stored on the centric server must be executed again to give updated and accurate results for the optimal assignment of EVs to CSs. Here we assume that the positions of EVs and CSs are fixed. The positions of EVs are represented by where their owners live. Each EV needs to communicate directly to the server in order to determine the optimal CS as shown in Fig. 4.4, which illustrates an example of charging process, starting from movement of EV to reach CS, then the waiting in a queue until a charger is available for charging. Finally, an EV leaves the CS after its battery is fully charged.

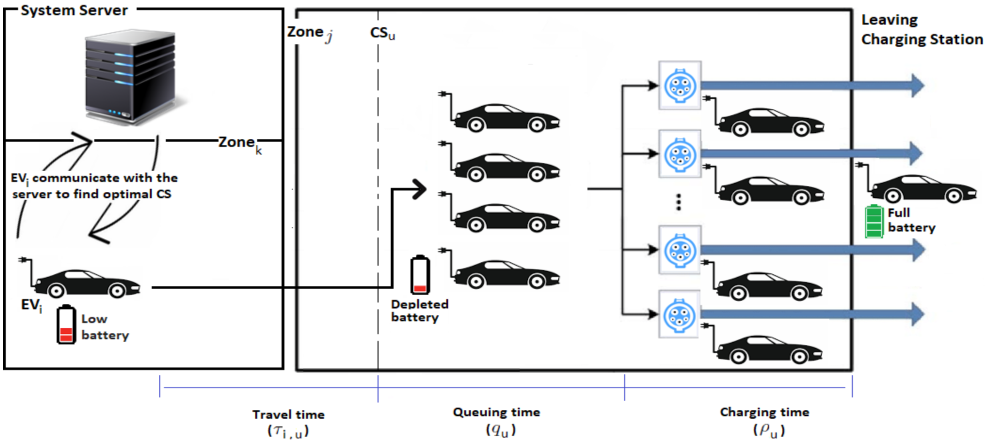

Figure 4.4: Illustration of charging process completion time.

Table 4.3: FOUR CORNERS OF THE STUDY AREA

Corner	Longitude	Latitude
SE	54.965405	-1.537112
NE	55.021271	-1.565240
NW	55.015563	-1.750658
SW	54.968385	-1.711929

4.3 Numerical Results

4.3.1 Base Scenario Settings

The proposed model is applied to the city of Newcastle upon Tyne considering a total of seven post codes from NE1 to NE7. Fig. 4.5 shows detailed map of the study area with a length of about 11 km and a width of about 6 km. As shown in Fig. 4.5, the available CSs are distributed on main roads in different zones in the study area. The coordinates of the four corners of the study area is shown in Table 4.3. Table 4.4 shows the information for each zone in terms of ID, EV population, ICEV population, the number and location of CSs at each zone, we assume 10 CSs in the study area as shown in Table 4.4. Table 4.5 shows the adjacency relations between zones.

According to the statistics of Newcastle upon Tyne city council in the second quarter 2020, the population of the personal ICEVs in Newcastle upon Tyne has reached around 82,850 [166]. 5%

Figure 4.5: Study area map

Table 4.4: ZONES INFORMATION

Zone ID	EVs Pop	ICEVs Pop	Zone CSs	CS's Coordinates	
				Latitude	Longitude
NE1	67	1349	CS2 CS3 CS4	54.9740967 54.9792671 54.9749156	-1.6212623 -1.6098994 -1.595424
NE2	268	5362	CS6	54.988027	-1.613854
NE3	1123	22466	CS9	55.0072571	-1.619521
NE4	499	9977	CS1 CS7	54.97448 54.9862673	-1.644712 -1.6594208
NE5	1150	23000	CS8	55.0023349	-1.6754294
NE6	708	14154	CS5	54.988743	-1.581588
NE7	333	6662	CS10	55.009272	-1.57895

Table 4.5: Adjacency relations between zones

Zone ID	Adjacent Zones	Zone Port Coordinates	
		Latitude	Longitude
NE1	NE2	54.982939	-1.612724
	NE4	54.975764	-1.626792
	NE6	54.976013	-1.589379
NE2	NE1	54.982939	-1.612724
	NE3	55.001376	-1.619571
	NE4	54.995152	-1.628682
	NE6	54.980327	-1.580731
	NE7	54.997546	-1.593246
NE3	NE2	55.001376	-1.619571
	NE4	54.989936	-1.656745
	NE5	55.00171	-1.667159
	NE7	55.006931	-1.601896
NE4	NE1	54.975764	-1.626792
	NE2	54.995152	-1.628682
	NE3	54.989936	-1.656745
	NE5	54.989939	-1.669187
NE5	NE3	55.00171	-1.667159
	NE4	54.989939	-1.669187
NE6	NE1	54.976013	-1.589379
	NE2	54.980327	-1.580731
	NE7	54.993012	-1.579443
NE7	NE2	54.997546	-1.593246
	NE3	55.006931	-1.601896
	NE6	54.993012	-1.579443

EV are assumed to be EVs. It is assumed that 10% of EV population needs to be charged at peak hour. We assume that 10% of ICEV use the same road as EVs per peak hour, also we assume that the capacity of the road in the study area is the same. Table 4.6 presents the value of the study parameters used in the current base scenario.

Besides the impact of charging activities of EVs and movement of EVs between adjacent zones, the movement of ICEVs is also taken into account in our proposed model. The assignment problem will be solved based on minimizing the overall completion time of charging EV batteries

Table 4.6: Base scenario parameters

Parameter	Value	Unit
N	415	-
M	10	-
V	8285	-
η_u^j	10	-
r_u^j	6	-
Z	7	-
ℓ	0.2	-
ζ	1590	-
Γ	120	minute
λ_u^j	48	-
β	10	-

considering our objective function in line with the system constraints. The proposed approach has been performed in MATLAB environment R2019a.

More studies have been evaluated to demonstrate the advantage of the proposed approach in determining the optimal assignment of EVs to the available CSs in the study area.

Four different case studies have been conducted as follows:

- Case A: With reduced congestion level on the road towards CS9 in NE3. We assume that the capacity of the road towards CS9 in NE3 is doubled, while the other CSs characteristics remain the same as the base scenario.
- Case B: With increased congestion level on the roads towards CSs in NE1. The road capacity towards CSs in zone NE1 is assumed to be reduced by a third, while the others CS conditions remain the same as the base scenario.
- Case C: With increased ICEVs. We assume that the number of ICEVs that share the roads with EVs moving towards CSs in NE1 is increased to be the same as in NE5, while the road capacity towards these CSs remain the same as the base scenario. The condition of other CSs remain the same as the base scenario.
- Case D: Increased charging rate of connectors. We assume that the maximum number of

EVs that can be charged per charger in CS1 and CS7 in NE4 to be 8 (r_1^4 and r_7^4 = 8) instead of 6 as assumed in other cases. The characteristics of other CSs remain the same.

- Case E: Future scenarios with increased EVs and ICEVs, in this case, we study the impact of increasing the number of EVs and ICEVs on the total time of charging EVs in Newcastle upon Tyne city in three different scenarios. Then we present suggested solutions in order to reduce the charging time caused by increasing the density of vehicles in the study area in these three scenarios.

In the result analysis section, we are going to analyze the impact of the total charging time on selecting the optimal CSs for EVs. In this chapter, the parameters that we are using to decide which CS is optimal for each EV includes; the travel time, queuing time, and charging time inside CSs. Moreover, the results will demonstrate the influence of these parameters on the satisfaction of EVs users, which in turn will positively affect the level of QoE for EVs users.

4.3.2 Result Analysis Discussion

In this section, we run experiments on the real data set from Newcastle upon Tyne city, results are presented in averages taken over 30 independent experiments. Error bars are used to represent the standard deviation obtained from these experiments.

Fig. 4.6 shows the comparison results between the base scenario and Cases A to D in terms of the assignment of EVs to CSs. EVs from different zones can select any CSs in adjacent zones, considering the constraint of CSs capabilities. It can be seen in Fig. 4.6 that the CSs at zones NE1, NE2, NE4, NE6 and NE7 in the base scenario have received a large number of EVs, the reason for this is the proximity of these CSs to the location of the majority of EVs in the study area, and also the congestion level in these zones are less compared to the other zones, which in turn reduces the time for these EVs to reach CSs due to the low level of congestion on the roads. Another observation in this case is that the assignment of EVs to CS8 in NE5 has reached to the

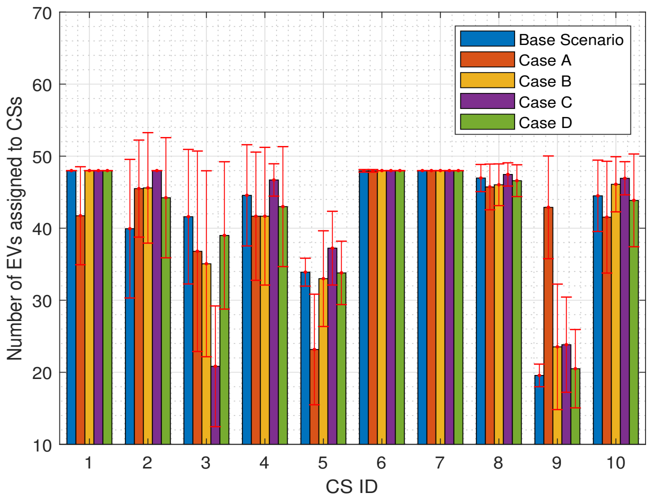

Figure 4.6: Comparison between all cases in terms of the number of EVs assigned to CSs

maximum number of EVs, although the congestion level in NE5 is very high due to the large number of ICEVs, and the reason behind this is that the location of EVs in NE3 is very close to CS8 in NE5. In addition, the EVs need to travel a long distance within a high congestion level in NE3 to reach other available adjacent CSs in NE2, NE4 and NE7. It can be observed that the EVs in the adjacent zones of NE3 has selected CS9 as shown in Fig. 4.6 in Case A, rather than selecting CS1, CS3 and CS5 as shown in the base scenario, and the reason behind this is that the road capacity towards CS9 in NE3 is doubled which in turn led to reduce the congestion level in NE3 as we assume in this case. In Case B, when the road capacity towards CSs in NE1 is reduced by a third while the road capacity of other CSs remain the same as the base scenario, it can be observed that the total number of EVs assigned to CS3 is less compared to the total number of EVs assigned to CS3 in the base scenario as shown in Fig. 4.6, and this is due to the high level of congestion on the roads resulting from the low road capacity towards this CS. The number of EVs that are assigned to CS2 and CS4 is almost the same as they are still the best CSs for EVs in NE4 and NE6, respectively.

The results obtained for Case C have shown the influence of the total number of ICEVs that

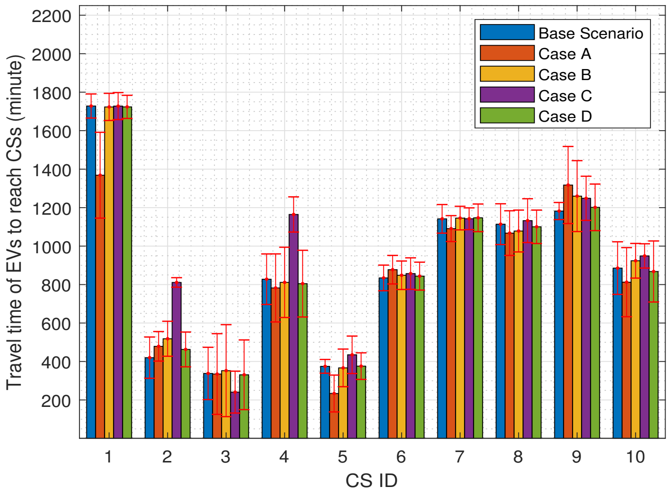

Figure 4.7: Comparison between all cases in terms of the travel time of EVs to reach CSs

share the same roads with EVs that are heading to charge at CSs in NE1, on the decision of assigning EVs to the optimal CSs. As shown in Fig. 4.6, the total number of EVs that have been assigned to CS3 is reduced more than a half compared to the base scenario. The main reason for this is the increased congestion due to the increase in the number of the ICEVs on the roads towards CS3. However, CS2 and CS4 in NE1 have the almost received the same number of EVs because they are still the best options for EVs in NE4 and NE6, respectively.

In Case D, we assume that the maximum number of EVs that can be charged per charger in NE4 is increased to 8 instead of 6, which in turn reduce the queuing time and charging time inside CSs. As shown in Fig. 4.6, the assignment of EVs to CSs in Case D is remain the same as in the base scenario, and the reason for this is, of course, the assignment of EVs to CS1 and CS7 have reached the maximum number of EVs in the base scenario. We will discuss the significant impact of this assumption, when it comes to talk about the figures and discussion of queuing time and charging time.

Fig. 4.7 shows the comparison between the base scenario and Cases A to D in terms of the travel time. Y-axis shows the total travel time of EVs that assigned with each CS. Knowing that EVs may have come from different zones. Several factors were taken into consideration to calculate the travel time of EVs en route to CSs, i.e, congestion level, road capacity towards CSs, total number of EVs and ICEVs that share the same route with these EVs that are heading to charge. In the base scenario, as can be seen in Fig. 4.7, the travel time of EVs that move from NE5 to reach CS1 in NE4 is significant, and the reason behind this is the large number of ICEVs inside NE5 and also the long distance between the locations of EVs in NE5 and CS1 in NE4. EVs in NE5 can be charged in two adjacent zones NE3 and NE4. However, they have selected CS1 in NE4 although CS9 in NE3 is much closer to their locations, and this is because of the high congestion level in NE3 due to the large number of ICEVs in this zone, compared to the number of the ICEVs in NE4 as shown in Table 4.4. It is easy to notice that the travel time of CS9 in NE3 is very high even though the number of EVs that are assigned to CS9 is very few as shown Fig. 4.6, and this is due to the high congestion level in this zone. Another observation in the base scenario in Fig. 4.7, is that the travel time of EVs that are assigned to CS2, CS3 and CS4 in NE1 is very low, although the EVs assignment to these CSs has almost reached to the maximum number of EVs that allowed to be assigned to CS, the reason for this is the low level of congestion in this zone, and the proximity of these CSs to the EVs locations.

It can be seen from Fig. 4.7, that the travel time of EVs that are assigned to CS9 in Case A is almost the same as in the base scenario, although the EVs assignment to CS9 has increased more than doubled, and also the number of ICEVs in this zone is very high, this is due to the assumption that the road capacity towards this CS has doubled. Another observation in the results of Case A in Fig. 4.7, is that the travel time of EVs to reach CS1 and CS5 are decreased, and the reason for this is that some of EVs in NE5 and NE7 have selected CS9 rather than selecting CS1 and CS5, this has reduced the travel time because of the low number of EVs that are assigned to them. In Case B, we assumed that the capacity of the roads towards CSs in NE1 is reduced by a third. As shown in Fig. 4.7, the travel time of EVs to reach CS9 is slightly increased compared to the base scenario, and the reason for this is that some of EVs in NE2 moved to NE3 for charging rather than selecting CS3 in NE1 due to the high congestion level because the road capacity towards NE1 is reduced as we assumed in this case, and this is also the reason why the travel time for CS3 is reduced. It is easy to see that the travel time to reach CS2 and CS4 is increased, this is also because of the congestion level in NE1 which is increased due to the assumption in this case.

In Case C, as shown in Fig. 4.7, the travel time of EVs to reach CS2 and CS4 has increased compared to the base scenario, this is due to the increase in the number of ICEVs in NE1 as we assumed in this case which in turn increased the congestion level on the roads towards these CSs. It is observed in Fig. 4.7 that the travel time of EVs to reach CS3 is reduced, the reason behind this is that the number of EVs that are assigned to CS3 has dramatically decreased because of the increase in the congestion level in this zone which encouraged some of EVs in NE2 to select CS9 in NE3 rather than selecting CS3 in NE1 as shown in Fig. 4.6. In Case D, we assumed that the maximum number of EVs that can be charged by a charger per hour in CS1 and CS7 in NE4 is 8 rather than 6 as assumed in the other cases, i.e, r_1 and $r_7 = 8$. As shown in Fig. 4.7, it is observed that the travel time of EVs to reach CS1 and CS7 in Case D and base scenario is almost the same, and the reason for this is that in both cases the number of EVs that are assigned to CS1 and CS4 have reached to the maximum number of EVs. As mentioned before, the effect of this assumption will be noticed when we study the figures of queuing time, charging time and total time.

Fig. 4.8 shows the queuing time inside each CS. As shown in Eq. (4.4), the queuing time is calculated considering the total number of EVs that are assigned to CS_u^j, the number of chargers at CS_u^j and the rated power of chargers. Y-axis shows the total queuing time of the EVs that assigned with each CS. In the base scenario and Cases A to D, we assumed that the number of chargers at each CS are the same, and the charger's rated power are the same for base scenario and Cases A, B and C, while it is different for Case D as mentioned earlier. As shown in Fig. 4.8, the queuing time at CS1, CS2, CS4, CS6, CS7, CS8 and CS10 in all cases is more than the other CSs, and the reason behind this is that the number of EVs that are assigned to these CSs is

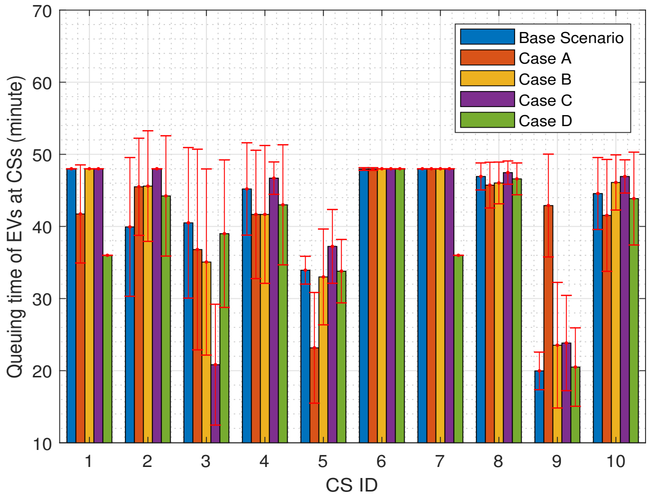

Figure 4.8: Comparison between all cases in terms of the queuing time of EVs at CSs

more than the other CSs as shown in Fig. 4.6. Quite the contrary, the queuing time at CS3, CS5 and CS9 is less, this is because the number of EVs are assigned to these CSs is less as shown in Fig. 4.6. Another observation in Fig. 4.8, is that the queuing time for CS1 and CS7 in Case D is less than the base scenario although the number of EVs that are assigned to them is the same, and this is because of the assumption of this case that the charger rated power is higher. As a result, the waiting time for EVs inside these CSs will be shorter. It is also shown in Fig. 4.8, that the queuing time at CS9 in Case A is higher than the other cases in CS9, and this is because of the assumption in this case that the road capacity towards this CS has doubled, which led to an increase in the number of EVs that are assigned to it, and thus an increase in queuing time inside it.

Fig. 4.9 shows the charging time of EVs that are assigned to each CS. The charging time for each EV inside CS_u^j is mainly depend on the number of EVs that can be charged by a charger in CS_u^j per hour as shown in Eq. (4.5). As shown in Fig. 4.9, it is obvious that the charging time of EVs that are assigned to CS1 and CS7 in Case D is less compared to the other cases, although the number of EVs that are assigned to them is the same, the reason behind this is that

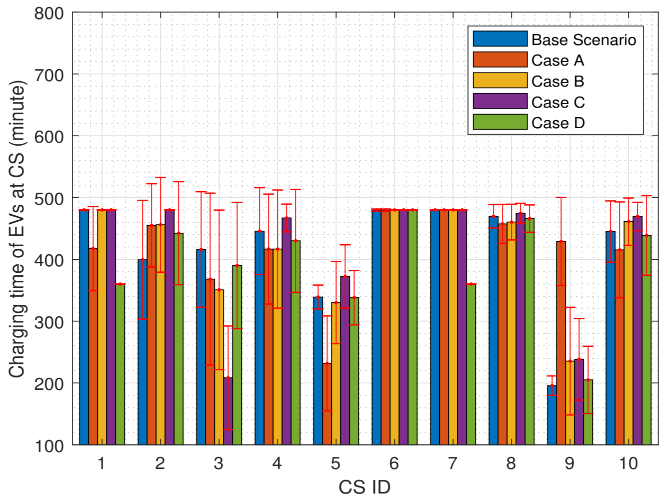

Figure 4.9: Comparison between all cases in terms of EVs charging time at CSs

the charger's rated power of CS1 and CS7 in Case D is higher than other cases in these CSs. As shown in Fig. 4.6 and Fig. 4.9, the CSs that received more EVs, the charging time is more, and the opposite is true for CSs that received fewer EVs. Therefore, the charging time at CS1, CS2, CS4, CS6, CS7, CS8 and CS10 in all cases is more than the other CSs.

Fig. 4.10 shows the total time of charging EVs at each selected CS, starting from movement towards CSs until departure as shown in Fig. 4.4. The total time consists of travel time, queuing time and charging time at CS. As shown in Fig. 4.10, CS1 has the highest total time compared to all CSs and in all cases, and the reason for this is that CS1 has almost reached the maximum number of EVs in the base scenario, and Cases B, C and D. Knowing that these EVs come from NE5, and as shown in Table 4.4, the number of ICEVs in NE5 is very high which increases the congestion level on the roads towards CS1 in NE4, also the distance that EVs need to move from NE5 to reach CS1 in NE4 is too long as shown in the study area map in Fig. 4.5. Another observation in Fig. 4.10, is that the total time of EVs that are assigned to CS2 and CS4 is low although the EVs assignment to these CSs has almost reached to the maximum number of EVs that allowed to be assigned to CS, the reason for this is the low level of congestion in this zone

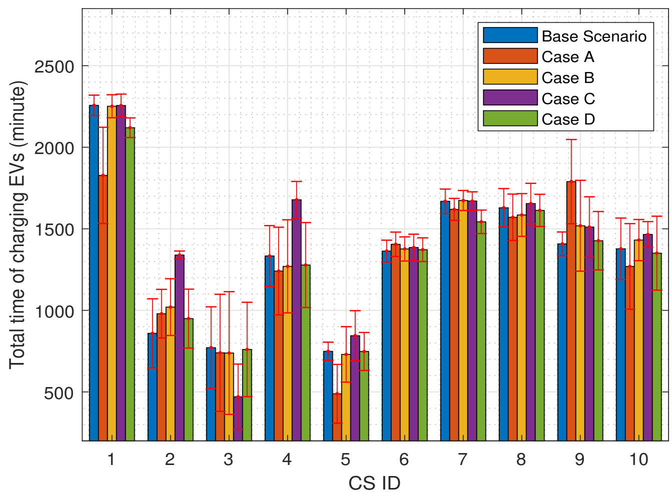

Figure 4.10: Comparison between all cases in terms of the total time of EVs with each selected CS

Table 4.7: Comparison between the base scenario and Case D in terms of the total charging time

CS ID	**Base scenario**		**Case D**	
	EVs	Charging Time (m)	EVs	Charging Time (m)
CS_1	48	2,256.897	48	2,119.686
CS_7	48	1,668.656	48	1,542.862
Total	**96**	**3,925.553**	**96**	**3,662.548**

the zones from which these EVs come, in addition to the proximity of these two CSs to the sites of EVs. As shown in Fig. 4.10, the total time of EVs that are assigned to CS1 and CS2 in Case D is the least compared to the others cases in these two CSs, and the reason for this is the assumption of this case that the chargers rated power in these CSs is higher than other cases. Table 4.7 shows comparison between the base scenario and Case D in terms of the total time for charging EVs in CS1 and CS7.

Fig. 4.11 shows the total time of charging EVs that are assigned to the best choice of CSs for the base scenario and the other cases that have been proposed in order to demonstrate the efficiency of the proposed scheme. As shown in Fig. 4.11, it is obvious that the total time for Case A is less compared to the base scenario, and the reason behind this is the assumption in this case

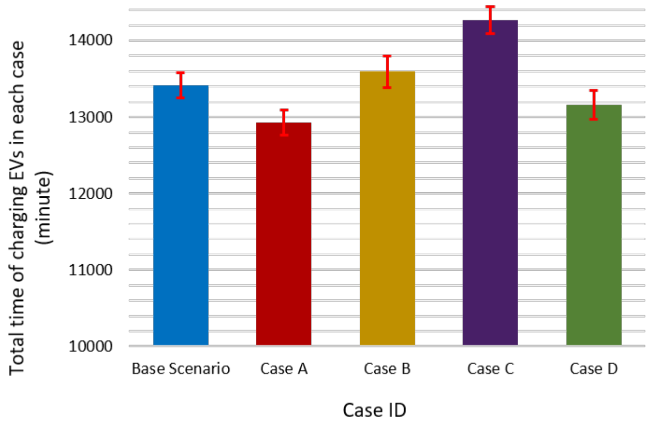

Figure 4.11: Total time required to fully charge EVs based on proposed cases

which is increasing the road capacity to the double towards CS9 in NE3. The number of ICEVs in this zone is large, and thus increasing the road capacity led to less congestion level on the road, therefore less travel time to reach CS9. In Case B, as shown in this figure, the total time is higher than the base scenario as shown in Fig. 4.11, and this is due to the decrease in the road capacity of CS2, CS3 and CS4 in NE1 by a third, which has resulted in an increase in the level of congestion on the roads leading to these CSs.

To demonstrate the influence of ICEVs on the congestion level and total time. In Case C, the number of ICEVs in NE1 was increased to be the same as in NE5 while the road capacity remain the same as in the base scenario. As a consequence, the total time for the EVs that are assigned to the CSs has increased compared to the base scenario as shown in Fig. 4.11,. In Case D, the total time has decreased compared to the base scenario as shown in Fig. 4.11, and the reason for this is the increase in the maximum number of EVs can be charged per charger in CS1 and CS7 in NE4, as the charging time inside the CS mainly depends on the rated power of charger.

Figs. 4.12 and 4.13 show the assignment of EVs to the optimal CSs as proposed for Case E, and also the total expected charging time for EVs which increased dramatically due to the increase number of vehicles in Newcastle upon Tyne as proposed in the three scenarios. Fig. 4.12 shows how the EVs are distributed to the available CSs based on the projection that the number of EVs

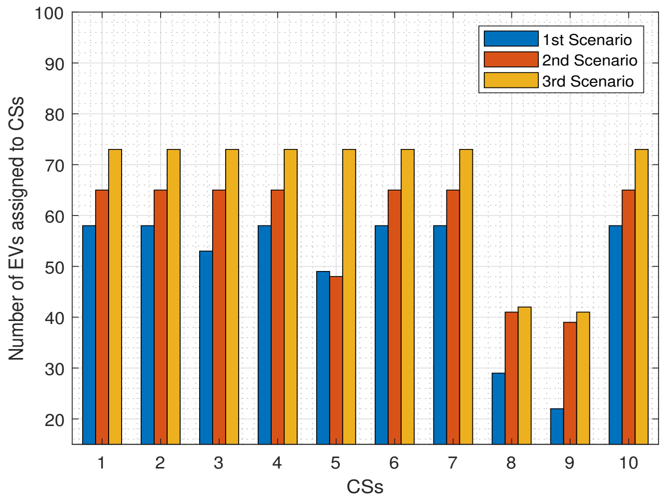

Figure 4.12: The number of EVs assigned to CSs for Case E

and ICEVs will increase by 20% and 10% for the first scenario, 40% and 15% for the second scenario, 60% and 20% for the third scenario, respectively, compared to the current vehicle density in the study area. It is assumed that the values of λ_1, λ_2, λ_3, ..., λ_M = 58, 65 and 73 for the three proposed scenarios, respectively. In this case we also assume that the rest of parameters remain the same as in the base scenario.

Fig. 4.13 shows the total expected time for charging EVs based on the assumption in this case. It is obvious that the total time has increased dramatically, as shown in Fig. 4.13. To overcome the increase in total time for the three proposed scenarios, the following two suggested solutions have been proposed:

- Selecting most recent chargers which can serve more EVs within one hour r_u^j.
- Increasing the number of chargers η_u^j at each CS.

In the first suggested solution, to minimize the overall charging time. We assume that the maximum number of EVs that can be charged per charger in CS_u^j is increased to 8 per hour, which means that r_1, r_2, r_3, ..., r_{10} = 8 instead of 6 as assumed in the previous three scenarios. The use of new technology and an advanced charger directly affects the total number of EVs that can be

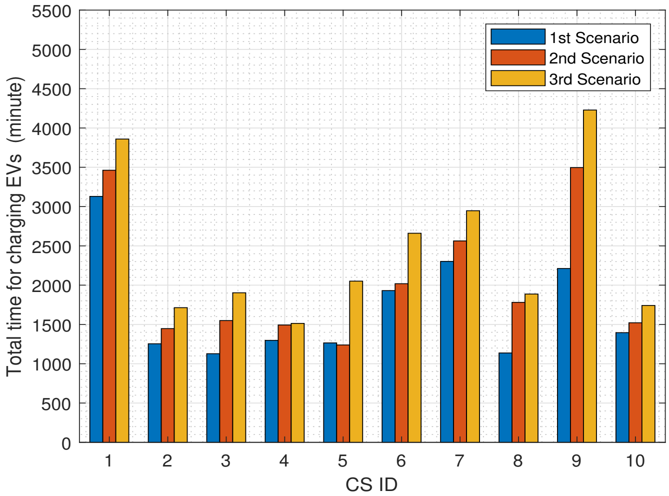

Figure 4.13: Case E results in terms of the total time to charge EVs

charged per hour. As a results, the total time of charging EVs has decreased. Table 4.8 show the impact of the charger's rated power on reducing the total time of charging EVs for the three proposed scenarios.

In the second suggested solution, to minimize the overall charging time for the three proposed scenarios, the number of chargers will be increased to 12 for all CSs, i.e, η_1, η_2, η_3, ..., η_{10} = 12, instead of 10 chargers as assumed before. The increase in the number of chargers in the CSs affects directly the performance of the CS in terms of the queuing time, as having a larger number of chargers reduces the overall charging time of EVs as shown in Table 4.9. As shown in the previous figures, it is obvious that increasing the charger rated power as proposed in the first solution has more impact on the total time than increasing the number of chargers as proposed in the second scenario, and the reason behind this is that the chargers rated power affects the queuing time and also the charging time, while the number of chargers at CS affects only on the queuing time inside the CS.

Table 4.8: Total time of charging EVs at each CS in Case E where r_u^j = 6 & 8 (minute)

CS ID	**First scenario**		**Second scenario**		**Third scenario**	
	r_u^j		r_u^j		r_u^j	
	6	8	6	8	6	8
CS_1	3129.436	2929.957	3462.292	3241.408	3859.115	3694.001
CS_2	1254.219	1094.370	1447.106	1271.255	1713.511	1529.704
CS_3	1127.682	825.532	1549.504	1515.246	1903.029	1215.131
CS_4	1297.453	1359.746	1493.089	1157.926	1513.397	1886.994
CS_5	1265.391	880.521	1239.194	1219.198	2051.236	1850.486
CS_6	1930.784	1528.256	2018.615	1834.006	2660.624	2465.614
CS_7	2302.362	2181.940	2563.098	2432.267	2947.114	2707.806
CS_8	1137.250	1396.896	1780.957	1711.818	1886.901	1497.118
CS_9	2211.886	2151.900	3496.111	3250.258	4228.490	4297.014
CS_{10}	1395.503	1253.178	1521.501	1342.022	1741.338	1541.407
Total	**17051.966**	**15602.296**	**20571.467**	**18975.404**	**24504.755**	**22685.275**

Table 4.9: Total time of charging EVs at each CS in Case E where η_u^j = 10 & 12 (minute)

CS ID	**First scenario**		**Second scenario**		**Third scenario**	
	η_u^j		η_u^j		η_u^j	
	10	12	10	12	10	12
CS_1	3129.436	3083.942	3462.292	3381.059	3859.115	3859.124
CS_2	1254.219	1222.939	1447.106	1450.238	1713.511	1803.638
CS_3	1127.682	1123.473	1549.504	1711.524	1903.029	1704.202
CS_4	1297.453	1374.078	1493.089	1382.053	1513.397	1690.162
CS_5	1265.391	983.107	1239.194	1231.533	2051.236	2038.787
CS_6	1930.784	1675.865	2018.615	2008.467	2660.624	2652.549
CS_7	2302.362	2328.274	2563.098	2621.245	2947.114	2911.251
CS_8	1137.250	1489.607	1780.957	1540.156	1886.901	1589.396
CS_9	2211.886	2206.676	3496.111	3644.655	4228.490	4419.275
CS_{10}	1395.503	1401.002	1521.501	1508.481	1741.338	1733.263
Total	**17051.966**	**16888.963**	**20571.467**	**20479.411**	**24504.755**	**24401.647**

4.3.3 A Comparison between QoE strategy and Greedy strategy

In this work, the greedy strategy that is used to find the optimal assignment of EVs to CSs is only depend on the distance between the locations of EVs and CSs and ignore the other parameters that we use in our approach, i.e., the proposed greedy strategy solves the EVs assignment problem based on minimizing the distance that EVs travel to reach CSs, and ignore all other parameters that we use in our QoE strategy. The comparison between the two strategies is done first based on the congestion level that is proposed in the base scenario, and then the congestion ratio is increased by 20%, 40%, 60%, 80% and 100% in order to see the impact of congestion level on the EV driver's QoE. Fig. 4.14 shows the comparison between the proposed QoE approach and the greedy strategy, in terms of the total number of EVs assigned to each CS. It is observed that the number of EVs that are assigned to some CSs has changed. As shown in Fig. 4.14, CS9 in NE3 in greedy strategy has reached the maximum number of EVs compared to low number of EVs in the QoE strategy, and the reason for this is that the EVs in NE5 moved to NE3 for charging because of the proximity to the location of CS9 in NE3 and also ignoring the high congestion level in both zones, knowing that the NE3 and NE5 have the highest congestion level because of the high number of ICEVs in these zones compared to the other zones as shown in Table 4.4. Another observation in Fig. 4.14, is that the assignment of EVs to CS1 and CS3 in greedy assignment has decreased dramatically, and the reason for this is that the EVs in NE5 selected CS9 in NE3 rather than selecting CS1 in NE4, and the EVs in NE2 selected CS5 instead of CS3 in NE1, and the reason for this is the long distance between the locations of EVs and CSs.

Figs. 4.15 and 4.16 show the comparison between the QoE strategy and greedy strategy in terms of the travel time and the total time for charging EVs, respectively. It is easy to see in both figures that the travel time and total time have increased in greedy scenario, and the reason for this is that the congestion level on the road towards CSs has been ignored when assigning EVs to CSs, whereas the only metric that has been considered is the distance between the EVs and

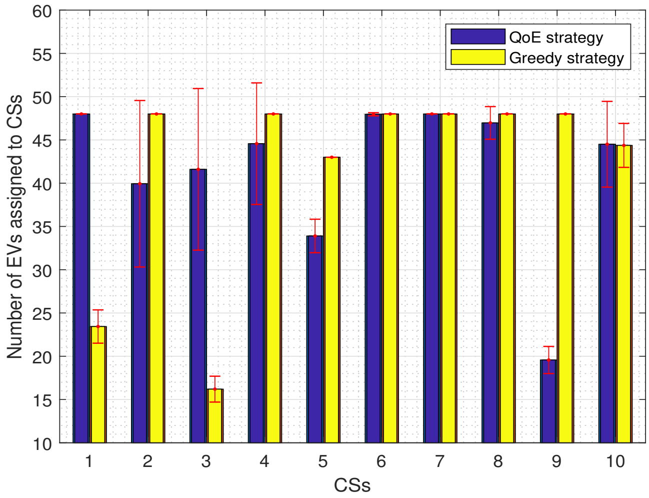

Figure 4.14: Comparison between QoE strategy and Greedy strategy in terms of EVs assigned to CSs

the locations of CSs.

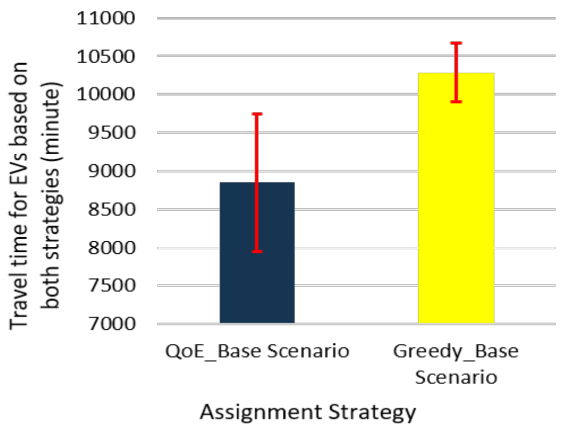

Figure 4.15: Comparison between QoE strategy and Greedy strategy in terms of travel time

Figs. 4.17 and 4.18 show the comparison between the QoE strategy and greedy strategy in terms of the travel time and the total time, respectively, taking into consideration different percentages of the level of congestion on the roads leading to the charging stations. It is obvious that the total time and travel time in QoE strategy is less compared to the greedy strategy, and the reason behind this is that in addition to the distance between the locations of EVs and CSs, the congestion

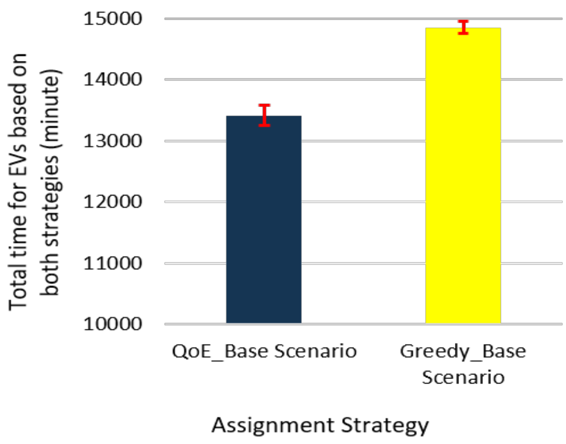

Figure 4.16: Comparison between QoE strategy and Greedy strategy in terms of total time of charging EVs

level has also been taken into account in this strategy.

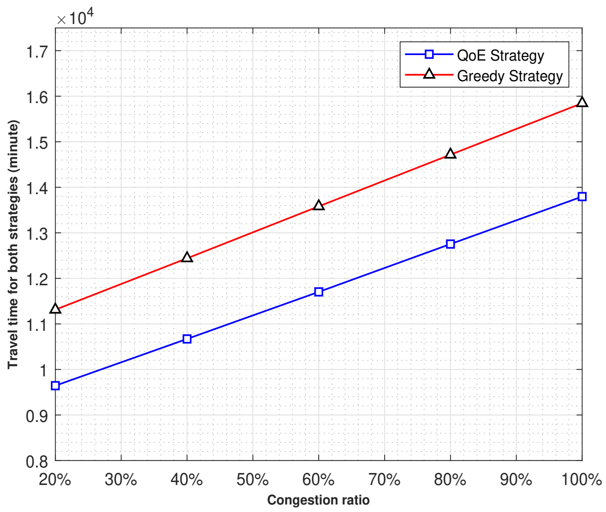

Figure 4.17: Travel time required for EVs to reach CSs based on the proposed scenarios taking into account the differences in congestion ratio

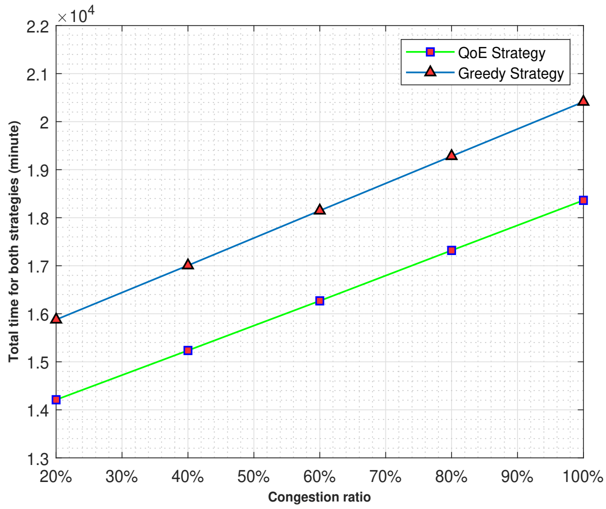

Figure 4.18: Total time required to fully charge EVs based on the proposed scenarios taking into account the differences in congestion ratio

4.4 Summary

In this chapter, we investigated a novel scheme to assign EVs to CSs using an optimization model. The assignment of EVs to the optimal charging stations has been done considering the EV user's QoE, in terms of the total completion time of charging EVs at CSs in the study area. In this chapter, the assignment problem has been formulated as MINLP problem, this is because the decision of selecting the optimal charging station is directly influenced by the interaction between the EVs themselves and between EVs and ICEVs in the investigated area. GA technique has been incorporated into this work in order to solve the assignment problem. The proposed approach has been applied to different cases using real world datasets of Newcastle upon Tyne, United Kingdom. The results of the proposed technique were compared with the greedy strategy, as well as with different case studies. Based on the results of the comparison between our proposed technique and the greedy technique, the total charging time of EVs was increased bout 12% when the assignment of EVs to the CSs has been done using the greedy strategy. Moreover, the obtained results have shown that the total charging time for EVs was dramatically affected by the level of the congestion on the roads leading to the CSs. On the contrary, the charging time was decreased about 7% when rated power of chargers has been increased a little more. These results demonstrate the influence of the parameters that have been used in this work on the EVs users' QoE, and also on the decision of assigning EVs to CSs.

Chapter 5

A Reinforcement Learning-based Assignment Scheme for EVs to Charging Stations

5.1 Introduction

Due to recent developments in E-mobility, public charging infrastructure will be essential for modern transportation systems. As the number of electric vehicles (EVs) increases, the public charging infrastructure needs to adopt efficient charging practices. A key challenge is the assignment of EVs to charging stations (CSs) in an energy efficient manner. In recent years, more attention has been paid to propose different approaches to solve the problem of finding the optimal CSs for EVs in metropolitan environments. Recently, various learning-based studies have been conducted in the literature in order to solve this problem. Reinforcement Learning (RL) is one of the fastest developing Machine Learning (ML) techniques in recent years. The Q-learning algorithm is one of the most important RL algorithms, which was presented by Watkins in 1989 [167]. Another technique of RL is the temporal difference (TD) learning algorithm [168], and some researchers classify Q-learning as a special case of TD learning [169, 170]. Q-learning and Deep Reinforcement Learning (DRL) algorithms have been extensively used in various applications such as robot soccer competition, time sequence prediction, industrial control, and many more. For any Finite Markov Decision Process (FMDP), Q-learning is a very effective algorithm that can be incorporated with different parameters and constraints to solve such kind of problems. The reason for this is that Q-learning is a model-free RL, which does not require a model for the environment in which the agent is deployed, and it can solve problems based on stochastic transitions and rewards without the need for adaptations.

To the best of our knowledge, the existing works that have been introduced to solve this problem did not take into account the interaction between CSs and Electrical Grids (EGs) in the investigated areas, or the difference in charging rate at the CSs, and also they did not include an EV's Battery State of Charge (SoC) as a constraint to limit the amount of energy consumption that an EV requires to reach CS. These parameters and constraints have great influence on the EV users' satisfaction and also on the percentage of overload on EGs. In [171], a reinforcement learning model was proposed to solve the problem of EVs routing problem. In this paper, a series of simulations have been performed based on energy consumption dataset from a real traffic scheme in urban environment. The objective of this paper is to minimize the amount of energy that EVs consume to reach destinations, and also minimize the risk of battery depletion while EVs moving to CSs for charging. The energy consumption that results from the movement of EVs to CSs was also considered in [172]. However, as mentioned earlier, the authors of two studies did not consider the difference in charging rates between the available CSs in the investigated area, also the EV's battery SoC.

To fill the research gap in this area, a RL-based EV Assignment Scheme is proposed to solve the problem of assigning an EV to the optimal CS in urban environments, aiming at minimizing the total cost of charging an EV, which in turn helps in reducing the overload on Electrical Grids (EGs). Travelling cost that is resulted from the movement of an EV to CS, and the charging cost at CS are considered. Moreover, an EV's SoC is taken into account in the proposed scheme as a constraint to limit the maximum amount of energy that an EV consumes during its movement to find CS. The proposed approach will approximate the solution by finding an optimal policy function in the sense of maximizing the expected value of the total reward over all successive steps using Q-learning algorithm, the Temporal Difference (TD) learning and Bellman expectation equation. Finally, the numerous simulation results illustrate that the proposed scheme can significantly reduce the total energy cost of EVs in various case studies and compared to the greedy algorithm, and also demonstrate its behavioural adaptation to any environmental conditions. The notations used in this chapter are listed in Table 5.1. In addition, parameters and variables are explained where they are first used.

The main contributions of the present chapter are summarized as follows:

- A RL-scheme for assignment of EVs to the optimal CSs in metropolitan environments is proposed in this chapter. The proposed scheme considers the energy consumption cost that is resulted from the movement of an EV towards CS (travelling cost), and the total expected cost to fully charge an EV at CS (total energy cost). An EV's battery SoC is also taken into account as a constraint to limit the amount of energy consumption that an EV consumes to reach CS.

- Q-learning algorithm has been utilized to solve this problem based on maximizing the cumulative reward of an EV during learning process by reducing the total cost of charging EVs.

- As a results of applying our proposed scheme, we minimize the load on the overwhelmed EGs, by assuming different rewards for the available CSs in the study area. The reward at each CS is determined based on the electricity price offered by electrical grids (EGs) to CSs, these prices vary according to the load and locations of EGs.

The rest of the chapter is organized as follows. EVs assignment problem formulation and optimization model are presented in Section 5.2. Then, a RL based approach is proposed in Section

Table 5.1: MAIN NOTATIONS AND THEIR DESCRIPTIONS

Notation	Description
$\mathcal{M}$	Set of CSs.
$\mathcal{S}$	Set of states.
$\mathcal{A}$	Set of actions.
j	index of CSs.
$E_{ev,j}$	The overall energy.
a, a'	The action that the agent takes in the current state, and target state, respectively.
$\vartheta_{ev,j}$	The energy consumption cost that is resulted from the movement of an EV towards CS.
$\xi_{ev,j}$	The total expected energy to fully charge an EV at CS, except the travelling cost.
$d_{ev,j}$	The total distance that an EV travels to reach CS.
ψ_{ev}, ψ_j	The latitude of EV and CS_j, respectively.
μ_{ev}, μ_j	The longitude of EV and CS_j, respectively.
$C_{ev,j}$	The overall cost of charging an EV.
$U_{ev,j}$	The accumulative reward for EV with CS_j.
Rw_j	The reward that is associated with CS_j.
V	The total number of actions that EV takes to arrive CS_j.
φ_j	The charging rate at CS_j.
ζ_{ev}	EV's battery capacity.
$x_{ev,j}$	A binary decision variable shows that the EV selects CS_j for charging.
$Q(s,a)$	A state-action value function, i.e., Q-value function.
α, γ	The learning rate and discount factor, respectively.
r	The immediate reward.
$Q^*(s,a)$	The optimal state-action value function.
$\pi^*(s)$	The optimal policy.
s, s'	The current state and target state, respectively.
M	The number of CSs in the study area.
Φ	A threshold value that restricts the maximum amount of energy consumption that an EV consumes to reach CS.

5.3. Section 5.4 shows the numerical results of our proposed approach. Finally, Section 5.5 draws a conclusion.

5.2 EVs Assignment Problem

5.2.1 Problem Formulation

The problem has been formulated as shown in the following sections:

5.2.1.1 EV

An EV is represented by a single agent that moves in the environment trying to find the optimal CS considering the possible actions and reward at each state. The EV has one attribute; (p^{ev}), where p^{ev} is the position (coordinates) of EV.

5.2.1.2 CSs

Define the CS set as $\mathcal{M} = \{1, ..., u, ..., M\}$. The cardinality of $\mathcal{M}$ is M, i.e., there are M CSs in the investigated area. CS_j in $\mathcal{M}$ has two attributes; b^u, r^u, where b^u, and r^u are the position and reward of the CS. The reward at CS_j, depends on the charging rate of CS_j.

5.2.1.3 Cost-based EV assignment

The proposed strategy uses a RL technique to assign an EV to the best CS based on minimizing the total cost of charging EVs, i.e, $C_{ev,j}$. To calculate the total expected cost of charging an EV, two factors should be investigated: the energy consumption cost that is resulted from the travelling of an EV towards CS, i.e., $\vartheta_{ev,j}$, and the total expected energy to fully charge an EV at CS, i.e., $\xi_{ev,j}$, considering the charging rate at each CS which is usually determined by the electricity price offered by EGs to the CS owners. Fig. 5.1 depicts the interaction between the three entities of the system, EV, CS, and the EG. The electricity price offered by EGs to CSs is different due to the load and location of each EG. CSs connected to the same EG have the same electricity price, and therefore the same charging rate. The overall energy, i.e, $E_{ev,j}$, can be calculated as follows:

$$E_{ev,j} = \vartheta_{ev,j} + \xi_{ev,j} \tag{5.1}$$

To calculate $\vartheta_{ev,j}$, we need to calculate the amount of energy that an EV consumes per km to reach CS, i.e., δ_{ev} [160, 162], and also calculate the total distance that an EV travels towards CS, i.e., $d_{ev,j}$. In this work, we assume that δ_{ev} is 0.16 kWh/km [173, 174]. The following illustrates how $d_{ev,j}$, $\vartheta_{ev,j}$, and $\xi_{ev,j}$ are calculated:

$$d_{ev,j} = \sqrt{\left(\psi_{ev} - \psi_j\right)^2 + \left(\mu_{ev} - \mu_j\right)^2} \tag{5.2}$$

where ψ_{ev}, ψ_j are the latitude of EV and CS_j, and μ_{ev}, μ_j are longitude, respectively.

$$\vartheta_{ev,j} = \delta_{ev} * d_{ev,j} \tag{5.3}$$

where δ_{ev} is the amount of energy that an EV consumes per km to reach CS. Eq. 5.4 shows how the total energy to fully charge EVs is calculated, except the travelling cost.

$$\xi_{ev,j} = (\zeta_{ev} - SoC) \tag{5.4}$$

where ζ_{ev} denotes the capacity of the battery, and SoC is the battery state of charge. The total cost of charging an EV can be calculated as follows:

$$C_{ev,j} = E_{ev,j} \times \varphi_j \tag{5.5}$$

where φ_j represents the charging rate at CS_j.

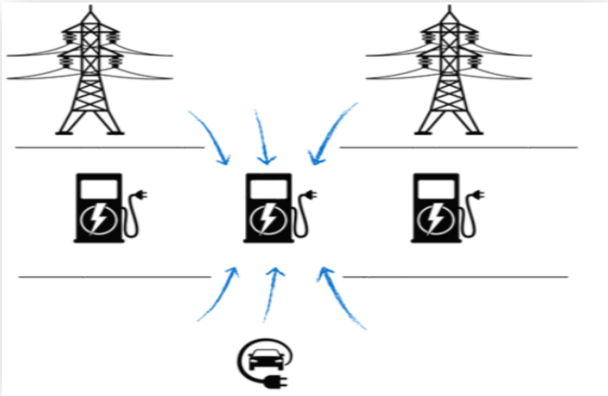

Figure 5.1: EVCS interaction strategy

5.2.2 Optimization Problem

The corresponding optimization problem of our proposed approach can be written as:

$$\min_{X} \quad \sum_{j=1}^{M} C_{ev,j}\, x_{ev,j} \tag{5.6}$$

$$s.t. \quad \sum_{j=1}^{M} x_{ev,j} = 1 \tag{5.7}$$

$$x_{ev,j} \in \{0, 1\}, \qquad \forall j \tag{5.8}$$

$$\vartheta_{ev,j} < \Phi, \qquad \forall j \tag{5.9}$$

where the variable $x_{ev,j}$ is used as a decision variable with binary values $\{0,1\}$ as shown in (5.8), to indicate whether the charging station j is selected by an EV or not, $x_{ev,j}$ is equal to 1 if the j is selected, otherwise it is equal to 0. Constraint (5.7) restricts that only one charging station is selected as a destination for charging. Constraint (5.9) is determined in the experiments, and used as a a certain threshold Φ to limit the total amount of energy that an EV consumes to reach

CS, as well as maintain an EV's battery SoC.

5.3 Reinforcement Learning Approach

Typically, RL techniques can be processed under two categories: off-policy and on-policy [175]. In particular, an off-policy learning method (e.g., Q-learning) earns an optimal target policy independent of the behavior policy used during exploration process as long as the different states are explored enough times. Whereas on-policy learning method finds the optimal policy taking into account the actual actions taken over the exploration process, which means that the target policy is the same as the behavior policy used in exploration process. Q-learning technique will be used in this work to addresses the problem of assignment EV to CS.

5.3.1 Q-learning-based EV Assignment

In this section, a RL technique is employed to solve our optimization problem (5.6)-(5.9) using Q-learning Algorithm technique. Q-learning is an incremental technique for dynamic programming, which is suitable for solving such kind of problems. This technique is agent-based that is the AI agent interacts with its environment and adapts its actions based on rewards or penalties received in response to its actions [176]. Mainly, there are mainly three basic elements in the Q-learning algorithm: environment, state, and action. We will introduce the algorithm after setting the elements.

5.3.1.1 Environment, State, and Action Set

The environment is an essential element in Q-learning, in which the AI agent selects its actions according to corresponding rewards. In our scenario, the environment should involve roads between EVs and those available CSs.

Fig. 5.2 shows part of the Newcastle upon Tyne, UK. The directions (actions) that an EV can select to move from the current to the next state in the study area, are represented by three colors

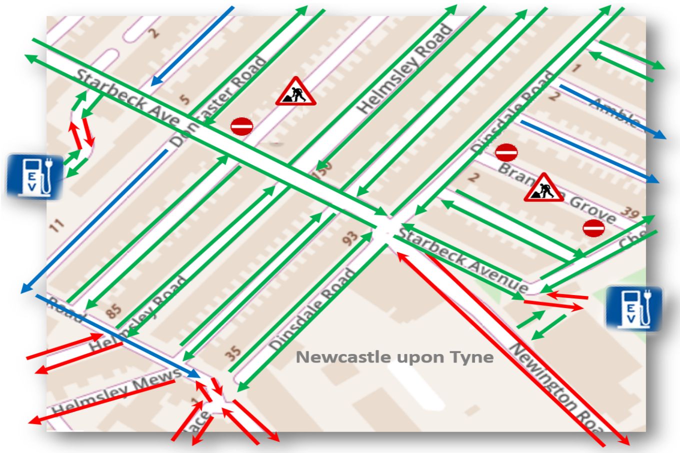

Figure 5.2: Sample area in the urban area of
Newcastle upon Tyne city, UK

of arrows. The green and blue arrows show that an EV can move in only four directions: South, North, East, and West. The difference between the green and blue arrows is that the green arrows show that an EV can move in both directions, while the blue arrows show that an EV can only move in one direction. The red arrows indicate that an EV can move in the other four directions: South-East, South-West, North-East, and North-West and also in both directions. Road works signs indicate that these streets are closed and cannot be used by vehicles, so the EV user needs to find other streets to reach CS. The CSs are distributed in fixed locations in the study area as shown in Fig. 5.2.

The state set in our scenario can be denoted by $\mathcal{S}$, and defined as following:

$$\mathcal{S} = \{(x_1, y_1), (x_2, y_2), (x_3, y_3), ..., (x_n, y_n)\} \tag{5.10}$$

where x and y represent the position (coordinate) of the state that an agent can visit during its journey to the destination. The cumulative reward is calculated based on the actions that have been taken by an EV in the environment, and can be calculated as follows:

$$U_{ev,j} = Rw_j - \sum_{i=1}^{V} r_i \tag{5.11}$$

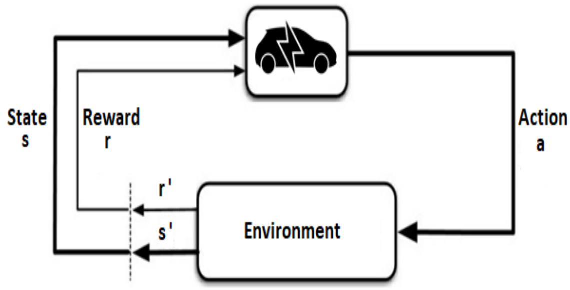

Figure 5.3: Example of a single movement of an EV

where $U_{ev,j}$ represents the accumulative reward for EV with CS_j, Rw_j denotes the reward that is associated with CS_j, V represents the total number of actions that EV takes to arrive CS_j, and r_i is the immediate reward that EV gets for each action in the environment.

The action set, i.e., $\mathcal{A}$, of an EV in the grid world denotes the way in which an EV can move to change its state (the interaction between an EV and the surrounding environment). In our scene, the directions that an EV is allowed to use are included in the following set:

$$\begin{aligned} \mathcal{A} = \{&South,\ North,\ East,\ West,\ South-East, South-West, \\ &North-East,\ and\ \ North-West\} \end{aligned} \tag{5.12}$$

The energy consumption cost that results from the movement of an EV towards CS, i.e., $\vartheta_{ev,j}$, is mainly dependent on the distance between the locations of an EV and CS. To minimize this cost, we need to reduce the covered distance that an EV needs to travel to reach the CS. To achieve this, an EV earns punishment (penalty) for every movement (hop) in the grid. The rewards associated with CSs depend on the charging rates at these CSs. Accordingly, the higher the CS charging rate, the lower its reward. The reward increases as the charging rate decreases. Fig. 5.3 shows an illustrative example of a single movement of an EV in the environment.

5.3.1.2 Q-learning Algorithm

Two input parameters are required for Q-learning algorithm: the state in which the agent is located, and an action that can be taken at the current state. Therefore, the Q-learning algorithm has a function that calculates the quality of these two parameters, as shown below:

$$Q : S \times R \rightarrow \mathbb{R} \tag{5.13}$$

Before an agent starts its learning process, Q is initialized to an arbitrary fixed value (zero in our approach). Then at each step the agent chooses an action a_t, earns a reward r_t, moves to a new state s_t, then Q is updated. In this work, the objective function is minimizing the total energy cost of an EV which can be calculated using the optimal strategy by recursively updating action-value function (Q). The value of this function is determined by the TD learning algorithm technique and the Bellman equation, as shown bellow:

$$Q(s, a) \leftarrow Q(s, a) + \alpha(r + \gamma\ max_{a'}\ Q(s', a') - Q(s, a)) \tag{5.14}$$

where $Q(s, a)$ represents the value of the state-action function, i.e, Q-value function (s, a), α and γ denotes the learning rate and discount factor between 0 and 1, and r is the immediate reward value received as the result of taking action a in state s. In the environment, there are many different Q-value functions according to the different actions and policies that can be used in the learning process. The optimal Q-value function is the value which yields maximum Q-value compared to all other Q-values that have been acquired during the learning process. So, mathematically the optimal Q-value function, i.e, state-value function, can be expressed as:

$$Q^*(s, a) = \max_{\pi} Q^{\pi}(s, a) \tag{5.15}$$

where $Q^*(s, a)$ denotes the optimal value-action function.

The purpose of an EV charging navigation process is to find the optimal policy π^* over all feasible policies that an EV can select during the learning process, which minimizes the cost or maximizes the reward. Therefore, Once we have $Q^*(s, a)$, then an EV can act optimally based on the optimal strategy as shown below:

$$\pi^*(s) = \underset{a}{\operatorname{argmax}}\, Q^*(s, a) \tag{5.16}$$

where $\pi^*(s)$ is the optimal policy that an EV can perform in the environment, which achieves the optimal value-action function.

Q-learning algorithm uses ϵ-greedy policy for the action selection step, which is also called behavior policy, to ensure a high level of balance between exploration and exploitation, i.e, exploration-exploitation trade-off, as well as to improve the learning level of the agent during the direct interaction with the environment. A simple strategy that has been proposed to deal with this problem is the ϵ-greedy (with $0 \leq \epsilon < 1$), with greater corresponding to greater probability of exploration. the value of ϵ has a significant impact on the performance and complexity of the Q-learning algorithm.

The complexity of the Q-learning algorithm is mainly depend on the set of the state-action of the problem, as well as the discount factor γ that is set in the Bellman equation, i.e., target Q-value. In the problems where the state-action set is finite and the γ is close to 0, the Q-learning algorithm converges to the optimal value-action function. The reason behind this is that the Q-value will be determined based on the current Q-value, instead of the target Q-value. However, Q-learning algorithm suffers from low convergence and time complexity, especially when γ is close to 1. The main reason for this is the incorporation of the sample-based stochastic approximation, and the fact that the operator of Bellman equation spreads information throughout the entire space, specially when γ is close to 1. Details of how the Q-learning algorithms works can be seen in Algorithm 2.

Algorithm 2 Training Process of Q-learning algorithm

Input: $\alpha, \gamma, \epsilon, Q$ (terminal-state), $s \in S, a \in \Lambda, N, M$

Output : Optimal $Q^*(s, a)$, and $\pi^*(s)$ for EV

```
    Initialization:
Initialize Q(s, a) arbitrary
Initialize fixed CS locations
K=maximum number of episodes
Initialize random s for the EV
for eps = 1 to K do
    Select a ∈ Λ for EV using ϵ-greedy policy
    Execute the action a
    Receive immediate reward r
    Observe the new state s'
    Select a' in s' for the EV using Eq. (5.14)
    Update Q(s, a) value in Q-table
    s ← s'
    if (s is terminal or ϑ_{ev,j} ≥ Φ) then
        Start new episode
    else
        Select a ∈ Λ
    end if
end for
Return Q*−values, and π* for the EV
```

5.4 Experiments

In this section, the evaluation of the proposed approach in different case studies are carried out within the proposed environment to demonstrate the effectiveness and feasibility of the proposed approach. Moreover, a comparison between the baseline case and the greedy strategy is also presented in this chapter. In Section 5.4.1, the details of experimental setup are presented. The training process and simulation results are discussed in Section 5.4.2.

5.4.1 Experimental Setup

The performance of the proposed approach is demonstrated within an area 25$\times$ 25 grid map. An agent (EV) earns -1 as penalty for each movement in the environment. The rewards that are associated with CSs vary depending on the charging rate of CS, which mainly depends on the electricity rates as mentioned earlier. Barriers have been placed on some of the roads that an EV takes in the directions leading to CSs, which in turn force an agent to search for another available roads. In this work, we assume that the rewards of CSs are two values 60 and 80, depending on the charging rate at CS. As mentioned earlier, The reward increases as the charging rate decreases. Each episode terminates, if an EV reaches to the CS or reaches the threshold value of the travelling energy consumption (Φ). All the following experimental results have been produced by Python 3.10 on Windows 10 Pro 64bits, V.20H2, Intel(R) Core(TM) i5-8250U CPU @ 1.60GHz (8 CPUs), 1.80 GHz. The simulation parameters related to the proposed scheme are presented in Table 5.2.

5.4.2 Results

The performance of the proposed scheme is evaluated with respect to two criteria:

- The maximum cumulative reward of the value function of the learned policy, reflecting the proposed objective function of this approach.
- The total energy cost of an EV, considering the cost resulting from the movement of an

Table 5.2: The baseline case parameters

Parameter	**Value**
Environment	25×25 grids
M	4
Penalty	-1
Rewards	60, 80
ζ_{ev}	62 kWh
φ	\$0.15, \$0.35
SoC	$\zeta_{ev} \times 60\%$ kWh
α	0.1
ϵ	0.1
γ	0.6
δ_{ev}	0.16 kWh/km
Φ	1.6 kWh

EV towards CS, and the cost of charging an EV at CS.

To this end, comparisons between the baseline case and different case studies, and also between the baseline case and the greedy strategy will be conducted in this work.

5.4.2.1 Case Studies

The following proposed case studies demonstrate the feasibility and effectiveness of the proposed scheme.

- Case A- With reduced number of actions. In this case, we assume that the number of actions that an EV can perform to interact with the environment at each state is just 4 as shown in Eq. (5.17), rather than 8 actions as assumed in the baseline case as presented in Eq. (5.12). As shown in Fig. 5.2, the green and blue arrows represent the possible actions that an EV can perform in Case A. While the possible actions that an EV can select in the baseline case to move to the next state are represented by the green, blue and red arrows. Finally, the other parameters remain the same as the baseline case.

$$\mathcal{A}_{CaseA} = \{South,\ North,\ East,\ West\} \tag{5.17}$$

- Case B- With the increase in the number of obstacles standing in the way of an EV towards CSs. In this case, we assume that the number of barriers is increased by 25%, 50%, and 75% compared to the baseline case with the same number of episodes. While the other parameters remain the same as the baseline case.

Fig. 5.4 and Table 5.3 show the comparison results between the baseline case and Case A. The X-axis in Fig. 5.4 represents the episodes, i.e., the execution that EV takes from a initial state to a destination (terminal state). It can be seen that the distance, travelling energy consumption, and travel time are less in the baseline case compared to Case A, which in turn minimizes the total amount of energy needed to charge an EV. As a result, the total energy cost is minimized as shown in Fig. 5.4, this is due to the assumption that the possible actions that EV can select in the baseline case is more compared to case A. Another observation in Fig. 5.4, is that the cumulative reward for the baseline case is higher compared to case A. The reason behind this is that the total number of timestep (the hops that EV needs to reach CS) is fewer compared to the case A as shown in Table 5.3. Each timestep is considered as an additional penalty for an EV. Accordingly, the cumulative penalty will finally be deducted from the reward that EV receives when it reaches CS. Based on the foregoing, it is noticeable that the cumulative reward is inversely related to the timestep.

Table 5.3: Comparison between the baseline case and Case A
in terms of Timestep, Total Energy and Travel Time

Episodes	**The Baseline Case**			**Case A**		
	Timestep	Total Energy (kwh/km)	Travel Time (minute)	Timestep	Total Energy (kwh/km)	Travel Time (minute)
2×10^5	5	37.584	3.6	7.45	37.77216	5.364
4×10^5	5.05	37.58784	3.636	6.95	37.73376	5.004
6×10^5	5.75	37.6416	4.14	7.75	37.79519	5.57985
8×10^5	5.9	37.65312	4.248	7.85	37.80288	5.652
10×10^5	7.35	37.76448	5.292	8.1	37.82208	5.831985
Average	**5.81**	**37.646208**	**4.9516**	**7.622**	**37.785215**	**5.486367**

Fig. 5.5 and Tables 5.4 - 5.6, show the comparison results between the baseline case and Case B. In this case, we assume three different scenarios. In the first scenario, we assume that the

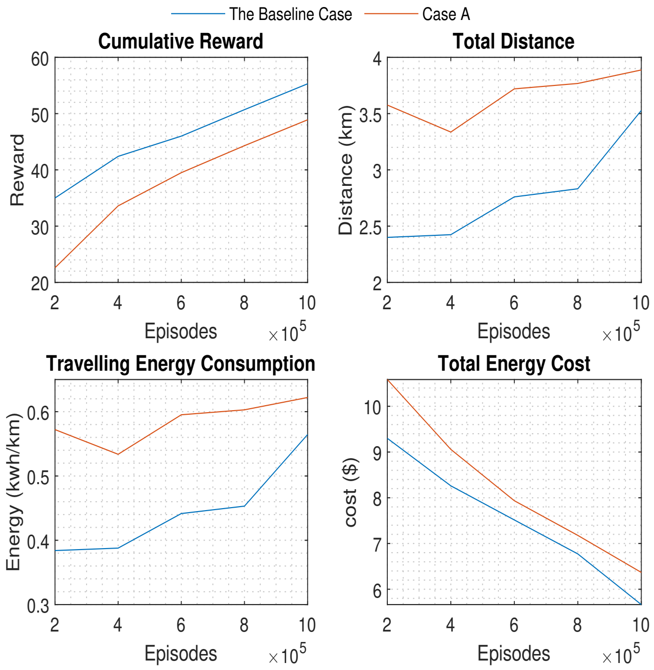

Figure 5.4: Comparison between the baseline case and case A

number of obstacles is increased by 25%, then in the second scenario we assume that the number is increased by 50%, while in the last scenario, we assume that the number is increased by 75%. The reason behind this assumption is that street conditions are not fixed and can change for several reasons, including, but not limited to, the works that may occur in the study area as shown in Fig. 5.2.

It is easy to notice that the total timestep, total distance, travelling energy consumption, and the

Table 5.4: Comparison between the baseline case and Case B
when the number of obstacles is increased by 25%

Episodes	**The Baseline Case**		**Case B**	
	Cumulative Reward	Total Energy Cost ($)	Cumulative Reward	Total Energy Cost ($)
2×10^5	35	9.3	34.27	9.8864
4×10^5	42.4	8.2613759	41.8	8.3891
6×10^5	46	7.515455	43.2	7.67741
8×10^5	50.7	6.772416	48.9	6.78912
Average	**43.525**	**7.9623117**	**42.0425**	**8.1855075**

Table 5.5: Comparison between the baseline case and Case B
when the number of obstacles is increased by 50%

Episodes	**The Baseline Case**		**Case B**	
	Cumulative Reward	Total Energy Cost ($)	Cumulative Reward	Total Energy Cost ($)
2×10^5	35	9.3	33.67	10.0879
4×10^5	42.4	8.2613759	38.9	8.4662
6×10^5	46	7.515455	44	7.62554
8×10^5	50.7	6.772416	47.9	6.82147
Average	**43.525**	**7.9623117**	**41.1175**	**8.2502775**

Table 5.6: Comparison between the baseline case and Case B
when the number of obstacles is increased by 75%

Episodes	**The Baseline Case**		**Case B**	
	Cumulative Reward	Total Energy Cost ($)	Cumulative Reward	Total Energy Cost ($)
2×10^5	35	9.3	32.87	10.32453
4×10^5	42.4	8.2613759	37	8.7986
6×10^5	46	7.515455	42	7.70554
8×10^5	50.7	6.772416	46.3	6.92374
Average	**43.525**	**7.9623117**	**39.5425**	**8.4381025**

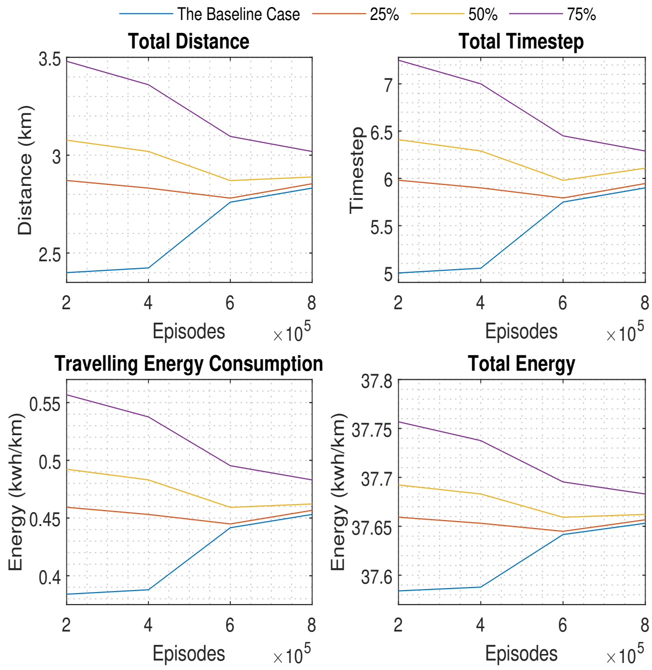

Figure 5.5: Comparison between the baseline case and Case B

total energy that is required to fully charge EV are less in the baseline case compared to all the 3 scenarios in Case B as shown in Fig. 5.5. The reason is the assumption of increasing the percentage of streets that an EV cannot use in the study area to access CS. To overcome this challenge, an EV will try to find other possible routes to reach CS, which in turn increases the number of hops (timestep) that an EV must take to reach CS. Consequently, it increases the distance between the location of an EV and the location of CS at any charging decision point, the energy consumed by EV on its way to CS, and also the total energy that is required to fully charge EV. It is also noticeable that the timestep, distance, travelling energy consumption and total energy decrease when the number of episodes is higher as shown in Fig. 5.5. This is due to the fact that the performance of an EV in the study area improves with the increase in the number of episodes, since an EV will have a higher chance of finding the optimal CS at any charging decision point, even though the number of available streets decreases.

As shown in Tables 5.4 - 5.6, the cumulative reward that has been achieved in the baseline case

Table 5.7: Comparison between the baseline case and Case B
in terms of the travel time (minute)

Episodes	**The Baseline Case**	**Case B**		
		25%	50%	75%
2×10^5	3.6	4.30618	4.6152	5.22
4×10^5	3.636	4.248	4.5288	5.04
6×10^5	4.14	4.17096	4.3056	4.644
8×10^5	4.248	4.28134	4.33318	4.52837
Average	**3.906**	**4.25162**	**4.4457**	**4.858075**

is higher compared to all scenarios of Case B. The reason for this is that the agent in the baseline case has chosen higher reward CSs rather than selecting CSs with lower rewards as an agent performed in Case B. As mentioned in Section 5.3.1.1, the charging rate at CS decreases as the given reward increases. This is the reason why the total energy cost for charging an EV at selected CSs in the baseline case is less, compared to all scenarios in Case B as shown in the above-mentioned tables.

Tables 5.7 shows the comparison between the baseline case and Case B, in terms of the travel time that an EV requires to reach CS. It is seen that the travel time for the baseline case is less compared to the all scenarios in Case B, with an improvement of up to 20%. The reason behind this is that the number of the streets that an EV cannot use to find CS with a lower charging rate is increased compared to the baseline case. Thus, an EV needs to travel longer distance, which leads to an increase in the travel time to reach CS.

5.4.2.2 A Comparison between the baseline case and Greedy strategy

Reinforcement learning algorithms have been used in many previous studies to solve the problem of charging EVs. In [177], the authors have proposed a RL approach to find the optimal scheduling and pricing for EV CSs, and they demonstrated the proposed approach by comparing it with a greedy heuristic that assigns EVs to nearest CSs.

In addition to the proposed case studies that have been assumed before, we also compare the baseline case with greedy strategy to demonstrate our proposed approach. In this work, the greedy strategy is only consider the distance that the agent move from the start state (s) to the terminal state (CS). The immediate rewards for each state, and also the rewards that are associated with each CS will not be taken into consideration in the greedy strategy. The comparison between the two strategies is done based on the total distance, travelling energy consumption, total energy that is required to fully charge EV, cumulative reward, and total energy cost. As mentioned before, the performance of the baseline case of the proposed approach is evaluated with the respect into two criteria: the cumulative reward, and total energy cost. Fig. 5.6 and Table 5.8 show the results of the comparison between the baseline case and the greedy approach.

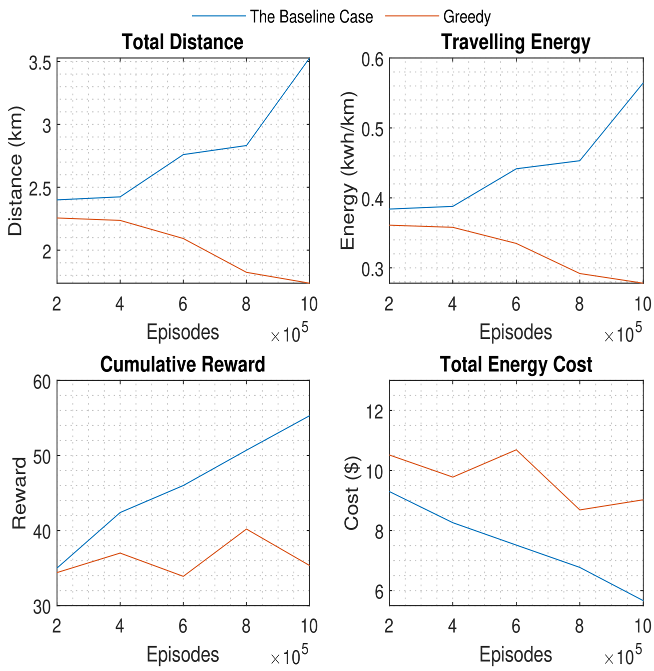

Figure 5.6: Comparison between the baseline case and Greedy strategy

Although the greedy algorithm has achieved comparable results in terms of total distance, travelling energy consumption, total energy that is required to fully charge EV as shown in Fig. 5.6 and Table 5.8. However, the baseline case was able to achieve the desired results, in terms of maximizing the cumulative reward and minimizing the total energy cost cost. The reason behind this, is that the greedy algorithm has selected the CS based only on the distance, which in turn reduced the energy consumption to reach CS, and the total energy required to fully charge EV.

Table 5.8: Comparison between the baseline case and the Greedy Strategy in terms of total energy and total energy cost

Episodes	**The Baseline Case**		**Greedy Strategy**	
	Total Energy (kwh/km)	Total Energy Cost ($)	Total Energy (kwh/km)	Total Energy Cost ($)
2×10^5	37.584	9.3	37.56096	10.51706
4×10^5	37.58784	8.26137	37.55788	9.78
6×10^5	37.6416	7.51545	37.53484	10.6891
8×10^5	37.65312	6.77241	37.49184	8.6871
10×10^5	37.76448	5.66467	37.47801	9.0247
Average	**37.64621**	**7.50278**	**37.52471**	**9.73959**

However, the greedy algorithm did not take into account the variance in the rewards that have been associated with each individual CS, and also the charging rate at each CS, which in turn led to reduce the cumulative reward and increase the total energy cost. On the contrary, the baseline case has taken into account the two parameters, thus achieved the goal of the system, which is maximizing the cumulative reward and minimizing the total energy cost.

5.5 Summary

This chapter has proposed a RL-based assignment scheme for EVs to CSs in urban environment. Several parameters have been taken into account, including the distance between the locations of EV and CS at any charging decision point, the EV travelling energy consumption, i.e., the amount of energy that EV needs to reach CS, charging rate at each CS, and the total energy cost of EV. An EV's battery SoC was also taken into account in order to calculate the total amount of energy needed to charge the EV at CSs. Experimental results demonstrate that the proposed scheme can approximate the solution of finding the optimal policy in the sense of maximizing the expected value of the total reward, and minimizing the total energy cost of EV using Q-learning algorithm. Moreover, the results of the comparisons we obtained showed that the proposed scheme has outperformed all the proposed case studies with an improvement of up to 23%, and with an improvement of up to 25% comparing to the greedy algorithm approach. Our future works will focus on improving the scalability of the proposed scheme for practical applications, and using the Deep Q-Network (DQN) algorithm to solve this problem using multi-agents in the study area.

Chapter 6

Conclusion and Future Work

Finding the optimal placement of EVCSs, and solving the problem of assigning EVs to the optimal CSs in urban environment have a major role in increasing reliance on EVs instead of ICEVs. This is due to the many advantages of EVs, such as a low-emission and environmentally friendly, running cost, low maintenance, etc. Various optimization models have been presented in the literature, to solve the problem of finding the optimal placement of EVs and assigning EVs to the optimal CSs in the metropolitan environment, using different objective functions considering several parameters and constraints. In the following, we would firstly summarize the contributions and conclusions from this research work. Then we discuss the future work and plan.

6.1 Conclusion

The aim of this research is to design and develop EV charging management for metropolitan traffic environments, based on finding the optimal locations of EVCSs, as well as choosing the best CSs to charge EVs in urban environments. We have presented three different schemes, in order to find effective solutions for charging EVs in metropolitan environments, which in turn increases the satisfaction of EV users' and helps in the spread of EVs in urban areas. The three approaches presented in this research work to solve both problems can be summarized as follows. Sections 6.1.1 - 6.1.3 discuss in detail the contributions, the parameters that have been incorporated with the objective functions, as well as the system constraints of the proposed approaches.

In the first approach, we have proposed a novel approach to find the best locations of EVCSs in metropolitan areas, based on the optimal assignment of EVs to CSs, considering the amount of energy consumption of EVs to reach the locations of CSs. In the second approach, a comprehensive approach to assign EVs to the optimal CSs has been introduced, based on optimizing the EV users' QoE in terms of the total time of charging EVs. Finally, a RL-based EV Assignment Scheme was proposed to solve the problem of assigning EVs to the optimal CSs inside cities, aiming at minimizing the total cost of charging EVs and reducing the overload on EGs.

6.1.1 Energy-efficient EV Charging Station Placement for E-Mobility

In Chapter 3, an energy efficient approach for EVCS placement has been proposed, that considers a combination of factors including the displacement of EVs towards CSs, the elevation, i.e., positive slope, between the locations of EVs and CSs in the study area, and the maximum number of EVs that CSs can serve. The contributions of this work are listed as follows;

- An energy efficient EVCS placement for E-mobility scheme was proposed that considers key metrics including overall transportation energy cost of EVs to reach CSs. The unique feature of this scheme is an accurate and realistic 3D energy consumption model to find the optimal placement of EVCSs taking into account the movement of EVs to CSs, the difference in positive slope between the locations of EVs and CSs. The maximum number of EVs that should be assigned to CSs has been considered as a constraint to select CS in our scheme.
- The EVCS placement problem is modeled as a MILP problem. A combination of the GA technique and the B&B algorithm have been utilized to solve the problem based on actual

data of the elevations and coordinates of EVs and candidate CSs taken from Google Maps.

6.1.2 QoE-based assignment of EVs to CSs in Metropolitan Environments

In Chapter 4, a novel approach to find the optimal assignment of EVs to CSs has been proposed based on the improvement of EV users' QoE. Our proposed approach considers the travel time of EV towards CS taking into account the distance between EV and CS, the impact of congestion level on the roads resulted from the Internal Combustion Engine Vehicles (ICEVs) and EVs, queuing time at the CS, and the charging time that is required to fully charge EV's battery inside CS. The adjacency between the different zones in a city environment was also considered in order to minimize the potential number of CSs for each EV. Specifically, the assignment problem has been formulated as a MINLP problem, and a heuristic solution was developed using the Genetic Algorithm (GA) technique. The performance evaluation in realistic metropolitan environment attests the benefits of the proposed CS assignment framework considering range of charging metrics.

The contributions of this work are list as follows;

- A novel approach for assignment of EVs to CSs in urban areas has been proposed in this work. The proposed model considers the EV drivers' QoE in terms of the total time to charge an EV. Travel time of EVs to reach CS, the queuing time at CSs, also the time needed to charge the EV's battery at CS have been taken into account in this work. The effect of road congestion level caused by both ICEVs and EVs was considered in this work. The results show the impact of congestion level on the travel times which in turn affects the EV drivers' QoE.
- Our model took into account the influence of the urban traffic movement of EVs between adjacent zones on finding the optimal assignment of EVs to CSs in urban areas.
- An optimization technique for selecting the optimal assignment of EVs to CSs has been introduced in this work. The problem has been formulated as a MINLP problem. The GA

technique has been utilized to solve this problem based on real world datasets. The Non-linear objective function of the proposed approach is set as minimizing the total charging time of EVs.

6.1.3 A RL-based Assignment Scheme for EVs to CSs

In Chapter 5, a RL-based EV Assignment Scheme (RL-EVAS) is proposed to solve the problem of assigning EVs to the optimal CSs in urban areas. The aim of this work is to minimize the total cost of charging EVs and reducing the overload on EGs. Travelling cost that is resulted from the movement of EVs to CSs, and the charging cost at CS have been considered. Moreover, an EV's Battery SoC was taken into account in the proposed scheme. The proposed RL-EVAS approach will approximate the solution by finding an optimal policy function in the sense of maximizing the expected value of the total reward over all successive steps using Q-learning algorithm, based on the Temporal Difference (TD) learning and Bellman expectation equation.

The main contributions of the present work are summarized as follows;

- A RL-scheme for assignment of EVs to the optimal CSs in metropolitan environments was proposed in this chapter. The proposed scheme has considered the energy consumption cost that is resulted from the movement of EV towards CS (travelling cost), and the total expected cost to fully charge EV at CS (total energy cost). EV's battery SoC in the process of finding the optimal CS was also taken into account in this work.
- Q-learning algorithm has been utilized to solve this problem based on maximizing the cumulative reward of the EV during learning process by reducing the total cost of charging EVs.
- As a results of applying our proposed scheme, we minimize the load on the overwhelmed EGs, by assuming different rewards for the available CSs in the study area. The reward at each CS is determined based on the electricity price offered by electrical grids (EGs) to CSs, these prices vary according to the load on EGs.

6.2 Direction for Future Work

We have proposed several efficient schemes regarding EVCSs placement and EV charging management in this thesis. Nevertheless, there are still many opportunities to expand the scope of relevant research. In continuation of this research work, the following topics are suggested for future works:

- Designing an integrated power distribution planning approach for distribution systems that includes EVs charging systems. The aim of this research work is to develop a comprehensive planning approach that is able to minimize the overall energy consumption cost of EVs to find CSs in urban environments, energy losses in CSs and EGs and investment cost of EVCSs providers, as well as maximizing the traffic flow of EVs charging systems. Therefore, the comprehensive planning model should consider EGs, EVs charging systems, as well as the design and construction of CSs.
- Developing a dynamic real-time charging management model, considering the smart interactions among EVs, CSs, Road side Units (RSUs). The objective of this model is to bring various benefits to all parties involved in the charging process, in terms of reduce the overall charging cost, and increase the EV users' satisfaction.
- Proposing a multi-objective function approach, considering various parameters and constraints related to EVs, CSs, and EGs. Then, solving this problem using Multi-Agent Reinforcement Learning (MARL) algorithm, and Cooperative Artificial Intelligence (AI). The objective of using the MARL with AI cooperative, is to make sure that all EVs (agents) working toward a common goal. Which is minimizing the charging cost of EVs and maximizing the benefits of CSs and EGs providers.
- Incorporating new alternative ways to charge EVs with the proposed approaches in this thesis, including but not limit the use of special wireless EVs charging lanes that enable EVs users to charge their vehicles as they pass them, EVs' battery switch service, etc.

These techniques can help reduce the queuing time inside CSs, and facilitating the process of charging EVs.

Acronyms

AEVs	All-Electric Vehicles. 16
AI	Artificial Intelligence. 131
APU	Auxiliary Power Unit. 16
B&B	Branch and Bound. 8
BEVs	Battery EVs. 16, 18, 22
BNEF	Bloomberg New Energy Finance. 13
BSSs	Battery Swap Stations. 21
CO_2	Carbon Dioxide. 1, 2, 18
CSs	Charging Stations. xx, 3–5, 15
DGs	Distributed Generations. 35
DLT	Distributed Ledger Technology. 40
DQN	Deep Q-Network. 36
DRL	Deep Reinforcement Learning. 36, 104
DSM	Demand Side Management. 25
EEI	Edison Electric Institute. 13

EG	Electrical Grid. 5, 29, 131
EGs	Electrical Grids. ix
EREVs	Extended Range Electric Vehicles. 16, 19
EVs	Electric Vehicles. 2–4, 19
EVSE	Electric Vehicle Supply Equipment. 23
FCEVs	Fuel Cell EVs. 16, 19
FDA	Flow Distribution Algorithm. 42
FMDP	Finite Markov Decision Process. 104
GA	Genetic Algorithm. 8, 9, 35, 42
GHG	Greenhouse Gas. 1, 2, 18, 19
GOA	Grasshopper Optimization Algorithm. 35
GPS	Global Positioning System. 42
HEVs	Hybrid Electric Vehicles. 16, 18
ICEVs	Internal Combustion Engine Vehicles. 1–3, 15, 16, 18, 19, 43, 68, 74
IEI	Institute for Electric Innovation. 13
ILP	Integer Linear Programming. 43
IoT	Internet of Things. 40
LGDG	Lazy Greedy with Direct Gain. 36
LGEG	Lazy Greedy with Effective Gain. 36
LP	Linear Programming. 42
MARL	Multi-Agent Reinforcement Learning. 131

MDP	Markov Decision Process. 36
MICP	Mixed Integer Convex Programming. 44
MILP	Mixed Integer Linear problem. 8, 43, 64
MINLP	Mixed Integer Nonlinear problem. 9, 44
NiMH	Nickel Metal Hydride Battery. 24
PHEVs	Plug-in Hybrid EVs. 16, 19, 22, 23
POIs	Points Of Interests. 6, 36
QoE	Quality of Experience. 7, 67
QoS	Quality of Service. 29, 31
REX	Range Extender. 16
RL	Reinforcement Learning. 36
RSUs	Road side Units. 131
SoC	State of Charge. 9, 10, 40, 41, 43, 105
TD	Temporal Difference. 105

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Appendix A

Implementation of Chapter 3

A.1 Code

Following is the code that was written to evaluate the base scenario of the proposed scheme of Chapter 3, i.e., Energy-efficient EV Charging Station Placement for E-Mobility:

```
close all
clear all
clc
l_b=[1 1 1 1 1];
u_b=[12 12 12 12 12];
S_CSs=5;
n_vars=5;
IntCon=[1:S_CSs];

options = optimoptions('ga',...
            'PopulationSize',5,...
```

```
            'MaxGenerations',5,...
            'MaxStallGenerations',inf,...
            'PlotFcns',{@gaplotbestf},...
            'display','iter');
generations_2 \# update option MaxGeneratons
'MaxGenerations',50,...
'MaxStallTime',30,...
'InitialPopulationMatrix',Pop1,...

f=@(Pop1)BandB(Pop1,S_CSs);
[x,fval,~,~,~,~]=ga(f,n_vars,[],[],[],[],l_b,u_b,[],IntCon,options);
function [Enr] = BandB(Pop1,S_CSs)
N_EVs=1000;
N_CSs=12;
ec=0.142;
Veh_Mass=1600;
gf=9.8;
bc=34;
pr=0.17;
crp=96;

load ('Newcastle_EVs_data.csv');
load ('Newcastle_CSs_data.csv');

for  i=1:S_CSs
    for  j=1:3
        S_Newcastle_CSs_data(i,j)=Newcastle_CSs_data(Pop1(i),j);
```

```
    end
end

for  i=1:N_EVs
for  j=1:S_CSs
dij(i,j)=pos2dist(Newcastle_EVs_data(i,1),Newcastle_EVs_data(i,2),
S_Newcastle_CSs_data(j,1),S_Newcastle_CSs_data(j,2),1);
end
end

eij=dij*ec;

for  j=1:S_CSs
    for  i=1:N_EVs
        if S_Newcastle_CSs_data(j,3)-Newcastle_EVs_data(i,3) > 0
            Elev.Opp(i,j)=S_Newcastle_CSs_data(j,3)-
            Newcastle_EVs_data(i,3);
        else
            Elev.Opp(i,j)=0;
        end
    end
end

Elev.Hypo=dij;

for  i=1:N_EVs
    for  j=1:S_CSs
```

```
        if Elev.Opp ==0
            Elev.Angle(i,j)=0;
        else
            Elev.Angle(i,j)=asind(Elev.Opp(i,j) / Elev.Hypo(i,j));
        end
    end
end



for  i=1:N_EVs
    for  j=1:S_CSs
        Elev.eij(i,j)=Veh_Mass*gf*sind(Elev.Angle(i,j))*0.000277;
        end
end

Elev.eij_F=dij.*Elev.eij;

F_eij=eij+Elev.eij_F;

k=1;
for  i=1:length(F_eij)
    for  j=1:size(F_eij,2)
         f(1,k)=F_eij(i,j)
         k=k+1;
    end
end
```

```
l_b=zeros(length(Newcastle_EVs_data).*length(S_Newcastle_CSs_data),1);
u_b=ones(length(Newcastle_EVs_data).*length(S_Newcastle_CSs_data),1);

Aeq=zeros(N_EVs,length(f));
kk=1;
for  i=1:N_EVs
    for  j=kk:(kk+S_CSs-1)
       Aeq(i,j)=1;
       kk=kk+1;
    end
end
beq=ones(N_EVs,1);

A=zeros(S_CSs,length(f));
kkk=1;
for  i=1:S_CSs
    for  j=kkk:S_CSs:length(f)
      A(i,j)=1;
    end
       kkk=kkk+1;
end
b(1:S_CSs,1)=300;

options = optimoptions(@intlinprog,'Display','iter','PlotFcn',
@optimplotmilp);[x_var,tot_Energy]=intlinprog(f,[],A,b,
Aeq,beq,l_b,u_b,[]);
```

```
fMat = vec2mat(x_var,S_CSs);
S_fMat= sum(fMat)

Enercon=sum(fMat.*F_eij)
Enr=sum(Enercon)

for  i=1:S_CSs
All_Candidate(1,i)=i;
All_Candidate(2,i)=S_fMat(1,i);
All_Candidate(3,i)=Enercon(1,i);
end

for  i=1:S_CSs
   if EVs_Distribution(1,i)==0
       return;
   end

Enr=sum(Enercon);

end

function dis_ev = pos2dist(lag11,lon11,lag22,lon22,meth_ev)

if ngin < 4
    dis_ev = -99999;
    dis_ev('# of input parameters error! dist=-99999');
```

```
    return;
end
if abs(lag11)>90 | abs(lag22)>90 | abs(lon11)>360 | abs(lon22)>360
    dis_ev = -99999;
    dis_ev('Illegal degrees! dist=-99999');
   return;
end
if lon11 < 0
    lon11 = lon11 + 360;
end
if lon22 < 0
    lon22 = lon22 + 360;
end
if ngin == 4
    meth_ev == 1;
end
if meth_ev == 1
    km_per_deg_lat = 111.3237;
    km_per_deg_lon = 111.1350;
    km_lat = km_per_deg_lat * (lag11-lag22);
    if abs(lon11-lon22) > 180
        dif_lon = abs(lon11-lon22)-180;
    else
        dif_lon = abs(lon11-lon22);
    end
    km_lon = km_per_deg_lon * dif_lon * cos((lag11+lag22)*pi/360);
    dis_ev = sqrt(km_lat^2 + km_lon^2);
```

```
else
    rr_ave = 6374;
    deg_2_rad = pi/180;
    lag11 = lag11 * deg_2_rad;
    lon11 = lon11 * deg_2_rad;
    lag22 = lag22 * deg_2_rad;
    lon22 = lon22 * deg_2_rad;
   dis_ev = rr_ave * acos(cos(lag11)*cos(lag22)*cos(lon11-lon22) +
   sin(lag11)*sin(lag22));
end
```

A.2 Dataset

Below is a sample of the dataset that has been incorporated into this work in order to solve the placement problem:

Table A.1: CSs' location

Longitude	Latitude	Elevations (meter)
54.97448	-1.644712	212
54.968961	-1.615008	70
54.969718	-1.581451	40
54.965464	-1.550075	66
54.982385	-1.55684	58
54.988743	-1.581588	96
54.988027	-1.613854	118
54.990201	-1.657449	214
55.005229	-1.670558	202
55.004507	-1.640343	164
55.005568	-1.611165	122
55.009274	-1.578951	136

Table A.2: Coordinates of the geographical center of zones

Longitude	Latitude	Elevations (meter)
54.973794	-1.613159	54
54.991147	-1.606178	51
55.004469	-1.619865	66
54.975669	-1.64145	109
55.013534	-1.723297	73
54.976903	-1.578135	42
54.998767	-1.588819	68

Appendix B

Implementation of Chapter 4

B.1 Code

Following is the code that was written to evaluate the base scenario of the proposed scheme of Chapter 4, i.e., QoE-based assignment of EVs to Charging Stations in Metropolitan Environments:

```
clear all
close all
clc

global F_val;
global F_var_x;
global TOTAL;
global Travel_time;
global Queuing_time;
global F_val_1;
```

```
global F_var_x_1;

global now1;
global now2;
global now3;
global now4;
global now5;
global now6;
global now7;

global Final_Final;
Final_Final=1;

global GA_counter;
GA_counter=1;

N_EVs=415;
N_Vehs=8285;
N_CSs=10;
N_Con=10;
R_Con=6;
Max_time=100;
N_zones=7;
L=0.2;
Cap=[1590 1590 1590 1590 1590 1590 1590 1590 1590 1590];

N_EVs_z1=7;
```

```
N_EVs_z2=27;
N_EVs_z3=112;
N_EVs_z4=50;
N_EVs_z5=115;
N_EVs_z6=71;
N_EVs_z7=33;

N_Veh_z1=140;
N_Veh_z2=539;
N_Veh_z3=2235;
N_Veh_z4=997;
N_Veh_z5=2300;
N_Veh_z6=1416;
N_Veh_z7=658;

load ('Newcastle_CSs_data.csv');

load ('Newcastle_EVs_NE1.csv');
load ('Newcastle_EVs_NE2.csv');
load ('Newcastle_EVs_NE3.csv');
load ('Newcastle_EVs_NE4.csv');
load ('Newcastle_EVs_NE5.csv');
load ('Newcastle_EVs_NE6.csv');
load ('Newcastle_EVs_NE7.csv');

load ('Newcastle_Ports_Z1_Z1.csv');
load ('Newcastle_Ports_Z2_Z2.csv');
```

```
load ('Newcastle_Ports_Z3_Z3.csv');

load ('Newcastle_Ports_Z4_Z4.csv');

load ('Newcastle_Ports_Z5_Z5.csv');

load ('Newcastle_Ports_Z6_Z6.csv');

load ('Newcastle_Ports_Z7_Z7.csv');



for  i=1:N_EVs_z1
    for  j=1:N_CSs
       Dit_z1(i,j)=pos2dist(Newcastle_EVs_NE1(i,1),
       Newcastle_EVs_NE1(i,2),Newcastle_Ports_Z1_Z1(j,1),
       Newcastle_Ports_Z1_Z1(j,2),1);
    end
end

for  i=1:N_EVs_z2
    for  j=1:N_CSs
        Dit_z2(i,j)=pos2dist(Newcastle_EVs_NE2(i,1),
        Newcastle_EVs_NE2(i,2),Newcastle_Ports_Z2_Z2(j,1),
        Newcastle_Ports_Z2_Z2(j,2),1);
    end
end



for  i=1:N_EVs_z3
    for  j=1:N_CSs
        Dit_z3(i,j)=pos2dist(Newcastle_EVs_NE3(i,1),
```

```
        Newcastle_EVs_NE3(i,2),Newcastle_Ports_Z3_Z3(j,1),
        Newcastle_Ports_Z3_Z3(j,2),1);
    end
end



for  i=1:N_EVs_z4
    for  j=1:N_CSs
        Dit_z4(i,j)=pos2dist(Newcastle_EVs_NE4(i,1),
        Newcastle_EVs_NE4(i,2),Newcastle_Ports_Z4_Z4(j,1),
        Newcastle_Ports_Z4_Z4(j,2),1);
    end
end

for  i=1:N_EVs_z5
    for  j=1:N_CSs
        Dit_z5(i,j)=pos2dist(Newcastle_EVs_NE5(i,1),
        Newcastle_EVs_NE5(i,2),Newcastle_Ports_Z5_Z5(j,1),
        Newcastle_Ports_Z5_Z5(j,2),1);
    end
end

for  i=1:N_EVs_z6
    for  j=1:N_CSs
        Dit_z6(i,j)=pos2dist(Newcastle_EVs_NE6(i,1),
        Newcastle_EVs_NE6(i,2),Newcastle_Ports_Z6_Z6(j,1),
        Newcastle_Ports_Z6_Z6(j,2),1);
```

```
    end
end

for  i=1:N_EVs_z7
    for  j=1:N_CSs
        Dit_z7(i,j)=pos2dist(Newcastle_EVs_NE7(i,1),
        Newcastle_EVs_NE7(i,2),Newcastle_Ports_Z7_Z7(j,1),
        Newcastle_Ports_Z7_Z7(j,2),1);
    end
end

Tit_z1= L*Dit_z1*(N_Veh_z1/Cap(1,1))*60;
Tit_z2= L*Dit_z2*(N_Veh_z2/Cap(1,2))*60;
Tit_z3= L*Dit_z3*(N_Veh_z3/Cap(1,3))*60;
Tit_z4= L*Dit_z4*(N_Veh_z4/Cap(1,4))*60;
Tit_z5= L*Dit_z5*(N_Veh_z5/Cap(1,5))*60;
Tit_z6= L*Dit_z6*(N_Veh_z6/Cap(1,6))*60;
Tit_z7= L*Dit_z7*(N_Veh_z7/Cap(1,7))*60;

Tit_z11= Tit_z1';
Tit_z1_F= reshape(Tit_z11,1,[]);

Tit_z22= Tit_z2';
Tit_z2_F= reshape(Tit_z22,1,[]);

Tit_z33= Tit_z3';
Tit_z3_F= reshape(Tit_z33,1,[]);
```

```
Tit_z44= Tit_z4';
Tit_z4_F= reshape(Tit_z44,1,[]);

Tit_z55= Tit_z5';
Tit_z5_F= reshape(Tit_z55,1,[]);

Tit_z66= Tit_z6';
Tit_z6_F= reshape(Tit_z66,1,[]);

Tit_z77= Tit_z7';
Tit_z7_F= reshape(Tit_z77,1,[]);


t_1=[Tit_z1_F,Tit_z2_F,Tit_z3_F,Tit_z4_F,Tit_z5_F,Tit_z6_F,
Tit_z7_F];

for  i=1:N_CSs
    Dtj_z1(1,i)=pos2dist(Newcastle_Ports_Z1_Z1(i,1),
    Newcastle_Ports_Z1_Z1(i,2),Newcastle_CSs_data(i,1),
    Newcastle_CSs_data(i,2),1);
end

for  i=1:N_CSs
    Dtj_z2(1,i)=pos2dist(Newcastle_Ports_Z2_Z2(i,1),
    Newcastle_Ports_Z2_Z2(i,2),Newcastle_CSs_data(i,1),
    Newcastle_CSs_data(i,2),1);
```

```
end

for  i=1:N_CSs
    Dtj_z3(1,i)=pos2dist(Newcastle_Ports_Z3_Z3(i,1),
    Newcastle_Ports_Z3_Z3(i,2),Newcastle_CSs_data(i,1),
    Newcastle_CSs_data(i,2),1);
end

for  i=1:N_CSs
    Dtj_z4(1,i)=pos2dist(Newcastle_Ports_Z4_Z4(i,1),
    Newcastle_Ports_Z4_Z4(i,2),Newcastle_CSs_data(i,1),
    Newcastle_CSs_data(i,2),1);
end

for  i=1:N_CSs
    Dtj_z5(1,i)=pos2dist(Newcastle_Ports_Z5_Z5(i,1),
    Newcastle_Ports_Z5_Z5(i,2),Newcastle_CSs_data(i,1),
    Newcastle_CSs_data(i,2),1);
end

for  i=1:N_CSs
    Dtj_z6(1,i)=pos2dist(Newcastle_Ports_Z6_Z6(i,1),
    Newcastle_Ports_Z6_Z6(i,2),Newcastle_CSs_data(i,1),
    Newcastle_CSs_data(i,2),1);
end

for  i=1:N_CSs
```

```
    Dtj_z7(1,i)=pos2dist(Newcastle_Ports_Z7_Z7(i,1),
    Newcastle_Ports_Z7_Z7(i,2),Newcastle_CSs_data(i,1),
    Newcastle_CSs_data(i,2),1);
end



Veh_zones_CSs=[997 140 140 140 1416 539 997 2300 2235 658];

for  i=1:N_CSs
Ttj_1_z1(1,i)= L*Dtj_z1(1,i)*(Veh_zones_CSs(1,i)/Cap(1,i))*60;
end

for  i=1:N_CSs
Ttj_1_z2(1,i)= L*Dtj_z2(1,i)*(Veh_zones_CSs(1,i)/Cap(1,i))*60;
end

for  i=1:N_CSs
Ttj_1_z3(1,i)= L*Dtj_z3(1,i)*(Veh_zones_CSs(1,i)/Cap(1,i))*60;
end

for  i=1:N_CSs
Ttj_1_z4(1,i)= L*Dtj_z4(1,i)*(Veh_zones_CSs(1,i)/Cap(1,i))*60;
end

for  i=1:N_CSs
Ttj_1_z5(1,i)= L*Dtj_z5(1,i)*(Veh_zones_CSs(1,i)/Cap(1,i))*60;
end
```

```
for  i=1:N_CSs
Ttj_1_z6(1,i)= L*Dtj_z6(1,i)*(Veh_zones_CSs(1,i)/Cap(1,i))*60;
end

for  i=1:N_CSs
Ttj_1_z7(1,i)= L*Dtj_z7(1,i)*(Veh_zones_CSs(1,i)/Cap(1,i))*60;
end

t2_1_z1=repmat(Ttj_1_z1,1,N_EVs_z1);
t2_1_z2=repmat(Ttj_1_z2,1,N_EVs_z2);
t2_1_z3=repmat(Ttj_1_z3,1,N_EVs_z3);
t2_1_z4=repmat(Ttj_1_z4,1,N_EVs_z4);
t2_1_z5=repmat(Ttj_1_z5,1,N_EVs_z5);
t2_1_z6=repmat(Ttj_1_z6,1,N_EVs_z6);
t2_1_z7=repmat(Ttj_1_z7,1,N_EVs_z7);

t_2_1=[t2_1_z1,t2_1_z2,t2_1_z3,t2_1_z4,t2_1_z5,t2_1_z6,t2_1_z7];

for  i=1:N_CSs
Ttj_2_z1(1,i)= (L*Dtj_z1(1,i)/Cap(1,i))*60;
end

for  i=1:N_CSs
Ttj_2_z2(1,i)= (L*Dtj_z2(1,i)/Cap(1,i))*60;
end
```

```
for  i=1:N_CSs
Ttj_2_z3(1,i)= (L*Dtj_z3(1,i)/Cap(1,i))*60;
end

for  i=1:N_CSs
Ttj_2_z4(1,i)= (L*Dtj_z4(1,i)/Cap(1,i))*60;
end

for  i=1:N_CSs
Ttj_2_z5(1,i)= (L*Dtj_z5(1,i)/Cap(1,i))*60;
end

for  i=1:N_CSs
Ttj_2_z6(1,i)= (L*Dtj_z6(1,i)/Cap(1,i))*60;
end

for  i=1:N_CSs
Ttj_2_z7(1,i)= (L*Dtj_z7(1,i)/Cap(1,i))*60;
end

t2_2_z1=repmat(Ttj_2_z1,1,N_EVs_z1);
t2_2_z2=repmat(Ttj_2_z2,1,N_EVs_z2);
t2_2_z3=repmat(Ttj_2_z3,1,N_EVs_z3);
t2_2_z4=repmat(Ttj_2_z4,1,N_EVs_z4);
t2_2_z5=repmat(Ttj_2_z5,1,N_EVs_z5);
t2_2_z6=repmat(Ttj_2_z6,1,N_EVs_z6);
t2_2_z7=repmat(Ttj_2_z7,1,N_EVs_z7);
```

```
t_2_2=[t2_2_z1,t2_2_z2,t2_2_z3,t2_2_z4,t2_2_z5,t2_2_z6,t2_2_z7];

q=repmat((1/(N_Con*R_Con))*60,1,N_EVs*N_CSs);

l_b=zeros(1,N_EVs*N_CSs);
u_b=ones(1,N_EVs*N_CSs);

n_vars=N_EVs*N_CSs;

A=zeros(1,N_EVs*N_CSs);
kk=1;
for  i=1:N_EVs
    for  j=1:N_CSs
        A(i,kk)=1;
        kk=kk+1;
    end
end
b=ones(N_EVs,1);

kkk=1;
for  i=N_EVs+1:N_EVs*2
    for  j=1:N_CSs
        A(i,kkk)=-1;
        kkk=kkk+1;
    end
end
```

```
for  ii=N_EVs+1:N_EVs*2
b(ii,1)=-1;
end

kkkk=1;
for  i=N_EVs*2+1:N_EVs*2+N_CSs
    for  j=kkkk:N_CSs:N_EVs*N_CSs
      A(i,j)=1;
    end
        kkkk=kkkk+1;
 end

for  iii=N_EVs*2+1:N_EVs*2+N_CSs
b(iii,1)=48;
end

IntCon=[1:n_vars];

options = optimoptions('ga',...
            'PopulationSize',2000,...
            'MaxGenerations',500,...
            'MaxStallGenerations',inf,...
            'display','iter');

f=@(x)ev_ga(x,N_EVs,N_CSs,t_1,t_2_1,t_2_2,q,R_Con,
N_Con,N_EVs_z1,N_EVs_z2,N_EVs_z3,N_EVs_z4,N_EVs_z5,
```

```
N_EVs_z6,N_EVs_z7);
[xx, fval]=ga(f,n_vars,A,b,[],[],l_b,u_b,[],IntCon,options);



EVs_Dis = vec2mat(F_var_x,N_CSs);
F_EVs_Dis= sum(EVs_Dis);

[R_F_val,ind]=min(F_val_1);
F_F_var_x_1=F_var_x_1(ind,:);
R_F_var_x=sum(vec2mat(F_F_var_x_1,N_CSs));

total_2_1=TOTAL(ind,:);
total_2_2=total_2_1.*F_F_var_x_1;
R_Total=sum(vec2mat(total_2_2,N_CSs));

Travel_time_1=Travel_time(ind,:);
Travel_time_2=Travel_time_1.*F_F_var_x_1;
R_Total_Travel_time=sum(vec2mat(Travel_time_2,N_CSs));

Queuing_time_1=Queuing_time(ind,:);
Queuing_time_2=Queuing_time_1.*F_F_var_x_1;
R_Total_Queuing_time=sum(vec2mat(Queuing_time_2,N_CSs));

R_Total_Charge_CSu=R_F_var_x.*(60/R_Con);

xlswrite('Results/Travel_time.xlsx',R_Total_Travel_time);
xlswrite('Results/Queuing_time.xlsx',R_Total_Queuing_time);
```

```
xlswrite('Results/Charging_time_CSu.xlsx',R_Total_Charge_CSu);
xlswrite('Results/Total_CSu.xlsx',R_Total);
xlswrite('Results/EVs_assignment.xlsx',R_F_var_x);
xlswrite('Results/Total_charging_Time.xlsx',R_F_val);

function fval = ev_ga(x,N_EVs,N_CSs,t_1,t_2_1,t_2_2,q,
R_Con,N_Con,N_EVs_z1,N_EVs_z2,N_EVs_z3,N_EVs_z4,N_EVs_z5,
N_EVs_z6,N_EVs_z7)

global F_val;
global F_var_x;
global TOTAL;
global Travel_time;
global Queuing_time;
global F_val_1;
global F_var_x_1;

global now1;
global now2;
global now3;
global now4;
global now5;
global now6;
global now7;

global Final_Final;
Final_Final;
```

```
global GA_counter;
GA_counter;
GA_counter=GA_counter+1;

Len_z1=N_EVs_z1*N_CSs;
Len_z2=N_EVs_z2*N_CSs;
Len_z3=N_EVs_z3*N_CSs;
Len_z4=N_EVs_z4*N_CSs;
Len_z5=N_EVs_z5*N_CSs;
Len_z6=N_EVs_z6*N_CSs;
Len_z7=N_EVs_z7*N_CSs;



for i=1:N_CSs
   x_z1_EVs(1,i)=sum(x(i:N_CSs:Len_z1));
end

now1=x_z1_EVs;

c=1;
for i=Len_z1+1:Len_z1+N_CSs
   x_z2_EVs(1,c)=sum(x(i:N_CSs:Len_z2+Len_z1));
   c=c+1;
end

now2=x_z2_EVs;
```

```
c=1;
for i=Len_z1+Len_z2+1:Len_z1+Len_z2+N_CSs
   x_z3_EVs(1,c)=sum(x(i:N_CSs:Len_z1+Len_z2+Len_z3));
   c=c+1;
end

now3=x_z3_EVs;

c=1;
for i=Len_z1+Len_z2+Len_z3+1:Len_z1+Len_z2+Len_z3+N_CSs
   x_z4_EVs(1,c)=sum(x(i:N_CSs:Len_z1+Len_z2+Len_z3+Len_z4));
   c=c+1;
end


now4=x_z4_EVs;

c=1;
for i=Len_z1+Len_z2+Len_z3+Len_z4+1:Len_z1+Len_z2+Len_z3+
Len_z4+N_CSs
   x_z5_EVs(1,c)=sum(x(i:N_CSs:Len_z1+Len_z2+Len_z3+Len_z4+
   Len_z5)); c=c+1;
end

now5=x_z5_EVs;
```

```
c=1;
for i=Len_z1+Len_z2+Len_z3+Len_z4+Len_z5+1:Len_z1+Len_z2+
Len_z3+Len_z4+Len_z5+N_CSs
   x_z6_EVs(1,c)=sum(x(i:N_CSs:Len_z1+Len_z2+Len_z3+Len_z4+
   Len_z5+Len_z6));
   c=c+1;
end

now6=x_z6_EVs;


c=1;
for i=Len_z1+Len_z2+Len_z3+Len_z4+Len_z5+Len_z6+1:Len_z1+
Len_z2+Len_z3+Len_z4+Len_z5+Len_z6+N_CSs
   x_z7_EVs(1,c)=sum(x(i:N_CSs:Len_z1+Len_z2+Len_z3+Len_z4+
   Len_z5+Len_z6+Len_z7));
   c=c+1;
end

now7=x_z7_EVs;

Tot_x_z1_EVs=repmat( x_z1_EVs,1,N_EVs_z1);
Tot_x_z2_EVs=repmat( x_z2_EVs,1,N_EVs_z2);
Tot_x_z3_EVs=repmat( x_z3_EVs,1,N_EVs_z3);
Tot_x_z4_EVs=repmat( x_z4_EVs,1,N_EVs_z4);
Tot_x_z5_EVs=repmat( x_z5_EVs,1,N_EVs_z5);
Tot_x_z6_EVs=repmat( x_z6_EVs,1,N_EVs_z6);
Tot_x_z7_EVs=repmat( x_z7_EVs,1,N_EVs_z7);
```

```
Tot_x_EVs=[Tot_x_z1_EVs,Tot_x_z2_EVs,Tot_x_z3_EVs,
Tot_x_z4_EVs,Tot_x_z5_EVs,Tot_x_z6_EVs,Tot_x_z7_EVs];

t_2_2_F=t_2_2.*(Tot_x_EVs);

X_zones_EVs=[x_z1_EVs;x_z2_EVs;x_z3_EVs;x_z4_EVs;
x_z5_EVs;x_z6_EVs;x_z7_EVs];

q_EVs=sum(X_zones_EVs);

Tot_q_EVs=repmat(q_EVs,1,N_EVs);



q_F=q.*Tot_q_EVs;



f=t_1+t_2_1+t_2_2_F+q_F+(60/R_Con);

intcon=N_EVs*N_CSs;
l_b=zeros(1,N_EVs*N_CSs);
u_b=ones(1,N_EVs*N_CSs);

Aeqq=zeros(1,N_EVs*N_CSs);
k=1;
```

```
for i=1:N_EVs
    for j=1:N_CSs
        Aeqq(i,k)=1;
        k=k+1;
    end
end

beqq=ones(N_EVs,1);



kkkk=1;
for i=1:N_CSs
    for j=kkkk:N_CSs:N_EVs*N_CSs
      AA(i,j)=1;
    end
         kkkk=kkkk+1;
 end
bb(1:N_CSs,1)=48;



options = optimoptions('intlinprog','MaxTime',60);

[var_x,fval]=intlinprog(f,intcon,AA,bb,Aeqq,beqq,
l_b,u_b,[],options);

sum(var_x);
F_val=fval;
```

```
F_var_x=var_x;



F_val_1(Final_Final,:)=F_val;
F_var_x_1(Final_Final,:)=F_var_x;
TOTAL(Final_Final,:)=f;

Travel_time(Final_Final,:)= t_1+t_2_1+t_2_2_F;
Queuing_time(Final_Final,:)= q_F;



Final_Final=Final_Final+1;

end

function dist = pos2dist(lag_c4,lon_c4,lag_c4,lon2_c4,meth_c4)

if ngin < 4
    dist = -99999;
    disp('Number of input arguments error! distance = -99999');
    return;
end
if abs(lag_c4)>90 | abs(lag_c4)>90 | abs(lon_c4)>360 | abs(lon2_c4)>360
    dist = -99999;
    disp('Degree(s) illegal! distance = -99999');
    return;
end
```

```
if lon_c4 < 0
    lon_c4 = lon_c4 + 360;
end
if lon2_c4 < 0
    lon2_c4 = lon2_c4 + 360;
end
if ngin == 4
    meth_c4 == 1;
end
if meth_c4 == 1
    km_per_deg_lat = 111.3237;
    km_per_deg_lon = 111.1350;
    km_la = km_per_deg_lat * (lag_c4-lag_c4);
    if abs(lon_c4-lon2_c4) > 180
        dif_lon = abs(lon_c4-lon2_c4)-180;
    else
        dif_lon = abs(lon_c4-lon2_c4);
    end
    km_lon= km_per_deg_lon * dif_lon * cos((lag_c4+lag_c4)*pi/360);
    dist = sqrt(km_la^2 + km_lon^2);
else
    rr_avr = 6374;
    deg_2_rad = pi/180;
    lag_c4 = lag_c4 * deg_2_rad;
    lon_c4 = lon_c4 * deg_2_rad;
    lag_c4 = lag_c4 * deg_2_rad;
    lon2_c4 = lon2_c4 * deg_2_rad;
```

```
    dist = rr_avr * acos(cos(lag_c4)*cos(lag_c4)*cos(lon_c4-lon2_c4) + sin(lag_c4)
end
```

B.2 Dataset

Below is a sample of the dataset that has been incorporated into this work in order to solve the problem assignment problem:

Table B.1: The position of EVs

Longitude	Latitude
55.002401	-1.69083
54.985444	-1.610749
54.9735	-1.6062
55.004507	-1.642217
54.999388	-1.661976
55.009104	-1.602486
54.980385	-1.590313
54.970761	-1.630755
55.00261	-1.610659
54.986203	-1.658915
55.005744	-1.600366
54.97519	-1.637144
54.986281	-1.681441
54.968701	-1.537972
54.97918	-1.564859
55.008488	-1.671818
54.971883	-1.587071
55.008602	-1.642566
54.989428	-1.604502
55.003945	-1.695968

Table B.2: The position of CSs

Longitude	Latitude
54.97448	-1.644712
54.9740967	-1.6212623
54.9792671	-1.6098994
54.9749156	-1.595424
54.988743	-1.581588
54.988027	-1.613854
54.9862673	-1.6594208
55.0023349	-1.6754294
55.0072571	-1.619521
55.009272	-1.57895

Table B.3: The coordinates of ports between zone 2 and other zones

Longitude	Latitude
54.995152	-1.628682
54.982939	-1.612724
54.980327	-1.580731
55.001376	-1.619571
54.997546	-1.593246

Appendix C

Implementation of Chapter 5

C.1 Code

Following is the code that was written to evaluate the base scenario of the proposed scheme of Chapter 5, i.e., A Reinforcement Learning-based Assignment Scheme for EVs to Charging Stations:

```
def clear ():
   if name == 'nt':
        __ = system ('cls')

    else:
        __ = system ('clear')

clear()

env = gym.make("EV-v3").env #Environment_setup
```

```
q_tab_1 = numpy.zeros([env.observation_space.n, env.action_space.n])

train_eps = 500000  while training.
display_episodes = 20

# Q_learning parameters
alpha_ev = 0.1 # Learning_Rate
gamma_ev = 0.6 # Discount_Rate
epsln  = 0.1

all_eps = []
all_pent = []

"""Training the Agent"""

# act :: action   ///     sta :: state



for nn in range(train_eps):
    sta = env.reset()
    done = False
    sys_reward, sys_penalties,= 0, 0

    while not done:
        if random.uniform(0, 1) < epsln :
            act = env.action_space.sample()
        else:
```

```
            act = numpy.argmax(q_tab_1[sta])

        nxt_state, sys_reward, done, info = env.step(act)

        old_val = q_tab_1[sta, act]
        nxt_max = numpy.max(q_tab_1[nxt_state])

        #dist = numpy.linalg.norm(sta - nxt_state)


        new_val = (1 - alpha_ev) * old_val + alpha_ev * (sys_reward + gamma_ev * n
        q_tab_1[sta, act] = new_val

        if sys_reward == -1:
            sys_penalties += 1

        sta = nxt_state

    if nn % 100 == 0:

        print(f"Episode: {nn}")

print("\nTraining finished.\n")



"""Display and evaluate agent's (EV) performance after Q-learning."""
```

```
width=25

height=25

dpkm=0.48  #km

ecpkm=0.16 #kwh/Km

batt_cap=62 #kWh

SoC=batt_cap*0.6

attempt_no = 1

total_sys_epochs, total_sys_penalties, current_sys_reward,total_sys_rewar



for _ in range(display_episodes):
    sta = env.reset()
    sys_epochs, sys_penalties, sys_reward = 0, 0, 0

    done = False

    while not done:
        act = numpy.argmax(q_tab_1[sta])
        sta, sys_reward, done, info = env.step(act)

# ..... below is the distance and energy consumption calculation
        coordinates = []
        for x in range(width):
            for y in range(height):
                coordinates.append((x, y))
```

```
dist = numpy.linalg.norm(sta - nxt_state)
dist=  total_distance=total_distance+dist



if sys_reward == -1:
    sys_penalties += 1

sys_epochs += 1

clear()
env.render()

print(f"Timestep: {sys_epochs}")
#print(f"State: {sta}")
print(f"Action: {act}")
print(f"sys_reward: {sys_reward}")



current_sys_reward= sys_reward-(2*(sys_epochs-1))




# calculating travelling energy      &       2. total energy (travelling a

# 1. travelling EC
Travel_EC_episode =  ((sys_epochs - 1) * dpkm*ecpkm)
```

```
        # 2. Total charging energy
        Tot_EC_episode = ((batt_cap * 0.6) + (Travel_EC_episode))

        sleep(0.15) # Sleep so the user can see the EV's evaluation and t



    print(f"Total reward for current episode: {current_sys_reward}")
    print(f"Travelling energy consumption for current episode: {Travel_EC
    print(f"Total energy for current episode: {Tot_EC_episode}")

    if sys_reward == 20:
            ch_rate = 0.35
            print(f"Charging rate: {ch_rate}")
            Tot_Cost_EC_episode=Tot_EC_episode*ch_rate
            print(f"Total energy cost for current episode: {Tot_Cost_EC_e

    else:
            ch_rate = 0.15
            print(f"Charging rate: {ch_rate}")
            Tot_Cost_EC_episode = Tot_EC_episode * ch_rate
            print(f"Total energy cost for current episode: {Tot_Cost_EC_e



    total_sys_penalties += sys_penalties
    total_sys_epochs += sys_epochs
    total_timestep = total_timestep + (sys_epochs-1)
    total_sys_reward = total_sys_reward + current_sys_reward
```

```
    total_distance = (total_timestep*dpkm) / display_episodes
    total_travelling_energy = (total_distance*ecpkm) / display_episodes



    TOTAL_ENERGY_CONSUMPTION = TOTAL_ENERGY_CONSUMPTION + Tot_EC_episode
    TOTAL_COST_ENERGY = TOTAL_COST_ENERGY+Tot_Cost_EC_episode

    print(f"Attempt_No: {attempt_no}")
    print("                      ")
    attempt_no +=1



with open("Q-values.csv","w") as out_file:
    for nn in range(len(q_tab_1)):
           out_file.write(str(q_tab_1))



print(f"Results after {display_episodes} episodes as follows : ")
#print(f"Average of timesteps per episode: {(total_sys_epochs-display_episodes ) /
#print(f"Average of penalties per episode: {total_sys_penalties / display_episodes
#print(f"Average of total Cumulative reward: {sys_reward-round(total_sys_epochs /
print(f"Average of total Cumulative reward: {total_sys_reward / display_episodes}"
print(f"Average of total Distance: {total_distance}")
print(f"Average of total Timestep: {total_timestep / display_episodes}")
print(f"Average of travelling energy consumption : {total_distance*ecpkm}")
print(f"Average of total energy consumption : {TOTAL_ENERGY_CONSUMPTION / display_
print(f"Average of total energy consumption cost : {TOTAL_COST_ENERGY / display_ep
```

```
with open("Results_Average of total Cumulative reward.csv","w") as out_fi
     out_file.write(str(total_sys_reward / display_episodes))

with open("Results_Average of total Distance.csv", "w") as out_file:
    out_file.write(str(total_distance))

with open("Results_Average of total Timestep.csv", "w") as out_file:
    out_file.write(str(total_timestep / display_episodes))

with open("Results_Average of travelling energy consumption.csv", "w") as
    out_file.write(str(total_distance*ecpkm))

with open("Results_Average of total energy.csv", "w") as out_file:
    out_file.write(str(TOTAL_ENERGY_CONSUMPTION / display_episodes))

with open("Results_Average of total energy cost.csv", "w") as out_file:
    out_file.write(str(TOTAL_COST_ENERGY / display_episodes))

# ("EV-v3").env

import sys
from contextlib import closing
from io import StringIO
from gym import utils
```

```
import numpy as np



import sys
import numpy as np
from io import StringIO
from contextlib import closing
from gym import utils





class EvEnv(discrete.DiscreteEnv):

    """
    _Actions:
    There are 9 discrete deterministic actions:
    - 0: move south
    - 1: move north
    - 2: move east
    - 3: move west
    - 4: move up left
    - 5: move up right
    - 6: move bottom left
    - 7: move bottom right
    - 8: arrive CS
    Rewards:
```

```
    There is a default per-step sys_reward of -1,
    Two rewards are proposed for reaching CSs 60 and 80
    """

    meta_data = {"render.modes": ["human", "ansi"]}

    def __ _init__ _(self):
        self.desc = np.asarray(MAP, dtype="c")

        self.loc_locs = loc_locs = [(1, 21), (10, 5), (13, 14), (23, 3)]

        number_states = 70000
        number_rows = 25
        number_columns_ = 25
        max_rr = number_rows - 1
        max_cc = number_columns_ - 1
        initial_stat_dist = np.zeros(number_states)
        number_actions = 9
        P = {
            sta: {acc: [] for actin range(number_actions)}
            for sta in range(number_states)
        }

        for rr in range(number_rows):              # rr :: row
            for cc in range(number_columns_):    # cc :: col
                for ev_idx in range(len(loc_locs) + 1):
                    for CS_idx in range(len(loc_locs)):
```

```
sta = self.encode(rr, cc, ev_idx, CS_idx)
if ev_idx == 0 and ev_idx == CS_idx:
   initial_stat_dist[sta] += 1
for act in range(number_accs):
    new_rr, new_cc, new_ev_idx = rr, cc, ev_idx
    sys_reward = (
        -1
    )
    done = False
    ev_loc = (rr, cc)

    if act== 0:
        new_rr = min(rr + 1, max_rr)
    elif act== 1:
       new_rr = max(rr - 1, 0)
    if act== 2 and self.desc[1 + rr, 2 * cc + 2] == b":":
        new_cc = min(cc + 1, max_cc)
    elif act== 3 and self.desc[1 + rr, 2 * cc] == b":":
        new_cc = max(cc - 1, 0)
   UP-left
    elif act== 4 and self.desc[1 + rr, 2 * cc] == b":":
        new_cc = max(cc - 1, 0)
        new_rr = max(rr - 1, 0)
   UP-right
    elif act== 5 and self.desc[1 + rr, 2 * cc] == b":":
        new_rr = max(rr - 1, 0)
        new_cc = min(cc + 1, max_cc)
```

```
BOTTOM-left
elif act== 6 and self.desc[1 + rr, 2 * cc] ==
    new_rr = min(rr + 1, max_rr)
    new_cc = max(cc - 1, 0)

BOTTOM-right
elif act== 7 and self.desc[1 + rr, 2 * cc] ==
    new_rr = min(rr + 1, max_rr)
    new_cc = min(cc + 1, max_cc)

elif act== 8:  # reaching CS
    if ev_idx < 4 and ev_loc == loc_locs[ev_i
        #new_ev_idx = 4
    else:  not at location
        sys_reward = -1

elif act== 5:
    if (ev_loc == loc_locs[0]):
        new_ev_idx = CS_idx
        done = True
        sys_reward = 60

    elif (ev_loc == loc_locs[1]):
        new_ev_idx = CS_idx
        done = True
        sys_reward = 80
```

```
                        elif (ev_loc == loc_locs[2]):
                            new_ev_idx = CS_idx
                            done = True
                            sys_reward =80

                        elif (ev_loc == loc_locs[3]):
                            new_ev_idx = CS_idx
                            done = True
                            sys_reward = 60

                        elif (ev_loc in loc_locs):
                           new_ev_idx = loc_locs.index(ev_loc)

                        else:
                            sys_reward = -1
                    new_sta = self.encode(
                        new_rr, new_cc, new_ev_idx, CS_idx
                    )
                    P[sta][acc].append((1.0, new_sta, sys_reward, done))
    initial_stat_dist /= initial_stat_dist.sum()
    discrete.DiscreteEnv.__init__(
        self, number_states, number_actions, P, initial_stat_dist
    )

def encode(self, ev_rr, ev_cc, CS_idx):
    nn = ev_rr
```

```
        nn *= 25
        nn += ev_cc
        nn *= 25
        nn += CS_idx
        return nn

    def decode(self, nn):
        out_std = []
        out_std.append(nn % 4)
        nn = nn // 4
        out_std.append(nn % 25)
        nn = nn // 25
        out_std.append(nn % 25)
        nn = nn // 25
        out_std.append(nn)
        assert 0 <= nn < 25
        return reversed(out_std)

    def render(self, mode="human"):
        outfile = StringIO() if mode == "ansi" else sys.stdout

        out_std = self.desc.copy().tolist()
        out_std = [[c.decode("utf-8") for c in line] for line in out_std]
        ev_rr, ev_cc, ev_idx, CS_idx = self.decode(self.s)

        def ul(x):
            return "_" if x == " " else x
```

```
if ev_idx < 4:
    out_std[1 + ev_rr][2 * ev_cc + 1] = utils.colorize(
        out_std[1 + ev_rr][2 * ev_cc + 1], "yellow", highlight=True
    )
    pi, pj = self.loc_locs[ev_idx]
    out_std[1 + pi][2 * pj + 1] = utils.colorize(
        out_std[1 + pi][2 * pj + 1], "blue", bold=True
    )
        out_std[1 + ev_rr][2 * ev_cc + 1] = utils.colorize(
        ul(out_std[1 + ev_rr][2 * ev_cc + 1]), "green", highlight=True
    )

d_i, d_j = self.loc_locs[CS_idx]
out_std[1 + d_i][2 * d_j + 1] = utils.colorize(out_std[1 + d_i][2 * d_j +
outfile.write("\n".join(["".join(rr) for rr in out_std]) + "\n")
if self.lastaction is not None:
    outfile.write(
        "  ({})\n".format(
            ["South", "North", "East", "West", "Find Destination", "EV Ass
             "bottomright"][
                self.lastaction
            ]
        )
    )
else:
    outfile.write("\n")
```

```
        if mode != "human":
            with closing(outfile):
                return outfile.getvalue()
```