Optimal Assignment of Mobile Charging Stations for On-The-Move Electric Vehicles

OPTIMAL ASSIGNMENT OF MOBILE CHARGING STATIONS FOR ON-THE-MOVE ELECTRIC VEHICLES

By

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Declaration of Authorship

I declare that this project/thesis/dissertation is my own work and, to the best of my knowledge and belief, it does not contain material published or written by a third party, except where permission has been obtained and/or appropriately cited through full and accurate referencing.

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Dedication

To my family…

Abstract

Electric vehicles (EVs) are gaining increasing interest due to their zero emissions and relatively reduced running cost. However, the availability of charging energy is a main concern for many EV users. Therefore, a mobile charging station (MCS) facility is a potential solution that helps overcome many of the EV charging issues. With MCSs, EVs can be charged more easily with less waiting time compared with traditional fixed charging stations (FCSs). This thesis proposes a new approach to mobile charging stations for electric vehicles. From the perspective of the MCS operator, the goal is to maximize the revenues by increasing the number of served EVs with high required energy among several requests raised to MCS while maintaining a minimum operation cost throughout the charging service. A mobile charging station operating agency (MCSOA) is proposed for running an assignment and dispatching mechanism (ADM). Considering the randomness of EV charging requests and MCS locations, the MCSOA runs a dynamic optimization problem that is formulated as a mixed integer non-linear programming (MINLP) model to assign the most profitable EVs and dispatch the MCS to the optimal charging location, aiming to maximize the total profits of MCSs. Furthermore, the performance of the proposed ADM mechanism has been simulated using real-world traffic flow data of Dubai and Sharjah – UAE. The performance of the proposed system over different system parameters is studied. Additionally, to improve the effectiveness and validity of this mechanism, the system's performance has been evaluated for some irregular conditions, such as road traffic and unbalanced energy demand over the service area. Furthermore, numerical simulations show that the proposed ADM mechanism increases the system profits besides the number of served EVs in comparison with other EV charging coordination approaches including conventional charging at fixed charging stations (FCS), Nearest-Job-Next assignments (NJN), First Come First Served assignments (FCFS) and Earliest Deadline-First (EDF).

Keywords_ Electric vehicles, mobile charging stations, fixed charging stations, optimal EV charging assignment.

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List of Abbreviations

ADM	Assignment and Dispatching Mechanism
BSS	Battery Swapping Stations
CP	Charging Port
D	Destination Region
DWC	Dynamic Wireless Charging
EDF	Earliest Deadline-First
ESS	Energy Storage System
EV	Electric Vehicle
FCFS	First Come First Served
FCS	Fixed Charging Station
GMM	Gaussian Mixture Model
MCS	Mobile Charging Station
MCSOA	Mobile Charging Station Operating Agency
MDOD	Maximum Depth of Discharge
MEGSS	Mobile Energy Generation and Storage System
MESS	Mobile Energy Storage System
MOPSO	Multi Objective Particle Swarm Optimization
MINLP	Mixed Integer Non-Linear Programming
NJN	Nearest Job Next
O	Origin Region
PSO	Particle Swarm Optimization

RHO	Rolling-Horizon Optimization
SOC	State of Charge
SP	Stop Point
TOU	Time Of-Use
TSP	Traveling Talesman Problem

Nomenclature

Indices

t	Time index.
i	Electric vehicle index.
j	Mobile charge station index.
s	Stop point index.
r	Region index.
w	Swapping points index.

Parameters

E_i^{req}	EV *i* required Energy (kWh).
t_i^{wait}	EV *i* waiting time (mins).
R_i^{orj}	EV *i* origin location.
R_i^{des}	EV *i* destination location.
φ_i	EV *i* request category.
$d_{j,s}$	Distance between MCS *j* and stop point *s* (km).
η_j^{dis}	MCS *j* efficiency.
P_j^{max}	MCS *j* maximum charging rate (kW).
E_j^{max}	MCS *j* maximum capacity (kWh).
$MDOD_j$	MCS *j* maximum depth of discharge.
γ_j	MCS *j* energy consumption (kWh/km).
Δt	Time step (mins).
C^{grid}	Cost of real power purchased from the grid ($/kWh).
d_p	Power-related battery degradation cost ($/kWh^2).
d_e	Energy throughput battery degradation cost ($/kWh).
α	Percentage of Extra price for emergency requests.

Variables

$C_{t,j,s}^{opr}$	Total operation cost of MCS *j* at time *t* to stop point *s*.
$C_{t,j,s}^{deg}$	Battery degradation cost of MCS *j* at time *t* to stop point *s*.
$C_{t,j,s}^{tra}$	Travel cost of MCS *j* at time *t* to stop point *s*.
$C_{t,i,j,s}^{ch-EV}$	Cost of EV *i* energy purchasing from MCS *j* at time *t* at stop point *s*.
$P_{t,i,j}^{dis}$	Power discharged from MCS *j* to EV *i* at time *t*.
$SOC_{t,j}$	Current stored energy in MCS *j* at time *t*.
$P_{j,s}^{tra}$	Power consumed in MCS *j* travel to stop point *s*.
$t_{j,s}^{tra}$	Travel time from MCS *j* to Stop point *s*.
$t_{i,s}^{tra}$	Travel time from EV *i* to stop point *s*.
t_{opt}^{run}	Optimization algorithm running time.
$t_{i,j}^{res}$	Time required to respond of EV *i* and MCS *j*.
$t_{i,j}^{start}$	Starting time of charging process of EV *i* and MCS *j*.
$t_{i,j}^{ch}$	Charging time of EV *i* and MCS *j*.
$t_{i,j}^{end}$	Completion time of charging process of EV *i* and MCS *j*.
N^{ass}	Total number of assigned EV *i*.
$\boldsymbol{N^{tot}}$	Total Number of EV *i* Requests.

Decision Variables

$a_{i,s,t}$	Binary decision to detect the stop point s zone of EV *i* at time *t*.
$b_{i,s,t}$	Binary decision to assign EV *i* to stop point *s* at time *t*.
$c_{j,s,t}$	Binary decision to assign MCS *j* to stop point *s* at time *t*.
$s_{j,s,t}$	Binary decision to assign MCS *j* to swapping point *w* at time *t*.

Chapter 1. Introduction

1.1. Overview

According to the Paris Agreement, which was signed in 2016, fossil-fueled transportation has become one of the highest contributors to worldwide emissions and is expected to increase by up to 60% by 2050. Additionally, fossil fuels are subject to price instability and resource depletion [1], [2]. To meet the goals of emission reduction and regulated fossil fuel consumption, electric vehicles (EVs) have been developed as a powerful asset in the transportation field. Furthermore, with advancements in battery technologies, EV energy efficiency and charging infrastructure, the number of EVs will rapidly increase. In the 21st century, EVs have captured the interest of researchers as a green transportation tool, resulting in an increased number of conducted studies in this field [8].

Despite numerous benefits of the expansion of electric vehicles, there are many challenges that must be considered before EVs are widely used. The increasing number of EVs poses new challenges to the power system due to random charging behavior, as well as an increase in electricity demand on the power grid, particularly during peak hours. The increasing EV volumes also requires improving the charging infrastructure to enable faster charging. This is addressed by equipping the conventional charging stations, also known as fixed charging stations (FCSs) with fast DC-chargers that reduce the charging times to about half an hour [9]. On another hand, from the standpoint of users, charging their batteries is considered as a challenge in some cases, such as when they suffer from limited battery capacity and the FCSs are fully occupied, while they fear waiting a long time to get the charging service, or in cases where the EVs are traveling in suburbs or villages where no FCSs are available [4].

Recently, improving FCSs have attracted much attention to tackle some charging issues, such as upgrading the charging infrastructure through installing level-3 DC fast chargers at charging stations that can supply 50-350 kW of power. This has partially overcome the issue of long charging time so that an EV battery can be fully charged in 20 to 40 minutes [1]. Nonetheless, in order to overcome most of these challenges and provide EV users with a faster, more convenient charging service, mobile charging stations (MCSs) have emerged as a practical and beneficial solution that complements the operation of FCSs. MCSs have the advantage of moving from one place to another since they are trucks carrying a substantial amount of energy storage batteries, so the EV users can get the charging service at their location without the need to drive to FCSs. In addition, MCSs also help in shortening the waiting time during the peak hours and are considered as a reliable solution for users with insufficient energy and those who may exhaust their battery energy before arriving at the FCS [5]. Furthermore, MCSs are considered as a potential assistance to the grid since they reduce the power required for EV charging [3][4].

1.2. Motivations

Motivated by the preceding discussions, MCS is deployed as a powerful service to solve the mentioned charging issues. Consequently, most recent studies focus on improving the quality of this service either from the standpoint of EV users, the grid or from the MCS operators' side. The operation strategies of MCSs vary from one system to another based on the application and the objective of implementing this facility. Meanwhile, the primary objectives of MCS operators are to minimize the operational costs and charging expenses or maximize their profits from providing this service. However, the grid benefits from MCS by reducing the energy demands during peak hours. Additionally, user satisfaction with this facility is regularly assessed by increasing the number of served EVs and providing the service promptly and at their preferred location.

Despite the numerous benefits of MCSs, there exist some significant challenges that should be addressed. One such challenge is that the MCS operators benefit from deploying this facility. In this work, the MCSs are assumed to belong to a private business aiming to maximize its profit while achieving a high-quality service and reducing its operating cost, which are primarily associated with moving between charging locations. In order to do so, an MINLP optimization problem is formulated in this study to optimally select the most profitable EVs and their location, resulting in maximum revenues for the MCS.

In this work, the MCSs are modeled as trucks equipped with a string of lithium-ion batteries and fast DC chargers to improve the efficiency of this service by decreasing the charging time. In addition, MCSs are moving from one location to another to provide a charging service for EVs traveling on roads in the proposed area without a barrier on location. However, the MCSs are allowed to meet with selected EVs in specific locations only [3].

On another hand, it should be considered in the MCS operation that EV charging requests are heterogeneous in terms of location and time, demanding different amounts of energy within each time frame. Furthermore, the travel times of the MCSs are stochastic as they have to operate during the congested periods that vary over the day in nature.

On the highways that link Dubai and Sharjah, as well as the service roads within the urban area, setting up residential chargers can be challenging. Moreover, waiting times at the fixed charging stations located on the main roads are long. However, from the standpoint of a business owner, Installing FCS poses a lot of costs, such as high infrastructure cost as well as the demand charge cost added to the monthly bill by the utility to non-residential customers based upon the maximum power drawn in a 15-minute period during the month. In such scenarios, a mobile charging service can offer an alternative charging solution that enables EVs to be charged during their journey without being limited by specific places or times.

1.3. Contributions

Overall, the contributions of this thesis can be summarized as follows.

First, this thesis proposes a new operating mechanism for mobile charging stations that receive charging requests in a particular region from on-the-move EVs in a stochastic manner, where each request has details of the EV trip and desired amount of energy. An optimization problem of dynamic assignment and dispatching is formulated to optimally dispatch MCSs to charge the selected EVs while maximizing the MCS profits.

The implementation of the proposed assignment and dispatching framework is tested on vehicular trip data for regions within Dubai and Sharjah, UAE, and the system performance is evaluated over the changes in system size and demanded energy. Finally, the proposed method is compared with similar approaches presented in the literature, such as the Nearest Job-Next (NJN), First Come first served (FCFS), Earliest Deadline-First (EDF) assignments as well as the benchmark case of charging at FCS, to validate the reliability and improved revenues of the proposed ADM.

1.4. Thesis Organization

This report is structured as follows: Chapter 2 presents some of the related works to EV charging strategies, particularly mobile charging station (MCSs) scheduling and routing approaches. In Chapter 3, the research methodology and optimization problem formulation are explained, along with the objective functions of the proposed optimization. In Chapter 4, the simulation results of the proposed scheme are presented and discussed. Finally, Chapter 5 summarizes all the work done on this thesis while providing recommendations for future works.

Chapter 2. Background and Literature Review

In this chapter, the different approaches to improving the EV charging infrastructure are discussed. Following this, the mobile charging system MCS is explained in detail, with an overview of different studies conducted on the implementation of this technology.

2.1. Challenges of Rapid Growth of EVs

In recent years, the world has witnessed high global warming and expected shortages in oil resources. This makes EVs a powerful solution to overcome these consequences. On the other hand, a numerous number of EVs results in an increase in the demanded energy, which increases the pressure on the charging stations. Therefore, charging infrastructure and improving the conventional charging approaches as well as deploying new charging approaches are accounted to be major challenges for both scientists and businesses.

2.1.1. Impacts of EVs growth on grid

Different aspects of EV charging challenges are currently taking place in several studies. One area of interest for some researchers is the impact of the EV demand growth on the power grid. One of the investigations analyzed the impact of EVs on households in Indianapolis. They utilized a four-step traffic flow model to detect the usage pattern of vehicles in the study area and coupled it with a model of residential electricity demand to identify the effect of EVs in an urban setting. The findings were categorized into various zones associated with households by determining the cost of each zone. The study revealed that the usage characteristics of EVs varied significantly from one zone to another, leading to distinct charging profiles for each zone [6]. Similar approach studies the impact of EVs on the California market by increasing the wind production fraction when high levels of wind energy are supplied [7][8].

One of the preceding investigations [9] develops a framework to help in ascertaining the effects of EV charging schedules on power quality. By comparing the effectiveness of unregulated and regulated charging options on variables such as voltage decline, fluctuation, distortion of harmonics, and the peak site load with reference to the EV depot in Hazelwood school district. The results allow insights into the operation and layout of EV depots.

2.2. EV Charging Development

Other studies focus on the EV users' concerns and challenges with charging their vehicles, such as the lack of conventional charging stations and the long waiting time to get charged. Hence, different charging approaches have been developed to overcome these challenges. In this section, we will go through some of these approaches.

2.2.1. FCS Development

With the rapid increase of EV users, the current charging infrastructure is not capable of accommodating this growing number of EVs. The major obstacles related to fixed charging stations are to detect the required number of charging stations as well as the optimal layout and location, to allow the EV users to recharge their batteries in a reasonable amount of time and in a suitable location.

Starting from the optimal location of the fixed charging station challenge, a genetic algorithm-based approach is developed in [11][12] to detect the optimal placement of fixed charging stations that aims to minimize the traveling time of EVs users and serve all EVs in a given area while satisfying the system budget constraints. Additionally, the study presented in [13] aimed to enhance profitability and customer satisfaction by utilizing MILP problem-solving techniques to locate potential charging station sites, based on the past routes of EVs in Istanbul.

This issue has also been addressed in other literature, such as [14]. The proposed problem is formulated to detect the optimal size and placement of EV charging stations according to the environmental factors and the charging stations service zone, to minimize the total cost of EV charging. Results show that the proposed approach reduces the network loss and improves the voltage profile. Another charging station allocation problem is addressed in [15][16], a multi-objective particle swarm optimization (MOPSO) optimization algorithm and sequential Monte Carlo simulation is formulated for allocation of two EVs charging stations based on the optimal EV charging/discharging schedules, where several objectives are addressed, such as reduction in power loss and voltage deviation in buses.

The latest strategy in creating permanent charging stations involves utilizing level-3 chargers, which are direct current chargers that deliver electricity at a high-power level, potentially cutting down charging duration to approximately 30 minutes. Nevertheless, these chargers are costly and necessitate the necessary electrical supply system to back them up. As a result, even though they significantly decrease charging times, they do assist in alleviating range anxiety [17][18].

2.2.2. Dynamic wireless charging (DWC)

The above works focus on proper allocation and sizing of fixed charging stations rather than deploying new charging approaches. In [19], a dynamic wireless charging (DWC) approach is addressed, where the electric energy is transferred from the grid to the moving EV is considered as a better charging solution for EVs. However, the challenge in this approach is in high infrastructure cost. Hence, they formulated a metaheuristic genetic algorithm to deploy the locations of the charging lanes at a minimum cost. A similar approach is examined in [20] about wireless chargers, such as the project done by the Korean Advanced Institute of Science and Technology. Their proposal involves the installation of charging lines laid under roads which results in extensive infrastructure investments.

2.2.3. EV battery swapping

The last popular option in most literature [21-26] is to utilize EV battery swapping stations, where the EVs depleted battery packs are swapped out for charged battery packs, which allows for less service time even when using fast DC chargers. To be precise, the exchange point presents a significant opportunity for the widespread use of electric vehicles, as well as the potential to enhance the utility's load factor. To this end, several optimization algorithms have been created for Battery Swapping Stations (BSS), and their effects on potential income generation have been explored by allowing the battery charging stake to be used as a backup energy storage which is designed to meet grid requirements [21].

A different exchange task is analyzed in [22], which focuses on the traffic jam at the swapping center during specific hours of the day. Ding and Huang suggest a technique for determining an optimal battery swapping plan and subsequently present a live formula for selecting a portion of the idle taxis to swap batteries early, granting them allowances to avoid congestion. Furthermore, the number of BSSs is not enough to serve all EV users. Hence, researchers in [23] proposed the concept of a mobile battery swapping service that utilizes a van and a taxi. When the battery swapping van (BSV) departs from the battery swapping station (BSS), it provides battery replacements to EV users upon request. This approach has been implemented in a battery swapping service using the Gaussian mixture model (GMM) and particle swarm optimization (PSO). Another area of interest related to swapping is highlighted in [24][25], where the focus is on analyzing the costs associated with swapping compared to conventional charging stations. The main costs identified are infrastructure costs and higher battery aging costs. It has been found that a battery-swapping station requires a significant capital investment of around $500,000 for EV companies.

A novel strategy is presented for optimizing the operation of an EV BSS in [26], utilizing Rolling-Horizon optimization (RHO). The proposed BSS model accounts for serving various types of EVs utilizing a heterogeneous battery stock, with the objective of maximizing daily profits through the formulation of a mixed-integer nonlinear programming (MINLP) problem to offer optimal swapping and charging/discharging processes. To demonstrate the validity and efficiency of the proposed algorithm, a series of case studies comparing the long-short term memory (LSTM)-based RHO mechanism to unscheduled operations and day-ahead scheduling were conducted. Simulation results indicate that the proposed dynamic scheduling mechanism increases profits by 10% to 25.7% compared to day-ahead scheduling. Additionally, the proposed approach serves between 11% and 14% more EVs than the day-ahead model.

2.3. Implementing Mobile Charging Stations (MCS)

Mobile charging stations (MCSs) are vehicles carrying battery banks and DC chargers. It helps to overcome more of the charging challenges since they have an ability to charge EVs quickly and efficiently at various locations, including homes, offices, parking lots, and during trips. Compared to fixed charging stations, MCSs offer a more convenient and flexible charging service for EV users. With the increasing number of EV users and advancements in mobile technologies, MCSs have gained significant attention [27]-[36]. In this section, we will discuss different deployment options for MCSs.

2.3.1. Implementing MCSs aligned with FCSs.

One of MCSs' operation approaches in the literatures is utilize MCSs that are deployed to support FCSs in addressing the EV energy demands. In [37], a mobile energy storage system (MESS) is deployed to support several fixed charging stations, as well as supplying power to the grid during overload and peak hours. The operational model is formulated as an MINLP problem aiming to minimize the total operating cost of the parking lots. Following the simulation of two scenarios, the proposed algorithm effectively decreased the overall operational expenses by a 30% reduction. Furthermore, the monthly charges for peak demand were minimized as the historical peak level was maintained with the assistance of MESS.

Chauhan and Gupta [38] formulated an optimization heuristic method to schedule the MCSs to different fixed charging stations (FCSs) based on EV charging demands. However, the time window and user constraints were not included. Further analysis from [39] addresses MCSs to reduce the workload of FCSs on a highway. In the proposed approach, MCS dispatching is decided based on the workload information of FCSs, such as the number of EVs which are waiting in FCS for charging service. The proposed experiment is simulated to compare the performance of FCS and MCS in terms of the EVs waiting time, and it has found that the MCS network has better waiting time performance compared to the FCS network.

2.3.2. Implementing independent MCSs

The above studies about MCSs in [37], [38] and [39] have utilized MCSs as alternative solutions for grid during the overladed periods. Hence, studying the MCS operations rather than FCSs is one of the latest research projects. The purpose of the model developed in [5] is to deploy the MCSs as a support for EVs with insufficient battery energy and their battery energy may be exhausted before arriving at their destinations, these EVs are referred to IEV. Therefore, a scheduling mechanism is formulated to assign the IEV with proper movable charging station MCS in a way to reduce the charging expenses of IEVs and increase the proportion of charged IEVs. Both traffic flows and specific locations where MCSs can charge IEVs, such as certain charging parks, are not taken into account.

Additionally, in their proposal, the MCS is considered as an unprofitable service. Hence, MCSs' constraints are not considered.

From MCSs perspective and to minimize the expenses of MCSs, Huang et al. [40] propose a nearest-job-next (NJN) approach in an urban environment. In this approach, the MCS services the closest EV when it is finished with its current request. They assumed the charging requests to be homogeneous. However, in practice, the charging requests are random and heterogeneous. Moreover, distance is not the only issue to be considered. Some issues such as waiting time and traffic are potential for users, rather than distance. Thus, the NJN strategy of scheduling the MCS is not going to be optimal as far as cost and time are concerned.

In [41], MCSs' supplying power within an internet of things (IoT) environment are addressed. The study takes into account the randomness of power supply and dynamic of EV users' arrival. Hence, a dynamic structure of power supply and the economic model have been formulated with the goal of maximizing the long-term average profits of MCSs, while also identifying the optimal approach to power management using the Lyapunov optimization theory. The effectiveness of the proposal's performance is confirmed by simulation results.

Both [3] and [42] also addressed the optimal operation of MCSs to serve more customers at different locations. In [42], a new approach for optimal routing of green mobile energy generation and storage systems (MEGSS) is deployed to maximize the profit of the MEGSS fleet while meeting customers' requirements and to find the optimal decisions regarding the served customers and the route to be followed by each MEGSS. The proposed strategy is effective in offering an almost perfect solution for the assigned customer and itinerary sequence. However, in this approach only one customer can be served at a time. Moreover, the fact of the spatial and temporal charging requests is not accounted.

Qureshi and Ghosh in [3] applied a similar routing and scheduling approach for mobile charging service to serve EV users without the constraints of time and location. They have formulated an optimization problem to minimize the cost and the number of MCSs required by detecting the optimal route which should be followed by MCS to the charging location while meeting the expense constraints. However, in nature, the charging requests are random and heterogenous, hence the online optimization deals with random EV requests that are dynamically altered and considering the traveling direction of EVs while applying the EV constraints is accounted in our work.

Chapter 3. System Description and Methodology

3.1. Problem Description

In this proposed system, several EVs are moving on roads, and they need to get on-the-move charging services for different reasons. In some cases, fixed charging stations (FCSs) are faraway or fully occupied, or the EVs are in rural areas where no FCSs are available. Moreover, in other cases, the EVs do not have enough energy to reach the FCS or their destination.

A mobile charging station (MCS) is considered as an alternative solution for providing charging services to these EVs. Hence, a MCS operating agency works as private business and gets profits out of this service. MCSs are distributed in regions through the serviced area as illustrated in Fig. 3-1 and equipped with limited energy storage and some onboard charging ports to provide this service. In other words, the MCS operating agency (MCSOA) is responsible for assigning and scheduling the EV charging service in the proposed serviced area. MCSOA receives the random charging requests from different EV users in different regions at a time, with various requirements and constraints. Each request message raised by an EV consists of parameters which are required for the MCS operating system to do the assignments.

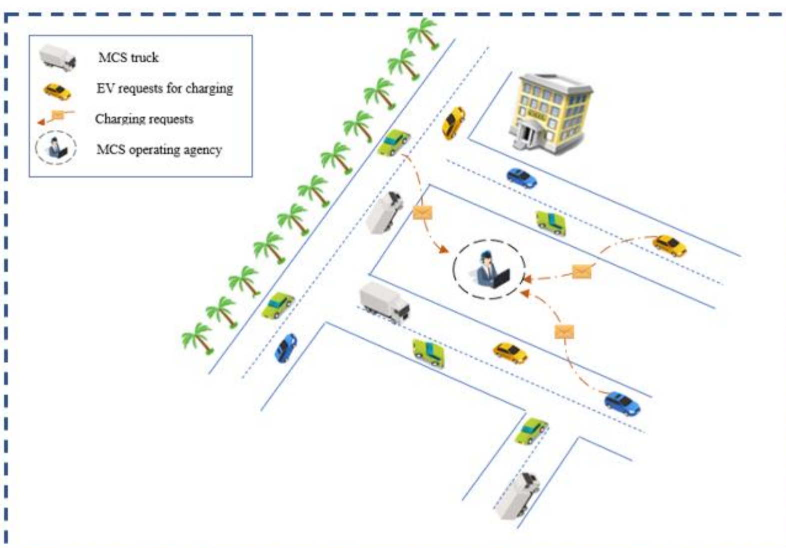

Fig. 3-1: Mobile charging service in a particular area.

The request is sent as, $\{R_i^{ori}, R_i^{des}, E_i^{req}, t_i^{wait}, \varphi_i\}$, where R_i^{ori} and R_i^{des} represent the EV origin region and destination region, respectively, E_i^{req} denotes the amount of energy required, while t_i^{wait} denotes the waiting time that EV can wait to receive an updates about the charging service, and φ_i denotes the type of request. In this framework, three different classifications of requests are considered. The job of the MCSOA is to optimize the assignment of EVs to maximize the profits of the MCSOA based on different constraints while accounting for optimal charging location that minimizes the traveling expenses. The proposed system consists mainly of MCSs and EVs as well as the service area. The following subsections explain the details of each part.

3.2. Service Area and Charging Locations

The service area is the total geographical area from which the charging requests are sent to the MCSOA in the proposed system. The service area is assumed to be part of Dubai and Sharjah, consisting of a number of squared regions. In this study, 100 regions were considered, as shown in Fig. 3-2. Each region in this area is given as a point $(\text{Avg\_Lat}_r, \text{Avg\_Long}_r)$.

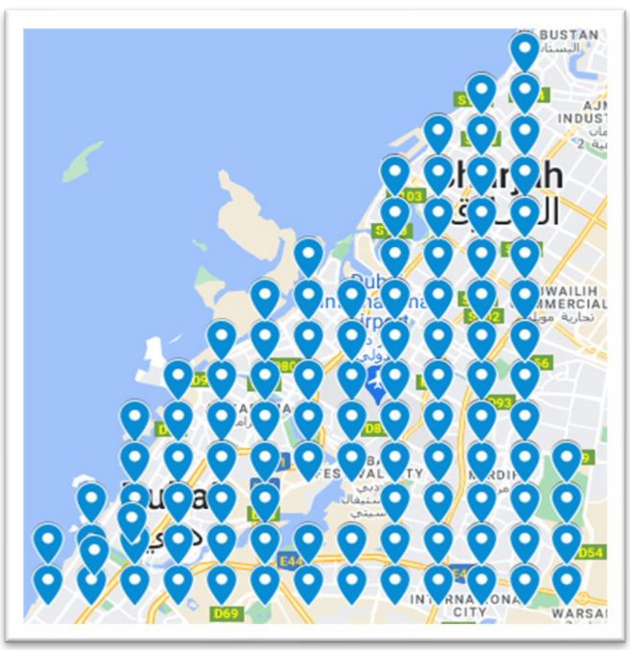

Fig. 3-2: Mobile charging service area.

The service area consists of a set of regions R= {1, 2, …, r}. Each region has a specific domain and includes some roads. The roads can be either main roads or service roads. All roads are taken in a two-way direction. Some regions are assumed to have stop points at which the assigned MCS and EVs can meet to start the charging process, the placement of these stop points in specific regions is crucial to guarantee comprehensive coverage of the service area. The number of stop points, S, is given as a subset of R, S = {1, 2, …., S} ∈ R. In addition, some stops point regions are assigned to apply the swapping facility, which is donated by W = {1, 2, …, W} ∈ S.

3.3. EV Charging Requests.

We consider a set of EVs $I = \{1, 2..., i, .., I\}$ that send the charging requests during the time interval ΔT, located at different regions and traveling to detected destinations, where the origin region and destination are given R_i^{ori} = (Avg_Lat$_{i,ori}$, Avg_Long$_{i,ori}$) and R_i^{des} = (Avg_Lat$_{i,des}$, Avg_Long$_{i,des}$), respectively. Hence, the trip of each EV will be known to the operating center. Each EV sends a message randomly to MCSOA in the service area requesting a charging service. The charging request message contains five different parameters $\{R_i^{ori}, R_i^{des}, E_i^{req}, t_i^{wait}, \varphi_i\}$, that are required for assignment and scheduling. This system considers three distinct categories of EV requests, which are categorized according to the users' charging requirements and donated with φ_i. The three categories are defined with specific names as explained.

- Regular requests: These are EVs that have enough energy to travel to their destinations but require charging services within their travel time.
- Flexible requests: These are the EV users who have the flexibility to wait for a specific time to get their energy.
- Emergency requests: These are EVs that have insufficient energy to travel to their intended destination or the nearest FCS and they need to get the charging service at the nearest stop point.

In return for the high priority of the emergency requests, these requests are modeled to pay a higher price for this priority, which is assumed as a factor of $\boldsymbol{\alpha}$ of the normal grid prices.

3.4. Mobile Charging Station (MCS)

Let $J = \{1, 2, \ldots, j\}$, to be a set of MCSs in the served area that will serve the EV users upon their request. Initially, each MCS in this area has two parameters that are required for the MCSOA to do the assignment $\{(\text{Avg\_Lat}_{j,s}, \text{Avg\_Long}_{j,s}),\ E_j^{mcs}\}$. $\left(\text{Avg\_Lat}_{j,s}, \text{Avg\_Long}_{j,s}\right)$ is the MCS coordination that represents its location considering that MCSs are allowed to park at the detected stop points S. E_j^{mcs} donates the current amount of energy in MCS. Moreover, the MCS are assumed to be identical in all other parameters. The MCS trucks in this system are chosen to be the Nikola two trucks, which are purely electric consist of a big container that includes the system components such as batteries and chargers. The main parts of MCSs are presented briefly.

3.4.1. Battery pack

These trucks are powered by different power sources. First, a fuel cell stack with a hydrogen tank is used to power the truck engine. Second, the energy storage system (ESS) in this proposed system is composed of a string of lithium-ion batteries as illustrated in Fig. 3-3. ESS stores energy in order to supply both truck motors and discharging power to EV users. The battery capacity assumed that the battery would store almost 80% of the maximum power generated, leading to a total capacity of 350 kWh.

3.4.2. DC fast chargers

In this proposed system, mobile EV chargers are used; these chargers are parts of DC fast chargers that provide powerful charging without the need for complex infrastructure. They can provide from 50 kW up to 350 kW of power and fully charge an EV in 15 – 40 minutes, depending on how much the EV battery can accept, where in this work a charger with 60 kW is used, since this will fit most EVs models. The mobile EV chargers are fixed inside truck containers. In this system, each truck is assumed to have three chargers as shown in Fig. 3-3.

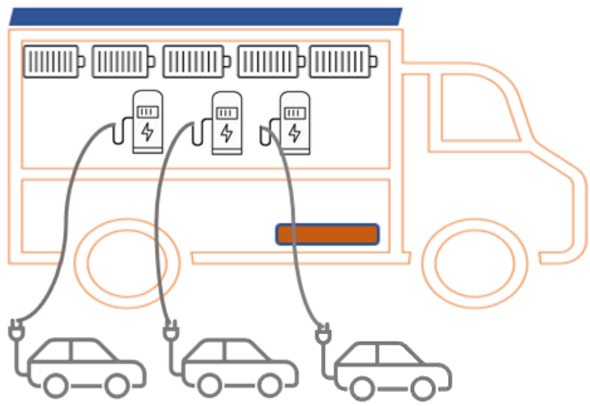

Fig. 3-3: MCS truck with DC fast chargers.

3.5. MCS Operating Agency (MCSOA)

The MCSOA is an agency responsible for facilitating the charging service and considering an interface between EVs and MCSs. MCSOA collects all charging requests raised from EV users and the updated location and capacity of MCSs to run the optimization problem to detect the assigned EVs that maximize their profits. The optimization algorithm assigns different charging requests to each MCS at the optimal stop charging point where all assigned EVs should meet with MCS to get the charging service. In our system, the total service area consists of 100 regions that are divided into two sets. Each set consists of 50 regions and is operated by MCSOA. Hence, two MCSOAs are required in this system with same size and parameters as illustrated in Fig. 3-4.

Fig. 3-4: Operating agency of total service area.

3.6. Problem Formulation

The main objective of this work is to maximize the MCSOA profits which can be achieved by selecting the most profitable EVs based on all the specifications as well as reducing the MCS expense due to the traveling to give the charging service. Hence, to achieve these goals, a Mixed Integer Nonlinear Programing (MINLP) model is formulated.

3.6.1. Optimization algorithm

The flowchart for the optimization process for EVs assignment and scheduling is proposed in Fig. 3-5, showing the optimization strategy that was developed to allow for maximum profits.

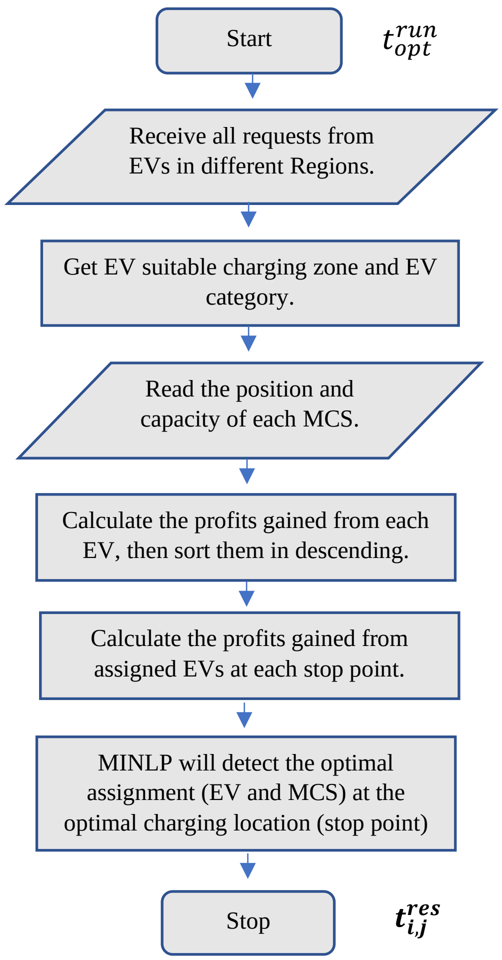

Fig. 3-5: MCSOA algorithm.

As can be seen from the flowchart, the assignment process is formulated through different steps. Initially, all the EV charging requests will be collected at a time defined as t_{opt}^{run}, at that moment, MCSOA will start computing the optimization algorithm for the collected requests and free MCSs. Through the simulation, the optimizer knows the travel journey of each EV, such as the EVs current region and the next region where the EV user passes through it. As a result, each EV could be assigned to a stop point in its current region or the next region. The MCSOA algorithm then sorts all EVs according to high profits, while the number of assigned EVs with each SP will be associated with the number of free charging ports and the capacity of MCSs.

The next stage of assignment starts with ordering the stop points according to the high profits predicted. The stop points with the maximum profits will have the highest priority in selection, while the number of assigned SPs is matched with the number of free MCSs. Moving to the last step in the assignment process, MCSOA will dispatch the MCSs to the optimal SP locations in the way of getting maximum profits. During each process, MCSOA sends messages to both MCS and EVs as the following:

Step 1: EVs send charging request to MCSOA "Requesting message "

Step 2: MCSOA runs the optimization algorithm, based on algorithm outputs will send a "Replying messages "for EVs and MCSs as following:

- For assigned EVs: "Request is confirmed ", [time, location, cost]
- For unassigned EVs within t_i^{wait}: "Request is bending."
- For unassigned EVs after t_i^{wait}: "Request is canceled."
- For assigned MCSs:" Process is assigned", [time, location]
- For unassigned MCSs: "Process is bending "

Now in order to start a new process, MCSOA has to estimate the MCS capacity after each process, to ensure that MCS is able to serve new requests, so both MCS capacity and location will be updated each Δt as well as the EV charging requests, where both new requests and the bending requests from the previous process will be considered. On another hand, if the energy reserve of the MCS is close to full depletion, the MCSOA schedules a battery swapping process, so that the MCS gets a new fully charged battery pack with enough energy for traveling and serving the incoming EVs on demand.

In this approach, EV users include a time factor in the charging request donated as t_i^{wait} , which indicates the time duration that users can wait to receive a message from MCSOA about the charging service. Therefore, during this time, MCSOA will keep running the optimization algorithm each Δt to update the users about their requests, which can be either "request is assigned" or "request is bending." After t_i^{wait}, if the user has not been assigned yet, MCSOA will send a message "request is canceled."

3.6.2. Objective function

The EVs assignment is the first step in this proposed optimization system to achieve the goal of maximum profits. This could be achieved by selecting the EVs with characteristics and conditions that ensure maximum revenues. Where the discharging energy delivered to the EVs in each process is high.

$$max(f1)$$

f1 = the total profits of all MCSs in the system

$$f1 = Max\ (\sum_{t,j,s}[C_{t,j,s}^{dis} - C_{t,j}^{ch-MCS} - C_{t,j,s}^{opr}] \tag{1}$$

where t is index of time, i is the index of EVs, j is the index of the MCS trucks and s is the index of the stop points. As clear from equation (1), $C_{t,j,s}^{dis}$ is the main variable that affects the overall profits, since it represents the money in dollars that MCS j will get from discharging power to all assigned EVs at the stop point s. Therefore, the total selling price around each stop point is formulated as in (2).

$$C_{t,j,s}^{dis} = \sum_i C_{t,i,j,s}^{ch-EV} \times a_{i,s,t} \times b_{i,s,t} \times c_{j,s,t} \tag{2}$$

where $C_{t,i,j,s}^{ch-EV}$ represents the price in \$ which each i should pay to MCS j for its charging power and it will be calculated according to its category, as in (3).

$$C_{t,i,j,s}^{ch-EV} = P_{t,i,j}^{dis} \times \Delta t \times \{C^{sell} \times (1 + \varphi_i \times \alpha)\} \tag{3}$$

$P_{t,i,j}^{dis}$ is the discharging power (kW) delivered to EV i during the time t from MCS j, while C^{sell} represents the selling prices in $/kWh following the derived pricing scheme as illustrated in Fig. 3-6, which is determined based on the demand pattern throughout the day.

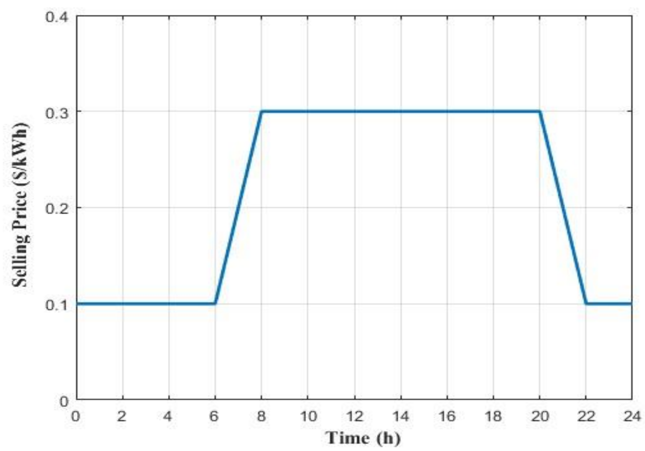

Fig. 3-6: MCSOA Selling Price scheme.

The EV category is characterized by factor φ_i which is given through the user's requests and categorized into three levels as shown in equation (4). Additionally, the pricing ratio α is expressed as a percentage of selling price, where the cost each EV user has to pay for MCS will differ upon users' categories.

$$\varphi_i = \begin{cases} 1 & , \ Emergency\ request \\ -1 & , \ Flexible\ request \\ 0 & , \ Regular\ request \end{cases} \tag{4}$$

Moving to the binary variables $a_{i,s,t}, b_{i,s,t}\ and\ \ c_{j,s,t}$ which are defined in equation (2), they have different identifications. First, a binary decision variable $a_{i,s}$ is defined in (5) to recognize all EVs in s zone.

$$a_{i,s,t} = \begin{cases} 1, & EV\ i\ is\ in\ \ stop\ point\ zone\ \ s \\ 0, & Otherwise. \end{cases} \tag{5}$$

In this work, a stop point zone is defined as a zone that includes all the EVs which are traveling in the region itself as well as the EVs that are coming from neighboring regions and expected to pass through the stop point after Δt. As illustrated in Fig. 3-7, the service area is composed of a set of zones, where each zone covers 5 different regions, and one stop point is allocated to one region of this zone. Zone 1 represents a service zone with a stop point located in region 3 and able to serve all EVs in the zone as well as the EVs coming from neighboring regions based on EVs trips.

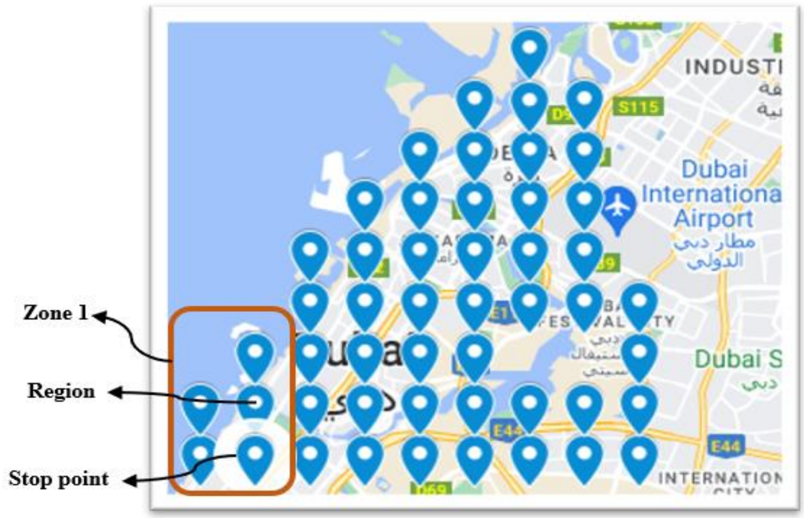

Fig. 3-7: Service zone for each stop point.

Subsequently, in order to select the most profitable EVs that would be assigned at each stop point, an additional binary decision variable $b_{i,s}$ is formulated as in (6).

$$b_{i,s,t} = \begin{cases} 1, & EV\ i\ is\ assigned\ with\ stop\ point\ s. \\ 0, & Otherwise. \end{cases} \tag{6}$$

Since the job of MCSOA is to assign the MCS j to stop point s to achieve a maximum profit goal, we associate a binary decision variable defined for MCS and SP assignment according to (7).

$$c_{j,s,t} = \begin{cases} 1, & MCS\ j\ is\ assigned\ with\ \ stop\ point\ s. \\ 0, & Otherwise. \end{cases} \tag{7}$$

Now moving to the other terms that are included in the objective function, which are MCS charging cost and operation cost. First, the charging cost is calculated as the cost of energy purchased from the grid to charge the MCS batteries as described in (8).

$$C_{t,j}^{ch-MCS} = \sum_i P_{t,i,j}^{dis} \times \Delta t \times C^{grid} \times s_{j,s,t} \tag{8}$$

Second, to estimate the system profits, the operating cost should be accounted for, which includes traveling expenses and battery degradation as illustrated in (9).

$$C_{t,j,s}^{opr} = C_{t,j,s}^{deg} + C_{t,j,s}^{tra} \tag{9}$$

Based on our framework both EVs and MCSs have to move toward the charging location, and that's led to traveling expenses for MCS, which is calculated in (10).

$$C_{t,j,s}^{tra} = d_{j,s} \times \gamma_j \times C^{grid} \times c_{j,s,t} \tag{10}$$

where γ_j represents the MCS truck consumption per km (kWh/km) and $d_{j,s}$ is the distance between MCS j and assigned stop point s in (km). C^{grid} represents the grid price in ($/kWh) follow TOU pricing scheme as shown in Fig.3-8.

Another expense that has been taken into account is the cost of degradation $C_{t,j,s}^{deg}$ [16], which is determined as shown in equation (11).

$$C_{t,j,s}^{deg} = (P_{t,i,j}^{dis} \times \Delta t \times \eta_j^{dis} \times c_{j,s,t})^2 \times d_p + \left(P_{t,i,j}^{dis} \times \Delta t \times c_{j,s,t} \right) \times d_e \tag{11}$$

d_p and d_e are power-related battery degradation cost in ($/kWh^2) and energy throughput battery degradation cost in ($/kWh), respectively.

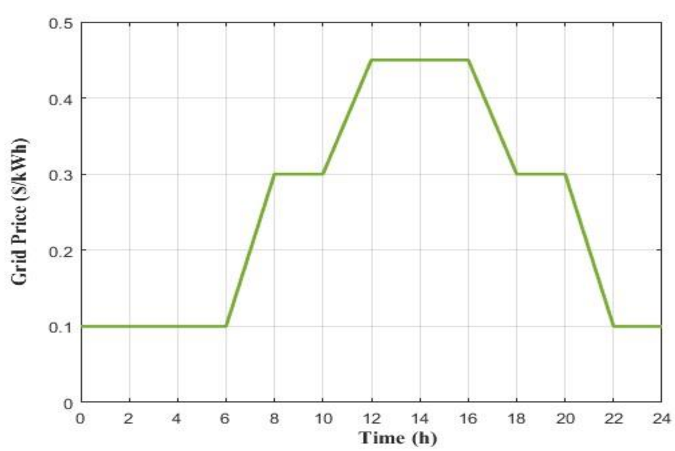

Fig. 3-8: TOU pricing profile.

3.6.3. System constraints

So far in the formulation, we have considered several constraints that ensure the optimality of the assignment decision. Therefore, decision, energy, and time constraints all are explained briefly.

3.6.3.1 Decision constraints

The following two constraints (12), (13) ensure that each MCS can charge a maximum of k EVs simultaneously as per our system size, and each EV can be charged from one MCS at one stop point. Initially, the number of EVs is set to $k = 3$.

$$\sum_i b_{i,s,t} \leq k \qquad \forall t \tag{12}$$

$$\sum_s b_{i,s,t} \leq 1 \qquad \forall t \tag{13}$$

Furthermore, in order to guarantee that every MCS is dedicated to one stop point at any given time, and that each stop point is serviced by one MCS, binary decisions are recognized as (14), (15).

$$\sum_j c_{j,s,t} \leq 1 \qquad \forall t \tag{14}$$

$$\sum_s c_{j,s,t} \leq 1 \qquad \forall t \tag{15}$$

3.6.3.2 Energy constraints

The total discharging energy at all assigned EVs at each stop point should not exceed the total capacity of the MCS as identified in (16).

$$\sum_i E_i^{req} \times b_{i,s} \times c_{j,s,t} \leq SOC_{t,j} \qquad , \forall j \tag{16}$$

The amount of stored energy $SOC_{t,j}$ in each MCS after the completion of its assigned charging process is calculated as (17). The battery limits constraints such that the energy stored cannot exceed the MCS maximum capacity (18)(19).

$$= SOC_{0,j} + \sum_{t,i}(P_{t,j}^{ch} / \eta_j^{ch} - P_{t,i,j}^{dis} \times \eta_j^{dis} - P_{j,s}^{tra}) \times \Delta t \times \frac{1}{E_j^{max}}, \tag{17}$$

$$\left(1 - MDOD_j\right) \times E_j^{max} < SOC_{t,j} < E_j^{max}, \tag{18}$$

$$P_{t,i,j}^{dis} \leq P_j^{max} \times b_{i,s,t}. \tag{19}$$

$MDOD_j$ *and* P_j^{max} represent the maximum depth of discharged and the maximum charging power rate respectively, while the η_j^{dis} donates the MCS discharging efficiency. $P_{j,s}^{tra}$ donates the power consumed during the journey from MCS's current location to the dispatching stop point and it is calculated as (20).

$$P_{j,s}^{tra} = \gamma_j \times d_{j,s} \qquad (20)$$

where $d_{j,s}$ is the distance from MCS j location to the stop charging point s, *and* γ_j represents *the* MCS consumption per km, while the charging power is formulated as in (21).

$$P_{t,j}^{ch} \leq P_j^{max} \times s_{j,s,t} \qquad (21)$$

A binary variable $s_{j,s,t}$, is defined to assign the MCS with swapping point in case the MCS has an insufficient amount of energy to allow the MCS to start a new charging process. Therefore, it will be assigned with a swapping point to replace its battery with a full charged battery. As described in (22).

$$SOC_{t,j} \times s_{j,s,t} \leq \left(1 - MDOD_j\right) \times E_j^{max} \qquad (22)$$

3.6.3.3 Time Constraints

Fig. 3-9 illustrates the time window for the proposed system, with different time segments and identifications.

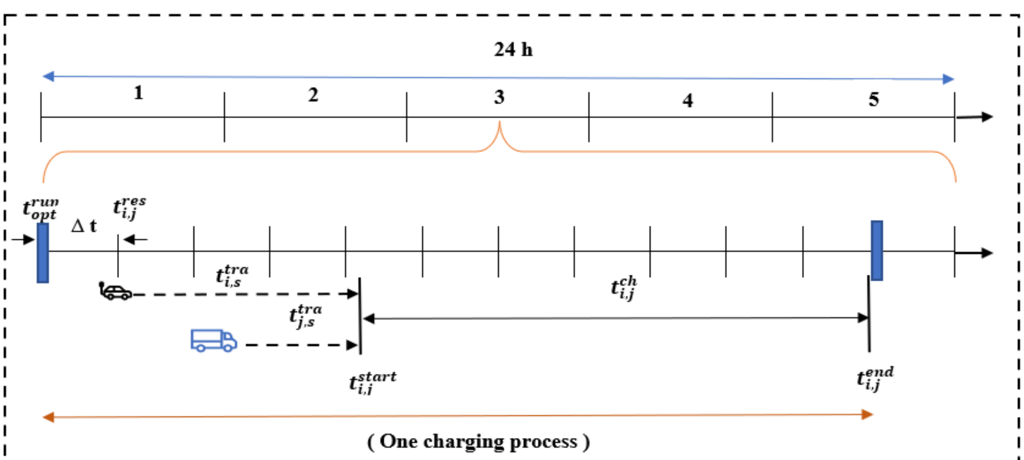

Fig. 3-9: System time window.

Starting at t_{opt}^{run}, MCSOA runs the first optimization algorithm to assign the EV to MCS at the dispatched stop point, where the maximum execution time to fulfill all constraints is denoted as Δt. After Δ t, once the optimization problem is completed, MCSOA will respond to both assigned EV and MCS about their charging request and assigned stop point location at a time donated as $t_{i,j}^{res}$. At that moment, both the EV and MCS truck start moving to the dispatched stop point with travel time computed as in (23) and (24).

$$t_{j,s}^{tra} = \left(\frac{d_{j,s}}{v_j}\right) \times 60 \tag{23}$$

$$t_{i,s}^{tra} = \left(\frac{d_{i,s}}{v_i}\right) \times 60 \tag{24}$$

where $t_{j,s}^{tra}$ and $t_{i,s}^{tra}$ are the times required for MCS and EV respectively to travel from their current locations to the assigned stop points at travel speed v_j , v_i respectively. After both the EV and MCS truck reach the stop point, the charging process can take place at $t_{i,j}^{start}$ which calculated as in (25).

$$t_{i,j}^{start} = t_{i,j}^{res} + \arg\max\left(t_{i,s}^{tra}, t_{j,s}^{tra}\right) \tag{25}$$

As the charging process starts, the time required to discharge the required energy and complete the charging process is donated as $t_{i,j}^{ch}$, and calculated as in (26).

$$t_{i,j}^{ch} = \left(\frac{E_i^{req}}{P_j^{max}}\right) \times 60 \tag{26}$$

$t_{i,j}^{end}$, is the time when the charging process is completed, and it is calculated as in (27).

$$t_{i,j}^{end} = t_{i,j}^{start} + t_{i,j}^{ch} \tag{27}$$

Meanwhile, by the end of each process at $t_{i,j}^{end}$, the amount of stored energy in each MCS should be estimated as in (17), if the MCS has enough energy to serve other EVs, the MCSOA will include it in the next optimization algorithm to serve new EV requests. However, if the MCS energy is less than the threshold value as in (22), the MCSOA will assign the MCS to the nearest swapping point to replace its depleted battery with a full energy battery. In this case, the next MCS assignment will consider the time required for the swapping process t_j^{swap}. Furthermore, it should be accounted that the next process will take place after finishing the previous process $t_{i,j}^{end}$.

$$t_{run}^{t+1} = t_{i,j}^{end} + t_{j}^{swap} \quad (28)$$

3.6. Operational Metrics

Within our MCS framework, there are certain parameters that need to be determined that will significantly impact the overall system's performance. We analyze the system performance using two primary metrics that assess the system's efficiency from both the MCSOA and EV user perspectives. These metrics are employed to evaluate the system's performance in various cases and compare it with other approaches.

The first metric that we consider which is the objective of our model is the total revenues that MCSOA gains from serving different EV requests in different regions throughout the day. In order to estimate the daily profits, we initially determine the profits generated by each process via the optimization algorithm outlined in equation (1). This refers to the profits earned by a single process that occurs at a specific time during the day and caters to the requests collected during that period and it is identified as Hourly profits. In the Results section, we utilize this profit term to evaluate the system's performance under unique scenarios where daily profits fail to gauge performance. The daily profits in ($), is defined as the total system revenue generated over 24 hours from all MCS trucks in the system and all charging requests that have been raised over the day. Considering the dynamics of charging requests, the profits vary over the day from one process to another, depending on the number of free charging ports and charging requests during that process.

The second metric that we consider is the percentage of assigned requests, which considers the number of requests that are assigned to MCS to get the charging service with respect to the total number of requests. To be more precise, we denote N^{ass} as the total number of requests served during the MCS charging process, and N^{tot} as the number of total requests raised to the MCSOA is calculated as in (29).

$$Assigned\ EVs\ \% = \frac{N^{ass}}{N^{tot}} \times 100\ \%. \quad (29)$$

Chapter 4. Results and Discussions

In this section, we provide a comprehensive performance evaluation of our proposed ADM approach. We conducted a numerical analysis to investigate the impact of changes in system parameters to enhance the effectiveness of this approach. Additionally, we verify the efficiency of our algorithm in irregular scenarios such as road traffic and imbalanced energy demand. Furthermore, we compare our proposed ADM approach with other methods utilized in MCS assignment and scheduling from existing literature. Furthermore, different operation mechanisms of the MCSOAs are discussed.

4.1. Simulation Setup

To evaluate our proposed algorithm, the charging requests from different users who are traveling within the served area in different regions heading to specific destinations at each interval of time ΔT are taken from real world data obtained from TomTom Move O/D Analysis portal, for January 26th, 2021. This data covers specific areas of Dubai and Sharjah, where the total area is divided into 200 regions, each region is assumed to be a square with an area of 2 x 2 km^2. The weekday traveling pattern of all vehicles traveling within the studied area was followed. Each vehicle has a specific trip starting from its origin (O) region to the destination (D) region, while during its trip it will pass through other regions. In this proposed work, we cover 100 regions in Dubai and Sharjah, and we assume that 5% of these vehicles are out of energy and request for charging service. The number of charging requests in each ΔT over a day as shown in Fig. 4-1.

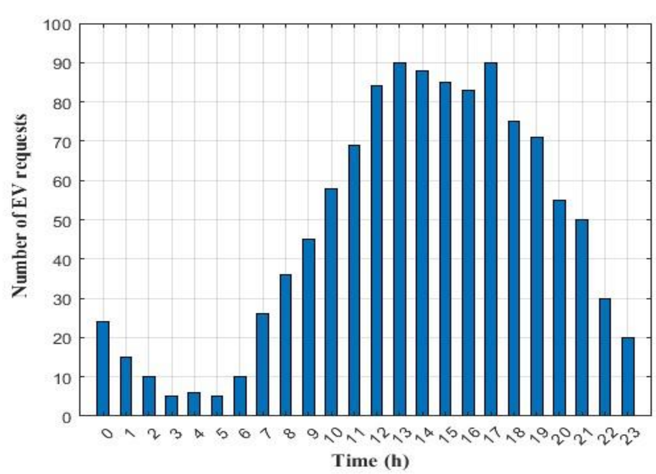

Fig. 4-1: Number of charging requests over day.

All EVs are assumed to be Tesla model 3 with the specifications in Table 4-1.

Table 4-1: Electric vehicle parameters [43].

EV Specifications (Tesla Model 3)	
Battery size	82 kWh
Battery usable	78 kWh
Efficiency	94%
MDOD	85%
Vehicle consumption	0.161 kWh/km
Charging rate	60 kW

Each EV charging request requires a proper amount of energy based on its requirements and capacity. Therefore, the energy required for each request is also derived from the energy consumption of TomTom Move O/D Analysis portal, which ranged between [30-50] kWh, depending on each EV requirement. The current SOC in each EV is not provided by the O/D Analysis portal. Hence, we have assumed SOC to be 30 kWh for all requests in our analysis. Moreover, all EVs are assumed to travel at an average speed of 80 km/h.

In the ADM approach, MCSOA runs the optimization algorithm for each ΔT to dispatch MCSs to the optimal stop charging points to serve the charging requests while maximizing system profit. One measure of the system's effectiveness is fast response. $t_{i,j}^{res}$ is donated as the time required for the MCSOA to finish the optimization execution and respond to EVs about their requests. Hence, the response time $t_{i,j}^{res}$ should be less than ΔT to achieve the goal of fast response. In this study, the time interval ΔT has been set as 5 minutes. All MCS trucks are assumed to be Nikola two with specifications are listed in Table 4-2.

Table 4-2: Mobile charging station parameters [44].

MCS Specifications (Nikola two)	
Battery size	350 kWh
Battery usable	306 kWh
Efficiency	90%
MDOD	85%
Vehicle consumption	0.975 kWh/km

Based on our analysis of running time, which will be discussed in the following section, we have determined that 5 MCS trucks meet the optimal response time of 5 minutes and cover the entire service area. Therefore, we assume that 5 MCS trucks will be deployed in each MCSOA to serve the charging requests. However, the number of occupied trucks will depend on the number of charging requests at any given time, and not all MCS trucks will be dispatched for charging requests. To simplify the analysis, only one MCSOA will be analyzed.

Initially at $t_{opt}^{run} = 0$ (12:00 AM), the MCSs in MCSOA1 are distributed on different roads as illustrated in Table 4-3, where all stay at the stop points till they receive a request from MCSOA to travel to the assigned point, the amount of stored energy at the beginning of scheduling is assumed to be 350 kWh for all.

Table 4-3: Mobile charging station initial position in MCSOA1.

MCS 1	MCS 2	MCS 3	MCS 4	MCS 5
Region 3	Region 13	Region 25	Region 36	Region 45

Each MCS is assumed to carry three mobile EV chargers in the truck container. The system uses an EVMO-60S fast charger with an output power of 60 kW. Table 4-4 shows the specifications of the DC fast charger.

Table 4-4: Mobile DC charger specifications [45].

Mobile DC charger (EVMO-60S)	
Output power	60 kW
Supply input	305-520 VAC
Charger weight	130 Kg
Charger dimension	(40.8-65.7-65.7) cm

The total service area of MCSOA1 in this work is composed of 50 regions. Out of those 50 regions, 10 regions are assumed to be stop charging points and they are allocated in the regions {3,7,13,20,25,34,36,41,45,50} in a way to cover all other regions as shown in Fig.4-2.

Fig. 4-2: Regions assumed to have stop points.

Furthermore, each stop point has a service zone. For example, the stop point in region 3 has a service zone donated as Zone 1 can serve regions {1,2,3,4,5}. Moreover, stop point 3 can serve the EVs which are coming from the neighboring zone as illustrated in Fig.4-3. As can be seen, stop point 3 would be able to serve all the green EVs in zone 1 including the one that is coming from neighboring zone 2.

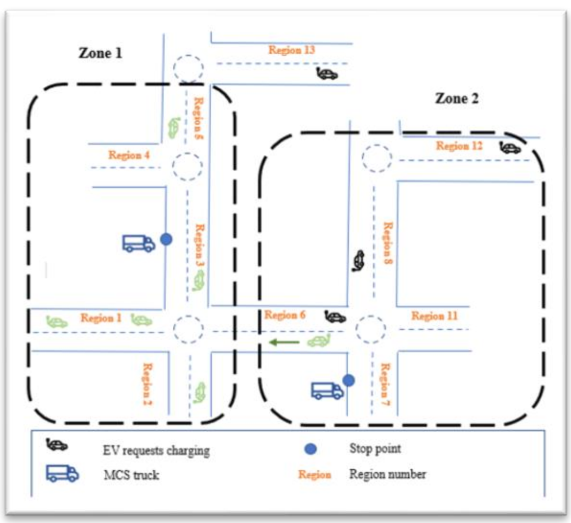

Fig. 4-3: stop point service zone.

In this study, we utilized the GAMS solver to execute the MINLP optimization problem. The time taken by the solver in this analysis was recorded on a computer with characteristics listed in Table 4-5. We assume that the MCSOA employs an identical computer to solve the ADM problem.

Table 4-5: Computer specifications

LAPTOP-KD425S2Q	
Processor	Intel(R) Core(TM) i5-8250U CPU @ 1.60GHz 1.80 GHz
Installed RAM	6.00 GB

4.2.Results Analysis

In this section, we present a case study of deploying MCSs technology in the selected regions of Dubai and Sharjah. The charge requests for the traveling journey of each request during 24 hours over these regions are given by the O/A portal, which have been used in the proposed simulation model. Then we provide a thorough numerical performance evaluation of our proposed Assignment and Dispatching Mechanism (ADM). The MCSOA performs the optimization algorithm within ΔT to dispatch the MCSs to assigned EVs at the dispatched stop point, with the objective of maximizing the system revenues.

Furthermore, different irregular scenarios such as road traffic and users' priorities are discussed. Finally, we compare our approach with other algorithms such as Nearest Job-Next (NJN), Earliest Deadline-First, First Come First Serve (FCFS) [19] and charging at fixed charging station (FCS), on the metrics of MCSOA daily profits and number of assigned EVs.

4.2.1. Performance evaluation

When designing a MCS framework, specific factors must be identified and assessed prior to its implementation, as they will significantly impact its effectiveness. Our framework primarily employs MCSOA, which operates the optimization algorithm. Moreover, the optimization algorithm comprises various constraints, variables, and parameters related to MCS Truck and EV charging requests.

Therefore, this section will analyze all the variables associated with the system's outcomes. Initially, we analyzed the optimization algorithm to detect the approximate size of the system, then we discussed how different parameters affect the performance of MCSOA and its revenues.

4.2.1.1.Optimization algorithm parameters

In this work, an optimization problem is formulated to assign the EV requests to charging ports and schedule the charging process throughout the day. The optimization algorithm is performed as a MINLP problem to maximize the MCSOA profits subject to several constraints. Like any optimization problem, this model is composed of several variables, sets, parameters, and constraints, and as per system methodology and requirements, MOCOA collects the requests and runs the optimization model to each Δt to assign the requests to the proper MCS. However, this running time is changing from the optimization process to another due to the changes in parameters over the time.

Meanwhile, to ensure the effectiveness of this approach, this system is modeled with a maximum running time of Δt, which improves the quality of the service from the user's side through shortness the responding time about their requests, while allowing the assigned MCS trucks to start their assigned process as fast as possible and increase the number of charging processes per day. From the analysis conducted throughout this work on the running time over the changes in different parameters, it has been founded that the running time is mainly changed with number of constraints and number of system variables such as number of CPs and number of charging requests.

Starting with the number of constraints which are required for the optimizer to give the optimal decision. Table 4-6 shows the different sets of constraints that have been applied in our model to achieve the optimal assignment and dispatching decision. It has been founded from simulation analyses that total of 15 constraints would be performed within assumed Δt. Hence, this number of constraints is matched with our optimal running time.

Table 4-6: Number of required constraints in ADM optimization problem.

Constraints	Number of constraints
Time	4
Energy	3
Binary decisions	4
Costs	4
Total number of constraints	15

Moving to the evolution of optimization running time with respect to the system size and number of requests. In order to do so, we performed the optimization algorithm several times through manipulating both the number of charging ports and the number of charging requests that would be included in each optimization process, to determine the approximated size of the proposed system that corresponds to the threshold running time Δt. As clear in Fig. 4-4, we conclude that as the number of free charging ports increases, the system running time increases regardless of the number of charging requests. However, it is notable from the curve that running time is also associated with the number of charging requests, where the increase in the charging requests results in a high running time. Hence, to ensure the validity of our proposed system size, we can conclude that a system with 15 charging ports which can handle up to 40 requests would be considered as a suitable size that maintains the optimal running time Δt.

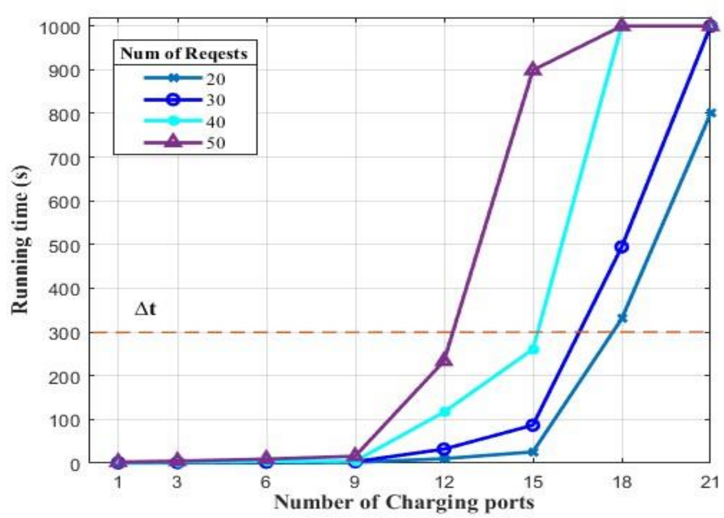

Fig. 4-4: Running time Vs changes in Number of CPs and Charging requests.

Any number of requests or charging ports beyond this number would require more than 7 minutes for the system to make an optimal decision and respond to users' queries, resulting in significant waiting delays.

4.2.1.2.MCSs parameters

MCS trucks are considered as a main part of our proposed system. Therefore, MCS variables should be analyzed to detect the impact of each variable on the system's performance. In this subsection, we will examine the effect of varying numbers of MCSs trucks and CPs on each truck along with the battery capacities of MCS and the CPs charging rates. The system's effectiveness will be assessed based on the number of EVs assigned and the daily profits.

4.2.1.2.1. Number of MCSs and CPs

First, keeping all EV parameters fixed as described before and changing the number of MCSs along with CPs on each MCS in the serving area of MCSOA1, the daily profits are obtained as shown in Fig. 4-5, while maintaining truck capacity and charging rates fixed to evaluate how changes in MCS and CP numbers in the system affect the daily profits.

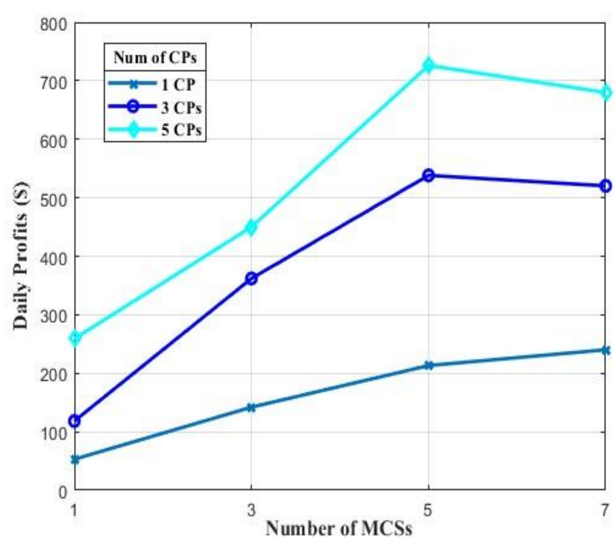

Fig. 4-5: Daily Profits Vs change in Number of MCSs and CPs.

Now from the EV users' side, to demonstrate how the changes in the number of charging ports would impact EV users, the percentage of selected EVs among all requests over the day as calculated in (28) is presented in Fig. 4-6 it is clear that as the number of MCSs within a served area with the same frequency of charging requests increases, most of these requests would be assigned up to the MCSs capacity and system size. Thus, the system's profits over the day increased and, since more requests are assigned, the percentage of selected EVs increased too.

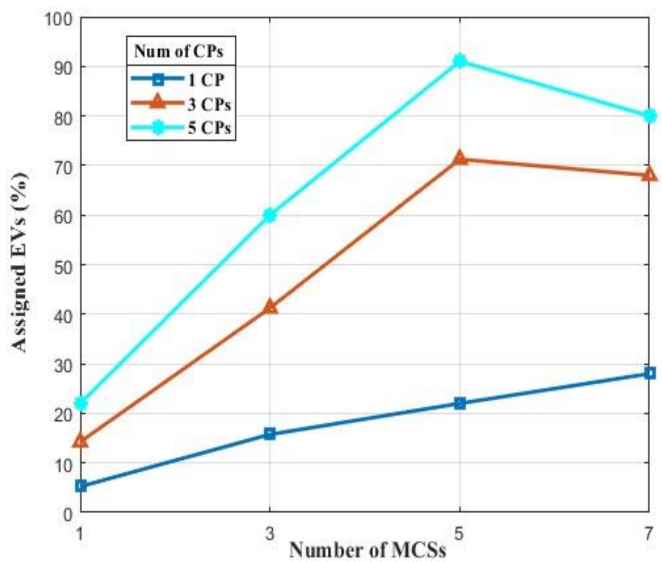

Fig. 4-6: Assigned EVs % Vs change in Number of MCSs and CPs.

As is observed from the curves in both Fig. 4-6 and Fig. 4-7, both daily profits and percentage of assigned EVs follow the same pattern in terms of the change in the number of charging ports. However, beyond the optimal number of charging ports, which is approximately 15, an increase in the number of MCSs and CPs results in a decrease in profits and assigned EVs. This is because, beyond the system size, the running time of the system will increase, resulting in fewer requests.

Additionally, for long-term studies, an increase in the system size will lead to high infrastructure and running costs that will surpass the system's profits. Therefore, in this study, we assumed a system size that is suitable for the service area.

4.2.1.2.2. MCS battery capacity and Charging Rate

Moving to the effects of MCS trucks' capacity on system profits and users' satisfaction, change the capacity of all MCS trucks in the system while maintaining the same charging requests. After running the optimization for one MCSOA, the Daily profits are as follows in Fig. 4-7. It shows that the curves of system profits rise with the increase of MCS's capacity. The reason is that the MCS is able to serve more EVs. Moreover, the curve with a larger charging rate is much higher than that with a smaller charging rate.

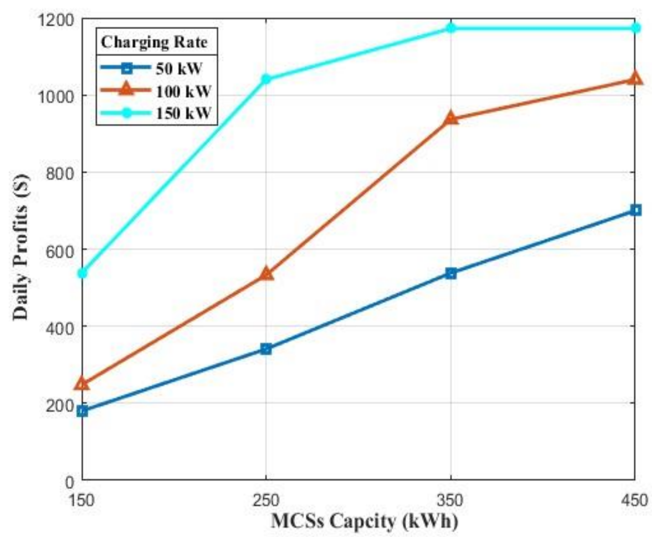

Fig. 4-7: Daily Profits Vs change in MCS capacity and charging rate.

This is because, CPs with a larger charging rate are able to complete the charging process in a shorter duration, thereby enabling MCSs to undertake more processes throughout the day and generate greater profits. For instance, with limited energy capacity, as indicated by the lowest SOC of 150, certain MCS trucks could only charge one EV at a time instead of three, resulting in decreased revenues.

On the other hand, it is notable that the curve is flattened beyond 350 kWh when utilizing rapid charging rates. This is because the system has a greater capacity than the number of requests. In other words, with the high battery capacity of MCSs, more EVs are assigned up to the system size. Hence, the percentage of selected EVs increases as follows in Fig. 4-8.

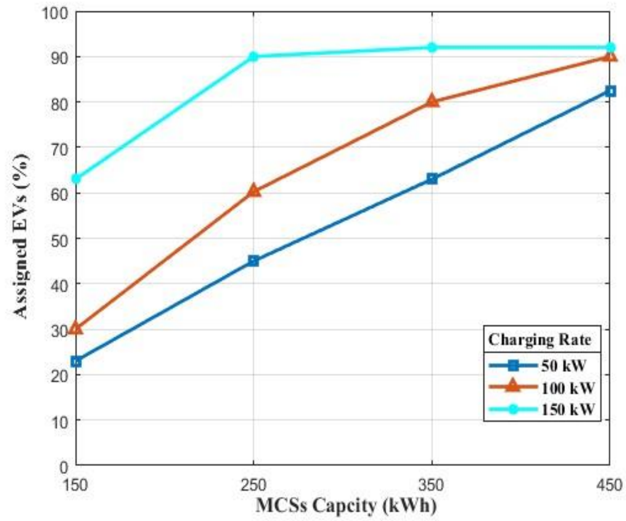

Fig. 4-8: Assigned EVs % versus change in MCS capacity and charging rate.

Overall, the system profits and percentage of the assigned EVs have fairly increased over the increase in the number of MCSs and number of CPs in the system, as well as the amount of stored energy on each MCS and their charging rates. However, the increase of charging rates needs high voltage which requires special infrastructure, the charging rate used in hour model is 60 kW. Furthermore, as observed from Fig. 4-7 and Fig. 4-8, the daily profits and percentage of assigned EVs are proportional to each other's. The increase in assigned EVs is followed by profit increases in the case of changes in the number of charging ports and MCS capacity.

4.2.1.3.EV users' parameters

In this part, we assess how the system output is affected by the parameters of EV users. These parameters include the total energy demanded, the number of requests for charging per interval, and the specifications of EV batteries. However, in this algorithm only the required energy is considered in optimization decision where, other parameters such as current SOC or EV battery size have no influence on the optimal assignment and dispatching decision.

On another hand, the Effect of Frequency of Charging Requests as clear in Fig. 4-9 shows that as the frequency of charging requests increases with the same amount of required energy, the daily profits of the system are slightly decreased, since the high frequency of requests with the same discharged energy at the end means high charging expenses, which results in less revenues.

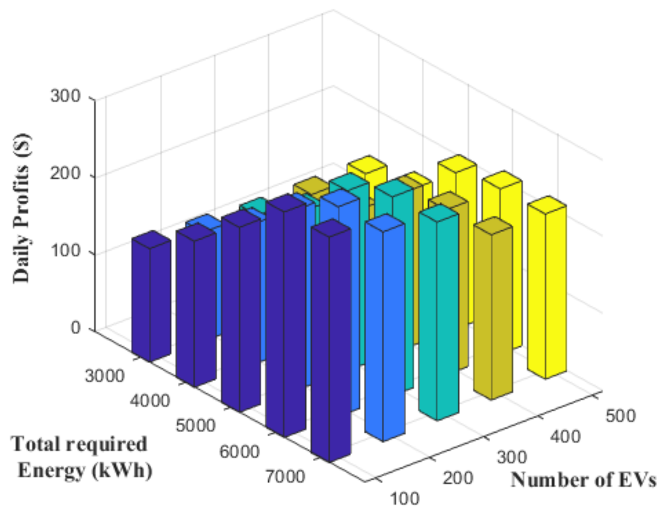

Fig. 4- 9: System Profits over the change in EVs required energy and number of requests.

In addition, it is obvious that the profits generated by the system gradually rise as the total energy demand increases with the same number of requests. Afterward, once the required energy surpasses 6000 kWh, the curve becomes less steep and eventually flattens. This occurs because the MCS trucks are unable to accommodate any additional charging requests due to the energy capacity limit of the proposed system, which can only serve up to 6000 kWh per day. Nevertheless, to increase revenues beyond these limits, the system must be expanded, while considering that the system's capacity must be aligned with the service area and infrastructure costs. Another term of comparison is presented in Fig. 4-10 for the system profits metrics against the number of charging requests with the assumption of that all EVs demand same amount of energy which is assumed to be 35 kWh.

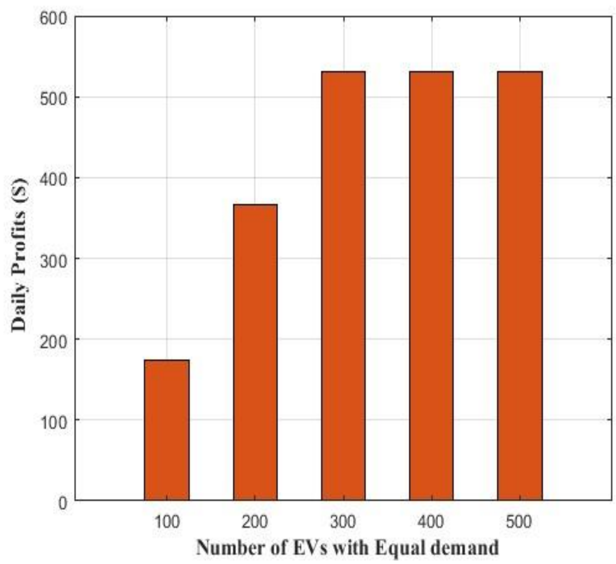

Fig. 4-10: System Profits over the change in EVs number.

Thus, the total required energy fluctuates depending on the frequency of charging requests. As is clear from the above chart, as the number of served EVs increases, the total revenues dramatically increase. Meanwhile, this expansion reaches a saturation point after 300 requests. This is because the number of charging requests has exceeded the maximum workload of MCSs and any further increase in the number of serviced EVs would require an expansion in the system's size.

4.3. Case Studies

In this section, three different case studies will be analyzed to evaluate the proposed system operation under specific irregular situations such as unbalanced energy demand, road traffic and request priorities of EV users. In all cases, the system will be compared based on the alterations in optimal assignment decision, system revenues and percentage of assigned users.

4.3.1. EV Distribution on service area

In this case study, we consider the operation of the system when an equal number of requests requiring the same amount of energy are distributed in various configurations around the stop points. In order to do so, two different scenarios are analyzed. In first scenario, the charging requests are distributed symmetrically over the service area as illustrated in Fig. 4-11.

Fig.4-11: Symmetrical distribution of charging requests (Scenario 1).

In contrast, the majority of charging requests are raised from two regions only in the second scenario as illustrated in Fig. 4-12.

Fig. 4-12: Unsymmetrical distribution of charging requests (scenario 2).

Upon analyzing the outcomes of both scenarios, the findings indicate that the system's earnings generated from an equal number of requests with the same amount of required energy, varied significantly due to the distribution of energy demand across different regions, as observed in Fig. 4-13.

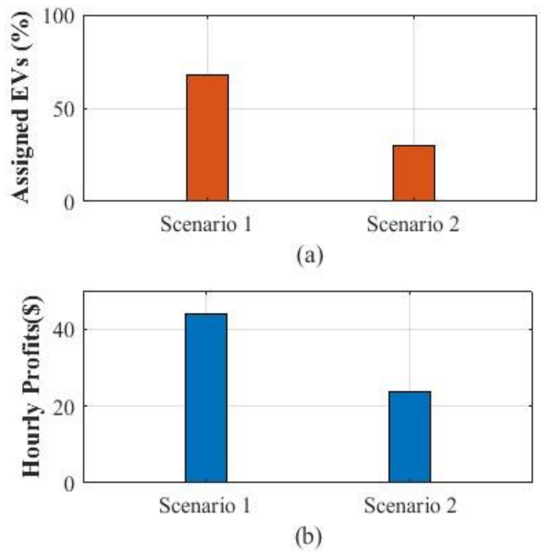

Fig. 4-13: Comparisons in terms of (a) assigned EVs %, and (b) hourly profits for both scenarios.

It is evident from the aforementioned findings, that the energy demand in the initial scenario is distributed symmetrically across the service area stop points. This would result in more EV requests being assigned as well as higher earnings for the system. In contrast, the percentage of assigned EVs in scenario 2 was determined to be 30%, which is less than half when compared to scenario 1. This is due to the fact that the requests in this scenario are directed towards appropriate regions, in accordance with the system constraint where only one MCS truck is authorized to park at each stop point in order to prevent high infrastructure expenses. The number of accommodated electric vehicles is restricted to a smaller number of stop points where the EVs are allocated. Thus, the system gains less revenue compared to the first scenario.

4.3.2. Road Congestion on some regions

Another special case to consider is the road congestion, where in the proposed ADM algorithm, the assignment decision is normally taken based on the travelling distance between MCS and the assigned stop point while assuming a constant travel speed. In actual operations, this assumption is obviously not practical in road congestion times, where during traffic congestion, the traveling time isn’t associated with travelling distance and speed only. However, it will correspond to the traffic density. To evaluate the influence of road congestion on the MCSOA dispatching decision, we ran the optimization algorithm twice. Initially, we simulated a typical scenario in the absence of congestion as in Fig 4-14 for a set of requests to assign these requests to MCS trucks which are allocated at detected locations at the beginning as seen in the Table 4-7.

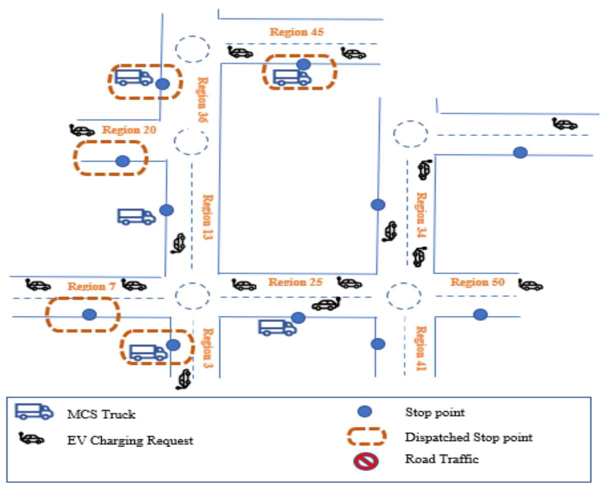

Fig. 4-14: Optimal MCSs assignment for a typical case.

Next, we repeated the process for the same set of requests, but this time we consider a traffic congestion exists in a particular region as illustrated in Fig. 4-15.

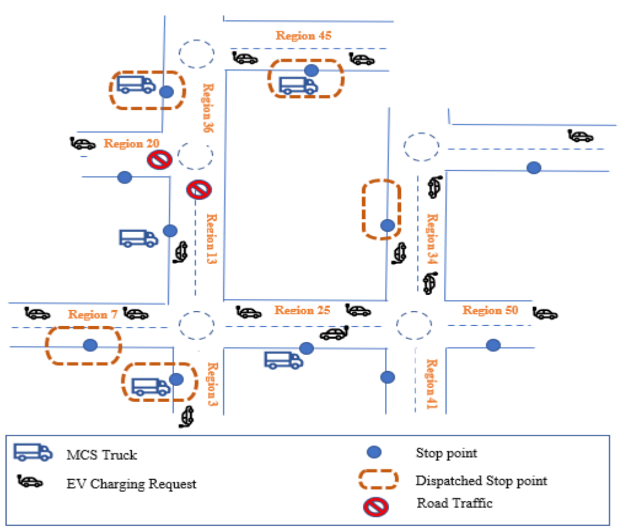

Fig. 4-15: Optimal MCSs assignment with traffic congestion case.

Moving to the impacts of traffic, while assuming the connection road between regions 13 and 20 has a traffic with a 15 mins delay. As clear from the above table, this delay consideration has changed the optimal solution as in Fig.4-15 and Table 4-7, where the

MCS truck allocated to region 13 has relocated to region 7 instead of 20 to avoid traffic, where the MCS choose the option of faster travel time over a longer distance. Furthermore, stop point at region 20 has not been dispatched at all. The optimal assignment and dispatching stop point that achieved the goal of max profits in both cases is illustrated in Table 4-7.

Table 4-7: MCS initial Locations and updated locations after assignment.

MCS #	MCS 1	MCS 2	MCS 3	MCS 4	MCS 5
Initial location	Region 3	Region 13	Region 25	Region 36	Region 45
Assigned location without traffic	Region 3	Region 20	Region 7	Region 36	Region 45
Assigned location with traffic	Region 3	Region 7	Region 34	Region 36	Region 45

As observed from simulation results, the optimal dispatching region is changed in the case of traffic roads. Additionally, the system's profits are affected by traffic as shown. This is because, in the traffic conditions the MCSOA assigns trucks in a way to avoid traffic, even if the profits generated from this destination is high. Therefore, it could be assigned with a lower profit charging point, which has less travelled time, rather than high profit points with high traveling time such in the traffic. Fig. 4-16 shows the comparison between two cases in terms of hourly profits and percentage of assigned EVs.

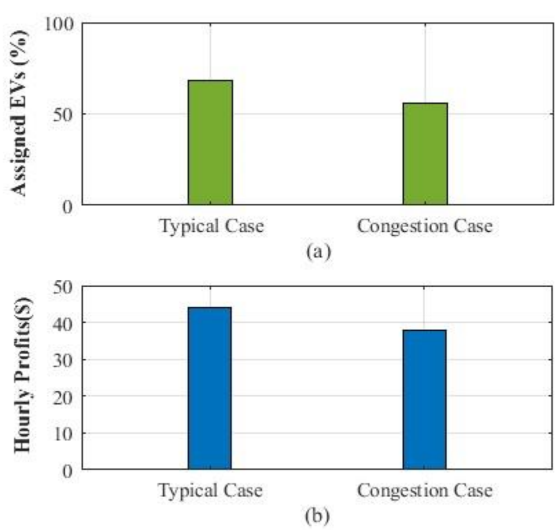

Fig. 4-16: Comparisons in terms of Assigned EVs % (a) and Hourly Profits (b) between typical and congestion cases.

As evident from the charts in Fig. 4-16, a minor decline in the number of assigned EVs in contrast to the regular situation. Nevertheless, in terms of profits, a presence of road congestion on one specific road causes a deduction of $6 in profits in a single operation.

4.3.3. EVs Request priorities

In this part, a comparison between three EV categories is presented. Emergency requests, regular requests and flexible time requests. The emergency requests are EVs with energy constraints. Therefore, they will not be able to travel to the next region due to the low SOC in their batteries. Hence, to increase their priority for being assigned, those EVs should pay a higher price with an increase in α percentage compared to other categories. On another hand, users with no constraints on their SOC should pay the regular energy prices and their request considered as a regular request. However, charging requests with the ability to wait for a proper time to get their charging process are defined as flexible requests and they are offered a discounted price from MCSOA for their flexibility. Table 4-8 describes the price that each category has to pay, where both are assumed 20% of the grid price.

Table 4-8: Purchasing Price for each EV category.

	Emergency requests	Regular Requests	Flexible Requests
Price ($)	$C^{grid}(1+\alpha)$	C^{grid}	$C^{grid}(\mathbf{1}-\ \beta)$

Initially, in order to demonstrate the selection priorities for various categories, two distinct situations will be assessed and compared with regards to the same set of charging requests and the same required amount of energy. The only difference between the two scenarios is the type of requests. In the first scenario, all requests are considered as regular as presented in Fig. 4-17, whereas in the second scenario, 20% of the requests are assumed to be emergencies and another 20% are flexible EVs, while the remaining requests are regular requests. Upon running the optimization algorithm for both scenarios, the optimal assignment and dispatching are illustrated in the Fig. 4-17 and Fig. 4-18, respectively. To indicate the priorities of requests, we assume that region 34 has two emergency requests, whereas two flexible requests are allocated to regions 7 and 50. With respect to the emergency requests in region 34 which are supposed to get the charging service within its region, while they will be charged a higher fee than others. Hence, region 34 stop point was not assigned in the first optimization. However, the optimal assignment has changed to dispatch the 34 stop point as shown in Fig.4-18.

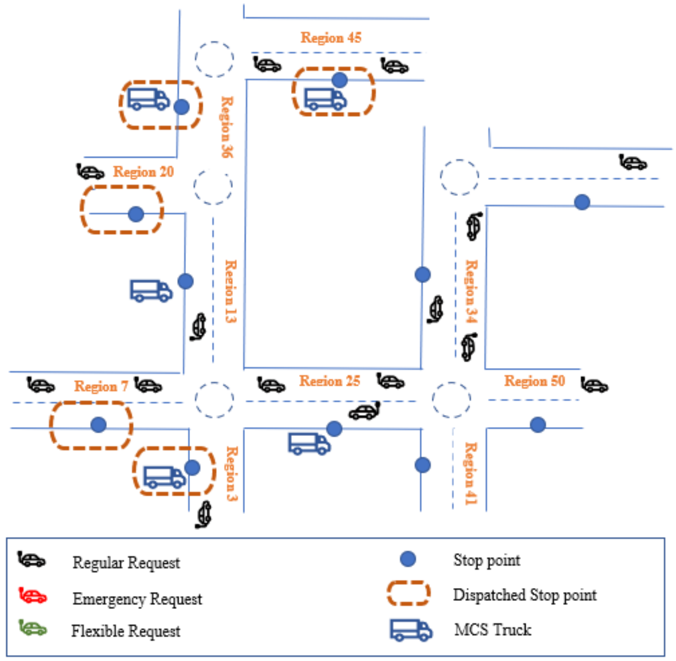

Fig. 4-17: Optimal MCSs assignment with Regular requests only.

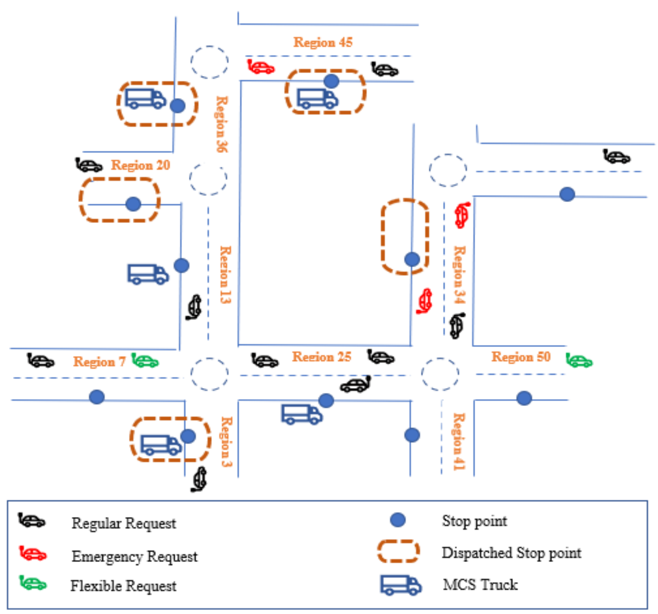

Fig. 4-18: Optimal MCSs assignment with Regular, Emergency and Fixable requests.

This is because the MCSOA aims to maximize its profits, while those EVs would pay higher price that results in high system revenues. In contrast, the region 50 with one flexible request has not been dispatched and it has been postponed to the next assignment since it has waiting options. Moreover, they will pay a discounted price, so they are not a profitable option for the agency. In terms of profits and percentage of Assigned EVs, the two scenarios are compared as in Fig. 4-19. It shows that incorporating the number of emergency requests with higher purchasing prices increases the revenues by almost 10 $ in one operation compared to scenario 1.

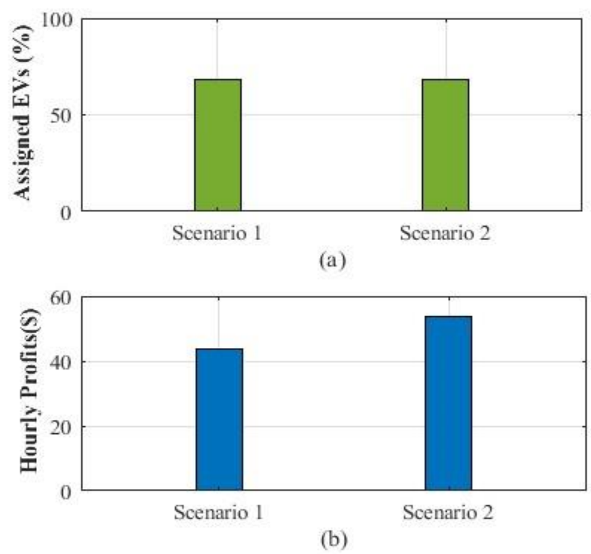

Fig. 4-19: Comparison between the scenarios in terms of (a) assigned EVs %, and (b) hourly profits.

Meanwhile, in both scenarios same number of EVs have been assigned, but the percentage of each assigned category are varied as can be observed in Table 4-9, which confirms that the emergency requests have the highest priority in selection over other categories, while Flexible requests witnessed the lowest priority.

Table 4-9: The percentage of assigned EVs based on their categories.

	Scenario 1	**Scenario 2**
Assigned EVs	68 %	
Regular Requests	68 %	40 %
Emergency Requests	-	20 %
Flexible Requests	-	8 %

4.4. Comparison with Other Approaches

Our proposed system is evaluated against alternative methods used in various literature for the optimal assignment and scheduling process of MCS. Firstly, the Nearest Job-Next (NJN) approach, which makes assignment decisions based on the minimum distance, so the MCS is required to serve the closest request to its location, regardless of the output profits gained from the service. Secondly, the earliest deadline-first (EDF) approach selects the EV whose charging process has to be accomplished the earliest, allowing the MCS to assign more EVs at the same time. Third, the first come first serve approach (FCFS) works by selecting EVs according to the order of their charge request times. Finally, our proposed system would be compared with conventional charging method where the MCS will be considered as a fixed charging station (FCS) and they don't have the ability to move to other locations, they can only deliver the charging request in their fixed locations. In contrast, our proposed approach assigns EVs based on high revenues with the constraint that EV should be within the MCS service area regardless of their charging time or current location. While maintaining all the system parameters and inputs are similar and applying all different approaches, the daily profits and percentage of assigned EVs % are presented in the Table 4-10.

Table 4-10: ADM approach compared to other approaches.

Compression criteria	Daily profits ($)	Assigned EVs %
Assignment and Dispatching Mechanism (ADM)	538.293	68
Nearest Job-Next (NJN)	490.322	50
Earliest Deadline-First (EDF)	481.515	78
First Come First Served (FCFS)	504.342	68
Fixed Charging Station (FCS)	463.918	43

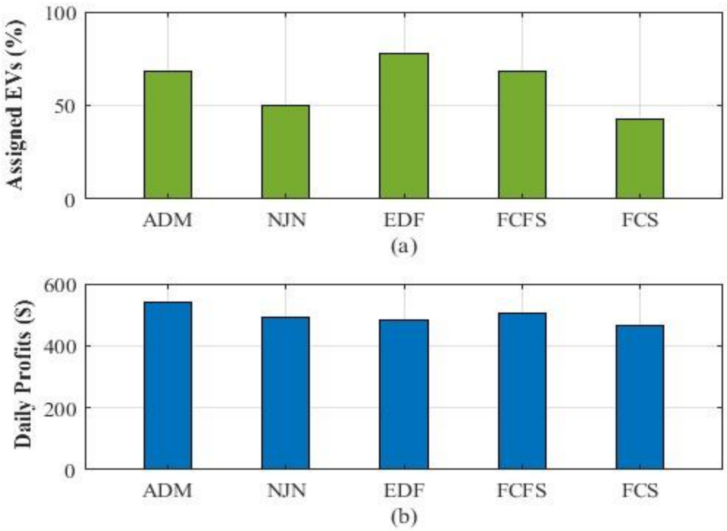

Fig. 4-20: Comparison between different assignment approaches in terms of (a) assigned EVs %, and hourly profits.

As evident from the charts provided, the ADM strategy shows high daily profits when compared to all other strategies. Nevertheless, the number of EVs served through the Earliest Deadline-First (EDF) technique is greater than ADM, as EDF assigns EVs based on the swiftest process without considering the generated profits. Consequently, even though a greater number of EVs are served through this approach, the daily profits are lower than the ADM approach. Which validates the effectiveness of our proposed approach.

4.5. MCSOAs Operation Modes

The suggested service area in this research is composed of 100 regions in Sharjah and Dubai. These 100 regions are split into two groups, with each group containing 50 regions and managed by a separate MCSOA. Each MCSOA will be accountable for dispatching charging requests with MCS trucks in their designated service area. The assumptions made are based on the system's running time and size constraints to ensure the desired running time is achieved and to simplify the system. Both agencies are assumed to have the same size, number of MCS trucks, and serve the same number of regions. However, the only difference lies in the location of stop points and served regions. This section will analyze and compare two different operational approaches.

4.5.1. Operation mode 1

In this approach, we assume that every MCSOA operates autonomously from other agencies. Assuming that both agencies receive an equal number of charging requests, we evaluate and compare the output revenues and the proportion assigned EVs between the two agencies at 2:00 PM. For each operational approach, we will simulate three distinct cases.

- Case 1: Both agencies experience high energy demand.
- Case 2: Both agencies are experiencing different levels of energy demand, with one agency facing high demand and the other facing low demand.
- Case 3: Both agencies experience low energy demand.

As shown from the Table 4-11, both agencies have same pattern of profits upon the energy demand in different cases.

Table 4-11: Operation Mode 1 outcomes.

Demanded Energy		Hourly Profits ($)			Assigned EVs (%)
Agency 1	Agency 2	Agency 1	Agency 2	Total Profits	Total
High	High	43.321	45.330	88.68	72
High	Low	43.321	28.909	72.229	58
Low	Low	25.782	28.909	54.691	41

4.5.2. Operation mode 2

In this operational strategy, a control agency is responsible for managing the collaboration between two agencies. If one agency experiences an excess demand, the trucks from the other agency can provide support during times of shortage. Additionally, a distance limitation is implemented, ensuring that the MCS trucks from one agency could assist the other agency only if the distance traveled is below a specified threshold value $d_{j,s,max}$.

Table 4-12 displays the system revenues and percentage of assigned EVs in various scenarios following the implementation of inter-agency coordination.

Table 4-12: Operation Mode 2 outcomes.

Demanded Energy		Hourly Profits ($)			Assigned EVs (%)
Agency 1	Agency 2	Agency 1	Agency 2	Total Profits	Total
High	High	43.321	45.330	88.68	72
High	Low	54.333	28.909	83.242S	63
Low	Low	25.782	28.909	54.691	41

To evaluate the advantages of coordination between two agencies, Fig. 4-21 illustrate how the profits of agency 1 which experience a high energy demand through the second mode of operation have increased as well as the percentage of assigned EVs. However, in other cases when both agencies face the same pattern of energy demand, both profits and number of assigned EVs remain constant, so the notable changes in profits appear in cases where the demand in one agency is significantly higher than the other one.

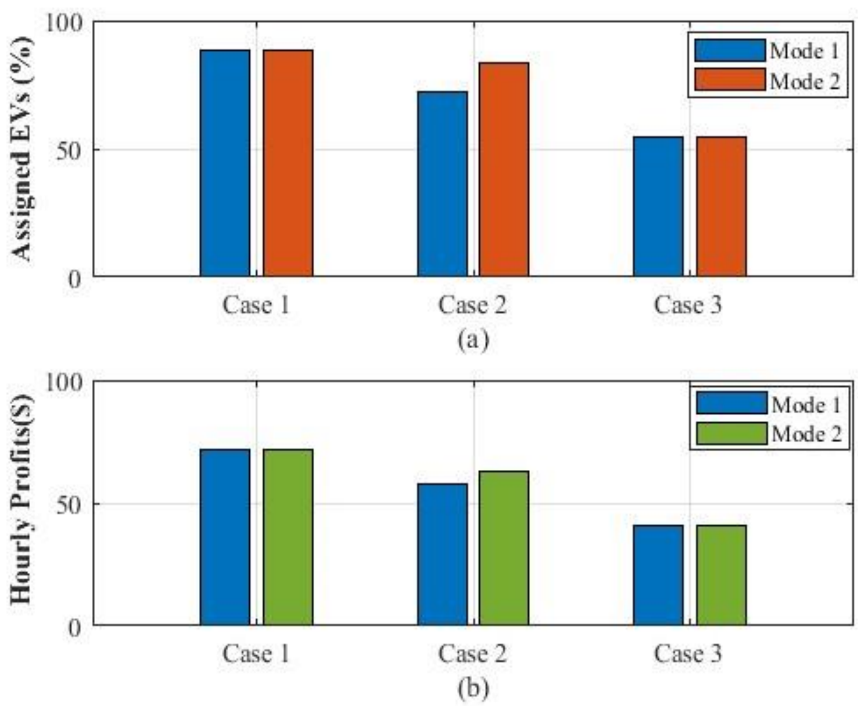

Fig. 4-21: compression between two operation approaches.

Chapter 5. Concluding Remarks

In this work, we proposed a new approach in mobile charging service ADM to allow the EVs to get their required energy during their trip without location or time constraints. It also accounts for the cases where the EVs have an emergency issue such as running out of charge and the EV is unable to reach the nearest fixed charging station. The proposed MCSs are operated by the private agency MCSOA that aims to get maximum profits out of this service. Therefore, a mixed integer non liner programing MINLP algorithm is formulated to assign the most profitable EVs with dispatched MCS's location where both assigned EVs and MCS meet to start the charging process. The optimization algorithm will be run frequently to enhance the dynamic charging requests and EV motion updates. The proposed approach is deployed on real-world data derived from Tom portal for real EV trips in some regions of Dubai and Sharjah. These regions are taken as a service area in this work, while the EV trips are considered as charging requests. Furthermore, to serve the charging requests within service area, sets of MCS trucks are proposed which carry several fast DC chargers to deliver a fast-charging process and serve more EVs at a time and they have an ability to serve users in different detected locations.

The effectiveness of this approach is assessed by examining the revenue generated by the system and the percentage of electric vehicles served using the BARON simulator. In addition, the effectiveness of this approach is confirmed by analyzing various factors, including the number of constraints in the system, the number of charging ports available, the system's capacity, and charging rates. Furthermore, the impact of user-related variables, such as the number of requests and energy requirements, is also discussed. Besides the running time, all these factors are considered on approximate system size. In addition, different irregular cases have been examined to assess the performance of this approach in addressing challenges such as traffic congestion and unbalanced energy requirements. We also discussed the performance of the optimization algorithm for different EV categories.

Finally, to prove the validity of this approach, it has been compared with conventional charging station FCS and other similar approaches deployed in MCSs such as, Nearest Job Next NJN, First Come First Served FCFS and earliest deadline-first (EDF). After compression, it has been founded that the ADM approach is performing well from the standpoint of MCS since it generates higher revenues compared to other approaches.

In this work we ran the optimization algorithm for short term study to evaluate the overall performance of this approach. Therefore, as a future recommendation work is studying the long-term profit of MCS's technology by including infrastructure and maintenance costs as well as power source costs. In addition, it is highly recommended to compare the MCS technology with the conventional FCS approach in terms of long-term profits as well as the infrastructure and operation costs of each approach.

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