

**SITE SELECTION AND OPERATIONAL PLANNING FOR EV CHARGING  
STATIONS IN CAR-SHARING SYSTEMS:  
INTEGRATION OF RENEWABLE ENERGY AND UPGRADING DECISIONS**

**BY**

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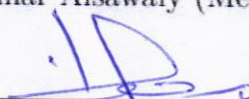
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*I dedicate this work to my advisor, Dr. Ismail Al Maraj, whose unwavering support, insightful mentorship, and belief in my potential have been a guiding force throughout this journey. I am deeply grateful to my family for their unconditional love, patience, and sacrifices, which gave me the strength to persevere. To my friends, thank you for your encouragement and the moments of lightness that helped balance the challenges. I also extend my sincere appreciation to King Fahd University of Petroleum Minerals for providing an environment rich with opportunity, resources, and support that enabled me to bring this research to fruition.*

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# LIST OF ABBREVIATIONS

|                 |                                      |
|-----------------|--------------------------------------|
| CO <sub>2</sub> | Carbon Dioxide                       |
| CS              | Charging Station                     |
| CSO             | Charging Station Owner               |
| CSS             | Car-Sharing System                   |
| EV              | Electric Vehicle                     |
| EVCS            | Electric Vehicle Charging Station    |
| EVSS            | Electric Vehicle Sharing System      |
| GA              | Genetic Algorithm                    |
| kWh             | Kilowatt hours                       |
| LP              | Linear Programming                   |
| MILP            | Mixed Integer Linear Programming     |
| MINLP           | Mixed Integer Non-Linear Programming |
| PSO             | Particle Swarm Optimization          |
| PV              | Photovoltaic                         |
| SAR             | Saudi Arabia Riyal                   |
| SOC             | State Of Charge                      |

|     |                              |
|-----|------------------------------|
| VNS | Variable Neighborhood Search |
| WHO | World Health Organization    |

# THESIS ABSTRACT

**NAME:** Ali Mohammed Almaslami  
Site Selection and Operational Planning for EV Charging

**TITLE OF STUDY:** Stations in Car-Sharing Systems: Integration of Renewable Energy and Upgrading Decisions

**MAJOR FIELD:** Industrial and System Engineering

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*The rapid growth of the EV market requires a significant increase in the number of EVCSs to support the shift towards cleaner and more sustainable transportation effectively. This research explores the strategic placement and optimization of EVCSs, particularly in the context of EVSSs. As global demand for EVs grows, integrating Photovoltaic (PV) systems into EVCS is crucial for enhancing sustainability and reducing reliance on fossil fuels. Key considerations include the total cost for the Charging Station Owners (CSOs), and planning for future upgrades. This research aims to identify the best practices for station placement and capacity planning, as well as to explore strategies for effective vehicle fleet management in a sharing system. By addressing relocation decisions, and ride splitting. This study will develop two mathematical models: one addressing the site selection problem, which incorporates*

*PV integration, upgrading decisions, and capacity planning, while also accounting for different types of chargers. The second model focuses on fleet management, integrating ride splitting, vehicle relocation decisions, and the assignment of EVs. Applying a customize variable neighborhood search heuristic for the site selection problem and a model incorporating fleet management problem, thereby providing comprehensive solutions to these challenges. For the site selection problem the heuristic approach demonstrated improvements of 4.53% over the commercial solver. Both methods were completed within the same total time frame of 24 hours, showcasing the heuristic's effectiveness in generating competitive solutions efficiently. Additionally, The findings demonstrate that by incorporating these factors, the models provide critical operational insights, facilitating improved decision-making in site selection, fleet management, and charging infrastructure. These insights contribute to optimizing efficiency, reducing costs, and enhancing sustainability in practice.*

## ملخص الرسالة

الاسم:

علي محمد عبد رب النبي المسلمي

عنوان الدراسة:

اختيار الموقع والتخطيط التشغيلي لمحطات شحن المركبات الكهربائية في أنظمة تقاسم السيارات إدخال الطاقة

المتجددة وقرارات التطوير

التخصص:

قسم الهندسة الصناعية و النظم

تاريخ الدرجة العلمية: ابريل 2025

النمو السريع لسوق المركبات الكهربائية يتطلب زيادة كبيرة في عدد محطات شحن المركبات الكهربائية لدعم التحول نحو وسائل النقل الأكثر نظافة واستدامة بشكل فعال. تستكشف هذه الدراسة تحديد المواقع الاستراتيجية وتحسين محطات شحن المركبات الكهربائية، خاصة في سياق أنظمة مشاركة المركبات الكهربائية. مع زيادة الطلب العالمي على المركبات الكهربائية، يصبح من الضروري دمج أنظمة الألواح الشمسية في محطات شحن المركبات الكهربائية لتعزيز الاستدامة وتقليل الاعتماد على الوقود الأحفوري. تشمل الاعتبارات الرئيسية التكلفة الإجمالية ل مالكي محطات الشحن والتخطيط للتحديثات المستقبلية. تهدف هذه الدراسة إلى تحديد أفضل الممارسات لتحديد المواقع وتخطيط السعة، بالإضافة إلى استكشاف استراتيجيات لإدارة الأسطول بشكل فعال في نظام المشاركة. من خلال معالجة قرارات النقل وتقسيم الرحلات. ستطور هذه الدراسة نموذجين رياضيين: الأول يعالج مشكلة اختيار الموقع، التي تتضمن دمج أنظمة الألواح الشمسية، وقرارات التحديث، وتخطيط السعة، مع مراعاة أنواع مختلفة من الشواحن. بينما يركز النموذج الثاني على إدارة الأسطول، من خلال دمج تقسيم الرحلات، وقرارات نقل المركبات، وتخصيص المركبات الكهربائية. من خلال تطبيق خوارزمية بحث متغير الجوار المخصص لمشكلة اختيار الموقع ونموذج يتضمن مشكلة إدارة الأسطول، مما يوفر حلولاً شاملة لهذه التحديات. بالنسبة لمشكلة اختيار الموقع، أظهرت الطريقة الخوارزمية تحسناً بنسبة 53%.4 مقارنة بالمحلل التجاري. تم تنفيذ كلا المنهجين في نفس الإطار الزمني الإجمالي البالغ 24 ساعة، مما يظهر فعالية الخوارزمية في توليد حلول تنافسية بكفاءة. بالإضافة إلى ذلك، تُظهر النتائج أنه من

خلال دمج هذه العوامل، توفر النماذج رؤى تشغيلية حاسمة، مما يسهل اتخاذ قرارات أفضل في اختيار المواقع، وإدارة الأسطول، والبنية التحتية للشحن. تساهم هذه الرؤى في تحسين الكفاءة، وتقليل التكاليف، وتعزيز الاستدامة في الممارسة العملية.

# CHAPTER 1

## INTRODUCTION AND LITERATURE REVIEW

This chapter introduces the key challenges related to EVs and EVSSs, with a focus on site selection and fleet management. It reviews existing literature on these topics, highlighting current practices, key issues, and gaps in research that inform the study's objectives.

### 1.1 Background

The rapid growth of the EV market has significantly increased the demand for EVCSs. As the global transportation industry transitions towards more sustainable and environmentally friendly solutions (1), integrating PV systems into EVCS has become crucial in promoting clean and sustainable mobility. The transition to alternative fuel vehicles is a highly effective strategy for reducing oil consumption. This shift is increasingly recognized as a crucial component in addressing some of the most pressing

environmental challenges of our era, including energy security, climate change, and sustainable development (2; 3). By adopting alternative fuels, we can significantly diminish our reliance on fossil fuels, mitigate greenhouse gas emissions, and advance towards a more sustainable and resilient energy future.

This shift towards sustainability is driven largely by the need to combat pollution. According to a 2018 report by the World Health Organization (WHO), approximately 90% of the global population is exposed to polluted air, resulting in an estimated 700,000 deaths annually (4). The WHO report also defines air pollution as the presence of one or more pollutants in the atmosphere at concentrations and durations sufficient to pose significant risks to human health (5).

The strategic location of EVCS is essential for the successful implementation of EVSS (6), where users can rent EVs and return them to designated stations. The accessibility and convenience of these stations are vital for the smooth operation of EVSS, ensuring that vehicles are readily available and easily chargeable at various locations. Additionally, the optimal placement of EVCS is beneficial for CSOs, who must consider infrastructural and operational costs to ensure financial viability. The challenge of locating CSs involves balancing the diverse requirements of all stakeholders, including operators, CSOs, users, and electricity suppliers as illustrated in Figure 1.1

Beyond merely determining the locations of EVCS, other significant challenges include optimizing the number and types of chargers, integrating solar panels, and making informed upgrade decisions. The landscape of EV charging technology encompasses three tiers of chargers, each offering different charging speeds and associ-

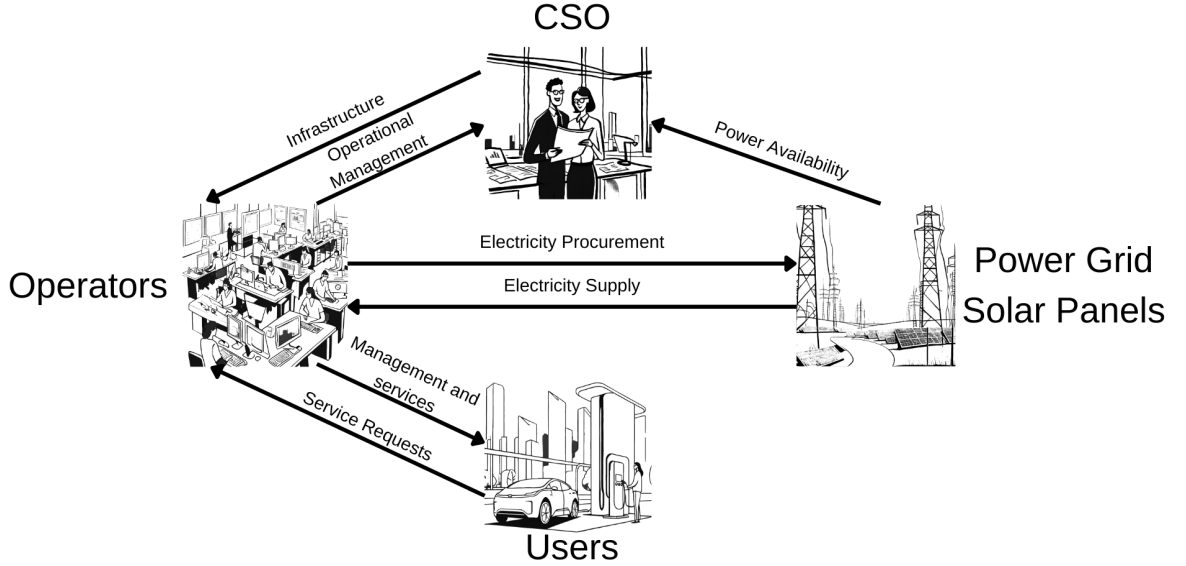


Figure 1.1: Flow of Relationships in EVCS with in EVSS

ated costs. These multifaceted considerations must be meticulously addressed in the strategic placement of EVCS to maximize the profit.

Another significant challenge is the application of the problem within the context of an EVSS. These systems, designed to provide a sustainable and flexible transportation solution, enable users to rent electric cars on a short-term basis. They operate fleets of EVs, which can be accessed through mobile applications that facilitate reservations, vehicle access, and real-time tracking. Users are responsible for picking up and returning vehicles to designated locations, with the service provider managing aspects such as charging and maintenance.

EVSS offers several benefits, including reducing individual car ownership, lowering transportation costs, and enhancing environmental sustainability. Studies have shown that car-sharing systems can lead to a significant reduction in vehicle ownership. (7) found that car-sharing system participants reduce their vehicle ownership by approximately 30% to 50%. Additionally, car-sharing system users can experience

lower overall transportation costs, with some research indicating cost reductions of around 40% compared to traditional car ownership (8). These systems help decrease greenhouse gas emissions and mitigate urban congestion, positioning them as a pivotal innovation in modern urban mobility and green transportation.

A critical aspect of successfully implementing these systems is the strategic placement of CSs. Identifying optimal locations is crucial, as these stations must be situated near high-density areas and frequented spots such as shopping malls and hospitals. To maximize effectiveness, it is essential that CSs are within walking distance of these key locations, ensuring convenience for users. The concept of walking distance, was first introduced by (9), highlights the importance of accessibility in urban planning. This thoughtful placement of charging infrastructure supports the overall effectiveness and adoption of EVSS services. This research examines the best locations and configurations for CS in EVSS. Identifying the optimal location and setups for the stations aims to enhance the usability of electric vehicles in urban transportation networks. This study seeks to contribute to sustainable transportation solutions by improving EV infrastructure placement, thereby encouraging wider adoption of electric mobility.

With the rising demand for EVs, what optimal strategies can EVCS implement to maximize profitability for CSOs? This study will specifically focus on:

- **Site Selection for EVSS:** What specific factors should be considered when selecting locations for EVCS that maximize profit margins for CSOs? How do factors like proximity to high-density areas, hospitals, universities, and other key locations impact profitability?

- **Integration of Renewable Energy:** How can PV systems be integrated into the model of EVSS to increase long-term profitability and operational efficiency? How can the power output of PV systems be accurately calculated to ensure optimal sizing and efficiency?
- **Infrastructure Upgrades:** What are the key criteria for determining when existing EVCS and PV infrastructure should be upgraded to enhance financial performance? How do factors such as increased charging capacity and rising demand influence the decision-making process for infrastructure investments?
- **Capacity Planning:** What is the optimal charging capacity for EVCS that maximizes revenue generation while minimizing operational costs and ensuring customer satisfaction? How do geographic location and anticipated EV adoption rates influence these decisions?
- **Charger Types:** Which specific types of EV chargers are most effective in generating revenue for CSOs? How do factors like installation costs, charging speed, and user demand vary across different charger types, and how do they impact profitability?

To successfully implement an EVSS system, it is crucial to manage its operational framework effectively. This framework includes several key components, such as vehicle maintenance, fleet management, user interface design, and real-time data monitoring, all of which play a critical role in ensuring smooth and efficient system performance.

Fleet management stands out as a distinct challenge, encompassing a wide range of responsibilities and processes. It involves various critical tasks, including the assignment of EVs to users, managing relocation decisions, ride splitting to ensure efficient distribution and availability, and tracking the State Of Charge (SOC) for the EVs.

These processes ensure that EVs are strategically positioned throughout the city, and that the SOC for each EV remains within the optimal range. To assign an EV to an order, it must have sufficient charge to complete the trip. Additionally, the vehicle's next assignment must be considered, as each order is interconnected, affecting the choice of vehicle for the current trip. Relocation is the process of moving EVs from low-demand to high-demand areas, usually done by a crew that drives the car from one station to another. Relocating EVs during operational hours is essential to maintain optimal balance across CSs. This proactive strategy helps ensure that stations are adequately supplied, ultimately leading to an increase in order fulfillment and customer satisfaction. Ride splitting allows users to take longer trips by providing multiple EVs throughout the journey, in cases where a single EV isn't sufficient for the entire trip. Lastly, these decisions can only be made by monitoring the SOC of all EVs, allowing for the selection of the appropriate vehicle for each trip or relocation.

In addressing the complex issue of sustainable transportation, several key entities play crucial roles: users, transportation companies, government bodies, CSOs, and platform companies responsible for EV apps and services. Users seek convenient and accessible EVs and CSs to facilitate their daily commutes. Transportation companies that operate EVSS require sufficient capacity at CSs to maintain efficient service and vehicle availability. Government bodies are involved in regulatory frameworks and

incentives to support the growth of electric mobility. Meanwhile, CSOs are focused on optimizing their investments and managing operational costs to ensure profitability. EV app or platform companies facilitate user access to EVs and charging locations, integrating technology to streamline the overall experience. In my research, I will focus on the perspective of CSOs, aiming to maximize their profit by managing fleet operations.

How can vehicle relocation decisions and ride splitting be integrated into an existing EVSS to effectively manage fleet operations to increase the profit of the owner? This study will specifically focus on the following:

- **Assignment of EVs:** How can EVs be assigned to orders based on sufficient SOC and consideration of the next assignment to optimize fleet operations?
- **Vehicle Relocation:** What strategies should be used for relocating EVs from low-demand to high-demand areas to maintain balance across CSs and ensure optimal order fulfillment?
- **Ride Splitting:** How can ride splitting be implemented to allow multiple EVs to complete longer trips, ensuring customers are not left stranded?
- **SOC Monitoring and Management:** How can continuous SOC monitoring be integrated to ensure vehicles are adequately charged for their current and future assignments, optimizing fleet performance?

This research aims to examine the best locations and configurations for EVCS in Car-Sharing Systems (CSSs) . Identifying the optimal locations and setups for the stations

aims to enhance the usability of electric vehicles in urban transportation networks. Additionally, the study will address the operational planning required to manage EV fleets effectively. This includes coordinating vehicle relocation and ride splitting to ensure that drivers can efficiently reach their destinations while maintaining vehicle availability and charge. By integrating these operational considerations with infrastructure placement, the study seeks to contribute to sustainable transportation solutions and encourage wider adoption of electric mobility.

## **1.2 Literature Survey**

Literature has delved extensively into the realms of long-term strategic planning and short-term operational tactics concerning one-way CSS with relocation, as comprehensively reviewed in (10). The literature review will be organized into two distinct sections: one dedicated to strategic planning, which will encompass topics such as the optimal placement and sizing of EVCS and the integration of PV systems with upgrading decisions. While the other section focused on operational planning, addressing the assignment of EV, relocation decisions, and ride splitting.

### **1.2.1 Strategic planning**

The extant literature extensively explores the EVCS location problem, covering various aspects. This literature review succinctly discusses key research contributions that enhance the formal understanding of the EVCS location problem in CSS.

Initially, literature treats the problem as a typical location problem. (11) formulate

the problem as Mixed Integer Linear Programming (MILP) and suggest the objective of minimizing the installation cost. They prove that the problem is NP-hard and propose four solution methods to tackle the problem. (12) extend the foundational work by incorporating a temporal dimension into the problem. They introduce a dynamic framework that not only determines the optimal locations for charging stations but also schedules their deployment over a specified time horizon. They formulate the problem as a MILP that minimizes the cost, and the problem is solved using a Genetic Algorithm (GA).

Recognizing that the location of the CS is not the only challenge, (13) takes a comprehensive approach by considering both the location and the size of the station, which is defined as the number of chargers at the station. The recommended number of chargers at each station is considered a decision variable, along with the location of the EVCS. The study focuses on minimizing the costs associated with meeting the charging demands of EV. However, the primary drawback of this paper is its presentation of the problem as Mixed Integer Non-Linear Programming (MINLP), which can be complex and computationally intensive to solve compared to MILP. In addition to (13), another noteworthy study in the field is conducted by (14). This study addresses the optimal location and size of charging stations, aiming to minimize both installation costs and inter-station distances. Unlike previous research, this paper formulates the problem as a MILP and uses GA for solution generation. This approach is significantly simpler to solve compared to the MINLP models used in earlier studies. They present a case study situated in China, offering insights into the real-world applicability of their methodology.

The integration of PV technology as an additional energy source for the EVCS alters the problem by introducing new complexities. In this context, (15) incorporated environmental factors into the site selection process for EVCS by integrating PV technology. They developed a probabilistic model and employed Particle Swarm Optimization (PSO) to solve it. Additionally, the authors factored in the number of chargers at each station as a decision variable. Furthermore, (16) constructed a MILP model incorporating PV technology, with the objective of minimizing both installation and operational costs. They tackled the optimization problem using a hybrid approach, combining Sample Average Approximation and an enhanced Progressive Hedging Algorithm.

Previous research has primarily addressed the issue of EVCS location as a general problem. In contrast, (17) developed a MILP model specifically for the EVCS location problem within a EVSS. Their model determines the optimal locations and quantities of chargers at each station while aiming to maximize overall profitability. To tackle this complex problem, they proposed two heuristic methods for effective problem-solving.

This research aims to address the complexities of EVCS and their properties, including the number and type of chargers and the integration of PV systems. This study aims to address existing gaps in the literature (see Table 1.1) by focusing on upgrade decisions for both the charging station's capacity and the capacity of the PV system within the station. Specifically, our research investigates the integration of these aspects within EVSS, an area often overlooked in studies addressing PV systems and upgrading decisions in the broader context of EVCS location problems. By adopting the perspective of CSO, this research aims to maximize total profit while

enhancing sustainability.

|                | I | II | III | IV | V |
|----------------|---|----|-----|----|---|
| (15)           | × | ✓  | ×   | ✓  | × |
| (11)           | × | ×  | ×   | ✓  | × |
| (14)           | × | ×  | ×   | ✓  | × |
| (18)           | ✓ | ×  | ×   | ×  | × |
| (19)           | × | ×  | ×   | ✓  | × |
| (20)           | × | ×  | ×   | ×  | ✓ |
| (16)           | × | ✓  | ×   | ×  | ✓ |
| (21)           | ✓ | ×  | ×   | ✓  | × |
| (22)           | ✓ | ×  | ×   | ✓  | × |
| (23)           | × | ×  | ✓   | ×  | × |
| (24)           | × | ×  | ✓   | ×  | × |
| (25)           | × | ✓  | ×   | ×  | ✓ |
| (26)           | × | ×  | ×   | ×  | ✓ |
| (27)           | × | ✓  | ×   | ×  | × |
| (28)           | × | ✓  | ×   | ×  | ✓ |
| (29)           | × | ✓  | ×   | ×  | ✓ |
| (30)           | ✓ | ✓  | ×   | ×  | ✓ |
| (31)           | × | ✓  | ×   | ×  | ✓ |
| Proposed Model | ✓ | ✓  | ✓   | ✓  | ✓ |

Table 1.1: Recent EVCS Placement Studies

**I:** Site selection for EVSS, **II:** Integration of Renewable Energy, **III:** Infrastructure

Upgrades, **IV:** Capacity Planning, **V:** Include Types of Chargers or Stations

Additionally, this study includes a case study conducted in three cities in Saudi Arabia, providing valuable insights into real-world applications and challenges in this domain. To effectively tackle the optimization problem, we constructed a MILP model that accounts for these complexities. This comprehensive approach ensures the model accurately reflects the intricacies of real-world EVCS operations. Furthermore, we developed heuristics to complement the MILP model, enabling the effective handling of large-scale scenarios that frequently arise in practice.

By addressing these key aspects, this research not only makes a significant contribution to academic literature but also provides practical implications for improving the profit and sustainability of CSs within an EVSS. The contribution of this paper can be summarized as follows: The integration of PV systems in EVSS is explored to enhance sustainability and energy efficiency within EVCSs. Upgrade decisions for both EVCSs and PV capacity are investigated to identify strategies that optimize system performance in response to growing demand. A MILP model is developed to address the complexities of the EVCS placement problem, incorporating aspects such as PV integration, upgrade decisions, multiple charger types, and capacity planning. To solve large-scale optimization problems efficiently, novel heuristic methods are introduced, consisting of a two-stage process: the first generates an initial solution, and the second iteratively improves and optimizes it to maximize profit. Finally, the proposed models are validated through a real-world case study conducted across three cities in Saudi Arabia, demonstrating their practical effectiveness and performance.

### 1.2.2 Operational planning

The existing literature provides a comprehensive examination of operational strategies in EVSS, emphasizing critical aspects such as EV assignment, relocation strategies, and ride splitting. This review aims to highlight significant research contributions that advance the understanding of fleet management process in EVSS.

Various methods have been explored in the literature to address the vehicle relocation problem in one-way CSS. (32) used MILP to maximize the profit. (33) developed a decision support system using real-time data to reduce the total cost. (34) introduced a heuristic algorithm for quick, near-optimal solutions to minimize the total cost. These studies demonstrate a range of approaches, from rigorous optimization to heuristic methods, each aiming to enhance profitability or cost and operational efficiency.

In a groundbreaking study by (35), the concept of incorporating vehicle relays or ride splitting is introduced to facilitate longer trips for users. They innovatively modified the EV assignment model to account for Ride Splitting. Additionally, they introduced a novel dimension to monitor the battery level of the EVs. The primary goal behind these modifications was to maximize profit while ensuring efficient and extended travel capabilities for EV users.

By addressing key challenges, this research not only advances academic understanding of EVSS but also provides practical solutions aimed at improving operational efficiency, increasing vehicle availability, and enhancing order fulfillment. The contribution of this paper can be summarized as follows:

- **Relocation Decisions:** Integration of vehicle relocation to balance the distribution of EVs across the stations, which will reflect in enhancing the service level.
- **Incorporating Ride Splitting:** Exploring the integration of ride splitting to enhance the availability of EVs and customer satisfaction.
- **MILP model development:** Building a MILP model for EVSS that incorporates ride splitting, vehicle relocation, vehicle assignment, and SOC tracking.
- **Case Study in Saudi Arabia:** Validating the proposed models through a real-world case study across three cities in Saudi Arabia, building on the findings from previous research, we use the outputs as inputs for the operational study to evaluate the performance of both models.

In this research, we aim to integrate insights from previous studies to explore a comprehensive approach to infrastructure and operational decision-making. For infrastructure decisions, our focus will encompass determining the optimal location and capacity of the charging stations, along with the seamless integration of PV systems to support sustainable energy supply for the stations. On the operational front, we will delve relocation decisions, vehicle selection criteria, and the integration of ride splitting. Our primary goal is to formulate a MILP model that encapsulates these multifaceted decisions. Additionally, we aim to develop a heuristic approach tailored to tackle large-scale problems effectively.

Strategic planning and operational decisions mutually influence each other, leading to their simultaneous consideration in literature. This interconnectedness ensures

cohesive alignment and effective execution for organizational success. (36) delved into the integration of infrastructure and operational decisions within EV sharing systems. They constructed a MILP model tailored to address the challenges of uncertain demand. This model was designed to optimize the placement of charging stations, determine relocation strategies, and make charging decisions. The goal was to minimize the cost within the one-way EVSS. Expanding on the research by (36), (37) undertook a similar approach but introduced a more complex dimension by incorporating multiple types of vehicles into their study. They extended the MILP model to accommodate diverse vehicle types, further enhancing the system’s adaptability and comprehensiveness.

This research will integrate both the strategic and operational aspects of EVSS. For the strategic side, we will incorporate PV and upgrading decisions in the process of locating the CS, using MILP and a heuristic approach to tackle the problem. In the operational planning phase, we will focus on the assignment of EVs, vehicle relocation decisions, and ride splitting. The model will be developed and solved using MILP model.

Although the models in each study remain separate, their combination provides a comprehensive optimization framework for EVSS with integrated PV systems and advanced operational strategies.

- **Site selection:** The strategic model, solved using heuristics, focuses on optimizing infrastructure, including the placement and capacity of both EVCS and PV systems. In addition, the model optimization maximizes profitability while

incorporating different types of chargers.

- **Fleet management:** An optimization model, which incorporates the input from the site selection model, addresses vehicle relocation, ride splitting, and vehicle assignment to improve profitability for the CSO .
- **Case Study Validation:** Both models are tested through case studies in Saudi Arabia, offering practical insights into the feasibility of the strategic and operational models in real-world settings.

# **CHAPTER 2**

## **SITE SELECTION FOR EVCS IN CSS: INTEGRATING PV SYSTEMS AND UPGRADE DECISIONS**

This chapter presents the mathematical model and heuristic approach developed to address the site selection problem for EVCS within CSS, focusing on the integration of PV systems and upgrading decisions as key strategic components of the research. The focus is on strategically determining optimal locations for EVCS with the focus on CSO prospective to maximize the total profit. By incorporating these elements, the chapter aims to provide a robust framework for improving the effectiveness of EVCS deployment in CSS.

## 2.1 Problem description

The study aims to tackle the challenges involved in establishing an efficient EVSS integrated with PV technology and upgrading decisions. Central to this initiative is the identification of optimal locations for CS, considering factors such as high-density areas, frequently visited locations, and the comprehensive costs associated with both establishing and maintaining these CSs. Additionally, the study will specify at which period a new station should be opened. This approach ensures a phased and strategic roll out that aligns with market demand.

Beside identifying the optimal location of the CS, it is crucial to thoroughly define the key characteristics and specifications that the CS should possess. These include the number and type of chargers, integration with renewable energy sources, namely the PV system and the number of panels required. Including decisions regarding upgrading, and determining the energy consumed from both the grid and the PV system at each station. Lastly, identify the proportion of demand that each station should satisfy at each demand point.

### 2.1.1 Type of chargers

EV chargers can be categorized into three basic types: Level I chargers use standard 120V AC outlets for slower home charging, Level II chargers use 240V AC for faster home and public charging, and DC fast chargers (Level III) provide rapid charging at public stations which is a convenient option for longer trips. In our model, we will consider mainly Levels II and III chargers due to the slow residential use limited to

Level I chargers. The model will determine the number and the type of chargers at each station.

### **2.1.2 Upgrade decisions**

Upgrading the CS is a critical step towards meeting the growing demand for sustainable transportation. This upgrade involves enhancing existing charging stations to increase their capacity, allowing them to accommodate more chargers and thus serve a larger number of vehicles simultaneously. Additionally, if a PV system is connected to the electrical grid, it can be upgraded to boost its capacity by increasing the number of PV panels. This improvement ensures that the stations can generate more renewable energy, contributing to a more eco-friendly and efficient charging process. The model will precisely identify which stations to upgrade and the optimal timing for these upgrades throughout the specified time horizon.

### **2.1.3 Outcomes and Objective**

The model will identify which station to open and when, determine if a PV system should be implemented, and decide if and when it should be upgraded. Additionally, the model will specify the station's characteristics, the energy required from the grid, and the energy produced by any existing PV systems. Ultimately, the primary objective is to maximize the organization's total profit by emphasizing a comprehensive approach that prioritizes cost-effectiveness within the PV-integrated EVSS.

## 2.2 Notations

### Sets:

$L$  Potential locations for CS,  $l \in \{1, \dots, L\}$

$D$  Demand points,  $d \in \{1, \dots, D\}$

$H$  Planning horizon in years,  $h \in \{1, \dots, H\}$

### Parameters:

$c_{lh}^{CS}$  Construction cost in SAR of CS  $l$  in year  $h$ .

$c_{lh}^{CSU}$  Upgrading cost in SAR of CS  $l$  in year  $h$ .

$o_{lh}^{CS}$  A CS's annual O&M cost in SAR of CS  $l$  in year  $h$ .

$c_{lh}^{II}$  Installation cost of Level II charger at station  $l$  in year  $h$ .

$c_{lh}^{III}$  Installation cost of Level III charger at station  $l$  in year  $h$ .

$c_{lh}^{PVS}$  Installation cost of PV system in SAR for station  $l$  in year  $h$ .

$c_{lh}^{PVU}$  Upgrading cost for PV system in SAR of CS  $l$  in year  $h$ .

$c_{lh}^{PV}$  Installation cost for one PV in SAR of CS  $l$  in year  $h$ .

$o_{lh}^{PV}$  A PV annual O&M cost in SAR of CS  $l$  in year  $h$ .

$\gamma$  Cost in SAR per kilowatt.

$DC^{II}$  Daily charging capacity of charger Level II in kWh.

$DC^{III}$  Daily charging capacity of charger Level III in kWh.

$C^C$  Capacity of chargers on a station.

$C^{CU}$  Additional capacity of chargers due to upgrading the station.

|            |                                                                  |
|------------|------------------------------------------------------------------|
| $C^{PV}$   | Capacity of PV panels on a station.                              |
| $C^{PVU}$  | Additional capacity of PV panels due to upgrading the PV system. |
| $B_h^{CS}$ | Budget for constructing and upgrading stations in year k.        |
| $B_h^{PV}$ | Budget for constructing and upgrading PV systems in year k.      |
| $P_{ld}$   | The proportion of demand that station l can satisfy for point d. |
| $O_{dh}$   | Expected Number of orders for demand point d in year h.          |
| $p_h$      | Average profit in SAR of one order in year h.                    |
| $u$        | Expected energy used to satisfy one order in kWh.                |
| $P_{inv}$  | Annual power generation per panel in kWh.                        |
| $OD$       | Operating days per year.                                         |
| $M$        | Large number.                                                    |

**Decision variables:**

**Continuous variables:**

|           |                                                                        |
|-----------|------------------------------------------------------------------------|
| $E_{lh}$  | The amount of grid electricity utilized at station l in year h in kWh. |
| $V_{lh}$  | The amount of PV electricity utilized at station l in year h in kWh.   |
| $y_{ldh}$ | Proportion of demand d satisfied by station l in year h.               |

**Integer variables:**

$C_{lh}^{II}$  Level II chargers at station  $l$  in year  $h$ .

$C_{lh}^{III}$  Level III chargers at station  $l$  in year  $h$ .

$N_{lh}$  Number of PV at station  $l$  in year  $h$ .

**Binary variables:**

$x_{lh}$  Equals to 1 if station  $l$  is implemented in year  $h$ , 0 otherwise.

$z_{lh}$  Equals to 1 if station  $l$  is equipped with PV system in year  $h$ , 0 otherwise.

$W_{lh}$  Equals to 1 if station  $l$  is upgraded in year  $h$ , 0 otherwise.

$G_{lh}$  Equals to 1 if the PV in station  $l$  is upgraded in year  $h$ , 0 otherwise.

## 2.3 Mathematical model

This section presents the problem as a MILP model aimed at maximizing the total profit of the CSOs. The model selects the optimal location for CSs among predefined potential sites. It also specifies the capacity of each station and suggests the opening year of each station. Integrating PV as a clean source of energy, which can be implemented at the station the model decides to open. Lastly, upgrading decisions for the selected stations are allowed to cover the rapid increase in the demand throughout the years.

**Objective function :**

$$\begin{aligned}
\text{Maximize } & \sum_{l=1}^L \sum_{d=1}^D \sum_{h=1}^H O_{dh} p_h y_{ldh} \\
& - \sum_{l=1}^L [c_{l1}^{CS} x_{l1} + c_{l1}^{CSU} W_{l1} + c_{l1}^{II} C_{l1}^{II} + c_{l1}^{III} C_{l1}^{III} + c_{l1}^{PVS} z_{l1} + c_{l1}^{PVU} G_{l1} + c_{l1}^{PV} N_{l1}] \\
& - \sum_{l=1}^L \sum_{h=2}^H [(c_{lh}^{CS} (x_{lh} - x_{lh-1}) + c_{lh}^{CSU} (W_{lh} - W_{lh-1}) + c_{lh}^{II} (C_{lh}^{II} - C_{lh-1}^{II}) \\
& + c_{lh}^{III} (C_{lh}^{III} - C_{lh-1}^{III}) + c_{lh}^{PVS} (z_{lh} - z_{lh-1}) + c_{lh}^{PVU} (G_{lh} - G_{lh-1}) + c_{lh}^{PV} (N_{lh} - N_{lh-1}))] \\
& - \sum_{l=1}^L \sum_{h=1}^H (o_{lh}^{CS} x_{lh} + o_{lh}^{PV} N_{lh} + \gamma E_{lh})
\end{aligned} \tag{2.1}$$

The objective function (2.1) seeks to maximize profit by calculating the difference between the revenue from fulfilled orders and the total costs incurred for implementing and maintaining the charging stations.

**Constraints :**

$$y_{ldh} \leq P_{ld} x_{lh} \quad \forall l, d, h \tag{2.2}$$

Constraint (2.2) ensures that the proportion of demand satisfied does not exceed the coverage capacity of each operating station.

$$\sum_{l=1}^L y_{ldh} \leq 1 \quad \forall d, h \tag{2.3}$$

Constraint (2.3) limits the sum of proportions of demand satisfied to 1.

$$u \sum_{d=1}^D y_{ldh} O_{dh} \leq E_{lh} + V_{lh} \quad \forall l, h \tag{2.4}$$

Constraint (2.4) guarantees that each station has sufficient electricity to meet all assigned orders.

$$E_{lh} \leq Mx_{lh} \quad \forall l, h \quad (2.5)$$

Constraint (2.5) allows the use of electricity from the grid only if the station is operational.

$$E_{lh} + V_{lh} \leq OD \left( DC^{II} C_{lh}^{II} + DC^{III} C_{lh}^{III} \right) \quad \forall l, h \quad (2.6)$$

Constraint (2.6) ensures that the combined electricity from the grid and PV sources does not exceed the charger's capacity.

$$V_{lh} \leq P_{inv} N_{lh} \quad \forall l, h \quad (2.7)$$

Constraint (2.7) limits the electricity generated from PV sources to their capacity.

$$\sum_{l=1}^L c_{l1}^{CS} x_{l1} + c_{l1}^{CSU} W_{l1} \leq B_1^{CS} \quad (2.8)$$

$$\sum_{l=1}^L c_{lh+1}^{CS} (x_{lh+1} - x_{lh}) + c_{lh+1}^{CSU} (W_{lh+1} - W_{lh}) \leq B_{h+1}^{CS} \quad \forall h < H \quad (2.9)$$

$$\sum_{l=1}^L (c_{l1}^{PVS} + C^{PV} c_{l1}^{PV}) z_{l1} + (c_{l1}^{PVU} + C^{PVU} c_{l1}^{PV}) G_{l1} \leq B_1^{PV} \quad (2.10)$$

$$\begin{aligned}
& \sum_{l=1}^L (c_{lh+1}^{PVS} + C^{PV} c_{lh+1}^{PV}) (z_{lh+1} - z_{lh}) \\
& + (c_{lh+1}^{PVU} + C^{PVU} c_{lh+1}^{PV}) (G_{lh+1} - G_{lh}) \leq B_{h+1}^{PV} \quad \forall h < H
\end{aligned} \tag{2.11}$$

Constraints (2.8-2.11) ensure that the budget for each year stays within the allowed amount for charging stations and PV systems.

$$C^C x_{lh} + C^{CU} W_{lh} = C_{lh}^{II} + C_{lh}^{III} \quad \forall l, h \tag{2.12}$$

$$C^{PV} z_{lh} + C^{PVU} G_{lh} = N_{lh} \quad \forall l, h \tag{2.13}$$

Constraints (2.12-2.13) ensure that the number of chargers and PV panels meets the station's full capacity.

$$x_{lh+1} \geq x_{lh} \quad \forall l, h < H \tag{2.14}$$

$$z_{lh+1} \geq z_{lh} \quad \forall l, h < H \tag{2.15}$$

$$W_{lh+1} \geq W_{lh} \quad \forall l, h < H \tag{2.16}$$

$$G_{lh+1} \geq G_{lh} \quad \forall l, h < H \tag{2.17}$$

$$C_{lh+1}^{II} \geq C_{lh}^{II} \quad \forall l, h < H \quad (2.18)$$

$$C_{lh+1}^{III} \geq C_{lh}^{III} \quad \forall l, h < H \quad (2.19)$$

$$N_{lh+1} \geq N_{lh} \quad \forall l, h < H \quad (2.20)$$

Constraints (2.14-2.20) stipulate that the operational stations, PV implementations, station upgrades, PV system upgrades, Level 2 and Level 3 chargers, and PV panels must remain the same or increase over time for all stations.

$$x_{lh} \geq z_{lh} \quad \forall l, h \quad (2.21)$$

$$x_{lh} \geq W_{lh}^I \quad \forall l, h \quad (2.22)$$

Constraints (2.21- 2.22) stipulate that PV system implementation and station upgrades occur only if the station exists.

$$z_{lh} \geq G_{lh}^I \quad \forall l, h \quad (2.23)$$

Constraint (2.23) ensures that PV system upgrades occur only if the PV system is in place.

$$z_{lh}, x_{lh}, G_{lh}^I, W_{lh}^I \in \{0, 1\} \quad \forall l, h \quad (2.24)$$

$$C_{lh}^{II}, C_{lh}^{III}, N_{lh} \in \mathbb{Z}^+ \quad \forall l, h \quad (2.25)$$

$$E_{lh}, V_{lh}, y_{ldh} \geq 0 \quad \forall l, d, h \quad (2.26)$$

Constraints (2.24-2.26) define the domain restrictions for binary, integer, and continuous variables

## 2.4 Input modeling

In this section, we will discuss the key components of input modeling for EVSS. We will examine how demand is quantified and explore the calculations for solar energy generation, focusing on PV and inverter efficiency.

### 2.4.1 Demand

The number of orders or demand for a given area can be calculated by multiplying the population by a specific factor, representing the number of orders per year for the demand point  $o_{jk}$ . The  $b_{ij}$  coefficient is defined as follows:

- $P_{ld} = 1$  if station  $i$  is within 531 meters of demand point  $j$  (full coverage).
- $P_{ld} = 0.5$  if the distance is between 531 and 1062 meters (partial coverage).
- $P_{ld} = 0.25$  for distances between 1062 and 1593 meters (minimal coverage).

Since we are assuming an EVSS, we expect customers to travel to and from well-known areas, such as malls, hospitals, and other prominent locations. Consequently,

we add significant weight to these areas to account for the increased demand they generate. This approach helps in determining the effectiveness and reach of each station by meeting the demand of various points within a given area, ensuring that high-demand locations are adequately serviced.

### 2.4.2 Solar panels

Generating power from solar panels is influenced by a variety of factors. To accurately determine the output power, a series of calculations and considerations are required. Equations (2.27-2.30), sourced from (38), represent crucial mathematical expressions that elucidate this relationship.

Based on the efficiency of the PV used  $\eta_{PV}$ , the area of the cell  $A$ , and the hourly solar irradiation  $I$ , we can estimate the output power from the PV as shown in the formula below (39):

$$P_{PV} = \eta_{PV} \times A \times I \quad (2.27)$$

Solar irradiation  $I$  depends on hourly global irradiation  $I_B$ , hourly diffuse irradiation  $I_D$ , and geometric factor to represent the ratio of the actual irradiation on the panel  $R_B$ , as shown in the following expression (40; 41):

$$I = (I_B + I_D)R_B + I_D \quad (2.28)$$

The efficiency  $\eta_{PV}$  depends on solar irradiation  $I$ , the ambient temperature  $T_A$ , the efficiency of the PV generator  $\eta_R$ , the referenced temperature of the cell  $T_R$ , the

coefficient of temperature for cell efficiency  $\beta$ , the cell temperature at normal operating cell temperature  $T_{C0}$ , the ambient temperature at normal operating cell temperature  $T_{A0}$ , and the average solar irradiation on the array under the normal operating cell temperature conditions  $I_0$ . The relationship is expressed as follows (41):

$$\eta_{PV} = \eta_R \left( 1 - 0.9\beta \frac{I(T_{C0} - T_{A0})}{I_0} - \beta(T_A - T_R) \right) \quad (2.29)$$

### 2.4.3 Inverter

After calculating PV power generation, we need to account for losses in the inverter. Inverter efficiency and other factors can reduce the output power, so it's crucial to adjust our calculations accordingly. The inverter converts DC from the solar panels to AC to charge the EV. The output power depends on both the PV's output power and the inverter's efficiency  $\eta_{inv}$ , as shown in the equation below (42):

$$P_{inv} = P_{PV} \times \eta_{inv} \quad (2.30)$$

## 2.5 Solution approach

In this section, we propose a heuristic approach to tackle the challenges of large-scale optimization. If the problem is enormous and too large to solve with the proposed MILP model, then we recommend employing a heuristic method to obtain an acceptable solution in a shorter time frame. One inspiration for our approach is the Variable Neighborhood Search (VNS), initially introduced by (43). While our method

draws on the general idea of systematic neighborhood changes, it introduces several novel elements tailored to our specific problem. In particular, the proposed heuristic consists of two phases: the first phase aims to generate an initial solution, as outlined in Algorithm 1.

Algorithm 1 outlines the initial step of the heuristic, which involves generating an initial solution. This initial solution serves as the starting point for the VNS described in Algorithm 2. Additionally, while solving the Linear Programming (LP) problem, we will remove constraints (2.8) to (2.26), as these will be addressed in subsequent steps of the heuristic. Swapping stations in terms of opening year, number of chargers, PV implementation, and upgrade decisions does not affect the feasibility of constraints (2.8) to (2.26). In other words, the station-swapping procedure in Algorithm 2 only impacts constraints (2.2) to (2.7), as these are responsible for allocating both the charging demand and electricity requirements across stations. Therefore, after performing any swap, it is sufficient to re-evaluate only these specific constraints, as the remaining constraints remain unaffected.

The initial step in the heuristic outlined in Algorithm 1 involves formulating the problem as a LP model. In this stage, binary and integer variables are treated as continuous variables to derive initial solutions. Following this, Step 3 entails rounding binary variables using a half-up approach. This rounding is essential for obtaining a feasible solution that adheres to the domain constraints. The constraints identified in equations (2.14) to (2.20) will be addressed through this rounding process.

Subsequent Steps (5 to 23) focus on ensuring compliance with constraints (2.12-2.13) and (2.21) to (2.23). For budgetary constraints specified in equations (2.8)

to (2.11), we implement a series of iterations (Steps 25 to 31) across all years to confirm that the budget is satisfied. In instances where the budget is not met, we will systematically remove stations or PV systems until compliance is achieved.

Steps (34 to 40) involve an assessment of the profitability of each station. If any station incurs costs exceeding its revenue, it will be decommissioned to further optimize the overall profit. Finally, we will resolve the problem as an LP model, employing the previously derived binary and integer variables as parameters while removing constraints (2.8) to (2.26), as these have already been satisfied in the earlier stages of the heuristic.

The second step of the heuristic involves employing a VNS to explore potential improvements to the solution. In this algorithm, we perform swaps between stations to identify better configurations. Specifically, the neighbor  $b$  of station  $l$  is defined as any station  $i$  where  $l \neq i$ . For each neighbor, we swap all binary and integer variables of station  $l$  with those of station  $i$ .

If this swap does not violate the budget constraints, we will then solve the LP model with constraints (2.2) to (2.7). If the resulting solution yields a better profit, we will update our current solution accordingly and restart the process from station 1. If no improvement is found, the algorithm will continue searching through different neighbors and stations until the allowed time for the search is exceeded.

---

**Algorithm 1** Generate an Initial Solution

---

```
1: Procedure Initialization
2: Solve as an LP using all constraints
3: Round half up for  $x_{lh}$ ,  $z_{lh}$ ,  $G_{lh}$ ,  $W_{lh}$ 
4:
5: for each year  $h$  do
6:   for each station  $l$  do
7:     if  $x_{lh} = 0$  then
8:       Set  $z_{lh}, G_{lh}, W_{lh}, C_{lh}^{II}, C_{lh}^{III}$  to 0
9:     end if
10:    if  $z_{lh} = 0$  then
11:      Set  $G_{lh}$  to 0
12:    end if
13:
14:    Set  $N_{lh} = C^{PV} z_{lh} + C^{PVU} G_{lh}$ 
15:    Set  $C_{lh}^{II} = (C^C x_{lh} + C^{CU} W_{lh}) \cdot \left( \frac{C_{lh}^{II}}{C_{lh}^{II} + C_{lh}^{III}} \right)$ 
16:    Round half up for  $C_{lh}^{II}$ 
17:    Set  $C_{lh}^{III} = (C^C x_{lh} + C^{CU} W_{lh}) - C_{lh}^{II}$ 
18:
19:    if  $C_{lh}^{II} < C_{lh-1}^{II}$  or  $C_{lh}^{III} < C_{lh-1}^{III}$  then
20:      Set  $C_{lh}^{II} = C_{lh-1}^{II}$ 
21:      Set  $C_{lh}^{III} = C_{lh-1}^{III}$ 
22:    end if
23:  end for
24:
25:  while CS budget constraint is not satisfied ( $B_h^{CS} < \text{cost}$ ): do
26:    Set  $x_{lh}, z_{lh}, G_{lh}, W_{lh}, C_{lh}^{II}, C_{lh}^{III}, N_{lh}$  to 0 for the lowest profitability CS.
27:  end while
28:
29:  while PV budget constraint is not satisfied ( $B_h^{PV} < \text{cost}$ ): do
30:    Set  $z_{lh}, G_{lh}, N_{lh}$  to 0 for the highest PV system cost.
31:  end while
32:
33: end for
34: for each station  $l$  do
35:   if profit for station  $l \leq 0$  then
36:     for each year  $h$  do
37:       Set  $x_{lh}, z_{lh}, G_{lh}, W_{lh}, C_{lh}^{II}, C_{lh}^{III}, N_{lh}$  to 0
38:     end for
39:   end if
40: end for
41:
42: Solve LP given  $x_{lh}, z_{lh}, G_{lh}, W_{lh}, C_{lh}^{II}, C_{lh}^{III}, N_{lh}$ 
43: End Procedure
```

---

---

**Algorithm 2** Procedure Neighborhood Search

---

```
1: Procedure Neighborhood Search
2: for each station  $l$  do
3:   for each  $b$  do
4:     if elapsed time > allowed time then
5:       break
6:     end if
7:
8:     if The budget is satisfied then
9:       Solve LP for  $N_b(l)$ 
10:
11:       if  $N_b(l)$  better than  $x_{lh}$  then
12:         Set the new solution to  $N_b(l)$ 
13:         Set  $l$  to 1
14:         Set  $b$  to 1
15:       end if
16:     end if
17:   end for
18:
19: end for
20:
21: End Procedure
```

---

## 2.6 Case Study (Site selection)

This section outlines the data collection process for the case study conducted in Saudi Arabia, presents various approaches used to address the identified problems, and discusses the results, including a sensitivity analysis.

### 2.6.1 Data collection

In this study, we focused on the cities of Dhahran, Dammam, and Khobar. Our initial step involved gathering population data for each 400 by 400-meter grid. To streamline the model, we excluded low population areas with fewer than 500 residents, which reduced the number of demand points from approximately 4,200 to 1,900.

Next, we identified potential sites for current stations and excluded those located within walking distance of each other to minimize redundancy. This process decreased the number of stations from over 300 to around 170. The study spanned a horizon of 7 years, guiding our planning and analysis throughout this period. Figure 2.1 illustrates the population distribution alongside the identified potential sites for CSs on the map.

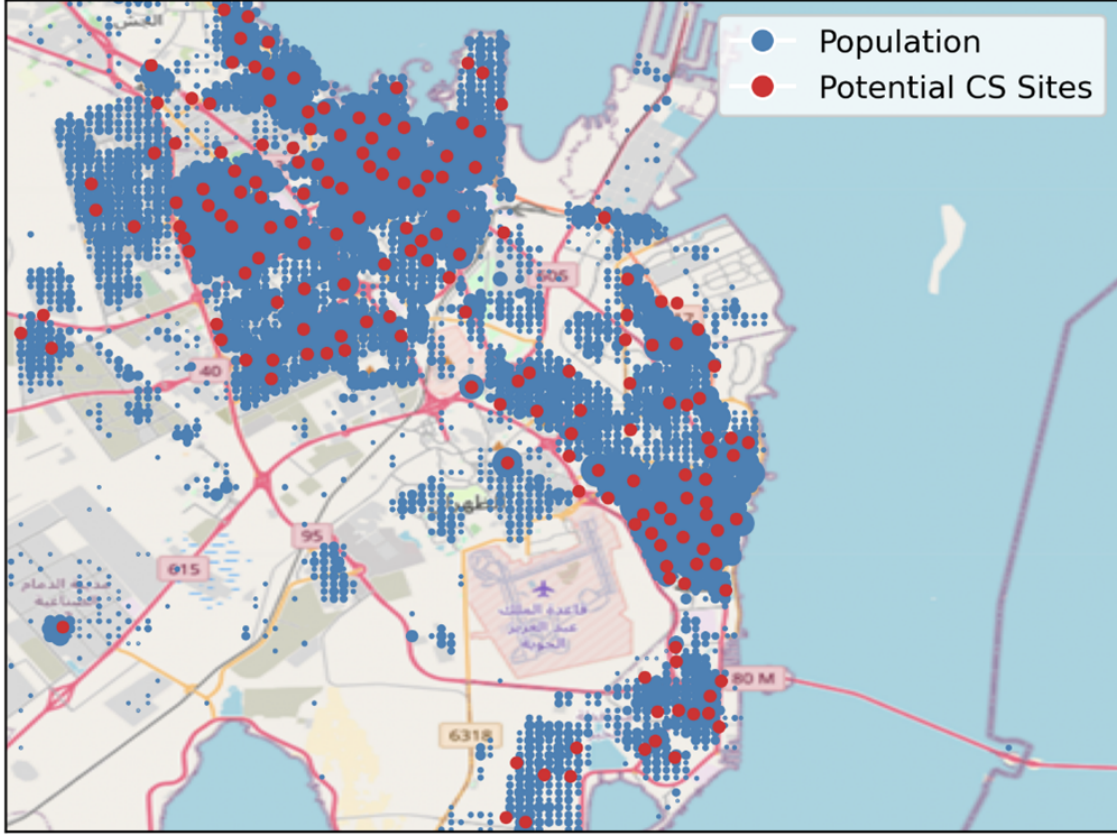


Figure 2.1: Population and Potential CS Sites

Subsequently, we constructed the matrix  $O_{dh}$  using population data and the matrix  $P_{ld}$  based on the distances between stations and demand points as described previously in the demand section.

The parameters utilized for calculating the energy generated by PV systems, as outlined in Equations (2.27-2.30), are presented in Table 2.1. A portion of these

parameters are sourced from (44). Additionally, further parameters employed in our model are detailed in table 2.2. It is noteworthy that any parameter indexed by  $k$  is assumed to vary annually according to a uniform distribution.

| Symbol       | Value                  |
|--------------|------------------------|
| $A$          | 1.6 m <sup>2</sup>     |
| $\eta_r$     | 0.185                  |
| $I_B$        | 5.085 W/m <sup>2</sup> |
| $I_D$        | 1.91 W/m <sup>2</sup>  |
| $R_B$        | 0.8                    |
| $\eta_{inv}$ | 0.95                   |
| $T_{A0}$     | 20 °C                  |
| $T_{C0}$     | 45 °C                  |
| $T_A$        | 30 °C                  |
| $T_R$        | 25 °C                  |
| $I_0$        | 5 W/m <sup>2</sup>     |
| $\beta$      | 0.004 °C <sup>-1</sup> |

Table 2.1: PV calculations Parameters

### 2.6.2 Solution Approach Implementation

In Step 1 of the heuristic, we refined the methodology to derive a more effective initial solution. In Step 3, instead of employing traditional half-up rounding, we explored a range of rounding values from 0.3 to 0.7. This approach enabled us to establish a customized rounding threshold, facilitating the selection of the most optimal initial solution from the evaluated options.

Furthermore, in Step 2 of the heuristics, the station swapping method was modified to selectively swap stations with differing opening years, ensuring that the swaps would have a significant impact on the profit. Additionally, prioritizing swapping high-demand stations with lowest demand stations, thereby enhancing the likelihood of achieving higher profit as a result of the swaps.

| Symbol         | Value                                                                   |
|----------------|-------------------------------------------------------------------------|
| $c_{lh}^{CS}$  | Uniform [150,000, 500,000] SAR, constant through all years h            |
| $c_{lh}^{CSU}$ | 10,000 SAR, constant through all stations l and years h                 |
| $o_{lh}^{CS}$  | 10,000 SAR increasing 2 to 5% annually, constant through all stations l |
| $c_{lh}^{II}$  | 3,000 SAR, constant through all stations l and years h                  |
| $c_{lh}^{III}$ | 5,000 SAR, constant through all stations l and years h                  |
| $c_{lh}^{PVS}$ | Uniform [20,000, 60,000] SAR, constant through all years h              |
| $c_{lh}^{PV}$  | 800 SAR, constant through all stations l and years h                    |
| $o_{lh}^{PV}$  | 10 SAR, constant through all stations l and years h                     |
| $c_{lh}^{PVU}$ | 1,500 SAR, constant through all stations l and years h                  |
| $\gamma$       | 0.3 SAR                                                                 |
| $DC^{II}$      | 80 kWh                                                                  |
| $DC^{III}$     | 1,600 kWh                                                               |
| $C^C$          | 6 Chargers                                                              |
| $C^{CU}$       | 8 Chargers                                                              |
| $C^{PV}$       | 100 Panels                                                              |
| $C^{PVU}$      | 50 Panels                                                               |
| $B_h^{CS}$     | 2,000,000 SAR, constant through all years h                             |
| $B_h^{PV}$     | 500,000 SAR through all years, constant through all years h             |
| $p_h$          | 10 SAR changing -5 to 15% annually                                      |
| $u$            | 8 kWh                                                                   |
| $OD$           | 365 Days                                                                |
| $P_{inv}$      | 650.91 kWh                                                              |

Table 2.2: Model Parameters

Lastly, it is crucial to ensure that no station negatively impacts the profit. Therefore, we assessed the profit for each station to confirm that it yields a positive value. If the station decreases the total profit, then all the following variables will be set to zero:  $x_{lh}, z_{lh}, G_{lh}, W_{lh}, C_{lh}^{II}, C_{lh}^{III}, N_{lh}$ .

### 2.6.3 Computational Results and Discussion

The experiment was conducted using Lingo 19.0 on a computer equipped with an Intel i7 processor and 16GB of RAM. For the heuristic approaches, we utilized Python in conjunction with the GLPK solver. Both experiments were conducted over a duration of 24 hours.

The total number of variables in the model, based on the inputs provided above, is 2,351,958, with only 0.36% of them being integers. The model also includes a total of 2,372,735 constraints. Although we only consider three cities, this exceptionally large number of variables and constraints highlights the critical importance of implementing the proposed heuristic approach.

Generating the initial solution with various rounding thresholds in the first step of the heuristic, ranging from 0.3 to 0.7 in increments of 0.05, significantly enhances the initial results. This customized rounding approach has led to substantial improvements, as illustrated in Figure 2.2. As shown in the figure, the customized rounding method with a rounding threshold of 0.6 generates an initial solution that is 1.41% more effective than the traditional round-half-up method.

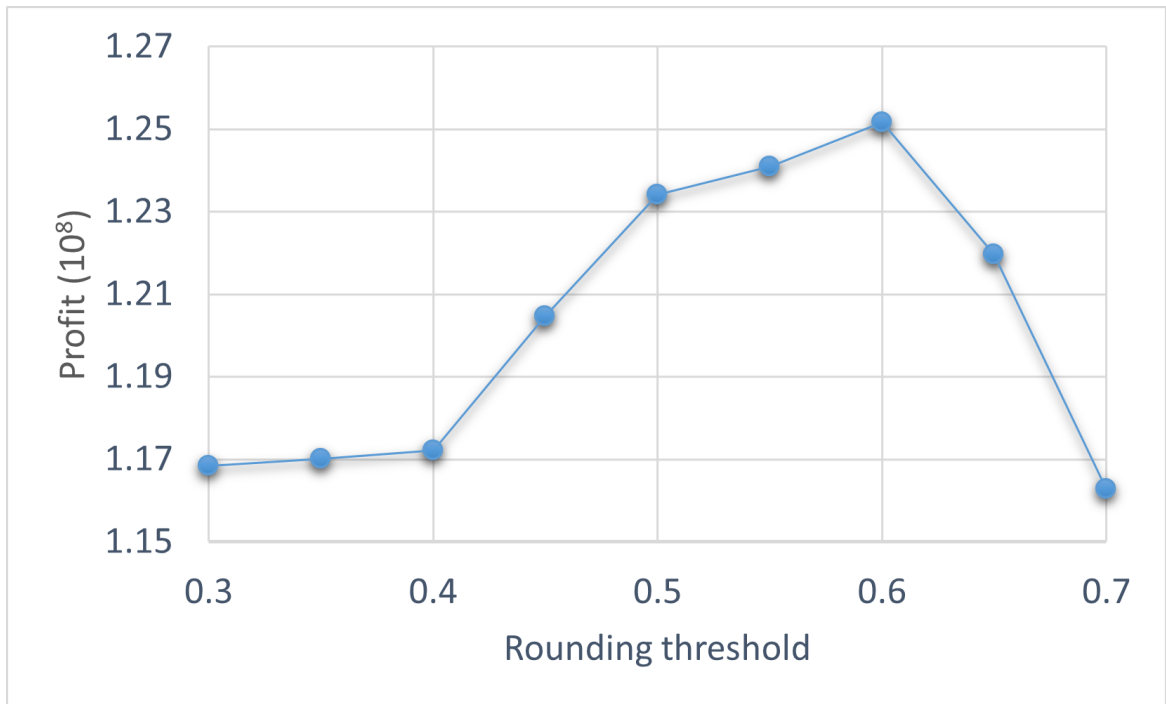


Figure 2.2: Rounding Thresholds vs. Profit

The solutions for the model are illustrated in Figures 2.3 and 2.4, showcasing the

results for the MILP approach and the heuristic method, respectively. A rounding-up threshold of 0.6 was employed, as it represented the best initial solution generated. The stations color-coded according to their respective opening years. Square markers indicate stations equipped with PV systems.

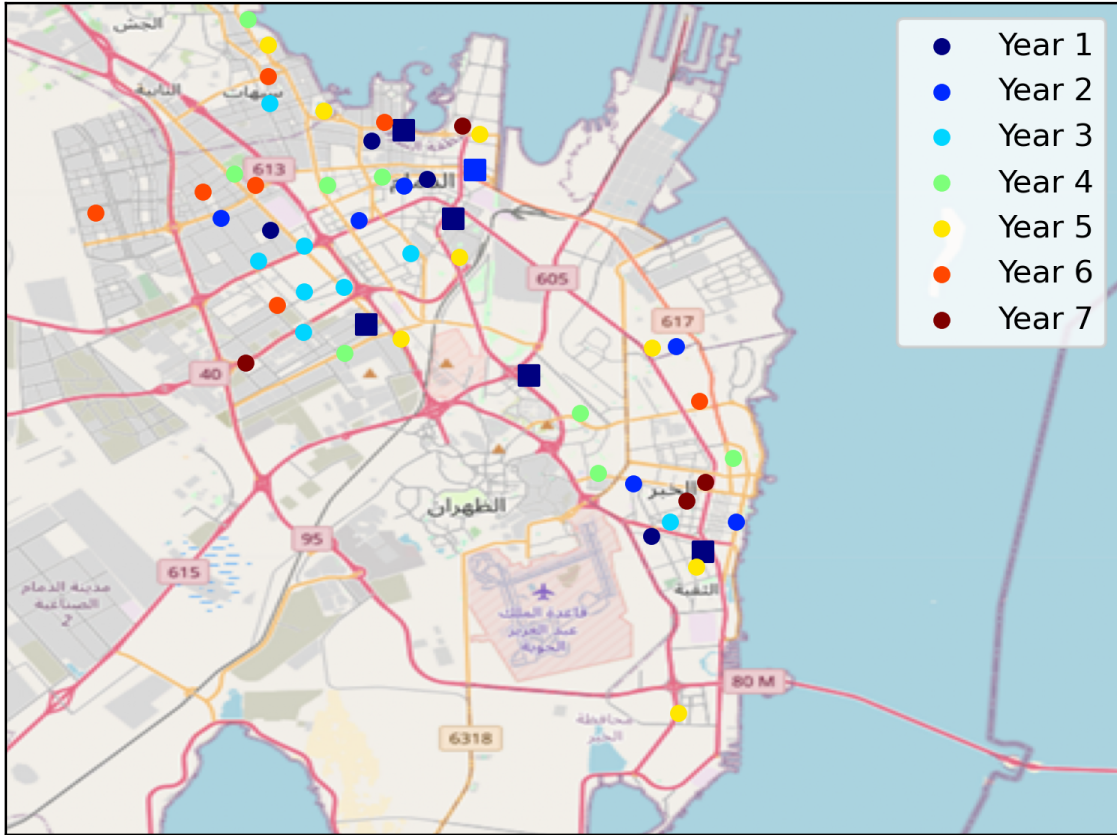


Figure 2.3: Selected Sites Using Commercial Solver

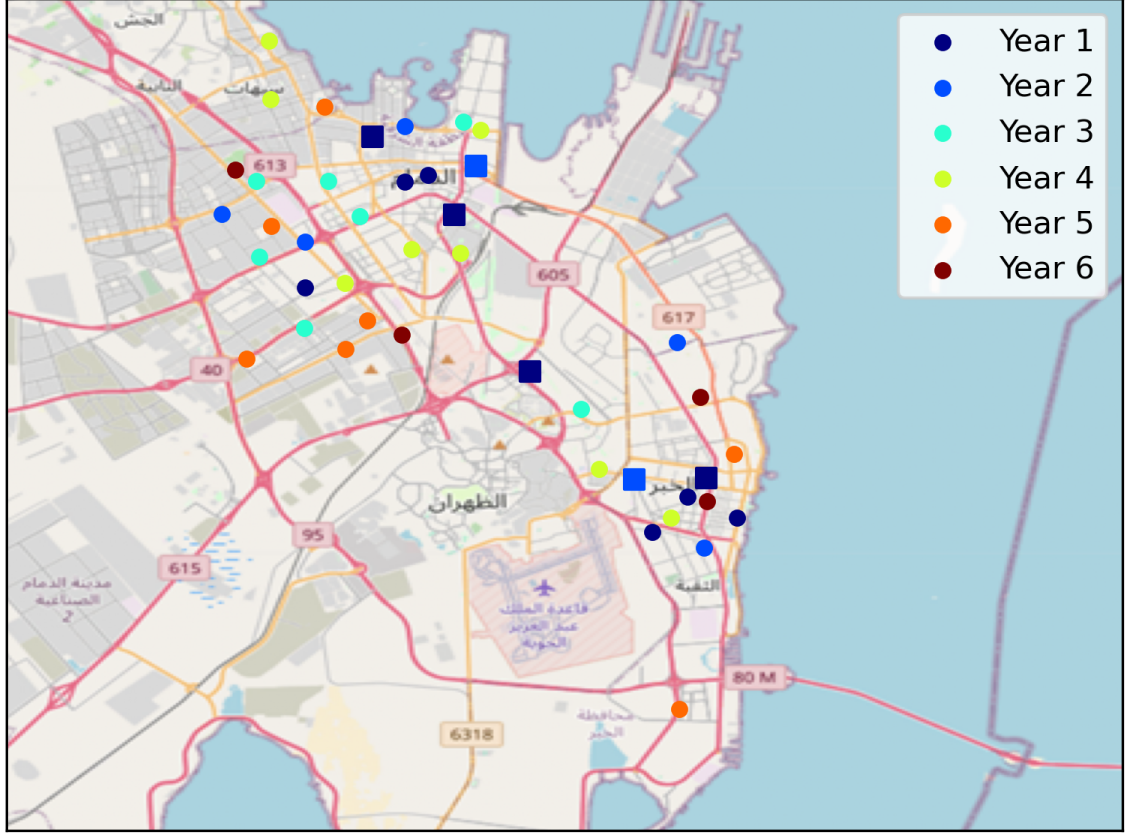


Figure 2.4: Selected Sites Using Heuristic Approach

The results of the profit for both methods are summarized in Table 2.3. It is important to note that the heuristic method required 1 hour for Step 1 and 23 hours for Step 2, totaling 24 hours for both the MILP approach and the heuristic method.

| Method           | Profit                | Improvement |
|------------------|-----------------------|-------------|
| MILP             | $1.20471 \times 10^8$ | -           |
| Heuristic step 1 | $1.25162 \times 10^8$ | 3.89%       |
| Heuristic step 2 | $1.25926 \times 10^8$ | 4.53%       |

Table 2.3: Comparison of Solution Approaches

Out of 174 potential sites for station development, the MILP method identifies a network of 51 stations over a 7-year period, while the heuristic method suggests

establishing 43 stations. Additionally, both approaches recommend integrating PV systems into six of the stations to enhance sustainability and minimize environmental impact; however, the specific stations equipped with PV systems differ between the two methods.

Each method suggests a different number of stations, resulting in varying quantities and types of chargers. The MILP model recommends a total of 330 chargers, with 18.5% of them being Type III chargers. Additionally, 6 stations are upgraded to accommodate more chargers. In contrast, the heuristic approach solution suggests implementing 258 chargers, with 17.5% being Type III chargers, and no stations are upgraded. The differences in the number of chargers and upgraded stations arise from the varying total number of stations selected by each method. However, it is noteworthy that the ratio of Type II to Type III chargers remains almost consistent across both methods, indicating that this ratio is relatively close to the optimal configuration.

It is noteworthy that while the implementation of PV systems and upgrading decisions have been recommended, not all stations may undergo these enhancements. This is primarily because the seven-year time horizon may not always justify immediate investments in upgrades or PV integration. Typically, these improvements require longer durations to yield significant returns on investment, which could impact their feasibility within the specified time frame.

Since budget allocation is one of the key parameters, we conduct a sensitivity analysis to examine its impact. The total annual budget of \$2,500,000 is divided such that 80% is allocated to CS and the remaining 20% to PV systems. We aim to explore the impact of adjusting this budget ratio, specifically by varying the CS

budget allocation from 90% to 70%, in 5% increments.

Using the initial solution generated by the first step of the heuristic, we evaluate the average yearly reduction in CO2 emission versus the corresponding profit. Figure 2.5 illustrates the results, showing that as the budget allocated to CSs is reduced, profit decreases while the reduction in CO2 emission increases. This trend is logical: decreasing the CS budget allows for a higher allocation to the implementation of PV systems, which contributes to greater emission reductions.

This analysis offers valuable insights for decision-makers, enabling them to explore alternative budget ratios and assess the trade-offs between profit and CO2 emission reduction. These considerations are crucial for selecting the optimal solution that aligns with the organization's long-term sustainability goals.

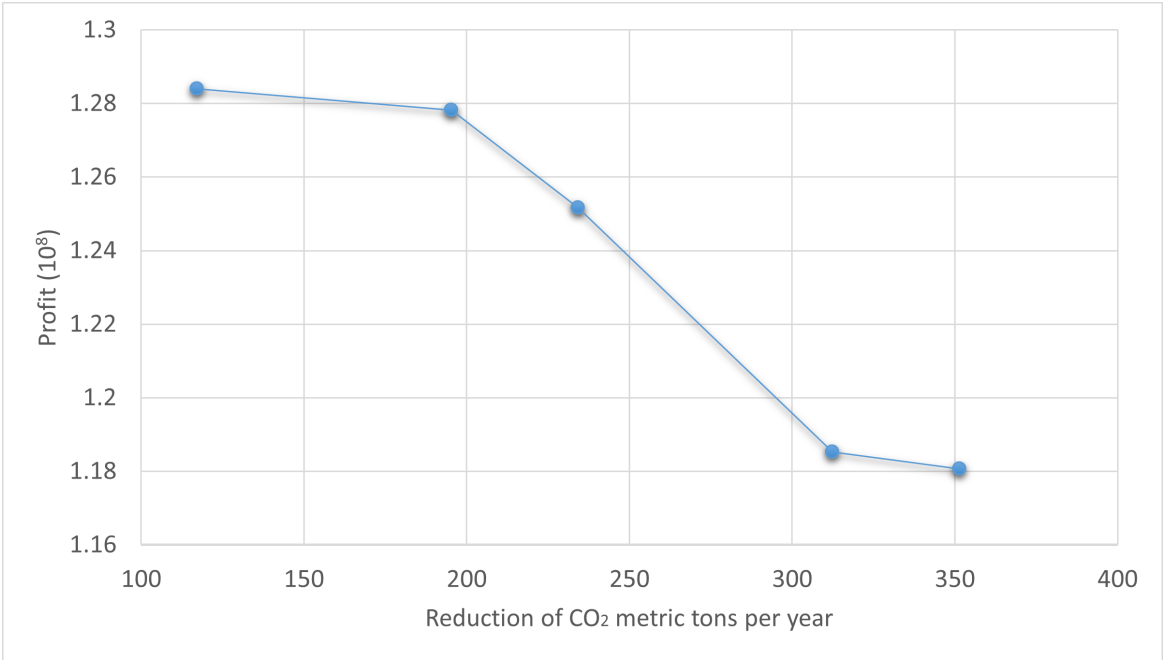


Figure 2.5: Average yearly reduction of CO2 vs. Profit

# **CHAPTER 3**

## **FLEET MANAGEMENT FOR EVS IN CSS: INTEGRATING RIDE SPLITTING, RELOCATION DECISIONS, AND EV ASSIGNMENT**

This chapter presents the fleet management model developed for EVs in CSS, which integrates key operational strategies such as ride splitting, vehicle relocation decisions, and the assignment of EVs to optimize fleet efficiency with the primary goal of maximizing profit for the prospective of CSO. By addressing these elements, the chapter offers a comprehensive approach to managing EV fleets effectively, improving operational performance, and improving service availability while focusing on maximizing

the total profit.

### **3.1 Problem description**

This study aims to tackle fleet management problem within an EVSS, considering the possibility of ride splitting and relocation decisions. The main idea of this model is to assign a vehicle for each order, or more in case of ride splitting. The objective is to maximize the total profit of the prospective of CSO. Demand and duration of each order are assumed to be deterministic, with a specified direction of flow from stations.

In addition, the model will determine the status of each vehicle at any point of time, wither the vehicle is on standby, charging, or in service. Furthermore, the SOC will be monitored at any point in time for all vehicles. This will help in ensuring the SOC remains within the desired range which will reflect on the life of the battery and its efficiency. Lastly, the model will assign EVs across the station at the beginning of each operation day, without exceeding the capacity for any station.

#### **3.1.1 Ride splitting**

Incorporate ride splitting into the model by allowing the model to split the order into two or more small splits. This addition to our system will increase the profit and increase customer satisfaction. Additionally, the split can be viewed as a relocation process, enabling the model to reposition the EVs in a more efficient manner than direct relocation process. It is assumed that there will be no waiting time when splitting and order. If an order is split from station  $i$  to  $j$  to  $k$ , the second EV at

station  $j$  will be available with sufficient charge to travel from station  $j$  to  $k$ . Lastly, there will be a cost associated with splitting any order, and the profit from direct orders will always exceed that from split orders.

It is important to note that split orders can be further divided multiple times, which will further reduce the profit, as each additional split introduces an extra cost to the objective function. Limiting the model to only consider a single split will not be sufficient in cases of long trips that require more than two EVs to fulfill.

### 3.1.2 Relocation decisions

In this model it is assumed that there are crew members who are responsible for relocating the EVs during the operating hours. Which will enhance the balance of EVs through all stations based on the current distribution of EVs across the stations. Each relocation decision incurs an additional cost, as the process requires a crew member and sufficient battery charge to move the EV from one station to another.

## 3.2 Notations

Sets:

$C$  CSs,  $c \in \{1, \dots, C\}$

$T$  Time steps,  $t \in \{1, \dots, T\}$

$V$  EVs,  $v \in \{1, \dots, V\}$

$M$  Trips for each order in case of spiting,  $m \in \{1, \dots, M\}$

**Parameters:**

|              |                                                                       |
|--------------|-----------------------------------------------------------------------|
| $D_{ijt}$    | Demand from station $i$ to $j$ at time $t$                            |
| $Z_i$        | Capacity of station $i$                                               |
| $C_i$        | Number of fast chargers at station $i$                                |
| $A_{ij}$     | Time steps required to go from station $i$ to $j$                     |
| $P_{ij}$     | Profit for order from station $i$ to $j$                              |
| $O_{ijk}$    | Cost of splitting the order from $i$ to $k$ using $j$ as intermediate |
| $L_{ij}$     | Cost of relocating one EV from station $i$ to $j$                     |
| $E^s$        | Energy charging rate for the slow charger                             |
| $E^f$        | Energy charging rate for the fast charger                             |
| $Q$          | Battery SOC decrease during a user's trip per time step               |
| $I_v$        | Initial battery level for vehicle $v$                                 |
| $SOC_{\min}$ | Minimum allowed state of charge                                       |
| $SOC_{\max}$ | Maximum allowed state of charge                                       |

**Decision variables:****Continuous variable:**

$SOC_{tv}$  SOC at time  $t$  for EV  $v$  (in percentage)

**Integer variables:**

$N_{ijkt}$  Number of split orders from station  $i$  to  $k$  passing through  $j$  at time  $t$

$S_{ijtm}^+$  Additional trips from station  $i$  to  $j$  at time  $t$  due to splitting, part  $m$

$S_{ijt}^-$  Reduced trips from station  $i$  to  $j$  at time  $t$  due to splitting

$R_{ijt}$  Number of EVs relocating from station  $i$  to  $j$  at time  $t$

**Binary variables:**

$x_{ijtv}$  1 if EV  $v$  goes from station  $i$  to  $j$  at time  $t$ , 0 otherwise

$b_{i1v}^s$  1 if EV  $v$  is being charged at station  $i$  at time  $t$  using the slow charger, 0 otherwise

$b_{i1v}^f$  1 if EV  $v$  is being charged at station  $i$  at time  $t$  using the fast charger, 0 otherwise

$w_{itv}$  1 if EV  $v$  is on standby at station  $i$  at time  $t$ , 0 otherwise

### 3.3 Mathematical model

This section presents the problem as a MILP model aimed at maximizing the total profit of the CSOs. The model manages operations by specifying which orders to satisfy and which vehicles to assign. By identifying the initial position of each EV at the beginning of the operational day, the model ensures that the EVs are distributed according to demand. It also tracks the SOC of each vehicle throughout the day. Additionally, the model allows for ride-splitting, which increases both service level and profit by enabling longer trips. Lastly, the model permits relocating EVs between stations by a crew member to further satisfy customer demand.

**Objective function:**

$$\text{Maximize } \sum_{i,j \in C} P_{ij} \sum_{t \in T} \sum_{v \in V} x_{ijtv} - \sum_{i,j,k \in C} O_{ijk} \sum_{t \in T} N_{ijkt} - \sum_{i,j \in C} L_{ij} \sum_{t \in T} R_{ijt} \quad (3.1)$$

The first term of the objective function presents the summation of the profit from satisfied orders, while the second and third terms account for the additional cost due to splitting orders and the relocation process, respectively.

**Constraints:**

$$\sum_{i,j \in C} x_{ij1v} = 1 \quad \forall v \in V \quad (3.2)$$

Constraint (3.2) determines the starting station of each EV at the beginning of the day.

$$\sum_{v \in V} x_{ijtv} \leq D_{ijt} + \sum_{m \in M} S_{ijtm}^+ - S_{ijt}^- + R_{ijt} \quad \forall i, j \in C, t \in T, i \neq j \quad (3.3)$$

Constraint (3.3) ensures that the number of EVs allocated to travel from station  $i$  to station  $j$  does not exceed the demand, which may be modified due to split orders and relocation.

$$\sum_{v \in V} x_{ijtv} \geq \sum_{m \in M} (S_{ijtm}^+ + R_{ijt}) \quad \forall i, j \in C, t \in T, i \neq j \quad (3.4)$$

Constraint (3.4) forces all split orders and relocations to be fully satisfied.

$$\sum_{j \in C, j \neq i, j \neq k} N_{ijkt} = S_{ikt}^- \quad \forall i, k \in C, t \in T, i \neq k \quad (3.5)$$

Constraint (3.5) ensures that the total number of split orders from  $i$  to  $k$  using any intermediate station  $j$  equals the reduced orders from station  $i$  to  $k$ .

$$\sum_{k \in C, k \neq i, k \neq j} N_{ijkt} = S_{ijt1}^+ \quad \forall i, j \in C, t \in T, i \neq j \quad (3.6)$$

Constraint (3.6) ensures that the total number of split orders that will pass through station  $i$  to  $j$  to any station  $k$  is equal to the number of additional trips from  $i$  to  $j$  at time  $t$  (first part of the split).

$$\sum_{\substack{i \in C, i \neq j, i \neq k \\ (t-A_{ij}) \geq 1}} N_{ijk(t-A_{ij})} = S_{jkt2}^+ \quad \forall j, k \in C, t \in T, j \neq k \quad (3.7)$$

Constraint (3.7) accounts for the second part of the split, considering the travel time needed to reach the intermediate station.

$$\sum_{j \in C} x_{ijtv} = \sum_{\substack{j \in C, i \neq j \\ (t-A_{ji}) \geq 1}} x_{ji(t-A_{ji})v} + x_{iit(t-1)v} \quad \forall i \in C, t \in T, v \in V, t \geq 2 \quad (3.8)$$

Constraint (3.8) balances the flow of vehicles across stations.

$$b_{itv}^s + b_{itv}^f + w_{itv} = x_{iitv} \quad \forall i \in C, t \in T, v \in V \quad (3.9)$$

Constraint (3.9) ensures that each EV is only in one state at a time: fast charging, slow charging, standby, or transferring.

$$\sum_{j \in C} \sum_{v \in V} x_{ijtv} \leq Z_i \quad \forall i \in C, t \in T \quad (3.10)$$

Constraint (3.10) limits the capacity of each station.

$$\sum_{v \in V} b_{itv}^f \leq C_i \quad \forall i \in C, t \in T \quad (3.11)$$

Constraint (3.11) limits use of fast chargers.

$$SOC_{1v} = I_v + E^s \sum_{i \in C} b_{i1v}^s + E^f \sum_{i \in C} b_{i1v}^f - Q \sum_{i,j \in C, i \neq j} A_{ij} x_{ij1v} \quad \forall v \in V \quad (3.12)$$

$$SOC_{tv} = SOC_{(t-1)v} + E^s \sum_{i \in C} b_{itv}^s + E^f \sum_{i \in C} b_{itv}^f - Q \sum_{i,j \in C, i \neq j} A_{ij} x_{ijtv} \quad \forall t \in T, v \in V, t \geq 2 \quad (3.13)$$

Constraints (3.12 - 3.13) track the SOC based on travel and charging actions.

$$SOC_{min} \leq SOC_{tv} \leq SOC_{max} \quad \forall t \in T, v \in V \quad (3.14)$$

Constraint (3.14) bounds the SOC between minimum and maximum thresholds.

$$N_{ijkt}, S_{ijtm}^+, S_{ijt}^- \in \mathbb{Z}^+ \quad \forall i, j, k \in C, t \in T, m \in M \quad (3.15)$$

$$x_{ijtv}, b_{itv}, w_{itv} \in \{0, 1\} \quad \forall i, j \in C, t \in T, v \in V \quad (3.16)$$

Constraints (3.15 - 3.16) define the variable domains (binary and integer).

## 3.4 Input modeling

In this section, we will discuss the key components of input modeling for fleet management problem within a CSS. The distribution of demand across the time horizon and stations, the traveling time between stations, profits and costs associated with splitting and relocation.

### 3.4.1 Demand

The demand in a fleet management problem is presented as the number of orders from station  $i$  to station  $j$  at time  $t$ . Using the demand data from the site selection problem, we can estimate the flow of demand from the stations. Spreading the allocated demand across the time steps requires knowing the rush hour throughout the day. The behavior of customers throughout the day will give a reasonable estimation of the distribution of the demand across the time steps.

The following steps explain the procedure of estimating the demand:

- Assign a distribution for each group of time steps.
- Calculate the probability of each individual time step using the distribution.
- Introduce some fluctuation to the probabilities and then normalize them.
- Calculate the demand from station  $i$  to station  $j$  using equation (3.17).
- Assign the resulting demand across all time steps based on their probability.

The demand from station  $i$  to station  $j$  at time  $t$  is calculated as follows:

$$D_{ijt} = \text{Demand}_i \left( \frac{\text{Demand}_j}{\sum_{k \in C} \text{Demand}_k - \text{Demand}_i} \right) \quad (3.17)$$

It is noteworthy that the demand assigned was extracted from the solution of the first model, which was presented in the variable  $y_{ijt}$ . Summing over the demand points  $j$  gives the total demand assigned for station  $i$  at time  $t$ .

### 3.4.2 Traveling time

The traveling time between stations is presented as the number of time steps required to travel from station  $i$  to station  $j$ . Since it must be an integer, rounding up all fractional values is essential. Equation (3.18) shows the method we adapt in calculating  $A_{ij}$ . The distance from station  $i$  to station  $j$  represents the routing distance, and therefore, the distance from  $i$  to  $j$  does not always equal the distance from  $j$  to  $i$ .

The calculation of the traveling time involves the average speed in kilometers per hour ( $AS$ ) and the time step duration ( $TD$ ).

The time to travel from station  $i$  to station  $j$ , denoted as  $A_{ij}$ , is calculated as:

$$A_{ij} = \left\lceil \frac{\text{Distance}_{ij}}{AS} \times \frac{60}{TD} \right\rceil \quad (3.18)$$

### 3.4.3 Profit

The rental fee is determined by the distance between the stations. To calculate the total revenue for the order, the fee coefficient ( $\alpha$ ) is multiplied by the distance. The

electricity cost, associated with fulfilling the order, is subtracted to calculate the profit. The electricity cost per unit of distance ( $\beta$ ) is multiplied by the distance to get the total cost of the order, as shown in equation (3.19):

$$P_{ij} = \alpha \cdot \text{Distance}_{ij} - \beta \cdot \text{Distance}_{ij} \quad (3.19)$$

Each order is subject to a minimum fee. If the calculated profit falls below this amount, the minimum fee will be treated as the profit.

#### 3.4.4 Cost of splitting

Although ride splitting increases the service level, it has a negative impact on customer experience due to the increased total duration of the ride. The users will be required to travel to an intermediate station and switch to a different EV to continue their journey. This not only increases the operational costs for the CSO but also leads to a decline in customer satisfaction and potential service efficiency.

Additionally, each split order assumes a small discount to accommodate for the inconvenience. The discount is represented by  $\gamma$ , where  $\gamma$  is less than 1, indicating the proportion of the profit lost from splitting the order from  $i$  to  $k$ , with  $j$  serving as the intermediate station, as outlined in equation (3.20):

$$O_{ijk} = P_{ij} + P_{jk} - (1 - \gamma) \cdot P_{ik} \quad (3.20)$$

The reason for adding  $P_{ij} + P_{jk}$  is to account for the profit generated from the trips from stations  $i$  to  $j$  and from  $j$  to  $k$ . These trips are considered as satisfied orders

while they are actually only part of the main trip from station  $i$  to station  $k$ . The term  $(1 - \gamma)P_{ik}$  represents the profit from the split order, which is less than  $P_{ik}$  due to the discount factor  $\gamma$ .

### 3.4.5 Cost of relocation

A crew will be responsible for relocating the EVs throughout the operational time. The total cost is determined by the hourly wage ( $h$ ) and the electricity expenses incurred due to the relocation, as outlined in equation (3.21):

$$L_{ij} = P_{ij} + h \cdot \frac{\text{Distance}_{ij}}{AS} + \beta \cdot \text{Distance}_{ij} \quad (3.21)$$

Similar to the splitting cost, the profit term from station  $i$  to  $j$  is added to remove the profit term in the first part of the objective function. The remaining term in the objective function is  $- \left( h \cdot \frac{\text{Distance}_{ij}}{AS} + \beta \cdot \text{Distance}_{ij} \right)$ , which represents the cost of the crew's wages and the electricity consumption associated with the relocation.

## 3.5 Case study

This section will discuss the results of the fleet management problem. Same case study of Dhahran, Dammam, and Khobar was used as an input to validate the model.

### 3.5.1 Inputs

Similar to the previous chapter in this study, we focused on the cities of Dhahran, Dammam, and Khobar. Using the output and the results of the previous model to

generate the input for this model as explained in input modeling section. The first year of the site selection model (heuristic approach) has selected the following stations as shown in figure 3.1 below:

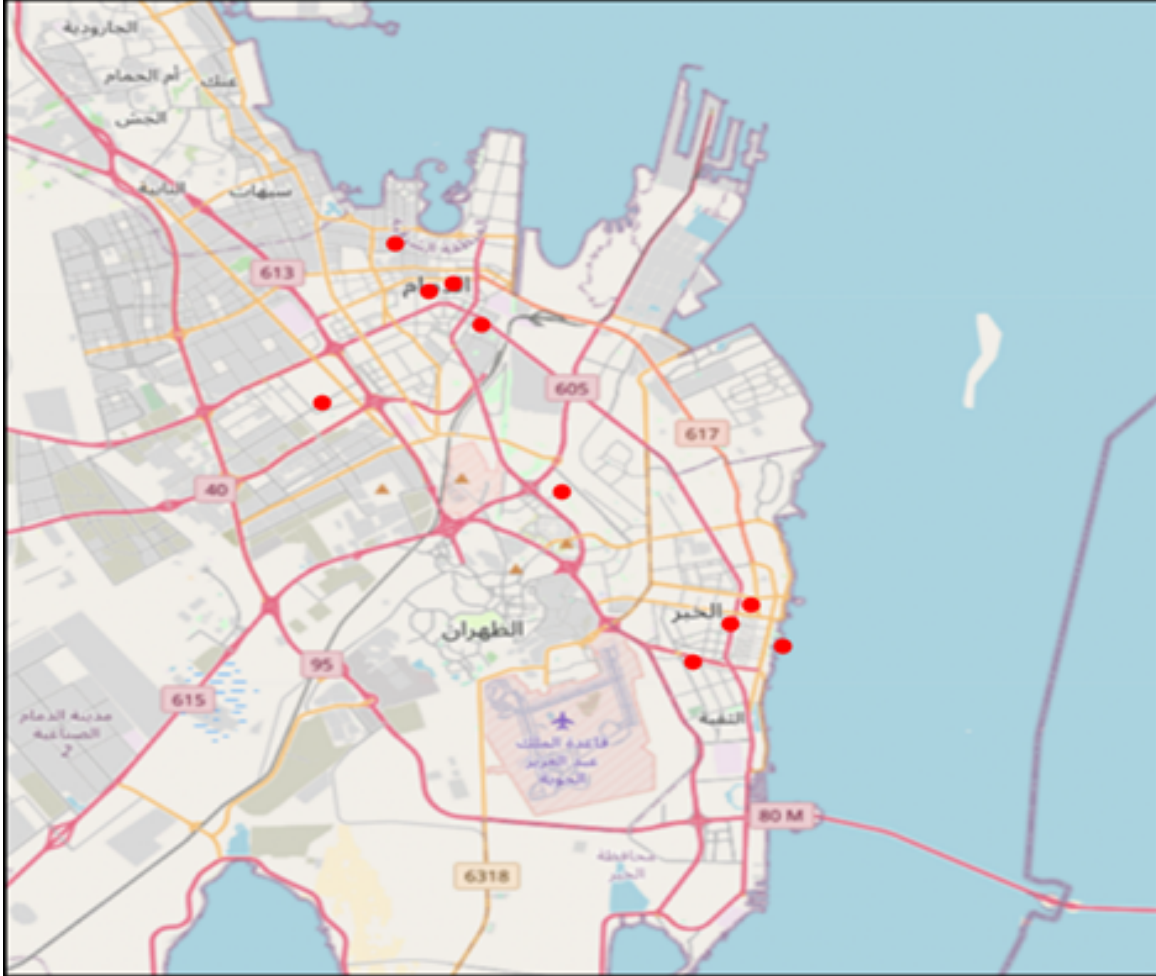


Figure 3.1: Selected Sites in the first year

The total number of stations opened in the first year using heuristics solution was 10 stations. For the time steps we assume each time step is 10 minutes length and total time is 16 hours per day, which results in 96 time steps. Lastly, we assume the total number of EVs across all stations is 30. Other parameters such as demand, travel time, profit, and costs associated with splitting or relocation are calculated using the

routing distance and corresponding coefficients, as described in equations (3.17 - 3.21).

The specific values for the coefficients and parameters are provided in Table 3.1 below.

| Symbol      | Value               |
|-------------|---------------------|
| $AS$        | 50 km/h             |
| $TD$        | 10 Minutes          |
| $\alpha$    | 3 SAR/km            |
| $\beta$     | 0.048 SAR/km        |
| $\gamma$    | 0.15                |
| $h$         | 25 SAR/h            |
| $E^s$       | 2.7% per time step  |
| $E^f$       | 53.3% per time step |
| $Q$         | 2.5% per time step  |
| $SOC_{min}$ | 20%                 |
| $SOC_{max}$ | 80%                 |

Table 3.1: Coefficients and Parameters (fleet management)

### 3.5.2 Computational Results and Discussion

The experiment was conducted using python on a computer equipped with an Intel i7 processor and 16GB of RAM. We used Python in conjunction with the Gurobi solver. The experiment was conducted over a duration of 2 hours. It is crucial to stop the solver for a short duration in order to simulate the real-life delay in the realization of demand.

The solution a profit of 15,028.276 SAR after 2 hours of solving. In this scenario, the model plans charging for around 300 time steps, with 10% of them being fast charging. When summed across all vehicles, the total charging time amounts to 3000 minutes in one operational day. The movement of the EVs through the first time step or the first 10 minutes from 6:00AM to 6:10AM is shown in the figure 3.2 below.

The movement of an individual EV through all time steps or the total operational

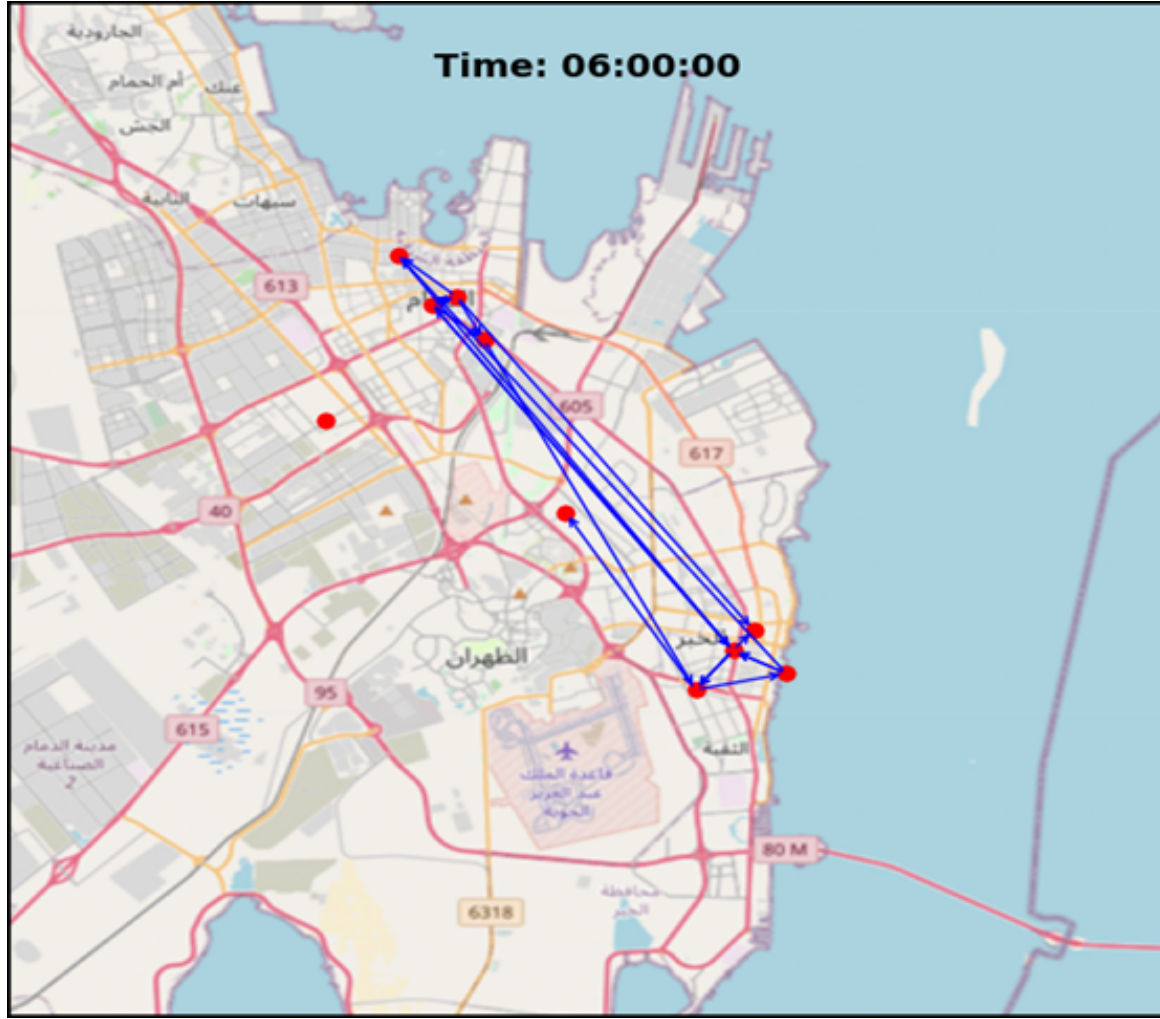


Figure 3.2: EVs movement in the first time step

day is shown in figure 3.3 below.

The movement of each EV shown in both figures includes trips made to meet customer demand, split rides, and relocation actions carried out by the crew. It is important to mention that Figure 3.3 shows only the movements during the first time slot. Since there are 96 time slots in total, 95 more figures would be needed to fully show all the movements. The same applies to Figure 3.4, which shows only one EV out of a total of 30. More figures would be needed to show the movements of the entire fleet.

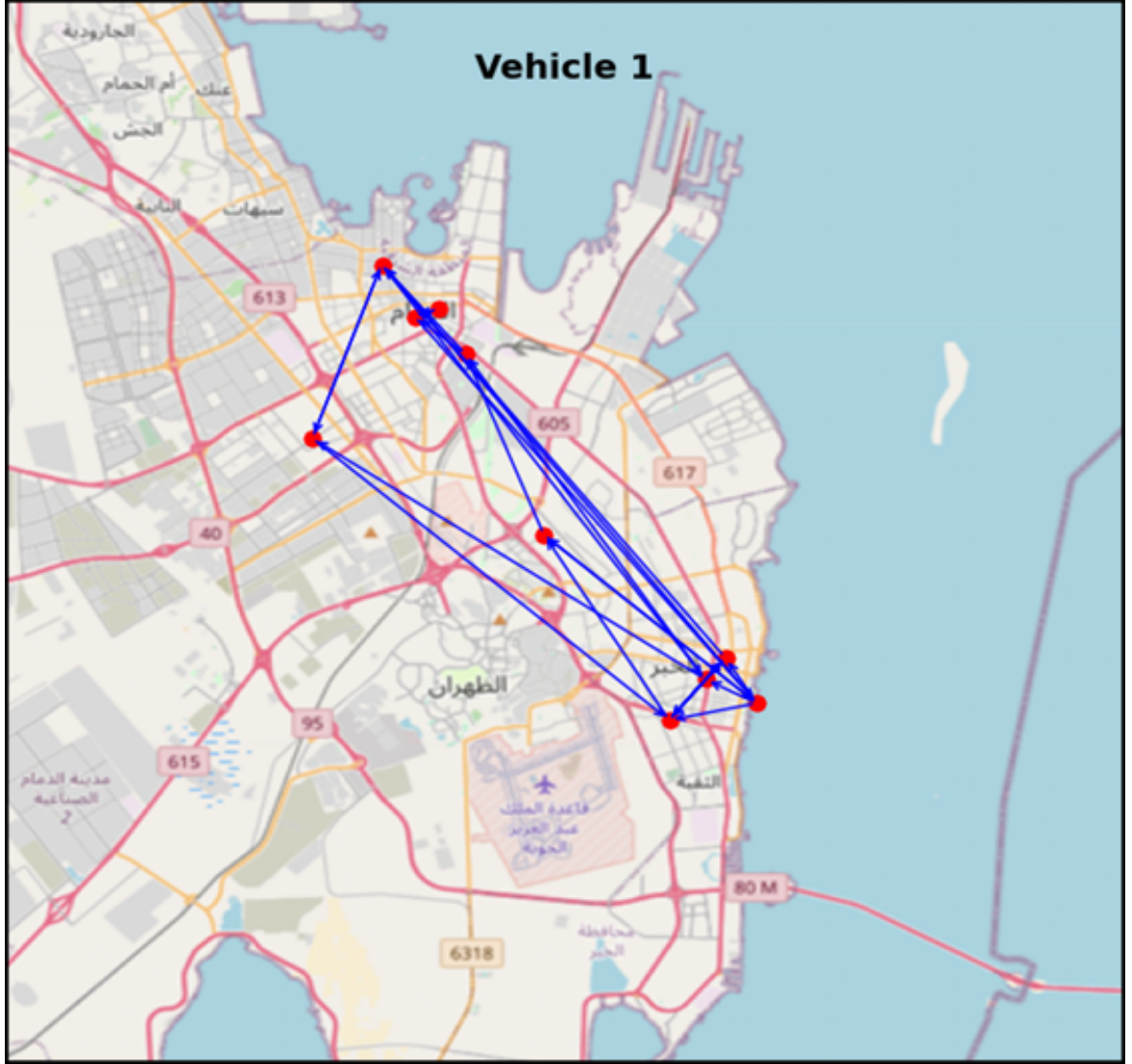


Figure 3.3: EV movement across all time steps

To gain a deeper understanding of how the model operates and how the variables interact, we will address the same problem but reduce the number of time slots by half—effectively managing only 8 hours of the day. In addition, we will vary the number of EVs to observe how this affects the solution and other related variables.

Figure 3.5 below illustrates the total profit as a function of the number of EVs, which ranges from 5 to 10. As expected, the total profit increases with the number of EVs, which is intuitive, as a higher number of vehicles allows the system to meet

more demand.

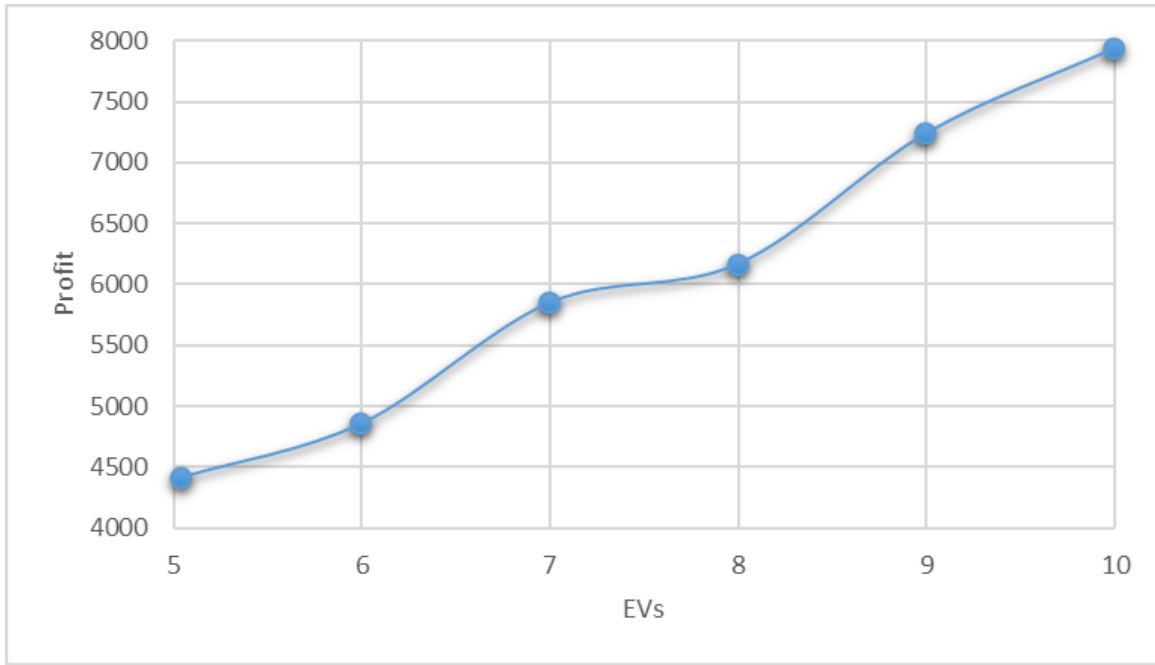


Figure 3.4: EVs vs. Profit

Additionally, the number of relocation decisions increases as the number of EVs rises. For instance, when five EVs are allocated, the solution suggests 10 relocations. However, when the number of EVs increases to 10, the total number of relocations jumps to 29. In contrast, the trend for ride splitting is less clear. There was no consistent pattern observed, as only one ride was split when using 7 and 9 EVs, while no ride splitting occurred in the other scenarios.

Lastly, as we increase the number of EVs from 5 to 10, the total number of orders satisfied rises from 107 to 229, representing an increase of approximately 113%, almost doubling the total number of satisfied orders. This suggests that, within a certain range, doubling the number of EVs roughly doubles the number of orders fulfilled. However, this relationship is not expected to hold indefinitely, as demand is finite and

each station has a limited capacity. As the number of EVs increases significantly, this trend may begin to plateau due to these constraints.

## CHAPTER 4

# CONCLUSION

In conclusion, this study advances a comprehensive approach to optimizing the location of CSs for EVSS, incorporating considerations for upgrades to both station infrastructure and PV systems. The research identifies optimal locations across Dhahran, Dammam, and Khobar using two approaches: The commercial solver suggests opening 51 stations, while the heuristic method recommends 43 stations.

The profit achieved through the commercial solver was  $1.2047 \times 10^8$ . In contrast, the heuristic method yielded varying results across two distinct steps: the initial solution (Step One) and the enhanced solution after swapping (Step Two).

In Step One, the heuristic generated a solution within one hour, showing a 3.89% improvement over the commercial solver's outcome. After dedicating an additional 23 hours in Step Two for further optimization, the solution improved even more, reaching a total increase of 4.53% compared to the commercial solver.

Importantly, both methods were executed within the same total time frame of 24 hours. This suggests that the heuristic approach can yield competitive improvements, highlighting its effectiveness in producing superior solutions without exceeding the

allocated time compared to the more traditional method. The results indicate that heuristics may be a valuable alternative for optimizing this type of problems.

The main reason for the lower number of upgraded stations and PV systems is the relatively short seven-year planning horizon. Infrastructure upgrades typically require longer periods to demonstrate their full benefits and justify the associated costs. Since significant increases in demand are expected to occur gradually over time, the immediate need for such enhancements may not be evident within this time frame. This also explains why the heuristic approach did not recommend any station upgrades, as the shorter horizon reduces the incentive for long-term investments. As for the chargers, the consistent ratio of Type II to Type I across both solutions suggests a shared understanding of optimal charger configuration, regardless of the chosen method.

Additionally, the study offers insights into the strategic deployment of chargers and PV panels at each station, highlighting the potential for enhanced sustainability and efficiency within the EV-charging infrastructure. However, it is acknowledged that practical constraints, such as investment timelines, may impede the immediate implementation of these enhancements across all stations. Nevertheless, by providing a holistic perspective on station optimization and upgrade strategies, this research contributes to the development of more sustainable and efficient EV-charging networks, thereby facilitating the transition towards greener transportation systems.

Future research could examine the uncertainty in demand as it is an important factor since demand changes over time as the behavior of users is uncertain, this can potentially affect the profitable and siting of CSs. Additionally, Future research

should also integrate the time value of money, as these investments have a long planning horizon and must factor in inflation. This would ensure a degree of mathematical realism in the financial assessment and long-term sustainability of the proposed solutions against cost inflation. Moreover, although this study considers solar energy, as a dominant renewable generation of charging stations, future study can be done to investigate the beneficial usage of green energy, like wind energy near CSs. Which will be highly beneficial, especially in parts of the world that experience variable solar irradiation throughout the year.

Addressing these aspects to future research could enhance the design, robustness, and sustainability of EVSS networks, ensuring they are better equipped to adapt to market uncertainties, remain economically viable, and effectively utilize a diverse range of renewable energy sources based on their need, contributing to a more sustainable transportation infrastructure with a robust model.

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