Transforming Parking Facilities to Accommodate Electric Vehicles: A Capacitated Multi-Facility Location Problem Approach

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Abstract

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Kimia Khalili

This study addresses the limitations of Electric Vehicles Charging Stations (EVCS) in Montréal, Québec. Momentum, the growth of Electric Vehicles (EVs) is projected to accelerate substantially. However, this growth is hindered by limited EVCS, particularly in shopping center settings where high cost, and spatial limitations pose significant challenges. This study addresses these gaps by proposing an optimization model to support cost effective EVCS placement.

The problem employs as a Mixed-Integer Nonlinear Programming (MINLP), categorizing as a capacitated multi-facility location allocation challenge. This approach is designed to minimize the total lifecycle costs for property owners, including costs related to equipment, electrical system equipment's, operational and maintenance, fixed costs, and dismantling expenses.

The optimization process involves determining the desired number of ports in the parking, based on the available estimation on the EV growth as a first step. Afterwards, determining parking blocks based on the parking size to allocate the different types of ports into them. Then, various port type combinations, distributed into all the generated block combinations. The proposed formulation is a Life Cycle Cost (LCC)-Based optimization designed to achieve minimum costs. The solution introduces a combinatorial optimization algorithm combines dynamic programming and brute-force search to ensure all potential configurations are considered.

In conclusion, this study provides a framework for shopping centers owners to adapt their parking facilities into EVs. The proposed cost formulation provides a financially sustainable solution for EVCS placements. Through this approach, these study offers a practical method to enhance EV infrastructure within commercial indoor parking environments, balancing financial and logistical considerations.

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List of abbreviations

Abbreviations	Stands for
CO_2	Carbon Dioxide
DG	Distributed Generation
DP	Dynamic Programming
EV	Electric Vehicle
EVs	Electric Vehicles
EVCP	Electric Vehicle Charging Port
EVCS	Electric Vehicle Charging Station
ICE	Internal Combustion Engines
LCC	Life Cycle Cost
MILP	Mixed Integer linear Programming
MINLP	Mixed Integer Nonlinear Programming
NPV	Net Present Value
PDN	Power Distribution Networks
PDNEP	Power Distribution Network Expansion Planning

List of Symbols

Symbol	Description
b	Parking block
c_b	Column index within the block
C	Number of columns in the block
C_{Annual}	Annual operating cost [$]
C_{cable}	Cost per unit length of the cable [$/m]
C_s	Life cycle cost [$]
$C_{Optimized}$	Optimized cost [$]
C_{S_E}	Cost of EV charging stations [$]
$C_{S_{EE}}$	Cost of electrical system equipment [$]
$C_{S_{End\ of\ Life}}$	End of life cost [$]
$C_{Initial}$	Initial cost [$]
C_{labour_Cable}	Cable installation labour cost per meter [$/m]
$C_{labour\_Conduit}$	Conduit installation labour cost per meter [$/m]
$C_{S_{OM}}$	Operation and maintenance cost [$]
$C_{Overhaul}$	Overhaul maintenance Cost [$]
C_{S_F}	Fixed cost [$]
CN 1	Number of single port EV charger locally
CN 2	Number of dual port EV charger locally
CN 4	Number of quad port EV charger locally
$C_{t,OM}$	Combined annual cost of operation and maintenance [$]
i	Spot number
I	Discount rate [%]
j	Charging station number
k	Charging station Type
k_a	Single port charger
k_b	Dual port charger

k_c	Quad-port charger
L_{sb}	Length of cable required from the source to block [m]
l	Number of quad port EV charger
m	Number of dual port EV charger
n	Number of single port EV charger
N	Maximum number of parking spots in the parking lot
N_{sb}	Number of ports occupying a target block
n_{ep}	Number estimated port to be added to the parking lot
NPV	Net Present Value [$]
p	EV port number
r_a	Row index within the block
R	Number of rows in the block
s	Power source location
t	Year number
T	Last year of lifespan
W_{sb}	Width of the cable required for block [m]

1. Introduction

As more and more countries formally commit to reduce their carbon footprint to tackle the climate change and global warming crisis, immediate measures need to be taken in all industrial, residential and transportation sectors to achieve the common goal.

1.1 Background

According to the Department of Environment and Climate Change [1] the transportation contributes to 24% of the total green house emissions in Canada in 2020, as shown in Figure 1-1. Over the recent decade, the demand on Electric Vehicles (EVs) have been accelerate significantly due to the rapid decrease in CO_2 emissions compared to the combustion engines (ICE).

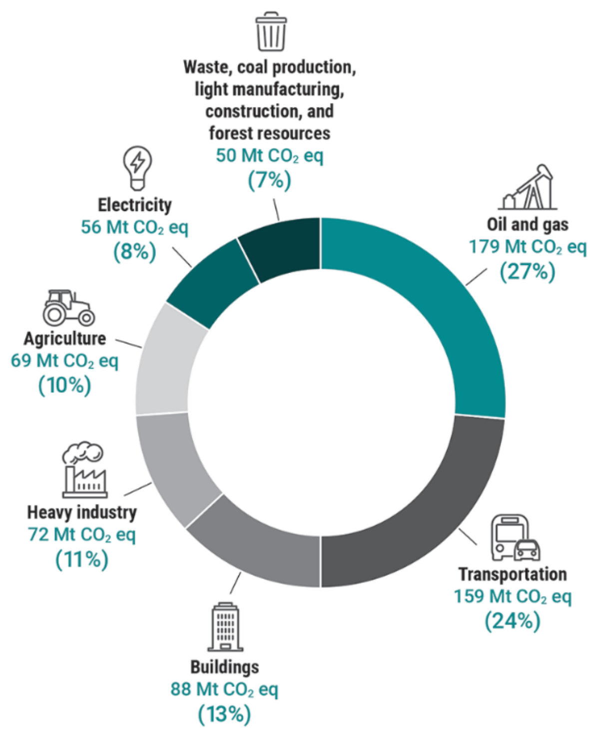


Figure 1-1 - Canada's total greenhouse gas emissions by sector in 2020 [1]

Statistically situations are still far away from the goal, as the global market share of electric vehicles is still under 1% [1] as shown in Figure 1-2, whereas the percentage projected growth of the same is promising as shown in Figure 1-3. While existing product line of the electric vehicles is close to achieving the desirability and practicality in terms of driving range and performance to replace their gasoline counterparts, lack of incentives and sufficient charging stations is the foremost reason hindering further market penetration of EVs. The lack of accessible fast charging stations on routes leads to range anxiety, which prevents more users from switching to electric vehicles. For context, the current range of most electric vehicles typically varies between 200 to 500 kilometers, equivalent to approximately 2 to 5 hours of travel time under peak-hour conditions during daily commutes, and comparable durations for long-range trips

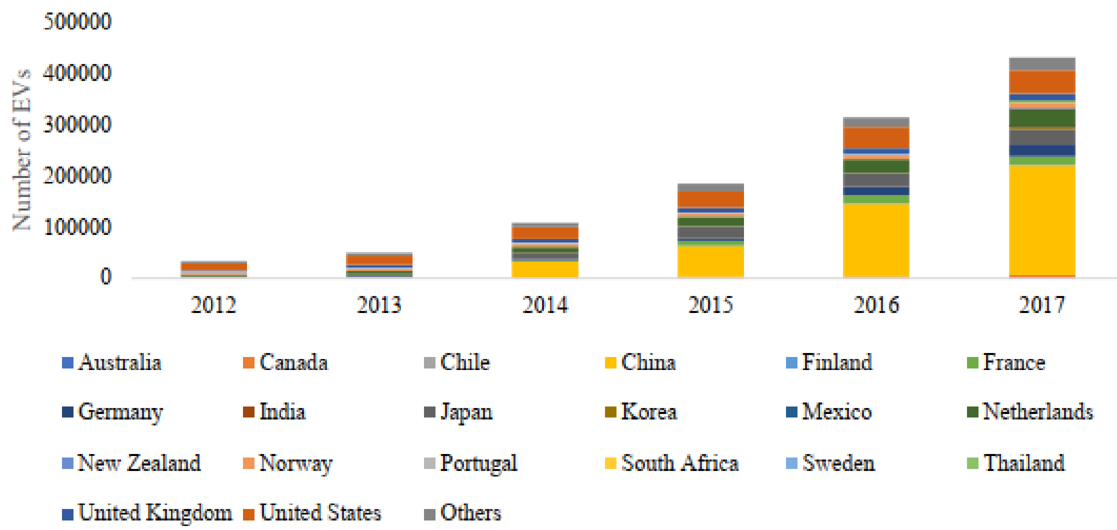


Figure 1-2 - Total number of electric vehicles over the years [2]

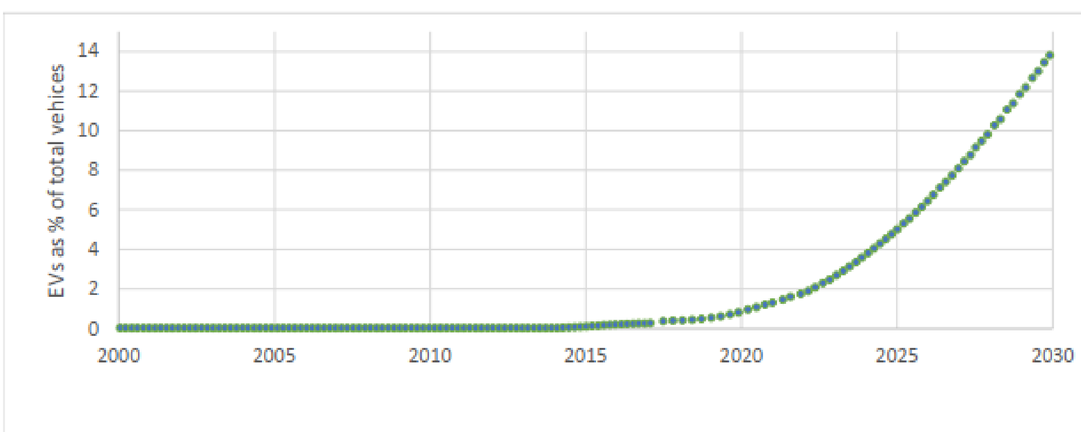


Figure 1-3 - Projected growth of Electric Vehicle Penetration (%of total vehicles) [2]

Based on the power and the range of voltages that are supported by EV chargers, they are classified into three levels [3] A) lower than 3.7 kW are Level 1 chargers, B) between 3.7 and 22kW are Level 2 chargers, and C) higher than 22kW are Level 3 chargers as illustrated.

a. Level 1 Chargers: lower than 3.7 kW
b. Level 2 chargers: between 3.7kW to 22 kW
c. Level 3 Chargers: higher than 22kW

1.2 Problem Statement

As the supply of electric vehicles (EVs) continues to grow, shopping center owners face increasing pressure to accommodate EV charging demands in their parking facilities. The existing parking infrastructure is generally not designed to support Electric Vehicle Charging Stations (EVCS). Therefore, in this study we are aiming to address this issue by determining an optimization algorithm that can accommodate the placement and distribution of EVCS in existing indoor parking areas of commercial buildings in a cost-effective manner. The city of Montreal, Quebec, is taken as our case study, focusing on the growth in EV charging station by the year 2035. The development of an optimization model that guides property owners in transforming traditional parking spots into EV charging spaces is what we are aiming for. The development of the model involves deciding on the types (pedestal, wall-mounted) and configurations of chargers (single-port, dual-port, quad-port) and their distribution across available parking spots, while minimizing life cycle cost for property owners.

1.3 Research Objectives

This study addresses the need for Electric Vehicle Charging Stations (EVCS) in the existing indoor parking spaces from the perspective of shopping center owners in Montreal, Quebec. Explores strategies for converting existing parking spots into EV charging spaces with an emphasis on cost optimization. Achieving this objective could be done through three main steps:

1) Considering the desired number of ports in the shopping center parking layout, based on the available estimation on the EV growth.
2) Determining parking blocks based on the parking size to allocate the different types of ports into each of them.

3) Generating total potential multi-port (Single port, dual port, quad port) combinations within the total desired number of ports.
4) Distributing the port combinations into the different parking blocks combinations to ensure that all the options considered.
5) Developing a Life Cycle Cost (LCC)-Based optimization model to achieve minimum costs for EVCS placements. An optimization algorithm will be developed to evaluate different placement scenarios, aiming to identify the most cost-effective configurations.

This study is proposing an optimization model to expand Electric Vehicle Charging Stations (EVCS) spot in the existing indoor parking facilities of the shopping centers depicted in Figure 1-4.

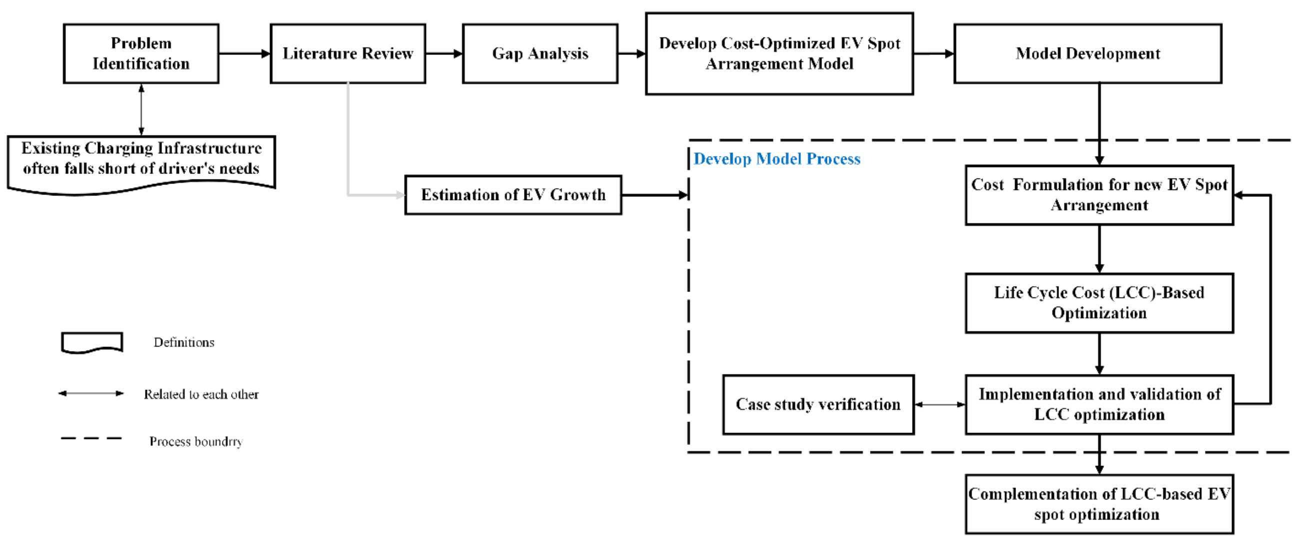


Figure 1-4 - Research Methodology framework

This model is designed to help property owners make informed decisions about EVCS placement. The framework emphasizes layout constraints essential for optimizing charger configurations within parking spots, ensuring efficient and feasible setups and placements.

1.4 Thesis Structure

This thesis is structured into five chapters, each focusing on a distinct aspect of the study on optimizing EVCS placement in shopping centers parking. The following is a brief overview of the remainder of the thesis:

Chapter 1 Introduction: This chapter establishes an overview and background information, focusing on problem statement and research objectives of this study.

Chapter 2 Literature review: This chapter presents a theoretical foundation, reviewing previous studies on EV charging infrastructure with an emphasis on urban planning, life cycle cost considerations, and multi-facility location optimization. It discusses global trends, types of EV chargers, and existing methodologies for EVCS placement, providing context for the research gap this study addresses.

Chapter 4 Model development: This chapter defines the scope of work and details the step-by-step development of the optimization model. It begins with the definition and combination of parking blocks within existing spaces, followed by the port distribution logic across single-port, dual-port, and quad-port configurations. The chapter then presents the mathematical formulation of the model, focusing on minimizing life cycle costs (LCC) for property owners.

Chapter 5 Model Implementation and Validation: This chapter presents the case study and validates the proposed model. Optimization result discussed to verify the model’s effectiveness.

Chapter 6 Conclusion and Recommendation: This chapter summarizes the research contributions, highlights the key assumptions and limitations of the thesis, and offers recommendations for future research.

2. Literature Review

This chapter provides a review of existing research on Electric Vehicle Charging Station (EVCS) placement, focusing on optimization techniques and challenges in the field. It establishes the foundation for the study by highlighting the significance of strategic EVCS placement and identifying gaps in current approaches.

2.1 Introduction

In recent years global automobile industry has taken major strides in transition to Electric Vehicles (EVs), to move towards sustainable energy goals and tackle climate change. Rapidly falling battery costs and continuously improving charging technologies are bringing EVs on par with conventional vehicles regarding practical usage and range. Researchers from electrical and transportation industry have been studying optimal ways of distributing the Electric Vehicle Charging Stations (EVCS) in the past decade. EVs can be broadly classified as:

A. All Electric Vehicles, where the battery charging is the only source of refilling, also known as plug-in Electric Vehicles (PEVs) or Battery Electric Vehicles (BEVs).
B. Plug-in Hybrid Vehicles (PHEVS), where the electric can be refueled through multiple sources like gasoline and battery charging.
C. Hybrid Electric Vehicles (HEVs), where the vehicle is propelled using both Electric Motor and IC engine, but the battery is charged through regenerative braking or IC engine only.

In this thesis, only All Electric Vehicles and Plug-in Hybrid Vehicles will be taken understudy since they are equipped with charging plugs and hybrid Electric Vehicles are not considered.

This study is focused on strategic EVCS placement. In literature, it is noticed that multiple modeling approaches and problem-solving algorithms were used to optimize the required parameters. Optimization is referred to as the process of finding the best feasible values (maximum or minimum) for some objective functions, while satisfying some given domains and constraints. Location Allocation (LA) solution methods have been in practice for a number of applications such as location citing for warehouses, gas stations, electric transformers, urban planning, etc. When an owner or decision maker faces the task of allocating new facilities, they typically want to optimize certain objectives.

As shown in Figure 2-1, the share of charging infrastructure varies across regions, and the percentage of public charging infrastructure in place by 2020 indicates progress towards the 2030 target. Montreal consists of five primary areas: Laval, Longueuil, the Northern Ring, the Southern Ring, and the Montreal Administrative Region, where the share of public charging infrastructure ranges from 17% to 21% [4] In the Figure 2-1, darker blue shades represent a higher percentage of infrastructure, while lighter blue indicates a lower percentage across the regions of Quebec and Montreal. Montreal, being the most populous city, is further divided into 19 districts.

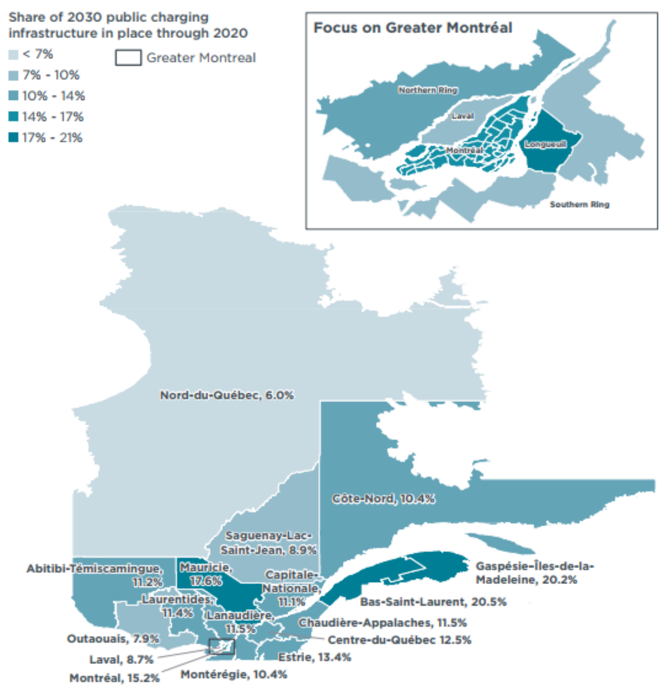


Figure 2-1 - Share of 2030 public charging infrastructure in place through 2020

2.2 Global Trends in Adoption of EV

The adoption of electric vehicles (EVs) is anticipated to accelerate globally, driven by factors such as government incentives, advancements in battery technology, and heightened environmental awareness. As a result, the global EV market is expected to experience substantial growth in the coming years, with rising demand from developing nations [5]

2.2.1 Europe

In Europe, countries like Norway, the Netherlands, and Germany are leading the charge in EV adoption. Norway's incentives have resulted in EVs accounting for more than 50% of new car sales. The European Union has set ambitious targets for reducing carbon emissions, which will further boost the adoption of electric vehicles. By 2035, the EU aims to have at least 30 million electric cars on the road [5]

- Norway: In 2020, electric cars accounted for 54.3% of all new car sales. By 2025, Norway aims to phase out the sale of new internal combustion engine cars entirely.
- Netherlands: Electric vehicles made up 20.6% of new car sales in 2020. The country plans to have all new cars be emission-free by 2030.
- Germany: Electric vehicles represented 13.5% of new car sales in 2020. The government has set a target of 7-10 million electric vehicles on the road by 2030.

2.2.2 United States

In the United States, California is at the forefront of EV adoption, with policies aimed at reducing greenhouse gas emissions and promoting clean energy. The state offers rebates and incentives for EV purchases and has an extensive network of charging stations. Other states are following suit, and the federal government is also providing support through tax credits and funding for charging infrastructure [5]

- California: EVs accounted for 8% of new car sales in 2020. The state aims to have 5 million zero-emission vehicles on the road by 2030.
- Nationally: EV sales in the U.S. reached about 2.5% of total car sales in 2020. The Biden administration aims to have 50% of all new vehicle sales be electric by 2030.

2.2.3 Asia-Pacific

The Asia-Pacific region, particularly China, is expected to continue dominating the electric vehicle market. China's government has set stringent targets for reducing air pollution and is heavily investing in EV infrastructure. Other countries in the region, such as South Korea and India, are also ramping up their efforts to promote electric vehicles [5]

- China: Electric vehicles accounted for 5.4% of all new car sales in 2020, with over 1.3 million EVs sold. By 2025, China aims for electric vehicles to make up 20% of all new car sales, which translates to about 7 million vehicles annually.
- South Korea: The government targets having 1.13 million electric vehicles on the road by 2025, with a focus on expanding charging infrastructure.
- India: The government aims to achieve 30% electric vehicle penetration by 2030, which would require about 10 million electric vehicles annually.

2.3 Estimation of required EV Charing Infrastructure

The number of expected EV charging stations plays a crucial role in the allocation of desired expansion from the property owner's perspective. This thesis aims to address the expected growth rate of EVs within the province of Quebec, with a focus on targeting Montreal, the most populous city in Quebec. Based on the available information in Quebec, the average annual growth rate for EVs is 48.7 from the year 2017 to 2020 and for charging stations is approximately 51.9 [4].

Table 2-1 - Average annual growth rate for EVs and charging stations in Quebec from year 2017 to 2020

Category	**Average annual growth rate (%)**
EVs	48.4
Charging stations	51.9

The number of current EV charging stations in Quebec is expected to reach 3,072,000 by year 2035 and for charging stations is around 69,000. This information simply can be used to effectively estimate the number of expected EV charging stations [4]

Table 2-2 - Expected number of EVs and charging stations in Quebec in 2035 [4]

Category	**Number**
EVs	3,072,000
Charging stations	69,000

Table 2-3 - The expected ratio of EV cars to the charging station in Quebec in the 10 years

Year	**Ratio of EV cars to the Charging station**
2020	36.4
2030	35.7

The growth projections for EVs and public chargers by year 2035 indicate a growth ratio of 34.9 for the number of EVs on the road and 11.5 for public chargers. This discrepancy is due to the utilization factor, which is expected to increase by 2035.

Table 2-4 - EVs and public charger's growth projection in 2035

	2020	**2035(Projected)**	**Growth Ratio**
Number of EV on the roads	88,000	3,072,000	34.9
Number of public charges	6,000	69,000	11.5

According to the 2022 report by the International Council on Clean Transportation (ICCT) [4] the utilization factor of public chargers remains low. This indicates that electric vehicle (EV) owners primarily prefer charging their cars at home. The daily usage of public chargers varies by region, with utilization rates typically higher in larger urban areas. These areas have a higher concentration of both EVs and charging stations, facilitating more frequent and convenient matches between EV trips and charger locations. Looking ahead, the utilization factor of chargers is expected to increase significantly by 2035. This anticipated growth aligns with the projected increase in EV adoption and the corresponding expansion of public EV charging infrastructure. Consequently, the growth rate of EVs should be mirrored by a proportional increase in the number of public EV charging stations.

Table 2-5 - Public EV charging station utilization factor in different regions in Quebec Province

Region	Normal AC charger utilization per day (in hours)	
	2020	2035
Abitibi-Témiscamingue	1.3	5.2
. . .	. . .	
Montreal	1.9	6
Quebec Province	1.84	5.88

We can contribute to increase of utilization factor by expansion of EVCS in city amenities: i.e., shopping centers.

2.3.1 Utilization factor modeling approach for EV Charging Stations [4]

The model is designed to increase the utilization time per charger by yearly increase in the penetration of electric vehicles. Due to penetration of electric vehicles in each region, the utilization time is expected to vary. As a first step, the model will predict the utilization duration of various stations in the region Based on the available information and planned EV growth. The utilization duration is a critical factor as it directly influences the energy consumption of charging stations. By combining the predicted utilization duration with the power consumption rates of the charging stations, we can compute the daily energy consumption in kilowatt-hours (kWh). This calculation encompasses the active charging time at home, workplaces, and public stations. Hence, providing a comprehensive distribution of utilization time is essential. Detailed information regarding the utilization time distribution will be discussed in subsequent sections. Following the estimation of utilization duration, the model will predict the future energy demand of electric vehicles. This involves projecting the growth in EV numbers and their corresponding energy requirements. To determine the number of required charging units, the model will divide the total energy required to charge the EVs by the energy provided by each charger. This step ensures that the charging infrastructure can meet the anticipated energy demand efficiently. The proposed model not only aims to enhance the utilization of existing chargers but also provides a framework for predicting future energy needs and infrastructure requirements. By aligning the growth rate of EVs with the expansion of charging stations, the model ensures a balanced and sustainable development of EV charging infrastructure.

2.3 Classification of location allocation problem

There are four components that can forms any location allocation problem. Here are some key considerations:

a. Static vs. Dynamic LA Problems: In static problem, locations and demands remain constant over the planning horizon. However, in dynamic problems, locations or demands evolve over time, requiring adjustments to the allocation plan [6].
b. Discrete vs. Continuos LA Problems: Discrete facilities can only be located at predefined candidate locations, and continuous facilities can be placed anywhere within a defined space [7].

c. Single-Facility vs. Multi-Facility LA Problems: Single-Facility involves finding the optimal location for a single facility, in contrast, multi-facility considers multiple facilities that need to be located simultaneously, often with interactions between them [8][9][10].

d. Capacitated vs. uncapacitated LA Problems

   Capacitated facilities have limited capacity, and allocations must respect these constraints. In contrast, uncapacitated facilities are typically modeled as having no capacity constraints, meaning they can serve unlimited demand. However, this assumption may not hold in practical scenarios. For instance, the ability of substations and redundancy in the power supply network can limit capacity. If multiple industries establish themselves in a nearby region, or a facility like a warehouse for 500 electric buses is added, the local or district electric circuit may face constraints that limit the ability to supply power effectively.[11]

The strategic considerations for allocation from the owner perspective, these considerations align with practical decision-making goals for facility placement. Here's an outline:

- Cost Minimization: Owners aim to minimize costs associated with facility placement, such as equipment costs and maintenance and operational costs
- Facilities to be located: Owners want to ensure that the allocated facilities adequately cover the demand from customers. This involves determining the right number of facilities and their locations to efficiently serve the target population.
- Market potential: Owners might analyze market potential in different areas to identify regions with high demand or growth prospects. Allocating facilities strategically can tap into these opportunities.

From the owner's perspective, models can be classified as follows:

- Deterministic models: These models assume that all input parameters, such as facility capacities, and locations, are fixed and known in advance. They are suitable when owners can rely on accurate and stable data, such as number of EV growth or specific parking lot capacities. There is no variability or randomness in parameters [12]
- Stochastic models: In contrast, a stochastic model incorporates probability distributions for, accounting for uncertainty and variability in these parameters [12]. This thesis does not

deal with uncertain parameters, as all input data is based on fixed and predefined assumptions.

In this thesis, the number of EV Charging Ports (EVCP) to be installed and the locations are fixed, with no variability. The parking blocks are predefined with specific capacities, and there is not randomness or uncertainty into the number of EVs or layout configuration. Based on these reasons, the approach is deterministic model since the parking capacity is fixed and known before the optimization process begin. In this thesis, a capacitated problem means that there are specific limits on how many blocks in the parking can be grouped or placed. The aim is to site Level 2 charger with different number of ports (single-port, double port, and quad-port) across different blocks in the parking lot. Hence, the problem is deterministic capacitated multi-facility problem.

2.4 Methods for solving location allocation problems

There are several algorithms used to solve or optimize the objective function or mathematical models. Exact solution methods are guaranteed to find the optimal solution for the problem. Whereas heuristic methods provide a feasible solution with no optimality guarantee, like genetic algorithms and particle swarm optimization. This Chapter discusses EVCS location planning by various research through an extensive literature review and are broadly categorized into: Exact solution methods and Heuristic methods.

Selecting the most sustainable site plays an important role in the life cycle of electric vehicle charging stations (EVCS), which needs to consider some conflicting criteria. In the most studies, large and urban areas are mostly used for the selection of site by using a limited number of criteria in their mathematical methods. Lin and Hua (2015) [13] provide a particle swarm optimisation model to establish flow capturing optimal location model for fast-charging station locations. This model considers the installation cost, the service area of a fast-charging station, and the rate of EVs in traffic flow. Several studies extend the set of input parameters according to the volume of EV use. Flow Capture Location Method (FCLM) is designed to optimize the placement of facilities in a network to capture the maximum flow of resources or services passing through the network [13]. Facilities are placed at nodes in the network to capture all the flow passing through those nodes. The earliest adaptions of the optimization techniques to plan EVCS location dealt with long distance travel in interstate highways using different forms of Flow Capture Location Methods (FCLM) for refueling stations. Wang and Wang (2010) [14] focus on the placement of refuelling stations to serve both inter-city and intra-city trips of alternative fuel vehicles using data on the distance matrix of O-D flows and considering the population coverage. The charging infrastructure was determined in two steps in Liu et al.[15]. First, the locations were selected considering the service radius of charging stations and environmental factors, such as location adaptability, land value, or power-supply reliability. In the second step, charging capacity was determined for each selected location. Charging locations based on O-D flows and expected EV use were proposed by Csaba Csiszár. (2020) [16]. Zhang and Zhao (2020) [17] defined three criteria groups that influence the utility of charging locations: sustainable development, operation efficiency, and service safety. Different from the previous studies which mostly utilize programming (optimization) models, this paper employed a multi-criteria decision-making (MCDM) method to consider some subjective but important criteria for EVCS site selection. To reflect the ambiguity and vagueness due to the subjective judgments of decision makers, fuzzy TOPSIS method was applied to select the optimal EVCS site. Yi and Bauer (2016) [17] established an optimisation model for charging station locations from an energy-aware viewpoint. Two criteria were combined in the model: reach the most customers or households by providing an energy cost constraint; minimise overall transport energy consumption required to perform charging processes. Boyac et al. [19] proposed an integrated multi-objective mixed integer linear programming model and discrete event simulation framework to optimize operational decisions for vehicle and personnel relocation in a carsharing system with reservations (Boyac et al.2017). He et al. [20] introduced a mixed integer second-order cone program to approximate the planning problem faced by service providers of electric vehicle sharing systems in designing a geographical service region (He et al. 2017). Rui Chen et Xinwu Qian [21] seek to address the optimal capacity and location problem of charging facilities for EVs by explicitly modeling queuing time at charging facilities and equilibrium response of EV drivers to travel time and waiting time. They formulate the problem as a bi-level optimization problem, with the upper-level objective being to minimize the joint cost of construction and drivers' travel time and waiting time. The lower-level problem captures equilibrium responses of EV drivers to the upper-level decisions. It is more natural to adopt the bi-level optimization method to tackle location problems considering a non-cooperative game. In their study proposed the first work to optimize both the location and capacity of charging facilities by considering the equilibrium responses of drivers to travel time and waiting times, then EVs at each charging facility are modeled as the M(t) queue, and approximation approaches are then developed, which accurately characterize the average waiting time and waiting probability. The problem is formulated as a mathematical program with complementarity constraints (MPCC), and the solution algorithm is developed, which solves the original problem as a sequence of relaxed nonlinear programming problems. Serdar Celik and Seyda Ok (2024) [21] by integrating location modeling with demand forecasts and market penetration they used genetic algorithm to solve the p-median problem for location selection and Arena 14 simulation software to model station traffic and optimize charging unit types and quantities. The model prioritizes public areas, considering potential demand points and station locations to propose optimal charging areas. Results indicate that the model minimizes travel distances and waiting times, offering a scalable solution. The p-median model is a typical node-based facility location model and is therefore particularly well-suited for processing such node-based charging demand. Consequently, we will utilize the p-median model to investigate how changes in the number of EVCS can affect station capacity and the type of charging module. In order to describe some of the inter-related elements in solving a p-median problem to optimality using MATLAB software. The p-median model aims to determine the locations of p facilities from among candidate locations by ensuring that each customer is served by one facility, thereby minimizing the transportation costs or weighted distances between customer and facilities. Liu and Zhang [23]considered geographic information, construction costs, and running costs in their study. Construction costs included land expenses and investment in distribution transformers, while running costs accounted for power supply losses. With traffic flow as a constraint, they addressed the core challenge of locating electric vehicle charging stations. The authors employed a particle swarm optimization algorithm to solve this problem.

Most existing studies concentrate on the placement of EVCS in large urban areas and network systems. This study [24] uses a geographic information system (GIS) to incorporate various demographic, neighborhood, presents novel methods for deploying charging infrastructure for both electric cars and buses. The authors developed weighted sum-models to assess candidate sites for public charging stations, considering factors like installation cost and service area The paper [39]proposes the use of Multi-Objective Particle Swarm Optimization to determine the optimal locations for fast-charging electric vehicle charging infrastructure within a distribution system. This method aims to minimize power loss and voltage deviations, ensuring efficient and reliable operation of the distribution network, paper includes a time-series analysis of distribution system and EV load variations using MATLAB. This analysis helps in understanding the impact of EV charging on the distribution network over time. Besides optimization, this paper also examines the economic and environmental factors influencing the placement of EV charging station. Moreover, numerous studies have investigated the optimal placement of charging stations (CSs) for electric vehicles (EVs) in various regions worldwide. These studies have utilized various optimization techniques, such as genetic algorithms, particle swarm optimization (PSO), machine learning algorithms, and linear programming to optimize EVCSs [26][27]. For instance, a Mixed Integer Linear Programming (MILP) model was developed to determine the best location and size of charging stations in cities. This model incorporated inputs such as land-use classifications, recharging descriptions, and traffic patterns to determine the optimal placement and number of charging stations [28]. Another study employed a genetic algorithm to determine the position and type of recharging outlets while considering budgetary constraints and optimizing the placement based on the number of travels ending at specific locations in the city [29]. Additionally, a quantum-based PSO algorithm was utilized as a multi-objective approach to optimize EVCS placement, considering factors such as grid stability, maximum coverage, customer demand, and cost reduction [30][31].

A Voronoi diagram is a type of geometric structure used in computational geometry. It partitions a plane into regions based on the distance to a specific set of points, known as seeds or sites. Each region contains all the points closer to one particular seed than to any other. This method is widely used in various fields such as geography, and urban planning due to its ability to model spatial structures and relationships effectively. Researchers have used Voronoi diagrams to optimize the placement of EV charging stations. By dividing the service area into Voronoi cells, each charging stations. By dividing the service area into Voronoi cells, each charging station can serve the nearest set of EVs, minimizing travel distance and improving accessibility [32]. A study Liu [33] proposed a model to assess the impact of incorporating three types of charging infrastructure, namely fast charging public stations, home charging posts and battery swapping stations and analyze its effects on the cost, charging time and impact on the distribution grid. This paper also considers retrofitting of existing gas stations with EVCS, considering their proximity from the electric distribution grid as a constraint for the selection. The location was determined based on the charging demand data through Voronoi diagram, due to the large geographical area to be covered.

The p-median model falls under the category of location-allocation models in operations research. It is used to determine the optimal placement of facilities to minimize the total distance between demand points and the nearest facility. This model is particularly useful in urban planning. Subject to the constraint that a fixed number of faculties (p) are to be located [34]. A study established an improved P-Median model to minimize time costs for EV charging stations. This model considered constraints such as the capacity of charging stations and customer demand. A greedy heuristic algorithm was proposed to solve the problem, and simulations showed the method’s effectiveness. Another research applied a genetic algorithm (heuristic method) to solve the P-Median problem for selecting optimal locations for EV charging stations. The model prioritized public areas and considered potential demand points to propose optimal charging areas. Some studies have integrated the P-Median model with other optimization techniques. For example, a bi-level optimization problem was formulated to minimize the fleet’s daily charging operation time for electric ridesharing services. Several location planning models have used this approach and its extended versions to calculate optimal locations considering various factors like user charging behaviors and EV range [35].

Dynamic Programming (DP) is a powerful algorithmic technique used for solving complex problems by breaking them down into simpler overlapping subproblems and solving each subproblem just once, storing its result for future use. The key idea behind dynamic programming is to avoid redundant calculations by memorizing the results of previously solved subproblems, thus significantly improving efficiency compared to brute force methods. The two primary strategies used in dynamic programming are:

- Top-down approach (also known as memoization): The problem is solved recursively, and the result of each subproblem is stored (memoized) so that it can be reused later when needed, rather than recalculated.
- Bottom-up approach: The problem is solved iteratively, starting from the smallest subproblems and building up to the solution of the larger problem. Each subproblem's result is stored in a table, which is used to compute solutions to larger subproblems.

Chen, Bo-Chiuan & Wu, Yuh-Yih [36] investigates power management strategies for Range-Extended Electric Vehicles (RE-EV) using Dynamic Programming (DP). The aim is to optimize the balance between fuel economy and battery life. Dynamic programming is applied as a horizon optimization technique that ensures a globally optimal strategy, given a predefined driving cycle. The optimization problem is approached using two cost functions: one for minimizing fuel energy losses and another for minimizing battery energy losses. These dual objectives reflect the trade-off between extending the vehicle's range and prolonging battery life. The DP algorithm evaluates both strategies to find the optimal power split between the battery and the generator. In the R. Wang and S. M. Lukic paper [38] titled: "Dynamic Programming Technique in Hybrid Electric Vehicle Optimization" focuses on the application of DP to optimize power management strategies in HEV's. DP is utilized as a global optimization technique to determine the optimal split between battery and engine power at each time step during a driving cycle. This paper is a comprehensive study of applying dynamic programming to optimize the energy management of hybrid electric vehicle.

The brute force method is a straightforward and exhaustive approach to solving computational problems by systematically enumerating all possible solutions and checking each one to find the best outcome. Despite its simplicity, the brute force method is a fundamental problem-solving technique in computer science and optimization theory. It guarantees finding the optimal solution, but it is often computationally expensive, making it impractical for large-scale problems. Brute force algorithms are characterized by their direct approach to problem-solving. They operate by:

1. Generating all possible solutions or configurations for a given problem.
2. Evaluating each solution to determine whether it satisfies the problem's requirements or optimizes the given objective.
3. Selecting the optimal solution after evaluating all possibilities.

The brute force method is applied across various domains, particularly when the problem size is small. Zhao N, Roberts C [38]applies an enhanced brute force method to optimize the driving speed curve of trains. The enhanced brute force algorithm proves effective in optimizing train operations by reducing both energy costs and delays, also the enhanced version reduces computational time by narrowing down the solution domain, focusing only on the most promising speed series, thus making the brute force search feasible for real-world applications. The paper titled “Real-Time Implementation of Green Light Optimal Speed Advisory for Electric Vehicles”, which aims to optimize the driving speeds of electric vehicles (EVs) to minimize both energy consumption and travel time by leveraging traffic light timing data. In particular, the solution’s performance was shown to be very close to a brute-force optimal solution but which much shorter calculation time and has significant potential for energy saving.

Heuristic methods like Agent Based Methods (ABM) and Particle Swarm Optimization (PSO) offers great options to explore a highly diverse data set to find optimal solutions for single objective and multi-objective solutions with modified versions. Heuristic approaches on the other hand do not give the ideal accurate solution but making them particularly useful in fields where time and computational resources are limited. The paper [39] discusses and applies heuristic methods for solving the EV Scheduling and Charging Problem. Alesiani, Francesco & Maslekar, Nitin [40] discusses a method to optimize the routing and charging stops for a fleet of electric vehicles (EVs) using a genetic algorithm. The genetic algorithm is chosen because it is well-suited for exploring large and complex solution spaces, such as vehicle routing with charging constraints. The algorithm is tested on a randomly generated network, simulating a fleet of vehicles that must visit charging stations. The results show that the proposed genetic algorithm effectively minimizes the number of charging stops and balances the load across charging stations, reducing congestion. Other study [41] uses genetic algorithm (GA) to optimize the charging stop scheduling for a fleet of electric vehicles, the algorithm is tested on a simulation network, with vehicles randomly assigned routes and charging stations placed in a grid while minimizing the combined costs of travel time, charging time, and energy consumption.

A recent review paper published in year 2024 [5] explores three key areas in EV integration: charging/discharging scheduling, charging navigation, and charging station planning. First, the paper discusses the features and importance of EV integrated traffic–power networks. Then, it examines key factors influencing EV strategy, such as user behavior, charging preferences, and battery performance. Next, the study establishes an EV charging and discharging model, with particular emphasis on the complexities introduced by factors such as pricing mechanisms and integration approaches. Furthermore, the charging navigation model and the role of real time traffic information are discussed. Additionally, the paper highlights the importance of multitype charging stations and the impact of uncertainty on charging station planning. The paper concludes by identifying significant challenges and potential opportunities for EV integration.

In Charging Station Planning approaches, studies have focused on optimizing the placement and sizing of charging stations to maximize captured traffic flow and minimize power loss [43]. This includes planning for different types of charging stations and integrated charging station types. Charging station planning, as a long-term optimization process, requires consideration of a broader range of uncertainties. Predicting future demand for EV charging is challenging due to the evolving nature of EV adoption rates and usage pattern [44]. Zare & Dejamkhooy (2023) [44] presents a Mixed-Integer Linear Programming (MILP) model for expansion planning of Radial Power Distribution (PDNs) and EVCS, the model takes into account the construction or reinforcement of substations and circuits, along with the integration of EVs, the installation of DGs, and the placement of capacitor banks, all regarded as traditional conventional expansion options alternatives. To address uncertainties associated with DG generation, conventional loads, and EV demand, our model identifies optimal installation and asset locations, Zare & Dejamkhooy (2023) [44]formulate this as a stochastic scenario-based program with chance constraints for Power Distribution Network Expansion Planning (PDNEP), minimizing investment, operational, and energy loss cost costs over a planning horizon. Through two deterministic and stochastic approaches, encompassing six case studies on an 18-node test system. Notably, the numerical findings underscore the substantial cost reduction achieved by including EVCSs in the stochastic expansion planning approach, demonstrating its cost-effectiveness. The proposed model underscored suitability for solving the PDNEP problem in PND. The proposed expansion planning horizon [44]is long-term and divided into three periods, with each period representing five years, totaling 15 years. When modeled realistically, the economic and physical characteristics of the PDNEP problem yield a large-scale Mixed-Integer Nonlinear Programming (MINLP) problem that is highly complex to solve. Therefore, linearization techniques can transform the MINLP into a more tractable MILP model. Figure 2-2 and Table 2-6 are summarises the existing studies around the proposed approach.

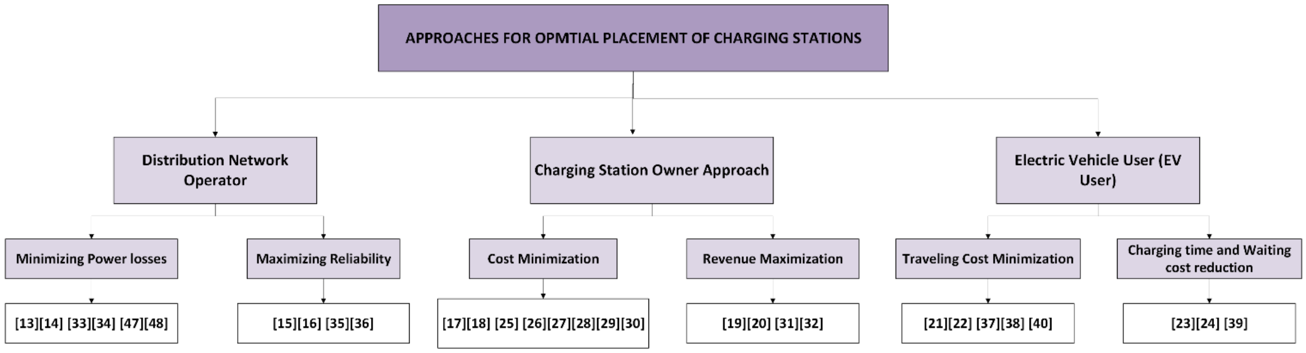


Figure 2-2 - Summary of the existing studies around the proposed approach in a flowchart form

Table 2-6 - Summary of the existing studies around the proposed approach

References	Research Objective	Modeling Approach	Exact	Heuristic	Other
[13, 14, 33, 34, 47, 48]	Minimize power losses, improve reliability	Mixed-Integer Linear Programming (MILP)	X		
[15, 16]	Optimize installation and operational costs	Mixed-Integer Nonlinear Programming (MINLP)	X		
[17, 18]	Optimize multi-objective systems	Genetic Algorithm (GA)			X
[21, 22, 37]	Minimize traveling costs	Particle Swarm Optimization (PSO)			X
[19, 20]	Spatial resource allocation	Voronoi Diagram		X	
[23, 24, 39]	Address multiple objectives, including environmental impacts	Integrated Multi-Objective Models			X
[25]	Minimize infrastructure costs	Linear Programming (LP)	X		
[26]	Minimize installation costs	Integer Programming (IP)	X		
[35]	Allocate resources spatially	Spatial Partitioning		X	
[30, 31, 32]	Optimize multi-objective problems	Multi-Objective Optimization			X
[37, 38]	Optimize grid impact and reliability	Grid Reliability and Impact Analysis			X
[39]	Optimize resource allocation and reliability	Combinatorial Optimization Problem	X		

[25, 27]	Sequential decision-making for cost and reliability	Sequential Decision-Making Problem (Markov Decision Process)	X		
[40, 41]	Combine solvers for complex systems	Hybrid Cost Optimization			X
[42]	Model demand uncertainty	Uncertainty Modeling Framework			X

2.5 Gap Analysis

In light of the literature review, several research gaps have become apparent in the current body of work on Electric Vehicle Charging Station (EVCS) placement and optimization. These gaps highlight areas where further investigation and innovation are necessary to address:

- Limited Focus on Localized and Non-Urban Environments: Most studies concentrate on the placement of EV charging stations in large urban areas or network-based systems. This leaves a significant gap in addressing localized environments such as shopping centers. These smaller-scale or constrained environments pose unique challenges, including limited space availability, and integration with existing infrastructure.
- The majority of studies prioritize EV users, often overlooking the perspective of property owners, such as those in commercial properties like shopping centers.
- Underrepresentation of Multi-Port Charger Configurations: The placement and optimization of multi-port chargers remain underexplored in the literature. Multi-port chargers, which can serve multiple vehicles simultaneously, introduce added complexity in terms of space allocation, and cost optimization. Addressing these challenges in capacitated layout, such as parking lots in commercial buildings, requires innovative solutions for space efficiency and resource allocation.

To conclude, in this thesis, the research addresses critical gaps in the placement and optimization of Electric Vehicle Charging Stations (EVCS), particularly within environments such as shopping centers. Furthermore, the combination and distribution of multi-port chargers in capacitated environments like indoor parking facilities requires specialized optimization model. This includes exploring innovative space allocation strategies and minimizing life cycle costs from the shopping center owner’s approach.

3. Methodology

This study integrates multi-port chargers into existing parking spots, with a special emphasis on the current layout and essential requirements for allocating dual-ports and quad-ports chargers across different spots and in various multi-port configuration.

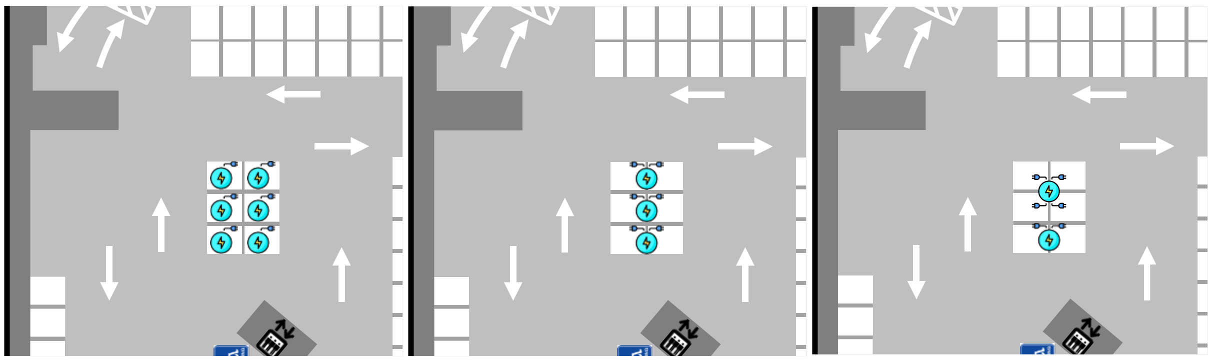


Figure 3-1 - Example of possible charging unit's configuration

From left to right in Figure 3-1, is the configuration of one port per charger, double-port configuration with two ports accommodating 2 vehicles simultaneously, and on the left side, quad-port configuration allows four EVs to charge at the same time, it is a mixed arrangement of quad port and double-port chargers due to the location limits.

3.1 Scope of Work

The LCC-based optimization model considers the expected number of EV Charing Ports (EVCPs) and life cycle cost components, including EV Charging Station Equipment Cost, Electrical System Equipment Cost, Operation and Maintenance Cost, End-of-life cost, and fixed costs. This model enables property owners to make informed and cost-effective decisions. The expected number of EV Charger Ports are distributed into chargers with standard configurations, including single port, double port, and quad-port chargers. (k ∈ (1,2,4).).

$$n_{ep} = n + m + l \qquad \text{Eq (1)}$$

n_{ep}: Number of estimated ports to be added to the parking lot

p: EV Port number $\quad 1 \leq p \leq n_{ep}$

k: Charging station Type k ∈ (1,2,4)

n: *Number of single port EV Charger*

m: *Number of dual port EV Charger*

l: *Number of quad port EV Charger*

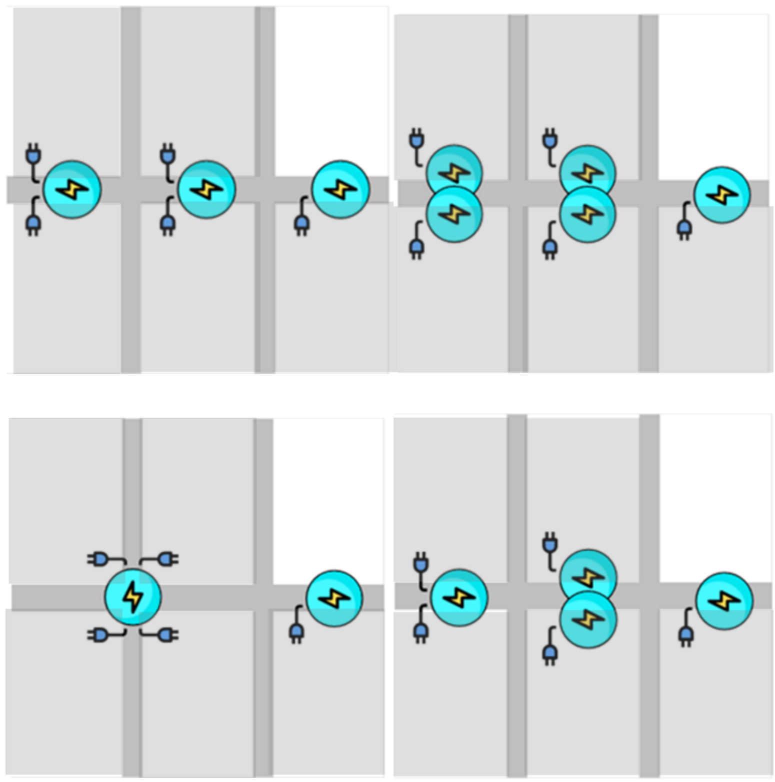


Figure 3-2 - Port Distribution Configurations

For example, if the total number of ports in the parking layout is equal to 5, there are four possible distribution options: [(1, 2, 2), (1, 1, 1, 1, 1), (1, 4), (1, 1, 1, 2)]. As illustrated in the figure, from left to right, represent two dual-port chargers and one single-port charger, five single-port chargers, one quad-port charger and one single-port charger, and finally, three single-port chargers and one dual-port charger. Correspondingly, the number of chargers required for each configuration would be 3, 5, 2, and 4, respectively. These examples show that the number of chargers and ports are not equal, and port distribution plays a crucial role in each block and the subsequent steps in the optimization process.

As shown in Fig.7, this flowchart illustrates the step-by-step methodology for optimizing the placement of EVCPs in parking facilities. The optimization process begins with dividing parking spaces into manageable blocks to generate different blocks based on the available space in the parking facility. Then, various configurations of EVCP placement are created, considering charger distributions and block arrangements. For every scenario, the total cost is calculated considering life cycle costs such as equipment cost, electrical system cost, operation and maintenance, and dismantling cost. Among all scenarios, the configuration with the lowest total cost is selected as the optimal solution.

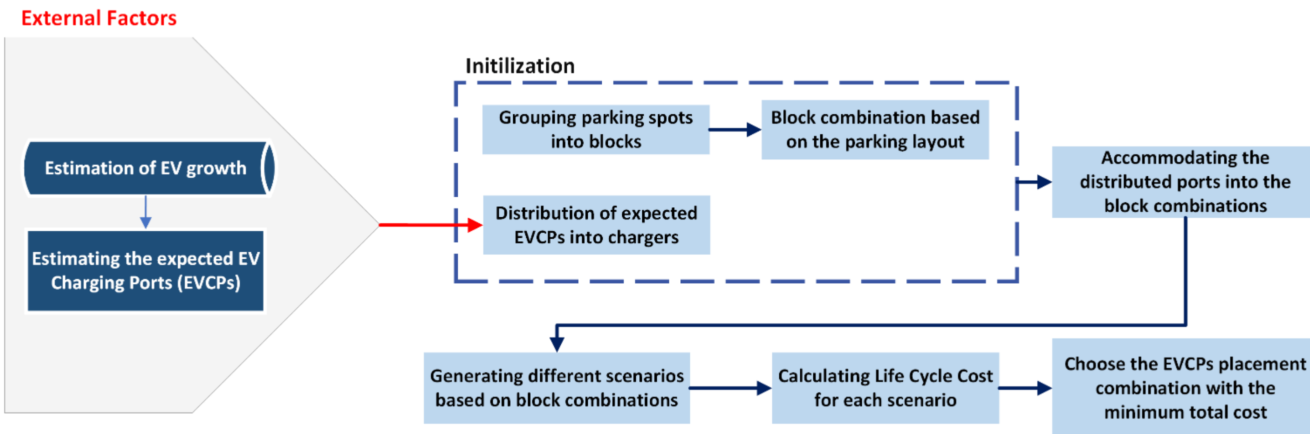


Figure 3-3 - Flow chart of the Proposed System

3.2 Block Definition and Combination in the parking layout

Parking sports are organized into blocks, which are sections or areas of the parking layout. This grouping helps in managing space (Figure 8).

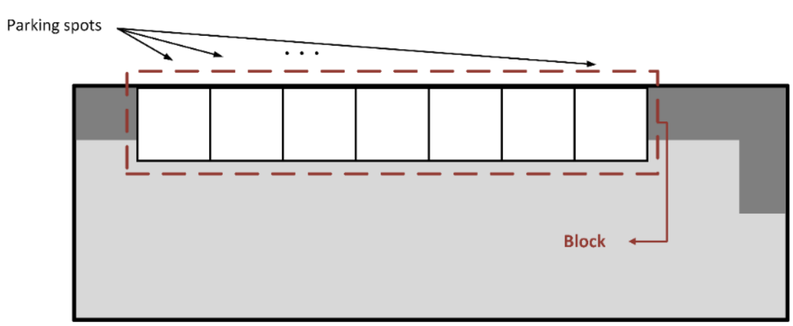


Figure 3-4 - Blocks are defined as a group of parking spots that are connecting together

This flowchart represents the initialization step, focusing on mapping the existing parking area and determining the block format as illustrated in figure 8. This step involves setting up the structure for port placement by mapping the parking area, defining possible block configurations, Parking lot is represented as a matrix to map the entire area and is divided into rows and columns. Blocks are represented in the format: (start row, end row, start column, end column). For instance, if block A is represented as (0, 0, 9, 20), this indicates that in row 0, the parking spots span from column 9 to column 20. Similarly, if block B is (1, 1, 22, 34), it represents a single row (row 1), covering parking spots from column 22 to column 34, and determining feasible block combinations. Combination number will be assumed based on the parking size and layout.

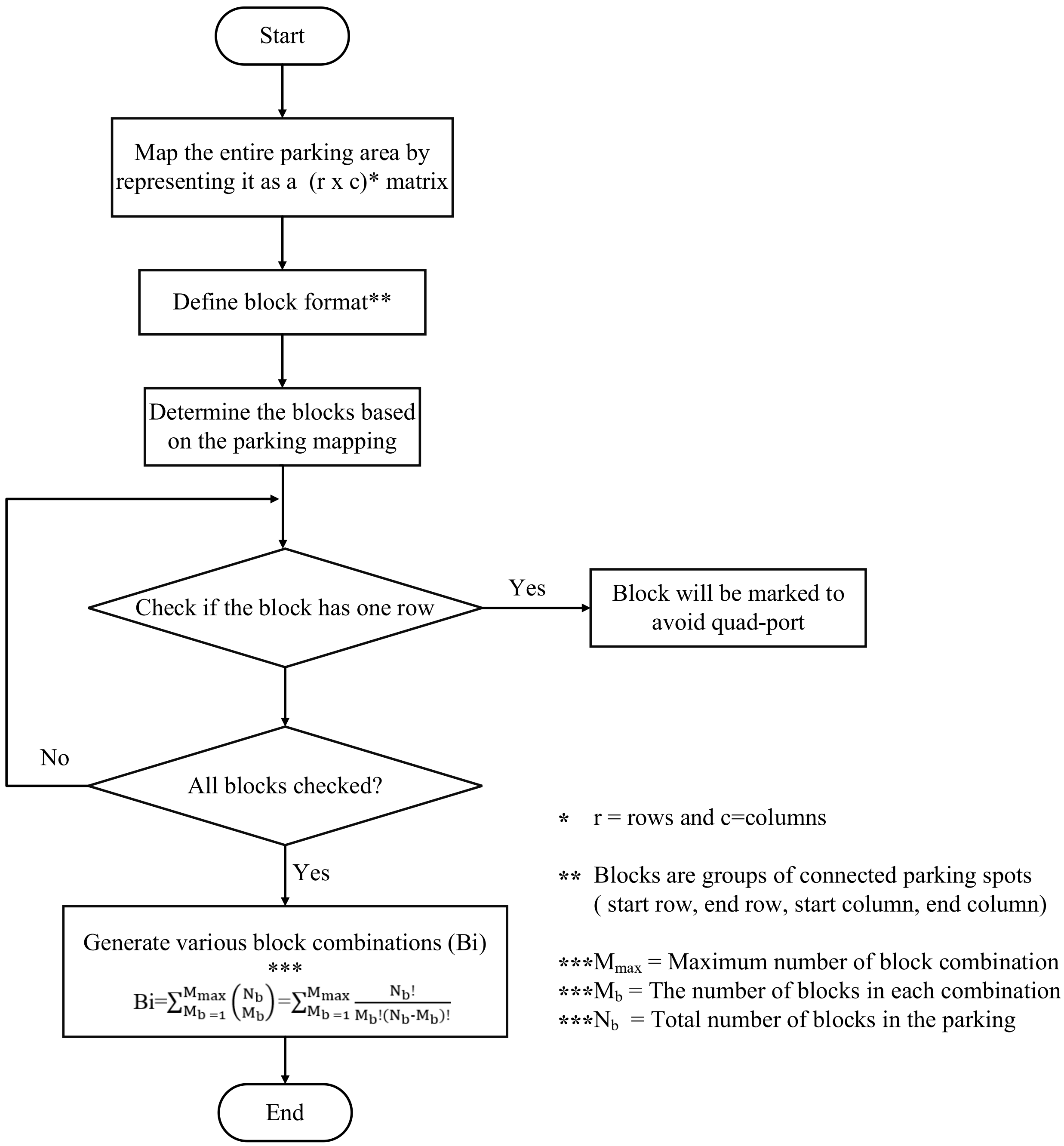


Figure 3-5 - Flow chart of Block Definition and Combination in the parking layout

Creating these blocks simplifies the process, and will be tested with various combinations, calculated using the formula:

$$\text{Bi}=\sum_{M_b=1}^{M_{max}} \binom{N_b}{M_b}=\sum_{M_b=1}^{M_{max}} \frac{N_b!}{M_b!(N_b-M_b)!} \qquad \text{Eq (2)}$$

Where N_b represents the total number of blocks in the parking and M_b represents the number of blocks, ranging from 1 up to a specified maximum $\mathrm{M_{max}}$. Factorials are essential in the binomial coefficient, as they calculate the number of ways to choose Bi from a total number of N_b without considering the order. A key step in identifying candidate parking spots is to avoid unnecessary combinations of blocks, focusing only on the meaningful configurations. Below is an example with 5 blocks, where combinations are selected such that 1≤Bi≤3. The number of ways to choose 3 blocks from 5 is given by:

$$\text{Bi} = \sum_{\mathrm{M_b}=1}^{3} \binom{5}{\mathrm{M_b}} = \binom{5}{1}+\binom{5}{2}+\binom{5}{3} = 5+10+10 = 25$$

Table 3-1 - An example of 5 blocks combinations

1 block	2 blocks combination	3 blocks combination
('A',)	('A', 'B')	('A', 'B', 'C')
('B',)	('A', 'C')	('A', 'B', 'D')
('C',)	('A', 'D')	('A', 'B', 'E')
('D',)	('A', 'E')	('A', 'C', 'D')
('E',)	('B', 'C')	('A', 'C', 'E')
	('B', 'D')	('A', 'D', 'E')
	('B', 'E')	('B', 'C', 'D')
	('C', 'D')	('B', 'C', 'E')
	('C', 'E')	('B', 'D', 'E')
	('D', 'E')	('C', 'D', 'E')

This step outlined as part of the modeling method, since involve the format of parking blocks, establishing criteria for valid block combinations, such as excluding single-row or single-column blocks from having quad-port chargers.

3.3 Objective Function's Subjective Conditions

This section outlines the subjective conditions necessary within a designated parking area. It stablishes criteria that guide the configuration and allocation of charges.

1. Number of spots connected to station (*j*):

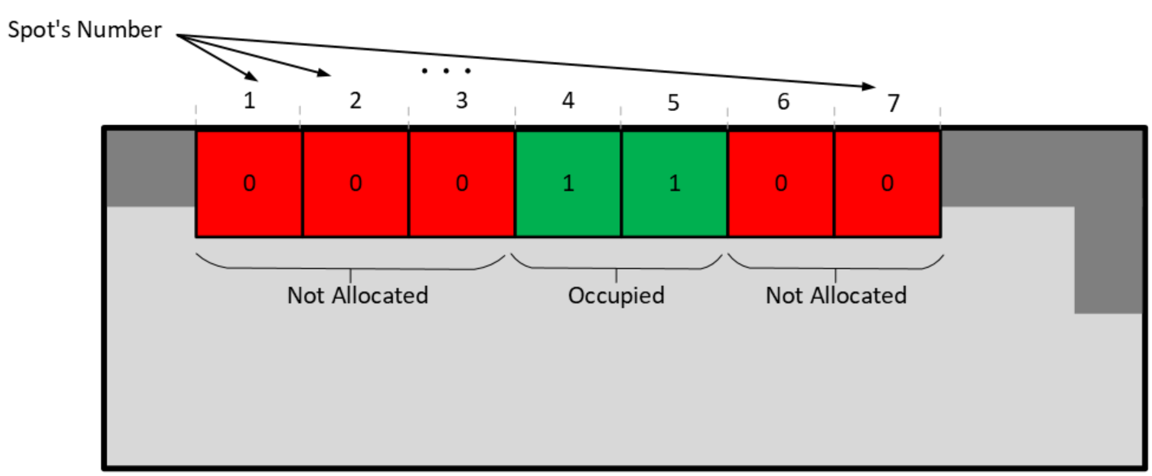
For each j: $\sum_{i=1}^{N} x_{ij} = \sum_k k.y_{jk} \mid k \in (1,2,4)$ Eq (3)

This condition ensures that each station j is connected to a certain number of parking spots. The number of spots connected to each station depends on the type of charger, defined by k, which represents the number of ports (1,2, or 4 ports). For each station j, the sum of occupied spots (x_{ij}) should match the sum of ports allocated to that station (y_{jk}).

Table 3-2 - List of Parameters for Eq (3)

List of Parameters	
x_{ij}:Combining i and j: Indicates parking spot i associated to EVCS j (binary variable 0 or 1)	
y_{jk} : Combining j and k: Indicates EVCS j allocated k number of ports (binary variable 0 or 1)	
j: Charging Station number	$\left\lfloor\frac{p}{4}\right\rfloor + \left\lfloor\frac{p \bmod 4}{2}\right\rfloor + (p \bmod 2) \leq j \leq \max(p)$
i: Spot number	$1 \leq i \leq N$
N: Maximum Number of parking spots in the parking lot excluding existing EV Charging Station	
p: EV Port number	$1 \leq p \leq n_{ep}$
n_{ep}: Number estimated port to be added to the parking lot	
k: Charging Station Type	$k \in (1,2,4)$

Example to clarify eq (3): $\begin{cases} i = 7 \\ j = 1 \textit{ considering station number } 5 \\ p = 2 \end{cases}$



If parking spot is occupied x_{ij} *= 1 otherwise* x_{ij} *= 0*

$\sum_{i=1}^{N=7} x_{ij} = x_{1,5} + x_{2,5} + x_{3,5} + x_{4,5} + x_{5,5} + x_{6,5} + x_{7,5}$

$\sum_{i=1}^{N=7} x_{ij} = 0+0+0+1+1+0+0 = 2$

$2 = 1\times y_{5,1} + 2\times y_{5,2} + 4\times y_{5,4}$

$2 = 1\times 0 + 2 \times 1 + 4 \times 0$

$2=2$ ✓

2. Distance $(r_{P1,j} - r_{P2,j}, c_{P1,j} - c_{P2,j}) = 1$ for $((p_1, p_2) \in [1,2] \mid p_1 \neq p_2)$ Eq (4)

Positing logic is a must check to ensure that ports are positioned according to the requirements. Each pair of ports is identified by its coordinates (r, c), where r denotes the row and c denotes the column. For each pair of ports, the spatial distance between them is calculated using the Manhattan distance formula. This is the sum of the absolute differences of the row and column coordinates:

Distance = $|r_1\ r_2| + |c_1\ c_2|$ Eq (5)

Table 3-3 - List of Parameters for Eq (5)

List of Parameters			
r: Row	*c*: Column	*p*: EV Port number	*j*: Charging Station number

For double-port chargers, it’s essential that the distance between the two ports is controlled to ensure they are positioned close enough to each other. If the distance does not equal one, the placement should be considered invalid and skipped. Only configurations that meet the positioning and distance requirements should be recorded. In Figure 3-6, moving from the top distribution to the bottom distribution indicates that if new 2-port unit get allocated in spot 1 and 4, it will create an invalid placement. This is since the distance of the two ports is more than 1.

$$(r_{P,i}, c_{P,i}) \begin{cases} (r_{1,2}, c_{1,2}) \rightarrow example(1,1) \\ (r_{2,2}, c_{2,2}) \rightarrow example(1,4) \end{cases} \rightarrow (0,3) \neq 1$$

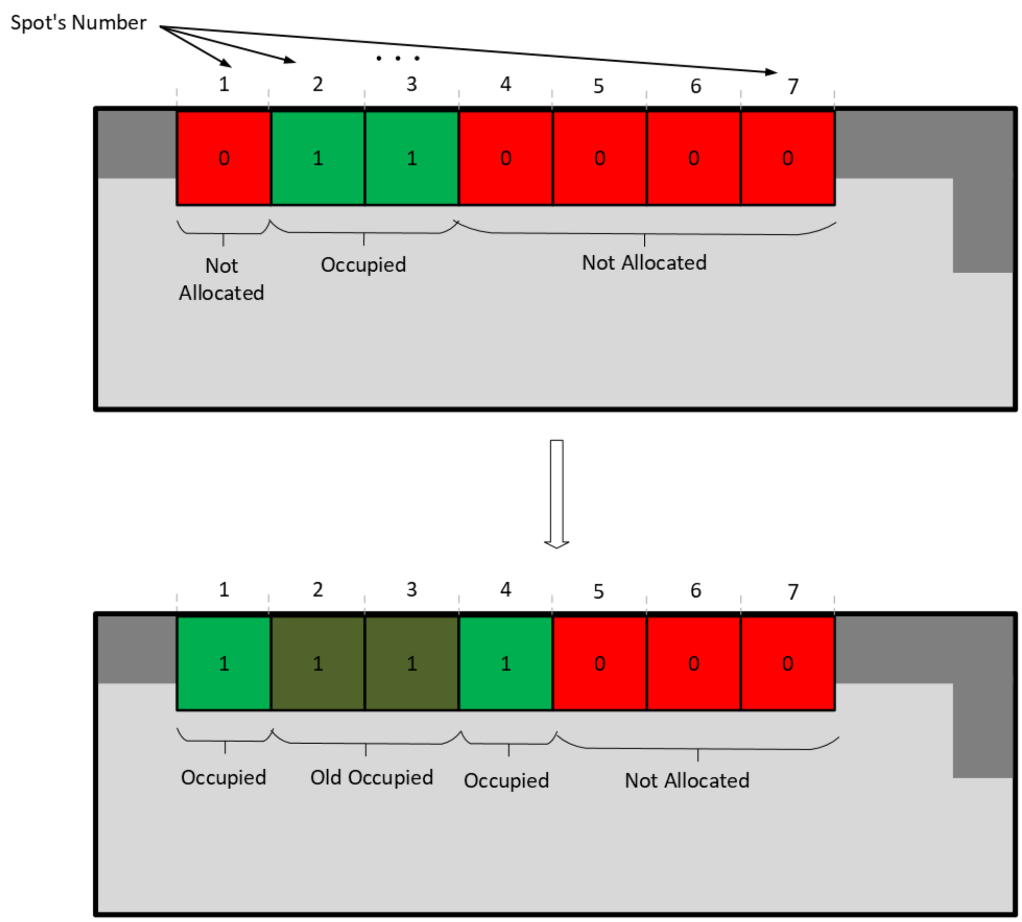


Figure 3-6 - Top: 2 ports valid placement recorded Bottom: invalid placement of 2 ports

In Figure 3-7 both steps show an invalid placement of dual-port charger within a block. The layout includes sport numbered from 1 to 7, with ports placed in spots 2 and 6, marked as "occupied". However, this placement is incorrect because it does not adhere to required spacing and alignment for dual-port chargers. Other spots are designed as "old occupied" or "Not Allocated". In the Bottom configuration, spots 1 and spot 7 are marked as "occupied" with a dual-port charger. This arrangement also fails to meet the required distance and positioning constraints for valid placement. These constraints are essential for ensuring the feasible charger placements, and they are considered within the model to guide the arrangement of EVCPs effectively.

Figure 3-7 - Both the top and bottom illustrations show invalid placements of a dual-port charger within a block

For quad-port chargers, placement should follow a 2x2 square configuration, with distances calculated accordingly. If the distance between ports does not equal one or fails to meet predefined constraints, the configuration should be disregarded, as it does not satisfy proximity requirements.

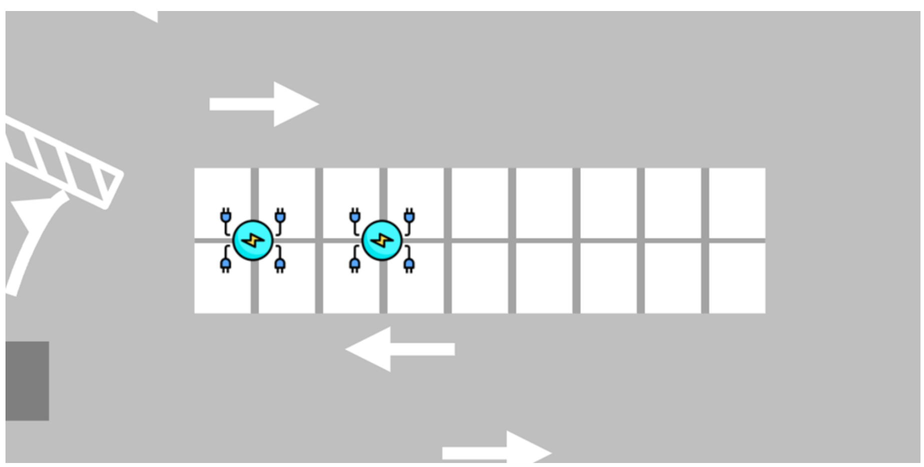


Figure 3-8 - A 4-port unit requires a 2x2 square allocation

Table 3-4 - Example of 2x2 square configuration

(r_a, c_b)	(r_{a+1}, c_b)	(r_{a-1}, c_b)
(r_a, c_{b+1})	(r_a, c_{b-1})	(r_{a-1}, c_{b-1})
(r_{a+1}, c_{b+1})	(r_{a+1}, c_{b-1})	(r_{a-1}, c_{b+1})

Where:

(r_a, c_b): Coordinates of a potential placement within the block, where (r_a is the row index and c_b is the column index.

Square formation condition:

$r_a + 1 \leq R+1$ $\quad\quad$ $c_b + 1 \leq C+1$

Where:

R: Number of rows in the block.

C: Number of columns in the block

$$k_c = \begin{cases} 1 \ if \ (r_a, c_b) \text{such that } r_a + 1 \leq R+1 \ \ and \ c_b + 1 \leq C+1 \ and \ the \ 2x2 \ square \ fits \ within \ the \ block \\ 0 \ otherwise \end{cases}$$

If any of these coordinates are within the block, then that spot will be equipped otherwise next position will be tested until 4 spots are equipped. For single-port chargers, it can be assigned to any available spot within the block. This decision-making logic is essential for ensuring that the right charger configuration is chosen depending on the physical layout of each block. If the block has one row, it assigns either a single-port or dual-port charger to the block (4-port units (k_c) can't be allocated where blocks are made of single row or column). This equation means that a 4-port charging station can only be allocated if both the number of rows and columns in the block are greater than 1.

$$k_c \begin{cases} 0 \ if \ (R = 1) \ or \ (C = 1) \\ 1 \ if \ (R > 1) \ and \ (C > 1) \end{cases} \quad \text{Eq (6)}$$

Where:

k_c: Quad port $\quad$ *R:* Number of rows in the block. $\quad$ *C:* Number of columns in the block.

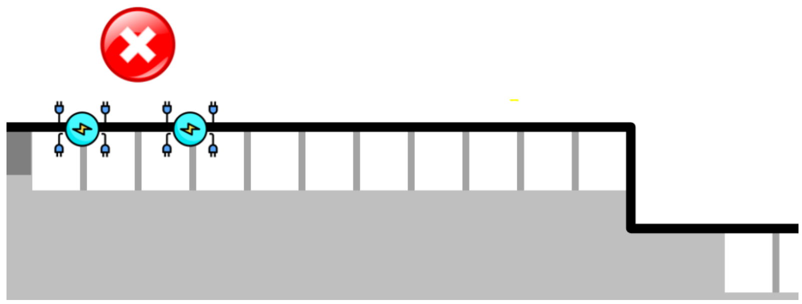


Figure 3-9 - Quad-port chargers cannot be allocated in the single row block

If the block has two rows, making them suitable for all three types of chargers (k ∈ (1,2,4).). This method ensures chargers are assigned appropriately, optimizing the parking layout for various configurations. It is important to note that the order of the port combinations in a block affects cost components calculations, the reason lies behind the fact that cable cost calculation, depends on the length of cable. The next figure illustrates the valid placement of two, dual-port chargers and single-port chargers within a block. Moving from top figure to the bottom figure indicates that the 1-port unit simple can be allocated in the spot 6 without violating any restrictions.

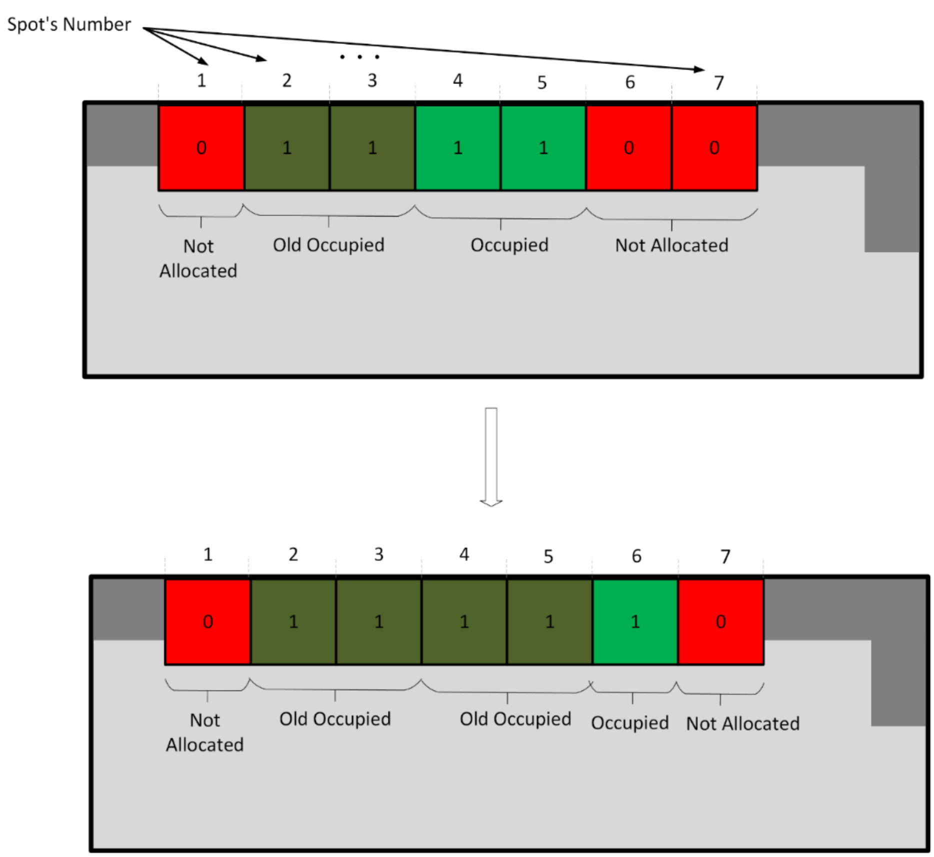


Figure 3-10 - Valid Configurations of Multi-Port Charger Placements in Parking Layout

For example, when considering three charging stations, assume that two stations have 2 ports each, and one station has 1 port. This example demonstrates option 1 from step 2, where the configuration is (2-port,2-port,1-port).

Figure 11 $j = 2$ and P = 2-port assigned to spot 1 and spot 2

Figure 12 $j = 2$ and P = 2-port assigned to spot 3 and spot 4

Figure 13 $j = 3$ and P = 2-port assigned to spot 5

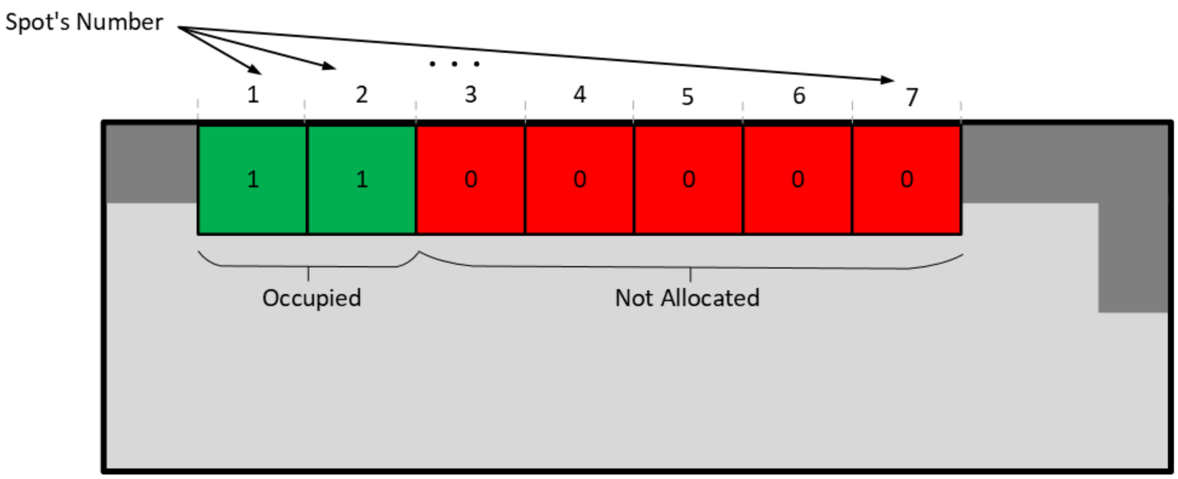


Figure 3-11 - $j = 2$ and P = 2-port assigned to spot 1 and spot 2

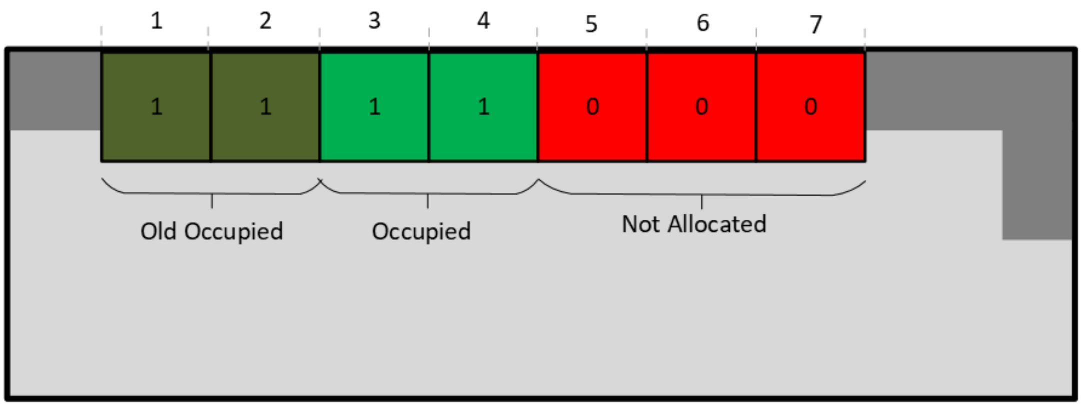


Figure 3-12 - $j = 2$ and P = 2-port assigned to spot 3 and spot 4

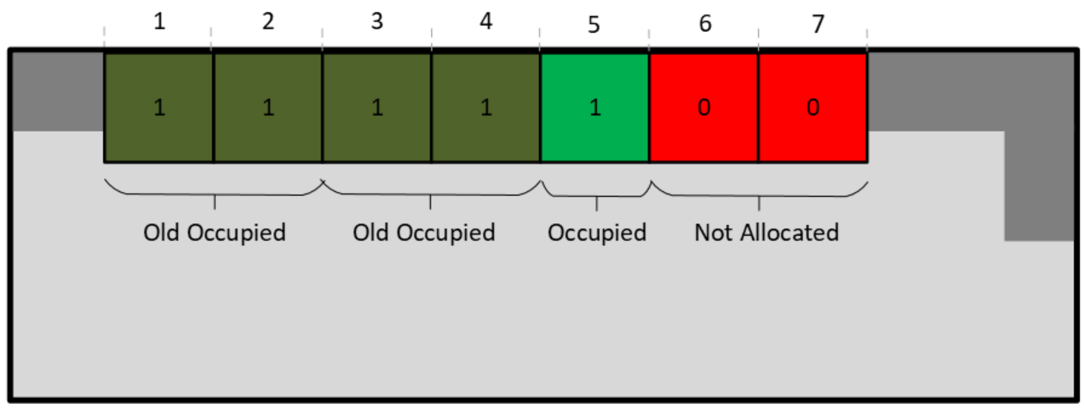


Figure 3-13 - j=3 and P = 2-port assigned to spot 5

3. Choice of number ports for station j with $k \in (1,2,4)$ ports:

$$\sum_k \sum_j^{max(p)} y_{jk} = max(p) \qquad k \in (1,2,4) \qquad \text{Eq (7)}$$

Equation (7) ensures that each charging station j is allocated an appropriate number of ports, either 1-port, 2-port, or 4-port, depending on the station's requirements.

Table 3-5 - List of Parameters for Eq (7)

List of Parameters	
y_{jk} : Combining j and k: Indicates EVCS j allocated k number of ports (binary variable 0 or 1)	
j: Charging Station number	$\left\lfloor \frac{p}{4} \right\rfloor + \left\lfloor \frac{p \bmod 4}{2} \right\rfloor + (p \bmod 2) \leq j \leq \max(p)$
p: EV Port number	$1 \leq p \leq n_{ep}$
n_{ep}: Number estimated port to be added to the parking lot	
k: Charging Station Type	$k \in (1,2,4)$

4. $max(\mathrm{p}) = n + m + l$ Eq (8)

The formulation ensures that the maximum port required is determined by the sum of all single-port, dual-port, and quad-port chargers.

Table 3-6 - List of Parameters for Eq (8)

List of Parameters
n: Number of single port EV Charger
m: Number of dual port EV Charger
l: Number of quad port EV Charger
p: EV Port number

5. Number of stations connected to a parking spot:

For each i: $\sum_{j}^{max(p)} x_{ij} \leq 1$ Eq (9)

Equation (9) ensures that each parking spot i is connected to at most one charging station.

Table 3-7 - List of Parameters for Eq (9)

List of Parameters	
x_{ij}:Combining i and j: Indicates parking spot i associated to EVCS j (binary variable 0 or 1)	
i: Spot number	$1 \leq i \leq N$
N: Maximum Number of parking spots in the parking lot excluding existing EV Charging Station	
j: Charging Station number	$\left\lfloor \frac{p}{4} \right\rfloor + \left\lfloor \frac{p \bmod 4}{2} \right\rfloor + (p \bmod 2) \leq j \leq \max(p)$
p: EV Port number	$1 \leq p \leq n_{ep}$
n_{ep}: Number estimated port to be added to the parking lot	
k: Charging Station Type	$k \in (1,2,4)$

3.4 Formulation of the Proposed Model

The problem is formulated as a Mixed-Integer Nonlinear Programming (MINLP), objective is to minimize the total costs associated with configuring and allocating multiport chargers within parking blocks, while ensuring efficient placement of EV Charging Ports (EVCP). Each port represents a facility, and the EVCP must be allocated to each block in accordance with the specified block combinations.

$C_{\text{Optimized}} = \text{Min}(C_s)$ Eq (10)

$C_{\text{Optimized}}$ represents the optimized cost, or the lowest possible total cost for the designated parking area, fulfilling the objective of cost minimization. This optimized cost is identified using Equation (1), which determines the Life Cycle Cost (LCC) for each scenario from the owner's perspective and selects the scenario with minimum cost. The goal is to find the placement configuration that yields the lowest total costs. By comparing cost of scenarios, the configuration with the lowest total cost will be chosen, which would be the most economical option for the EV Charger placement.

$C_s = C_{s_E} + C_{s_{EE}} + C_{s_{OM}} + C_{s_F} + C_{s_{End\ of\ Life}}$ Eq (11)

s: scenario number

C_s represents the LCC calculation for each scenario, based on the potential block combinations. The goal at the end is to select the minimum C_s value among several scenario costs, where s denotes different scenarios. Equation (2) incorporates multiple cost components to calculate the LCC, including:C_{s_E} (cost of EVCS equipment), $C_{s_{EE}}$ (cost of electrical system equipment), $C_{s_{OM}}$ ($maintenance\ and\ operation\ cost$ cost), C_{s_F} (fixed cost; which defined as software licensing fees, security measures cost, communication system costs), and $C_{s_{End\ of\ Life}}$ (Equipment End of Life Cost)).

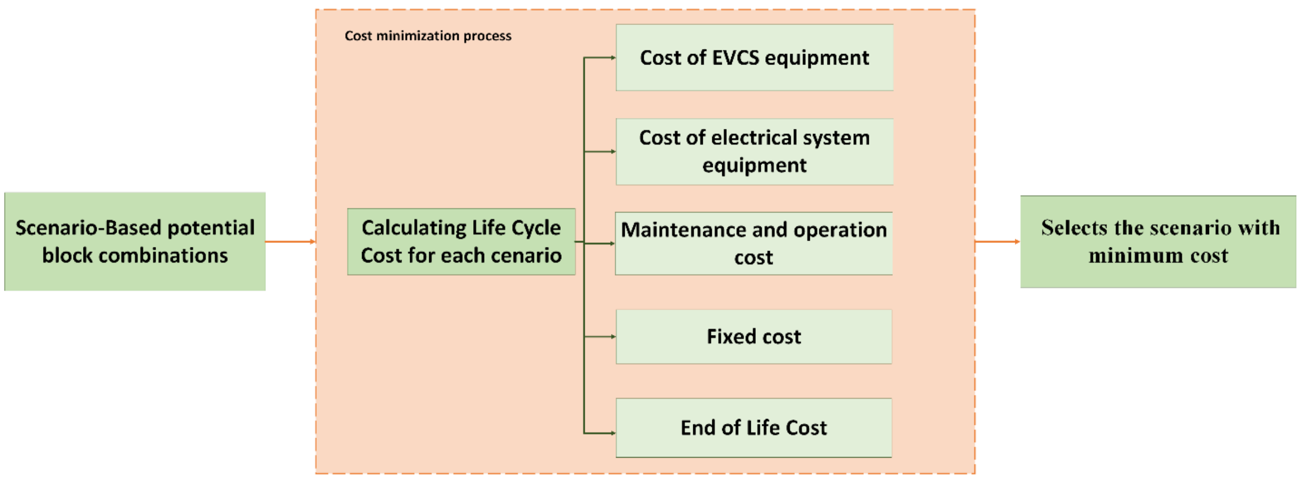


Figure 3-14 - Cost Formulation Framework

The cost of EV Charging Station includes the initial equipment cost of EVCS as part of the LCC, as this is critical to the total cost over the lifespan within the designated parking area. It accounts for the different types of charging stations, such as wall-mounted or pedestal chargers, as well as various type of port (single port, dual-port, and quad-port) represents one-time cost. The cost is calculated as follows:

$$C_{s_E} = \sum_{\boldsymbol{k}} \sum_{i=1}^{N} \sum_{\boldsymbol{j=1}}^{\boldsymbol{max}\ (\boldsymbol{j})} x_{ij} \times y_{jk} \times C_{s_{E\_i,j,k}} \quad \mid k \in (1,2,4) \qquad \text{Eq (12)}$$

Table 3-8 - List of Parameters for Eq (12)

List of parameters
C_{s_E}= Total cost of EVCS
$C_{s_{E\_i,j,k}}$= Cost per EVCS unit with station j and k ports
x_{ij}:Combining i and j: Indicates parking spot i associated to EVCS j (binary variable 0 or 1)

y_{jk} : Combining j and k: Indicates EVCS j allocated k number of ports (binary variable 0 or 1)

max (j): Maximum number of stations acquired from Port Distribution

j, k: Each EVCS will be assigned a k ported device based on the Port Distribution

j: Charging Station number	$\left\lfloor\frac{p}{4}\right\rfloor + \left\lfloor\frac{p \bmod 4}{2}\right\rfloor + (p \bmod 2) \leq j \leq \max(p)$
k: Charging Station Type	$k \in (1,2,4)$

This formulation ensures that the total cost C_{s_E} accounts for both the port configuration type and the type of charger (pedestal or wall-mounted) based on the block position relative to the wall.

The cost of Electrical System Equipment ($C_{s_{EE}}$) represents the expenses required to establish the electrical equipment that connects the power source to each block and individual charging station, based on the parking layout. It is typically considered part of the initial costs in the LCC calculation, as it comprises one-time expenses incurred during installation. Alongside other initial expenses like EVCS equipment, this cost component include expenses to support the required expenses with setting up the electrical system equipment's, such as cable and conduit costs (determined by length and width requirements), breaker cost, fuse costs, and junction box costs.

$$C_{s_{EE}} = \sum_{i=1}^{N} \sum_{\boldsymbol{j=1}}^{\boldsymbol{max\,(j)}} x_{ij} \times C_{s_{EE\_i,j}} \qquad \text{Eq (13)}$$

Table 3-9 - List of Parameters for Eq (13)

List of Symbols and parameters

$C_{s_{EE}}$= Total cost of Electrical System Equipment

$C_{s_{EE\_i,j}}$: Combination of constant cost and variable cost of electrical system equipment (cable cost connection from the power source to the blocks, and then from the junction box to each spot.

$$C_{cable} \times L_{sb} + C_{Breaker} + C_{Fuse} + C_{Junction\ box} + C_{Conduit} \times L_{sb} + C_{labour\_Cable} \times L_{sb} + C_{labour\_Conduit} \times L_{sb}$$

x_{ij}:Combining i and j: Indicates parking spot i associated to EVCS j (binary variable 0 or 1)

max (j): Maximum number of stations acquired from Port Distribution

i: Spot number	$1 \leq i \leq N$
j: Charging Station number	$\left\lfloor\frac{p}{4}\right\rfloor + \left\lfloor\frac{p \bmod 4}{2}\right\rfloor + (p \bmod 2) \leq j \leq \max(p)$

L_{sb}: Length of cable required from the source to block

W_{sb}: Width of the cable required for block is a function of the number of ports.

N_{sb}: Number of ports occupying a target block

C_{cable}: Cost per unit length of the cable.

C_{labour_Cable}: Cable installation labour cost per meter

$C_{labour\_Conduit}$: Conduit installation labour cost per meter

$C_{Breaker}$: Breaker Cost

C_{Fuse}: Fuse Cost

$C_{Junction\ box}$: Junction box cost

$C_{Conduit}$: Cost of Conduit

Variable Cost (Cable Cost) is based on the cable length (L_{sb}) from the power source to each block and width (W_{sb}), which scales with the number of ports.

N_{sb}. Assume the cable width increases with the number of ports:

W_{sb}: $= f\,(N_{sb})$ Eq (14)

where f (N_{sb}) is a function that defines cable width based on the number of ports or carried power.

For simplicity, we will define a table with the standard cable sizes.

W_{sb}: $= G \cdot N_{sb}$ Eq (15)

where G is a constant that defines the width per port. Formulation incorporates both cable costs and electrical constant costs (e.g., junction boxes, fuses, breakers) based on the distance requirements shown in the figure below.

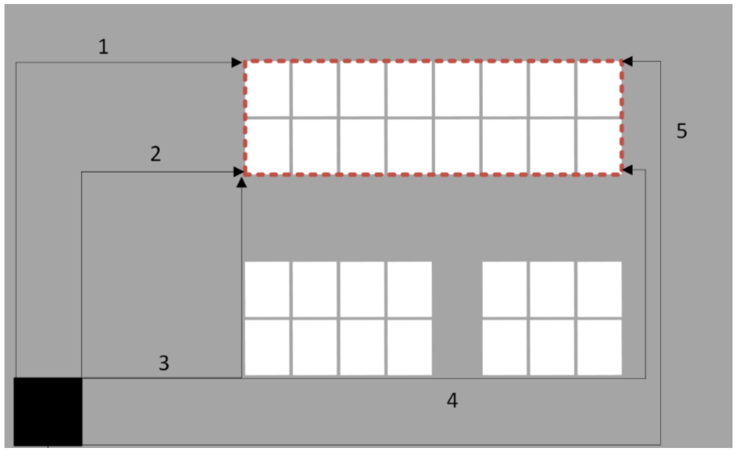


Figure 3-15 - Cable length options from the electricity source to the closet corner

Only the closet cable from the electricity source to the closet corner would be taken into account.

In equation below, total operation and maintenance cost ($C_{S_{OM}}$) accounts for all stations, parking spots, port configuration, and charger type, $C_{S_{OM}}$are recurring costs associated with the daily functioning of each station. They include cost such as electricity, routine inspections (is usually to keep the equipment running), and minor tasks. Formula accounts for differences in charger type (pedestal and wall-mounted chargers) and in number of ports. Maintenance cost for pedestal multi-port chargers have slightly higher costs due to their complexity and structure.

$$C_{S_{OM}} = \sum_{\boldsymbol{k}} \sum_{i=1}^{N} \sum_{\boldsymbol{j=1}}^{\boldsymbol{max}\,(j)} x_{ij} \times y_{jk} \times C_{S_{OM\_i,j,k}} \quad | \; k \in (1,2,4) \qquad \text{Eq (16)}$$

Table 3-10 - List of Parameters for Eq (16)

List of Symbols and parameters	
$C_{S_{OM}}$= Total Operation and Maintenance Cost for the charging station	
$C_{S_{OM\_i,j,k}}$= Operation and maintenance cost for each station (more explanation below) *	
x_{ij}:Combining i and j: Indicates parking spot i associated to EVCS j (binary variable 0 or 1)	
y_{jk} : Combining j and k: Indicates EVCS j allocated k number of ports (binary variable 0 or 1)	
max (j): Maximum number of stations acquired from Port Distribution	
i: Spot number	$1 \leq i \leq N$
N: Maximum Number of parking spots in the parking lot excluding existing EV Charging Station	
j: Charging Station number	$\left\lfloor \frac{p}{4} \right\rfloor + \left\lfloor \frac{p \bmod 4}{2} \right\rfloor + (p \bmod 2) \leq j \leq \max(p)$
max (j): Maximum number of stations acquired from Port Distribution	

k: Port configuration Type	$k \in (1,2,4)$

*For $C_{s_{OM\_i,j,k}}$, cost for each station can vary based on three factors, each individual station in particular spot, with the specific port configuration and station type (pedestal or wall-mounted charger).

The fixed Cost for EVCS represents the one-time expenses, such as software licensing fees, security measures, and communication systems, which support the charging stations across the parking lot.

$$C_{s_F} = \sum_{i=1}^{N} \sum_{\boldsymbol{j=1}}^{\boldsymbol{max}\,(j)} x_{ij} \times C_{s_{F\_i,j}} \qquad \text{Eq (17)}$$

Table 3-11 - List of Parameters for Eq (17)

List of Symbols and parameters	
C_{s_F}= Total Fixed cost	
$C_{s_{F\_i,j}}$= Fixed cost associated with parking spot i and EVCS j	
x_{ij}:Combining i and j: Indicates parking spot i associated to EVCS j (binary variable 0 or 1)	
max (j): Maximum number of stations acquired from Port Distribution	
i: Spot number	$1 \leq i \leq N$
N: Maximum Number of parking spots in the parking lot excluding existing EV Charging Station	
j: Charging Station number	$\left\lfloor\frac{p}{4}\right\rfloor + \left\lfloor\frac{p \bmod 4}{2}\right\rfloor + (p \bmod 2) \leq j \leq \max(p)$

The end-of-life cost ($C_{s_{End\ of\ life}}$)represents the expenses required for dismantling chargers at the end of their lifespan, it covers the final year of life. The end-of-life cost is calculated as follows:

$$C_{s_{End\ of\ life}} = \sum_{\boldsymbol{k}} \sum_{i=1}^{N} \sum_{\boldsymbol{j=1}}^{\boldsymbol{max}\,(j)} x_{ij} \times y_{jk} \times C_{s_{End\ of\ Life\ \_i,j,k}} \mid k \in (1,2,4) \qquad \text{Eq (18)}$$

Table 3-12 - List of Parameters for Eq (18)

List of Symbols and parameters
$C_{s_{End\ of\ Life}}$= Total End-of-Life Cost of charging stations
$C_{s_{End\ of\ Life\ \_i,j,k}}$= Associated with parking spot I, charging station j, and port configuration k, which may include the cost of dismantling.
x_{ij}:Combining i and j: Indicates parking spot i associated to EVCS j (binary variable 0 or 1)

y_{jk} : Combining j and k: Indicates EVCS j allocated k number of ports (binary variable 0 or 1)

max (j): Maximum number of stations acquired from Port Distribution

i: Spot number	1≤ i ≤ N
N: Maximum Number of parking spots in the parking lot excluding existing EV Charging Station	
j: Charging Station number	$\left\lfloor\frac{p}{4}\right\rfloor + \left\lfloor\frac{p \bmod 4}{2}\right\rfloor + (p \bmod 2) \leq j \leq \max(p)$
k: Port configuration Type	$k \in (1,2,4)$

The Life Cycle Cost for EV Charging Stations in the parking lor evaluates all cost components over the 10-year lifespan. The LCC begins with one-time costs, including initial purchase of charging station equipment, installation of electrical equipment, and fixed costs for supporting infrastructure such a s software, security, and communication systems. Annual Operation and Maintenance costs cover recurring expenses related to daily functioning such as electricity, routine inspections (is usually to keep the equipment running, like oiling, lubricants, etc.), and minor tasks annually.), and one-time overhaul mid-way (year 5) through the lifespan to ensure the charging stations remain functional, which is included as a part of the maintenance cost in the calculation. End-of-life costs, incurred only the final year, account for dismantling of equipment.

3.5 Annual Discounting for LCC Minimization

The goal is to find the placement configuration that yields the lowest Net Present Value (NPV) to total costs. NPV result will reflect the total expense associated with each scenario. By comparing scenarios, the configuration with the lowest total cost will be chosen, which would be the most economical option from a cost perspective. Approach remains a pure cost-minimization strategy aimed at achieving the most cost-effective placement of EVCP.

To determine the total cost, each component is calculated for every scenario and then discounted to its present value using Net Present Value (NPV). NPV captures the time value of money, using a discount rate (*I)* over a total life. By summing the NPV of each component, the scenario with the lowest total NPV can be identified, toward the most cost-effective configuration (or best scenario) in the placement of EVCP. Since this analysis aims to minimize the total NPV of all costs over the lifespan T with no cash inflow, each cost component is discounted annually to account for the time value of money. The total NPV of Costs is given by:

$$NPV_{Total} = C_{Initial} + \sum_{t=1}^{T} \frac{C_{t,OM}}{(1+I)^t} + \frac{C_{Overhaul}}{(1+I)^5} + \frac{C_{End\ of\ Life}}{(1+I)^T} \quad \text{Eq (19)}$$

Where:

Initial Cost ($C_{Initial}$): is one-time upfront expense, which doesn't require discounting because it occurs at t=0

$$C_{Initial} = C_{S_E} + C_{S_{EE}} + C_{S_F} \quad \text{Eq (20)}$$

Table 3-13 - List of Parameters for Eq (20)

List of Symbols and parameters
$C_{Initial}$ = Initial cost
C_{S_E}= Total cost of EVCS
$C_{S_{EE}}$= Total cost of Electrical System Equipment
C_{S_F}= Total Fixed cost, which defined as software licensing fees, security measures cost, communication system costs

Annual Operation and maintenance cost: Recurring operation and maintenance costs, discounted annually:

$$C_{Annual\ OM} = \sum_{t=1}^{T} \frac{C_{t,OM}}{(1+I)^t} \quad \text{Eq (21)}$$

Table 3-14 - List of Parameters for Eq (21)

List of Symbols and parameters
$C_{Annual\ OM}$ = Annual operation and maintenance cost
$C_{t,OM}$ =Combined annual cost of operation and maintenance
I= Discount Rate
T= Last year of lifespan
t= Year number

Overhaul Cost: A one-tome, mid-life overhaul expense, applied at t=5 to ensure station functionality discounted to present value:

$$\frac{C_{Overhaul}}{(1+I)^5} \quad \text{Eq (22)}$$

End-of-Life Cost ($C_{End\ of\ Life}$): One-time dismantling cost at the end of the lifespan, discounted in year T:

$\frac{C_{End\ of\ Life}}{(1+I)^T}$ Eq (23)

Table 3-15 - List of Parameters for Eq (22) and Eq (23)

List of Symbols and parameters
$C_{End\ of\ Life}$ = Dismantling cost
$C_{Overhaul}$ = Overhaul maintenance cost
t= Year number
T= Last year of lifespan

Objective is to minimize the NPV_{Total} :The objective is to minimize the NPV of total discounted costs:

$$min\ NPV_{Total} = C_{Initial} + \sum_{t=1}^{T} \frac{C_{t,OM}}{(1+I)^t} + \frac{C_{Overhaul}}{(1+I)^5} + \frac{C_{End\ of\ Life}}{(1+I)^T} \quad \text{Eq (24)}$$

This formulation captures the total cost over the project lifespan, with separate treatment for the annual operation and maintenance costs, a one-time overhaul cost, and end-of-life costs, all discounted to reflect the time value of money. The configuration with the lowest NPV_{Total} would represent the most cost-effective placement strategy.

Table 3-16 - LCC Calculation using NPV

Year	t=0	t=1	t=2	…………	t=5	………..	T = 10
Annual Cost ($C_{t,OM}$)	0	C_{OM}	C_{OM}	C_{OM}	C_{OM}+$C_{Overhaul}$	C_{OM}	C_{OM}
Initial Cost ($C_{Initial}$)	$C_{Initial}$	0	0	0	0	0	0
Annual Net Cash Flow	$C_{Initial}$	C_{OM}	C_{OM}	C_{OM}	C_{OM}+$C_{Overhaul}$	C_{OM}	$C_{OM} + C_{End\ of\ Life}$
Discounted Factor $\frac{1}{(1+I)^t}$	1	$\frac{1}{(1+I)^1}$	$\frac{1}{(1+I)^2}$	$\frac{1}{(1+I)^t}$	$\frac{1}{(1+I)^5}$	$\frac{1}{(1+I)^t}$	$\frac{1}{(1+I)^{10}}$
Discounted Cash Flow	$C_{Initial}$	$C_{OM} \times \frac{1}{(1+I)^1}$	$C_{OM} \times \frac{1}{(1+I)^2}$	$C_{OM} \times \frac{1}{(1+I)^t}$	$(C_{OM} + C_{Overhaul}) \times \frac{1}{(1+I)^5}$	$C_{OM} \times \frac{1}{(1+I)^t}$	$(C_{OM} + C_{End\ of\ Life}) \times \frac{1}{(1+I)^{10}}$

This table presents a structured approach to calculating the total LCC for EV Charging Stations over a 10-year lifespan. Each row represents different cost components and how they are discounted to determine the total NPV, which helps identify the most cost-effective placement scenario.

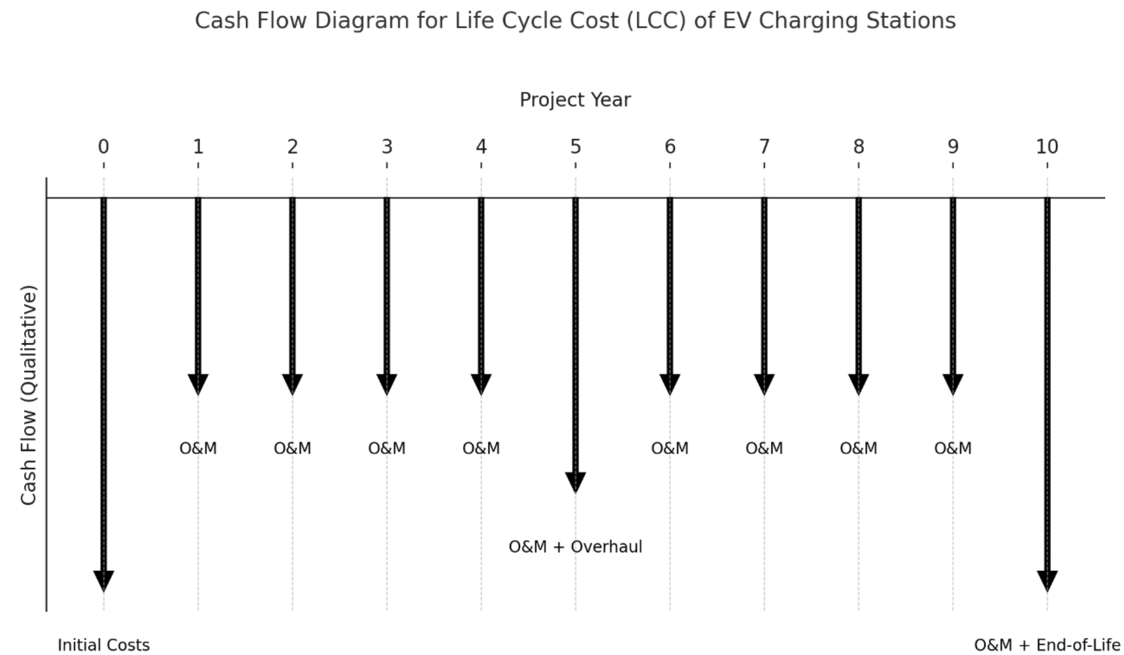


Figure 3-16 - Cash Flow Diagram for LCC (expenses or costs)

This cash flow diagram represents the Life Cycle Cost (LCC) over a 10-year project lifespan, with costs shown as downward arrows (indicating cash outflows) in financial diagrams. This diagram includes costs (all outflows), using downward arrows.

4. Model Implementation and Validation

Optimizing EVCS in the existing parking involves balancing multiple factors, such as the number of ports, and charger types. Each configuration of chargers across blocks represents a unique scenario, and the number of possible combinations grows exponentially with additional parking spots, and configuration options.

4.1 Combinatorial Optimization Algorithm

This model requires to explore many possible combinations of ports within various blocks and calculate the financial aspect of each possible configuration. Model must consider various cost factors; these are affected by the distribution of ports within blocks. There are spatial and distance constraints (e.g., port placement within blocks and distance from the power source), making some configuration infeasible. Algorithm needs systematic exploration of the configurations, and memorization for the efficient combinations to reduce the redundant calculations. Given the importance of cost accuracy in this model, a systematic combinatorial search is preferable to achieve the best configuration that minimizes the LCC of the EVCPs placements.

The algorithm used to solve the problem is a combinatorial optimization algorithm with both dynamic programming and brute force search components. The goal of the algorithm is to find the best distribution of EV charging ports within blocks. It helps manage and optimize the computational process by storing and reusing intermediate results, which is especially useful in problems with overlapping subproblems, like generating all valid port configurations. The combined use of dynamic programming and brute force search is well-suited to address the problem.

- The algorithm employs brute force to explore all possible combinations of blocks and port placements. It systematically evaluates each valid configuration to calculate the total cost and selects the one with the lowest cost.
- Dynamic Programming aspect helps reduce computational effort in finding all the port configurations that sum up to a desired number of charging ports. Memoization is used to

avoid redundant calculations by storing previously computed combinations and reusing them when needed.

- This technique solves problems by breaking them into smaller, subproblems. The results are then stored to be reused so the same problem will not have to be computed again. For example, when using the dynamic programming technique to figure out all possible results from a set of numbers, the first time the results are calculated, they are saved and put into the equation later instead of being calculated again. So, when dealing with long, complicated equations and processes, it saves time and makes solutions faster by doing less work. The dynamic programming algorithm tries to find the shortest way to a solution when solving a problem.

Figure 4-1 represents the steps in the solution algorithm used to determine the optimal distribution of EVCPs within a parking facility, aiming to minimize life cycle costs (LCC). Each decision point and action in the flowchart addresses critical factors in the layout, cost, and feasibility of placing different types of EV charging ports.

- All possible port combinations are generated; this includes different configurations of single, dual, and quad-port chargers.
- Ports are distributed within the assigned blocks, considering spatial constraints and requirements for different port types.
- Once all ports are positioned within the blocks, the algorithm proceeds to finalize the configuration.
- For feasible configurations where all ports are correctly placed, the algorithm calculates the total LCC (This cost calculation includes initial costs, operation and maintenance costs over the charger’s lifespan, end-of-life cost).

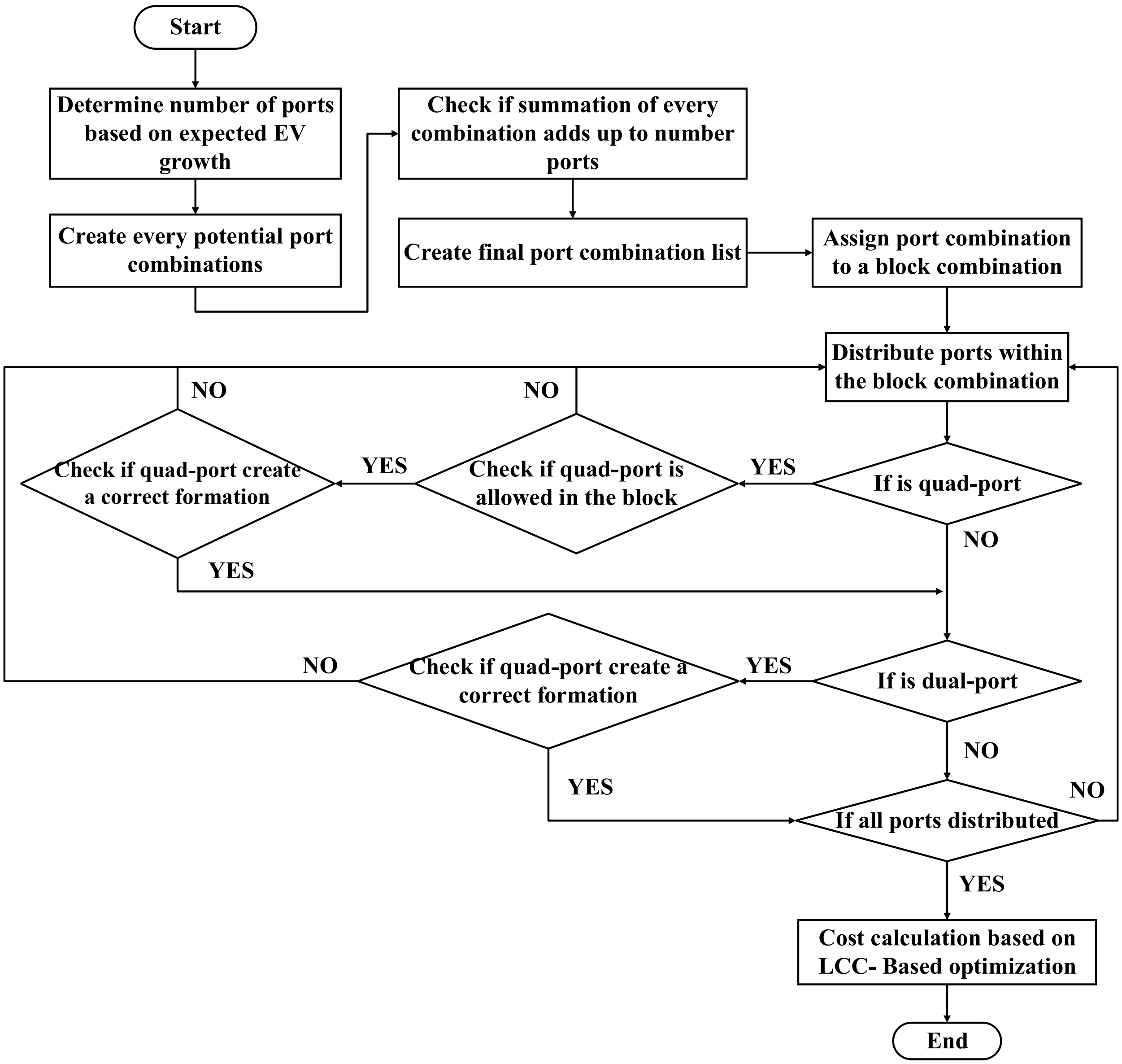


Figure 4-1 - Algorithm Flowchart for port distribution within the block combination

Flowchart below outlines the model's algorithmic approach to optimizing EV charging station (EVCS) placement within a parking facility. It demonstrates the workflow, from defining the inputs and generating possible configurations to evaluating costs and selecting the optimal configuration. The flowchart is structured in three main steps: Input, Port and Block Configuration, and Distribution and Cost Calculation as shown in Figure 4-2.

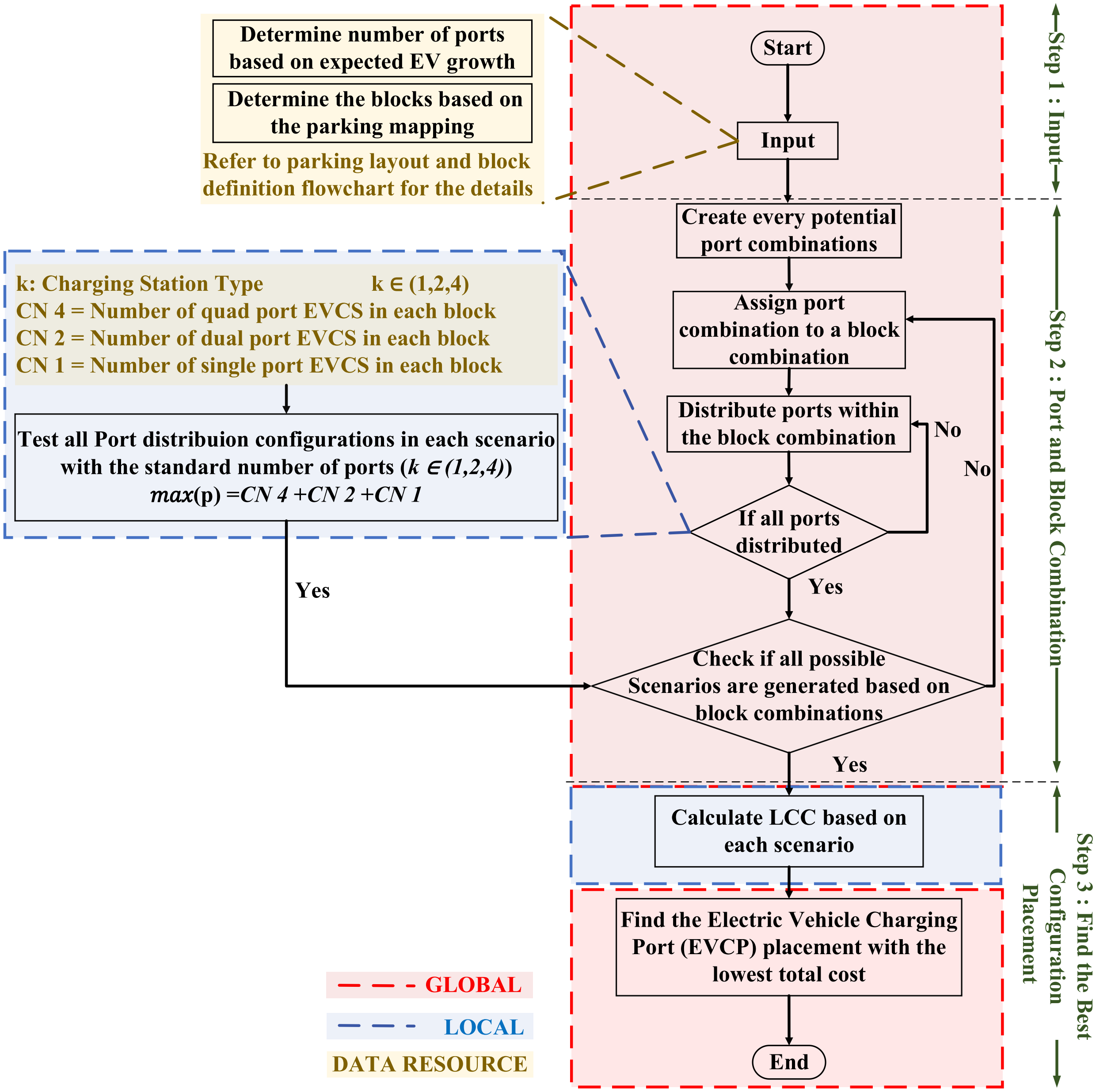


Figure 4-2 - Model Implementation Flowchart

Global vs. Local Process Boundaries:

- Red Dotted Border (Global) represents processes or inputs that apply globally across the entire parking layout.
- Blue Dotted Border (Local) represents localized calculations or configurations, specific to each block or subset of the layout.

Steps Breakdown:

Step 1: Input (Top Section)

- The entire parking layout is defined, creating blocks based on available space and physical size. This includes identifying the range of block combinations.
- The required number of charging ports is determined from external factors, such as projected EV growth.
- All potential combinations of ports (1-port, 2-port, and 4-port) are generated, establishing the foundational options that will be used in configuration testing.

Step 2: Port and Block Configuration (Middle Section)

- Distribute Combinations into Blocks: The algorithm distributes each combination of ports across different blocks, testing each feasible block combination for its suitability.
- Validation of Block Combinations: Ensures that each block combination falls within the defined maximum and minimum number of allowable blocks.
- The dynamic programming approach is highlighted in second step. It is used to efficiently manage the combinations of ports, storing and reusing valid configurations to avoid redundant calculations.
- Valid Placement Check: Ensures that the configurations meet spatial constraints and any specific requirements.
- Scenario Generation: Based on the block configurations, different scenarios are generated, detailing how ports could be distributed across blocks.

Step 3: Find the Best Configuration (Bottom Section)

- Cost Calculation (LCC): Each scenario's life cycle cost (LCC) is calculated, incorporating initial setup, operational, and maintenance costs over time. This cost metric guides the selection of the most cost-effective configuration.

- The core objective of the algorithm is to minimize the LCC. Once all configurations are evaluated, the scenario with the lowest LCC is identified as the optimal solution for EVCS placement.

4.2 Utilized Tool

The User Interface (UI) for this model is designed to streamline user interaction, allowing for easy input of all essential parameters needed for the optimization process. Key features of the UI include a Tabbed Layout that organizes settings and options into categories such as "General Settings," "Lifecycle Cost component Prices," and "Blocks Definition based on the parking layout", and “help Tab” providing clear navigation and guiding users systematically through data input. This model is implemented in Python, using libraries essential for both functionality and user experience. Key libraries include:

- The “itertools” module in Python provides efficient tools for creating iterators that perform combinatorial operations. In the context of this algorithm, “itertools.combinations” and “itertools.product” are crucial for generating all possible combinations and permutations of blocks and port placements.“itertools.combinations” function is used to generate combinations of blocks (facilities) without repeating the order. The algorithm relies on this to create all feasible subsets of blocks, from a minimum to maximum number of blocks, for port placement. “Once valid block and port combinations are identified, “itertools.product” is used to generate Cartesian products of block placements. This ensures that all possible valid distributions of ports are explored across the blocks.
- The panda’s library is used for data manipulation, storage, and exporting results. It plays a key role in: After processing scenarios and calculating the costs for each configuration, the results are stored in a “pandas.DataFrame”. This structured storage allows easy manipulation, filtering, and analysis of results.
- The json library allows for efficient reading, writing, and manipulation of data in JSON format. In this algorithm, json is used to manage and store intermediate results or configuration data (such as block layouts and port details) in a structured, lightweight format that is easy to read and modify.
- The multiprocessing module in Python enables the parallel execution of multiple processes, which is essential for improving the performance of the algorithm. Given that the brute-

force approach to evaluating block and port combinations can be computationally expensive, multiprocessing is employed to parallelize the processing of different configurations. The function “process_scenarios” makes use of the multiprocessing Pool to distribute the evaluation of different combinations across multiple processors. This reduces the overall runtime by splitting the workload.

- The ‘lru_cache’ decorator from the ‘functools’ module is a key optimization technique used in the algorithm. It enables ‘memoization’, which stores the results of expensive function calls and returns the cached result when the same inputs occur again.
- Tkinter for building the interactive UI, with a Progress Bar and tabs that enhance usability and workflow.

The Results Dashboard displays the best result, with a structured table format to show metrics such as total cost. Tooltips and a comprehensive Help Tab guide users through the application’s functionality, improving usability for both novice and experienced users.

This UI and dashboard, coupled with the libraries and tools used, are integral to the model’s functionality, making it a robust, user-friendly system for optimal charging port placement analysis.

4.3 Case Study General Information

Downtown Montreal is selected as the location for this thesis due to its unique infrastructure challenges. A notable example of these challenges is the Eaton Centre, one of Montreal's most popular shopping centers, located in the heart of downtown on Sainte-Catherine Street West, between Peel and de la Montagne streets, the Eaton Centre is a massive commercial complex with over 175 stores. Since its inauguration in 1990, the shopping center has undergone major renovations, most recently in 2019, to modernize its appearance and enhance the customer experience. The Eaton Centre's direct connection to the Montreal metro and several other buildings, including the Fairmont the Queen Elizabeth Hotel, further exemplifies the complex interplay between urban development, transportation, and infrastructure planning in the city. There are 472 parking spots in 2 parking levels available in the underground (236 parking spots in level -1) parking lot of the Montreal Eaton Centre, accessible from McGill College Avenue.

Following the EV charger ratio in Montreal, the expected number of ports in the shopping center parking will be defined. Based on the information on chapter 2, section 2.3, the number of chargers in Quebec Province and city of Montreal in the year 2023 and 2035 is estimated [4]. The values can be viewed in Table 4-1.

Table 4-1 - Estimated number of Chargers in Quebec province and Montreal

Region	Public EV chargers	
	Year 2023	Year 2035
Quebec province (numbers)	9,200	69,000
Montreal (numbers)	2,093	12,810

Using the similar approach [section 2.3] and due to the fact, that provided calculations are designed for the city of Montreal, number of public EV chargers in the existing shopping center can be estimated as given in Table 4-2:

Table 4-2 - Estimated number of chargers in case study according to the utilization rate

Case study Eaton Centre	Public EV chargers	
	Year 2023	Year 2035
According to QC utilization rate (numbers)	4	30
According to Montreal utilization rate (numbers)	4	25

The following Figure 4-3 and Figure 4-4 shows the parking layout of level -1 and level -2:

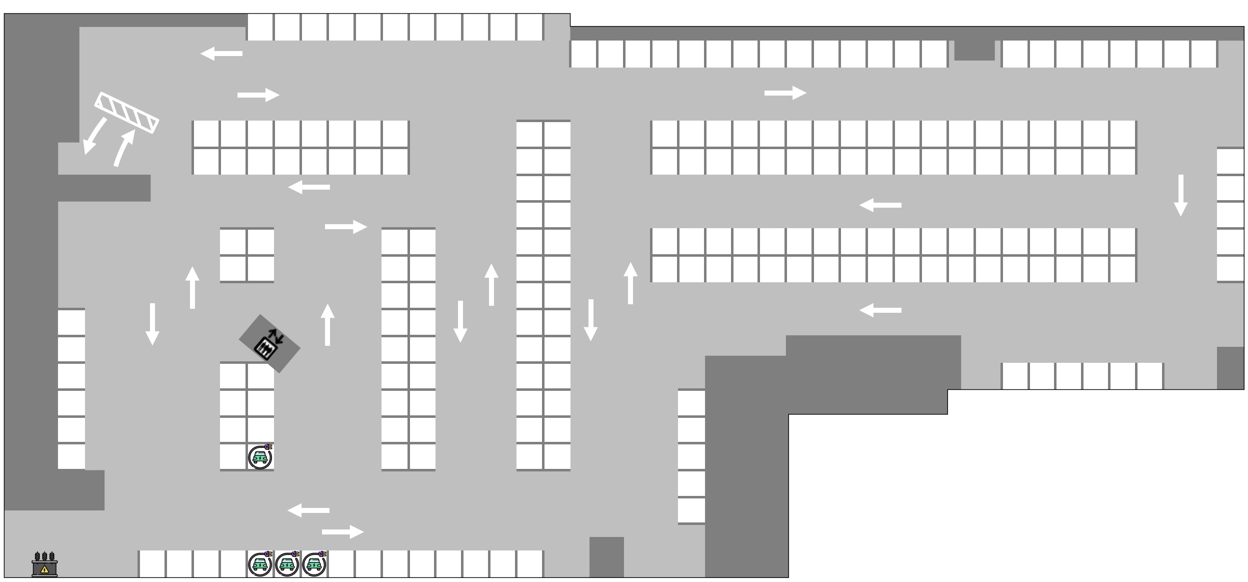


Figure 4-3 - Schematic design of case study layout Basement -1

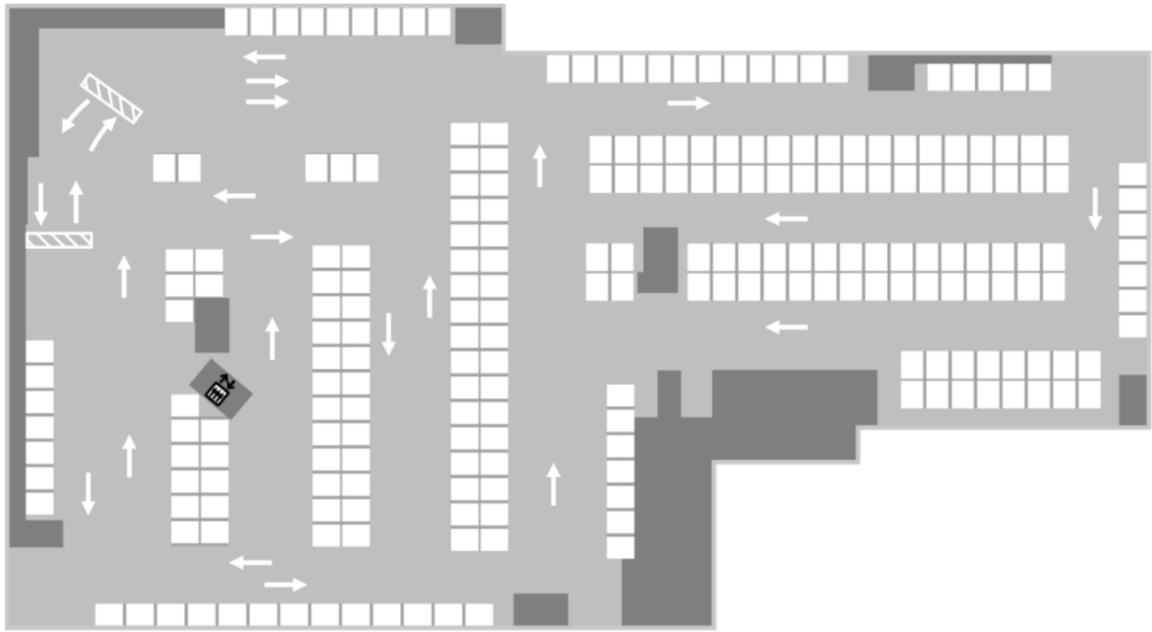


Figure 4-4 - Schematic design of case study layout Basement -2

4.4 Algorithm UI and Inputs

The model's UI includes a feature for users to easily input the desired number of ports (n_{ep}). This inputs field, located in the "General Settings" tab, allows users to specify the exact number of charging ports they wish to deploy. The general setting tab in the model's UI is designed to gather essential parameters for configurating the model as shown in Figure 4-5.

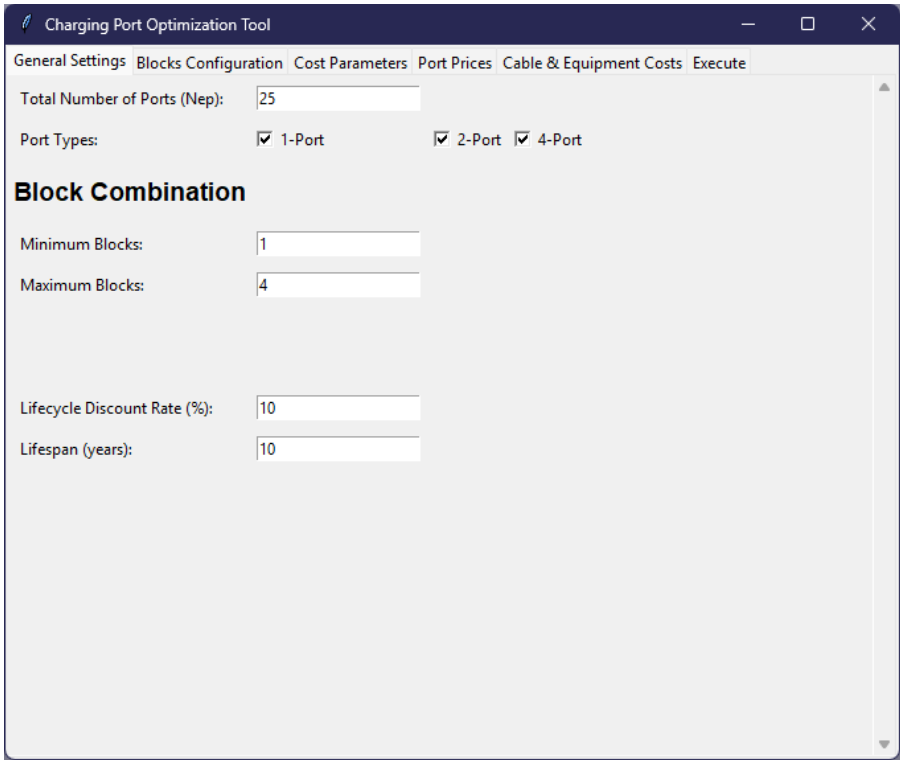


Figure 4-5 - General Settings Inputs of the Proposed Method

Figure 4-5 illustrates the general setting tab, which allows users to input key parameters:

1. The Port Options field enables the user to define the available port types, specifically allowing 1-port, 2-port, and 4-port units in the placement configuration. This customization helps the system understand the variety of charging units available for deployment.
2. The Minimum and Maximum Block Combination settings define the range of block groupings that can be considered. For instance, setting a maximum combination allows the model to explore configurations that use up to a specified number of blocks in a scenario.
3. Finally, the life cycle discount rate and the estimated lifespan period of the units are available for the user to adjust.

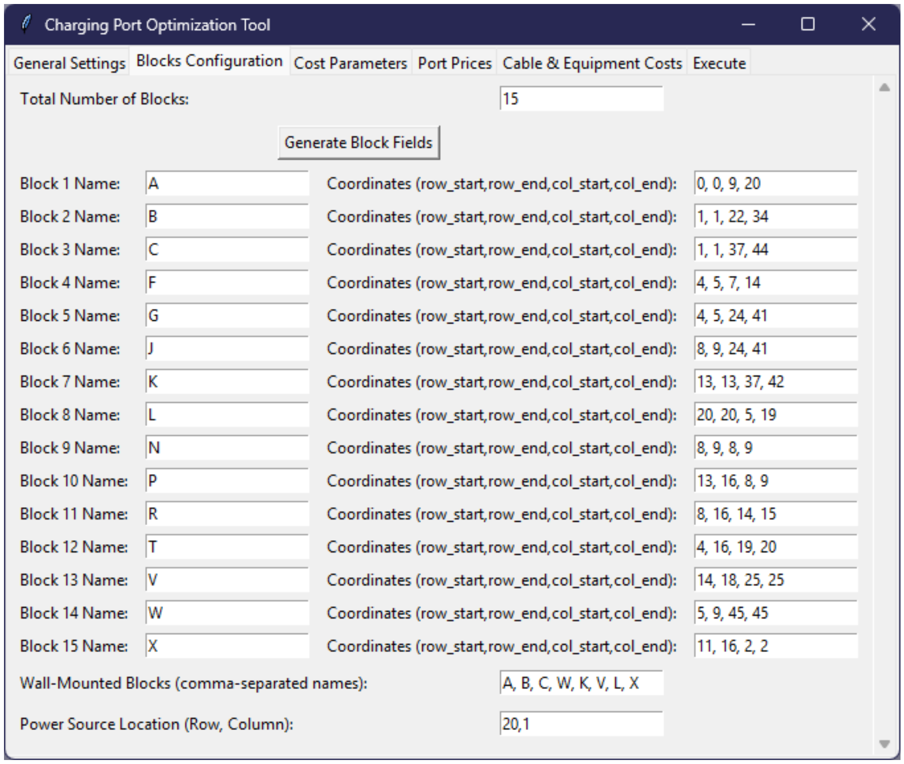


Figure 4-6 - Interface for blocks definition section

Figure 4-6 displays the Blocks Configuration section of the model's UI, where users can define the number of blocks in the layout, their dimension, and location within the parking lot. Each block is specified with starting and ending row and column coordinates, which indicate the spatial area it occupies. This setup allows the model to understand the layout of available spaces for EV charging port placement, enabling accurate calculations of distances and optimal port distribution. Each block is labeled with a unique identifier (e.g., Block A, Block B, etc.). Start row and End row fields define the vertical range of each block. For example, Block A has a Start Row of 0 and an End Row of 0, meaning it occupies only one row, while Block T spans rows 4 to 16. Start column and End column field specify the horizontal range of each block. For instance, Block A starts at column 9 and ends at column 20, indicating its width across these columns.

The parking layout will serve as input for the model, where the existing parking blocks will be conveyed in form of matrixes for simpler mathematical manipulation and visualization as shown in Figure 4-7. In this matrix, parking spots are grouped into blocks; with each block containing multiple parking spots. In the Model, parking spots are assigned a value of one, and unconsidered areas are assigned zero. By structuring the parking layout in this manner, the model can effectively evaluate and optimize charging port placement across the defined blocks.

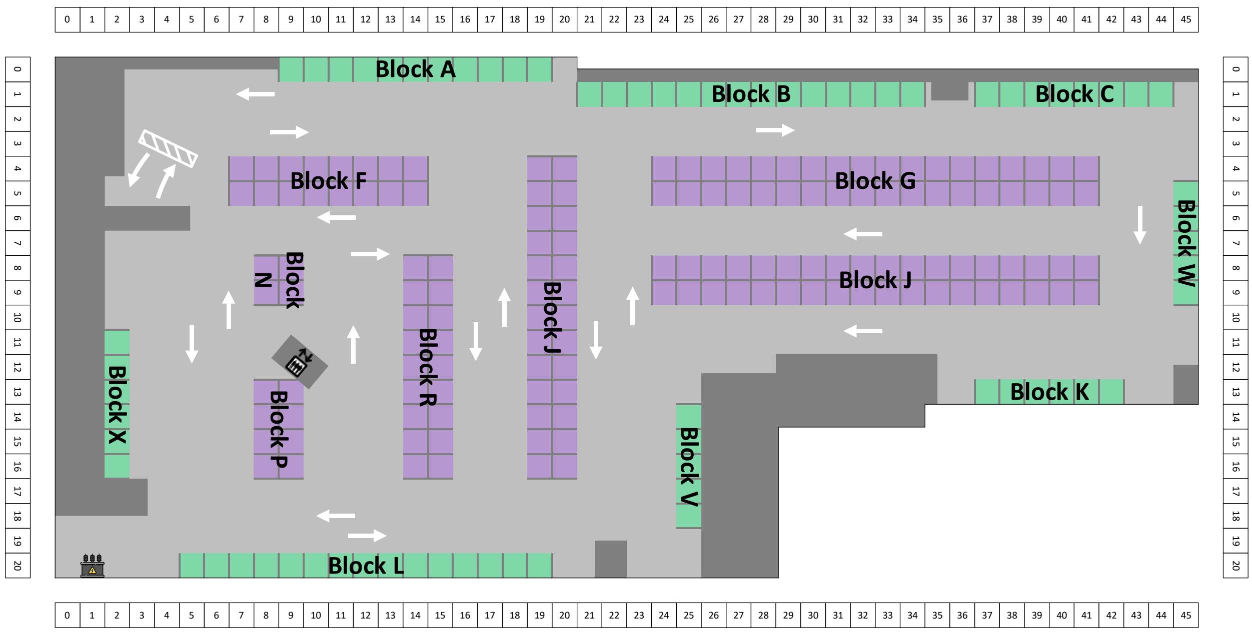


Figure 4-7 - Eaton Center shopping mall Parking Layout

The Power Source Location input field specifies the location of the main power source as a coordinate (row, col) is also accessible in this tab. This setting is essential for calculating distances for cable routing between the power source and the designated charging blocks, which directly affects cable costs.

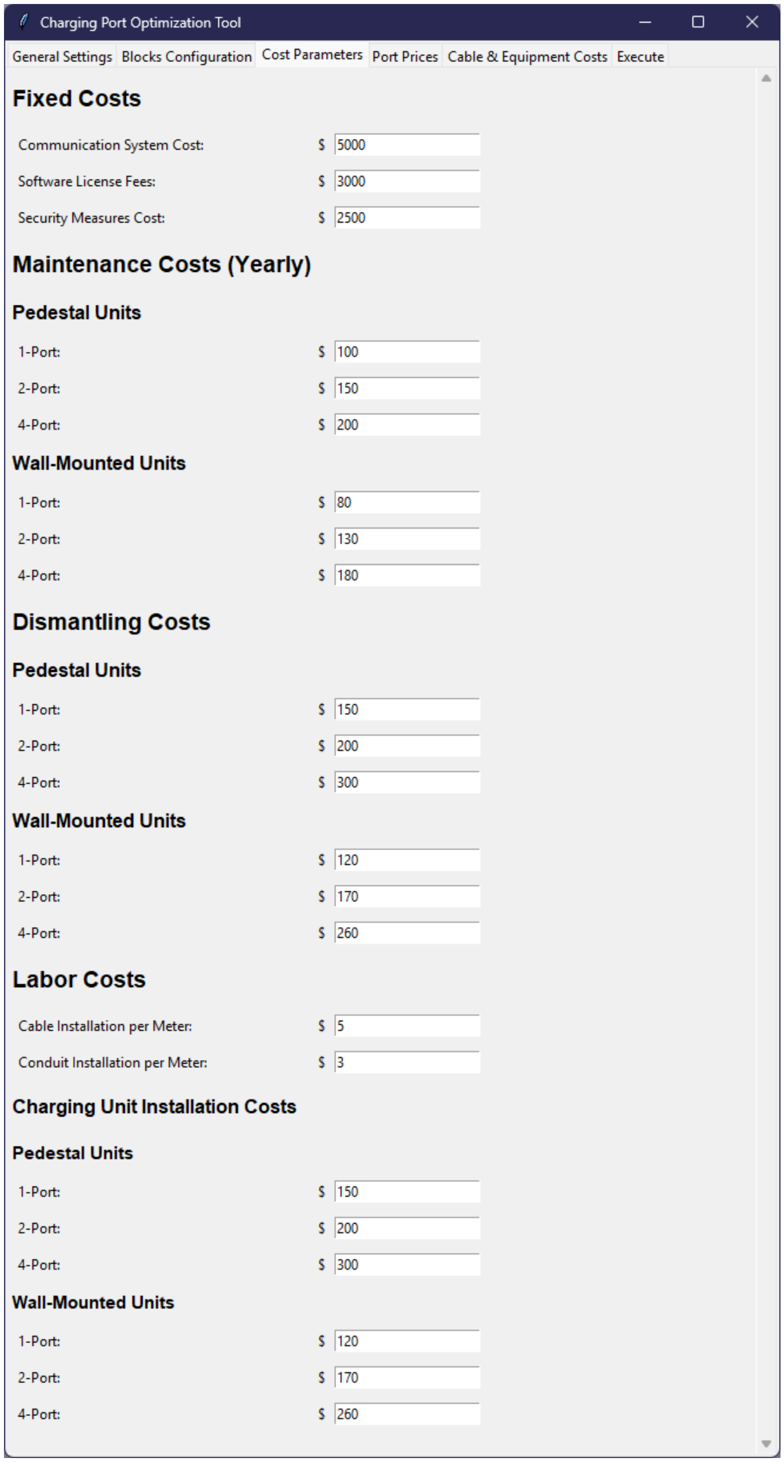


Figure 4-8 - Cost Parameters Tab

The Cost Parameters tab of the algorithm contain essential cost related inputs of the model. Each cost component is provided as an input, which the model then uses in its calculations. By defining these costs individually, the model can accurately project the total cost of scenario over the infrastructure's lifespan. As can be seen in Figure 4-8, yearly operation cost, fixed costs, labor cost, pedestal and wall-mounted (1-port to 4-port) chargers installation cost are can be defined by the user in this tab. Also, in this tab the maintenance and demolition costs for various charging units, separated by type and block placement. Maintenance Costs defined separately for normal and wall-mounted units across 1-port, 2-port, and 4-port configurations. Demolition Costs specified by unit type and configuration, representing costs for removing units if necessary. For example, maintenance costs for a 1-port wall-mounted unit are lower than those for a 4-port unit, reflecting the relative complexity and size of the installations.

The EV charging units device cost can be found in the Port Price tab of the UI. The prices are distinguished based on the port number (1, 2, and 4) and installation configuration (wall-mounted and pedestal). The depiction of Port Prices tab is shown in Figure 4-9.

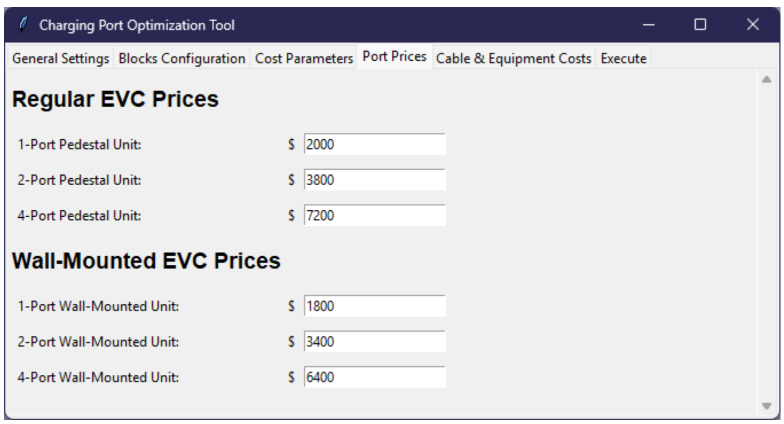


Figure 4-9 - Port Prices Tab

The electrical equipment plays an essential role in installation of the EV chargers. As shown in Figure 4-10, the generic electrical equipment cost such as Breakers, Fuse, Junction Box, and Conduits are definable by the user.

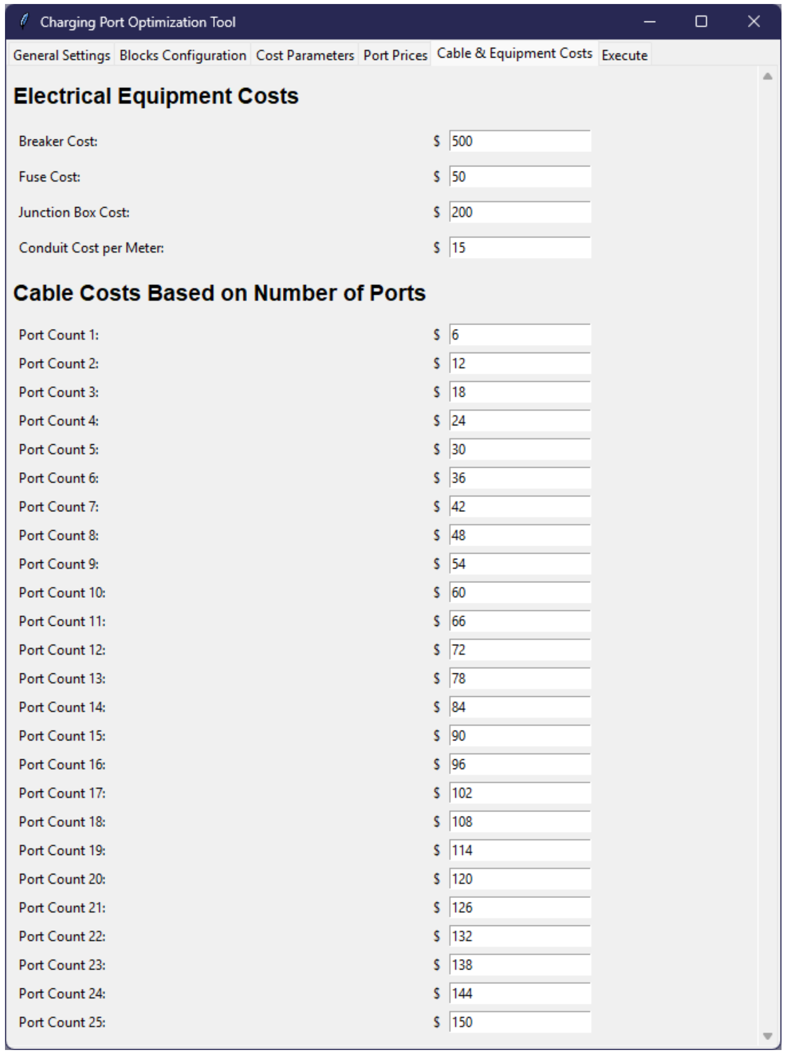


Figure 4-10 - Cable & Equipment Costs Tab

- Default Breaker Cost ($): Cost for circuit breakers used in the setup.
- Default Fuse Cost ($): Cost of fuses to protect electrical circuits.
- Default Junction Box Cost ($): Cost of junction boxes for safely connecting wiring.
- Conduit Cost per Meter ($/m): Cost for conduit per meter, which protects the wiring between blocks.

Furthermore, cable cost per port is defined in this tab as well. The power rating of the cables and consequently its price can be defined by the number of charging ports connected to the cable. Cable Costs per Total Ports in Block ($/m): This section specifies the cost per meter of cable based on the total number of ports in a block, ranging from 1 port up to 12 ports. Higher port counts typically increase the cabling cost.

4.5 Result and Discussion

This section discusses the results of the case study analyzed using the proposed approach. As given in Table 4-3, the number of desired ports to be added to the layout is assumed to be 25. The minimum and maximum number of blocks combination that algorithm will be used to come up with the most optimize results are taken 1 and 3 respectively. Furthermore, the user can define the chargers existing ports that algorithm can use for its calculations. This is important to take into consideration that 4-port units are limited to the block's with at least one 2x2 cell configuration.

Table 4-3 - Model Inputs General Setting

Parameter	Value
Number of Desired Ports (n_{ep}):	25
Maximum Number of Block Combination (M):	3
Minimum Number of Block Combination	1
Available port configuration (k):	$k \in (1,2,4)$
Lifecycle Discount Rate (%)	10
Lifespan (year)	10

The explained before based on the basic information provided the algorithm will try to optimize the best locations for the given desired number of ports with consideration of maximum and minimum block combinations while every port configuration is respected in the case study. Clearly as given before, there are several factors that will determine the optimized result. The algorithm is designed to minimize the allocation cost of EVCS within the designated area from the case study owner's point of view.

In the second tab of the algorithm configuration the number of parking layout blocks and their location/dimension is defined. In this case study 15 blocks are taken into consideration with their location/dimensions being as defined in the following Table 4-4.

Table 4-4 - Case Study Block Configuration/Location

Block	Dimension/Location[1]	Block	Dimension/Location
A	(0, 0, 9, 20)	B	(1, 1, 22, 34)
C	(1, 1, 37, 44)	F	(4, 5, 7, 14)
G	(4, 5, 24, 41)	J	(8, 9, 24, 41)

[1] The dimensions/locations are defined with this pattern **(Start Row, End Row, Start Column, End Column)**

K	(13, 13, 37, 42)	L	(20, 20, 5, 19)
N	(8, 9, 8, 9)	P	(13, 16, 8, 9)
R	(8, 16, 14, 15)	T	(4, 16, 19, 20)
V	(14, 18, 25, 25)	W	(5, 9, 45, 45)
X	(11, 16, 2, 2)		

Also, the blocks that are located beside the parking lots surrounding walls are A, B, C, W, K, V, L, and X. These blocks are suitable for installation of wall-mounted chargers that as explained before potentially cost lower compared to their pedestal counterparts. The location of the power source also defined as (20, 1) meaning the power source in the case study is assumed to be at row 20 and column 1 of the parking layout. The location of power source is a critical factor in the optimal result estimation. This value can directly influence the electrical equipment cost impacting final results.

Cost parameters are defined as given in Table 4-5.

Table 4-5 - Case Study Cost Parameters

<table>
<tr><th colspan="3">Parameter</th><th>Cost ($)</th><th colspan="3">Parameter</th><th>Cost ($)</th></tr>
<tr><td colspan="3">Communication System Cost</td><td>5000</td><td colspan="3">Cable Installation Per-Meter Labour cost</td><td>5</td></tr>
<tr><td colspan="3">Software License Fees</td><td>3000</td><td colspan="3">Conduit Installation Per-Meter Labour cost</td><td>3</td></tr>
<tr><td colspan="3" rowspan="6">Security Measures Cost</td><td rowspan="6">2500</td><td rowspan="6">Charging Units Installation Cost</td><td colspan="2" rowspan="3">Pedestal</td><td>150</td></tr>
<tr><td>200</td></tr>
<tr><td>300</td></tr>
<tr><td colspan="2" rowspan="3">Wall-mounted</td><td>120</td></tr>
<tr><td>170</td></tr>
<tr><td>260</td></tr>
<tr><td rowspan="6">Maintenance Cost</td><td rowspan="3">Pedestal</td><td>1-Port</td><td>100</td><td rowspan="6">Dismantling Cost</td><td rowspan="3">Pedestal</td><td>1-Port</td><td>150</td></tr>
<tr><td>2-Port</td><td>150</td><td>2-Port</td><td>200</td></tr>
<tr><td>4-Port</td><td>200</td><td>4-Port</td><td>300</td></tr>
<tr><td rowspan="3">Wall-mounted</td><td>1-Port</td><td>80</td><td rowspan="3">Wall-mounted</td><td>1-Port</td><td>120</td></tr>
<tr><td>2-Port</td><td>130</td><td>2-Port</td><td>170</td></tr>
<tr><td>4-Port</td><td>180</td><td>4-Port</td><td>260</td></tr>
</table>

The EVC units' prices can be found in Table 4-6.

Table 4-6 - Case Study Port Prices

Parameter		Cost ($)	Parameter		Cost ($)
Pedestal	1-Port	2000	Wall-Mounted	1-Port	1800
	2-Port	3800		2-Port	3400
	4-Port	7200		4-Port	6400

In order to calculate the electrical equipment, cost table 15 will be used. In this table the cost associated with some of the essential electrical equipment can be found. Also, the cost of the cables according to their port size can be found in Table 4-7.

Table 4-7 - Case Study Cable and Equipment Cost

Electrical Equipment	Cost ($)	Electrical Equipment	Cost ($)
Breaker Cost	500	Cable 12-port	72
Fuse Cost	50	Cable 13-port	78
Junction Box Cost	200	Cable 14-port	84
Conduit Cost Per Meter	15	Cable 15-port	90
Cable 1-port	6	Cable 16-port	96
Cable 2-port	12	Cable 17-port	102
Cable 3-port	18	Cable 18-port	108
Cable 4-port	24	Cable 19-port	114
Cable 5-port	30	Cable 20-port	120
Cable 6-port	36	Cable 21-port	126
Cable 7-port	42	Cable 22-port	132
Cable 8-port	48	Cable 23-port	138
Cable 9-port	54	Cable 24-port	144
Cable 10-port	60	Cable 25-port	150
Cable 11-port	66		

The specifications of the computer system used for this optimization is as follows:

CPU: AMD Ryzen 7 4800HS

RAM: 16.0 GB

Operating System: Windows 11 Pro, Version 24H2

Below is the most optimised result for our case study shown in Table 4-8. As can be seen the F and L blocks are producing the best results. The results include a combination of single-port, dual-port, and quad-port EVCs. As can be seen in Figure 4-11 and Table 4-8, the optimized results are distributed between the block F and Block L. As expected, the pedestal quad-ports and wall-mounted dual ports are creating our best result. This is due to the fact that the combination of these two types of EVC will end up with the least cost. It took <u>**2 hours**</u> for the in-use computer system to run the optimization algorithm and produce the optimal results.

Table 4-8 - Optimization Result of The Case Study

Top Result	
Block Combination	F, L
Port Combination	[1, 2, 2, 2, 2, 2, 2, 4, 4, 4]
Port Distribution in Block F	Three Quad-ports
Port Distribution in Block L	One Single-port, Six Dual-ports

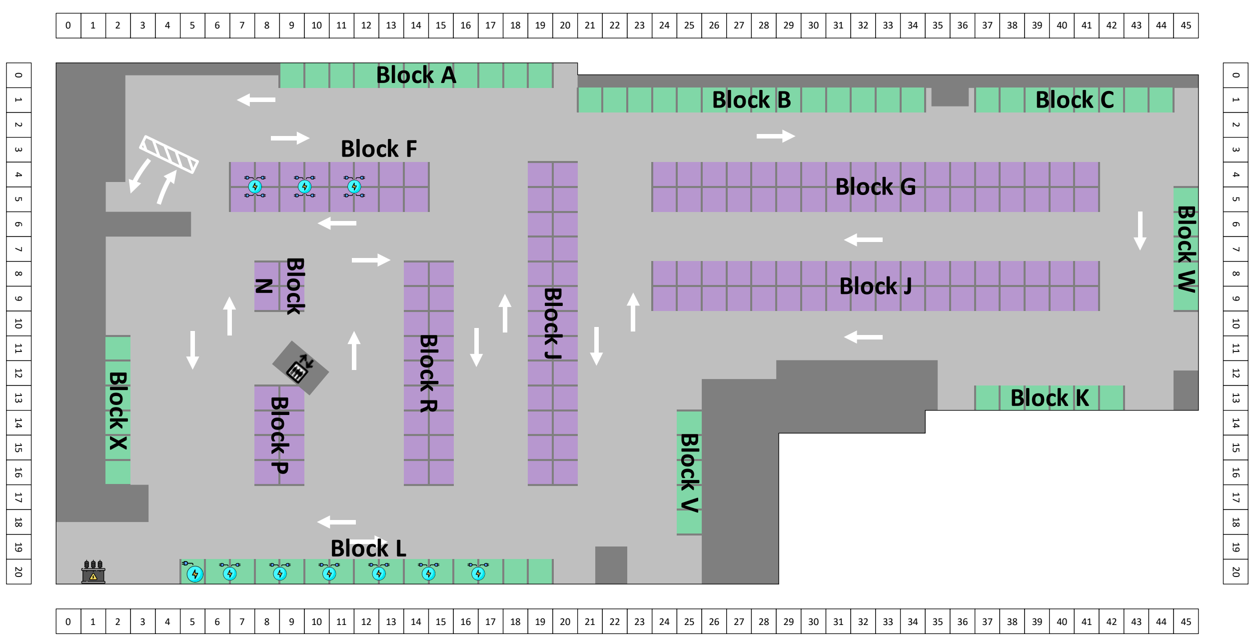


Figure 4-11 - EVCP Optimization Result Case Study

As we can the top result, identified by the minimum total cost over a 10-year lifespan. The selected blocks for charger installation are F, L. The optimal setup includes a mix of port types, single-port (4% of total), dual-port (48% of total), quad-port (48% of total). Initial high cost in year 0 correspond to EVCS Equipment cost, Electrical System Equipment cost, and fixed cost. The Table 4-9 at the bottom provides a breakdown of the LCC calculation based on Total NPV (Discount Rate = 10%).

Table 4-9 - LCC Calculation for Minimum Total Cost Result

Year	**Zero**	**One**	**…**	**Five**	**…**	**Ten**
Annual Cost ($)	0	11,840.00	…	11,840.00	…	11,840.00
One-time Cost ($)	60,358.75	0		11,840.00		8,700.00
Annual Net Cash Flow ($)	60,358.75	11,860.00		23,680.0		20,540.0
Discounted Rate ($)	1	0.90		0.62		0.38
Discounted Cash Flow ($)	60,358.75	10,763.63		14,703.4		7,919.05
Total Cost (NPV) ($)	**$ 143,816.35**					

The discounted cash flow of the optimal result is depicted in Figure 4-12.

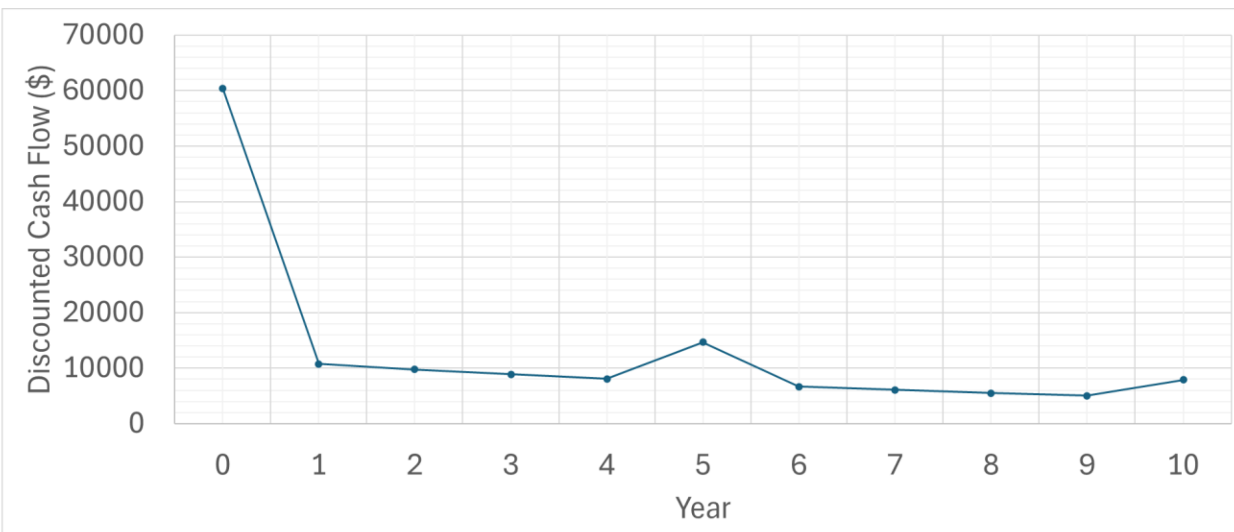


Figure 4-12 - Discounted Cashflow for The Optimal Result

Also, the percentage of the yearly discounted cash flow over the optimal result's initial cost can be found in Figure 4-13. As expected, the yearly discounted cashflow is a portion of the initial cost.

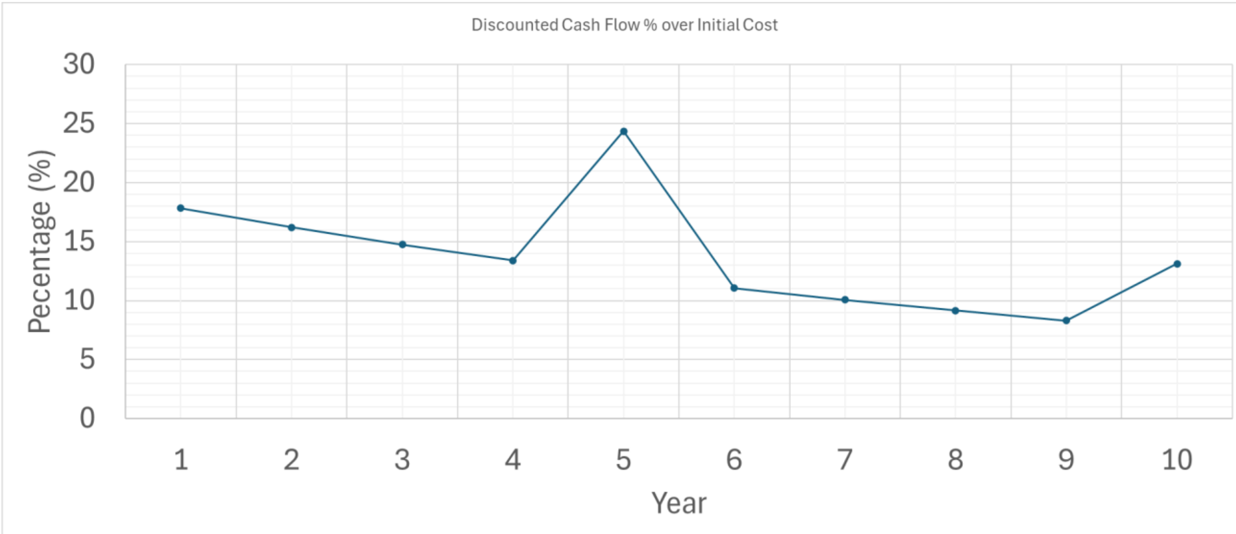


Figure 4-13 - Discounted Cashflow Percentage Over Initial Cost

The comparison between the number of wall-mounted and pedestal EVC for the optimize result can be seen in Figure 4-14. As expected, the number of wall-mounted and pedestal EVC has a balance of each type due to the direct impact cost distribution of EVCs, electrical equipment, and electrical equipment associated labour cost.

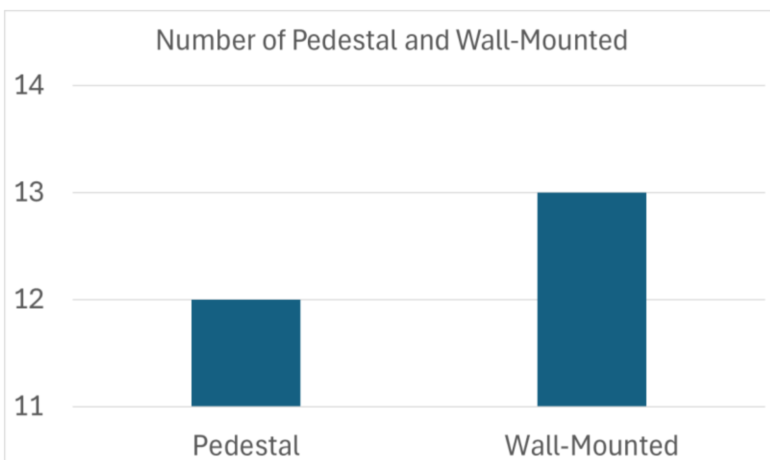


Figure 4-14 - Number of wall-mounted vs pedestal EVCs of the Optimal Result

For the demonstration purposes the optimization general setting will be changed to include only single-port and dual-port, and also single-port and quad-port combinations. This is mostly helpful for the condition when the user is obligated to or has a desire to only use certain type of EVCs.

The models' general setting for the practical suggestion one will be used as given in the Table 4-10.

Table 4-10 - Model Inputs General Setting for Practical Suggestion One

Parameter	Value
Number of Desired Ports (n_{ep}):	25
Maximum Number of Block Combination (M):	3
Minimum Number of Block Combination	1
Available port configuration (k):	k ∈ (1, 4)
Lifecycle Discount Rate (%)	10
Lifespan (year)	10

It took 45 minutes for the system to run the algorithm. The results for this case study are provided in Table 4-11. The parking lots EVC distribution is shown in Figure 4-15.

Table 4-11 - Optimization Result of The Practical Suggestion One

Top Result	
Block Combination	P, R, X
Port Combination	[1, 1, 1, 1, 1, 4, 4, 4, 4, 4]
Port Distribution in Block P	Two Quad-ports
Port Distribution in Block R	Three Quad-ports
Port Distribution in Block X	Five Single-ports

The optimal setup includes a mix of port types, single-port (20% of total), and quad-port (80% of total). The Table 4-12 at the bottom provides a breakdown of the LCC calculation based on Total NPV (Discount Rate = 10%).

Table 4-12 - LCC Calculation of The Practical Suggestion One

Year	**Zero**	**One**	**…**	**Five**	**…**	**Ten**
Annual Cost ($)	0	11,800.00	…	11,800.00	…	11,800.00
One-time Cost ($)	61,078.5	0		11,800.00		8,500.00
Annual Net Cash Flow ($)	61,078.5	11,860.00		23,600.0		20,300.0
Discounted Rate ($)	1	0.90		0.62		0.38
Discounted Cash Flow ($)	61,078.5	10,727.27		14,653.74		7,826.52
Total Cost (NPV) ($)	**$ 144,188.4**					

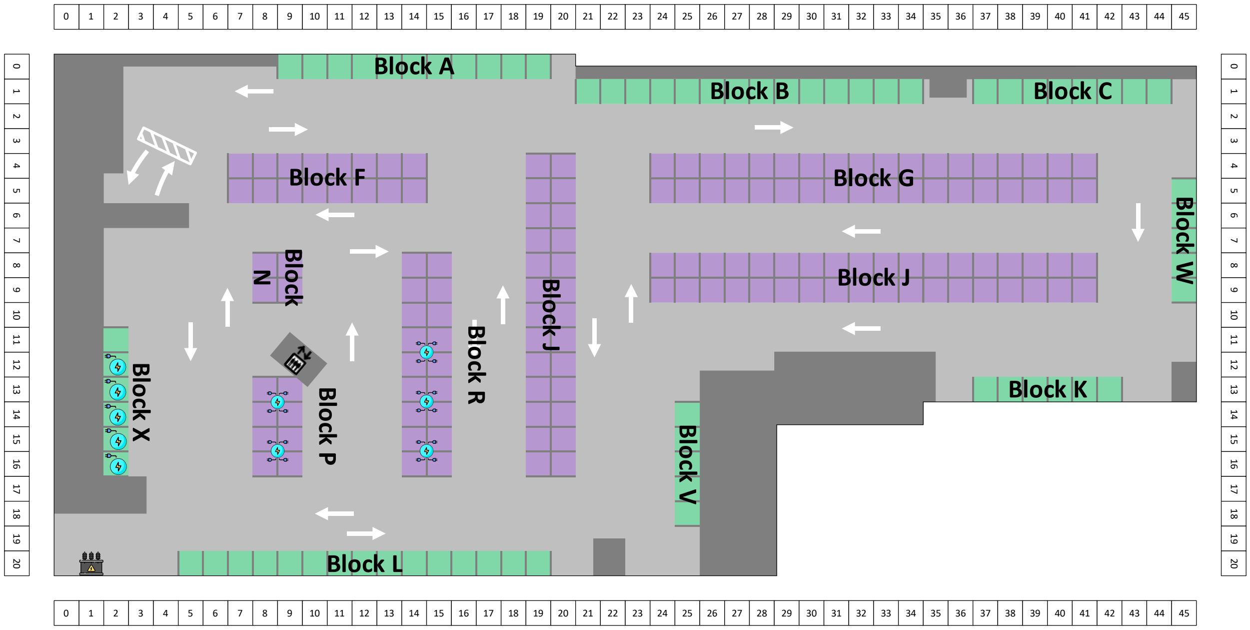


Figure 4-15 - EVCP Optimization Result of The Practical Suggestion One

The discounted cash flow of the optimal result is depicted in Figure 4-16.

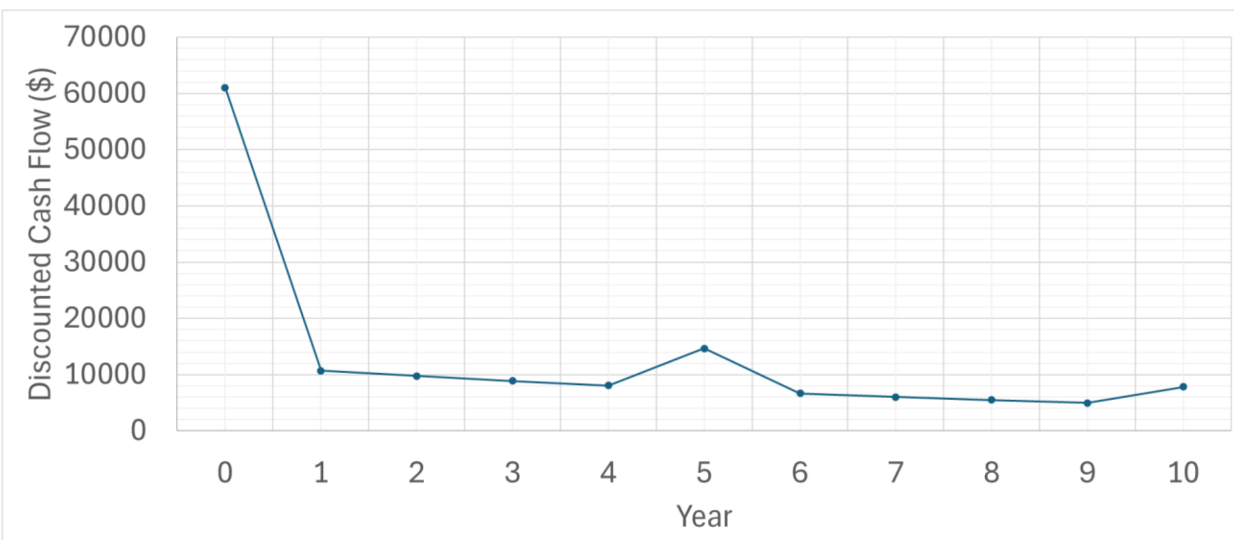


Figure 4-16 - Discounted Cashflow of The Practical Suggestion One

The percentage of the yearly discounted cash flow over the optimal result's initial cost can be found in Figure 4-17.

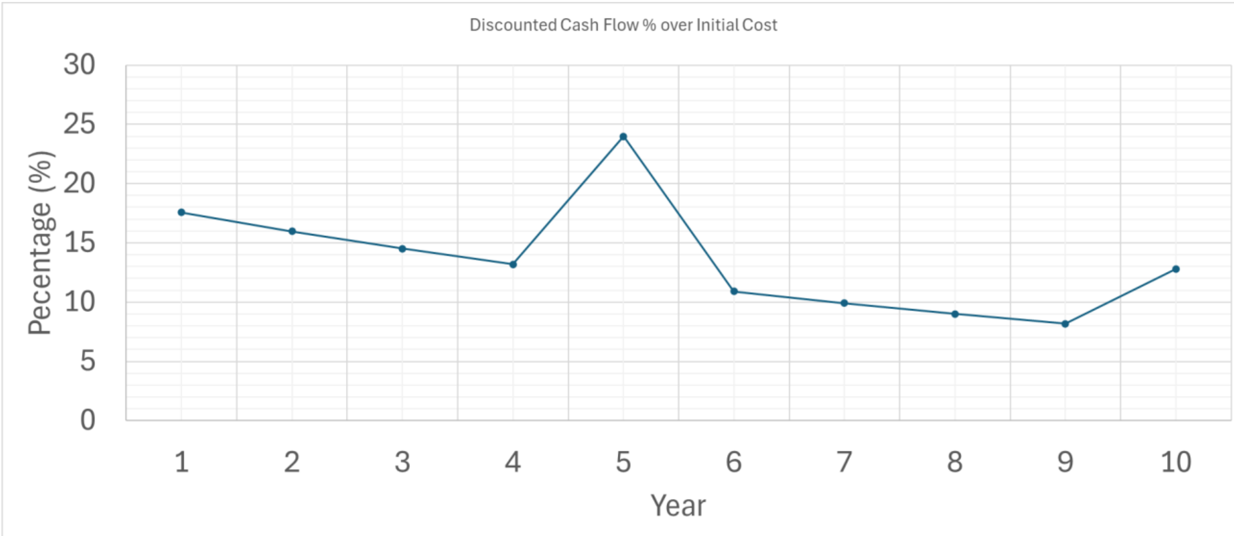


Figure 4-17 - Discounted Cashflow of The Practical Suggestion One

The comparison between the number of wall-mounted and pedestal EVC for the optimize result can be seen in Figure 4-14.

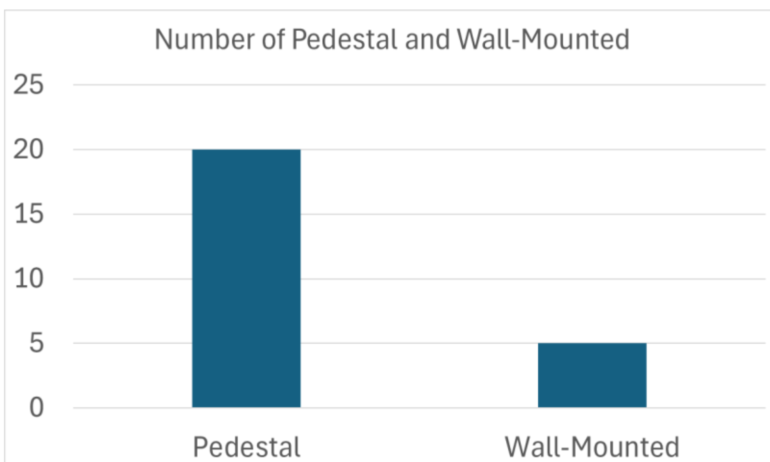


Figure 4-18 - Number of wall-mounted vs pedestal EVCs of The Practical Suggestion One

The models' general setting for the practical suggestion two will be used as given in the Table 4-13.

Table 4-13 - Model Inputs General Setting for Practical Suggestion Two

Parameter	Value
Number of Desired Ports (n_{ep}):	25
Maximum Number of Block Combination (M):	3
Minimum Number of Block Combination	1
Available port configuration (k):	k ∈ (1, 2)
Lifecycle Discount Rate (%)	10
Lifespan (year)	10

It took 1.5 hours for the system to run the algorithm. The results for this case study are provided in Table 4-14. The parking lots EVC distribution is shown in Figure 4-19.

Table 4-14 - Optimization Result of The Practical Suggestion Two

Top Result	
Block Combination	L, V, X
Port Combination	[1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2]
Port Distribution in Block L	Seven Double-ports
Port Distribution in Block V	One Single-ports, Two Double-ports
Port Distribution in Block X	Three Double-ports

The optimal setup includes a mix of port types, single-port (4% of total), and quad-port (96% of total). The Table 4-15 at the bottom provides a breakdown of the LCC calculation based on Total NPV (Discount Rate = 10%).

Table 4-15 - LCC Calculation of The Practical Suggestion Two

Year	**Zero**	**One**	**…**	**Five**	**…**	**Ten**
Annual Cost ($)	0	11,880.00	…	11,880.00	…	11,880.00
One-time Cost ($)	61,391.5	0		11,800.00		8,500.00
Annual Net Cash Flow ($)	61,391.5	11,880.00		23,760.0		20,680.0
Discounted Rate ($)	1	0.90		0.62		0.38
Discounted Cash Flow ($)	61,078.5	10,800		14,753.09		7,973.03
Total Cost (NPV) ($)	**$ 145,158.3**					

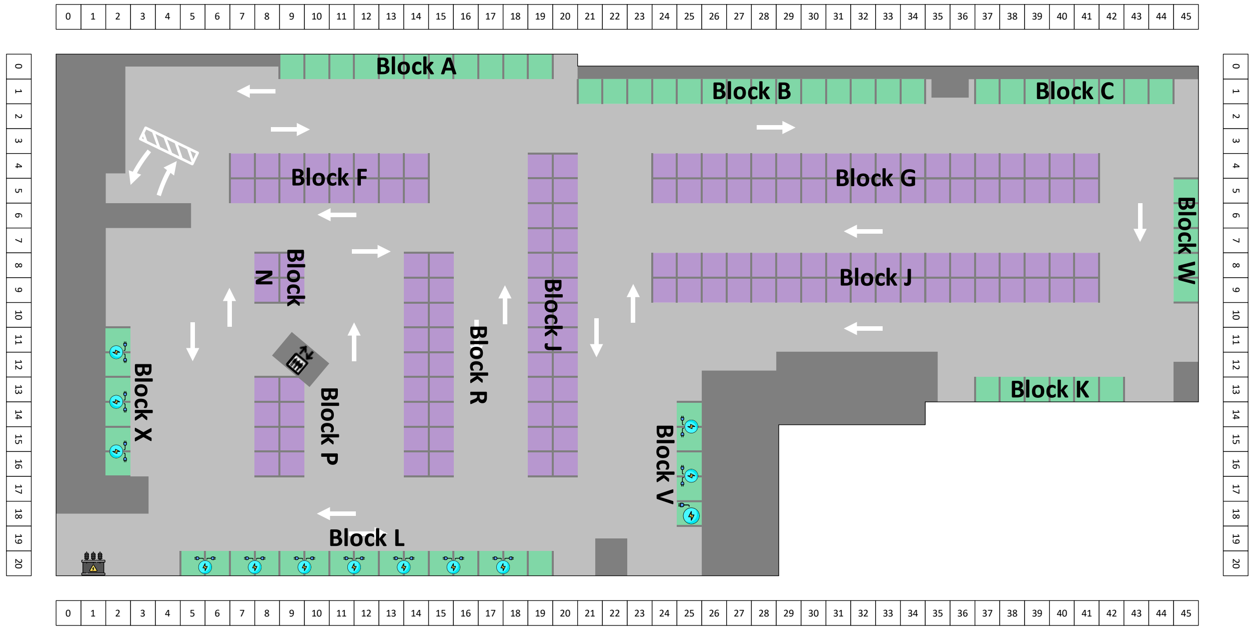


Figure 4-19 - EVCP Optimization Result of The Practical Suggestion Two

The discounted cash flow of the optimal result is depicted in Figure 4-20.

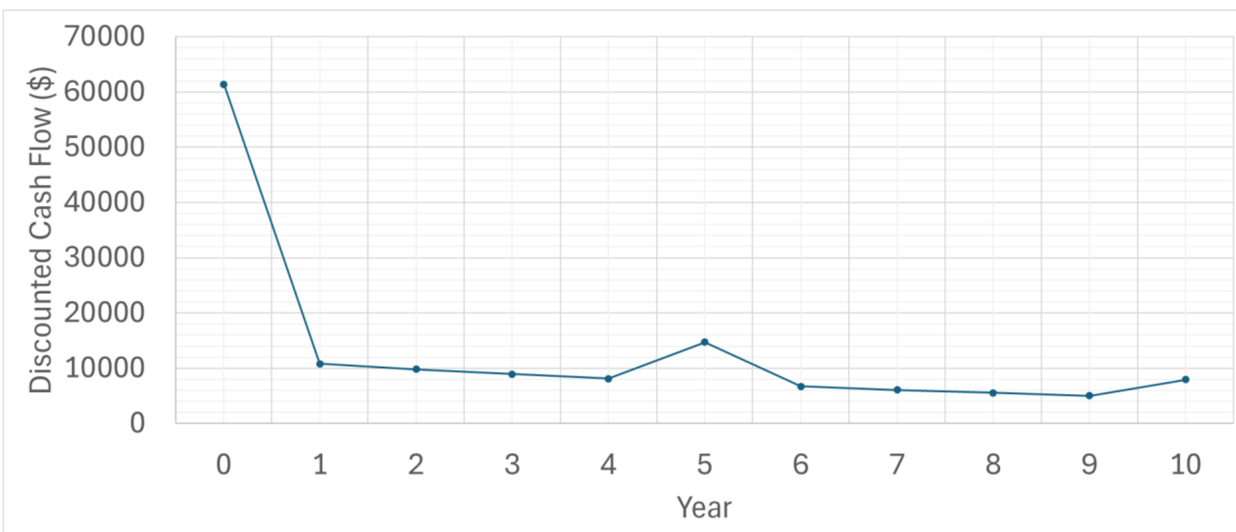


Figure 4-20 - Discounted Cashflow of The Practical Suggestion Two

The percentage of the yearly discounted cash flow over the optimal result's initial cost can be found in Figure 4-21.

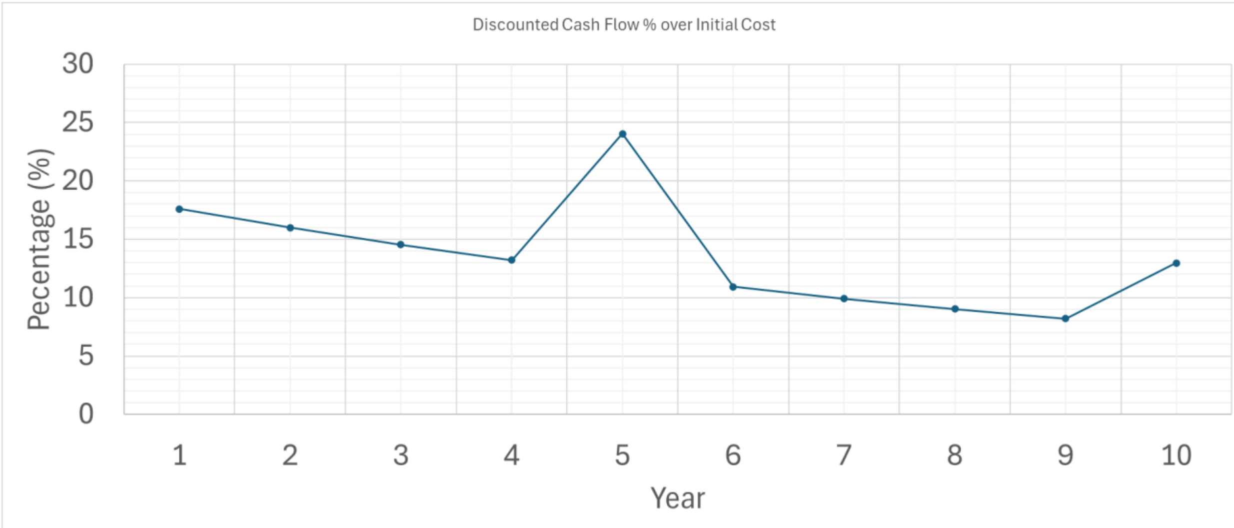


Figure 4-21 - Discounted Cashflow of The Practical Suggestion Two

The comparison between the number of wall-mounted and pedestal EVC for the optimize result can be seen in Figure 4-22.

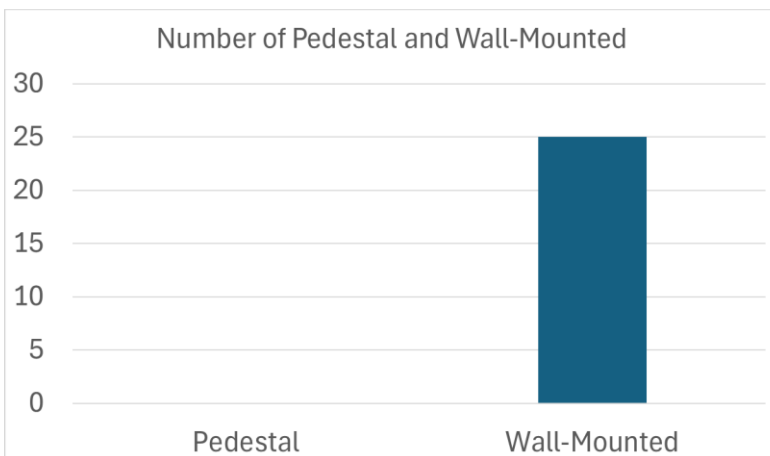


Figure 4-22 - Number of wall-mounted vs pedestal EVCs of The Practical Suggestion Two

The results for the worst case scenario are provided in Table 4-16.

Table 4-16 - Optimization Result of The Practical Suggestion Two

Top Result	
Block Combination	C, G, W
Port Combination	[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]
Port Distribution in Block C	One Single-ports
Port Distribution in Block G	Twenty-three Single-ports
Port Distribution in Block W	One Single-ports

The worst-case scenario's cost results for the case study and the two practical suggestions are also provided below in Table 4-17. As expected, all the optimizations generate the same worst scenario.

Table 4-17 - LCC Calculation of The Worst-Case Scenario

Year	**Zero**	**One**	**…**	**Five**	**…**	**Ten**
Annual Cost ($)	0	12,460.00	…	12,460.00	…	12,460.00
One-time Cost ($)	79,245.0	0		12,460.00		12,300.00
Annual Net Cash Flow ($)	79,245.0	12,460.00		24,920.0		24,760.0
Discounted Rate ($)	1	0.90		0.62		0.38
Discounted Cash Flow ($)	79,245.0	11,327.27		15,473.36		9,546.05
Total Cost (NPV) ($)	**$ 168,285.2**					

As expected, the worst-case scenario is demanding higher cost compared to our optimized result and even suggested practical results one and two. Based on the existing results comparing total cost of our optimized result, the worst-case scenario costs 17% more. Also, it can be found that the worst-case scenario costs 16.7% and 15.9% more compared to the suggested practical scenarios one and two respectively.

5. Conclusions and Future Recommendations

5.1 Conclusions

In this thesis, proposed mathematical model is formulated as a Mixed-Integer Nonlinear Programming (MINLP), to minimize the total costs associated with allocating multiport chargers within parking spots, while ensuring efficient placement of EV Charging Ports (EVCP). Each charger with different port types represents a facility, and the EVCP must be allocated to each block in accordance with the specified block combinations (Capacitated multi-facility location problem approach). The combinatorial optimization algorithm integrated dynamic programming and brute-force search techniques to generate port configurations across designated parking blocks. Optimization process, which determines the Life Cycle Cost (LCC) for each scenario from the owner's perspective and selects the scenario with minimum cost. The goal is to find the placement configuration that yields the lowest total costs. By comparing cost of scenarios, the configuration with the lowest total cost will be chosen, which would be the most economical option for the EV Charger placement. Overall, the findings indicate that strategic placement of multi-port chargers can effectively meet projected EV growth while minimizing long-term lifespan expenses for property owners.

5.2 Contributions of the research

The main research contributions of this thesis can be categorized as:

- Developed an optimization model for placing Electric Vehicle Charging Stations (EVCS) in the existing indoor parking. The cost formulation is designed as LCC-Based optimization approach, enabling property owners to make informed, cost-effective decisions on EVCS placement. This LCC-Based framework accounts for EVCS Equipment, Electrical System Equipment Cost, Operational and Maintenance costs, and dismantling cost.
- Provided a framework for integrating single-port, dual-port, and quad-port chargers into existing parking blocks, with a special emphasis on ports placement constraints and requirements crucial for the EV allocation within parking spots.
- Developed a combinatorial optimization algorithm that utilizes dynamic programming for efficient port combination and port distribution within the block generation, reducing

computational redundancy by storing solution for reuse. Additionally, a brute-force search is employed to systematically evaluate all feasible port and block configurations, ensuring that the model explores the possible solutions. This dual-method approach provides an exact solution to the EVCS placement problem.

5.3 Key assumptions and limitations

- It is assumed that the existing building infrastructure can accommodate the additional electrical load required to power the EV chargers.
- In this research, public charging is referred to the private parking area accessible for publics.
- In this research, it is assumed that power source location to be fixed in one level area.
- The maximum number of block combinations considered is limited to three, based on the size and layout constraints of a typical shopping center parking facility. This assumption simplifies the computational complexity and reflects practical limitations in real-world parking areas. Expanding beyond three block combinations may be feasible for larger facilities but would require additional computational resources.
- The model is designed specifically for indoor parking facilities within commercial shopping centers. Consequently, its applicability to other types of settings—such as outdoor lots, residential complexes, or public EV charging stations—may be limited. Different contexts could require adjustments to the model to account for varying spatial constraints, user behavior, and environmental factors.

5.4 Recommendations for future research

- Algorithmic Technique Improvement: Future research could extend the model to achieve more advanced optimization with reduced computation time.
- Complex Layouts: Additionally, applying the model to more complex parking layouts could be explored in future studies, allowing for broader applicability in diverse architectural settings.
- Extend the model to include the scheduling of charging sessions, optimizing not only where chargers are placed but also how charging is managed throughout the day to reduce wait times and maximize usage.

- Investigate models that incorporate power load balancing and demand response strategies, allowing the system to adjust charging rates and prioritize certain chargers during peak hours or based on grid load.
- User-Centric Approach: Adopting a user-centric approach by prioritizing the convenience and accessibility of EV charging stations could improve the model. Future studies could consider factors like ease of access, visibility, and proximity to key areas within parking facilities, making the model more adaptable to user needs and preferences.
- The model could be extended to incorporate revenue generation and profit maximization. Future research could explore strategies for setting optimal charging fees, and maximizing revenue streams, thereby transforming EV charging infrastructure from a cost center to a potential profit center for property owners.
- For new or highly adaptable facilities, considering a non-fixed (variable) power source might offer more optimized solutions, especially for large-scale implementations where minimizing cabling costs and improving load distribution are priorities.
- An alternative approach could involve designating a limited number of potential power source locations and allowing the model to select the most optimal one based on cost and distance.
- Future research should investigate the impact on road maintenance funding from a reduction on the overall taxes raised from gasoline excise tax after significant proportions of the vehicle fleet had evolved towards electric vehicles.
- Future research could integrate renewable energy sources, such as solar panels or wind turbines, into the EV charging infrastructure model. This would involve creating a hybrid power system where EV charging stations are powered by a mix of grid electricity and on-site renewable sources.
- The model could be extended to hydrogen long range regional buses and truck logistics.
- The model could be extended to the problem of allocation of charging depots for buses within a Great Metro Area, including the logistics behind the best location for overnight charging and early morning service.
- Future research could explore integrating power source locations across multiple levels to better account for the hierarchical nature of energy distribution and demand.

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