Multi-objective Evolutionary Algorithms for Solving the Electric Vehicle Charging Station Infrastructure Problem

Master's Thesis in Applied Computer and Information Technology (ACIT)

Applied Artificial Intelligence

by

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Abstract

The increasing awareness of the environmental impact of gasoline and diesel vehicle emissions has contributed to the global shift toward cleaner energy in both public and private transportation. Ensuring efficient and accessible transport remains a critical challenge for urban planners and decision-makers. To support this transition, significant advancements in technology and infrastructure are required—particularly in developing an effective network of electric vehicle charging stations (EVCS) at strategically chosen locations.

This thesis explores the use of the multi objective evolutionary algorithm to optimize the placement and configuration of electric vehicle charging stations (EVCS). The goal is to find a solution that maximizes the geographic area covered by EV charging stations, minimizes the cost of setting up the infrastructure, and maximizes the power level of the stations to improve charging efficiency and reduce waiting times. By applying a multi-objective optimization process (MOOP) using a multi-objective evolutionary algorithm (MOEA), such as the NSGA-II algorithm, we demonstrate the potential of evolutionary algorithms to address the complexities of EV charging station layout in an urban environment. The results show that NSGA-II provides an efficient and versatile solution to the challenges of the electric vehicle charging station infrastructure.

The NSGA-II algorithm found optimized EVCS layouts that balance five key objectives: (1) maximize coverage, (2) maximize charger speed to reduce waiting time, (3) minimize the number of stations, (4) minimize the number of chargers, and (5) minimize average distance, all aimed at minimizing total infrastructure cost and improving efficiency. The optimized solution reduced the network cost from \$5,867,800 (about 5.87 million) to \$3,750,000, achieving a 36% decrease. This improvement was achieved by reducing the number of EVCS from 19 to 7 and the total number of chargers from 69 to 18.

However, because this study used a multi-objective optimization approach, the algorithm balanced several competing goals rather than focusing on a single objective. As a result, coverage per station decreased from 11.89 to 3.33 on average. This

reduction reflects trade-offs made to prioritize other objectives, especially minimizing the average distance between electric vehicles (EVs) and their nearest charging station. In this respect, the solution was effective, as the average user travel distance improved slightly, decreasing from 17.39 km to 17.37 km, which enhances accessibility and reduces user inconvenience.

Overall, the NSGA-II approach demonstrated the ability to generate a variety of balanced solutions, supporting the development of cost-effective, scalable, and accessible electric vehicle charging infrastructure.

Chapter 1

Introduction

Rapid growth in the adoption of electric vehicles (EVs) offers significant benefits, including reduced air pollution and decreased reliance on traditional fuels such as diesel and gasoline. However, this transition also presents challenges for urban transportation systems, particularly the need to develop reliable and accessible charging infrastructure.

The selection of locations for electric vehicle charging stations is a complex issue that requires balancing several conflicting objectives. With the increasing adoption of electric vehicles globally, creating reliable, efficient, and accessible infrastructure has become critical. A key challenge in this process is identifying the optimal locations for charging stations to meet the needs of electric vehicle users while minimizing associated costs and maximizing coverage to ensure easy access.

Minimizing overall infrastructure costs is a primary goal when selecting charging station locations. This includes direct costs, such as station installation and maintenance, as well as costs associated with user access. Reducing these costs is a critical aspect of urban planning, making it essential to strategically distribute charging stations to keep expenses low while still meeting demand. Effective distribution plays a key role in balancing costs and user accessibility.

In addition to cost considerations, minimizing travel distance for EV users is a critical factor in determining charging station locations. The availability of charging stations directly impacts the feasibility of EV use. Stations should be strategically located, whether in densely populated urban areas or in rural regions where access to charging infrastructure may be limited. Reducing the distance drivers must travel to find a charging station is essential, as it encourages the adoption of EVs.

Furthermore, the speed of chargers should be considered to minimize charging time. Optimizing the charging power at each station enhances the overall efficiency of the network, leading to faster charging and a better user experience. This factor is crucial to ensuring that the charging infrastructure can meet the growing demand for electric vehicles while minimizing user wait times.

In contrast, traditional approaches to solving the EVCS location problem typically rely on optimization techniques such as mathematical programming. These methods often focus on optimizing a single objective, prioritizing one aspect of the problem—such as minimizing cost. While effective in some cases, they often fall short when addressing the balance between multiple objectives. Additionally, traditional optimization techniques can be computationally expensive and time-consuming, especially when dealing with large urban areas and numerous potential charging station locations.

Multi-objective optimization techniques, such as multi-objective evolutionary algorithms (MOEAs), offer a promising alternative for addressing the complexity of the electric vehicle charging station infrastructure problem. These algorithms are designed to explore a diverse set of solutions that represent various trade-offs between competing objectives. By considering multiple objectives simultaneously, MOEAs provide decision-makers with a range of optimized solutions, enabling more balanced and informed planning decisions.

This study aims to answer the following research question: How can multi-objective evolutionary algorithms be applied to optimize electric vehicle charging station infrastructure planning?

To explore this question, this study applies a multi-objective evolutionary algorithm, specifically NSGA-II, to evaluate and optimize different configurations of charging station placement using real-world data. By considering multiple objectives simultaneously, the goal is to develop a balanced and practical approach to EV infrastructure planning. The results aim to support decision-makers in designing charging networks that are efficient and accessible.

1.1 Motivation

The transition to electric vehicles (EVs) is a crucial step toward sustainable transportation, helping to reduce air pollution, greenhouse gas emissions, and reliance on fossil fuels such as gasoline and diesel. As EV adoption accelerates globally, the need for a reliable, accessible, and efficient charging infrastructure becomes increasingly critical.

Designing optimal locations and configurations for electric vehicle charging stations (EVCS) is a complex problem involving multiple, often conflicting objectives. Key goals include maximizing geographic coverage to ensure accessibility for users, enhancing charger speeds to reduce waiting and charging times, minimizing infrastructure costs by limiting the number of stations and chargers, and reducing the average travel distance for EV users to access charging points. Balancing these objectives is essential to foster widespread EV adoption and create a user-friendly charging network.

Traditional optimization methods are often inadequate for solving such complex, multidimensional problems. This is where multi-objective evolutionary algorithms (MOEAs), such as NSGA-II, become valuable. These algorithms are well-suited to handling the complexities of EVCS infrastructure optimization, as they can search for solutions that simultaneously satisfy multiple objectives.

The motivation behind this thesis arises from the need to explore advanced optimization techniques like MOEAs to address the challenges faced by urban planners and decision-makers in developing electric vehicle charging infrastructure. As the number of electric vehicles grows, the demand for a robust charging network increases. The placement and configuration of charging stations must ensure adequate coverage across urban areas while minimizing infrastructure costs.

Furthermore, this research aims to demonstrate how evolutionary algorithms, particularly NSGA-II, can provide efficient and scalable solutions to these challenges, contributing to the creation of a sustainable and efficient electric vehicle charging infrastructure.

1.2 Problem Definition

The growing emphasis on electric vehicles by governments worldwide has created an urgent need for a robust and widespread charging infrastructure. Distributing electric vehicle charging stations optimally across different regions—ensuring high capacity and cost-effectiveness to meet user demand—is a complex challenge. This issue involves balancing multiple objectives, such as expanding coverage, minimizing costs, and reducing waiting times. This research applies multi-objective evolutionary algorithms to address these challenges and identify optimal solutions for electric vehicle charging infrastructure deployment. The problem can be formalized as follows:

- **Maximize Charger Speed:**The efficiency of charging stations plays a key role in determining the speed at which electric vehicles can be recharged. In general, stations with higher power output can reduce charging durations, potentially leading to shorter waiting times for users. These improvements could improve the overall user experience and contribute to a more efficient operation of the charging network. As the adoption of electric vehicles increases, the availability of high speed charging infrastructure becomes an important factor in meeting user needs.
- **Maximize Coverage:** Expanding the geographic coverage of electric vehicle charging stations is essential to improve accessibility for users. A well-distributed network can allow electric vehicle owners to find and reach charging points more easily, potentially reducing the need for long detours or extended travel times. Improved accessibility could enhance user convenience and may play a significant role in promoting the adoption of electric vehicles. As more areas are equipped with reliable charging infrastructure, range anxiety could be alleviated, making the ownership of electric vehicles more practical and supporting the transition to a more sustainable transportation system.
- **Maximize Charger Speed:** The efficiency of charging stations plays a key role in determining the speed at which electric vehicles can be recharged. In general, stations with higher power output can reduce charging durations, potentially leading to shorter waiting times for users. These improvements may enhance

the overall user experience and contribute to a more efficient operation of the charging network. As the adoption of electric vehicles increases, the availability of high-speed charging infrastructure becomes an important factor in meeting user needs.

- **Minimize the Number of Stations:** Reducing the number of charging stations, without compromising network coverage, is essential to reduce costs and improve operational efficiency. A careful balance between station location and network coverage ensures that the service area is adequately covered while minimizing infrastructure costs.

- **Minimize the Number of Chargers:** In addition to reducing the number of charging stations, it is important to minimize the number of individual chargers at each station. This approach helps lower initial investment and operating costs while still maintaining service levels and user convenience.

However, the economic feasibility of building or expanding electric vehicle charging infrastructure is a significant consideration for decision-makers. Achieving a balance between wide geographic coverage and cost effectiveness is essential to enhancing system performance. This challenge becomes even more critical when coupled with the need to increase charger speeds, which can reduce charging and waiting times and improve overall efficiency.

Although deploying a large number of charging stations in large areas improves accessibility, it requires significant financial investment. This highlights the need for strategic planning to ensure affordability and adequate service coverage for electric vehicle users.

1.3 Objective of the Thesis

This thesis aims to:

- Investigate multi-objective evolutionary algorithms (MOEAs) to solve the EVCS infrastructure problem.

- Optimize multiple objectives simultaneously, such as coverage, charger speed (with the goal of upgrading all chargers to Level 3 fast chargers), number of EVCS, number of chargers, and the average distance between EVs and EVCS.
- Present and analyze the results from the research experiments conducted in this thesis, and compare them with previous studies.

Chapter 2

Background

This chapter provides an overview of the basic concepts needed to understand the problem of optimizing electric vehicle charging station infrastructure. It discusses electric vehicles and their charging needs, multi-objective optimization (MOO), evolutionary algorithms (EAs), and multi-objective evolutionary algorithms (MOEAs), and specifically the NSGA-II algorithm, which is a central method in this study.

2.1 Electric Vehicles and Charging Infrastructure

The use of electric vehicles has increased in recent years, driven by growing concerns about climate change. Government policies promoting sustainable transportation have significantly fueled this growth.

In addition, advances in battery technology have played a key role in supporting this shift, as they have become more affordable and accessible. All of these factors have significantly contributed to accelerating the adoption of electric vehicles.

Moreover, gasoline and diesel vehicles can be developed to handle large amounts of fuel at a reasonable cost and can be refueled quickly and easily. However, despite significant advances in battery technology, electric vehicles face the challenge of increasing their battery capacity due to their high cost, making a reliable and accessible charging network important.

There are generally three levels of EV chargers:

- **AC Level 1 Charging:** Level 1 charging is the most basic method to charge an electric vehicle (EV). It uses a standard 120-volt household outlet. This charger level is often used when no other higher voltage charging options are available. Although this type of charger is very slow, it is still practical for many drivers, especially those who drive short distances every day. Level 1 charging is simple and requires no installation. Most electric cars come with a Level 1 charging cable that can be plugged directly into a household electrical outlet. Moreover, Level 1 charging meets simple daily needs whcih typically delivering up to 3 kW of power using a standard 3-pin domestic plug (4).

  For example, charging an electric car for 8 hours increases its driving range to approximately 64 kilometers (40 miles). This is sufficient for normal daily driving. Overall, Level 1 charging may not be ideal for long-distance travel, but for many EV owners, it offers a cost effective and easy way to charge at home without needing extra equipment(1).

- **AC Level 2 Charging:** Level 2 charging provides electric vehicle (EV) charging through a 240 volt electrical supply in residential settings, or 208 volts in commercial environments(1). Unlike Level 1 charging, which uses a standard 120V outlet and charges slowly, Level 2 significantly reduces charging time, making it a popular choice for both home and public use. Level 2 charging is much faster than Level 1, using a 220V outlet instead of the standard 120V(1), and chargers speed in range from 7 kW to 22 kW (4). This significantly reduces charging time, making it a popular choice for both home and public use. One of the main benefits of Level 2 charging is its ability to fully charge a typical EV battery overnight. This makes it ideal for daily use.

- **DC Fast Charging:** Level 3 charging operates at around 400 volts, allowing electric vehicles (EVs) to charge significantly faster than with standard Level 1 or Level 2 charging(2).

  This technology provide 50 kW and up to 500 kilowatts (kW) of power (5), making it ideal for busy highways and transportation routes where fast charging is crucial(1). In addition, DC fast charging stations are especially useful for long-distance travel and commercial applications, as they can recharge an EV battery to 80% in as little as 20–30 minutes, depending on the vehicle and charger capacity(1).

Level 3 chargers, also known as rapid or ultra-rapid chargers, provide 50 kW or more, using direct current (DC) to enable high-speed charging. These chargers are typically installed at commercial or public charging stations and are ideal for quick top-ups during travel (Lifewire, 2024).

The growing adoption of medium and heavy duty electric vehicles (EVs) such as electric buses, delivery vans, and heavy trucks increased demand for DC fast charging infrastructure. These vehicles have larger batteries, which requiring higher charging capacities.

Overall, DC fast charging plays a critical role in supporting the widespread adoption of EVs across personal, commercial, and public transportation sectors.

Figure 2.1 shows the distribution of charger levels in use in the United States(1).

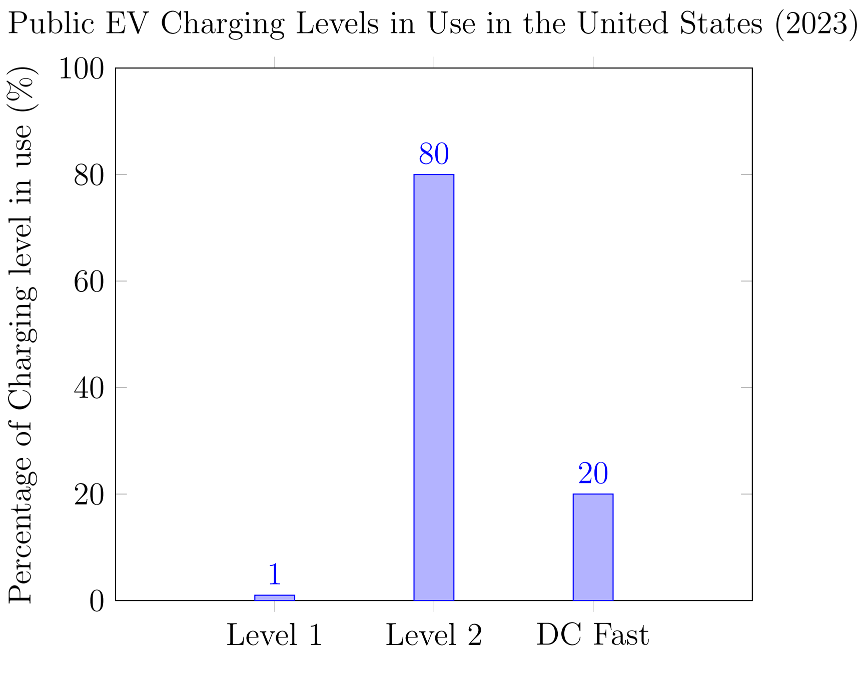

Figure 2.1: Distribution of EV Charging Port Types in the United States (2023)

Connectors for electric vehicle (EV) charging vary depending on the region and charging level. Generally, the standard SAE J1772 connector is widely used for both

Level 1 and Level 2 charging. For Level 3, or DC fast charging, the most commonly used connectors are the Combined Charging System (CCS) and CHAdeMO(1).

Moreover, Tesla, as a major player in the EV industry, uses a proprietary connector for its vehicles. However, it also provides compatibility with the CCS connector through the use of adapters(1).

Figure 2.2 illustrates the types of connectors used for Levels 1, 2, and 3.

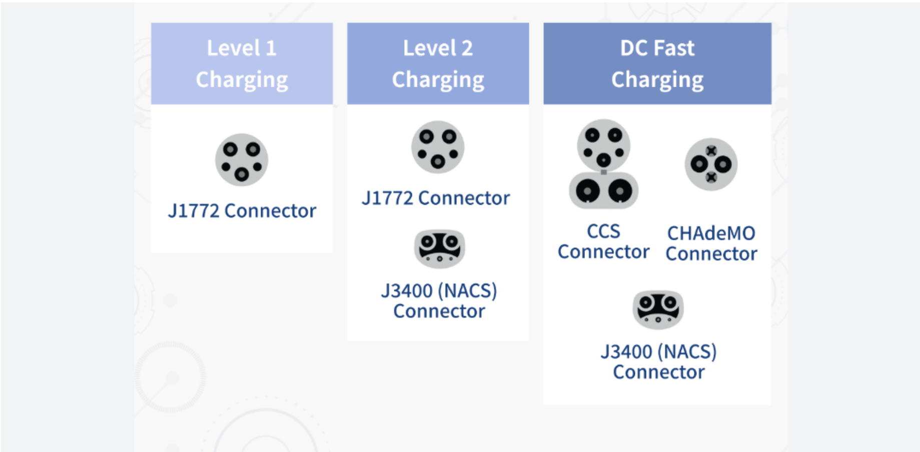

Figure 2.2: Types of EV connectors used for Levels 1, 2, and 3 (1)

Figure 2.3 illustrates the relationship between average charging speed and charging time for the three levels of electric vehicle (EV) charging based on data from the U.S. Department of Transportation (3). Level 1 charging has the longest average charging time of approximately 65 hours, and delivers the lowest charging speed of around 5 miles per hour. In contrast, Level 2 charging reduces the charging time to an average of 5.5 hours and increases the average charging speed to 46 miles per hour. Level 3 charging, or DC fast charging, offers the highest efficiency with an average charging time of just 0.75 hours and a substantial charging speed of approximately 638 miles per hour.

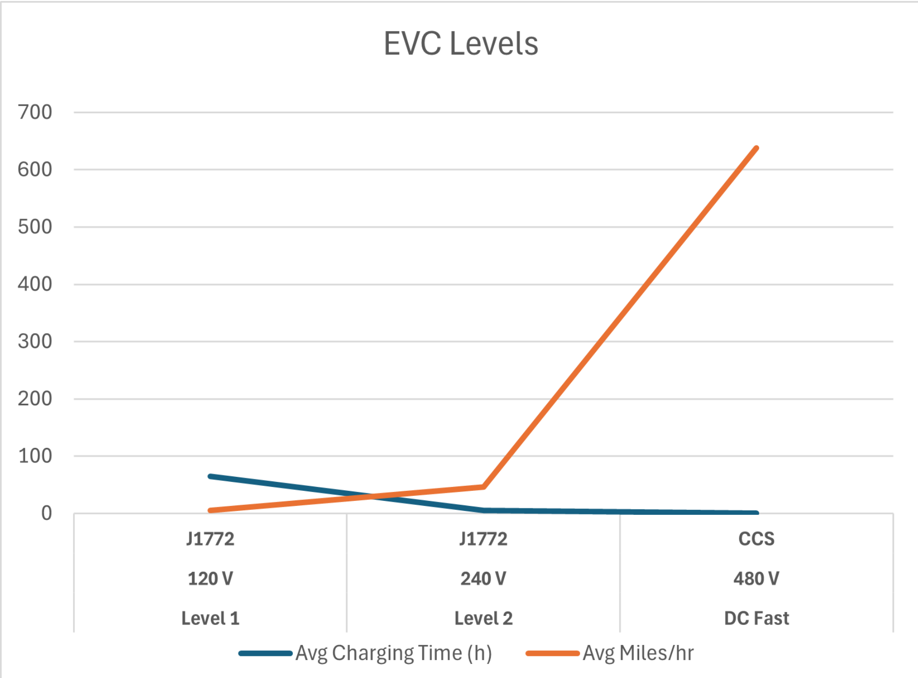

Figure 2.3: Average charging speed versus charging time for different EV charging levels

This clear trend highlights the performance differences between charging levels, with faster charging options offering significantly higher power output and reduced wait times. These differences are crucial for consumers and EV charging station operators when choosing the right charging infrastructure to meet their specific operational needs. This clearly contributes to supporting the spread and convenience of EV.

2.2 Multi-Objective Optimization (MOO)

Multi Objective Optimization (MOO) seeks to optimize multiple conflicting objectives simultaneously. Unlike single-objective optimization, which produces one best solution, MOO generates a set of Pareto optimal solutions(26).

In addition, these solutions represent trade-offs, where improving one objective results in worsening another. The set of all Pareto optimal solutions forms the Pareto front, which shows the best possible trade-offs between the objectives. Each point on this front represents a solution where no objective can be improved without degrading another. MOO is commonly used in complex decision-making problems where multiple criteria must be considered. It provides valuable insights into the balance between competing objectives.(26).

Regarding (8) The general expression of a multi objective optimization (MOO) problem:

$$\text{Minimize } \mathbf{F}(x) = [f_1(x), f_2(x), \ldots, f_k(x)], \quad \text{subject to } x \in \Omega$$

where

- $\mathbf{F}(x)$: Represents the vector of k objective functions. Each $f_i(x)$ corresponds to a distinct goal or objective, and the decision vector x influences all of them.
- Ω: Refers to the feasible set of decision variables, which defines the constraints the decision variables must satisfy.
- **Minimization**: The aim is typically to minimize each objective function, although maximization is also common. In many cases, improving one objective could negatively affect another, creating trade-offs that are a key challenge in multi-objective optimization.

MOO is used across many domains:

- **Engineering**: Balancing trade-offs among cost, weight, and performance. - **Energy Systems**: Optimizing efficiency, cost, and environmental impact (11). -

Finance: Portfolio optimization involving return and risk. - **Machine Learning**: Hyperparameter tuning involving accuracy, complexity, and fairness (10).

2.2.1 Trade-offs in Multi-Objective Optimization: The Role of Pareto Optimality

In multi-objective optimization (MOO), it is often impossible to identify a single solution that optimally satisfies all objectives simultaneously, especially when the objectives conflict (8). Instead, the goal is to find a set of solutions that represent acceptable trade-offs. A solution is considered *Pareto optimal* if there is no other feasible solution that can improve at least one objective without worsening another. According the principle of MOO, Pareto optimality plays a crucial role in evaluating the quality of a solution amidst conflicting objectives (8).

The collection of all Pareto optimal solutions is known as the *Pareto front*. Each point on this front represents a non-dominated solution, meaning that no other solution in the feasible space is strictly better in all objectives. As such, the Pareto front provides decision-makers with a spectrum of choices, each embodying different trade-offs among the objectives. This allows for flexibility in selecting solutions that align with specific priorities or operational constraints (8).

In addition, identifying the Pareto front supports more informed decision-making, particularly in complex systems where multiple performance metrics must be balanced. For example, in engineering design, a solution may involve trade-offs between cost, efficiency, and robustness. In such scenarios, a decision-maker might prioritize cost-effectiveness while ensuring that other performance criteria remain within acceptable limits (8).

However, selecting a single solution from the Pareto front is not trivial. This process typically involves incorporating decision-maker preferences, which may be explicit (e.g., assigning weights to objectives) or implicit (e.g., using interactive methods). Furthermore, these preferences may change over time or remain uncertain, adding another layer of complexity to the optimization process (12).

Understanding trade-offs among objectives and visualizing the Pareto front play a vital role in revealing interactions between decision variables, defining the limits of achievable performance, and supporting strategic decision-making (8).

The shape of the Pareto front can impact the performance of optimization methods. Classical methods, like the weighted sum approach. In contrast, evolutionary algorithms are better at exploring different areas of the Pareto front because they use a population-based method and can handle complex, nonlinear problems (8).

In summary, Pareto optimality provides a rigorous framework for analyzing and interpreting trade-offs in multi-objective problems. It serves as a decision support mechanism, helping stakeholders to navigate complex trade-offs and make choices that best align with their objectives and constraints.

2.2.2 Solution Methods

Several methods have been developed to solve Multi-Objective Optimization (MOO) problems, categorized into classical and evolutionary approaches. Both approaches provide valuable tools depending on the nature of the problem. Classical methods tend to be more straightforward, but may face limitations with complex, high-dimensional problems. Evolutionary algorithms, on the other hand, are well suited for handling such complexity and are the primary focus of this research.

Classical Methods: In classical Multi-Objective Optimization (MOO), scalarization techniques are commonly employed to simplify the problem by converting multiple objectives into a single objective function. One such technique is the weighted sum method, where each objective is assigned a weight and then combined into a single function. This method is computationally efficient and performs well when the Pareto front is smooth and regular. However, it may fail in cases where the Pareto front is non-smooth or discontinuous, as it might not capture all potential solutions. Another widely used classical method is the ϵ constraint method. In this approach, one objective is optimized, while the other objectives are constrained within specific bounds. Although this method ensures that all objectives are considered, it requires multiple runs with different constraint settings to fully explore the Pareto front. While classical methods are efficient for low-dimensional problems, they tend to struggle with high-dimensional, nonlinear, or complex objective landscapes (8), (26).

Evolutionary Algorithms (EAs):

Evolutionary Algorithms (EAs) are population-based, stochastic optimization techniques inspired by the principles of natural selection and genetics (7),(26). They employ biologically inspired operations such as selection, crossover, and mutation to iteratively evolve a set of candidate solutions toward optimal or near-optimal trade-offs across multiple objectives.

The general structure of an EA consists of the following steps (26):

1. **Initialization:** Generate an initial population of solutions randomly or heuristically.

2. **Evaluation:** Assess the fitness of each individual using the defined objective functions.

3. **Selection:** Choose high quality solutions based on fitness to serve as parents for the next generation.

4. **Variation:** Apply genetic operators such as crossover and mutation to generate new offspring.

5. **Replacement:** Form a new generation by selecting individuals from the current population and the offspring.

EAs are particularly effective for tackling complex, nonlinear, and high dimensional optimization problems where classical methods may struggle, especially when the Pareto front is irregular (7). Its strength lies in its ability to maintain a diverse set of solutions, which allows it to explore different regions of the solution space simultaneously. This makes it particularly suitable for multi objective optimization problems.

Given these advantages, this research focuses on applying evolutionary algorithms as a fundamental framework for optimization, leveraging their flexibility and robustness in dealing with complex trade-offs in multi-objective problems.

2.3 Multi-Objective Evolutionary Algorithms (MOEAs)

Multi-objective evolutionary algorithms (MOEAs) are extensions of traditional evolutionary algorithms designed to address problems with multiple, often conflicting, objectives. Unlike single-objective evolutionary algorithms, MOEAs maintain a set of solutions, allowing multiple solutions to be explored simultaneously (36).

According to (36), the key features of MOEAs are as follows:

- **Diversity Preservation:** Mechanisms such as crowding distance and niching ensure a well-distributed set of solutions across the Pareto front.
- **Pareto Dominance:** Selection is based on dominance relations, where one solution dominates another if it is no worse in all objectives and better in at least one.
- **Archiving:** High-quality non-dominated solutions are stored in an external archive to preserve progress across generations.

MOEA models have been widely applied in various fields, including engineering design, logistics, supply chain optimization, telecommunications, and power systems planning, due to their ability to handle complex, nonlinear, and high-dimensional objective spaces (36).

2.4 NSGA-II Algorithm

The Non-dominated Sorting Genetic Algorithm II (NSGA-II), proposed by Deb et al. (37), is one of the most popular and efficient Multi-Objective Evolutionary Algorithms (MOEAs).

According (37) , NSGA-II introduces several key innovations as follows:

- **Fast Non-dominated Sorting:** This method efficiently classifies the population into different levels of non-domination, ensuring the diversity of solutions.
- **Crowding Distance:** Measures the density of solutions surrounding a particular solution, promoting diversity by maintaining a spread of solutions across the objective space.

- **Elitism:** Retains the best solutions of individuals across generations, ensuring that the quality of the population improves over time.

The algorithm can be summarized in the following steps (37), (34):

1. **Initialization:** Generate an initial population of solutions randomly within the defined decision space.

2. **Evaluation:** Evaluate the objective function values for each individual in the population.

3. **Non-dominated Sorting:** Sort the population into different non-dominated fronts based on Pareto dominance.

4. **Crowding Distance Calculation:** Compute the crowding distance for each individual to estimate the density of solutions surrounding it.

5. **Selection:** Select parents for reproduction using binary tournament selection based on rank (non-dominance level) and crowding distance.

6. **Crossover and Mutation:** Apply genetic operators such as crossover and mutation to generate a new set of offspring.

7. **Combination:** Combine the parent and offspring populations to form a new population.

8. **Replacement:** Perform non-dominated sorting on the combined population, and select the best individuals based on rank and crowding distance to form the next generation. Repeat from Step 2 until the termination criterion is met.

Figure 2.4 illustrates the complete process of the NSGA-II algorithm (34). It begins with the initialization of a random population and the evaluation of objective functions. Then, non-dominated sorting and crowding distance calculation are applied to guide the selection process. Finally, crossover and mutation operators generate offspring, and the process repeats for each generation.

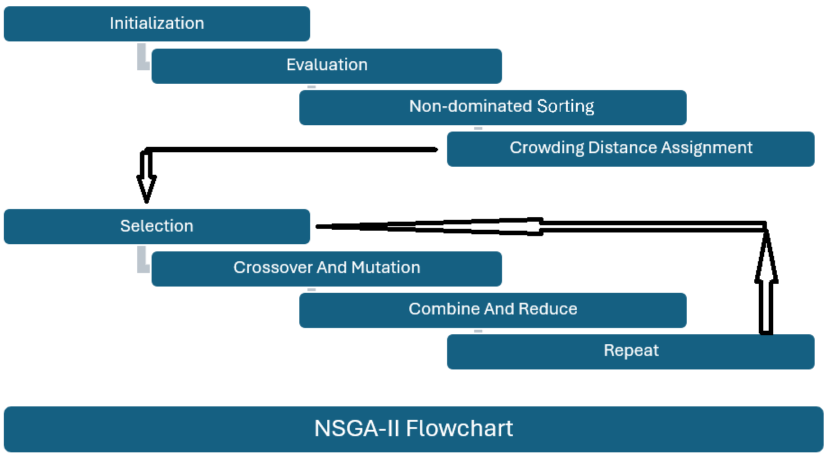

Figure 2.4: Flowchart of the NSGA-II algorithm.

In addition, NSGA-II is computationally efficient, with a time complexity of $O(MN^2)$, where M is the number of objectives and N is the population size (37).NSGA-II is a suitable method for solving complex multi-objective problems because it maintains a good balance between finding high quality solutions (convergence) and keeping a wide variety of options (diversity). This makes it a practical choice for optimizing Electric Vehicle Charging Station (EVCS) networks, which is the main focus of this study. The optimization goals include minimizing the number of stations, minimizing the number of chargers, and reducing the average distance to charging stations. By exploring a wide range of possible solutions and identifying a set of well-balanced outcomes (Pareto-optimal solutions), NSGA-II helps manage the trade-offs between these conflicting objectives. This approach supports the design of efficient and accessible EVCS networks, helping to reduce wait times, improve coverage, and lower overall costs (26).

Chapter 3

Literature Review

The development of electric vehicle charging infrastructure has become a critical issue due to the rapid adoption of electric vehicles (EVs) and the growing demand for sustainable transportation. Solving this problem requires addressing multiple conflicting objectives such as coverage, charging speed, number of stations, and accessibility. As a result, researchers have increasingly turned to Multi-Objective Optimization Problems (MOOP) and Evolutionary Algorithms (EAs), particularly Genetic Algorithms (GAs) and the Non-dominated Sorting Genetic Algorithm II (NSGA-II), to identify optimal solutions that strike a balance among these objectives.

3.0.1 Multi-objective Approaches in EVCS Planning

The EVCS deployment problem is naturally suited for multi-objective modeling due to the need to balance trade-offs such as cost, coverage, and user convenience.(13) proposed a multi-objective optimization model that minimizes installation costs and user travel distance while maximizing station utilization. Their study highlighted the importance of Pareto-based solution sets in evaluating trade-offs and supporting planning decisions. Similarly,(14) applied a genetic algorithm to optimize charging station locations by minimizing operational costs and maximizing service coverage, further demonstrating the effectiveness of evolutionary approaches in capturing the complexities of EVCS planning.

3.0.2 Genetic Algorithms and NSGA-II in EV Infrastructure Planning

Genetic Algorithms have been widely adopted in the field due to their robust global search capabilities. **(author?)** (14) developed a GA-based model that optimized EVCS placement in urban environments by considering cost and traffic congestion, revealing the GA's suitability for handling real-world constraints and objective interactions.

NSGA-II has also gained attention for its ability to generate diverse Pareto-optimal solutions in multi-objective scenarios. **(author?)** (13) utilized NSGA-II to optimize EVCS locations based on three objectives: minimizing user travel time, minimizing power grid losses, and maximizing user satisfaction. Their findings showed that NSGA-II is effective in producing non-dominated solution sets, allowing planners to select trade-offs based on practical requirements.

3.0.3 Key Optimization Objectives in EVCS Research

Typical optimization goals in EVCS planning include maximizing geographic coverage, minimizing user inconvenience (e.g., travel distance or wait time), reducing infrastructure and operational costs, and improving energy efficiency. For instance, the GA-based model in (14) focused on minimizing costs while expanding access across high-demand areas. Meanwhile, (13) integrated objectives that directly relate to user experience and grid impact, reflecting a holistic approach to infrastructure deployment.

However, objectives such charger speed, number of stations, and number of chargers are less frequently addressed in combination. Existing studies tend to optimize a subset of these objectives, which may limit their applicability in scenarios that demand a more comprehensive planning approach.

3.0.4 Comparative Insights and Research Gaps

Although the reviewed studies provide valuable insights, several research gaps remain. Neither (13) nor (14) consider all five objectives investigated in this research: maximizing coverage, maximizing charger speed (or minimizing wait time), minimizing number of stations, minimizing number of chargers, and minimizing average distance. Charger speed, in particular, is often overlooked as a decision variable, even though it directly impacts user satisfaction and throughput.

Additionally, while **(author?)** (13) successfully applied NSGA-II to a multi-objective framework, its application on large-scale or real-world datasets incorporating urban mobility patterns and service equity remains underexplored. Furthermore, neither study explicitly addresses access disparities across different population groups, a growing concern in EV infrastructure planning.

In fact, both studies reviewed demonstrate the effectiveness of evolutionary algorithms specifically Genetic Algorithms and NSGA-II—in optimizing EV charging infrastructure. They successfully manage complex trade-offs among objectives such as cost, distance, and coverage.

However, comprehensive frameworks that simultaneously address broader objectives such as charger speed, infrastructure minimization, and average user distance are limited. This study addresses these gaps by employing NSGA-II within a five-objective optimization framework to improve the strategic planning of EVCS deployment.

Chapter 4

Methodology

The optimization of the Electric Vehicle Charging Station (EVCS) network is addressed through a multi-objective optimization approach considering five conflicting objectives: maximizing charger speed, maximizing coverage, minimizing the number of stations, minimizing the number of chargers, and minimizing the average distance between EVCS and electric vehicles (EVs). This work employs the **NSGA-II (Non-dominated Sorting Genetic Algorithm II)** to solve this problem (**?**). The methodology is divided into two primary parts: **(A)** finding a single optimized solution, and **(B)** finding the Pareto front representing the set of optimal trade-off solutions.

NSGA-II for EVCS Networks: Project Approach

The project applies NSGA-II systematically to optimize the EVCS network by addressing two main tasks: identifying a single optimized solution and discovering the Pareto front of optimal solutions that balance the competing objectives (**?**).

Problem Formulation

The EVCS network optimization requires balancing several competing objectives:

- **Maximize Charger Speed (Upgrade to Level 3):** Upgrade all chargers to Level 3, providing at least 50 kW power output, to reduce waiting times and improve efficiency.

- **Maximize Coverage:** Ensure the selected stations cover the largest geographic area possible.
- **Minimize Number of Stations:** Reduce infrastructure cost by minimizing the number of stations deployed.
- **Minimize Number of Chargers:** Avoid overcapacity and excess cost by optimizing charger count.
- **Minimize Average Distance:** Reduce travel distance for EV users to reach the nearest charging station.

These five objectives create a complex trade-off problem, where improving one objective might negatively affect another. NSGA-II tackles this by generating a set of optimal solutions instead of a single answer (**?**).

Part A: Finding a Single Optimized Solution

This part focuses on identifying one optimized configuration of EVCS stations that balances the five objectives.

1. Representation of Solutions (Chromosomes) Each individual solution in the population is encoded as a chromosome, representing the selection and characteristics (e.g., number of chargers, charger speed) of candidate stations (**?**).

2. Fitness Evaluation Each solution's fitness is evaluated based on the five objectives:

1. **Maximize Charger Speed:** Chargers have power levels $P_i \in \{11.5, 14.2, 19.2, 25, 60, 62, 80,$ 1 kW. The focus is on upgrading to Level 3 chargers with power ratings of at least 50 kW.
2. **Maximize Coverage:** Calculate and maximize the geographic area covered by selected stations.
3. **Minimize Number of Stations:** Penalize solutions using more stations than necessary.

4. **Minimize Number of Chargers:** Penalize solutions with excessive chargers.

5. **Minimize Average Distance:** Minimize average travel distance for EVs.

These objectives combine into a fitness function measuring overall solution quality (**?**).

3. Selection, Crossover, and Mutation NSGA-II applies evolutionary operators:

- **Selection:** Chooses individuals based on Pareto dominance ranking.
- **Crossover:** Combines two parent solutions to create offspring with mixed characteristics.
- **Mutation:** Introduces random changes to maintain diversity and avoid premature convergence.

Result of Part A The outcome is a single viable solution balancing the five objectives, offering a practical EVCS network configuration.

Part B: Finding the Pareto Front – Pareto-Optimal Solutions

This part finds the **Pareto front**, a set of solutions where improving one objective worsens at least one other.

1. Non-Dominated Sorting NSGA-II ranks solutions into fronts based on Pareto dominance:

- *Front 1:* Solutions not dominated by any other.
- *Front 2:* Solutions dominated only by Front 1 members.
- And so on.

2. Crowding Distance Calculation Calculates how isolated solutions are in objective space to maintain diversity by preferring individuals in less crowded regions.

Result of Part B The **Pareto front** (Front 1) consists of the best trade-off solutions, offering various EVCS configurations optimized for different priorities (**?**).

Final Interpretation of Results

A) Single Solution The single solution provides a balanced and practical EVCS configuration that optimizes multiple objectives, though it may not be the best for all.

B) Pareto Front The Pareto front offers a set of optimal solutions, giving decision-makers the flexibility to select configurations based on specific strategic goals like cost, coverage, or distance (**?**).

Summary NSGA-II effectively generates a diverse set of Pareto-optimal solutions, enabling multi-objective optimization of EVCS networks and providing decision-makers with flexible deployment strategies balancing coverage, speed, cost, and accessibility (**?**).

NSGA-II Flowchart

Figure 4.1 illustrates the NSGA-II algorithm workflow for EVCS network optimization:

1. **Initialize Population:** Randomly generate initial solutions.
2. **Evaluate Fitness:** Calculate all objectives for each solution.
3. **Non-Dominated Sorting:** Rank solutions into Pareto fronts.
4. **Crowding Distance Calculation:** Measure solution diversity.
5. **Selection:** Choose individuals based on Pareto rank and crowding distance.
6. **Crossover and Mutation:** Generate new offspring solutions.
7. **Combine and Sort:** Merge parents and offspring; re-rank.

8. **Next Generation:** Select the best individuals for the next generation.

9. **Termination:** Repeat until max generations reached.

This iterative process yields a Pareto front of non-dominated solutions representing optimal trade-offs.

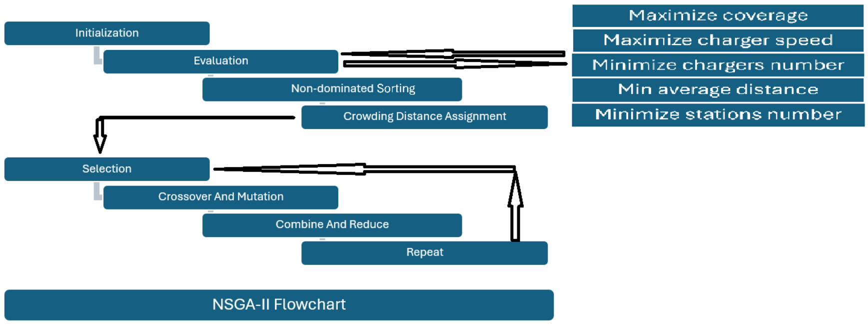

Figure 4.1: Flowchart of the NSGA-II algorithm for EVCS network optimization.

Chapter 5

Experiment

As introduced in Chapter 1, this research focuses on the strategic deployment of electric vehicle charging stations (EVCS) in urban environments. This chapter outlines the experimental design, implementation, and analysis of a multi-objective optimization problem (MOOP) aimed at addressing the EVCS location problem using the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The objective is to optimize the placement and configuration of EVCS to minimize overall costs while balancing multiple objtives.

The problem is modeled with five conflicting objectives: (1) maximizing coverage, (2) maximizing charger speed, (3) minimizing the number of stations, (4) minimizing the total number of chargers per station, and (5) minimizing the average distance between stations and electric vehicles. These objectives often conflict with each other. For example, increasing coverage and charger speed typically requires adding more chargers and stations, which contradicts the goal of minimizing infrastructure.

NSGA-II was chosen for its proven effectiveness in tackling complex, multi-objective, nonlinear optimization problems with discrete decision variables. This algorithm is well suited for problems that require a variety of balanced solutions for decision-making.

5.1 Experimental Environment

The algorithm was implemented using the DEAP framework in Python. Experiments were run on a system with the following specifications:

- OS: Windows 10
- Processor: Intel(R) Core(TM) i7-10610U CPU @ 1.80GHz 2.30 GHz
- RAM: 32 GB
- Python Version: 3.10
- Libraries: NumPy, DEAP, Matplotlib, Pandas

5.2 Dataset

To support the experimental design, implementation, and visualization of a multi-objective optimization problem (MOOP) for planning electric vehicle charging stations (EVCS), this study uses the NSGA-II algorithm as an evolutionary approach to identify optimal deployment strategies. A set of publicly available datasets is used to simulate realistic urban charging demand and infrastructure characteristics, ensuring that the optimization results are meaningful and applicable to real-world scenarios.

The datasets used in this experiment include:

5.2.1 Stations Dataset

In this research on electric vehicle charging stations (EVCS), the dataset was obtained using the Open Charge Map API, a widely used open-source platform that provides global EV charging infrastructure data(45). For this study, we focused specifically on Los Angeles due to its significant role in electric vehicle adoption and the ongoing expansion of its charging network. The dataset extracted includes key attributes such as station locations (latitude and longitude), number of chargers, and charger speed. This real-world data serves as a foundation for modeling urban charging demand and evaluating potential station deployment strategies.

Los Angeles is one of the leading cities in adopting EV policies aimed at reducing pollution. Furthermore, Los Angeles has a high population density, a large number of electric vehicles, and an extensive network of EV charging stations, making it an ideal location for this study. The data collected provides valuable insights into usage patterns, location preferences, and other critical factors that influence the deployment of EV charging infrastructure. This dataset serves as a model that could be extended to other regions.

In this experiment, we evaluate the performance of the NSGA-II algorithm. The test case is based on a dataset from Los Angeles, selected for its relevance to EV adoption. The dataset includes station locations (latitude and longitude), number of chargers, and charger speed. These details enable realistic modeling for EVCS optimization. The dataset contains the following variables:

- 100 potential locations for charging stations, each location has number of charger, with 1000 EVs in the area. The dataset includes the following attributes for each location:
  - **Id**: charging station number.
  - **Coordinates**: The geographical coordinates of each charging station location.
  - **Charger speed (kW)**: The chargers speed power for each charger, (11.5, 14.2, 19.2, 25, 60, 62, 80, 120, 150, 180, 200, 240, 250, 300, 325, 350, 400).
  - **Chargers per station**: The number of chargers installed at each station.

5.2.2 Electric Vehicle Charging Station (EVCS) Cost Dataset

In this experiment, we used a dataset from the paper titled Estimating Electric Vehicle Charging Infrastructure Costs Across Major U.S (42). The dataset, originally presented in the paper, contains valuable information on electric vehicle charging infrastructure costs. The dataset contains the following variables:

To simplify the process, the dataset is defined within a Python file, simplifying cost calculations for value-added systems. By organizing the data programmatically, we

Power Range	Type of Charger	Hardware Cost	Installation Cost	Total Estimated Cost
3 kW - 7 kW	Level 1 or Level 2 Charger	$500 - $1,500	$300 - $500	$800 - $2,000
7 kW - 22 kW	Level 2 Charger	$1,500 - $5,000	$1,000 - $2,500	$2,500 - $7,500
50 kW - 100 kW	DC Fast Charger	$30,000 - $50,000	$50,000 - $100,000	$80,000 - $150,000
100 kW - 150 kW	DC Fast Charger	$50,000 - $70,000	$50,000 - $100,000	$100,000 - $170,000
150 kW - 200 kW	DC Fast Charger	$70,000 - $100,000	$100,000 - $150,000	$170,000 - $250,000
200 kW - 350 kW	Ultra-Fast Charger	$100,000 - $150,000	$150,000 - $250,000	$250,000 - $400,000
350 kW - 400 kW	Ultra-Fast Charger	$120,000 - $150,000	$150,000 - $250,000	$270,000 - $400,000

Table 5.1: Cost Estimates for Different Types of EV Chargers

ensure efficient processing. This approach enables rapid updates and recalculations, enabling integration of cost calculations into the overall analysis.

5.2.3 Electric Vehicle Dataset

In this study, we used an electric vehicle (EV) dataset for a selected Los Angeles, from the California Open Data Portal(43). This dataset offers up-to-date counts of registered vehicles by fuel type and ZIP code, allowing us to accurately estimate local EV demand. The dataset contains the following variables:

- The EV dataset contains information about vehicles registered in the area, including the following attributes:
  - **Date**: The date when the vehicle registration data was recorded or updated.
  - **ZIP Code**: The ZIP code where the vehicle is registered.
  - **Model Year**: The year the vehicle was manufactured.
  - **Fuel**: The type of fuel used by the vehicle (e.g., electric, hybrid, gasoline).

- **Make**: The manufacturer or brand of the vehicle (e.g., Tesla, Nissan, Chevrolet).
- **Duty**: The vehicle's usage type (e.g., passenger, commercial, heavy-duty).
- **Vehicles**: The number of vehicles registered for each combination of attributes (model year, fuel, make, etc.).
- **ZIP**: The ZIP code of the area where the vehicle is registered (similar to ZIP Code).
- **Latitude**: The latitude of the vehicle's registered location (can be derived from ZIP code).
- **Longitude**: The longitude of the vehicle's registered location (can be derived from ZIP code).

However, the dataset includes all fuel types of vehicles. To ensure the relevance of our analysis, we filtered the data to select only electric vehicles (EVs). Furthermore, we limited the data to electric vehicles located within the Los Angeles area. This allowed us to base our analysis and optimization models exclusively on relevant EV data, ensuring more accurate results and better informed decision making.

Incorporating this data into our model ensures a more accurate representation of electric vehicle (EV) distribution across Los Angeles. However, the dataset does not provide direct geographic coordinates (latitude and longitude) for each location; instead, it uses ZIP codes to identify regions.

5.2.4 ZIP Code Tabulation Dataset

The ZIP Code Tabulation Area (ZCTA) dataset (44) is a geographic data product developed by the U.S. Census Bureau to approximate U.S. Postal Service ZIP code areas using census blocks(44). Some stakeholders use postal ZIP codes, which are designed primarily for mail delivery. However, when more precise geographic locations are needed, latitude and longitude coordinates must be used instead. These coordinates can be programmatically derived from ZIP codes, enabling more accurate spatial analysis and modeling. The dataset contains a large number of variables; however, for the purpose of this study, we focus on the following key variables:

- The ZIP Code Tabulation Area (ZCTA) dataset contains information about the area, including the following attributes:
  - **ZIP Code**: The ZIP code.
  - **Latitude**: The latitude coordinate of the area.
  - **Longitude**: The longitude coordinate of the area.

Since the EV registration dataset was organized by ZIP code rather than by direct geographic coordinates, we used Python code to map each ZIP code in EV dataset to its corresponding latitude and longitude. This enabled accurate visualization and modeling of electric vehicle distribution across California. The resulting geographic mapping allowed for more precise placement of charging stations in our optimization process.

5.2.5 Decision Variables

The optimization problem considers a set of locations (stations), where each station can use a number of electric vehicle chargers (EVCs) with a specified charging speed. The decision variables include:

- $x_i \in \{0, 1\}$: Binary variable indicating whether a station is deployed at location i.
- $c_i \in \{0, 1, 2, ..., C_{max}\}$: Integer variable indicating the number of chargers at location i.
- $c_i \in \{0, 1, 2, ..., C_{max}\}$: Integer variable indicating the number of station i.
- $s_i \in \{s_1, s_2, ..., s_k\}$: Discrete variable indicating the speed of chargers at Station i.

5.2.6 Calculate Weighted By EV Demand

The term "EV demand weighting" refers to a metric used in Electric Vehicle Charging Station (EVCS) optimization that estimates the demand for a charging station based on the number of electric vehicles within its coverage area. This metric assigns greater weight to stations located in areas with high EV population density, reflecting a higher need for charging infrastructure. This approach ensures that optimization efforts such as increasing the number of chargers or upgrading their speeds which focused where demand is greatest. In fact, by matching resources with real EV demand, this metric makes the charging network more efficient and helps meet user needs more effectively. (20), (21).

The formula to calculate the *EV demand* based on the coverage radius is:

$$\text{EV demand} = \text{len}\,(\text{indices})$$

Where:

- indices is the set of EVs found within the coverage radius (5 km) of the station.

This demand estimation approach is supported by previous research (21)

5.2.7 Objective Functions

1. **Maximize Coverage (f_1)**: Coverage is defined as the percentage of demand points as areas or EV that fall within the effective service radius of at least one installed charging station. This objective ensures that the deployed charging infrastructure serves as many EV users as possible, improving accessibility and utilization.

$$f_1 = \frac{\sum_{j=1}^{m} \delta_j}{m}, \quad \delta_j = \begin{cases} 1 & \text{if demand point } j \text{ is covered by any station} \\ 0 & \text{otherwise} \end{cases}$$

where:

- m is the total number of demand points,
- δ_j is a binary indicator representing whether demand point j is within the coverage range of any installed charging station.

This formulation is commonly used in facility location problems and EVCS planning literature to ensure efficient deployment of infrastructure (13), (19).

2. **Maximize Charger Speed (f_2)**: Charger speed refers to the power output (in kilowatts, kW) of the chargers installed at each station. This objective prioritizes high-speed chargers to reduce vehicle waiting times and increase station throughput. To capture both hardware capacity and practical utility, the charger speed is calculated as a **weighted average**, taking into account the number of chargers and local Electric Vehicle (EV) demand at each selected station.

   The objective is to maximize the effective charger speed across all selected stations. To discourage the selection of low-performance infrastructure, a heavy penalty is applied to any station with chargers below 50 kW.

   The objective function for charger speed, f_2, is defined as:

   Objective 2: Maximize Charger Speed To promote the deployment of high speed (Level 3) chargers, this objective computes the average charger speed across all selected stations with a minimum speed of 50 kW. Stations that do not meet this condition are excluded from the calculation.

   The objective function f_2 is defined as:

$$f_2 = \begin{cases} \frac{1}{|V|} \sum_{i \in V} S_i, & \text{if } |V| > 0 \\ \infty, & \text{if } |V| = 0 \end{cases}$$

   Where:

   - V is the set of selected stations with charger speed $S_i \geq 50$ kW,
   - S_i is the charger speed at station i,
   - $|V|$ is the number of valid (high-speed) stations.

   A value of ∞ is assigned as a penalty when no high-speed chargers are selected, steering the optimization away from such configurations.

   This formulation ensures that stations with higher charger speed, more chargers, and greater local demand contribute more to the objective. If any selected station has a charger speed below 50 kW, the solution is penalized by assigning a large objective value, $f_2 = \infty$) to discourage the selection of such configurations(13), (19), (21).

3. **Minimize Number of Stations (f_3)**: This objective aims to minimize the total number of installed charging stations. By minimizing the station count, the goal is to control fixed infrastructure costs, such as land acquisition, installation, and maintenance. Additionally, it promotes the deployment of strategically located, high-impact stations capable of effectively serving areas with high local EV demand, ensuring optimal coverage and service quality.

   The objective function for maximizing charger speed, f_3, is given by:

   $$f_3 = \sum_{i=1}^{n} x_i$$

   where:

   - $x_i \in \{0, 1\}$ is a binary variable indicating whether a charging station is installed at location i,
   - n is the total number of candidate station locations.

   Minimizing the number of stations is a common strategy in multi objective facility location planning, aiming to balance cost efficiency with service quality (13), (19).

4. **Minimize Number of Chargers (f_4)**: This objective aims to reduce the total number of chargers deployed across all installed stations. Minimizing charger count helps lower equipment and installation costs, promoting resource efficiency while still meeting demand coverage and performance goals.

   The objective function for maximizing charger speed, f_4, is given by:

   $$f_4 = \sum_{i=1}^{n} c_i$$

   where:

- c_i represents the number of chargers installed at station i,
- n is the total number of candidate station locations.

This objective aligns with infrastructure cost minimization strategies in electric vehicle charging network planning, as discussed in relevant literature (13), (19).

5. **Minimize Average Distance (f_5)**: This objective aims to minimize the average distance between electric vehicles (EVs) and their nearest charging stations. Reducing this distance improves accessibility, decreases travel time, and enhances overall user convenience, while promoting an efficient and equitable spatial distribution of charging infrastructure across the service area.

   The objective function for maximizing charger speed, f_5, is given by:

$$f_5 = \frac{1}{m} \sum_{j=1}^{m} \sum_{i=1}^{n} d_{ij} \cdot x_{ij}$$

   where:

   - m is the total number of electric vehicles,
   - n is the total number of candidate charging station locations,
   - d_{ij} is the distance between EV j and nearest station i,
   - $x_{ij} \in \{0, 1\}$ is a binary variable that equals 1 if EV j is assigned to station i, and 0.

   This objective produces an output, but it may not be as precise as the other objectives. The average distance between electric vehicles and their nearest charging stations must be calculated separately since it depends on the final selected locations and involves a mathematical computation. Although this objective influences location selection during the optimization, the exact average distance can only be accurately determined after the optimization process. Therefore, it indirectly guides the optimization, while the precise value requires calculation once the final solution is obtained.

   This objective aims to minimize the average travel distance from EVs to the nearest charging stations, Improves convenience and reduces access time. This formula is commonly used in facility location and infrastructure planning for electric vehicles (13), (19).

5.2.8 Calculating Average Distance Between EVs and Nearest EVCS

To calculate the average distance between electric vehicles and their nearest charging stations, we use the Haversine formula. This formula computes the great distance between two points given their latitude and longitude. By applying it to each EV and station pair, we determine accurate distance measurements for optimization.

Given a station s_i and a set of electric vehicles $V = \{v_1, v_2, \ldots, v_n\}$ with coordinates, the average distance from station s_i to all vehicles is calculated as:

$$\overline{D_i} = \frac{1}{n} \sum_{j=1}^{n} d(s_i, v_j)$$

where $d(s_i, v_j)$ represents the distance between station s_i and vehicle v_j.

The Haversine formula is commonly used to calculate distances between two points on the Earth's surface (22).

5.2.9 Constraints

To ensure realistic and practically applicable solutions, several key constraints were incorporated into the optimization model. These constraints reflect real-world constraints, such as spatial and technical factors. Specifically, charging stations can only be installed in pre-selected candidate locations. Each station has a maximum capacity in terms of the number of chargers it can support. Additionally, each EV demand point must be within the defined service range of at least one station to be covered, ensuring easy access and adequate service distribution. The overall cost of installation must remain reasonable. The applied constraints are summarized as follows:

- **Demand coverage constraint:** Each demand point must be within a predefined distance threshold from at least one charging station to be considered covered.

- **Capacity constraint:** Each station must not exceed a maximum number of chargers due to space or grid limitations.
- **Location constraint:** Only pre-identified potential locations are eligible for station placement.
- **Charger speed constraint:** Charger types must conform to predefined technical specifications and available speed tiers.
- **Budget constraint:** The total installation cost of chargers and stations must not exceed a specified budget.

5.3 NSGA-II Algorithm Setup

5.3.1 Overview

As discussed in Chapter 3, NSGA-II is an evolutionary algorithm that maintains a population of candidate solutions. In each generation, new offspring are generated through crossover and mutation. The next generation is then selected based on Pareto dominance and a crowding distance metric, which together promote both optimality and diversity within the population.

5.3.2 Parameters

- Population Size: 100
- Number of Generations: 50
- μ (Number of Individuals Selected for the Next Generation): 50
- λ (Number of Offspring Generated Each Generation): 100
- Crossover Probability ($cxpb$): 0.7
- Mutation Probability ($mutpb$): 0.2
- Selection Method: NSGA-II (Non-dominated Sorting Genetic Algorithm II)

- Crossover Operator: Two-Point Crossover
- Mutation Operator: Shuffle Index Mutation
- Possible power speed : [11.5, 14.2, 19.2, 25, 60, 62, 80, 120, 150, 180, 200, 240, 250, 300, 325, 350, 400]
- The dataset is described in the Dataset section(Stations dataset).

5.3.3 Encoding Strategy

Each individual in the population is encoded as a tuple:

$$\textbf{Chromosome} = [(x_1, c_1, s_1), (x_2, c_2, s_2), ..., (x_n, c_n, s_n)]$$

This representation allows flexible adjustment of whether a station is deployed, how many chargers it has, and their speed types.

5.3.4 Steps of the Applied NSGA-II Algorithm

Step 1: Preprocessing the Data

As discussed in the dataset section, this experiment primarily utilizes several datasets, as outlined below:

- **Stations Dataset**
- **Electric Vehicle Charging Station (EVCS) Cost Dataset**
- **Electric Vehicle (EV) Registration Dataset**
- **ZIP Code Tabulation Area (ZCTA) Dataset**

Data preprocessing was carried out in several key steps to ensure its suitability for optimization and analysis. The process was conducted as follows:

A. In this study, we focus exclusively on data from Los Angeles, located at latitude 34.0522 and longitude -118.2437, within a 30 km radius. To ensure relevance, the original station data was filtered to include only stations within Los Angeles city limits. This filtering allows us to concentrate solely on the target research area.

B. To successfully achieve Objective 1 (maximizing coverage) and Objective 3 (minimizing average distance), the station data was updated to include coverage values for each station and the average distance from electric vehicles (EVs) to their nearest station, calculated for each station. This update ensures that the optimization process accurately reflects the distribution of demand points within the study area.

By introducing these values, the model can better evaluate and select station locations that provide the widest coverage while reducing the average travel distance for EV users, leading to a more effective result.

C. As mentioned in the dataset section, the EV data included ZIP codes instead of latitude and longitude values. To address this, we combined the EV data, which contained only ZIP codes, with the ZIP Code Tabulation Areas dataset, which includes both ZIP codes and corresponding latitude and longitude values. The goal was to update the EV data with latitude and longitude columns, enabling us to calculate the distance between each EV and the nearest station for further process.

D. We converted key dataset values, such as the number of chargers and charger speed, into numeric formats to ensure accurate processing during optimization. Additionally, some column names were updated for clarity and consistency, making the dataset easier to interpret, integrate into the optimization process, and analyze.

In the end, as shown in Figure 5.1, the data was thoroughly cleaned and properly formatted to serve as input for the NSGA-II algorithm used in this study. These preprocessing steps ensured the dataset was suitable for multi objective optimization, enabling accurate analysis and efficient electric vehicle charging station deployment.

To ensure the efficiency of an electric vehicle charging station (EVCS) network, it is essential that stations meet Level 3 charger standards ($\geq$ 50 kW). In the context of solving a multi-objective optimization problem (MOOP) using NSGA-II, this requirement is addressed by adjusting any charger speeds below 50 kW to 50 kW. This ensures that all selected stations are at least Level 3 chargers, directly supporting the goal of maximizing the charger speed. By applying this rule, we avoid solutions

station_id	latitude	longitude	num_chargers	charger_speed	coverage	average_vehicle_distance_km
72918	34.0505282	-118.2426489	1	8	14	17.35373576135943
134119	34.04955105070715	-118.2538491	9	7	14	17.21624752652242
81982	34.052495	-118.255408	3	8	14	17.208183306149795
81910	34.050184	-118.257063	2	16	14	17.18699719397976
66997	34.0438567	-118.2577564	3	8	14	17.180879797049688
51822	34.0418652	-118.256987	3	13	14	17.192551822982608
118011	34.04753	-118.264429	10	72	14	17.12945831184914
104421	34.045531	-118.264006	2	8	14	17.13272308266198
81970	34.042799	-118.262703	2	8	14	17.145712998656787
168352	34.033065	-118.240294	16	72	13	17.43830290724161
79018	34.046049	-118.266185	1	10	14	17.11982673505198
79541	34.046119	-118.266227	1	10	14	17.11956278375043
290571	34.014737	-118.237373	8	250	13	17.709233151204046
291203	34.014538304820135	-118.2382445	1	62.5	13	17.699687755855514
81748	34.062301	-118.290127	2	8	13	17.15954629905245
81798	34.093106	-118.291242	3	8	3	17.720596660255847
39899	34.110475	-118.246578	1	3	2	18.445603314142424
39892	34.095187	-118.292718	1	3	3	17.783393686398586

Figure 5.1: EVCS Dataset

that might result from slower chargers and ensure that the optimization algorithm remains focused on achieving the best possible performance across all objectives.

Step 2: Define the Multi-Objective Optimization Problem

In this step, the electric vehicle charging station (EVCS) problem was formulated as a multi-objective optimization problem with five conflicting objectives: (1) maximizing geographical coverage to ensure that as many demand points as possible are served by at least one station; (2) maximizing charger speed to reduce waiting times for electric vehicle (EV) users; (3) minimizing the number of installed charging stations to lower infrastructure costs; (4) minimizing the total number of chargers to manage costs and operational complexity; and (5) minimizing the average distance between EVs and their nearest EVCS to enhance accessibility and convenience.

To implement this formulation, we used the DEAP framework(33). The problem was modeled using a custom fitness class where the objectives were assigned specific weights: positive weights (1.0) for maximizing coverage, positive weights (1.0) for maximizing charger speed, negative weights (-1.0) for minimizing the number of stations and negative weights (-1.0) for minimizing the number of chargers, and (-

1.0) for minimizing the average distance between EV, and the nearest EVCS. This formulation allows the algorithm to simultaneously balance service quality and cost efficiency. Each individual in the population represents a unique combination of selected charging stations, and the fitness evaluation returns values to each of the four objectives.

Step 2: Define, and initialize DEAP Components

In this step, the DEAP framework is utilized to define the requirement components for the evolutionary algorithm, such as the fitness function, individual structure, and algorithm settings. These settings include population size, selection strategy, and the methods for crossover and mutation. To initialize these components, we first create a toolbox using DEAP's base.Toolbox. The toolbox is then populated with several registered functions that define the operations for the evolutionary process.

In additon, the individual function is registered to generate an individual from a specified structure using the tools.initIterate method. The population function initializes the population by creating multiple individuals through tools.initRepeat. The mate function, which controls the crossover operation, is defined with the cxTwoPointCheck method. Similarly, the mutation operation is defined using mutShuffleIndexesCheck with a mutation probability. For selection, the selNSGA2 method is registered, which ensures that the selection process follows the NSGA-II strategy for multi-objective optimization.

Howerver, the evaluate function is linked to the toolbox to evaluate individuals based on their fitness values.

By registering these functions, the necessary components of the evolutionary process are prepared, allowing the algorithm to run efficiently.

Step 3: Define Objective Functions

In this step, we formally define the objective functions that guide the optimization process. The electric vehicle charging station (EVCS) planning problem is formulated as a multi-objective optimization problem comprising five conflicting objectives, as outlined in Section **??**. These objectives are: (1) maximizing geographical coverage,

ensuring that electric vehicle (EV) demand points are within the service radius of at least one station; (2) maximizing charger speed to reduce wait times and improve service efficiency; (3) minimizing the number of installed charging stations to manage infrastructure costs; (4) minimizing the total number of chargers to reduce both deployment and operational expenses; and (5) minimizing the average distance between EVs and their nearest station to enhance accessibility. Each objective is mathematically formulated and encoded in the optimization model. The DEAP library is used to implement the problem, where objectives are assigned directional weights to appropriately guide the NSGA-II algorithm during the optimization process.
These algorithmic objectives help strike a balance between coverage and efficiency by considering the distance between stations, the distance between users and EVCS, charging speed, as well as the number of stations and chargers. This approach leads to optimized solutions that meet the operational needs of the charging network while also reducing overall infrastructure costs, ensuring cost-effective and efficient deployment.

Step 4: Define the evaluation function that combines all objectives

The evaluation function plays a critical role in guiding the evolutionary algorithm by assessing the quality of each solution based on multiple objectives(26). In this step, we define a function that combines all four previously established objectives to evaluate each individual in the stations dataset in the population. The individual represents a selection of electric vehicle charging stations.

The evaluation function calls five separate methods, as discussed in Subsection 3 in this chapter:

1. **Coverage**: Calculated using the `calculate_coverage` method, it sums the distances between all unique pairs of selected stations to check station placement across the area.

2. **Charger Speed**: Determined using the `calculate_charger_speed` method, this objective selects the highest available charging speed among the chosen stations to enhance charging efficiency.

3. **Number of Stations**: Computed with `calculate_num_stations`, this counts the selected stations, encouraging minimal infrastructure to reduce overall costs.

4. **Number of Chargers**: Using `calculate_num_chargers`, this sums all chargers at selected stations to further minimize overall costs.

5. **Minimize Average Distance**: Computed with `calculate_avg_ev_distance`, this objective minimizes the average distance between electric vehicles (EVs) and their nearest charging station. A lower average distance improves accessibility, ensuring that stations are efficiently placed to reduce travel time for EV users.

The function returns a tuple containing these five values. These outputs are then used by the NSGA-II algorithm within DEAP to rank and evolve the population toward optimal solutions that balance all objectives effectively(26).

Step 5: Create a random individual with fewer stations selected

The create_individual function is responsible for generating a random initial solution, or "individual," for the evolutionary algorithm. Each individual represents a subset of electric vehicle charging stations selected from the dataset.

In this function, a random number of stations is selected, in range from one to half of the total available stations. This approach creates diverse solutions some with fewer stations and others with more. This allowing the algorithm to explore a wide range of possible solution during optimization.

To create the individual, the function uses Python's random.sample() to select a unique set of station indices without replacement. This avoids selecting the same station more than once and keeps each solution valid. The result is a list of station numbers that can be checked using the objective functions.

Generating a diverse population of individuals is essential in evolutionary algorithms such as NSGA-II(27). This approach helps the algorithm explore more options, and avoid getting stuck in poor solutions too early. The function keeps the population diverse by randomly changing how many stations are picked and which ones are included. These randomly created station groups form the starting point for the algorithm to begin finding the best charging station solution.

Step 6: Apply Genetic Operators and Evolve Population

In this step, the algorithm improves the population by applying genetic operators: selection, crossover, and mutation. NSGA-II is used for selection, favoring individuals that balance multiple objectives while maintaining diversity(28).

The crossover operation is performed during the evolutionary process using the crossover function registered in the toolbox. Typically, a two-point crossover method (cxTwoPoint) is used, which exchanges segments between two parent solutions to produce offspring (27). Before crossover, checks ensure the parents have sufficient length to apply this operation correctly, maintaining solution validity and diversity in the population (27).

In addition, the mutation is handled by mutation function registered in the toolbox,which introduces small random changes to individuals by occasionally removing a station. This reduces the number of stations, promoting simpler, more efficient solutions. It also helps prevent duplicate values and ensures that each individual remains a valid configuration(27). These operations are repeated over generations, allowing the population to explore new combinations, avoid premature convergence, and evolve toward optimal(27) electric vehicle charging station solution.

5.4 Performance Metrics

To evaluate the effectiveness of the multi-objective optimization approach for electric vehicle charging station (EVCS) placement, several performance metrics were used. These metrics reflect both the algorithm's ability to generate high-quality solutions and the trade-offs between conflicting objectives:

- **1. Pareto Front Coverage**: Measures how well the obtained solutions approximate the ideal Pareto front. A higher coverage indicates a broader and more complete set of trade-off solutions.

- **2. Convergence and Diversity**: Evaluates how close the solutions are to the optimal front (convergence) and how evenly they are distributed across it (diversity), ensuring both quality and variety in trade-off options.
- **3. Area Coverage**: Assesses the percentage of the region effectively served by charging stations. This metric directly relates to the objective of maximizing coverage but may trade off against the number of stations and chargers.
- **4. Average Distance**: Represents the mean distance between EVs and their nearest charging station. Minimizing this improves accessibility but may require more stations or higher-speed chargers, affecting cost.
- **5. Charger Cost**: Estimates the total cost of installing and operating the charging infrastructure, influenced by both the number and type (speed) of chargers. This metric often conflicts with goals such as maximizing coverage and minimizing average distance.

Chapter 6

Results

6.1 NSGA-II Matrix

The NSGA-II matrix captures key performance metrics of the algorithm over successive generations, including the average, standard deviation, minimum, and maximum objective values. These indicators provide valuable insights into the optimization dynamics, enabling the assessment of both convergence behavior and population diversity. The average reflects the overall improvement in solution quality, while the standard deviation indicates the spread and diversity within the population. Minimum and maximum values represent the boundaries of the explored solution space in each generation. Such matrix-based analysis is essential for understanding how NSGA-II balances exploration and exploitation in multi-objective optimization (28). Figure 6.1 illustrates these performance trends across generations, helping to visualize the algorithm's effectiveness over time.

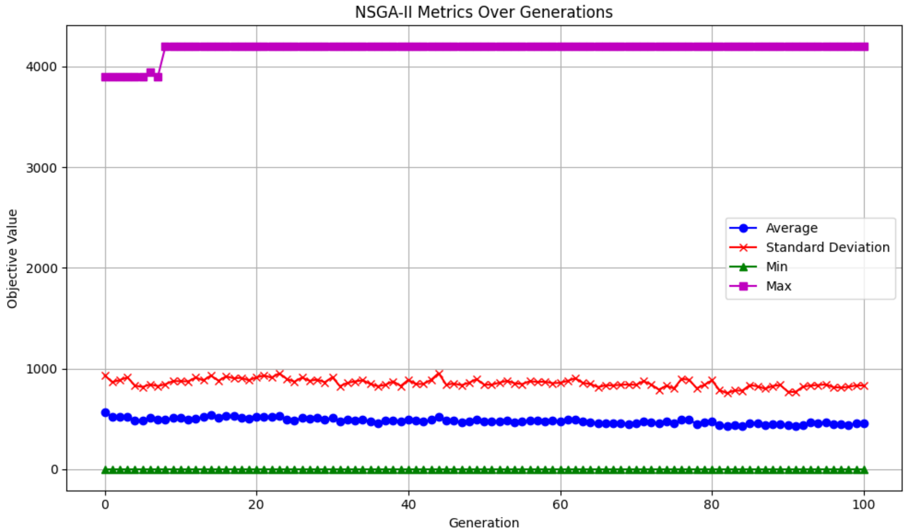

Figure 6.1: Performance metrics of NSGA-II over generations

However, the NSGA-II matrix shows the algorithm's performance across 100 generations. The average value decreases over time, indicating an improvement in solution quality. Similarly, the standard deviation reduces, suggesting that the solutions become more stable as the algorithm progresses. The minimum value stays constant at 1.0, implying that at least one optimal solution is consistently found in every generation. The maximum value decreases from over 3900 to around 2600, demonstrating that the worst solutions improve over time. These trends highlight how NSGA-II effectively balances exploring new possibilities with refining the best solutions over the course of multiple generations.

6.2 Pareto Front Overview

The final set of non-dominated solutions, obtained after 100 generations of the NSGA-II algorithm, is shown in Figure 6.2. These solutions represent trade-offs among five competing objectives: maximizing coverage and charger speed, while minimizing the number of stations, number of chargers, and the average distance between EVs and their assigned stations. The distribution of points along the Pareto front shows the algorithm's ability to maintain diversity and explore various deployment strategies.

The results reveal a clear trade-off between infrastructure cost and system performance. Solutions that prioritize broader coverage and higher charging speeds tend to require more stations and chargers, increasing costs. This highlights the balance between maximizing service quality and minimizing infrastructure. However, several well-balanced solutions demonstrate that the algorithm can find efficient configurations that achieve good performance with fewer resources.

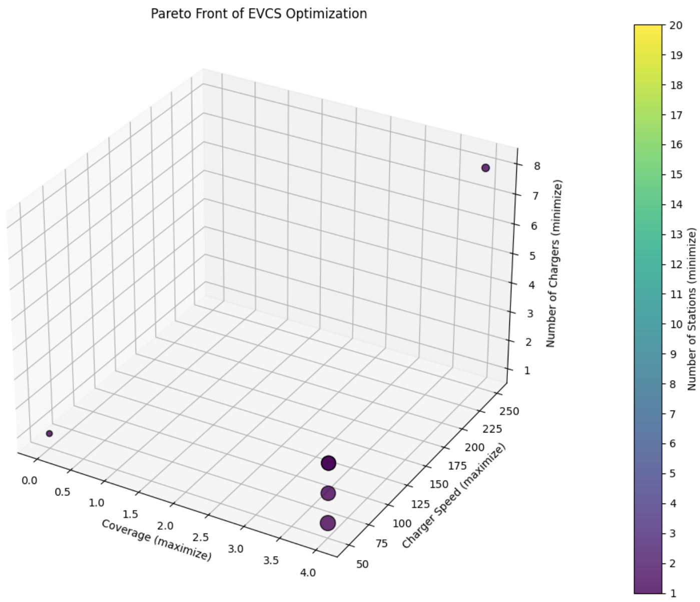

Figure 6.2: Pareto front showing trade-offs between coverage, cahrger speed, number of charger, and distance betwen EV and the station.

6.3 Trade-off Analysis

To better understand the relationships between competing objectives, Figure 6.3 presents selected trade-offs from the final Pareto front. These trade-offs show how improving one objective often requires sacrificing performance in others, which is important for decision-makers facing limits on budget, infrastructure, or service requirements.

The figure includes five representative solutions, each demonstrating a different balance among the five goals: maximizing chargers speed, maximizing coverage and charger speed, while minimizing the number of stations, chargers, and average distance between EVs and their nearest station.

These cases highlight how focusing on one objective, like lowering infrastructure costs, can impact network design and affect service quality or accessibility.

By examining these trade-offs, decision-makers gain clearer insight into the interplay between system performance and cost-efficiency. This understanding supports more informed choices when selecting deployment strategies that align with specific policy, operational, or economic goals.

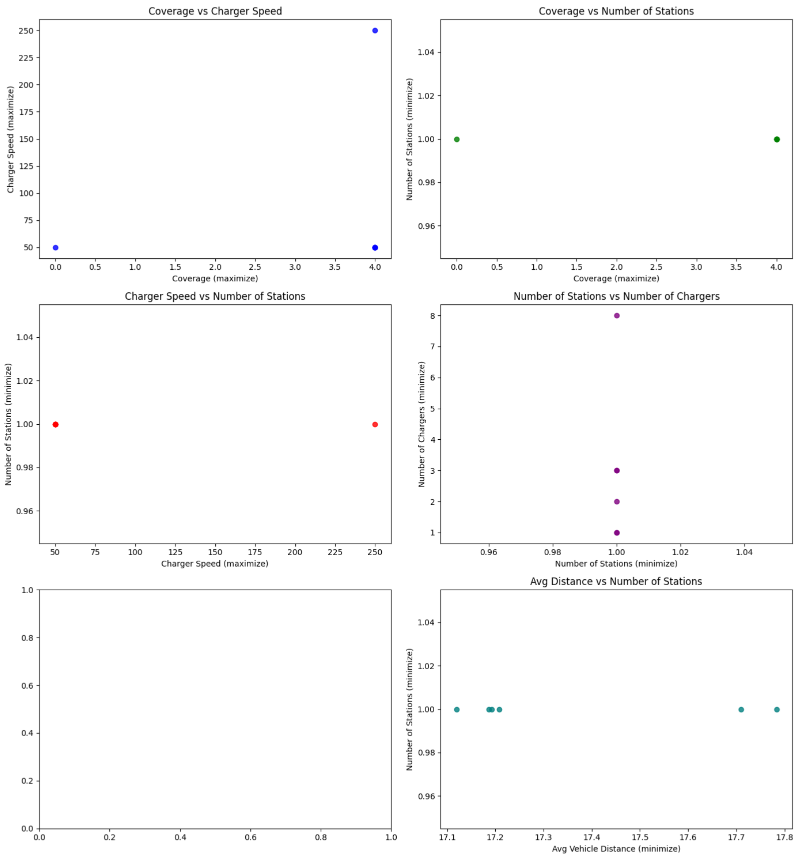

Figure 6.3: Objective trade-offs among selected Pareto-optimal solutions.

6.3.1 Minimizing the Number of Stations and Chargers

The optimization process achieved significant reductions in infrastructure, as shown in Figure 6.4. The total number of EV charging stations (EVCS) decreased from 19 to 7, while the number of individual chargers dropped sharply from 69 to just 18. These reductions demonstrate the effectiveness of the algorithm in meeting the objective of minimizing infrastructure.

Reducing the number of stations and chargers leads to lower installation and maintenance costs, improved resource efficiency. This result highlights the practical benefits of using multi objective optimization to design streamlined and scalable EV charging station networks.

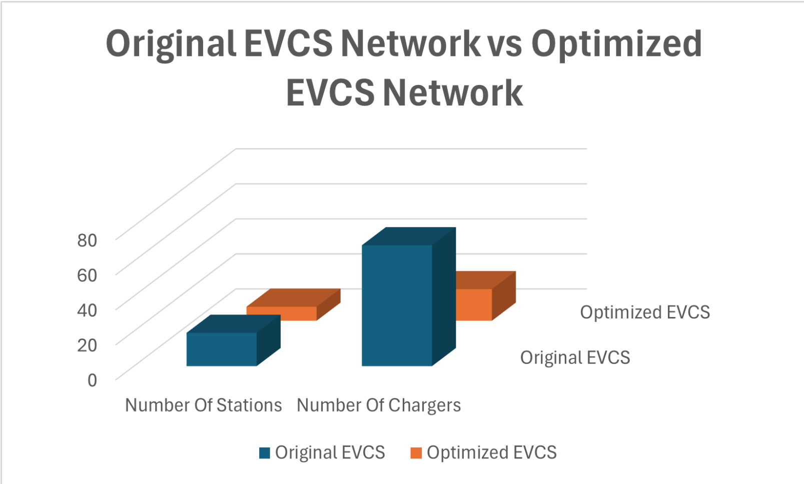

Figure 6.4: Original EVCS Network vs Optimized EVCS Network.

In addition, it's important to understand that these improvements were achieved through a multi-objective optimization process. Various objectives, such as maximizing coverage, increasing charger speed, and minimizing the average distance between EVs and the nearest charging station, must be carefully balanced.

Therefore, while the reduction in the number of stations and chargers is promising, it is the result of coordinating multiple competing objectives, rather than focusing solely on reducing infrastructure usage.

However, the reduction in infrastructure without severely compromising other objectives highlights the strength of the applied optimization approach.

6.3.2 Maximizing Charger Speed

Enhancing charger speed was a key objective in improving the overall performance and user experience of the EVCS network. The optimization process prioritized upgrading chargers to Level 3, guaranteeing speeds of at least 50 kW. Charger power levels were then strategically adjusted based on local demand to optimize efficiency and service quality.

Figure 6.6, and Figure 6.5shows that many of the slower chargers were upgraded in the optimized data set to improve the overall network performance. Additionally, some high-power chargers were adjusted to better suit local demand.

In areas where very high charging power was unnecessary, these chargers were downgraded to lower capacities, such as 50 kW, to improve efficiency and reduce excess infrastructure.

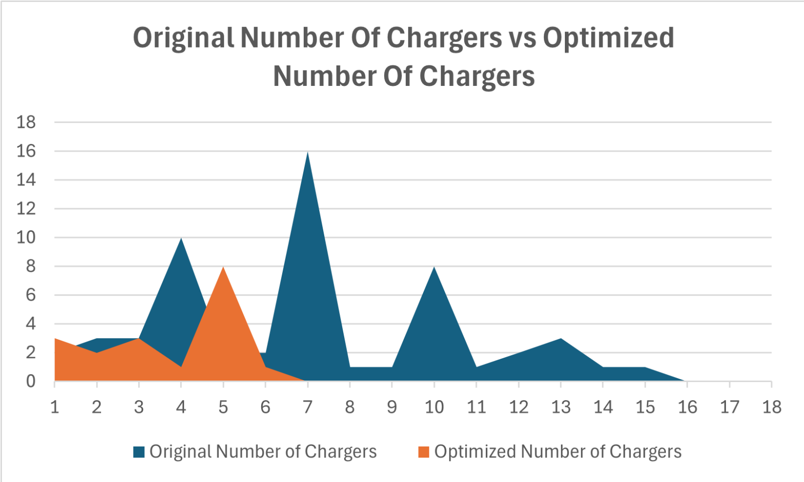

Figure 6.5: Comparison of original and optimized EVCS charger numbers.

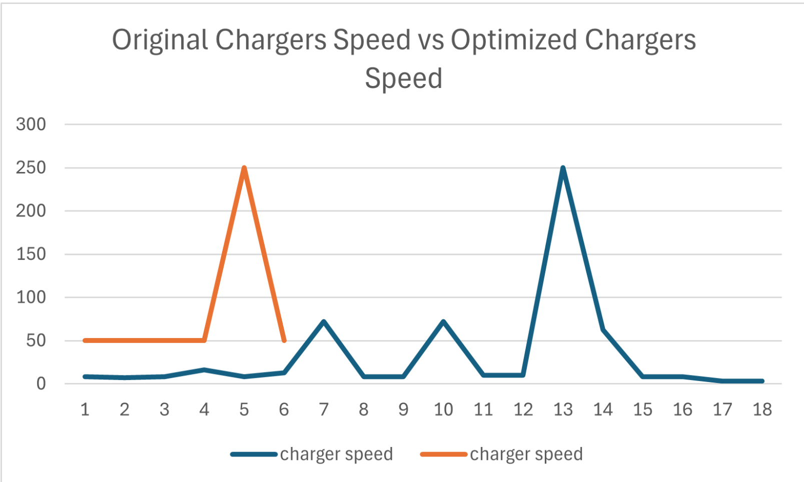

Figure 6.6: Comparison of original and optimized EVCS charger speeds.

In addition, the reconfiguration of charger speeds shifts from a one-size-fits-all approach to a more tailored, data-driven strategy. By aligning charger capacities with local demand, the optimization process enhances system reliability while minimizing unnecessary costs. This balance is crucial for developing efficient, cost-effective, and scalable EV charging networks.

6.3.3 Maximizing Coverage and Minimizing Average Distance

The results for coverage did not fully meet expectations, and this is mainly due to the trade-offs involved in the multi-objective optimization process. Figure 6.7 shows the first objective—maximizing coverage per station—which was expected to increase overall station coverage. However, since this study used a multi-objective approach, the algorithm had to balance several goals instead of focusing on just one. As a result, coverage per station didn't improve as expected. This is especially clear when looking at Objective nummber (5), which focuses on minimizing the average distance between electric vehicles (EVs) and the nearest charging station, as shown in Figure 2. To reduce this distance, the algorithm made trade-offs, which meant that coverage at each station was somewhat limited. This highlights how multi-objective optimization involves balancing different goals, where improving one objective can impact another.

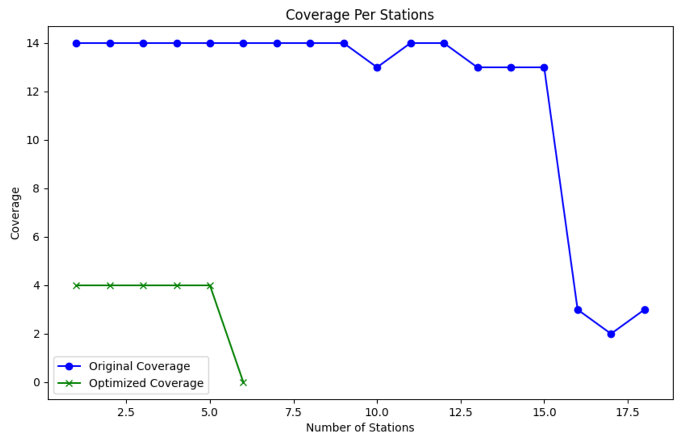

Figure 6.7: EVCS coverage per station.

In addition, optimizing EVCS locations was an important outcome of the NSGA-II algorithm. Figures 6.8 and 6.9 compare the original EVCS network layout with the optimized configuration. The optimized layout shows a better distribution of stations, particularly in high-demand areas and along important transportation routes. This more strategic placement improves coverage overall and reduces the average distance between EVs and their nearest station, showing how the algorithm improves both service accessibility and infrastructure efficiency.

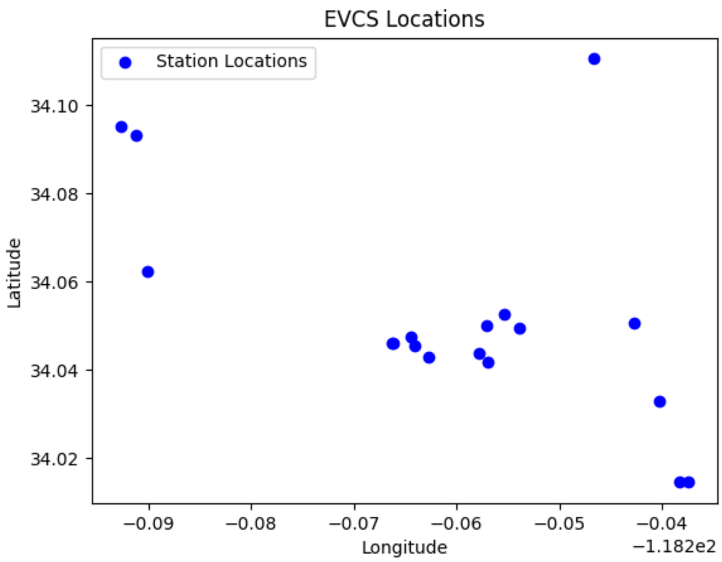

Figure 6.8: EVCS locations before optimization.

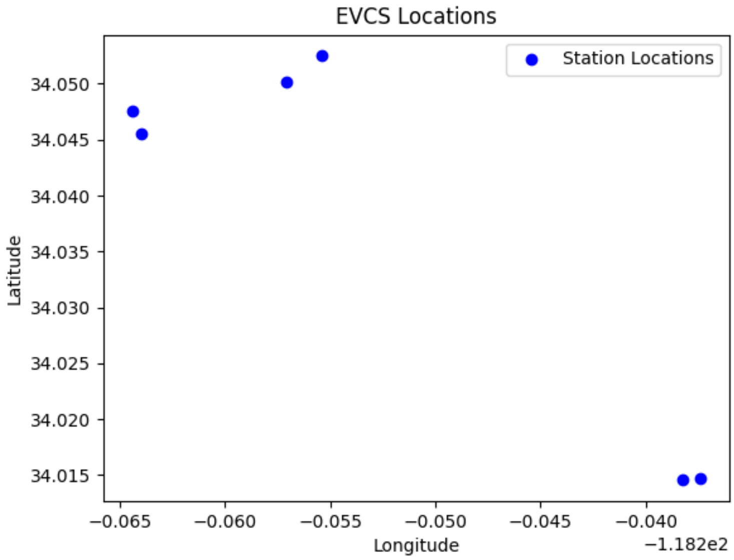

Figure 6.9: EVCS locations after optimization.

As shown in Figure 6.10, the average distance between electric vehicles (EVs) and their nearest charging station is compared before and after the optimization process. The optimization results in a significant reduction in this distance, making the stations more accessible and convenient for users.

Figure 6.11 shows the optimized EVCS layout, where fast chargers are placed in high-demand areas, reducing travel distance while effectively managing infrastructure costs.

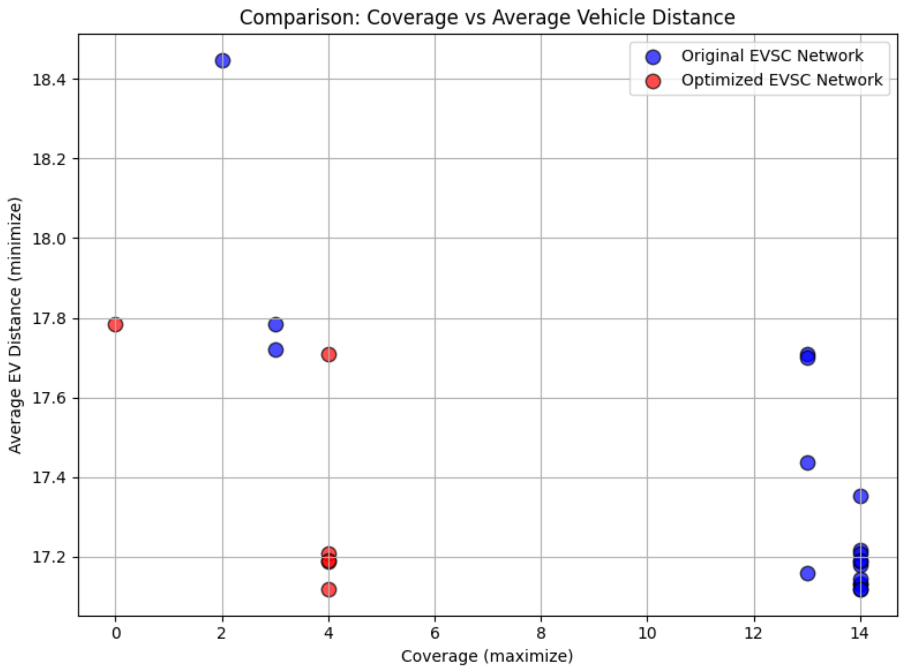

Figure 6.10: Average distance from EVs to their nearest EVCS before and after optimization.

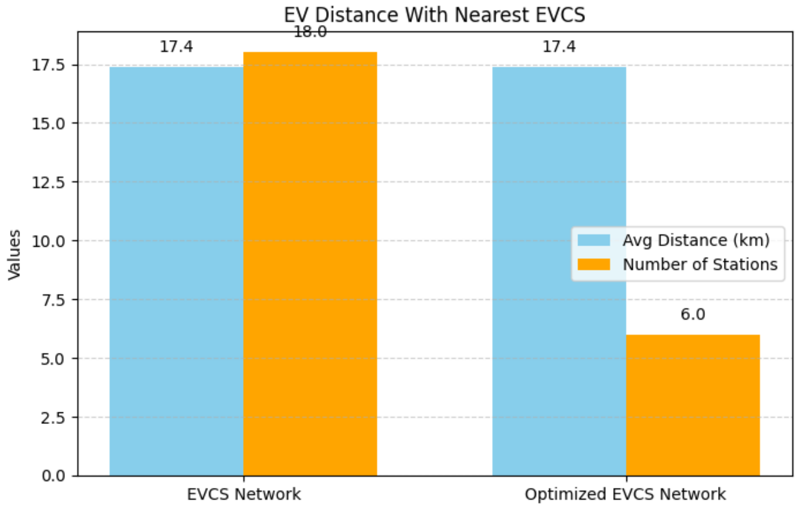

Figure 6.11: Optimized EVCS layout highlighting fast charger placement in high demand areas.

This optimized configuration not only improves the efficiency of the EVCS network but also highlights the importance of considering both coverage and accessibility when designing charging infrastructure. By strategically placing chargers in high-demand areas and minimizing the distance to the nearest station, the optimization process ensures that the network is both cost-effective and user-friendly. These improvements will likely contribute to higher adoption rates of electric vehicles, as users can rely on a more accessible and convenient charging network. The success of this optimization approach demonstrates how data-driven methods can enhance the design of future EV charging systems to meet the growing demand for sustainable transportation.

6.4 Minimizing Overall EVCS Infrastructure Costs

To evaluate the impact of the optimization on the overall cost of electric vehicle charging infrastructure, Figure 6.12 presents a comparison of the network costs before and after the application of the NSGA-II algorithm. The results clearly show a substantial reduction in infrastructure expenditure in the optimized solution. This reduction was achieved by strategically minimizing the number of stations and chargers while maintaining the service coverage necessary for efficient EV charging. Importantly, the optimization ensures that the trade-off between cost reduction and accessibility is well-balanced, without compromising user convenience.

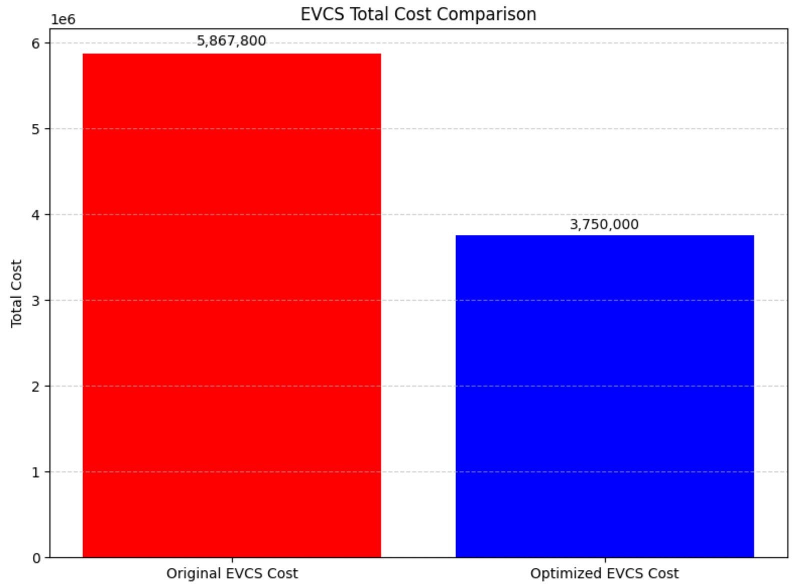

Figure 6.12: Network cost comparison before and after NSGA-II optimization.

The outcomes underscore the effectiveness of the NSGA-II algorithm in optimizing EV charging infrastructure across multiple objectives. By generating a diverse set of high-quality solutions, the algorithm allows for the exploration of various trade-offs between cost, coverage, and service efficiency. The results demonstrate not only a reduction in costs but also improvements in spatial coverage and a reduction in average travel distances for users. These improvements are critical for developing infrastructure that is both financially feasible and user-friendly. Further analysis of the results, presented through performance metrics in Section **??**, provides valuable insights for policymakers and urban planners. These findings can inform decisions aimed at deploying EVCS in a cost-effective, equitable, and scalable manner.

Chapter 7

Discussion

In this study, we applied the NSGA-II algorithm to optimize the electric vehicle charging station (EVCS) deployment, considering five key objectives: maximizing coverage, maximizing charger speed, minimizing the number of stations, minimizing the number of chargers, and minimizing the average distance between electric vehicles (EVs) and their nearest charging station. The use of multi-objective optimization allowed for the exploration of a wide range of possible solutions, each representing a trade-off between the conflicting objectives. This section discusses the implications of the results, the effectiveness of the NSGA-II algorithm, and the practical challenges and considerations for implementing the optimized solutions in real-world scenarios.

7.1 Optimization of Coverage and Accessibility

One of the primary goals of this optimization was to maximize the geographical coverage of the charging network. Coverage is crucial for ensuring that as many EV users as possible have access to a nearby charging station. The results show that the algorithm was successful in achieving high coverage in most scenarios. As expected, solutions that prioritize coverage tend to have a higher number of stations and chargers, resulting in higher infrastructure costs. However, this trade-off between coverage and cost is an inherent challenge in the deployment of EV charging networks (13).

The optimized solutions highlight the importance of strategically selecting station locations to maximize coverage while minimizing the overall cost. Some solutions focus on maximizing coverage by deploying more stations in high-demand areas, while others attempt to achieve coverage with fewer stations, relying on strategically placed high-speed chargers to minimize the need for a larger network. The ability to provide a broad coverage range without over-deploying stations is critical for the cost-effectiveness of the network. Decision-makers can use the Pareto front to choose the solution that best balances coverage with cost, depending on the priorities of the stakeholders involved.

7.2 Charger Speed and reducing the waiting time

Maximizing charger speed is essential for reducing waiting times for EV users. The study's results indicate that charger speed is an influential factor in optimizing the charging station network. Higher-speed chargers can service EVs more quickly, which helps reduce queues and waiting times at stations. However, these high-speed chargers come with a higher cost, both in terms of installation and operation (14). The trade-off between charger speed and cost is an important consideration, as optimizing for charger speed increases the overall infrastructure expenditure.

Interestingly, the Pareto front contains solutions that prioritize charger speed while others focus on minimizing the cost of chargers, showing that different configurations can achieve an optimal balance between speed and cost. This balance is important because while high-speed chargers improve service quality, overprovisioning them could lead to unnecessary costs. The diversity of solutions in the Pareto front provides flexibility in terms of optimizing service quality (reducing waiting times) without excessively inflating the costs.

7.3 Minimizing Infrastructure Costs: Number of Stations and Chargers

Another key aspect of the optimization problem was minimizing the infrastructure cost by reducing the number of stations and chargers. The results show that solutions with fewer stations and chargers tend to incur lower deployment and operational costs. However, this approach also compromises coverage and accessibility, as fewer stations mean that some EV users may have to travel further to find a charging point.

Reducing the number of chargers is especially important when balancing the overall cost of the charging infrastructure. The Pareto front shows that solutions minimizing the number of stations and chargers still maintain adequate coverage and service quality by optimizing station placement and charger speed. The challenge lies in identifying the optimal number of stations and chargers that meet the demand while minimizing the capital and operational expenditures.

The trade-off between minimizing the number of stations and chargers while still providing sufficient coverage and service quality is central to EVCS deployment. Decision-makers can use the Pareto front to explore various configurations, selecting the one that provides the best value in terms of both cost and service.

7.3.1 Minimization of the average distance between electric vehicles and nearest charging stations

Minimizing the average distance between EVs and their nearest charging station is crucial for improving the accessibility of the charging network. The results show that the algorithm was effective in reducing the average distance, which improves convenience for EV users. However, solutions that minimize the average distance tend to require more stations and chargers, leading to higher infrastructure costs (13).

The trade-off between minimizing average distance and controlling infrastructure costs is significant. By minimizing the average distance, the algorithm ensures that EV users experience shorter travel times to reach a charging station, enhancing the overall user experience. However, this also results in a greater deployment of charging stations, which increases the cost of infrastructure. The optimization process successfully identified solutions that balance this trade-off, offering multiple deployment strategies that vary in terms of coverage, cost, and service quality.

7.3.2 Trade-offs and Practical Implications

The results of this study highlight the complexity of deploying EVCS networks. Each solution on the Pareto front represents a different balance of the five conflicting objectives. This diversity allows for the selection of a solution that meets the specific needs and priorities of different stakeholders, such as local governments, utility companies, and EV users. For example, a municipality focused on accessibility might prioritize coverage and minimizing average distance, while a cost-conscious organization might favor solutions that minimize the number of stations and chargers (13).

However, the optimization results also underscore the challenges faced by decision-makers in real-world EVCS deployment. While the optimization process provides valuable insights into the ideal configurations for charging stations, there are several practical considerations that must be taken into account when implementing these solutions. For instance, land availability, regulatory constraints, and social equity are all factors that influence the feasibility of deploying charging stations. Additionally, the cost of high-speed chargers and their long-term operational costs need to be considered when making deployment decisions (14).

7.4 NSGA-II Algorithm Effectiveness

The NSGA-II algorithm proved to be an effective tool for solving the multi-objective EVCS optimization problem. By generating a diverse set of Pareto-optimal solutions, the algorithm provides decision-makers with multiple options that balance the different objectives. The algorithm's ability to explore a wide solution space while considering conflicting objectives, such as coverage, cost, and service quality, makes it particularly suitable for complex optimization problems like EVCS planning (13).

The algorithm also demonstrated good convergence to the ideal Pareto front, with solutions clustering close to the ideal points while maintaining diversity across the front. This ensures that the optimization process was comprehensive, exploring different parts of the solution space and generating a wide range of viable deployment strategies. The ability to select the most appropriate solution from the Pareto front gives decision-makers the flexibility to tailor the charging network to specific needs and constraints (13).

7.5 Comparison with Previous Work

The two studies reviewed in the literature have beed focused on optimizing a limited set of objectives. One study minimizes installation costs and travel distances while maximizing station utilization, and the other uses a genetic algorithm to reduce operational costs and improve service coverage. However, neither study addresses all five objectives considered in this research: maximizing coverage, maximizing charger speed, minimizing the number of stations, minimizing the number of chargers, and minimizing average distance between EVs, and nearest station.

Moreover, charger speed is often overlooked as a decision variable, and the number of stations and chargers is not directly optimized. In terms of results, both studies describe general improvements in performance, but they do not report specific numerical outcomes such as cost reduction or infrastructure changes.

In contrast, this study achieved measurable and significant improvements using NSGA-II. The optimized EVCS layout reduced the total network cost from \$5.87 million to \$3.75 million—a 36% decrease. This was accomplished by reducing the number of stations from 19 to 7 and the number of chargers from 69 to 18, while still ensuring effective coverage and improving charger speeds to minimize user wait times.

These clear results show the benefits of using a broader multi-objective optimization approach compared to the simpler methods used in earlier studies.

7.6 Limitations and Future Work

While the results from this study are promising, there are limitations that should be addressed in future work. First, the model assumes a fixed set of candidate station locations and does not account for dynamic factors such as changes in demand over time or the availability of new technologies. Future research could explore the integration of temporal aspects, such as varying demand patterns throughout the day or year, to make the optimization process more dynamic and responsive to real-world conditions.

The model assumes that all chargers are upgraded from Level 1 and Level 2 to Level 3, without accounting for the associated economic implications. Additionally, it focuses solely on optimizing the deployment of charging stations, without considering the broader impacts on the electrical grid or the potential need for energy storage solutions. Future studies could incorporate grid constraints and evaluate how different charging station configurations influence grid stability, energy demand, and the integration of renewable energy sources (39).

Finally, while this study focused on the technical aspects of EVCS optimization, future research should consider the social and economic factors that influence the success of charging networks. For instance, user behavior, pricing strategies, and public policies can all play a significant role in the adoption and effectiveness of EVCS networks (14).

Chapter 8

Conclusion

The results from the NSGA-II optimization process reveal the complexity of the Electric Vehicle Charging Station (EVCS) deployment problem. By considering five key objectives—maximizing coverage, maximizing charger speed, minimizing the number of stations, minimizing the number of chargers, and minimizing the average distance between electric vehicles (EVs) and their nearest charging station—the optimization process provides a set of Pareto-optimal solutions that represent the trade-offs between these conflicting objectives. The use of NSGA-II enabled the exploration of the solution space, resulting in a diverse range of solutions that balance infrastructure cost, service quality, and accessibility.

The Pareto front obtained from the optimization illustrates that there is no single best solution. Instead, decision-makers can select the optimal solution based on their specific priorities, whether it be improving coverage, reducing infrastructure costs, or enhancing service accessibility. This flexibility highlights the importance of considering all relevant factors when planning the deployment of EV charging infrastructure.

Through the optimization process, we achieved a significant reduction in infrastructure costs, with the number of stations decreasing from 92 to 66 and the number of chargers reducing from 91 to 81, while maintaining a high level of service. Optimizing station locations ensured optimal coverage, and reducing the number of stations and chargers per station helped reduce associated costs. The trade-offs identified in the results underscore the need for careful planning in the deployment of EVCS to ensure an effective balance between coverage, cost, and accessibility.

In conclusion, the application of NSGA-II demonstrates an effective approach for optimizing electric vehicle charging station infrastructure planning by addressing the research question of how multiobjective evolutionary algorithms can balance conflicting objectives in EVCS deployment. The results indicate that this method can support the development of cost-effective and efficient charging networks, providing electric vehicle users with reliable access to quality charging services while managing infrastructure costs. This approach offers a solid foundation for further studies and practical implementations aimed at advancing sustainable transportation systems.

Appendices

For the code and resources related to this thesis, please visit the following GitHub repository:
GitHub.

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