University of Twente

YesHugo

Industrial Engeneering & Management

Bachelor Thesis

Computing EV charging policies based on battery status, charging rates, charging prices, and detour distances

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Preface

Dear reader,

I am pleased to present the thesis in front of you titled: "Computing EV charging policies based on battery status, charging rates, charging prices, and detour distances", which is the result of my research at YesHugo.

I want to take this opportunity to express my gratitude to my company supervisor Hans Schaap for the opportunity to conduct this research at his company and to Daan Nuijts for the constant guidance throughout the research period. Furthermore, I want to thank the employees at the company for their warm welcome and helping hand.

Additionally, I want to thank the staff from the university who assisted me in all parts of the research. A special thanks go out to Dr. A. Trivella, who was my first supervisor from the University of Twente. His advice and feedback were incredibly helpful from the beginning to the end of conducting this research. Secondly, I want to thank S.M. Meisel for being my second supervisor.

Enjoy reading,

Maarten Timmer
Enschede, June 2024

Management Summary

Introduction
YesHugo, a 2019 startup under Curious Inc., is an expert in fleet management software and trip registration. They provide information on the performance of the electric vehicle and the driver's behavior.

The lack of recommendations for drivers in selecting optimal charging stations results in them often suffering from range anxiety, then inefficient decisions are made when selecting charging stations. This research tests certain charging strategies aiming to minimize the cost of implementing charging stations into a route. The model in which the experiments are conducted takes into account various factors such as vehicle battery status, distance to charging stations, charging rates, and energy prices. Thus the main research question of this research is formulated as follows:

What are the most cost-effective strategies for optimizing electric vehicle charging decisions, considering battery status, detour distances, charging rates, and energy prices?

Approach
The experimental setup for addressing the optimization problem for optimally selecting charging stations for electric vehicle routes involves conducting numerical experiments. These are done in a controlled environment that simulates certain real-world conditions. The experiments focus on selecting the most efficient charging station along a predefined route while adhering to their constraints.

The controlled environment mimics real-world EV operations with specific parameters. The EV must follow the predetermined route visiting 10 locations after leaving the depot. The locations between these locations are fixed. At each location, ten potential charging stations are available, each with varying distances, charging rates, and energy prices. The vehicle's battery consumption is set at 0.4 kWh per km, and the battery capacity is fixed at 70 kWh. To account for additional use after the route, the EV must return to the depot with at least 20% battery capacity (only in experiments 1 and 2). The model includes costs for travel distance, energy prices at charging stations, and the time spent charging, considering the hourly rate of the driver. The objective is to minimize the total cost of implementing charging stations into the route, balancing the costs associated with charging, travel distance, and charging time. Three experiments are conducted to compare the strategies against the optimal solution:

- Experiment 1: Exact solution with variable charging.
- Experiment 2: Exact solution with a charging policy forcing 100% charge.
- Experiment 3: Near-optimal solution using battery level thresholds (every 5% from 25% to 80%) and a greedy heuristic.

Results
The thesis aimed to determine the most cost-effective strategies for optimizing electric vehicle (EV) routes considering battery status, detour distances, charging rates, and energy prices. .

The results of three experiments: exact solution, a full charge policy, and a threshold percentage policy with a greedy heuristic. The first experiment established a baseline with an optimal route cost of €93.99 by visiting two charging stations and charging to 100% initially, then to 20% at the end. The second experiment required full charges at each stop, resulting in a slightly higher cost of €103.55 due to the increased kWh charged. The third experiment tested battery thresholds from 25% to 80%, with the best results between 25% and 35%, and costs rising significantly at higher thresholds, the worst being €212.45 at 80%.

The analysis underscored the need to balance charging stops, kWh charged, travel distance, and route cost. The first experiment was the most cost-effective, minimizing unnecessary charging and detours. The full charge policy, while simpler, was less efficient. The threshold policy offered a balance between cost and computational efficiency, possibly better suitable for real-time applications with more locations and data.

The study revealed that optimal thresholds vary with route length and distances. While the exact solution from the first experiment is ideal for short computation times, real-world scenarios with dynamic data and multiple variables necessitate efficient (heuristic) algorithms to manage longer runtimes and complexity, ensuring timely optimization in dynamic environments.

Recommendations
Despite identifying the gap between the norm and current practice in offering a tested near-optimal charging strategy, this gap remains unfilled. YesHugo should implement a dynamic optimization model using real-time data to select charging stations, which can reduce computation time while finding near-optimal solutions. Incorporating data such as traffic, energy prices, charging rates, and station availability can enhance the accuracy and efficiency of YesHugo's charging policies.

Additionally, the thesis recommends evaluating different threshold percentages for charging, as this strategy might be time-efficient but requires further testing to determine the most effective threshold for various routes. Simulations with different thresholds and route types can help identify the best strategy to use for all possible scenarios.

However, the current model does not account for factors such as hourly charging rates, station availability, and the runtime needed to process real-time data. Including these variables will improve the model's robustness and real-world resemblance.

Contents

List of Abbreviations

KPI Key Performance Indicator

ICT Information and Communications Technology

EV Electric Vehicle

LP Linear Programming

ILP Integer Linear Programming

MILP Mixed-Integer Linear Programming

VRP Vehicle Routing Problem

E-VRP Electric Vehicle Routing Problem

kWh Kilo-watt hours

EVSCP Electric Vehicle Scheduling and Charging Problem

API Application Programming Interface

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1 Introduction

This section introduces YesHugo, a company that focuses on fleet management software. The action & research problems of the study are identified through problem identification and the gap between norm and reality.

1.1 Introduction to YesHugo

1.1.1 Background Information

Globally, the use of electric vehicles (EVs) has increased drastically. There are numerous causes, including government subsidies supporting clean energy transportation, environmental concerns, and advancements in battery technology, contribute to this rise. According to recent data, the sales of EVs have been steadily increasing worldwide, with millions of EVs sold annually [Rietmann et al., 2020]. Despite this growth, the distribution and accessibility of charging stations remain significant obstacles. A major issue for EV drivers is range anxiety, due to the relatively sparse infrastructure for charging stations compared to gas stations. Range anxiety is the fear of not being able to reach the next location or charging station with the remaining battery level. Consequently, drivers might choose longer and more expensive ways to reach charging stations, leading to increased energy consumption and higher charging costs. Moreover, the limited charging infrastructure discourages potential buyers from switching to electric vehicles.

In response to these challenges, industry-led initiatives by energy suppliers, car manufacturers, and tech companies aim to accelerate the deployment and accessibility of charging stations. Investments in fast charging technology and partnerships to install charging stations in cities, along highways, and in public locations are ongoing efforts to enhance the EV charging infrastructure [Patil, 2019]. Companies like YesHugo can play a crucial role by developing strategies to improve the selection of charging stations within EV routes, thereby enhancing the overall experience of owning an EV.

1.1.2 Company Description

YesHugo, based in Enschede and founded in 2019, is part of Curious Inc., an ICT services and consultancy company. YesHugo offers fleet management software that includes features such as track and trace, trip registration, consumption analysis, and driving behavior analysis. These services are enabled by their “eco-box,” a hardware device installed in electric vehicles to read live data from the car. YesHugo’s system specializes in registering vehicle movements, including sharp curves, acceleration, location, and routes, providing clients with valuable insights into their fleet operations. For certain car brands, the system can also monitor the battery status of electric vehicles through integration with the car brand’s application.

YesHugo aims to provide companies with tools to monitor live vehicle movements and register routes efficiently. By making data visible, companies can optimize their operations, becoming more mindful of electric vehicle usage and energy consumption, which are both economic and environmental concerns.

The eco-box collects real-time data from the vehicle, including live GPS locations, the number of sharp curves, acceleration, routes, and stops. Additionally, some car applications can connect to YesHugo’s system to track battery percentages, demonstrating vehicle performance and ranking them. This information helps companies monitor and potentially improve their drivers’ behavior.

1.2 Problem Identification

1.2.1 Problem Context

YesHugo's eco-box registers most vehicle movements and shares this data with YesHugo's system, accessible only to planners and managers, not the drivers. An EV driver cannot always predict if they can reach their destination with the current battery level, leading to range anxiety. Unlike fuel stations, charging stations are not always conveniently located. Consequently, drivers might choose longer routes to ensure they can charge their vehicles, resulting in increased time, energy consumption, and costs, which are detrimental to both the environment and efficiency.

YesHugo aims to enhance its service by offering companies advice on the most efficient charging strategy for their routes, ensuring drivers can reach their destinations while optimizing time and costs.

1.2.2 Action Problem

Currently, YesHugo focuses on providing insights into vehicle usage. This research aims to develop a policy for optimally selecting charging stations to integrate into predefined routes for one vehicle. Range anxiety, where drivers are unsure if they have enough battery to reach their destination, often leads to an inefficient selection of charging stations. YesHugo wants to leverage the data collected by their product to provide real-time charging advice to chauffeurs. The action problem is stated as follows:

"Range anxiety results in inefficient charging station selection, increasing energy consumption, time spent at charging station, and higher charging prices."

1.2.3 Problem Cluster

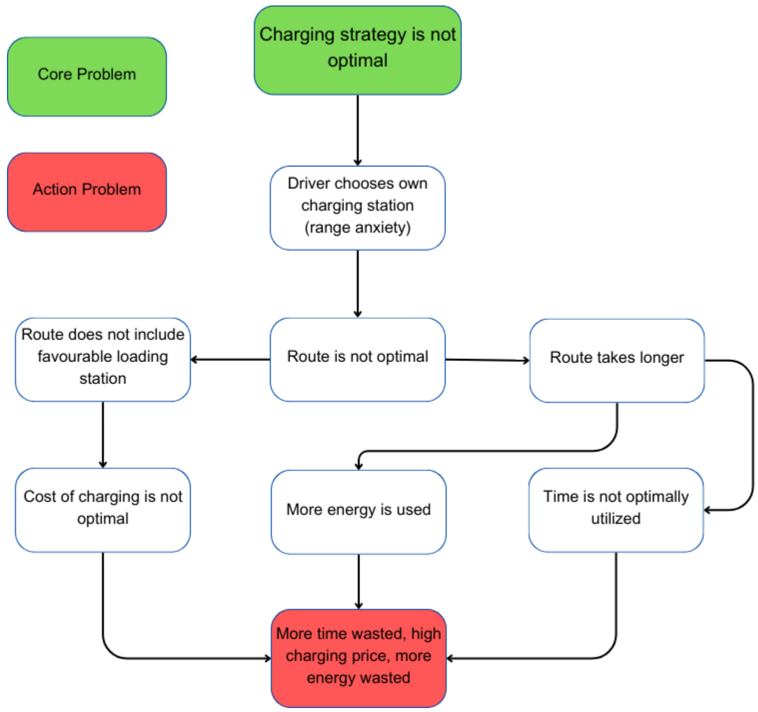


Figure 1: Problem Cluster

Currently, YesHugo does not offer a charging strategy to its customers, leaving drivers to choose charging stations on their own. This often leads to range anxiety and an inefficient selection of charging stations. The core problem can be summarized as follows:

Core Problem: *"YesHugo has no optimal charging strategy for the driver to adhere to."*

1.2.4 Gap Between Norm and Reality

As outlined in the book "Solving Managerial Problems Systematically" by [Heerkens and Winden, 2021], a core problem should contain a gap between norm and reality. This gap can be measured using variables. The current reality is that YesHugo's eco-box collects data, which the system then displays to managers. However, the system only provides descriptive analytics, not predictive or prescriptive analytics. The norm is that YesHugo aims to include a service that offers a proven, near-optimal charging strategy. The gap is that YesHugo currently lacks such a strategy.

1.3 Research Design

The main focus of this chapter is to develop a research question based on the identified problem. The research question is divided into sub-questions, allowing a systematic approach to addressing the main research question and shaping the overall research.

1.3.1 Research Question

YesHugo faces the challenge of their collected data being merely displayed in their system rather than being implemented to create and recommend routes, including charging stations, to drivers. This results in EV drivers not selecting the efficient routes due to range anxiety. By using a model with a specific strategy to calculate optimal routes, energy consumption, charging costs, and driver time can be optimized. Therefore, the main research question is:

> *"What are the most cost-effective strategies for optimizing electric vehicle charging decisions, considering battery status, detour distances, charging rates, and energy prices?"*

This research question aims to address YesHugo's challenge by focusing on the analysis of techniques that aim to find near-optimal routes, thereby reducing range anxiety and improving the overall efficiency of charging decisions.

1.3.2 Sub-Questions

To structure this research logically, the main research question is divided into several sub-questions. These sub-questions help maintain clarity and structure throughout the research process. The sub-questions are based on the following steps:

1. Understanding the current situation of YesHugo;
2. Conducting a literature review to identify the best problem-solving methods;
3. Developing a model to test charging policies;
4. Analyzing the charging policies;
5. Making recommendations based on experimental results.

The sub-questions are as follows:

Sub-Question 1: *What is YesHugo currently doing to assist EV drivers?*

- What data does YesHugo collect to help EV drivers?
- What are the important features of YesHugo's dashboard?

Sub-Question 2: *What are ways of solving the optimization problem?*

- What are similar optimization problems?
- What approaches are already used to tackle optimization problems?
- What methods can be used to gain a near-optimal charging strategy?

Sub-Question 3: *What is the mathematical formulation for the optimization problem?*

- How can this problem be formulated mathematically?
- What variables and constraints are necessary for selecting the optimal charging station in the model?
- What assumptions must be made to make the model represent the real world?

Sub-Question 4: *How should the experiments be analyzed?*

- What is the framework for conducting the experiments?
- What are the policies that will be tested in each experiment?
- How do the experiments perform compared to each other?

Sub-Question 5: *What recommendations can be made based on the results of the experiments?*

- How accurate are the results of the experiments?
- What conclusions can be drawn from the results?
- What are the limitations of the model?
- Are the results applicable in every situation?

Answers to these sub-questions will lead to a final answer to the research question. Based on that answer, conclusions and recommendations can be drawn.

1.3.3 Scope of the Research

The scope of the research sets boundaries for the study. It focuses on policies to improve the efficiency of EV route scheduling. The primary topic is experimenting with selecting the optimal charging station in a predefined route for one electric vehicle. Furthermore, some elements, such as battery, charging, and route constraints, are tailored to meet the needs of YesHugo and their clients.

1.3.4 Deliverables

The study will test certain policies for selecting charging stations in a predefined route. The results of these experiments will be analyzed, and recommendations will be made. The deliverables include:

- A framework for testing strategies for selecting charging stations;
- Insights into specific policies and their performance, including a comparative analysis;
- A thesis that includes recommendations for YesHugo to address their problem.

2 Context Analysis

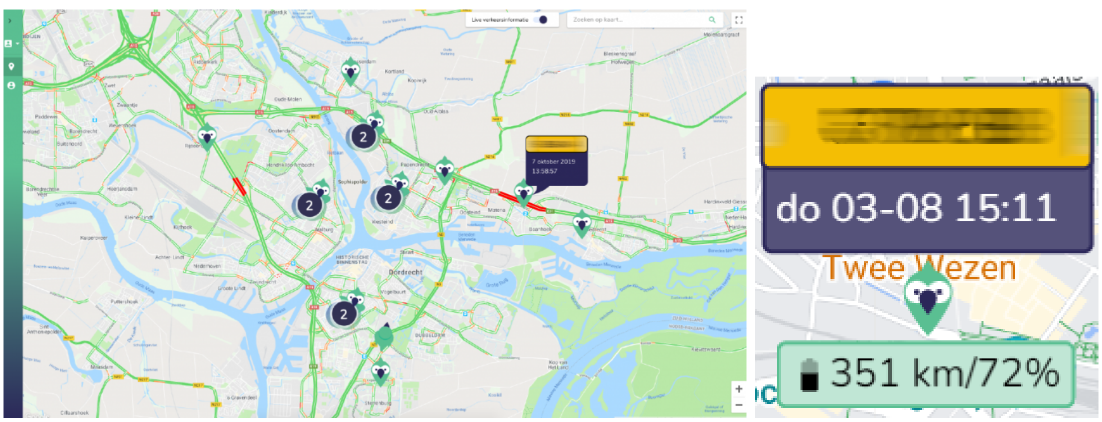
This chapter analyzes the context of the problem, aiming to provide insights into YesHugo's dashboard and the current operational situation.

2.1 YesHugo's Dashboard

YesHugo's dashboard provides valuable information to customers, requiring login credentials for access. Key components of the dashboard include:

1. Fleet management and live location;
2. Trip registration;
3. Driving behavior analysis.

Fleet Management and Live Location
The primary feature of YesHugo's dashboard is fleet management, which displays live vehicle locations. Planners and managers can view the current status of each vehicle—whether it is parked, charging, or in motion—using a user-friendly interface similar to Google Maps. The status indicators, such as the direction of the YesHugo logo (the bird), provide quick insights into vehicle movement. Hovering over a vehicle reveals additional details, including the license plate number, the last seen date and time, and for electric vehicles, the current battery percentage and remaining range. Figures 2a and 2b illustrate the live location map and vehicle details, respectively.

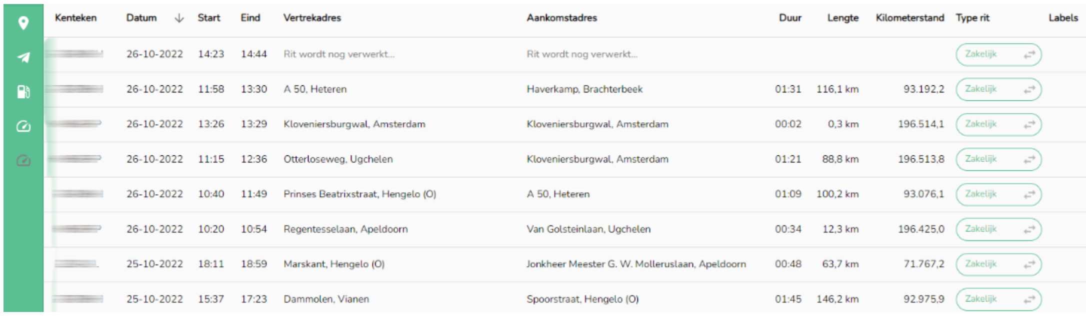


(a) Map with Live Location of Vehicles (b) Live Details Vehicle

Figure 2: YesHugo's Fleet Management Software

Trip Registration

The eco-box collects comprehensive data, enabling the registration and analysis of vehicle routes. Collected data includes the starting and ending points, times, total driving duration, and kilometers driven, filtered by license plate. Users can edit trips and label routes, facilitating easy declaration of work-related trips to tax authorities. Figure 3 shows how registered trips are displayed on YesHugo's dashboard.



Kenteken	Datum	Start	Eind	Vertrekadres	Aankomstadres	Duur	Lengte	Kilometerstand	Type rit	Labels
	26-10-2022	14:23	14:44	Rit wordt nog verwerkt...	Rit wordt nog verwerkt...				Zakelijk	
	26-10-2022	11:58	13:30	A 50, Heteren	Haverkamp, Brachterbeek	01:31	116,1 km	93.192,2	Zakelijk	
	26-10-2022	13:26	13:29	Kloveniersburgwal, Amsterdam	Kloveniersburgwal, Amsterdam	00:02	0,3 km	196.514,1	Zakelijk	
	26-10-2022	11:15	12:36	Otterloseweg, Ugchelen	Kloveniersburgwal, Amsterdam	01:21	88,8 km	196.513,8	Zakelijk	
	26-10-2022	10:40	11:49	Prinses Beatrixstraat, Hengelo (O)	A 50, Heteren	01:09	100,2 km	93.076,1	Zakelijk	
	26-10-2022	10:20	10:54	Regentesselaan, Apeldoorn	Van Golsteinlaan, Ugchelen	00:34	12,3 km	196.425,0	Zakelijk	
	25-10-2022	18:11	18:59	Marskant, Hengelo (O)	Jonkheer Meester G. W. Molleruslaan, Apeldoorn	00:48	63,7 km	71.767,2	Zakelijk	
	25-10-2022	15:37	17:23	Dammolen, Vianen	Spoorstraat, Hengelo (O)	01:45	146,2 km	92.975,9	Zakelijk	

Figure 3: YesHugo's Trip Registration

Driving Behavior Analysis

YesHugo's dashboard provides detailed driving behavior analysis, tracking metrics such as speed, instances of rapid acceleration or deceleration, and hard braking events. Locations of these events are mapped along the route, allowing for thorough review and improvement of driving practices. Figure 4 illustrates the driving behavior analysis tool.

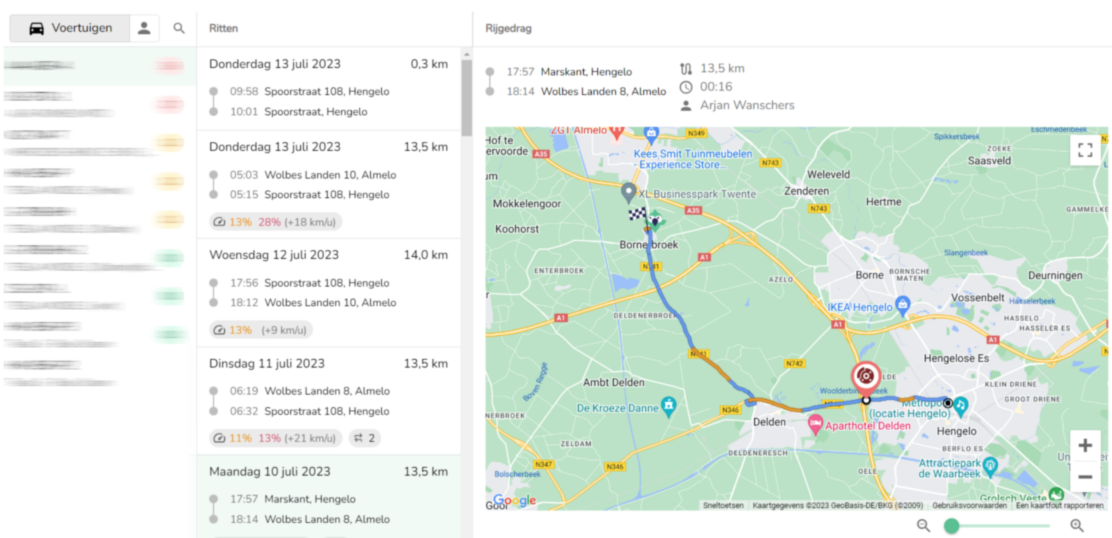


Figure 4: YesHugo's Driving Behavior Analysis Tool

2.2 Charging Stations

The Netherlands has one of the densest networks of public chargers in the world, with over 100,000 public charging stations and 5,000 public fast charging stations. Chargers are classified based on their charging speed. The two main types are AC and DC chargers. AC chargers are usually less than 22kW, while DC chargers charge over 50kW. DC chargers are mostly known as fast chargers [Carlier, 2023].

Charging stations differ in terms of charging speed but also in costs. The differences in costs come from several factors, including the installation and maintenance expenses, the cost of electricity, the speed and efficiency of the charging technology, and the operational costs associated with running the stations. For example, DC fast chargers require more sophisticated infrastructure and higher power capacity, which contribute to their higher prices compared to AC chargers.

Charging stations vary in terms of charging speed but also in costs. The main types include:

1. **Level 1 Chargers:** These use a standard household outlet and provide a slow charging option, typically adding about 6-8 kilometers of range per hour with a power output of around 1.4 kW. They are usually not practical for commercial use due to the long charging time. The cost is typically around €0.20 per kWh.

2. **Level 2 Chargers:** Mostly found in commercial and public settings, these chargers use a 240-volt outlet and can add 24-40 kilometers of range per hour with a power output ranging from 3.3 kW to 19.2 kW. They are suitable for mid-route charging due to their faster charging times compared to Level 1. The cost ranges from €0.25 to €0.30 per kWh.

3. **DC Fast Chargers:** These provide the quickest charging, capable of charging an EV up to 80% in about 20-30 minutes, with a power output from 50 kW to 350 kW. This can add approximately 80–120 kilometers of range in just 20 minutes. However, they are more expensive to use and may not be as widely available as Level 2 chargers. The cost is typically between €0.40 to €0.80 per kWh based on how fast it charges.

2.3 Current Situation

Currently, YesHugo lacks policies or methods for drivers to minimize costs when selecting charging stations. Discussions with YesHugo's customers reveal that drivers receive predefined routes with specified pick-up and drop-off locations. Charging can only occur when the vehicle is not transporting customers, typically after visiting a drop-off location. Planners manually select charging stations, often leading to inefficient decisions that increase route distance and charging costs.

2.4 Summary

This chapter provides insights into YesHugo's operations, focusing on dashboard features, the infrastructure of charging stations, and the current challenges faced by the company. The dashboard offers live vehicle tracking, trip registration, and driving behavior analysis. The Netherlands has a dense network of AC and DC chargers, each varying in speed and cost. YesHugo currently relies on manual decision-making for charging station selection, leading to inefficiencies. Implementing an optimized, automated approach could significantly improve efficiency and reduce costs.

3 Theoretical Framework

This section explores diverse methodologies utilized in solving optimization problems, specifically addressing the crucial sub-question: ”What are ways of solving the optimization problem?” This chapter is organized into three main sections for clarity. First, we provide an overview of optimization problems to build a foundational understanding (sections 3.1 & 3.2). Next, we contextualize these problems within current scientific discussions (section 3.3). Finally, we delve into various methods to solve these problems, including both exact approaches and heuristic techniques (sections 3.4 & 3.5). This structured approach ensures that readers are equipped with the necessary information to comprehend the remainder of the study.

3.1 Classes of Optimization Programs

According to [Schrijver, 1998], linear programming involves an objective function and constraints that are linear. This class is one of the most well-established and simplest forms of optimization, making it highly popular for problems like resource allocation, logistics, and scheduling. Despite its relative simplicity, the size and scale of LP problems can sometimes make them computationally demanding.

3.1.1 Linear Programming (LP):

Following from [Schrijver, 1998] linear programming involves an objective function and constraints that are linear. This class is one of the most well-established and simplest forms of optimization, making it highly popular for problems like resource allocation, logistics, and scheduling. Despite its relative simplicity, the size and scale of LP problems can sometimes make them computationally demanding.

3.1.2 Integer Linear Programming (ILP):

Also following from [Schrijver, 1998] integer linear programming restricts all decision variables to integer values within a linear objective function and constraints framework. ILP is particularly challenging as it often leads to NP-hard problems, making them computationally intensive as the problem size increases. It is widely used in sectors like logistics, where scheduling and allocation tasks require discrete decisions.

3.1.3 Mixed-Integer Linear Programming (MILP):

Following from [Vielma, 2015] MILP is extensively used for optimizing logistics, production planning, and many other industrial and financial applications due to its powerful formulation. However, the addition of integer constraints significantly increases the computational difficulty.

By exploring these classes, researchers and practitioners can better formulate their optimization problems, choose suitable solving methods, and understand the complexities involved in solving them. Each class offers unique tools and approaches that, when matched correctly with the problem at hand, can lead to optimal solutions that are both effective and efficient. The mathematical formulation presented in chapter 4, fits into the class of the MILP.

3.2 Fundamental Components of Optimization Problems

An optimization problem aims to determine the optimal solution given certain constraints. The goal is to optimize an objective function, which represents the quantity to be minimized or maximized. An optimization problem can be broken down into several components:

1. **Sets:** These represent collections of distinct elements that are relevant to the problem. These could represent many different types of objects, locations, jobs, resources, or any other entities related to the problem. Sets provide a structured manner to define and manipulate the components of the problem, making it easier to formulate and solve the optimization problem. For example, the types of ice cream flavors in inventory.

2. **Parameters:** These are values that are known or fixed in the optimization problem, but they are not decision variables. The values represent the constants, coefficients, or inputs that influence the behavior of the problem and the objective function. Parameters provide essential information about the problem's characteristics and constraints, helping to define the problem's boundaries and conditions. For example, the price of each flavor ice cream.

3. **Decision Variables:** These are variables that can control or adjust influence to the outcome. The values of these variables have a direct impact on the objective function and the solution. Decision variables can represent quantities such as battery level, scheduling choices, or other factors that can affect the problem's outcome. For example, the amount of inventory of a certain flavor ice cream.

4. **Objective Function:** This is the function that must be optimized. It could represent any quantifiable goal. The objective function is typically expressed as a mathematical formula involving decision variables. The objective function always has a goal, to minimize or to maximize the result. For example, maximize the profit of selling ice cream.

5. **Constraints:** These are the conditions or limitations that must be respected throughout the calculation of the best answer. Real-world limitations such as resource availability, capacity restrictions, or physical limitations. The optimal solution must adhere to all constraints imposed by the problem. For example, with each ice cream, a cone must be sold.

In general, optimization problems can be found in numerous fields and applications, including engineering, finance, transportation, logistics, healthcare, and many others. They are crucial for increasing efficiency and making informed decisions. In Chapter 4, the research dives deeper into formulating a mathematical formulation for solving the optimization problem.

3.3 Optimization Problems for Electric Vehicles

In this chapter, we'll delve into the problem that will be further explored in the thesis. The objective is to gain an understanding of the vehicle routing problem (VRP) and its electric vehicle counterpart (E-VRP). These essential concepts lay the groundwork for comprehending the complexities of implementing optimal charging stations into a route. This is the problem that will be tackled later in the research.

3.3.1 Vehicle Routing Problem

The vehicle routing problem is one of the most studied problems in optimization and operations research. Following from [Toth and Vigo, 2002] it is aimed at designing the most efficient routes for a fleet of vehicles delivering goods or services to a series of customers. The primary goal is to minimize total operational costs, such as distance or number of vehicles, while maximizing service quality, like adhering to customer time windows. Key components include:

- **Depot:** The location from where vehicles are dispatched and to which they return.
- **Customers/locations:** Points requiring service, each with specific demands.
- **Vehicle(s):** Each vehicle has a maximum capacity it cannot exceed.
- **Routes:** Each route starts and ends at the depot, serving a subset of customers without exceeding vehicle capacities.

3.3.2 Electric Vehicle Routing Problem

One of the many variants of the VRP is the electric vehicle routing problem. The E-VRP creates optimal routes based on the battery capacity of the vehicles. Within the basic E-VRP, charging is not always taken into account. It focuses on finding a route that fits within the battery capacity. In some cases, charging may be taken into account [Kucukoglu et al., 2021]. A couple of extra assumptions of an E-VRP are:

- Electric vehicles may only visit a charging station in between jobs;
- Charging stations may be visited by more than one vehicle;

3.3.3 Electric Vehicle Scheduling and Charging Problem

The electric vehicle scheduling and charging problem (EVSCP) for one vehicle represents a specialized variant of the electric vehicle routing problem. The primary challenge in the EVSCP is to minimize the charging costs along a predefined route, making it distinct from typical E-VRP scenarios where the route itself is to be determined. In the context of YesHugo, the route is already established; hence, the focus shifts to strategically integrating the optimal charging station stops to ensure cost-efficiency and operational feasibility [Sassi and Oulamara, 2017]. Key considerations in the EVSCP are battery level, energy prices, charging rates, charging time, and distance to charging stations. Various mathematical models, primarily mixed-integer linear programming formulations, are employed to solve this problem efficiently. These models are complemented by heuristic approaches that accelerate finding near-optimal solutions under real-world operational conditions [Sassi and Oulamara, 2017].

3.4 Exact Approaches for Solving EVSCP

In tackling optimization problems, exact methods play a crucial role, especially when precision is critical. These methods are designed to find the optimal solution by exploring all possible configurations of the decision variables within the given constraints. Exact methods ensure the computation of the globally optimal solution to an optimization problem, adhering strictly to mathematical precision. These methods typically involve systematic exploration of the entire solution space.

Although exact methods guarantee an optimal solution, they face significant limitations in terms of computational feasibility when applied to large-scale or highly complex problems. As the size and complexity of the problem increase, the computation time and resource requirements grow exponentially. Despite these challenges, exact methods are invaluable as benchmarks in the field of optimization. They provide a standard against which heuristic and approximate methods can be measured, enabling researchers to assess the effectiveness and efficiency of these faster, albeit less precise, techniques.

3.4.1 Cutting Plane Method:

This method refines the feasible region of a linear programming relaxation by systematically adding linear constraints, known as cuts, which are designed to eliminate fractional components of solutions without excluding any feasible integer solutions. This method enhances the efficiency of branch-and-bound frameworks by improving the bounding process and effectively reducing the solution space. It converges to the optimal solution through successive iterations, each tightening the LP relaxation. While cutting planes can dramatically improve solution times and accuracy, they can be computationally demanding. Each iteration involves solving a large LP problem and generating effective cuts to significantly reduce the solution space. However, this approach may not scale well with very large or highly complex problems.

Process and Mechanism

1. **LP Relaxation:** Begins by solving the linear programming relaxation of the MILP, disregarding the integer constraints.
2. **Violation Check:** If the solution does not satisfy the integer constraints, identify the fractional violations.
3. **Generate Cuts:** Construct and add cutting planes that remove the fractional parts of the solution but keep the integer-constrained feasible region intact.
4. **Iterate:** Resolve the modified LP relaxation with new cuts and repeat the process until a feasible integer solution is obtained.

The Cutting Plane Method is ideally suited for optimization problems that combine continuous and discrete decisions, such as in logistics and scheduling, where it is crucial to adhere to strict operational constraints while seeking an optimal solution.

3.4.2 Mixed-Integer Linear Programming Method

MILP (Mixed-Integer Linear Programming) is an exact optimization approach that combines linear programming with integer constraints. It is particularly useful for problems where decision variables must be integers, and it is widely used in fields such as logistics, scheduling, and other areas requiring precise solutions under complex conditions [Vielma, 2015].

In the context of the Electric Vehicle Scheduling and Optimal Charging Problem (EVSCP), MILP can optimize both the routing and charging decisions by considering multiple constraints, such as battery capacity, required energy, and the availability of charging stations. Formulating the problem within a MILP framework ensures that the solution is not only feasible but also optimally reduces charging and detour costs, thus ensuring operational efficiency. The primary benefit of MILP is that it provides exact, globally optimal solutions, ensuring the highest levels of efficiency and cost-effectiveness. However, the inclusion of integer constraints significantly increases the computational difficulty, which can be particularly challenging as the problem's scale grows [Vielma, 2015].

This method's capability to handle complex decision-making processes with precision makes it an essential tool in demanding optimization strategies.

3.5 Heuristic Approach to Solve EVCSP

Heuristic methods are essential tools in the field of optimization, particularly valuable when exact solutions are impractical due to the size and complexity of the problem. Heuristics simplify the decision-making process by taking practical shortcuts, often leading to near-optimal solutions with significantly reduced computational effort [Lenat, 1982]. In complex scenarios like the Electric Vehicle Scheduling and Optimal Charging Problem, where decisions about selecting optimal charging stations need to balance multiple constraints, heuristics can efficiently navigate through options. They are great at managing variations in operational conditions such as battery levels and driving distances. The main advantage of heuristic methods lies in their operational efficiency, they can deliver sufficiently good solutions much faster than exact methods, which is vital in time-critical applications. However, the trade-off is that these solutions are not guaranteed to be optimal. The performance of heuristics can also differ significantly based on the specific characteristics of the problem and the heuristic design. A prominent example is the greedy heuristic, which selects the best option available at each decision point without considering the larger impact [Hojati, 2018]. This approach is especially useful in problems where choices must be made sequentially and quickly, such as in routing or scheduling tasks.

While considering various heuristic approaches for electric vehicle scheduling and optimal charging problems, the Greedy Heuristic emerged as the most suitable due to its prompt decision-making capability. Alternative heuristics like Simulated Annealing or Genetic Algorithms, though powerful for extensive search, require longer computation times and more complex implementation. The Greedy Heuristic's straightforward approach of selecting the most immediately beneficial option ensures rapid, efficient solutions, making it ideally suited for solving the EVCSP. Underneath, a more detailed explanation of the greedy heuristic is given.

3.5.1 Greedy Heuristic Approach

The greedy heuristic is a decision-making algorithm that selects the most favorable option available at each step, optimizing for immediate benefits without considering long-term consequences [Hojati, 2018]. This heuristic evaluates all available options at a given decision point, prioritizing actions that minimize costs or reduce travel time, thus providing rapid solutions in EV route scheduling.

The advantages of the greedy heuristic approach include its simplicity and speed. Its straightforward design allows for quick implementation, which is valuable in scenarios where decision-making speed is crucial. It is particularly effective in environments where decisions are incremental, optimizing for immediate benefits at each step.

The main disadvantage of the greedy heuristic approach is the risk of settling for local optima. While it may find a locally optimal solution, it might miss the globally optimal one. This is illustrated in Figure 5, where the route locally chooses the lowest number at each stage. The route ends in place G with a cost of $8+6=14$, while place H would have resulted in a cost of $10+3=13$. This example demonstrates that the greedy heuristic does not consider global optima and only aims to find the local optimum.

Despite the potential for suboptimal long-term outcomes, the greedy heuristic's ability to provide quick and effective solutions under tight operational constraints makes it invaluable. This is especially true in logistics and scheduling, where decisions must be both swift and economically rational. Therefore, this heuristic is particularly well-suited for managing the complex decision-making involved in integrating optimal charging station stops into predefined EV routes, balancing speed, simplicity, and operational effectiveness.

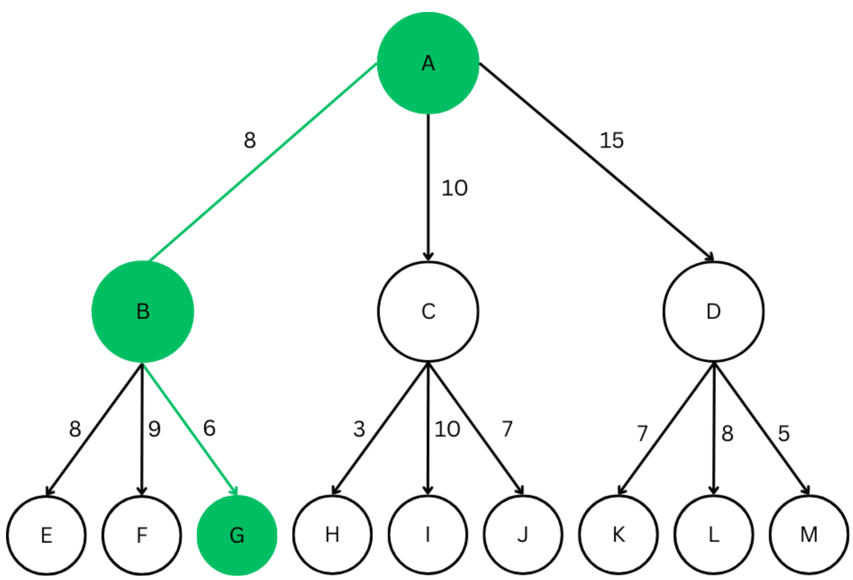


Figure 5: Greedy Heuristic Approach

3.6 Summary

This chapter explored diverse methodologies utilized in solving optimization problems, specifically addressing the sub-question: ”What are ways of solving the optimization problem?”

We began by examining the essential classes of optimization problems: linear programming (LP), integer linear programming (ILP), and mixed-integer linear programming (MILP). MILP, in particular, is crucial for integrating continuous and integer variables, making it incredibly relevant for the operational challenges in EV logistics.

Next, we discussed the fundamental components of optimization problems, including sets, parameters, decision variables, objective functions, and constraints. Understanding these components is essential for formulating and solving optimization problems effectively.

We then provided an overview of the vehicle routing problem (VRP) and its electric vehicle counterpart (E-VRP), highlighting the additional complexities introduced by the need to manage battery levels. The electric vehicle scheduling and charging problem (EVSCP), central to this thesis, specifically addresses the optimal integration of charging stations into predetermined routes to enhance efficiency and reduce operational costs.

Both exact and heuristic methods were explored in detail. Exact methods, such as the Cutting Plane Method and MILP formulations, offer the precision necessary for finding globally optimal solutions but often come with increased computational resource requirements. On the other hand, heuristic methods like the Greedy Heuristic provide practical and time-efficient solutions, though they may not always yield globally optimal results.

In chapters 4 and 5, the study will dive deeper into the EVSCP. The exact method using MILP will be employed to find the optimal solution and serve as a benchmark. Additionally, the exact solution from the full charge policy will be evaluated. Finally, the Greedy Heuristic will be used in the numerical study.

4 Solution Design for EVCSP

The goal of this section is to determine the mathematical formulation of the electric vehicle with charging stations problem (EVCSP). The thesis will detail a comprehensive problem definition, outline the requirements for the solution model, demonstrate the mathematical model, and describe the model's assumptions.

4.1 Problem Description

YesHugo's clients frequently face challenges in selecting suitable charging stations for their EV routes. Since most of YesHugo's clients are taxi companies with pre-scheduled appointments, their routes are fixed, and ensuring adequate charging is essential for route completion. Currently, planners or taxi drivers manually choose charging stations, which is time-consuming due to the need to evaluate all possible options. This becomes difficult when factors such as charging speed, charging price, and distances to charging stations are all taken into account. The solution presented in this thesis will be a model that efficiently calculates the best charging station(s) through certain policies to incorporate into the route, aiming to minimize the costs associated with charging.

4.1.1 Locations

The locations in this optimization problem are the points that the EV must visit. As mentioned before, the route is fixed, so the order of these locations is predefined. The charging stations are optional locations. At each point in the route, a decision must be made between selecting one of the charging stations or driving to the next point on the route. The distance between locations is known in advance.

In a real-world scenario, EV drivers must pick up and drop off customers at specified locations, emptying the vehicle of its customers. Since the chauffeur cannot charge the EV with customers in the vehicle, there are only a few locations where charging can be considered. To simplify the model, the distances between these potential charging locations are grouped. The vehicle may only decide on charging after reaching a location where customers are dropped off. Figure 6 illustrates a possible route, showing locations where charging can and cannot be considered and how the distance is bundled in the model. The green border indicates that charging may be considered after visiting that location, while the red border indicates that charging cannot be considered because one or more customers are still in the vehicle.

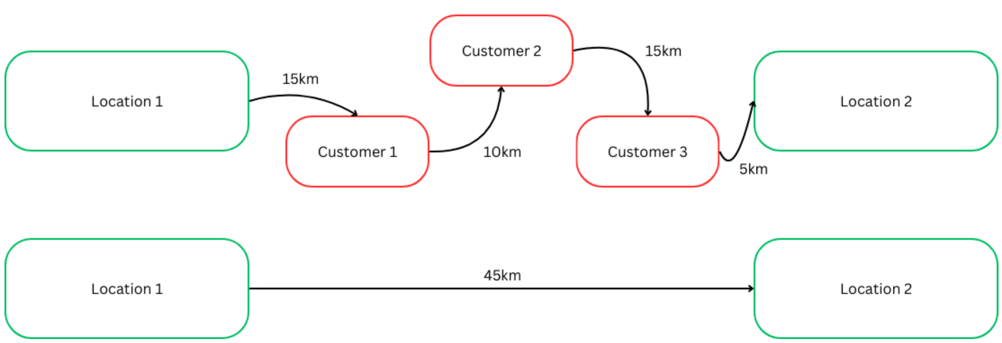


Figure 6: Example Route Between Locations

4.1.2 Objective Function & Decision Variables

An objective function is the main calculation that takes place in the model. It serves as a measure of the ”goodness” or ”badness” of a solution to a problem. Within this problem, the goal is to minimize the cost of implementing a charging station in the route. The objective function consists of three components:

- **Cost of Charging**: This part of the model represents the expense of the energy used to charge the vehicle. It takes into account the price per kilowatt-hour (kWh) at each charging station and the amount of energy charged.
- **Cost of Driving to the Charging Station(s)**: This component accounts for the additional cost incurred due to detours taken to reach the charging stations. It includes the detour distance in kilometers and the cost per kilometer for the vehicle.
- **Charging Time Cost**: This part considers the cost related to the time spent charging the vehicle. It factors in the amount of energy charged, the charging rate at each station, and a constant that converts the charging time into a monetary cost.

The decision variables in this model play a crucial role in determining the optimal solution by directly influencing the objective function and adhering to the problem constraints. Specifically, this model employs both binary and continuous decision variables. The binary decision variables determine the vehicle's route choices, enforcing decisions on whether to follow the predefined route or detour to a charging station. The variable X_{ij} indicates whether the vehicle travels from location i to location j, while Z_{ik} indicates whether the vehicle travels from location i to charging station k.

In addition to binary variables, continuous decision variables are used to track essential metrics related to the vehicle's battery management. The variable E_i represents the battery level of the electric vehicle at location i throughout the route, and A_{ik} represents the amount of energy (in kWh) charged at charging station k from location i. By effectively manipulating these decision variables, the model calculates the optimal solution that minimizes the overall cost while satisfying all constraints related to route adherence, battery levels, and charging requirements.

4.2 Mathematical Model

This chapter dives into the mathematical model. The goal is to create an optimization model that accurately represents the real-world dynamics of route planning and electric vehicle charging decisions. The chapter provides a mathematical framework that is used in the experiments in Chapter 5.

Sets

- I: Set of locations. $I = \{0, 1, 2, \ldots, N\}$
- J: Set of charging stations, available from each location. $J_i = \{1, 2, \ldots, M_i\}$ for each $i \in I$

Parameters

- d_{ij}: Distance between customer locations i and j, for all $i, j \in I$.
- C_{ik}: Distance to charging station k from location i, for all $i \in I, k \in J$.
- Q: Maximum battery capacity in kWh.
- α: Amount of kWh consumed per kilometer, set to 0,40.
- p_k: Cost of charging one kWh at station k, for all $k \in J$.
- T: Cost per kilometer, set to €1.
- r_k: Charging rate (kWh per minute) at station k.
- H: Hourly rate of chauffeur, set to €20.
- B: Minimum end battery level, set to 0.20 (20% of Q).

Decision Variables

- $X_{ij} \in \{0, 1\}$: Binary variable indicating if edge from i to j is taken, for all $i, j \in I$.
- $Z_{ik} \in \{0, 1\}$: Binary variable indicating if charging station k is visited from location i, for all $i \in I, k \in J$.
- A_{ik}: Amount of kWh charged at charging station k from location i, for all $i \in I, k \in J$.
- E_i: Energy level in kWh at location i, for all $i \in I$.

Objective Function

The objective is to minimize the total cost, which consists of three components; the cost of charging, the cost of driving to the charging station(s), and the charging time cost. The objective function is:

$$\min \quad \sum_{i \in I} \sum_{k \in J} p_k A_{ik} + \sum_{i \in I} \sum_{k \in J} \frac{C_{ik} H}{50} Z_{ik} + \sum_{i \in I} \sum_{k \in J} \left(\frac{A_{ik}}{r_k \cdot 60} \right) H$$

1. **Charging Cost**:

$$\sum_{i \in I} \sum_{k \in J} p_k A_{ik}$$

This part represents the total cost of the energy charged at various stations. It is the sum of the product of the energy charged (A_{ik}) and the cost per kWh (p_k) across all locations i and charging stations k.

2. **Driving to Charging Station Cost**:

$$\sum_{i \in I} \sum_{k \in J} \frac{C_{ik} H}{50} Z_{ik}$$

This component accounts for the cost of the extra driving distance required to reach a charging station. It is calculated by multiplying the distance (C_{ik}) by the driver's hourly rate (H), divided by a constant (50km/h) that represents the average driving speed, and then summing over all possible location-station pairs where a visit occurs ($Z_{ik} = 1$).

3. **Charging Time Cost**:

$$\sum_{i \in I} \sum_{k \in J} \left(\frac{A_{ik}}{r_k \cdot 60} \right) H$$

This term captures the cost associated with the time spent charging the vehicle. It is derived by dividing the amount of energy charged (A_{ik}) by the charging rate (r_k), converting the time from minutes to hours, and then multiplying by the driver's hourly rate (H).

Constraint (1) - Fixed Route

$$\sum_{j \in I} X_{ij} = 1, \quad \forall i \in I \backslash \{N\} \tag{1}$$

This constraint ensures that the vehicle proceeds directly from each location i to the next location $i + 1$.

Constraint (2) - Optional Charging Station Selection

$$\sum_{k \in J_i} Z_{ik} \leq 1, \quad \forall i \in I \backslash \{N\} \tag{2}$$

This constraint gives the vehicle the freedom to optionally visit a charging station from any location i except for the final location, providing the possibility of implementing charging stations into the route.

Constraint (3) - Continue Route also after Charging

$$X_{i,i+1} + \sum_{k \in J_i} Z_{ik} = 1, \quad \forall i \in I \backslash \{N\} \tag{3}$$

This ensures that after any optional visit to a charging station, the vehicle must continue to the next location $i + 1$ in the route, maintaining the route's completeness.

Constraint (4) - Energy Balance

$$E_j = E_i - \alpha \cdot d_{ij} \cdot X_{ij} + \sum_{k \in J_i} (A_{ik} - \alpha \cdot C_{ik} \cdot Z_{ik}), \quad \forall i \in I \backslash \{N\}, j \in I \backslash \{0\} \tag{4}$$

This constraint guarantees that the energy level E_j at destination j takes into consideration the energy used in the journey from i to j as well as, if relevant, the energy obtained from charging at station k.

Constraint (5) - Avoiding Overcharging

$$\sum_{k \in J_i} A_{ik} \leq Q - E_i, \quad \forall i \in I \tag{5}$$

This limitation makes sure that the total charge obtained at any location does not exceed the available capacity, taking into account the current energy level E_i, in order to avoid the vehicle's battery from surpassing its maximum capacity.

Constraint (6) - Initial Energy Level

$$E_{\mathrm{i=0}} = Q \tag{6}$$

The maximum battery capacity Q is the starting energy level of the vehicle at the depot. It sets the vehicle's initial state, guaranteeing that it has a fully charged battery at the beginning of the route.

Constraint (7) - Minimum End Energy Requirement

$$E_{\mathrm{i=N}} \geq Q \cdot B \tag{7}$$

This constraint places a lower bound on the energy level $E_{\mathrm{i=N}}$ at the end of the journey by ensuring the vehicle completes its route with at least a minimum percentage B of its battery capacity. This is necessary to guarantee that the car can reach its destination without running out of electricity and to preserve operating safety margins.

4.3 Assumptions

A couple of assumptions are made to help create the model and make sure the problem is manageable. By making the following assumptions, the model will be able to make more feasible routes for charging the electric vehicle.

1. **Fixed Route:** The locations that must be visited are known beforehand and the route is predefined. This is because the clients of YesHugo plan the routes for their chauffeurs in advance.

2. **Uniform Charging and Consumption Rates:** The model assumes that the charging rates across different charging stations and the consumption rate for the vehicle per distance unit are consistent and known beforehand. This assumption is made to reduce complexity.

3. **Instantaneous Charging:** Waiting times at the charging stations are not considered when choosing which station to visit. When the vehicle arrives at the selected charging station it can immediately charge.
4. **Deterministic Parameters:** Parameters such as distances between locations, charging station locations, charging speeds at charging stations, energy consumption rates, and charging costs are considered deterministic and known with certainty when the route is planned at the beginning of the day.
5. **Single Vehicle:** The model considers that only one vehicle is visiting the locations in the route and makes decisions accordingly. YesHugo's customers plan their routes one vehicle at a time.

4.4 Summary

This chapter outlines the mathematical formulation of the electric vehicle charging station problem (EVCSP). It begins with a detailed problem description, highlighting the challenges faced by YesHugo's clients, primarily taxi companies with fixed routes and scheduled appointments, in selecting suitable charging stations. The proposed solution is a model designed to efficiently determine the optimal charging stations to minimize associated costs.

The chapter describes the locations involved in the problem, emphasizing that while the route is fixed, decisions about whether to charge or proceed to the next location must be made at each point. Real-world constraints, such as not charging while customers are in the vehicle, are considered.

The objective function and decision variables are introduced, aiming to minimize the total cost of incorporating charging stations into the route. The objective function consists of three main components: the cost of charging, the cost of driving to charging stations, and the charging time cost. Decision variables include binary variables for route and charging station selection and continuous variables for battery level and energy charged.

The mathematical model is then presented, detailing the sets, parameters, decision variables, and the objective function. Seven key constraints are defined to ensure the model accurately represents the problem, including fixed route progression, optional charging station selection, route continuation after charging, energy balance, avoiding overcharging, initial energy level, and minimum end energy requirement.

Finally, the chapter discusses several assumptions made to simplify the model, such as fixed routes, uniform charging and consumption rates, instantaneous charging, deterministic parameters, single vehicle consideration, and battery capacity constraints.

This comprehensive framework sets the stage for the optimization model used in subsequent experiments, aiming to provide a practical solution for integrating charging stations into electric vehicle routes.

5 Numerical Experiments

This section details the study's experiments, where three different solving approaches are conducted to find solutions to the problem. Initially, the testing environment and experimental setup are explained. The chapter then illustrates the model's components, crucial metrics, and heuristic approaches. After conducting the experiments, a thorough analysis of the results is performed, followed by a comparative analysis of the experiments.

5.1 Testing Environment

The experiments are conducted in a controlled environment to ensure consistency. The vehicle must visit specific locations in a predefined order, reflecting real-world scenarios. After each location, decisions are made whether to charge the vehicle or proceed to the next location. For each node except for the final, ten possible charging stations can be visited, each with varying distances and charging prices. The vehicle starts at 'Depot' and must visit all locations before concluding the route at 'DepotEnd'. Table 1 demonstrates the distances between the locations that must be visited in a given order.

From	**To**	**Distance in km**
Depot	Location 1	40
Location 1	Location 2	50
Location 2	Location 3	40
Location 3	Location 4	30
Location 4	Location 5	45
Location 5	Location 6	50
Location 6	Location 7	40
Location 7	Location 8	45
Location 8	Location 9	30
Location 9	DepotEnd	30
Total		**400**

Table 1: Distances between Locations

Distance and Energy Consumption
The vehicle's battery level is tracked throughout the route to make charging decisions. Typically, 1 km would consume about 0.20-0.40 kWh, for these experiments, it is set to 0.4 kWh per km. Using a constant makes the problem slightly less complex. The battery capacity is set to 70 kWh, similar to real-world EVs used by YesHugo's customers. An overview of these parameters is shown in Table 3. The route is long enough to require a decision where a charging station must be selected, enabling the testing of the different policies. The distances from each location to each charging station can be found in Table 2.

Distances in km	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6	Station 7	Station 8	Station 9	Station 10
Depot	4	5	5	5	10	6	7	8	9	10
Location 1	7	8	9	10	11	7	8	9	10	11
Location 2	8	9	10	11	12	8	9	10	11	12
Location 3	9	10	11	12	13	9	10	11	12	13
Location 4	6	7	8	9	10	6	7	8	9	10
Location 5	7	8	9	10	11	7	8	9	10	11
Location 6	9	10	11	12	13	9	10	11	12	13
Location 7	6	7	8	9	10	6	7	8	9	10
Location 8	7	8	9	10	11	7	8	9	10	11
Location 9	5	6	7	8	9	5	6	7	8	9

Table 2: Distances from Locations to Charging Stations with Prices

Minimum End Battery Level

On many occasions, when the vehicle returns to the depot it is still used by employees for personal use or other purposes. A minimum end-of-route battery level is used to ensure that the EV is not empty when returning to the depot. This is a percentage of the total capacity and is set to 20%, see Table 3. This number is chosen by YesHugo and is based on their client's experience. In the real world, a lot of variables affect the vehicle's consumption of energy such as, driving behavior can differ a lot, especially when frequently accelerating rapidly, terrain such as rough unpaved roads or steep environments, locations where the vehicle must stop a lot, and battery performance in hot weather decreases.

Parameter	**Value**
Battery capacity	70 kWh
Minimum End Battery Level	20%
Cost per km	€1.00
Consumption Rate per km	0.4 kWh
Chauffeur Hourly Rate	€20

Table 3: Overview of Parameters

Charging Rates and Cost per Charging Station

The charging rates for each station vary, reflecting real-world conditions. Different stations offer different rates of charging speeds, which impacts the time a vehicle spends charging and thus affects the overall route efficiency and cost. The charging rate, measured in kWh per minute, indicates how quickly a station can charge the vehicle's battery. For example, a higher charging rate means that the vehicle can replenish its battery more quickly, allowing it to resume its route sooner but potentially at a higher cost. Conversely, a lower charging rate means longer charging times but could be less expensive. The decision of which charging station to use at each point in the route is therefore crucial for optimizing both time and cost.

Table 4 shows the charging rates for each station in kWh per minute. This information is essential for calculating the total time spent at each charging station and the total operational cost, considering both the energy cost and the driver's time cost. In the real world, the charging cost can be different per charging station. The charging stations all have different prices to replicate this. The prices can be found in Table 4. The charging rates and costs are realistic, with some stations being Level 2 chargers and others being DC Fast (Level 3) chargers, as discussed in Chapter 2.

Charging Station	Charging Rate (kWh/min)	Price per kWh (€)
Station 1	0.10	0.25
Station 2	0.20	0.26
Station 3	0.25	0.27
Station 4	0.15	0.26
Station 5	0.30	0.30
Station 6	0.40	0.40
Station 7	1.00	0.50
Station 8	2.00	0.55
Station 9	4.00	0.60
Station 10	5.50	0.72

Table 4: Charging Rates and Prices of Each Station

Program Selection
The selected program in which the model is built is Python[1]. The motivation for using this program is that it can be easily integrated with many things, its syntax is clear and concise, and it has numerous libraries that can be used for handling large data sets. Gurobi[2] is one of the best solvers that can be integrated into Python. Gurobi is often used for comparable optimization problems and is known for its robustness, efficiency, and wide support for linear and integer programming problems. It is substantially well-suited for solving complex routing and scheduling problems, making the solutions of the experiments more reliable and easier to make, and to compare with each other.

5.2 Experimental Setup

The numerical experiments are conducted using sets of data, which simulate real-world conditions. The model has a predefined route and multiple charging station options for each location, as discussed in the Testing Environment section.

Optimally selecting a charging station for a route can present a significant challenge. The complexity of the decision-making process increases substantially with the number of locations, variables considered, and charging station options. For smaller-size problems, an optimal solution can be found relatively easily using exact methods. As more elements are included, using exact methods to solve the problem becomes progressively impractical. Finding a solution could take a significant amount of time. Therefore, the threshold percentage policy with the greedy heuristic will be tested for its cost-effectiveness.

In this setup, there are ten possible locations where a charging station may be included, and for all these locations, there are ten charging station options. Additionally, the option to drive to the next location without charging is available, making it eleven choices per location. Since only one charging station or none can be chosen at each location, there are $11^{10} = 25.937.424.601$ possible routes. This includes the possibility that in the optimal route, the vehicle could visit from zero to ten charging stations in one route.

[1]Python is a programming language that lets you work more quickly and integrate your systems more effectively *(https://www.python.org/)*.

[2]Gurobi Solver is a high-performance mathematical optimization solver used to find solutions to complex optimization problems *(https://www.gurobi.com/)*.

The goal of this thesis is to compare strategies to the exact solution where variable charging is considered. To understand the balance between computational complexity and solution quality and to measure how close the heuristic strategy performs compared to the optimal solution. The following experiments will be conducted:

- Experiment 1: exact solution with variable charging;
- Experiment 2: exact solution with charging policy forcing 100% charge;
- Experiment 3: solution using battery level thresholds and a greedy heuristic.

Experiment 1 - Variable Charging
The situation used for the experiment is small enough to be able to quickly find optimal solutions with an exact calculation. The solution is the global optimum of the model, meaning there is no better solution.

In this experiment, the model calculates the minimum amount of energy needed to complete the route and still adhere to the constraints and the minimum battery level at the end of the route. Compared to the other experiments, this experiment can variably choose the amount of kWh to charge at each charging station. Its objective is to minimize the total route cost, which is the cost of the route and the cost of charging. The model calculates if driving further would be preferable based on the prices and charging speed of charging at each station and the extra distance to reach this station.

Experiment 2 - Full Charge
When more locations are to be visited and more charging stations can be visited it takes more time for an exact model to find an optimal solution. Via a full charge policy, a comparison can be made between a full charge policy and a variable charging policy. It is interesting to compare the difference between this experiment and the exact solution of experiment 1. The solution will be the global optimum, considering the full charge policy. The solution should not be as efficient as the first experiment. This is due to the fact that the vehicle must charge to full capacity instead of choosing a variable charging strategy. The focus shifts from determining precise charging amounts at selected charging stations to selecting an optimal charging station.

Experiment 3 - Battery Level Threshold
The third experiment focuses on finding the optimal route using a battery-level threshold and the greedy heuristic. This simplifies decision-making by adopting a short-term, local optimal strategy for selecting a charging station. In the context of this problem, the heuristic sets a predefined lower bound for the vehicle's battery level. If the battery level drops to or below the threshold, the vehicle is directed to a charging station. The battery is charged to full capacity when visiting a charging station. In this experiment, the final battery level is not taken into account. This to examine the final battery percentages if the EV only adheres to the threshold policy. The greedy heuristic decides on immediate objectives, meaning reaching the next destination with the shortest possible path. In this case, the cost of the extra distance, the cost of time spent charging, and the cost of charging at the selected charging station are considered. The minimal cost of the combination will be the charging station that is chosen, this calculation is explained in the section "Heuristic Benchmark". This policy might not result in the optimal solution but could provide a solution that would work well enough to be usable in big and more complex situations. The thresholds that will be tested are from 25% up to 80% hopefully finding a solution as close as possible to the first and second experiment.

5.2.1 Heuristic Benchmark

The greedy heuristic is used to simplify finding a result for the problem. The greedy heuristic is an algorithmic approach that makes choices with the intention of achieving the best result possible at that particular time. It does not take any future alternatives into account, hence the name "greedy". It is a practical problem-solving strategy designed to find quick approximate solutions compared to exact solutions.

The greedy heuristic will be used in the third experiment combined with a threshold. The threshold is used as a signal for when the vehicle must consider charging. This means that if the battery level reaches a certain percentage of the total capacity, the model searches for the local optimal charging station. In this instance, optimal means the minimum cost for distance and charging combined. This calculation for choosing the optimal charging station takes the length and the cost of the detour into account and the price of that station. If the detour is longer, the vehicle is also able to charge more to fill the battery. Table 5 demonstrates an example of what the calculation takes into account.

Variable	**Value**
Distance to Charging Station (km)	6
Detour Cost (€1/km)	6.00
Battery Level at Arrival (kWh)	4
Charge Needed (kWh)	66
Charging Rate (kWh/min)	2.20
Charging Time (minutes)	30
Charging Time Cost (€20/hour)	10.00
Charge Cost (€0,45/kWh)	29.70
Total Cost at Charging Station X (€)	**45.70**

Table 5: Calculation for Selecting Charging Station X

In short, the total cost of choosing this charging station is the sum of the detour cost, the charging time cost, and the charge cost. When the threshold is reached, the cheapest charging station will be selected and implemented in the route.

5.3 Experiment Results

5.3.1 Variable Charging Analysis

This experiment focuses on finding an exact solution through variable charging, aiming to minimize the total cost while adhering to predefined constraints. The results indicate a carefully optimized route and charging strategy, ensuring cost-efficiency and effective battery management. Figure 7 illustrates the final route, where charging station 9 is visited twice: once after Location 4 and again after Location 7. In the first instance, the EV charges to full capacity (70 kWh), and in the second, it charges to 56 kWh to minimize the overall route cost. The optimal solution shows that delaying charging until absolutely necessary is most beneficial and then charging as much as needed in one session. This strategy is evident in Figure 7, where the EV visits a charging station only when it is nearly out of energy.

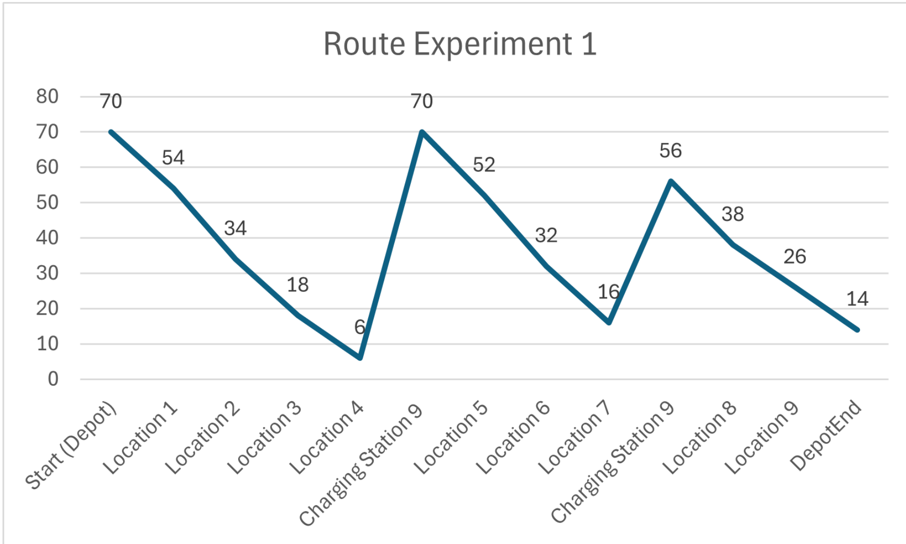


Figure 7: Route of Experiment 1, with Battery Level

Route Costs
The total cost for adding charging stations in the route is €93.99, which is divided into several components as shown in Table 6. The breakdown includes extra distance costs for reaching the charging stations, the direct cost for charging a certain amount of kWh for a certain price at the chosen station, and the chauffeur's time cost associated with the charging duration. The breakdown of the costs is as follows:

Category	**Cost (€)**
Extra Distance Cost	18.00
Charging Cost	66.72
Charging Time Cost	9.27
Total Cost	**93.99**

Table 6: Cost Breakdown for the Variable Charging Experiment

- **Extra Distance Cost (€18.00)**: This cost accounts for the additional travel distance required to reach the selected charging stations. The detours to Station 9 from Location 4 and Location 7 happen to both be 9km, therefore the extra distance cost is $2 * 9 = 18$.
- **Charging Cost (€66.72)**: This is the cost incurred for the actual charging of EV. The vehicle charges a total of 111.2 kWh at an average price of €0.60 per kWh. The calculation is as follows: $111.2 * 0.60 = 66.72$
- **Charging Time Cost (€9.27)**: This cost represents the time spent charging the vehicle at the stations, the charging rate of charging station 9 is 4.0 kWh per minute. One hour of charging costs €20. The calculation is as follows: $(111.2/4) * (20/60) = 9.27$.

Charging Details
The route charges two times at charging station 9, with a cost of €0.60 per kWh and a charge rate of 4.00 kWh per minute. The final battery percentage is the same as the predefined minimum required battery level. This is logical since that would minimize the amount of kWh charged, resulting in minimal costs. The charging details can be seen in Table 7.

Category	**Detail**
Times Charged	2
Total Amount kWh Charged	111.2
Average Price per kWh Charged (€)	0.60
Final Battery Percentage (%)	20.00
Average Charged Percentage (%)	79.43
Charging Stations Visited	Station 9
Location Charging Decision	Location 4, Location 7

Table 7: Charging Details for the Variable Charging Experiment

5.3.2 Charge to full Capacity Policy

This experiment examines the route when a charge to full capacity policy is used. The second experiment should reduce the gap between the first and third experiments. The results highlight the different cost components and the charging behavior under this policy, ensuring an optimal route considering the charging constraint. The EV stops two times throughout the route, both times at charging station 9. The visits are after visiting Locations 4 and 7.

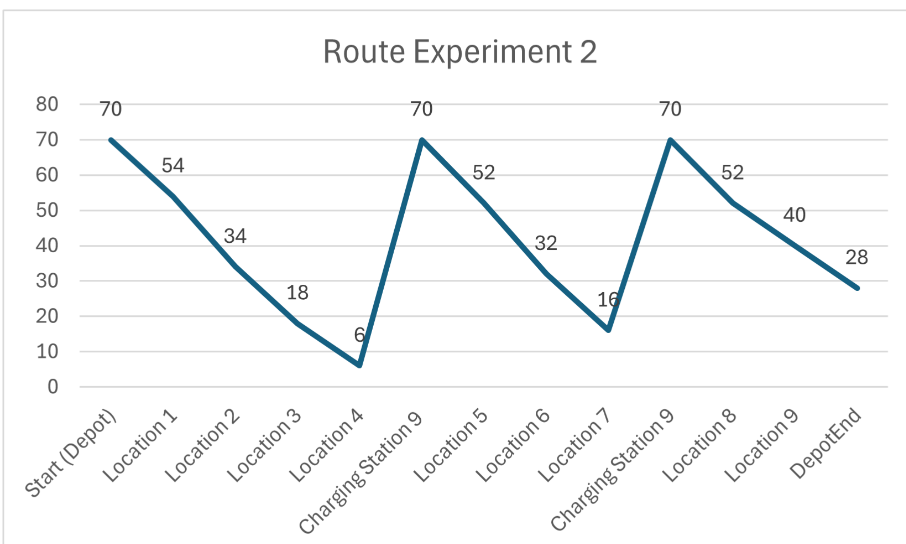


Figure 8: Route Experiment 2, with Battery Level

Route Costs

The total cost for adhering to the 100% charging policy is €103.55, as described in Table 8. The formula for calculating the cost components is the same as mentioned earlier, a breakdown of these costs is as follows:

Policy	**100% Charge**
Extra Distance Cost (€)	18.00
Total Charging Cost (€)	75.12
Charging Time Cost (€)	10.43
Total Cost (€)	**103.55**

Table 8: Experiment 2: Route Cost for 100% Charge

Charging Details

The 100% charging policy necessitated charging the EV two times during the route, with specific details provided in Table 9. The results show that under the 100% charge policy, the EV visits Station 9 both times, after Location 4 and Location 7. The same charging stations as in experiment 1. The costs are different only because of the full charge policy because more kWh is charged the second time and more time is needed to charge those kWh.

Policy	**100% Charge**
Times Charged	2
Total Charge Amount (kWh)	125.2
Final Battery Level (%)	40.00
Average Price per kWh Charged (€)	0.60
Average Charged Percentage (%)	89.43
Charging Stations Visited	Station 9
Charging Decision Location	Location 4, Location 7

Table 9: Experiment 2: Route Charging Details for 100% Charge

5.3.3 Greedy Heuristic with Threshold

The third experiment focuses on a battery percentage threshold for selecting a charging station. The tested battery percentages differ from 25% to 80% with steps of 5%, testing 12 different percentages. The situation is the same as in the other experiments, but the solutions will be found using the greedy heuristic and may not be optimal. The greedy heuristic focuses on finding a local optimum when the threshold is reached. The goal is to find a route with a total cost that lies as close as possible to the first experiment where an exact solution is found.

Kwh/Location	**25%**	**30%**	**35%**	**40%**	**45%**	**50%**	**55%**	**60%**	**65%**	**70%**	**75%**	**80%**
1	70	70	70	70	70	70	70	70	70	70	70	70
2	54	54	54	54	54	54	54	54	54	54	54	54
3	34	34	34	34	34	34	34	34	34	34	34	70
4	18	18	18	18	18	70	70	70	70	70	70	50
5	6	70	70	70	70	54	54	54	54	54	54	70
6	70	58	58	58	58	42	42	42	42	42	42	54
7	52	40	40	40	40	24	24	24	70	70	70	70
8	32	20	20	20	20	70	70	70	52	52	52	58
9	16	70	70	70	70	50	50	50	32	32	70	40
10	70	54	54	54	54	34	34	34	70	70	50	70
11	52	36	36	36	36	70	70	70	54	54	70	50
12	40	24	24	24	24	52	52	52	36	36	54	70
13	28	12	70	70	70	40	40	40	70	70	36	54
14	X	X	58	58	58	28	28	70	58	58	70	70
15	X	X	X	X	X	X	X	58	46	46	58	52
16	X	X	X	X	X	X	X	X	X	X	46	70
17	X	X	X	X	X	X	X	X	X	X	X	58
18	X	X	X	X	X	X	X	X	X	X	X	46

Table 10: Amount of Kwh at each location visited in the route

Table 10 shows the routes of each of the tests of the third experiment. The percentages at the top indicate which policy is used when calculating the route. The light-blue colored cells are charging station locations that are implemented into the route. The "X" means that the route is finished and the vehicle has returned to the end location. The tiniest number of locations in the route is 13, which are the 11 predefined locations and 2 implemented charging stations. Thresholds lower than 25% are not included because the route would not be feasible. Logically when the threshold for charging increases, more charming stations are implemented into the route.

Selected Charging Stations

Experiment 3 uses the Greedy heuristic to select charging stations to implement into the route. The locally best option is selected. In the case of this experiment, this happens to be charging station 10 every time, as can be seen in Table 11. Charging station 10 offers the highest charging rate with 5.50 kWh/min a cost of €0.72 per kWh (see Table 4). The high charging speed enables the driver to minimize the time spent charging their EV. It appears that the charging time is prioritized over the cost per kWh because this results in minimal route costs.

Similar Routes

Some of the threshold percentages result in the same route, which is the case for 35% to 45%, 50% and 55%, and 65% and 70%. When the EV drives to the next location it can happen that multiple thresholds are reached. The battery percentage from location 2 to location 3, without earlier charging, goes from 48.6% to 25.7%. So thresholds 30% to 45% are reached, forcing the selection of a charging station and resulting in the same charging decision for those thresholds at that location. This example happens often throughout the experiment, as can be seen in Tables 10 and 11.

Threshold	Visit 1	Visit 2	Visit 3	Visit 4	Visit 5	Visit 6	Visit 7
25%	L4 -> CS10	L7 -> CS10					
30%	L3 -> CS10	L6 -> CS10					
35%	L3 -> CS10	L6 -> CS10	L9 -> CS10				
40%	L3 -> CS10	L6 -> CS10	L9 -> CS10				
45%	L3 -> CS10	L6 -> CS10	L9 -> CS10				
50%	L2 -> CS10	L5 -> CS10	L7 -> CS10				
55%	L2 -> CS10	L5 -> CS10	L7 -> CS10				
60%	L2 -> CS10	L5 -> CS10	L7 -> CS10	L9 -> CS10			
65%	L2 -> CS10	L4 -> CS10	L6 -> CS10	L8 -> CS10			
70%	L2 -> CS10	L4 -> CS10	L6 -> CS10	L8 -> CS10			
75%	L2 -> CS10	L4 -> CS10	L5 -> CS10	L6 -> CS10	L8 -> CS10		
80%	L1 -> CS10	L2 -> CS10	L3 -> CS10	L5 -> CS10	L6 -> CS10	L7 -> CS10	L8 -> CS10

Table 11: Experiment 3: From Location (L) Visit Charging Stations (CS)

Routes Costs

The cost components of each threshold tested are outlined in the bar chart in Figure 9. The biggest component of the total costs is the charging cost. Thereafter, the extra distance cost for reaching the charging station. As can be seen in Table 10, when the threshold percentage increases more charging stations must be visited. This has an effect on how large the extra distance cost becomes. The charging time cost has the least impact on the total costs. This is because selecting a faster charger is cheaper. This raises the cost of charging but reduces the time required to charge. Consequently, the charging time cost slightly increases as more charging stations are visited increasing the total kWh needed for the route. The results for the cost components of all the threshold's percentages are:

Low Thresholds (25% & 30%)

- **25% Threshold**: The total cost is €118.36, with a charging cost of €90.72, extra distance cost of €20.00, and a charging time cost of €7.64.
- **30% Threshold**: The total cost decreases slightly to €113.74, with a lower charging cost of €80.93, a higher extra distance cost of €26.00, and a reduced charging time cost of €6.81.
- These lower thresholds result in the least total cost, highlighting efficient routes with minimal deviations and time spent charging.

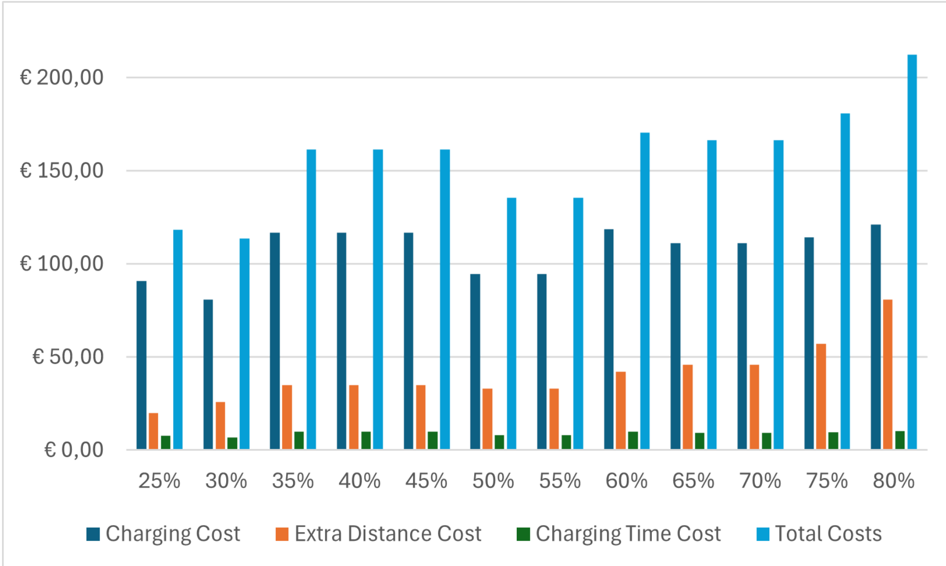


Figure 9: Costs per Threshold Percentage Policy

Mid-Range Thresholds (35% - 55%)

- **35% to 45% Thresholds**: The total cost remains constant at €161.46. This consistency suggests that the route and the charging stations chosen are identical for these thresholds, with a higher charging cost of €116.64 and extra distance cost of €35.00.
- **50% and 55% Thresholds**: The total cost drops to €135.42, indicating more efficient charging at these levels. The charging cost decreases to €94.46 with a slightly lower extra distance cost of €33.00.
- The similar costs for 35% to 45%, 50%, and 55% indicate that the vehicle's route overlaps for these thresholds, resulting in similar charging and distance costs.

High Thresholds (60% - 80%)

- **60% Threshold**: The total cost increases to €170.64, driven by higher charging (€118.66) and extra distance (€42.00) costs.
- **65% and 70% Thresholds**: The total cost slightly decreases to €166.53. These thresholds also share similar routes, as reflected in the identical costs.
- **75% Threshold**: The total cost increases to €180.96, reflecting a rise in both charging (€114.34) and extra distance (€57.00) costs.
- **80% Threshold**: The highest total cost at €212.45 is observed, with the highest extra distance (€81.00) and charging time (€10.21) costs.

The results indicate that lower thresholds lead to the lowest total costs, mainly because of the minimal extra distance and charging time costs. The mid-range thresholds (35% to 55%) result in higher costs. Especially the thresholds from 35% to 45% where the charging costs increase a lot compared to the thresholds at 50% and 55%. The higher thresholds result in the highest total costs. The reason for this is mostly the extra distance costs and a slight increase in charging costs.

Charging Details

The graph shown in Figure 10 shows for each threshold percentage the route's amount of charging station visits, total kWh charged, and the average charged percentage. As mentioned earlier, the largest cost component of the total cost for each route is the charging cost. So it is essential to understand what happens in the routes regarding the charging.

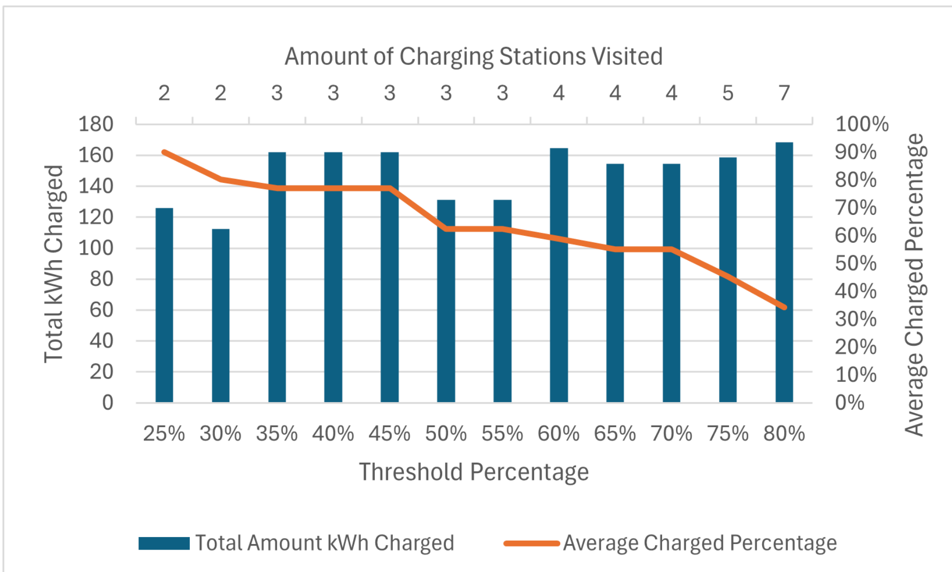


Figure 10: Charging Details per Threshold Percentage Policy

Total Amount of kWh Charged

The total amount of kWh charged is the most important component in minimizing total route costs. Figure 10 shows that the lower thresholds result in the least amount of kWh charged. From the threshold at 35% the EV must charge from 3 to 7 times in the route. The extra visits cost additional kWh in order to reach the charging station. Making the overall route longer and less efficient. The thresholds from 35% to 45% happen to charge right before finishing the route, resulting in "unnecessary" charging making the route more expensive. If the EV would not visit this third charging station it would have the same result as the threshold at 30%, which holds the minimal amount of total kWh charged.

Average Charged Percentage
The orange line in Figure 10 shows the average charged percentage for each tested threshold percentage. It has a negative correlation with the threshold percentage. When the threshold value increases, the average charged percentage decreases. This decline indicates that when the threshold is set higher, the vehicle charges more often but with lesser amounts. A possible strategy behind this could be to optimize charging times and reduce waiting periods at when charging sessions are smaller. It could be beneficial in some situations to have smaller "downtimes" in between charging sessions. Although this approach increases the number of stops, the total route distance, and the overall route costs. This is an important trade-off that is crucial for balancing time, distance, and costs.

Amount of times charged vs Extra distance
The number of charging station visits directly increases the extra distance that the route takes. As can be seen in the graph in Figure 11. The orange line represents the number of charging stops, and the blue bars represent the total extra distance needed for reaching those charging stations. There is a clear correlation between the threshold percentages, the number of charges and the extra distance costs. As the percentages for the thresholds increase, so does the number of charges and the total extra distance. Lower thresholds result in fewer charges and lower extra distance costs, suggesting more efficient route planning.

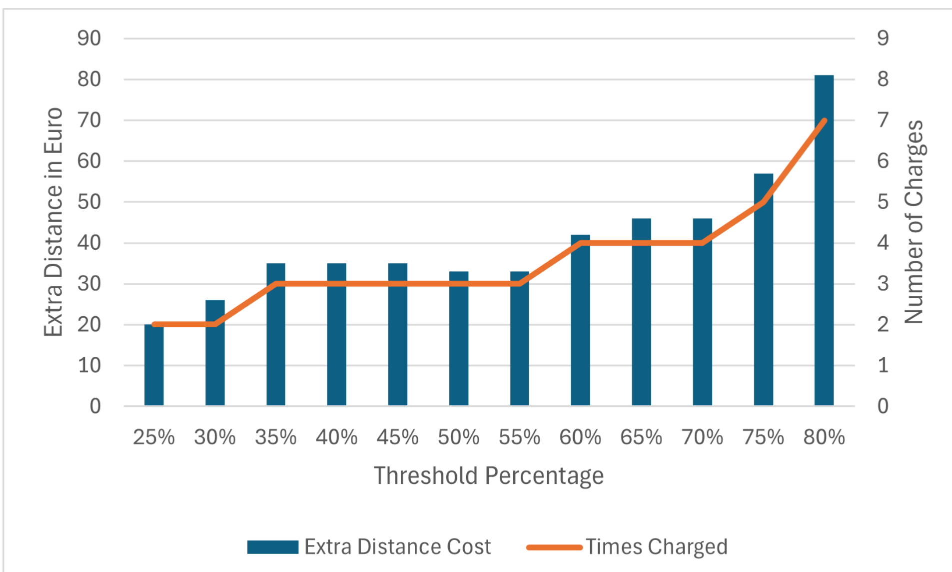


Figure 11: Number of Charging Stations Visited vs Total Extra Distance

Final Battery Level

The final battery level is the remaining energy in the EV at the end of the whole route. Finishing the route with a lot of energy still in the vehicle is not optimal. The EVs can be charged overnight at the depot for a lower price compared to public charging stations. So in an optimal situation, the vehicle returns to the depot with the least amount of kWh left in the battery. In Figure 12 the orange line represents the number of times the vehicle charges during the route and the bars represent the battery percentage at the end of the route. The final battery percentage is the same for some of the thresholds. This occurs due to the policy where the EV must charge to 100% battery capacity before driving the remaining distance to the end location. Therefore, if the last visited charging station is the same across multiple thresholds, the final battery percentage will also be the same. There is not a specific correlation to be seen, the final battery percentage is dependent on the moment of the last charging session in the route.

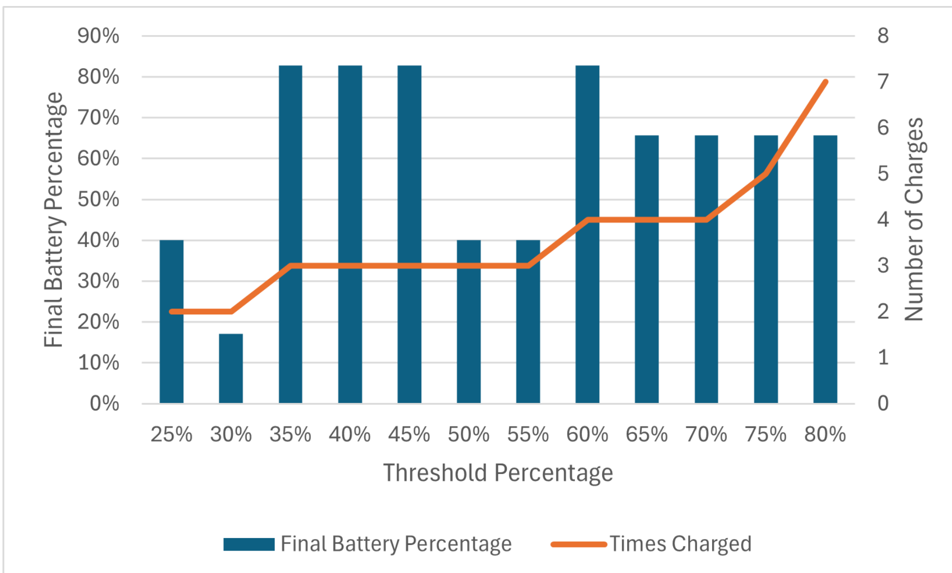


Figure 12: Final Battery Percentage vs Number of Charges

5.4 Comparative Analysis of the Experiments

Now that all experiments have been analyzed separately, a comparative analysis can be done. The results of the three experiments will be compared to each other to analyze their performance. The total route costs, charging strategy, final battery level, and computation time are important.

Costs Comparison Total Route

Figure 13 demonstrates the total route costs for each policy. The percentages are the threshold percentage policy tests of experiment 3. As expected, the first and second experiment performed the best, resulting in the lowest total route cost: €93.99 and € 103.55 respectively. The best result from the third experiment was with the threshold set at 30% and had a total route cost of €113.74. A notable mention is the performance of the threshold set at 25% which came quite close with a total route cost of €118.36. After that, the total route costs increased a lot. Starting at €135.42 until the worst-performing route resulted in a cost of €212.45.

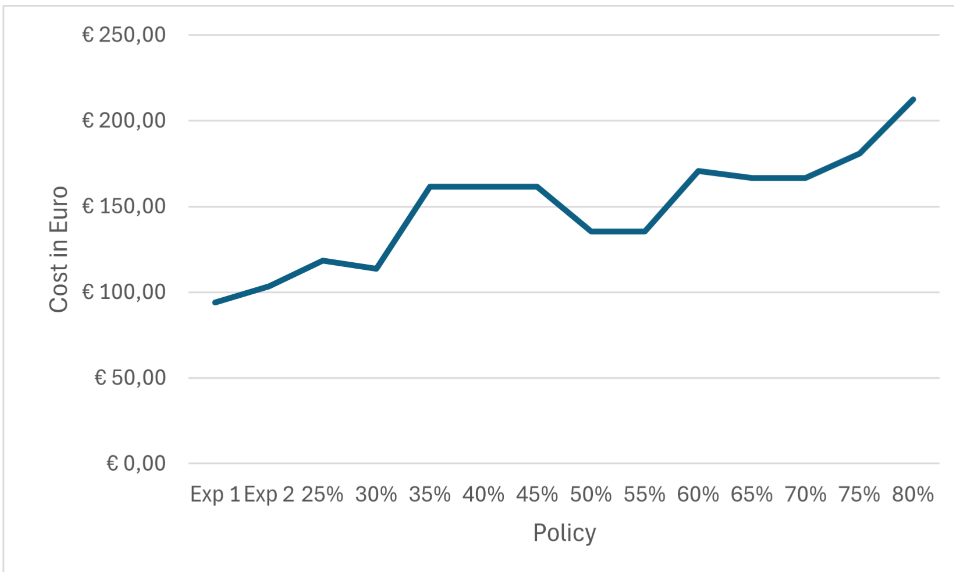


Figure 13: Graph of Total Route Costs

Costs per Component

As mentioned previously, four policies have shown promising results. In this section, we will examine the cost components of these policies in greater detail. Figure 14 presents a bar chart illustrating the cost breakdown for each policy. From this chart, it can be concluded that charging costs have the greatest impact on the total route costs. Following charging costs, extra distance costs also contribute, but less significantly. Finally, charging time costs have the smallest effect on the overall route cost.

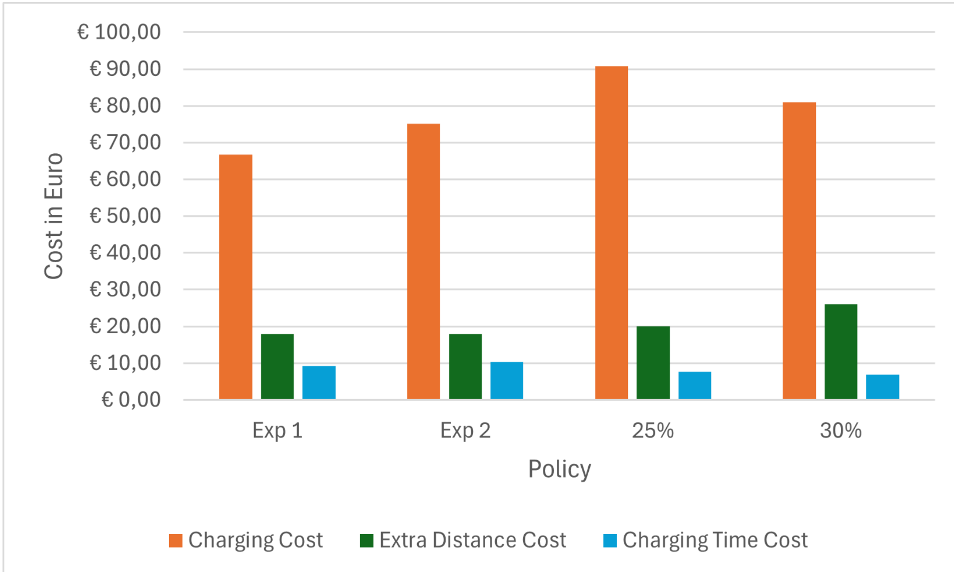


Figure 14: Cost Components of Best Performing Policies

Total kWh Charged

As explained earlier, the amount of kWh charged during the route has the greatest impact on the total route costs. The bar chart in Figure 15 shows the total kWh charged for each route. Similar to the total route costs, the first four policies perform the best. This is not a coincidence, considering the impact of the kWh charge on the overall route costs.

The total kWh charged depends on the distance the EV must travel; as more charging stations are visited, the total distance increases. Thus, increasing the threshold results in a larger total kWh charged because the extra consumption must be recharged as part of the full charge policy. While there is not a perfectly steady correlation visible in the chart, it can generally be observed that when more charging stations are visited, the total kWh charged increases. This, in turn, significantly impacts the total route costs.

Final battery level

As mentioned earlier, the final battery level is as low as possible in an optimal situation. The first experiment ends the route with the minimum required battery level at 20% of the capacity. The other experiments were forced to charge the vehicle to 100% of its battery capacity each time they had to visit a charging station. This resulted in different final battery percentages, those can be found in Figure 16.

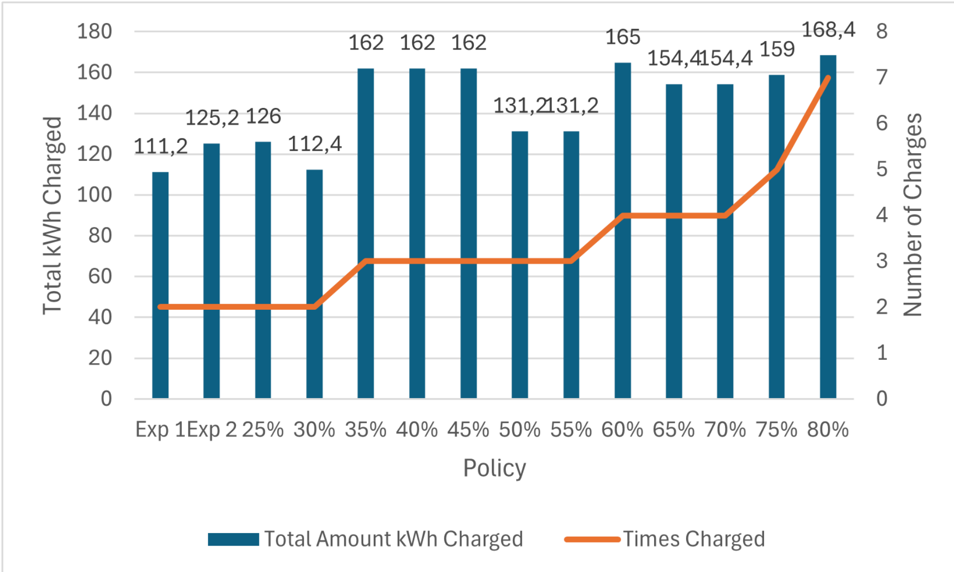


Figure 15: Total kWh Charged for each Policy

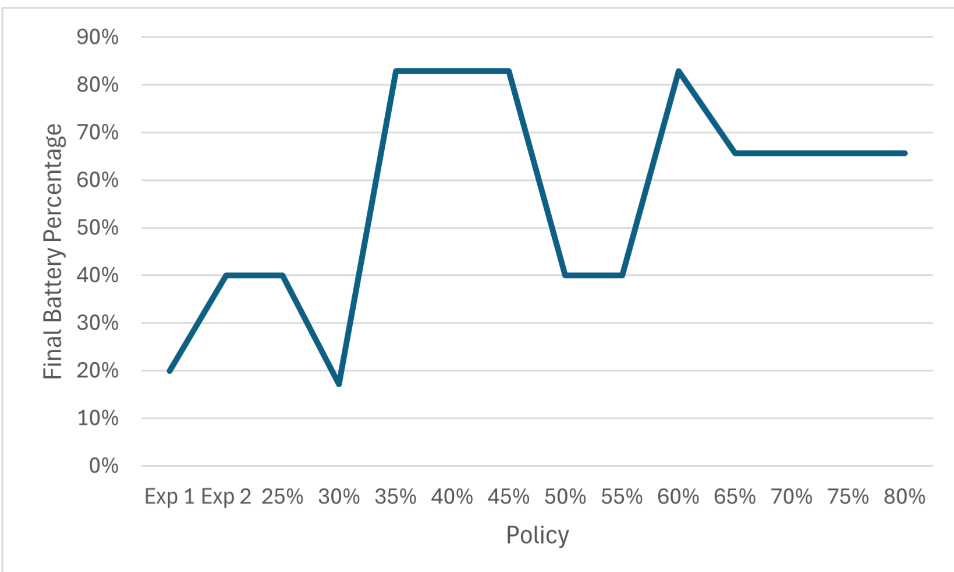


Figure 16: Final Battery Percentage

Computation Time
The computation time of the model is the time that it takes to find a solution. For real-world implementation, it is important that the computation time is relatively fast. A taxi company does not need a perfect route that takes a day to calculate. They are satisfied with a near-optimal route that is calculated quickly. In table 12 the runtime for each separate route is shown. The runtime of the experiments in this thesis is very fast. The reason for this is that the data is known in advance and predefined. For example, the distances from/to each location are predefined, the charging prices are predefined, and the charging rates are predefined. When using real-time traffic data, more charging station locations, charging rates, and charging prices the runtime can significantly increase. It is difficult to predict how these elements will affect the runtime.

Policy	**Computation Time (s)**
Exp 1	0.048159122
Exp 2	0.188021183
Exp 3 - 25%	0.001276255
Exp 3 - 30%	0.001002073
Exp 3 - 35%	0.002312422
Exp 3 - 40%	0.002001524
Exp 3 - 45%	0.002244949
Exp 3 - 50%	0.002374649
Exp 3 - 55%	0.002408743
Exp 3 - 60%	0.002007246
Exp 3 - 65%	0.002062082
Exp 3 - 70%	0.000997782
Exp 3 - 75%	0.002625942
Exp 3 - 80%	0.003371239

Table 12: Computation Time for the Different Policies

The table shows a significant difference in computation times between the experiments. The first experiment has a runtime of 0.048159122 seconds, while the second experiment takes 0.188021183 seconds to compute. Compared to experiment three, which follows the threshold policy, has runtimes ranging from 0.000997782 to 0.003371239 seconds. The fastest computed route (Exp 3 - 70%) is $0.048159122/0.000997782 = 48.28$ times faster than the first experiment. Even the slowest policy of experiment 3 (80%) is $0.048159122/0.003371239 = 14.28$ times faster. Compared to the second experiment the fastest computation time of the third experiment is 188.47 times faster and the slowest is still 55.77 times faster.

5.5 Summary

This section summarizes the findings of the numerical experiments, focusing on evaluating different strategies to optimize the charging and route planning of an electric vehicle (EV). The goal was to improve cost-efficiency while ensuring that the vehicle completes its route within predefined constraints.

First, the context for the experiments was established, detailing the testing environment and the parameters used for the EV's battery, charging stations, and route distances. Then, various experiments were described, starting with a baseline variable charging strategy, followed by a full charge policy, and finally, a series of tests using a battery level threshold and a greedy heuristic.

The first experiment evaluated the variable charging strategy, which sought to minimize total route costs by charging only when necessary and to the exact amount needed. This experiment served as the benchmark, achieving the lowest total cost of €93.99. The variable strategy demonstrated the efficiency of delaying charging until critical and minimizing the amount of charging to just meet the route requirements.

The second experiment applied a full charge policy, where the EV charged to full capacity whenever it stopped at a charging station. While this strategy was less cost-effective than variable charging, it still performed relatively well with a total cost of €103.55. This experiment highlighted the impact of charging strategies on overall costs, with the full charge policy being more straightforward but less optimized.

The third experiment explored the use of a greedy heuristic with various battery level thresholds ranging from 25% to 80%. The results showed that lower thresholds (25% and 30%) led to the most cost-effective routes within this strategy, with total costs of €118.36 and €113.74, respectively. As the thresholds increased, the costs rose significantly, reaching up to €212.45 for the 80% threshold. This indicated that higher thresholds resulted in more frequent and less efficient charging, thus increasing the total route cost.

Comparative analysis revealed that the variable charging strategy (Experiment 1) and the full charge policy (Experiment 2) were the most cost-efficient. The greedy heuristic with lower thresholds provided a feasible alternative but was still more costly. Additionally, the analysis showed that the total kWh charged and the extra distance traveled were critical factors affecting the total route cost.

The computation times for each strategy varied significantly, with the variable and full charge policies taking longer to compute compared to the greedy heuristic. However, the differences in computation time were minimal in practical terms, considering the controlled testing environment and predefined data.

Overall, the experiments demonstrated that while variable charging offers the best cost efficiency, simpler strategies like the full charge policy and the greedy heuristic with lower thresholds can still provide reasonable solutions, especially in more complex or real-time scenarios where computation speed is crucial.

6 Conclusions, Limitations, Recommendations, and Further Research

In this final chapter the thesis' results are concluded. The section is divided into multiple components. Section 6.1 addresses the main research question formulated in Section 1.7. Section 6.2 outlines the limitations of the research in greater depth. Section 6.3 will discuss recommendations for YesHugo based on the findings, and finally, Section 6.4 will suggest directions for further research.

6.1 Conclusion

The main research question of this thesis:

"What are the most cost-effective strategies for optimizing electric vehicle routes, considering battery status, detour distances, charging rates, and energy prices?"

To answer this research question, the question was split up into several sub-questions. Which were covered in chapters 2 to 5.

Chapter 2 goes in-depth on YesHugo as a company and its operations, as well as where it wants to improve its service. It provides context on how optimizing the routes can reduce operational costs, improve service reliability, and enhance customer satisfaction.

Chapter 3 focuses on the literature related to mathematical optimization problems. Fundamental components of optimization problems are explained. It tackles how vehicle routing problems work and goes further into detail about implementing charging stations. The chapter introduces various approaches, from exact methods to heuristic techniques that are suited for tackling complex optimization problems.

Chapter 4 introduces the mathematical formulation of the optimization problem that YesHugo is facing. It details the necessary components: sets, parameters, decision variables, objective function, and constraints. The chapter also dives deeper into the limitations and assumptions of the model. These are made to simplify the model.

In chapter 5 the results of the three experiments are conducted. The testing environment for the experiments is explained in detail. The three experiments conducted were variable charging, full charge policy, and threshold policy with a greedy heuristic. The experiments were designed to evaluate the efficiency and cost-effectiveness.

This first experiment is conducted to form a baseline for the study. This experiment finds the exact optimal solution. This strategy resulted in a total route cost of €93.99. It visits two charging stations where it charges to 100% battery capacity the first time. The second time it charges the remaining needed kWh to end the route at 20% battery capacity.

The second experiment enforced a policy where, when the vehicle visited a charging station, it must charge to full capacity removing the possibility to consider different charging amounts. The resulting route cost was €103.55, but the route ended up being the same. Both experiments 1 and 2 visited charging station 9 from locations 4 and 7. So the difference was the amount of kWh charged and the time it took to charge those extra kWh. This experiment illustrates the impact of implementing a policy, making the route slightly more expensive while using a more straightforward charging strategy.

The third experiment tested various thresholds for battery levels, ranging from 25% to 80%. A greedy heuristic is used to find local optimal charging stations whenever the battery level drops to or below the assigned threshold. The best results were obtained when the thresholds were between 25% and 35%, with total cost of €113.74 to 118.36. As the thresholds increased, the cost rose significantly. The worst performing threshold was at 80% resulting in 7 charging station visits and a total cost of €212.45. This indicates that higher thresholds lead to more frequent and less efficient charging decisions.

The comparative analysis of these strategies highlights the importance of balancing different factors, such as the number of charging stops, total kWh charged, extra distance traveled, and overall route cost. The variable charging method performed the best in minimizing unnecessary charging and detours, thereby achieving the lowest cost. In contrast, the full charge policy, while straightforward, resulted in slightly higher costs due to its more conservative approach to charging. The threshold percentage policy with greedy heuristic offered a practical compromise, balancing cost and computational efficiency, making it more suitable for real-time applications when more locations and real-world data are implemented.

The thesis revealed that for the specific route used in this study, certain thresholds proved to be more effective than others. However, the optimal threshold can vary significantly with different route lengths and distances in between locations. This is evident from the results of the final battery percentage, the number of charging stops, and the similarity of routes throughout different thresholds. When the EV must drive other route lengths, different threshold percentages might yield better results.

Lastly, the runtime for the experiments conducted was extremely short making the runtime practically irrelevant. This means the route created in the first experiment with the exact solution should always be used, making the other experiments irrelevant. However, in real-world scenarios, using real-time data and considering more locations, routing options, and charging station possibilities would significantly increase computation time. Factors such as real-time traffic, fluctuating energy prices, and varying charging station availability add complexity, potentially leading to longer runtimes. Efficient optimization algorithms and computational techniques are crucial to ensure timely solutions in these more complex and dynamic environments.

6.2 Limitations

Although the model offers a framework to solve the optimization problem it has limitations in its direct application to the real world. The assumptions make the problem easier to solve, but with the cost, it becomes less realistic. Understanding the limitations of the model is crucial in understanding how realistic the results are.

Firstly, YesHugo does not have its own optimization model at this moment. So the experiments in this thesis could not be compared to something they were already using. So without a realistic reference point, it is not easy to make a relatively accurate comparison. A comparison is made against two exact solutions that are based on static predefined data. No real-life uncertainties are taken into account. It would have been interesting to compare results to an already existing optimization model.

Secondly, the model does not take real-world changes regarding traffic or the availability of charging stations into account. Routes are dynamic in the real world and real-time data provides a more accurate representation of the real world. The experiments are conducted in a controlled, hypothetical environment, which does not fully capture the real-time complexities of calculating a route for example, in the real world there usually are more possible routes to go from A to B.

Thirdly, the model assumes consistent energy consumption and charging rates. However real-world factors such as traffic, weather, road conditions, and driving behavior have a significant effect on the energy consumption of an electric vehicle. In the model the energy consumption is linear, but these factors make the consumption non-linear. Also, recharging a battery is faster when it is almost empty compared to when it's almost full. This can have an impact on what strategy would be preferable. It could be more time-efficient to not fully charge and visit charging stations more often.

Lastly, in the model, there are ten charging station options at each location from where charging may be considered. In real-world situations, this number is way larger if all charging stations are considered. Even if all the charging stations in the range of the battery level are considered, this number could be more or less than ten. The charging stations in the model all have a different charging rate and are, most of the time, all reachable for the EV. The model chooses the two fastest chargers in the experiments, but these might not be close or possibly occupied.

6.3 Recommendations

This section discusses recommendations drawn from conducting the research. The goal is to identify possible actions YesHugo can undertake to improve its services.

The gap between norm and reality explained in the first chapter has not been filled entirely. The norm is that YesHugo wants to include a service that offers a tested near-optimal charging strategy. Currently, they are not doing this.

To bridge this gap, YesHugo should implement the charging station selection strategy into a dynamic optimization model that uses real-time data. This thesis highlights that such a strategy can significantly reduce computation time, while still finding a near-optimal solution. By integrating real-time data such as traffic circumstances, energy prices, charging rates, and the availability of charging stations, YesHugo can enhance the accuracy and efficiency of its charging policies.

Furthermore, it is recommended that YesHugo evaluate different threshold percentages for charging. While the study suggests that a threshold percentage strategy can be more time-efficient, it is not yet clear which specific threshold works best for most routes. Different routes may have varying locations and distances between them. Conducting simulations with various thresholds and route types can help identify the most efficient charging strategy for specific scenarios.

However, it is important to understand that not all real-world variables have been included in this thesis. The current model does not account for factors such as hourly charging rates, the availability of charging stations, and the runtime required to process real-time data. Including these variables will make the model more robust and applicable to practical situations, thereby improving its reliability and effectiveness.

By following these recommendations, YesHugo can significantly enhance its services, providing reliable and efficient charging strategies that fit the requests of its clients.

6.4 Further Research

This thesis takes a look at how certain threshold percentages would perform against the exact solution and an exact solution considering a full charge policy. However, the thesis did not tackle all possible components that may affect the charging station selection within an EV route.

Firstly, the distance between location visits has a significant effect on the moment of charging in the third experiment. When distances in between locations are longer, the battery level can pass multiple threshold percentages by the time the EV arrives at the next location. This means the EV must find a charging station to charge. Results show that similar routes were created. Further research could consider adjusting the distances between locations to see how well the same thresholds perform.

Secondly, the current model could be extended to more accurately simulate real-world decisions by incorporating additional variables such as exponential charging rates, hourly pricing of energy, and the availability of separate charging stations. These factors can have a big influence on the charging decisions that are made throughout the route. To implement this, the model should use real-time data and shift from a static model to a dynamic model. This data can be extracted from Google's "Places" application programming interface (API).

Thirdly, conducting a sensitivity analysis on specific components can be useful because it helps to understand how important parameters affect the overall performance of the optimization model. Further analysis could consider exploring the effect of fluctuations in energy prices and charging rates on the selection of charging stations in the model. For example, it may be more cost-efficient to drive a longer distance to a different charging station if the energy prices are higher at a nearby station.

Similarly, examining how modifications in the hourly rate of the chauffeur affect the charging decisions made throughout the route would be interesting. This would only work in the first experiment, where the amount that the EV must charge is not forced to 100%. However, if availability of charging stations is taken into account and therefore possible waiting times. This would also work for experiments 2 and 3 where the vehicle must charge to 100% each time. It would be interesting to analyze how the hourly rate of the chauffeur affects the selection of charging stations.

Finally, future research could specifically focus on the remaining battery percentage at the end of a route, imposing penalties for finishing with excess energy. This strategy contrasts with the 100% charge policy and could offer new insights into optimizing charging strategies. Developing an optimization model that penalizes higher remaining battery levels would encourage minimal charging, which is found to be the largest cost component in this thesis. This approach may provide a different interpretation of EV charging optimization, possibly leading to more cost-effective strategies.

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