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Faculty of Electrical Engineering
Department of Cybernetics

Bachelor's Thesis

Optimal Charging Station Siting and Sizing For Corporate Electric Vehicle Fleets

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BACHELOR‘S THESIS ASSIGNMENT

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Optimal Charging Station Siting and Sizing for Corporate Electric Vehicle Fleets

Bachelor’s thesis title in Czech:

Optimální rozmístění nabíjecích bodů pro firemní flotily

Guidelines:

The electric vehicles are becoming part of large company fleets. The companies are investing in installing charging stations in their facilities.
The historical fleet operation data can be analyzed to make more informed decisions about the sizing of the charging stations. Recently, simplified optimization problem was formulated to solve the sizing of stations with apriori given demand assigned to stations [1].
1. Research the related problems to multiple charging stations sizing and describe the limits of the current solutions.
2. Formulate the charging stations sizing with a consideration of possible transfers between stations.
3. Discuss the consequences of the more general model to the algorithms to solve the problem.
4. Propose and evaluate the usage of the available fleet operation data to optimize the investment into the charging infrastructure.

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III. Assignment receipt

The student acknowledges that the bachelor's thesis is an individual work. The student must produce his thesis without the assistance of others, with the exception of provided consultations. Within the bachelor's thesis, the author must state the names of consultants and include a list of references.

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Declaration

I declare that the presented work was developed independently and that I have listed all sources of information used within it in accordance with the methodical instructions for observing the ethical principles in the preparation of university theses.

Prague, 21st May 2021

Abstrakt / Abstract

V posledních letech se elektrická vozidla stala významnou alternativou k tradičním dopravním prostředkům využívajícím spalovací motor. Navzdory tomu, osvojení elektromobility širokou veřejností stále čelí výzvám, spjatým s omezenou dojezdovou vzdáleností a relativně pomalým nabíjením. Ve snaze usnadnit přechod firemních flotil na elektrická vozidla, formulujeme problém optimálního rozmístění a škálování nabíjecí infrastruktury jako celočíselný lineární program s deterministickým modelem nabíjecí poptávky, vytvořeným z historických dat o pohybu daných flotil. Omezený finanční rozpočet a změny nabíjecí poptávky v čase, např. vlivem dopravních špiček, jsou v předkládaném modelu taktéž zohledněny. Praktické a výpočetní vlivy zjednodušení některých omezení, která jsou v modelu vyjádřena, jsou zkoumány a různé varianty řešení jsou navrženy pro případy, kdy zachování kompletní formulace problému, včetně složitých omezení, je nezbytné. Efektivitu různých přístupů srovnáváme na praktickém příkladu firemní flotily. Stavění menšího počtu nabíjecích lokací s větším množstvím nabíječek na každou lokaci, kdy je brán ohled na pevně danou maximální přijatelnou vzdálenost mezi poptávkou a stanicemi, se ukazuje být nadmíru výhodné vzhledem k maximálnímu uspokojení poptávky, zvláště pro omezené finanční rozpočty, a zároveň dostatečně robustní vůči předem neznámým změnám poptávky.

Klíčová slova: nabíjecí stanice, nabíjecí infrastruktura, elektrická vozidla, elektromobilita, problém s umístěním zařízení, celočíselné lineární programování

Překlad titulu: Optimální rozmístění nabíjecích bodů pro firemní flotily

In recent years, electric vehicles became an ever-increasingly prominent alternative to more traditional, combustion-engine based means of transportation. However, the adoption of electric vehicles is still faced with challenges, especially due to limited driving range and slow charging times. To help facilitate electrification of business vehicle fleets, the problem of finding optimal charging infrastructure sizing and siting is formulated as an integer linear program with deterministic charging demand based on historical combustion-engine vehicle fleet driving data. Limited financial budget, as well as the effect of dynamic changes to charging demand caused by peak hours, is reflected in the model. Practical and computational implications of relaxation of different constraints are discussed, and alternative solution approaches are proposed for instances of problems where the preservation of the complex constraints is mandatory. The effectiveness of the proposed solutions is evaluated on the basis of a case study. For limited financial budgets, building less charging stations and supplying each station with more chargers, with respect to an upper limit on acceptable distance to station, stands out in terms of charging demand satisfaction, as well as robustness to unseen charging demand data.

Keywords: charging station, charging infrastructure, electric vehicle, electromobility, facility location problem, integer linear programming

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Chapter 1
Introduction

In recent years, ever-growing worldwide interest in lowering negative environmental impact caused by human activity, such as greenhouse gas emissions and excessive air pollution, among other things, is evident. For example, the objective of the European Union is to reduce greenhouse gas emissions by 80 to 95 % by 2050 compared to the level in 1990; the reduction in transport sector being 54 to 67 % [1]. The transport sector specifically currently represents about a quarter of Europe's greenhouse gas emissions and is the main cause of air pollution in European cities [2].

With this in mind, battery electric vehicles (further referred to as EVs) are a promising alternative to regular combustion-engine vehicles in terms of reducing dependency on fossil fuels and lowering carbon dioxide emissions. However, the level of adoption of EVs is still very low, range anxiety being one of the reasons, caused by perceived limited driving range due to various reasons such as limited battery capacity and long charging times [3].

Charging station (further referred to as CS) infrastructure, among other things, is a key area with potential for improvement in order to allow for positive perception and subsequent adoption of EVs by the general public. For private companies, this means not only satisfactory infrastructure in cities, along highway corridors, et cetera, but also the ability to provide convenient charging solutions to their employees within the company's own premises. This has to be cost-effective, but without compromise on accessibility and convenience of use.

With the introduction of EVs to a corporate vehicle fleet, the following properties of the new charging station infrastructure are to be optimized:

1. CS building & maintenance expenses
2. Driver satisfaction
3. Charging demand coverage

Given the first point, when electrifying a corporate vehicle fleet, we are most likely limited to CS building within corporate premises, however large they may be. Therefore, a downside might be that driving schedules containing trips with sections that are longer than EV driving range and entirely outside of corporate premises cannot be accounted for, although this is not necessarily a breaking point given existing outer infrastructure. On the upside, greater level of focus can be applied to the unique needs and behavior of the particular vehicle fleet in question. For example, corporate scenarios are likely to exhibit a great degree of periodically repeating, routine driving patterns. Thus, a unique approach, more directed towards the individual needs of the fleet, can be taken, as opposed to working with large-scale public places.

To further elaborate on driver satisfaction, it is preferable that EV drivers are not required to change their driving habits due to the new necessity to charge periodically. In other words, they should neither be required to park further away from their destinations than they used to, nor charge at other times or for longer than what their original driving schedules would have comfortably allowed. Furthermore, drivers might be unable or unwilling to charge their corporate EVs at home, for example due to related personal expenses, which also contributes to the charging demand in the workplace.

For these reasons, we study an optimization model for siting (finding optimal locations) and sizing (finding optimal capacities — the number of chargers at each location) of CSs based on existing (combustion-engine based) vehicle fleet driving data. The aim is to be able to optimize the three aforementioned properties of the new infrastructure, in order to allow for faster and easier EV adoption by private companies. Less than ideal conditions, such as limited financial budget, are also considered — the optimization potential is studied for all budgets.

1.1 Informal Problem Statement

We represent a feasible solution to both CS siting and sizing via a distribution of chargers among all potential CS locations — the numbers of chargers assigned to each location, such that the total number of built chargers fits within allowed budget. All potential CS locations that are assigned zero chargers by a charger distribution are assumed to be unused (the corresponding stations are not built; therefore without financial expense). Hence, not only sizing, but also the subset of locations at which a station is built is represented in the charger distribution.

Charging demand is represented deterministically as a set of individual charging requests, where each request is a vehicle demanding transfer of some amount of energy at a given location and given time. The closer a charging station is to the location of the vehicle, the more we assume the vehicle to be willing to drive to the station and attempt obtaining a charger there. In addition, drivers are assumed to be unwilling to charge at stations that are too distant. Given the fact that EV charging is often a long process, upon arrival at a fully occupied station, drivers are assumed to be more willing to relocate to a different charging station, instead of waiting for a charger; however, vehicles arriving at fully occupied stations should be an uncommon occurrence in the first place.

For a given charger distribution, the decisions of the individual instances of charging demand can be evaluated (taking the aforementioned assumptions on driver behavior into consideration), determining how many chargers are occupied at any given station in any given point in time, as well as which vehicles were able or unable to obtain a charger, given the station capacities. Based on this, a satisfaction metric, such as the amount of satisfied charging requests or the total amount of transferred energy, is evaluated. The aim is to obtain a charger distribution that maximizes the metric.

1.2 Thesis Structure

In Chapter 2, existing literature is reviewed and comparisons to this work are drawn. Chapter 3 contains the general problem formulation. In Chapter 4, various solutions to the problem formulation are proposed. The effectiveness of the proposed solutions is evaluated in a case study in Chapter 5. Chapter 6 is the conclusion.

Chapter 2
Literature Review

The first publication on the topic of EV charging infrastructure appeared as early as 1986 [4]; however, the topic gained major traction in 2012, as recognized by a 2019 review, which found 163 total publications with a modeling approach for CS siting and/or sizing [5].

For the purposes of this thesis, related existing publications were mainly compared based on chosen optimization criteria and constraints. Most works either establish financial cost as one of its optimization criteria, or operate with financial cost in the form of a constraint. This is an important distinction because it often reflects whether a model requires fully satisfied demand or allows relaxing such requirement if useful.

2.1 Works Requiring Complete Charging Demand Fulfillment

Some optimization models minimize either CS building and operation costs or the cost of access to the CSs. This requires authors of such models to constrain in such a way that the resulting CS locations and sizing always fully satisfy given/expected demand [6–9]. However, relaxing such requirement could allow for better understanding of its significance, as the unfulfilled demand caused by additional financial savings may be marginal in some instances.

In [6], total cost is minimized and spatial coverage is maximized (by minimizing the average distance between every pair of charging stations adjacent on the same road). A fixed requirement is that the sum of the capacities of all CSs in the studied area must be greater than or equal to the total charging demand in the area, estimated based on average trip distance, average maximum EV driving distance for a single full charge, average EV battery capacity and the total number of EVs in the area.

The goal of [7] is to minimize CS construction costs and the cost of travelling (walking) from a CS to the destination for a given round-trip in a graph representation of a city region. The number of chargers in a given node is required to be no less than the *total* number of EVs expected to charge at the node for a given solution — the representation of vehicles charging at non-overlapping times is missing in the model.

In [8], the demand is represented statistically through a scalar value for each vertex in a road network graph. The CS construction and operation costs, as well as the cost of transferring the demand to the closest CS is minimized. However, as in the works mentioned above, the total charging demand is required to be accounted for by the infrastructure.

Similarly, the model in [9] minimizes both the construction costs of fast CSs and the travel distance between demand (which is assumed to occur at fixed nodes of a traffic network graph) and CSs. However, the paper introduces a unique second step to the model, where the number of chargers at each CS is minimized and queuing theory is used in order to specify an upper limit on queuing length. This means that the requirement to be able to fully satisfy expected demand has been relaxed through users' ability to wait, although the demand is still expected to be fully satisfiable within given waiting time. This approach is mostly useful for fast charging solutions due to the simple fact that waiting in line for a regular (slow) EV charger is infeasible in practice, given that the expected waiting time under such circumstances is simply too long.

2.2 Works Allowing Incomplete Charging Demand Satisfaction

Other models, similarly to ours, described below in Chapter 3, do allow for partial demand satisfaction through the use of a budget constraint. Most of them maximize the rate of satisfied charging demand in some way, often also having some form of an upper limit on distance between demand and closest CS [10–14].

Optimization with regard to the amount of successfully completed round-trips for a given budget constraint is done in [10–11]. Charging station sizing is not considered. Specifically, [11] builds the demand model from GPS data of regular combustion-engine vehicles, from which said round-trips are modeled, including dwell times between two consecutive trips. Trips' end locations are considered as stops. Varying EV charger speeds are taken into consideration. Every driver is assumed to have access to a charger at home.

In [12], a charging demand model is built from parking data. Demand transference through successive trips made between different parking locations is considered, as well as the effect of peak hours on the solution by splitting the day into time intervals. It is assumed that every EV charges the entire time it is parked, and also that the expected number of times an EV charges in one day is constant, which yields a simple equation for the probability that a vehicle charges at a certain location ($\frac{T_j^m}{\sum_j T_j^m}$, where T_j^m is time spent parking by an EV m at a given stop j). The model does not consider varying EV charger speeds.

Lack of available information on EV driver behavior is recognized in [14]. Therefore, a unique approach is proposed. Estimates of daily traffic volumes are considered by the authors to often be the best available information about traffic, and are therefore used to approximate the minimum spatial station density required in order for the demand to be satisfiable. In addition, graph based models are intentionally avoided in the paper due to the fact that they tend to over-simplify the problem by assuming specific rules that the charging demand conforms to. The paper is meant to propose a method which gives solutions despite uncertain input data. The output of the optimization model is optimal density guidelines rather than exact CS locations and sizing, leaving the final decision, which is expected to be subject to considerations that are hard to model, to the user. The total distance from charging demand to charging stations is minimized, subject to a budget constraint. However, the optimization is done along highway corridors, which indicates a difference in the class of problems studied by the model as opposed to this thesis, which studies charging demand in areas with a relatively higher density of points of interest.

2.3 Other Works

There is a variety of works which focuses on finding optimal CS locations and sizing with the aim to mitigate negative impact of CSs on electricity distribution systems

[15–16, 6, 17–19, 13]. This is because higher peak load caused by EVs increases power losses and voltage deviations, while also posing a potential risk of causing thermal limit violations of transformers and lines [15]. Optimal use of different types of chargers with varying charging speeds is studied in [15]. The consideration of the effect of CS locations on distribution systems is out of the scope of this thesis.

2.4 Review Summary

To conclude the review of existing literature, it appears that existing models are mostly directed towards the problem of CS siting, as opposed to sizing, possibly due to large-scale applications being in the centre of collective focus. In addition, the question of operating under a limited budget has received modest attention thus far, as a significant portion of existing literature overlooks solutions with partially satisfied demand, making applications with suboptimal budgets infeasible. The difference in utilization of CS infrastructure in different hours also appears to be represented only in a portion of existing literature on CS sizing. All aforementioned concerns are recognized by this thesis.

Chapter 3
Problem Formulation

We will now introduce a formalization of the problem statement from Section 1.1. The aim is to find a subset of charging stations to build from a set of potential charging station locations, as well as a distribution of the total amount of chargers (the total financial budget) among the stations, such that the rate of served charging demand is maximized.

Given (continuous) location space $\mathbb{L}$, timestamp space $\mathbb{T}$ and a set of all vehicles V, let $(v, l, t_a, z) \in V \times \mathbb{L} \times \mathbb{T} \times \mathbb{R}^+$ be a single instance of a vehicle v in need of charging at a given location l and arrival timestamp t_a, requesting the transfer of energy of quantity z (of an arbitrary unit). Let $E \subset V \times \mathbb{L} \times \mathbb{T} \times \mathbb{R}^+$ be a finite set of all such instances (within a studied time period), i.e. the *charging demand.*

Let $S \subset \mathbb{L}$ be a finite, discrete set of viable charging station locations. Let $M \subseteq E \times S$ be a set of viable assignments of instances of charging demand to charging stations. M is determined by the charging demand itself, where each vehicle at a certain location is only willing to be charged at some, not all, charging station locations (for example, a driver may only be willing to request charging at a location $s \in S \subset \mathbb{L}$ if it is no further from their location $l \in \mathbb{L}$ than a given distance limit).

Let $t_d\colon E \times S \to \mathbb{T}$ be a departure timestamp mapping, such that $t_d(e, s) \in \mathbb{T}$ is the departure timestamp of an instance of charging demand $e \in E$ if it is being charged at a station $s \in S$. The departure timestamp value is most likely determined by the arrival timestamp t_a of e, the requested energy z of e and the station s (the charging speed of chargers at s). If the charging speed (and consequently also the departure of a vehicle) is independent from the choice of a charging station, then the departure of each instance of charging demand can be specified in the charging demand set E directly, using the following definition: $E \subset V \times \mathbb{L} \times \mathbb{T}^2$, where for each instance of charging demand $(v, l, t_a, t_d) \in E$, t_d represents the departure time. In such case, the mapping, as well as the requested energy z, is not needed in our charging demand representation.

Let $B \in \mathbb{R}^+$ be the total financial budget. Let $f\colon S \times \mathbb{N}_0 \to \mathbb{R}_0^+$ be the cost function, where $f(s, n)$ is the financial cost of building n chargers at charging station location $s \in S$. It holds $f(s, n) = 0 \iff n = 0$ for any $s \in S$, meaning that with zero chargers, a charging station location is considered to be unused and free of any cost.

Let us define a *charger distribution* (i.e. a feasible solution) as a mapping $b\colon S \to \mathbb{N}_0^+$, which determines how many chargers should be built at each of the candidate charging station locations. A charger distribution b exactly determines the set $S_b \subseteq S$ of *built* charging stations: $S_b = \{s \mid s \in S,\ b(s) \geq 1\} = \{s \mid s \in S,\ f(s, b(s)) > 0\}$. A charging station is only built if its building cost is greater than 0, which is when there is at least one charger assigned to s by the charger distribution b.

Let $g_{E,M,b}\colon E \to S \cup \{\text{None}\}$ be a *charging demand assignment* function for a charger distribution b, where $g_{E,M,b}(e) = s \in S$ if and only if the instance of charging demand $e \in E$ is charged at station s, and $g_{E,M,b}(e) = \text{None}$ if and only if e is not served charging at any charging station, both assuming that CSs are built in accordance with the distribution $b\colon S \to \mathbb{N}_0$. Please note that the value of $g_{E,M,b}(e)$ for an instance of charging demand e is not only determined by b, but also by the whole set E, the set of viable demand to station assignments M, as well as additional charging demand behavior constraints/assumptions, which will be introduced in Section 3.1. For example, if a station $s \in S$ has all chargers occupied (this is determined by the arrival and departure timestamps of the charging demand at s) in the time of arrival t_a of $e \in E$, then $g_{E,M,b}(e) \neq s$.

The aim is to find an optimal charger distribution b^*, maximizing demand satisfaction, as outlined in Equation (3.1).

$$b^* = \underset{b\colon\ S \to \mathbb{N}_0}{\arg\max}\ X_{E,M}(b) \tag{3.1}$$

For given E, S and $M \subseteq E \times S$, we define a charger distribution objective function $X_{E,M}\colon\ (S \to \mathbb{N}_0) \to \mathbb{R}_0^+$, where $X_{E,M}(b)$ is the value of the objective function for a charger distribution b. $X_{E,M}$ is defined as shown in Equation (3.2), using an objective function x for a single instance of charging demand.

$$X_{E,M}(b) := \sum_{e \in E} x(e, g_{E,M,b}(e)) \tag{3.2}$$

Function x uses values of $g_{E,M,b}$ and the definition of x determines the optimization criterion. Equation (3.3) must hold for any definition of x.

$$x(e,s) \geq x(e, \text{None}) \quad \forall e \in E,\ s \in S \tag{3.3}$$

The total number of satisfied charging requests is maximized when the definition in Equation (3.4) is used for x.

$$x\left(e, g_{E,M,b}(e)\right) := \begin{cases} 1 & \text{if } g_{E,M,b}(e) \in S, \\ 0 & \text{if } g_{E,M,b}(e) = \text{None}. \end{cases} \tag{3.4}$$

Alternatively, x may be defined as the amount of transferred energy by the value of $g_{E,M,b}$ (either energy transfer by a station s, or no energy transfer). Given such definition, b^* would maximize the total collective transferred energy.

The optimization is done subject to a budget constraint, as well as other charging demand constraints.

$$\sum_{s \in S} f\left(s, b\left(s\right)\right) \leq B \tag{3.5}$$

Inequality (3.5) is the budget constraint. It establishes that the total financial building cost of the charger distribution b is less than or equal to the total financial budget B.

3.1 Charging Demand Constraints

The assumptions and/or constraints on charging demand determine M, the function $g_{E,M,b}$ and consequently also the values of the charger distribution objective function $X_{E,M}$. Therefore, used constraints affect whether the problem formulation matches the objective of finding optimal CS siting and sizing.

A *first come, first served* constraint, together with a *station preference* constraint, are sufficient for the assignment of charging demand to stations $g_{E,M,b}$ to be *deterministic* (please note that the complete charging demand E is known when using $g_{E,M,b}$). If either of the constraints is omitted, the assignment function $g_{E,M,b}$ becomes arbitrary. Both constraints are defined below.

In addition, a *no-retry* constraint will be defined in order to ensure proper focus on CS siting by disallowing potentially undesirable cases of charging demand transfer across modeled CS locations.

If any of the constraints is omitted, the optimal objective value is an upper bound on the objective function for problem formulations with all the constraints present.

3.1.1 First Come, First Served

The FCFS constraint establishes that an instance of charging demand is always accepted for charging by a station upon the arrival of a vehicle if at least one charger is unoccupied at the station at that moment — the vehicle immediately begins charging at an unoccupied charger and cannot be rejected by the station for any other reason (such as potential benefit of doing so). The opposite implication that if no unoccupied chargers exist at a CS, then the vehicle cannot charge at the CS, holds regardless of the FCFS constraint.

If the constraint is omitted, the *optimal* definition of (now non-deterministic) $g_{E,M,b}$ may be found among the possible definitions, with respect to the objective function. In such case, the decision whether a charging request is fulfilled is not only based on the immediate ability of a vehicle to obtain a charger, but also on *overall expediency with respect to future traffic*. In other words, the omission of FCFS models situations in which future traffic is *known* a priori and taken into consideration, such as via the use of a scheduler. The term 'scheduler' refers to any form of a dynamic system employed in real-time that introduces a registration step for vehicles prior to their charging in order to optimize their allocation to chargers and/or stations for most effective charging.

While the employment of such systems may provide a range of benefits, the intent of this thesis is not to require them. Therefore, the FCFS constraint is mostly used.

3.1.2 Station Subset Assignment and Station Preference

Charging demand should be constrained such that each instance can only be served charging at a subset of CS locations — not at all of them. Any such constraint is reflected in the set of allowed assignments M. In addition, the *preference* of charging station locations by each instance of charging demand must be known, in order to be able to determine which station a vehicle drives to if presented with a choice (such that multiple stations were built close to the vehicle). Without such preference being present, values of $g_{E,M,b}$ become non-deterministic.

In order to appropriately represent siting in the model, we will be using an upper limit on allowed distance between the original position of a vehicle and a station location. Preference of stations will be determined such that the closer a station is to the original location of a vehicle, the higher preference it receives from the vehicle. Let us refer to this as *vehicle-based station assignment*.

Alternatively, we may define each follow-up charging attempt to be located at the station that is closest to *the station location in the previous attempt*, as opposed to the original vehicle location. This determines the allowed assignments, as well as the station preference, provided that an upper limit on distance is set. If siting were pre-determined, this would represent a vehicle driving to the closest station location, and driving to the next closest station upon rejection by the original station. However, given the fact that neither siting, nor sizing is pre-determined, the practical use of this station assignment approach is low. Therefore, we will only be using it for comparison. Let us refer to this approach as *attempt-based* station assignment.

In addition, an upper limit on the size of the subset of allowed stations per each instance of charging demand may be defined. Such constraint simplifies the charging demand model.

3.1.3 No-Retry

Demand transfer among CS locations is represented in the model via different charging attempts of each instance of charging demand, which are ordered based on the preference of stations by the instance. There are two practical meanings applicable to follow-up charging attempts. CS siting is represented in the model via follow-up charging attempts caused by zero chargers at the previous location, meaning that if the previous station was not built, an instance of charging demand is transferred to another station. In addition, a follow-up charging attempt may occur due to all chargers being occupied at the previous station in the given moment — this either represents willingness of drivers to relocate and retry at different locations, or is an undesirable side effect of the model. "No-retry" refers to a constraint that disallows the latter type of charging attempts. This constraint cannot be represented in M due to the subset of built charging stations being unknown a priori.

3.2 Obtaining Charging Demand

EV charging demand data is needed in order to use the problem formulation as outlined. Having said that, real EV charging demand data cannot be expected to be available.

It has been mentioned that we model EV charging demand from existing driving behavior data of the original, combustion-engine based, vehicle fleet. However, complex approaches of doing so are out of the scope of this thesis. We have been using a relatively simple modeling approach thus far, explained later in Chapter 5.

Chapter 4
Methodology

Based on the charging demand constraints used (i.e. viable assignments of charging demand to stations, as well as the assumptions on EV driver behavior), the solution complexity of a problem differs, as well as the approach for finding a solution.

We will be working with a single type of charger — a single charging speed. Therefore, the departure timestamp is independent from the charging station and a simplified definition of charging demand E may be used: $E \subset V \times \mathbb{L} \times \mathbb{T}^2$, where $(v, l, t_a, t_d) \in E$ is a single instance of a vehicle v at location l requesting charging from its arrival timestamp t_a until its departure timestamp t_d.

In addition, we will be using a simplified financial cost function $f\colon\ S \times \mathbb{N}_0 \to \mathbb{R}_0^+$, such that $f(s, n) := n \quad \forall s \in S, n \in \mathbb{N}_0$. In plain English, we will represent financial budget as the number of installed chargers.

Prior to explaining different problem classes, a simple algorithm for the computation of the charging demand assignment function $g_{E,M,b}$ for a given charger distribution b is explained in Section 4.1 and our ability to split a problem into independent sub-problems is explored in Section 4.2. Then, different classes of problems are studied, as well as possible approaches for finding their solutions. Class of problems with hard-assignment of charging demand to stations is studied in Section 4.3. Soft-assignment class of problems is studied in Section 4.4. A two-stage approach, separating CS siting and sizing stages of the problem, is explained in Section 4.5.

4.1 Charging Demand Assignment Evaluation

If the FCFS constraint is used and a preference of charging stations for each instance of charging demand is known, the function $g_{E,M,b}$, assigning demand to CSs, is deterministic and can be computed for any given charger distribution b. This is needed in order to evaluate any charger distribution objective function $X_{E,M}$ as defined in Equation (3.2) on p. 7.

In other words, if charging station preference of each instance of charging demand is given and customers obtain charging simply based on their times of arrival (first-come, first-served principle applies), the behavior of the entire charging demand can be simulated deterministically for a given charger distribution with respect to the station capacities, and the final assignment to stations is obtained.

The time complexity of the computation of $g_{E,M,b}$ is linear in the size of charging demand. However, a slightly modified definition of charging demand is needed.

4.1.1 Expanded Charging Demand

Given charging demand E and a set $M \subseteq E \times S$ of viable assignments of CSs to charging demand instances, let $\hat{E} \subset E \times S \times \mathbb{T} \times \{-1, 1\}$ be *expanded charging demand*, where $\hat{e} = ((v, l, t_a, t_d), s, t, \alpha) \in \hat{E}$ is one *event*, where $e = (v, l, t_a, t_d) \in E$ is an instance of charging demand and $(e, s) \in M$.

If $\alpha = 1$, then $\hat{e}$ is an *arrival event* of e, where $t = t_a$. If $\alpha = -1$, then $\hat{e}$ is a *departure event* of e, where $t = t_d$. The value of α will later be referred to as *status*.

Please note that an instance of charging demand $e \in E$ has $|M_e| = |\{s \mid (e, s) \in M\}|$ arrival events and $|M_e|$ departure events. Therefore, a single element $e \in E$ has $2\,|M_e|$ corresponding elements in $\hat{E}$.

4.1.2 Ordering of Expanded Charging Demand

Assuming that there exists a preference of stations for each $e \in E$, then $\hat{E}$ can be *ordered* lexicographically. The first ordering key is the timestamp t (either arrival or departure timestamp, depending on the event status — the value of $\alpha \in \{-1, 1\}$). The second ordering key (used when there are values in $\hat{E}$ that are incomparable using the first key) is the status, where departures are ordered before arrivals for events occurring at the same timestamp. The third ordering key (used when there are values in $\hat{E}$ that are incomparable using the first two keys) is the station preference.

The third ordering key is important because for a single instance of charging demand $e \in E$, there may be an element (e, s, t, α) present multiple times in $\hat{E}$ for the same values of t and α, only the values $s \in S$ being different. In such cases, the events must be ordered by the station preference.

4.1.3 The Evaluation Algorithm

Given *ordered* expanded charging demand $\hat{E}$ and a charger distribution b, we iterate over ordered $\hat{E}$ to compute the numbers of occupied chargers at each CS at each timestamp t. Based on these numbers, constrained by the charger distribution b, we determine if and where each instance of charging demand is served. In other words, we simulate the driver behavior. This gives us the values of $g_{E,M,b}$, as well as values of any objective function based on $g_{E,M,b}$.

Algorithm 4.1 shows the pseudocode used to compute $g_{E,M,b}$. The algorithm works as follows: If an encountered event $\hat{e}$ is an arrival event, the corresponding $e \in E$ has no charging station assigned yet (i.e. the charging request is yet to be satisfied somewhere) and there is currently at least one unoccupied charger at station s where the event $\hat{e}$ is located, then $g_{E,M,b}(e) := s$ and the number of occupied chargers at s is incremented. If a departure event $\hat{e}$ is encountered at station s and the corresponding arrival event (located at the same station) was previously satisfied ($g_{E,M,b}(e) = s$), then the number of occupied chargers at s is decremented (the vehicle departs the station). After the event $\hat{e}$ is processed, the algorithm proceeds onto the next event in ordered $\hat{E}$.

Please note that constraints such as an attempt constraint or a distance constraint are already reflected in M and consequently also in $\hat{E}$. Therefore, the algorithm does not have to explicitly account for them.

4.2 Separability into Independent Sub-Problems

Before any solution algorithms and approaches are discussed, in order to allow for potential computational time reductions, it is useful to investigate the ability to partition a problem, as previously formulated, into independently solvable sub-problems. This can be done by partitioning the set of potential station locations S such that the subsets are pairwise independent with respect to viable assignments of charging demand to stations M. Independent subsets of station locations can be found via a station dependency graph, as defined below.

input: $\hat{E},\ M,\ S,\ b$

output: $g_{E,M,b}(e) \quad \forall e \in E$

init $c_s := 0 \quad \forall s \in S$
init $g_{E,M,b}(e) :=$ None $\quad \forall e \in E$
for all $\hat{e} = ((v, l, t_a, t_d) = e, s, t, \alpha)$ in *ordered* $\hat{E}$ do
  if $\alpha = 1 \wedge g_{E,M,b}(e) =$ None $\wedge\, c_s < b(s)$, then
    $g_{E,M,b}(e) := s$
    $c_s := c_s + 1$
  else if $\alpha = -1 \wedge g_{E,M,b}(e) = s$, then
    $c_s := c_s - 1$
  end if
end for

Algorithm 4.1. Evaluation of assignment of charging demand to stations

4.2.1 Definition of Independent Sub-Problems

Given E, S, $M \subseteq E \times S$, let us define (E, S, M) as a *problem.* For a given problem, we define a *station dependency graph* as follows: The set of nodes is the set S of potential station locations. The set of edges is the following: $\{(s_1, s_2) \mid s_1, s_2 \in S,\ \exists e \in E\colon\ (e, s_1), (e, s_2) \in M\}$

Two station locations are *directly dependent* if there exists at least one instance of charging demand that can be satisfied at either of the locations, as represented in M (i.e. there exists an edge between them in the graph). Two station locations are *dependent* if there exists a path in the dependency graph that connects them. Otherwise, station locations are *independent.*

We say that two disjoint subsets of stations S_1 and S_2 are dependent if there exist $s_1 \in S_1$, $s_2 \in S_2$ that are dependent. Otherwise, S_1 and S_2 are independent. Please note that two sets of station locations must be disjoint in order for them to be independent. However, disjointness of two station sets is not by itself sufficient for independence.

Based on these definitions, every two connected components of the dependency graph are independent.

To proceed, E and M must be partitioned as well. Let $S^* = \{S_1, S_2, \ldots, S_k\}$, $S_i \subseteq S\ \forall i \in \{1, \ldots, k\}$ be a partition of S, such that each subset $S_i \in S^*$ is a connected component of stations in the station dependency graph. For a component S_i, we define corresponding $E_i \subseteq E$ and $M_i \subseteq M$ as follows:

$$\begin{aligned} E_i &= \{e \quad &\mid \forall (e, s) \in M,\ s \in S_i\} \\ M_i &= \{(e, s) \quad &\mid \forall (e, s) \in M,\ s \in S_i\} \end{aligned} \tag{4.1}$$

It can be easily shown that $E^* = \{E_1, \ldots, E_k\}$ is a correctly constructed partition of E (i.e. it is pairwise disjoint): If there were such $e \in E$ that $e \in E_i \wedge e \in E_j$ for some $i \neq j$, then, by definition of E_i and E_j, there exist $s_1 \in S_i$ and $s_2 \in S_j$ such that $(e, s_1), (e, s_2) \in M$. However, this is in conflict with the definition of S^*, based on which $s_1 \in S_i$ and $s_2 \in S_j$ are independent. Therefore, E^* is pairwise disjoint. Analogically, $M^* = \{M_1, \ldots, M_k\}$ is also a partition of M.

Any $(E_i, S_i, M_i) \in E^* \times S^* \times M^*$ as defined above, where S_i is a connected component of the station dependency graph, is an *irreducible sub-problem*.

Let us define a *sub-problem* as the following:

- An irreducible sub-problem is a sub-problem.
- Given two sub-problems $P_1 = (E_1, S_1, M_1)$ and $P_2 = (E_2, S_2, M_2)$, $P_{1,2} = (E_1 \cup E_2, S_1 \cup S_2, M_1 \cup M_2)$ is also a sub-problem.

Given two sub-problems $P_1 = (E_1, S_1, M_1)$, $P_2 = (E_2, S_2, M_2) \in E^* \times S^* \times M^*$, if it holds that S_1 and S_2 are independent with respect to (E, S, M), we say that the sub-problems P_1 and P_2 are *independent*.

Any two non-equal irreducible sub-problems are independent by definition.

Next, we will show that optimal solutions to multiple independent sub-problems can be found independently and merged back together to obtain the correct optimal solution to the original problem.

4.2.2 Objective Function of Combined Sub-Problems

Let us define a + operation on two budget distributions $b_1\colon S_1 \to \mathbb{N}_0$ and $b_2\colon S_2 \to \mathbb{N}_0$ as shown in Equation (4.2) below.

$$
\begin{aligned}
+\colon\ (S_1 \to \mathbb{N}_0) \times (S_2 \to \mathbb{N}_0) &\to ((S_1 \cup S_2) \to \mathbb{N}_0) \\
(b_1 + b_2)(s) &= \begin{cases} b_1(s) + b_2(s) & \text{if } s \in S_1 \text{ and } s \in S_2, \\ b_1(s) & \text{if } s \in S_1 \text{ and } s \notin S_2, \\ b_2(s) & \text{otherwise.} \end{cases}
\end{aligned}
\tag{4.2}
$$

Given a problem (E, S, M) and a charger distribution objective function $X_{E,M}$, as defined in Equation (3.2) on p. 7, let us assume that we have obtained two solutions $b_1\colon S_1 \to \mathbb{N}_0$ and $b_2\colon S_2 \to \mathbb{N}_0$ to the respective sub-problems $P_1 = (E_1, S_1, M_1), P_2 = (E_2, S_2, M_2) \in E^* \times S^* \times M^*$. Let $B_1 = \sum_{s \in S_1} b_1(s)$ and $B_2 = \sum_{s \in S_2} b_2(s)$. Charger distribution $b_{1,2} = b_1 + b_2$ is a feasible[1] solution to the sub-problem $P_{1,2} = (E_1 \cup E_2, S_1 \cup S_2, M_1 \cup M_2)$ for maximum allowed budget $B_1 + B_2$. If the sub-problems are independent, Equation (4.3) holds.

$$
X_{E,M}(b_1 + b_2) = X_{E,M}(b_1) + X_{E,M}(b_2) \tag{4.3}
$$

In order to better understand the intuition behind why Eq. (4.3) holds for independent sub-problems, let us show the following toy example with exactly two station locations s_1 and s_2:

For brevity, let us represent a charger distribution b as a vector of two values: $b = [b(s_1),\ b(s_2)]$. Let us consider three different charger distributions for some non-zero values $u, v \in \mathbb{N}$:

$$
\begin{aligned}
b_1 &= [u, 0] \\
b_2 &= [0, v] \\
b_1 + b_2 = b_{1,2} &= [u, v]
\end{aligned}
$$

If s_1 and s_2 are independent with respect to some E and M, Equation (4.3) holds. Otherwise, only Equation (4.4) holds.

[1] Please note that $b_1 + b_2$ is not necessarily *optimal* for maximum allowed budget $B_1 + B_2$ even if b_1 and b_2 are optimal for their respective maximum allowed budgets B_1 and B_2. More on this in Section 4.2.3.

$$X_{E,M}(b_1 + b_2) \leq X_{E,M}(b_1) + X_{E,M}(b_2) \tag{4.4}$$

The reason for this is the following: If s_1 and s_2 are directly dependent, then there exists non-empty $E_{s_1,s_2} \subseteq E$ such that $\forall e \in E_{s_1,s_2}$: $(e, s_1), (e, s_2) \in M$. All $e \in E_{s_1,s_2}$ that prefer charging at s_1 over s_2 will charge at s_1 (unless full) under distributions b_1 and $b_1 + b_2$, but will charge at s_2 (unless full) under distribution b_2. Hence, Eq. (4.3) *cannot hold* because that would require any $e \in E_{s_1,s_2}$ to be charged at *both* stations s_1 and s_2 at the same time under distribution $b_1 + b_2$. This is, however, impossible because an instance of charging demand can only be satisfied at one station at most. Therefore, for sub-problems that are not independent, only inequality (4.4) holds; a *strict* inequality in this particular example.

If s_1 and s_2 are independent, Equation (4.3) *does* hold because the number of chargers at station s_1 does not affect the charging demand (and values of $g_{E,M,b}$) at s_2, and vice versa.

This example can be generalized to two independent subsets of stations S_1 and S_2 (instead of two individual stations) and the same principles would apply.

4.2.3 Optimal Solution to Combined Problem For Two Sub-Problems

In practice, each i-th sub-problem has different optimal solutions (charger distributions) given different budget constraints, based on the maximum allowed total budget (number of chargers) $B \in \{1, 2, \ldots, B_i, \ldots\}$. We must be able to obtain all such solutions to the combined problem as well, while also preserving optimality.

Let B_i be the minimum allowed total budget for which the entire charging demand $E_i \subseteq E$ can be satisfied (100 % demand satisfaction is achieved for E_i), as shown in Equation (4.5). If 100 % demand satisfaction is achieved for E_i given some distribution b, $X_{E_i,M_i}(b)$ is the maximum possible value of X_{E_i,M_i} for E_i.

$$g_{E,M,b^{(i)}_{B_i}}(e) \neq \text{None} \quad \forall e \in E_i \tag{4.5}$$

Given two sub-problems $P_1 = (E_1, S_1, M_1)$ and $P_2 = (E_2, S_2, M_2)$ of a problem $P = (E, S, M)$, let $O_1 = \{b^{(1)}_1, \ldots, b^{(1)}_{B_1}\}$ and $O_2 = \{b^{(2)}_1, \ldots, b^{(2)}_{B_2}\}$ be two sets of optimal charger distributions for P_1 and P_2 respectively, such that:

- $b^{(1)}_{B_1}$ and $B^{(2)}_{B_2}$ provide 100 % demand satisfaction to their respective charging demands $E_1, E_2 \subset E$,
- for each $B \in \{1, 2, \ldots\}$, the distributions $b^{(1)}_B \in O_1$ and $b^{(2)}_B \in O_2$ are optimal wrt. X_{E_1,M_1} and X_{E_2,M_2} respectively, under the budget Constraint (4.6) for B.

$$\begin{aligned} \sum_{s \in S_1} b^{(1)}_B(s) \leq B \\ \sum_{s \in S_2} b^{(2)}_B(s) \leq B \end{aligned} \tag{4.6}$$

Each set O_i contains optimal solutions to its respective sub-problem for *any* possible maximum allowed total budget $B \in \{1, 2, \ldots\}$. Even though O_i is finite and the set of possible values of B is infinite, the aforementioned is true because $b^{(1)}_{B_1}$ and $b^{(2)}_{B_2}$ are optimal for any $B \geq B_1$ and $B \geq B_2$, respectively. The reason for this is that $b^{(1)}_{B_1}$ and

$b^{(2)}_{B_2}$ provide 100 % charging demand satisfaction, therefore the values $X_{E_1,M_1}(b^{(1)}_{B_1})$ and $X_{E_2,M_2}(b^{(2)}_{B_2})$ are the maximum values of X_{E_1,M_1} and X_{E_2,M_2}, respectively.

Assuming that sub-problems P_1 and P_2 are independent, Equation (4.3) holds and can be applied to maximum values as well, as shown in Equation (4.7).

$$
\begin{aligned}
&\max_{b_1:\ S_1\to\mathbb{N}_0} X(b_1) + \max_{b_2:\ S_2\to\mathbb{N}_0} X(b_2) = \\
&= X\left[\arg\max_{b_1:\ S_1\to\mathbb{N}_0} X(b_1) + \arg\max_{b_2:\ S_2\to\mathbb{N}_0} X(b_2)\right] = \max_{b:\ S_1\cup S_2\to\mathbb{N}_0} X(b)
\end{aligned}
\tag{4.7}
$$

Therefore, in order to obtain a single solution to the combined problem for maximum allowed total budget $B \in \{1,\dots,B_1+B_2\}$, the optimal solution is the following:

$$b^{(1,2)}_B = \arg\max_b X(b),$$

such that

$$b \in \left\{ \left(b^{(1)} + b^{(2)}\right) \,\middle|\, b^{(1)} \in O_1,\ b^{(2)} \in O_2,\ \sum_{s\in S_1\cup S_2} \left(b^{(1)} + b^{(2)}\right)(s) \le B \right\}.$$

By first obtaining the optimal solution to the optimization problem for $B = 1$ and gradually incrementing B, we can rewrite the set of candidate solutions to $b^{(1,2)}_B$ as follows:

$$
\begin{aligned}
b^{(1,2)}_B \in &\left\{ \left(b^{(1)} + b^{(2)}\right) \,\middle|\, b^{(1)} \in O_1,\ b^{(2)} \in O_2,\ \sum_{s\in S_1\cup S_2} \left(b^{(1)} + b^{(2)}\right)(s) = B \right\} \\
&\cup \left\{ b^{(1,2)}_{B-1},\ \text{if } B-1 \ge 1 \right\}
\end{aligned}
$$

Given that we have just 2 sub-problems, the solution to the combined problem can be obtained by exhaustive comparison of all alternatives, which there are no more than $B + 2$ of:

$$b^{(1,2)}_B \in \left\{ b^{(2)}_B,\ b^{(1)}_1 + b^{(2)}_{B-1},\ b^{(1)}_2 + b^{(2)}_{B-2},\ \dots,\ b^{(1)}_{B-1} + b^{(2)}_1,\ b^{(1)}_B \right\} \cup \left\{ b^{(1,2)}_{B-1},\ \text{if } B-1 \ge 1 \right\}$$

If $\min(B_1, B_2) < B \le (B_1 + B_2)$, then

$$
\begin{aligned}
b^{(1,2)}_B \in \Big\{ &b^{(1)}_{B-\min(B_2,B)} + b^{(2)}_{\min(B_2,B)},\ b^{(1)}_{B-\min(B_2,B)+1} + b^{(2)}_{\min(B_2,B)-1}, \\
&\dots,\ b^{(1)}_{\min(B_1,B)-1} + b^{(2)}_{B-\min(B_1,B)+1},\ b^{(1)}_{\min(B_1,B)} + b^{(2)}_{B-\min(B_1,B)} \Big\} \\
&\cup \left\{ b^{(1,2)}_{B-1},\ \text{if } B-1 \ge 1 \right\},
\end{aligned}
$$

where we define

$$b^{(1)}_0(s) := 0\ \forall s \in S_1, \quad b^{(2)}_0(s) := 0\ \forall s \in S_2.$$

Using the above approach, an optimal solution $b^{(1,2)}_B$ to the combined problem can be obtained for each $B \in \{1,\dots,B_1+B_2\}$. $b^{(1,2)}_{B_1+B_2}$ provides 100 % satisfaction to the combined charging demand $E = E_1 \cup E_2$ because Equations (4.3) and (4.7) hold. Therefore, the complete set of optimal charger distributions $O_{1,2} = \{b^{(1,2)}_1, \dots, b^{(1,2)}_{B_1+B_2}\}$ for the combined problem and all possible budget constraints is obtained.

4.2.4 Optimal Solution to Combined Problem For k Sub-Problems

Let $X_{E,M}$ be the charger distribution objective function. Given k sub-problems $P_1, \ldots, P_k$, let $O_1, \ldots, O_k$ be their respective sets of optimal charger distributions, each O_i containing optimal solutions for all possible upper limits on allowed total budget. In order to continue, sub-problems $P_1, \ldots, P_k$ must be pairwise independent.

First, using the process described in Sec. 4.2.3 we merge O_1 with O_2 and obtain $O_{1,2}$. The combined sub-problem $P_{1,2}$ is independent from P_3; therefore, we can merge $O_{1,2}$ with O_3 using the very same process and obtain $O_{1,2,3}$. We continue until we obtain $O_{1,\ldots,k}$. This is the complete solution to the combined problem.

The aforementioned approach is a principle used in *dynamic programming* (DP). For example, a well-known solution algorithm for *the 0-1 knapsack problem* is based on a similar concept [20].

4.2.5 Time Complexity

The time complexity of merging solutions of two sub-problems for a single value of B is linear, as long as the optimal solution for $B-1$ is already known. Then, at most $B+2$ values must be compared (as shown in Sec. 4.2.3); that is $B+1$ comparison operations. For $B=1$, only one comparison operation is needed.

Merging solutions of two sub-problems for all values $B \in \{1, \ldots, B_{\max}\}$ requires at most $1 + \sum_{B=2}^{B_{\max}} (B+1) = 1 + \frac{1}{2}(B_{\max}-1)(B_{\max}+4) = O(B_{\max}^2)$ operations.

The time complexity of merging k independent sub-problem solutions for all possible total budgets requires the aforementioned to be performed $k-1$ times. The worst-case time complexity in such case is therefore as shown in Equation (4.8), where $B_{\max} = \max\{B_1, \ldots, B_k\}$.

$$O(kB_{\max}^2) \tag{4.8}$$

4.3 Hard-Assignment Model

The simplest version of the model assumes one charging attempt per vehicle and simplifies the problem by hard-assigning each instance of charging demand $e \in E$ to the CS location that is closest to e.

Note that the hard-assignment model, as is, is significantly limited, especially in terms of siting, as it does not allow any charging demand transfer between different charging stations. Using this model, in order to achieve full charging demand satisfaction, a CS must be built at all locations $\{s \mid s \in S,\ \exists e \in E\colon\ (e,s) \in M\}$ or, in plain English, each CS that has at least one instance of charging demand assigned must be built. Therefore, siting is only pre-determined by the subset of potential charging station locations S.

The advantage of this model is that obtaining the optimal solution for any budget is a simple task.

4.3.1 Solution Algorithm

The hard-assignment condition means that there is no $e \in E,\ s_1, s_2 \in S$ such that $s_1 \neq s_2,\ (e, s_1), (e, s_2) \in M$. Therefore, *any two station locations are independent* and the set of edges of the station dependence graph is empty.

First, we discard all unused CS locations by only considering a subset of CS locations $S' \subseteq S,\ S' = \{s \mid s \in S,\ \exists e \in E\colon\ (e,s) \in M\}$. Next, we use a partition of S', where each subset is a single station: $S^* = \{\{s\} \mid s \in S'\}$. For each $S_i = \{s_i\} \in S^*$, a corresponding sub-problem to solve is (E_i, S_i, M_i), where E_i and M_i are defined as in Equation (4.1) on page 12.

Given that each sub-problem only contains *one* CS location, the task of finding the optimal solution $b_B^{(i)}$ (wrt. $X_{E,M}$) to a sub-problem $(E_i, \{s_i\}, M_i)$ for any possible maximum allowed total budget $B \in \{1, 2, \ldots\}$ is trivial: we either assign B chargers to the single station s_i, or less if the value of the objective function does not decrease by doing so. In addition, there exists a value $B_{\text{Full}}^{(i)}$ for which all instances of charging demand assigned to station s_i are satisfied; therefore, for any $B > B_{\text{Full}}^{(i)}$, assigning $B_{\text{Full}}^{(i)}$ chargers to the station is sufficient for optimality.

The optimal charger distribution for a sub-problem $(E_i, \{s_i\}, M_i)$ and maximum allowed total budget $B \in \{1, 2, \ldots\}$ can be written as follows:

$$b_B^{(i)}(s) = \begin{cases} 0 & \text{if } s \neq s_i \vee B = 0, \\ b_{B-1}^{(i)}(s_i) & \text{if } s = s_i \wedge B \geq 2 \wedge X_{E,M}\left(\beta_B^{(i)}\right) = X_{E,M}\left(b_{B-1}^{(i)}\right), \\ B & \text{if } s = s_i \wedge \left(B = 1 \vee X_{E,M}\left(\beta_B^{(i)}\right) > X_{E,M}\left(b_{B-1}^{(i)}\right)\right), \end{cases}$$

where

$$\beta_B^{(i)}(s) = \begin{cases} B & \text{if } s = s_i, \\ 0 & \text{otherwise.} \end{cases}$$

Due to the hard-assignment condition, the given sub-problems are pairwise independent; thus, the trivially obtained sub-problem solutions can be merged using the DP method described in Section 4.2.4 and the solution to the original problem (E, S, M) is obtained.

4.3.2 Time Complexity

$O(|\hat{E}_i|)$ is the time complexity of obtaining the values of $g_{\hat{E}_i, M_i, b}$ for a single sub-problem P_i and a charger distribution b.

When obtaining a solution for all possible total budgets to a single station s_i (a single sub-problem P_i), B_i evaluations of the function $g_{\hat{E}_i, M_i, b}$ must be performed (for B_i different charger distributions b), where B_i is the minimum budget needed for 100 % satisfaction of demand $\hat{E}_i$. The worst-case time complexity of this is therefore $O(B_i\,|\hat{E}_i|)$. When this is performed for all k charging stations, the worst-case time complexity is $O(kB_{\max}\,|\hat{E}_{\max}|)$, where $B_{\max} = \max\{B_1, \ldots, B_k\}$ and $|\hat{E}_{\max}| = \max_{i=1}^{k} |\hat{E}_i|$.

The worst-case time complexity of the optimization step of merging individual solutions, using the DP approach described in Sec. 4.2.4, is $O(kB_{\max}^2)$ for k sub-problems, where $B_{\max} = \max\{B_1, \ldots, B_k\}$. In the case of hard-assignment, k equals to the number of used charging station locations $|S'|$.

The combined worst-case time complexity is therefore as per Equation (4.9).

$$O(kB_{\max}\,|\hat{E}_{\max}| + kB_{\max}^2) = O(kB_{\max}^2\,|\hat{E}_{\max}|) \tag{4.9}$$

4.4 Soft-Assignment Model

In order to represent the task of CS siting in the model, as opposed to only modeling CS sizing, we assume more than one charging attempt per vehicle, meaning that there exist values $e \in E$ such that $|\{s \mid \forall s \in S,\ (e, s) \in M\}| \geq 2$. In such case, it is also sometimes possible to partition the problem into irreducible sub-problems. However, an irreducible sub-problem may contain more than one station location. In fact, some problems themselves may already be irreducible, with the station dependency graph being one large connected component. Therefore, while we may still be able to partition the original problem into independent irreducible sub-problems and merge their individual results, *the sub-problems themselves may have non-trivial solutions*. For this reason, we formulate each irreducible sub-problem as an integer linear program (ILP). We will first introduce an integer program (IP) and then replace non-linear constraints with their linear counterparts.

4.4.1 IP Formulation

V	Set of vehicles
S	Set of CS locations
$\hat{E}$	*Ordered* expanded charging demand
$i \in \{1, \dots, \lvert\hat{E}\rvert\}$	Indices of elements in ordered $\hat{E}$
$\hat{e}_i = (e_i = (v_i, l_i, \dots), s_i, t_i, \alpha_i) \in \hat{E}$	A single event in $\hat{E}$
$\hat{E}_A = \{\hat{e}_i \in \hat{E} \mid \alpha_i = 1\}$	Arrival events in $\hat{E}$
$\hat{E}_D = \{\hat{e}_i \in \hat{E} \mid \alpha_i = -1\}$	Departure events in $\hat{E}$
B	Total budget
$b_s \in \mathbb{N}_0 \quad \forall s \in S$	Amount of chargers assigned to station s (an integer variable)
$x_i \in \{0,1\} \quad \forall \hat{e}_i \in \hat{E}$	Whether event $\hat{e}_i$ is satisfied (a boolean variable)

Table 4.1. IP and ILP soft-assignment model parameters and variables

We will formulate parameters, variables, the objective function and all constraints. Constraint sets marked with an asterisk may be omitted, as explained below.

Table 4.1 shows all parameters and optimization variables used in the IP (and the ILP) soft-assignment problem formulation.

The objective function and constraints are as follows:

$$\underset{x_i\, \forall \hat{e}_i \in \hat{E},\; b_s\, \forall s \in S}{\arg\max} \sum\nolimits_{\hat{e}_i \in \hat{E}_A} x_i \tag{4.10}$$

$$\sum_{s \in S} b_s \le B \quad \forall s \in S \tag{4.11}$$

$$x_i = x_j \quad \begin{array}{l} \forall \hat{e}_i = (e, s, t_i, \alpha_i) \in \hat{E}, \\ \hat{e}_j = (e, s, t_j, \alpha_j) \in \hat{E} \end{array} \tag{4.12}$$

$$\sum_{\hat{e}_j \in R} x_j \le 1 \quad \begin{array}{l} \forall e \in E, \\ R = \{\hat{e}_j = (e_j, \dots) \\ \quad \in \hat{E}_A \mid e_j = e\} \end{array} \tag{4.13}$$

$$\sum_{j=1}^{i-1} x_j \alpha_j [\![s_j = s_i]\!] < b_{s_i} \Rightarrow \sum_{\substack{\hat{e}_j \in R, \\ j \le i}} x_j = 1 \quad \begin{array}{l} \forall \hat{e}_i = (e_i, s_i, t_i, 1) \in \hat{E}_A \\ R = \{\hat{e}_j = (e_j, \dots) \\ \quad \in \hat{E}_A \mid e_j = e\} \end{array} \tag*{*(4.14)}$$

$$\sum_{j=1}^{i-1} x_j \alpha_j [\![s_j = s_i]\!] < b_{s_i} \Leftarrow x_i = 1 \quad \forall \hat{e}_i = (e_i, s_i, t_i, 1) \in \hat{E}_A \tag{4.15}$$

$$b_{s_i} \geq 1 \Rightarrow x_j = 0 \quad \begin{array}{l} \forall \hat{e}_i = (e, s_i, \ldots) \in \hat{E}, \\ \hat{e}_j = (e, s_j \ldots) \in \hat{E}, \\ i < j \end{array} \tag*{*(4.16)}$$

$$x_i \in \{0, 1\} \quad \forall \hat{e}_i \in \hat{E} \tag{4.17}$$

$$b_s \geq 0 \quad \forall s \in S \tag{4.18}$$

The objective function (4.10) is the number of satisfied arrival events, which, given other constraints, is equal to the number of satisfied instances of charging demand. This objective function is equivalent to the use of function x as defined in the original problem formulation in Eq. (3.4) on p. 7.

Constraint (4.11) is the budget constraint.

Constraint set (4.12) establishes that all arrival/departure event pairs corresponding to the same instance of charging demand and the same station must be either both rejected or both satisfied. In other words, if and only if an arrival event is satisfied, its corresponding departure event at the same station s is also satisfied.

Constraint set (4.13) specifies that every instance of charging demand will not be satisfied more than once, allowing at most one arrival event to be satisfied per instance of charging demand.

The left hand side of constraint sets (4.14) and (4.15) is a cumulative sum of α values of the ordered expanded charging demand $\hat{E}$, where only events that are satisfied ($x_j = 1$), occur at the same station as and *earlier* than $\hat{e}_i$, are selected. In other words, the left hand side value is equal to the *number of occupied chargers* at station s_i just prior to the occurrence of the event $\hat{e}_i$. Here, let $[\![c]\!]$ be defined for a condition c as 1 if c is true, 0 otherwise. Optional constraint set (4.14) establishes the FCFS condition: if there are unoccupied chargers at station s_i upon the arrival event $\hat{e}_i$, the event must be satisfied there, unless the corresponding instance of charging demand was already satisfied at a different station in an earlier attempt. Constraint set (4.15) establishes that an arrival event at station s_i cannot be satisfied if all chargers at s_i are occupied. In other words, the number of *occupied* chargers at any location s_i cannot at any point in time i surpass the number of chargers that are *assigned* to s_i.

Optional constraint set (4.16) is the no-retry condition, dictating that follow-up charging attempts are only modeled in order to represent siting, but not to model drivers re-trying at different stations if the station of their previous attempt had all chargers occupied. In other words, the constraint ensures that all instances of charging demand attempt charging only *once*, but they do so at a station with at least one charger (i.e. a station that is actually *built*). The constraint works as follows: if a charging station s has at least one charger installed, all attempts (at any station) that follow attempts at station s (for the same instances of charging demand) are disallowed.

Constraint sets (4.17) and (4.18) are variable domains.

The result of the optimization of this IP is not only a charger distribution b, where $b(s) = b_s \ \forall s \in S$, but also $g_{E,M,b}$ from the values of x_i, where $g_{E,M,b}(e) = s$ if exists $\hat{e}_i = (e, s, \ldots)$ such that $x_i = 1$ (remember that for each $e \in E$, there cannot be more than one such value s), and $g_{E,M,b}(e) =$ None otherwise.

4.4.2 ILP Formulation

Non-linear constraints in sets (4.14), (4.15) and (4.16) (two of which are optional) must be replaced with linear counterparts.

For constraint sets (4.14) and (4.15), this involves adding new additional optimization variables $g_i \in \{0, 1\}\ \forall \hat{e}_i \in \hat{E}$. Constraint sets (4.19) and (4.20) are together the linear replacement for both aforementioned constraint sets.

$$g_i \le \gamma_i \le B g_i \qquad \begin{aligned} &\forall \hat{e}_i = (e_i, s_i, t_i, 1) \in \hat{E}_A \\ &\gamma_i = b_s - \sum_{j=1}^{i-1} x_j \alpha_j [\![s_j = s]\!] \end{aligned} \tag{4.19}$$

$$x_i \le g_i \le \sum_{\hat{e}_j \in R,\ j \le i} x_j \qquad \begin{aligned} &\forall \hat{e}_i = (e_i, s_i, t_i, 1) \in \hat{E}_A, \\ &R = \{\hat{e}_j \in \hat{E}_A \mid e_j = e_i\} \end{aligned} \tag{4.20}$$

Given that $g_i \in \{0, 1\}$, constraint set (4.19) specifies that $g_i = \text{sign}(\gamma_i)$. This means that $g_i = 1$ if there is *at least* one unoccupied charger at station s_i just before arrival event $\hat{e}_i$, $g_i = 0$ otherwise. The left inequality of constraint set (4.20) ensures that if $g_i = \gamma_i = 0$, meaning that there are no available chargers at s_i just before arrival event $\hat{e}_i$, then $\hat{e}_i$ must be rejected, but previous charging attempts of the same instance of charging demand are unrestricted. This is a linear replacement for constraint set (4.15). The right inequality establishes that if $g_i = 1$, meaning that there is at least one available charger at s_i, then either $\hat{e}_i$ or one of the previous attempts of the corresponding instance of charging demand must be satisfied ($\hat{e}_i$ by itself is unrestricted), which is a linear replacement for the FCFS constraint set (4.14).

If the FCFS constraint set (4.14) is unused, a simpler linear replacement exists for the (compulsory) constraint set (4.15). In such case, no additional variables g_i are needed. Constraint set (4.21) is the replacement.

$$\sum_{j=1}^{i} x_j \alpha_j [\![s_j = s_i]\!] \le b_{s_i} \quad \forall \hat{e}_i = (e_i, s_i, t_i, 1) \in \hat{E}_A \tag{4.21}$$

The linear replacement for the no-retry constraint set (4.16) (optional) requires new additional optimization variables $h_s \in \{0, 1\}\ \forall s \in S$. Constraint set (4.22) establishes that $h_s = \text{sign}(b_s)$ and constraint set (4.23) is the linear replacement.

$$h_s \le b_s \le B h_s \quad \forall s \in S \tag{4.22}$$

$$x_j \le 1 - h_{s_i} \qquad \begin{aligned} &\forall \hat{e}_i = (e, s_i, \dots) \in \hat{E}, \\ &\hat{e}_j = (e, s_j \dots) \in \hat{E}, \\ &i < j \end{aligned} \tag{4.23}$$

4.4.3 Time Complexity

Let us consider a relaxation of the soft-assignment model, where all arrival times of all instances of charging demand are assumed equal to the start of the entire measured period, and all departure times are assumed equal to the end of the entire measured period. For such relaxation to be meaningful, we must either:

- consider only a subset of the original charging demand that concerns only a sufficiently short time period,
- or discard the sizing aspect of the model entirely and only focus on siting.

In the latter case, if we discard the sizing aspect of the model by defining each budget variable b_s as a binary variable, merely representing whether a station is built, but not constraining its capacity, we obtain a problem definition equivalent to the *uncapacitated facility location problem* (UFLP), also known as the *simple plant location problem* (SPLP), which is NP-hard [21–22]. In the case where sizing is also considered, the problem definition is similar to the *capacitated facility location problem* (CFLP), which is a version of UFLP with additional constraints [23]; however, CFLP defines location capacities as *constants*, whereas our soft-assignment model defines their *sum* to be constant.

As elaborated on later in Chapter 5, the soft-assignment ILP with FCFS is *very difficult to solve* even for the state-of-the-art commercial solver Gurobi, unless the charging demand set is very small. Convergence is *significantly* faster when the FCFS condition is relaxed; although, at times, such ILPs may still be computationally difficult to solve. To the best of authors' knowledge, no efficient algorithms have been developed for solving the soft-assignment IP model with FCFS optimally. A possible approach may be via a tailored branch-and-bound algorithm utilizing the FCFS condition to its advantage by proceeding chronologically (as opposed to universal ILP branch-and-bound algorithms used in state-of-the-art solvers); however, this is mere speculation.

4.5 Two-Stage Approach

A combined approach may be used, where the siting and sizing stages of the problem are resolved independently: the first stage is the siting stage, where the smallest subset of CS locations that can satisfy the entire demand is found. In the second stage, a hard-assignment problem is solved, where each instance of charging demand is hard-assigned to the closest station in the subset of stations from the first stage.

Of course, this approach does not provide an optimal solution to the soft-assignment problem as formulated in Section 4.4; however, it does provide a good compromise between computational complexity and versatility of the problem formulation.

4.5.1 Minimal Complete Charging Station Subset Using ILP

The first stage of the approach is finding the smallest subset of charging station locations to build, such that all instances of charging demand can still be satisfied by it, given enough chargers. In this stage, charging station sizing and budget is not considered.

We will be using the ILP formulation from Section 4.4.1 as a baseline, and we will modify the formulation for the purposes of this stage accordingly.

All parameters and optimization variables as previously defined in Table 4.1 will be used, with the exception of variables b_s, which will be *redefined as boolean* variables denoting whether a CS location s is contained in the minimum subset of CS locations.

A different objective function must be used: a subset of charging stations will be found such that the total number of stations is minimized and the whole charging demand is satisfiable (with respect to a distance constraint, as represented in M). Equation (4.24) specifies the objective function.

$$\underset{b_s\ \forall s \in S}{\arg\min} \sum\nolimits_{s \in S} b_s \tag{4.24}$$

Multiple optimal solutions may exist for this optimization criterion when used alone. To combat this, a secondary objective function may be defined, such that the sum of euclidean distances between instances of charging demand and their assigned stations is minimized. For this, values $d_{e,s}$ $\forall(e,s) \in M$, representing euclidean distances between all possible pairs of charging demand instances and CS locations, must be available. If they are, the secondary criterion may be defined as shown in Equation (4.25).

$$\begin{gathered}\underset{x_i\,\forall \hat{e}_i \in \hat{E},\ b_s\,\forall s \in S}{\arg\min} \sum\nolimits_{\hat{e}_i \in \hat{E}} x_i d_{e_i,s_i}, \\ \text{where } \hat{e}_i = (e_i, s_i, \ldots)\end{gathered} \tag{4.25}$$

Constraint sets (4.12), (4.13) and (4.17) are the only constraint sets from the original soft-assignment ILP definition to be used. The variable domain of variables b_s is defined in constraint set (4.26).

$$b_s \in \{0, 1\} \quad \forall s \in S \tag{4.26}$$

The state-of-the-art commercial solver Gurobi is able to obtain the optimal solution to this ILP within seconds or minutes on a consumer-grade laptop, even for charging demands of large sizes.

4.5.2 Minimal Complete Charging Station Subset Iteratively

A satisfactory solution to the first stage may also be obtained using a greedy, iterative approach: we start with the complete set of CS locations S and iteratively remove a station such that the maximum distance between an instance of charging demand and the new CS closest to it is minimized.

Chapter 5
Case Study

To illustrate the use of the proposed models and to evaluate and compare the computational performance of the solution methods, as well as the quality of their results, we will apply the models to a case of a business vehicle fleet operating within premises of approx. 3,6 km^2.

Floating car data (FCD) of a combustion-engine based business vehicle fleet was provided to us by a Czech automobile manufacturer. The data contains anonymized timestamped GPS coordinates of 4 476 various vehicles owned by the company, captured between March and September 2019, with intervals between consecutive captures ranging from 1 to 25 seconds in 89,9 % of cases, the majority being 5 seconds apart. There are longer intervals between consecutive captures not only due to vehicle inactivity, but also due to the fact that personal trips were not tracked by the company.

The task was to find optimal charging station locations among pre-determined suitable locations, as well as their sizing, given varying financial budget. All 33 suitable CS locations were pre-selected by the company executives and are all located within company-owned premises. The locations are shown on Figure 5.1.

5.1 Charging Demand Model

In order to model the charging demand of a future electric vehicle fleet, pairs of consecutive GPS captures were used as instances of charging demand. A pair was only considered as an instance of charging demand if the captures were within 5 metres of distance (to account for GPS error) and if the interval between captures was at least 15 minutes long, as all such captures appear to be due to parking. Such model of charging demand is in line with the attempt to provide charging seamlessly without affecting drivers' original schedules, as they are assumed to be charging during their original parking times. Charging/parking intervals were capped at 8 hours if longer. Battery capacities of EVs were not modeled, and thus are not reflected in the charging demand model.

An upper limit on acceptable distance between an instance of charging demand and a considered station location was set to 300 m. All instances of charging demand for which there are no potential CS locations in the 300 m radius, were discarded (there exists no feasible solution where any of such instances can be satisfied within the distance limit). The resulting model contains 269 585 instances of charging demand made by 2 873 different vehicles. Figure 5.2 shows the spatial distribution of the charging demand, as well as their spatial relation to the suitable CS locations.

Figure 5.3 shows 5-day rolling mean of daily volumes of traffic (total instances of charging demand) for the resulting model of charging demand; workdays and weekends marked separately. In addition, three specific days were highlighted for future reference.

Figure 5.1. Suitable charging station locations

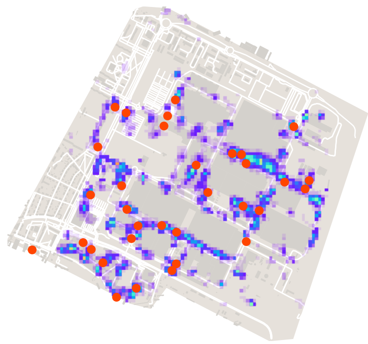

Figure 5.2. Spatial heatmap of charging demand

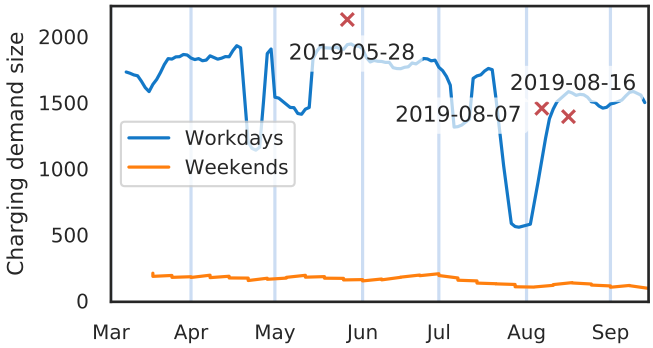

Figure 5.3. Daily volumes of traffic of modeled charging demand (5-day rolling mean)

5.2 Computational Performance

Tests were performed on a 4-core consumer grade Intel i7-7700HQ laptop CPU from 2017 for computationally efficient tasks, and on a high performance computing cluster[1] for more demanding tasks. All used code is available on GitHub[2].

Practical results show that the convergence of the branch-and-bound program used in the state-of-the-art commercial solver Gurobi[3] is significantly handicapped by the FCFS condition[4], and dependant on the size of charging demand and the interconnection of charging stations in terms of their dependence wrt. the charging demand.

5.2.1 Problem Decomposability

In order to find an optimal charger distribution with respect to CS siting and sizing, such that any vehicle is assumed to drive to the charging station closest to it (if there is any within the 300 m radius), we must define viable assignments of charging demand to stations using the vehicle-based approach, as specified earlier in Section 3.1.2: all stations within the 300 m radius from the original vehicle location must be considered as charging attempts, with order based on increasing distance from the original vehicle location. Figure 5.4 shows that the charging station dependence graph (as formally

[1] The access to the computational infrastructure of the OP VVV funded project CZ.02.1.01/0.0/0.0/16_019/0000765 “Research Center for Informatics” is gratefully acknowledged.
[2] `https://github.com/neumannjan/charging-station-siting-sizing`
[3] `https://www.gurobi.com/`
[4] All ILP problems were solved without the no-retry constraint (4.16) (or its linear counterpart (4.23)) due to the constraint not being formulated at the time of testing.

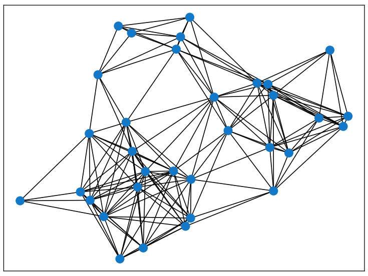

Figure 5.4. Station dependence graph for vehicle-based station assignment

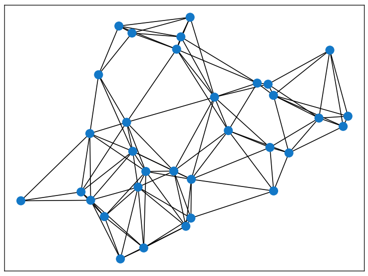

Figure 5.5. Station dependence graph for vehicle-based station assignment (max. 2)

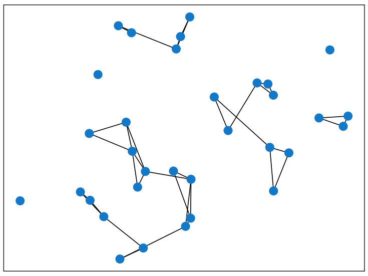

Figure 5.6. Station dependence graph for attempt-based station assignment (max. 3)

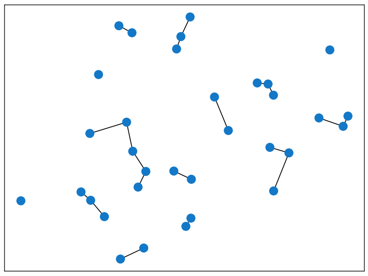

Figure 5.7. Station dependence graph for attempt-based station assignment (max. 2)

defined in Section 4.2.1) for vehicle-based station assignment with 300 m upper limit on distance is a single large connected component of stations, which means that such problem cannot be decomposed into smaller, independent sub-problems. Figure 5.5 shows the same station dependence graph when additional maximum limit of 2 CS locations per instance of charging demand is imposed. Imposing such limit results in loss of optimality for the problem of CS siting and sizing. Even so, such limit still does not allow us to decompose the currently studied problem into sub-problems.

An alternate station assignment approach was previously referred to as attempt-based: the closest potential station location is considered as the first attempt of each vehicle, with each additional attempt based on distance from the location of the *station in the previous attempt*, as opposed to the original vehicle location. Figures 5.6 and 5.7 show station dependence graphs for attempt-based station assignment for the maximum limit of 3 and 2 CS locations per instance of charging demand, respectively. Such problem definitions are decomposable into many small, independently solvable sub-problems. However, please note that such demand-station assignment approach breaks optimality in terms of the original problem formulation. Therefore, it is useful purely for studying computational performance of solving the ILPs.

5.2.2 FCFS ILP Performance

For groups of 1, 2, even 3 stations, the solution is trivially obtainable via comparison of all possible charger distributions for given total budget. With growing number of charging stations, the number of possible charger distributions grows with factorial complexity. However, for the Gurobi program, even in some cases of sub-problems of 3 stations (especially for large enough charging demands), the convergence can still be extremely slow if the FCFS constraint is used (although may not always be, depending on the complexity of constraints for the particular charging demand).

As an example of a very difficult 3 station sub-problem to solve, for charging demand based on a month of data with 5 270 unique instances of charging demand and 10 540

(Sub-)problem Time period	$\lvert S\rvert$	$\lvert E\rvert$	$\lvert M\rvert$	Execution time cap	Optimal solutions Obtained	Total	%
1 day	5	382	727	02:07:19	88	88	100,00
1 month	3	1356	4068	03:54:30	25	25	100,00
1 month	4	2289	5208	3 days	29	49	59,18
1 month	5	1973	5626	1 day	22	45	48,89
1 day	8	460	1380	1 day	32	98	32,65
1 day	8	572	1485	1 day	40	145	27,59
1 month	3	5270	10540	3 days	16	71	22,54
1 month	4	7018	17968	1 day	7	84	8,33
1 day	**33**	**1425**	**4616**	**1 day**	**0**	**?**	**0.00**
1 month	6	12437	27821	1 day	0	?	0,00
1 month	**33**	**37444**	**122799**	**1 day**	**0**	**?**	**0,00**

Table 5.1. Performance statistics for selected **FCFS ILP sub-problems**. $|S|$ — number of stations in the sub-problem. $|E|$ — total instances of charging demand. $|M|$ — total considered charging attempts (i.e. total modeled arrival events). 'Total solutions' is equivalent to the number of different values of max. allowed budget, for which a different optimal solution exists.

different charging attempts total, the solver converged to an optimal solution for total budget of 52 chargers after 7 hours, 37 minutes and 24 seconds of execution on the cluster. In this example, the optimal solution was given to Gurobi as the starter solution; however, from the very start of the execution of the branch-and-bound program, the difference between best known upper bound on objective value and the best known value itself was 36 instances of charging demand, and this gap was first lowered after 7 hours, 31 minutes and 49 seconds.

Overall, for FCFS ILPs, results are obtainable within reasonable time of execution for toy examples only. Table 5.1 shows percentages of completion for selected FCFS sub-problems of various sizes, when executed on the cluster for all possible total budgets, with execution time limit up to 3 days. Results for all total budgets were obtainable within 24 hours of execution for sub-problems with 5 stations or less and for charging demand data collected in a single day only (up to approx. 400 unique instances of charging demand and approx. 700 different charging attempts total). One exception was a sub-problem of 3 stations with charging demand dataset collected over 1 month, with 1 356 unique instances of charging demand and 4 068 different charging attempts total, where the solution for all possible total budgets was obtained in 3 hours, 54 minutes and 30 seconds, as shown in the second row of Table 5.1. However, again, such problem is solvable trivially via brute-force comparison of all possible charger distributions.

Results were usually obtainable within 24 hours for at least *some* values of total budget unless either the set of CS locations or the charging demand set was too large; although this is also individual based on the charging demand. For the "ideal" problem formulations (highlighted in bold), the program did not finish within 24 hours for a single value of total budget.

5.2.3 Non-FCFS ILP Performance

When the FCFS constraint is omitted, the ILP solutions are obtained *significantly faster*. For *almost all* (sub-)problems, all results were obtained within minutes to hours of execution. The only exception were problems with vehicle-based station assignment

(Sub-)problem Time period	$\lvert S \rvert$	$\lvert E \rvert$	$\lvert M \rvert$	Execution time cap	Optimal solutions Obtained	Total	%
1 month	10	15625	51407	15:50:04	176	176	100,00
1 month	14	16115	48345	07:48:37	219	219	100,00
1 month	9	12190	35909	03:28:06	190	190	100,00
1 month	4	7018	17968	00:18:24	84	84	100,00
1 day	33	1425	4616	00:09:51	320	320	100,00
1 month	33	28504	93143	2 days	133	412	32,28
1 month	33	28504	104942	2 days	105	407	25,80
1 month	33	37444	122799	2 days	78	427	18,27
1 month	33	37444	139892	2 days	52	420	12,38

Table 5.2. Performance statistics for selected **ILP sub-problems without FCFS**. $\lvert S \rvert$ — number of stations in the sub-problem. $\lvert E \rvert$ — total instances of charging demand. $\lvert M \rvert$ — total considered charging attempts (i.e. total modeled arrival events). 'Total solutions' is equivalent to the number of different values of max. allowed budget, for which a different optimal solution exists.

and charging demand based on one month of data or more, for which the program did not finish within 48 hours of execution, as shown in Table 5.2.

5.3 Objective Values

Resulting objective values were studied for hard-assignment, two-stage and no-FCFS ILP methods. The no-FCFS ILP method was included in order to provide an upper bound on objective values of the other methods, all of which assume the FCFS condition, as well as to illustrate potential benefits resulting from using scheduling for the assignment of chargers to EVs.

The maximized objective function is the total amount of satisfied instances of charging demand.

For methods with soft-assignment of demand to stations (ILP and first stage of the two-stage method), the viable station assignments of each instance of charging demand were specified using the vehicle-based approach, where stations are prioritized based on their distance from the original vehicle location, with an upper limit of 300 m. Such assignment models CS siting fully and is in line with the objective to encourage vehicles obtaining chargers upon their first arrival at a station, i.e. discourage the need for retries at different stations.

Furthermore, the no-FCFS ILP method was also executed with additional upper limits of 3 stations and 1 station per each instance of charging demand. The latter is essentially hard-assignment without FCFS, allowing “smart rejection” of vehicles with respect to future traffic and the objective function.

Lastly, both variants of the station subset stage of the two-stage method, ILP-based and iterative, were compared.

5.3.1 Effect of Charging Demand Conditions

Objective values for different solution methods differ mainly due to different assumptions on charging demand behavior. Figure 5.8 shows the objective values for the different solution methods, utilizing different charging demand assumptions, used on

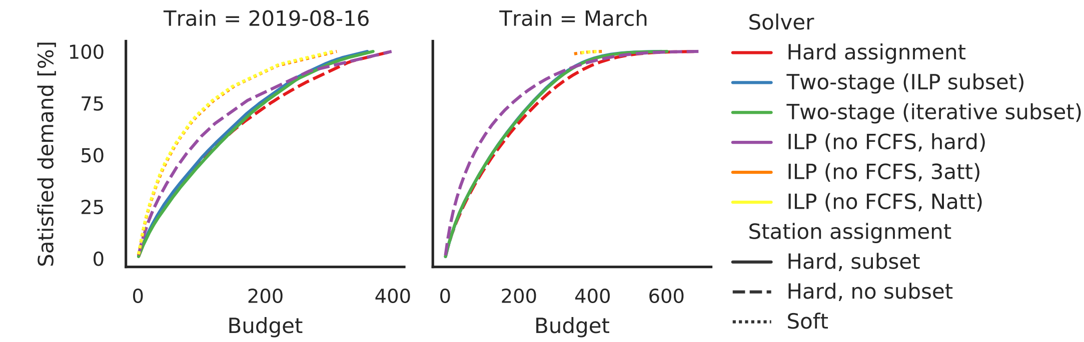

Figure 5.8. Objective values of different solution methods

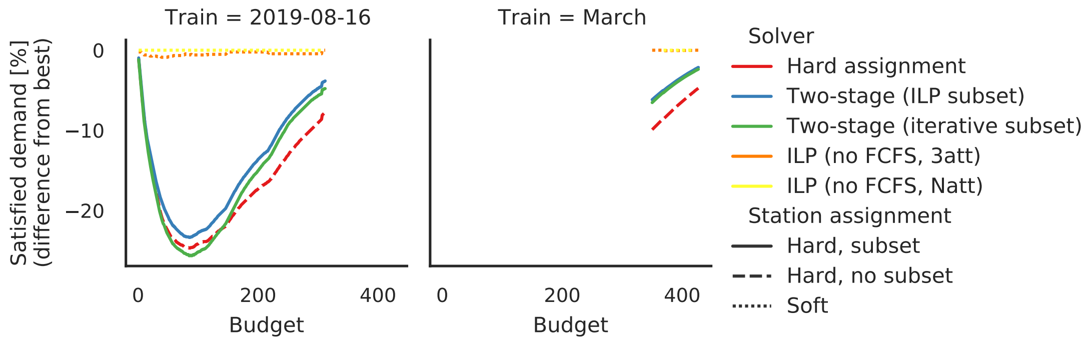

Figure 5.9. Objective value increase for ILP no-FCFS soft-assignment solutions

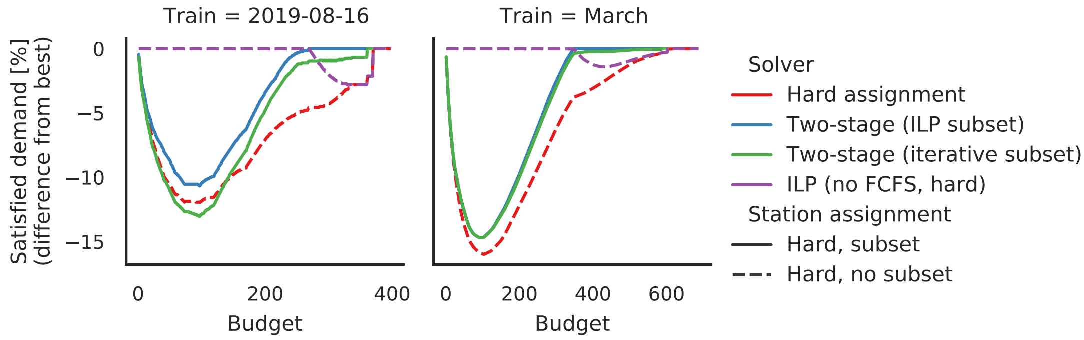

Figure 5.10. Objective value increase for ILP no-FCFS hard-assignment solution

training data based on 1 day and 1 month of measuring. In the case of the March dataset, results for the ILP method are available only for a subset of all possible upper budgets, due to computational limits.

Figure 5.9 shows in greater detail that the no-FCFS ILP solutions produce significantly greater objective values in comparison to other solutions, satisfying up to 24,7 % of additional demand in the soft-assignment case as opposed to the plain hard-assignment solution, with 17,7 % average over all budgets (for the day dataset, where complete data is available). In the hard-assignment case (max. 1 station location considered per each instance of charging demand), the difference from the plain hard-assignment solution (with FCFS) was as high as 15 % and approx. 6 % on average per budget for the month dataset, as shown in Fig. 5.10.

There are three reasons for this:

- station soft assignment (not in effect in the case of hard-assignment ILP),
- relaxation of the no-retry condition (not in effect in the case of hard-assignment ILP),
- relaxation of the FCFS condition.

Firstly, in all hard-assignment solutions (i.e. plain hard-assignment, two-stage, hard-assignment no-FCFS ILP), customers are only satisfiable at their originally assigned station locations. However, if we consider all charging station locations, for 90,8 % of vehicles there are two or more locations in the 300 m radius, three or more for 82 %. Hard-assignment solutions are unable to take advantage of this: a customer "drives" to their originally assigned station location *even if the station is not built at all* (has zero assigned chargers) and the request is therefore automatically rejected; whereas in practice, a customer would not drive to a non-existent station but instead to any built station within the 300 m radius. The two-stage solution is merely an attempt to mitigate the effect of this limitation of the hard-assignment model via reduction of options that a vehicle may choose from.

Secondly, any solution with hard assignment of demand to stations implicitly assumes the no-retry condition, stating that a driver must first arrive at a station to know if there are any unoccupied chargers, and if there are none, the driver *does not retry elsewhere*. However, even for the minimal subset of all charging station locations used in two-stage solutions, there are two or more locations in proximity for 63,7 % of vehicles, three or more for 21,2 %, and it is likely that only *some* of the stations have all chargers occupied. The no-FCFS ILP solutions are modeled *without* the no-retry condition, which can be interpreted as the drivers *knowing* which stations have unoccupied chargers prior to them arriving at the stations (this is achievable in practice for example by monitoring stations and providing vacancy information on a website). An alternate interpretation is that each driver is willing to attempt charging at all nearby stations.

Thirdly (and this is the *only* factor causing the 6 % average increase in the hard-assignment case), the omission of the FCFS condition can be interpreted as follows: a real-time reservation system (scheduler) is used, capable of *rejecting users with overly high demands entirely*, with respect to the objective function and future traffic. Provided that the objective function is the total number of satisfied requests, the model may reject a single request *even if there are unoccupied chargers available* if such decision allows a large number of other requests (expected to arrive at a later time) to be satisfied.

Therefore, when compared to the plain hard-assignment solution (which is significantly limited siting-wise), we can approximate that a 10 % average charging demand satisfaction increase can be achieved by either providing users with information on station vacancy, or by assuming that they are willing to attempt charging at all stations in their proximity. Additional approx. 6 % average increase is achievable by rejecting overly demanding customers via a real-time reservation system. Both are especially significant for lower total budgets. The two-stage solution is known to take advantage of the former only partially via the reduction of options that each vehicle may have.

5.3.2 Available FCFS Solution Comparison

As shown in Fig. 5.11, any two-stage solution is generally better than the plain hard-assignment solution for a given total budget. Intuitively, the reason for this is that with lower total number of stations, the average number of chargers per station must be greater given the same total budget, and an instance of charging demand generally

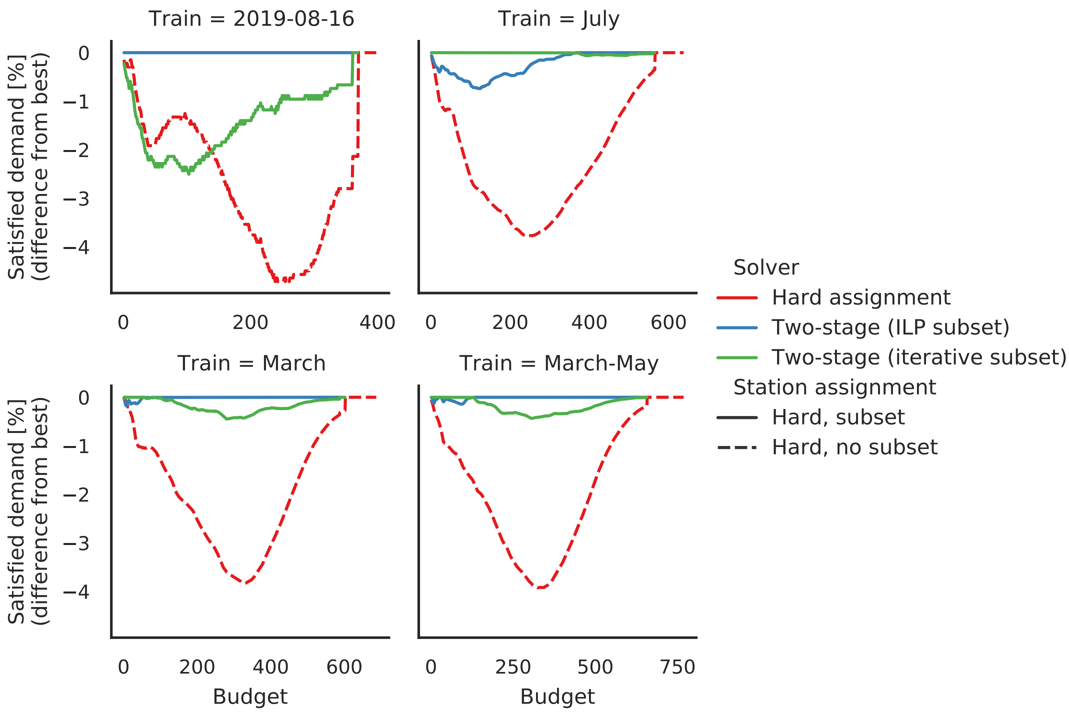

Figure 5.11. Objective value difference for plain hard-assignment and two-stage solutions

has less stations to choose from within its allowed distance radius. Therefore, a station is more likely to arrive at a station with unoccupied chargers.

From this perspective, the question of CS siting is a trade-off between budget and user convenience — the less stations we build, the less chargers are needed in total to fulfill the same demand, given sufficient upper limit on viable distance to station. Therefore, in terms of user convenience, only for larger budgets it becomes better to build more stations to decrease the average distance to the closest station. For lower budgets, the use of more stations comes with the trade-off that a driver is less likely to arrive at a station with vacant chargers, unless they know the vacancy a priori.

It is also worth noting that, for the two-stage solver, station subset stage done via ILP generally, *but not always*, provides solutions with greater demand satisfaction than via iterative reduction, as shown in Fig. 5.11. This is because the true optimality of the station subset selection stage (as guaranteed by the ILP solver) does not necessarily transfer to lower budget solutions found in the second stage, where the station subset is fixed.

5.4 Solution Crossvalidation

We have compared the solution methods based on their objective values; however, each solution method contains different assumptions, such as the first-come-first-served assumption (or lack thereof), or the assumption that drivers are (or are not) willing to retry at different stations upon rejection. Let us now compare the charger distributions provided by the different methods in an identical setting: with identical assumptions, as well as identical charging demand, different from any of the charging demands used in optimization, so as to determine the robustness of the methods with respect to changing conditions as well.

We will assume the first-come-first-served condition, as well as either unwillingness of each driver to retry at a different station, or willingness to try at as many as three different stations (i.e. each driver is willing to be rejected twice and still attempt charging a third time). However, even under the assumption that drivers are unwilling to retry, there will be no hard-assignment of charging demand to stations, meaning that any vehicle will drive to the closest *built* charging station (provided that there is any within the 300 m radius), whichever it is for the given tested charger distribution (unlike in the case of hard-assignment *optimization*, where the assignment was determined prior to the subset of built stations being known).

Please note that in the case of three attempts per instance of charging demand, the attempts are simulated using the *attempt-based* approach, but with the true subset of built stations taken into consideration. In other words, a vehicle first drives to the station closest to it, and upon rejection, drives to the next closest station *from its current location* (at the first station), as opposed to driving to the next closest station from its *original* location.

Validation data will be based on two halves of the full charging demand, separated so that the total number of instances of charging demand for each half is equal: either from March (incl.) to June (excl.), or from June (incl.) to 15th of September (excl.). For each of the two validation datasets, charging distributions based on optimization on a subset of the *opposite* dataset will be used. Training datasets of the extent of 1 day and 1 month will be used. As shown in Fig. 5.3, in the case of March-June data being used for validation, there is an *increase* in daily charging demand, as opposed to training data (subset of June-September data).

5.4.1 Single-Attempt Solution Comparison

For the assumption of max. 1 attempt per each instance of charging demand, results show that two-stage solutions retain their slight advantage over all other solutions, as shown in Figure 5.12 and in greater detail in Figure 5.13. In the case of the month-long training datasets, the two-stage ILP subset solution is capable of charging up to approx. 4 % additional demand, with approx. 2,4 % average, as opposed to the plain hard-assignment solution. For day-long training datasets, the difference is up to approx. 7 %, with approx. 3.6 % average.

In terms of the effect of conditional shifts caused by the use of a different set of data, we compared all solutions with the best known solution obtained via direct optimization of each validation dataset ('Baseline' in Fig. 5.13). Here, the two-stage ILP subset solution lost up to 1,26 % (0,76 % average) for the July training dataset, and up to 0,73 % (0,36 % average) for the March training dataset, in crossvalidation. Here, the effect of an increase in daily charging demand from training to validation, as opposed to a decrease, was only slightly noticeable.

Looking at the effect of the FCFS constraint in training, the hard-assignment solutions produce similar results in FCFS crossvalidation regardless of whether FCFS was assumed in training. The soft-assignment no-FCFS solutions, however, show a significant *loss* in satisfied charging demand when the resulting budget distributions are tested in FCFS simulations, especially when trained on the larger, 1 month datasets, as shown in Fig. 5.12. This is unsurprising, considering that the solutions are tailored to situations in which a scheduler is assumed to be employed. In other words, the no-FCFS models appear to be too permissive for the FCFS simulations; therefore, the relaxation of the FCFS constraint is not a satisfactory approach to obtaining good results for FCFS problems.

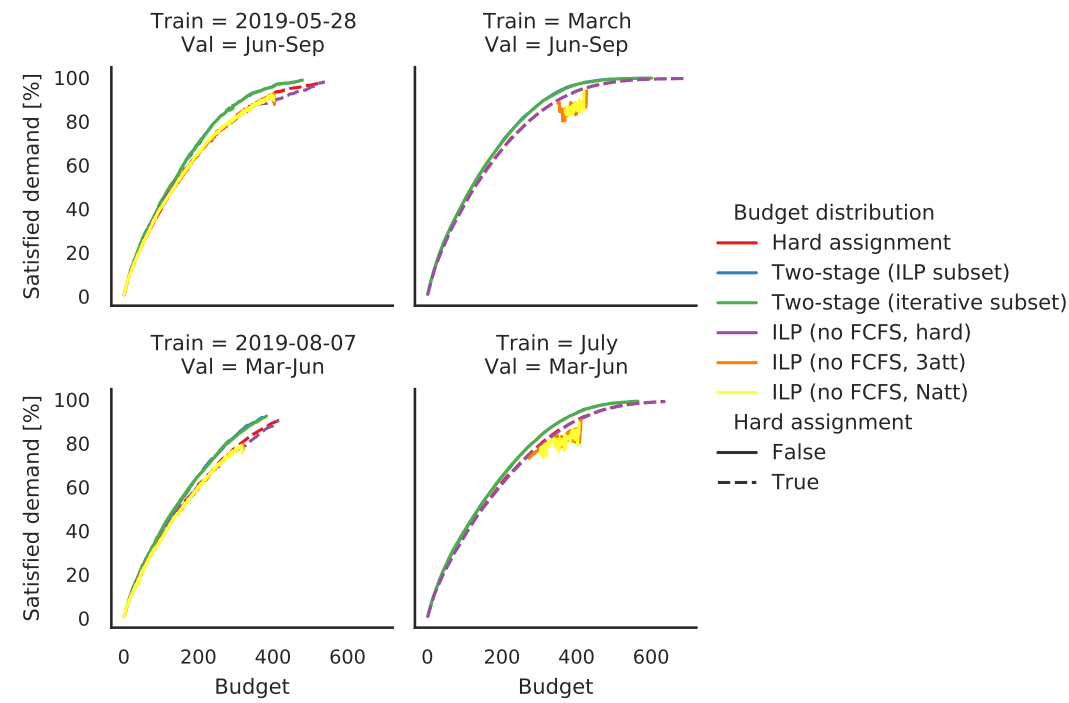

Figure 5.12. Crossvalidation demand satisfaction for simulation with 1 charging attempt

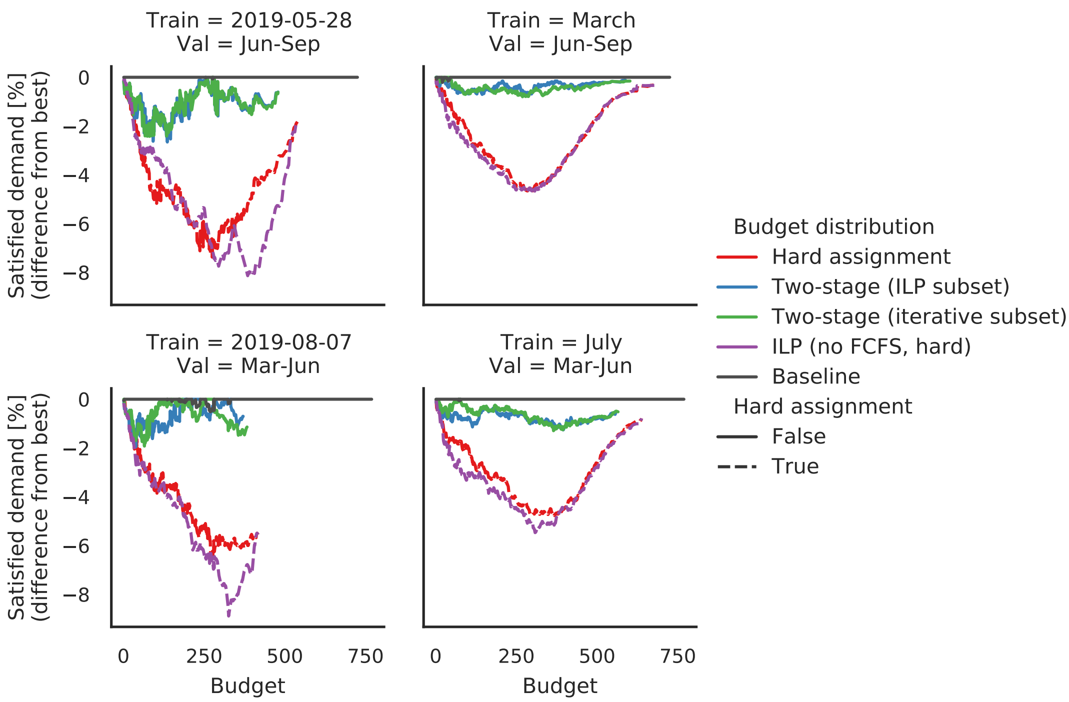

Figure 5.13. Crossvalidation difference from baseline for simulation with 1 charging attempt

5.4.2 Three-Attempt Solution Comparison

Figures 5.14 and 5.15 show results of crossvalidation in cases where max. 3 attempts per each instance of charging demand are assumed. Here, the advantage of the two-stage solution that we observed in the single-attempt case is *not present*; in fact, the hard-assignment solution often provides better results than the two-stage solution. However, all differences are within 1,6 % for month-long training datasets, approx. 0,8 % on average. Therefore, it can be said that the assumption that drivers are willing to attempt charging up to three times per one instance of charging demand is permissive enough to mitigate differences between charging distributions.

5.4.3 Effect of Training Dataset Size

Given the fact that using smaller training datasets is computationally advantageous, it is useful to determine the effect of training dataset size on results in crossvalidation. We compared solutions for day-long and month-long training datasets, such that for any total budget, solutions that performed best on a validation dataset for either of the training datasets are compared. For the Mar-Jun validation dataset, the median losses caused by training on only one day of data (as opposed to one month of data) for 1 and 3 max. charging attempts are 0,26 % and 0,11 %, respectively, as shown in Fig. 5.16. For the Jun-Sep validation dataset, the median losses are 0,54 % and 0,46 %, respectively, as shown in Fig. 5.17.

Please note that training on small datasets does not necessarily provide all results. Charging demand subsets based on short time periods are often fully satisfiable for a *lower* value of total budget than needed to fully satisfy the complete demand (unless the subset contains all usage peaks). In our crossvalidation testing, a solution trained on a single day of data was in some cases unable to charge more than 91 % of the 3-month validation dataset, whereas solutions trained on a month of data provided results for greater total budgets as well, allowing to charge up to 99 to 100 % of the validation dataset, depending on the solution. On the other hand, the additional budget needed to charge the upper 9 % can be up to 400 additional chargers needed — not necessarily a reasonable upgrade.

In addition to this, there are noticeable spikes in demand satisfaction loss for the day-long dataset, up to 4,95 %, as shown in Fig. 5.16.

In conclusion, for the studied solution methods, it appears that short training datasets may be sufficient, as long as they are selected carefully enough.

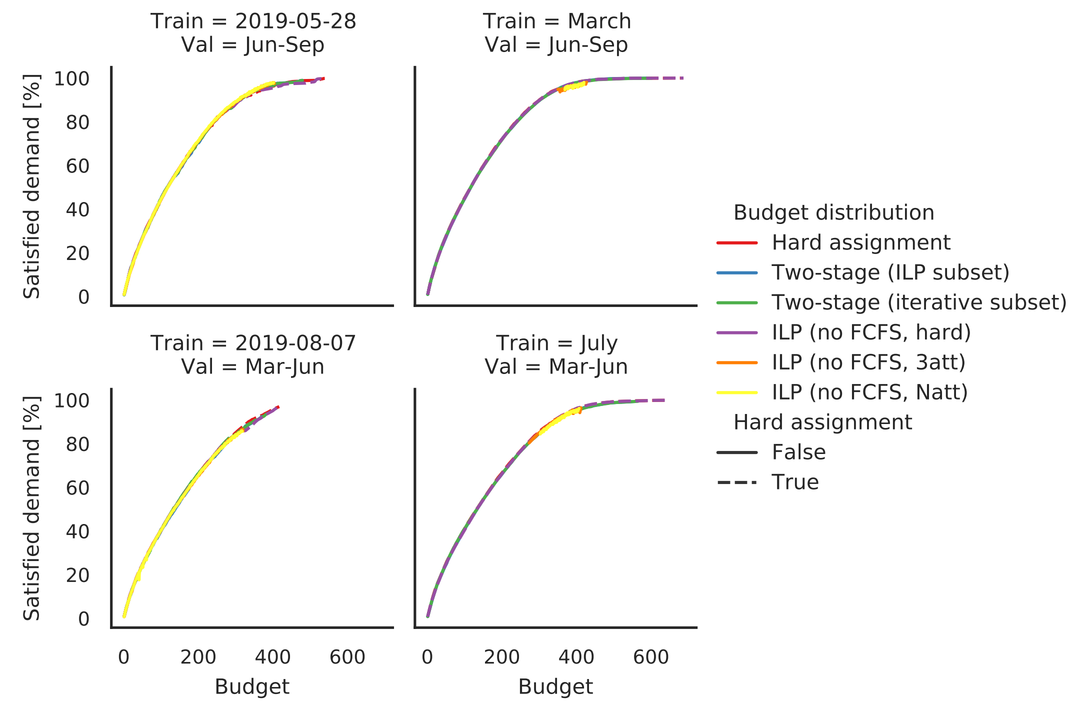

Figure 5.14. Crossvalidation demand satisfaction for simulation with 3 charging attempts

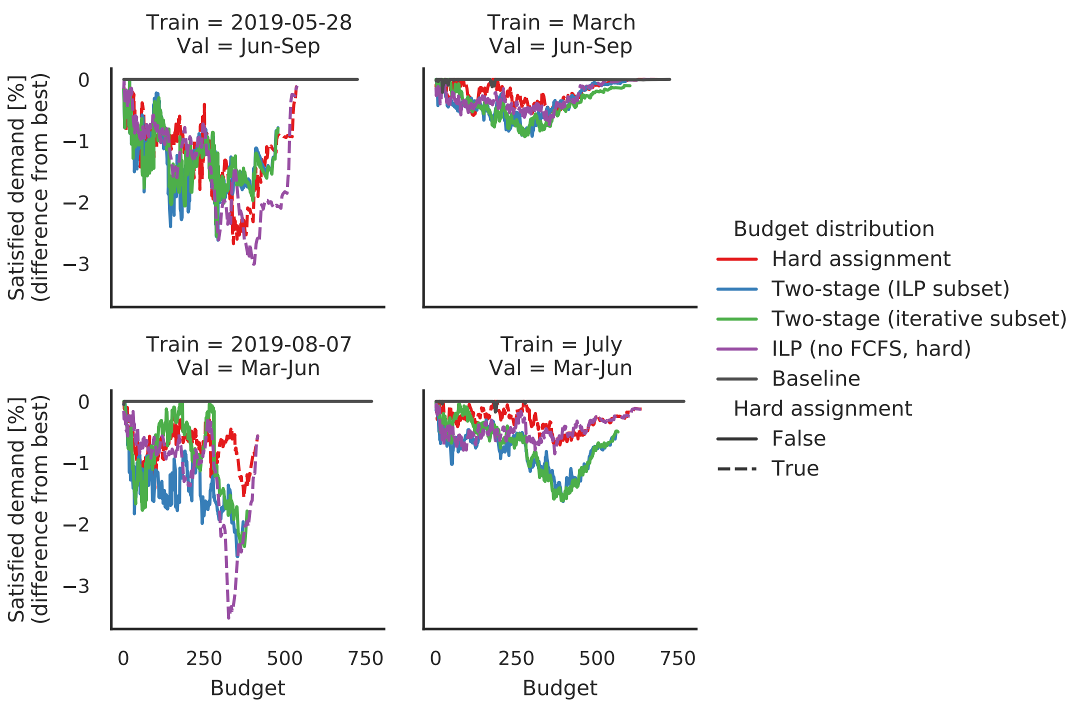

Figure 5.15. Crossvalidation difference from baseline for simulation with 3 charging attempts

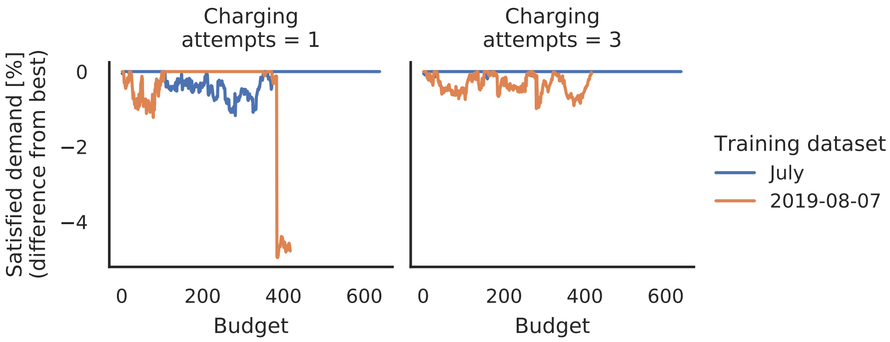

Figure 5.16. Crossvalidation difference for different training dataset sizes for the Mar-Jun validation dataset

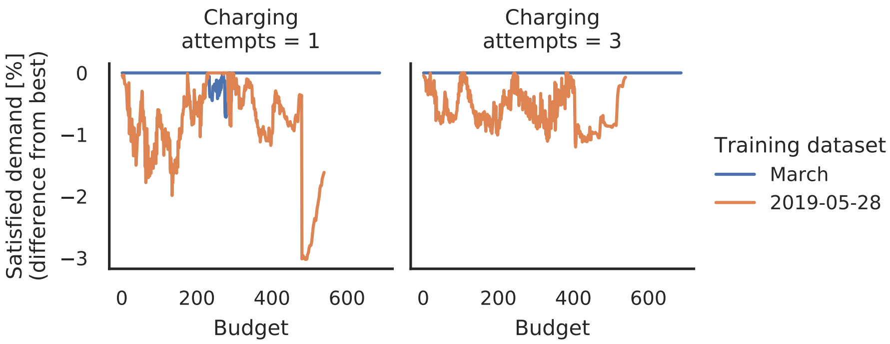

Figure 5.17. Crossvalidation difference for different training dataset sizes for the Jun-Sep validation dataset

Chapter 6
Conclusion

With the aim of aiding private companies in seamlessly upgrading existing business vehicle fleets to electric mobility, the question of finding optimal charging station siting and sizing, with respect to historical fleet operation data, as well as a restriction to company-owned premises and fixed financial budget, was studied. As per the thesis assignment, an overview of existing literature on optimal EV charging infrastructure was conducted, evaluating the correspondence of existing approaches with the aforementioned motivations.

The problem was formulated as an integer linear program with a deterministic charging demand model and a representation allowing for demand transfers among different stations. The program is foundationally based in existing facility location (siting) problem formulations (UFLP and CFLP), with additional unique constraints; namely, the representation of chronological occurrence of events, reflecting dynamically changing demand, such as due to peak hours. To the best of authors' knowledge, the formulation of the constraint representing chronological order of events is uncommon enough that the baseline problem formulation is difficult to solve via universal techniques used for finding optimal solutions to more common ILPs.

Thus, the effect of various modifications to the problem formulation, such as via different constraint relaxations, was studied on the basis of a case study, so as to determine the consequences of obtaining solutions via less computationally demanding approaches. Specifically, ILP formulations in which the constraint establishing the chronological occurrence of events is relaxed, were found to produce solutions that are inadequate for problems where the use of the constraint is well-founded. By contrast, solutions minimizing the number of built charging stations with respect to an upper limit on acceptable distance to station, stood out as very effective, especially for lower budgets, as well as robust to unseen charging demand data. The benefit of building less charging stations becomes insignificant either with large enough financial budget, or by providing customers with real-time information on charger vacancy at all stations, so that a customer is not required to drive to a station to know if there are unoccupied chargers. Only under such conditions it becomes beneficial to minimize average distance to station by building more stations. Lastly, advantages of the introduction of a mandatory charger reservation stage, as opposed to offering charging infrastructure as-is, were studied, with results showing that additional non-negligible increase in the number of total satisfied customers can be achieved by rejecting customers with excessive demands.

In summary, companies were presented with a modeling approach that serves as an aid in effective decision-making in terms of building EV charging station infrastructure. A truly optimal solution per se to the model was not established; nonetheless, effective solutions to the problem were provided, as backed by the results of the case study.

Future work may expand on this thesis by exploring effective algorithms for obtaining mathematically optimal solutions to the proposed problem formulation. For example, branch-and-bound algorithms, not too different from those commonly used for solving more standard ILPs, may potentially be utilized in a way that capitalizes on the non-standard constraints, as opposed to being hindered by them. In addition, further case studies may be conducted, e.g. to study optimal budget distributions with respect to different charger speeds, given that the problem formulation is capable of such representations (via different vehicle departure times based on the station assignment), or simply to further evaluate scalability and robustness of the proposed solutions.

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Appendix A
Glossary

CFLP	Capacitated facility location problem
CS	Charging station
DP	Dynamic programming
EV	Electric vehicle
FCD	Floating car data
FCFS	First come, first served
ILP	Integer linear programming/program
IP	Integer programming/program
SPLP	Simple plant location problem
UFLP	Uncapacitated facility location problem

Appendix B
Code Guide

The following is the structure of the attached code implementation of the models. In order to comply with the data provider's policy, charging demand input data, necessary for successful execution, is not provided. Contact thesis supervisor Ing. Martin Schaefer for information about the input data.

- `lib` — directory containing Python source files
- `cpp` — directory containing C++ source files, built as a Python extension (using pybind11[1]) in order to increase the speed of selected algorithms (most notably Algorithm 4.1 for simulating charging demand)
- `station_distance_graphs.ipynb` — Jupyter[2] notebook containing source code for producing station distance graphs used in the thesis
- `testing_pipeline.ipynb` — Jupyter notebook containing source code for executing all tests used in the thesis
- `model_run_iterative.py` — Python executable file for running Gurobi optimization on ILPs (used on the computational cluster, input produced in `testing_pipeline.ipynb`)
- `run_crossval.py` — Python executable file for running crossvalidation tests (used on the computational cluster, input produced in `testing_pipeline.ipynb`)
- `traffic_full.gz`, `charging_stations.gz`, `station_distances_mtx.gz` — Data files (unavailable in the `.zip` file)
- `environment.yml` — Python Conda[3] environment file, containing information on required Python dependencies
- `CMakeLists.txt`, `pyproject.toml`, `setup.py` — files needed for compilation of the Python extension written in C++

See also the GitHub repository[4].

[1] https://pybind11.readthedocs.io/en/stable/
[2] https://jupyter.org/
[3] https://docs.conda.io/en/latest/
[4] https://github.com/neumannjan/charging-station-siting-sizing