# Electromobility in Public Transport: Scheduling of Electric Vehicles and Location Planning of the Charging Infrastructure

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*For my parents*

# Publications

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- Olsen, N. and N. Kliewer (2020). "Scheduling Electric Buses in Public Transport: Modeling of the Charging Process and Analysis of Assumptions". In: *Logistics Research, 13:4*, DOI: `https://doi.org/10.23773/2020_4`.

- Olsen, N. and N. Kliewer (2016). "Electric Vehicle Scheduling - A study on charging modeling for electric vehicles". In: *Operations Research Proceedings*, pp. 653-658.

# Abstract

In recent years, considerable efforts have been made to make public transport more environmentally friendly. This should primarily be achieved by reducing greenhouse gas emissions. Electromobility is considered to be a key technology as electric vehicles create a variety of benefits. However, the use of electric vehicles involves a number of challenges. Modern battery electric vehicles have only a fractional part of the ranges of combustion engine vehicles. Thus, a major challenge is charging the vehicles at specific charging stations to compensate for this disadvantage. Technological aspects of electric vehicles are also of importance and have to be considered.

Planning tasks of public transport companies are affected by these challanges, especially vehicle scheduling. Vehicle scheduling is a well-studied optimization problem. The objective is to cover a given set of timetabled service trips by a set of vehicles at minimum costs. An issue strongly related to vehicle scheduling is location planning of the charging infrastructure. For an efficient use of electric vehicles, charging stations must be located at suitable locations in order to minimize operational costs. Location planning of charging stations is a long-term planning task whereas vehicle scheduling is a more short-term planning task in public transport.

This thesis examines optimization methods for scheduling electric vehicles in public transport and location planning of the charging infrastructure. Electric vehicles' technological aspects are particularly considered. Case studies based on real-world data are used for evaluation of the artifacts developed. An exact optimization method addresses scheduling of mixed vehicles fleets consisting of electric vehicles and vehicles without range limitations. It is examined whether traditional solution methods for vehicle scheduling are able to cope with the challenges imposed by electric vehicles. The results show, that solution methods for vehicle scheduling are able to deal with the additional challenges to a certain degree. However, novel methods are required to fully deal with the requirements of electric vehicles. A heuristic solution method for scheduling electric vehicles and models for the charging process of batteries are developed. The impact of the detail level of electric vehicles' technological aspects on resulting solutions is analyzed. A computational study reveales major discrepancies between model assumptions and real charging behaviours. A metaheuristic solution method for the simultaneous optimization of location planning of charging stations and scheduling electric vehicles is designed to connect the optimization problems and to open up synergy effects. In comparison to a sequential planning, the simultaneous problem solving is necessary because a sequential planning generally leads to either infeasible solutions or to significant increases in costs.

# Zusammenfassung

In den letzten Jahren wurden erhebliche Anstrengungen unternommen, um den öffentlichen Personennahverkehr (ÖPNV) umweltfreundlicher zu gestalten. Dabei sollen insbesondere Treibhausgasemissionen reduziert werden. Elektromobilität wird dabei auf Grund der zahlreichen Vorteile von Elektrofahrzeugen als Schlüsseltechnologie angesehen. Der Einsatz von Elektrofahrzeugen ist jedoch mit Herausforderungen verbunden, da diese über weitaus geringere Reichweiten im Vergleich zu Fahrzeugen mit Verbrennungsmotoren verfügen, weshalb ein Nachladen der Fahrzeugbatterien während des Betriebs notwendig ist. Zudem müssen technische Aspekte von Elektrofahrzeugen, wie beispielsweise Batteriealterungsprozesse, berücksichtigt werden.

Die Fahrzeugeinsatzplanung als Teil des Planungsprozesses von Verkehrsunternehmen im ÖPNV ist besonders von diesen Herausforderungen betroffen. Diese legt den Fahrzeugeinsatz für die Bedienung der angebotenen Fahrplanfahrten bei Minimierung der Gesamtkosten fest. Die Standortplanung der Ladeinfrastruktur ist eng mit dieser Aufgabe verbunden, da für einen effizienten Einsatz der Fahrzeuge Ladestationen an geeigneten Orten errichtet werden müssen, um Betriebskosten zu minimieren. Die Planung der Ladeinfrastruktur ist ein langfristiges Planungsproblem, wohingegen die Fahrzeugeinsatzplanung eine eher kurzfristige Planungsaufgabe darstellt.

Diese Dissertation befasst sich mit Optimierungsmethoden für die Fahrzeugeinsatzplanung mit Elektrofahrzeugen und mit der Standortplanung der Ladeinfrastruktur. Technische Aspekte von Elektrofahrzeugen werden dabei berücksichtigt. Die entwickelten Artefakte werden mit Hilfe von realen Datensätzen evaluiert. Durch eine exakte Optimierungsmethode für die Fahrzeugeinsatzplanung mit gemischten Fahrzeugflotten bestehend aus Fahrzeugen mit und ohne Reichweiterestriktionen wird die Anwendbarkeit von Optimierungsmethoden ohne Berücksichtigung von Reichweitebeschränkungen auf die Herausforderungen von Elektrofahrzeugen untersucht. Die Ergebnisse zeigen, dass herkömmliche Optimierungsmethoden für die neuen Herausforderungen bis zu einem gewissen Grad geeignet sind, es jedoch neuartige Lösungsmethoden erfordert, um den Anforderungen von Elektrofahrzeugen vollstän- dig gerecht zu werden. Mit Hilfe einer heuristischen Lösungsmethode für die Fahrzeugeinsatzplanung mit Elektrofahrzeugen und Modellen für den Ladeprozess von Batterien wird untersucht, inwiefern sich der Detailgrad bei der Abbildung von Ladeprozessen auf resultierende Lösungen auswirkt. Erhebliche Unterschiede zwischen Modellannahmen und realen Gegebenheiten von Ladeprozessen werden herausgearbeitet. Durch ein metaheuristisches Lösungsverfahren für die simultane Optimierung der Standortplanung der Ladeinfrastruktur und der Fahrzeugeinsatzplanung werden beide Problemstellungen miteinander verbunden, um Synergieeffekte offenzulegen. Im Vergleich zu einer sequentiellen Planung ist ein simultanes Lösen notwendig, da ein sequentielles Lösen entweder zu unzulässigen Ergebnissen oder zu erheblichen Kostensteigerungen führt.

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# Chapter 1

# Electromobility in Public Transport

Public transport represents an indispensable component of urban mobility. The term public transport refers to the generally accessible transport of people by means of regular services. Its task is to satisfy the demand for urban, suburban, and regional transport. Generally, the operating range does not exceed 50 kilometers within the services provided. Public transport can be basically subdivided into passenger land transport carried out by buses and rail passenger transport conducted by trains (cf. Schnieder, 2015). Efficient public transport systems increase the quality of life in urban areas and represent an important economic and location factor. Public transport relieves urban agglomerations of individual traffic and thus contributes to environmental protection.

In recent years, considerable efforts have been made to make the transport sector more environmentally friendly. This goal should be achieved primarily by reducing greenhouse gas emissions. This development arose through the social and political trend towards a sustainable management of resources and the subsequent rejection of fossil energy sources in favor of renewable energies. For that reason, the importance of alternative engines in public transport has increased strongly. Public transport that is carried out by buses is of particular importance for these aspirations because buses with combustion engines are mainly used at the present time. However, more and more buses with alternative engines have started to operate recently[1]. In contrast to passenger transport by buses, public rail transport is already operated largely electrically, at least in the industrial nations[2].

Electromobility has become increasingly important within the scope of alternative engines. It is considered a key technology for sustainable urban mobility particularly in connection with renewable energies. Electromobility basically denotes the application of vehicles with electric propulsion for the transport of people and goods. Such a vehicle is generally referred to as an electric vehicle. In Germany, for example, the proportion of electric vehicles in relation to the total number of registered vehicles has increased significantly in recent years (cf. Plötz et al., 2014).

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[1] https://www.vdv.de/nahverkehr-10-2015-der-bus-im-oepnv.pdfx [Online accessed on 11-June-2020; in German]

[2] https://ec.europa.eu/transport/sites/transport/files/2019-transport-in-the-eu-current-trends-and-issues.pdf [Online accessed on 05-June-2020]

The deployment of electric vehicles creates a variety of benefits that are particularly important for public transport. Electric vehicles are locally emission-free, which means that almost no greenhouse gases, fine particles, and nitrogen oxides are being emitted during their operation. Nowadays, where thresholds for these emissions are largely being exceeded, especially in urban areas, the use of electric vehicles represents a key factor in order to reduce the negative effects on public health (cf. Woodcock et al., 2009). Furthermore, electric vehicles enable a significant reduction of noise, which is especially important for metropolitan areas (cf. Schallaböck, 2012). In comparison to vehicles with combustion engines, electric engines also have a much higher degree of efficiency.

In addition to the environmental advantages specified, there are, however, also controversial debates about electric vehicles. In particular, as stated by Ryghaug and Toftaker (2014), the environmental impact of the electricity generation, the manufacture of the vehicles and batteries, and the disposal of the batteries has not yet been completely clarified. Following Ajanovic and Haas (2016), the electricity generation in particular plays an outstanding role in the question of electric vehicles' environmental friendliness. Another major disadvantage is the insufficiently developed charging infrastructure. Nevertheless, driven especially by politics, a substitution of combustion engine vehicles with electric vehicles is intended at present time[3].

In the last few years, in a variety of public transport systems around the world, projects were launched aiming at substituting combustion engine buses with electric buses. For example, during the EXPO 2010 in Shanghai, connections between different exhibition halls were served by electric buses (cf. Chao and Xiaohong, 2013). In Paris, France, several bus lines have been served by more than 50 electric buses since 2017[4]. As part of a major contract of the RATP, the public transport operator in Paris, the entire transportation network of the Île-de-France is to be served by electric buses from the start of 2025[5]. In Berlin, Germany the Berliner Verkehrsbetriebe (BVG), the local public transport operator, is carrying out the pilot project *E-Bus Berlin*[6] whereby electric buses are operating on a single bus line. An extension to multiple bus lines is intended.

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[3]https://www.bmwi.de/Redaktion/DE/Dossier/elektromobilitaet.html [Last accessed on 01-June-2020; in German]

[4]https://www.ratp.fr/groupe-ratp/newsroom/mobilite-durable/les-lignes-de-bus-115-et-126-passent-lelectrique [Online accessed on 07-June-2020; in French]

[5]https://www.ratp.fr/en/groupe-ratp/join-us/a-100-environmentally-friendly-bus-fleet-thanks-bus2025-plan [Online accessed on 07-June-2020]

[6]http://www.e-bus.berlin [Online accessed on 13-August-2019]

Natalia Kliewer[7]. A number of publications associated with planning and optimization in public transport have been created previously at this chair (cf. Kliewer, 2005, Reuer et al., 2015, and Amberg, 2017). This work is based on those contributions and continues the line of research.

## 1.1 Technological Aspects of Electric Vehicles and their Application

A substantial research expenditure in alternative engine technologies has resulted in various forms of electric engines. With today's state of the art there are three main different types of electric vehicles: *hybrid electric vehicles*, *fuel cell electric vehicles*, and *fully electric vehicles* (cf. Ogden et al., 1999 and Pihlatie et al., 2014). Hybrid electric vehicles contain an electric engine that is powered by a battery and a traditional combustion engine. The latter engine can be switched on when required in order to extend the vehicles' ranges. Fuel cell electric vehicles contain an electric engine as well as a fuel cell. The energy that is needed for powering the electric engine is directly generated by the fuel cell. Hydrogen or methanol are generally used for this process. Fully electric vehicles merely contain an electric engine for movement. The electric energy needed for powering the engine is provided either by an electric battery or by overhead wires distributed in the road network. The term *battery electric vehicle* was established for the first case (cf. Pihlatie et al., 2014).

As things stand, the deployment of electric vehicles involves a number of challenges. Despite extensive research efforts in the area of battery technologies, modern battery electric vehicles have only a fractional part of the ranges of vehicles powered by traditional combustion engines (cf. Ogden et al., 1999 or Felipe et al., 2014). Thus, one major challenge is charging the vehicles at specific charging stations during their operation in order to compensate for this disadvantage. Three main different options for charging are distinguished. First, a vehicle battery can be charged *overnight* during longer idle times, for example at the vehicle depot. Second, a battery can be charged during smaller breaks within a vehicle's operation, which is called *opportunity charging*. Lastly, a vehicle battery can be *swapped* for a fully charged battery. Different charging technologies are available for transferring energy into the batteries. Nowadays, this transfer is mainly performed either conductively by a wire or inductively. For instance, within the pilot project in Berlin, the buses deployed are charged inductively at intermediate stops and conductively at terminal stops during operation. For an overview of wireless charging technologies for electric vehicles we refer to Young (2018a).

In addition to limited driving ranges and the necessity to recharge the batteries, further technological aspects of electric vehicles are also of importance. Particularly

[7] https://www.wiwiss.fu-berlin.de/en/fachbereich/bwl/pwo/kliewer/index.html

worthwhile mentioning are different battery types, characteristics of the charging and discharging process of vehicle batteries, and energy consumption of the vehicles. Nowadays, there are a number of different battery types that are used in practice such as lithium-ion, nickel zinc, or lithium metal polymer batteries. In most practical operations lithium-ion batteries are used and mainly charged by fast charging technologies (cf. Wang et al., 2016). Battery charging is generally a complex process with regard to real conditions. Following Montoya et al. (2017) and Olsen and Kliewer (2020b), battery charging is a nonlinear process that is influenced by numerous factors. For example, the outdoor temperature, chemical composition of the battery, or the technology used have an influence on the charging process. Furthermore, battery aging effects that result from the charging method are of particular relevance. In the course of battery aging, the battery capacity diminishes more and more during a battery's lifetime (Rohrbeck, 2018). The discharging process is determined mainly by the energy consumption of electric vehicles. Factors that influence the energy consumption are line topologies, road gradients, weather and traffic conditions, or a vehicle's air conditioning (cf. De Cauwer et al., 2015 and Deflorio and Castello, 2017).

## 1.2 Challenges for the Planning Process of Companies in Public Transport imposed by Electric Vehicles

The planning process of companies in public transport generally consists of long- and short-term planning tasks. Long-term planning includes forecasting of passenger demand, determination of the public transport infrastructure, and planning of routes and stop points. Short-term planning consists of line planning, timetabling, and resource allocation. It is the task of resource allocation to determine the most efficient vehicle and driver deployment in order to serve all timetabled trips. The associated planning tasks are vehicle and duty scheduling (cf. Bunte and Kliewer, 2009).

With regard to the technological aspects presented, the deployment of electric vehicles brings significant challenges for the planning tasks that public transport companies face: vehicle scheduling is affected especially. Vehicle scheduling is an optimization problem that has been extensively studied in the research community (cf. Bunte and Kliewer, 2009). The basic objective is to cover a given set of timetabled service trips by a set of vehicles at minimum costs. Service trips denote trips for transporting passengers from a departure location to an arrival location via intermediate stops at specific times. A vehicle can perform deadhead trips without passengers in order to change its location. Solutions to this problem contain vehicle rotations that represent sets of trips that are executed by the vehicles. It has to be guaranteed that each vehicle rotation begins and ends at a depot and that the trips of each rotation can be performed without time overlaps. The number of vehicles required and the amount of deadhead distances are to be minimized. Beyond this general research problem, there are numerous extensions such as the consideration of multiple depots or multiple vehicle types (cf. Kliewer, 2005).

One issue strongly related to scheduling electric vehicles is location planning of the charging infrastructure. For an efficient deployment of electric vehicles in public transport, charging stations must be located at suitable places within the road network in order to minimize operational costs. However, attention must also be paid to construction costs and further restrictions such as space limitations and constraints imposed by the electricity grid. For instance, it is more expensive to build a charging station at a busy crossing than in a quiet side street. As described above, location planning of charging stations is a long-term planning problem, whereas vehicle scheduling is a shorter-term planning task for public transport companies.

## 1.3 Research Questions and Research Approach

This thesis focuses on the mathematical optimization problems of scheduling electric vehicles in public transport and the location planning of the charging infrastructure. Special attention is given to the consideration of electric vehicles' technological aspects. This work addresses three main research questions (Q) that emerge in the scope of these two major optimization problems:

> $Q_1$: Are traditional solution methods for vehicle scheduling in public transport able to cope with the challenges imposed by electric vehicles, or is it necessary to develop novel solution methods?
>
> $Q_2$: What impact does the detail level of the reflection of electric vehicles' technological aspects have on scheduling electric vehicles in public transport?
>
> $Q_3$: How can scheduling of electric vehicles in public transport and planning of the charging infrastructure be connected in a reasonable way, such that synergy effects are released?

This thesis provides the scientific foundations for answering the research questions presented by reviewing the literature on scheduling electric vehicles in public transport and location planning of the charging infrastructure. In this context, the consideration of electric vehicles' technological aspects is addressed in particular. The literature overview is presented in Olsen (2020).

In order to provide answers to the research questions $Q_1$, $Q_2$, and $Q_3$, several artifacts in the sense of Hevner et al. (2004) are developed. The general research approach used within this work follows the research paradigm of *Design Science*

*Research*. The central subject of Design Science Research is the development of innovative methods for solving problems. The particular focus is on the development of artifacts, since the underlying assumption is that understanding and solving a problem goes hand in hand with the development and application of these.

Hevner et al. (2004) present seven guidelines that should be included in design science work. The basis of scientific contributions according to design science is the development of an innovative artifact with which a specific purpose is pursued in a targeted manner (guideline 1). The scope of the artifact must be clearly defined and delimited (guideline 2). The artifact created must represent added value, which is why this or its quality is then precisely analyzed on the basis of well-defined analyses (guideline 3). The basis of the analyses is the area of application of the artifact, whereby the artifact created is integrated into the area of application. The results obtained from the analyses carried out must be clear, verifiable and clearly assignable to the context of design science (guideline 4). The methods used in the analysis must be continuously analyzed and reflect the current state of research (guideline 5). The basic procedure of design science corresponds to a process of constant iterations in which the artifact to be developed is improved continuously (guideline 6). As part of this development process, progress made is communicated to both practical and specialist groups of people. This enables the artifact to be used directly in practice and the results obtained to be made available for further research (guideline 7).

Within this contribution, the optimization models and methods developed represent the innovative artifacts that form the central subject of design science research. These are to be considered as possible components of decision support systems, so enabling their applicability in practice or their integration into the application area. A case study was performed for each artifact in order to evaluate its added value. With the help of the models and methods developed, results were achieved that can be used directly for practice as well as for further research.

Table 1.1 illustrates the relationship between the research questions, artifacts developed, case studies performed, and the research publications in which the results are published. Artifact $A_1$ addresses question $Q_1$. This artifact represents a three-phase optimization method for scheduling a mixed fleet of vehicles consisting of electric vehicles and vehicles without range limitations. The objective is to maximize the proportion of feasible vehicle rotations for electric vehicles within the full set of vehicle rotations, while retaining optimal numbers of vehicles used and deadhead trips required. The optimal numbers of vehicles used and deadhead trips are obtained by solving the traditional vehicle scheduling problem (VSP) without range limitations. To a certain degree, traditional solution methods for the VSP are able to deal with the challenges imposed by electric vehicles. However, these findings strongly depend on the instances' data and further aspects. Novel methods are required to fully deal with the requirements of electric vehicles. These results are obtained by solving problem instances based on real-world bus timetables within

| Research Question | Artifact | Case Study | Publication |
|---|---|---|---|
| $Q_1$ | $A_1$ | $C_1$ | Olsen et al. (2020) |
| $Q_2$ | $A_2$ | $C_2$ | Olsen and Kliewer (2016) |
| | $A_3$ | | Olsen and Kliewer (2020b) |
| $Q_3$ | $A_4$ | $C_3$ | Olsen and Kliewer (2020a) |

Table 1.1: Research questions, developed artifacts, case studies, and corresponding research publications.

case study $C_1$. The contribution is presented in Olsen et al. (2020).

The artifacts $A_2$ and $A_3$ are designed in order to provide answers to question $Q_2$. Artifact $A_2$ was developed in Olsen and Kliewer (2016). Both artifacts were analyzed by using the same data sets ($C_2$). $A_2$ entails a heuristic solution method for scheduling electric vehicles, and models for the charging process of vehicle batteries. Through a computational study ($C_2$), major discrepancies between model assumptions and real charging behaviours of vehicle batteries are outlined, leading to widely inconsistent vehicle rotations. Artifact $A_3$ extends the solution methodology and the charging models significantly by incorporating the essential technological aspects partial and opportunity charging. Due to the methodical extensions, the case study $C_2$ was greatly expanded. The results strongly support the findings obtained by artifact $A_2$ and indicate in addition that partial charging may reduce the negative impact of insufficient models for charging on resulting vehicle rotations. Furthermore, different capacities of the vehicle batteries are examined. It is demonstrated that increasing ranges of electric vehicles due to higher battery capacities can alleviate the negative effects of inaccurate charging models, since the numbers of charging procedures needed within the vehicles' operation decrease. The findings are presented in Olsen and Kliewer (2020b).

Artifact $A_4$ tackles research question $Q_3$. This artifact comprises a solution method for the simultaneous optimization of location planning of charging stations and vehicle scheduling of electric vehicles in public transport. The solution method is based on the metaheuristic variable neighborhood search. A computational study ($C_3$) proves that a simultaneous consideration of both optimization problems is necessary. Therefore, the solution method is compared to a sequential planning, where both problems are solved consecutively. A sequential planning approach generally leads to either infeasible vehicle rotations or to significant increases in costs by comparison to simultaneous problem solving. The contribution is presented in Olsen and Kliewer (2020a).

## 1.4 Thesis Outline

This thesis consists of seven chapters. This introduction is followed by chapters 2 - 6, which are independent research papers. Table 1.2 comprises the mapping of research publications to chapters of this thesis. Chapter 2 provides the research foundations by containing a literature overview about scheduling electric vehicles in public transport and location planning of the charging infrastructure. Chapter 3 addresses research question $Q_1$ by presenting a solution method for scheduling mixed vehicle fleets in public transport. Chapter 4 deals with question $Q_2$ in a brief way by introducing a heuristic solution approach for scheduling electric vehicles and models for the charging process of electric vehicles. Chapter 5 contains a significant extension of this work. Within Chapter 6, a heuristic solution method for the simultaneous solving of vehicle scheduling of electric vehicles in public transport and location planning of the charging infrastructure is presented. Chapter 7 concludes this work by providing a summary and further research potentials.

| Chapter | Title | Authors | Year | Publisher |
|---|---|---|---|---|
| 2 | A Literature Overview on Scheduling Electric Vehicles in Public Transport and Location Planning of the Charging Infrastructure | Nils Olsen | 2020 | Diskussionsbeiträge Fachbereich Wirtschaftswissenschaft |
| 3 | Electric Vehicle Scheduling - A study on charging modeling for electric vehicles | Nils Olsen, Natalia Kliewer | 2016 | Operations Research Proceedings 2016 |
| 4 | Scheduling Electric Buses in Public Transport: Modeling of the Charging Process and Analysis of Assumptions | Nils Olsen, Natalia Kliewer | 2020 | Logistics Research |
| 5 | A study on flow decomposition methods for scheduling of electric buses in public transport based on aggregated time-space network models | Nils Olsen, Lena Wolbeck, Natalia Kliewer | 2020 | Central European Journal of Operations Research |
| 6 | Location planning of charging stations for electric buses in public transport considering vehicle scheduling: a variable neighborhood search based approach | Nils Olsen, Natalia Kliewer | 2020 | Submitted to Omega |

Table 1.2: Mapping of research publications to chapters.

# Chapter 2

# A Literature Overview on Scheduling Electric Vehicles in Public Transport and Location Planning of the Charging Infrastructure


## Abstract

The Vehicle Scheduling Problem (VSP) is a well-studied combinatorial optimization problem arising for bus companies in public transport. The objective is to cover a given set of timetabled trips by a set of buses at minimum costs. The Electric Vehicle Scheduling Problem (E-VSP) complicates traditional bus scheduling by considering electric buses with limited driving ranges. To compensate for these limitations, detours to charging stations become necessary for charging the vehicle batteries during operations. To save costs, the charging stations must be located within the road network in such a way that the required deadhead trips are as short as possible or even redundant. A variety of solution approaches to solving the traditional VSP exist, capable of solving even real-world instances with large networks and timetables to optimality. In contrast, the problem complexity increases significantly when considering limited ranges and chargings of the batteries. For this reason, there are mainly solution approaches for the E-VSP that are based von heuristic procedures, as exact methods do not provide solutions within a reasonable time. In this paper, we present a literature review of solution approaches for scheduling electric vehicles in public transport and location planning of charging stations. Since existing works differ not only in the solution methodology but also in the mapping of electric vehicles' technical aspects, we pay particular attention to these characteristics. To conclude, we provide a perspective for potential further research.

## Keywords

Vehicle Scheduling, Public Transport, Electric Buses, Charging Stations, Location Planning

## Contents

## 2.1 Introduction

Scheduling of vehicles is a task arising in the operational planning process of companies in public transport. The corresponding mathematical optimization problem is denoted as the *Vehicle Scheduling Problem* (VSP), which has been extensively studied in the research community. Within modern public transport systems, electric vehicles are being used increasingly to replace traditional combustion engine vehicles. However, the use of electric vehicles complicates traditional vehicle scheduling significantly, since limited driving ranges and the possibility of charging the vehicle batteries have to be considered. This extension of the basic problem is denoted as the *Electric Vehicle Scheduling Problem* (E-VSP). In the following, we define both the VSP and E-VSP.

### 2.1.1 Traditional Vehicle Scheduling

The objective of the basic VSP is to cover a set of service trips contained in a timetable by a set of vehicles while minimizing the total costs. Service trips denote trips for transporting passengers from a departure location to an arrival location at specific times. A vehicle can perform deadhead trips without passengers in order to change its location. The set of all trips executed by a vehicle is denoted as its rotation. Vehicle rotations need to satisfy some basic constraints:

(1) The trips of a vehicle rotation must be mutually compatible, that is, the trips have to be executable without time overlaps.

(2) Every service trip is covered exactly once, and

(3) a vehicle begins and ends its rotation at the same depot.

The costs of a solution consist of fixed costs for buses used and operational costs considering the distances covered and the drivers' working hours. Beside the basic problem, there is a number of extensions such as multiple vehicle depots or heterogeneous fleets with multiple vehicle types.

The basic VSP and its extensions are well studied problems in the research community and have been widely analyzed. Hence, there is a wide variety of solution approaches for the VSP at the present time. Bunte and Kliewer (2009) give an overview of model approaches and solution methods for the VSP and its extensions. The authors address several variants of the single and multi-depot VSP such as multiple vehicle types, vehicle type groups, time windows, or route constraints.

The runtime of the different solution methods depends strongly on the way of modeling and the problem features. It is a matter of common knowledge that the VSP with a single vehicle depot can be solved to optimality in polynomial time. In contrast, Bertossi et al. (1987) show that the VSP with multiple vehicle depots and/or multiple vehicle types becomes NP-hard. However, Kliewer et al. (2006) introduced a solution method based on a time-space network capable of solving even real-world instances with large networks and timetables to optimality considering multiple depots and multiple vehicle types. Furthermore, Gintner et al. (2005) developed a two-phase heuristic model for the VSP based on a time-space network capable of solving extremely large real-world instances with thousands of service trips, many depots, and numerous vehicle types. Generally, the problem complexity depends on numerous factors such as the number of timetabled service trips, the number of depots/vehicle types, and the size of the network. The latter aspect is of importance as larger networks lead to more possible connections between the service trips within a vehicle rotation and thus lead to higher problem complexities.

### 2.1.2 Scheduling Electric Vehicles

Within modern public transport systems, traditional combustion engine vehicles are being substituted for increasingly by electric vehicles. This is because electric vehicles are locally emission-free, meaning that almost no greenhouse gases, fine dust, and nitrogen oxides are being emitted during operations. Beyond that, electric vehicles enable a significant reduction of noise (cf. Schallaböck, 2012). The advantages outlined are especially important for urban areas.

The term *electric vehicle* usually includes three different types of electric propulsion: *hybrid electric vehicles* (HEV), *fuel cell electric vehicles* (FCEV), and *fully electric vehicles* (EV) (cf. Ogden et al., 1999 and Pihlatie et al., 2014). An HEV contains a battery for powering an electric engine and a traditional combustion engine, which can be switched on in order to extend its range. An FCEV contains an electric engine powered by a fuel cell that generates electric energy directly from hydrogen or methanol. An EV merely contains an electric engine for movement. The electric energy needed for powering the engine is provided either by an electric battery or by overhead wires located within the road network. The first case corresponds to the term *battery electric vehicle* (BEV) and the second case to *trolley vehicle*.

Despite these advantages, the use of EVs complicates traditional vehicle scheduling, since EVs have much shorter driving ranges compared to traditional vehicles due to limited battery capacities. To compensate for these limitations, detours to charging stations become necessary for charging the vehicle batteries during operations. The consideration of these additional challenges imposed by EVs leads to the E-VSP. Therefore, the following additional requirements have to be satisfied besides the traditional restrictions given by the VSP:

(4) The residual energy of a vehicle battery cannot fall below zero and cannot exceed the battery capacity, and

(5) the vehicle batteries can only be recharged at specified charging stations.

The residual energy of a battery is often denoted as its *State-of-Charge* (SoC).

When considering EVs, specific technical aspects are of particular importance. Particularly worthwhile mentioning are different battery types, characteristics of the charging and discharging process of vehicle batteries, and energy consumption of the vehicles used. As things stand, there are a number of different battery types that are used in practice such as lithium-ion, nickel zinc, or lithium metal polymer batteries. In most practical operations lithium-ion batteries are used and mainly charged by fast charging technologies (cf. Wang et al., 2016). The discharging process is mainly determined by the energy consumption of EVs. Factors that influence the energy consumption are line topologies, road gradients, weather and traffic conditions, or a vehicle's air conditioning (cf. De Cauwer et al., 2015 and Deflorio and Castello, 2017).

Three main different options exist for charging a vehicle battery. First, a vehicle battery can be charged overnight during longer idle times at the depot. Second, a battery can be charged during smaller breaks within a vehicle's operation, which is called opportunity charging. Lastly, a vehicle battery can be swapped for a fully charged battery. Different charging technologies are available for transferring energy into the batteries. Nowadays, this transfer is mainly performed either by a wire (conductively) or inductively (cf. Young, 2018). Regardless of how a vehicle battery is charged, a key distinction is made between full and partial chargings. In general, battery charging is a complex process with regard to real conditions and has to be modeled in a precise way within solution methods for the E-VSP. Olsen and Kliewer (2020) demonstrate that imprecise models for representing battery charging processes lead to inconsistent solutions in the E-VSP and related optimization problems.

Haghani and Banihashemi (2002) show that the traditional VSP with route and time constraints is NP-hard. Consequently, the E-VSP is NP-hard as well because it is an extension of the basic problem.

### 2.1.3 Location Planning of Charging Stations

For a cost-efficient use of electric buses, the charging stations must be located within the road network in such a way that required deadhead trips are as short as possible or even redundant. This is due to the fact that longer deadhead trips increase the operational costs of the vehicles deployed, and to the probability of missing connections to subsequent trips, which leads to higher demands for vehicles. However, attention must also be paid to construction costs and further restrictions such as local restrictions or constraints imposed by the energy supply. For instance, it is more expensive to build a charging station at a busy crossing than in a quiet side street. In contrast to vehicle scheduling, which is a more short-term planning task of public transport companies, location planning of charging stations is a long-term planning problem.

### 2.1.4 Research Objective and Outline

Due to the great complexity of the E-VSP and in order to be able to solve real-world instances of the problem with extremely large road networks and timetables as well, heuristic solution methods have been predominantly established for solving the E-VSP. The existing contributions for the E-VSP differ, not only in regard to their solution methodologies but also in the mapping of electric vehicles' technical characteristics. Furthermore, the location planning of charging stations is of central importance for the efficient deployment of EVs. In this paper, we provide a literature review of solution approaches for scheduling EVs in public transport and the location planning of charging stations for EVs. We outline differences between the works with regard to the solution methodologies and in particular, we address their way of considering technical characteristics.

The paper is structured as follows: In Section 2.2 we present solution approaches that consider limited driving ranges of vehicles within the traditional VSP. Following this, we discuss solution methods that consider the recharging of the vehicle batteries in addition to limited driving ranges in Section 2.3. As the distribution of charging stations within the road network plays a major role for EVs, we present solution methods for location planning of charging stations within Section 2.4. A conclusion to this report and a perspective for potential further research is given by Section 2.5.

## 2.2 Vehicle Scheduling Problem with Limited Driving Ranges

As a first approach towards a consideration of EVs within vehicle scheduling in public transport, the traditional VSP has been extended in order to reflect the limited driving ranges of the vehicles used.

As one of the first contributions to consider the limited operating ranges of the vehicles deployed, Freling and Paixão (1995) deal with the VSP with time constraints. Within this work, the maximum travel times of vehicles during their rotations are restricted. To solve this enhanced problem, the authors present a two-stage heuristic solution approach. First, initial solutions are generated, which are then improved by local search strategies. Although the limited travel times of the vehicles are taken into account, the vehicles' driving ranges are not directly limited in this work. Furthermore, battery charging is not incorporated.

Desrosiers et al. (1995) and Haghani and Banihashemi (2002) introduce the *Time Window Constraint Scheduling Problem* as an extension of the traditional VSP. In contrast to the work of Freling and Paixão (1995), the authors restrict both the durations and lengths of vehicle rotations. Therefore, they add constraints to the traditional problem formulation of the VSP to incorporate the restricted fuel consumptions of the vehicles used. To solve this increased optimization problem, the authors present one exact and two heuristic solution methods.

The exact solution method consists of an iterative procedure. First, the traditional VSP is solved to optimality. Standard optimization software libraries are used for this. In the second step, it is checked whether all the vehicle rotations computed satisfy the newly added fuel constraints. If this is the case, the procedure stops and the current solution is returned. If at least one vehicle rotation violates the fuel constraints, additional constraints are added to the problem formulation in order to further reduce the solution space. Then, the solution procedure is repeated with the resulting extended problem formulation. The first heuristic solution approach is closely based on the procedure of the exact solution method. The key difference is that for each vehicle rotation that violates fuel constraints the set of trips contained in the specific rotation is reduced until the rotation becomes feasible. The trips removed are inserted into a new vehicle rotation. The other steps of the exact procedure are retained. The second heuristic method is also based on the iterative procedure. The main idea of this approach is to build feasible integer solutions to the extended VSP formulation but without solving an integer optimization problem. Instead, feasible vehicle rotations are built from integer and non-integer solutions to the problem.

In order to be able to solve even larger-scale instances using the solution methods presented, the authors propose two techniques for decreasing the problem size. First, they introduce an algorithm that aims at combining multiple trips into one trip. Within this procedure, the number of trips can be reduced by up to about 20%. Second, they introduce a preprocessing algorithm for reducing the number of decision variables of the optimization problem. Using this technique, a reduction of up to about 80% can be achieved. The authors do not focus on further characteristics of EVs or related issues within this work. In particular, the possibility of recharging a vehicle battery at charging stations is not considered.

## 2.3 Vehicle Scheduling Problem with Limited Driving Ranges and Battery Recharging

Besides the limited driving ranges of the vehicles the possibility of recharging the vehicle batteries is of particular importance. For that reason, a lot of research has emerged that addresses both aspects of EVs. As described in Section 4.3, this problem refers to the E-VSP.

The existing contributions differ particularly with regard to the way of reflecting the battery charging process. Basically, there is literature assuming battery chargings in constant and in linear time. Charging in linear time refers to a linear increase in energy depending on the waiting time of a vehicle at a charging station. The assumption of charging in constant time implies that vehicles remain idle at a charging station for a fixed time period, whether or not the vehicle batteries have already been fully charged. In the following, we divide the literature into those that consider constant times and those approaches that consider linear times for charging.

### 2.3.1 Battery Charging in Constant Time

As one of the first contributions that address both the limited driving ranges of the vehicles and the opportunity to recharge the batteries, Wang and Shen (2007) define the *Vehicle Scheduling Problem with Route and Fueling Time Constraints*. The authors develop a heuristic solution method based on a multiple ant colony algorithm that incorporates route time constraints and generates vehicle rotations starting and ending at a depot. Subsequently, they introduce a bipartite graph model and an optimization algorithm in order to connect the rotations generated with respect to fuel time restrictions. Fueling times are assumed to be constant time windows within which a full battery charging is performed. Furthermore, charging is only possible in the depot. The algorithm aims at minimizing the number of vehicles deployed. Therefore, the maximum matching of the bipartite graph is determined by computing the maximum inflow with the Ford–Fulkerson algorithm.

Chao and Xiaohong (2013) propose a heuristic solution method for the E-VSP based on a Non-dominated Sorting Genetic Algorithm (NSGA-II). The authors focus on battery electric buses and consider the possibility of swapping the vehicle batteries at specific stop points besides the restricted driving ranges. The battery replacement is carried out within a constant time frame, which is synonymous with a constant charging time. After the removal of the battery, a fully charged battery is inserted. The solution method aims at minimizing vehicle costs as well as the total charging demand. The solution procedure is analyzed using real-world data taken from a project in Shanghai. A problem instance with 119 service trips is being solved using the technical data of battery exchange systems that are deployed within this project.

Li (2014) also consider the important aspect of battery swapping. Therefore, the authors propose a solution model for the E-VSP with either battery swapping or fast charging. Both options are performed within constant time frames; however, the time for fast charging depends on the stop point. The vehicle batteries are always fully charged. Furthermore, capacities of charging stations, i.e. the maximum number of simultaneous charging procedures, are incorporated. The author presents a construction heuristic producing vehicle rotations that serve as initial solutions for different column-generation-based solution methods.

Adler and Mirchandani (2016) introduces the *Alternative-Fuel Multiple Depot Vehicle Scheduling Problem*. The proposed optimization problem extends the traditional VSP by incorporating a given set of fueling stations and fuel capacities for the vehicles. To solve the problem, the author presents an exact solution model and introduces a solution approach based on branch-and-price. In order to obtain initial solutions for the solution method, the concurrent scheduler algorithm by Bodin et al. (1978) is extended to take into account the additional restrictions caused by BEVs. The charging procedures are carried out in constant time and the vehicle batteries are always charged to full capacity. An incorporation of additional characteristics of EVs was not made. The solution method is tested on real-world instances with up to 4,000 service trips taken from a real-world project in Phoenix, Arizona.

Homogeneous vehicle fleets consisting exclusively of EVs have been considered within the literature presented so far. Reuer et al. (2015) address the aspect of scheduling a mixed vehicle fleet. For that purpose, the authors extend the traditional VSP by considering a vehicle fleet consisting of EVs and traditional combustion engine vehicles without range limitations. They denote this problem as the *Multi-Vehicle-Type Vehicle Scheduling Problem with Electric Vehicles*. This optimization problem aims at maximizing the proportion of feasible vehicle rotations for EVs within the full set of vehicle rotations while retaining optimal numbers of vehicles used and deadhead trips required. This measure is obtained by solving the standard VSP without range limitations. Vehicle rotations that are infeasible for EVs are served by traditional combustion engine vehicles. To solve the problem, the authors use a time-space network based exact solution method for the VSP, as introduced by Kliewer et al. (2006). Since solutions to this problem comprise optimal flow values through the network, strategies for flow decomposition are necessary in order to obtain vehicle rotations enabling additional degrees of freedom while generating multiple vehicle rotations, all cost-minimal. To do this, they develop strategies for flow decomposition. Within this work, constant time windows are assumed for charging the vehicle batteries.

### 2.3.2 Battery Charging in Linear Time

All of the solution approaches discussed so far have in common that charging processes are performed within constant time windows. This assumption leads to a substantial simplification of the battery charging process because the actual process of modern batteries is very complex (Montoya et al., 2017 or Olsen and Kliewer, 2020). For this reason, research has been completed that incorporates charging procedures in linear time.

In one of the first contributions towards a more realistic reflection of battery charging processes, Kooten Niekerk et al. (2017) introduce a column-generation-based solution approach for the E-VSP with a single depot that incorporates chargings in linear time. Furthermore, they take into account the aspects of partial charging, battery aging effects, and time-dependent energy prices. Battery aging effects are reflected by means of exponential modeling. Since taking these technical aspects into account complicates the problem significantly, the authors propose two different solution models that differ in their level of detail in terms of these aspects. Within the first model, energy prices are assumed to be constant throughout the day and battery degradation is not considered. However, time-dependent energy prices and battery degradation are incorporated within the second model. In order to be able to solve the second model in a reasonable time, the linear charging process is approximated to by assuming discrete states of the vehicle battery's SoC. To solve both optimization problems, standard optimization libraries are used for small and medium instances and the column-generation-based solution approach is used for larger instances. The authors show that in some cases, the consideration of partial charging procedures leads to cost savings in comparison to full chargings of the vehicle batteries.

Janoveca and Kohánia (2019) present an exact solution approach for the E-VSP in the form of a mixed integer linear program. The authors extend an existing mathematical model for the E-VSP from Rogge et al. (2018) by incorporating partial charging in the depot and at terminal stops of the service trips. The charging infrastructure is assumed to be given in advance. They use standard optimization software libraries for solving. Based on real-world data provided by a public transport company in the city of Žilina, Slovakia, the authors point out the correctness of the solution model but also the limits of its applicability due to the runtime required. They conclude that heuristic solution methods are generally more suitable in order to solve larger instances arising within real-world applications as well.

Yao et al. (2020) propose a heuristic solution method based on a genetic algorithm for the E-VSP with multiple vehicle types. Specifically, they analyse the impact on the solution quality of different driving ranges, recharging durations, and energy consumptions that result from the vehicle types. Even though the authors consider a significantly higher number of technical characteristics in comparison to previous work, they also assume that chargings are performed in linear time. Based on a computational study using public transport data taken from the district Daxing in Beijing, China, the authors show that the incorporation of different vehicle types reduces the total scheduling costs.

## 2.4 Location Planning of Charging Stations for Electric Vehicles

If we look at the literature presented so far, we can see that there is no work at all dealing with the impact of different scenarios of the charging infrastructure on resulting vehicle rotations when solving the E-VSP. At the present time, few publications exist that deal with the location planning of charging stations for EVs in public transport. However, when regarding these publications location planning is considered as a separate optimization problem.

Kunith et al. (2014) propose a mixed integer linear optimization model for determining locations for charging stations for a bus route. The model is based on a set covering problem. The objective is to minimize the number of charging stations required. Within this solution model, the authors take into account constraints imposed by the buses' operation and the battery charging process. Furthermore, different energy consumption scenarios are considered in order to reflect external influencing factors on the buses' energy consumption, such as traffic volume and weather conditions. Standard optimization libraries are used for solving the problem.

Berthold et al. (2015) deal with the electrification of a single bus route in Mannheim, Germany. The authors present a mixed integer linear program in order to determine optimal locations of charging stations alongside the stops to be served by the buses. The sequences of stops that are operated by EVs are given in advance. Within this solution model, partial charging procedures, battery aging effects over multiple time periods, and different scenarios regarding the passenger volume and traffic density are considered. The objective is to minimize the total costs consisting of construction costs for the charging stations and the acquisition costs for the vehicles used. The problem is solved by using standard optimization libraries. Due to the consideration of multiple time periods and technical characteristics, the optimization problem becomes very complex. As a consequence, the solution approach is not suitable for larger instances and larger public transportation networks respectively.

Xyliaa et al. (2017) develop a dynamic optimization model to establish a charging infrastructure for EVs in Stockholm, Sweden. Within this model, the authors consider restricted waiting times of the vehicles at intermediate stops of service trips that are given by the schedule, and unrestricted waiting times at the depot. Furthermore, different currents of the charging systems imposed by local conditions and the technology type that is installed at a specific charging station are taken into account. Battery charging can either be performed conductively or inductively. Again, the problem is solved by using standard optimization libraries. In contrast to the previous work by Berthold et al. (2015), now multiple bus lines are optimized together. However, no line changes for the buses used are considered. Based on a computational study, the authors provide statements about the application possibilities of EVs in urban areas and effects on vehicle rotations. They point out that the capacities of electricity grids in urban areas have a strong impact on the number of electrifiable bus lines.

Liu et al. (2018) take into account energy consumption uncertainties within location planning of charging stations for BEBs. To do this, the authors introduce a robust optimization approach represented by a mixed integer linear program. Using real-world data, the authors demonstrate that the proposed solution model can provide optimal locations for charging stations that are robust against uncertain energy consumption of BEBs.

Lin et al. (2019) propose a spatial-temporal model for a large-scale planning of charging-stations for BEBs in public transport. The authors take into account characteristics of BEBs' operation and plug-in fast charging technologies. The model corresponds to a mixed-integer second-order cone programming formulation with high computational efficiency. A case study using data from Shenzhen, China is used to analyse the robustness of the solution model to timetable changes.

With a view to other optimization problems in the scope of transportation, there are further contributions dealing with the charging infrastructure planning for EVs. Frade et al. (2011) deal with the location planning of public charging stations for private transport with EVs. The authors introduce a solution model for planning the locations of charging stations in the city of Lisbon, Portugal, based on a maximum coverage problem. The number of charging stations to be located is given in advance and the objective is to maximize the coverage rate of the demand. The charging demand for a day was estimated approximately from the number of jobs, and the charging demand for a night by the number of households per geographical unit. The problem is solved using standard optimization libraries.

Chen et al. (2013) propose a mixed integer programming model to determine locations for public charging stations for private EVs within the city of Seattle, Washington, USA. The authors use regression equations in order to estimate parking demands. Site accessibility, local job and population density, parking fees, and trip attributes are used among others as dependent variables for the regression analysis. The objective is to minimize walking distances from charging stations to destinations weighted by parking durations. Standard optimization libraries are used for solving.

Regarding *Vehicle Routing Problems* with electric vehicles, Worley et al. (2012) present a mixed integer linear program for the simultaneous determination of optimal locations for charging stations and vehicle routes. They show that this approach leads to lower total costs for the vehicle deployment by comparison to when locations of charging stations are determined in advance.

## 2.5 Conclusion and Potential Future Research

Cost-efficient scheduling of EVs in public transport is essential for increasing sustainability in the transport sector. This applies particularly to urban areas where thresholds for greenhouse gases, fine particles, nitrogen oxides, and other emissions are largely being exceeded. Closely associated with scheduling of EVs is the planning of the charging infrastructure. This is because longer deadhead trips to charging stations during the vehicles' operation increase the operational costs and may lead to higher demands for vehicles. In this paper, we have provided a first comprehensive overview of the existing literature dealing with scheduling of EVs and the location planning of charging stations in public transport.

We have structured the literature overview provided on the basis of the following aspects: First, we have presented literature incorporating limited driving ranges within the traditional VSP. Second, we have discussed contributions that consider battery charging in addition to limited driving ranges. This problem is generally denoted as the E-VSP within the scope of research. Basically, the works presented can be divided into those that assume charging in constant time and those that assume charging in linear time. Lastly, we have presented literature that deals with the location planning of charging stations. However, there are only publications that deal with location planning as a separate optimization problem at the present time. Table 2.1 provides an overview of the contributions presented within this paper.

| | reference | lim. driv. ranges | batt. chrg./ swap. | purely e-veh. fleet | fixed chrg. infra. | fixed veh. rotat. | part. chrg. |
|---|---|---|---|---|---|---|---|
| Scheduling Electric Vehicles | Freling and Paixão (1995) | • | | • | • | | |
| | Desrosiers et al. (1995) | • | | • | • | | |
| | Haghani and Banihashemi (2002) | • | | • | • | | |
| | Wang and Shen (2007) | • | • | • | • | | |
| | Chao and Xiaohong (2013) | • | • | • | • | | |
| | Li (2014) | • | • | • | • | | |
| | Reuer et al. (2015) | • | • | | • | | |
| | Adler and Mirchandani (2016) | • | • | • | • | | |
| | Kooten Niekerk et al. (2017) | • | • | • | • | | • |
| | Janoveca and Kohánia (2019) | • | • | • | • | | • |
| | Yao et al. (2020) | • | • | • | • | | • |
| Charging Infrastructure | Frade et al. (2011) | • | • | • | | | |
| | Worley et al. (2012) | • | • | • | | | |
| | Chen et al. (2013) | • | • | • | | | |
| | Kunith et al. (2014) | • | • | • | | • | • |
| | Berthold et al. (2015) | • | • | • | | • | • |
| | Xyliaa et al. (2017) | • | • | • | | • | • |
| | Liu et al. (2018) | • | • | • | | • | • |
| | Lin et al. (2019) | • | • | • | | • | • |

Table 2.1: Overview of the main characteristics of the literature presented.

Based on the literature overview provided, there are a number of interesting future research avenues. Basically, most of the work presented involves heuristic solution methods. Only a few contributions provide exact methods which, however, are only applicable to small problem instances. The development of exact solution methods for the E-VSP also capable of solving larger real-world instances would be of great interest. Regarding the technical characteristics of EVs, it would be interesting to see how more precise models for the charging and discharging process of vehicle batteries might affect the solutions to the E-VSP. Furthermore, battery aging effects are particularly important for the deployment of EVs. So far, these technical aspects have been insufficiently considered within existing solution approaches and should be better reflected in future models. Likewise, external factors that influence the operation of EVs should also be taken into account. To be mentioned in this context are energy consumption, depending on traffic volume, and energy prices, which may depend on the demand or utilization of the electricity grid. Finally, so far the task of location planning for charging stations has been addressed as a standalone optimization problem. However, as vehicle scheduling and location planning mutually depend on each other, location planning should be integrated into vehicle scheduling.

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# Chapter 3

# Electric Vehicle Scheduling - A study on charging modeling for electric vehicles

This chapter is omitted due to copyright. The corresponding book chapter was published in:

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# Chapter 4

# Scheduling Electric Buses in Public Transport: Modeling of the Charging Process and Analysis of Assumptions

## Abstract

The Electric Vehicle Scheduling Problem (E-VSP) complicates traditional bus scheduling for public transport by restricting the range of the buses. To compensate for these limitations, detours to charging stations become necessary in order to charge the vehicle batteries. Charging is a nonlinear process with regard to real conditions, especially when taking partial and opportunity charging into account. However, within most existing solution methods for the E-VSP, the work of charging a vehicle battery is substantially simplified. In most cases, charging is assumed to be performed within linear or even constant time windows. In this paper, we analyze the impact of simplifying assumptions about charging times of electric buses on solutions of the E-VSP. Therefore, we propose charging models reflecting the nonlinear charging process precisely. Furthermore, we enhance an existing solution method for the E-VSP and provide an algorithm for incorporating partial and opportunity charging. Through a comprehensive computational study using real-world bus timetables, we identify major discrepancies between model assumptions and real charging behaviours of electric buses. On the one hand, we show that the assumption of constant charging times generally leads to overestimated time windows for charging, which increases the total costs. On the other hand, we demonstrate that assuming linear charging times underestimates the time windows actually required for charging, widely leading to infeasible vehicle rotations. We investigate this issue by using the technical data of lithium-ion batteries, which are mainly used in practice at present.

## Keywords

Vehicle Scheduling, Public Transport, Electric Buses, Electric Battery, Charging Process

## Contents

## 4.1 Introduction and Problem Description

The electrification of public transport fleets and thus the deployment of electric buses brings many important advantages. First, electric engines have a much higher degree of efficiency compared to combustion engines. Second, electric buses are locally emission-free, which means that almost no greenhouse gases, fine particles, and nitrogen oxides are being emitted during their operation. Nowadays, where thresholds for these emissions are largely exceeded, especially in urban areas, the use of electric buses represents a key component in order to reduce the negative effects on public health. Beyond that, electric buses enable a significant reduction of noise, which is especially important for urban areas (cf. Schallaböck, 2012).

As things stand, the term *electric bus* includes mainly three different types of electric propulsions: *hybrid electric buses* (HEB), *fuel cell electric buses* (FCEB), and *fully electric buses* (EB) (cf. Ogden et al., 1999 and Pihlatie et al., 2014). A HEB contains a battery and an electric engine together with a traditional combustion engine, in order to extend its range. A FCEB contains an electric engine as well as a fuel cell that generates electric energy directly from hydrogen or methanol to power the engine. An EB merely contains an electric engine for movement. The electric energy needed for powering the engine is provided either by an electric battery or by overhead wires distributed through the road network. The term used in the first case is *battery electric bus* (BEB) and in the second is *trolley bus*. Since BEBs involve the strictest restrictions for daily operations, we will focus on this type of bus in this paper and use the term electric bus and battery electric bus synonymously.

Despite significant research efforts in the area of battery technologies, modern battery buses merely reach a fraction of the ranges of buses with traditional combustion engines (cf. Ogden et al., 1999 or Felipe et al., 2014). For example, the Berliner Verkehrsbetriebe (BVG) is carrying out the pilot project *E-Bus Berlin*[1] whereby electric buses (Solaris Urbino 12 electric), each equipped with a lithium-ion-battery capable of storing 90 kWh, operate on a single line. Measured in terms of their consumptions (1.5 - 1.8 kWh, depending on many influencing factors), this results in a range of approximately 54 km. By comparison, the same bus type with a traditional diesel engine (*Solaris Urbino 12*) is able to cover a distance of about 450 km[2]. Apart from this, state-of-the-art buses like the *Proterra Catalyst Transit Vehicle*[3] capable of storing about 300 kWh achieve longer but still not comparable ranges. In order to compensate for this disadvantage, BEBs perform detours to charging stations during their operations in order to recharge the vehicle batteries. Therefore, three main different options for recharging exist. First, a vehicle battery

[1] http://www.e-bus.berlin [Online accessed on 13-August-2019]

[2] http://www.busmagazin.de/fileadmin/user_upload/Busmagazin/Fahrzeugtests/Solaris-Urbino_03
_2015.pdf [Online accessed on 18-September-2019]

[3] https://www.proterra.com/products/40-foot-catalyst [Online accessed on 20-September-2019]

can be recharged *overnight* during longer idle times at the depot. Second, a battery can be recharged during smaller breaks within a vehicle's operation, which is called *opportunity charging*. Lastly, a vehicle battery can be *swapped* for a fully charged battery. Different charging technologies are available for transferring energy into the batteries. Nowadays, this transfer is mainly performed either by a wire (conductively) or inductively. For instance, within the pilot project in Berlin, the buses deployed are charged inductively at intermediate stops and conductively at terminal stops of operated service trips, which is denoted as opportunity charging. Young (2018) gives an overview of the operation of wireless charging for electric vehicles.

Vehicle scheduling, as one essential planning task of public transport companies, is especially affected by the challenges of BEBs such as limited ranges and the need for charging. This task involves specifying the vehicle deployment for operating the timetable daily offered. A timetable contains service trips for transporting passengers from an origin via intermediate stops to a destination at specific times. The general objective of vehicle scheduling is to determine an assignment of a company's vehicles to the set of timetabled service trips at minimum cost. A vehicle can perform deadhead trips, which represent trips without carrying passengers, in order to change its location, which is especially important when the same bus can serve different bus lines (line-mixed planning). The set of all trips executed successively by a vehicle is described as its rotation. In turn, the set of vehicle rotations is denoted as the vehicle schedule. Vehicle rotations need to satisfy the following constraints: (1) A vehicle rotation consist of compatible trips, that is, the trips have to be executable in succession without time overlaps. (2) Every service trip is assigned exactly once, and (3) a vehicle begins and ends its rotation at the same depot. This basic optimization problem is widely known as the *Vehicle Scheduling Problem* (VSP). When deploying BEBs, additional restrictions have to be taken into account: (4) BEBs have limited ranges due to their limited battery capacities, and (5) the vehicle batteries can only be recharged at charging stations located within the route network. This problem is denoted as the *Electric Vehicle Scheduling Problem* (E-VSP) as an extension of the traditional VSP. A vehicle rotation is termed *feasible* for BEVs if all of the restrictions introduced are satisfied. Otherwise it is termed *infeasible*. While charging, a vehicle remains idle at a particular charging station for a certain time period. This time period generally depends on the remaining energy of a vehicle battery, often denoted as the *State-of-Charge* (SoC). Vehicle batteries can either be fully or partially charged. The consideration of partial charging procedures complicates the problem significantly but also enables further optimization potentials due to higher degrees of freedom.

While many authors have focused on developing solution approaches for the E-VSP, most solution methods presented do not incorporate the specific technical conditions of BEBs and charging stations sufficiently. Particularly worthwhile mentioning are predictions of energy consumption as well as the charging and discharging process of modern batteries. The discharging process is mainly determined by the energy consumption of an BEB. Factors that determine the consumption are line topologies, road gradients, weather and traffic conditions, or a vehicle's air conditioning (cf. De Cauwer et al., 2015 and Deflorio and Castello, 2017). Furthermore, the functioning of a battery's charging process has to be considered. As things stand, there are a number of different battery types that are used in practice such as lithium-ion, nickel zinc, or lithium metal polymer batteries. In most practical operations lithium-ion batteries are used and mainly charged by fast charging technologies (cf. Wang et al., 2016). Generally, lithium-ion-batteries are charged with the widely used charging procedure *constant current/constant voltage* (CC/CV), which is characterized by two phases of charging (cf. Dearborn, 2018). Within the first phase, the battery is charged linearly, measured by its capacity, by applying a constant current. After exceeding a threshold of approximately 65% of the maximum battery capacity - the actual percentage value depends on the C-rate of the battery - the battery is charged with a constant voltage. Within this second stage, the current decreases exponentially, leading to a nonlinear profile. Figure 4.1 illustrates this procedure (according to Dearborn, 2018). Within most existing solution methods for the E-VSP, the special feature of the nonlinear charging process of vehicle batteries has not been adequately incorporated. Instead, the functioning of charging has been substantially simplified by assuming linear or even constant time windows.

With a view to other optimization problems in transportation, in particular vehicle routing with electric vehicles, when the departure and arrival times of trips to be assigned are not fixed, we can determine that aforementioned problem of simplified assumptions about charging times of EVs is also highly relevant. In this respect, Montoya et al. (2017) extend existing solution methods for the electric vehicle routing problem by incorporating nonlinear charging procedures. They evaluate resulting tours with regard to their feasibility and cost-efficiency using a piecewise linear approximation of the current. They disclose that an oversimplification of charging vehicle batteries generally leads to inconsistent solutions. However, due to the fact that vehicle routing has different prerequisites compared to vehicle scheduling and requires different solution methods, no direct conclusions regarding the E-VSP can be made.

In this paper, we analyze the impact of simplifying assumptions about charging times of BEBs, in our case constant and linear time windows for charging, on solutions of the E-VSP. This involves examining impacts on cost-efficiency, feasibility, and the practical operations of BEBs. Therefore, we propose precise charging models to reflect the nonlinear charging process accurately, especially in regard to CC/CV. Towards solving the E-VSP, we enhance an existing solution method and provide an algorithm for incorporating partial and opportunity charging. Since a consideration of partial charging extends the problem significantly, we differentiate specifically between complete and partial charging procedures in the analysis of the solutions.

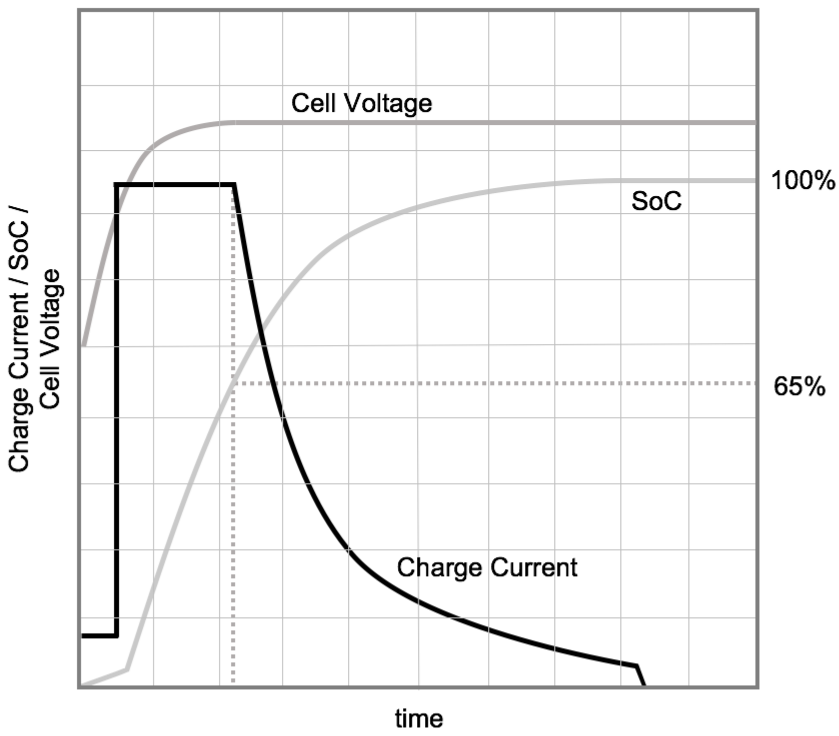


Figure 4.1: Profiles of the current, cell voltage, and SoC within the charging procedure CC/CV of lithium-ion-batteries.

In order to arrive at these contributions, the paper is structured as follows: In Section 6.2 we give an overview of related work especially mentioning the consideration of technical conditions. In Section 4.3 we define the E-VSP formally. Afterwards, we introduce the solution methodology in Section 6.4. Then, we present models for the charging procedure CC/CV in Section 4.5 and perform a computational study in Section 6.5. We conclude our contribution with Section 6.6, providing a summary and a perspective for potential further research.

## 4.2 Related Literature

In the following, we provide an overview of related literature. We discuss existing solution approaches to the E-VSP that focus on technical conditions in particular.

There is a lot of literature dealing with vehicle scheduling for public transport. For an overview, we refer to Bunte and Kliewer (2009). With regard to the issue to be investigated within this paper, solution approaches incorporating limited lengths of vehicle rotations are especially relevant. Desrosiers et al. (1995) and Haghani and

Banihashemi (2002) extend the basic VSP by restricting the lengths and durations of the vehicle rotations. Therefore, they add constraints to the problem formulation that restrict fuel consumption. The possibility of recharging a vehicle battery at charging stations is not considered, though. A closer monitoring of any of the characterized technical aspects was dispensed with. The authors present an exact and two heuristic solution methods. In order to solve even larger-scale instances, they develop techniques for decreasing the problem size.

Chao and Xiaohong (2013) take into account the possibility of swapping a vehicle battery at specific stop points besides the restricted travel times of BEBs. The replacement is carried out within a constant time frame. After the removal, a fully charged battery is inserted. An approach based on a Non-dominated Sorting Genetic Algorithm (NSGA-II) is presented for solving the problem. The solution method is being analyzed using real data taken from a project in Shanghai.

Li (2014) proposes a model with either battery swapping or fast charging. Both options are performed within constant time frames; however, the time for fast charging depends on the stop point. The solution approach is based on column generation. The vehicle batteries are always fully charged.

Reuer et al. (2015) extend the traditional VSP by considering a mixed fleet of vehicles consisting of battery buses and traditional buses without range restrictions. To solve the problem, the authors use a time-space network based exact solution method for the VSP as introduced by Kliewer et al. (2006). As solutions to this problem comprise optimal flow values through the network, strategies for flow decomposition are necessary, in order to obtain vehicle rotations enabling additional degrees of freedom while generating multiple, all cost-minimal, vehicle rotations. Therefore, they develop strategies for flow decomposition which aim at maximizing the proportion of feasible vehicle rotations for BEBs. Constant time windows are assumed for charging the vehicle batteries in a very simplifying way.

Adler and Mirchandani (2016) present a column generation approach to the E-VSP incorporating both limited ranges and charging procedures at charging stations. The charging procedures are also greatly simplified, they are carried out in constant time, and the vehicle batteries are always charged to full capacity. To obtain initial solutions, a heuristic algorithm is proposed, which generates vehicle rotations according to a greedy algorithm with respect to range limitations and recharging. An incorporation of additional electric issues such predictions of energy consumptions or the discharging process of batteries was not made.

Kooten Niekerk et al. (2017) develop a column generation approach, first incorporating partial chargings. Charging is assumed to be performed in linear time depending on the SoC. In addition, battery aging effects are incorporated by means of exponential modeling and costs for charging are assumed to be time-dependent. Due to runtime reasons, the charging procedures are, however, approximated by using discrete scenarios.

In summary, some first approaches exist that address the E-VSP. However, the question remains how assumptions made about technical aspects of BEBs effect the cost-efficiency, feasibility, and practicability of resulting vehicle rotations. Within this paper, we investigate the aspect of charging vehicle batteries within the scope of the E-VSP by proposing more precise models for the charging process and experimentally quantifying their impacts on solutions.

## 4.3 Problem Description and Cost Model

In this section, we derive a formal model of the E-VSP. We consider a road network given by a set $S = \{s_1, \ldots, s_n\}$ of $n \in \mathbb{N}$ stop points including the set of depots $D \subseteq S$. The service trips to be assigned are given by a set $T = \{t_1, ..., t_m\}$ with $m \in \mathbb{N}$. Each service trip $t \in T$ is identified precisely by its departure time, arrival time, departure stop, and arrival stop. The distances and travel times between any two stop points $a, b \in S$ are each given by a matrix. Distances and travel times may differ between service and deadhead trips. We seek to serve the set $T$ of service trips with a set of BEBs. BEBs are mainly characterized by their battery capacities, which denote the maximum amounts of energy that can be stored. In addition, there may be further vehicle properties like height, length or passenger capacity. An BEB can charge its battery at charging stations located within the road network. We assume that stop points of $S$ can serve exclusively as charging stations. Therefore, a stop point can be equipped with charging technology. The charging technology primarily determines the time required for the intake of energy, the *charging time*. This is due to the current, which may differ between different charging technologies. We assume that charging procedures and deadhead trips start immediately on arrival at a stop point, without buffer times. Possible turning times at final stops and changeover times at charging stations are assumed to be already part of previous trips.

The use of an BEB incurs fixed costs $c^{bus}_{fix} > 0$ independently of its rotation. A vehicle rotation may consist of deadhead trips, service trips, and charging procedures, each causing operational costs. We assume that an BEB causes costs per hour of operation $c^{bus}_{hour} > 0$ in order to reflect the drivers' wages. To take into account maintenance and wear of the buses as well as energy consumption, we assume costs $c^{bus}_{km} > 0$ per kilometer driven. Since energy costs may depend on external factors like the time of the day or the utilization of the energy grid, this parameter can be time-dependent. The overall objective of the E-VSP is to minimize the total costs for operating given timetabled service trips. This implies the minimization of fixed costs for buses used and costs for the operation of the buses. The total costs $c^{total} \geq 0$ of a given solution for the E-VSP containing a set $V$ of buses used and sets $T_v$ each containing the set of trips that a bus $v \in V$ executes can be specified by

$$c^{total} = \underbrace{\sum_{v \in V} c^{bus}_{fix}}_{vehicle\ costs} + \underbrace{\sum_{v \in V} \sum_{t \in T_v} \left( c^{bus}_{hour} \cdot d(t) + c^{bus}_{km} \cdot l(t) \right)}_{operational\ costs}.$$

Here, $d(t) \geq 0$ denotes the duration and $l(t) \geq 0$ the length of a vehicle's trip. In this paper, we assume a given, fixed charging infrastructure. Hence, the set of charging stations is given in advance and is not included in the total costs.

## 4.4 Solution Method

We now introduce the solution method that we use within our computational study to solve the E-VSP. As the VSP with route and time constraints is NP-hard (cf. Haghani and Banihashemi, 2002), the E-VSP is NP-hard as well because it is an extension of the basic problem. Due to the great complexity and in order to be able to solve also real-world instances with extremely large road networks and timetables as well, especially when taking partial charging into account, we first adapt a heuristic solution method from Adler and Mirchandani (2016). Afterwards, we present a backtracking-algorithm for the incorporation of partial charging procedures within the solution method. Within our computational study we consider the single-depot E-VSP, which is why the following solution method works for a unique depot. However, the algorithms can be easily adapted to multiple depots.

### 4.4.1 Basic Heuristic Solution Method for the E-VSP

Algorithm `ConstructVS` shows the procedure, which is principally based on a concurrent greedy algorithm. The basic procedure is to assign service trips consecutively to the set of BEBs already used with respect to limited ranges and the option to charge a vehicle battery at charging stations. The set $T$ of timetabled service trips to be assigned, listed by their departure times in ascending order and a set $C \subseteq S$ of charging stations distributed within the road network serve as the input.

The algorithm is initialized by an empty set $V$ of vehicle rotations. Then, a new vehicle rotation is constructed that only contains the first service trip $t_1 \in T$ together with the necessary deadhead trips from the depot to the departure stop of $t_1$ and from the arrival stop of $t_1$ to the depot (line 1). It is assumed that this kind of vehicle rotation is always feasible because otherwise the entire optimization problem is infeasible. After initialization, the remaining service trips of $T$ are processed successively (line 2). For each service trip $t$ the subset $V_u \subseteq V$ of vehicles already used is determined, which are able to execute $t$ (ine 3). Therefore, the nearest charging station from the arrival stop of $t$ is determined (line 4). Then, each vehicle already used is considered successively (line 5). For each vehicle, we check whether $t$ is compatible in terms of temporal restrictions (line 6). If this is not the case, the next vehicle is considered. If temporal restrictions are not violated, we check whether the SoC is sufficient for executing $t$ and performing a potentially necessary deadhead trip from the arrival stop of $t$ to the nearest charging station (line 7). This is to ensure the feasibility of all vehicle rotations. If these trips can be performed by the current vehicle it is added to $V_u$ (line 8). If this is not the case, we check whether there is enough time to performe a charging procedure at the nearest charging station to the current vehicle's latest position with the potentially necessary deadhead trips (line 9). This procedure is feasible with regard to the SoC due to the previous condition. Amounts of energy that may be charged by opportunity charging during the execution of $t$ are considered. If the current vehicle rotation remains feasible in terms of time despite this detour, the vehicle is added to $V_u$ (line 10). After processing each vehicle already used, the current service trip $t$ is assigned to the vehicle that causes the smallest increase in operational costs arising from the assignment (line 17 & line 18). Amounts of energy charged by opportunity charging are added (line 19). If there is no vehicle able to execute $t$ (line 14), a new vehicle rotation is added to $V$. It contains $t$ together with the necessary deadhead trips from and to the depot. The algorithm terminates when all service trips have been processed and the set of vehicle rotations is returned. Note that algorithm `ConstructVS` always provides feasible solutions due to the previous assumption made about the feasibility of vehicle rotations containing only a single service trip.

**Algorithm 1** Computing a feasible Vehicle Schedule for BEBs (`ConstructVS`) (according to Adler and Mirchandani, 2016)

**Input:** service trips $T = \{t_1, t_2, \dots, t_n\}$ by ascending departure times, charging stations $C$
**Output:** feasible vehicle rotations $V = \{v_1, v_2, ...\}$.

1: $v_1 \leftarrow \{t_1\}$, $V \leftarrow \{v_1\}$;
2: **for** $i \leftarrow 2$ **to** $n$ **do**
3: $\quad V_u \leftarrow \emptyset$;
4: $\quad$ Determine the nearest charging station $c \in C$ from the arrival stop of $t_i$;
5: $\quad$ **for all** $v \in V$ **do**
6: $\quad\quad$ **if** $v$ is compatible with $t_i$ **then**
7: $\quad\quad\quad$ **if** SoC is sufficient to execute $t_i$ and perform a deadhead trip after $t_i$ to $c$ **then**
8: $\quad\quad\quad\quad V_u \leftarrow V_u \cup \{v\}$;
9: $\quad\quad\quad$ **else if** There is enough time for deadhead trips and charging before $t_i$ **then**
10: $\quad\quad\quad\quad V_u \leftarrow V_u \cup \{v\}$;
11: $\quad\quad\quad$ **end if**
12: $\quad\quad$ **end if**
13: $\quad$ **end for**
14: $\quad$ **if** $V_u = \emptyset$ **then**
15: $\quad\quad v \leftarrow \{t_i\}$, $V \leftarrow V \cup \{v\}$;
16: $\quad$ **else**
17: $\quad\quad$ Select $v \in V_u$ causing minimum additional costs when assigning $t_i$ to $v$;
18: $\quad\quad$ Assign $t_i$ to $v$ with necessary deadhead trips and charging procedure;
19: $\quad\quad$ Add corresponding amounts of energy charged at intermediate stops during the execu-
20: $\quad\quad$ tion of $t_i$;
21: $\quad$ **end if**
22: **end for**
23: **return** $V$;

## 4.4.2 Incorporation of Partial Charging Procedures

Within our computational study, we consider both complete and partial chargings of the vehicle batteries. In the first case, a battery is always fully charged. In the latter case, however, partial energy intakes are allowed, depending on conditions given by the vehicle rotations such as, for example, waiting times between successive service trips. So far, full chargings can be implemented within algorithm `ConstructVS` (line 9 & line 18) without modifying the procedure. In this case, the waiting time at a charging station is determined by the SoC of the vehicle on arrival. However, the incorporation of partial chargings requires more algorithmic effort because the decision when and to what extent to charge a battery is very complex. To determine whether a vehicle rotation remains feasible after the assignment of a service trip considering partial chargings, we extend the present procedure of algorithm `ConstructVS` by considering the following cases: First, if the range restriction of a vehicle is not violated after assigning a service trip (line 7), the procedure remains unchanged. Second, if a charging procedure is needed, we check whether at least the amount of energy required to execute the current service trip and a possibly necessary deadhead trip from the arrival stop to the nearest charging station can be charged before executing the current service trip. If this is the case, the current vehicle is added to the set $V_u$ of vehicles able to execute the service trip. Lastly, if the previous procedure does not lead to a feasible vehicle rotation we use the subsequent recursive algorithm `AddPC`, which is based on backtracking. The algorithm either returns the set of partial chargings that are needed within a vehicle rotation or indicates its infeasibility.

The basic procedure is to check iteratively, for the current and each already assigned service trip, whether a detour from the respective arrival stop to the nearest charging station is possible with regard to temporal restrictions. Each feasible detour is saved as a charging possibility. Charging procedures already established are not considered. If no charging possibilities exist, the algorithm returns the infeasibility of the vehicle rotation and the next vehicle is processed within algorithm `AddPC`. Among all charging possibilities found, the one that enables the greatest energy intake is selected. The intention of this procedure is to reduce the number of chargings and so minimize the operational costs. If the remaining vehicle rotation after inserting the charging procedure is feasible, the algorithm returns the vehicle rotation, all partial charging procedures, and its feasibility. Within this step, at the charging possibility the vehicle rotation is split into two subsequences containing the previous and subsequent trips. Then, the algorithm is applied to each subsequence with which it is recursive. If the remaining rotation is infeasible, the current charging possibility is removed and the next best one is considered. As this procedure processes already assigned service trips, the vehicle rotations may change after each application of the Algorithm.

**Algorithm 2** Adding Partial Charging Procedures to Vehicle Rotations (`AddPC`)

**Input:** vehicle rotation $v = \{t_1, \ldots, t_n\}$, charging stations $C$
**Output:** vehicle rotation $v$, decision whether $v$ is feasible or not

1: $P \leftarrow \emptyset$
2: **for** $i \leftarrow n$ **to** 1 **do**
3:     **if** Charging can be performed after $t_i$ and is not already done **then**
4:         Add charging possibility to $P$;
5:     **end if**
6: **end for**
7: **if** $P = \emptyset$ **then**
8:     **return** $v$, **false**;
9: **end if**
10: Insert charging procedure with the greatest energy intake into $v$;
11: **if** Remaining vehicle rotation is feasible **then**
12:     **return** $v$, **true**;
13: **else**
14:     Remove charging procedure from $P$;
15:     Go to 7;
16: **end if**

As in the original procedure of algorithm `ConstructVS`, the current service trip is assigned to the vehicle causing the smallest increase in operational costs arising from the assignment (line 17 & line 18).

So far, we have specified when and to what extent a vehicle battery should be charged. Within the following section, we discuss the functionality of charging processes. This allows us to model charging procedures within the E-VSP precisely.

## 4.5 Modeling the Charging Process

In the following, we derive formal models for the charging process of vehicle batteries. When a vehicle arrives at a charging station in order to charge its battery, the required waiting time is influenced by several factors. Besides the SoC and the extent to which a battery should be charged, there are additional factors such as the condition of the battery, the charging technology used, and weather conditions that have to be considered (cf. Wu and Niu, 2017). In the following the extent to which a battery is charged is denoted as the *target energy*, which is especially required when considering partial chargings. In order to incorporate a variety of influencing factors, we assume a set of countable many factors $X_1, \ldots, X_n$ with $n \in \mathbb{N}$ and an arbitrary charging function

$$F : X_1 \times \cdots \times X_n \to \mathbb{N}, \tag{4.1}$$

that indicates the resulting charging time, for our purposes measured in minutes, depending on the specific input factors. The basic procedure of charging a battery is illustrated in a simplified form by Figure 4.2, where $a(v)$ denotes the arrival time of a vehicle, $d(v)$ the departure time after charging, and $F(x_1, \ldots, x_n)$ the charging time.

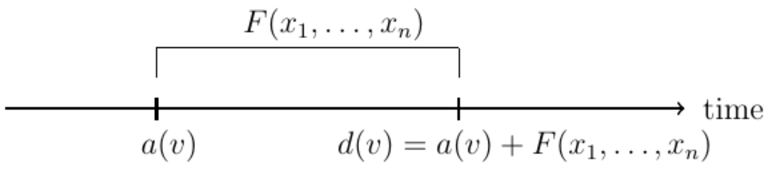


Figure 4.2: Temporal representation of an electric vehicle's charging process.

To represent the nonlinear profile of the current within the charging procedure CC/CV of lithium-ion-batteries, we assume a function

$$e\left(x_1, \ldots, x_n\right) : X_1 \times \cdots \times X_n \to \mathbb{R}_{\geq 0}, \tag{4.2}$$

which measures the amount of energy in kWh that can be fed into a battery per minute (kWh/min). For the following analysis, we focus on the SoC of a battery and disregard any additional influencing factors. Therefore, we denote the SoC as $c \in [0, c_{max}]$ with $c_{max} > 0$ representing the battery capacity and the target energy as $\beta \in [c, c_{max}]$. Since $\beta$ has no impact on the charging ratio, we obtain $X_1 = [0, c_{max}]$ and $X_2, \ldots, X_n = \emptyset$. Then, if a vehicle arrives at a charging station with a specific SoC $c$, the required charging time $F(c)$ in minutes for charging its battery to an extent $\beta$ is given implicitly by

$$\beta = c + \int_c^\alpha e(x)dx \tag{4.3}$$

with $\alpha \geq c$ and $F(c) = \lceil \alpha - c \rceil$. Depending on the shape of (2), the charging time $F(c)$ may be computed analytically or may need to be approximated if the integral of (3) is not computable or does not exist. In these cases, we use Newton-Cotes formulas for the representation of the integral and Newton's method for solving the equation (cf. Schwarz and Köckler, 2006).

As outlined above, the charging procedure CC/CV of lithium-ion-batteries comprises a linear and a nonlinear stage with regard to the current. To model this property, we propose three different types of functions that gradually better approach the actual profile of the current outlined in figure 4.1. Each function entails a case distinction for the two stages of CC/CV. First, we use a linear approximation of the second stage in the form of

$$e(x) = \begin{cases} a \cdot x + b & , lb \leq x \leq c_{max} \\ b & , otherwise \end{cases} \tag{4.4}$$

with $a < 0$, $b > 0$, and a lower bound $lb \in [0, c_{max}]$, which specifies the threshold when entering the second stage of CC/CV. After the first phase of charging with constant current $b$, the current decreases linearly by the term $a$ within this approximation. Thus, (4) can be considered as a strong simplification of the nonlinear charging profile. The parameters $a$ and $b$ must be chosen so that (4) always remains positive within its domain. With regard to existing literature presented in section 6.2, this kind of charging model is used within the work of Kooten Niekerk et al. (2017).

As a slightly enhanced charging model, we propose a logarithmical function for the second stage in the form of

$$e(x) = \begin{cases} a \cdot log(x) + b & , lb \leq x \leq c_{max} \\ b & , otherwise \end{cases} \tag{4.5}$$

with $a, b \in \mathbb{R}$, and a lower bound $lb \in [0, c_{max}]$ for the transition from the first to the second stage of CC/CV. This type of charging model enables a disproportionate decrease in the current within the second stage of CC/CV which is the most relevant difference compared to the linear approximation.

Lastly, we use an exponential function for representing the second stage of CC/CV. Hõimoja et al. (2012) develop and discuss a calculation method for representing the profile of the current during charging processes precisely considering modern fast charging systems. Based on real-world data, they identify that a realistic mapping of the decreasing current within the second stage of CC/CV can only be carried out by using exponential function models. However, as the presented calculation method is very difficult to solve analytically, we use an approximation within this paper. Based on the findings of Himoja et al., we consider the following charging function model as the most realistic one that best reflects the actual descent in the current.

$$e(x) = \begin{cases} a \cdot exp(x) + b & , lb \leq x \leq c_{max} \\ b & , otherwise \end{cases} \tag{4.6}$$

with $a, b \in \mathbb{R}$, and a lower bound $lb \in [0, c_{max}]$. The shapes of the derived charging function models are illustrated by figure 4.3, reflecting the actual profile of the current with regard to CC/CV given by figure 4.1 in the different ways.

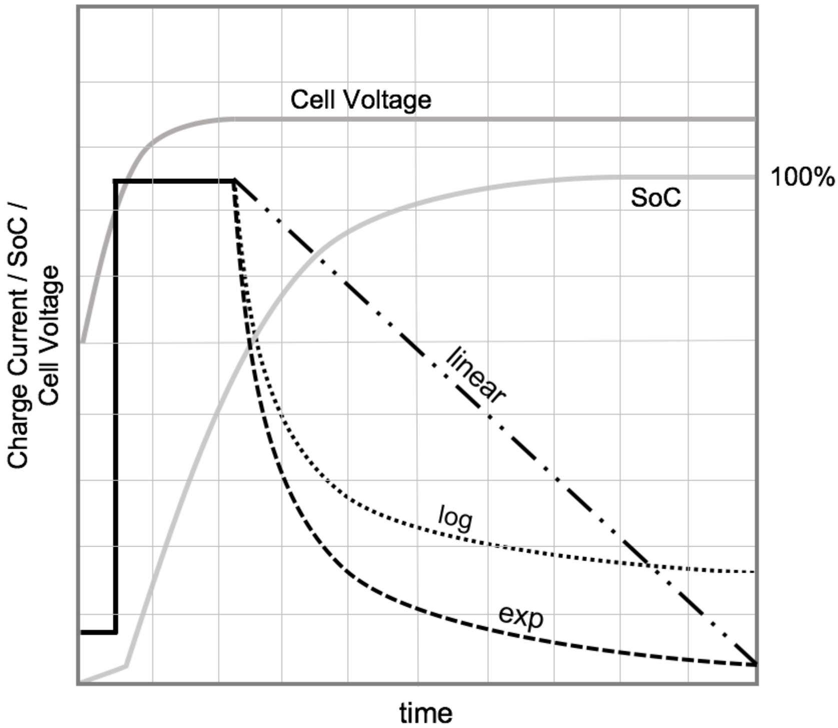


Figure 4.3: Schematic profiles of the derived charging function models with regard to CC/CV.

## 4.6 Computational Analysis

In this section, we present the results of our computational study. We start by introducing the instances to be solved and our experimental parameters. Afterwards, we specify precise models for the current during a charging process based on Section 4.5. Then, we look at the results of two major experiments to evaluate constant and linear charging times of BEBs with regard to the proposed nonlinear charging process of lithium-ion-batteries. For both experiments, we use the solution method introduced in Section 4.3. Within the first experiment described in Section 4.6.3, we evaluate constant time windows as waiting times of BEBs at charging stations with regard to the charging times effectively required. In this context, we analyze impacts on BEBs' cost-efficiency and practical operations. Within the second experiment, we investigate impacts of BEBs' assumed linear charging times on the feasibility of resulting vehicle rotations with respect to the nonlinear charging process. Here we differentiate specifically between complete and partial charging procedures.

### 4.6.1 Problem Instances and Parameter Settings

Within each experiment we solve five instances of the E-VSP that differ in the number of service trips, their distribution over the day, and numbers of stop points. The instances are based on real-world data from German public transport companies enriched with further parameters to address the use of BEBs, such as battery capacities and charging systems. The names of the instances contain the numbers of service trips and stop points. Figure 5.3 comprises the distribution of the amounts of simultaneously performed, timetabled service trips over the day for each instance. As can be observed, the distribution differs considerably from instances containing rather flat distributions to instances containing peak times during rush hours. Furthermore, the densities of the transport systems are different in respect to the numbers of stop points. Following these characteristics, the instances used cover the most popular patterns in public transport. Within the respective road networks, 5% of all stop points are equipped with charging technology and their distributions are sampled 20 times. Consequently, the following results comprise average values. The decision whether a stop point is equipped with charging technology or not is thus evenly distributed.

We now clarify the parameters of the E-VSP. For the purposes of this contribution we consider a single vehicle depot within the road network. Consequently, each vehicle in use begins and ends its rotation at the same depot. In addition, we assume a single charging system. This assumption implies that each vehicle used can be charged at every stop point that is equipped with charging technology. We assume the capacities of charging stations to be unlimited. As this assumption represents a broad generalization, especially with regard to highly frequented traffic hubs, we investigate this issue in greater detail within our study.

Nowadays, public transport companies may choose among different battery sizes according to the different ranges of the BEBs available. To reflect this aspect, we use battery capacities of 90, 300, and 500 kWh. We use these battery capacities to incorporate the current project *E-Bus Berlin* using BEBs storing 90 kWh, state-of-the-art buses such as the Proterra Catalyst Transit Vehicle storing 300 kWh, and future developments. It is expected that battery capacities will increase in the future. To incorporate battery degradation, we assume that the SoC of a battery ranges between 20% and 80% of a battery's capacity (cf. Jossen, 2005 and Pelletier et al., 2017). In the first experiment, we assume that a vehicle battery is always charged up to 80% of its capacity. In the second experiment, we also consider partial charging procedures as is mostly done within pilot projects.

In carrying out our computational study, we conduct the experiments for each battery capacity one after the other. Hence, we consider a homogeneous vehicle fleet at each run. For this it is assumed that each timetabled service trip can be executed by every available vehicle. Note that the findings generated within this paper can also be applied to heterogeneous vehicle fleets and to the multi-depot

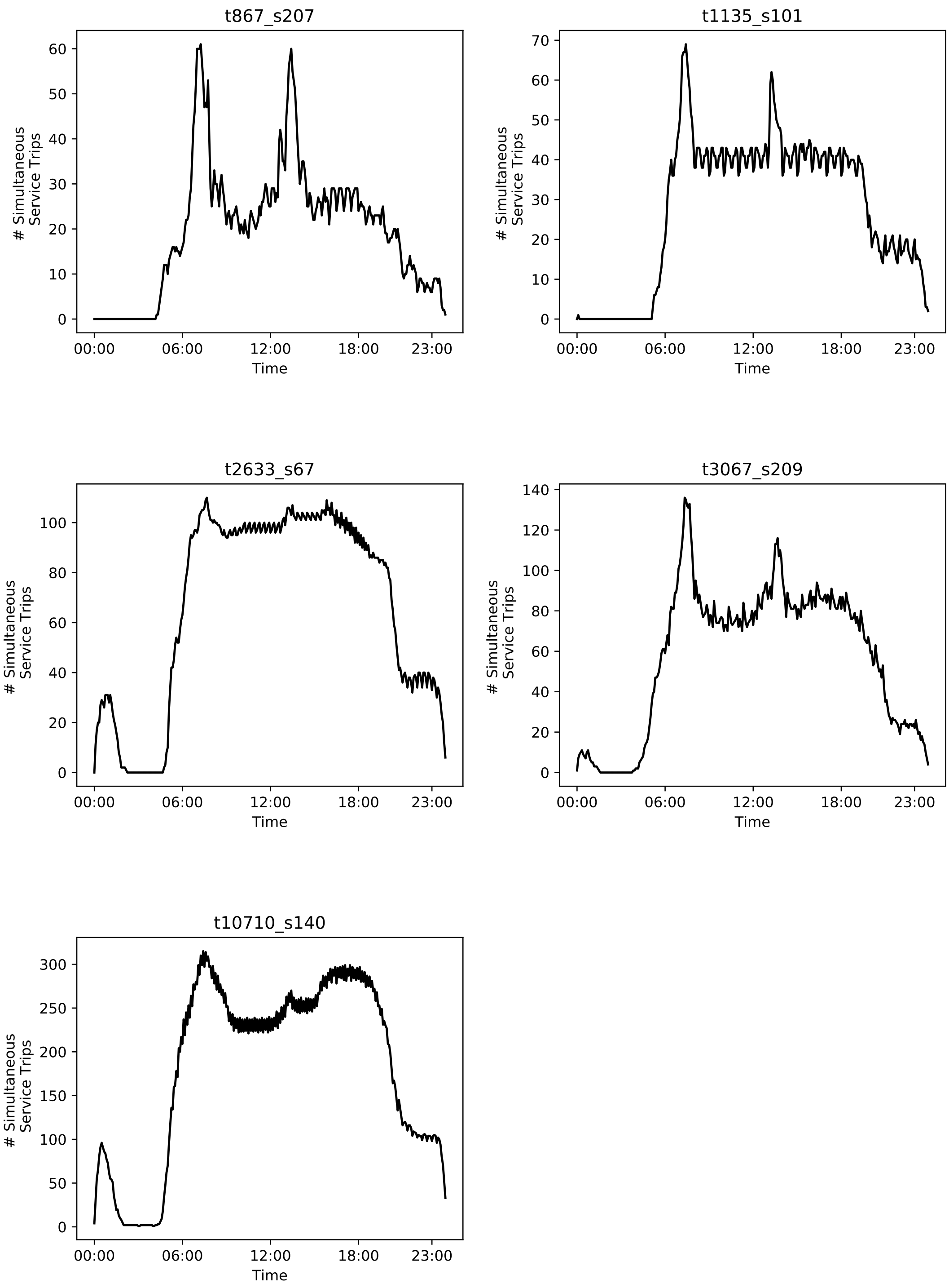


Figure 4.4: Distributions of timetabled service trips over the day for each instance to be solved.

E-VSP without loss of generality. In our experiments, a vehicle always leaves its depot with a fully charged battery due to overnight charging. Therefore, we assume a sufficiently large number of charging systems in the depot. To reflect an BEB's lower weight and consumption of an BEB when no passengers are being transported, we assume a consumption of 1.5 kWh per driven kilometer on a deadhead trip and 1.8 kWh per driven kilometer on a service trip, motivated by the technical data of the pilot project in Berlin. In our study we particularly consider chargings before the departure or after the arrival of service trips as well as opportunity chargings at intermediate stops. Opportunity chargings are determined by waiting times at the specific stops given by the timetable.

Within the subsequent study we use imputed costs measured in estimated cost units based on the particularly known relation of different cost components. To approximate fixed costs of vehicles in relation to operational costs we take into account the specifications presented in Pihlatie et al. (2014). Some sources explicitly state the currency units (e.g. USD in a study by *McKinsey & Company*[4] from 2017), others generally speak of "monetary units" (e.g. Chen et al., 2017). We assume here that the units are roughly comparable - at least in terms of scale - and on this basis, in combination with values known to us, we form a system of imputed cost components. Based on Pihlatie et al. (2014), an BEB in use, equipped with a 90-kWh battery, causes fixed costs of 355.000 cost units. According to the previously mentioned study by *McKinsey & Company*, the costs per kWh of a vehicle battery amount to approximately 230 USD. As a result, this leads to fixed costs for the other vehicles with a battery size of 300 and 500 kWh of 405.000 and 450.000 cost units. Depending on the trips of a vehicle rotation, operational costs arise consisting of 0.5 units per kilometer driven (exemplary energy costs) and 50 units per hour of driving (exemplary personnel and maintenance costs incurred in deploying the buses). Since the costs for charging a vehicle battery are already included within the operational costs, no additional costs arise for performing a charging procedure.

### 4.6.2 Charging Models

We now specify the charging models of our study. Within the project in Berlin, modern fast charging systems are used, providing a charging capacity of 200 kW with an efficiency of about 90% (cf. Laporte et al., 2019). This leads to an effective charging capacity of 180 kW. Within the first stage of CC/CV a battery is charged linearly up to a threshold of approximately 65% of the battery capacity, which is 58.5 kWh for a 90 kWh-battery. Consequently, charging a battery from 20% (18 kWh) up to 65% takes 13.5 minutes since (58.5 kWh - 18 kWh)/180 kW = 0.225

[4] https://www.mckinsey.com/business-functions/sustainability-and-resource-productivity/our-insights/battery-storage-the-next-disruptive-technology-in-the-power-sector [Online accessed on 26-January-2020]

h. To approximately meet the nonlinear profile of CC/CV after exceeding the 65%-threshold, we assume that charging from 65% up to 80% of the battery capacity takes twice as long as charging within the first phase. This leads to 27 minutes for a 90 kWh-battery. In total, charging from 20% to 80% takes 40.5 minutes, which we assume to be the constant charging time for our experiments. When we neglect the nonlinear second phase of CC/CV and assume a constant current during the entire charging process, we obtain 3 kW/min. In the following, we denote charging with a constant current as the linear charging time. A fast charging system is used for the operation of the Proterra Catalyst Transit bus equipped with a 300 kWh-battery, providing a charging capacity of 300 kW[5]. Following the previous explanations, this leads to 27 minutes needed for charging from 20% up to 65% of the battery capacity with 5 kW/min, which is again used for computing linear charging times. Doubling the charging time of the first phase of CC/CV for the second phase leads to a constant charging time of 81 minutes.

Following Pihlatie et al. (2014) and Pelletier et al. (2017), the higher the batteries' capacities are, the higher capacities of charging systems can be applied for charging, especially with regard to battery aging effects. As we consider future developments in this contribution, such as the 500 kWh-battery, and we do not have the technical data of this battery size, we use a linear approximation for the current and charging time. Table 4.1 provides an overview of the technical data of the batteries used within our study.

| **battery cap. (kWh)** | **65% thresh. (kWh)** | **charg. cap. (kW)** | **kW/min** | **charg. time 1st phase (min)** | **charg. time 2nd phase (min)** | **constant charg. time (min)** |
|---|---|---|---|---|---|---|
| 90 | 58.5 | 180 | 3 | 13.5 | 27 | 40.5 |
| 300 | 195 | 300 | 5 | 27 | 54 | 81 |
| 500 | 325 | 414 | 6.9 | 32.5 | 65 | 97.5 |

Table 4.1: Charging parameters for each battery size.

The technical data enables us to specify precise models for the current during a charging process for each battery size. Based on the charging function models introduced in Section 4.5, we fit the functions so that the charging times of the first and second phase given in Table 4.1 are reflected exactly. Table 4.2 contains the exact parameters for each function model and battery capacity. In the most realistic model where we use an exponential function, we divide the SoC by the 80% threshold of the respective battery capacity to obtain considerable values.

[5]https://www.proterra.com/wp-content/uploads/2019/08/Proterra-Catalyst-35-Ft-Bus-Spec-Sheet-CANADA.pdf [Online accessed on 21-September-2019]

| charging function model | battery cap. | lb | $c_{max}$ | a | b |
|---|---|---|---|---|---|
| $e(x) = \begin{cases} a \cdot x + b & , lb \leq x \leq c_{max} \\ b & , otherwise \end{cases}$ | 90 | 58.5 | 72 | -0.035 | 3 |
| | 300 | 195 | 240 | -0.009 | 5 |
| | 500 | 325 | 400 | -0.005 | 6.9 |
| $e(x) = \begin{cases} a \cdot log(x) + b & , lb \leq x \leq c_{max} \\ b & , otherwise \end{cases}$ | 90 | 58.5 | 72 | -0.585 | 3 |
| | 300 | 195 | 240 | -0.401 | 5 |
| | 500 | 325 | 400 | -0.314 | 6.9 |
| $e(x) = \begin{cases} a \cdot exp(\frac{x}{\alpha}) + b & , lb \leq x \leq c_{max} \\ b & , otherwise \end{cases}$ | 90 | 58.5 | 72 | -42.338 | 3 |
| | 300 | 195 | 240 | -134.900 | 5 |
| | 500 | 325 | 400 | -199.390 | 6.9 |

Table 4.2: Parameters for each charging function model and battery capacity.

### 4.6.3 Cost-Efficiency of Vehicle Rotations using Constant Charging Time Models

In this section, we present the results of the first experiment. At this point, we evaluate the assumption of constant charging times within the E-VSP with regard to the cost-efficiency of the resulting vehicle rotations. Therefore, we solve the instances of the E-VSP by algorithm `ConstructVS` using constant time windows as BEBs' waiting times at charging stations. However, we use the precise charging models introduced in the previous section for computing the charging times effectively required and compare the resulting vehicle rotations to the initial case. In this experiment, we specifically address different battery capacities. To consider opportunity charging, we use constant time windows for charging between subsequent service trips because waiting times at intermediate stops on service trips are determined by the timetable. Table 4.3 provides the average values of vehicles used, total and operational costs, and the effectively required charging times within generated vehicle rotations for each charging model and each battery capacity. For further analysis, the average maximum numbers of simultaneous charging procedures at a charging station are specified.

| instance | battery capacity | charging model | veh. used | tot. costs (mio) | operat. costs (mio) | charging time (min) | avg. max. sim. charg. |
|---|---|---|---|---|---|---|---|
| **t876_s207** | **90** | constant time | 95.2 | 35.71 | 1.91 | 40.5 | 5.8 |
| | | real. curr. | 83.8 | 31.93 | 2.18 | 27.36 | 4.2 |
| | | log. curr. | 82.4 | 31.43 | 2.18 | 23.82 | 4.1 |
| | | lin. curr. | 80.8 | 30.95 | 2.27 | 23.19 | 3.4 |
| | **300** | constant time | 80.4 | 34.18 | 1.62 | 81 | 4.2 |
| | | real. curr. | 78.3 | 33.52 | 1.81 | 57.34 | 3.6 |
| | | log. curr. | 75.8 | 32.59 | 1.89 | 51.18 | 3.4 |
| | | lin. curr. | 72.1 | 31.32 | 2.12 | 49.74 | 2.8 |
| | **500** | constant time | 73.6 | 34.66 | 1.54 | 97.5 | 3.8 |
| | | real. curr. | 71.9 | 34.07 | 1.71 | 61.74 | 3.2 |
| | | log. curr. | 70.4 | 33.46 | 1.78 | 55.63 | 2.7 |
| | | lin. curr. | 69.3 | 33.23 | 2.04 | 54.27 | 2.4 |
| **t1135_s101** | **90** | constant time | 110.8 | 42.15 | 2.82 | 40.5 | 6.2 |
| | | real. curr. | 95.1 | 37.08 | 3.32 | 27.308 | 5.8 |
| | | log. curr. | 91.4 | 34.73 | 3.28 | 25.422 | 5.6 |
| | | lin. curr. | 87.8 | 34.46 | 3.29 | 27.286 | 5.1 |
| | **300** | constant time | 86.3 | 37.38 | 2.43 | 81 | 5.6 |
| | | real. curr. | 84.7 | 37.08 | 2.78 | 58.28 | 5.1 |
| | | log. curr. | 81.8 | 36.07 | 2.94 | 54.92 | 4.8 |
| | | lin. curr. | 79.1 | 35.25 | 3.21 | 51.12 | 4.2 |
| | **500** | constant time | 78.9 | 37.82 | 2.31 | 97.5 | 4.7 |
| | | real. curr. | 77.8 | 37.73 | 2.72 | 62.04 | 4.1 |
| | | log. curr. | 76.2 | 37.10 | 2.81 | 59.81 | 3.8 |
| | | lin. curr. | 75.1 | 36.96 | 3.16 | 60.43 | 3.5 |
| **t2633_s67** | **90** | constant time | 191.2 | 75.61 | 7.73 | 40.5 | 6.7 |
| | | real. curr. | 183.2 | 73.59 | 8.55 | 32.108 | 6.1 |
| | | log. curr. | 176.6 | 71.55 | 8.86 | 25.13 | 5.7 |
| | | lin. curr. | 173.4 | 70.87 | 9.31 | 23.598 | 5.5 |
| | **300** | constant time | 153.7 | 69.08 | 6.83 | 81 | 6.2 |
| | | real. curr. | 144.8 | 65.82 | 7.18 | 57.57 | 5.7 |
| | | log. curr. | 136.2 | 62.50 | 7.34 | 53.49 | 5.2 |
| | | lin. curr. | 131.9 | 61.58 | 8.16 | 51.91 | 4.8 |
| | **500** | constant time | 138.6 | 68.60 | 6.23 | 97.5 | 5.6 |
| | | real. curr. | 131.7 | 66.08 | 6.81 | 63.41 | 5.1 |
| | | log. curr. | 128.1 | 64.62 | 6.97 | 61.78 | 4.3 |
| | | lin. curr. | 126.6 | 64.11 | 7.14 | 60.07 | 3.9 |
| **t3067_s209** | **90** | constant time | 225.8 | 86.43 | 6.27 | 40.5 | 6.2 |
| | | real. curr. | 204.2 | 80.58 | 8.09 | 27.052 | 5.7 |
| | | log. curr. | 199.8 | 79.08 | 8.15 | 25.288 | 5.2 |
| | | lin. curr. | 197.4 | 78.31 | 8.23 | 25.276 | 4.5 |
| | **300** | constant time | 207.3 | 89.80 | 5.84 | 81 | 5.8 |
| | | real. curr. | 189.6 | 83.22 | 6.43 | 58.81 | 5.1 |
| | | log. curr. | 176.1 | 77.93 | 6.61 | 53.49 | 4.7 |
| | | lin. curr. | 170.3 | 76.40 | 7.43 | 52.27 | 4.1 |
| | **500** | constant time | 197.8 | 94.22 | 5.21 | 97.5 | 4.6 |
| | | real. curr. | 184.4 | 88.72 | 5.74 | 64.71 | 4.1 |
| | | log. curr. | 171.7 | 83.23 | 5.96 | 63.29 | 3.5 |
| | | lin. curr. | 166.8 | 81.55 | 6.49 | 61.83 | 2.8 |
| **t10710_s140** | **90** | constant time | 448.3 | 173.02 | 13.87 | 40.5 | 7.4 |
| | | real. curr. | 426.1 | 165.75 | 14.48 | 28.07 | 6.1 |
| | | log. curr. | 401.5 | 157.72 | 15.19 | 27.31 | 5.7 |
| | | lin. curr. | 382.7 | 153.35 | 17.49 | 26.98 | 5.6 |
| | **300** | constant time | 411.9 | 178.98 | 12.16 | 81 | 6.5 |
| | | real. curr. | 398.1 | 174.70 | 13.47 | 59.78 | 5.7 |
| | | log. curr. | 379.3 | 167.60 | 13.98 | 52.91 | 5.4 |
| | | lin. curr. | 364.5 | 163.09 | 15.47 | 51.46 | 5.1 |
| | **500** | constant time | 391.8 | 188.05 | 11.74 | 97.5 | 4.3 |
| | | real. curr. | 379.6 | 183.10 | 12.28 | 66.86 | 3.8 |
| | | log. curr. | 366.2 | 177.73 | 12.94 | 65.31 | 3.2 |
| | | lin. curr. | 357.8 | 175.19 | 14.18 | 46.29 | 2.1 |

Table 4.3: Average values of vehicles used, total and operational costs, charging

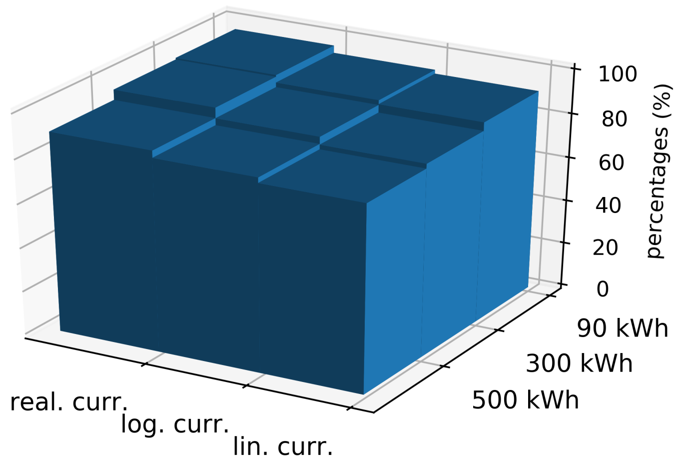


Figure 4.5: Average percentages of vehicles needed over all instances by comparison to constant charging times for each battery capacity and charging function model.

In the table, we see that the total costs of generated solutions for the E-VSP when using constant charging times are significantly higher than in those cases where more accurate models are considered. This holds true for all instances and battery capacities. The cost increases are mainly caused by the higher numbers of vehicles used, which in turn results from overestimated waiting times at charging stations. Because constant time frames for charging do not consider the batteries' residual energies, vehicles remain idle at charging stations although their charging process has actually ended. This is mainly based on the first stage of CC/CV within which vehicles are charged in linear time depending on their SoC. This aspect is reinforced by the omitted possibility of partial charging when using constant charging times. The temporal differences between assumed and actually required charging times lead to unused time frames, which cause higher demands for vehicles because subsequent connections may be missed. Among the different instances and battery sizes, we see that the more vehicles are needed, the higher is the additional demand for vehicles when using constant charging times compared to the precise models. For example, within instance t876_s207 and a 90 kWh-battery, the average difference between the use of constant charging times and a realistic modeling is 11.4, while the average difference within instance t10710_s140 and a 90 kWh-battery is 22.2.

Due to the higher numbers of vehicles used, the operational costs are lower when using constant charging times compared to any other charging model. This observation can be justified by fewer charging procedures and deadhead trips needed within the vehicle rotations, as each vehicle executes fewer trips on average. As the savings in operational costs are well below the increase in costs for additional vehicles, solutions entail significantly higher total costs when using constant charging times.

Regarding the linear, logarithmic and realistic charging model, we see that the more precisely the nonlinear charging process of CC/CV is represented, the more vehicles are needed. This can be observed for all instances and battery capacities, mainly resulting from the shape of the proposed models. The linear charging model does not consider the nonlinear coherence between the SoC and the current after exceeding the 65%-threshold, as it approximates this connection in a linear way. Consequently, the assumed amounts of charged energy generally exceed the actual amounts. This leads to shorter waiting times at charging stations and to less vehicles in use by comparison to more precise models. In contrast, the charging models based on a logarithmical, respectively realistic function both enable a disproportionate modeling of the current within the second stage of CC/CV, which leads to higher vehicle demands. However, the logarithmical function still overestimates the actual profile when getting closer to the 80%-threshold of the SoC, caused by its significantly flatter tail compared to the realistic model using an exponential function. This explains the additional need for vehicles when using the realistic charging model. However, the use of a realistic model still leads to considerably fewer vehicles needed compared to the use of constant charging times. Figure 4.5 illustrates this observation by containing averages percentages of vehicles needed overall all instances by comparison to constant charging times for each battery capacity and charging function model. In practice, it may be the case that realiatic models cannot be calculated analytically. Following Figure 4.5, at least an approximation based on logarithmical functions should be incorporated.

Another important aspect that is closely linked to charging procedures is their implementation in practice. It is particularly important that the numbers of simultaneous charging procedures at each charging station within the road network remain within a reasonable range because building sites for charging systems are usually restricted. This is particularly true for densely built urban areas. To investigate this issue, the average maximum numbers of simultaneous chargings at a single charging station are specified for all instances, charging models, and battery capacities in the last column of Table 4.3. Across all instances and battery capacities, we see that the maximum numbers of simultaneous chargings are always higher when using constant charging times compared to any other charging model. For example, within instance t876_s207 a maximum of 5.8 simultaneous chargings on average are performed when using constant charging times, and the use of the realistic model already achieves a significantly lower maximum number of 4.2 chargings at the same time and location. Again, this can be justified by the longer idle times of the vehicles used at charging stations. The assumption of constant charging times thus also leads to problems in the practical operation of BEBs, as the number of charging systems available at each charging station is generally restricted. With a view to the different battery capacities, we can conclude that all statements made hold true, independent of the specific capacity. However, the impacts of the effects detected on solutions to the E-VSP are less serious when the battery capacities grow because less charging procedures are needed within the vehicle rotations. However, since the 500 kWh-battery in particular can be considered as a future development in the scope of battery technology and does not yet exist, the issues described will certainly not be overcome in the foreseeable future.

In conclusion, constant charging times of BEBs overestimate the time windows actually required for charging and lead to unused waiting times at charging stations, causing higher demands for vehicles and thus higher total costs. This follows from the fact that constant charging times do not consider a battery's SoC when starting a charging process and do not provide any conclusions about the time windows actually required for charging. According to these findings, optimization potentials for vehicle scheduling of BEBs enabled by partial charging remain largely untapped. Furthermore, additional problems arise for the practical implementation of BEBs, since higher numbers of simultaneous chargings at the same location are achieved when using constant charging times.

### 4.6.4 Feasibility of Vehicle Rotations using Linear Charging Time Models

We now discuss the results of the second experiment. We evaluate the assumption of linear charging times within the E-VSP with regard to the feasibility of the vehicle rotations generated. Therefore, we again solve the instances of the E-VSP using algorithm `ConstructVS` but now using linear time windows for the charging of BEBs at charging stations. Simultaneously, we compute the amounts of energy being effectively charged using the proposed precise charging models. Then, we analyze whether range restrictions within computed vehicle rotations are violated, especially considering different battery sizes. Following Section 6.1, a vehicle rotation is termed feasible if all restrictions of the E-VSP are satisfied, in particular range restrictions. Linear time windows for charging assume a constant current during the entire charging process, independently of a battery's SoC. It is assumed that the second stage of CC/CV is similar to the first. In this experiment, we incorporate opportunity charging at intermediate stops on service trips as well as chargings at terminal stops between two successive service trips. Here, we specifically analyze the impact of considering partial charging procedures among complete chargings on resulting vehicle rotations. To incorporate partial chargings, we use algorithm `AddPC` within the solution procedure. Table 4.4 shows average percentages of feasible vehicle rotations and average amounts of energy being charged for each instance, battery capacity, and charging model in both complete and partial charging procedures.

| instance | battery capacity | charging model | complete chargings | | | partial chargings | | |
|---|---|---|---|---|---|---|---|---|
| | | | feas. veh. rotation | charging time (min) | energy charged | feas. veh. rotation | charging time (min) | energy charged |
| **t876_s207** | **90** | linear time | - | 15.24 | 45.72 kWh | - | 11.46 | 34.38 kWh |
| | | real. curr. | 53.23% | - | 23.79 kWh | 66.74% | - | 19.87 kWh |
| | | log. curr. | 57.42% | - | 25.89 kWh | 72.81% | - | 21.43 kWh |
| | | lin. curr. | 80.19% | - | 27.14 kWh | 86.12% | - | 24.91 kWh |
| | **300** | linear time | - | 32.46 | 162.3 kWh | - | 27.43 | 137.15 kWh |
| | | real. curr. | 61.73% | - | 101.12 kWh | 72.37% | - | 93.46 kWh |
| | | log. curr. | 67.14% | - | 104.75 kWh | 79.81% | - | 97.81 kWh |
| | | lin. curr. | 69.92% | - | 106.31 kWh | 82.75% | - | 102.43 kWh |
| | **500** | linear time | - | 40.81 | 281.59 kWh | - | 36.09 | 249.02 kWh |
| | | real. curr. | 75.69% | - | 212.75 kWh | 93.76% | - | 193.57 kWh |
| | | log. curr. | 83.76% | - | 218.63 kWh | 96.17% | - | 202.43 kWh |
| | | lin. curr. | 85.12% | - | 202.01 kWh | 97.83% | - | 204.16 kWh |
| **t1135_s101** | **90** | linear time | - | 15.49 | 46.47 kWh | - | 10.41 | 31.23 kWh |
| | | real. curr. | 42.95% | - | 26.21 kWh | 48.17% | - | 21.76 kWh |
| | | log. curr. | 48.91% | - | 30.97 kWh | 61.43% | - | 23.87 kWh |
| | | lin. curr. | 70.43% | - | 31.67 kWh | 85.96% | - | 26.48 kWh |
| | **300** | linear time | - | 33.81 | 169.05 kWh | - | 25.14 | 125.7 kWh |
| | | real. curr. | 53.36% | - | 90.74 kWh | 61.43% | - | 78.61 kWh |
| | | log. curr. | 59.82% | - | 93.81 kWh | 69.71% | - | 82.14 kWh |
| | | lin. curr. | 64.79% | - | 97.18 kWh | 78.46% | - | 84.51 kWh |
| | **500** | linear time | - | 41.46 | 286.07 kWh | - | 32.16 | 221.91 kWh |
| | | real. curr. | 68.74% | - | 188.43 kWh | 79.43% | - | 157.33 kWh |
| | | log. curr. | 72.19% | - | 191.56 kWh | 84.71% | - | 165.27 kWh |
| | | lin. curr. | 74.57% | - | 193.16 kWh | 87.91% | - | 171.49 kWh |
| **t2633_s67** | **90** | linear time | - | 14.12 | 42.35kWh | - | 9.76 | 29.28 kWh |
| | | real. curr. | 12.04% | - | 29.91 kWh | 28.76% | - | 23.41 kWh |
| | | log. curr. | 30.41% | - | 32.34 kWh | 51.64% | - | 24.86 kWh |
| | | lin. curr. | 40.73% | - | 33.16 kWh | 64.81% | - | 25.81 kWh |
| | **300** | linear time | - | 31.46 | 157.3 kWh | - | 23.95 | 119.75 kWh |
| | | real. curr. | 33.46% | - | 62.12 kWh | 47.16% | - | 49.57 kWh |
| | | log. curr. | 43.81% | - | 74.84 kWh | 59.87% | - | 57.43 kWh |
| | | lin. curr. | 45.93% | - | 76.91 kWh | 67.14% | - | 59.88 kWh |
| | **500** | linear time | - | 39.35 | 271.52 kWh | - | 30.71 | 211.9 kWh |
| | | real. curr. | 57.18% | - | 186.73 kWh | 67.13% | - | 134.17 kWh |
| | | log. curr. | 66.14% | - | 192.81 kWh | 75.87% | - | 141.87 kWh |
| | | lin. curr. | 68.39% | - | 197.43 kWh | 82.14% | - | 153.47 kWh |
| **t3067_s209** | **90** | linear time | - | 13.01 | 39.03 kWh | - | 8.13 | 24.39 kWh |
| | | real. curr. | 37.91% | - | 24.55 kWh | 57.91% | - | 17.43 kWh |
| | | log. curr. | 43.07% | - | 28.21 kWh | 67.01% | - | 20.14 kWh |
| | | lin. curr. | 47.38% | - | 28.67 kWh | 72.13% | - | 22.07 kWh |
| | **300** | linear time | - | 30.18 | 150.9 kWh | - | 21.94 | 109.7 kWh |
| | | real. curr. | 51.48% | - | 78.41 kWh | 72.57% | - | 62.14 kWh |
| | | log. curr. | 57.23% | - | 84.68 kWh | 84.57% | - | 71.99 kWh |
| | | lin. curr. | 59.12% | - | 89.41 kWh | 86.31% | - | 73.41 kWh |
| | **500** | linear time | - | 38.71 | 267.1 kWh | - | 29.76 | 205.34 kWh |
| | | real. curr. | 78.45% | - | 210.41 kWh | 84.27% | - | 157.98 kWh |
| | | log. curr. | 83.54% | - | 221.68 kWh | 91.26% | - | 166.12 kWh |
| | | lin. curr. | 84.39% | - | 224.12 kWh | 93.46% | - | 181.46 kWh |
| **t10710_s140** | **90** | linear time | - | 12.74 | 38.22 kWh | - | 7.81 | 23.43 kWh |
| | | real. curr. | 22.93% | - | 10.14 kWh | 31.94% | - | 8.71 kWh |
| | | log. curr. | 28.47% | - | 14.98 kWh | 39.71% | - | 11.38 kWh |
| | | lin. curr. | 30.01% | - | 17.43 kWh | 41.23% | - | 13.46 kWh |
| | **300** | linear time | - | 28.74 | 143.7 kWh | - | 20.39 | 101.95 kWh |
| | | real. curr. | 33.46% | - | 51.07 kWh | 47.65% | - | 43.96 kWh |
| | | log. curr. | 39.64% | - | 50.71 kWh | 54.41% | - | 45.14 kWh |
| | | lin. curr. | 40.01% | - | 52.17 kWh | 56.09% | - | 47.88 kWh |
| | **500** | linear time | - | 36.91 | 254.68 kWh | - | 27.88 | 192.37 kWh |
| | | real. curr. | 49.75% | - | 128.04 kWh | 63.81% | - | 74.53 kWh |
| | | log. curr. | 54.71% | - | 137.53 kWh | 78.03% | - | 81.46 kWh |
| | | lin. curr. | 56.19% | - | 141.09 kWh | 80.41% | - | 84.01 kWh |

Table 4.4: Average percentages of feasible vehicle rotations and average amounts of energy being charged for each instance, battery capacity, and charging model for both complete and partial charging procedures.

Looking at the detailed results, we see that the feasibility of generated vehicle rotations for each instance and battery capacity is violated independently of the charging model used. This is because linear time windows for charging generally underestimate the charging times actually required as they do not consider the nonlinear profile of the current during the second phase of CC/CV. As a consequence, lower amounts of energy than originally planned are charged during the vehicle rotations when considering more realistic models for charging. These gaps occur within charging procedures at terminal stops as well as at intermediate stops. Further on, we can conclude that the proportion of infeasible vehicle rotations in relation to their total numbers increase when approximating the actual nonlinear profile of the current more precisely with the proposed charging models. This is because a consideration of more realistic models leads to less amounts of energy effectively charged compared to planned amounts of energy computed under the assumption of linear time windows. The gaps between the actual and the planned amounts of energy being charged mainly result from the fact that the disproportionate decrease in the current within the second phase of CC/CV is reflected within nonlinear models. However, linear time windows for charging do not consider this crucial aspect. The better the actual profile of the current is reflected, the less energy is actually charged within a specific time window. Consequently, the proportion of infeasible vehicle rotations increases when considering charging models that approximate the actual nonlinear profile of the current more closely. This effect is being intensified by opportunity chargings at intermediate stops during a service trip when the SoC of a battery is higher than the 65%-threshold.

In regard to the different battery capacities, we see that the proportion of feasible vehicle rotations grows with increasing battery capacities. As longer ranges of BEBs given by higher battery capacities lead to fewer charging procedures being needed within the rotations, the effects of an inaccurate modeling of the charging process are less serious. However, in none of the cases is a feasibility of 100% achieved. Similarly to the first experiment, as the 500 kWh-battery can be considered as a future development and does not yet exist, the issues described cannot be ignored. Moreover, we observe that incorporating partial charging procedures within vehicle rotations has a positive influence on the solutions' feasibility. Table 4.4 shows that enabling partial charging leads to a significantly higher proportion of feasible rotations for each instance, charging model, and battery capacity. As partial charging leads to considerably more charging procedures within a vehicle rotation, fewer amounts of energy are charged on average. Since the effects of inaccurate models for charging are alleviated in this way, especially within the second phase of CC/CV, more feasible vehicle rotations are obtained.

In conclusion, linear charging times of BEBs underestimate the time windows actually required for charging and generally lead to violations of range restrictions. This is because the nonlinear profile of the current during the second phase of CC/CV in a charging process is not considered. Transferred to practical implementations, BEBs would likely stop within their rotations when using linear charging times during operational planning due to significant gaps between planned and effectively charged amounts of energy. These matters would lead to serious consequences for the daily services of public transport companies. In the event of BEBs' battery capacities growing in the future, the problem will be alleviated but still not negligible.

## 4.7 Summary and Conclusion

In this paper, we have explored the nonlinear charging process of BEBs in the context of the E-VSP. We have analyzed the impact of simplifying assumptions about BEBs' charging times, in our case constant and linear time windows for charging, on resulting vehicle rotations. To do this, we considered the nonlinear charging process of BEBs accurately and have introduced precise models for the current in respect to the charging procedure CC/CV of lithium-ion-batteries. We then performed a comprehensive computational study based on real-world instances with up to 10.000 service trips and different ranges of the buses used. To solve the instances, we enhanced a heuristic algorithm for the E-VSP and provided an algorithm for incorporating partial charging procedures within vehicle rotations. In our study, we specifically investigated the consideration of both complete and partial chargings.

Through our experiments we identified major gaps between model assumptions and the real conditions of charging processes within the E-VSP. First, we showed that the assumption of constant charging times generally leads to *overestimated* time windows for charging, which in turn increases the demand for BEBs and thus causes higher total costs. Moreover, challenges arise for the practical implementation of BEBs because more simultaneous chargings at the same stop point are needed. Second, we have demonstrated that assuming linear charging times *underestimates* the time windows actually required for charging, leading to violations of range restrictions of the buses used. As a consequence, BEBs would stop within their rotations and cause serious problems for operative services. Enabling partial chargings can reduce the impact of the problem slightly by comparison to complete chargings. With regard to different battery capacities, we found that increasing the ranges of BEBs can alleviate the negative effects of inaccurate charging models, since the numbers of charging procedures needed decrease. However, both problems remain relevant, as the largest battery capacity within our study is not yet available and battery research will, in all likelihood, not be sufficiently advanced in the foreseeable future. In conclusion, more precise charging models need to be incorporated into solution methods for the E-VSP. If this does not happen, solutions may either not utilize the available resources sufficiently or comprise non-executable vehicle rotations. In cases where realistic models for charging processes cannot be calculated analytically approximations should be used. Therefore, charging models based at least on logarithmical functions should be used. It is worth mentioning that the statements provided hold true no matter what solution method is chosen because we focused on the charging process as part of the general problem and not on the solutions' quality. Similar results are to be expected when solving the problem by exact solution methods.

There are a number of interesting future research avenues. Similar to the charging process, it would be interesting to see how more accurate models for the discharging process of vehicle batteries might affect the solutions of the E-VSP. Precise models for the energy consumption would be especially significant. It could be reasonable to assume, for example, that energy consumption depends on the traffic volume or weather conditions. Furthermore, as mentioned earlier, the charging and aging effects of vehicle batteries are closely linked. One important aspect to consider may be how to solve the E-VSP under such considerations. Finally, the solution method proposed within this contribution solves the E-VSP heuristically. In that respect, it would be interesting to know how and if the effects described within this paper possibly change when using exact solution methods.

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# Chapter 5

# A study on flow decomposition methods for scheduling of electric buses in public transport based on aggregated time-space network models


## Abstract

Over the past few years, many public transport companies have launched pilot projects testing the operation of electric buses. The basic objective of these projects is to substitute diesel buses with electric buses within the companies' daily operations. Despite an extensive media coverage, the share of electric buses deployed still remains very small in practice. In this context, new challenges arise for a company's planning process due to the considerably shorter ranges of electric buses compared to traditional combustion engine buses and to the necessity to recharge their batteries at charging stations. Vehicle scheduling, an essential planning task within the planning process, is especially affected by these additional challenges. In this paper, we define the *mixed fleet vehicle scheduling problem with electric vehicles*. We extend the traditional vehicle scheduling problem by considering a mixed fleet consisting of electric buses with limited driving ranges and rechargeable batteries as well as traditional diesel buses without such range limitations. To solve the problem, we introduce a three-phase solution approach based on an aggregated time-space network consisting of an exact solution method for the vehicle scheduling problem without range limitations, innovative flow decomposition methods, and a novel algorithm for the consideration of charging procedures. Through a computational study using real-world bus timetables, we show that our solution approach meets the requirements of a first application of electric buses in practice. Since the employment of electric buses is mainly influenced by the availability of charging infrastructure, which is determined by the distribution of charging stations within the

route network, we particularly focus on the influence of the charging infrastructure.

## Keywords

Electric Vehicles, Vehicle Scheduling, Public Transport, Time-Space Network, Flow Decomposition

## Contents

## 5.1 Introduction

Scheduling a fleet of vehicles is an essential task within the planning process of public transport companies. The mathematical optimization problem that arises from this task is widely known as the *Vehicle Scheduling Problem* (VSP). The objective is to determine the assignment of a company's vehicles to a set of timetabled service trips at minimum cost. In general, the costs consist of fixed costs for the acquisition of the buses used and costs for the buses' operation. Service trips denote trips for transporting passengers from a departure stop to an arrival stop at specific times. A vehicle can also perform deadhead trips without passengers in order to change its location. The set of all trips executed by a vehicle is denoted as its rotation. Vehicle rotations need to satisfy some basic constraints. (1) The trips of a vehicle rotation must be mutually compatible, that is, the trips have to be executable without time overlaps. (2) Every trip is covered exactly once, and (3) a vehicle begins and ends its rotation at one specific depot. Depending on the number of depots, the resulting problem is denoted as the *Single* or *Multi Depot Vehicle Scheduling Problem*. Moreover, multiple vehicle types may be considered (cf. Ferland and Michelon, 1988). The VSP and its extensions are well studied problems in the research community and have been widely analyzed (cf. Bertossi et al., 1987, Daduna and Paixão, 1995 or Bunte and Kliewer, 2009).

Driven by the social and political trend towards sustainable management of resources and the subsequent rejection of fossil energy sources in favor of renewable energies, the importance of alternative engines in urban traffic and public transportation has increased strongly. Electric vehicles (EVs) occupy a special position within the range of vehicles with alternative engines, since they have numerous important advantages. First, electric engines have a much higher degree of efficiency compared to combustion engines. Second, EVs are locally emission-free, which means that almost no greenhouse gases, fine particles, and nitrogen oxides are being emitted during their operation. Nowadays, where thresholds for these emissions are largely exceeded, especially in urban areas, the use of EVs represents a key factor in order to reduce the negative effects on public health. Furthermore, electric buses enable a significant reduction of noise, which is especially important for urban areas (cf. Schallaböck, 2012).

Currently, three main different types of EVs exist: (I) fuel cell electric vehicles containing an electric engine as well as a fuel cell, which generates electric energy directly from hydrogen or methanol, (II) hybrid electric vehicles containing an electric engine and a traditional combustion engine, which can be switched on when required, and (III) battery electric vehicles (BEV), which merely contain an electric engine. The latter type of vehicle has the shortest range of the aforementioned vehicle types, because no additional engines can be switched on. The last two vehicle types contain a battery to store the electric energy needed for powering their engines. In this paper we consider BEVs, since this type of vehicle implies the strongest restrictions for vehicle scheduling.

To compensate for their range limitations, BEVs perform detours to charging stations during their operations in order to recharge their batteries. There are three main different options for this. First, a vehicle battery can be recharged overnight during longer idle times at the depot. Second, a battery can be recharged during smaller breaks within a vehicle's operation, which is called opportunity charging. Lastly, a vehicle battery can be swapped for a fully charged battery. Depending on the charging option and the waiting time at a charging station, a battery can be fully or partially charged. In this context, the current of a charging system is particularly important because it determines the charging time. Different charging technologies are available for transferring energy into the batteries. Nowadays, this transfer is mainly performed either by a wire (conductively) or inductively.

Many companies have launched pilot projects testing the operation of electric buses during the provision of their services. For example, the German cities of Munich, Leipzig, and Dresden started in 2009 with deploying hybrid electric buses[1]. In 2011, the first BEVs started operations in Germany within the public transport system of Osnabrück. Since 2015, the Berliner Verkehrsbetriebe (BVG) is carrying out the pilot project *E-Bus Berlin*[2] whereby BEVs operate on a single line in the city center of Berlin. An extension to include other bus lines is being considered. The buses used are partially charged by inductive charging systems at intermediate stops on service trips. To oppose battery aging effects, the vehicle batteries are charged conductively up to 70% of their capacities at terminal stations (cf. Millner, 2010, Pelletier et al., 2017).

As things stand, companies in public transportation face considerable challenges when deploying electric buses for their daily services. Electric buses have much shorter ranges compared to traditional diesel buses due to their restricted battery capacities, and they need to make detours to charging stations to recharge their batteries in order to overcome this disadvantage (cf. Wang et al., 2016). Within the pilot project *E-Bus Berlin*, electric buses (Solaris Urbino 12 electric), equipped with a lithium-ion-battery capable of storing 90 kWh, are deployed. Assuming consumptions of about 1.5 - 1.8 kWh (depending on several influencing factors), this results in a range of approximately 54 km[3]. The same bus type with a traditional diesel engine (Solaris Urbino 12) is able to cover a distance of about 450 km. Another challenge of electric buses is the significant increase in costs for their deployment.

[1]https://www.starterset-elektromobilität.de/content/1-Bausteine/5-OEPNV/2016-projektuebersicht-20152016-hybrid-und-elektrobusprojekte-in-deutschland.pdf [Online accessed on 19-March-2020, in German]

[2]https://www.mpm.tu-berlin.de/menue/forschung/projekte/e_bus_berlin [Online accessed on 16-March-2020, in German]

[3]https://www.bsvg.net/fileadmin/user_upload/downloads/Emil/Datenblatt_E12.pdf [Online accessed on 22-March-2020, in German]

The reasons for this are the additional need for vehicles due to their lower ranges, high acquisition costs due to high battery costs, and necessary charging stations within the route network (cf. Pihlatie et al., 2014). According to a study by *Transport & Environment*[4] from 2018, the acquisition costs for a BEV are approximately 60% higher than the traditional combustion engine alternative. For that reason, the electrification of public transport systems still remains a very slow, gradual process. It is presumed that the proportion of BEVs will increase in the future. Accordingly, companies in public transport must nowadays deploy a fleet of vehicles consisting of both combustion engine vehicles and BEVs for their daily operations.

In this paper, we introduce a three-phase solution approach based on an aggregated time-space network (TSN) for scheduling a mixed fleet of vehicles consisting of BEVs with limited driving ranges and traditional combustion engine vehicles without range restrictions. To do so, we define the *mixed fleet vehicle scheduling problem with electric vehicles* (MF-(E)VSP) as an extension of the traditional VSP. The solution approach consists of an exact solution method for the VSP without range limitations, based on a TSN in the form of a mixed-integer linear program, followed by a second phase, in which limited driving ranges will be taken into account by applying innovative flow decomposition methods, and a third phase in which charging procedures are inserted into the vehicle rotations. The approach aims at maximizing the proportion of feasible vehicle rotations for BEVs within the full set of vehicle rotations while retaining optimal numbers of vehicles used and deadhead trips required. The numbers of vehicles used and deadhead trips are obtained by solving the standard VSP without range limitations. Vehicle rotations that are infeasible for BEVs continue to be served by traditional combustion engine vehicles. The TSN based solution method has been proven as highly efficient and has already been used for real-world applications. Since the charging infrastructure has a significant influence on the deployment of BEVs, we also analyse the impact of different settings on generated solutions. With this in mind, the experiments conducted and their results may help to speed up the switch from combustion engine to BEVs in public transport.

The paper is organized as follows: In Section 5.2 we present related literature before defining the MF-(E)VSP (Section 5.3). Then, we introduce the three-phase solution approach based on an aggregated time-space network in Section 6.4. In Section 5.5 we perform a computational study and evaluate the solution approach with regard to proportions of applicable BEVs and changes in the charging infrastructure. Concluding this paper, Section 6.6 provides a summary and a prospect for further research.

[4]https://www.euractiv.com/wp-content/uploads/sites/2/2018/11/2018_11_electric_bus_paper_final.pdf [Online accessed on 24-March-2020]

## 5.2 E-VSP and Related Problems in the Literature

In the following, we provide an overview of related literature. There is a wide range of literature dealing with vehicle scheduling for public transport. For an overview, we refer to Bunte and Kliewer (2009). With regard to the contribution of this paper, solution approaches addressing the deployment of EVs are especially relevant. In recent years, a variety of optimization problems have been introduced that incorporate limited driving ranges of the vehicles used and the possibility to restore their ranges. The literature presented below mainly differ in their way of incorporating the additional restrictions caused by the deployment of EVs as well as the level of reality they reflect regarding electric issues.

First, Desrosiers et al. (1995) and Haghani and Banihashemi (2002) introduced the *Time Window Constraint Scheduling Problem* as an extension of the traditional VSP by restricting the lengths and durations of vehicle rotations. The authors use a definition of the VSP from Bodin et al. (1978). For this purpose, they added constraints to the problem formulation that restrict fuel consumption of the vehicles deployed. However, the authors neglected the possibility to recharge a vehicle's battery at some charging stations within its rotation. The authors present exact and heuristic solution methods. In order to solve even larger-scale instances, they propose techniques for decreasing the problem size. Wang and Shen (2007) defined the *Vehicle Scheduling Problem with Route and Fueling Time Constraints* as a first approach to incorporate both vehicles' limited ranges and the option to recharge a battery. They develop a heuristic solution method that incorporates route time constraints and finds vehicle rotations starting and ending at the depot. Subsequently, they use a bipartite graph model to connect these rotations in relation to fuel time restrictions. In general, the term *Electric Vehicle Scheduling Problem* (E-VSP) has been established when considering both limited driving ranges of vehicles and the opportunity to recharge their batteries at specific charging stations. Li (2014) proposed the VSP with limited energy using time-expanded station nodes, thus considering the possibility to recharge and the capacities of charging stations. The author presents a construction heuristic producing vehicle rotations which serve as initial solutions for different column generation based solution approaches. Chao and Xiaohong (2013) proposed a heuristic method based on a Non-dominated Sorting Genetic Algorithm (NSGA-II) which they tested on a real-world instance with 119 service trips. They aim at minimizing vehicle costs as well as total charging demand. Besides a limited range, the authors consider the possibility of swapping a vehicle's battery. After the removal, a fully charged battery is inserted. Adler and Mirchandani (2016) presented a column-generation approach for the E-VSP. In order to obtain initial solutions for the solution method the concurrent scheduler algorithm by Bodin et al. (1978) is extended to take into account the additional restrictions caused by BEVs. The solution method is tested on real-world instances with up to 4,000 service trips.

All of the solution approaches discussed have in common that charging processes are performed within constant time windows. The assumption of constant time windows for charging implies that vehicles remain idle at a charging station for a fixed time period, whether or not the vehicle batteries have already been fully charged. This assumption leads to a substantial simplification because the actual charging process of modern batteries is very complex (Montoya et al., 2017). As a first solution towards a more realistic reflection of battery charging processes, Kooten Niekerk et al. (2017) developed a column-generation approach, which considers partial chargings in linear time in order to adapt this aspect. Linear time windows for charging refer to a linear increase in energy depending on the waiting time of a vehicle at a charging station. In technical terms, this means that vehicle batteries are charged with a constant current during the entire charging process (Olsen and Kliewer, 2020). Janoveca and Kohánia (2019) presented an exact solution model for the E-VSP based on a mixed-integer linear program. For solving, they use standard optimization software libraries. Regarding technical aspects, they also consider linear charging times of the vehicle batteries. Yao et al. (2020) proposed a heuristic solution method based on a genetic algorithm for the E-VSP with multiple vehicle types. They analyse the impact of different driving ranges, recharging durations, and energy consumptions of vehicles on the solution quality. Even though the authors consider a significant higher level of technical characteristics in comparison to previous work, they also assume that chargings are performed in linear time. Regarding further literature, there is no work at all dealing with the impact of different scenarios of the charging infrastructure on resulting vehicle rotations. Furthermore, homogeneous vehicle fleets basically consisting of only one major type of propulsion are assumed. Within the solution approach presented in this paper, we consider a heterogeneous fleet of vehicles, apply linear time windows for battery charging, and evaluate different settings of the charging infrastructure to point out interrelations.

## 5.3 Problem Description

In this section, we introduce the MF-(E)VSP as the essential problem of this paper and present the TSN based solution approach together with methods for flow decomposition.

The objective of the traditional VSP is to assign a given set of timetabled service trips to a set of vehicles at minimum costs while satisfying the following constraints:

- each service trip is assigned exactly once,
- each vehicle starts and ends its rotation at the same depot,
- each vehicle rotation contains a feasible sequence of trips.

A vehicle rotation represents a sequence of trips that a vehicle executes consecutively. The trips may be pull-out or pull-in trips from or to the depot, deadhead trips, and service trips. The public transportation network is assumed to be given by a set of stop points including the vehicle depots. Each service trip is defined precisely by its departure time, arrival time, departure stop, and arrival stop. Distances and travel times between any two stop points in the network are each given by a matrix. The distances and travel times may differ between service and deadhead trips. Although travel times may vary, depending on the time of the day, we will assume fixed durations between any two stop points.

Any solution of the VSP generated is assessed by the total costs caused, consisting of operational and fixed costs. Each vehicle in use causes fixed costs, independently of the rotation to be performed. The fixed costs represent the vehicle's acquisition costs. Operational costs comprise costs per hour in order to reflect the drivers' wages and costs per kilometer to take into account buses' maintenance and wear.

The use of BEVs leads to additional restrictions that have to be satisfied in order to enable regular operations:

- a BEV's residual energy cannot fall below zero and cannot exceed its battery capacity,
- a BEV can only be recharged at specified charging stations.

The residual energy of a battery is often denoted as its *State of Charge* (SoC) respectively *Depth of Discharge* (DoD). In order to incorporate BEVs, the network is extended by introducing a set of charging stations representing stop points equipped with charging technology. The charging technology determines the time which is needed for the intake of energy, the *charging time*. This is due to the current, which may differ between different charging technologies. We assume that charging procedures start immediately on arrival at a stop point without buffer times. Possible turning times at final stops and changeover times at charging stations are assumed to be part of previous trips. In order to take charging procedures into account, we assume specific costs for charging arising from energy prices and maintenance. Each vehicle contains a battery, which is mainly characterized by its capacity, denoting the maximum amount of energy that can be stored. Furthermore, a vehicle consumes a specific amount of energy per kilometer driven, which differs on service and deadhead trips due to the greater weight when passengers are being carried. A vehicle rotation is termed feasible for BEVs if the restrictions introduced are satisfied. If every vehicle used satisfies the restrictions, the problem is denoted as the E-VSP.

As indicated by the real-world project in Berlin, many companies in public transport deploy a mixed fleet consisting of both BEVs with range limitations and traditional combustion engine vehicles without range restrictions. Consequently, neither a pure form of the VSP nor the E-VSP can be used for operational planning. This challenge leads to the MF-(E)VSP as the essential problem of this paper, which considers a mixed form of these two problems. Formally, the set of vehicles now consists of two major subsets: The first subset contains combustion engine vehicles and the second subset BEVs. Range restrictions must be satisfied for each vehicle of the second subset.

## 5.4 Three-Phase Solution Approach based on an aggregated Time-Space Network

We now discuss our three-phase solution approach for solving the MF-(E)VSP based on an aggregated TSN. Kliewer et al. (2006) introduced a modeling approach for the multi depot VSP with multiple vehicle types using a TSN. This solution method generally comprises three consecutive steps: First, the TSN is constructed, based on the underlying public transportation network and the timetable. Second, optimal flow values through the TSN are computed by solving a multi-commodity flow problem. Last, decomposition strategies are applied in order to obtain executable vehicle rotations from the flow values.

As previously described, the aim of the MF-(E)VSP is to maximize the proportion of feasible vehicle rotations for BEVs within the entire set while retaining optimal numbers of vehicles used and deadhead trips required obtained by solving the standard VSP. Consequently, the first two steps of the solution procedure remain unchanged. However, the step of flow decomposition needs to be modified to consider challenges arising from the use of BEVs. In addition, charging procedures have to be inserted into the vehicle rotations. This results in the following three phases of our solution approach:

Phase I: Construction of the TSN and determination of optimal flow values without consideration of range limitations,

Phase II: Decomposition of the flow into executable vehicle rotations,

Phase III: Insertion of charging procedures.

The following sections describe the specific phases of the solution approach.

### 5.4.1 Phase I: Aggregated Time-Space Network and Exact Solution Method for the VSP without Range Limitations

A TSN generally shows activities in time and space. A TSN for multi-depot vehicle scheduling consists of multiple layers, whereby each layer corresponds to a combination of depot and vehicle type. A layer basically consists of time lines, arcs, and nodes. For each stop point of the route network, a time line is created representing all possible arrival and departure events at the specific stop. Arcs represent service trips, deadhead trips, and idle times of the vehicles. Deadhead trips starting at the depot are denoted as pull-out trips and deadhead trips ending at the depot as pull-in trips. Thereby, the vertical axis of the network describes the spatial and the horizontal axis the temporal component. A node of the TSN connects a group of possible arrivals to a subsequent group of possible departures. The arcs of both groups are sorted in ascending order by the arrival/departure times. Hence, all stop points are represented as ordered sets of nodes that are connected by waiting arcs. To set up a TSN model, an arc is added between the corresponding time lines for each service trip that can be served by a layer's vehicle type. Then, a node is inserted for every group of consecutive arrival and departure events on a time line. For each arc, the horizontal distance between the arrival and departure node of a trip represents its duration. The nodes of each time line are linked by waiting-arcs to represent the vehicles' idle times. Series of compatible trips from different time lines are linked by aggregated deadhead-arcs between the corresponding nodes, representing possible deadhead trips. Possible pull-out and pull-in-arcs from/to the depot are inserted for every service trip. As it must be ensured that each vehicle returns to its original depot at the end of a day, a circulation-arc from the last node to the first node of the time line, belonging to the depot, is added to each layer.

The concept of time lines enables a significant reduction of the problem's complexity by aggregating the deadhead-arcs into groups of compatible connections, which represents the main advantage of the TSN formulation. The concept of transitivity in the compatibility of trips is used to do this. A deadhead-arc can be omitted if the same connection can be reached using a combination of other deadhead- and waiting-arcs. For further details of the procedure for reducing deadhead-arcs, we refer to Kliewer et al. (2006). Figure 5.1 illustrates an example of a TSN after applying the reduction procedure (according to Kliewer et al., 2006). The figure shows one time line that represents the depot and two time lines that represent stop points. There are three service trips that operate between the two stops. However, the directions of travel are different. As this figure illustrates by way of example, a deadhead-arc to connect service trip 1 with service trip 3 is not necessary because this connection is provided by a sequence of waiting-arcs within the time line of stop point 1. Likewise, it does not need a deadhead-arc from the depot to the departure of service trip 3 as this node can be reached by the deadhead-arc from the depot to service trip 2 and a waiting-arc on the time line of stop point 1. The application of this procedure to the entire set of service trips enables a major reduction in the number of deadhead-arcs. Following Kliewer et al. (2006), a reduction of up to 97% can be achieved for real-world timetables.

The resulting TSN model corresponds to a multi-commodity flow problem (according to Kliewer et al., 2008). Let $N = \{1, 2, \dots, n\}$ be the set of trips and $D$ the set of depots. For each depot $d \in D$, a network $G^d = (V^d, A^d)$ is defined which consists of nodes $V^d$ and arcs $A^d$. Let $N^d(n) \in A^d$ be the arc that corresponds to trip $n$ of the network $G^d$. Let $u^d \in \mathbb{N}$ be the maximum number of available vehicles

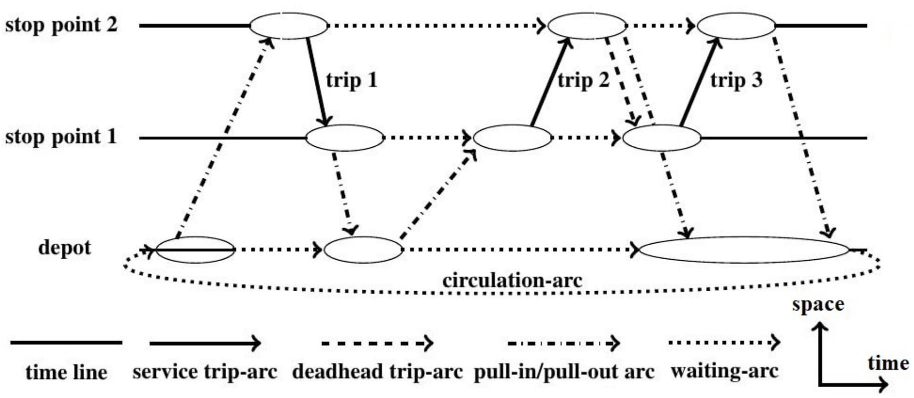


Figure 5.1: Example of a time-space network with three time lines and three service trips

within a depot $d$ and $M \in \mathbb{N}$ the total number of available vehicles over all depots. Let the parameters $c_{ij}^d \geq 0$ be vehicle costs of arcs $(i,j) \in A^d$ reflecting travel and idle times. The costs of waiting arcs in the depot is set to 0. On the circulation arc of the network a fixed cost for using a vehicle is set. Decision variables $x_{ij}^d \in \mathbb{N}$ indicate whether an arc $(i,j)$ is used and assigned to the depot $d$ or not. Therefore, the following upper bound is defined for each decision variable:

$$u_{ij}^d = \begin{cases} 1 \text{ , if } x_{ij}^d \text{ corresponds to a service trip} \\ u^d \text{ , if } x_{ij}^d \text{ corresponds to a circulation arc} \\ M \text{ , otherwise} \end{cases}$$

With this we can formulate the multi-commodity flow problem as the following mixed-integer linear program (MIP) (1) - (5). Due to the significant reduction of connections within the TSN, even real-world instances with very large networks and timetables can be solved to optimality using standard optimization software libraries.

$$min \quad \sum_{d \in D} \sum_{(i,j) \in A^d} c_{ij}^d x_{ij}^d \tag{5.1}$$

$$\sum_{\{j:(i,j) \in A^d\}} x_{ij}^d - \sum_{\{j:(j,i) \in A^d\}} x_{ji}^d = 0 \qquad \forall\, i \in V^d, \forall\, d \in D \tag{5.2}$$

$$\sum_{d \in D, (i,j) \in N^d(n)} x_{ij}^d = 1 \qquad \forall\, n \in N \tag{5.3}$$

$$0 \leq x_{ij}^d \leq u_{ij}^d \qquad \forall\, (i,j) \in A^d, \forall\, d \in D \tag{5.4}$$

$$x_{ij}^d \in \mathbb{N} \qquad \forall\, (i,j) \in A^d, \forall\, d \in D \tag{5.5}$$

The objective (5.1) is to minimize the sum of total vehicle costs. Constraint (5.2) ensures the flow conservation, indicating that the flow into each node equals the flow out of each node. Constraint (5.3) secures that each trip is covered by exactly one vehicle. Constraint (5.4) ensures that the upper bound of each decision variable is not exceeded. According to constraint (5.5), all decision variables are non-negative integers.

Due to the formulation of the VSP as a multi-commodity flow problem, solutions provide optimal flow values for each arc of the network. Consequently, no path-related constraints can be considered because the problem formulation does not contain an optimization of the paths. The flow values allow many different paths through the network. All of them represent optimal solutions with regard to the number of vehicles needed and deadhead trips required, but differ in the distribution of waiting times. In order to obtain executable vehicle rotations, flow decomposition methods are used to break down the optimal flow.

### 5.4.2 Phase II: Flow Decomposition Methods for the Deployment of BEVs

To divide the optimal flow values into executable paths through the TSN, we propose eight decomposition methods. All of the methods are local procedures since they solve a decision-making problem at each node of the TSN without considering the entire network. For all methods, incoming arcs are connected to outgoing arcs within each node of the TSN. The first two decomposition methods presented in Section 5.4.2 and Section 5.4.2 are taken from Kliewer et al. (2006) whereas the other strategies are novel procedures explicitly designed for the consideration of electric vehicles' characteristics.

#### FIFO

The widely known, simple procedure *FirstIn-FirstOut* (`FIFO`), which is often used within database applications, can also be used for flow decomposition. `FIFO` combines the first incoming arc within each node of a time line with the first outgoing arc, the second incoming with the second outgoing, etc. (all of them with positive flow values). Figure 5.2 shows an example of a node within a time line of a TSN. On the left side of the figure, the procedure `FIFO` is illustrated by an example with three incoming resp. outgoing arcs.

#### LIFO

The procedure *LastIn-FirstOut* (`LIFO`) proceeds contrarily: The last incoming arc is linked to the first outgoing one. On the right side of Figure 5.2, the procedure `LIFO` is illustrated. Although the decomposition strategies `FIFO` and `LIFO` are not directly related to the use of BEVs, we use them in our computational study in order to compare standard to more complex decomposition methods.

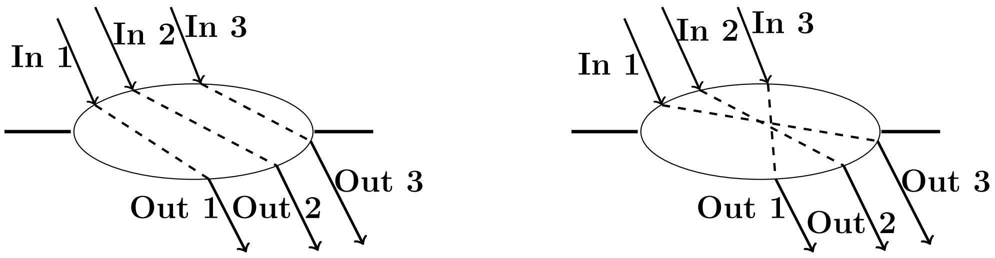


Figure 5.2: `FIFO` (left) and `LIFO` (right) illustrated by one node of a time line within a time-space network.

### MaxMinChargingTime

The procedures `FIFO` and `LIFO` have in common that they are fairly simple and do not consider any characteristics of BEVs, such as charging times or energy consumption. In contrast, we propose the novel strategy `MaxMinChargingTime`, which aims at maximizing the minimum waiting times at charging stations within vehicle rotations in order to enable vehicles to recharge. Since overlong time windows for charging for some vehicles would result in too short charging times for other vehicles, we solve an assignment problem that maximizes the minimum waiting time for each possible connection.

Let $n \in \mathbb{N}$ be the number of incoming arcs for a node and $m \in \mathbb{N}$ the number of outgoing arcs. Let $b_{ij} \geq 0 \ \forall i = 1, \dots, n, \ j = 1, \dots, m$ be parameters that reflect waiting times at the stop point of the node between each incoming arc $i$ and each outgoing arc $j$. Decision variables $x_{i,j} \in \{0, 1\}$ indicate whether an incoming arc $i$ is connected with an outgoing arc $j$ ($x_{i,j} = 1$) or not ($x_{i,j} = 0$). The assignment problem can be represented by the following mathematical optimization problem:

$$\max \min_{i,j} b_{ij} \cdot x_{ij} \tag{5.6}$$

$$\text{s.t.} \sum_{j=1}^{m} x_{ij} = 1, \qquad i = 1, \dots, n \tag{5.7}$$

$$\sum_{i=1}^{n} x_{ij} = 1, \qquad j = 1, \dots, m \tag{5.8}$$

$$x_{ij} \in \{0, 1\}, \qquad i = 1, \dots, n, \ j = 1, \dots, m. \tag{5.9}$$

The objective (5.6) is to maximizing the minimum waiting times. Constraint (5.7) of the problem formulation ensures that each incoming arc is connected with precisely one outgoing arc. Constraint (5.8) ensures the same for each outgoing and incoming arc. According to constraint (5.9), all decision variables are binary. The optimization problem is solved using standard optimization software libraries, since the number of choices is small even for large real-world instances.

### BalanceConsumption

An alternative view enables the decomposition method `BalanceConsumption`. The main idea of this procedure is to consider the energy consumption of the vehicle rotations with regard to potential connections of incoming and outgoing arcs. The objective is to balance the consumption of the different vehicle rotations. To this purpose, a bottleneck problem is solved. In this way, the maximum sum of consumption over every possible connection between incoming and outgoing arcs is minimized. The mathematical optimization problem is identical to the proposed with regard to `MaxMinChargingTime` but now the parameters $b_{ij}$ reflect the sum of consumption of any connection between an incoming arc $i$ and an outgoing arc $j$.

### MaxMinChargingTime-BalanceConsumption

As an extension of the previous strategies, `MaxMinChargingTime-BalanceConsumption` combines the methods `MaxMinChargingTime` and `BalanceConsumption`, so that the first strategy is applied at every charging station and the second at every non-charging station. This should maximize waiting times of vehicles at charging stations and balance the vehicles' consumption at every non-charging station. This way, the benefits of the two decomposition methods can be combined.

### Extended-MaxMinChargingTime-BalanceConsumption

For some instances it might be advantageous to consider the consumption even at charging stations. Therefore, the `Extended-MaxMinChargingTime-BalanceConsumption` strategy solves a bottleneck problem at every node but includes both possible waiting times for charging and consumption of the different vehicle rotations. Thus, a weighted sum of both components is considered. Besides the adjusted objective function, the mathematical optimization problem is identical to the model used within `MaxMinChargingTime` and again solved by standard software libraries.

### Extended-BalanceConsumption

Within the strategy of `BalanceConsumption` it might be useful to consider only the consumption between two charging stations within a vehicle rotation instead of the entire vehicle rotation. Furthermore, it is likely beneficial to link two already infeasible parts of vehicle rotations to avoid additional infeasibilities. These two components are considered within `Extended-BalanceConsumption`. For this purpose, the sum of consumption for all pairs of incoming and outgoing arcs is computed but now considering the consumption between any two directly consecutive charging stations. If both the incoming and outgoing part of the corresponding vehicle rotations are infeasible for BEVs, the consumption of the specific connection is set to a sufficiently high value in order to rule out this connection for BEVs. In that way, the procedure aims at connecting infeasible parts of vehicle rotations.

#### MaxMinChargingTime-Extended-BalanceConsumption

As a last strategy, we use `MaxMinChargingTime-Extended-BalanceConsumption` which is a combination of the previously introduced strategies. At this point, the assignment of arcs at charging stations is done by `MaxMinChargingTime` and at non-charging stations by `Extended-BalanceConsumption`. Analogous to `MaxMinChargingTime-BalanceConsumption`, the benefits of the two strategies should be exploited.

Table 5.1 illustrates the main characteristics of the methods presented for flow decomposition.

| decomposition method | chrg. time | energy con. | multiple strategies | feas. of rot. |
|---|---|---|---|---|
| `FIFO` | | | | |
| `LIFO` | | | | |
| `MaxMinChargingTime` | • | • | | |
| `BalanceConsumption` | | • | | |
| `MaxMinChargingTime-BalanceConsumption` | • | • | • | |
| `Extended-MaxMinChargingTime-BalanceConsumption` | • | • | • | |
| `Extended-BalanceConsumption` | | • | • | • |
| `MaxMinChargingTime-Extended-BalanceConsumption` | • | • | • | • |

Table 5.1: Overview of the main characteristics of the flow decomposition methods.

### 5.4.3 Phase III: Charging Insertion Procedure

After dividing the optimal flow values into executable paths considering charging times and energy consumption, charging procedures have to be inserted into the vehicle rotations in order to enable operation by BEVs. Therefore, we now introduce an algorithm that adds charging procedures to vehicle rotations. Since waiting times at intermediate stops of service trips are determined by the timetable, we focus on waiting times between consecutive service trips. The basic procedure is illustrated by Algorithm 3.

The set of vehicle rotations $V$ obtained by flow decomposition, the set of charging stations $S$, and a specific lower and upper bound for the SoC serve as the input data. The bounds for the SoC will be used within our computational study to incorporate battery aging effects. Therefore, we assume that the SoC of a vehicle battery cannot fall below the lower bound and cannot exceed the upper bound after leaving the depot.

The set $V$ of vehicle rotations is processed consecutively and the current rotation $v$ is considered (l. 1). Initially, each vehicle rotation is assumed to be feasible for BEVs (l. 2). Then, after each trip $t$ of $v$ the SoC is computed by subtracting the energy consumption of $t$. If trip $t$ is a service trip, the amount of energy being charged by opportunity charging at intermediate stops is added (l. 4). If the current vehicle rotation remains feasible after executing $t$ waiting times before and after the trip can be used for charging if corresponding time windows are positive and the current departure stop point is a charging station (l. 5). Since service trips are fixed by their departure and arrival times and deadhead trips can be shifted, we use a case differentiation to insert charging procedures. To do this, we consider the previous trip $previous(t)$ of $t$ as the first case. If $previous(t)$ is a deadhead trip, we check whether the waiting time before trip $previous(t)$ plus the waiting time before trip $t$ is positive (l. 6 & l. 7). If this is the case, trip $previous(t)$ is shifted backwards in order to increase possible charging times, a charging procedure is added before executing trip $t$, and the SoC is updated (l. 8 - l. 10). Within this step, we take into account charging procedures already inserted by the algorithm in order to prevent that earlier charging procedures are shortened or even removed. If $previous(t)$ is a service trip, we perform this procedure by considering the waiting time before trip $t$, add a possible charging procedure, and update the SoC (l. 12 & l.13). In all cases where charging is possible the specific upper bounds for the SoC of the batteries are considered. If the updated SoC falls below the lower bound, the current vehicle rotation is infeasible and, thus, cannot be executed by BEVs (l. 15). In this case, charging procedures already inserted into the rotation are removed and the next vehicle rotation is processed (l. 16). After each vehicle rotation has been processed the algorithm returns the modified vehicle rotations and their feasibility resp. infeasibility (l. 18).

## 5.5 Computational Study

In this section, we present the results of our computational study. We start by introducing the instances to be solved and the experimental parameters. Then, we look at the results of solving the MF-(E)VSP according to the procedure introduced in Section 6.4. In this context, we analyze the percentages of feasible vehicle rotations for BEVs as the crucial aspect of this paper. In particular, we investigate the impact of the proposed decomposition methods on resulting vehicle rotations considering different settings of the charging infrastructure.

### 5.5.1 Problem Instances and Parameters

Our computational experiments are performed on six real-world instances, with up to 10,000 service trips, which differ in their number of service trips, their distributions over the day, and numbers of stop points. The instances are based on real-world data from German public transport companies. The names of the instances contain the total number of service trips. The instances are characterized by different kinds of distribution of the numbers of simultaneously performed timetabled trips over the day, see Figure 5.3, and differ in the number of stop points. The different profiles of service trips cover the most popular patterns in public transport, since the instances $t867$, $t1135$, and $t3067$ can be associated with urban areas comprising peak times in the morning and afternoon, whereas $t1296$, $t2633$, and $t10710$ represent rather rural areas characterized by constant services throughout the day. For our study, the instances' original data have been adapted in order to address the requirements of BEVs.

Within this study, we assume two major engine types of the vehicles deployed: BEVs with range limitations and traditional combustion engine vehicles without range limitations. For reasons of simplification, we consider a single vehicle depot. Consequently, every vehicle starts and ends its rotation at the depot regardless of the vehicle type. Furthermore, we assume that both types of vehicles are able to cover every timetabled service trip.

Inspired by the real-world project in Berlin, we assume a battery capacity of 90 kWh for all BEVs. A BEV always leaves the depot with a fully charged battery. Therefore, we assume a sufficiently large number of charging systems in the depot and a sufficient period of time between arrivals and departures of the vehicles. To take battery aging effects into account, we assume a lower and upper bound within a battery's SoC ranges during its operations after leaving the depot (cf. Jossen, 2005). We will use 20% of the battery capacity for the lower and 80% for the upper bound. Although the consumption of BEVs is influenced by several factors such as line topologies, road gradients, and traffic conditions, we assume constant consumption by a BEV per kilometer driven. However, we assume that consumption per kilometer differ on service (1.8 kWh/km) and deadhead trips (1.5 kWh/km). This leads to a maximum range of 60 km on deadhead trips and 50 km on service trips for each BEV.

An important part of this study will be the analysis of different settings of the charging infrastructure. Therefore, we consider different scenarios that differ with regard to the proportion of charging stations at highly frequented stops in the full set of stop points. We use proportions of charging stations of 10%, 20%, and 50% within the following study. To achieve this, stop points are ordered by the number of service trips departing or arriving at the respective stop points and the corresponding subset of stop points is equipped with charging systems. We assume unbounded capacities of charging stations, which means the number of simultaneous charging procedures

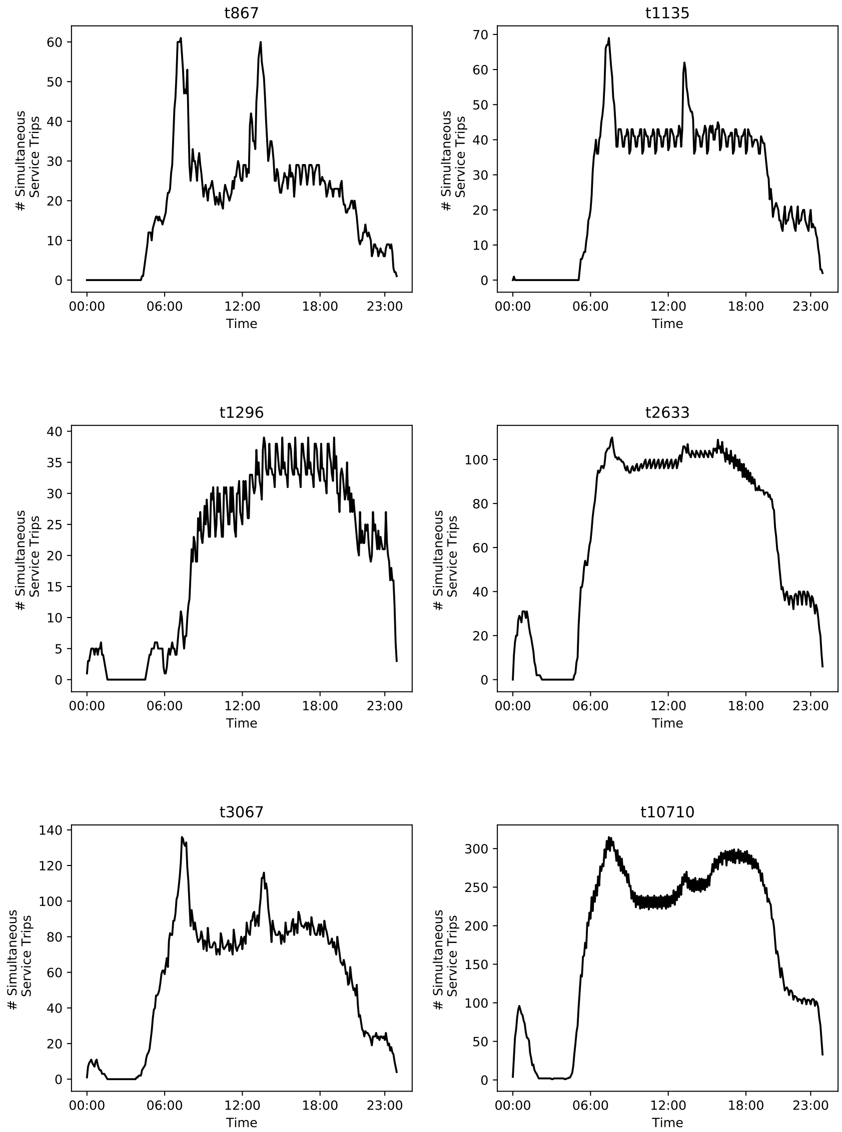


Figure 5.3: Temporal distribution of timetabled service trips over the day for each instance.

and amounts of energy that can be charged at a charging station are unbounded. As this assumption represents a broad generalization, especially with regard to highly frequented traffic hubs, we investigate this issue in greater detail within our study.

A battery can be charged either between two successive service trips or at intermediate stop points during the execution of a service trip if corresponding stop points are equipped with charging technology. As described earlier, different charging systems exist at the present time, mainly differing in terms of the energy transfer and the current provided during a charging process. To incorporate this crucial aspect, we consider different currents provided at the charging stations. We use currents of 1.8, 3, and 9 kWh/min. Since we consider only one type of BEV at the same time, we conduct our study for each current. Despite having explained the need for complex models to incorporate the nonlinear charging process of modern lithium-ion batteries, we assume a constant current during the entire charging process of BEVs for each charging system, and thus linear charging times. Following the real-world project in Berlin, we first assume 50 minutes for charging a battery to full capacity if it is completely empty, which leads to a current of 90 kWh/50 minutes = 1.8 kWh/minute. Building on this, we assume 30 and 10 minutes for a complete charging of the battery leading to 3 kWh/minute and 9 kWh/minute to represent more efficient fast-charging systems. Since we focus on the feasibility of vehicle rotations for BEVs computed at minimum costs for traditional diesel busses, we do not consider any additional cost parameters arising from the use of BEVs, like energy costs or fixed costs for charging stations. Finally, as we consider a single type of BEVs, we assume that each BEV can be charged at every available charging station.

### 5.5.2 Results of Solving the MF-(E)VSP using the Three-Phase Solution Approach

We now discuss the results of solving the MF-(E)VSP. With regard to the implementation of BEVs in public transport, not only the percentages of feasible vehicle rotations for BEVs are important but also related aspects such as percentages of service trips covered by BEVs, kilometers driven by BEVs, and characteristics of the charging procedures. In the following, we discuss each of the specified aspects. The solution approach provided is implemented in C# under .Net using the optimization library of IBM ILOG CPLEX 12.5. All of the results have been obtained by using a CPU with a 2.7 GHz processor. We receive acceptable run times for all instances with the standard optimizer of CPLEX. The maximum runtime over all instances was approximately 30 seconds.

#### Percentages of Feasible Vehicle Rotations for BEVs

We first analyse the percentages of feasible vehicle rotations for BEVs within solutions of the MF-(E)VSP. Table 5.2 and Table 5.3 provide an overview of the results, according to the assumed distribution of charging stations, the current provided by the charging systems, and the method used for flow decomposition. Additionally, the number of vehicles needed in the optimal solution of the standard VSP is given for each instance.

Looking at the detailed results, we can observe that the entire set of vehicle rotations cannot be served by BEVs in any of the cases examined. Furthermore, the percentage of feasible vehicle rotations for BEVs differs significantly according to the assumed distribution of charging stations, the current provided, and the instances. In all cases, an increasing distribution of charging stations as well as increasing currents both lead to an increase in feasible vehicle rotations for BEVs. However, the impacts of these two factors differ significantly. It can be stated that, in general, the charging stations' influence on the feasibility of rotations for BEVs depends strongly on the instances themselves. If an instance's distribution of timetabled trips over the day contains peak times (see Figure 5.3), the influence of an increasing distribution of charging stations is significantly higher than in the case of an almost unvarying offer of service trips. With regard to the specific data of this study, an increase in charging stations leads to more feasible vehicle rotations when solving instances $t867$, $t1135$, and $t3067$ that can be associated with urban areas but has very little impact on the solutions for instances $t1296$, $t2633$, and $t10710$ that correspond to rural areas. Similar observations can be made regarding the currents provided at charging stations. Again, an increase in the current leads to higher percentages of feasible rotations when the corresponding instances contain peak times in service trips over the day than in the case without peak times. Independently of the respective instance, we can observe that the higher the current provided at charging stations, the higher is the impact of an increasing distribution of charging stations on the solutions. This is reasonable because longer charging times caused by lower currents almost entirely cancel out the higher degrees of freedom caused by a greater number of charging stations. However, in the case of 9 kWh/min as the current, these advantages can be used to obtain better solutions.

With regard to the different flow decomposition methods, we identify that the use of more complex methods especially designed for the deployment of BEVs generally leads to a higher percentage of feasible vehicle rotations by comparison to methods not considering the special features of BEVs. The traditional methods `FIFO` and `LIFO` achieve worse results than any other method in all of the cases examined. It is worth noting that the lower the number of charging stations is, the better results are obtained when using more specific methods for flow decomposition. This is reasonable because more charging stations distributed within the network enable more degrees of freedom and thus compensate for the unspecific procedures of traditional methods such as `FIFO` or `LIFO`. The application of more complex methods leads to particularly good results when solving the instances $t867$, $t1135$, and $t3067$. This is because these instances contain peak times of timetabled trips over the day, which allow the vehicles to recharge their

**Instance t867** (69 vehicles in optimal solution)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 38.2% | 40.3% | 42.6% | 39.7% | 44.9% | 50.9% | 41.2% | 47.6% | 59.8% |
| `LIFO` | 37.3% | 39.7% | 39.9% | 38.7% | 41.4% | 42.0% | 39.8% | 43.7% | 44.9% |
| `MaxMinChargingTime` | 36.7% | 38.9% | 42.3% | 37.2% | 40.2% | 44.2% | 39.6% | 42.5% | 46.3% |
| `BalanceConsumption` | 36.9% | 38.2% | 42.1% | 37.4% | 40.7% | 43.9.2% | 40.1% | 42.7% | 45.3% |
| `MaxMinChargingTime-BalanceConsumption` | 40.3% | 43.2% | 46.8% | 42.7% | 47.3% | 62.7% | 44.9% | 50.3% | 66.8% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 40.0% | 43.7% | 45.2% | 42.7% | 48.2% | 63.7% | 48.6% | 62.9% | 69.4% |
| `Extended-BalanceConsumption` | 43.7% | 49.4% | 50.9% | 45.2% | 50.8% | 66.7% | 49.4% | 64.9% | 70.3% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 44.3% | 51.5% | 55.3% | 48.3% | 53.9% | 68.3% | 52.2% | 64.9% | 72.1% |

**Instance t1135** (75 vehicles in optimal solution)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 35.5% | 36.8% | 39.4% | 36.8% | 40.7% | 57.9% | 39.4% | 56.6% | 61.8% |
| `LIFO` | 35.5% | 39.5% | 39.5% | 36.8% | 40.8% | 57.9% | 42.1% | 56.6% | 61.8% |
| `MaxMinChargingTime` | 36.8% | 39.5% | 42.1% | 38.2% | 42.1% | 63.2% | 43.4% | 61.8% | 63.2% |
| `BalanceConsumption` | 36.8% | 39.5% | 40.8% | 38.2% | 40.8% | 63.2% | 40.8% | 59.2% | 64.5% |
| `MaxMinChargingTime-BalanceConsumption` | 38.2% | 43.4% | 46.1% | 39.5% | 46.1% | 61.8% | 43.4% | 60.5% | 65.8% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 39.5% | 43.4% | 44.7% | 42.1% | 47.4% | 61.8% | 47.4% | 60.5% | 65.8% |
| `Extended-BalanceConsumption` | 42.1% | 48.7% | 48.7% | 43.4% | 47.4% | 67.1% | 44.7% | 61.8% | 65.8% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 42.1% | 48.7% | 48.7% | 43.4% | 46.1% | 67.1% | 44.7% | 63.2% | 67.1% |

**Instance t1296** (47 vehicles in optimal solution)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 5.8% | 6.6% | 7.1% | 8.2% | 8.9% | 9.4% | 9.1% | 9.5% | 19.2% |
| `LIFO` | 5.4% | 5.7% | 6.1% | 8.1% | 8.9% | 9.3% | 8.7% | 11.2% | 18.3% |
| `MaxMinChargingTime` | 6.0% | 6.4% | 6.9% | 7.5% | 8.5% | 10.9% | 9.3% | 12.4% | 23.1% |
| `BalanceConsumption` | 6.2% | 7.5% | 8.2% | 7.9% | 9.1% | 10.3% | 9.2% | 11.4% | 23.1% |
| `MaxMinChargingTime-BalanceConsumption` | 7.7% | 8.3% | 9.6% | 8.7% | 9.8% | 10.3% | 10.8% | 12.7% | 20.9% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 7.3% | 7.9% | 8.4% | 8.4% | 9.7% | 10.2% | 9.7% | 11.8% | 21.7s% |
| `Extended-BalanceConsumption` | 9.0% | 9.2% | 9.2% | 10.6% | 10.8% | 11.9% | 10.5% | 12.7% | 24.1% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 9.0% | 9.2% | 9.2% | 11.0% | 11.8% | 12.2% | 9.6% | 12.9% | 24.6% |

**Instance t2633** (125 vehicles in optimal solution)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 5.6% | 6.4% | 6.4% | 8.0% | 8.8% | 9.6% | 8.8% | 10.4% | 20.8% |
| `LIFO` | 5.6% | 5.6% | 5.6% | 8.0% | 8.0% | 9.6% | 8.0% | 10.4% | 21.6% |
| `MaxMinChargingTime` | 5.6% | 6.4% | 6.4% | 8.0% | 8.8% | 10.4% | 8.8% | 12.0% | 22.4% |
| `BalanceConsumption` | 6.4% | 7.2% | 8.0% | 8.0% | 8.8% | 10.4% | 8.8% | 10.4% | 22.4% |
| `MaxMinChargingTime-BalanceConsumption` | 5.6% | 8.0% | 8.8% | 8.0% | 8.8% | 9.6% | 8.8% | 12.0% | 22.4% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 5.6% | 8.0% | 8.8% | 8.0% | 8.8% | 9.6% | 9.6% | 11.2% | 22.4% |
| `Extended-BalanceConsumption` | 8.0% | 8.0% | 8.0% | 8.8% | 9.6% | 10.4% | 9.6% | 10.4% | 22.4% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 8.0% | 8.0% | 8.0% | 9.6% | 9.6% | 10.4% | 9.6% | 12.0% | 22.4% |

Table 5.2: Summary of percentages of feasible vehicle rotations for all instances divided by the decomposition method used, the assumed charging infrastructure, and the current provided at charging stations.

**Instance t3067** (165 vehicles in optimal solution)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 30.3% | 32.1% | 42.4% | 32.7% | 38.8% | 42.4% | 47.9% | 48.5% | 61.8% |
| `LIFO` | 31.5% | 32.7% | 42.4% | 32.7% | 38.8% | 43.0% | 48.5% | 49.1% | 62.4% |
| `MaxMinChargingTime` | 31.5% | 35.2% | 43.0% | 32.7% | 39.4% | 44.2% | 49.1% | 49.7% | 63.6% |
| `BalanceConsumption` | 31.5% | 32.1% | 42.4% | 35.2% | 33.9% | 44.8% | 49.7% | 49.7% | 65.5% |
| `MaxMinChargingTime-BalanceConsumption` | 33.3% | 37.0% | 42.4% | 35.8% | 39.4% | 47.3% | 49.1% | 49.7% | 63.6% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 34.5% | 37.0% | 42.4% | 35.8% | 38.8% | 47.9% | 49.7% | 50.9% | 65.5% |
| `Extended-BalanceConsumption` | 37.0% | 40.0% | 43.6% | 38.2% | 40.0% | 49.1% | 50.3% | 50.9% | 66.1% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 37.0% | 40.0% | 43.0% | 38.2% | 40.6% | 48.5% | 50.9% | 51.5% | 66.1% |

**Instance t10710** (349 vehicles in optimal solution)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 9.7% | 10.9% | 12.3% | 11.2% | 12.0% | 16.9% | 14.3% | 17.5% | 27.2% |
| `LIFO` | 10.6% | 11.2% | 12.3% | 11.2% | 13.2% | 14.9% | 14.9% | 18.1% | 27.2% |
| `MaxMinChargingTime` | 12.3% | 13.2% | 14.3% | 14.9% | 15.5% | 16.6% | 14.9% | 18.3% | 28.1% |
| `BalanceConsumption` | 11.2% | 12.3% | 14.0% | 11.7% | 15.2% | 14.6% | 15.5% | 18.3% | 27.8% |
| `MaxMinChargingTime-BalanceConsumption` | 12.3% | 12.6% | 14.3% | 12.9% | 14.6% | 16.6% | 16.0% | 18.1% | 28.4% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 11.7% | 12.0% | 14.3% | 13.5% | 14.9% | 15.2% | 16.6% | 19.8% | 28.4% |
| `Extended-BalanceConsumption` | 14.0% | 16.3% | 19.2% | 14.9% | 16.3% | 18.6% | 17.2% | 18.6% | 28.4% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 14.6% | 16.3% | 18.9% | 15.2% | 15.5% | 18.9% | 16.6% | 18.3% | 28.9% |

Table 5.3: Summary of percentages of feasible vehicle rotations for all instances divided by the decomposition method used, the assumed charging infrastructure, and the current provided at charging stations. (continued)

batteries during times with reduced offers. At this point, methods that consider charging times and energy consumptions take better advantage of these conditions. Regarding the instances $t1296$, $t2633$, and $t10710$, more specific methods still provide better solutions but have less impact. In all the cases examined, the method `MaxMinChargingTime-Extended-BalanceConsumption` provides the best results. This is because this method covers most aspects of BEVs.

### Percentage of Service Trips Covered by BEVs

Another interesting aspect is the percentage of service trips covered by BEVs because service trips represent a core service of public transport companies. Table 5.4 and Table 5.5 contain the percentage of service trips covered by BEVs, again divided according to the assumed distribution of charging stations, the current provided by the charging systems, and the method used for flow decomposition.

Basically, we can observe that the proportion of service trips covered by BEVs is very similar to the proportion of feasible vehicle rotations. The statements previously made can also be justified with regard to Table 5.4 and Table 5.5. However, we can observe that in all cases, the percentage of service trips covered is smaller than the corresponding percentage of feasible vehicle rotations. This may be explained by the lengths of the vehicle rotations. Feasible rotations tend to be shorter than infeasible ones and, thus, contain less service trips. In contrast to the data of Table 5.2 and Table 5.3, we now observe significant improvements in the distribution of charging stations. Now, increasing numbers of charging stations cause a steady increase in service trips covered by BEVs, even with the same current provided. In concrete terms, this means that longer vehicle rotations become feasible when the number of charging stations is increased. Regarding the methods used for flow decomposition, we observe that more specific methods lead to higher percentages of service trips covered by BEVs. As in the previous case, the method `MaxMinChargingTime-Extended-BalanceConsumption` achieves the best results. Again, the use of traditional methods without considering the vehicles' limited ranges and the possibility to recharge batteries leads to the worst results.

### Percentage of kilometers covered by BEVs

Especially interesting for companies in public transport, particularly in urban areas, is the share of kilometers that can be covered by BEVs. This is because every kilometer that is served by an BEV leads to a reduction of noise, gases, and fine particles and may contribute to public health. Table 5.6 and Table 5.7 show percentages of driven kilometers by BEVs.

The observations with regard to the share of kilometers driven by BEVs essentially correspond to the previously obtained statements. The use of decomposition methods taking into account the special features of BEVs is still preferable by comparison

**Instance t867** (867 service trips)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 18.9% | 20.7% | 21.3% | 22.4% | 25.9% | 43.8% | 24.9% | 47.3% | 48.9% |
| `LIFO` | 21.6% | 23.2% | 24.6% | 24.2% | 24.2% | 43.9% | 27.1% | 44.2% | 53.1% |
| `MaxMinChargingTime` | 19.4% | 23.3% | 24.9% | 20.9% | 24.4% | 48.9% | 24.2% | 48.7% | 51.3% |
| `BalanceConsumption` | 24.2% | 24.7% | 25.7% | 25.9% | 32.8% | 52.1% | 29.3% | 47.0% | 54.2% |
| `MaxMinChargingTime-BalanceConsumption` | 20.1% | 26.4% | 27.3% | 23.7% | 28.1% | 48.9% | 30.1% | 47.4% | 52.9% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 21.7% | 26.8% | 28.4% | 26.2% | 30.0% | 48.1% | 29.9% | 39.4% | 52.1% |
| `Extended-BalanceConsumption` | 25.8% | 29.9% | 30.8% | 28.1% | 38.6% | 51.9% | 34.1% | 45.9% | 52.7% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 26.1% | 30.9% | 32.1% | 29.6% | 31.6% | 52.5% | 35.0% | 47.8% | 53.0% |

**Instance t1135** (1135 service trips)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 18.7% | 20.4% | 20.4% | 21.6% | 25.2% | 43.0% | 24.4% | 46.6% | 48.4% |
| `LIFO` | 21.2% | 22.8% | 24.0% | 24.0% | 23.0% | 43.1% | 26.3% | 43.5% | 51.8% |
| `MaxMinChargingTime` | 18.7% | 22.6% | 24.4% | 20.7% | 23.9% | 48.2% | 23.8% | 48.0% | 50.7% |
| `BalanceConsumption` | 23.8% | 24.1% | 25.0% | 25.0% | 31.6% | 50.9% | 29.0% | 46.3% | 53.6% |
| `MaxMinChargingTime-BalanceConsumption` | 20.0% | 26.2% | 27.1% | 23.7% | 27.9% | 48.3% | 29.7% | 46.9% | 54.4% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 20.9% | 26.2% | 27.8% | 25.9% | 29.9% | 47.8% | 29.5% | 38.1% | 53.0% |
| `Extended-BalanceConsumption` | 25.4% | 29.7% | 28.8% | 27.8% | 37.5% | 51.3% | 33.7% | 45.2% | 51.1% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 25.3% | 27.9% | 29.9% | 27.6% | 29.4% | 51.5% | 29.0% | 47.5% | 51.4% |

**Instance t1296** (1296 service trips)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 1.8% | 2.1% | 2.8% | 4.2% | 4.8% | 6.2% | 4.5% | 6.8% | 18.1% |
| `LIFO` | 1.7% | 2.2% | 2.3% | 4.2% | 4.4% | 6.8% | 4.4% | 6.6% | 17.8% |
| `MaxMinChargingTime` | 2.2% | 2.4% | 2.9% | 4.5% | 5.0% | 7.1% | 5.2% | 8.2% | 18.0% |
| `BalanceConsumption` | 3.5% | 4.3% | 4.5% | 5.2% | 5.8% | 7.0% | 5.5% | 6.9% | 19.1% |
| `MaxMinChargingTime-BalanceConsumption` | 2.1% | 4.8% | 5.4% | 4.3% | 5.6% | 6.9% | 5.2% | 6.9% | 19.1% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 2.0% | 4.5% | 5.1% | 4.5% | 5.3% | 6.5% | 5.3% | 7.5% | 18.6% |
| `Extended-BalanceConsumption` | 3.5% | 4.1% | 4.2% | 5.2% | 5.8% | 6.4% | 5.8% | 7.4% | 19.0% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 3.5% | 3.8% | 4.2% | 5.5% | 6.1% | 6.6% | 5.8% | 8.9% | 17.9% |

**Instance t2633** (2633 service trips)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 1.7% | 2.1% | 2.6% | 4.2% | 4.9% | 6.0% | 4.6% | 6.2% | 17.2% |
| `LIFO` | 1.7% | 2.1% | 2.1% | 4.1% | 4.4% | 6.6% | 4.4% | 6.5% | 17.3% |
| `MaxMinChargingTime` | 2.1% | 2.1% | 2.7% | 4.4% | 4.9% | 6.8% | 5.0% | 7.9% | 18.3% |
| `BalanceConsumption` | 3.6% | 4.5% | 4.1% | 4.9% | 5.6% | 6.8% | 5.1% | 6.7% | 18.5% |
| `MaxMinChargingTime-BalanceConsumption` | 2.1% | 4.7% | 5.2% | 4.5% | 5.4% | 6.4% | 5.0% | 6.5% | 18.4% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 2.1% | 4.7% | 5.2% | 4.6% | 5.4% | 6.7% | 5.2% | 7.3% | 18.2% |
| `Extended-BalanceConsumption` | 3.6% | 4.0% | 4.0% | 5.0% | 5.6% | 6.0% | 5.6% | 7.2% | 18.8% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 3.6% | 3.9% | 4.0% | 5.6% | 6.0% | 6.4% | 5.6% | 8.1% | 18.4% |

Table 5.4: Summary of percentages of covered service trips by BEVs for all instances divided by the decomposition method used, the assumed charging infrastructure, and the current provided at charging stations.

**Instance t3067** (3067 service trips)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 15.4% | 18.8% | 28.6% | 16.1% | 22.3% | 29.3% | 33.8% | 32.2% | 53.4% |
| `LIFO` | 18.7% | 18.9% | 24.8% | 20.3% | 21.2% | 29.8% | 32.8% | 32.6% | 53.8% |
| `MaxMinChargingTime` | 15.4% | 18.8% | 27.3% | 16.1% | 22.3% | 30.0% | 30.1% | 36.6% | 57.3% |
| `BalanceConsumption` | 15.8% | 17.2% | 24.0% | 17.8% | 20.2% | 30.7% | 35.7% | 36.8% | 60.9% |
| `MaxMinChargingTime-BalanceConsumption` | 16.8% | 20.9% | 24.4% | 19.1% | 22.9% | 33.2% | 35.9% | 35.6% | 57.2% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 18.8% | 20.9% | 26.8% | 19.1% | 23.5% | 34.0% | 37.2% | 37.2% | 61.0% |
| `Extended-BalanceConsumption` | 17.2% | 21.1% | 26.4% | 20.4% | 21.3% | 33.5% | 34.9% | 36.9% | 58.0% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 17.3% | 21.3% | 22.9% | 20.9% | 22.3% | 32.6% | 33.5% | 37.2% | 59.9% |

**Instance t10710** (10710 service trips)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 4.3% | 4.7% | 5.5% | 4.1% | 5.9% | 6.6% | 5.8% | 8.1% | 17.6% |
| `LIFO` | 4.0% | 3.9% | 5.5% | 4.3% | 4.7% | 6.6% | 5.8% | 7.8% | 17.2% |
| `MaxMinChargingTime` | 4.3% | 4.7% | 6.0% | 4.3% | 5.9% | 7.3% | 6.3% | 8.1% | 17.8% |
| `BalanceConsumption` | 4.4% | 5.4% | 6.0% | 4.8% | 6.2% | 7.7% | 6.4% | 8.8% | 17.9% |
| `MaxMinChargingTime-BalanceConsumption` | 4.5% | 5.8% | 6.1% | 5.3% | 6.5% | 8.9% | 7.6% | 8.3% | 18.1% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 4.4% | 5.5% | 6.2% | 4.6% | 7.0% | 7.0% | 7.6% | 9.3% | 18.8% |
| `Extended-BalanceConsumption` | 5.8% | 6.8% | 8.7% | 6.5% | 7.9% | 9.3% | 7.8% | 8.6% | 18.6% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 6.2% | 6.8% | 8.2% | 6.5% | 7.1% | 9.3% | 6.8% | 9.9% | 19.6% |

Table 5.5: Summary of percentages of covered service trips by BEVs for all instances divided by the decomposition method used, the assumed charging infrastructure, and the current provided at charging stations. (continued)

**Instance t867** (10144.6 km in optimal solution)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 15.2% | 16.8% | 17.1% | 15.8% | 21.3% | 40.1% | 17.5% | 45.6% | 46.9% |
| `LIFO` | 15.2% | 16.3% | 20.9% | 22.0% | 19.1% | 39.3% | 19.2% | 43.7% | 48.9% |
| `MaxMinChargingTime` | 17.8% | 22.9% | 24.1% | 18.3% | 23.3% | 46.9% | 28.3% | 45.4% | 49.8% |
| `BalanceConsumption` | 20.6% | 21.8% | 25.0% | 21.4% | 22.5% | 49.4% | 24.1% | 43.6% | 52.4% |
| `MaxMinChargingTime-BalanceConsumption` | 16.7% | 20.1% | 27.4% | 22.1% | 27.1% | 39.2% | 28.1% | 42.6% | 54.0% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 17.1% | 22.2% | 26.0% | 21.8% | 25.7% | 40.2% | 28.4% | 34.5% | 49.8% |
| `Extended-BalanceConsumption` | 23.3% | 24.5% | 26.0% | 23.8% | 26.2% | 49.1% | 27.5% | 42.5% | 51.0% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 25.0% | 27.8% | 28.4% | 28.7% | 32.0% | 47.5% | 29.9% | 44.2% | 52.8% |

**Instance t1135** (13192.7 km in optimal solution)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 15.5% | 16.3% | 17.1% | 15.9% | 21.7% | 39.4% | 17.3% | 45.1% | 46.2% |
| `LIFO` | 15.7% | 16.1% | 20.7% | 22.5% | 18.8% | 38.7% | 18.9% | 43.4% | 48.1% |
| `MaxMinChargingTime` | 17.3% | 22.3% | 23.6% | 18.2% | 23.3% | 46.6% | 28.6% | 46.9% | 48.6% |
| `BalanceConsumption` | 20.4% | 21.6% | 24.9% | 21.3% | 22.5% | 49.1% | 23.8% | 43.2% | 52.0% |
| `MaxMinChargingTime-BalanceConsumption` | 16.9% | 20.4% | 27.0% | 22.1% | 26.7% | 40.0% | 27.8% | 41.1% | 53.1% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 17.0% | 22.2% | 25.9% | 21.6% | 25.3% | 40.3% | 28.2% | 34.1% | 49.7% |
| `Extended-BalanceConsumption` | 23.3% | 24.1% | 25.9% | 23.9% | 26.6% | 49.6% | 27.3% | 42.0% | 50.4% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 24.9% | 27.3% | 28.0% | 27.7% | 31.8% | 47.0% | 28.9% | 43.4% | 50.8% |

**Instance t1296** (15623.8 km in optimal solution)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 1.5% | 1.8% | 2.5% | 3.8% | 4.4% | 5.8% | 4.2% | 6.2% | 16.4% |
| `LIFO` | 1.2% | 1.6% | 1.9% | 3.7% | 4.1% | 5.2% | 4.3% | 6.5% | 16.2% |
| `MaxMinChargingTime` | 1.5% | 1.9% | 2.3% | 4.0% | 4.6% | 6.2% | 4.3% | 7.5% | 17.7% |
| `BalanceConsumption` | 3.5% | 3.8% | 4.2% | 4.3% | 5.4% | 5.8% | 4.8% | 6.8% | 18.1% |
| `MaxMinChargingTime-BalanceConsumption` | 2.0% | 4.5% | 5.2% | 3.9% | 5.2% | 6.0% | 4.8% | 8.0% | 17.3% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 1.8% | 4.6% | 5.2% | 4.2% | 5.0% | 6.2% | 5.2% | 7.5% | 18.4% |
| `Extended-BalanceConsumption` | 3.3% | 3.7% | 3.8% | 4.9% | 5.5% | 6.4% | 5.8% | 7.2% | 18.4% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 3.4% | 4.7% | 5.8% | 5.6% | 6.5% | 6.9% | 6.1% | 6.9% | 18.9% |

**Instance t2633** (30905.7 km in optimal solution)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 1.4% | 1.8% | 2.4% | 3.7% | 4.3% | 5.8% | 4.1% | 6.2% | 16.4% |
| `LIFO` | 1.4% | 1.6% | 1.8% | 3.9% | 4.0% | 5.2% | 4.2% | 6.4% | 16.7% |
| `MaxMinChargingTime` | 1.6% | 2.0% | 2.5% | 4.2% | 4.5% | 6.5% | 4.5% | 7.8% | 18.0% |
| `BalanceConsumption` | 3.6% | 3.8% | 4.3% | 4.4% | 5.3% | 5.9% | 4.7% | 6.6% | 17.7% |
| `MaxMinChargingTime-BalanceConsumption` | 2.0% | 4.4% | 5.0% | 3.8% | 5.3% | 6.0% | 4.5% | 7.9% | 17.8% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 1.8% | 4.5% | 5.0% | 4.1% | 4.9% | 5.8% | 5.0% | 6.9% | 17.8% |
| `Extended-BalanceConsumption` | 3.3% | 3.6% | 3.9% | 4.7% | 5.3% | 6.0% | 5.4% | 6.8% | 17.1% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 3.2% | 4.5% | 5.4% | 5.2% | 5.9% | 6.0% | 5.4% | 6.2% | 17.9% |

Table 5.6: Summary of percentages of kilometers driven by BEVs for all instances divided by the decomposition method used, the assumed charging infrastructure, and the current provided at charging stations.

**Instance t3067** (31111.5 km in optimal solution)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 13.4% | 16.3% | 21.1% | 14.3% | 18.0% | 25.7% | 26.2% | 28.8% | 45.9% |
| `LIFO` | 13.8% | 15.4% | 21.3% | 14.0% | 18.7% | 26.5% | 28.8% | 28.9% | 46.4% |
| `MaxMinChargingTime` | 16.3% | 16.5% | 23.9% | 17.7% | 19.3% | 26.1% | 29.2% | 29.9% | 49.2% |
| `BalanceConsumption` | 14.0% | 16.5% | 25.1% | 15.7% | 19.7% | 26.0% | 31.2% | 32.0% | 52.9% |
| `MaxMinChargingTime-BalanceConsumption` | 14.6% | 18.2% | 21.2% | 16.6% | 20.2% | 29.0% | 31.2% | 31.8% | 49.4% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 16.5% | 18.2% | 23.2% | 16.7% | 20.5% | 29.3% | 32.0% | 34.7% | 52.4% |
| `Extended-BalanceConsumption` | 15.4% | 18.2% | 22.7% | 18.0% | 19.4% | 29.3% | 30.2% | 31.8% | 50.2% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 15.3% | 18.3% | 22.1% | 18.2% | 19.7% | 28.1% | 33.0% | 34.9% | 51.9% |

**Instance t10710** (85807.2 km in optimal solution)

| decomposition method | 10% charging stations | | | 20% charging stations | | | 50% charging stations | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m | 1.8 kWh/m | 3 kWh/m | 9 kWh/m |
| `FIFO` | 3.9% | 4.3% | 5.5% | 4.0% | 5.3% | 6.5% | 5.4% | 7.6% | 17.4% |
| `LIFO` | 3.5% | 3.7% | 5.1% | 4.3% | 4.4% | 6.6% | 5.5% | 7.5% | 17.5% |
| `MaxMinChargingTime` | 4.1% | 4.4% | 5.6% | 4.1% | 5.5% | 7.3% | 6.2% | 7.9% | 17.9% |
| `BalanceConsumption` | 4.3% | 4.9% | 5.8% | 4.7% | 5.9% | 6.8% | 6.2% | 8.7% | 17.8% |
| `MaxMinChargingTime-BalanceConsumption` | 3.9% | 5.4% | 5.5% | 5.0% | 6.2% | 8.5% | 7.1% | 7.8% | 18.1% |
| `Extended-MaxMinChargingTime-BalanceConsumption` | 4.0% | 5.3% | 5.7% | 4.6% | 6.8% | 6.8% | 7.3% | 9.1% | 19.4% |
| `Extended-BalanceConsumption` | 5.3% | 6.4% | 8.5% | 6.5% | 7.7% | 9.0% | 7.6% | 8.3% | 18.2% |
| `MaxMinChargingTime-Extended-BalanceConsumption` | 6.1% | 6.7% | 8.1% | 6.5% | 7.0% | 8.9% | 6.8% | 7.4% | 19.5% |

Table 5.7: Summary of percentages of kilometers driven by BEVs for all instances divided by the decomposition method used, the assumed charging infrastructure, and the current provided at charging stations. (continued)

to traditional methods. The more complex methods achieve higher percentages of kilometers driven by BEVs in all cases. However, throughout the results, we can identify a further reduction in the percentages compared to our previous results. The vehicle rotations that are feasible for BEVs tend to contain shorter service trips than the rotations that cannot be executed by BEVs. Consequently, the total numbers of kilometers driven by BEVs are reduced.

### Charging Characteristics

So far, the implementation of resulting vehicle rotations in practice was not of major importance. Thereby, it is especially important that the charging procedures performed by BEVs are reasonably distributed over the day for all charging stations. Uneven distribution may lead to significant problems concerning the practical operation of BEVs because building sites for charging systems are usually restricted, especially in urban areas. Therefore, we analyse the charging data of the vehicle rotations at this point. Table 5.8 provides the maximum, minimum, and average maximum numbers of simultaneous charging procedures at the same charging station over all decomposition methods, for all instances, distributions of charging stations, and currents. Furthermore, the average numbers of charging stations actually used over all BEVs deployed are specified. Here, we do not address each flow decomposition method separately, since we are analyzing the general usability of our solution approach. Moreover, the following data does not consider opportunity charging during the execution of service trips. This is because corresponding charging times are usually very short and therefore do not have a significant impact on practical operations. In order to be able to better assess the findings, we additionally indicated the number of stop points for each instance.

With regard to the average numbers of charging stations that are actually used over all BEVs deployed, we can see from the data in Table 5.8 that the more stop points are equipped with charging systems, the more are actually used; however, in a disproportionately limited way considering corresponding percentages. Furthermore, the higher the assumed current at a charging station, the more charging stations are used. Both observations can be explained by the increased number of feasible vehicle rotations for BEVs. If this proportion rises, the more longer rotations can be executed by BEVs and, thus, more charging stations are used. However, this behaviour depends on the instances' distributions of timetabled service trips. If instances contain peak times, both the increasing proportion of charging stations available as well as increasing currents lead to higher percentages of charging stations used. If this is not the case, the number of charging stations used is mainly increased by a rise of charging stations available but not significantly by increasing currents.

Regarding the maximum number of simultaneous charging procedures at the same charging station, we can make similar observations when considering instances with peak times of service trips. Both increasing proportions of available charging stations and increasing currents lead to higher numbers of simultaneous chargings. When solving instance $t867$, the average maximum number of chargings varies between 2.1 and 5.0, regarding instance $t1135$ between 2.3 and 5.3, and with regard to instance $t3067$ between 4.1 and 8.9. When we look at the results of instance $t10710$ without peak times of timetabled service trips, we obtain rather contrary observations. The lower the current at a charging station, the higher is the average maximum number of chargings. In addition, a rise in the distribution of charging stations reduces the resulting maximum numbers independently of the assumed current. In the worst case, with a current of 1.8 kWh/min and 10% charging stations, we obtain 14.8 and in the best case 6.4 simultaneous chargings on average. Looking at the instances $t1296$ and $t2633$, we observe only slight changes without any apparent relation. In contrast to previous instances, the corresponding numbers are much lower and vary between 1.2 and 1.9 and between 1.4 and 2.3 simultaneous chargings respectively.

The results may give the impression that some solutions generated cannot be realized in practice due to the particularly high numbers of simultaneous charging procedures. The exact maximum number of simultaneous chargings that can be carried out at a charging station depends on several factors. For example, space limitations, numbers of charging points, or restrictions imposed by the electricity grid are of importance. However, the absolute numbers of simultaneous chargings can be reduced by subsequently optimizing buffer times entailed in the vehicle rotations. Each vehicle rotation contains service trips, deadhead trips, and charging procedures, of which the last two can be shifted, whereas service trips are fully fixed. By shifting deadheads and chargings, the maximum number of simultaneous chargings may be balanced and, thus, may be reduced, which generally enables a better realization in practice.

## 5.6 Summary and Further Research

In this paper we introduced the MF-(E)VSP as an extension of the traditional VSP to consider a heterogeneous fleet of vehicles consisting of BEVs with limited driving ranges and traditional combustion engine vehicles without range limitations. To solve the problem, we proposed a three-phase solution approach based on an aggregated time-space network. The approach consists of an exact solution method for the VSP without range limitations in the form of a mixed-integer linear program, followed by a second phase, in which limited driving ranges are considered by applying flow decomposition methods and a third phase, in which charging procedures are inserted into the vehicle rotations. The aim is to maximize the proportion of feasible vehicle rotations for BEVs within the entire set of vehicle rotations while retaining the optimal number of vehicles used and deadhead trips required obtained by solving a standard VSP. Our approach was evaluated by solving real-world instances with up to 10,000 service trips.

Essentially, it can be stated that the percentage of feasible vehicle rotations for BEVs within solutions generated, together with corresponding characteristics, meet the requirements of a first application of BEVs in practice, especially when considering the slow shift towards their use in public transport. However, there are remarkable differences between the solutions generated. The results show that the performance of the solution approach presented depends strongly on the instances' distributions of service trips and the methods used for flow decomposition. If an instance's distribution contains peak times we generate significantly better results than in the case of an almost unvarying distribution. Similarly, the impact on resulting percentages of increasing numbers of charging stations and increasing currents provided by the charging systems is much greater when timetabled trips have peak times. Furthermore, flow decomposition methods especially developed for the use of BEVs achieve significantly better results than traditional methods not considering the special features of BEVs. With regard to the percentages, we are able to cover up to 72.1% of vehicle rotations with BEVs when peak times exist, and merely up to 28.9% when this is not the case. This is mainly because instances that contain peak times of timetabled trips over the day allow the vehicles to recharge their batteries during times with reduced offers. Nevertheless, we cover a minimum of 37% in the first and 8.0% in the second case. Compared to this, traditional methods for flow decomposition without considering the limited driving ranges of BEVs have significantly poorer outcomes. Furthermore, the shares of service trips covered and kilometers driven by BEVs have a strong positive correlation to the previous aspect. Particularly, with regard to environmental issues such as noise, dust, and air pollution, this coherence plays a significant role, since public transport companies are aiming to reduce negative effects on public health by deploying BEVs.

In summary, this study remains only a first step towards more realistic concepts, models, and solution approaches for the application of BEVs in public transport companies' practice. Subsequent research should conduct further analysis with regard to the input parameters as well as the underlying assumptions about the vehicle and charging technology in order to evaluate our findings and gain further insights into the problem. The determination of the underlying charging infrastructure in particular represents an essential research topic, which may likely lead to further optimization potentials. This aspect of electro-mobility may be considered as a stand-alone problem or may be integrated into vehicle scheduling. In addition, it would be interesting to see how the consideration of multiple vehicle types with different driving ranges affect the solutions to be generated. Finally, one could extend the solution methods used for solving the E-VSP. In addition to the development of exact solution methods, heuristic solution methods capable of solving extremely large real-world problem instances with many depots and vehicle types are particularly interesting. This has already been developed for the traditional VSP without range-limited vehicles by Gintner et al., 2005.

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**Algorithm 3** Charging Insertion Procedure

**Input:** vehicle rotations $V$, charging stations $S$, lower bound $\underline{E}$ and upper bound $\overline{E}$ for the SoC

**Output:** vehicle rotations $V$ with feasibility for all $v \in V$

**for all** $v \in V$ **do**
  Set $v$ as $feasible$;
  **for all** $t \in v$ **do**
    Update SoC after executing $t$ w.r.t. energy consumption and opportunity charging;
    **if** Departure stop of $t$ is in $S$ **and** updated SoC $< \overline{E}$ **then**
      **if** $previous(t)$ is a deadhead trip **then**
        **if** Waiting time before $previous(t)$ plus after $previous(t)$ is positive **then**
          Shift $previous(t)$ backwards;
          Add charging procedure before $t$;
          Update SoC;
        **end if**
      **else if** Waiting time before $t$ is positive **then**
        Add charging procedure before $t$;
        Update SoC;
      **end if**
    **end if**
    **if** SoC $< \underline{E}$ **then**
      Set $v$ as $infeasible$;
      Delete all charging procedures within $v$;
      **break**;
    **end if**
  **end for**
**end for**
**return** $V$;

| **Instance 867** (207 stop points) | | | | | |
|---|---|---|---|---|---|
| chrg.stat. (%) | current (kWh/min) | avg. max. | min | max | chrg.stat. used |
| 10 | 1.8 | 2.1 | 1 | 3 | 6.1/20 |
| 10 | 3 | 2.5 | 2 | 3 | 7.9/20 |
| 10 | 9 | 3.1 | 2 | 4 | 12.3/20 |
| 20 | 1.8 | 2.2 | 2 | 4 | 7.8/40 |
| 20 | 3 | 2.8 | 2 | 4 | 10.2/40 |
| 20 | 9 | 3.8 | 3 | 5 | 14.7/40 |
| 50 | 1.8 | 2.9 | 2 | 4 | 9.3/100 |
| 50 | 3 | 3.7 | 3 | 4 | 15.8/100 |
| 50 | 9 | 5.0 | 4 | 5 | 19.7/100 |

| **Instance t1135** (101 stop points) | | | | | |
|---|---|---|---|---|---|
| chrg.stat. (%) | current (kWh/min) | avg. max. | min | max | chrg.stat. used |
| 10 | 1.8 | 2.3 | 1 | 4 | 3.3/14 |
| 10 | 3 | 2.9 | 2 | 4 | 4.9/14 |
| 10 | 9 | 4.9 | 3 | 6 | 7/14 |
| 20 | 1.8 | 2.5 | 1 | 4 | 4/28 |
| 20 | 3 | 3.8 | 3 | 4 | 5.6/28 |
| 20 | 9 | 5 | 3 | 6 | 7.1/28 |
| 50 | 1.8 | 3 | 2 | 4 | 4.9/70 |
| 50 | 3 | 4.3 | 4 | 6 | 8.6/70 |
| 50 | 9 | 5.3 | 3 | 6 | 13.3/70 |

| **Instance 1296** (88 stop points) | | | | | |
|---|---|---|---|---|---|
| chrg.stat. (%) | current (kWh/min) | avg. max. | min | max | chrg.stat. used |
| 10 | 1.8 | 1.9 | 1 | 3 | 3.3/9 |
| 10 | 3 | 1.6 | 1 | 2 | 4.9/9 |
| 10 | 9 | 1.2 | 1 | 2 | 7/9 |
| 20 | 1.8 | 1.2 | 1 | 2 | 4/18 |
| 20 | 3 | 1.5 | 1 | 2 | 5.6/18 |
| 20 | 9 | 1.9 | 1 | 3 | 9.3/18 |
| 50 | 1.8 | 1.6 | 1 | 2 | 4.9/27 |
| 50 | 3 | 1.8 | 1 | 2 | 8.6/27 |
| 50 | 9 | 1.9 | 2 | 3 | 13.3/27 |

| **Instance t2633** (67 stop points) | | | | | |
|---|---|---|---|---|---|
| chrg.stat. (%) | current (kWh/min) | avg. max. | min | max | chrg.stat. used |
| 10 | 1.8 | 2.3 | 1 | 4 | 2.6/8 |
| 10 | 3 | 1.9 | 1 | 2 | 2.9/8 |
| 10 | 9 | 1.4 | 1 | 2 | 3.3/8 |
| 20 | 1.8 | 1.6 | 1 | 2 | 4.6/16 |
| 20 | 3 | 1.9 | 1 | 2 | 4.9/16 |
| 20 | 9 | 2 | 1 | 3 | 6.3/16 |
| 50 | 1.8 | 1.8 | 1 | 2 | 5.3/40 |
| 50 | 3 | 2 | 2 | 2 | 5.5/40 |
| 50 | 9 | 2.1 | 2 | 3 | 10.5/40 |

| **Instance t3067** (209 stop points) | | | | | |
|---|---|---|---|---|---|
| chrg.stat. (%) | current (kWh/min) | avg. max. | min | max | chrg.stat. used |
| 10 | 1.8 | 5.9 | 4 | 7 | 5.6/21 |
| 10 | 3 | 4.1 | 3 | 5 | 6.6/21 |
| 10 | 9 | 4.8 | 3 | 6 | 9.5/21 |
| 20 | 1.8 | 5.4 | 4 | 7 | 7.3/42 |
| 20 | 3 | 5.9 | 4 | 7 | 10.1/42 |
| 20 | 9 | 5.8 | 5 | 7 | 19.3/42 |
| 50 | 1.8 | 7 | 6 | 9 | 15.4/105 |
| 50 | 3 | 7.6 | 5 | 11 | 19/105 |
| 50 | 9 | 8.9 | 8 | 9 | 38.6/105 |

| **Instance t10710** (140 stop points) | | | | | |
|---|---|---|---|---|---|
| chrg.stat. (%) | current (kWh/min) | avg. max. | min | max | chrg.stat. used |
| 10 | 1.8 | 14.8 | 13 | 17 | 5.4/15 |
| 10 | 3 | 12 | 10 | 15 | 5.5/15 |
| 10 | 9 | 7.4 | 7 | 9 | 11.5/15 |
| 20 | 1.8 | 12 | 10 | 17 | 7.4/30 |
| 20 | 3 | 9.5 | 8 | 12 | 7.6/30 |
| 20 | 9 | 6.4 | 5 | 8 | 14.6/30 |
| 50 | 1.8 | 11.4 | 10 | 13 | 13.3/75 |
| 50 | 3 | 10.6 | 9 | 13 | 13.9/75 |
| 50 | 9 | 8.9 | 8 | 11 | 31.3/75 |

Table 5.8: Maximum, minimum, and average maximum numbers of simultaneous chargings at the same charging station over all decomposition methods divided by the assumed charging infrastructure and the current provided at charging stations.

# Chapter 6

# Location planning of charging stations for electric buses in public transport considering vehicle scheduling: a variable neighborhood search based approach

## Abstract

In recent years, many public transport companies have launched projects testing the operation of electric buses. Within most projects initiated, traditional buses with combustion engines are being progressively replaced by electric buses while retaining cost-minimal vehicle rotations. In such cases, some stops on the bus lines are equipped with charging technology. Traditional combustion engine buses can operate for an entire day without having to refuel. By contrast, modern electric buses have considerably shorter ranges and need to recharge their batteries several times a day. For a cost-efficient use of electric buses, the charging stations must be located within the road network in such a way that required deadhead trips are as short as possible or even redundant, but attention must also be paid to construction costs. In contrast to vehicle scheduling, which is a more short-term planning task of public transport companies, location planning of charging stations is a long-term planning problem and requires a simultaneous solving of both optimization problems. Specifically, location planning and vehicle scheduling have to be considered simultaneously in order to open up optimization potentials by comparison to sequential planning, since locations of charging stations directly influence the resulting vehicle rotations. To this purpose, we present a novel solution method for the simultaneous optimization of location planning of charging stations and vehicle scheduling for electric buses in public transport, using variable neighborhood search. By a computational study, we show that a simultaneous consideration of both problems is necessary because a sequential planning generally leads to either infeasible vehicle rotations or

to significant increases in costs.

## Keywords

Location Planning, Vehicle Scheduling, Electric Buses, Charging Stations, Partial Charging

## Contents

## 6.1 Introduction

In the last years, awareness of climate change and sustainable operations has increased significantly throughout the entire economy and public life. Electromobility is currently considered as a highly relevant technology in order to make public transport systems more sustainable and environmentally friendly. Therefore, traditional buses with combustion engines are being progressively replaced by electric buses. Electrically powered buses facilitate a locally emission-free movement which leads to minimal emission levels of greenhouse gases, dust particles, and nitrogen oxides. Seeking to improve the quality of life especially in congested urban areas, electric buses enable much more quietly operations (cf. Requia et al., 2018).

At present, the electric energy required for powering electric buses is either provided by batteries or is generated by fuel cells from hydrogen, methanol, or similar fuel (cf. Kunith et al., 2014). Due to the lower energy density of modern electric batteries compared to common tank capacities for hydrogen or methanol, battery-powered buses involve the greatest challenges for bus operations. For this reason, we focus on battery electric buses (BEB) within this work. However, the methodology and results of this work can be transferred to any other type of electric engine. We will consider electric bus and battery electric bus as synonyms.

Traditional combustion engine buses can often operate for an entire day without having to refuel. By contrast, modern BEBs have only a fractional part of the ranges of combustion engines buses and need to recharge their batteries several times a day (cf. Deilami and Muyeen, 2020). Nowadays, BEBs are charged *overnight* at vehicle depots after the completion of their daily operations. In addition, the vehicles are charged at charging stations during shorter waiting periods while operating (*opportunity charging*). Energy transmission occurs either conductively by a wire or inductively. In some cases, the vehicle batteries are also replaced with a fully charged battery (*battery swapping*).

With a view, for example, to the current real-world bus project at the Schiphol Airport in Amsterdam, Netherlands, the bus company Connexxion operates with up to 100 BEBs at the present time[1]. Electric VDL Citea buses are operated within this project storing batteries capable of storing 215 kWh which results in a range between 80 and 120 kilometers. The batteries are charged inductively with fast charging systems. Most modern electric buses like the *Irizar ie Bus*[2] are able to store about 350 kWh and may operate up to 17 hours in urban bus systems without charging.

In recent years, many other public transport companies have launched similar pilot projects testing the operation of BEBs. Hydrogen and Technology (2018) gives an overview on current projects. Most projects initiated aim towards substituting

[1] https://www.mobilityhouse.com/int_en/our-references/connexxion-electric-bus-fleet

[2] https://www.irizar-emobility.com/solutions-and-services/vehicles/ie-bus/?lang=en

diesel buses with BEBs during the daily services while retaining cost-minimal vehicle rotations. In such cases, charging systems are established at some stops on the bus lines to facilitate the recharging of the vehicle batteries during operation. For a cost-efficient deployment of BEBs, the charging stations must be built within the road network so that deadhead trips are as short as possible or are not necessary at all. Longer deadhead trips increase the operational costs and may lead to higher demands for buses.

Therefore, construction costs for charging stations as well as the buses' purchase and operational costs have to be considered at the planning stage. The planning process of public transport companies consists principally of strategic, tactical, and operational planning tasks, which differ with regard to the time periods considered. Figure 6.1 provides an overview of the planning process. Strategic planning comprises the network design and line planning. The network design determines stop points and necessary infrastructure, particularly including the distribution of charging stations within the road network. In this scope, specific technical aspects such as energy grids' transmission capacities or restrictions imposed by local conditions may be considered (cf. Alonso et al., 2014 and Märkle-Huß et al., 2020). Within the tactical planning, timetables are constructed according to the previously planned lines. Operational planning determines the deployment of vehicles and personnel.

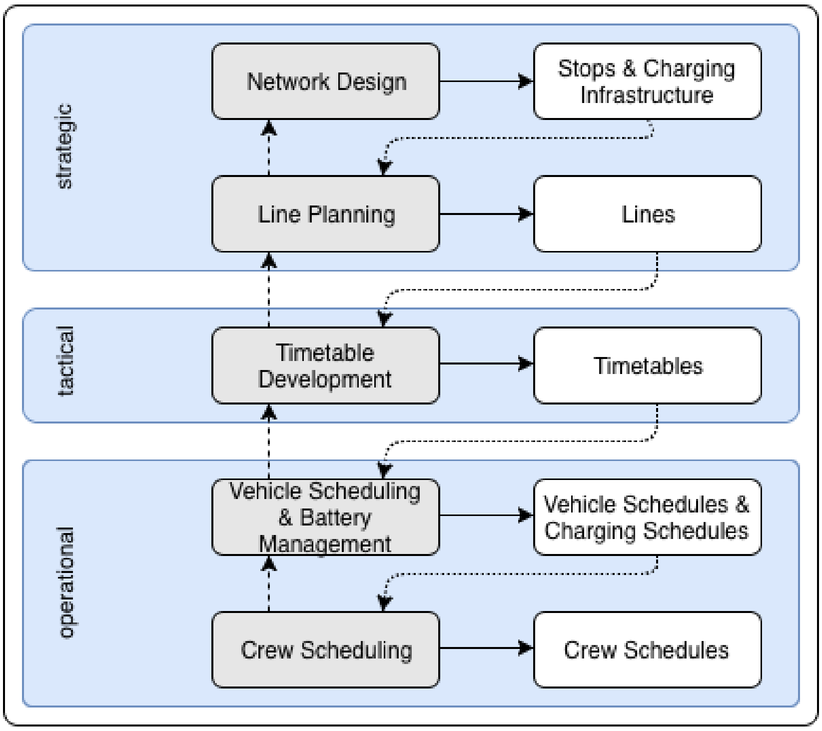


Figure 6.1: Overview of the planning process arising for companies in public transport when deploying BEBs.

The first operational planning task is vehicle scheduling which specifies the vehicle deployment for operating service trips offered daily. Service trips denote trips to transport passengers from a departure stop via intermediate stops to an arrival stop at fixed times determined by a timetable. The objective is to assign the set of service trips to vehicles at minimum costs. As part of this task, each service trip must be covered exactly once, each vehicle must execute a feasible sequence of trips (vehicle rotation) without time overlaps, and each vehicle must start and end its rotation at the same depot. This optimization problem commonly refers to the term *Vehicle Scheduling Problem* (VSP). Between successive service trips a vehicle can perform deadhead trips without transporting passengers if necessary. If BEBs are considered within vehicle scheduling, restricted operating ranges due to limited battery capacities and battery charging must be taken into account. This extended optimization problem is commonly denoted as the *Electric Vehicle Scheduling Problem* (E-VSP). While charging, a vehicle stops at a charging station for a specific time period depending on the battery's remaining energy (State of Charge, SoC). Batteries can be either fully or partially charged. The task of determining when, where, and to what extent a battery is charged is denoted as battery management which is closely related to vehicle scheduling.

Unlike vehicle scheduling, that is a more short-term planning task in operational planning, location planning of charging stations is a long-term planning task belonging to the strategic network planning and requires a simultaneous optimization of location planning of charging stations and vehicle scheduling for BEBs. Both optimization problems have to be considered simultaneously in order to open up optimization potentials by comparison to sequential planning. At the present time, there are solution approaches to the E-VSP considering fixed locations of charging stations determined in advance, on the one hand. On the other hand, location planning problems for charging stations are being solved to provide for the operation of cost-minimal vehicle rotations computed for buses without range limitations by BEBs. Both approaches belong to a sequential planning. To the best of our knowledge no solution approaches exist that consider both problems.

Simultaneous problem solving is always applicable when a public transport company fully or partially substitutes its fleet of diesel buses with BEBs for the first time. This is particularly the case because charging stations are not usually available within public transport systems yet and need to be built. Furthermore, it is expected that in the future private energy companies will operate networks of charging stations, especially within urban areas, that can be used by vehicles and buses. Some of these networks already exist, such as *E.on Drive*[3] in Germany, but it is expected that such offers will be expended in the future. In this scenario, each transport company has to pay a usage fee in order to charge a vehicle at specific

[3]https://www.eonenergy.com/for-your-business/large-energy-users/energy-solutions/electric-vehicle-charging

stations. While location planning of charging stations is a long-term planning problem, vehicle scheduling is carried out every time the timetable changes. However, the simultaneous approach is still applicable because then it is based on the modified timetable and the set of charging stations provided by the energy companies. The construction costs for building a charging station then correspond to the usage fees.

In this paper, we present a novel solution method for the simultaneous optimization of location planning of charging stations and vehicle scheduling for BEBs in public transport to open up potentials for cost savings in comparison to a sequential planning. To do so, we develop a solution approach based on *Variable Neighborhood Search* (VNS), which has been successfully applied to real-world combinatorial optimization problems in a variety of application areas (cf. Hansen et al., 2010b). We propose a heuristic solution approach because the E-VSP and the location planning problem are both difficult to solve, especially with regard to larger instances. Following Lenstra and Rinnooy (1981) and Yang and Sun (2015), both problems are NP-hard. Simultaneous problem solving is expected to be no less difficult. Within our solution approach we incorporate complete as well as partial charging procedures of the vehicle batteries. By a computational study, we prove the need for simultaneous optimization as opposed to sequential planning. We show that simultaneous problem solving is necessary because a sequential planning generally leads to either infeasible vehicle rotations or to significant increases in costs. Further on, we discern that the incorporation of partial charging procedures leads in principle to major cost savings.

This paper is outlined as follows: In Section 6.2 we provide an overview of existing work about scheduling of electric vehicles and location planning of charging stations for BEBs. In Section 6.3 we define the problem to be solved formally. Following this, we introduce the metaheuristic solution method in Section 6.4. In Section 6.5 we perform comprehensive computational experiments and analyze the results in order to make key statements. We provide conclusions and present potentials for further research in Section 6.6.

## 6.2 Literature Overview

In this section, we give an overview of related work. As mentioned above, existing work can generally be divided into scheduling of BEBs assuming fixed locations of charging stations and location planning of charging stations for given vehicle rotations. Consequently, we begin by discussing existing solution approaches for scheduling BEBs in public transport. We then present literature on location planning of charging stations.

### 6.2.1 Scheduling of Electric Buses in Public Transport

As one of the first contributions dealing with alternative engine types within vehicle scheduling, Stasko and Gao (2010) present a solution method for the VSP taking into account different engine options. The solution approach is based on integer programming. Engines powered by compressed natural gas (CNG) are considered besides combustion engines. The approach aims at reducing emission levels within vehicle scheduling.

Reuer et al. (2015) consider a mixed fleet of vehicles consisting of electrically powered buses and buses without range limitations within the basic VSP. The authors apply a time-space network based exact solution method for the VSP introduced by Kliewer et al. (2006) to solve the enhanced optimization problem. Solutions obtained to this problem contain optimal flow values through the network. Therefore, strategies for flow decomposition are necessary to obtain vehicle rotations. The authors analyze six strategies for flow decomposition that aim at maximizing the proportion of feasible vehicle rotations for BEBs. Battery charging is assumed to be performed within constant time periods. The authors show that a simple substitution of traditional buses with BEBs leads to widely infeasible vehicle schedules.

Haghani and Banihashemi (2002) consider a fleet consisting entirely of range restricted vehicles. They consider vehicle scheduling with route and time constraints in order to limit the lengths and durations of vehicle rotations. However, battery charging is not considered. The authors propose one exact and two heuristic solution models together with techniques for reducing the problem sizes in order to solve even larger-scale problem instances.

Chao and Xiaohong (2013) consider battery swapping in addition to limited operating ranges of BEBs within the VSP. To solve the problem, a solution method based on a Non-dominated Sorting Genetic Algorithm (NSGA-II) is introduced. A case study based on real-world data taken from a project in Shanghai is performed to analyze the solution approach.

Li (2014) addresses vehicle scheduling of BEBs with either battery swapping or charging and presents a model for restricting the maximum route distance. Both fast charging and battery swapping are presumed to be performed within constant time windows, but the time for fast charging depends on the location.

Adler and Mirchandani (2016) deal with scheduling of BEBs incorporating charging procedures at given charging stations located within the road network. To solve the problem, they present a column-generation approach. A heuristic method is presented to obtain necessary initial solution. The algorithm is based on a greedy algorithm and computes vehicle rotations under consideration of range limitations and charging. In this work, again full chargings of vehicle batteries are assumed.

As one of the first authors, Wen et al. (2016) address the E-VSP with partial chargings. They present an exact solution method based on mixed integer programming and an adaptive large neighborhood search heuristic approach. The results demonstrate that the exact solution methods is only applicable to small problem instances. However, the heurstic solution approach also solves larger instances in a reasonable amount of time.

Kooten Niekerk et al. (2017) also consider partial charging procedures of BEBs. The authors introduce a solution approach based on column generation. Charging times depend linearly on a battery's SoC. Furthermore, battery aging and time-dependent energy prices are considered. The authors show that in some cases, the consideration of partial charging procedures leads to cost savings.

Recently, Wang et al. (2020) proposed an exact solution method for the E-VSP based on dynamic programming. Within this contribution, battery aging is particularly considered. The objective of the solution method is minimize the total costs especially incorporating costs for battery replacements during the life spans of the vehicles deployed. By a computational study, the authors analyze the influence of different working loads, battery management, and working temperatures of batteries on resulting vehicle schedules.

### 6.2.2 Location Planning of Charging Stations for Electric Buses

At the present time, only few publications deal with location planning of charging stations for BEBs in public transport. Kunith et al. (2014) present a mixed integer linear optimization model for determining locations for charging stations for a bus route. The model is based on a set covering problem. The objective is to minimize the number of charging stations needed. The authors consider constraints imposed by the buses' operation and the battery charging process. In addition, different energy consumption scenarios are considered to reflect external influencing factors on the buses' energy consumption, such as traffic volume and weather conditions. Standard optimization libraries are used for solving the problem.

Berthold et al. (2015) propose a mixed integer linear program in order to determine optimal locations of charging stations for the electrification of a single bus line in Mannheim. The problem is solved by using standard optimization libraries. Furthermore, partial charging procedures and battery aging effects over several time periods are considered. Since the problem is very complex, the solution approach is not suitable for larger instances.

Xyliaa et al. (2017) develop a dynamic optimization model to establish a charging infrastructure for BEBs in Stockholm, Sweden, considering restricted waiting times at intermediate stops on service trips given by the schedule and different currents of the charging systems imposed by local conditions. They provide statements about the application possibilities of BEBs in urban areas and effects on vehicle rotations. Within both works, no line changes of the buses used are considered.

Liu et al. (2018) consider energy consumption uncertainties within location planning of charging stations for BEBs in public transport. Therefore, the authors propose a robust optimization model represented by a mixed integer linear program.

Using real-world data, the authors show that the proposed solution model can provide optimal locations for charging stations that are robust against uncertain energy consumption of BEBs.

Lin et al. (2019) introduce a spatial-temporal model for a large-scale planning of charging-stations for BEBs in public transport. The authors consider characteristics of BEBs operation and plug-in fast charging technologies. The model is represented by a mixed-integer second-order cone programming formulation with high computational efficiency. A case study using data from Shenzhen, China is used to analyse the robustness of the solution model to timetable changes.

Regarding related optimization problems in the scope of transportation, there are some contributions dealing with the charging infrastructure for electric vehicles. Regarding *Vehicle Routing Problems* (VRP) with electric vehicles, Worley et al. (2012) propose a solution approach for the simultaneous determination of optimal locations for charging stations and vehicle routes. They show that this approach leads to lower total costs of the vehicle deployment by comparison to locations of charging stations known a priori. Schiffer and Walther (2018) also deal with the simultaneous determination of locations for charging stations and routes for electric vehicles. The authors extend this optimization problem by considering uncertain characteristics of the customers to be served. Uncertain spatial customer distributions, demand, and service time windows are particularly addressed. The authors introduce a robust optimization approach based on adaptive large neighborhood search. Vehicle routing comprises different challenges and conditions than vehicle scheduling and therefore needs other solution approaches. Consequently, it is not possible to draw concrete statements with regard to the E-VSP.

| reference | E-VSP | E-VRP | mixed veh. fleet | electric veh. fleet | w/o line changes | fixed chrg. stat. | fixed veh. rot. | partial charging |
|---|---|---|---|---|---|---|---|---|
| Stasko and Gao (2010) | • | | • | | | • | • | |
| Haghani and Banihashemi (2002) | • | | | • | | • | | |
| Worley et al. (2012) | | • | | • | | | | |
| Chao and Xiaohong (2013) | • | | | • | | • | | |
| Li (2014) | • | | | • | | • | | |
| Reuer et al. (2015) | • | | • | | | • | • | |
| Adler and Mirchandani (2016) | • | | | • | | • | | |
| Wen et al. (2016) | • | | | • | | • | | • |
| Berthold et al. (2015) | • | | | • | • | | • | • |
| Kooten Niekerk et al. (2017) | • | | | • | | • | | • |
| Xyliaa et al. (2017) | • | | | • | • | | • | • |
| Liu et al. (2018) | • | | | • | | | • | • |
| Schiffer and Walther (2018) | | • | | • | | | | • |
| Lin et al. (2019) | • | | | • | | | • | • |
| Wang et al. (2020) | • | | | • | | • | | • |

Table 6.1: Overview of the main characteristics of related literature

### 6.2.3 Summary and Need for Further Research

Table 6.1 presents the main characteristics of the presented literature. As described there, there is no existing work that deals with scheduling of BEBs and location planning of charging stations simultaneously. However, as underlined by Worley et al. (2012) with regard to vehicle routing, a simultaneous optimization opens up potentials for cost savings. It is to be expected that a simultaneous problem solving will also be beneficial for scheduling of BEBs in public transport. In addition, partial charging procedures have not yet been considered sufficiently within the scope of scheduling BEBs. As shown by Kooten Niekerk et al. (2017) for fixed locations of charging stations, the incorporation of partial charging procedures facilitates further optimization potentials. Simultaneous problem solving under consideration of partial charging procedures forms the basic idea of our contribution.

## 6.3 Formal Model and Costs

In this section, we present the *Electric Vehicle Scheduling Problem with Location Planning of Charging Stations* (E-VSP-LP) as the key problem being solved in this paper. We assume a public transportation network given by a set $S = \{s_1, \ldots, s_n\}$ of $n \in \mathbb{N}$ stop points also containing the set of vehicle depots $D \subseteq S$. Service trips are defined by a given timetable as a set $T = \{t_1, ..., t_m\}$ with $m \in \mathbb{N}$. A service trip $t \in T$ is characterized by its departure and arrival time as well as its departure and arrival stop. For any pair $(s_i, s_j) \in S \times S$ of stop points there is a specific distance and travel time that can be different depending on whether the trip is a service or deadhead trip. In our study, we do not consider opportunity charging of BEBs during the execution of service trips. Consequently, the set $S$ contains the departure and arrival stop of each service trip $t \in T$ as well as the set of depots. The aim is to assign the service trips contained in $T$ to a set of BEBs that are substantially determined by their battery capacities. There may be other specifications such as vehicle dimensions or passenger capacities. Each combination of these features is denoted as a *vehicle type*. To recharge the vehicle batteries, charging stations can be built at each stop point of $S$. The installed charging system at a charging station considerably influences the time needed for charging. A vehicle can be either fully or partially charged, which also affects the charging time.

For the deployment of a BEB fixed costs $c^{bus}_{fixed} > 0$ incure independently of the executed trips. Each charging or trip operated during a vehicle rotation results in operational costs. Therefore, we consider time costs per hour $c^{bus}_{time} > 0$ and for the distances covered of $c^{bus}_{distance} > 0$. The equipment of stop points with charging technology causes fixed costs $c^{charging}_{fixed} > 0$. These costs may be different, depending on the type of the charging system to be installed or the location. For instance, it is more expensive to build a charging station at a busy crossing than in a quiet side street. The objective of the simultaneous optimization problem is to minimize the total costs for a given timetable and potential locations of charging stations. Accordingly, fixed costs for BEBs as well as charging stations and operational costs for the buses' operation must be minimized. Given decision variables $y_s \in \{0,1\},\ \forall s \in S$ and $x_v \in \{0,1\},\ \forall v \in V$ denoting the decision whether a charging station is built at stop point $s$ or respectively, whether a vehicle $v$ is used or not, the objective function can be formulated as

$$min \qquad \underbrace{\sum_{s \in S} c^{charging}_{fixed} \cdot y_s}_{location\ planning} + \underbrace{\underbrace{\sum_{v \in V} c^{bus}_{fixed} \cdot x_v}_{vehicle\ costs} + \underbrace{\sum_{v \in V} \sum_{t \in v} \left( c^{bus}_{time} \cdot dur(t) + c^{bus}_{distance} \cdot len(t) \right)}_{operative\ costs}}_{vehicle\ scheduling} .$$

A trip's duration is specified by $dur(t) \geq 0$ and a trip's length by $len(t) \geq 0$.

## 6.4 A Variable Neighborhood Search based Solution Method for the E-VSP-LP

In this section, we discuss our solution approach for the E-VSP-LP. The objective is to find vehicle rotations for BEBs and locations for charging stations simultaneously and at a minimum cost. We begin by presenting the basic procedure of our heuristic solution method. The solution method consists primarily of generating initial solutions first and then finding new solutions with lower total costs. To do so, we introduce a savings algorithm for generating initial solutions in Section 6.4.2. Afterwards, we present an algorithm for improvement based on VNS in Section 6.4.3.

### 6.4.1 General Approach

Algorithm `MAIN-VNS` provides the main procedure of our solution method. The set of scheduled service trips to be assigned and an initial set of charging stations, together with their locations, serve as the input data. Already existing charging infrastructure, for example due to the implementation of previous pilot projects, may be included in the set of charging stations. Usually, at the beginning of the algorithm the set of charging stations is empty. The algorithm basically consists of two consecutive steps: First, we use a savings algorithm `SA` to generate initial sets of vehicle rotations for BEBs and charging stations (l. 1). Subsequently, we use this initial solution as the input for an improvement method based on VNS, which we denote as `BVNS` (l. 2). The algorithm terminates by returning the best solution found. The two key methods `SA` and `BVNS` are explained in the following sections.

**Algorithm 4** Main Variable Neighborhood Search (`MAIN-VNS`)

**Input:** scheduled service trips $T$, charging stations $S$
**Output:** vehicle rotations $V$, charging stations $\overline{S}$

$(V', S') \leftarrow \texttt{SA}(T, S)$;
$(V'', S'') \leftarrow \texttt{BVNS}(V', S')$;
**return** $V'', S''$;

### 6.4.2 Savings Algorithm for Generating Initial Solutions

The savings algorithm was first introduced by Clarke and Wright (1964) to solve VRPs heuristically. The objective of vehicle routing is to determine an optimal set of routes seeking to service a number of customers with a fleet of vehicles. Following Cordeau et al. (2007), the savings algorithm is one of the most commonly used methods for vehicle routing in practice. Starting from routes each containing one customer the basic procedure is to compute cost savings iteratively for merging two routes into the same one. Within each iteration the merging that results in the highest saving is performed. A saving consists of fixed and operative costs saved. This procedure terminates when no further mergings can be performed. Although this algorithm has been applied generally to VRPs, we adapt this algorithm hereinafter in order to apply the same procedure to the E-VSP-LP.

Algorithm `SA` shows the procedure for generating initial solutions to the E-VSP-LP formally using the idea of cost savings. The set of scheduled service trips to be assigned and an initial set of charging stations, together with their locations, serve as the input data. The algorithm begins by adding a vehicle rotation for each scheduled service trip, now containing only the associated trip together with a deadhead trip from and to the depot (l. 4). If these vehicle rotations are not feasible for BEBs the entire optimization problem is infeasible. Within each iteration of the algorithm those two vehicle rotations (l. 7 & 8) are merged that lead to a feasible rotation and entail the highest saving. Therefore, the set of service trips of both rotations to be merged are processed consecutively, in order of departure times (l. 9). Since the SoC mostly influences the feasibility of a vehicle rotation besides temporal restrictions the algorithm aims at adding charging procedures as often as possible. For this purpose, starting with a new and empty vehicle rotation (l. 10), four different cases are considered for each service trip of the rotations to be merged. First, we check whether a charging procedure can be performed at an existing charging station of $S$ before executing the current service trip, taking into account necessary deadhead trips (l. 12). If this can be done, necessary deadhead trips, the charging procedure, and the service trip are added (l. 13). If this is not possible, we examine whether the current service trip can be executed without detours to charging stations (l. 14). If the SoC is insufficient, we check whether the current service trip can be executed by building a new charging station at the trip's departure stop and performing a charging procedure (l. 16). Lastly, the same is checked but for the latest position of the vehicle, which is less strict because the deadhead trip is executed after the charging procedure (l. 18). If none of these options can be carried out, the current merging is aborted (l. 20). When a merging is feasible, the saving for merging two vehicle rotations $v, w \in V$ into a new rotation $\overline{v,w}$ is given by

$$s(v,w) = c_{fix}^{bus} - \delta \cdot c_{fix}^{charging} - (o(\overline{v,w}) - o(v) - o(w))$$

where $o(v) \geq 0,\ \forall v \in V$ denotes the operational costs for each vehicle rotation and $\delta \in \mathbb{N}$ the number of additionally respectively fewer needed charging stations. After each iteration the merging is performed that involves the highest positive saving (l. 25). Then, the set $S$ of charging stations is modified, the new vehicle rotation is added, and the rotations merged are removed (l. 26 & 27). If no positive savings exist, the algorithm terminates and returns the sets of vehicle rotations and charging stations (l. 29). Hence, solutions generated by this procedure are always feasible.

The procedure of `SA` is based on the heuristic solution method proposed for the E-VSP by Adler and Mirchandani (2016). Within this algorithm, the charging stations are assumed to be known a priori and cannot be changed. However, within algorithm `SA`, we extend the procedure from Adler and Mirchandani (2016) significantly by incorporating location planning for charging stations.

### 6.4.3 Variable Neighborhood Search for Improvement

To finding new solutions with lower total costs, we use a VNS based solution method. VNS was first introduced by Hansen et al. (2010b). The underlying concept of VNS is a systematic change of neighborhoods, both in an improvement phase to find a local optimum and in a perturbation phase to escape from local optima. In the perturbation phase, a so-called shaking method is applied, which exerts a stochastic influence on an incumbent solution by performing stochastic changes. Even this procedure can cause a deterioration in the objective function value it has used to escape from local optima. In the improvement phase, a local search method is used to find new solutions with lower total costs.

Adapting the basic VNS concept to solve the E-VSP-LP thus requires the definition of a problem specific neighborhood structure and methods for shaking, a local search, and changing the neighborhood. Algorithm `BVNS` provides the procedure for our solution method. The algorithm follows the *basic* VNS adapted from Hansen et al. (2010a). Note, that the following procedure is applicable not only for solutions generated by Algorithm `SA` but also for every possible feasible solution.

We first define a neighborhood $N_k$ of size $k \in \mathbb{N}$ by selecting $k$ vehicle rotations. The choice of the vehicle rotations will be made randomly from the entire set in order to incorporate stochastic influences. It follows the maximum neighborhood size $k_{max} \in \mathbb{N}$ as the number of vehicles used within the incumbent solution. After each iteration of shaking and local search, a neighborhood change is performed. In this step, the objective function values of the incumbent and improved solution are compared. If the improved solution is better than the incumbent, it is accepted and the size of the neighborhood is being reset to the smallest possible value. Otherwise, the size of the neighborhood is increased and the procedure is repeated. The procedure terminates when the maximum computational time is exceeded. Algorithm `NEIGHBORHOODCHANGE` shows the procedure formally.

Second, we use the algorithm `BESTIMPROVEMENT` as the local search method within `BVNS` for improving a solution. As the total costs of a solution consist of operational costs for deadheading as well as fixed costs for vehicles and charging stations, `BESTIMPROVEMENT` combines the three following algorithms `EXST`, `SST`, and `SCP`, each aiming towards reducing one cost component. In `BESTIMPROVEMENT`, the move is performed that involves the highest cost saving.

Algorithm `EXST` is used to reduce operational costs for deadheading by exchanging service trips between different vehicle rotations of a corresponding neighborhood. Therefore, a saving is computed for each pair of service trips for the neighborhood's set of vehicles that can be exchanged, and the move with the highest saving is returned.

Algorithm `SST` aims at inserting service trips of vehicle rotations with a lower number of service trips into vehicle rotations with a higher number of service trips, again based on a neighborhood. If an insertion is possible, a saving is computed containing proportionate fixed costs for the remaining service trips, fixed costs for additional charging stations, and operational costs for possible detours. Again, the best move found is returned. The algorithm attempts to omit vehicle rotations whereby no service trips are being executed any more.

Algorithm `SCP` aims at decreasing the number of charging stations used by moving charging procedures from less frequented charging stations to higher frequented charging stations, considering the vehicle rotations of a neighborhood. The move is returned that is feasible and entails the highest saving including proportionate fixed costs for remaining charging procedures at a specific charging station and operational costs for additional detours. Similar to algorithm `SST`, this procedure aims at omitting charging stations where chargings are no longer being performed at a specific stop point.

Although, stochastic influences on incumbent solutions are already incorporated by the random selection of a neighborhood's set of vehicles, the algorithm `Shake` is applied additionally within `BVNS`. This approach is intended to enable more stochastic changes to the procedure aiming to escape from local optima. Shaking is based on the procedures given by `EXST`, `SST`, and `SCP`. Within each method call of `Shake`, one of the three algorithms is randomly applied if the corresponding move is feasible. This is done even though the objective function value is being worsened.

### 6.4.4 Inserting Partial Chargings

In our computational study, which follows this section, we incorporate complete and partial charging procedures. So far, the algorithms presented operate with any kind of charging procedures. However, we need more algorithmic effort in order to incorporate partial chargings within algorithms `SA` and `BVNS`. To that purpose, we consider the following algorithm `PCP` by Olsen and Kliewer (2020). It is applied to each vehicle rotation that is generated respectively modified within the solution procedure. As a result, algorithm `PCP` either returns the set of partial charging procedures that have to be inserted into the corresponding vehicle rotation or its infeasibility. Only if a resulting vehicle rotation is feasible is it taken into further consideration.

Algorithm `PCP` checks iteratively, after each trip of a rotation, whether the SoC has been violated (l. 2). If this is the case, the previous trips are considered (l. 3). Each trip that begins or ends at a charging station represents a charging opportunity (l. 5). If no such possibilities are being found the vehicle rotations is infeasible (l. 9). Over all charging possibilities determined, the one performed at the most highly frequented charging station is processed (l. 11). This aims at reducing the number of charging stations by shifting charging procedures from less to more highly frequented charging stations. In the next step, the vehicle rotation is divided at the specific charging station into two sub-rotations containing the previous and subsequent trips. Then, both sub-rotations are processed by the algorithm. In the case that all sub-rotations are feasible, the algorithm terminates (l. 13). If a charging station is no longer needed it is omitted. If at least one sub-rotation is infeasible, the next charging opportunity is processed (l. 15 and l.16).

## 6.5 Computational Analysis

In the following, we perform our computational experiments. We first present the instances to be solved and the problem parameters. Then, we look at the results of a sequential planning approach. In this case, location planning of charging stations and vehicle scheduling of BEBs are solved one by one. Therefore, our analysis is twofold: First, we discuss the results of solving a location planning problem for charging stations to enable the operation of given cost-optimal vehicle rotations computed for traditional buses without the range limitations of BEBs. Second, we present the results of solving an E-VSP given the locations of charging stations computed in the previous step. Last, we analyze the results of simultaneous problem solving using our heuristic solution method `BVNS` for the E-VSP-LP and compare the results to the sequential planning approaches. We specifically investigate the impact of considering complete and partial charging procedures on solutions.

### 6.5.1 Experimental Design

Our computational experiments are performed on 10 real-world instances that are inspired by real-world public transport data. The instances are characterized by different numbers of stop points and service trips as well as different distributions of service trips over a day. The instances' labels reflect these characteristics. The instances' distributions of cumulative service trips over the day are presented by Figure 6.2. The figure shows that the instances differ substantially with regard to the distributions. It is worth mentioning that the last five instances consist of subsets of the service trips taken from instance t3067_s209 for runtime reasons. In the case of instances t1580_s209 and t1487_s209 the original set of service trips was halved randomly, and in the case of instances t1060_s209, t1074_s209, and t933_s209 the set was divided into three parts also in a random way.

Within our experiments, we presume a single vehicle depot, a single vehicle type, and a single charging system. Accordingly, each timetabled service trip can be executed by every available BEB. Additionally, each BEB can charge its battery at every charging station. With regard to the practical implementations of BEBs, we assume that three buses at most can be charged at a charging station at the same time. This is because building sites for charging systems are usually restricted, especially in urban areas. In our study, we distinguish between complete and partial charging procedures. In order to incorporate battery aging, we presume that a battery's SoC ranges between 20% and 80% of a battery's capacity (cf. Fernandez et al., 2013). In our experiments, we first presume that a vehicle is always charged up to a SoC of 80%. After that, we consider partial chargings. In that regard, the threshold until a battery is charged may vary depending on the idle times at charging stations. Irrespective of the threshold until a battery is charged during its rotation, we assume that a vehicle always begins its rotation with a fully charged battery.

Following Stamati and Bauer (2013), charging modern batteries is a nonlinear and therefore complex procedure. The current during a charging process is of particular importance. As demonstrated by Olsen and Kliewer (2020), the current decreases quickly when a battery is charged to over 80% of its capacity. Below this threshold, the current is almost constant. For that reason, we assume a constant current and thus linear charging times for vehicle batteries within this paper. We assume that 5 kWh can be transferred into a vehicle battery per minute. In our study we consider chargings before the start or after the end of service trips. To reflect the lower consumption of BEBs on deadhead trips we therefore assume a consumption of 1.5 kWh per kilometer and of 1.8 kWh per kilometer driving on service trips. These parameters are inspired by the data of the previously introduced project at the Schiphol Airport in Amsterdam. At present, there is a wide range of battery capacities offered on the market. For this reason, we consider different battery capacities of 60, 120, 300 and 500 kWh within our experiments. Since we consider only one vehicle type at the same time, we conduct our study for each capacity. Based on Stamati and Bauer (2013), a BEB in use and equipped with a 60-kWh battery causes fixed costs of about 350.000 monetary units. Measured by the battery sizes this results to fixed costs for the other vehicles of 365.000, 405.000, and 450.000 monetary units. With regard to the operational costs, we presume 0.5 units per driven kilometer and 50 units per hour of operation. Again based on the bus project in Amsterdam, the equipment of a stop point with charging technology is incorporated with fixed costs of 200.000 monetary units.

### 6.5.2 Location Planning of Charging Stations for the Electrification of Cost-Minimal Vehicle Rotations, Computed without Range Limitations

We begin our computational analysis by discussing the results of solving a location planning problem for charging stations for the electrification of given cost-minimal vehicle rotations computed without range limitations. The vehicle rotations were generated using the exact optimization method for the traditional VSP by Kliewer et al. (2006), which is based on a time-space network. In order to enable the operation of these rotations by BEBs, charging stations are added to the network and charging procedures are inserted into the vehicle rotations. Partial charging procedures are performed, since the idle times at potential charging stations are given by the vehicle rotations. The objective is to maximize the proportion of vehicle rotations that are feasible for BEBs. Ideally, this procedure should ensure the holistic operation of the timetabled service trips by BEBs. For this purpose, we adapt the location planning problem for charging stations introduced by Berthold et al. (2015) and solve it using standard optimization libraries.

Table 6.2 provides the results, containing the proportions and absolute numbers of feasible vehicle rotations for BEBs together with the numbers and proportions of charging stations needed for each instance and each battery capacity. Additionally, the optimal number of vehicles used is indicated when no range limitations are considered. If the totality of all vehicle rotations is feasible for BEBs, the operational and total costs are specified for subsequent analyses. First, we observe that in the vast majority of cases the holistic electrification of vehicle rotations by means of inserting charging procedures is not possible. It is apparent that this observation holds regardless of the instance to be solved. However, the proportion of feasible vehicle rotations grows with increasing battery capacities. We can observe that every instance can be entirely served by BEBs in the case of a battery capacity of 500 kWh. In some cases, this situation already occurs with a battery capacity of 300 kWh and in a single case with 120 kWh. However, none of the instances can be entirely served by BEBs with a battery capacity of 60 kWh. Regarding a battery capacity of 60 kWh, the proportions of feasible vehicle rotations fluctuates widely

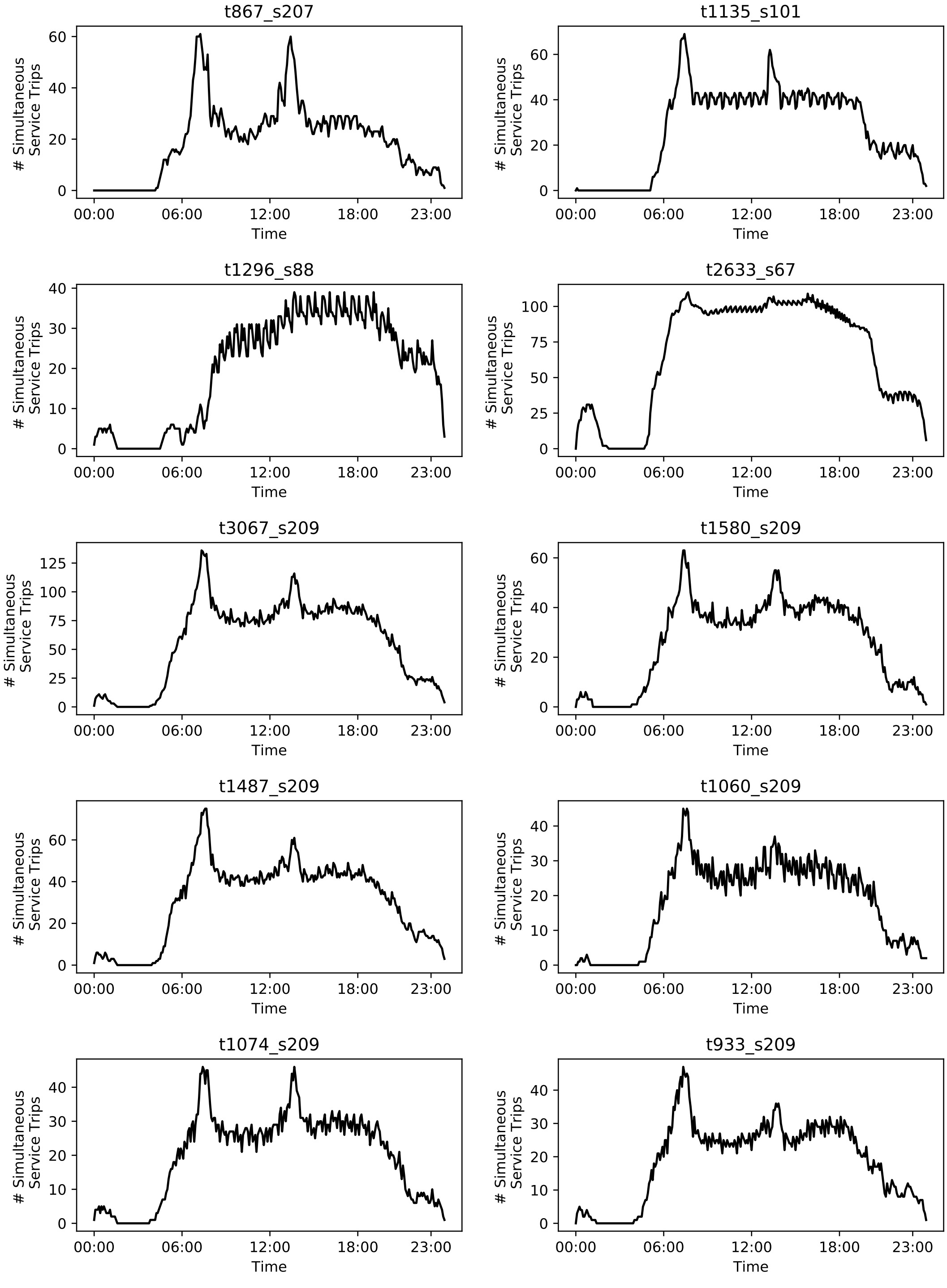


Figure 6.2: Profiles of cumulative service trips

and ranges between 7.25% and 79.63%. With regard to charging stations, it can be concluded that the numbers of stop points equipped with charging technology decreases significantly when the battery capacities grow. Instance t1296_s88 shows the biggest reduction in the number of charging stations needed from 48.86% to 6.81%. The operational costs of feasible vehicle rotations decrease slightly when the battery capacities grow, which can be attributed to fewer charging procedures required.

In summary, a sequential planning solving at first a standard VSP without incorporating the special features of BEBs and subsequently a location planning problem for charging stations is generally insufficient, leading to widely infeasible solutions. This approach is only suitable if the ranges of BEBs rise sharply in the future. The results obtained serve as lower bounds for the numbers of BEBs used and as an upper bound for the numbers of charging stations needed in the evaluation of the simultaneous solution approach.

### 6.5.3 Scheduling of Electric Buses Given Fixed Locations of Charging Stations

We now discuss the results of solving an E-VSP with given locations of charging stations. The set of charging stations determined by the previous experiment within Section 6.5.2 serves as the input, since this set is already optimal if corresponding solutions are feasible for BEBs. Following Section 6.1, the objective of the E-VSP is to minimize the number of buses in use and the operational costs for deadheading while covering each service trip. In order to ensure comparability, partial chargings are performed. Because the E-VSP is NP-hard and exact solution methods are not suitable for solving large real-world instances in general, as in our experiments, we solve the E-VSP heuristically here.

To do so, we use our main solution method `MAIN-VNS` in a reduced version. Within both algorithms `SA` and `BVNS`, which represent the main components of `MAIN-VNS`, we disable modifications of the charging stations. Within algorithm `SA`, we only allow the assignment of service trips to vehicles without charging or with detours to existing charging stations. The other two cases are omitted. Within `BVNS`, we modify the algorithms `SHAKE` and `BESTIMPROVEMENT` by disabling algorithm `SCP` within each procedure. This approach means that the set of charging stations cannot change in this experiment. Although the following results are not necessarily optimal due to the heuristic solving, we show that they provide reasonable bounds for our analysis within the next section.

An overview of the results of this experiment is given by Table 6.3, providing the numbers of vehicles used as well as operational and total costs. The number of charging stations is taken from the previous experiment. In contrast to that, now each solution is feasible, which was to be expected because of the constraints imposed by the E-VSP. Consequently, the total costs are specified for each instance and each battery capacity, containing fixed costs for buses used and charging stations as well as operational costs. First of all, the results show that in most cases where feasible vehicle rotations were computed in the first experiment described in Section 6.5.2, the solving of an E-VSP provides similar results regarding the numbers of vehicles used and total costs. In some cases, the number of vehicles required is slightly higher than in the first experiment, which can be traced back to the heuristic solution approach. Furthermore, the operational costs are marginally increased. However, the solutions of this experiment converge towards the optimal solutions and thus provide a reasonable benchmark for subsequent analyses. Regarding the numbers of vehicles used, one can observe that the fewer the proportions of feasible vehicle rotations determined within the first experiment, the more vehicles are required when solving the E-VSP. This is understandable because the closely-timed service trips of the vehicle rotations when no range limitations are considered do not provide enough time for rechargings. This leads to an increasing demand for vehicles. For example, considering instance t1580_s209, the optimal numbers of vehicles used is obtained for battery capacities of 500 kWh and 300 kWh. As the proportion of feasible vehicle rotations reduces rapidly for 120 kWh and 60 kWh within the first experiment (81.33% respectively 52%), the need for additional vehicles rises significantly (6 respectively 12 additional vehicles). Regarding the operational costs, we note that higher demands for vehicles generally leads to decreasing operational costs. This is because less deadhead trips and chargings have to be performed due to the shorter rotations.

In conclusion, solving an E-VSP with given locations of charging stations always leads to feasible vehicle rotations, which is in contrast to the first experiment. However, this solution approach generally entails increases in costs due to additional deadhead trips, likely leading to increasing demands for vehicles. The results obtained serve as upper bounds for the analysis of the simultaneous problem solving to be conducted in the following section.

### 6.5.4 Simultaneous Optimization of Vehicle Scheduling and Charging Infrastructure

We now discuss the results of simultaneous optimization of scheduling of BEBs and location planning for charging stations, i.e. solving the E-VSP-LP, using our solution method `MAIN-VNS`. We begin by presenting the results obtained by algorithm `SA` for generating initial solutions. Then, we discuss the results of algorithm `BVNS` for finding new solutions with lower total costs. In this experiment we consider complete as well as partial charging procedures in order to enable a comparison with the previous experiments.

### Summary of Results for Generating Initial Solutions

Table 6.4 provides the results of using algorithm `SA` for generating initial solutions containing feasible sets of vehicle rotations and charging stations. The results contain the total and operational costs as well as the numbers of buses and charging stations used for each instance and each battery capacity. Additionally, the differences in the total costs are specified when enabling partial charging procedures, and the best solutions found are in bold.

We first compare the results to the first experiment conducted and described in Section 6.5.2. We observe that in two of the 17 cases, when the first experiment lead to feasible vehicle rotations, the total costs obtained by the application of the savings algorithm were already lower by comparison to solving a location planning problem for charging stations. In the other cases, higher total costs are obtained. In general, the higher total costs arise from higher demands for vehicles needed within the savings algorithm. Regarding each instance, the numbers of vehicles used has increased, which is reasonable due to the heuristic solution procedure of the savings algorithm. The solving of instance $t1296\_s88$ leads to the highest increase of 23.4%. By contrast, the number of charging stations used decreases in every case. In some cases, such as instance $t1060\_s209$, the number of charging stations needed is enormously reduced (30 to two). However, since the costs for additional vehicles prevail over the cost savings arising from the lower number of charging stations used, the total costs increase. This holds true both for complete and partial charging procedures. Regarding these two charging procedures, the total costs obtained are lower in seven of the ten instances for all battery capacities when partial charging procedures are enabled. On average, total cost savings of about 1.2% are achieved. Only in three cases are the total costs higher when considering partial chargings.

We now compare the initial solutions with the results obtained and described in Section 6.5.3. With regard to the total costs, our observations are twofold: In those cases in which the solving of a location planning problem led to infeasible vehicle rotations, the application of algorithm `SA` leads to lower total costs by comparison to the results obtained by solving an E-VSP. In the other cases where feasible solutions were obtained, the total costs are higher, arising from a higher demand for vehicles needed as indicated previously. Basically, the results computed by algorithm `SA` merely serve as the input for improvement methods and thus do not serve as the final results. For this reason, the clarified statements are not particularly significant. In the next section, we present the results of improvement using our solution approach based on VNS.

### Summary of Results for Variable Neighborhood Search for Improvement

In order to carry out a final comparison between sequential planning and simultaneous problem solving, we now present the results of our solution method `BVNS` for finding new solutions with lower total costs. We use the initial solutions presented in the previous section as the input data. Table 6.5 shows the results, containing numbers of vehicles and charging stations used, as well as operational and total costs for each instance and each battery capacity. Additionally, the differences in the total costs are specified when enabling partial charging procedures, and the best solutions found are in bold.

Again, we first compare the results to solving a location planning problem for charging stations at given vehicle rotations. In those cases, where feasible solutions were computed and shown in Section 6.5.2, the total costs obtained by applying algorithm `BVNS` are almost of the same quality. In some cases, the total costs are slightly higher, which is most likely due to the heuristic solving. However, in certain scenarios, even better solutions are achieved which can be explained by the utilization of the degrees of freedom. Simultaneous problem solving enables shorter and fewer deadhead trips to charging stations, leading to lower operational and fixed costs for vehicles. As the sequential planning approach leads mostly to infeasible solutions, the simultaneous problem solving is generally preferable.

We now discuss the results with regard to solving an E-VSP with given locations of charging stations as carried out and described in Section 6.5.3. The most significant observation is that the total costs obtained by the simultaneous problem solving are always below the results of solving an E-VSP with fixed charging stations. This holds true for each combination of instance and battery capacity. The primary reasons for this are that the VNS based approach leads either to the same or slightly higher numbers of vehicles. Similarly, considerably lower numbers of charging stations needed are achieved due to the simultaneous solution procedure, leading to significant cost savings. Additionally, the operational costs are being reduced for the most part, which can be explained by the shorter deadhead trips to charging stations. As the cost savings exceed the increased costs for additional vehicles, the solutions generated entail significantly lower total costs. In conclusion, simultaneous problem solving enables significant cost savings and is always preferable to solving an E-VSP with given locations of charging stations.

Lastly, we investigate the impact of enabling partial charging procedures within vehicle rotations. The results clearly specify that the incorporation of partial chargings is more realistic and opens up optimization potentials. The number of vehicles as well as charging stations used is lower in almost all cases. This leads to significant cost savings. The same total costs are achieved in only one case. Furthermore, the more vehicles are used, the higher the cost savings are. For this reason, the cost savings generally decrease when the battery capacities increase.

It is worth noting that the clarified statements would also hold true for exact solution methods for the E-VSP-LP, which, to the best of our knowledge, do not exist. Exact solving would even strengthen the results because of the expected lower total costs.

## 6.6 Conclusions

We have introduced a novel solution method for simultaneous optimization of location planning of charging stations and vehicle scheduling for BEBs in public transport. To do so, we introduced the E-VSP-LP, which extends the standard E-VSP to incorporate location planning of charging stations. To solve the problem we developed a metaheuristic solution method based on VNS, as both problems are difficult to solve. To generate the necessary initial solutions we adapted the traditional savings algorithm. To evaluate the solution approach we performed a computational study based on real-world public transport data, with up to 3000 service trips and different battery capacities of the buses deployed. We also focused on a consideration of complete and partial battery charging procedures of the batteries within vehicle rotations. In our study we compared the simultaneous solution approach to sequential planning to tackle the underlying problems.

Our experiments showed that simultaneous solving of location planning of charging stations and vehicle scheduling of BEBs is necessary as opposed to sequential planning. First, we demonstrated that sequential planning, first solving a standard VSP and afterwards a location planning problem for charging stations, generally leads to infeasible vehicle rotations for BEBs with regard to current battery technologies. Second, solving an E-VSP with given locations of charging stations entails significant increases in costs. Solving the E-VSP-LP, on the one hand, ensures the feasibility of the vehicle rotations. On the other hand, significantly lower total costs are achieved by comparison to solving an E-VSP, due to the higher degrees of freedom. With regard to complete and partial battery chargings, we found large cost savings in most cases when enabling partial chargings within the vehicle rotations.

Our paper can be extended by the following aspects. First, the proposed models do not deal with multiple depots. Incorporating this extension would most likely open up further potentials for cost savings, as already shown for the traditional VSP. Second, our solution method solves the E-VSP-LP heuristically. Exact solution approaches would be interesting for a better verification of the quality of heuristic solution methods. In addition, an interesting path for future research would be to develop additional algorithms for the generation of initial solutions as well as for improvement. Finally, more accurate models regarding the technical aspects of BEBs may be considered. It is conceivable, to presume uncertain energy consumptions that may depend on weather conditions or the volume of traffic.

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**Algorithm 5** Savings Algorithm (`SA`)

**Input:** scheduled service trips $T$, charging stations $S$
**Output:** vehicle rotations $V$, charging stations $\overline{S}$

$V \leftarrow \emptyset$
$\overline{S} \leftarrow S$
**for all** $t \in T$ **do**
    Add a vehicle rotation to $V$ containing only $t$;
**end for**
**while** TRUE **do**
    **for all** $v \in V$ **do**
        **for all** $w \in V \setminus \{v\}$ **do**
            Determine the set $\overline{T}$ of service trips of $v \cup w$;
            Create a new vehicle rotation $\overline{v}$ without trips;
            **for all** $t \in \overline{T}$ **do**
                **if** $\overline{v}$ can be recharged at an existing charging station and execute $t$ **then**
                    Add necessary deadhead trips, charging, $t$ to $\overline{v}$;
                **else if** $\overline{v}$ can execute $t$ **then**
                    Add necessary deadhead trips, $t$ to $\overline{v}$;
                **else if** $\overline{v}$ can be recharged at the departure stop of $t$ and execute $t$ **then**
                    Add charging station to $\overline{S}$, necessary deadhead trips, charging, $t$ to $\overline{v}$;
                **else if** $\overline{v}$ can be recharged at its current position and execute $t$ **then**
                    Add charging station to $\overline{S}$, charging, necessary deadhead trips, $t$ to $\overline{v}$;
                **else break**;
                **end if**
            **end for**
        **end for**
    **end for**
    Make move with the highest saving $s(v, w)$;
    Remove rotations $v$ and $w$ from $V$; Add $\overline{v}$ to $V$;
    Add new charging stations to $\overline{S}$;
    **if** No positive savings exist **then**
        **return** $V, \overline{S}$;
    **end if**
**end while**

---

**Algorithm 6** Basic Variable Neighborhood Search (`BVNS`)

**Input:** vehicle rotations $V$, charging stations $S$, $t_{max}$, $k_{max}$
**Output:** vehicle rotations $V$, charging stations $S$

$t \leftarrow 0$
**while** $t < t_{max}$ **do**
  $k \leftarrow 1$;
  **while** $k \leq k_{max}$ **do**
    $(V', S') \leftarrow$ `SHAKE`$(V, S, k)$;
    $(V'', S'') \leftarrow$ `BESTIMPROVEMENT`$(V', S', k)$;
    $(V, S, k) \leftarrow$ `NEIGHBORHOODCHANGE`$((V, S), (V'', S''), k)$;
  **end while**
  $t \leftarrow CPUTIME()$;
**end while**
**return** $(V, S)$;

---

**Algorithm 7** `NEIGHBORHOODCHANGE`

**Input:** solutions $(V, S)$, $(V', S')$, neighborhood size $k$, objective function $f$
**Output:** solution $(V, S)$, neighborhood size $k$

**if** $f(V', S') < f(V, S)$ **then**
  $(V, S) \leftarrow (V', S')$;
  $k \leftarrow 1$;
**else** $k \leftarrow k + 1$;
**end if**
**return** $(V, S)$, $k$;

---

**Algorithm 8** `BESTIMPROVEMENT`

**Input:** neighborhood $N_k$, objective function $f$
**Output:** neighborhood $N_k$

**return** $\min_f\{EXST(N_k), SST(N_k), SCP(N_k)\}$;

---

**Algorithm 9** Exchange of Service Trips (`EXST`)

**Input:** neighborhood $N_k$
**Output:** neighborhood $N_k$

**for all** $v \in V$ **do**
  **for all** $w \in V \setminus \{v\}$ **do**
    **for all** $t_v \in v$ **do**
      **for all** $t_w \in w$ **do**
        **if** $t_v$ and $t_w$ can be exchanged **then**
          Compute saving;
        **end if**
      **end for**
    **end for**
  **end for**
**end for**
Perform exchange with the highest saving;
**return** $N_k$;

**Algorithm 10** Shift Service Trips (`SST`)

**Input:** neighborhood $N_k$, fixed costs for an BEB $c_{fix}^{bus}$
**Output:** neighborhood $N_k$

**for all** $v \in V$ **do**
  **for all** $w \in V : |ST_w| < |ST_v|$ **do**
    **for all** $t_w \in w$ **do**
      **if** $t_w$ can be inserted in $v$ **then**
        Compute saving ($c_{fix}^{bus}/|ST_w|$) less the costs for newly built charging stations
        and additional operational costs;
      **end if**
    **end for**
  **end for**
**end for**
Perform move with the highest saving, omit a vehicle if no trips are being performed;
**return** $N_k$;

**Algorithm 11** Shift Charging Procedures (`SCP`)

**Input:** neighborhood $N_k$, charging stations $S$
**Output:** neighborhood $N_k$, charging stations $S$

Sort $S$ by the number of charging procedures performed within the entire set of vehicle rotations in ascending order;
**for** $s = 1$ **to** $|S|$ - 1 **do**
    **for all** $t = |S|$ **to** $s + 1$ **do**
        **if** A charging of a vehicle in $N_k$ is performed at $s$ and can be shifted to $t$ **then**
            Compute saving ($c_{fix}^{charging}/|CP_s|$) less additional operational costs;
        **end if**
    **end for**
**end for**
Perform move with the highest saving, omit a charging stations if no chargings are being performed;
**return** $N_k$, $S$;

**Algorithm 12** `SHAKE`

**Input:** neighborhood $N_k$
**Output:** neighborhood $N_k$

Choose `EXST`, `SST` or `SCP` as $f$ at random;
**if** $f(N_k)$ is feasible **then**
    **return** $f(N_k)$;
**else** Go to 1
**end if**

**Algorithm 13** Inserting Partial Chargings (`PCP`)

**Input:** vehicle rotation $v$, set $S$ of charging stations
**Output:** vehicle rotation $v$, feasibility or infeasibility of $v$

```
1: for all t_1 ∈ v do
2:     if SoC after executing t_1 is not sufficient then
3:         for all t_2 ∈ v previous to t_1 do
4:             if Departure stop is a charging station then
5:                 Save charging opportunity;
6:             end if
7:         end for
8:         if Set of charging opportunity is empty then
9:             return v, infeasible;
10:        end if
11:        Add charging opportunity at the highest frequented charging station;
12:        if Vehicle rotation can be performed then
13:            return v, feasible;
14:        else
15:            Exclude charging opportunity from the set of all opportunities;
16:            Go to 8;
17:        end if
18:    end if
19: end for
```

| Instance | Battery Capacity (kWh) | # Vehicles | # Stations | Operational Costs | Feasible Rotations | Total Costs (Mio) |
|---|---|---|---|---|---|---|
| t876_s207 | 60 | 69 | 47 (22.71%) | - | 5 (7.25%) | - |
| | 120 | 69 | 44 (21.25%) | - | 31 (44.93%) | - |
| | 300 | 69 | 33 (15.94%) | - | 62 (89.86%) | - |
| | 500 | 69 | 7 (3.38%) | 1127370.93 | 69 (100%) | 33.93 |
| t1135_s101 | 60 | 75 | 33 (32.67%) | - | 43 (57.33%) | - |
| | 120 | 75 | 27 (26.73%) | - | 69 (92%) | - |
| | 300 | 75 | 15 (14.85%) | 1351136.56 | 75 (100%) | 35.48 |
| | 500 | 75 | 2 (1.98%) | 1349832.27 | 75 (100%) | 35.60 |
| t1296_s88 | 60 | 47 | 43 (48.86%) | - | 28 (59.68%) | - |
| | 120 | 47 | 32 (36.36%) | - | 42 (80.37%) | - |
| | 300 | 47 | 25 (28.40%) | - | 42 (80.37%) | - |
| | 500 | 47 | 6 (6.81%) | 114701.82 | 47 (100%) | 22.76 |
| t2633_s67 | 60 | 125 | 29 (43.28%) | - | 74 (58.4%) | - |
| | 120 | 125 | 21 (32.34%) | - | 80 (64%) | - |
| | 300 | 125 | 17 (25.37%) | - | 117 (93.6%) | - |
| | 500 | 125 | 8 (11.94%) | 2652324.76 | 125 (100%) | 60.91 |
| t3067_s209 | 60 | 165 | 90 (43.06%) | - | 88 (53.33%) | - |
| | 120 | 165 | 69 (33.01%) | - | 154 (93.33%) | - |
| | 300 | 165 | 39 (18.66%) | - | 162 (96.97%) | - |
| | 500 | 165 | 14 (6.69%) | 3045359.60 | 165 (100%) | 80.79 |
| t1580_s209 | 60 | 75 | 55 (26.31%) | - | 39 (52%) | - |
| | 120 | 75 | 45 (21.53%) | - | 61 (81.33%) | - |
| | 300 | 75 | 20 (9.56%) | 1342076.51 | 75 (100%) | 36.71 |
| | 500 | 75 | 7 (3.34%) | 1319174.47 | 75 (100%) | 36.82 |
| t1487_s209 | 60 | 89 | 53 (25.35%) | - | 46 (51.79%) | - |
| | 120 | 89 | 37 (17.71%) | - | 87 (97.76%) | - |
| | 300 | 89 | 24 (11.48%) | 1696749.70 | 89 (100%) | 43.74 |
| | 500 | 89 | 7 (3.34%) | 1672581.34 | 89 (100%) | 43.47 |
| t1060_s209 | 60 | 54 | 43 (20.57%) | - | 43 (79.63%) | - |
| | 120 | 54 | 30 (14.35%) | 988628.59 | 54 (100%) | 28.20 |
| | 300 | 54 | 13 (6.22%) | 987371.38 | 54 (100%) | 26.11 |
| | 500 | 54 | 3 (1.43%) | 985934.19 | 54 (100%) | 26.04 |
| t1074_s209 | 60 | 56 | 39 (18.66%) | - | 31 (55.36%) | - |
| | 120 | 56 | 33 (15.78%) | - | 52 (92.86%) | - |
| | 300 | 56 | 16 (7.65%) | 986721.35 | 56 (100%) | 27.67 |
| | 500 | 56 | 6 (2.87%) | 985148.27 | 56 (100%) | 27.69 |
| t933_s209 | 60 | 54 | 35 (16.74%) | - | 23 (42.60%) | - |
| | 120 | 54 | 25 (11.96%) | - | 32 (77.78%) | - |
| | 300 | 54 | 15 (7.17%) | 971517.06 | 54 (100%) | 26.59 |
| | 500 | 54 | 4 (1.91%) | 963385.75 | 54 (100%) | 26.26 |

Table 6.2: Results of solving a location planning problem for charging stations for the electrification of cost-minimal vehicle rotations computed without range restrictions incorporating partial charging procedure.

| Instance | Battery Capacity (kWh) | # Vehicles | # Stations | Operational Costs | Total Costs (Mio) |
|---|---|---|---|---|---|
| t876_s207 | 60 | 80 (+10) | 47 | 1019364.53 | 40.77 |
| | 120 | 75 (+6) | 44 | 1060784.42 | 39.72 |
| | 300 | 72 (+3) | 33 | 1098365.83 | 38.51 |
| | 500 | 69 (+0) | 7 | 1157364.34 | 33.96 |
| t1135_s101 | 60 | 87 (+12) | 33 | 1187345.17 | 39.89 |
| | 120 | 82 (+7) | 27 | 1219475.57 | 37.90 |
| | 300 | 76 (+1) | 15 | 1265738.33 | 35.79 |
| | 500 | 75 (+0) | 2 | 1379576.58 | 35.62 |
| t1296_s88 | 60 | 61 (+14) | 43 | 82581.43 | 32.18 |
| | 120 | 49 (+3) | 32 | 112634.97 | 28.16 |
| | 300 | 49 (+3) | 25 | 108736.13 | 25.79 |
| | 500 | 47 (+0) | 6 | 116375.72 | 22.77 |
| t2633_s67 | 60 | 144 (+19) | 29 | 2193479.22 | 59.84 |
| | 120 | 137 (+12) | 21 | 2438972.34 | 57.69 |
| | 300 | 131 (+6) | 17 | 2514637.91 | 59.82 |
| | 500 | 126 (+1) | 8 | 2621823.46 | 61.32 |
| t3067_s209 | 60 | 179 (+14) | 90 | 2681356.37 | 87.83 |
| | 120 | 171 (+6) | 69 | 2820942.45 | 82.49 |
| | 300 | 169 (+4) | 39 | 2871844.67 | 81.07 |
| | 500 | 166 (+1) | 14 | 2994187.53 | 81.19 |
| t1580_s209 | 60 | 87 (+12) | 55 | 1133448.81 | 45.33 |
| | 120 | 81 (+6) | 45 | 1289589.71 | 42.10 |
| | 300 | 75 (+0) | 20 | 1367866.41 | 36.74 |
| | 500 | 75 (+0) | 7 | 1323546.82 | 36.83 |
| t1487_s209 | 60 | 101 (+12) | 53 | 1421173.45 | 50.02 |
| | 120 | 92 (+3) | 37 | 1573887.92 | 44.40 |
| | 300 | 90 (+1) | 24 | 1682793.87 | 44.13 |
| | 500 | 89 (+0) | 7 | 1753748.11 | 43.53 |
| t1060_s209 | 60 | 59 (+5) | 43 | 952776.42 | 32.35 |
| | 120 | 55 (+1) | 30 | 991541.91 | 28.56 |
| | 300 | 54 (+0) | 13 | 989187.34 | 26.11 |
| | 500 | 54 (+0) | 3 | 986723.42 | 26.04 |
| t1074_s20 | 60 | 64 (+8) | 39 | 897636.99 | 33.05 |
| | 120 | 59 (+3) | 33 | 971429.78 | 30.76 |
| | 300 | 57 (+1) | 16 | 988324.67 | 28.07 |
| | 500 | 56 (+0) | 6 | 994761.41 | 27.69 |
| t933_s209 | 60 | 64 (+10) | 35 | 956249.27 | 32.06 |
| | 120 | 58 (+4) | 25 | 961772.87 | 28.38 |
| | 300 | 55 (+1) | 15 | 970683.93 | 26.99 |
| | 500 | 54 (+0) | 4 | 969784.44 | 26.27 |

Table 6.3: Results of solving an E-VSP given locations of charging stations incorporating partial charging procedures

| Instance | Battery Cap.(kWh) | Complete Chargings | | | | Partial Chargings | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | # Vehicles | # Stations | Operat. Costs | Tot. Costs (Mio) | # Vehicles | # Stations | Operat. Costs | Tot. Costs (Mio) (Δ) |
| t876_s207 | 60 | 90 | 2 | 1620760.49 | 33.62 | 86 | 2 | 1621459.71 | 32.22 (**-1.40**) |
| | 120 | 76 | 1 | 1392377.95 | 29.38 | 75 | 1 | 1397127.43 | 29.02 (**-0.36**) |
| | 300 | 76 | 1 | 1322090.14 | 32.35 | 75 | 1 | 1322972.32 | 31.94 (**-0.40**) |
| | 500 | 76 | 1 | 1307837.62 | 35.75 | 75 | 1 | 1307139.36 | 35.31 (**-0.45**) |
| t1135_s101 | 60 | 107 | 1 | 1990165.13 | 39.69 | 104 | 2 | 1991283.43 | 38.89 (**-0.80**) |
| | 120 | 94 | 2 | 1644783.78 | 36.45 | 92 | 3 | 1644989.16 | 35.97 (**-0.48**) |
| | 300 | 91 | 1 | 1528068.15 | 38.63 | 89 | 2 | 1529827.34 | 38.07 (**-0.56**) |
| | 500 | 80 | 1 | 1493329.81 | 37.74 | 79 | 1 | 1501038.89 | 37.30 (**-0.44**) |
| t1296_s88 | 60 | 86 | 6 | 729287.86 | 32.33 | 82 | 7 | 730154.66 | 31.18 (**-1.15**) |
| | 120 | 74 | 3 | 487054.13 | 28.25 | 71 | 4 | 489187.98 | 27.40 (**-0.84**) |
| | 300 | 64 | 1 | 408026.08 | 26.58 | 62 | 1 | 412098.73 | 25.77 (**-0.81**) |
| | 500 | 58 | 1 | 384780.59 | 26.73 | 56 | 1 | 391267.43 | 25.84 (**-0.89**) |
| t2633_s67 | 60 | 148 | 18 | 3818174.45 | **60.11** | 151 | 16 | 3709761.32 | 60.56 (+0.44) |
| | 120 | 144 | 16 | 3307776.23 | **59.87** | 146 | 14 | 3292684.77 | 60.08 (+0.21) |
| | 300 | 139 | 12 | 2978469.76 | **62.27** | 141 | 11 | 2787724.91 | 62.64 (+0.37) |
| | 500 | 134 | 6 | 2892713.49 | **64.69** | 135 | 5 | 2815498.24 | 64.82 (+0.12) |
| t3067_s209 | 60 | 182 | 50 | 3618471.29 | 79.81 | 180 | 46 | 3621160.73 | 78.12 (**-1.70**) |
| | 120 | 178 | 48 | 3346199.25 | 80.31 | 175 | 43 | 3378824.71 | 78.00 (**-2.31**) |
| | 300 | 174 | 36 | 3114782.19 | 82.58 | 171 | 33 | 3164987.78 | 80.67 (**-1.91**) |
| | 500 | 171 | 12 | 3087556.21 | 83.03 | 169 | 12 | 3096674.53 | 82.14 (**-0.89**) |
| t1580_s209 | 60 | 108 | 5 | 1966650.21 | 41.01 | 109 | 2 | 1721383.19 | 40.37 (**-0.65**) |
| | 120 | 98 | 1 | 1601372.27 | 37.62 | 98 | 1 | 1583844.87 | 37.60 (**-0.02**) |
| | 300 | 91 | 1 | 1474455.69 | 38.58 | 91 | 1 | 1462359.18 | 38.57 (**-0.01**) |
| | 500 | 87 | 1 | 1287982.38 | 40.68 | 87 | 1 | 1276387.44 | 40.67 (**-0.01**) |
| t1487_s209 | 60 | 124 | 4 | 2464733.14 | 46.86 | 118 | 4 | 2464123.98 | 44.76 (**-2.10**) |
| | 120 | 102 | 1 | 1940619.27 | 39.42 | 99 | 2 | 1940034.81 | 38.58 (**-0.85**) |
| | 300 | 102 | 1 | 1797466.88 | 43.36 | 98 | 2 | 1792375.98 | 41.98 (**-1.38**) |
| | 500 | 98 | 1 | 1752138.88 | 46.10 | 95 | 2 | 1751078.51 | 45.01 (**-1.10**) |
| t1060_s209 | 60 | 82 | 2 | 1490621.05 | 30.69 | 78 | 3 | 1493471.98 | 29.54 (**-1.15**) |
| | 120 | 66 | 2 | 1218955.77 | 25.81 | 64 | 3 | 1219073.18 | 25.33 (**-0.48**) |
| | 300 | 63 | 1 | 1132734.03 | 26.89 | 61 | 2 | 1134184.24 | 26.34 (**-0.56**) |
| | 500 | 60 | 1 | 1112108.98 | 28.36 | 57 | 2 | 1121097.87 | 27.27 (**-1.09**) |
| t1074_s209 | 60 | 86 | 2 | 1496222.00 | **32.09** | 85 | 5 | 1499873.19 | 32.49 (+0.40) |
| | 120 | 72 | 1 | 1216449.55 | **27.74** | 71 | 4 | 1218991.27 | 28.13 (+0.39) |
| | 300 | 72 | 1 | 1132428.45 | **30.54** | 71 | 3 | 1194787.18 | 30.69 (+0.16) |
| | 500 | 67 | 1 | 1105839.18 | **31.50** | 66 | 3 | 1184719.37 | 31.63 (+0.13) |
| t933_s209 | 60 | 81 | 6 | 1527761.57 | **31.37** | 82 | 7 | 1498344.61 | 31.95 (+0.57) |
| | 120 | 66 | 1 | 1171878.79 | **25.51** | 67 | 2 | 1169763.22 | 26.12 (+0.61) |
| | 300 | 65 | 1 | 1081101.44 | **27.66** | 66 | 2 | 1089913.34 | 28.32 (+0.66) |
| | 500 | 60 | 1 | 1044521.50 | **28.29** | 61 | 2 | 1075728.41 | 29.03 (+0.73) |

Table 6.4: Results of algorithm `SA` for generating initial vehicle rotations for electric buses and locations for charging stations considering complete and partial charging procedures

| Instance | Battery Cap.(kWh) | Complete Chargings # Veh. | # Chrg. Stations | Operat. Costs | Tot. Costs (Mio) | Partial Chargings # Veh. | # Chrg. Stations | Operat. Costs | Tot. Costs (Mio) (Δ) |
|---|---|---|---|---|---|---|---|---|---|
| t876_s207 | 60 | 79 | 6 | 1317285.53 | 30.46 | 77 | 4 | 1348495.49 | 29.29 (**-1.17**) |
| | 120 | 76 | 3 | 1334788.19 | 30.57 | 75 | 2 | 1392377.95 | 29.26 (**-1.31**) |
| | 300 | 74 | 3 | 1317883.42 | 32.03 | 73 | 2 | 1322090.14 | 31.38 (**-0.65**) |
| | 500 | 73 | 2 | 1254329.87 | 34.60 | 72 | 1 | 1277837.62 | 33.92 (**-0.68**) |
| t1135_s101 | 60 | 86 | 31 | 1592741.22 | 39.44 | 85 | 30 | 1617186.47 | 38.86 (**-0.58**) |
| | 120 | 81 | 22 | 1512564.77 | 36.57 | 79 | 20 | 1550110.17 | 35.38 (**-1.19**) |
| | 300 | 77 | 13 | 1617823.71 | 36.05 | 76 | 13 | 1656467.22 | 35.68 (**-0.37**) |
| | 500 | 76 | 2 | 1267288.41 | 35.96 | 75 | 2 | 1293329.81 | 35.54 (**-0.42**) |
| t1296_s88 | 60 | 58 | 37 | 89549.72 | 26.63 | 56 | 32 | 89668.11 | 27.68 (**-1.95**) |
| | 120 | 49 | 24 | 112788.93 | 23.99 | 49 | 21 | 112663.49 | 23.24 (**-0.75**) |
| | 300 | 49 | 21 | 108668.43 | 25.20 | 48 | 20 | 110493.77 | 24.55 (**-0.65**) |
| | 500 | 48 | 9 | 112809.33 | 23.96 | 48 | 7 | 113498.21 | 23.46 (**-0.50**) |
| t2633_s67 | 60 | 139 | 21 | 2217631.99 | 56.11 | 138 | 19 | 2219473.22 | 55.26 (**-0.85**) |
| | 120 | 136 | 18 | 2445671.42 | 56.58 | 135 | 16 | 2450912.76 | 55.72 (**-0.86**) |
| | 300 | 130 | 16 | 2528556.79 | 59.17 | 129 | 14 | 2534473.91 | 58.27 (**-0.90**) |
| | 500 | 128 | 7 | 1609133.61 | 61.95 | 127 | 6 | 1617484.91 | 61.26 (**-0.69**) |
| t3067_s209 | 60 | 182 | 48 | 2627938.41 | 78.32 | 177 | 36 | 2694773.55 | 73.64 (**-4.68**) |
| | 120 | 172 | 37 | 2796641.92 | 74.82 | 170 | 27 | 2809488.17 | 71.60 (**-3.22**) |
| | 300 | 171 | 26 | 2854493.71 | 78.60 | 169 | 18 | 2819741.93 | 75.76 (**-2.84**) |
| | 500 | 169 | 12 | 2894718.42 | 81.94 | 167 | 11 | 2937418.93 | 80.83 (**-1.11**) |
| t1580_s209 | 60 | 80 | 41 | 1698449.32 | 39.94 | 79 | 39 | 1706088.71 | 39.10 (**-0.84**) |
| | 120 | 79 | 41 | 1751008.18 | 40.83 | 78 | 36 | 1754706.68 | 39.22 (**-1.61**) |
| | 300 | 77 | 14 | 1318772.54 | 36.00 | 76 | 12 | 1324455.69 | 35.10 (**-0.90**) |
| | 500 | 75 | 8 | 1317482.33 | 37.06 | 75 | 7 | 1318937.44 | 36.81 (**-0.25**) |
| t1487_s209 | 60 | 99 | 38 | 1448742.93 | 45.59 | 96 | 31 | 1451973.49 | 42.81 (**-2.80**) |
| | 120 | 92 | 31 | 1567438.53 | 42.89 | 91 | 24 | 1569943.53 | 40.78 (**-2.11**) |
| | 300 | 92 | 23 | 1534887.38 | 44.54 | 90 | 19 | 1561287.55 | 42.76 (**-1.78**) |
| | 500 | 90 | 6 | 1494778.18 | 43.49 | 89 | 6 | 1533849.44 | 43.08 (**-0.41**) |
| t1060_s209 | 60 | 59 | 37 | 951773.81 | 30.85 | 57 | 31 | 958282.41 | 28.65 (**-2.19**) |
| | 120 | 56 | 30 | 982735.18 | 28.92 | 56 | 27 | 983887.41 | 28.17 (**-0.75**) |
| | 300 | 55 | 15 | 983194.53 | 27.00 | 54 | 13 | 988593.32 | 26.10 (**-0.90**) |
| | 500 | 55 | 2 | 984137.83 | 26.23 | 54 | 3 | 985934.19 | 26.03 (**-0.20**) |
| t1074_s209 | 60 | 64 | 26 | 913477.39 | 29.81 | 62 | 23 | 912849.87 | 28.36 (**-1.45**) |
| | 120 | 59 | 19 | 963492.86 | 27.24 | 57 | 19 | 968443.91 | 26.52 (**-0.73**) |
| | 300 | 57 | 14 | 981249.87 | 27.56 | 56 | 16 | 981749.81 | 27.66 (+0.00) |
| | 500 | 56 | 7 | 982774.19 | 27.93 | 56 | 4 | 983497.18 | 27.18 (**-0.75**) |
| t933_s209 | 60 | 61 | 27 | 939771.45 | 29.03 | 60 | 24 | 941661.01 | 27.94 (**-1.10**) |
| | 120 | 58 | 23 | 948192.78 | 27.86 | 56 | 19 | 951884.93 | 26.14 (**-1.73**) |
| | 300 | 55 | 15 | 964387.23 | 26.98 | 54 | 15 | 970882.41 | 26.59 (**-0.40**) |
| | 500 | 55 | 4 | 959877.19 | 26.70 | 54 | 4 | 962718.43 | 26.26 (**-0.45**) |

Table 6.5: Results of `BVNS` containing vehicle schedules for electric buses and charging infrastructure after 100.000 iterations considering complete and partial charging procedures

# Chapter 7

# Conclusion and Outlook

This thesis focuses on the mathematical optimization problems of scheduling electric vehicles in public transport and the location planning of the charging infrastructure. The technological aspects of electric vehicles are particularly considered. Five research publications document the research process. In order to provide answers to the three research questions introduced in Chapter 1, the literature is studied extensively and several artifacts are developed. The research approach used within this thesis follows the research paradigm Design Science Research of Hevner et al. (2004). The results achieved have been presented to scientific audiences and published in scientific journals.

## 7.1 Summary of Findings

In order to provide answers to the research questions introduced, the scientific foundations are given in Chapter 2 by reviewing the literature on scheduling electric vehicles in public transport and the location planning of the charging infrastructure. As things stand, existing literature can be divided into three basic categories: First, there are contributions that incorporate limited driving ranges within traditional vehicle scheduling. Second, there are contributions that consider battery charging in addition to limited driving ranges. Essentially, this problem refers to the term electric vehicle scheduling. In this context, the charging infrastructure is assumed to be predefined and fixed. Lastly, there is literature that addresses the planning of the charging infrastructure as a separate optimization problem. The publications discussed differ significantly on the detail level of reflecting electric vehicles' technological aspects. In the context of battery charging, it is noteworthy that charging processes are assumed to be performed either in a constant time window or in linear time, depending on a battery's state-of-charge.

The artifact $A_1$ developed in Chapter 3 addresses the research question whether traditional solution methods for vehicle scheduling in public transport are able to cope with the challenges imposed by electric vehicles, or whether it is necessary to develop novel solution methods ($Q_1$). Heterogeneous vehicle fleets consisting of electric vehicles and traditional combustion engine vehicles without range limitations are therefore considered within the VSP. To solve this extended optimization problem, a three-phase solution approach based on an aggregated time-space network is developed, which constitutes the artifact. The objective is to maximize the proportion of feasible vehicle rotations for electric vehicles within the entire set of vehicle rotations while retaining the optimal numbers of vehicles used and deadhead trips required, as obtained by solving a standard VSP. The solution method was evaluated by solving real-world problem instances with many thousands of service trips. A computational study ($C_1$) shows that to a certain degree, traditional solution methods for the VSP are able to cope with the challenges imposed by electric vehicles. However, this finding strongly depends on the instances' data and further aspects. Novel methods are required to deal fully with the requirements of electric vehicles.

The second research question $Q_2$ is discussed in Chapter 4 and Chapter 5. In both chapters, it is examined what impact the detail level of reflecting electric vehicles' technological aspects has on scheduling electric vehicles in public transport. In Chapter 4, the artifact $A_2$ is designed, entailing a heuristic solution method for scheduling electric vehicles in public transport and models for the charging process of electric vehicles' batteries. A computational study ($C_2$) based on real-world data is performed, by which means major gaps between model assumptions about the charging times of electric vehicles and actually loaded amounts of energy are revealed. It is shown that the specified inconsistency leads to shorter vehicle rotations between charging stations than actually computed and to an increased number of vehicles needed.

The previous contribution has been significantly extended in Chapter 5. The focus of this chapter is on the artifact $A_3$, which considerably extends and improves the solution methodology and the models for the charging process presented in Chapter 4. In particular, the essential technological aspects, of partial and opportunity charging are incorporated into the solution method. In addition, different capacities of the vehicle batteries are considered. Due to the methodological extensions, the case study $C_2$ was also greatly expanded. The results strongly support the findings obtained in Chapter 4 and indicate in addition that partial charging may reduce the negative impact of insufficient models for battery charging on resulting vehicle rotations. Regarding the use of different battery capacities, it is demonstrated how increasing ranges of electric vehicles due to higher battery capacities can alleviate the negative effects of inaccurate charging models, since the number of charging procedures needed within the vehicles' operation decreases.

Finally, the artifact $A_4$ is developed in Chapter 6, addressing research question $Q_3$. This artifact comprises a solution method for the simultaneous optimization of the location planning of charging stations and vehicle scheduling of electric vehicles in public transport based on the metaheuristic variable neighborhood search. The solution method is used to link both optimization problems in order to open up synergy effects and potentials for cost-savings. A comprehensive computational study

($C_3$) proves that simultaneous consideration of both optimization problems is necessary. For this purpose, the solution method presented is compared to a sequential planning approach, whereby both optimization problems are solved consecutively. The results demonstrate that sequential planning generally leads to either infeasible vehicle rotations or to significant increases in costs compared to simultaneous problem solving.

## 7.2 Future Research Potentials

Following the results of this work and the current state of research, there are a number of interesting future research avenues. With regard to scheduling electric vehicles in public transport, the major challenge is the problem complexity and the associated solution methodology. The development of exact and heuristic solution methods capable of solving extremely large real-world problem instances is of particular relevance. As a further improvement, multiple depots and vehicle types should be incorporated into the problem definition in order to reflect real conditions of metropolitan areas. A similar approach was already developed for traditional vehicle scheduling without range-limited vehicles by Gintner et al. (2005). The same goal should be pursued regarding the location planning of the charging infrastructure. Regardless of whether the problem is solved separately or as an integrated optimization problem, current solution methods are not suitable for large real-world problem instances.

There is a considerable need for research on the reflection and consideration of technological aspects concerning electric vehicles and the charging infrastructure within solution methods for vehicle scheduling and location planning. As identified in this work, insufficient assumptions made about the charging procedures of electric vehicles' batteries widely lead to inconsistencies. In addition to battery charging, numerous other aspects should be examined. It is particularly relevant to examine the energy consumption of electric vehicles, as a vehicle's consumption generally depends on a large number of factors, some of which are subject to uncertainties. Random factors, for example, are weather and traffic conditions and deterministic parameters are route topologies and road gradients. As demonstrated by Berthold et al. (2015) and Rohrbeck (2018), battery aging represents a crucial aspect of electric batteries. Only a sufficiently precise reflection of this technical aspect within solution methods can ensures the applicability of electric vehicles in practice over longer periods of time. If this aspect is not taken into account, computed vehicle rotations may no longer be executable in later stages. Battery capacities are also closely related to battery aging. A consideration of different battery capacities within planning problems may open up potentials for cost savings. Regarding the charging infrastructure, technical conditions such as spatial limitations and power grid constraints have not yet been sufficiently considered. In most contributions associated with location planning, the amount of energy provided by the charging infrastructure is assumed to be unlimited. Furthermore, it is generally assumed that charging systems can be built at almost all the available stop points. According to Konga et al. (2019), however, these assumptions can hardly be justified in reality and need to be reflected on precisely.

Besides technological issues, there are also economic aspects that are important in the scope of electric vehicles and charging infrastructure. Kooten Niekerk et al. (2017) point out that the price of electricity may vary significantly over the day. Following this, a time-dependent energy price may be considered within solution methodologies. In addition, the construction costs of charging stations may depend on several factors such as ground prices, availability of the electricity grid, or governmental requirements.

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# Declaration of Authorship

Except where reference is made in the text, this thesis contains no material published elsewhere or extracted in whole or in part from a thesis presented by me for another degree or diploma. No other person's work has been used without due acknowledgment in the main text of the thesis. This thesis has not been submitted for the award of any other degree or diploma in any other tertiary institution.

Berlin, December $6^{th}$, 2020

Name