Integrated Vehicle and Crew Planning of Electric Busses using Lagrangian Relaxation and Battery Degredation

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1 Introduction

Electrification of public transport has become the norm over recent years. Many public transport poviders, such as the Dutch bus provider Qbuzz [1], have been replacing traditional vehicles with electric vehicles (EVs) in their fleet with the aim of reducing their carbon footprint in order to match the stricter regulations set out by organizations such as the European Union [2]. This electrification introduces new challenges in every step of the planning process as laid out in Figure 1. The limits of both electric infrastructure and electric vehicles add new constraints to an already complex operation. Existing techniques that minimize operational costs are therefore being revised in order to take into account these operational constraints [*TODO: beter formuleren*].

In this work, we will focus on incorporating electric vehicle restrictions two of the highest operational cost steps in the planning process: vehicle scheduling and crew scheduling. Crew scheduling in particular is of great importance, as crew costs make up a majority of the overall operational costs. A recent estimate puts crew costs at circa 60% of the total operational costs for bus companies in Northern Europe [3]. The set of feasible crew schedules is however directly influenced by the routes that are determined while planning vehicles. It has therefore long been known that integrating the vehicle and crew planning operations can lead to significant reductions in costs, as routes can be better tailored to suit crew planning needs [4].

We will now give an informal overview of the problems at hand. A more formal overview can be found in Section 3. The Vehicle Scheduling Problem (VSP) aims to find a set of minimum cost vehicle tasks such that all trips that need to be driven throughout a timeperiod are covered. In this, a trip is defined as full or partial travel of a vehicle along a predetermined route, and a vehicle task is defined as a set of sequential operations that a vehicle will perform. Note that for the same route, multiple trips might be present on a single day if that route is scheduled multiple times.

Given a set of these trips, a set of depots and a set of vehicles, the goal is to find a vehicle task (or schedule) for each of the vehicles throughout the day. In this, a task for an individual vehicle must start at a depot, perform a number of compatible trips (that is, trips which can be performed sequentially while respecting driving times between trips), before finally returning to its original depot. In order to minimize operational costs, both the number of vehicles and the overall driven distance between trips (also called deadheads) need to be minimized.

The VSP with a single depot and unconstrained vehicle ranges can be solved in polynomial time [5]. The multi-depot variant of the problem on the other hand is known to be NP-hard [4, 6, 7], and the addition of constrained vehicle ranges such as those found in EVs also make the problem NP-hard

[4, 8]. We consider a general depot case with constrained vehicle ranges due to the inclusion of EVs, and will therefore refer to the VSP as being NP-Hard.

The Crew Scheduling Problem (CSP) on the other hand aims to find a minimum cost assignment of crew members to vehicle tasks. Given a set of vehicle tasks and crew members, the goal is to find an assignment of crew members such that each vehicle is always driven by exactly one driver. In this, constraints such as maximum working time on a day, driver breaks and handovers between different drivers on the same vehicle need to be considered. The primary goal for minimization here is the total amount of workers needed and hours worked. The CSP is also known to be an NP-hard problem [9].
[*TODO: Info over oplossingen*]

As can be seen, the VSP and CSP are closely related. The vehicle schedules that are selected in the VSP directly determine what crew assignments are possible within the CSP. It is therefore not always optimal to fully minimize costs in the vehicle scheduling process, as this might incur higher overall costs due to crew scheduling. We can therefore roughly split the solving of vehicle and crew assignments into two seperate approaches: sequential, in which the VSP and CSP are solved seperately, or integrated, in which the VSP and CSP are solved such that overall costs are minimized simultaniously. The integrated approach is often refered to as the vehicle and crew scheduling problem, or VSCP. The VSCP can also still be further subdivided into full and partial integration, partial integration adds some additional crew hueristics to the VSP and full integration actually minimizes costs of both. In this work, we will only focus on full integration. [*TODO: beter formuleren*]

A lot of work has already been done for the VSP, CSP and VSCP. Both the sequential and integrated approach have been extensively studied since the [*TODO: 1980s?*], and we refer the reader to a recent survey in order to get a sense of the current state of the art [*TODO: citiation met survey*]. The introduction of electric vehicles has however introduced new constraints. The most important constraint is the limited range of electric vehicles, combined with charging times which are much greater than refeuling times found on traditional combustion based buses. This most directly effects the VSP, as charging periods now need to be added throughout the day in order to effectively use buses. This new version of the problem, refered to as the E-VSP, has also been studied extensively in recent years. We refer the reader to a survey by Perumal et al. for a detailed overview of recent progress [10].

Most research related to the scheduling of electric public transport vehicles up until now has focused on the sequential approach. Limited literature does exist on the E-VSCP problem, however simplifying assumptions are made which might limit real world applicability or accurate modeling of costs. Most notably, assumptions are made about charging locations (such as only being able to charge at a bus depot) or charging behavior (such as modeling the process as being purely linear or only allowing full charges). Additionally, to the best of our knowledge battery degradation due to usage patterns has not been included in any integrated models at the time of writing. The contribution of this work is therefore threefold:

- Incorporating nonlinear battery charging times.

- Including battery degredation due to usage patterns into the objective function.

- Using Lagrangian relaxation in order to link the VSP and CSP instead of currently used methods.

This work is organised as follows. In Section 2, we will discuss work related to the E-VSCP and give an overview of common ways of modeling the problem. In Section 3, we give our formal problem definition. [*TODO: uitbreiden zodra je meer info hebt*].
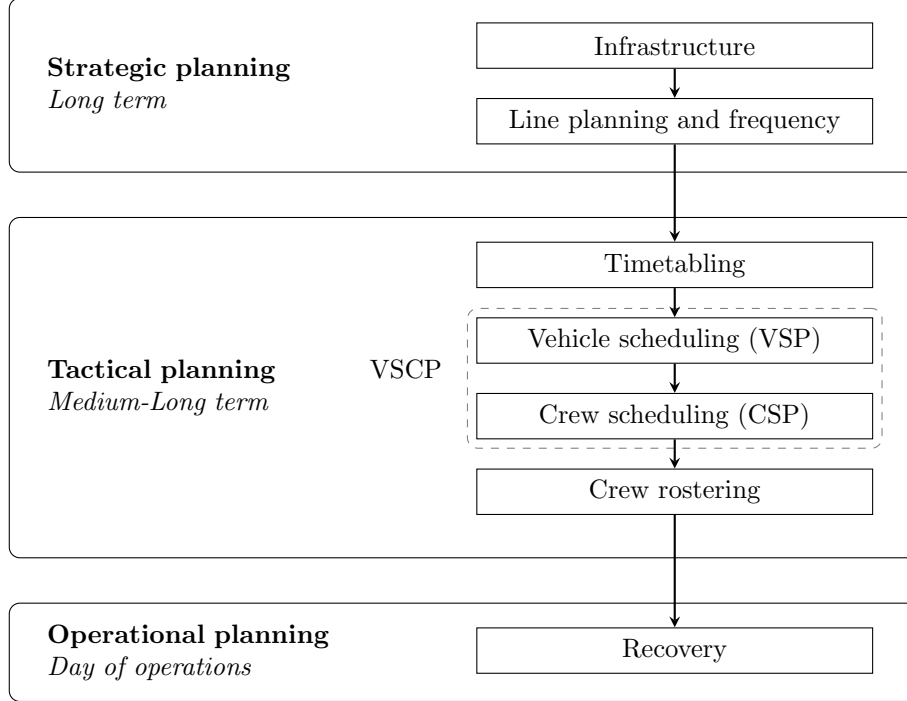

Figure 1: A general overview of the public transport planning process, based on [10, 11, 12].

2 Related work

In this section, we will discuss work related to our research into the E-VSCP. An overview of how batteries and charging behavior is modeled in different E-VS(C)P approaches has also been included in Table 2.

(E-)VSP

[*TODO: modeleer methode toevoegen*]
The SDVSP has long been known to be polynomially solvable, however the inclusion of multiple depots has been shown to make the problem NP-hard under the assumption that busses must return to the same depot from which they originated [13]. Additionally, the introduction of any resource constraints such as limited ranges within the VSP has also been shown to be NP-hard by Bodin et al. [4]. As the E-VSP deals with the limited range associated with electric vehicles, it is quite closely related to the multiple depot vehicle scheduling problem with route time constraints (MDVSP-RTC) [14]. The key difference between these two problems is that the E-VSP allows for (partial) recharging of a vehicle throughout the operating period, whereas the MDVSP-RTC assumes a fixed maximum

Abbreviation	Definition
ALNS	Adaptive Large Neighbourhood Search
B&P	Branch-and-Price
CG	Column Generation
CSP	Crew Scheduling Problem
E-...	Problem ... with electric vehicles
LNS	Large Neighbourhood Search
LS	Local Search
MDVSP	Multi Depot Vehicle Scheduling Problem
MIP	Mixed Integer Program
SAA	Simulated Annealing Algorithm
SDVSP	Single Depot Vehicle Scheduling Problem
SoC	State of Charge
TCO	Total Cost of Ownership
ToU	Time of Usage
TVSP	Integrated Timetabling and Vehicle Scheduling Problem
VCSP	Integrated Vehicle and Crew Scheduling Problem
VSP	Vehicle Scheduling Problem

Table 1: Nomenclature used in this work

travel time for the vehicle within the given period. The E-VSP specifically been shown to be NP-hard by Oulamara and Sassi [8].

Li was one of the first to consider the E-VSP back in 2014 [15]. The model is based on an extension of the traditional network based approach to solving the VSP, with the additional constraint of total driving time. It additionally assumes that fast charging or battery swaps are possible, ensuring full charges in a fixed timespan. The model is solved using a column generation approach with branch-and-price, followed by a local search to find a local optimum. The proposed methods are tested on trips in the San Fransisco Bay Area, with a maximum instance size of 242 trips. These tests resulted in optimality gaps of $< 5\%$ for busses able to drive 150km, and between 7-15% for a range of 120km depending on the instance.

[*TODO: meer info*] van Kooten Niekerk et al. introduce a pair of models which aim to solve the E-VSP while taking into account ToU energy prices, nonlinear charging times and battery degredation due to depth of discharge [16]. They do this by extending the graph underlying the traditional VSP using either continuous or discrete state of charge variables for the trip nodes, and solve using CG. They test using data provided by Belgian bus company De Lijn in the city Leuven, using a total of 543 trips. They show that the discretized model can be solved in a shorter timeframe with similar results to the continuous model.

Jiang et al. use a LNS approach to solve the E-VSP [17]. They consider time of use energy costs and opportunisitic charging. They use test data in Shenzhen, China with a total of 778 trips. [*TODO: meer info maar de paper is saai*].

De Vos et al. introduce an E-VSP solution method which deals with partial recharges and capacitated charging stations [18]. They model this using discrete battery charge levels in a connection-based network of trips and charging actions, in which a primal network is created using pessemistic rounding. In order to solve, they apply CG with two seperate hueristics: branch-and-price and a diving hueristic. To overcome the limitations of dual bounds resulting from a discretized model, they incorporate ideas from Boland et al. resulting in a dual network with optimistic connections [19]. This gives the same bounds as the ones found in the non-discretized model. Testing is performed on a bus concession south of Amsterdam with 816 trips, with subsets being used as smaller instances. Optimality gaps of 1.5-2.7% are achieved across instances. They additionally note that the framework as provided can easily be extended for nonlinear charging functions and depth-of-discharge battery degredation.

Olsen and Kliewer introduce a solution to the E-VSP which aims to incorporate more accurate nonlinear charging times [20]. They focus on showing that a linear approximation for the second phase of vehicle charging (such as the one found in van Kooten Niekerk [16]) can misrepresent the SoC and required charging times, and therefore advocate for the use of an exponential function to model this phase instead.

Parmentier et al. consider a scalable approach to the E-VSP which is based on the concept of nondominated charging arcs with nonlinear charging [21]. They use these in order to formulate a more computationally efficient version of the pricing problem given uniform charging infrastructure. Using CG and B&P techniques, they test on the *large* instances introduced by Wen et al. [22] which included up to 8 depots, 16 charging stations and 500 trips. Here, they are able to find solutions that are only up to 0.06% away from the optimum.

Pulyassary et al. show that the E-VSP is solvable in polynomial time given the assumption that the shortest path between two trips in the flow network is equal to the path with lowest battery usage [23]. They consider the case in which charging at a select number of capacity bound nodes is allowed with nonlinear charging behavior. For the single depot case, a $O^*(|T|^6)$ algorithm for finding a set of vehicle schedules with lowest cost given trips T is provided based on DP. Additionally, polynomial algorithms for determining maximum feasible charging capacity and minimum-cost flows based on LP are provided. No computational experiments are performed.

Zhang et al. apply a similar method to the one found in van Kooten Niekerk [24]. They consider a single depot with charging infrastructure, where multiple round trip lines originating from the depot. They model nonlinear charging behavior, battery depreciation due to depth of discharge and capacitated charging infrastructure using discretized timesteps. They solve using a combination of CG and B&P. Tests are done on both randomly generated instances as well as 6 not yet electrified lines with up to 160 and 197 trips respectively. Cost savings of 10.1–27.3% in the real life line based on different battery capacities. [*TODO: waar de fuck vergelijken ze mee*] [*TODO: Bekijken*] multidepot multivehicle type esvp, multi-commodity flow, proximal bundle method https://epubs.siam.org/doi/10.1137/040603929 [*TODO: lezen*][25]

(E-)CSP

The CSP is often solved as a set partitioning (or set covering) problem. Here, the tasks described by the sequences of trips generated during the VSP must be covered by the individual schedules of crew members. Research into this subject is primarily done in the airline space; crew costs here are generally even higher than those found in the more general public transport sector [26]. Additionally, strong labor unions and restrictive labor legislation due to safety concerns cause a large number of constraints to be applied to crew schedules, resulting in a non-trivial problem to solve.

Results achieved in the aviation space quite easily generalize to other sectors, and we will therefore discuss some of note. For a more detailed overview, we refer the reader to a recent review by Deveci and Demirel [27].

(E-)VSCP

As far as we are aware, at the time of writing only five other works discuss the fully integrated E-VSCP.

Perumal et al. were the first to offer a solution to the E-VSCP in 2021 [28]. They introduced an ALNS which incorporates a B&P hueristic which has been previously used to solve the MDVSP, E-VSP and VCSP [16, 29, 30]. Additionally, they adapt an embedding of a B&P hueristic into the ALNS as introduced by Pepin et al. [29]. They only consider full recharges with a fixed duration of 120 minutes, charging at the depot and fixed maximum ranges for vehicles. The authors tested using real life data from lines in Denmark and Sweden with a maximum instance size of 1109 trips, and report an improvement of $1.17 - 4.37\%$ across different instances when compared to a sequential approach.

Sistig and Sauer also offered a ALNS based approach in 2023, which aimed to improve upon the approach presented by Perumal et al. by including partial recharges, opportunisitic charging at terminal stops of trips and non-fixed ranges for the vehicles [31]. In order to solve, they implement a selection of 3-step ALNS neighborhoods consisting of E-VSP modification, finding a solution to the corresponding CSP and consequently modifying the CSP solution. Tests were done using an instance of a city route in Germany, with a total of 282 trips. Different scenarios based on possible crew break and relief locations were considered in order to compare diesel and electric TCO. Additionally, sensitivity analysis of the TCO was done for parameters such as electricity, driver and fixed costs.

Wang et al. introduce a two layered model using particle swarms and a ϵ-constraint based mechanism which allows for a mix of traditional combustion and electric busses [32]. The model incorporates partial depot charging, as well as measures to ensure that crew is primarily assigned the same vehicle throughout the day. A circular bus route in Changchun, China with 68 daily trips is used as a basis for testing, with a focus on electric versus diesel usage and driver satisfaction.

Shen and Li provide a minimum-cost flow framework for the E-VSP which is integrated with a set partitioning based approach for the E-CSP [33]. They only provide full recharge capabilities at the depot, however focus on the inclusion of a distinction between driving and standstill time of vehicles in order to more accurately model real life traffic. A city line in China with 270 daily trips is used for testing, resulting in cost savings of up to 8.7% when compared to a sequential approach.

Cong et al. provide a hybrid MIP and SAA based approach to optimizing a mixed fleet of combustion and electric vehicles with ToU electricity pricing [34]. In each SAA iteration, a collection of new E-VSP trip assignments are created using neighborhood operations, after which two MIP models are sequentially employed to solve for charging and crew schedules. The methods are tested on a collection of 3 bus routes originating from the same depot in Changchun City, China with a total of 520 trips across all routes. When compared to the sequential approach, the integrated vehicle schedule was able to reduce costs by 0.8%. [*TODO: miss nog iets zeggen over hoe ze dit eerst hadden ingesteld*]

Other related fields
The VSP is also very closely related to the vehicle routing problem (VRP). The VRP with time windows is of particular interest, as this allows us to define the same precedence constraints as those naturally defined by trips. [*TODO: Uitbreiden met papers, betere beschrijving*] [*TODO: Meer related werk:*] [*TODO: E-VRPTWR*] Research has also been done into integrating the E-VSP with timetable planning (E-TVSP). A recent example can be found in the work of Stadnichuk et al., who allowed results of the E-VSP to introduce optimality cuts into the MIP used for creating timetable plans as a way to reduce costs [35]. This is achieved by transforming the E-VSP problem into one of bin packing with conflicts, after which three different hueristic methods are applied and compared. [*TODO: iets beter formuleren allemaal*].

3   Problem definition

Let T be a set of trips that needs to be run.
[*TODO: csp bus variant*] [*TODO: E-VRPTWRC*] [*TODO: Inkorten wat niet interessant is*] [*TODO: onderzoeksgat*]

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		Model	ToU	SoC	Nonlinear Ch.	Partial Ch.	Ch. Location	Degredation
[15]	2014	E-VSP	No	D	No	No	D	No
[16]	2017	E-VSP	Yes	C/D	Yes	Yes	D/O	Yes
[20]	2020	E-VSP	No	C	Yes	Yes	D/O	No
[17]	2021	E-VSP	Yes	C	No	Yes	O	No
[24]	2021	E-VSP	No	C/D	Yes	Yes	D	Yes
[21]	2023	E-VSP	No	C	Yes	Yes	D/O	No
[18]	2024	E-VSP	No	D	Yes	Yes	D/O	No
[23]	2024	E-VSP	No	C/D	Yes	Yes	O	No
[28]	2021	E-VSCP	No	C	No	No	D	No
[31]	2023	E-VSCP	No	C	No	Yes	D/O	No
[32]	2022	E-VSCP	Yes	C	No	Yes	D	No
[33]	2023	E-VSCP	No	C	No	No	D/O	No
[34]	2024	E-VSCP	Yes	C	No	Yes	D	No
[35]	2024	E-TVSP	No	C	No	Yes	D/O	No

Table 2: A brief overview of battery modeling in E-VSCP related literature. SoC modeled as (D)iscrete or (C)ontinuous variable, Charge locations at (D)epot, (T)erminal trip stops, (I)n motion, Degredation of battery in cost function

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