Integrated Vehicle and Crew Scheduling for Electric Buses with Realistic Charging Behavior

Thomas van der Plas, Han Hoogeveen, Philip de Bruin

July 2025

1 Introduction

Electric vehicles are beginning to make up large portions of the fleet for public transport providers. In The Netherlands for instance, around 21% of all registered buses are already electric according to the RDW (2025). However, in order to meet European regulations (2018) on climate and sustainability, individual line operators such as the Dutch Qbuzz (2024) are slowly replacing even more of their old combustion based fleet with electric vehicles. It is therefore almost certain that this share will only grow in coming years across different countries.

This shift in energy source has introduced new challenges to the methods currently in use to keep our public transport moving. Of primary concern are charging infrastructure and vehicle ranges, both of which are much more limited than their traditional combustion based counterparts. The planning process which has traditionally been used, as outlined in Figure 1, therefore requires additional research into each of its steps in order to incorporate these newly relevant constraints.

In this work, we will focus on incorporating electric vehicle restrictions into two of these steps: vehicle scheduling and crew scheduling. Specifically, we will consider the scheduling of electric buses and their drivers, as these two steps make up a majority of day-to-day costs within the bus transit sector.

The goal of vehicle scheduling (also referred to as the vehicle scheduling problem or VSP) is to find a minimum cost schedule for vehicles in order to cover a set of predetermined trips. In the case of buses our trips are given by a timetable for each individual route, which is the result of the previous step of the planning process. Using the trips defined in such a timetable, our goal is therefore to assign sequences of compatible trips to buses such that each individual trip is driven.

In order to do this, a collection of vehicle tasks must be generated. A vehicle task can be seen as the individual schedule that a bus will follow throughout the day: it may start at a bus storage facility (more commonly called a depot), then perform one or more trips, before finally returning to the depot. The driving actions performed between between a depot and a trip, as well as those between trips themselves are called deadheads. The costs of driven deadheads along with the total number of buses used are the main focus for minimization, as the costs incurred for driving the trips themselves is fixed.

Once vehicle schedules are known, we can move on to the crew scheduling problem (CSP). Here, our goal is to find minimum cost assignment of crew members to vehicles. Continuing within the context of bus planning, we now need to match drivers with our previously planned buses. Driving time for a driver is often limited in a single day, and for longer shifts breaks might be mandatory as well; it is therefore not always possible to create a one to one matching between crew and vehicle tasks. It is therefore necessary to split vehicle tasks up into multiple segments, whereafter we can

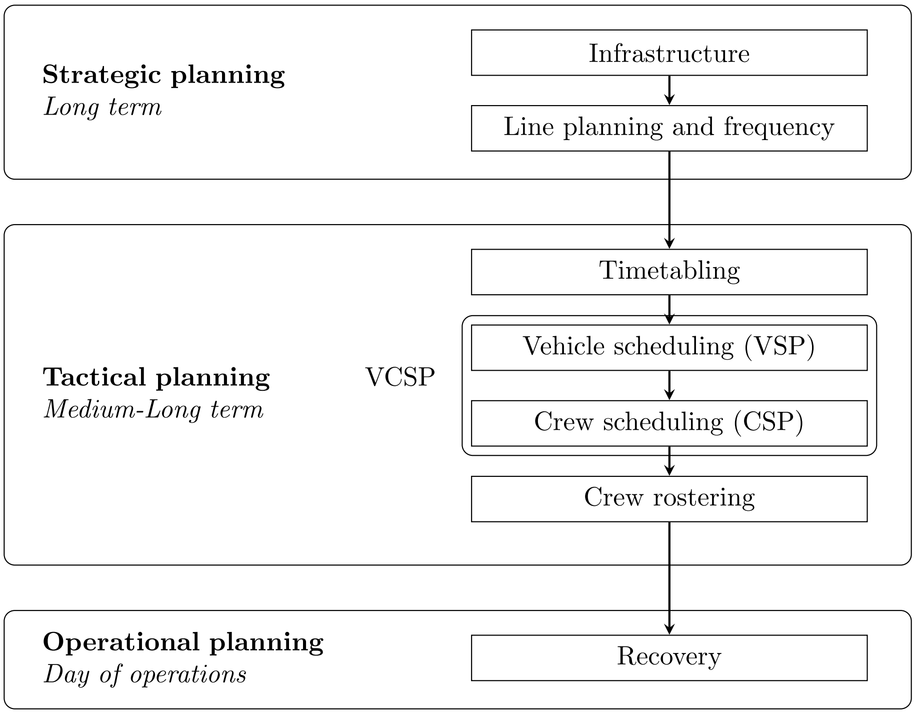

Figure 1: A general overview of the public transport planning process, based on Ceder and Wilson (1986), Ibarra-Rojas et al. (2015), and Perumal et al. (2022).

create crew tasks that consist of one or more compatible segments. As before with the trips, the vehicle tasks themselves are fixed; in order to minimize costs, we must find a covering set of crew tasks which minimizes the number of required crew members and unused paid hours.

Crew scheduling is the greatest contributor to day-to-day costs; a recent estimate by Perumal et al. (2019) puts it at around 60% of the overall operational costs for bus transit providers in Northern Europe. As can be seen however, the VSP and CSP are very closely related. The vehicle tasks that are selected in the VSP directly determine what crew tasks are feasible 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 separate approaches: sequential, in which the VSP and CSP are solved separately, or integrated, in which the VSP and CSP are solved such that overall costs are minimized simultaneously. The integrated approach is often referred to as the vehicle and crew scheduling problem, or VCSP.

A lot of work has already been done for the VSP, CSP and VCSP. Both the sequential and integrated approach have been extensively studied since the 1980s, as shown by surveys such as Bodin and Golden (1983). The introduction of electric vehicles has however introduced significant constraints on charging and vehicle ranges, invalidating a formerly often made assumption that a vehicle was able to drive an entire day without being refueled. This most directly effects the VSP, as charging periods now need to be added throughout the day in order to effectively use buses. The version of the vehicle scheduling problem which incorporates these constraints, referred to as the E-VSP, has been the focus of many studies going back to around 2014. We refer the reader to a survey by

Abbreviation	Definition
ALNS	Adaptive Large Neighborhood Search
B&P	Branch-and-Price
CG	Column Generation
CP	Constraint Programming
CSP	Crew Scheduling Problem
E-...	Problem ... with electric vehicles
LNS	Large Neighborhood 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

Perumal et al. (2022) for a detailed overview of recent progress.
Limited literature does exist on the integrated VCSP with electric vehicles (E-VCSP), however simplifying assumptions are made which might limit real world applicability or accurate modeling of costs. Most notably, assumptions are currently 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. Our aim is to introduce a model which incorporates more realistic behavior for battery charging and usage, by including the following:

- Including nonlinear battery charging times.
- Considering the cost of battery degradation due to usage patterns.
- Allowing for capacitated charging stations at both depots and the endpoints of a trip.
- Allowing partial charging of the battery throughout the day.

This work is organized as follows. In Section 2, we will discuss work related to the E-VCSP and give an overview of common ways of modeling and solving the problem. In Section 3, we give our formal problem definition. [*TODO: Meer secties*].

2 Related work

In this section, we will discuss work related to our research into the E-VCSP. An overview of the nomenclature used has been included in Table 1, and an summary of how batteries and charging behavior is modeled in the discussed works has been included in Table 2.

	Model	ToU	SoC	Nonlinear Ch.	Partial Ch.	Ch. Location	Degradation
Li (2014)	E-VSP	No	D	No	No	D	No
Kooten Niekerk et al. (2017)	E-VSP	Yes	C/D	Yes	Yes	D/T	Yes
Olsen and Kliewer (2020)	E-VSP	No	C	Yes	Yes	D/T	No
Zhang et al. (2021)	E-VSP	No	C/D	Yes	Yes	D	Yes
Parmentier et al. (2023)	E-VSP	No	C	Yes	Yes	D/T	No
Vos et al. (2024)	E-VSP	No	D	Yes	Yes	D/T	No
Perumal et al. (2021)	E-VCSP	No	C	No	No	D	No
Wang et al. (2022)	E-VCSP	Yes	C	No	Yes	D	No
Sistig and Sauer (2023)	E-VCSP	No	C	No	Yes	D/T	No
Shen and Li (2023)	E-VCSP	No	C	No	No	D/T	No
Cong et al. (2024)	E-VCSP	Yes	C	No	Yes	D	No
Ham and Park (2021)	E-VRPTW	Yes	C	No	Yes	D	No
Stadnichuk et al. (2024)	E-TVSP	No	C	No	Yes	D/T	No

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

[*TODO: uitleg van de SDVSP*] **(E-)VSP**
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 buses must return to the same depot from which they originated. We refer to Bunte and Kliewer (2009) for proofs of both of these facts.
The introduction of any resource constraints such as limited ranges within the VSP has also been shown to be NP-hard by Bodin and Golden (1983). As the E-VSP deals with the limited range associated with electric vehicles, it is quite closely related to the vehicle scheduling problem with route time constraints (VSP-RTC) as described by Haghani and Banihashemi (2002). 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 VSP-RTC assumes a fixed maximum travel time for the vehicle within the given period. The E-VSP specifically been shown to be NP-hard by Sassi and Oulamara (2014).

Li (2014) was one of the first to consider the E-VSP. 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 time span. 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 Francisco Bay Area, with a maximum instance size of 242 trips. These tests resulted in optimality gaps of $< 5\%$ for buses able to drive 150km, and between 7-15% for a range of 120km depending on the instance.

Kooten Niekerk et al., 2017 introduce a two models which aim to solve the single depot E-VSP while taking into account ToU energy prices, nonlinear charging times and battery degradation due to depth of discharge. The first model only allows for linear charging and no consideration for degradation or ToU, but uses continuous SoC variables. The second model does allow for the extra inclusions, at the cost of discretizing SoC and solving using CG for a possibly non-optimal solution. 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 considerably shorter time frame for large instances with similar results to the continuous model.

[*TODO: langer!*] Olsen and Kliewer, 2020 introduce a solution to the E-VSP which models the nonlinear phase of charging as an exponential function. They focus on showing that a (piecewise) linear approximation for the second phase of charging can misrepresent the SoC and required charging times.

Zhang et al. (2021) apply a similar method to the one found in Kooten Niekerk et al., 2017. They consider a single depot with capacitated charging infrastructure, with multiple round trip lines originating from the depot. They model nonlinear charging behavior and battery depreciation due to depth of discharge using discretized time steps. 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.

[*TODO: beter formuleren*] Parmentier et al. (2023) consider a scalable approach to the E-VSP with non-linear charging. They introduce the concept of nondominated charging arcs, which are defined as a deadhead arc between two trips during which charging is allowed with lower or equal cost and higher or equal resulting charge than all others deadhead arcs between the trips. In order to solve, a combination of CG and B&P techniques are used. The nondominated charging arcs are used in order to formulate a more computationally efficient version of the pricing problem given uniform charging infrastructure. Testing is done on the *large* instances introduced by Wen et al. (2016) which included up to 8 depots, 16 charging stations and 500 trips. Here, they are able to find solutions that only have an 0.06% optimality gap.

[*TODO: beter schrijven*] Vos et al. (2024) consider the E-VSP with partial recharges and capacitated charging stations. They model this using discrete SoC levels for each trip, as well as discrete time and SoC nodes for charging spots within the traditional network. This discretization is similar to that of Kooten Niekerk et al., 2017, however now with the inclusion of capacitated charging nodes. Using this, a primal network is created using pessimistic rounding. In order to solve, they apply CG with two separate approaches: branch-and-price and a diving heuristic. To overcome the limitations of dual bounds resulting from a discretized model, they incorporate ideas from Boland et al. (2017) resulting in a dual network with optimistic connections. 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 degradation.

CSP

[*TODO: gegeven een oplossing voor de vsp*] Given a solution to the (E-)VSP, the corresponding CSP is most often solved as a set partitioning (or set covering) problem. Here, the tasks described by the sequences of trips generated during vehicle scheduling must be covered by the individual schedules of crew members. This problem has been shown to be NP-hard in general by Fischetti et al. (1989). Research into this subject is primarily done in the context of airline crew planning; crew costs in this field are generally even higher than those found in the more general public transport sector, as shown in Barnhart et al. (2003). 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 therefore refer the reader to a recent review by Deveci and Demirel (2018) for an overview of the state of the art.

(E-)VCSP

The VCSP has been a widely studied problem. Following the call for integrated methods by Bodin and Golden (1983) and others in the 1980s, a large number of different methods has been applied to integrate the VSP and CSP. We refer the reader to a recent review by Ge et al. (2024) for a more general overview of work done in the field in the past years.

One work that we will individually highlight is that of Huisman et al. (2005), due to its use of Lagrangian relaxation to connect the VSP and CSP . For readers unfamiliar with the technique, we recommend an introduction by Beasley (1993). Huisman et al. consider the multi-depot variant, and use a combination of CG and Lagrangian relaxation to solve both the MDVSP as well as the connection with the CSP. Of note is their assumption that crew members from each individual depot are only allowed to work on trips connected to said depot, allowing for individual depot CSPs to be solved as a subproblem. They test on instances in the Randstad metro area in the Netherlands with a maximum of 653 trips and 4 depots.

As for the electric counterpart of the VCSP, at time of writing we are aware of only five other works that discuss the integrated variant.

Perumal et al. (2021) were the first to offer a solution to the E-VCSP. They introduced an ALNS which incorporates a B&P heuristic which has been previously used to solve the MDVSP, E-VSP and VCSP. They only consider full recharges with a fixed duration of 120 minutes and charging at the depot. The authors tested using real life data from lines in Denmark and Sweden with a maximum instance size of 1109 trips and multiple depots, and report an improvement of $1.17 - 4.37\%$ across different instances when compared to a sequential approach.

Wang et al. (2022) introduce a two layered model using particle swarms and an ϵ-constraint based mechanism which allows for a mix of traditional combustion and electric buses. The model incorporates partial depot charging, as well as measures to ensure that crew is primarily assigned to the same vehicle throughout the day. A circular bus route with a single depot 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.

Sistig and Sauer (2023) also offered an ALNS based approach, which aimed to improve upon the approach presented by Perumal et al., 2021 by including partial recharges, opportunistic charging at terminal stops of trips and non-fixed ranges for the vehicles. 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 single depot and 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 costs for electricity and drivers.

Shen and Li (2023) provide a minimum-cost flow framework for the E-VSP which is integrated with a set partitioning based approach for the E-CSP. They only provide full recharge capabilities at the depot, however focus on the inclusion of a distinction between energy use when driving and standing still in order to more accurately model real life traffic. A city line in China with 270 daily trips and a single depot is used for testing, resulting in cost savings of up to 8.7% when compared to a sequential approach.

Cong et al. (2024) provide a hybrid MIP and SAA based approach to optimizing a mixed fleet of combustion and electric vehicles with ToU electricity pricing. 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%.

Other related fields
The VSP is closely related to the vehicle routing problem (VRP); in this problem, the aim is to find minimum cost routes for vehicles originating from a depot and needing to pass multiple stops, most commonly for pickup or delivery with capacity constraints. The extension of the E-VRP which includes arrival time windows (E-VRPTW) is most closely related to the E-VSP, as the use of 0-width windows allows us to define the same precedence constraints as those naturally defined by trips in the VSP.
An example of work done on the E-VRPTW is that of Ham and Park (2021). They consider a single depot case in which they model ToU pricing and partial recharges during delivery routes. In order to model costs, a lexicographical minimization is done over the number of vehicles used, total distance traveled and energy recharged. In order to solve, a hybrid MIP and CP algorithm is used in which CP is used to model ToU related variables, and MIP is used to model the rest of the constraints.

Research has also been done into integrating the E-VSP with the step before it in the planning sequence: timetable planning. This problem, the E-TVSP, has recently been studied in the work of Stadnichuk et al. (2024). They allowed results of the E-VSP to introduce optimality cuts into the MIP used for creating timetable plans, thereby reducing overall cost. This is achieved by transforming the E-VSP problem into one of bin packing with conflicts, after which three different heuristic methods are applied and compared. They additionally prove that the bounds of the used heuristics are tight for their given instances.

3 Problem definition

Let T be a set of trips to be covered, and let D be the set of depots from which vehicles may originate. For a given trip i, let $s(i)$ and $e(i)$ be the planned starting and ending time of the trip respectively. Additionally, let $c(i)$ represent the amount of battery charge used by the trip. For a pair of locations (trip or depot) l and l' with $l \neq l'$, let $d(l, l')$ and $c(l, l')$ be defined as the duration of and amount of charge used driving the deadhead from l to l' respectively. Lastly for two trips i and i', let $u(i, i')$ be the maximum amount of charging that can be done during the time between i and i' after driving the deadhead.

For each trip $i \in T$, let us introduce a node $t_{i\sigma}$ representing a trip at a certain vehicle starting SoC σ. Here, σ must fall in a discretized range Σ which is defined as $\{0, \ldots, \sigma_{\max}\}$, where $\sigma_{\max}$ is the maximum usable capacity of a bus, and step size must be chosen to balance computational speed and accuracy. Let us call the collection of these nodes $\mathcal{T}$.
For depots, we model similarly. For each depot $j \in D$, let $d_{jt\sigma}$ represent depot j at time step t, considering only vehicles with SoC σ. As with σ, let t be inside a discretized range Θ consisting of $\{0, \ldots, 1919\}$, representing 1920 seconds (32 hours) allowing for modeling of overnight buses. Let us call the collection of all depot nodes $\mathcal{D}$.

We now model connections between the nodes. For each pair of nodes $(t_{i\sigma}, t_{i'\sigma'}) \in \mathcal{T} \times \mathcal{T}$ with $i \neq i'$, introduce an arc $a_{i\sigma i'\sigma'}$ between the nodes if it is feasible for a single vehicle task to drive trip i and then i' sequentially. In this, we define feasibility as the combination of:

- **Time-feasibility**, in which $e(i) + d(i, i') \leq s(i')$. Put simply, it must be possible to drive the deadhead from i to i' while respecting the scheduled trip times.

- **Charge-feasibility**, in which $\sigma - c(i) - c(i,i') \geq 0$ and $\sigma - c(i) - c(i,i') + \sigma^* = \sigma'$, with $0 \leq \sigma^* \leq u(i,i')$. Put simply, the starting charge σ must be sufficient to get from the start of i to the start of i', and we must be able to recharge to such an extent that we match the modeled charge level of σ'.

Now, let us include the depot nodes. We will begin with pull-in and pull-out arcs. For each pair of nodes $(d_{jt\sigma}, t_{i\sigma'}) \in \mathcal{D} \times \mathcal{T}$ introduce a pull-in arc $p_{jt\sigma,i\sigma'}$ between them if the connection between $d_{jt\sigma}$ and $t_{i\sigma'}$ is time-feasible and charge-feasible. For pull-out arcs, we do the same over the set of pairs $(t_{i\sigma}, d_{jt\sigma'}) \in \mathcal{T} \times \mathcal{D}$ by introducing an arc $q_{i\sigma,jt\sigma'}$ if driving from $t_{i\sigma}$ to $d_{jt\sigma'}$ is feasible. Lastly, let us model arcs for vehicles that occupy the depot. For each depot $j \in D$, create an arc between $d_{jt\sigma}$ and $d_{j(t+1 mod|\Theta|)\sigma'}$ for $t \in \Theta$ and $\sigma \in \Sigma$. Here, σ' is the battery level achieved after charging for a single unit of time from σ; if no charging at the depot is desired, let $\sigma' = \sigma$. [*TODO: Misschien is het handig om dit een keer aan Marcel/Han te vragen, maar waarom wordt er vanuit gegaan dat een vehicle altijd oplaadt tijdens het een depot verblijf*]

References

RDW (2025). *Opendata*. URL: https://opendata.rdw.nl/.

European regulations (2018). *Regulation - 2018/1999 - EN - EUR-Lex — eur-lex.europa.eu*. https://eur-lex.europa.eu/eli/reg/2018/1999/oj. [Accessed 08-12-2024].

Qbuzz (2024). *Qbuzz — qbuzz.nl*. https://www.qbuzz.nl/gd/actueel/laatste-nieuws/ZBnQDREAACEAlo3q/busvervoer-90-uitstootvrij-vanaf-2024. [Accessed 08-12-2024].

Ceder, A. and N. H. Wilson (1986). "Bus network design". In: *Transportation Research Part B: Methodological* 20.4, pp. 331–344. ISSN: 0191-2615. DOI: https://doi.org/10.1016/0191-2615(86)90047-0. URL: https://www.sciencedirect.com/science/article/pii/0191261586900470.

Ibarra-Rojas, O. et al. (2015). "Planning, operation, and control of bus transport systems: A literature review". In: *Transportation Research Part B: Methodological* 77, pp. 38–75. ISSN: 0191-2615. DOI: https://doi.org/10.1016/j.trb.2015.03.002. URL: https://www.sciencedirect.com/science/article/pii/S0191261515000454.

Perumal, S. S., R. M. Lusby, and J. Larsen (2022). "Electric bus planning & scheduling: A review of related problems and methodologies". In: *European Journal of Operational Research* 301.2, pp. 395–413. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2021.10.058. URL: https://www.sciencedirect.com/science/article/pii/S0377221721009140.

Perumal, S. S. et al. (2019). "A matheuristic for the driver scheduling problem with staff cars". In: *European Journal of Operational Research* 275.1, pp. 280–294. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2018.11.011. URL: https://www.sciencedirect.com/science/article/pii/S0377221718309366.

Bodin, L. and B. Golden (1983). "Routing and scheduling of vehicles and crews: The state of the art". In: *Computers & Operations Research* 10.2. Routing and Scheduling of Vehicles and Crews. The State of the Art, pp. 63–211. ISSN: 0305-0548. DOI: https://doi.org/10.1016/0305-0548(83)90030-8. URL: https://www.sciencedirect.com/science/article/pii/0305054883900308.

Li, J.-Q. (2014). "Transit Bus Scheduling with Limited Energy". In: *Transportation Science* 48.4, pp. 521–539. ISSN: 00411655, 15265447. URL: http://www.jstor.org/stable/43666940 (visited on 12/20/2024).

Kooten Niekerk, M. E. van, J. M. van den Akker, and J. A. Hoogeveen (2017). "Scheduling electric vehicles". In: *Public Transport* 9.1, pp. 155–176. ISSN: 1613-7159. DOI: 10.1007/s12469-017-0164-0. URL: https://doi.org/10.1007/s12469-017-0164-0.

Olsen, N. and N. Kliewer (2020). “Scheduling electric buses in public transport: Modeling of the charging process and analysis of assumptions”. In: *Logistics Research* 13.1, pp. 1–17.

Zhang, L., S. Wang, and X. Qu (2021). “Optimal electric bus fleet scheduling considering battery degradation and non-linear charging profile”. In: *Transportation Research Part E: Logistics and Transportation Review* 154, p. 102445. ISSN: 1366-5545. DOI: https://doi.org/10.1016/j.tre.2021.102445. URL: https://www.sciencedirect.com/science/article/pii/S136655452100209X.

Parmentier, A., R. Martinelli, and T. Vidal (2023). “Electric Vehicle Fleets: Scalable Route and Recharge Scheduling Through Column Generation”. In: *Transportation Science* 57.3, pp. 631–646. DOI: 10.1287/trsc.2023.1199. eprint: https://doi.org/10.1287/trsc.2023.1199. URL: https://doi.org/10.1287/trsc.2023.1199.

Vos, M. H. de, R. N. van Lieshout, and T. Dollevoet (2024). “Electric Vehicle Scheduling in Public Transit with Capacitated Charging Stations”. In: *Transportation Science* 58.2, pp. 279–294. DOI: 10.1287/trsc.2022.0253. eprint: https://doi.org/10.1287/trsc.2022.0253. URL: https://doi.org/10.1287/trsc.2022.0253.

Perumal, S. S. et al. (2021). “Solution approaches for integrated vehicle and crew scheduling with electric buses”. In: *Computers & Operations Research* 132, p. 105268. ISSN: 0305-0548. DOI: https://doi.org/10.1016/j.cor.2021.105268. URL: https://www.sciencedirect.com/science/article/pii/S0305054821000605.

Wang, J. et al. (2022). “Collaborative Optimization of Vehicle and Crew Scheduling for a Mixed Fleet with Electric and Conventional Buses”. In: *Sustainability* 14.6. ISSN: 2071-1050. DOI: 10.3390/su14063627. URL: https://www.mdpi.com/2071-1050/14/6/3627.

Sistig, H. M. and D. U. Sauer (2023). “Metaheuristic for the integrated electric vehicle and crew scheduling problem”. In: *Applied Energy* 339, p. 120915. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2023.120915. URL: https://www.sciencedirect.com/science/article/pii/S0306261923002799.

Shen, Y. and Y. Li (Nov. 2023). “Minimum Cost Flow-Based Integrated Model for Electric Vehicle and Crew Scheduling”. In: *Journal of Advanced Transportation* 2023, pp. 1–23. DOI: 10.1155/2023/6658030.

Cong, Y. et al. (2024). “Collaborative vehicle-crew scheduling for multiple routes with a mixed fleet of electric and fuel buses”. In: *Energy* 298, p. 131400. ISSN: 0360-5442. DOI: https://doi.org/10.1016/j.energy.2024.131400. URL: https://www.sciencedirect.com/science/article/pii/S0360544224011733.

Ham, A. and M.-J. Park (2021). “Electric Vehicle Route Optimization Under Time-of-Use Electricity Pricing”. In: *IEEE Access* 9, pp. 37220–37228. DOI: 10.1109/ACCESS.2021.3063316.

Stadnichuk, V. et al. (2024). *Integrated Optimization of Timetabling and Electric Vehicle Scheduling: A Case Study of Aachen, Germany*. https://optimization-online.org/2024/09/integrated-optimization-of-timetabling-and-electric-vehicle-scheduling-a-case-study-of-aachen-germany/. [Accessed 13-01-2025].

Bunte, S. and N. Kliewer (2009). “An overview on vehicle scheduling models”. In: *Public Transport* 1.4, pp. 299–317. ISSN: 1613-7159. DOI: 10.1007/s12469-010-0018-5. URL: https://doi.org/10.1007/s12469-010-0018-5.

Haghani, A. and M. Banihashemi (2002). “Heuristic approaches for solving large-scale bus transit vehicle scheduling problem with route time constraints”. In: *Transportation Research Part A: Policy and Practice* 36.4, pp. 309–333. ISSN: 0965-8564. DOI: https://doi.org/10.1016/S0965-8564(01)00004-0. URL: https://www.sciencedirect.com/science/article/pii/S0965856401000040.

Sassi, O. and A. Oulamara (Mar. 2014). “Electric Vehicle Scheduling and Optimal Charging Problem: Complexity, Exact and Heuristic Approaches”. In: *International Journal of Production Research* 55. DOI: 10.1080/00207543.2016.1192695.

Wen, M. et al. (2016). “An adaptive large neighborhood search heuristic for the Electric Vehicle Scheduling Problem”. In: *Computers & Operations Research* 76, pp. 73–83. ISSN: 0305-0548. DOI: https://doi.org/10.1016/j.cor.2016.06.013. URL: https://www.sciencedirect.com/science/article/pii/S0305054816301460.

Boland, N. et al. (2017). “The Continuous-Time Service Network Design Problem”. In: *Operations Research* 65.5, pp. 1303–1321. DOI: 10.1287/opre.2017.1624. eprint: https://doi.org/10.1287/opre.2017.1624. URL: https://doi.org/10.1287/opre.2017.1624.

Fischetti, M., S. Martello, and P. Toth (1989). “The Fixed Job Schedule Problem with Working-Time Constraints”. In: *Operations Research* 37.3, pp. 395–403. ISSN: 0030364X, 15265463. URL: http://www.jstor.org/stable/171059 (visited on 12/15/2024).

Barnhart, C. et al. (2003). “Airline Crew Scheduling”. In: *Handbook of Transportation Science*. Ed. by R. W. Hall. Boston, MA: Springer US, pp. 517–560. ISBN: 978-0-306-48058-4. DOI: 10.1007/0-306-48058-1_14. URL: https://doi.org/10.1007/0-306-48058-1_14.

Deveci, M. and N. C. Demirel (2018). “A survey of the literature on airline crew scheduling”. In: *Engineering Applications of Artificial Intelligence* 74, pp. 54–69. ISSN: 0952-1976. DOI: https://doi.org/10.1016/j.engappai.2018.05.008. URL: https://www.sciencedirect.com/science/article/pii/S0952197618301234.

Ge, L. et al. (2024). “Revisiting the richness of integrated vehicle and crew scheduling”. In: *Public Transport* 16.3, pp. 775–801. ISSN: 1613-7159. DOI: 10.1007/s12469-022-00292-6. URL: https://doi.org/10.1007/s12469-022-00292-6.

Huisman, D., R. Freling, and A. P. M. Wagelmans (2005). “Multiple-Depot Integrated Vehicle and Crew Scheduling”. In: *Transportation Science* 39.4, pp. 491–502. DOI: 10.1287/trsc.1040.0104. eprint: https://doi.org/10.1287/trsc.1040.0104. URL: https://doi.org/10.1287/trsc.1040.0104.

Beasley, J. E. (1993). “Lagrangian relaxation”. In: *Modern Heuristic Techniques for Combinatorial Problems*. USA: John Wiley & Sons, Inc., 243–303. ISBN: 0470220791.