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The Electric Vehicle Scheduling Problem

A study on time-space network based and heuristic solution approaches

Josephine Reuer · Natalia Kliewer · Lena Wolbeck

Abstract In the last years, many public transport companies have launched pilot projects testing the operation of electric buses. Therewith new challenges arise in the planning process. In this work, we define the electric vehicle scheduling problem (EVSP) and multi-vehicle-type vehicle scheduling problem with electric vehicles (MVT-(E)VSP). For both problems we present solution approaches and results. Therefore, we extend the traditional definition of the vehicle scheduling problem (VSP) and consider the limited battery capacity restriction as well as the vehicles' possibility to recharge their batteries. First, we use an existing time-space network based exact solution approach for the VSP and provide an algorithm that adds chargings to the schedule when necessary in order to build vehicle blocks for electric vehicles. For this, we tested different strategies for the network flow decomposition. Second, we use two heuristic approaches in order to obtain feasible vehicle schedules for the EVSP and upper bounds for the required number of vehicles.

Keywords electric vehicle · public transport · time-space network · vehicle scheduling

1 Introduction

The scarcity of fossil fuels as well as many countries' current climate targets in regard to the reduction of CO_2 emission require a paradigm shift to renewable energies. Albeit, electric vehicles (EVs) still only represent a small share of

Josephine Reuer
Freie Universität Berlin, Garystr. 21, 14195 Berlin, Germany
Tel.: +49-30-838-65495
Fax: +49-30-838-53692
E-mail: josephine.reuer@fu-berlin.de

Natalia Kliewer · Lena Wolbeck
Freie Universität Berlin, Garystr. 21, 14195 Berlin, Germany

the vehicle market, we can observe an increasing electro-mobility particularly in urban areas. Also many public transport companies have launched pilot projects testing the operation of electric buses. In Germany, for instance, the public transport operator in Brunswick already introduced two electric buses[1] in 2014 and is preparing three more for line operation.[2] This only accounts for a share of about 3 %[3] of the total fleet, but still entails additional restrictions for vehicle scheduling. The traditional vehicle scheduling problem (VSP) is the task of assigning a given set of timetabled trips to a set of vehicles while considering operational restrictions and minimizing total costs. While this is a well studied problem (cf. Bunte and Kliewer, 2009), new challenges arise due to the use of EVs: (1) The vehicles have a much smaller range due to battery capacity than traditional diesel vehicles and (2) they can be recharged at specified stations only.

Thus, the transit operator faces several decision problems of which the two most significant will be considered in the following. First, he has to decide on the EV type. In general one distinguishes between hybrid electric vehicles (HEVs), fuel cell vehicles (FCVs) and battery electric vehicles (BEVs). HEVs use an electric drive as well as a combustion engine and thus do not belong to the zero emission vehicles. FCVs generate electricity, that is stored in the battery, in fuel cells mostly from hydrogen. BEVs store energy in a battery or ultracapacitor and of all EVs have the smallest range. For further descriptions on the technology we refer to Chan (2007). Second, the chosen vehicle type determines greatly the range of a bus and in conclusion the necessary charging (or refueling) infrastructure. If either HEVs or BEVs are used the operator has to choose a charging technology. Yilmaz and Krein (2013) distinguish three power levels: Level 1 slow charging overnight, Level 2 semifast charging and Level 3 fast charging. In Brunswick different charging technologies are used. While the buses are primary recharged overnight in the depot, the battery can also be charged inductively during passenger boarding and alighting as well as about 11 minutes at the final stop. Additionally one can choose battery swapping instead of charging, as used e. g. during Shanghai World Expo (Li, 2014).

Right now, it is difficult to forecast which technology will prevail. In this paper we focus on BEVs as they set the greatest range restrictions. Furthermore, for the first we assume a given charging infrastructure where battery recharging is possible at certain final stops only and takes about the time of battery swapping. For reason of convenience we will still talk about charging.

The VSP with limited range is similar to the vehicle scheduling problem with route constraints (VSP-RC). Bunte and Kliewer (2009) give an overview on these models as well as on modeling and solution approaches for the classical VSP. Yet, there exist only few approaches for considering refueling or recharging. Wang and Shen (2007) first defined the vehicle scheduling problem

[1] BEV (Solaris Urbino 12/18 electric) with Li-Ion-battery 60kW/90kW and 600 V.
[2] http://www.verkehr-bs.de/unternehmen/forschungsprojekt-emil.html
[3] http://www.verkehr-bs.de/unternehmen/fuhrpark.html

with route and fueling time constraints (VSPRFTC). They develop a heuristic that incorporates route time constrictions and finds vehicle blocks starting and ending at the depot. After that they use a bipartite graphic model to connect these blocks regarding fuel time restrictions. Zhu and Chen (2013) propose a heuristic approach for the EVSP which they tested on a real-world instance with 119 service trips. They aim at minimizing vehicle costs as well as total charging demand. Li (2013) models the VSP with limited energy using time-expanded station nodes, thus considering the possibility to recharge and the capacity of charging stations. The author presents a construction heuristic producing schedules which serve as initial solutions for different column generation based approaches. To generate a feasible solution, Adler (2014) enhances the concurrent scheduler algorithm (cf. Bodin et al, 1978) using an algorithm that regards fueling constraints. The heuristic is tested on real-world instances with up to 4,000 service trips. Besides he develops and evaluates an exact column generation algorithm for small instances.

All of these approaches use connection based network models. In contrast, time-space networks (TSN) used for solving the traditional VSP have proven to build significantly more compact models and thus are able to generate optimal solutions applying directly MIP-solver even for large instances.[4] That is, because a TSN does not consider every possible connection between service trips but aggregates these to groups of compatible connections. As a solution of TSN based MIP-optimization one derives a network flow. Next, this flow is decomposed into paths, i. e. vehicle blocks. Because of the aggregation of connections many different schedules may be constructed depending on the decomposition strategy used. Such strategies have successfully been used before for different restrictions such as line change considerations (Kliewer et al, 2008). In this paper we want to transfer those findings to vehicle scheduling with EVs and evaluate its applicability.

In this paper another difference to previous research is that we support a mixed fleet composed of both internal combustion engine vehicles (ICEVs) and electric buses. Given that electric buses induce high fixed costs and ICEVs will be replaced only slowly, this is a reasonable assumption. We define this problem as multi-vehicle-type vehicle scheduling with EVs (MVT-(E)VSP). Despite, we also consider the electric vehicle scheduling problem (EVSP) that uses only EVs.

Hence, the contributions of this paper are twofold: First, we apply the TSN approach and we extend it by proposing different strategies for flow decomposition that support, for instance, the creation of waiting times at charging stations. Therefore, we provide an algorithm that adds chargings to the schedule if necessary. This way, we test the adaptability of the optimal schedules to the new requirements due to electric vehicles and receive a feasible schedule for the MVT-(E)VSP. That gives us a bound on the minimal percentage of EVs in a mixed fleet that can be used without making major changes to the optimal schedule and requiring more buses. Second, we present two heuristics

[4] For a detailed description of the TSN model we refer to Kliewer et al (2006).

in order to construct feasible schedules for the EVSP from scratch. Therefore, we follow the ideas of Adler (2014) by extending the concurrent scheduler algorithm (cf. Bodin et al, 1978).

In the following, we first define the EVSP and the MVT-(E)VSP as extensions of the standard VSP for one depot. Note that although we use the concepts for BEVs, i. e. battery capacity and charging instead of battery swapping or refueling, the concepts can easily be adapted to other electric or alternative-fuel vehicles. Section 3 describes the methods used for solving those problems and section 4 presents our test results for several real-world instances. In order to gain further knowledge on the problems, many experiments can be conducted by changing the input parameters, e. g. charging technology, consumption or battery capacity. Here, we will give one extension of the model where we drop the restriction of limited charging facilities (cf. section 5). This enables further insights into the necessary charging infrastructure. We summarize our contributions and give a brief outlook on further extensions in section 6.

2 Problem definition

We define the EVSP as an extension of the standard VSP (cf. Bertossi et al, 1987). The objective is to find an assignment for a given set of timetabled trips to a homogeneous set of vehicles which minimizes the number of vehicles and operational costs such that:

- each service trip is assigned exactly once,
- each vehicle starts and ends its schedule at the same depot,
- each vehicle block contains a feasible sequence of trips,
- a vehicle's battery capacity cannot fall below zero and,
- a vehicle can only be charged at defined stop points.

We assume a constant consumption in kWh per kilometer which differs on service and deadhead trips. That is due to the higher weight and consumption when passengers are transported. In addition, a vehicle's battery capacity is assumed to be constant as well. A vehicle always leaves the depot with a full battery and, when recharged, it is charged to full capacity. The charging time and costs do not depend on the capacity left when arriving at a charging station. Besides we do not presume any capacity restrictions at stations. Furthermore, chargings and deadhead trips start initially on arrival of the previous trip. However, we do not consider chains of chargings, i. e. driving from one charging station to another without serving a passenger trip. Hence, any trip can be served with a fully charged battery.

Furthermore, we also define the multi-vehicle-type vehicle scheduling problem with electric vehicles (MVT-(E)VSP). Therefor, we assume a heterogeneous fleet consisting of both internal combustion engine vehicles (ICEVs) and electric vehicles. For ICEVs the above described restrictions regarding electric engines do not apply and we assume an unlimited range for those vehicles. Moreover, no changes are made opposite to the standard VSP.

3 Solution approaches

In the following, we extend a TSN based approach using six different strategies for flow decomposition and develop an algorithm that inserts necessary chargings to a given vehicle schedule. That way, we compute a solution for the MVT-(E)VSP that uses the maximum possible number of EVs based on the solution of a standard VSP. In addition, we test two heuristics that construct feasible vehicle schedules for the EVSP following the ideas of Adler (2014).

3.1 TSN based approach

To consider electric vehicles in vehicle scheduling, we take up the TSN based solution method from Kliewer et al (2006) and propose the following additional six strategies for flow decomposition:

- **MaxChargings (MaxCh)** connects in- and out-going activities at each charging station node in such a way that potential charging times are maximized.
- **MinConsumption (MinCon)** solves a bottleneck assignment problem at each node with the goal to minimize the maximum consumption.
- **MaxChargingsMinConsumption (MaxChMinCon)** uses MaxCh at charging station nodes and MinCon at the other nodes.
- **Extended MaxChargingsMinConsumption (XMaxChMinCon)** connects MaxCh and MinCon in one weighting function at each node.
- **Extended MinConsumption (XMinCon)** extends MinCon in such a way that the consumption between two chargings is regarded.
- **MaxChargings Extended MinConsumption (MaxChXMinCon)** uses MaxCh at each charging station node and XMinCon at all other nodes.

The presented strategies were developed in order to promote the possibility to build vehicle blocks for electric vehicles, for instance by increasing possible charging times or by minimizing the total consumption for a vehicle block. The strategies all act locally and are more or less myopic as they solve an optimization problem at each node. The nodes that represent stop points at different times are handled sequentially. In addition, we used simple first-in, first-out (FIFO) and last-in, first-out (LIFO) flow decomposition.

After decomposition we use the vehicle schedule without chargings and develop an algorithm that identifies when a vehicle needs to be recharged and, if possible, inserts chargings into the schedule. The algorithm incorporates the fact that deadhead trips may be shifted forwards or backwards in scope of the attached buffered times if necessary to add chargings. By this means, we receive a vehicle schedule using a limited percentage of EVs as well as standard ICEVs. Thus, by slightly modifying well-studied solution methods incorporated by different strategies for flow decomposition, we estimate a bound on the maximum number of EVs in a MVT-(E)VSP based on the optimal solution of a standard VSP.

3.2 Heuristic approach

We develop two versions of a heuristic method inspired by the conception in Adler (2014). The approach focuses on both simple and fast generation of a vehicle schedule as well as reducing the number of vehicles and the operating costs. Both algorithms construct solutions for the EVSP iteratively starting with an ordered list of service trips. The fundamental procedure is as follows:

1. Set $i = 1$. Assign the uncovered trip t_i to vehicle 1.
2. Increment i. Find vehicle v that minimizes total operating costs resulting from the assignment. Consider that deadhead trip to nearest charging station after trip t_i must be possible. If no existing vehicle can take the trip add new vehicle. If charging before trip t_i is necessary go to step 2a, else go to step 2b.
   (a) Insert charging and necessary deadhead trips.
   (b) Insert deadhead trip if necessary.
3. Assign trip t_i to vehicle v.
4. If unassigned trips are left go to step 2, otherwise return vehicle schedule.

Both heuristic versions follow this schema but differ in the number of vehicles at initialization. The first heuristic *H1* starts with only one vehicle while heuristic *H2* starts with the number of vehicles which corresponds to the maximum number of trips at times of peak load.

4 Results

The provided approaches are implemented in C# under .Net using the optimization library of IBM ILOG CPLEX 12.5. Our computational experiments are conducted on ten real-world instances with up to 10,000 service trips. These instances are characterized by different kinds of distributions of the timetabled trips over the day as shown in figure 1. The names of the instances contain the total number of service trips. We distinguish three groups: (1) small-size instances with up to 1,000 service trips, (2) medium-size instances with between 1,000 and 5,000 service trips and (3) large instances with more than 5,000 service trips.

For this study the instances were adjusted in order to capture the requirements of electric vehicles in the following way:

- Depending on the size of the instance we added between 5 and 26 charging stations at highly frequented stop points. For reasons of comparability, the charging stations were chosen to cover about 50 % of all service trip departure and arrival stations. Thus, the probability of passing a charging station is nearly the same for all instances.
- Battery capacity is set to 120 kWh.
- We assume a consumption of 1 kWh/km on service and 0.8 kWh/km on deadhead trips.
- We consider a charging time of 10 minutes.

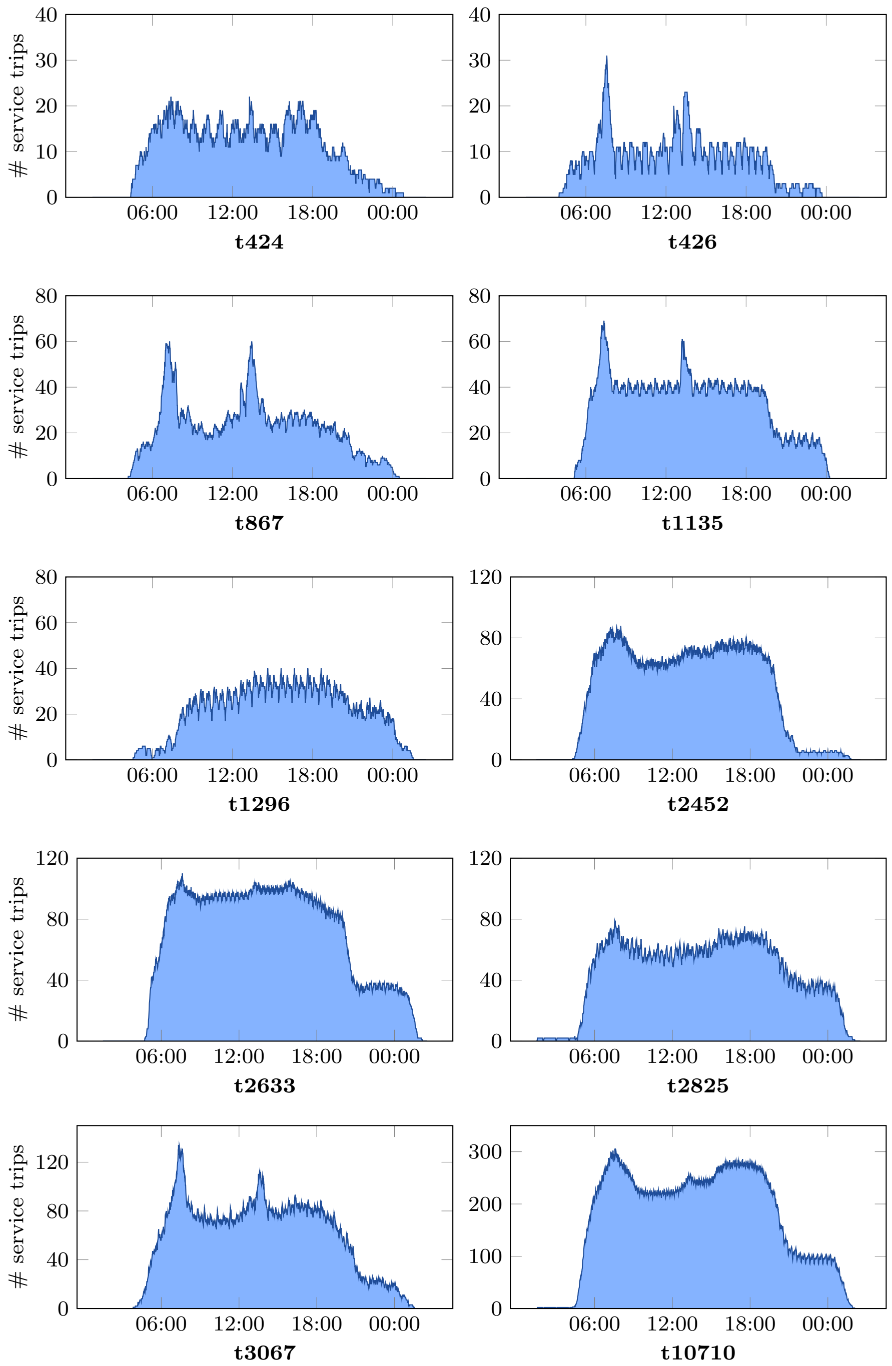

Fig. 1 Profile of active service trips for each instance

These figures chosen for battery capacity, consumption and charging time were motivated by research as well as practice. For instance, Li (2013) and Adler (2014) assume ranges between 120 km to 150 km and 10 minutes for service at charging stations. Another example are the buses used during Shanghai World Expo. They had a range of 150 km and needed 10 minutes for battery swapping (Li, 2014). We confer to Li (2014) for a review on recent developments of electric buses where more figures concerning range and charging technology is given.

In the following, we first present our results regarding the TSN based solution approach for the MVT-(E)VSP. Second, we discuss our findings for the heuristic solution of the EVSP.

4.1 Results for the MVT-(E)VSP using the TSN based solution method

The MVT-(E)VSP is solved using the TSN based solution approach described in section 3.1. As this paper does not focus on the comparison of different decomposition strategies, we choose the best strategy based on the maximal possible number of EVs for each instance. If two strategies produce the same number then we select the best one on the basis of the total cost, so that the schedule with the fewest chargings is chosen. Note, that flow decomposition only takes a few seconds for all instances and thus represents a small part of the overall runtime. Hence, all decomposition strategies can be run one after another without major effect on the runtime.

Table 1 depicts different figures of the best solution found for the MVT-(E)VSP. It shows the number of vehicles needed in the optimal solution of the standard VSP and the maximal percentage of blocks served by electric vehicles as well as those that can be served without needing to recharge. Besides, the average number of trips before an EV needs to recharge is given.

Table 1 Results for the TSN based approach

instance	no. of vehicles	max. pct. of EVs	pct. of EV blocks w/o charging	avg. service trips before charging
t424	29	51.72 %	6.90 %	5.53
t426	32	100.00 %	56.25 %	30.43
t867	69	57.97 %	37.68 %	20.87
t1135	75	72.00 %	28.00 %	16.74
t1296	47	82.98 %	4.26 %	23.38
t2452	101	35.64 %	10.89 %	22.57
t2633	125	18.40 %	5.60 %	21.00
t2825	92	45.65 %	6.52 %	18.09
t3067	165	60.61 %	30.91 %	25.62
t10710	349	28.94 %	9.74 %	23.78

The small instances produce diverse results. For *t426* we obtain a vehicle schedule that can be served using only EVs and is thus a solution to the EVSP. This is also due to the high percentage of vehicle blocks that do not exceed the capacity restriction of the battery. In comparison, *t424* has almost the same number of service trips but only uses half as much EVs. This might be a result of the high energy consumption for this plan due to long deadhead distances. The figures suggest that for *t426* six times as much service trips can be served before a vehicle needs to be recharged. It can also be assumed that the distribution of timetabled trips for *t426* supports the insertion of chargings as it has long off-peak hours with far less need of vehicles. Nevertheless, if we only consider the absolute number of vehicles for which chargings were added, it is almost the same for both schedules.

For the medium-size instances there is a slight negative correlation between the number of vehicles and the percentage of EVs: the more vehicle blocks a solution the less the percentage of EVs. One exception is the schedule with 3067 service trips which holds more than 60 % of EVs. The smallest percentage of EVs appears for *t2633* which also has the highest average consumption of the medium-size instances. In comparison, the vehicle schedule for the large instance uses about 29 % of EVs which is a lot if we consider the total number of vehicle blocks.

Our results show that there is not only one criteria that is responsible for the performance of the TSN based approach but several influencing factors. One is the average consumption of a vehicle block: naturally, if it is low, there are more blocks that are feasible for EVs without needing to recharge. Another factor is the distribution of timetabled trips as there is more time to recharge a vehicle during off-peak hours. Other parameters are the number of vehicle blocks in total and the number of service trips.

Nevertheless, considering the slow shift towards the operation of electric buses in public transport our results suggest that for the first years in which only few EVs are used, the proposed modified TSN based approach is sufficient. Note that the solution we get is not optimal for the MVT-(E)VSP but feasible. As it only made slight changes to the optimal solution of the VSP it is interesting to look at the new cost component, namely the costs for chargings and charging infrastructure. Table 2 shows figures associated with these costs. Here, we only show the charging stations that are actually used in the solution.

The schedules distinguish greatly in the number of charging stations needed. There is no significant correlation between the number of charging stations and neither the percentage of EVs nor the size of the instance. For instance, *t867* uses as many charging stations as *t2825* but charges four times less on average.

Although, we did not incorporate charging station capacities in our model we evaluated those afterwards. Recognize that the capacity of a charging station seldom exceeds 2 buses. For the largest instance the exceeding is only 13 minutes in total and less for the other instances. Even exceeding 1 bus occurs seldom in our results. In most cases for less than 4 % of the total charging time a charging station is occupied by 2 or more buses.

Table 2 Charging station statistics for the TSN based approach

instance	no. of chargings	avg. chargings per EV	no. of charging stations used (in %)	max. capacity of charging station	pct. of total charging time with occupancy ≥ 2	avg. chargings per charging station
t424	32	2.13	5 (100 %)	2	0.63 %	6.40
t426	14	0.44	4 (67 %)	1	0.00 %	3.50
t867	15	0.38	9 (75 %)	1	0.00 %	1.67
t1135	43	0.80	9 (82 %)	2	1.42 %	4.78
t1296	48	1.23	11 (65 %)	1	0.00 %	4.36
t2452	28	0.78	5 (56 %)	3	2.74 %	5.60
t2633	22	0.96	6 (55 %)	1	0.00 %	3.67
t2825	58	1.38	9 (75 %)	2	0.87 %	6.44
t3067	53	0.53	12 (46 %)	2	3.52 %	4.42
t10710	93	0.92	18 (82 %)	4	8.19 %	5.17

4.2 Results for the EVSP using the heuristic method

The EVSP is solved with the heuristic approach described in section 3.2.[5] The focus of this approach is on finding an upper bound on the number of necessary EVs for the EVSP. A comparison with the results of the TSN based solution method does not take place because of the different underlying vehicle set for the MVT-(E)VSP. Comparing the two versions of the heuristic *H1* and *H2* with each other shows that two vehicle schedules contain one respectively two vehicles less if they are produced with *H2*. For *t426* and *t1296* the initialization with the minimum number of vehicles leads to a slightly better distribution of service trips on the EVs.

Due to the rather similar results for both heuristic versions, we will not distinguish between them in the following. Instead, we look at the most economic solution for each instance. Table 3 depicts selected figures of the best solution found for the EVSP and the optimal number of vehicles for the VSP. To also examine the influence of the heuristic method irrespective of the consideration of EVs, we use a similar heuristic approach to solve the VSP. Furthermore, the table shows the percentage of EVs that can be served without charging and the average number of trips before an EV needs to recharge.

The number of vehicles is slightly higher in five vehicle schedules due to the heuristic. For instance, the results of *t3067* show four and of *t10710* two vehicles more than the optimal solution. Otherwise, the increased number of vehicles of three other instances is due to the use of electric vehicles. *t424*, *t1296* and *t2633* produce vehicle schedules with 12 to 17 % more vehicles than the optimal and the heuristic solution for the VSP. We assume that the distribution of the timetabled trips (shown in figure 1) is responsible for these outcomes. Their services trips are relatively evenly spread throughout the day, which causes an accumulation of trips and chargings at the same time

[5] Note that all schedules were computed in less than five seconds.

Table 3 Results for the heuristic approach

instance	opt. no. of vehicles for VSP	no. of vehicles for VSP (heuristic)	no. of vehicles for EVSP (heuristic)	pct. of EV w/o charging	avg. service trips before charging
t424	29	**29**	34	8.82 %	7.31
t426	32	**32**	**32**	75 %	53.25
t867	69	70	70	90 %	123.86
t1135	75	**75**	**75**	60 %	37.83
t1296	47	48	53	9.43 %	19.06
t2452	101	102	102	11.76 %	25.28
t2633	125	**125**	140	2.86 %	9.37
t2825	92	**92**	**92**	3.26 %	18.59
t3067	165	169	169	27.81 %	20.72
t10710	349	351	351	2.85 %	19.76

and thus increases the number of vehicles needed. Compared to other instances of similar sizes, they have a much lower percentage of electric vehicles without charging and the number of executable service trips before a recharge is lower. These are also indications for an increased number of vehicles. Whereas we do not know the optimal number of vehicles for the EVSP, we cannot assess the results to their full extent.

Table 4 depicts figures of the heuristic method relating to the costs for chargings and charging infrastructure. The results for the small instances differ greatly. For *t426* and *t867* we obtain a vehicle schedule containing very few chargings and with low occupancy of the charging stations. This is due to the fact that only a few of the vehicles need to load at all and many service trips can be served before recharging (see table 3). In contrast, the schedule for *t424* contains seven times more chargings and the charging stations' occupancy is in every respect higher. This might be an outcome of the heuristic approach which does not operate well in this case or it might be due to the distribution of the timetabled trips.

There is a slight correlation between the number of chargings and the percentage of charging stations needed as well as the size of the instance. In four solutions all possible charging stations are used and in the other cases over 70 % are needed. An exception of this are *t426* and *t867* which only use three or two chargings stations while having significantly lower number of chargings.

Furthermore, we evaluate the charging station capacities. There is a correlation between the chargings per station and the concurrent occupation of the charging station. For instance, the vehicle schedule of *t2825* has an average of 12.67 chargings per charging station and the capacity exceeds two vehicles for more than 85 minutes. Accordingly, the result of *t2633* show twice the number of chargings per station and the capacity exceeds two vehicles for 420 minutes of which four vehicles load simultaneously for five minutes only.

Table 4 Charging station statistics for the heuristic approach

instance	no. of chargings	avg. chargings per EV	no. of charging stations used (in %)	max. capacity of charging station	pct. of total charging time with occupancy ≥ 2	avg. chargings per charging station
t424	58	1.71	4 (80 %)	3	7.82 %	14.50
t426	8	0.25	3 (50 %)	1	0.00 %	2.67
t867	7	0.10	2 (17 %)	1	0.00 %	3.50
t1135	30	0.40	8 (73 %)	2	1.01 %	3.75
t1296	68	1.28	15 (88 %)	2	0.74 %	4.53
t2452	97	0.95	9 (100 %)	3	11.70 %	10.78
t2633	281	2.01	11 (100 %)	4	14.95 %	25.55
t2825	152	1.65	12 (100 %)	2	5.63 %	12.67
t3067	148	0.88	21 (81 %)	2	5.11 %	7.05
t10710	542	1.54	22 (100 %)	5	19.08 %	24.64

5 Problem extension: variation of charging infrastructure

So far we assumed a fixed charging infrastructure, thus limiting the upper bound for EVs in a schedule. Now, we will drop this restriction by allowing to recharge at every start or end station, i. e. every station is a potential charging station. By this means, we will also receive an upper bound on the necessary charging infrastructure. Note that charging during a service trip is still not allowed.

Table 5 displays the maximal percentage of EVs and the number of necessary charging stations in the extended model as well as the percentage change towards the model with a given charging infrastructure as shown in tables 1 and 2 for the MVT-(E)VSP. Furthermore, it gives the maximal capacity of a charging station and the average number of chargings per charging station as an indicator of occupancy rate.

Table 5 Results for the TSN based approach with all possible charging stations

instance	max. pct. of EVs	– change	no. of charging stations	– change	max. capacity of charging station	avg. chargings per charging station
t424	82.76 %	60.00 %	13	160.00 %	2	4.31
t426	100.00 %	0.00 %	6	50.00 %	2	2.33
t867	73.91 %	27.50 %	19	111.11 %	1	1.79
t1135	80.00 %	11.11 %	18	100.00 %	1	3.17
t1296	89.36 %	7.69 %	23	109.09 %	2	2.04
t2452	55.45 %	55.56 %	17	240.00 %	1	4.53
t2633	30.40 %	65.22 %	16	166.67 %	2	3.06
t2825	72.83 %	59.52 %	23	155.56 %	2	4.48
t3067	87.27 %	44.00 %	41	241.67 %	2	3.22
t10710	41.26 %	42.57 %	43	138.89 %	2	3.93

As expected, we now receive a higher percentage of EVs for each instance. At the same time, this entails a stronger increase on the number of charging stations which in practice leads to higher fixed costs for the construction of charging infrastructure. Except for one instance the results also show a decreased occupancy rate on average for each charging station. The capacity of a charging station never exceeds two vehicles.

These results imply interesting questions for practical use that can be addressed in future research. For instance, as there is a trade-off between the number of EVs and the number of necessary charging stations – both entailing fixed costs for public transport companies – we could use multi-criteria optimization to determine a good solution for the MVT-(E)VSP with a high percentage of EVs and a small number of charging stations.

For the EVSP the heuristic results for the extended model are given in table 6. It depicts the number of vehicles, charging stations and chargings as well as the percentage change towards the results described in section 4.2.

Table 6 Results for the heuristic approach with all possible charging stations

instance	no. of EVs	– change	no. of charging stations	– change	no. of chargings	– change
t424	33	-2.94 %	18	350.00 %	67	15.52 %
t426	32	0.00 %	8	166.67 %	15	87.50 %
t867	70	0.00 %	7	250.00 %	16	128.57 %
t1135	75	0.00 %	21	162.50 %	33	10.00 %
t1296	52	-1.89 %	37	146.67 %	70	2.94 %
t2452	102	0.00 %	25	177.78 %	100	3.09 %
t2633	133	-5.00 %	36	227.27 %	277	-1.42 %
t2825	95	3.26 %	41	241.67 %	168	10.53 %
t3067	169	0.00 %	64	204.76 %	167	12.84 %
t10710	351	0.00 %	87	295.45 %	563	64.62 %

For four instances the number of vehicles was reduced due to the newly won charging possibilities. But it is striking that the number of charging stations highly increases for all plans, i. e. for each instance it has more than doubled. This is also apparent for the number of chargings needed (except for one instance), although the change is not as high for most plans. As a result, for most instances we receive a schedule with higher fixed costs for infrastructure without reducing neither the fixed costs for EVs nor the operational costs for charging. This implies that the heuristics perform better if less degrees of freedom are given. Hence, it is necessary to either determine a good charging infrastructure in advance or to incorporate the reduction of necessary charging stations in the heuristic.

6 Summary and further research

In this contribution we define both the MVT-(E)VSP and the EVSP as an extension of the standard VSP considering a limited battery capacity as well as the possibility of recharging. For each problem we developed a solution method: (1) a TSN based approach enhanced by six decomposition strategies that is used to solve the MVT-(E)VSP and give bounds on the percentage of EVs and (2) two heuristics to construct feasible vehicle schedules for the EVSP. The approaches were tested on ten real-world instances with up to 10,000 service trips.

The results show that the performance of the presented methods depends on the problem size as well as on the distribution of timetabled trips. Further influencing factors of the TSN based method are for instance the average consumption of a vehicle block and the number of vehicle blocks in total. For the MVT-(E)VSP we got schedules containing between 18 and 100 % EVs, which is a reasonable number for the first applications with EVs considering the slow shift towards their use in public transport. The computation of these plans is fast due to the small changes to the optimal schedule for the VSP, although the schedules themselves are not optimal. The analysis of charging statistics has shown no significant correlation between the number of charging stations and the percentage of EVs or the problem size.

For the heuristics used to solve the EVSP we have shown that an even spread distribution of timetabled trips is responsible for a higher increase in the total number of vehicles towards the standard VSP. Regarding the number of charging stations we have found a slight correlation with the number of chargings as well as the size of the instance.

In an extension of our study we dropped the assumption of a given charging infrastructure, thus analyzing the change in performance and necessary charging infrastructure. For the MVT-(E)VSP we received a higher number of EVs for all plans but at the same time a decreased occupancy rate for each charging station. In contrast, the heuristics for the EVSP have proven to perform better if the charging infrastructure is determined in advance.

This study remains only the first step towards more realistic concepts and solution approaches for the MVT-(E)VSP. For subsequent research, on the one hand, further analysis should be conducted varying 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. On the other hand, one could extend the solution methods used. For instance, new heuristics or metaheuristics can be implemented to improve the solutions found for the EVSP. Next, the focus should be on finding the optimal solution to the EVSP using exact methods. In addition, the positioning and the amount of charging infrastructure can be considered – as a stand-alone problem or integrated in the scheduling process using multi-criteria optimization.

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