Optimal placement of private electric charging stations for a commercial fleet operator

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1. Motivation

Recently, electric vehicles (EVs) have been vividly discussed as a promising solution for clean and sustainable transport. Especially for inner-city transport, EVs bear an additional potential to mitigate fine dust emissions. Although municipalities established first (ultra) low emission zones and politicians offered subsidies for EVs, the market uptake of EVs fell short of expectations. A major obstacle that hinders this market uptake is the limited availability of charging infrastructure. This holds especially for commercial fleets (e.g., taxi services) with a high utilization, where a reliable charging infrastructure is mandatory to offer a sufficient service. Hence, such fleets often require personally owned infrastructure. Accordingly, this requirement increases the operators investment costs, and vice versa decreases their perception of economic viable deployment scenarios. In this course, an optimization-based framework that determines a cost efficient charging infrastructure network appears as a necessary decision support tool to convince taxi fleet operators to shift towards electrified taxi fleets.

So far, modeling approaches for charging station network design range from node-based (Asamer et al. 2016) to flow-based (Kuby and Lim 2005) planning approaches, which determine a charging station network based on a static, yet aggregated demand representation. In contrast, a detailed modeling approach which secures that a charging station network is sufficient to operate a large fleet of electric taxis that can use many but small time slots for recharging in between customer trips is necessary to convince a taxi fleet operator to shift her fleet towards EVs.

With this work, we provide such a framework, which allows to determine a charging station network for a large-scale electrified taxi fleet while taking fleet operations, non-linear recharging, and charging station capacities into account. Specifically, our contribution is threefold: First, we develop a novel methodology that designs a cost-optimal charging station network for an electrified tax fleet and takes real-world constraints into account. The resulting algorithm bases on a combinatorial Bender's decomposition which leverages a subsequent column generation procedure and provides exact solutions for large-scale taxi fleets. Second, we show how this, yet deterministic, algorithm can be embedded into a robust solution approach to derive tangible results for real-world decision making. Third, we apply this framework to a real-world case study of a major European city and derive managerial insights for academics and practitioners.

2. Problem Statement

In the deterministic variant of this planning problem, we consider a fleet of $v \in \mathcal{V}$ taxis, each associated to a fixed sequence of customer trips C_v. Every customer trip $c \in C_v$ consists of an origin L_c^s, a start time T_c^s, a destination L_c^f, and an arrival time T_c^f. Between two consecutive customer trips c and $c+1$, the taxi can use the resulting idle time ($T_c^i = T_{c+1}^s - T_c^f$) for a detour to a charging station to recharge its battery. The taxi fleet operates in a European city, where a charging station can be built at dedicated charging station sites $s \in \mathcal{S}$, which have heterogeneous opening cost λ_s, and consider heterogeneous charging station capacities γ_s (i.e., the number of charging stations that can be built at each location varies). In this setting, we aim at determining the cost-optimal charging station placement $\mathcal{S}^* \subseteq \mathcal{S}$ that allows to complete all customer trips for a fully electrified taxi fleet.

To allow for a real-world application, we can then leverage this deterministic problem variant into a scenario-based robust framework, where each vehicle is associated with a set of customer trip sequences $C_v \in \mathcal{C}_v$.

3. Approach

To keep this abstract concise, we detail our solution approach for the deterministic problem variant in the following. We embed this approach into scenario-based robust optimization framework, which we solve by an adversarial approach as proposed in Bienstock and Özbay (2008).

In general, our planning problem comprises two decisions: *i*) placing charging stations to determine the network infrastructure, and *ii*) determining a taxi routing and charging schedule to keep the fleet operational. While the first decision affects our objective value, the latter preserves operational feasibility. Accordingly, we embed these decisions into a combinatorial Bender's decomposition framework (cf. Codato and Fischetti (2006)) where we keep the charging station placement decision in a combinatorial master problem and shift the operational decision to a subproblem that yields a feasibility oracle.

Combinatorial master problem (CMP): We state the CMP as an initially unbounded optimization problem that determines, which charging stations should remain closed. We then iteratively create cover inequalities that forbid to close station combinations which result in operational routing infeasibility. We use decision variable $x_s \in \{0,1\}$ to state whether a station s is closed ($x_s = 1$) or open ($x_s = 0$). With the station opening cost λ_s, we can then define the CMP as

$$\begin{aligned} &\max \sum_{s \in \mathcal{S}} \lambda_s \cdot x_s \\ &\text{s.t.} \quad x_s \in \{0,1\}, \quad \forall s \in \mathcal{S} \end{aligned}$$

When we solve the CMP in the first iteration in its initial definition, all charging stations remain closed. In each iteration, we convert the solution vector x_s into a charging station network configuration and check its feasibility by solving the sub problem. If the sub problem finds the current network configuration to be infeasible we create a cover inequality I,

$$\sum_{i \in I} x_i \leq |I| - 1, \quad I \subseteq \mathcal{S}.$$

Moreover, we lift this cover inequality by a tailored heuristic. The cost of charging station configurations determined by this CMP increase with every iteration such that the first feasible configuration remains the cost minimal global optimum.

The CMP in this basic version does not consider a decision on charging station capacities. To incorporate deciding on the charging station capacity, we split the cost parameter λ_s into an opening cost λ_s^{fix} and variable charge point cost λ_s^{var}. For every site we define a set of capacity options $z \in \mathcal{Z}_s$ and add a binary variable x_{zs} with an objective function coefficient matching the cost saved by closing the capacity at the site. We add additional constraints

$$\sum_{z \in \mathcal{Z}_s} x_{zs} \leq 1, \ \forall s \in \mathcal{S},$$

which ensure that at maximum one size level per site is chosen.

Subproblem Oracle: We solve the remaining routing subproblem via branch-and-price. Here, a column $p \in \mathcal{P}_v$ represents a specific routing and charging schedule for a single vehicle v. Accordingly, we select one column p for every vehicle v in the column generation master problem (CGMP) such that the charging demand at any charging station is within the capacity limits. We solve the relaxed CGMP until no columns with negative reduced costs remain. In case we obtain fractional solutions, we branch on two criteria: *i*) fractional charging station usage and *ii*) time spent at a charging station.

In the pricing problem, we model the solution space for each vehicle v as a time-expanded network, represented as a directed graph $G_v = (\mathcal{H}_v \cup \mathcal{Q}_v, \mathcal{R}_v \cup \mathcal{W}_v \cup \mathcal{B}_v)$. Here, the vertex set $\mathcal{H}_v$ contains a timed vertex for every customer c with the start time (c, T_c^s) and finish time (c, T_c^f) respectively. The arc set $\mathcal{R}_v$ contains arcs that connect the start and finish of a customer trip $((c, T_c^s), (c, T_c^f))$, and direct successor trips $((c, T_c^f), (c+1, T_{c+1}^s))$. The vertex set $\mathcal{Q}_v$ contains a timed charging action vertex (c, s, t) for every site $s \in \mathcal{S}$ and period $t \in \mathcal{T}$ of idle time after every customer $c \in C_v$. The arc set $\mathcal{W}_v$ contains holdover arcs $((c, s, t), (c, s, t+1))$ between the charging action vertices $\mathcal{Q}_v$. The arc set $\mathcal{B}_v$ contains arcs from customer trip vertices to the charging vertices $((c, T_c^f), (c, s, t))$ and from the charging vertices to the start of the next customer trip $((c, s, t), (c, T_{c+1}^s))$. For vertices in set $\mathcal{Q}_v$ we set a charging cost parameter π_i to the dual value obtained from the respective charging

station capacity constraint in the CGMP. We can then formulate and solve the pricing problem as a resource constrained shortest path problem (RCSP) to find the cost-minimal path through the time-expanded network, which preserves a vehicle's constraints on its state of charge.

4. Results

We apply our approach to a taxi trip data set from a taxi association operating in a large European city which contains origin destination pairs of customer trips and taxi shift information. For each day we have approximately 1 000 taxis serving 14 000 customers. We choose seven representative days from the data as scenarios for our robust framework approach, generate instances of 20, 30, 40 and 50 potential charging station locations, and estimate opening costs λ_s of a site based on the distance to the city center. Table 1 shows that instances of up to 50 potential charging station locations can be solved within reasonable time. A solution for a size $|\mathcal{S}| = 50$ is shown in Figure 1.

Table 1 **Computational results for the robust approach over 7 scenarios (each approx. 1 000 taxis) for increasing instance sizes.**

$\lvert\mathcal{S}\rvert$	$\lvert\mathcal{S}^*\rvert$	Obj. Val.	Time [min]
20	16	600	1.8
30	14	555	9.4
40	14	551	38.8
50	14	546	710.9

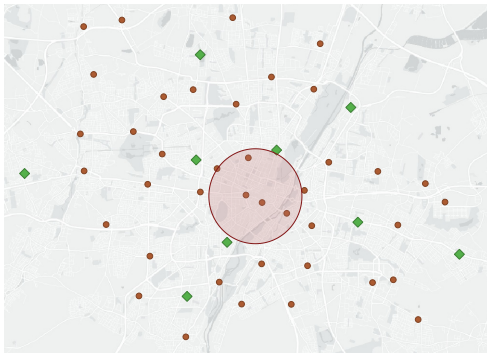


Figure 1 **Examplary solution with $|\mathcal{S}| = 50$ shown as circles, opened sites shown as green diamonds. City center marked with large circle.**

5. Conclusion

In this work we have presented a framework for the design of a closed charging station network for a commercial EV fleet. When applied to a real-world case, our results show that charging stations can be placed in a way that maintains operational feasibility when fully electrifying a taxi fleet, without having to use the cost intensive inner city charging station locations.

References

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