# Station Planning by Simulating User Behavior for Electric Car-Sharing Systems*

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**Abstract.** The planing of a full battery electric car sharing system involves several strategic decisions. These decisions include the placement of recharging stations, the number of recharging slots per station, and the total number of cars. The evaluation of such decisions clearly depends on the demand that is to be expected within the operational area as well as the user behavior. In this work we model this as combinatorial optimization problem and solve it heuristically using a variable neighborhood search approach. For the solution evaluation we use a probability model for the user behavior and approximate the expected profit with a Monte-Carlo method. The proposed algorithm is evaluated on a set of benchmark instances based on real world data of Vienna, Austria. Computational results show that by simulating user behavior the expected profit can increase significantly and that other methods assuming the best case for user behavior are likely to overestimate the profit.

## 1 Introduction

Over the last years the increased air pollution and the awareness for sustainability has lead to a steady growth of the market for privately owned electric vehicles. While so far the high acquisition costs and the limited battery range of these vehicles hinder the wide-spread use, car-sharing systems with electric cars could potentially decrease the use for conventional vehicles in urban areas [9]. Such car-sharing systems offer cars in a pre-defined area which can be rented by customers to perform their desired trips. Compared to systems using conventional cars, in electric car-sharing systems charging stations have to be available within the operational area to recharge the battery of the vehicles. In this work, we consider station-based (in contrast to free-floating) systems in which cars can only be rented and returned at specific stations. The most important strategic decisions when introducing such a system in a new area are where to place the

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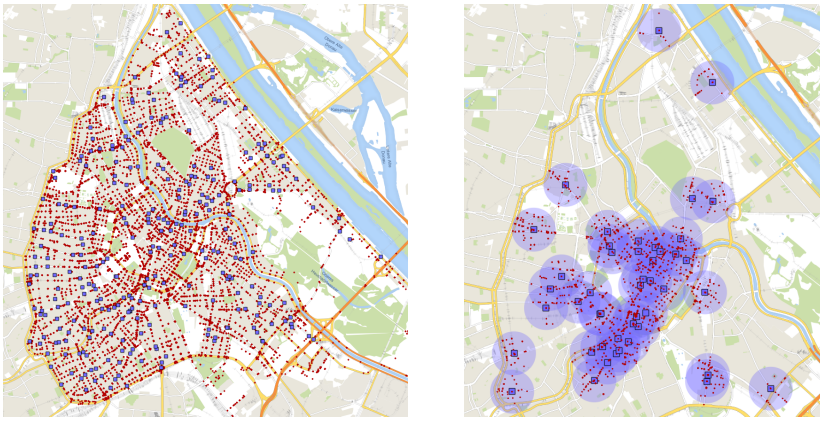

**Fig. 1.** Example of a real-world instance of Vienna, Austria. The red dots are the start and end points of the requested trips and the blue rectangles denote possible locations for recharging stations. On the right side a solution candidate is shown with the chosen station locations, their approximated area of attraction, and the acceptable trip requests.

stations, how many charging slots to install, and how many electrical cars to deploy. For being able to make a statement about the viability a demand model is needed which gives a forecast of the customer requests, i.e., when the potential customers want to use a shared car and where they want to go. As the customers are usually willing to walk a short distance to or from a station which is close to their desired starting or ending point, each customer request has a set of potential starting and ending stations. In this work, we model the strategic decisions on the locations of stations, the number of charging slots per station, and the total number of deployed cars with respect to a limited budget as a combinatorial optimization problem and solve it heuristically using a variable neighborhood search approach. For evaluating of these strategic decisions we simulate user behavior by using a probability model and thereby model how the cars are used over time. The user behavior determines which trips are fulfilled, resulting in an expected profit value that is used to assess the quality of the station and car decisions. Figure 1 shows an example of a real-world instance of this problem for the inner part of Vienna, Austria. Possible station locations are shown along with origin and destination points for all requested trips in this area. This example indicates that real-world instances tend to involve a lot of decisions and a large solution space, which makes the use of fast heuristics appealing.

In Section 2 we formally define the station planning problem and in Section 3 we give an overview of related work. Then, the solution approach is presented including the description of the modeling of the user behavior in Section 4. The evaluation of the algorithm is shown in Section 5, in which also the benchmark instances are described. Finally, conclusions are drawn in Section 6 where also a view on possible future work is given.

## 2 Problem Definition

The formal problem definition, which is based on [6] and [2], is as follows. The charging station location problem with user decisions (CSLP-UD) is defined on a road network $G = (V, A)$, where the set $A$ represents road segments, and $V$ the crossings. Each arc $a = (i, j) \in A$, $i, j \in V$ with length $l_{ij}$ has an associated travel time $\delta_{ij}$ needed to travel from vertex $i$ to $j$. Possible station locations $S \subseteq V$ are given by a subset of the vertices and each potential station $i \in S$ has an associated opening cost $F_i \geq 0$, a capacity $C_i \in \mathbb{N}$, and a cost per slot $Q_i \geq 0$. The maximum number of cars is given by $H$, and each car has the same acquisition cost $F_c$, battery capacity $B^{\max}$, and charging rate per time unit $\rho$.

The demand model is given by a set of trip requests $K$, where each trip $k \in K$ has a starting $s_k$ and ending time $e_k$, where $s_k, e_k \in T = \{0, \ldots, T_{\max}\}$ with $e_k > s_k$, an origin $o_k \in V$, and a destination $d_k \in V$. Furthermore, a duration $\delta_k$, an estimated battery consumption $b_k$, and a profit $p_k$ is given which is proportional to the trip duration. A parameter for maximum walking distance $\beta^w$ determines the set of possible starting $N(o_k)$ and ending stations $N(d_k)$ for a request $k \in K$. If one of the sets of a request $k$ is empty or none of these stations are opened, then $k$ is not fulfillable and not considered anymore. The right part of figure 1 shows a selection of the stations and the resulting fullfilable trip requests.

The goal of the CSLP-UD is to find the set of stations to open $S' \subseteq S$, the number of slots $z_s$ to use for each open station $s \in S'$, and the total number of cars $H' \leq H$ in the system with a limited budget $W$ such that the total expected profit under the given user decision model is maximized. The user decision model defines probabilities how the users behave, i.e., which user gets the car in case of concurrent demand and which ending station is chosen for returning the car. This randomness can cause strongly different sets of fulfilled trip requests and the goal is to maximize the average profit over all possible scenarios. One scenario can be described as a set of fulfilled trips $K'_c$ for each car $c = 1 \ldots, H'$. These sets have to fulfill several constraints to represent a feasible solution. *Capacity feasibility* is given when at each time-step $t \in T$ there are no more cars in station $s \in S$ than the available number of slots. *Battery feasibility* is given if the battery capacity of the car is sufficient for performing the requested trip taking potential preceding battery charging into account. More formally, the solution is battery feasible if between two consecutive trips $k^1, k^2 \in K$ starting / ending at station $i$ of a car $\min\{(s_{k^2} - e_{k^1})\rho + B^{k^1}, B^{\max}\} \geq b_{k^2}$ is valid, where $B^{k^1}$ is the remaining battery capacity of the car after performing trip $k^1$. *Connectivity* is given when the ending station of a trip is equal to the starting station of the next trip.

## 3 Related Work

Although the literature about optimization problems in the domain of car-sharing is huge, when considering battery electric vehicles within such a system

the literature is scarce. Brandstätter et al. [4] give an overview of this and several other optimization problems arising in the domain of e-car sharing systems and suggest possible research directions. The problem described in this article without consideration of user behavior has already been approached with exact algorithms in the form of mixed integer linear programming formulations by Brandstätter et al. [7, 6] and with metaheuristic methods in our previous work by Biesinger et al. [2]. A variant of this problem focusing on the stochastic aspects of the CSLP is presented by Brandstätter et al. [5]. Considering relocation decisions for moving cars from areas of low density to high density regions within the location problem is described by [3]. Weikl and Bogenberger [11] investigated variants of relocation strategies for free-floating car sharing system with conventional vehicles. A related problem of choosing locations for recharging stations for electric taxis is described by Asamer et al. [1] who suggest regions for placing stations.

## 4 Solution Approach

Similar to Biesinger et al. [2], the algorithm uses the vector $z = (z_0, \ldots, z_{|S'|-1})$ and $H'$ as solution representation. After an initial solution is generated using a method described shortly, a variable neighborhood search (VNS) [8] approach is employed, which uses neighborhood structures (NBs) that only operate on $z$, whereas $H'$ is determined by the remaining budget.

### 4.1 Initial Solution and Variable Neighborhood Search

For generating an initial solution, each station is assigned a value representing an attractiveness factor which is computed by counting the number of requests that can either start or end at this station. Then, in descending order, a new station is iteratively opened with a randomly chosen number of slots until the budget limit is reached. This initial solution is taken as input by the VNS, which uses four NBs in the following order: The *close station* NB closes a previously opened station and thereby increases $H'$. The *open station* NB opens a previously closed station while respecting the budget constraint. The *change slots* NB changes the number of slots of an open station, and the *swap* NB swaps the number of slots of two open stations. For the last NB we use a repair method, which iteratively reduces the number of slots of either station, to ensure budget feasibility.

### 4.2 Solution Evaluation

The solution evaluation is an essential part of the algorithm and involves the decisions which trip requests can be fulfilled. As this problem is itself a difficult optimization problem, in previous work we developed several heuristics based on a greedy criterion [2]. They all use a time discretization and generate a time-expanded location network in which the vehicle paths through space and time are iteratively computed. In this work we do the same, however, as already

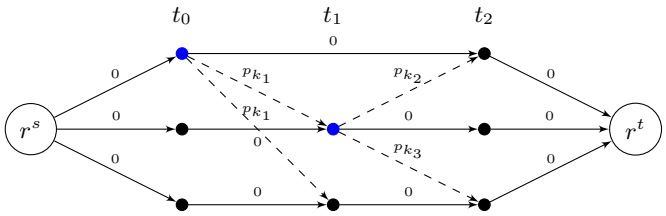


**Fig. 2.** Time-expanded location network used for solution evaluation.

mentioned in Section 1, we do not assume the best case in which the profit is maximized as all state-of-the-art approaches (e.g., [3]) but we simulate user behavior.

Figure 2 shows an example of the generated time expanded location network (TELN). The TELN consists of a node for each open station and time slot, an artificial source $r^s$ and target $r^t$ node. There are three different sets of arcs: *Initialization arcs* exist between $r^s$ and all station nodes at time instant $t_0$ and between all station nodes at time instant $t^{\max}$ ($t_2$ in this example) and $r^t$. *Waiting arcs* exist between any two consecutive time slots of each station but a node can possibly be skipped if it is not relevant (i.e., degree of two). They correspond to a vehicle waiting at a station. *Travel arcs* exist for each trip $k \in K$ between all start and end station combination. All waiting and travel arcs have two types of weight; an energy consumption value and a profit value. Waiting arcs have a negative energy consumption value indicating the loading of the battery and a profit value of zero. Travel arcs have a positive energy consumption value and a profit value corresponding to the profit $p_k$ of the corresponding trip $k$.

During solution evaluation, for each $H'$ cars a path from $r^s$ to $r^t$ is computed and the TELN is updated. The user decision is modeled in the choice of the path: Whenever there are two or more outgoing travel arcs at the current node, each of these arcs gets assigned a probability as follows. Assume that there are $K' \subset K$ trips that can start at the current node. First, a $k \in K'$ is chosen uniformly at random, and then the destination station $s' \in N(d_k)$ is chosen uniformly at random as well. When $r^t$ is reached a path of a car has been successfully found, and the TELN is updated by deleting all trip arcs of the performed trips and for all stations at full capacity the incoming arcs are deleted. Then, another path for the next car is computed in the updated TELN. A Monte-Carlo simulation (see, e.g., [10]) is used by repeating this process of finding $H'$ paths for a number of times, which is determined by the sample size parameter of the overall algorithm. The average of the achieved profit during these repetitions is the expected profit and the objective value of the solution candidate.

## 5 Computational Results

The proposed algorithm is evaluated on a set of benchmark instances based on real-world data from Vienna, Austria. OpenStreetMap data is used for the

underlying road network and we assume potential locations for stations at supermarkets, parking lots, and areas next to subway stations. The number of slots for each station is between 1 and 10, chosen uniformly at random, and the costs are $F_i \in \{9000, \ldots, 64000\}$ and $Q_i \in \{22000, \ldots, 32000\}$ Euro. The customer demand model is based on real taxi data while only trips longer than 500 meters are considered. We set the maximum walking distance to / from stations to 5 minutes, consider a time horizon of 8 hours, and use a time discretization of 15 minutes. The car data is based on the real data from a Smart ED, which is a small full battery electric vehicle and we choose a maximum budget $W$ between 1 and 5 million Euro. The overall instance contains 693 potential station locations and 37965 trip requests but we only use 4 subsets $I_1, \ldots, I_4$ of increasing size of the inner part of Vienna corresponding to viable business areas. These subsets contain between 105 and 280 station locations and between 108 and 1347 trip requests.

We compare the proposed simulation-based evaluation with a greedy-based evaluation, which also uses the TELN as described in Section 4.2, but finds the paths through the TELN deterministically using a greedy criterion based on a potential profit value (see [2] for a more detailed description). For the simulation-based evaluations a sample size of 10 is used and the time limit of both algorithm variants is 1 hour. The following questions are approached by the computational study: How large is the error if we assume the best case of the user behavior when planing recharging stations? Is it viable to use a more realistic but time-consuming method? We answer these questions in Table 1 which shows the above described comparison between the simulation (Sim. Eval.) and the greedy evaluation (Greedy Eval.) for the different instances and maximum number of cars $H$ aggregated over the budget sizes of 1 to 5 million. The final solution of these methods is evaluated both with the simulation and the greedy method and their geometric means are shown in the column $\overline{obj^*_{\text{sim}}}$ and $\overline{obj^*_g}$, respectively. Furthermore, the relative differences are shown in column *diff.*

For answering the first question, we take a look at the final profits of the greedy evaluation and compare them to the final simulation profits. The difference between these values vary between about 65% and 80% and seems to be getting larger for bigger instances. This shows that the error introduced by always choosing the best case for trip-acceptance and user behavior is large and does not correspond to the more realistic value. Only because these values have a large gap does not necessarily mean that the greedy evaluation is not a good approximation to the real profit; the expected profit could just have a large variance. When we inspect the final simulation profits of the simulation evaluation, however, we see a higher value than the final simulation profits of the greedy evaluation for all instances which shows that in the same amount of time, a better solution is found when the simulation evaluation is used, which also answers the second question.

Finally, Figure 3 shows a comparison of station locations of two solutions from the greedy and simulation pathfinder, respectively. The locations obtained by the simulation evaluation seem to be more clustered in area with a high trip

**Table 1.** Results of the simulation-based compared to the greedy-based evaluation.

| Instance | | Sim. Eval. | | | Greedy Eval. | | |
|---|---|---|---|---|---|---|---|
| I | H | $\overline{obj^*_{\text{sim}}}$ | $\overline{obj^*_g}$ | diff. | $\overline{obj^*_{\text{sim}}}$ | $\overline{obj^*_g}$ | diff. |
| | 10 | 7493.2 | 12633.0 | 39.08% | 5973.0 | 18755.1 | 67.61% |
| $I_1$ | 25 | 11577.6 | 16842.1 | 30.49% | 5368.0 | 24434.4 | 76.19% |
| | 50 | 12616.7 | 17360.7 | 26.90% | 5170.8 | 25724.4 | 77.11% |
| | 10 | 10238.6 | 17411.3 | 39.42% | 10870.4 | 31720.7 | 65.36% |
| $I_2$ | 25 | 17064.9 | 24587.9 | 29.92% | 10811.7 | 41394.5 | 73.85% |
| | 50 | 17402.1 | 24815.9 | 29.28% | 10256.5 | 43920.6 | 75.94% |
| | 10 | 23472.2 | 40739.0 | 40.07% | 16575.2 | 63650.0 | 73.70% |
| $I_3$ | 25 | 31040.2 | 47649.2 | 33.49% | 17814.4 | 87202.0 | 79.56% |
| | 50 | 31981.6 | 48075.5 | 32.34% | 18025.0 | 93342.3 | 80.57% |
| | 10 | 24624.2 | 41758.9 | 39.22% | 21054.6 | 67233.5 | 68.40% |
| $I_4$ | 25 | 33083.8 | 49996.7 | 32.76% | 20047.4 | 93056.8 | 78.35% |
| | 50 | 32413.1 | 49254.6 | 33.26% | 19072.8 | 101595.1 | 80.77% |

density, while the locations obtained by the greedy evaluation are more dispersed over the whole operational area. This corresponds to the intuition that in the latter solution the potentially accepted trips are longer and thus more profitable. This only works out, however, in a best case scenario where all trips take place in an optimal way. Since this cannot be guaranteed in practice, the simulation evaluation leads to solutions that are more robust with respect to expected profit.

## 6 Conclusions and Future Work

In this work we propose a more realistic evaluation of strategic decisions for a full electric car sharing system. User decisions are modeled as random variables and Monte-Carlo simulations are used for computing the expected profit. For the station locations and design a variable neighborhood search with several neighborhood structures is used. The results show that by using so-far used evaluation methods large errors can be made by assuming the best case of the user behavior which can negatively influence the strategic decisions. Furthermore, it pays off to invest more time into the more realistic approximation of the expected profit. For future work we plan to also consider relocation of vehicles which can influence the strategic decisions and is in many practical systems a major factor of the operational costs. Another future research direction is to model free-floating car sharing systems in which the users can rent and return cars anywhere within the operational area.

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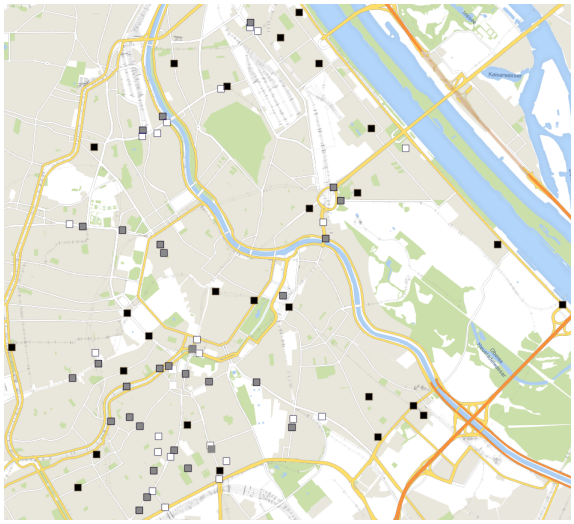

**Fig. 3.** Graphical comparison of a solution from the simulation (□) and the greedy (■) evaluation. Locations chosen in both solutions are marked with (▣).


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