Location-Scheduling Model to Design Charging Infrastructure for a Fleet of Electric Vehicles

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Motivation

- It is expected to continue electrification of individual and public transport in order to reduce CO_2 emission in densely populated urban areas.
- Advances in battery technologies and continuously decreasing prices of electric vehicles may soon increase the interest in converting fleets of vehicles serving urban areas into electric.
- High purchase costs of a new electric vehicle can be more easily compensated by lower operational costs.
- To overcome problems with insufficient changing infrastructure or to avoid delays in charging, caused by interaction with other electric vehicles, a choice of a fleet operator can be to build their own charging infrastructure.

Motivation

We focus on the efficient design of a **private** charging infrastructure for a fleet of electric vehicles operating in large urban areas (currently operating using ICE vehicles).

Typical examples:

- fleet of taxi cabs,
- fleet of vans used in the city logistics,
- fleet of shared vehicles.

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Literature review

Refuelling literature

Mehrez, A. Stern H., I., (1985) Optimal refuelling strategies for a mixed-vehicle fleet, Naval Research Logistics Quarterly, Vol. 32, pp. 315–328.

Prediction of the future expansion of electric vehicles

Sears, J., Glitman, K., and Roberts, D. (2014). Forecasting demand of public electric vehicle charging infrastructure. In Technologies for Sustainability, 2014 IEEE Conference, pages 250–254.

Paffumi, E., Gennaro, M. D., Martini, G., and Scholz, H. (2015). Assessment of the potential of electric vehicles and charging strategies to meet urban mobility requirements. Transportmetrica A: Transport Science, 11(1):22–60.

Flow refuelling location model

Kuby M., Lim S. (2005) The flow-refuelling location problem for alternative-fuel vehicles. Socio-Econom. Planning Sciences, Vol. 39(2):125–145.

MirHassani, S. A. and Ebrazi, R. (2013). A Flexible Reformulation of the Refuelling Station Location Problem. Transportation Science, 47(4):617–628.

Yildiz, B., Arslan, O., and Karasan, O. E. (2016). A branch and price approach for routing and refuelling station location model. European Journal of Operational Research, 248(3):815–826.

Literature review

GPS Data – MIP – Metaheuristics – Simulation

Tu, W., et. al. (2016) Optimizing the locations of electric taxi charging stations: A spatial-temporal demand coverage approach, Transportation Research Part C, Vol. 65, pp. 172–189.

Xi, X., Sioshansi, R., and Marano, V. (2013). Simulation–optimization model for location of a public electric vehicle charging infrastructure. Transportation Research Part D: Transport and Environment, 22:60–69.

Our previous contribution

Kohání M., Czimmermann P., Váňa, Matej Cebecauer and Ľuboš Buzna (2017). Location-scheduling optimization problem to design private charging infrastructure for electric vehicles, In: Operations Research and Enterprise Systems, Revised selected papers from ICORES 2017, Communications in Computer and Information Science, Springer (Accepter for publication).

Methodology

1.Set of candidate locations

We use a practical procedure where the outcomes can be simply controlled by setting few parameter values.

2. Mathematical model

Mathematical model that combines location and scheduling decisions to ensure the maximum number of vehicles that can be recharged.

3. Role of available information

We evaluate the role of available information on the number of vehicles that can be re-charged.

The proposed methodology allows studying the proportion of vehicles that could be transformed to electric vehicles **without significantly affecting their operation**.

Data requirements

Dataset

- **historical low frequency GPS data** describing the mobility patterns of individual vehicles of the fleet,
- data should be collected for several, typical and sufficiently long time periods,

+ much easier to collect,
+ no need to use expensive GPS trackers,

- not precise enough to determine the travel distances.

Map matching procedure

- more precise positions of vehicles and travel distances,
- the graph model of the road network including data about nodes, edges and their elevation is needed
- estimation of the travel distances much more precisely by inducing them from the road network

Rahmani, M. and Koutsopoulos, H. N. (2013). Path inference from sparse floating car data for urban networks. Transportation Research Part C: Emerging Technologies, 30:41–54.

Determine candidate set locations

Basic idea

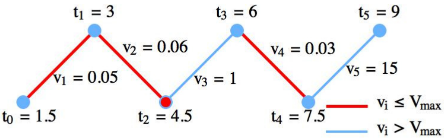
We use the historic GPS data to identify the set of suitable candidate locations for charging stations. We aim to identify locations where **the large number of vehicles frequently parks for long enough time**.

Procedure

Input: GPS traces, **Output:** set of candidate locations I, **Parameters:** V_{max}, T_{min}, R_{max}, M_{min}
Process all GPS traces by executing the following steps:

1: Identify in the GPS trace the traversals that have the average speed below the speed limit V_{max}.
2: Identify in the GPS trace the maximum connected sequences of traversals longer than the time period T_{min}.
3: Identify as a candidate location the last node of each connected sequence if there is no other candidate location within the distance R_{max}.

After processing all GPS traces we remove all candidate locations that are associated with less than M_{min} parking events.



Mathematical model: Notation

C - the set of vehicles,

I - the set of candidate locations to locate charging stations,

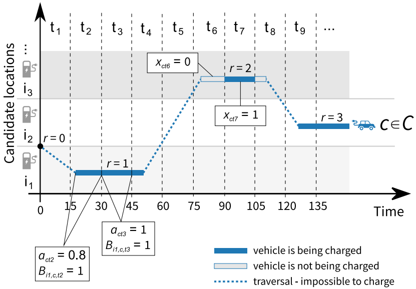
$\mathbf{R_c}$ - ordered sequence of parking events for vehicle $c \in C$,

$\mathbf{N_{cr}}$ - the list of time intervals $t \in T$ that overlap with parking event $r \in R_c$,

$\mathbf{u_{rc}}$ - driving distance of the vehicle $c \in C$ between parking events $r-1$ and r,

$\mathbf{B_{itc}} \in \{0,1\}$ - $B_{itc} = 1$ when vehicle $c \in C$ is parking at location $i \in I$ during the time interval $t \in T$.

$\mathbf{a_{ct}} \in \langle 0,1 \rangle$ - the fraction of the time interval $t \in T$ while vehicle $c \in C$ is parking,



β - capacity of battery (maximum driving range),

S - the set of charging speeds (here we consider $|S| = 3$),

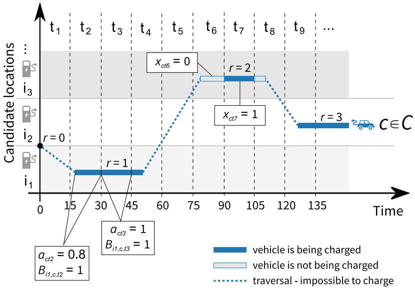
$\mathbf{p_s}$ - the price to build a charging point of type $s \in S$,

G - upper limit on available budget,

γ - large positive penalty constants,

Mathematical model: Decision variables

- $w_{is} \in Z^+$ represents the number of charging points of speed $s \in S$ allocated to station $i \in I$,
- $z_c \in \{0, 1\}$, where $z_c = 1$ when vehicle $c \in C$ exceeds driving range and thus cannot be successfully converted to electric, otherwise $z_c = 0$,



- $x_{cts} \in \{0, 1\}$, if vehicle $c \in C$ is being charged at speed $s \in S$ during the time interval $t \in T$, then $x_{cts} = 1$, and otherwise $x_{cts} = 0$,
- $q_{cts} \geq 0$ represents the part of interval $t \in T$ when vehicle $c \in C$ is being charged at speed $s \in S$,
- $d_{cr} \geq 0$ corresponds to the state of charge of the vehicle $c \in C$ at the beginning of the parking event $r \in R_c$.

Mathematical model

The number of vehicles that exceed driving range is minimized.

$$\text{Minimize} \sum_{c \in C} z_c$$

subject to

At each station and time interval we cannot use more charging points of a given type than available.

$$\text{subject to} \sum_{c \in C} B_{itc} x_{cts} \leq w_{is} \qquad \text{for } i \in I, t \in T, s \in S$$

Initial (final) state of charge of each vehicle is not more (less) than 50% of the battery capacity.

$$d_{c0} \leq 0.5\beta + z_c\gamma \qquad \text{for } c \in C$$

$$d_{c,r_c} + z_c\gamma \geq 0.5\beta \qquad \text{for } c \in C$$

When charging vehicles, the battery capacity cannot be exceeded.

$$d_{cr} + \sum_{s \in S, t \in N_{cr}} q_{cts} s \leq \beta \qquad \text{for } c \in C, r \in R_c - \{0\}$$

Mathematical model - Continuation

The contiguity in charging and discharging of vehicles.

$$d_{cr} \leq d_{c,r-1} - u_{cr} + \sum_{s \in S, t \in N_{c,r-1}} q_{cts} s + z_c \gamma \qquad \text{for } c \in C, r \in R_c - \{0\}$$

A vehicle cannot be charged simultaneously at more than one speed.

$$\sum_{s \in S} x_{cts} \leq 1 \qquad \text{for } c \in C, t \in T, s \in S$$

A vehicle can be charged only a part of the time interval $t \in T$ when it is parking and when $x_{cts} = 1$.

$$q_{cts} \leq x_{cts} a_{ct} \qquad \text{for } c \in C, t \in T, s \in S$$

The costs to set up the charging infrastructure are less or equal than the budget limit G

$$\sum_{i \in I, s \in S} w_{is} p_s \leq G$$

Role of available information

- Mathematical model assumes that complete information about the demand to charge vehicles has been available.
- The reality is often different. To evaluate designs of charging stations we consider two approaches, which work with various levels of information (coordinated and uncoordinated charging strategies).

Additional notation:

$\bar{I}$ -the set of charging stations found by solving the mathematical model,
K_i - the set of charging points placed at station $i \in \bar{I}$ (we suppose that $0 \notin K_i$),
s_k - the charging speed of point $k \in K_i$,
$R = \cup_{c \in C} R_c$ - the set of possible charging events,
P - the set of movements of taxicabs ($E = R \cup P$ is the set of all events),
$l(e)$ - the driving distance for $e \in P$,
$c(e)$ - the vehicle associated with $e \in E$,
$b(e)$ and $z(e)$ - the start time and the end time, respectively, of the event $e \in E$,
ρ_{max} - the maximum acceptable proximity of a vehicle from a station to make the charging still possible,
T_k - the end time of the most recent charging event at point $k \in K_i$, for $i \in \bar{I}$,
d_c - the level of the battery of vehicle $c \in C$

Role of available information

We evaluate the performance of charging infrastructure by running the following algorithm:

Step 1: (Initialization)

For $c \in C$ set $d_c = \beta/2$. Order events from E ascendingly with respect to $b(e)$. Set $T_k = 0$ for $k \in K_i$ and $i \in \bar{I}$.

Step 2: (Event list processing)

For each $e \in E$ do:

> If $e \in R$, then order the set $\bar{I}$ descendingly with respect to the sum of speeds s_k over charging points $k \in K_i$ that are free in time $b(e)$.
>
> For $i \in \bar{I}$ do:
>
> > If the distance of vehicle $c(e)$ at time $b(e)$ from station i is less than ρ_{max}, then process the charging event following **a strategy**.
>
> If $e \in P$, then set $d_{c(e)} = d_{c(e)} - l(e)$.

Step 3: (Evaluation)

If $d_c \geq 0$ all the time during the run of the algorithm and $d_c \geq \beta/2$ at the time when the algorithm is terminated, then $c \in C$ is feasible.

Strategy 1: Coordinated charging:

Coordinated charging assumes that drivers, when selecting the charging point, know the departure times of other vehicles and unplug their vehicle when it is fully charged.

Identify the set $K_{full} = \{k \in K_i | (z(e) - max\{b(e), T_k\})s_k \geq \beta - d_{c(e)}\}$ of charging points that allow for recharging battery to full capacity.

If $K_{full} \neq \emptyset$:

Choose element $k_{min} \in argmin(s_k)$[a] , where $k \in K_{full}$ and set $T_{k_{min}} = b(e) + (\beta - d_{c(e)})/(s_{k_{min}})$ and $d_{c(e)} = \beta$,

else:

Find $k_{max} \in argmax((z(e) - max\{b(e), T_k\})s_k)$, where $k \in K_i$.

If $k_{max} \neq 0$:

If $z(e) - max\{b(e), T_{k_{max}}\} > 0$:

Set $d_{c(e)} = d_{c(e)} + (z(e) - max\{b(e), T_{k_{max}}\})s_{k_{max}}$.
Set $T_{k_{max}} = z(e)$ and $k_{max} = 0$. Continue with step 2 and process the next event.

[a] If *argmin* (*argmax*) returns a non-empty set, then k_{min} (k_{max}) can be an arbitrary element from this set.

Strategy 2: Uncoordinated charging:

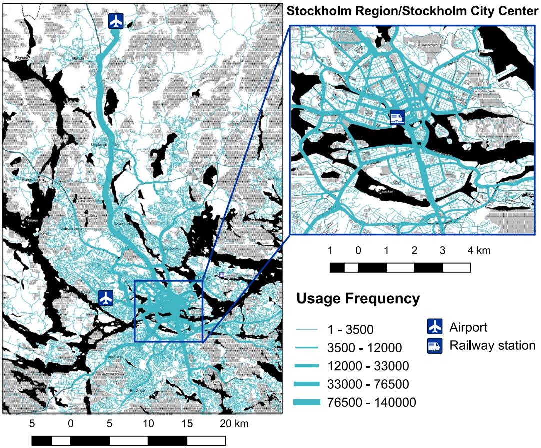
When using uncoordinated strategy drivers have only information about the actual occupancy of charging points and unplug their vehicles at the time of departure for the next trip.

Find $k_{max} \in argmax(s_k)$[1], where $k \in K_i$ and $T_k \leq b(e)$.
If $k_{max} \neq 0$:

Set $d_{c(e)} = \min\{\beta, d_{c(e)} + (z(e) - b(e))s_{k_{max}}\}$. Set $T_{k_{max}} = z(e)$, $k_{max} = 0$ and continue with step 2, and process the next event.

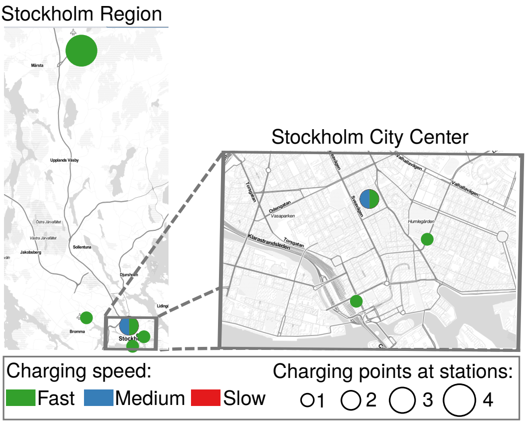
[1] If *argmin* (*argmax*) returns a non-empty set, then k_{min} (k_{max}) can be an arbitrary element from this set.

Numerical experiments - Data



- **Area:** Stockholm region,
- **Time period:** 28/05/2014 - 30/06/2014 ,
- **Vehicles:** 500 (1526),
- each vehicle reported on average every 90 seconds its ID, GPS position, timestamps and information whether it is hired or not,
- mathematical model was solved using IP solver FICO Xpress IVE 7.3,
- we used a personal computer equipped with CPU Intel (R) Core i7-5500U CPU with two 3 GHz cores and with 8 GB RAM.

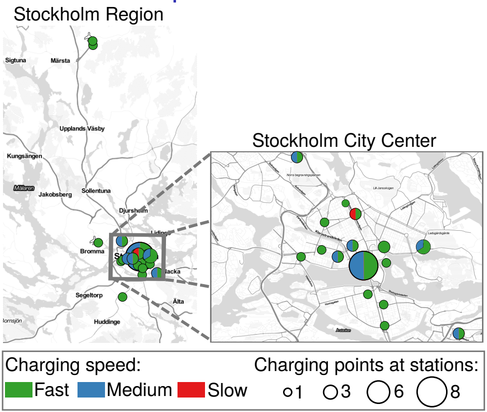
Results: Experiment 1



- **Period:** 28/05/2014-03/06/2014 (1 week),
- $V_{max} = 0.1$ m/s, $T_{min} = 900$ s, $R_{max} = 500$ m, $M_{min} = 300$ cars,
- $|I| = 5$,
- **Speeds:** $S = \{5.3, 21.3, 74.6\}$ km/hour,
- **Costs:** $S = \{500, 2500, 25000\}$ USD,
- $\beta = 300$ km.

- **Charging points:** 9 (slows: 0, medium: 1, fast: 8),
- **Coverable vehicles:** 42,
- **Costs:** 202 500 USD,
- $t_1 = 20.5$ s (minimal number of uncovered vehicles, when the budget is unlimited),
- $t_2 = 123.3$ s (minimal infrastructure, while satisfying the maximum number of covered vehicles),
- $t_3 > 3$ days (minimal infrastructure, while satisfying budget limit G).

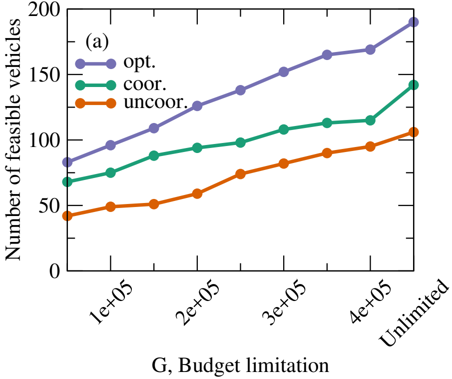
Results: Experiment 2

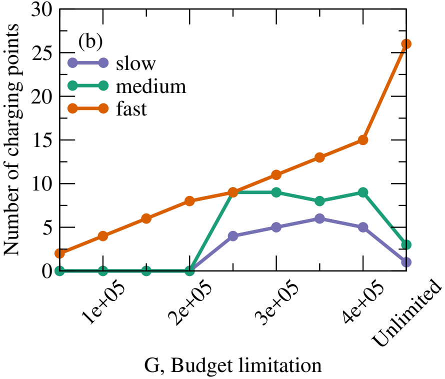


- **Period:** 28/05/2014-03/06/2014 (1 week)
- $V_{max} = 0.1$ m/s, $T_{min} = 900$ s, $R_{max} = 500$ m, $M_{min} = 110$ cars
- $|I| = 20$
- **Speeds:** $S = \{5.3, 21.3, 74.6\}$ km/hour
- **Costs:** $S = \{500, 2500, 25000\}$ USD
- $\beta = 300$ km.

- **Charging points:** 35 (slows: 1, medium: 9, fast: 25)
- **Coverable vehicles:** 195
- **Costs:** 648 000 USD
- $t_1 = 23.1$ s (minimal number of uncovered vehicles, when the budget is unlimited)
- $t_2 = 14.4$ hours (minimal infrastructure, while satisfying the maximum number of covered vehicles)
- $t_3 > 3$ days (minimal infrastructure, while satisfying budget limit G)

Results: Experiment 4





- **Period:** 1 day, **Vehicles:** 500,
- $|I| = 20$ (M_{min}),
- $V_{max} = 0.1$ m/s, $T_{min} = 900$ s, $R_{max} = 500$ m, $\beta = 300$ km,
- **Speeds:** $S = \{5.3, 21.3, 74.6\}$ km/hour,
- **Costs:** $S = \{500, 2500, 25000\}$ USD.

Conclusions: Summary

- If $|I|$ is large enough, **the optimization model has the tendency to select the large set of charging stations with only few charging points** more frequently than locating only few charging stations with many charging points. Such design can be **favourable for the electricity network** as it will not load the network largely at few locations, but the load is spatially more distributed.
- Charging points are typically located at parking lots in the vicinity of airports, railways stations and other public spaces, which seem to be **natural locations** for them.
- Optimization is able to serve significantly larger number of vehicles than coordinated and uncoordinated charging, while the difference between coordinated and uncoordinated charging is small. Thus, **the possibility to postpone the charging** for later **and prioritization of vehicles plays an important role** (not so many cases of interrupted charging were observed).
- Our results indicate that if the problem size is limited this approach can be used to determine the minimal infrastructure that meets the demand, however, to determine minimal requirements to set up the charging infrastructure when the budget is limited becomes quickly computationally very costly.

Conclusions: Future work

Simplified model:

$$\text{Minimize} \sum_{i \in I} s_i$$

subject to

$$\sum_{c \in C} B_{itc} x_{ct} \le s_i \ \forall i \in I, t \in T$$

$$d_{cr} + \sum_{t \in N_{c,r}} x_{ct} s \le \beta \ \forall c \in C, r \in R_c \cup \{r_c\}$$

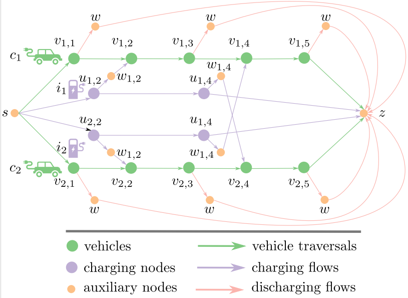
$$d_{cr} \le d_{c,r-1} - u_{cr} + \sum_{t \in N_{c,r-1}} x_{ct} s$$

$$\forall c \in C, r \in R_c \cup \{r_c\}$$

$$d_{c0} \le 0.5\beta \ \forall c \in C$$

$$d_{c,r_c} \ge 0.5\beta \ \forall c \in C$$

Network flow problem



Solving algorithms:

- path augmenting heuristic,
- convex optimization to find sparse flows.

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