# Methodology for designing charging infrastructure for a fleet of electric vehicles operating in large urban areas



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- It is expected to continue electrification of individual and public transport in order to reduce CO<sub>2</sub> emission in densely populated urban areas.
- Advances in battery technologies and continuously decreasing prices of electric vehicles may soon increase the interest in converting large 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 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.

**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

# Literature review



#### Models that would be able to predict 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.

#### Estimation of size of the future demand for charging vehicles

- Yi, Z. and Bauer, P. H. (2014). Spatio-Temporal Energy Demand Models for Electric Vehicles. In 2014 IEEE Vehicle Power and Propulsion Conference (VPPC), pages 1–6.
- 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.

#### **Optimization algorithms**

- Dickerman, L. and Harrison, J. (2010). A New Car, a New Grid. IEEE Power and Energy Magazine, 8(2):55–61.
- 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.

#### Location problem leading to a mixed integer programming problem

- Chen, T., Kockelman, K., and Khan, M. (2013). Locating Electric Vehicle Charging Stations. Transportation Research Record: Journal of the Transportation Research Board, 2385:28–36.
- Cavadas, J., Correia, G., and Gouveia, J. (2014). Electric Vehicles Charging Network Planning, pages 85–100. Springer International Publishing, Cham.
- Momtazpour, M., Butler, P., Hossain, M. S., Bozchalui, M. C., Ramakrishnan, N., and Sharma, R. (2012). Coordinated Clustering Algorithms to Support Charging Infrastructure Design for Electric Vehicles. In Proceedings of the ACM SIGKDD International Workshop on Urban Computing, UrbComp '12, pages 126–133, New York, NY, USA. ACM.

# METHODOLOGY

- First stage: Procedure to derive a suitable set of candidate locations
- from GPS data
  a practical procedure where the outcomes can be simply controlled by setting few parameter values.
- **Second stage:** Solution of the mathematical model that combines location and scheduling decisions to ensure that requirements of vehicles can be satisfied.
- The proposed methodology allows then **to evaluate what percentage of** vehicles could be transformed to electric vehicles without affecting their operation with the minimal requirements on building the charging infrastructure.

# METHODOLOGY 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

- Estimation of the 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. 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.

We proposed the following two-phase procedure:

- **Phase 1:** Identify the set of candidate locations for charging stations as locations where many vehicles tend to park for a long enough time.
- **Phase 2:** Identify the set of vehicles that can be served by selected set of candidate locations.

**Step 1:** Identify in the GPS trace the traversals that have the average speed below the speed limit  $V_{max}$ .

**Step 2:** Identify in the GPS trace the maximum connected sequences of traversals longer than the time period  $T_{min}$ .

**Step 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.



For each vehicle we evaluate:

- its trajectory,
- whether it could be sufficiently recharged during parking events, to cover the travel distances.

#### Unlimited capacity of charging points in each candidate location.

Capacity of each vehicle's battery is K (in kilometers - reachable driving distance).

As a vehicle is driven its state of charge is decreasing by substracting from it the travel distance.

Each time unit when the vehicle is charged we increase its state of charge by the value of **P**.

We record the number of vehicles that cannot be served by a given set of candidate locations, these are not included in the mathematical model.



We aim to minimize the costs that are required to set up the charging infrastructure. (locating charging stations of the same type >>> minimizing just the number of charging points).

**Location optimization problem** considering the **scheduling problem** to ensure that there exist a feasible schedule how to recharge vehicles.

- *I* the set of candidate location where it is possible to locate the charging station,
- T the set of non-overlapping time intervals individual charging time slots,
- p maximum number of charging stations,
- C set of vehicles, each equipped by the battery with maximal driving distance K,
- $R_c$  ordered sequence of parking events the list
- $N_{cr}$  list of all time intervals  $t \in T$  that have an overlap with parking event  $r \in R_{cr}$ ,
- $a_{ct} \in [0;1]$  fraction of the time interval  $t \in T$  the vehicle  $c \in C$  is parking,
- $B_{itc} \in \{0;1\}, B_{itc}=1$  if vehicle  $c \in C$  parks at location  $i \in I$  during time interval  $t \in T$
- $u_{cr}$  driving distance of the vehicle  $c \in C$  between parking events r-1 and r

# METHODOLOGY Second stage – Mathematical model



 $y_i \in \{0;1\}$  for  $i \in I$ , where  $y_i = 1$  if the charging station is located at the candidate location *i* and  $y_i = 0$  otherwise,

 $s_i \in Z^+$  for  $i \in I$ , representing the number of charging points allocated to station  $i \in I$ ,

 $x_{ct} \in \{0;1\}$  for  $c \in C$ ;  $t \in T$ , where  $x_{ct} = 1$  when vehicle  $c \in C$  is being charged during the time interval  $t \in T$  and  $x_{ct} = 0$  otherwise,

 $d_{cr} \ge 0$  for  $c \in C$ ;  $r \in R_c \{0\} \{r_c\}$  corresponds to the distance that the vehicle  $c \in C$  at the beginning of the parking event  $r \in R_c$  is able to drive.





# Numerical Experiments Data



A fleet of more than 1,500 taxicabs operating in the area of Stockholm district, in Sweden.

Each vehicle reported on average every 90 seconds its ID, GPS position, timestamp and information whether it is hired or not.

For the case study we selected four weeks altogether comprised of 8,989,143 probe data records.

Scenarios:

- week 1 is a typical spring week with 1542 taxicabs,
- week 2 represents typical summer week with 1526 taxicabs,
- week 3 is the Christmas week with 1491 taxicabs,
- week 4 is a special week with 1550 taxicabs, when the major disruption of the public transport occurred.



### Numerical Experiments Data







#### **Usage Frequency**

- 1 3500
- 3500 12000
- 12000 33000
- 33000 76500
- 76500 140000
- Airport Railway station



Maximum driving distance K = 300 km, Initial fraction of the driving range  $\alpha = 0.5$ 

Charging speed P = 5 km/min., we do not limit the number of charging stations, i.e., p = |I|,  $V_{max} = 0.1 \text{ m/s}$ ,  $T_{min} = 15 \text{ min}$ .

We discretize the time in steps of 15 minutes.

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R_{max} \in \{100; 500; 1000\} meters
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 $M_{min} \in \{100; 150; 800\}$ 

Numerical experiments were performed on the computer equipped with CPU Intel (R) Core i7-5500U CPU with two 3 GHz cores and with 8 GB RAM. Mathematical model was solved using IP solver FICO Xpress IVE 7.3.

# **Numerical Experiments** Results

1000

800

150

100

1409

1506

1513

8

50

69



Table 1: Results of numerical experiments for the scenario Week 1.										
$R_{max}$	$M_{min}$	Cars	I	Stations	$CP_{total}$	$CP_{max}$	Time[s]	Gap[%]		
100	800	609	3	3	14	9	1.88	0.00		
	150	1186	27	27	38	6	1800.00	5.26		
	100	1287	44	44	54	6	22.10	0.00		
500	800	1102	5	5	20	10	46.05	0.00		
	150	1442	46	40	44	5	1800.00	2.27		
	100	1475	77	51	54	4	1800.00	4.50		
1000	800	1347	7	7	19	6	1800.00	21.05		
	150	1499	51	39	42	3	1800.00	4.57		
	100	1510	70	51	55	3	1800.00	46.90		
Table 2: Results of numerical experiments for the scenario Week 2.										
R <sub>max</sub>	$M_{min}$	Cars	I	Stations	$CP_{total}$	$CP_{max}$	Time[s]	Gap[%]		
100	800	785	4	4	17	9	2.828	0.00		
	150	1292	30	30	35	4	16.642	0.00		
	100	1363	46	44	49	4	27.673	0.00		
500	800	1188	5	5	18	7	1800.00	22.22		
	150	1477	46	36	38	2	218.37	0.00		
	100	1498	73	47	49	2	1800.00	272.97		

8

38

\*\*\*

19

63

\*\*\*

1800.00

1800.00

\*\*\*

5

3

\*\*\*

30.84

72.03

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# Numerical Experiments Results



Table 3: Results of numerical experiments for the scenario Week 3.										
R <sub>max</sub>	$M_{min}$	Cars	I	Stations	CP <sub>total</sub>	$CP_{max}$	Time[s]	Gap[%]		
100	800	449	2	2	4	2	0.34	0.00		
	150	1019	24	24	27	2	2.84	0.00		
	100	1094	36	36	37	2	6.83	0.00		
500	800	843	4	4	5	2	6.17	0.00		
	150	1324	39	37	39	2	46.86	0.00		
	100	1359	57	52	53	2	291.05	0.00		
1000	800	1172	6	6	11	2	27.80	0.00		
	150	1417	43	38	39	2	547.72	0.00		
	100	1445	65	47	48	2	898.37	0.00		
Table 4: Results of numerical experiments for the scenario Week 4.										
	Table	4: Resul	ts of nu	umerical expo	eriments fo	r the scena	ario Week 4.			
R <sub>max</sub>	Table M <sub>min</sub>	4: Result	ts of nu   <i>I</i>	umerical expe Stations	eriments fo CP <sub>total</sub>	r the scena CPmax	ario Week 4. <i>Time</i> [s]	Gap[%]		
<i>R<sub>max</sub></i> 100	Table M <sub>min</sub> 800	4: Result Cars 631	ts of nu   <i>I</i>   3	umerical expe Stations 3	eriments fo CP <sub>total</sub> 17	r the scena CP <sub>max</sub> 13	ario Week 4. <i>Time</i> [s] 7.66	Gap[%] 0.00		
<i>R<sub>max</sub></i> 100	Table <u>M<sub>min</sub></u> 800 150	4: Result Cars 631 1221	ts of nu   <i>I</i>   3 33	umerical expo Stations 3 33	eriments fo CP <sub>total</sub> 17 39	The scenar $CP_{max}$ 13 7	ario Week 4. <u>Time[s]</u> 7.66 1800.00	Gap[%] 0.00 2.56		
<i>R<sub>max</sub></i> 100	Table <u>M<sub>min</sub></u> 800 150 100	4: Result Cars 631 1221 1325	ts of nu   I   33 50	umerical expo Stations 3 33 49	eriments fo CP <sub>total</sub> 17 39 53	The scenario $CP_{max}$ 13 7 5	ario Week 4. <u>Time[s]</u> 7.66 1800.00 38.21	Gap[%] 0.00 2.56 0.00		
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## Numerical Experiments Results





### Stockholm Region / Stockholm City Centre



# Conclusions

- Our results indicate that this approach can be used to estimate the minimal requirements to set up the charging infrastructure. The proposed method is able to handle relatively large instances of problems independently on the scenario.
- Problems with R<sub>max</sub> ∈ {100;500} and M<sub>min</sub> ∈ {150;800} are often solved to optimality or with small gap only.
- 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.
- When comparing the results across selected scenarios we find similar numbers of located stations in weeks 1, 2 and 4 and significantly smaller number of charging points in week 3, which is the most quiet week.

# Conclusions

- We did not limit the number of charging stations by setting the value of the parameter *p*. From the solutions we can see that 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 also **favorable for the electricity network** as it will not load the network largely at few locations, but the load is spatially more distributed.
- When we set the radius of charging points to  $R_{max} = 1000$  meters, the number of charging opportunities gets high and the solved problem, especially during the busy weeks, becomes intractable when solved by a general purpose solver. This result indicates the limits of this methodology.



# Thank you for your attention.