

OPTIMAL LOCATION OF CHARGING STATIONS IN SMART CITIES: A POINT OF INTEREST BASED APPROACH

Completed Research Paper

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Abstract

Electric vehicles (EV) have become one of the most promising transportation alternatives in recent years. Due to continuously increasing gas prices and CO₂ taxes, while at the same time subsidies of electrified cars run into millions, many countries such as the USA, UK, and Germany intend to bring large amounts of EVs onto their roads in the near future. As a prerequisite, an adequate charging infrastructure is needed to supply these vehicles with electrical fuel. In this paper we present a point of interest based business intelligence system to determine the optimal locations for charging stations. The underlying methodology is exploiting the potential of Big Data by analyzing and evaluating real charging sessions on the one hand and urban trip destination for vehicle owners on the other hand. Based on that, we formulate schemes to calculate an optimal charging infrastructure. A case study for Amsterdam and Brussels validates our results.

Keywords: E-Mobility, Smart Planet, Urban Economics, Business Intelligence, E-government

Introduction

Electric vehicles (EV) have received a great deal of attention recently, not only in broad public, but also in academia. With CO₂ emissions in focus for traditional means of transportation (gas fueled cars, busses, etc.), EVs are sometimes even seen as the “*green*” savior. Apparently e-mobility is on the rise, as the investments for battery technologies and charge point infrastructures in various countries such as the USA, UK and Germany run into billions. Projects within these countries intend to bring large amounts of EVs onto the roads by 2020 (The White House (2011), HM Government 2009, and Federal Government of Germany (2009)). However, the sales figures for EVs are far away from achieving the above desired goal (Electric Drive Transportation Association 2013). The main reasons for this lie in high acquisition costs of EVs on the one hand and also short driving ranges, due to insufficient battery technologies on the other hand. “*Range anxiety*” as described by Eberle and Helmolt (2010) is one of the reasons, why EV adoption in the mass market is limited. Furthermore, handling new transportation technology and the distrust in electricity as fuel, is one of the main reasons people are not willing to change their habits. The anxiety of running out of power, also caused by a small number of charging opportunities reinforced this attitude. Eventually, these flaws currently predominate the advantages of electrified cars, like CO₂ free emissions or cheap fuel. In order to take the “*range anxiety*” concern from people’s minds, city and infrastructure planners are focused on providing an adequate charging infrastructure to a planning area.

Millions of euros are invested to expand the current *charge point* (CP) infrastructure and to enable the opportunity to supply each customer with electrical fuel at any given place. In this context, the European commission claims to install a minimum of one CP at each conventional gas station, in order to promote electric mobility. Such agreements are one of many steps towards a new CO₂ free transportation system, as combustion engines are substituted with electric motors. Additionally, a comprehensive charge point infrastructure is one of the most important investments to reduce people’s anxiety and to increase the sales figures of EVs in the long run. Planning of the locations and the spatial setup of EV charging infrastructure is thus a central theme to foster EV adoption in the mass market.

In this paper we develop a business intelligence system to support city planners in finding the optimal location to set up a predefined number of CPs based on Big Data. As such our work on smart city planning is targeting related objectives as the IBM’s smarter planet initiative at the interface between business intelligence, e-government and urban economics.

Our approach is mainly user-centric and correspondingly data driven. More specifically we associate optimal CP locations with urban infrastructure buildings, such as restaurants, stores, parks, and all other possible *points of interest* (POIs), as these constitute potential trip destinations for users of EVs. Since currently charging EVs consumes more time than traditional gas refueling, people will most likely recharge their vehicles while running errands. According to a study by Sommer (2011), the longest car parking times tend to be over night or during work. While charging infrastructure at home can be realized individually, at work people might use public stations or the ones being provided by their employers. Thus, activities such as private errands, recreational activities or shopping, require the use of public infrastructure. As people spend time in the area, while their vehicles are parking, it is natural that POIs should be an integral part in the planning of EV charging infrastructure. Additionally, different categories, such as restaurants, stores, parks, etc., allow to take a differentiated view on various areas in a city. This is consistent with the land use theory introduced by Giuliano (1995) and with the urban economics by McDonald and McMillen (2011). Figure 1 presents the positioning of E-Transportation within urban land use theory. As the available CP infrastructure influences the land usage, meaning i.e. the frequency of visits of individual POIs, it also determines the charging activity. Hence, to derive optimal locations for new CPs it is important to analyze the influence of POIs on the actual charge point usage behavior – an area where city planners can tap into Big Data information on traffic and user behavior. Consequently, we have collected usage data from one of the best constructed cities regarding CP infrastructure worldwide – Amsterdam. The acquired set is composed of more than 100,000 data points, respectively 32,000 charging sessions. From the usage data of each individual CP, such as daily utilization and number of users, we can infer on the importance of POIs, which are in the sphere of influence of each CP. To explain the usage behavior we further acquire a set of POI containing more than 30,000 individual data points in the city of Amsterdam. The analysis of CP usage linked with POI location provides a ranking of POI categories. This ranking then can be applied to a green field planning of CP infrastructure, in order to deduce an optimal CP setup.

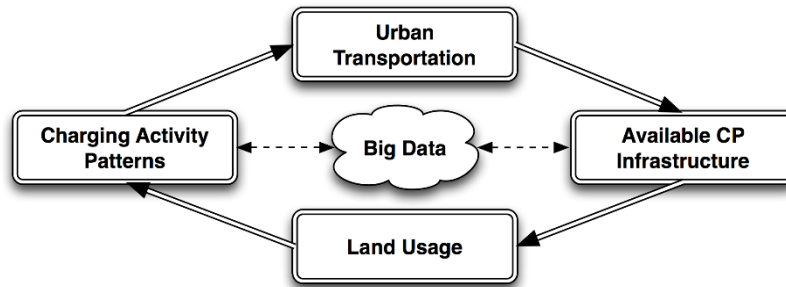


Figure 1. Land use theory in context of E-Transportation

Hence, the research introduced in this paper provides the following contributions:

- Determining the importance of points of interests, concerning the establishment of a charge point infrastructure.
- Deriving optimal locations for CPs based on actual charging infrastructure usage.
- Developing an algorithm to calculate an optimal charge point infrastructure, based on urban economics and big data.
- Providing a tool for city planners.

The paper is structured as follows. In the next section, we provide an overview of research and case studies related to our work, followed by an introduction of the methodology and formal aspects of our optimal planning schemes. Afterwards, we validate our simulation results with case studies conducted for Amsterdam and Brussels. Finally, we conclude by summarizing this paper and provide an outlook on our future research.

Related Work

Since EVs are entering the mass market progressively, academic work to determine the optimal EV charging infrastructure becomes more important these days. In the following we want to present an overview of related work in this area.

As aforementioned, studies on urban transportation as a subarea of urban economics deal with a general perspective of land usage. Rodrigue (2013) illustrates the basic principles of land rent theory. It is assumed that the rent of land is a function of the availability of a specific area. As we move away from the center of this area the rent drops substantially since the amount of available land increases exponentially. Further, a recent mobility study of Sommer (2011) indicates that private transportation aims primarily at getting to work, shopping, recreational activities, private errands and private transport. The study indicates that parking time varies between one and seven hours.

The actual development of charging infrastructures for EVs has been discussed extensively in recent years, especially under consideration of governments' budget constraints. Various case studies in e.g. Beijing, Stockholm or Taiwan have been realized to plan an urban charge point infrastructure using programming and optimization schemes, in order to minimize investments and operation cost (Liu et al. 2012, Long et al. 2012, Wang 2008, Wang and Liu 2011). In this research we do not go directly into investment details but rather introduce an optimization approach to place charge points in the planning area, which in turn indirectly minimizes the overall investment in the charging infrastructure. This is due to the fact that less CPs in total are required to cover a specific region.

Further, a model introduced by Chen et al. (2013) combines regressions to predict parking demand with a facility location problem to assign optimal charge point locations. The models' objective function minimizes total access cost as a function of walk distance between zones weighted by parking duration. Similar to this research we also provide a method based on a facility location problem to determine optimal locations for charging stations. However, our approach is based on expected CP utilizations and not on parking demands.

Ge et al. (2012) introduce a planning model for a charge point infrastructure, by combining aspects of the road network, traffic flow, structure, and capacity constraints. The model minimizes investment and

operation costs for all stakeholders. The authors also present a case study to validate their model, using Voronoi diagrams to determine the service area of individual CPs. In addition, Feng et al. (2012a) and Tang et al. (2011) use a weighted Voronoi diagram, too, to minimize user's power loss for reaching the next charging station on the one hand and to maximize the annual operating income of CPs on the other hand. In a further research, Ge et al. (2012) determine charging demands by traffic flow to optimize CP locations. With respect to our work, we also use a ranking procedure with different weights based on a specific grid metric. Moreover, Feng et al. (2012) design a charge point infrastructure on trunk roads using queuing theory. The location decision is derived from maximizing the expectation of EVs that need to be charged, having regard to service cost and waiting fees for customers.

From a societal perspective, Timothy et al. (2012) develop an agent based model to identify patterns in residential EV ownership and driving activities, with regard to the influence of social interaction for EV purchasing decisions. The research aims on simulating the effects of charging infrastructure on EV adoption, taking into account the recharging behavior of EV owners and relations between driver and vehicle. Nevertheless, different charge point scenarios allow the use for strategic deployment of a new charging infrastructure. Compared to the research introduced in this paper, we aim to maximize the expected CP utilization also considering the influence of different trip destinations and, therefore, indirectly the driving behavior of vehicle owners.

Moreover, there is additional research considering geographical and environmental constraints regarding trip and charging times of EVs. Frade et al. (2011) formulate a discrete maximum covering model with decay and capacity restrictions to determine CP locations. The model considers temperature, daytime, and charging demands and was tested in a case study for a neighborhood in Lisbon, Portugal, with the number of charge points to be located as an exogenous number. Case studies for Chicago, Seattle and Ohio try to investigate the optimal locations for charging stations, applying integer programming schemes (Xi et al. 2013 and Andrews et al. 2013). In order to validate the introduced model, demographic, traffic, and trip data is utilized. The optimization approach introduced in this paper will be evaluated by a case study as well. Furthermore, Hess et al. (2012) set up a genetic programming model to find charge point locations by minimizing the average trip time of EVs. The siting of CPs is determined by the expected mobility of EV and the approach includes a depletion and charging model, as well as a general mobility model for route adaption. Ip et al. (2010) also formulate a linear programming model to optimize charge point allocation. Therefore, road traffic information is prepared and aggregated into demand clusters through hierarchical analysis. Hanabusa and Horiguchi (2011) develop an analytical method for charge point facility location. The model aims to minimize total trip time and to equalize the demand for each charging station.

Additional research by He et al. (2013) deals with a game theoretical approach that examines the interactions among availability of public charging opportunities, destination, price of electricity, and route choices of EVs. Optimal allocation of CPs is then conducted by a mathematical program, based on an equilibrium model. However, as the model is of strategic nature, it does not optimize exact locations and capacities of the allocated charging stations as it will be introduced in this paper. Further, Wirges et al. (2012) formulate a dynamic spatial EV charging infrastructure model for 2020 in the region of Stuttgart.

Finally, Nakano et al. (2011) examine the tradeoff between extra waiting time for recharging a vehicle, in cases where errand time is smaller than recharging time, and the possibility of running out of battery in a network model. The density of charging stations at points of interest and the number of outlets at each station, in order to keep a sufficiently high probability of finishing a trip and minimizing waiting time is additionally considered. Similar to this, we will incorporate real data concerning the utilization of several charging stations in a reference city to determine the attractiveness of a given location. We use specific POIs to investigate their influence on the charging behavior of electric vehicle owners.

As can be seen in the literature review above, manifold approaches exist in order to locate and optimize EV charge point locations. Most studies focus on demand modeled by demographic, traffic or individual trip data. In our study we use the reference city Amsterdam as basis with an existing, well developed public EV charging infrastructure. By referring to the respective city, we derive the attractiveness of a charge point based on its surrounding POIs from available charge point usage data. It is assumed that the POIs, which represent trip destinations of EV users, have a significant influence on charge point usage. Matching POI information and charge point usage enables us to rate and rank different POI categories. This information is subsequently used to determine the "*charge point attractiveness*" of a spatial area based on its POIs.

Definitions and Attractiveness of Charge Points

This section presents the analysis of CP usage data and how the CP importance factor is derived. Therefore, we collected charge point usage data of the urban infrastructure of the city of Amsterdam. Amsterdam is known for its pioneering role with regard to EVs and has set itself high targets: *Amsterdam Electric*, an e-mobility initiative, aims at eliminating CO2 emissions of the entire transport system of the city by 2040, targeting 200,000 EVs (City of Amsterdam 2009). The present charging infrastructure is among the best developed ones in the world. As Amsterdam already operates a quite reasonable number of EVs on their roads, we have chosen this city as a reference and collected over 100,000 data points regarding the usage of more than 230 CPs. The collected data holds information about the average utilization per day and the usage frequency, i.e. how many customers use a specific CP at a given day. The data was collected over a period of several months with a number of more than 32,000 charging sessions in total, including only sessions with a duration of more than 5 minutes. Figure 2 illustrates a histogram of the charging session durations at current Amsterdam's CPs. The graphical representation shows that approximately one third of all performed sessions are shorter than 30 minutes, even due to the fact that this amount of time is insufficient to fully charge a EVs' battery using a normal outlet of 230 volts and 15 ampere.

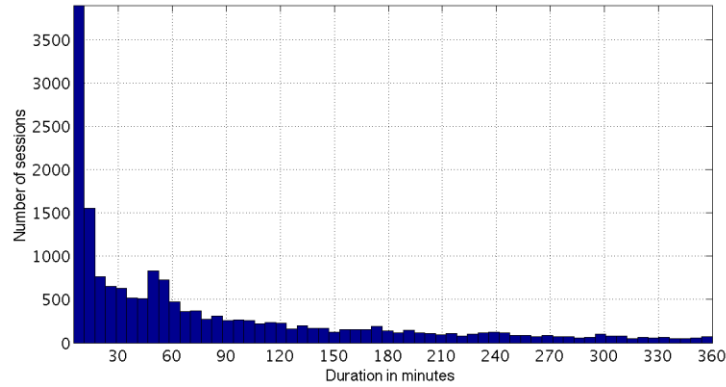


Figure 2. Charging session duration histogram

Based on the collected data points we define a set of charge points \mathbb{C} , located in Amsterdam, as

$$\mathbb{C} = \{C_1, \dots, C_n\}, \quad (1)$$

where each charge point $C_i \in \mathbb{C}$ is defined as the following 5-tuple

$$C_i = \{c_i^{lat}, c_i^{lon}, c_i^{fq}, c_i^{dur}, c_i^{rank}\}, \quad (2)$$

with c_i^{lat} as the CP's latitude, c_i^{lon} as the CP's longitude, c_i^{fq} as the average daily usage frequency and c_i^{dur} as the average daily usage duration of the respective charge point C_i . From the average daily usage frequency and duration we derive an overall CP importance factor c_i^{rank} , calculated as

$$c_i^{rank} = \sum_{d=1}^n \frac{c_{d,i}^{fq} \cdot c_{d,i}^{dur}}{n}, \quad (3)$$

for a CP $C_i \in \mathbb{C}$ and d_1, \dots, d_n as the respective data collection days. In Equation 3 above, we imply that, the longer a CP is used and the more users patronize it in the course of a day, the more important it is.

In the further course of this section, the introduced CP rank is applied to POIs in a predefined radius, in order to derive their importance. Subsequently, we use the empirical analysis to design optimal CP locations for smart cities.

Points of Interests and their Impact on Charge Points

Points of interests represent potential trip destinations of vehicle owners in general, as previously mentioned. The underlying assumption is that POIs exhibit an influence on the CP usage. Two important factors determine this influence: On the one hand, the influence of POIs is diminishing with distance, being dependent on a certain proximity to the CP. On the other hand, not all POIs will require the same duration of stay, i.e. the time available for recharging the EV. It can be assumed that dining at a restaurant will most likely consume a longer time period than withdrawing money from an ATM and spending time at a beauty salon will take longer than a purchase in a pharmacy. Thus, different POI categories have a varying influence on CP usage.

The POIs are clustered in categories such as e.g. restaurants, bars, banks or parks. To use these kind of data in our model, we define a set of points of interests \mathbb{P} , located in the planning area, as

$$\mathbb{P} = \{P_1, \dots, P_n\}, \quad (4)$$

while each $P_i \in \mathbb{P}$ consists of a 4-tuple defined as follows

$$P_i = \{p_i^{lat}, p_i^{lon}, p_i^{type}, p_i^{rank}\}. \quad (5)$$

The POI properties p_i^{lat} and p_i^{lon} are the GPS-coordinates of the respective POI location and p_i^{type} declares a specific category as mentioned above. The POI rank value p_i^{rank} declares an individual importance factor, based on the charge point rankings c_i^{rank} of the surrounding CPs $C_i, \dots, C_j \in \mathbb{C}$ within a predefined range. To decide whether a point of interest $P_j \in \mathbb{P}$ is in the predefined range of a charge point $C_i \in \mathbb{C}$, we calculate the geographic distance $dist(C_i, P_j)$ between these two points using the following *haversine* formula (Gellert and Küstner 1977)

$$dist(C_i, P_j) = 2 \cdot r \cdot \arcsin \left(\sqrt{\sin^2 \left(\frac{p_j^{lat} - c_i^{lat}}{2} \right) + \cos(c_i^{lat}) \cdot \cos(p_j^{lat}) \cdot \sin^2 \left(\frac{p_j^{lon} - c_i^{lon}}{2} \right)} \right), \quad (6)$$

with an earth mean radius of $r = 6,371$ kilometer.

We calculate the distances between CPs and POIs using the geographical distances in contrast to the Euclidean distances, because even for short ranges the deviation is often above one meter. Since differences of only a few meters can lead to calculation deviations, we prefer geographical distances.

In the following, we have carried out a regression analysis using the CP and POI data of Amsterdam. The Amsterdam POI database comprises 92 categories (e.g. food, store, health) with over 30,000 POI locations. We used the CP importance factor c_i^{rank} as the dependent variable. The POIs and the boroughs of Amsterdam denominate the independent variables. In order to avoid an endogeneity bias, we considered all POIs which already existed when the CP was first placed. This way, it is assured that the POIs determine the attractiveness of CP locations and not vice versa. Fortunately, most CPs have been established quite recently so that endogeneity is not an issue for our analysis.

For the regression we have chosen the main POI categories such as finance, food, store, etc. The POI input factors consist of the number of POIs of each category within a distance of 500 meters, (cf. Equation 6). Figure 3 for instance illustrates a CP (blue marker) and a number of POIs (red markers) at a given radius of 500m, located at the public *Vondelpark* in Amsterdam. The following maps have all been generated using *Pygmaps* version 0.1.1, which is a Python wrapper for Google Maps JavaScript API V3.

The CP usage data has been limited to weekdays (Monday – Friday) in order to account for POI availabilities. To control for regional differences, we have clustered the six boroughs of Amsterdam as control variables. Table 1 summarizes the regression results. As can be deduced from the t-values of the coefficients the influence of the POI categories, such as food, store, health, bus station, museum, and school on the charge point usage is significant. We have additionally conducted the regression for coverage radiuses of 250m and 750m, in order to test for the radius of influence of POIs on CPs. The results were less significant. Thus, we can conclude that a radius of 500m is adequate as a walking distance from the CPs to the stores.



Figure 3. POIs within a given radius of a CP in Amsterdam

These results lead to two conclusions. Firstly, the empirical analysis suggests that we can use the CP usage reference data of Amsterdam in order to measure the importance of different POI categories on CP usage behavior. Secondly, we can further rate the POIs of a city in order to derive a proxy for CP infrastructure demand. As Table 1 shows, the adjusted R-squared value is at 0.1, which is acceptable in social studies. In our result we focus on the t-values to find out which factors need to be incorporated in our subsequent optimization step. Furthermore, the category types *food*, *health*, and *museum* show a significance value of more than 95%, with a t-statistic value greater than 2, which indicates a positive influence on charge point usage. Since, visiting a museum is a time consuming activity, the charging session durations of EVs will be substantially higher in contrast to withdrawing money from an ATM. This is also the reason, why e.g. the *finance* category type provides no significance at all. Overall, POIs have a significant influence on the usage of charge points and, thus, have to be considered when developing a future charging infrastructure for smart cities.

From this information we can then build up a location model which is able to provide city planners with the optimal locations for new CP infrastructure based on POI locations, which again are trip destinations of EV users.

Table 1. POI Regression

Regression Statistics	
R ²	0.164
Adjusted R ²	0.101
F-value	2.593
p-value	0.001

	Coefficients	t-statistic	Significance ¹	p-value
Intercept	0.31	5.72	***	0.000
Food	0.55	2.14	**	0.034
Store	-0.66	-2.21	**	0.028
Health	0.56	2.55	**	0.012
Finance	-0.18	-1.47		0.144
Bus station	-0.12	-1.68	*	0.095
Museum	0.35	2.15	**	0.033
School	-0.30	-1.92	*	0.056
Church	-0.02	-0.16		0.874
Travel agency	-0.03	-0.19		0.850
Hair care	-0.03	-0.26		0.794

1. significance: *** 99%, ** 95%, * 90%, blank <90% Observations: 229

Eventually, we calculate for each POI $P_i \in \mathbb{P}$ its ranking value p_i^{rank} , based on the subset of surrounding CPs $\hat{\mathbb{C}} = C_k, \dots, C_l$ as follows

$$p_i^{rank} = \sum_{j=1}^n c_j^{rank} \mid dist(C_j, P_i) \leq \rho, \quad (7)$$

with $\hat{\mathbb{C}} \subseteq \mathbb{C}$ and ρ as a predefined range. For our calculation we assumed a ρ value of 500m, which is equivalent to a six minutes' walk, as this is a natural threshold an individual is willing to walk to get to the desired destination (POI). Based on each individual POI rank p_i^{rank} , we then derive a POI category index. Thus, we define a set of POI categories in such a way that each subset includes all POIs of the same category as

$$\mathbb{PT} = \{PT_1, \dots, PT_n\}, \quad (8)$$

with $\mathbb{PT} \subseteq \mathbb{P}$. Further each category $PT_i \in \mathbb{PT}$ is defined as the following tuple

$$PT_i = \{pt_i^{type}, pt_i^{rank}\}, \quad (9)$$

while pt_i^{type} is the respective POI category type. The ranking values pt_i^{rank} for each POI category $PT_i \in \mathbb{PT}$ are derived from the sum of all individual POI ranks p_i^{rank} of a category divided by all POIs of this category as follows

$$pt_i^{rank} = \left(\frac{\sum_{j=1}^n p_j^{rank}}{n} \right) \mid p_j^{type} = pt_i^{type}. \quad (10)$$

Hence, the ranking index of each POI category $PT_i \in \mathbb{PT}$, calculated using Equation 10, will be used to further assess POIs in a predefined planning area to finally derive optimal CP locations. After we have calculated a specific ranking for each category based on the usage behavior of Amsterdam's charge points, we are now also able to use this data to derive the POI rankings in other cities without a given CP infrastructure.

Maximum Coverage Optimization

Having established a relationship between the *attractiveness* of CPs on POIs, we can subsequently exploit it to locate EV charge points optimally – i.e. in terms of the POI category index – in a planning area. The POI category index, can now be used to allow for green field planning of charge point infrastructure.

Preliminaries for the optimization are a predefined spatial planning area \mathbb{A} and a database holding relevant POI information i.e. spatial location and category. In a first step the planning area is divided into a set \mathbb{B} of subareas defined by

$$\mathbb{B} = \{B_1, \dots, B_n\}. \quad (11)$$

The size and shape of the subareas are subject to the city planner's preferences and can be defined independently. However, a simple and effective approach is to divide the planning area into a grid with boxes of the same edges length. The models introduced later in this section are to support the strategic planning process of city planners and thus it is sufficient to provide an optimal box area, e.g. a 100 x 100 meter, as opposed to an exact micro location, such as e.g. street address. The planning of the exact CP location is usually carried out in a consecutive planning step, in which non-quantitative, so called "soft" factors play an important role. These factors include land and parking space availability or power supply. Furthermore, each subarea $B_i \in \mathbb{B}$ is defined as the following triple

$$B_i = \{b_i^{lat}, b_i^{lon}, b_i^{rank}\}, \quad (12)$$

with b_i^{lat} , b_i^{lon} as the GPS coordinates of subarea's center and b_i^{rank} as the total *box factor* (BF). The center of each box serves as its reference point. The box factor is determined by summing up all POI category ranks of all POIs within a radius of influence σ calculated by

$$b_i^{rank} = \sum_{j=1}^n pt_j^{rank} \mid dist(B_i, P_j) \leq \sigma, \quad (13)$$

with $b_i \in \mathbb{B}$ and $pt_j \in \mathbb{PT}$. Thus, all POIs that fall into the radius σ of an individual box contribute to its BF. A radius of influence that is greater than the box itself mitigates the risk of dividing the planning area in unfortunate ways e.g. splitting up a conglomerate of POIs into four adjacent boxes, and thus weakening its combined weight. Hence, the BF denominates the charge point attractiveness of a spatial area based on its surrounding POIs. The higher the weight of a box, the more important it is for a charge point. The BF thus can be seen as a proxy for EV charging demand.

Moreover, each box $B_i \in \mathbb{B}$ of the grid is a potential location area for a charge point. Figure 4 illustrates the grid placed over a section in Amsterdam. For the center box we have visualized the radius $\sigma = 100m$ and illustratively the POIs of one category that contribute to the BF of this box. Hence, the radius is intentionally selected bigger than the box itself.



Figure 4. Illustrative box factor calculation: 100x100 meter grid with box center as reference point and POIs within 100m radius

Based on the demand proxy we develop a maximum coverage facility location model (MCP). It is formulated as a linear program, which is maximizing the demand (i.e. box factor) served by a given number of CPs. Depending on the models parameters, the demand covered by a CP can include the demand of surrounding boxes. CP locations are selected simultaneously by the program in order to maximize total demand covered.

In the following we introduce the mathematical formulation of the linear program. The maximum coverage facility location model is based on the one presented in Drezner and Hamacher (2002). The following listing of sets and symbols is required for the general notation of the MCP.

- \mathbb{B} = set of grid's boxes, indexed by i
- \mathbb{B}' = set of potential facility locations, indexed by j (equivalent to the grid's boxes \mathbb{B})
- $d_{i,j}$ = distance between box i and potential facility site j , calculated as $dist(B_i, B'_j)$
- dc = coverage distance, i.e. all boxes within this distance are covered by located CPs
- $N_i = \{j \mid d_{i,j} \leq dc\}$ = set of all potential facility locations that cover demand of box i
- p = number of charge points to be located
- $x_j = \begin{cases} 1 & \text{if location (box) is selected to locate CP} \\ 0 & \text{otherwise} \end{cases}$
- $z_i = \begin{cases} 1 & \text{if demand node } i \text{ is covered} \\ 0 & \text{otherwise} \end{cases}$

Finally the optimization problem, including the objective function of the MCP as well as the constraints to place charge points in an optimal way is defined as follows

$$\text{Maximize} \quad \sum_{B_i \in \mathbb{B}} b_i^{rank} \cdot z_i \quad (14)$$

$$\text{Subject to} \quad \sum_{j \in N_i} x_j - z_i \geq 0 \quad \forall i \in B_i \quad (14.1)$$

$$\sum_{j \in J} x_j = p \quad (14.2)$$

$$x_j \in \{0,1\} \quad \forall j \in B'_j \quad (14.3)$$

$$z_i \in \{0,1\} \quad \forall i \in B_i \quad (14.4)$$

The Objective function (14) maximizes the total demand coverage. Constraint (14.1) ensures that the demand of box B_i is not counted as covered unless a CP is located at a candidate site which covers box B_i . Constraint (14.2) guarantees the number of facilities to be sited. Constraint (14.3) and (14.4) ensure the binary nature of variables x and z . The sets N_i of candidate locations that cover demand of box B_i can be set individually by the city planner. In the case study we will use a simple approach to determine the CP coverage: Around each CP to be located, a circle with a predetermined radius r is drawn. All boxes that fall into that radius are covered by the located CPs. The linear program is NP-hard (Drezner and Hamacher 2002), but can be solved effectively with the application of Lagrangean relaxation and branch-and-bound algorithms. For our case study we are using the *General Algebraic Modeling System 23.7.3* (GAMS) to formulate the program and IBM ILOG CPLEX 12.3.0.0 to solve it optimally.

Iterative Optimization Using Penalties

In the following we introduce an iterative scheme to find optimal CP locations using penalties. However, based on the land rent theory for urban transportation introduced by Rodrigue (2013), we further assume that with increasing distance between CP and surrounding POIs the influence of the respective POIs decreases. The underlying assumption is that trip destinations which are in the immediate vicinity determine most of the charging demands. Hence, we need a function to incorporate such vehicle owner habits and also to consider POIs in context of their distance to the next charging station. The following penalty function $\Delta(B_i)$ is defined to recalculate the individual ranks p_j^{rank} for all surrounding POIs $P_j \in \mathbb{P}$ after a CP is placed. Since each POI rank is equal to its respective type rank pt_j^{rank} the penalty function $\Delta(B_i)$ is defined as follows

$$\Delta(B_i) = \sum_{j=1}^n pt_j^{rank} \cdot \frac{dist(B_i, P_j)}{\delta_{dist} \cdot \delta_{fac}} \mid dist(B_i, P_j) \leq \delta_{dist}, \quad (15)$$

with a predefined penalty distance δ_{dist} in km and a penalty factor δ_{fac} . The respective output will be set as new POI rank $p_j^{rank} \in P_j$.

Hence, the penalty input values determine the resulting POI ranks after placing an optimal CP in the subarea. We set the penalty factor to 1 by default, thus, the only value that reduces the individual rankings around the optimal CP is the penalty distance. For example if we apply the above Function 15 with a δ_{dist} value of 0.5km, the ranking of a POI with a distance of 0.1km to the respective CP will reduce by factor 0.2. Note that for reducing the rankings of all surrounding POIs, the multiplied factor is always between 0 and 1, ensured by condition $dist(B_i, P_j) \leq \delta_{dist}$ of Function 15. Furthermore, the POI ranks linearly decrease with respect to their distance to the placed CP. On the one hand, the function attains that the farther a POI is away, the lower is its penalty. On the other hand, this implies the assumption that the influence of a certain POI decreases with respect to its distance to the customers charging location. This is a reasonable assumption, since EV owners rather search for the nearest charge point, than accept a long walk to their destination, even taking into account the time for finding a free CP close to their destination.

Due to applying the above penalty Function 15, the most important difference between the MCP and this optimization scheme arises. While the POI ranks at MCP do not change at any time, this procedure reduces and, thereby, changes individual ranks during runtime. This enables the opportunity to execute the approach iteratively using the set of recalculated POIs as new input. As a result, the optimization scheme will quite likely select a different position for the next CP location. However, if a subarea e.g. at the city

center has an extraordinary high sum of POI ranks in contrast to any other location, this iterative procedure will place another CP within this subarea.

Case Study

Having outlined our optimization schemes, we present a case study for locating EV charging stations in different cities with different CP infrastructures. Overall, we conduct two case studies, where the first pertains to results for our reference city Amsterdam, whereas the second addresses a different city with inferior CP infrastructure, so that we can apply our approach as a kind of green field planning experiment. While we use the utilization of current CPs in Amsterdam as well as the POI in the planning area as described in the aforementioned sections as benchmark, we assume that no charging infrastructure is available for the second reference city, Brussels.

Amsterdam

The first case study has been conducted with POI data of our reference city, Amsterdam. Coming from the usage data of Amsterdam's existing EV charging infrastructure, we have derived individual POI category ranks for e.g. restaurants, stores, banks, etc. These result are used to calculate an EV charging demand proxy based on given POI data, using above methodology.

First we divide the city of Amsterdam into a grid. We have chosen an edges length of 100 meters for each box and an overall planning area of approximately 9 square kilometers, which proved to be the best value in our test runs with regard to granularity and run time. For each of the grid's boxes, the *box factor* has been calculated according to Equation 13. The *BF* of the maximum coverage problem is determined by a radius of 100 meters around the boxes center, in order to account for surrounding boxes and POIs. Figure 5 shows the box factors (i.e. EV charging demand proxy) in a heat map for both methodologies. The greener the boxes are, the higher is the box factor and, thus, the anticipated charging demand.

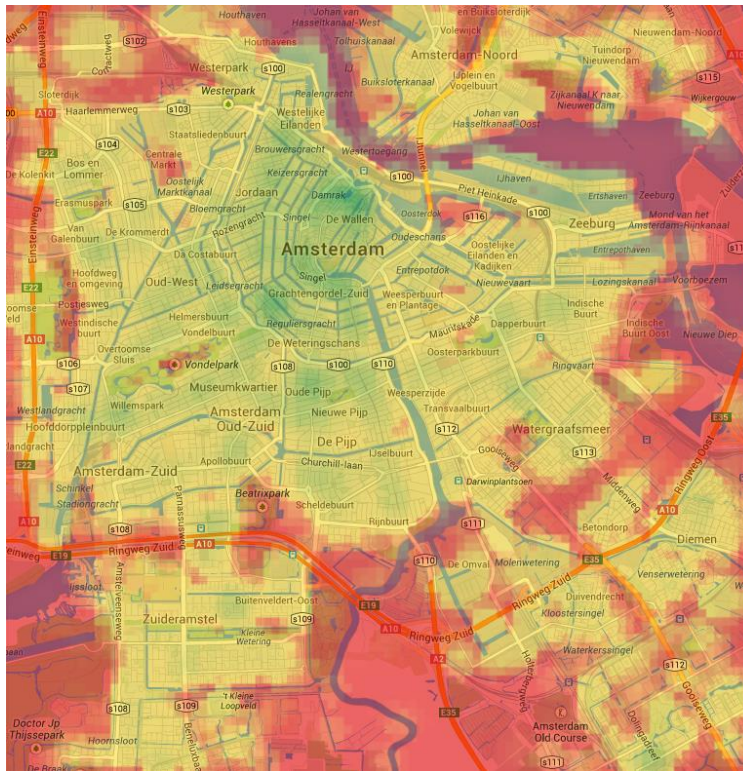
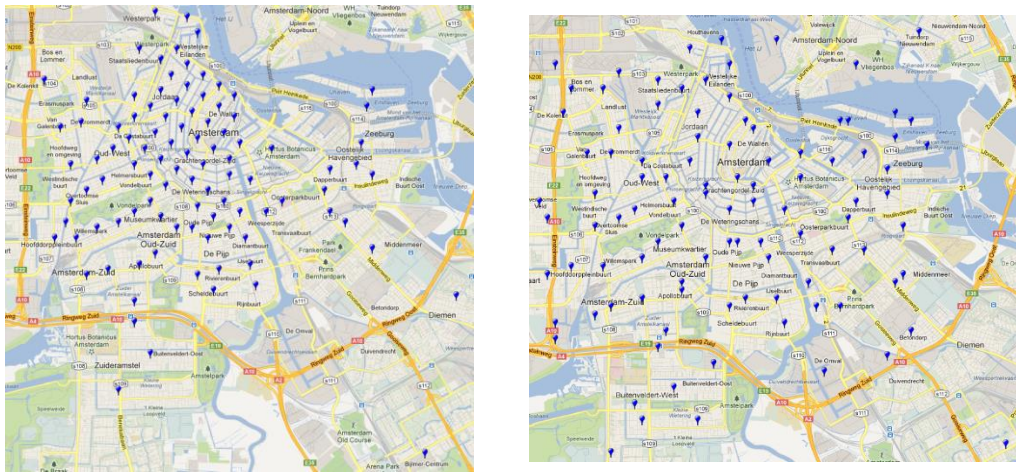


Figure 5. Heat map of Amsterdam showing box factors of MCP with coverage $\sigma = 100m$

The calculated demand per box is then passed to the maximum coverage facility location problem and the iterative algorithm as an input variable. Figure 6a shows the result of the MCP with $p = 100$ CPs to be

located and a CP coverage radius r of 200 meters. Again, the coverage radius defines how many boxes of the grid are covered by a CP. The objective of the MCP is to maximize demand covered by located CPs. This approach is especially suitable for cities where no or less CP infrastructure exists, as a widespread area is covered with CPs. As a consequence this counteracts the range anxiety of EV users, which fear to run out of battery in a place without charging infrastructure. The coverage radius r can be used by planners for sizing the coverage of a CP infrastructure in a city accordingly. As the approach supports strategic planning aspects, city planners can decide in a consecutive planning step, which qualitative factors such as land availability etc. play a role. They can then also make decision about where to locate the charge points in the selected 100 x 100 meter boxes and how many plugs to install. The solution time for CPLEX was 18.61 seconds. In contrast to that Figure 6b shows the results for the iterative algorithm with penalties. We use a penalty distance value δ_{dist} of 0.5 and a penalty factor δ_{fac} of 1. This means that the influence of all POIs within a radius of 0.5 km will linearly decrease, once the iterative optimization approach places a CP. Since the penalty factor is equal to 1, POI ranks in a distance of for example 200 meters will be decreased by multiplying their current ranks by 0.4, according to Equation 15.



(a) Maximum coverage optimization

(b) Iterative optimization using penalties

Figure 6. Optimal CP locations for Amsterdam ($p=100$)

This approach is especially applicable, if city planners aim at covering high demand regions with a denser CP infrastructure, as CP selection is carried out in an iterative way. The POI influence in this approach is weakened as a function of distance from the located CP. Depending on the parameters, city planners can choose to locate more CP in dense demand areas. In contrast to the iterative algorithm, the charging locations using the MCP scheme are selected simultaneously and POI influence is constant during the planning run.

Subsequently, we compare the calculated charge point positions based on our data analysis with the actual charging infrastructure in Amsterdam. Since the city of Amsterdam already has a working CP system with more than 230 stations in total, we performed our optimization scheme with $p = 230$ to produce a comparable output. Note that electric mobility is still a very new technology and currently several charging stations were installed at popular places just for promotion and advertisement and not to pursue an optimal charging purpose. This is also the reason for a very low CP utilization at specific stations. However, as soon as the electric vehicle is not just a fad but an essential part of daily traffic, the corresponding charging infrastructure needs to be adjusted or adapted in a proper way.

Therefore, Figure 7 illustrates the comparison between the existing charge point infrastructure and the calculated one for the north of Amsterdam. The red markers represent the actual CPs and the blue markers the calculated CPs. As one can see, the optimization scheme placed 16 CPs (blue markers) within this district, while currently there are just 10 stations (blue markers) installed in this area. Thus, as a first result based on statistics and computations, this region is more important than it is currently developed. Additionally, some of the calculated charging stations are rather located closer to the main streets, however, in contrast

some of them were placed just a few meters away (circled charge points). Further calculations have shown that more than 20% of the calculated locations are placed less than 100 meters away from the currently available infrastructure.

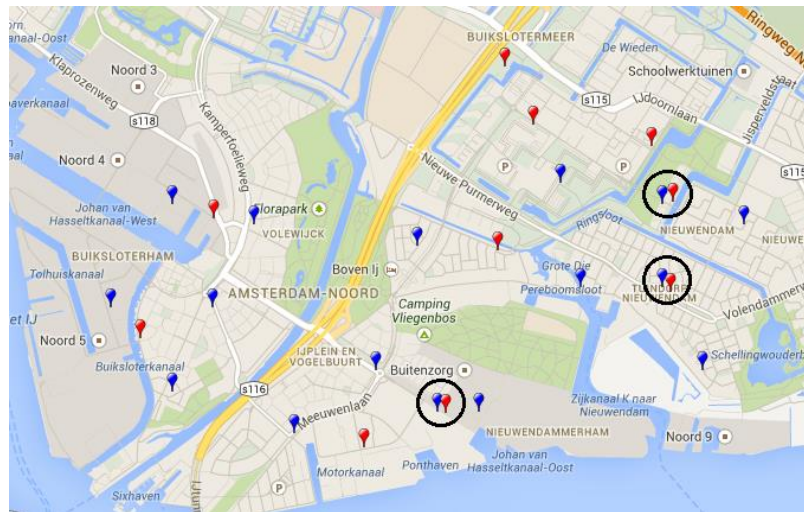


Figure 7. Comparison between actual (red) and calculated (blue) charge point infrastructure

In other areas especially in the city center, but also in the western districts of Amsterdam, the infrastructure is quite similar for both the current and the optimized one. The exact position of all CPs differs from 100 to a maximum of approximately 500 meters. The actual improvement from placing the charging stations as provided by the optimization schemes can only be validated by new field tests and cannot be calculated using statistics or computational procedures. However, in many cases the algorithm suggests to place the CP just at the opposite side of the street. Finding the precise location is, in turn, the task of urban city planners and cannot be specified by an algorithm because of construction restrictions and conditions like the access to the power grid.

Brussels

In the second case study, we apply the methodology and POI category ranks we have derived from our reference city Amsterdam to the city of Brussels. The results show, that our approach is applicable to other planning areas and, thus, allows for green field planning of EV charging infrastructure. In this case we assumed that currently there is no active charging infrastructure available in Brussels. Hence, we computed the following results using the statistical and computational analysis of Amsterdam as well as the POIs in the planning area of Brussels.

In a first step, Figure 8 shows again the demand distribution for both approaches in a heat map. In order to compare the calculated results, we also use an overall planning area of approximately 9 square kilometers and an edge length of 100 meters for each box. As you can see the city center of Brussels is obviously a promising location to establish charging stations. However, in contrast to Amsterdam the optimal subareas are rather spread more throughout the entire planning field and are not mainly focused on the center.

Figure 9 shows the optimal planning result for Brussels using the MCP and the iterative algorithm. Input parameter settings are identical with the ones used for the Amsterdam case study. It can be seen that both optimization schemes do not directly place most of the CPs in the city center of Brussels but rather spread to the southeastern areas. Further, our results show that some residential suburbs like “Laeken” in the north, especially the park area is minor important for placing charging stations. One explanation for this outcome is that even with popular sights like the “Royal Palace of Laeken” the CP utilization at this location is expected to be low, because this area is not a frequently approached destination for citizens. Hence, the calculated charge point importance tends to be low in general based on our statistical and computational calculations, even if the advent of tourists is high at this specific POI.

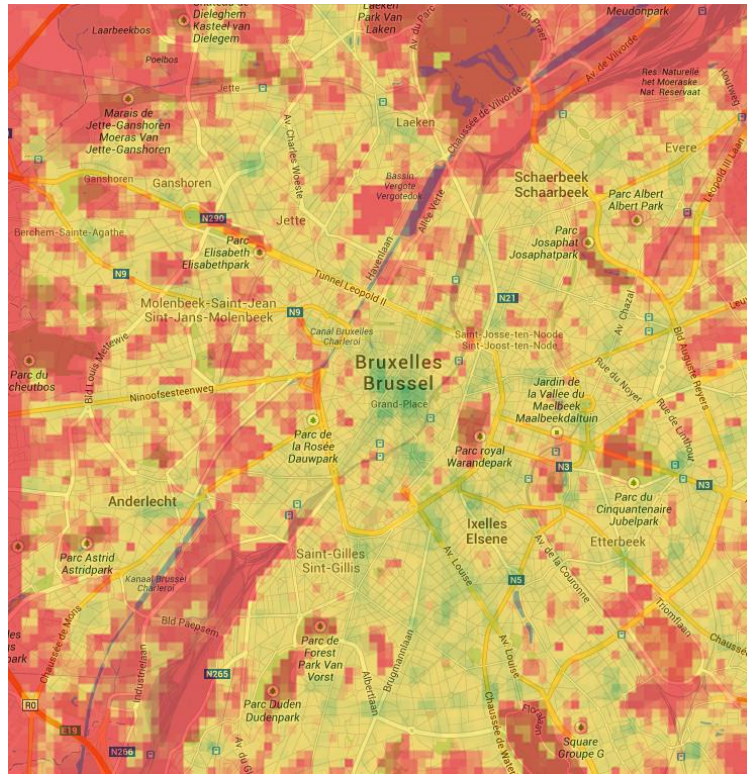
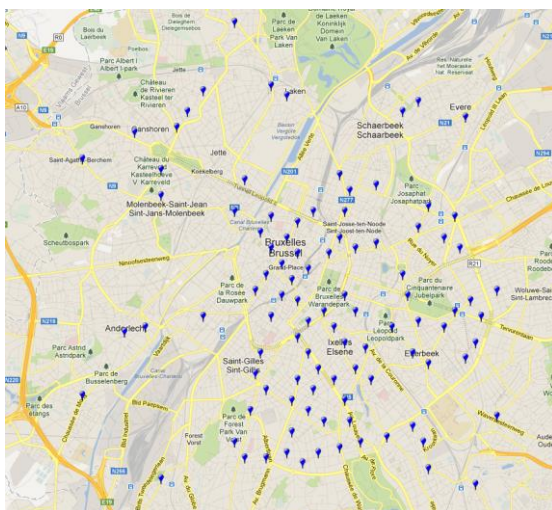
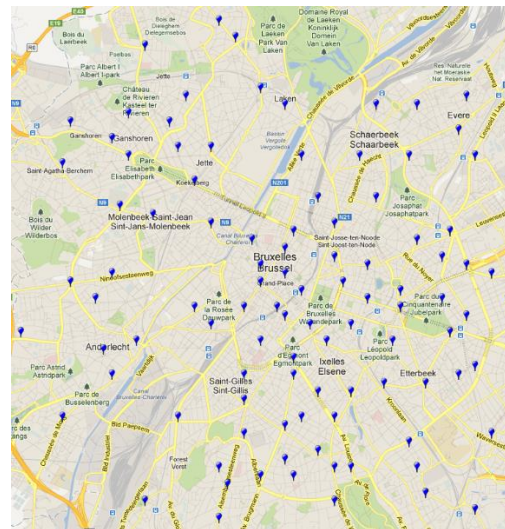


Figure 8. Heat map of Brussels showing box factors of MCP with coverage $\sigma = 100m$

Comparing the results of Amsterdam and Brussels, it is obvious, that the demand in Amsterdam is more concentrated on the city centers. This is reflected by demand distribution (cf. Figure 5 and Figure 8, heat maps), as well as the planning results of CP locations. In contrast, Brussels’ demand is scattered at different spots of the city. Charge points are densely located in the city center, but much more spread out to regional demand peaks.



(a) Maximum coverage optimization



(b) Iterative optimization using penalties

Figure 9. Optimal CP locations for Brussels ($p=100$)

City planners are able to use these approach as a tool for strategic green field planning, since their main objectives should be to cover a given area optimally. In this case we take into account the expected utilization of the respective charge point locations as well as the ability to reduce the prevailing range anxiety of electric vehicle owners.

Evaluation and Managerial implications

The case studies showed that our approach provides a valuable methodology to city planners in order to configure a charging infrastructure for a planning region. One advantage of the planning tool is that city planners have various options to customize the planning approach to their individual needs and city specificities. Four general and additional approach specific parameters exist in total, which allow to adjust the results. The general ones are POI category ranks, definition of the planning area, box factor calculation, and number of CP to be located. Specific ones consist of coverage radius r for the MCP and penalty distance δ_{dist} and penalty factor δ_{fac} for the iterative algorithm. POI category ranks can be adjusted in order to account for local specificities. Planners can weight individual categories higher or lower, depending on local conditions. In some cities people spend e.g. more time in a restaurant and less time at a hairdresser or vice versa. The planning area \mathbb{A} can also be divided individually: The higher the number of subareas \mathbb{B} is chosen, the more precise is the CP location information. However, on the other hand runtime increases. This aspect is certainly acceptable to some degree as the tool supports strategic planning and is not a real time application. Box factor calculation is an integral step of the planning approach: Selecting a high radius σ smoothens the influence of POIs, as an individual POI contributes to the box factor of many boxes. Choosing a lower radius allows to take a more differentiated look at the expected EV charging demand in a city based on POI data, as city regions/boxes set themselves apart from each other more sharply. The number of charge points p to be located permits to select how many CPs are to be placed in each planning run.

In the MCP the coverage radius r allows city planners to define how dense the CP infrastructure network is to be established. A high coverage radius will result in a spacious layout of CPs in the planning area, whereas a low coverage leads to a denser result. For the iterative algorithm penalty distance δ_{dist} and penalty factor δ_{fac} are the input values to determine the charging infrastructure. If the penalty distance increases the number of affected POIs increases, too. However, points of interests within the outer edge will be affected only negligible. The increase of the penalty factor δ_{fac} , only effects the penalty of POI ranks and the number of involved POIs remains the same.

Finally, the computed results are based on statistical analysis and optimize the expected CP utilization of a predefined planning area. Some of the calculated positions differ from the actual CPs in Amsterdam only by a few meters, which in turn may lead to the conclusion that the actual charging stations were also set up by environmental factors, such as surrounding stores. In order to measure and evaluate the quality of the computed infrastructure we need to pursue future developments. However, the actual improvement of the computed infrastructure is based on statistical analysis. Further, we will continuously collect data to validate our findings on the one hand but also to improve this approach by incorporating new data sources like traffic on the other hand.

The case study for Brussels showed that this approach is applicable to plan a charging infrastructure for any city, even if there is not a single charging station available currently. However, in this case we need to derive the influence of each POI category from a reference city, in our case Amsterdam, and transfer these results to the desired planning area. Hence, we need to assume a similar driving behavior, or more explicitly a charging behavior in both cities, since the optimization scheme generates a charging infrastructure based on the findings of the reference city. Hence, the basis of the planning approach introduced in this research is a general method to establish or adapt a charging infrastructure in any city.

In contrast to the research introduced in the related work section, our work differs in many areas. Although, points of interest have been used in research before, but to our best knowledge neither for calculating the expected utilization of charging stations nor to determine an optimal CP infrastructure for smart cities. In addition, a lot of research in this field lacks closeness to reality, whereas our work is completely based on real data or on results derived from real data.

Conclusion

In this paper we have presented a business intelligence system for city planners incorporating a novel methodology in order to plan an optimal EV charging infrastructure in an urban setting. As a data basis, we evaluated more than 32,000 charging sessions, including daily usage frequency and actual demand from one of the best developed charging infrastructure in the world, Amsterdam. Further, we investigated the influence of possible local trip destinations of EV owners on CP usage. The destinations, so called “*points of interest*”, are grouped in 92 different categories, such as restaurants, stores or banks. We show that these POIs have significant influence on the actual charging behavior of EV owners in Amsterdam by performing a linear regression. On this basis, we defined a ranking procedure to rate individual POIs based on the surrounding charge point usage behavior. The individual ranking then contributed to the POI category ranks, which in turn can be used to assess the “charge point attractiveness” of selected urban areas. This EV charging demand proxy served then as an input to our location models.

We developed two different approaches to derive optimal charge point locations for urban green field planning – the city planners can choose among the approaches depending on their preferences. The first approach is a maximum coverage facility location problem, which maximizes the total demand covered and simultaneously calculates the optimal locations for CPs. As the MCP maximizes the total demand covered, it is best suitable for planners who want to achieve a high coverage of EV charging infrastructure in the planning area and, thus, take EV users concerns with regard to range anxiety. A parameter coverage radius allows planners to design the network dense or spacious. However, the MCP places charge points simultaneously and thus a subarea is considered as covered. It is less likely for the MCP that additional charge points are placed in a location that is covered by another charge point, as the potential marginal demand gain is in most cases smaller than placing it outside the covered area. In order to deal with this MCP characteristic and also to enable city planners the opportunity to rate the individual areas in a fine-grained manner, we additionally introduced an iterative algorithm based on land rent theory. For this purpose we defined a penalty function that recalculates the individual POI ranks located in the specific subarea, after a CP is placed. The influence of each POI decreases linearly as a function of distance to the set CP, depending on special input values for penalty distance and factor. This offers an opportunity to change the initial POI rankings during runtime and, eventually, calculate the optimal locations for a predefined number of charging station iteratively.

Finally, we succeeded in developing a methodology to derive future charge point infrastructures for smart cities, by analyzing real charging behaviors. As electric vehicles are not yet part of the everyday life it is important to find such an opportunity to determine CP locations based on daily routines. Accordingly, the presented approaches use real charging behaviors as a benchmark to develop a generally applicable method. We show that these approaches are practicable for any desired city and, moreover, the results are self-adapting as soon as the usage of EVs increases in the near future. In addition, city planners are able to modify the introduced methods depending on individual city characteristics. This can be achieved by e.g. adjusting the POI category ranks or choosing reasonable input values for the coverage distance adapted to the planning areas specificities.

While our approach realized the benefits, but only scratched the surface of Big Data, the full potential for smart city planning is enormous. In our future work we will include more structural and environmental data (e.g. traffic flows, walking patterns, urban population) into our analysis. This way we aim at developing a guideline for city planners helping them to select the right input parameters with regard to grid size, POI category ranks, box factor calculation, and specific parameters, such as the coverage radius r for the MCP and penalty distance δ_{dist} and penalty factor δ_{fac} for the iterative algorithm.

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