**Read the *Related Work* sections and highlight the words/phrases that introduce or compare different points of view.**

**Optimal location of charging stations in smart cities: a point of interest based approach**

**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 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