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Assessment of Demand-Oriented Charging Infrastructure at City-Regional Level – A GIS and Model Based Approach

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Summary

We developed a model-based approach to assess the future demand of charging infrastructure relative to given market diffusion of electric vehicles. After having estimated the demand for charging infrastructure at the regional level, we then determined possible locations for charging points at the city/street level and simulated demand for each location. Finally, we developed a GIS tool to further assess and evaluate each location under different scenario settings.

The paper presents the methodological framework to estimate the charging demand for daily and long-distance travel at the city-regional level, which is unique and innovative, as similar comprehensive and consistent analytical tools do not exist to date.

Keywords: BEV, modelling, charging,

1 Introduction

Innovative and new mobility offerings have never been as abundant and varied as the present. While these new mobility options are highly welcomed by users, they also present a challenge for authorities that plan, organize, and operate such services. In particular, integrating new mobility services into existing infrastructure systems can generate problems of acceptance, co-operability and compatibility. This problem is especially relevant for electric vehicles. The development of electric mobility has a substantial role in mitigating the negative effects of fossil fuels, given the fact that around 14% of global greenhouse gas emissions result from transport sector [1]. However, despite developments in battery technology and charging infrastructure, desired acceptance of electric mobility by the masses has not been realized yet. Beside the well-known arguments against electric vehicles like limited range, higher costs and lack of charging infrastructure, political willingness and interventions at different administrative levels also affect the expansion of electric mobility. Whereas some communities are highly motivated to develop their charging infrastructure, others, do not even have an agenda on electric mobility. Financing public charging infrastructure could be a heavy burden on municipal budgets, therefore lacking interest in promoting them is understandable. Consequently, assessing the real demand for charging infrastructure and their optimal allocation is an important task for local authorities to prevent malinvestments.

The objective of this paper is to provide a methodology to estimate the demand for charging infrastructure and to determine the optimal areas to allocate them at a city-regional level. We developed a model-based geospatial analysis tool to assess the demand and allocation of charging infrastructure within a city-region. Our approach enables to determine possible locations for fast-charging infrastructure and evaluate the economic feasibility based on simulations and the demand for infrastructure for different market diffusion scenarios of electric vehicles. We integrated our approach in a GIS-tool for the state of Baden-Württemberg and the region of Stuttgart, Germany, enabling policy makers and possible investors to apply the model for planning purposes.

2 Data and Methods

Site analysis and allocation are common tasks in infrastructure planning. Sound methods have been developed and been implemented as tools among others in GIS software. These methods have been also inherited for the analysis of charging infrastructure. Previous studies have addressed the problem of optimal location allocation by using complex mathematical models, such as discrete, graph theory based methods [2], [3], diverse location models [4], [5] and capturing models [6]. The main difficulty in location allocation problem is in the contradiction that spatially detailed complex models are time and cost inefficient.

Our method focuses on a flexible and easy to compute modelling approach, which consists of three parts. First, we estimate the demand for charging infrastructure at the regional level. Then, we determine optimal locations for possible fast-charging infrastructure and simulate the charging demand for each location using an agent-based microsimulation for travel demand. Finally, we assess each location and calculate the necessary charging points based on different criteria and structural characteristics by using the GIS-based assessment tool. The main emphasis in this paper is on the first and third part of the approach.

2.1 Estimation of Charging Demand

We estimate the charging demand at the regional level by using a Germany-wide traffic demand model (VALIDATE) [7] and socio-demographic data at the communal level. The travel demand model VALIDATE contains a Germany-wide attributed digital street network which is comprised of around two million nodes, 120 million links, and 10,200 traffic zones. The model is calibrated with the data of around 70,000 traffic counters. The assignment results in eight million O-D-relations and supplies all necessary information to nodes and links in the form of georeferenced points (around 250 million) with attributes such as “from node,” “to node,” and “traffic volume.” According to the assignment results we obtain at least one route with all used nodes and links as geo-referenced points for each assigned origin-destination (O-D) relation. The share of trips by EVs on these routes is also calculated at this step. We calculate the distances between each node on each route based on the list of routes from the model. By doing so, it is possible to measure the distance between the starting node and any other node on the route. This allows us to spatially locate each charging event on the freeway depending on the various ranges of EVs. According to the assumptions of a) the battery range, b) the charging state of the battery at the beginning of the trip, and c) the amount of energy which can be recharged in 30 minutes, for each O-D-relation we display every charging event as a point on the relevant route. Afterwards all these charging events are cumulated along the routes.

Since the traffic load curves are aggregated values and different routes can have a greater variability, hourly variations are expected. This aspect can be represented in queuing models. A queuing model helps in estimating the utilization of service points depending on arrival time distribution and waiting time. To calculate the charging infrastructure needed a queuing model is applied. This approach enables us to calculate the required number of charging points for different arrival rates and corresponding utilization rates. As an example, for an arrival rate of $\lambda = 10$ (10 vehicle arrivals at charging station per hour) and service rate of $\mu = 2$ (2 charges / hour per charging point), results in 5 charging points with 100% utilization rate and 18 minutes of wait time. Increasing the number of service points to 7 results in a 70% utilization rate and 5 minutes of waiting time. Thus, the total charging demand along the routes (in kWh per day respective of number of charging events per day) is summed and mapped as displayed in Figure 1.

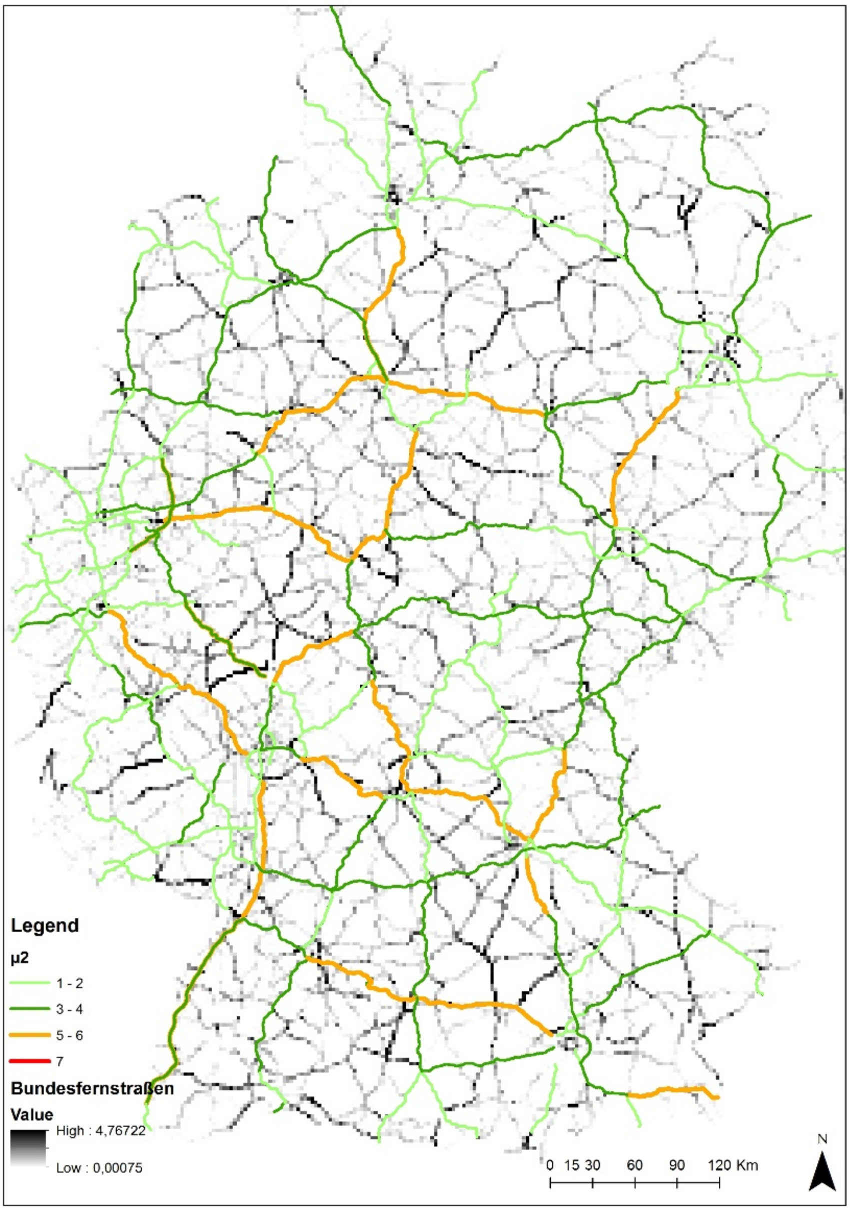

Figure1: Number of charging points with waiting times less than five minutes.

We use the results of charging demand at the regional level as input for the microscopic simulations later at the city level.

2.2 Allocation of Charging Locations

Our methodology for the allocation of charging locations is based on the analysis of road network, travel times and build-up environment for the optimal location of fast-charging infrastructure. We used an existing travel demand model for the region of Stuttgart in Germany, which has a population of around 2.7 million and a total area of 3.654 km2. Road networks, travel demand and travel times are imported into GIS from this demand model for further analysis. A GIS-based network analysis of travel times on a weekday with the typical demand for the given weekday and time intervals delivers a solution for the accessible charging locations. This is a location-allocation kind of network analysis problem, solved in ArcGIS®, can be formulated as follows: the maximum demand (Z) needs to be served with a fixed number of facilities and within a minimum level of service distance (S).

Its mathematical expression follows the form:

$$Minimize\ Z = \sum_{i \in l} X_i\, B_i$$

subject to:

$$\sum_{j \in Ni} A_j\, B_i \geq 1 \text{ for all } i\ \in I$$

$$\sum_{j \in J} A_j = Q$$

$$A_j = (0,1) \quad \text{for all } j\ \in J$$

$$B_i = (0,1) \quad \text{for all } i\ \in I$$

where;

I = the set of demand nodes;

J = the set of facility sites;

Aj = {1 if a facility is allocated to site j; 0 otherwise}

$N_i\ =\ \{j\ \in\ J\ |d_{ij}\ \leq\ S\}$ is the set of sites likely to cover demand point I with;

S = desired service distance level for a given facility to cover the maximum demand (the distance level S can be chosen differently for each demand point, if desired);

dij = the shortest distance from node i to node j;

Xi = population that needs to be covered at demand node i;

Q = number of facilities to be located;

Basically, it allocates a given number of demand points on the network to an optimal number of service points or vice versa. Criteria such as accessibility to service points within a given time or minimum number of demand points that should be served are user-defined parameters for the calculation. In our approach, we set accessibility times for service points (charging infrastructure) from each demand point (residential areas) as such parameter. For the identification of demand points on the network some additional spatial analysis are undertaken. Since the population in the travel demand model is represented for the whole zones as a single atttribute, a spatially precise localization of population within the zone is not possible. We used open source data (OpenStreetMap) of building footprints in the region and calculated a weighted distribution of population in residential areas as demand points within zones.

Depending on the calculated travel times on the network, locations for fast-charging points were then determined under the condition that these points would be accessible within five or ten minutes and yet the smallest possible number of points have to be installed. Specific areas such as natural reserves, tracks for rail traffic etc. were not considered as potential locations and are excluded from the analysis. The defined locations are then used as input for the simulations in the microscopic demand model, which will be introduced in the following subchapter.

As a result, this analysis provides locations in the network considering travel times and traffic loads. Based on an aspired accessibility of fast-charging points for all inhabitants in the region of Stuttgart within five minutes in normal traffic conditions, 218 potential locations were determined, against 58 potential locations for an accessibility within ten minutes. The spatial distribution of charging stations within 5-minute accessibility is displayed in Figure 2.

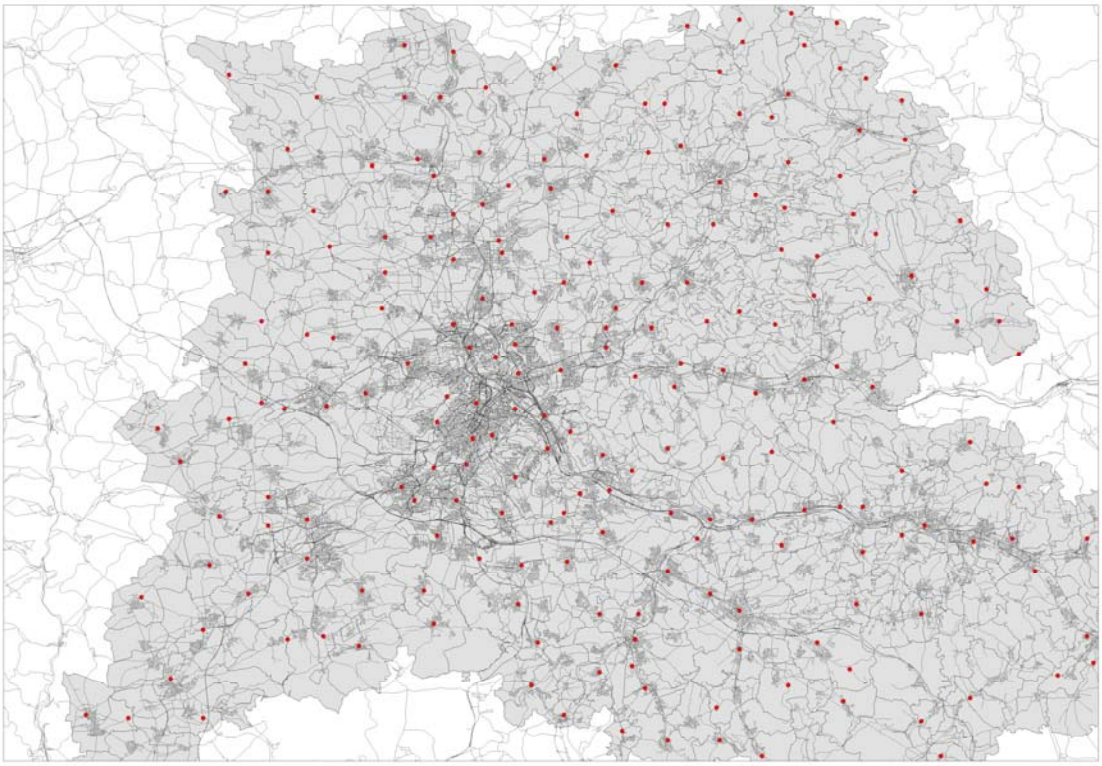

Figure2: Spatial distribution of charging locations within 5-minute accessibility

2.3 Agent-based Microsimulation and Assessment Tool

The evaluation of potential locations for fast-charging points is based on simulations of the travel demand model mobiTopp [8] in the Stuttgart Region. mobiTopp is a multi-agent travel demand model, which models every person and household as well as cars and charging points of the planning area. People are modelled as individual agents, who are grouped together into households. Each agent is assigned an activity program for a whole week. This activity program is created in the first of two stages of mobiTopp, the long term model. In the second stage, all agents are simulated simultaneously. During the simulation, every agent selects the location and mode for their trips.

When using electric cars, the agent decides when the car has to be charged. The decision depends on the remaining capacity and the availability of charging facilities inside the destination zone. Charging facilities are assigned to each zone based on the simulated scenario. All charging events were then extracted from the simulation results and local demand for fast-charging infrastructure at the determined location was derived using queuing models. The simulation results include the number of charging events and the amount of energy consumed for each point and for each market penetration scenario for an average weekday.

The most important part of our developed method is the assessment tool and its results. Aim of the scalable assessment tool is to calculate the number of necessary charging points for each location, evaluate and rank them based on different criteria and structural characteristics (number of electric vehicles, number of charging activities, economic efficiency). The tool allows the user to weight these criteria and characteristics individually, depending on the preferences of the user (for example, economic aspects could be more important than structural characteristics for the ranking of locations). Each location will be ranked differently.

For the economic efficiency, total costs were calculated, which took into consideration the purchase and sales prices for electricity as well as the estimated costs for construction, connection to power supply and operation for each location individually. As structural characteristics, the total population in the investigation area of fast-charging location (areas that can be reached in 5 or 10 minutes from the location), the number of jobs within the investigation area, the number of POIs and private parking space in the area as well as the distance to the next junction with a non-built-up road (motorway of federal highway) were considered.

The number of potential charging points was evaluated depending on the demand. For each location an individual regression and queuing model (M/G/c model with 5 minutes waiting time) was set up. For each of these characteristics, an independent quantitative ranking was set up, resulting in a value between 0% and 100% for each variable – 100% being the best and 0% the worst value. The total ranking was then calculated using a weighted sum for the different variables.

The assessment tool is implemented in a GIS-environment using ModelBuilder in ArcGIS®, which offers a user interface for entering the input parameters interactively by the user. The results of the model, i.e. number of charging events and individual rankings, can also be visualized geographically in thematic maps as in Figure 3.

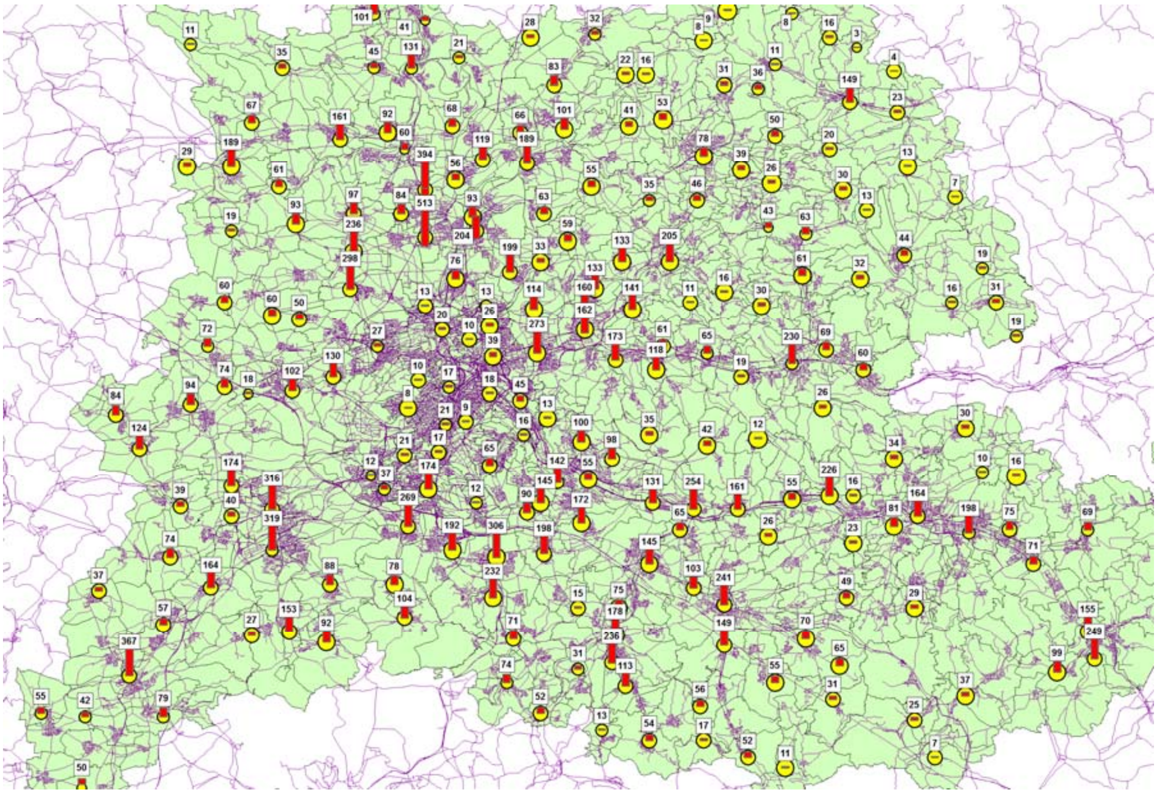

Figure3: Results of the assessment tool for a scenario of 300000 BEVs

Figure 3 shows the number of charging processes (red bars) over the energy consumption (yellow dots). In the city center of Stuttgart, there are fewer charging processes than in the suburban area and can be explained by the fact that in the city center, there is already a very dense grid of slow-chargers. This indicates, however, that slow chargers are used and can be a complementary benefit to charging infrastructure.

3 Results and Conclusions

At the regional level for the state of Baden-Württemberg we estimated a demand of around 4.500 charging points. We then determined locations of charging points at the city level for the city of Stuttgart. Based on an aspired accessibility of fast-charging points for all inhabitants in the Stuttgart Region within five minutes, 218 potential locations were determined, against 58 potential locations for an accessibility within ten minutes. Each location includes several charging points in order to minimize waiting times. The number of potential charging points was evaluated depending on the demand; however, a minimum of four charging points should be available at each location to ensure comfortable customer service.

Results of the tool for a market penetration of 300.000 electric vehicles and assuming 0.1 €/kWh buying and 0.3 €/kWh selling electricity show that the most profitable location is near to a highway and in the middle of a large commercial area. The amortization will take less than two years. The less profitable location will never redeem and is located in a rural area, where most electric vehicle users are able to charge their car at home anyway.

We created a tool for the assessment of predetermined locations for fast charging infrastructure, which is effortless to use and has brief computational times. It allows for individual weighting factors, which makes it suitable to be used for decision-making processes. It is well suited for future tasks of assessing possible locations of charging infrastructure. Most assumptions can also be adopted and having the travel demand model applied, it can also be adapted to other regions.

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