

A dynamic location model for charging infrastructure taking into account future EV adoption

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Abstract

To efficiently plan the roll-out of charging infrastructure for EVs, we present a time-dynamic location model based on a spatio-temporal estimation of the future adoption of EVs. The model is applied in a Belgian case study on Brussels.

Keywords: charging, infrastructure, prediction, optimisation

1 Introduction

Electric vehicles (EV's) provide a cleaner alternative to conventional internal combustion engine (ICE) vehicles in terms of emissions, which is particularly interesting in an urban setting such as the Brussels Capital Region and in a densely population region such as Flanders. However, market adoption of this vehicle technology in Brussels (and Belgium in general) is lagging behind in comparison with neighbouring European capitals such as Amsterdam and Paris. (For an up-to-date overview of the current vehicle and infrastructure statistics in Europe, we refer to the European Alternative Fuel Observatory [3].)

Given that access to charging infrastructure has great predictive power for the sales of electric vehicles [7], one of the main barriers of market adaption in Belgium currently is the lack of public charging infrastructure. This is also recognized in the 'Clean Power for Transport' Directive of the European Commission, which imposes the task of developing an action plan for the roll-out of the infrastructure for vehicles on alternative fuel on the member states. In this study we present the results of a location model for charging infrastructure taking into account future EV adoption.

2 Method and Data

The methodological approach is twofold: first we estimate the spatio-temporal distribution of EV adoption, next we use this information as demand parameter in the location model. Based on socio-demographic characteristics of households in a neighbourhood, such as income, housing surface and household size, we apply regression analysis to estimate ownership of EVs at neighbourhood level for the next five years. This information provides an estimation of the need for public charging.

Different location models have been applied to the EV charging infrastructure problem. In this study we present a multi-period maximal covering model taking into account the estimated need for public charging for the next five years.

2.1 EV uptake: horizon 2020

Based on the results of a previously conducted choice-based conjoint analysis [6], we make a prognosis of the EV uptake for the Brussels Capital Region. The total number of vehicles registered in a municipality are used to allocate the total forecasted EV demand for the region to the municipalities. Next,

we calculate an "EV suitability score" for each district to take into account spatial socio-demographic characteristics and we proportionally distribute the forecasted demand to each district in the respective municipality. The final step involves the uniform allocation of the district demand to building blocks. In figure 1 this procedure is depicted; in the following paragraphs each step is discussed in detail.

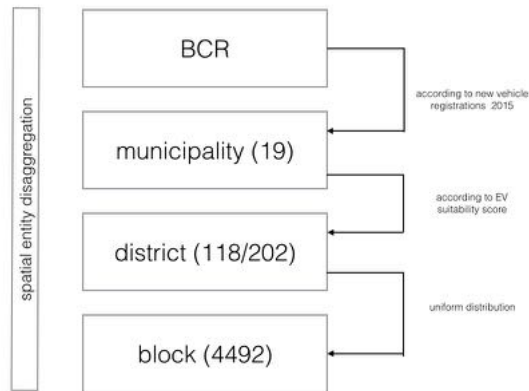


Figure 1: Procedure for demand estimation at block level

2.1.1 Spatial Entity: Brussels Capital Region

Beginning 2015 in Belgium 7.402.851 vehicles were registered, of which 637.809 in the Brussels Capital Region [4]. The number of newly registered vehicles in the Brussels Capital Region was 78.470 [4] in 2014 and 82.889 in 2015 [1]. Among these new registrations, 435 in 2014 and 882 in 2015 were electric vehicles (both battery electric (BEV) or plugin-hybrid electric vehicles (PHEV)).

Based on the results of a CBC-study [6], we forecast the market share of BEVs and PHEVs for the newly registered vehicles from 2016-2020. Taking into account the actual sales in 2014 and 2015 and the forecasted sales, we obtain the cumulative number of BEVs and PHEVs for the next five years. This prognosis is carried out for three scenarios: Business as Usual (BAU), Incentive and Incentive + Infrastructure. In the scenario "BAU", the sales are forecasted based on the assumption that no policy measures to increase the adoption of EVs are implemented. This results in a total number of electric vehicles of about 14,000 in 2020. In the scenario "Incentive", we have assumed that a financial incentive (an eco-bonus) is issued to stimulate the market adoption. In 2016, the bonus is 6.000 € and this decreases over time: 3.000 € in 2017, 2.000 € in 2018 and 1.500 € in 2019. The effect of this stimulating measure in comparison with the BAU scenario is a quicker uptake of EVs and a higher total cumulative number of EVs in the Brussels Capital Region of more than 16.000 EVs. The scenario "Incentive + Infrastructure" supplements the previous scenario "Incentive" with the assumption that additional investments in charging infrastructure are made, elevating the number of charging points each year with 100. The combination of these measures was also analysed based on the results of the CBC-study, and this would result in first instance in similar effects as the "Incentive" scenario, but in the longer run – from 2019 on – the total number of electric vehicles increases to over 18,000 EVs. This lagged effect can be explained by the temporally progressive number of charging stations in combination with the temporally degressive financial incentive. The results of the scenario-based demand forecast are depicted in figure 2.

The subsequent analysis is based on the results of the BAU baseline scenario.

2.1.2 Spatial Entity: Municipalities

The Brussels Capital Region consists of 19 municipalities. Given the inherent spatial nature of our analysis, the forecasted demand needs to be assigned to spatial entities of a finer granularity. In an ideal world, all data are available on the same spatial level, however that is not the case and therefore this stepwise approach is implemented.

In this first assignment stage (see figure 1), the forecasted number of electric vehicles is proportionally distributed across the 19 municipalities based on the number of newly registered electric vehicles by private persons in each municipality in the year 2015. Given that the aim of this study is to optimally locate public charging infrastructure, only the electric vehicles sold to private persons are taken into account.

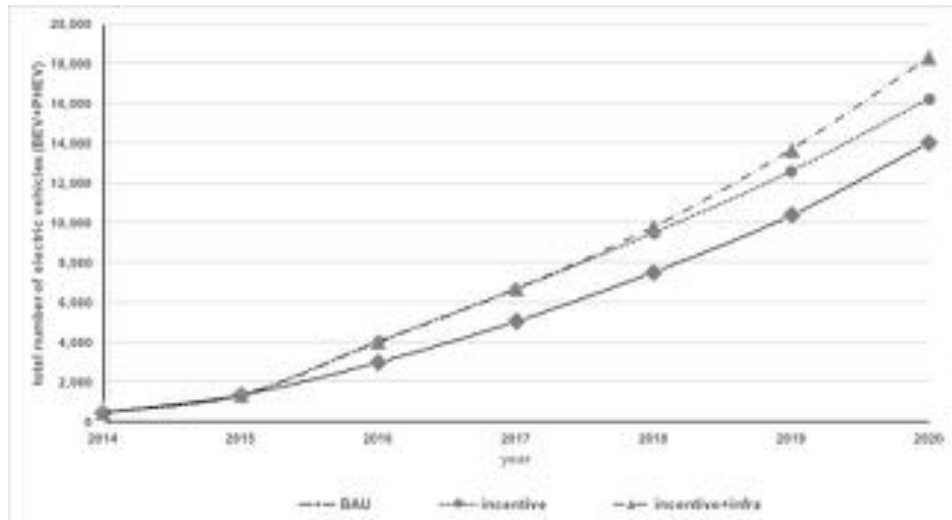


Figure 2: Forecasted demand for EVs in BCR: Business As Usual, Incentive, Incentive + Infrastructure

This is visualised in the map in figure 3. In 2 municipalities, Berchem-Saint-Agathe and Saint-Gilles, there were no private EV registrations. The highest number was achieved in Uccle.

2.1.3 Spatial Entity: Districts

Next, the demand for PHEVs and EVs is divided across the different districts in a municipality. This step is crucial in order to take the spatial variation into account with respect to the socio-demographic characteristics of the inhabitants. The Brussels' District Monitoring database [9] is used as source for this information.

Note that the Region is divided in 118 residential neighbourhoods (in which 99,7% of the population lives), 6 industrial zones and stations, 18 green zones and 3 cemeteries. In our analysis we excluded the 3 cemeteries and no block data was available for the districts Vijverpark and Astridpark (in Anderlecht), Schaarbeek station and Jubelpark (in Brussels).

Also remark that the borders of the monitoring districts do not necessarily correspond to the borders of the municipalities, therefore the demand of a district is calculated in proportion with the surface it contains of the two (or sporadically three or four) enclosing municipalities. This results in 202 district or district parts.

To account for the socio-demographic profiles, the variables income, housing surface per inhabitant and household size are used in order to disaggregate the demand on municipality level across the districts. To this end we compiled an "EV suitability score" for each district, this score is multiplicatively proportional to the average income and housing surface per inhabitant in a district and inversely proportional to the average household size. The distribution of the "EV suitability scores" visualised in figure 4.

The average forecasted demand per district varies from 14,68 EVs in 2016 to 69,45 in 2020; the median from 9,18 to 43,43.

2.1.4 Spatial Entity: Building Blocks

In the final step towards creating the demand points for the location model, the demand in a district is uniformly allocated according to the number of building blocks in the district. A building block is delimited by streets or by the municipality borders. In the analysis we take into account 4992 building blocks. The average forecasted demand per block varies from 0,6 EVs in 2016 to 2,81 in 2020; the median from 0,26 to 1,23. We do not separately depict the building blocks, however these can be identified from their centroids in the figure with the result of the location model (see figure 5) as dots, with shades ranging from yellow (low demand) to dark brown (high demand).

2.2 Location model

The ambition of the public authority is to provide maximal coverage with the opened charging stations given a budget constraint. To mathematically model this, we use the classical maximal covering location model (MCLP), introduced by [2].

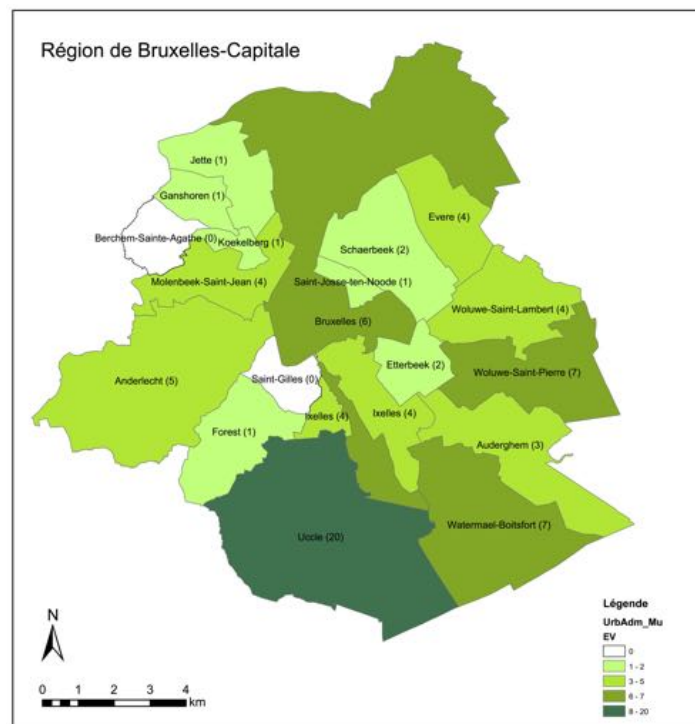


Figure 3: Registered EVs in municipalities Brussels Capital Region - 2015

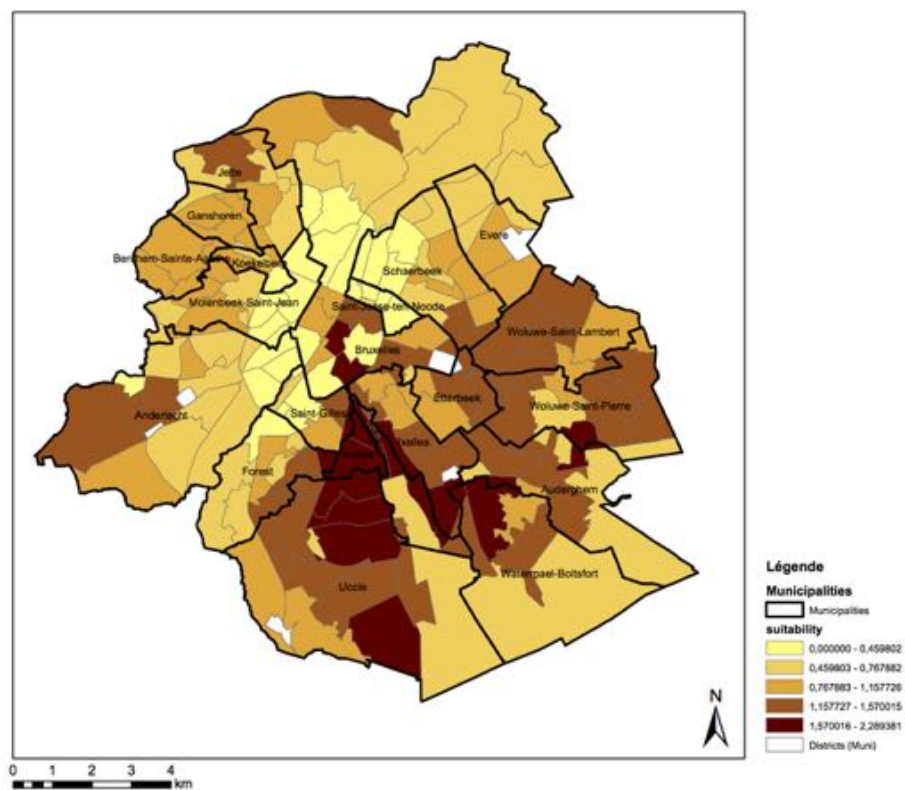


Figure 4: EV Suitability scores for the Brussels Capital Region Districts

2.2.1 MCLP

We consider a market for charging infrastructure with the above forecasted demand $d_i > 0$ given for the blocks $i \in I$. The policy maker has a given budget B to spend on opening charging points in order to provide the best service possible with public charging stations to EV owners. Charging stations may be opened at the candidate locations $j \in J$.

Patronising sets $N_i \subset N$ ($i \in I$) describe the service for the demand points: as soon as a charging station is opened within N_i , the charging need of block i will be serviced and its full demand is taken into account.

The patronising sets N_i are determined as follows: the candidate locations lying within a threshold distance d from block i 's location.

$$N_i = \{j \in J : d_{ij} \geq d\} \quad \forall i \in I \quad (1)$$

This threshold distance typically depends on the type of service. In the case of charging facilities for residents, we assume the threshold distance is 350m. To assess the sensitivity of the solution to the distance threshold, we also performed analyses under the assumption of a threshold distance of 200m and 500m.

The full model formulation is as follows:

$$\max \quad \sum_{i \in I} d_i x_i \quad (2)$$

$$s.t. \quad \sum_{j \in N_i} y_j \geq x_i \quad \forall i \in I \quad (3)$$

$$\sum_{j \in J} y_j \leq B \quad (4)$$

$$x_i \in \{0, 1\} \quad \forall i \in I \quad (5)$$

$$y_j \in \{0, 1\} \quad \forall j \in J \quad (6)$$

where we maximize the service of charging stations, subject to the set of covering constraints (3) and the budget constraint (4).

The candidate locations J for the charging stations are determined by an evaluation of the accessibility to the electricity grid at a reasonable cost. In total, 1292 candidate location are considered. Next, the OD matrix with distances between the blocks and the candidate locations is generated.

The model was implemented in AMPL and solved with CPLEX 12.5 on a MacBook Air 1,7GHz Intel Core i7 with 8GB RAM.

2.2.2 DMCLP

To simulate the roll-out through time, we use the dynamic maximal covering location model. However, to make sure that the solution in the long run (horizon 2020) is optimal, the candidate locations are restricted to the subset of candidate locations that are optimal for the maximal covering location model. The full model formulation (based on [5]) is:

$$\min \quad \sum_{i \in I, t \in T} d_{it} x_{it} \quad (7)$$

$$s.t. \quad \sum_{j \in N_i} y_{jt} + x_{it} \geq 1 \quad \forall i \in I, t \in T \quad (8)$$

$$\sum_{j \in J} y_{jt} \leq B_t \quad \forall t \in T \quad (9)$$

$$y_{jt} \geq y_{j,t-1} \quad \forall j \in J, t \in T \quad (10)$$

$$x_{it} \in \{0, 1\} \quad \forall i \in I, t \in T \quad (11)$$

$$y_{jt} \in \{0, 1\} \quad \forall j \in J, t \in T \quad (12)$$

3 Results and discussion

First the result of the MCLP in 2020 is presented and then the roll-out scenario is depicted.

3.1 MCLP

The roll-out of the infrastructure in the BAU scenario is based on a yearly opening of 100 charging stations. With the installation of 500 charging stations, 9.512 out of 14.000 demand points are serviced in 2020.

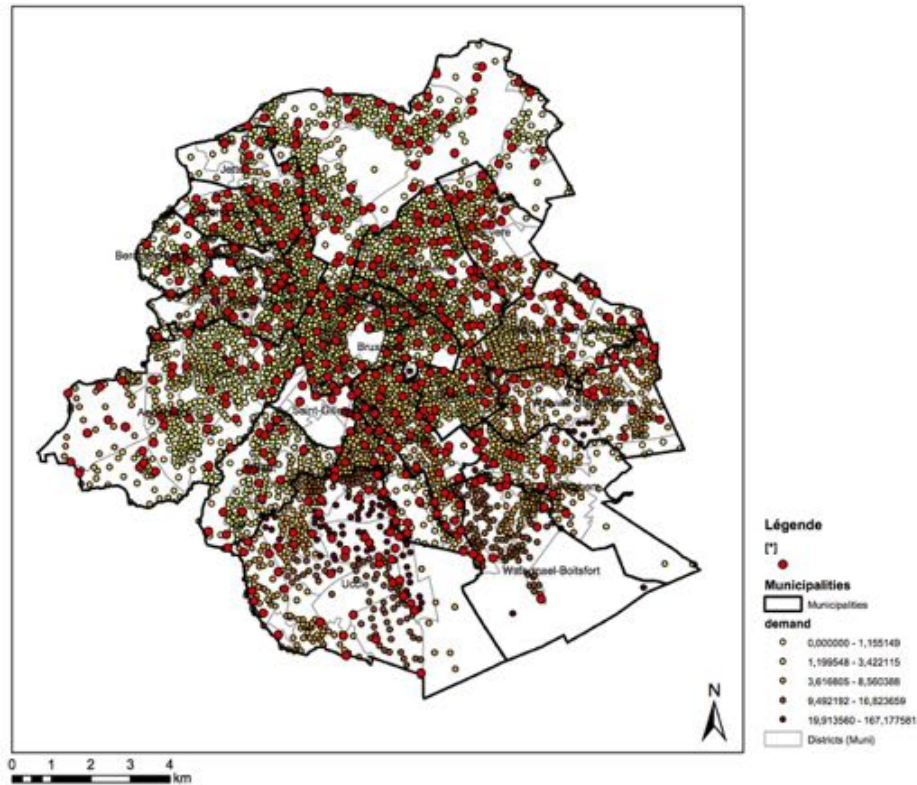


Figure 5: Location of charging stations in 2020

3.2 DMCLP

To plan the roll-out in a time-dynamic manner, the DMCLP is solved based on the forecasted demand estimated in each year. The candidate locations are limited to the solution of the MCLP to guarantee an optimum in the long-term. This results in an incremental roll-out as shown in figure 7. Changing the threshold distance from 350m to 200m and to 500m shows the robustness of the solution In figure 6 with respect to the assumption about service level (in terms of walking distance on the network).

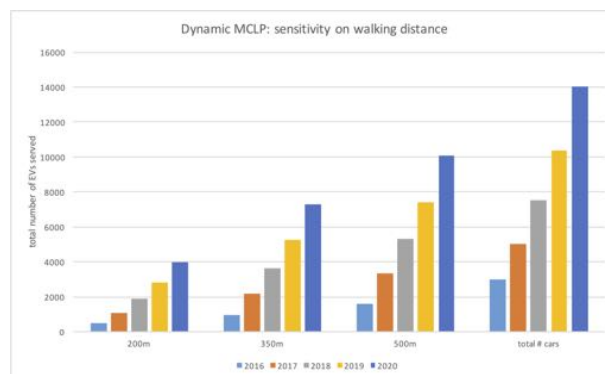


Figure 6: Sensitivity analysis on the walking distance for the DMCLP

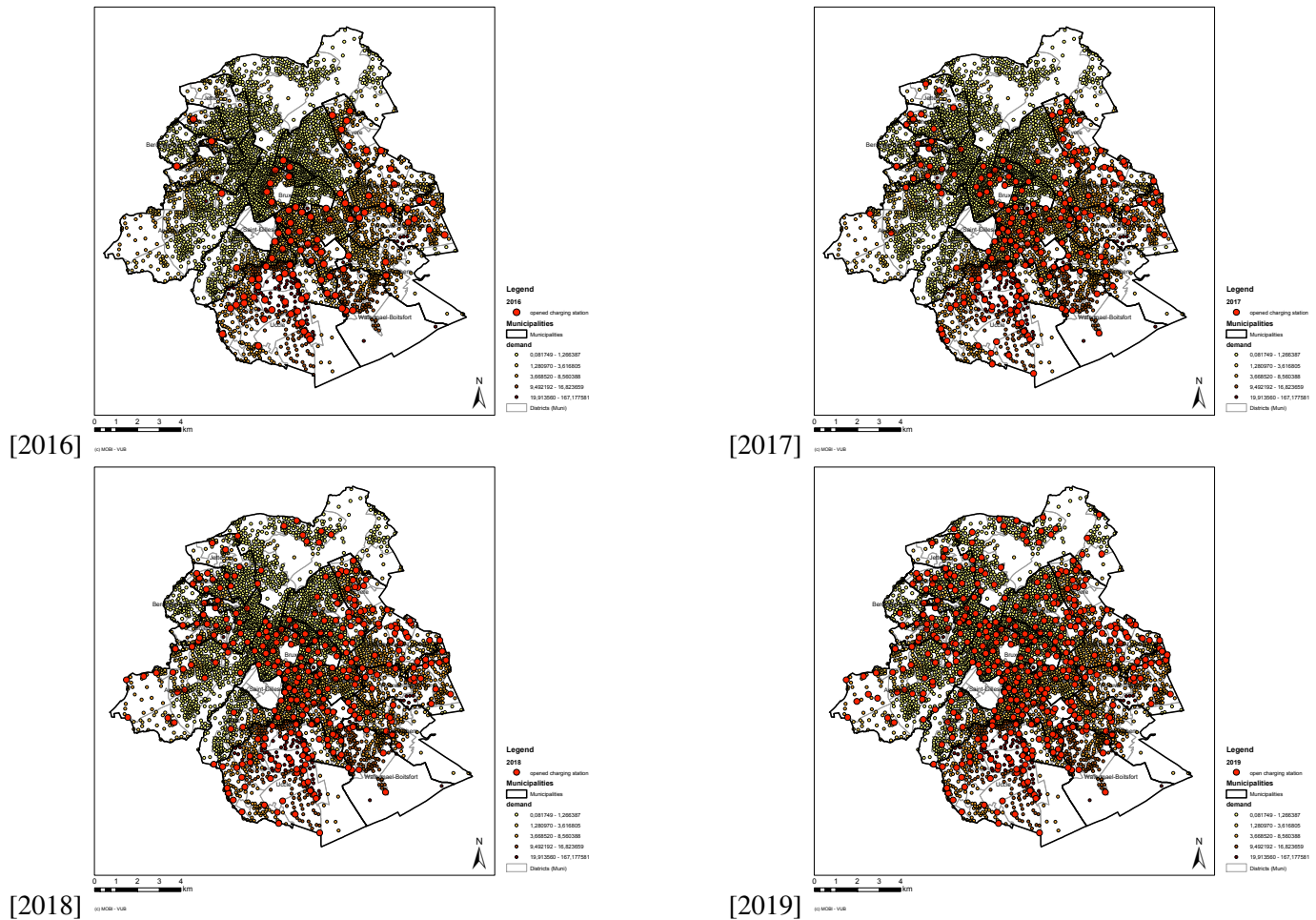


Figure 7: Planning of roll-out 2016-2019

4 Conclusion and future work

In this study we applied a time-dynamic location model based on a spatio-temporal estimation of the future adoption of EVs in the Brussels Capital Region. Based on the results of this study, currently ongoing is the assessment of investment in the grid and the development of a business case for the roll-out of the infrastructure.

Future work involves the overlay and integration of an opportunity charging location approach whereby the charging stations are planned at public transit hubs and other points of interest that attract high amounts of traffic, such as commercial centres or public service facilities [8]. Additionally the planning of fast-charging infrastructure, aimed at for example electric taxis, can be integrated in the location model.

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