MINIMUM COST FAST-CHARGING INFRASTRUCTURE PLANNING FOR ELECTRIC VEHICLES ON THE AUSTRIAN HIGH-LEVEL ROAD NETWORK

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Motivation

Given the ongoing transformation of the transportation sector towards electrification, the expansion of the current charging infrastructure is essential to meet the future charging demand of the battery electric vehicle (BEV) fleet. The lack of fast-charging infrastructure along highways and freeways is still an obstacle for long-distance travel with BEVs [1]. However, when it comes to the necessary expansion of fast-charging infrastructure, it is essential to plan for the long term on the one hand, while at the same time considering the impact of continuous improvements in charging and battery technologies on this infrastructure (by, e.g., accelerated charging and improvement in driving range).

Most studies allocating charging infrastructure along highway networks follow location-allocation models [2]. Such approaches often neglect to estimate the sizing of individual charging stations or to incorporate limitations given by local grid constraints. Other highway charging station allocation studies follow iterative methods or develop methodologies requiring detailed data on individual trips, resulting in a restriction of optimality in the allocation and data-intensive methods [3].

Methodology

We propose the approach of a Mixed Inter Linear Programming (MILP) optimization model, which adopts graph attributes of a street network, by considering potential charging station sites and the network connections between these. For each node i, a certain demand d_i exists. This demand can be covered locally ($E_i^{charged}$) or shifted to an adjacent node (E_i^{output}). Next to the potential coverage of local demand, there is also demand which has not been covered and shifted to node i (E_i^{input}). The values of these variables are in balance in each node:

$$E_i^{input} + d_i - E_i^{charged} - E_i^{output} = 0 \tag{1}$$

The energy shift from one node i to an adjacent $i+1$ is expressed by the following constraint $E_i^{output} = E_{i+1}^{input}$.Further, optimization variables $X_i \in \{0,1\}$ and $Y_i \in \mathbb{Z}^+$ are introduced to imply whether a charging station is built and how many charging poles are installed at a node. These variables are optimized in regards to the minimization of infrastructure costs along all network segments $\sum h$ for both driving directions $\sum k$:

$$\min_{X_{ih}, Y_{ihk}, E_{ihk}^{charged}, E_{ihk}^{input}, E_{ihk}^{output}} \sum_{ihk} (c_X X_{ih} + c_Y Y_{ihk}) \tag{2}$$

Moreover, the optimization model includes constraints considering local grid limitations, a maximum distance between charging opportunities, and already existing fast-charging infrastructure. The spatially varying charging demand is estimated by calculating local traffic counts applying General Regression Neural Networks (GRNN) on real traffic count data [4].

Overall, this top-down approach is easily applicable to different highway and motorway networks of varying locations and extend. It only requires geographic data representing the street network of interest, a set of potential sites for installing charging stations, and spatially distributed traffic count data input.

Results

This modeling framework is applied to the Austrian highway and motorway network, considering different future scenarios originating from the *openEntrance* project (https://openentrance.eu). Within these

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scenarios, the technological parameters of BEVs and the share of BEV cars in the car fleet, including the effects of modal shifts, are varied. In addition, the results of a sensitivity analysis based on the change in charging speed and battery capacity of BEVs and the simultaneous growth of the BEV passenger car fleet will show the direct impact of technological learning on the need for fast charging infrastructure.

Figure 1 displays preliminary results indicating the needed expansion of the current fast-charging infrastructure along Austrian highways based on a BEV car share of 5% (approximate share for 2030, given the growth of this number during the last decade, https://www.beoe.at/statistik/). Next to the optimal allocation and sizing, results will encompass estimates of the electricity demand of BEV cars traveling on the Austrian high-level network.

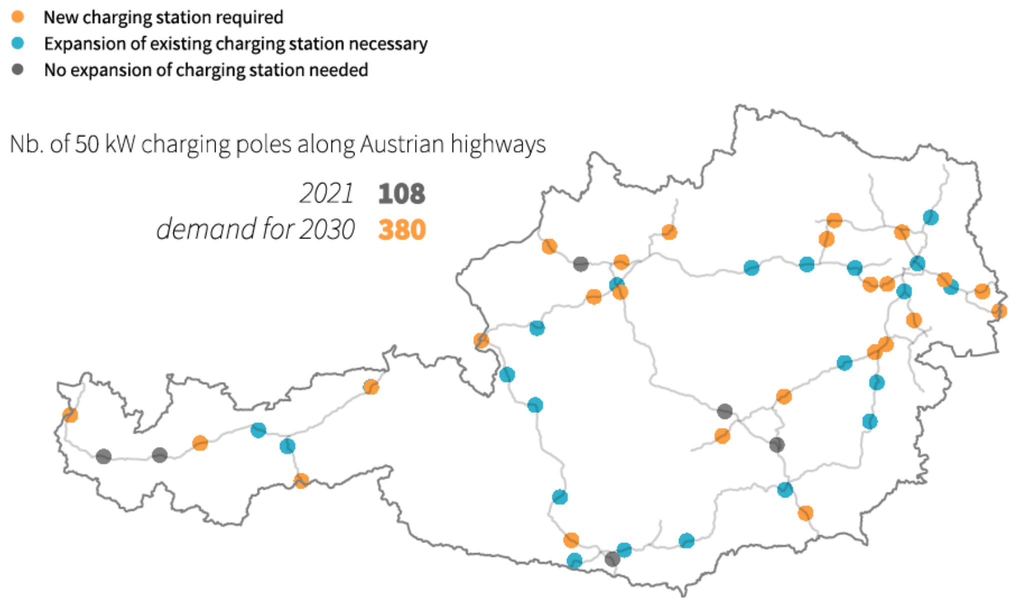

Figure 1: Preliminary results indicating the needed expansion of the fast-charging infrastructure (50kW) given a 5% BEV share in the car fleet.

References

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