Overview

Driven by the European climate targets to be achieved as well as their associated reduction of greenhouse gas emissions, the electrification of the transport and mobility sector is amongst other potential contributors on the agenda of the German government. Therefore, the “Ampel” coalition agreement of the current German government sets a goal of at least 15 million of only purely electrically powered vehicles on German roads and one million public charging points by 2030 [1]. Considering the current stock of electrical vehicles (EV) and charging points in Germany, about 14,483,000 EVs and 945,000 charging stations must be added in order to meet the goals of the coalition agreement.

While an increased market penetration of EVs accompanied by a nationwide expansion of the charging infrastructure might cause grid congestions, it also provides an opportunity of electrical flexibility to tackle future grid challenges, acting as pro-consumers. To insure the security of electricity supply, it is therefore imperative to estimate the impact of the additional electricity demand on the security of electricity supply. Consequently, the evaluation of the additional electricity demand necessitates the estimate of the electricity demand of electric mobility using charging load profiles. By modelling the charging load profiles in a spatial and timely resolution manner, the window of flexibility can be derived. While few studies model the time dependent charging profiles of EVs, a gap in the spatial dependent charging profiles was noticed. Therefore, modelling the interdependency of charging profiles with the characteristics of spatial mobility classification is introduced in this study.

Methods

Estimation of the future spatial distribution of electrical vehicles

In order to estimate the regional impacts on the charging time series, a spatial distribution of the forecasted number of EVs is necessary. For this reason a multiple linear regression model, to estimate the number of EV by the year 2030 for each of the 401 NUTS3-areas in Germany, is conducted according to [2]. The multiple linear regression model takes various variables such as the current stock of vehicles, the population and the area of each NUTS3 region into account. By combining the aforementioned independent variables with the targeted German-wide market diffusion of EVs, we obtain a regional distribution of projected EVs in the year 2030. Based on the EV stock and its regional distribution, the required number of charging points is subsequently determined.

Allocation of NUTS3-areas to a spatial mobility classification

With the aim of generating charging profiles of EVs dependent on the region type, a further investigation of the characteristics of the 401 NUTS3-areas of Germany is inherent. Due to the fact that interdependencies between transport and spatial structures exist, it is important to make spatially different mobility behaviour visible. According to the RegioStar classification, introduced by the Federal Ministry for Digital and Transport (BMVI), the main differentiation of urban and rural regions can be further differentiated into seven regions (RegioStar7) in total [3]. Each of the approximately 11,000 municipality regions in Germany can be assigned to one of the RegioStar7 classifications. Meanwhile each of those municipalities is also appointed to one of the NUTS3-areas of Germany. Using the municipality regions and their classification to the RegioStar7 categories, the NUTS3-areas will be allocated to the RegioStar7 classification. On that account the RegioStar classification, is used in this research to assign certain user behavioural attributes to the NUTS3-areas of Germany.
Generation of load profiles under consideration of spatial characteristics

For the third part of the methodology, the characteristic of each of the RegioStar7 classifications will be overlaid on the aggregated load profiles in the considered NUTS3-area to achieve spatially dependent refined electric demand of EVs. In this regard, different approaches for generating charging profiles dependent on the characteristics of the area will be considered. These approaches will take into consideration various variables such as the charging location and the level of charging needed.

Results

The preliminary results show the share of EVs in each of the 401 NUTS3-areas. Considerably high shares of EVs were found to be in cities in which car manufacturers have their headquarters, and considerably low shares of EVs were found to be in rural regions. Nevertheless, the model tends to underestimate or respectively overestimate the penetration of EVs in the aforementioned regions. By determining the stock of EVs in each NUTS3 region and classifying the regions according to the RegioStar7, it is expected that the electricity demand resulting from the integration of electric mobility in each of the regions can be calculated. By taking into account, the mobility characteristics of the RegioStar7, each region can be assigned to a different classification than the one it is designated to originally in order to depict the changes in the development of the region and derive more realistic charging profiles for the future.

Conclusions

Through the described approach, synergies regarding mobility characteristics and charging profiles in different types of regions will be derived. By deriving such synergies, a promising primary method for determining future aggregated charging profiles in each of the NUTS3-areas can be composed. With that, the electric flexibility dependent on the characteristics of a region can be derived, which will enable an enhanced planning of future electricity grids.

References