COPING WITH UNCERTAINTIES INDUCED BY BATTERY ELECTRIC DRIVEN VEHICLES IN DISTRIBUTION GRIDS

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Overview

In 2017 the transportation sector accounted for nearly 20 % of all CO_2-emissions in Germany [1]. In view of pollutant emissions like NOx, resource constraints and climate change, the vehicle fleet which generally consists of combustion engine driven vehicles has to undergo a substantial transformation. Alternative propulsion technologies like fuel cell vehicles or battery driven electric (BEV) vehicles provide opportunities to shape the transportation sector in a more environmental friendly and sustainable way. Regarding the current market development of these two technologies, BEV are more likely to achieve substantial market penetration in the near future. Yet it is unclear when this will happen and as a consequence, distribution grids especially at the medium and low voltage levels are facing unprecedented challenges. Especially during the market introduction, it is expected that BEV owners will mostly charge their battery at home using predominantly dumb charging [2]. In order to secure the electricity supply, network operators need to cope with the uncertainties related to simultaneous uncoordinated charging along with other imponderables related to uncertain penetration rates and uncertain charging rates.This paper presents a systematic approach to address this issue, making notably use of a large mobility data set, a stochastic diffusion model for vehicle adoption rates and distributional assumptions on charging power. On this basis, we develop a stochastic model which enables predictions about the peak demand induced by electric vehicles. We make use of the model to investigate the role of the different short-term and longer-term uncertainties when it comes to plan grid enhancements a few years ahead.

Methods

For the dimensioning of electric systems, the highest level of load is a key design criterion. Taking the sum of electrical ratings - here the sum of charging power of BEV - will generally lead to an oversized system, because it is very unlikely that all BEV will charge at the same time - at least in dumb charging. In order to design the system efficiently, rather the coincident demand based on a simultaneity factor should be used. The coincident demand represents the demand that occurs simultaneously [3]. For a given BEV fleet, we first determine the average share of simultaneously charging BEV for each time step to identify the coincident demand. This share is highly dependent on driving profiles, the energy consumption and the average charging power of BEV as well as on the charging behaviour. The driving profiles of commercial and private car owners are taken from two large-scale surveys [4,5], which provide data about the start as well as end time and the driven distance for more than 10,000 observed vehicles. From that information the average travel speed is derived, which can be also used to compute the electricity energy consumption of BEV based on data in [6]. Besides travel speed also ambient air temperature strongly impacts EV consumption. Yet this influence is neglected in the current version of the analysis for sake of simplicity.Regarding the charging behaviour, many surveys have shown that most people with the intention of buying a BEV would generally charge their car at home or near their home [7]. In this paper it is assumed that each private owner has the possibility to charge his BEV at home and is exclusively doing so. Hence, the share of simultaneously charging BEV tends to be somewhat overestimated since both charging at public fast charging stations and at work are ignored.

According to the study (KiD), the average driven distance of an automobile is about 36 km, which implies that a charging power of 3.7 kW is largely sufficient when BEV are charging during night-time for many hours [5]. However, many studies expect considerably higher charging power. Given the lack of reliable data on that issue, we base our analysis on simple distributional assumptions between the main charging types (3.7, 11 and 22 kW) with an increase in the average charging power of private households from 7.4 kW in 2020 to 16 kW in the year 2030. For commercially used BEV a charging power between 11 kW and 22 kW is assumed. The average share of simultaneously charging BEV is then determined by using the sample of travel data per car owner group and day type and the previously described assumptions. Thereby private and commercial car owners are handled separately and travel data are split between weekdays, Saturdays and Sundays. At any given time, a local sample of BEV will have a mix of usage profiles and each of them will either charge or not charge. This local sample can be understood as a subsample of the driving profiles of the relevant group and daytype. The charging at a given point in time can then be described as a drawing from a binomial distribution (either charging or no charging). In order to determine the coincident demand, the 99 % quantile of the binomial distribution is then taken. It is evaluated for the time of day where the expected share p of charging BEV is highest – since this is also the point in time with the highest cumulative probability. The quantile is then obtained from the cumulative distribution function (cdf)

$$F(x) = Prob(X \leq x) = \sum_{k=0}^{x} \binom{n}{k} \cdot p^k \cdot (1-p)^{(n-k)} \geq 0.99$$

Taking the inverse of the cdf and inserting the required quantile (here 99 %), we obtain the number x of charging vehicles out of n, which is not exceeded with 99 % probability. The coincident demand $W_{coincid}$ is then obtained by multiplying the amount of charging BEV x with the charging power. If the uncertainty in charging ratings (with m different types) is taken into account, we have to compute directly the cumulative probability of charging power. It results then from the sum of the cumulative probabilities for each of the m different types coinciding with a charging event and taking into account the charging power

$$F(W_{coincid}) = Prob\left(\sum_{j=1}^{m} X \cdot W_j \leq W_{coincid}\right) = \sum_{j=1}^{m} \sum_{k=0}^{\lfloor W_{coincid} / W_j \rfloor} \binom{n}{k} \cdot (p \cdot p_j)^{k} \cdot (1 - p \cdot p_j)^{(n-k)} \geq 0.99$$

If additionally there is uncertainty about adoption of BEVs, the formula has to be further extended to include the probability of ownership along with the probability for charging powers and for actual charging.

Results

The developed approach allows to cope with multiple uncertainties. It is obvious that the coincident load is depending on many factors like charging power, consumption of the vehicle, the number of existent BEV and driving profiles. First results indicate that most drivers arrive at home around 6 o'clock in the evening, where a high household demand will coincice with charging BEV. The cumulative binomial distribution applied for a given charging power then shows that the simultaneity factor is rather high when only few electric vehicles exist and that correspondingly planning will take into account almost the nameplate capacities of the vehicles.With higher numbers of BEV, the coincident demand moves closer to the average share of simultaneous charging BEV, while the overall electric load obviously increases. Thus, substations in low voltage grids will need to be prepared for a relatively larger load than higher voltage levels. The simulation also shows that a higher charging power lowers the simultaneity factor for charging BEVs, but the resulting network load increases. Furthermore, the first results demonstrate that with a rapid market penetration of BEV, the network load can rapidly increase within a few years.

Conclusions

In this paper an approach is presented to handle comprehensively uncertainties related to dumb charging BEV in order to face coming challenges of peak load in electric systems. For simultaneously charging electric vehicles, the coincident demand may be determined on the basis of driving profiles from German mobility studies and distributional assumptins on the BEV adoption, the charging power and an assumed charging behaviour. Due to higher charging power, the simultaneity factor is expected to decrease over the years. In addition, the number of electric vehicles affects the simultaneity factor: the smaller the sample, the higher the simultaneity factor. As the number of electric vehicles increases, the simultaneity factor decreases. The requirements for grids are rising despite decreasing simultaneity, since with increasing number of BEV and with higher charging power, the electric load by BEV increases. For further research the consideration of seasonal temperature variations may be taken into account as well as the correlation with household load, which has its peak load in similar hours.

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