Role of battery capacity in charging habits of battery electric vehicle users

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Abstract—This paper is focused on the role of battery capacity in charging habits of battery electric vehicle (BEV) users. For this purpose, a simulation that mimics the users' behavior was created. Using this simulation, the differences in charging frequencies in vehicles with different battery capacities were studied. Using the same simulation, a load shape of power demand was derived that showcases how the technological advances in regard to increased battery capacities may affect this power demand.

Keywords—Battery electric vehicle, battery capacity, load modeling, electric vehicle charging

1. INTRODUCTION

The share of BEV among the vehicle fleet is gradually growing. Consequently, the impact of this rise on the power grid is being explored in many research papers. The main effect to consider is the increased demand created by charging of BEVs. Load shape of such demand depends partially on the behavior of individual drivers, especially regarding daily driven distances, conditions and time of connection to charging, etc. The demand created by charging also depends on the structure and parameters of the vehicle fleet, such as consumption of energy and battery capacity. Charging infrastructure in the place of frequent charging also plays a role. This paper aims to show this demand created by BEV charging with special focus on the role of battery capacity on the charging habits of drivers.

2. SIMULATION PARAMETRS

To evaluate the aforementioned effect of rise in battery sizes the simulation aims to mimic the behavior of BEV users to derive the load shape created by the consumption of BEV during their charging over the course of one week. The simulation considers conditions in small sub-urban municipality. The key parameters of the simulation are mentioned in the next paragraphs.

Key parameter is daily energy consumption, that can be calculated by estimating daily driven distance and multiplying it by consumption of energy per km. To estimate the daily driven distance, data from study *Česko v pohybu* were used [1]. On average, one-way trip distance is 15.5 km. Standard deviation of these data is 26.8. According to [2], for estimation of daily driven distances, a log-normal probability distribution function (PDF) can be assumed. Considering that the number of trips in given day is usually 2 (as per data in [1]), the daily driven distance for each BEV is assigned according to log-normal PDF with mean distance of 31 km and standard deviation of 26.8. Logarithmic values calculated from arithmetic values of the associated normal distribution are equal to $\mu=3.155$ and $\sigma=0.747$. In respect to consumption, there are three types of BEV considered in the simulation. Type A with 180 Wh/km consumption and 20 % share in the fleet, type B with 207 Wh/km with 65 % share in the fleet and type C with 263 Wh/km with 15 % share in the fleet.

Another aspect of the simulation is the conditions in which the connection to charging can be assumed. If the mentioned daily driven distances and consumptions are considered, the battery state of charge (SoC) at the end of the day may still remain on a level that does not warrant a plug in for charging. For this reason, a model that does not consider daily charging was created. Specifically, to model driver behavior regarding charging habits a probability of connection is calculated based on SoC at the end of the day. For this calculation an exponential dependence between SoC and probability of connection to charging (p) is assumed, based on [2].

$$p = \frac{1}{1+e^{-k_p \cdot (-SoC + x_p)}}, \quad (1)$$

where k_p represents a coefficient of range anxiety, SoC is state of charge (%), x_p represents a SoC in which $p = 0.5$. In [2], parameters k_p and x_p were set, based on empirical evidence, to $x_p = 35$ and $k_p = 0.13$. Same parameters are assumed in the simulation.

The simulation considers conditions in a small sub-urban municipality, where high share of home charging is to be expected [3] due to higher number of private parking spaces with access to a private charger [3]. The simulation considers three types of chargers, in respect to power. Specifically, 3.6 kW, 6.9 kW and 11 kW chargers are considered. Power delivered from chargers is lowered by expected losses that are defined by the consideration of 95 % efficiency of charging**.** Another important aspect of the simulation is the time in which the connection to charging can be expected. According to [2], normal PDF can be assumed. The simulation used in this paper also uses normal PDF with mean time of connection set to 16.53 h with standard deviation set to 1.99 h. In the simulation it is assumed that all vehicles get charged to maximum SoC.

3. BATTERY SIZE

As mentioned in the beginning, the battery size of vehicles can be one of many factors that play a role in drivers charging behavior. It can be expected that with the growing market share of BEVs, the capacities of battery packs will increase in efforts to make the drivable single charge distance longer. The change in battery sizes could lead to change in users behavior in regard to charging habits.

Based on information in [5], the average battery capacity of the most used BEVs in Czech Republic for year 2017 was about 40 kWh. Based on the top 10 most used BEVs in CZ for year 2021 (as per statistic in [6]) the average capacity is around 54 kWh (battery capacities for each BEV were gathered in electric vehicle database [7]). The average capacity of the top 10 newly sold BEVs in 2021 is about 60 kWh, according to information in [7] and [6]. The analysis [5] assumed the rise in battery sizes to be 2 kWh/year and according to another study in this field [8], a rise in battery capacity by 2030 is expected to be 50 %. For baseline simulation a current condition of the battery sizes was considered. This variant of simulation assumes three types of BEVs with their capacity and share in fleet. Type A is a vehicle with 35 kWh capacity and 20 % share in fleet, type B has a 50 kWh capacity and 65 % share, type C has a 80 kWh capacity and 15 % share. The simulation assumes 1709 BEVs, which simulates a condition that would be present at the place of interest, if all the vehicles would be electric. The availability of charging infrastructure in the place of the longest stay is also important. Because of that another simulation assuming that only BEVs parked in garages would be charged in home was carried out. The number of garages in the place of interest is 742. Results of both simulations are in the following figure.

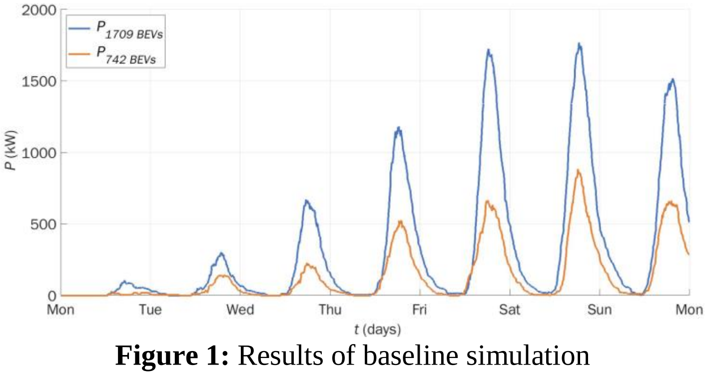

Figure 1: Results of baseline simulation

Important note is that the simulation assumes that all BEVs start the given week fully charged. This situation may not be far from reality as it is quite possible that drivers would want to start weekend fully charged. Since only a few users make trips in lengths, that would warrant a charge after just one day, the load level in the beginning of week is quite low. As the week progresses the expended energy cumulates, and the SoC of vehicle decreases resulting in higher peaks in demand for charging in later days of the week. These peaks directly correlate to number of users that charge their vehicle. In the figure below, the number of drivers charging their vehicles is shown (numbers are relevant for simulation considering 1709 BEVs). Compared to Figure 1, the correlation can be seen quite clearly.

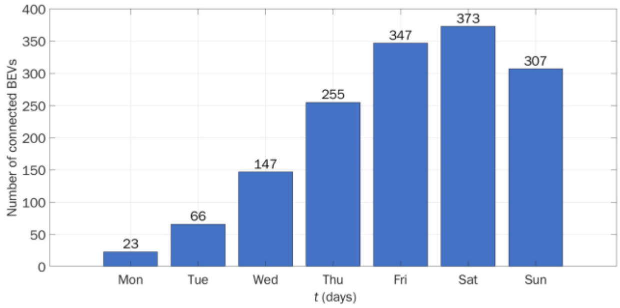

Figure 2: Number of drivers connected to charging each day

Figure 2 shows that the number of drivers connected to charging each day is a key factor, for the total load demand. The number of drivers that will connect is dependent on the capacity of the vehicles, which can be demonstrated by figure 3. It shows how many vehicles from specified vehicle category are being charged each day of the week.

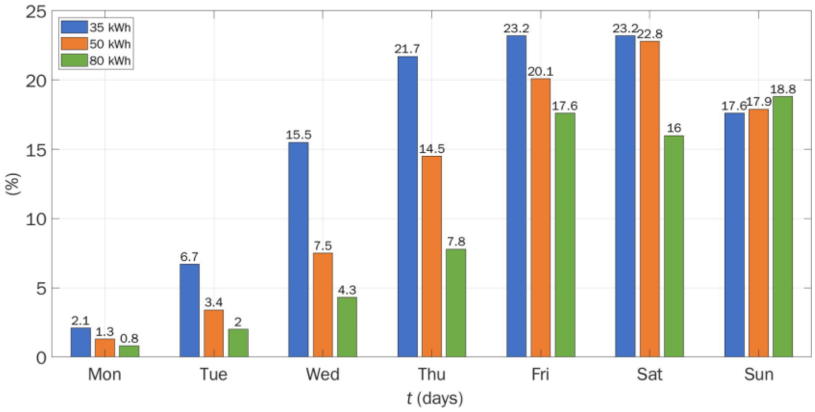

Figure 3: Relative number of drivers (from each vehicle category) that connect to charging

The share of vehicle types is not uniform, so to compare the number of connections across the categories, the number of drivers that connect to charging is shown in values relative to the amount of vehicles in given category. The figure shows that vehicles with the lowest battery capacity (35 kWh) are charged more frequently than the vehicles with higher capacity batteries. Since the role of battery capacity has been established, an analysis of the effect of growing vehicle capacity on the demand created by charging can be examined. The assumed battery capacity growth is 10 kWh over 5-year period. The growth is similar to the one assumed in [5]. Important statistics from the simulation are shown in following table.

Table I: Number of charged vehicles per week

Year	Number of vehicles connected to charging per week	Average recharged energy	Maximum recharged energy	Average charging time	Average charging end time
(-)	(-)	(kWh)	(kWh)	(h)	(hh:mm)
2020	1527	35.8	75.6	6.6	23:12
2025	1242	40.7	80.3	7.5	00:12
2030	906	45.4	91.0	8.2	00:54
2035	649	50.0	104.3	9.3	01:36
2040	483	54.5	106.1	9.9	02:24

With growing battery capacities, vehicles stay in the range of SoC that does not warrant charging for longer time, which in turn results in users charging their vehicles less frequently, this leads to lower number of charged vehicles per week. It should be noted that vehicles that do not get charged in shown week will have to be charged in the next week. The simulation was made to simulate just one week. Because vehicles stay longer without charging, they expand more energy between charges, which leads to increased amount of energy, that needs to be recharged. With this the time it takes vehicles to fully charge increases and subsequently the time when vehicle is fully charged moves more into the following day. As shown earlier vehicles with higher capacities are not charged as often as vehicles with lower capacities. Because the simulation shows only one week, vehicles with high capacities (especially type C) have lower share among vehicles being charged. If a subsequent week was simulated, these vehicles would probably have to be charged, with amount of energy to be recharged higher than shown averages. To show the amount of energy recharged by the vehicles with highest battery capacities among the fleet, the maximum energy recharged is shown. This energy increases with battery capacities as well.

4. CONCLUSION

The main aim of this paper was to show the correlation between BEV user behavior and battery capacity. It was shown that vehicles with smaller battery capacities tend to be charged more frequently. Same effect was shown in simulation that attempted to see how the technological advance leading to increased battery capacities may affect the load demand created by charging. It was shown that growing battery capacities lead to higher amount of energy that needs to be recharged. The charging time for vehicles depends on the amount of energy being recharged and the power of the charger. Increase in recharged energy leads to increase in charging duration and point at which BEV reaches full SoC shifts to later time. If BEV users would want to fully charge their vehicle, increased battery capacities could lead to increased need for higher power chargers, so the vehicles can reach full SoC before their next use (typically overnight). This in turn could lead to increased peaks in power load created by charging. Another possibility is that users may utilize lower power chargers, possibly due to financial reasons and charge their vehicles more frequently, so the amount of recharged energy is not as high. The model shows an ideal situation, where no effects other than battery capacity come to play. It is important to note that there are more factors influence charging behavior. For example, it is possible that in the future some users may utilize devices allowing for charging in times when electricity is cheaper or utilize electricity from photovoltaic panels. These external influences could result in deviation from examined effect of increased battery sizes. The simulation itself is a groundwork for research that will follow.

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