Develop 800V battery architecture to speed up electric vehicle charging: trade-off between charging infrastructure cost and time spent in station.

Anastasia POPIOLEK* [1] [2], **Zlatina DIMITROVA**[1], **Marc PETIT**[2], **Philippe DESSANTE**[2]

[1]Stellantis
Rte de Gisy - 78140 Velizy-Villacoublay (France)
[2] GeePs - Group of electrical engineering Paris, UMR CNRS 8507, CentraleSupélec, Université Paris-Saclay, Sorbonne Université
3 & 11 rue Joliot-Curie, 91192 Gif-sur-Yvette CEDEX (France)
*(Corresponding author: anastasia.popiolek@centralesupelec.fr)

Abstract - Reducing charging time for electric vehicles (EVs) is one of the major targets toward EV's acceptance, especially for long-distance trips and now, some private EV models propose promising low charging times. Thanks to an 800V-system for their battery architecture, those models can charge with a higher power (350kW) compared to the majority of EV models on the road today with a classic 400V-system. However, the question then arises as to whether the reduction of the charging time is worthwhile to improve the quality of the charging service compared to the additional charging infrastructure cost it may generate.

Nomenclature

N_{CS}	Number of charging stations along the highway
N_{fleets}	Number of fleets in the test sample
N_{EV}	Number of EVs per fleet
$C_{station}$	Daily equivalent annual cost of the total added infrastructure, €
r	Discounted rate, %
l	Life time of a charger, $year$
$\bar{t}_{station}$	Average time spent in station by EV drivers during they whole trip, min

1. Introduction

In order to meet environmental standard requirements, the automakers are guiding production towards plug-in electric vehicles (EVs). However, one of the key elements they have to consider for EV design is the battery architecture. For the same capacity of energy, the two possible architectures (400V and 800V) do not permit the same charging power and consequently, do not enable the same charging speed [1], [2]. The 800V system enables to reduce the charging time by increasing to 350 kW the charging power handled by the architecture of the battery whereas the 400V-system configuration does not permit a charge over 175 kW.

Therefore, the 800V-system can reduce drastically the charging time from around 30 minutes (400V-system) to less than 15 minutes and gets closer to the time needed to refuel a conventional internal combustion engine car. However, developing the 800V-battery architecture for light electric vehicles should be made in parallel with the development of DC fast-charging stations proposing 350kW-charging rates on motorways. Yet, the development of such an infrastructure might be expensive if it is not planned as the cost almost doubles for networked 350kW chargers compared with 150kW chargers and quadruple compared with 50kW chargers [3] [4]. The use of very high power levels might also be a burden for the electric grid and cause significant expenses in grid reinforcement to palliate the higher power demand.

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Concerning that last point, a recent report [5] by Enedis and RTE, French operators respectively of the distribution and transmission networks, states that the connections and reinforcements of the grid needed to ensure the power supply of the ultra-fast-charging infrastructure on highways, even in the highest-power demand scenario, will have relatively low costs and that the balance of the grid will not be much impacted by the increase of charging rates. Nevertheless, the electric grid operators need to know which battery architecture will be developed by automotive makers to anticipate the grid reinforcements needed to support the potential higher power demand.

Thus, as the electric grid will be able to handle the higher power demand, we should only consider the impact of the 800V-system EV models development on the cost of the adequate charging infrastructure to be built. For that purpose, we need to find the optimal position and sizing of the charging stations. J. Liu *et al.* [6] propose an optimization of the charging station planning (location and sizing) along motorways in Germany that minimizes the construction cost of the infrastructure and the waiting cost for the drivers. The problem in this paper is solved using a genetic algorithm. T. Bräunl *et al.* [3] also estimate the optimal location and sizing in terms of power level and chargers numbers of fast-charging stations for Western Australia.

In our study, we evaluate the optimal charging infrastructure layouts in function of the share of 800V-system EVs on the road in order to determine how far the 800V architecture should be developed in the next ten years. For a given percentage of 800V models on the road, we aim to find the number of chargers that minimize the cost of the charging infrastructure and the time spent in stations by EV drivers. We use, like in [6], a genetic algorithm to find the optimal solutions and to plot the Pareto-curve associated to different percentage of 800V EVs. Those curves depict the trade-off between service quality provided by the infrastructure (reduction of time spent in station thanks to higher power rates) and cost of this infrastructure. The time spent in station for a given infrastructure layout was computed thanks to a dedicated framework we implemented and that simulates a flow of electric vehicles with the a certain proportion of 800V-sytem EVs and 400V-system on a highway during a day [7].

The first part of this paper presents the methodology used to evaluate to what extent the 800V-system battery can improve the quality of the charging service by saving time in the stations and to determine the infrastructure cost associated. The simulation framework and the objective of the genetic algorithm are described in this section. The second part gives the results obtained for a case study led on the French A6 highway. The last sections conclude and give the perspectives on that research topic.

2. Methodology

2.1. Simulation framework

We implemented a framework that simulate a flow of electric vehicles on the highway during one day [7]. The framework takes as input the parameters of a fleet and of a highway.

- The fleet contains a fix number of electric vehicles. Each EV has its specific characteristics like its battery capacity or its maximum charging power but also trip characteristics like the entry/exit of the highway they take or the time they enter the highway. The trip characteristics are randomly selected according to laws of probability defined in the section 3. The fleet contains a certain share of 800V-system EVs and those EVs can charge up to 350 kW whereas the other EVs of the fleet only charge at 100 kW (400V-system Evs).

- The highway is described by its entrances/exits positions and the positions of its service areas. The potential location of the charging stations along the highway are chosen on the service areas since they are the only areas of the highway allowed to sell energy. As we want to determine the number of charging points best suited for each percentage of 800V-system EVs, the sizing (number and power level of chargers) of each station are the variables of the optimization problem described in the section 2.3.

At the end of the day, according to the scenario followed by the drivers, the framework computes for all EVs of the fleet the time spent in the stations (charging time and waiting time if any). For this study, as the attendance rate at each station (and thus the waiting time there) highly depends on the trip characteristics that are randomly selected, we need to evaluate, given a charging infrastructure, the average time spent in the stations for a large number N_{fleets} of fleets. Indeed, in a random context, we need numerous simulations to be as exhaustive as possible concerning the traffic situations the charging infrastructure can encounter.

2.2. Scenario

The drivers follow the strategy of the "last reachable station" to report on the behaviour of EV drivers who prefer to charge the maximum of energy they can (80% of the battery) before leaving the station. In this scenario, drivers stop at the last station they can reach with their state of charge (SoC) at highway entrance and, there, they charge their battery until 80% of its capacity. They resume their trip until the last reachable station or the highway exit if their remaining energy when leaving the highway is sufficient to reach their final destination. Between stations, the EVs drive on the highway at the maximum speed allowed ($130km/h$). When in charging station, as a station can have different level of charging power, the EVs start charging at the most powerful chargers by order of arrival and if one level of power is saturated, the EVs charge at a lower level. When all chargers are used, the EVs start waiting until a charger become free. There is only one waiting queue at the station.

2.3. Genetic algorithm objective

For a given share of 800V-system EVs in the fleet, we search for the optimal distribution of chargers that should be added to the existing charging infrastructure on highway to meet the charging needs for the next ten years. We define x as the vector describing the number of chargers added to each station depending on their power levels, with n the number of different charging rates:
For $i = 1, ..., N_{CS}$,

$$\begin{cases} x(n.i) = \text{number of 350kW chargers added to the station } i, \\ x(n.i-1) = \text{number of chargers with a power lower than 350 kW added to the station } i, \\ ... \\ x(n.i-(n-1)) = \text{number of lowest-power chargers added to the station } i. \end{cases}$$

For one vector x, we deduce the final number of chargers in each station by adding the chargers from x to the existing ones. Then, we use the framework explained in the section 2.1 to compute the time spent in station $t_{station,i,j}(x)$ of all the EVs in each fleet of the sample. As there are N_{fleets} fleets in the sample, $\bar{t}_{station}$ corresponds to the mean of the average time spent in stations over the N_{fleets} fleets of the sample (see equation 1).

$$\bar{t}_{station}(x) = \frac{1}{N_{fleets} \times N_{EV}} \sum_{i=1}^{N_{fleets}} \sum_{j=1}^{N_{EV}} t_{station,i,j}(x) \tag{1}$$

The daily equivalent annual cost of the added chargers over their lifetime l is calculated according to the investment cost given in [4]. With r the discounted rate, the daily equivalent annual cost $C_{station}$ is given by the equation 2, where $c_i(x)$ represents the cost of the chargers (mentioned in x) added to the station i.

$$C_{station} = \frac{1}{365} \times \frac{r(1+r)^l}{(1+r)^l - 1} \times \sum_{i=1}^{N_{CS}} c_i(x) \tag{2}$$

The equation 3 gives the formulation of the final multi-objective problem for a given percentage of 800V-system EVs in the fleet. X is the trade-off parameter we tune from 0 to 1 in order to find the different Pareto-optimal solutions x_{opt} thanks to the Matlab genetic algorithm. To avoid solution with no added chargers, we set a constraint on the waiting time: this waiting time t_{wait} should not extend 15 minutes for each EV.

$$\begin{gathered} Objective : \min_x C_{total}(x) = X.\bar{t}_{station}(x) + (1-X).C_{station}(x) \\ s.t. \ \forall \text{ EVs}, t_{wait} < 15 \text{ minutes} \end{gathered} \tag{3}$$

3. Case study

3.1. Highway details

The parameters of the highway correspond to the ones of the French A6 highway (direction Paris - Lyon) and the possible charging stations are located on the service areas as indicated in the section 2.1. We do not have the exact amount of chargers in service in each station so the current state of the charging infrastructure on the A6 is cross-referenced with data from [8], [9], etc. The French A6 highway have 13 service areas and 51 entries/exists. The entrance/exit and service areas position are depicted on the figure 1. The current state of the highway in terms of number of charging points is showed on the first plot of the figure 4.

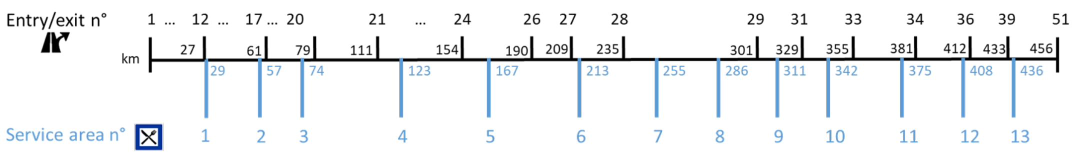

Figure 1 : *A6 highway infrastructure in the framework.*

To compute the infrastructure cost, we consider the cost of the networked added charging points, including cost of hardware and connection to the grid. To simplify the study, we selected only two levels of possible charging rates: 150 kW and 350 kW. The networked 150KW and 350kW chargers cost respectively €$65,000$ and €$120,000$ per unit [4].

3.2. Fleet details

To only focus on the influence of the charging rate of the EVs, we choose to set the same characteristics for all EV models except for the maximum charging power an EV can reach: 70

kWh for the battery capacity, 0.25 kWh/km for the energy consumption and 130 km/h for the maximum speed of the EV [10] and [5].
Concerning the charging power, an EV will charge at the minimum power between its own maximum charging power and the power of the socket. Thus, a 400V-system EV can charge on a 350kW socket but the charging power will be limited and less than 350kW. In this study, the EV can either charge at a maximum of 100 kW (current average charging rate for the 400V-system EV) or 350 kW according to the situation we are simulating. We choose to study three situations with different percentages of 800V-system electric vehicles in the fleet. The first case, with 1% of 800V-system EVs could represent the current situation with few electric vehicles able to charge at 350 kW DC. The second and the third situation, with respectively 50 and 100% of 350kW-charging EVs, are meant to evaluate if automotive makers should develop 800V architecture or keep the 400V-system.
As the charge is not done in reality at a constant power level, we model the charging rate evolution in function of the SoC as in [7] with a slope of $-\frac{500}{EV_{capacity}}$. The SoC of each EV at entrance of the highway follows a normal distribution (80%,15%) truncated at 40% and 95%. The SoC of an EV when it leaves the highway should be higher than 20%. The time of entrance on the highway is randomly determined using the same simplified vehicle flow presented in [7] and given by Fig. 2.

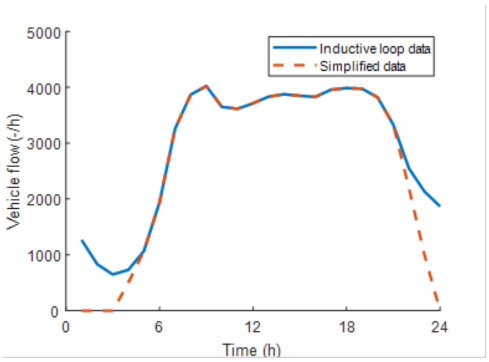

Figure 2 : *Average vehicle flow per hour entering the highway A6 in Île-de-France (direction: Paris to Lyon) during one day. The data comes from inductive loop sensor counting at entrance of the A6.*

3.3. Results

The figure 3 gives the Pareto-front for the three situations studied in this paper: 1%, 50% and 100% of 800V-system EVs in the fleet. Even if the third situation, with 100% of EVs on the road able to charge at 350 kW, will unlikely be reached in the next ten years, studying this situation enables to evaluate the maximum time we can save with a fleet fully adapted to a 350kW charge. As we can see on the figure 3, increasing the share of 800V-system EVs in the fleet always decrease the average time spent in station for optimal distribution of added chargers. Indeed, if we focus on the Pareto-front of a given percentage, all the point on other Pareto-fronts corresponding to a higher share of 800V EVs are on the left of this Pareto-front. Moreover, for the same (and sometimes even lower) cost of added infrastructure, increasing the share significantly reduce the time spent in station. For instance, the labeled points on figure 3 are on different Pareto-front and correspond almost to the same cost per day $C_{station}$ (approx. €400) but the time spent in station for fleets with 1% of 800V-system EVs is reduced by nearly 20% in the case with 50% and divided by more than 2 in the 100% case. We even have a solution on the 100% Pareto curve (point (29 min,€359)) where time is reduced by 47%

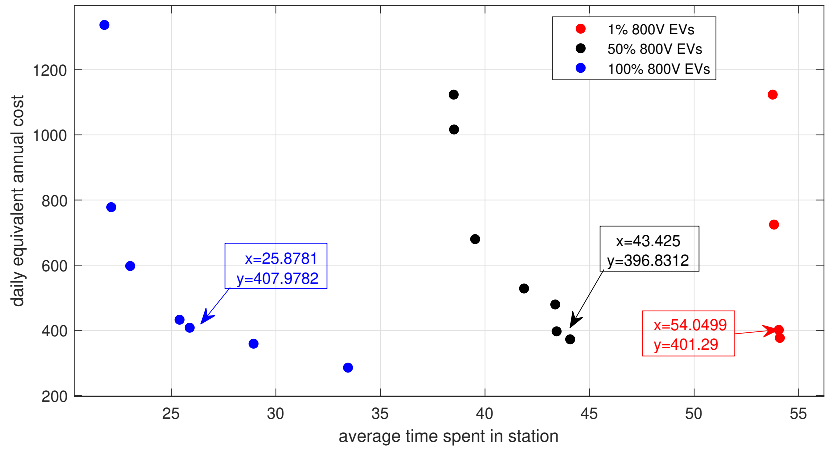

Figure 3 : *Pareto-front for 100 fleets with 1%, 50% and 100% 800V-system EVs. The labeled points are the ones pointed by an arrow.*

while guaranteeing a 5% decrease for the infrastructure cost compared with the optimal solution presenting the lowest cost in the situation with 1% (point (54 min, €377)).

The figure 4 depicts the solution associated to the labeled points on figure 3. For the same cost (approx. €400), the increasing share of 800V EVs makes the total optimal number of chargers to add decrease while the average power level in station increase (due to more 350 kW chargers added). We can notice that the distribution of the added chargers in the 1% case and the 50% case are quite the same, yet, as seen in the previous paragraph, the time spent in the stations is 20% lower in the 50% case than in the 1% case. We can also observe that the optimal solution presented here for the 100% situation is not exclusively with 350 kW chargers and the solution still have the lowest time spent in station. Both observations can be explained by the fact that the right distribution of available 350kW chargers enable the 800V EVs of the fleet to charge faster and consequently reduce the average waiting time for the whole fleet. Indeed, reducing the charging time for some EVs logically reduce the time the other EVs will wait before a charger become free and thus, benefit the entire fleet. Still on the same figure 4, we can see that, for certain service areas with no charger in the current state of the highway (service area n°10 and 13), the three optimal solutions do not propose to add new charging point, whereas they add chargers to the service area n°8, also empty in the current state. This mean that leaving those two service areas (n°10 and 13) with no charger at all is better in our case study than adding a charging station there.

We can also observe on figure 3 the effect of the constraint on the time interval accessible for the 1% Pareto front. Setting the maximum waiting time to 15 minutes impedes to find less expensive infrastructure with higher time spent in station than 54.1 minutes. Moreover, the limitation induced by the lower charging power of the majority of the EVs do not allow to find an average time under 53.75 min. Thus, the interval of possible average times for the 1% Pareto-front is very short (53.75 min to 54.1 min) whereas the one possible for the 100% Pareto-font is 33 times wider.

In view of the foregoing, developing the 800V-battery architecture for EVs going on long-distance trip is worthwhile since, with the optimal distribution of charger mix along the highway, it can improve drivers satisfaction by reducing the time spent in station without increasing infrastructure cost.

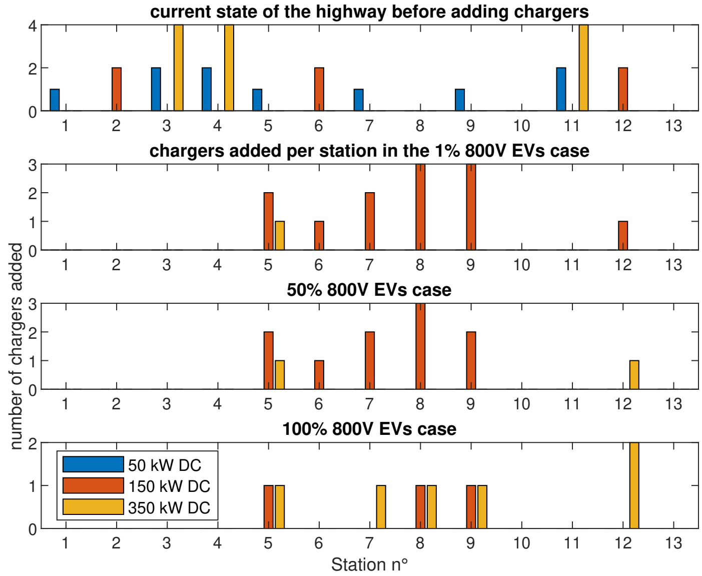

Figure 4 : *Number of chargers added to the current state of the highway for each labeled point on figure 3*

3.4. Limitation

We should bear in mind that we are not assured to find the absolute best Pareto-front with a genetic algorithm, especially for this study where the objective function is costly to evaluate (high number fleets to test, so high number of average times to compute for each x). However, it is possible to find manually the lowest time we can obtain for a percentage of 800V EVs by incrementally adding 350kW chargers until the average time spent in the stations stop decreasing. Yet, we have observed that keeping some service areas with no chargers at all (like the area n°10 and 13) enables to reach a better trade-off. Though, if the incremental adding of 350 kW chargers is done wisely we can at least get the abscissa limit on the left of each Pareto front. Finding the lowest cost is more difficult but, with the results of the genetic algorithm, we can find solution we would not think of and keep searching manually in the same direction to get close to the real limit on the y-axis.

4. Conclusion

This study proposed to evaluate the impact of the development of 800V-system electric vehicle models on driver's satisfaction and on infrastructure cost. We used a genetic algorithm to find, for some chosen shares of 800V-system EVs, the optimal charging infrastructure layouts we should add to the French highway A6 in order to establish a trade-off between time spent in the station (influencing drivers' satisfaction) and added infrastructure cost. To compute the time spent in the stations according to the infrastructure layout tested in the algorithm, we simulated a high number of different EV flows on the highway based on real traffic data and see how the EVs fan out in the charging stations.

After studying three situations with in each case a different share of 800V-system EVs going on long-distance trip, we can conclude that increasing the use of 800V battery architecture significantly reduce the time spent in station for the user while it is possible to find optimal infrastructure layouts that even lower the cost of the chargers to be installed.

5. Perspectives

We did not take into account in this study the economic impact of the 800V-system EV development on the users. Indeed, 800V-system car can be more expensive to purchase than 400V-system EV and the charging price might be higher on 350kW sockets so studies should be led to evaluate this aspect in the trade-off. Concerning the accuracy of the EV flow model, more accurate and precise data would be helpful to determine the real traffic flow on highway during a day (departure time, entries and exits statistics in long distance trip, etc.) and then use the method in this paper to plan the optimal position and sizing of the charging stations. We also plan to consider more fleets in the testing sample used to evaluate the time spent in station (1000 fleets instead of 100) in order to get more exhaustiveness in terms of traffic situations. As for the hypothesis we have made about the drivers following the last reachable station scenario, we might introduce more random behaviour to study other possible distribution of charging events over the stations and see how the optimal planning of the charging infrastructure change to determine the more restrictive scenario.

References

[1] C. Jung, Power Up with 800-V Systems: The benefits of upgrading voltage power for battery-electric passenger vehicles, *IEEE Electrification Magazine*, vol. 5, no. 1, pp. 53–58, Mar. 2017, doi: 10.1109/MELE.2016.2644560.

[2] Voiture électrique: comment le 800 volts va révolutionner la charge, *Automobile Propre*, Sep. 26, 2021. https://www.automobile-propre.com/voiture-electrique-comment-le-800-volts-va-revolutionner-la-charge/ (accessed Jan. 04, 2022).

[3] T. Bräunl, D. Harries, M. McHenry, and G. Wager, Determining the optimal electric vehicle DC-charging infrastructure for Western Australia, *Transportation Research Part D: Transport and Environment*, vol. 84, p. 102250, Jul. 2020, doi: 10.1016/j.trd.2020.102250.

[4] M. Nicholas, Estimating electric vehicle charging infrastructure costs across major U.S. metropolitan areas, International Council on Clean Transportation, Working Paper, Aug. 2019.

[5] enedis and rte, “Etude-les-besoins-electriques-de-la-mobilite-longue-distance-sur-autoroute,” study, Jul. 2021. Accessed: Aug. 30, 2021. [Online]. Available: https://www.enedis.fr/sites/default/files/documents/pdf/enedis-etude-les-besoins-electriques-de-la-mobilite-longue-distance-sur-autoroute.pdf

[6] J. Liu *et al.*, A planning strategy considering multiple factors for electric vehicle charging stations along German motorways, *International Journal of Electrical Power & Energy Systems*, vol. 124, p. 106379, Jan. 2021, doi: 10.1016/j.ijepes.2020.106379.

[7] J. Hassler, Z. Dimitrova, M. Petit, and P. Dessante, Optimization and Coordination of Electric Vehicle Charging Process for Long-Distance Trips, *Energies*, vol. 14, no. 13, Art. no. 13, Jan. 2021, doi: 10.3390/en14134054.

[8] Charging station map for electric cars — Chargemap. https://chargemap.com/map (accessed Jan. 21, 2022).

[9] Autoroute A6: aires d’autoroute, péage, restaurant d’autoroute. https://ulys.vinci-autoroutes.com/autoroute/a6/ (accessed Jan. 21, 2022).

[10] E. Suomalainen and F. Colet, A Corridor-Based Approach to Estimating the Costs of Electric Vehicle Charging Infrastructure on Highways, *World Electric Vehicle Journal*, vol. 10, no. 4, Art. no. 4, Dec. 2019, doi: 10.3390/wevj10040068.

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