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# Enabling ultra-fast charging with 800V-battery architecture: balance between time spent at stations and charging infrastructure profitability

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## Abstract:

The reduction of the charging time for long-distance trips is one of the major levers for improving the acceptance of electric vehicles (EVs). Today, some passenger EV models already propose relatively low charging times thanks to an 800V system for their battery architecture. That battery architecture enables to charge with a higher power (350 kW) than the one permitted by most EV models on the road today with a classic 400V system. However, if EVs can handle higher charging power, the infrastructure should be adapted accordingly. As installing ultra-fast charging points (350 kW) generates higher costs, we can wonder to what extent the gain of time induced by an 800V-system battery and high power infrastructure is worthwhile compared with the additional cost of the adapted infrastructure. To answer that question, we tuned the share of 800V-system EVs travelling on the highway and, for a given percentage, we determined, thanks to a differential evolution algorithm, the Pareto-front that compares the cost of the charging infrastructure built and the time saved with that infrastructure layout. At an identical or even lower cost, increasing the percentage of 800V-system EVs reduces significantly the average time spent at stations. The Pareto curves show that the optimal results are reached for the vehicle fleets with 100% of 800V batteries. Indeed, for those fleets, we can find solutions where time is reduced by 47% while guaranteeing a 27% decrease in the infrastructure cost compared with the optimal solution presenting the lowest cost in the situation today (with barely 1% of 800V EVs on the road).

## Keywords:

400/800V battery architecture, Battery electric vehicle, Charging infrastructure equivalent annual cost, Charging speed.

## 1. Introduction

Nowadays, automakers focus on massively producing plug-in electric vehicles (EVs) to meet environmental standard objectives. Yet, the selection of the battery architecture is a crucial element they must consider for the conception of EV models in terms of design and maximum charging power withstood by the vehicle. The two possible architectures (400V and 800V) do not permit the same charging power for the same onboard energy capacity. By increasing the voltage of the battery architecture, the 800V system increases the charging power handled by the battery pack and reduces this way the charging time. Indeed, higher voltage makes the intensity current in wires, and consequently, the wire section, decrease for the same power. Thus, with different voltages but with the same current intensity delivered by the charging station (with the same DC cable section), the charging power can go up to 350 kW in an 800V-system configuration. In contrast, it cannot exceed 175 kW in a 400V architecture [1].

Therefore, as increasing the charging power accelerate the charging, the 800V architecture for the battery can reduce the charging time drastically from 30 minutes (with a 400V architecture) to around 15 minutes, getting closer to the refuelling time for a conventional internal combustion engine vehicle. The 800V system proposes another advantage: it can also handle a charge at 400V if the voltage delivered by the charging station is limited. However, the development of the 800V-system architecture for light electric vehicles should be led together with the installation of a suitable charging infrastructure offering 350kW-charging rates to be valuable. As the installation costs of such chargers double compared with 150kW chargers, and quadruple compared with 50kW sockets [3] [4], the development of an adapted infrastructure must be planned wisely. Charging at a very high rate might also introduce an imbalance in the electric grid that might force expensive grid reinforcements. As for the last point, RTE and Enedis (operators of respectively the French transmission and distribution networks) stated in a recent report [5] that the reinforcements and connections of the grid needed to avoid congestion caused by fast charging on highways would have relatively low costs even in the highest-power-demand scenario. Nevertheless, to anticipate grid reinforcements adapted to a potential higher

power demand, the grid operators will require to know the battery architecture selected by automakers.

Consequently, as the electric grid should withstand at minor costs the increase of ultra-fast charging demand on the highway, we only focus in this paper on the infrastructure cost generated by the adaptation of the charging network to higher penetration of 800V-system EV models. To find the adapted charging infrastructure, we propose computing the optimal sizing and position of the charging stations, but we need first to define the optimisation objectives. J. Liu *et al.* [6] optimise the planning of the charging stations (location and sizing) with a genetic algorithm to minimise the infrastructure construction cost and the waiting time experienced by the EV drivers. T. Bräunl *et al.* [3] also determine the position and size of the charging stations best suited to Western Australian charging demand on the motorway and add the possibility of having different power levels per station, which is not studied in [6]. The paper takes into account an estimation of the charging demand according to real traffic data and charging time constraints to evaluate the best charging infrastructure planning.

Our study estimates the optimal charging network layouts depending on the share of 800V-system EVs on the road to evaluate how far the 800V architecture battery should grow during the next ten years. Considering a given percentage of 800V-system models on highways, we seek the number of charging points that minimise the equivalent annual cost (EAC) of the charging infrastructure and the time spent at stations by EV drivers. To find the optimal solutions and to plot the Pareto-curve associated with different percentages of 800V EVs, we use a differential evolution algorithm, an algorithm from the same class than the genetic algorithm considered in [6], combined with the convergence method of the NSGA-II algorithm [12]. The curves show the trade-off between the service quality the charging network can provide (reducing the time spent at stations thanks to higher power rates) and the equivalent annual cost of this infrastructure. Contrary to J. Liu *et al.* [6] where the charging infrastructure cost is evaluated with the construction costs only, we choose to compute the total equivalent annual cost of the infrastructure to take into account, besides the construction costs, the maintenance costs and the revenues generated by the infrastructure. This way, we can establish the profitability of the infrastructure for the charging operators. Indeed, the high infrastructure costs prevent the development of the charging network by public institutions only and need a public-private partnership to work. Still, the investment should be profitable for private investors to join the project. We computed the time spent at stations for a given infrastructure layout thanks to a dedicated framework we implemented. This framework simulates a flow of electric vehicles with a certain proportion of 800V-system and 400V-system EV models on a highway during a day [7].

Sections 2. and 3. of this paper introduce the methodology implemented to assess how the 800V architecture for the EV battery can improve the charging service's quality regarding the associated infrastructure cost. The simulation framework and the objective of the differential evolution algorithm are characterised respectively in Sections 2. and 3.. We use the method proposed in this paper on a case study conducted on the French highway A6 and provide the results in Section 4.. Section 5. concludes, and Section 6. proposes perspectives on the topic.

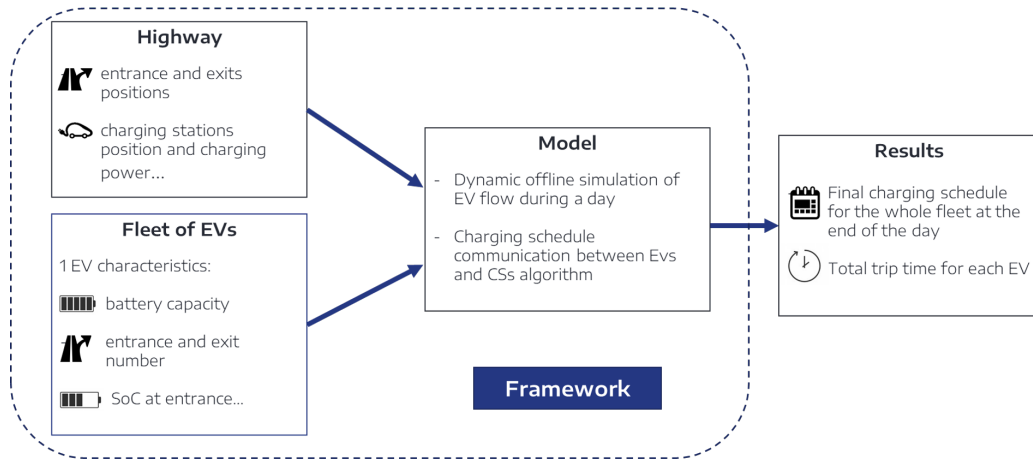
## 2. Simulation methodology

### 2.1. Simulation framework

To evaluate the time spent in stations according to the layout of the charging infrastructure, we have developed a framework simulating a stream of electric vehicles during one day on a highway [7]. The characteristics of the fleet representing the stream of vehicles and the details of the considered highway are given as input of the framework (Fig. 1).

- The fleet consists of a fixed number of electric vehicles going on a long-distance trip. For each EV of the fleet, we randomly select specific characteristics (the battery capacity or maximum charging power) and journey characteristics (when, where and with which state of charge they enter the highway) according to laws of probability defined in Section 4.2.. The fleet has a particular share of 800V-system EVs. As explained in the introduction (see Section 1.), those EVs can charge at a rate of up to 350 kW, while the other EVs in the fleet charge at a lower charging power (400V-system EVs).
- The positions of entries/exits and service areas of the highway are filled out as parameters of the framework. In this study, we consider service areas as the possible locations for the charging stations since they are the only places authorised to sell energy on highways [9]. Considering the objective of this study, we set the sizing (number of chargers per charging rate) of each charging station as the optimisation variables of the problem detailed in Section 3.1.

Depending on the charging strategy chosen by the drivers (Section 2.2.), the framework knows at the end of the day where all EVs stopped to charge and calculates for all EVs in the fleet the time spent at stations (charging time and potential waiting time). In our study, places where an EV driver stops to charge are deduced individually from the EV's journey characteristics and battery capacity. As those parameters are chosen randomly, we need many simulations (so a high number  $N_f$  of fleets) to be as exhaustive as possible regarding the



**Figure 1:** Description of the framework implemented

attendance profile each charging station can face. Thus, we use the previously described framework to retrieve the time spent at stations for all the EVs in each fleet and then, we deduce the average time spent in stations  $\bar{t}_{station}$  for all the fleets.

## 2.2. Charging strategy

EV drivers' behaviour on the highway is uneasy to predict, so we hypothesise that drivers adopt the "last reachable station" strategy. That charging strategy consists of stopping at the last station reachable with a given state of charge at the highway entrance and then charging the battery to 80% of the capacity (maximum an EV can charge at high speed) before resuming the trip until the next reachable station or the end of the journey. We add another feature to consider the case where the drivers stop at the last reachable station and notice they only have less than 80% of their mid-range to go til the end of the trip: they will only charge up to 50% of the battery capacity instead of 80%. Adding that functionality in the scenario enables to take into account with more accuracy the EV driver's behaviour. Indeed, we avoid that the modelled EV agent spends more time charging (to 80%) than a real EV driver who would stop charging before (at 50% of SoC, for instance) because they need far less than 50% of their battery to reach their destination.

When in a charging station, as a station can have different levels of charging power, the EVs start charging at the most powerful chargers by order of arrival. 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 becomes free. There is only one waiting queue at the station.

## 3. Optimization

### 3.1. Variable: number of chargers per station

Given a penetration rate of 800V-system models in the fleet, we seek the optimal number of chargers that have to be built in each service area to satisfy the fast-charging demand for the next ten years. The vector  $x$  describes the distribution of chargers per station according to their rate, so, with  $n$  the number of different charging rates, we have:

for  $i = 1, \dots, N_{area}$ ,

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

### 3.2. Determination of the time spent at stations

We use the framework explained in Section 2.1. to compute the time spent in stations  $t_{station,j,k}(x)$  of all the EVs in each fleet of the sample. As there are  $N_f$  fleets in the sample,  $\bar{t}_{station}$  corresponds to the mean of the average time spent in stations over the  $N_f$  fleets of the sample (see (1)).

$$\bar{t}_{station}(x) = \frac{1}{N_f \times N_{EV}} \sum_{j=1}^{N_f} \sum_{k=1}^{N_{EV}} t_{station,j,k}(x) \quad (1)$$

### 3.3. Evaluation of the charging infrastructure cost

To reflect the cost-efficiency of the charging infrastructure, we choose to compute the equivalent annual cost (EAC) of the infrastructure. The infrastructure EAC corresponds to the equivalent constant annuity whose net present value (NPV) over the lifetime of the infrastructure is equal to the net present value of the installed infrastructure itself [11]. The EAC is not very precise concerning the revenue the installation will retrieve because the consumption of the EV fleet over the lifetime of the infrastructure will fluctuate; still, it can give an idea of the future profitability of the investment and evaluate if the infrastructure is too over-sized. Indeed, a charging station over-sized will be less efficiently used than a fitted charging station and thus, for the same revenue, the investment costs of the over-sized infrastructure will be higher, and so the EAC. The use of the EAC also enables to take into account the maintenance costs (proportional to the number of installed chargers) and the reduction of installation cost per charger permitted when multiple chargers of the same power are installed in the same station [4].

The expression of the EAC of the charging infrastructure  $EAC_{CI}$  is given in (2) with  $r$  the discount rate and  $L$  the lifetime of the infrastructure.  $c_i(x)$  corresponds to the cost of the chargers (mentioned in  $x$ ) installed in the station  $i$  and  $C_M(x)$  describes the maintenance cost of the infrastructure. Finally,  $R(x)$  details the annual net revenue computed from the daily net revenue.

$$EAC_{CI} = \frac{r(1+r)^L}{(1+r)^L - 1} \times \sum_{i=1}^{N_{area}} (c_i(x)) + C_M(x) - R(x) \quad (2)$$

The daily net revenue  $\bar{R}_{daily}$  is calculated according to the average energy consumption over the  $N_f$  fleets of the sample during one day (3). The charging operators buy the electricity that will power their chargers at an industrial price  $p_{el}$ , and they charge the service at a price depending on the power  $p_{sales}$ . We consider that the previously computed daily net revenue is constant over the year, so the annual net revenue  $R(x)$  is simply  $365 \times \bar{R}_{daily}$

$$\bar{R}_{daily} = \frac{1}{N_f} \times \sum_{j=1}^{N_f} E_{cons..j}(x) \times (p_{sales} - p_{el}) \quad (3)$$

### 3.4. Range constraints

Before solving the final problem, we need to determine the constraints linked to the limited range of EVs. Indeed, as we accept that the number of charging points can be null in some stations, it means that EVs will have to drive more to reach the next station and sometimes, they will not have enough range to do so. Hence, we define a matrix  $A_{ineq}$  and a vector  $b_{ineq}$  such as: If  $A_{ineq} \cdot x < b_{ineq}$ , then  $\forall j \in [1, N_f] \forall EV \in fleet_j$  EV can reach its final destination.

$A_{ineq}$  is the matrix representing clusters of service areas where the installation of only one charging station in any service area of the cluster will prevent the EVs from being out of range without a charging station reachable. One line in  $A_{ineq}$  corresponds to a cluster of service areas: there is a coefficient  $-1$  in the columns associated with the areas of the cluster and a coefficient  $0$  in the others. Hence,  $A_{ineq}$  has as many lines as the number of clusters and a number of columns equal to the number of service areas on the highway times the number of levels of charge.  $b_{ineq}$  is equal to a vector of  $-0.5$  to, as soon as  $x$  contains at least one charger in one of the service areas of each cluster, the constraint  $A_{ineq} \cdot x < b_{ineq}$  is fulfilled.

In order to ensure that all the EVs can reach their destination, clusters are determined according either to the minimum range in the fleet or to the SoC at entrance of EVs or to the SoC required when leaving the motorway.

### 3.5. Multi-objective problem formulation for a given percentage of 800V-system EVs

Equation (4) gives the formulation of the final multi-objective problem for a given percentage of 800V-system EVs in the fleet. To avoid solutions with a high waiting time, we set the following constraint: the waiting time  $t_{wait}$  should not extend 15 minutes for each EV.

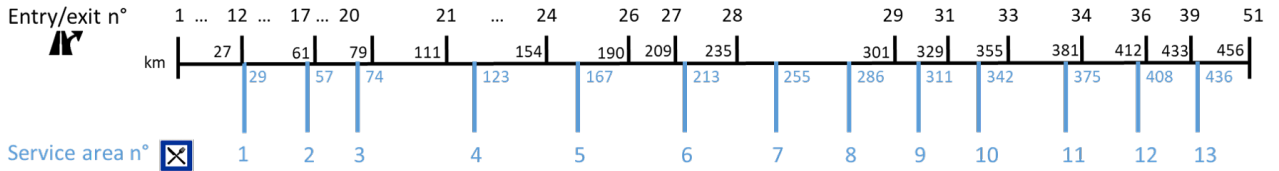
$$\begin{aligned} \text{Objective : } \min_x [ \bar{t}_{station}(x), EAC_{CI}(x) ] \\ \text{s.t. } \forall \text{ EVs, } t_{wait} < 15 \text{ minutes} \\ A_{ineq} \cdot x < b_{ineq} \end{aligned} \quad (4)$$

The problem is solved using a differential evolution algorithm to perform the mutation and the cross-over in the population of chargers distribution while the selection of the new population (the convergence) is done in the same way as in the NSGA-II algorithm [12] with a non dominated sorting of the population before selection.

## 4. Case study

### 4.1. Highway details

The characteristics of the highway in the framework match the ones of the French highway A6 (from Paris to Lyon). The locations of the potential charging stations are chosen in the service areas as mentioned in Section 2.1.. Nowadays, the number of chargers is rapidly growing in service areas of the highway A6. However, the distribution of chargers in areas is uneven and not correlated with the actual needs. Hence, we aim to determine the optimal infrastructure configuration we should install along that highway for the next ten years. There are 51 entries/exits and 13 service areas on the French highway A6. The Fig. 2 depicts the entrance/exit and service areas positions.



**Figure 2:** Highway A6 infrastructure in the framework. The position of some entry/exit of the highway are not shown

As the French government plan to equip all highway service areas with a fast-charging station by the end of 2022, we suppose that, after 2022, the transformers already in service areas will be adapted to the load represented by the charging station. Consequently, we only consider the cost of the networked charging points (including the cost of hardware and connection to the grid), with no consideration of the transformer cost. 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]. As we mentioned it before in Section 3.3., the installation cost per charger depends on the level of the charger but also on the number of chargers with the same charging power level installed in the station (Section 3.3.) [4].

**Table 1:** Charger hardware installation cost according to the level of power. The figures were obtained from [4] by multiplying the installation costs expressed in dollar by the changing rate 0.88 to convert the costs in euros

Installation cost per charger depending on the number of chargers to install in the station				
charger power	1 charger	2	3 - 5	more than 6
150 kW	€42047.28	€33481.36	€24914.56	€16347.76
350 kW	€58065.92	€46236.08	€34405.36	€22575.52

The maintenance costs are evaluated to 1% of the investment cost, and the discount rate  $r$  is chosen equal to 5% as the infrastructure development is a public-private partnership [10].

**Table 2:** Values of the parameters used in the study

parameter	description	value %
$p_{el}$	electricity price per kWh for industrials	€0.08
$p_{sales}$	energy price per kWh for EV drivers	€0.59 (150 kW)/ €0.79 (350 kW) <sup>1</sup>
$C_{charger}$	hardware cost per networked charger	€65,000 (150 kW)/ €120,000 (350 kW)
$C_M$	maintenance cost	1% of the investment
$r$	discount rate	5%
$L$	lifetime of the chargers	10 years
$N_{area}$	number of service areas along the highway	13
$N_f$	number of fleets in the sample	100

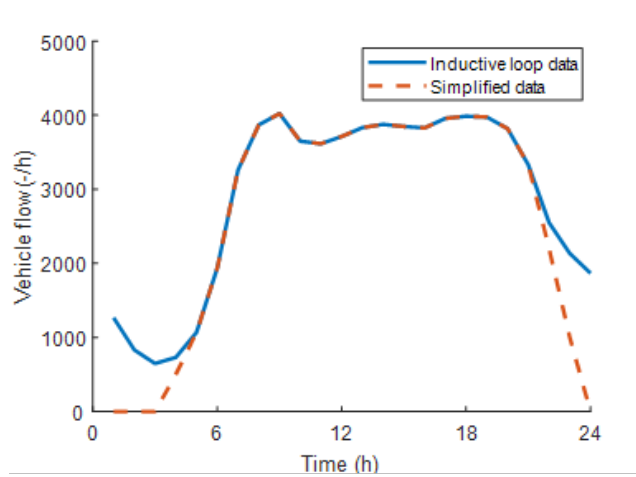
<sup>1</sup>prices charged by Fastned [13] for charging at 150kW chargers and by Ionity [14] at 350kW chargers. We can note that in France,

## 4.2. Fleet details

As we want to study the influence of the charging rate limit of the EVs on the service quality and the infrastructure cost, we set the same specific characteristics for all EVs in the fleet except for the maximum level of charge. Thus, the EVs have the same battery capacity (70 kWh), the same energy consumption on the highway (0.25 kWh/km) and the same maximum speed (130 km/h). We select those characteristics based on the hypotheses made in [10] and [5].

Regarding the maximum charging speed, the EVs with a 400V-architecture battery can charge at a rate of up to 100 kW (current average maximum charging power), whereas the rate for 800V-architecture EVs can go up to 350 kW. We run the method described in this paper for three percentages of 800V-architecture EVs going on the highway during one day. With 1% of 800V-system EVs in the fleet, the first case could stand for today's situation with few electric cars charging at 350 kW DC. The second and third cases, with 50% and 100% of 350-kW-charging EVs in the fleet, will help the automotive makers decide whether they should propose 800V-system models or keep a classic 400V-system for future vehicles.

We should also take into account that the charging rate varies during the charge: we model the evolution of the charging power according to the SoC linearly with a slope of  $-\frac{500}{EV_{capacity}}$  (see [7] for the equation details). We use a normal distribution (80%,15%) truncated at 40% and 95% to determine the SoC of each EV when it enters the highway. We randomly determine the time of entrance on the road using the vehicle flow given by Fig. 3 and presented in [7]. When leaving the motorway, the EV should have a SoC superior to 20%.



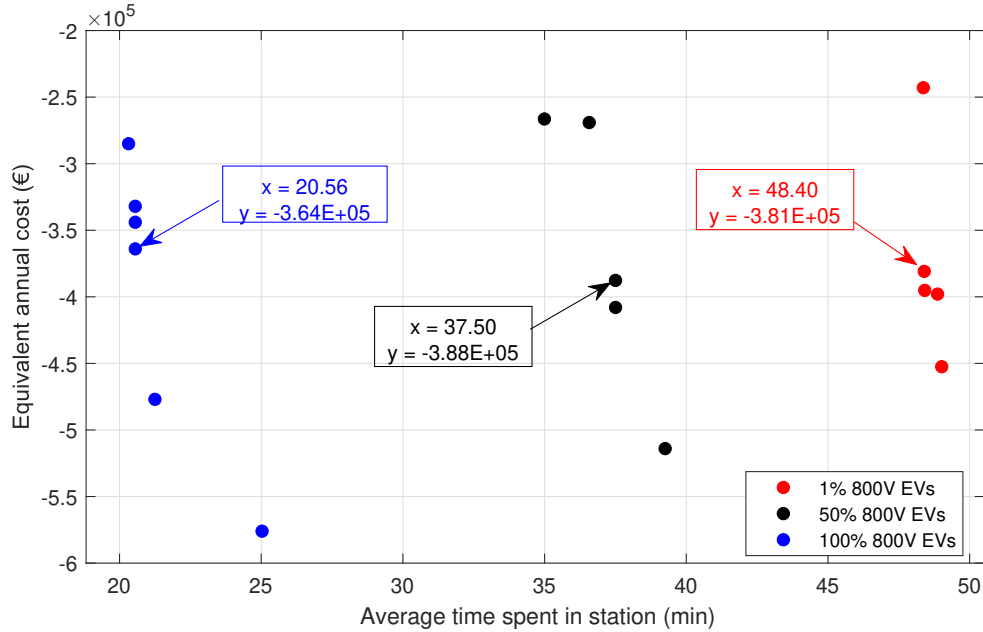
**Figure 3:** Average EV stream per hour entering the French highway A6 in Île-de-France (direction: Paris to Lyon) during one day. The inductive loop data curve was deduced from inductive loop sensor counting at entrance of the highway.

## 4.3. Results

The Pareto-front found for 1%, 50% and 100% of 800V-system EVs in the fleet are given in Fig. 4. We can first notice that all the points on the different Pareto-fronts have negative EAC which means that all those distributions of 150 and 350kW chargers are profitable for the charging operators.

We can then observe that the best Pareto-front is obtained for the 100% 800V-system EVs share with time spent in stations running from approximately 20 minutes to 25 minutes for benefit evaluated respectively to €285,000 and €576,000 ( $-EAC_{CI}$ ). This front is the best since all the points of the other Pareto-fronts are dominated by at least one point of the 100% front. More generally, it appears that the increase of the share of 800V-system EVs in the fleet always decrease the average time spent in stations for optimal distributions of 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 the stations. For instance, the labelled points on Fig. 4 are on different Pareto-front and correspond almost to the same equivalent annual cost  $EAC_{CI}$  (approx.  $-\text{€}378,000$ ) but the time spent in stations for fleets with 1% of 800V-system EVs is reduced by more than 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 (25 min,  $-\text{€}576,000$ )) where time is reduced by 48% while guaranteeing a 27% decrease for the infrastructure EAC compared with the optimal

contrary to the majority of European countries, the price charged by Ionity depends on the charging time and not on the amount of energy charged but for uniformity of the implementation we choose to evaluate in function of energy and not of charging time



**Figure 4:** Pareto curves for 1%, 50% and 100% of 800V-system EVs in the fleet

solution presenting the minimum EAC (and so the maximum benefit since  $EAC < 0$ ) in the situation with 1% (point (49 min,  $-\text{€}452,000$ )).

If we have a look to the distribution of chargers corresponding to the labelled point on Fig. 4, we see that the power installed per station increase with the share of 800V-system EVs: 6300 kW installed for 1%, and respectively 6850 kW and 8050 kW for the 50% and 100% share (Fig. 5). The power installed in the stations logically increases with the rise of the share but the power only grows by 27% from the 1% to the 100% case whereas the time spent in stations is reduced by more than 55%. Thus, the reduction of the time spent in stations will be made with a manageable increase of installed power and the 8 MW of installed power for the 100% share is lower than the average installed power per station computed in the study by Enedis and RTE [5] for the scenario with the highest-power demand (12 MW). The 100% distribution does not have any 150 kW charger, but it is not always the case for all optimal distributions found for the 100% share: for instance, the point (25 min,  $-\text{€}576,000$ ) with the lowest EAC corresponds to an infrastructure with the installation of 150 kW chargers at several service areas.

#### 4.4. Limitations

In the model, we did not consider the charging cost for an EV in the optimisation. Consequently, for some stations where enough EV drivers stop to generate revenue that can compensate for the higher cost of one or more 350 kW chargers, the charging operators can obtain a lower EAC by replacing some 150 kW sockets with 350 kW chargers whereas most of the EV models can only charge at 100 kW and do not fully benefit from 350 kW sockets. The 400V-system EVs will pay more when charging at the 350 kW socket than at 150 kW sockets but they will charge at the same speed than with a 150 kW socket. Therefore, this service will not benefit the EV drivers in that case but only the charging operator. One solution would be to enable the driver to choose the charging level best suited for their EV instead of always taking the highest-rate socket available, as it was implemented for this study. Then, if necessary, this solution can be combined with the consideration of the charging cost for the EV as an objective of the optimisation problem.

Moreover, the higher purchase cost of the current 800V system was not considered in the equation on purpose since we estimate that if the automotive makers choose to develop 800V-system EVs instead of 400V vehicles, the purchase prices of 800V EVs will rapidly drop with the increase of sales and the purchase price difference will be marginal.

Another limitation concerns the use of a differential evolution algorithm as a solver since it does not ensure that the solutions found are on the absolute best Pareto-front. Moreover, as the objective function is costly to evaluate (high number of fleets to test for one evaluation), the algorithm is slow to converge. But we use the results found by the differential evolution algorithm to manually decrease for each station the number of chargers or keep the same number of chargers per station but change their allocation between 150kW and 350kW power to reduce the EAC while maintaining the same  $\bar{t}_{station}$ . That manual process could be automatised and used as a new mutation to speed up the convergence of the algorithm.



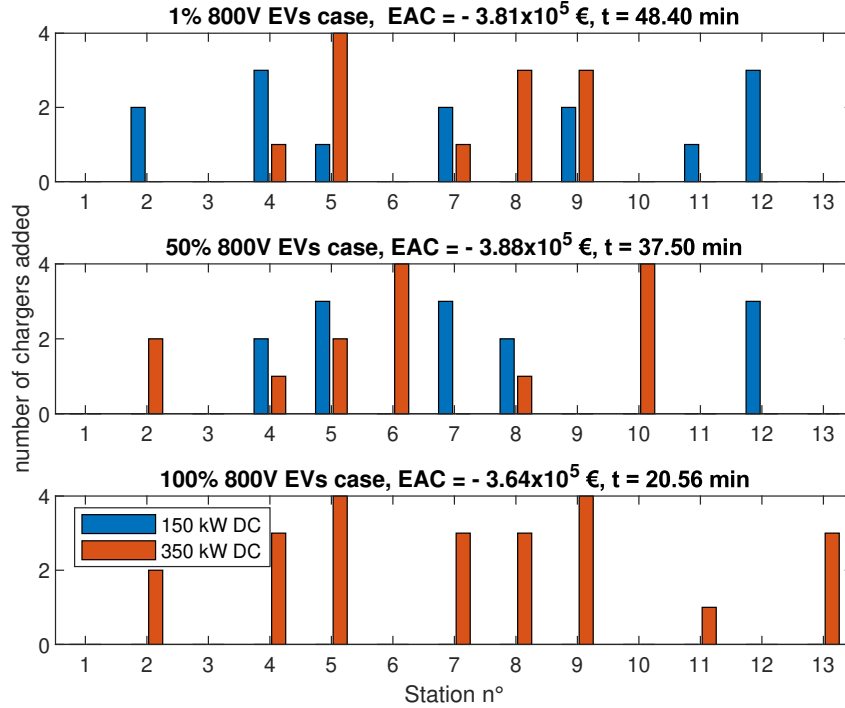


Figure 5: Example of 150 and 350 kW charger distribution for the labelled points on the Fig. 4.

## 5. Conclusion

We proposed in this study a methodology to evaluate the impact of developing 800V-system electric vehicles on the cost of the charging infrastructure to be installed on the highway and on EV drivers' satisfaction. For that purpose, we simulated 3 cases with different percentages of 800V EVs in fleets going on the French highway A6: 1%, 50% and 100%. For each share of 800V-system EVs, we determined the optimal distribution of 150 kW and 350 kW chargers over the different service areas of the highway to save time in charging stations while reducing the equivalent annual cost of the infrastructure to make it as profitable as possible ( $EAC < 0$ ). The time spent in stations and the average annual energy consumption used to compute the installation revenue were obtained thanks to a framework we implemented and that simulates a stream of EVs going on long-distance trips on the highway during one day.

The results showed that we could find several layouts of charging infrastructure for each percentage of 800V-system EVs that are all profitable ( $EAC < 0$ ) and that enable drivers to save as much time as possible. The increase of the share of 800V systems logically always induces an important decrease in time spent at stations. Still, we can find optimal infrastructure layouts for that increasing share with even lower equivalent annual cost.

## 6. Perspectives

As mentioned in Section 4.4., we need to consider the charging cost for the user in the optimisation problem and allow the drivers to charge at the power level best suited for their EV model (400V or 800V-system models). To speed up the convergence of the differential algorithm, we could introduce new mutations that can wisely re-organise the chargers distribution in one station to decrease the EAC while maintaining the same time in stations.

For the study, we have considered a fleet size of 50 EVs to reduce the evaluation cost of the objective function since we simulated 100 fleets of 50 EVs to compute the average time spent at stations. In reality, the number of EVs going on long-distance trips will be much higher (especially for holiday departure periods). Hence, we should see how the optimal layouts will evolve to see if any trend emerges or if we need to perform the study for each fleet size we want to consider.

As for the chosen strategy of "last reachable station", we could also evaluate other strategies for the charging behaviour of the EV. For instance, we can compute the optimal infrastructure in a case where EVs dynamically communicate their charging plan to stations to obtain from them an estimation of the waiting time there and adapt their charging plan as it was proposed in [7]. The EAC of the infrastructure might even be lower than what we have found so far since the EVs will use the infrastructure more efficiently.

## Acknowledgments

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## Nomenclature

- $A_{ineq}$  matrix with 0 and -1 describing the inequality constraints associated with stations clusters,
- $b_{ineq}$  constant vector of -0.5 representing the right part of the inequality associated with stations clusters,
- $c_i(x)$  total hardware and installation costs of the chargers installed in the station  $i$ , €,
- $C_M(x)$  cost of maintenance of the infrastructure during one year, €,
- $EAC_{CI}$  equivalent annual cost of the charging infrastructure, €,
- $E_{cons.,j}(x)$  energy consumed by the fleet  $j$  during one day, kWh
- $EV_{capacity}$  capacity of the EV battery, kWh
- $n$  number of different charging rates considered in the study,
- $N_{area}$  number of service areas on the highway,
- $N_f$  number of fleets in the sample to test,
- $N_{EV}$  number of EVs per fleet,
- $L$  lifetime of a charger, yr
- $p_{el}$  electricity price for industrials, €/kWh
- $p_{sales}$  energy price for the client, €/kWh
- $r$  discounted rate,
- $R(x)$  annual net revenue generated by the sales of energy in station, kWh,
- $\bar{R}_{daily}$  average on the  $N_f$  fleets of the daily net revenue generated by the sales of energy in station, kWh
- $soC_{in}$  SoC of an EV when entering on highway, %
- $soC_{out,req}$  SoC required for an EV when leaving the highway to reach its final destination, %
- $t_{station,j,k}(x)$  time spent by an EV  $k$  from the fleet  $j$  in station for a given  $x$ , min
- $\bar{t}_{station}(x)$  average time spent in station over the EVs of all the fleets of the sample, min
- $t_{wait}$  waiting time for an EV during one charging stop, min
- $x$  vector describing the number of 150 and 350 kW chargers per station,

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