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Coordination interest in electric vehicles long distance trips

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Abstract

In a context of CO_2 emissions reduction, carmakers are looking toward battery Electric Vehicle (EV), a mature technology which is considered as zero tank-to-wheels emissions. Even if this technology is perfectly adapted to daily commute, it encounters two issues for long trips utilization: short ranges and small amount of charging stations in public spaces. The drop in battery prices and the rise of their energy density permitted the introduction of consumer cars with more than 400 km range, while improvements in high power charging point units (with a rate 100 kW and above) offer hundreds of kilometers range gain in 20 minutes. In those conditions long distance trips can also be performed. One risk remains: the travel time depends on the availability of charging stations, which can drop during rush hours, due to long queue, or grid power overload. This paper discusses about systems that can coordinate electric vehicles during long distance trips, where they have to use fast charging stations. We will provide a framework to highlight potential benefits of such system. It will be illustrated with an application over a highway with 100 EV. Results show a better distribution of EV in all charging stations and a average time gain of 27%.

Keywords: Electric Vehicle, Fast charge, Simulation, Optimization.

1 Literature review

The main design criteria for the modern sustainable development of vehicle powertrains are the high energy efficiency of the conversion system, the competitive cost and the lowest possible environmental impacts. An innovative decision making methodology, using multi-objective optimization technics is developed in [1]. The idea is to obtain a population of possible design solutions corresponding to the most efficient energy system definition. These solutions meet technical, economic and environmental optimality. The authors apply the methodology on an electric vehicle, in order to define the powertrain configuration of the vehicle, to estimate the cost of the equipment and to show the environmental impacts of the technical choices of the powertrain configurations in a life cycle perspective.

The deployment of charging infrastructure is the prerequisite for the spread of electric vehicles. A well-established charging network increases vehicle miles using electricity, relieves range anxiety and reduces inconvenience concerning charging process. The research question in [2] was: where to install the charging stations to facilitate the long-distance travels and to meet the urban (local) demands considering both the existing stations and the installations are to be realized by legal regulations ? The authors have elaborated weighted multi-criteria methods for both the national roads and the counties or districts. Several demographic, economic, environmental and transportation-related attributes, as well as the available services (points of interests) that influence the potential for charging station use, have been identified and their effects have been revealed in system approach.

Mobility offerings have never been as abundant and varied as the present, as highlighted in [3]. While users welcome new and innovative mobility options, this current paradigm shift presents a challenge for authorities that plan, organize, and operate such services. In particular, integrating new mobility services into existing infrastructure systems can generate problems of acceptance, co-operability, and compatibility. This problem is especially relevant for electric vehicles. Limited range and battery capacity of battery electric vehicles make them dependent on charging infrastructure, which in turn hinders their acceptance.

The authors investigate in [4] the deployment of two types of charging facilities, namely charging lanes and charging stations, along a long traffic corridor to explore the competitiveness of charging lanes. Given the charging infrastructure supply, i.e., the number of charging stations, the number of chargers installed at each station, the length of charging lanes, and the charging prices at charging stations and lanes, we analyze the charging-facility-choice equilibrium of EVs. The authors discuss the optimal deployment of charging infrastructure considering either the public or private provision.

The work presented in [5] established a mathematical model to optimize the layout of charging infrastructure based on the real-world driving data of 196 battery electric vehicles in Wuhan. Two hundred and thirty-three candidate locations of the charging site were designated by analyzing these data. The mathematical model was implemented, using genetic algorithm with Matlab software. The life of power battery of battery electric vehicle was shortened under over discharge (state of charge below 20%). The work presented in [6] uses market analysis and simulation to explore the potential of public charging infrastructure to supply US battery electric vehicle (BEV) sales, increase national electrified mileage, and lower greenhouse gas (GHG) emissions. Some infrastructure deployment costs can be defrayed by passing them back to electric vehicle consumers, but once those costs to the consumer reach the equivalent of approximately 12/kWh for all miles driven, almost all gains to BEV sales and GHG emissions reductions from infrastructure construction are lost.

In this paper we are motivated by the means that have to be implemented in order to coordinate the choices of EVs quick charge, especially during long distance trips. By allowing electric vehicle drivers to avoid queues, it shows great potential time savings for users and better use of the charging infrastructure. However, these means must be designed in such a way that they can be easily implemented. Reference [7] offers a model that guarantees the confidentiality of users' data, in particular their vehicle condition and destination. It is based on reservations, transmitted by mobile networks, which allow charging stations to estimate their waiting times and vehicles to choose stations based on these data. The authors in [8] offer a solution that only requires local communications, including a cooperative exchange between vehicles to determine who should stop at the next charging station. They are based in particular on the work of [9], which shows that the optimal solution to this relaxed problem is achieved when the occupancy rate is constant, this means when the vehicles are equally distributed at the different charging points. The authors of [10], on the other hand, use game theory tools to allow users to optimize their travel costs and recharging stations to maximize their earnings, assuming that hourly prices are freely set: this results in a non-collaborative game. Overloading of the electricity grid is also taken into account. A cooperative approach to game theory is developed in [11], which makes it possible to gain in convergence speed and robustness.However, these articles only compare the performance of their solutions with theoretical solutions, and which does not permit to evaluate the remaining potential gain. We therefore proposed an approach to find an optimal recharging choice solution based on a differential evolution algorithm.

In the following we will present how the problem is modeled, the resolution method implemented as well as an application to a simulation of the vehicles flow on a highway.

2 Proposed approach

2.1 Model

2.1.1 Situation

In the present paper we develop a model to simulate a flow of electric vehicles on a highway. This function takes as input :

- A highway layout, specified by its entrance, exits and charging stations characteristics: position, number of charging points, available power
- A fleet of vehicles, defined by their intrinsic attributes: battery capacity, maximum charging power, consumption…

- Their trip characteristics (start time, state of charge (SoC) at entrance, origin and destination)
- The vehicles charging schedules, stored as triplets (Vehicle id, Station id, recharged Energy (kW.h))

The function then compute traveling times for all vehicles, taking into account queues at charging stations. Traveling times (T_{Trip}) are composed of driving time $T_{Driving}$ and time in charging stations $T_{Station}$, as described in (1). In the upcoming sections we will develop a method to find an optimal solution to minimize the total travelling time for a given highway and fleet of vehicles. The solution will be the set of charging schedule for each electric vehicle that minimize the sum of all traveling times.

$$\begin{aligned} T_{Trip} &= T_{Driving} + T_{Station} \\ T_{Station} &= T_{Wait} + T_{Charge} + T_{Other} \end{aligned} \tag{1}$$

where:

T_{Wait}	$=$	Waiting time for an available charging point, when the station is full
T_{Charge}	$=$	Time required to store the intended amount of energy
T_{Other}	$=$	Constant representing time needed for all other operation: decelerating, accessing the station, launching the charging session *(here set to 5 min)*

Figure 1 shows the structure of the developed model. Thereafter the highway characteristics and the vehicles planned trips are constant and we will optimize the choice of places to stop and the quantity of energy to store for each vehicle. The objective will be to reduce the output of the model: the sum of all waiting and charging time for all vehicles. We then define the function f in (2).

$$f(x, y) = \sum_{EV} \sum_{CS} T_{Trip} \tag{2}$$

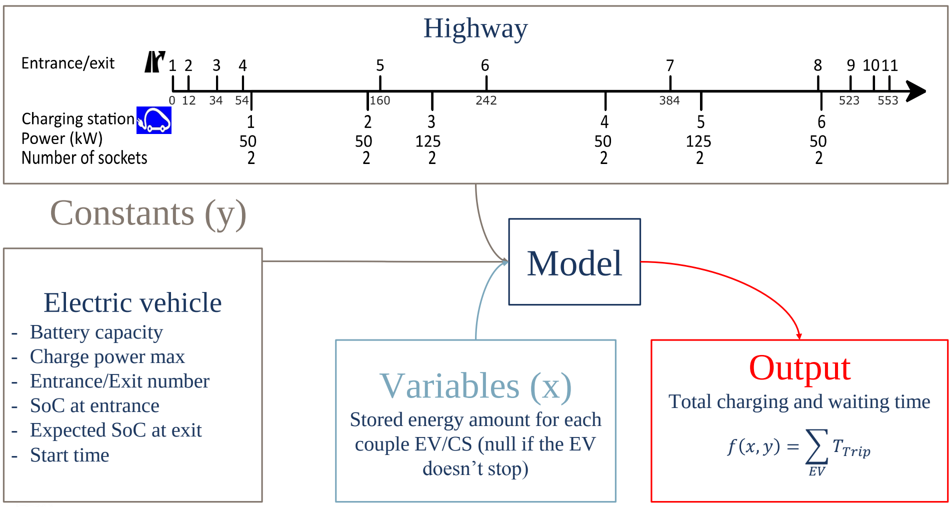

Figure 1: Conducted simulation

2.1.2 Assumptions

We made the assumption in this article that the vehicles speed and energy consumption are constant during the drive and equal for all vehicles of the same type. Those assumptions are not too strong as the related approximations (few minutes) are negligible compared to waiting times (around half an hour).
Even if batteries charging power are given as constants, in reality these powers depend on many factors, as the battery temperature, state of charge and state of health, but also availability on the grid power. Charging profile can then be very complex and not reproducible, but some characteristics remain:

- Charging power is almost constant and equal to the max until the SoC reaches 80%
- It is easier to charge a battery when its SoC is low

We used the approach developed in [12], where the charging power is given by equation 3. This model is applicable for SoC between 0 to 80%.

$$P^{car}(t) = P^{car}_{max} - \alpha^{car} * \frac{SoC^{car}(t)}{Capacity^{car}} \tag{3}$$

where :

$$\begin{aligned} P^{car}(t) &= \text{Charging power of vehicle "car" (kW)} \\ P^{car}_{max} &= \text{Maximum supported power (kW)} \\ \alpha^{car} &= \text{Charging power decrease coefficient} \\ SoC^{car}(t) &= \text{State of charge} \\ Capacity^{car} &= \text{Battery capacity (kW.h)} \end{aligned}$$

Numeric values for various cars are given on table 1.

Table 1: Vehicle characteristics

Car type	Urban	Sedan	Luxury
Battery capacity (kW.h)	41	60	100
P^{car}_{max} (kW)	50	100	150
α^{car}	250	1062	1500

Figure 2 shows the numerical application of the equation 3. For all cars, the charging power when the SoC is 0% is equal to the maximum charging power. It then slowly decreases when the SoC increases, the slope depending on the vehicle.

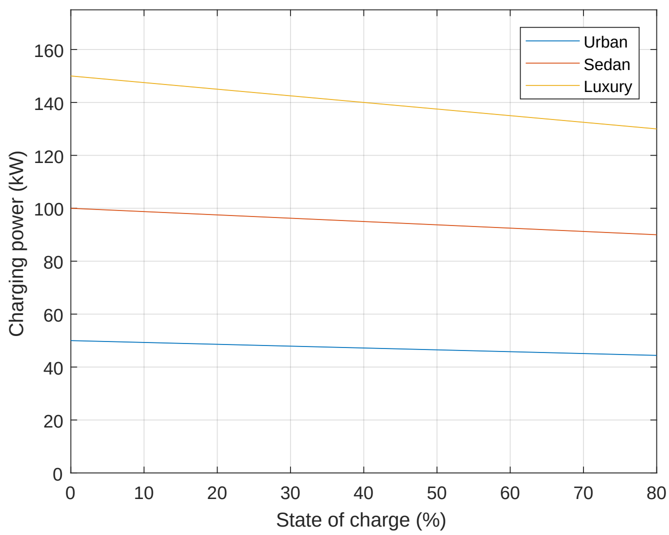

Figure 2: Evolution of maximum charging power

2.2 Resolution

The model resolution can be sum up by (4): we want to minimize f as a function of the decision variables x and constants y, as defined in Figure 1, under constraints of State of Charge (SoC). $SoC_{EV_n}(t)$, SoC_{min_n} and SoC_{max_n} respectively represent state of charge of vehicle n at time t, minimum and maximum and $SoC_{EV_n exit}$, $SoC_{EV_n exit\, required}$ represent the SoC at highway exit obtained and required.

$$\begin{aligned} \min_x \quad & f(x, y) \\ \text{u.c.} \quad & \forall t, \forall n, SoC_{min_n} \leq SoC_{EV_n}(t) \leq SoC_{max_n} \\ & \forall n, SoC_{EV_n exit} \leq SoC_{EV_n exit\, required} \end{aligned} \tag{4}$$

The chosen method to solve this problem is a differential evolution algorithm. This kind of algorithm uses a population of solutions and repeats a process of mutation and selection. Some of the mutations used are vectorial research techniques and we developed some others, more specific for this problem.

3 Application

3.1 Problem definition

The data we generated represents the situation of a highway during a day with 100 electric vehicles. The road has one way, 11 entrance/exits and is 553 km long. It includes six charging stations, with two charging points of 50 or 125 kW maximum available power. Figure 1 displays their implantation. There is three types of vehicles on this simulation, Table 2 gives their characteristics. We based our daily highway flow modelling on the data found on [13]. Figure 3 shows a daily flow of vehicles, averaged over the various entrances and exits of the French A6 motorway in Ile de France during the year 2017. It indicates that the flow variations between 8 a.m. to 9 p.m. are low, and that the low traffic during the night should not lead to saturation of the charging stations, so we modeled this by a uniform distribution over a time period, between 6h30 a.m. to 12 p.m. SoC at departure is also distributed homogenously, between 50 to 100%. SoC at arrival is required to be above 30%.

Table 2: Used vehicles

Car type	Urban	Sedan	Luxury
Battery (kW.h)	41	60	100
Consumption (kW.h/km)	0.15	0.18	0.18
Max Speed (km/h)	110	130	130
Generation probability	0.3	0.6	0.1

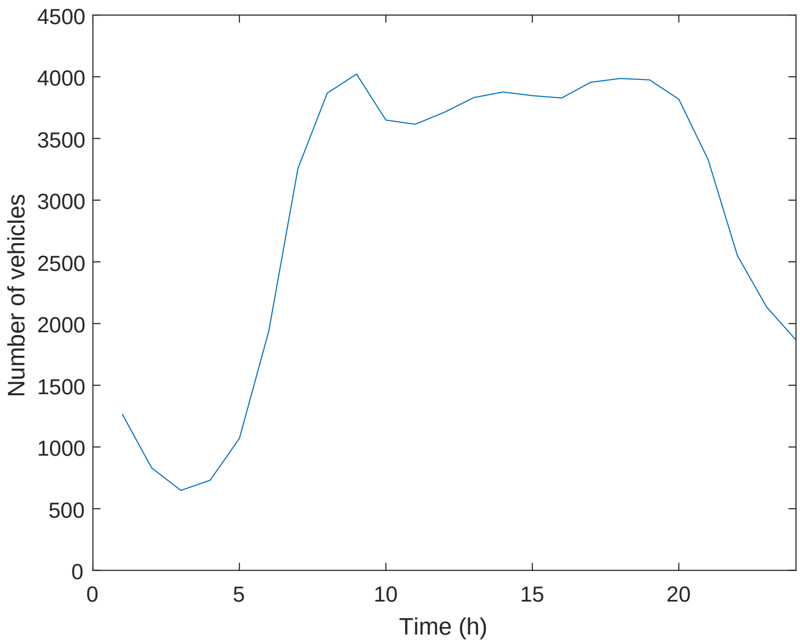

Figure 3: Average daily vehicle flow

3.2 Scenarios

The following of this article compares two scenarios of driver's choice optimization:

- *Without coordination*: EV drivers have no information about choices made by other EVs. Charging schedules are optimized for each vehicle separately, reproducing the choices that a driver can make, only knowing the charging stations position and power.

- *Global optimization*: Situation in which all information is centralized and choices are made in an optimal way, taking into account waiting times when making choices. This is made by using the differential evolution algorithm.

In both cases charging plans are optimized using a differential evolution algorithm by minimizing function f defined in equation (2).

3.3 Quality thresholds

In order to qualify a situation as satisfactory for users, we have defined a quality criterion. The infrastructure will therefore be considered sufficient if it meets the following thresholds:

- 90% of EVs entering a charging station will have less than 5 minutes to wait
- All waiting times are less than half an hour.

Those two indicators are named below as the ninth decile and maximum value.

3.4 Results

3.4.1 Benefits for users

In this first study we measured the time savings for users that could be achieved by setting up a communication system. Therefore we applied the scenarios defined in 3.2 to the same set of data. Figure 4 shows box diagram (with range, median and quartiles) of EV waiting times in all charging stations, for both scenarios. Figure 5 display queues length at the six charging stations during the day. Without coordination station 3 seems in high demand, leading to considerable waiting times, up to eight hours. It appears that the coordination permits a better allocation of vehicles and thus avoids waiting times of more than two hours.

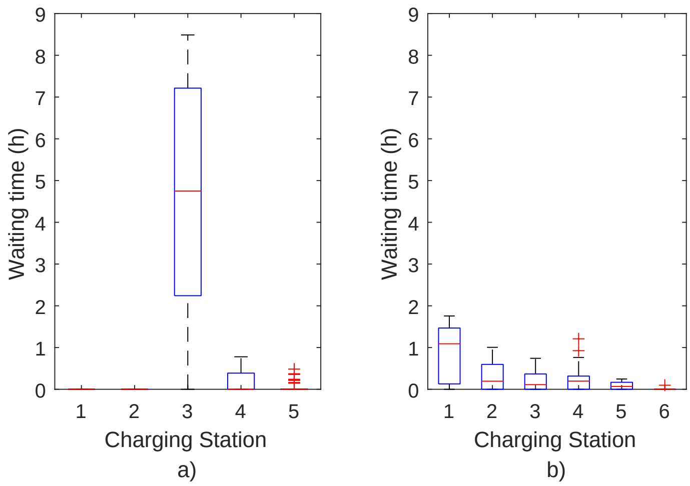

Figure 4: Waiting times at charging station, a) Without coordination b) Global optimization

Figure 6 displays an histogram of travel time reduction for each of the users when adding the coordination. Most of them are saving time, with trips up to 80% shorter, but some of them (13%) are experiencing longer trips. Indeed, some stations are receiving more visitors, to the disadvantage of those who planned to go there. In average, people are saving 2h42 with coordination, witch means a 27% travel time reduction.

3.4.2 Reduction of the needed infrastructure

In this paragraph we will use another approach, looking for the minimum infrastructure required to meet the quality criteria defined in 3.3 for the vehicle flow studied. For both scenarios, we added iteratively charging points in existing stations, at locations where they reduce the most the total traveling time. We stop when the quality criteria are met. Figure 7 displays the evolution of the two indicators, the ninth decile (D9) and the maximum (Max) of waiting times, for both scenarios. Quality thresholds are reached with 12 points added for the scenario without coordination and with 7 points for the global optimization

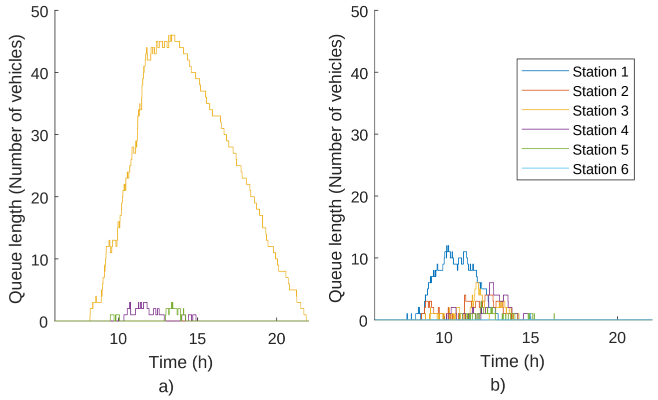

Figure 5: Queues length at charging station, a) Without coordination b) Global optimization

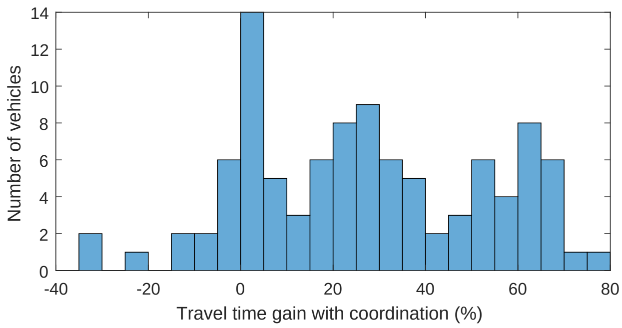

Figure 6: Time saved with coordination

scenario, besides the 12 charging points already installed. It illustrates that the implementation of a communication and optimization system could save up to 20% of the total infrastructure investment amount while providing the same quality of service.

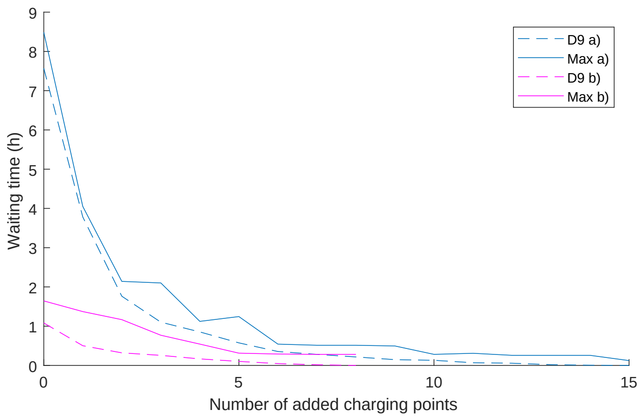

Figure 7: Quality indicator evolution, a) Without coordination b) Global optimization

4 Conclusion

This article proposes an optimization method to minimize travel time of electric vehicle during long distance trips. It brings out the benefits of providing a solution of communication between vehicles and the charging infrastructure. We demonstrated that an accurate communication scenario would permit a better usage of the existing infrastructure and reduce user's average travel time, in our study case by 27%. It also results in a reduction in the needed infrastructure of 20%. In future works it might be interesting to adapt this solution to take into account the constraints of real time execution, deploy facility and confidentiality. In these conditions, we would be able to ensure a good quality of service during the usage of electric vehicles to perform long distances drives, thus enhancing their acceptability.

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