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Service for optimization of charging stations selection for electric vehicles users during long distances drives

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Abstract:

One of the major curb to electric vehicles (EV) acceptability is their constraints when performing long distance trips. Even if improvements made on fast charging technology enable to recover up to 400 km range in 20 minutes, the low density of this kind of infrastructure and the variability in their availability can lead to significant waiting times for users. Many articles develop communication scenario between vehicles in order to coordinate users charging places choices, permitting a better distribution that minimize waiting queue. The authors compare their approaches performances with theoretical resolution of the relaxed problem. In this article, the authors deal with a situation where many electric vehicles run along a highway with few charging stations, representing a usual daily traffic flow. It provides an approach that permits to find an optimal charging schedule for all users, minimizing their waiting and charging time at charging stations, using an all-knowing point of view. A differential evolution algorithm is used, with some improvements to better adapt it to this problem and speed the convergence.

Keywords:

Electric vehicles, Long way electric mobility, Quick charge, Optimization.

1. Introduction

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.

What will interest us afterwards will be the study of the means 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, not allowing to evaluate the remaining potential gain. We therefore proposed an approach to find an optimal recharging choice solution based on a differential evolution algorithm.

Next we will present the modeling made of our problem, the optimization method implemented as well as an application to a simulation of the vehicles flow on a highway.

2. Model

2.1. Situation

In the present paper we develop a function to simulate a flow of electric vehicles on a highway presented in Figure (1). This function takes as input:

- A highway layout, with entrances / exits and charging stations, as well
- A fleet of vehicles specified with intrinsic characteristic: battery capacity, consumption, maximum charging power. . .
- 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.

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

With :

$T_{Waiting}$ Waiting time before accessing an available charging point when the station is full

$T_{Charging}$ 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 (set here to 5 minutes)

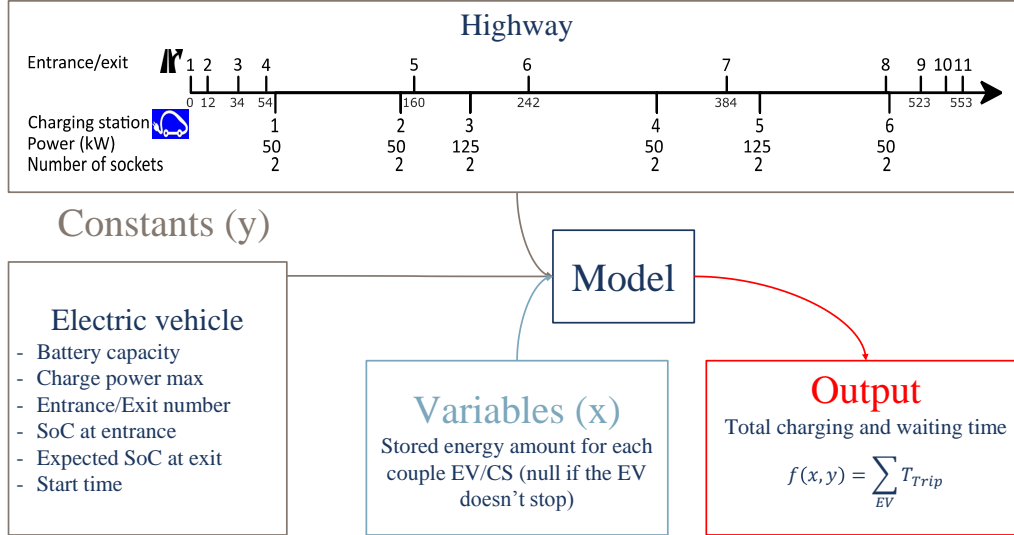


Figure 1: Model inputs and outputs

2.2. Assumptions

In this paper, the following assumptions are made:

- The vehicles speed and consumption are constant during the drive and equal for all vehicles of the same type.
- The charging power is constant during the charge up to a SoC of 80% and equal to the minimum between the maximum charging power of the EV and the charging station.

Those assumptions are not too strong as the related approximations (few minutes) are negligible in front of waiting times (around half an hour).

3. Optimization

3.1. Algorithm

In order to solve this nonlinear problem, which has numerous variables, we choose a differential evolution algorithm. It is based on genetic algorithm, as described in [12], according to the following steps :

1. We generate randomly an initial population of input variables.
2. We create new elements, obtained from the previous population by mutations and crossover.
3. We select the best elements between the old and the new population.
4. We repeat step 2 and 3 iteratively until reaching convergence criterion.

Mutations used in this algorithm are based on vector differences. In particular, differential mutation adds a scaled, randomly sampled, vector difference to a third vector. Equation 2 shows how to combine those three elements. The mutant vector, v , is composed of x_1 , the random base vector and the difference between two vectors, also randomly selected once per mutant. The scale factor, F , is a positive real number that controls the rate at which the population evolves. It is generally included in $]0, 1[$. Many variants exist, especially by choosing the best vector from the population.

$$v = x_1 + F * (x_2 - x_3) \quad (2)$$

States of charge of vehicle n should be above $SoC_{min,n}$ when the vehicle enters the station and under $SoC_{max,n}$ when it leaves it. This respectively represents the security margin in order to avoid going down and the advised margin above which the charging rate drops. $SoC_{exitreq,n}$ stands for the power level needed to end the trip, after going out of the highway.

In order to take into account the constraints, a penalty is added to the result if they are not fulfilled. The penalty value depends on the difference with the target.

3.2. Function variations

We will now focus on the function variations. Figure (2) presents its value when varying two variables for the same EV, E_1 and E_2 , respectively the energy refueled at station 1 and 2. The range of variables depends on the battery capacity and the defined $SoC_{Min,n}$ and $SoC_{Max,n}$. We can observe that the triangle at the bottom left corner represents the variables that does not permit to satisfy the targeted SoC. When the sum of the two energy decrease, the function decrease down to a line of optimal solutions, L_1 . Indeed, as we made the assumption of constant charging rate and if there is no charging queue, it is equivalent to charge more energy at first station or at the second one as long as the sum is constant. Equation (3) then gives the characteristic equation of the optimal solution line L_1 , with $E_{Required}$ a constant representing the total energy needed to perform the trip.

$$E_1 + E_2 = E_{Required} \quad (3)$$

The fact that the line cross the axis $E_1 = 0$ or $E_2 = 0$, as in points P_1 and P_2 , means that there is at least one solution with only one charge. This is a better situation, as it saves T_{Other} . Thereafter we noticed that, if the algorithm converged quickly towards the solution points of the generalized N-variable (4), it was more problematic to minimize the number of stops, i.e. find the points P_i in the previous example.

$$\sum_i^N E_i = E_{Required} \quad (4)$$

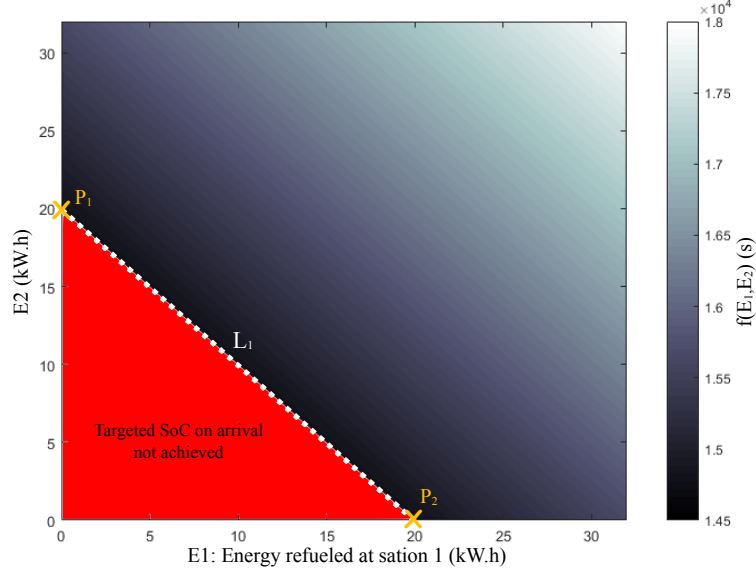


Figure 2: Function variation

3.3. Modifications of the differential evolution algorithm

In order to solve the problem mentioned in previous paragraph that affect the convergence speed, the authors developed two mutations, shown in Fig (3). The algorithm will choose randomly between those mutations and other geometrical ones (as defined in 3). The first one, mutation *Move*, transfer the charge from one station to another station in front of which this electric vehicle will pass, whether it intended to stop or not. The second one, *Distribute*, spreads the charge from one station to other random stations where this EV already intended to stop.

3.4. Performance analysis

To verify that these new mutations give enhancement the performances of the modified algorithm are tested, three cases are considered: the first is the normal differential evolution mutation, the second and third ones are respectively enhanced by the *move* and *distribute* mutations.

We then ran the algorithm fifty times in each of the configurations. The results are given in Fig (4). The graph on the left shows the box plot of the different results obtained by optimization. We can observe a decrease in the median value obtained as well as the maximum value when adding the proposed mutations. The minimum value is the same for the three configurations; we can assume that it is the absolute minimum according to our scenario. The middle graph

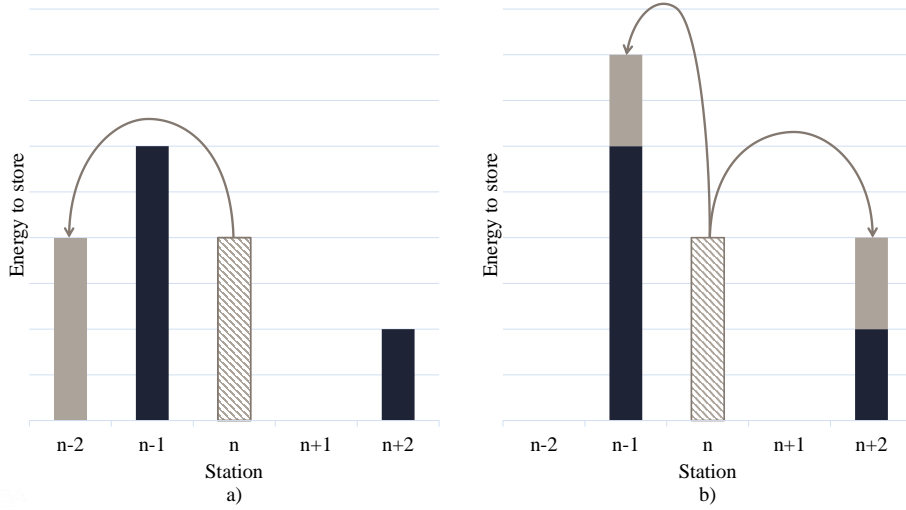


Figure 3: Proposed mutation, a) Move, b) Distribute

shows the number of evaluations of the function, which is an image of the computation time spent: it shows no significant grow. The graph on the right displays the number of vehicles stops in obtained solutions. The addition of mutations therefore reduced the median value of these results from 20 to 11 stops. This confirms the relevance of our additions for solving this problem.

4. Application

4.1. Case study

The proposed case study describes the situation of a highway during a day with 100 electric vehicles. Time and SoC at departure are distributed using a uniform distribution, respectively between 6h30 to 12h and 50 to 100%. Vehicles are charged at most between $SoC_{min} = 15\%$ up to $SoC_{max} = 80\%$. SoC at arrival is required to be above $SoC_{exitreq} = 30\%$. Table 1 gives vehicle characteristics and Fig (1) describes highway map.

We have then studied two scenarios: one with no coordination, where EV drivers have no information about choices made by other EVs, and the other one with a global optimization, as described in previous part, knowing all information of all cars during the day.

Table 1: Studied vehicles characteristics

Vehicle	Urban car	Sedan car	Luxury car
Battery (kW.h)	41	60	100
Charge Power (kW)	44	100	125
Max Speed (km/h)	110	130	130
Generation Probability	0.3	0.6	0.1

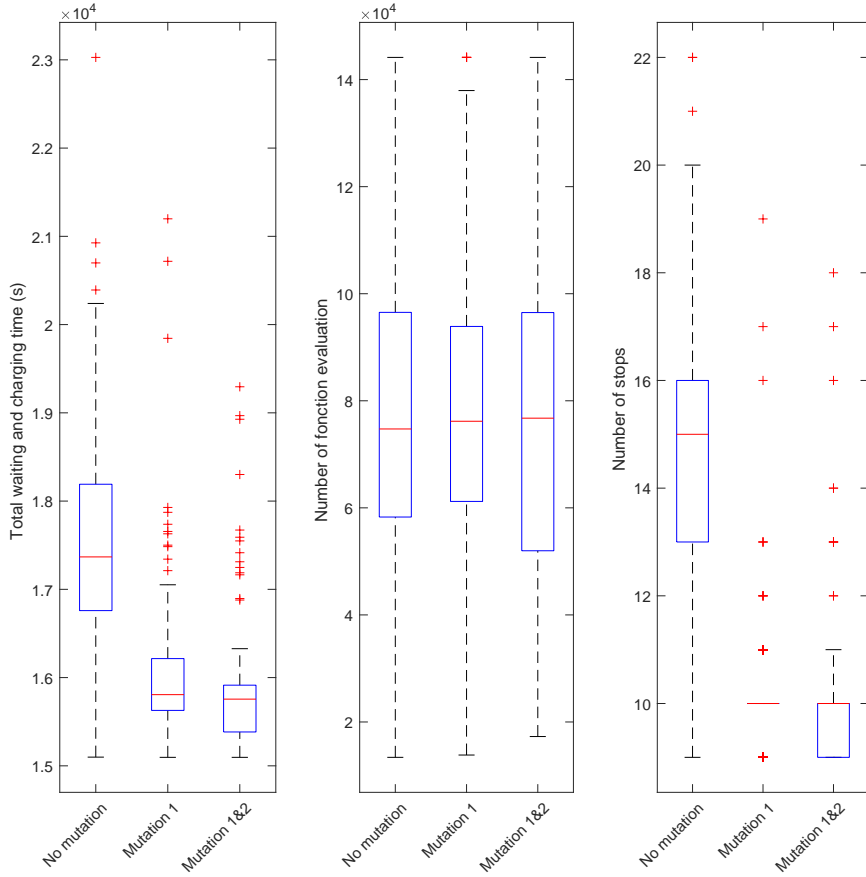


Figure 4: Modified algorithm performance

4.2. Optimization results

Charging plans are optimized using a differential evolution algorithm under two scenarios :

- *Without coordination:* 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.

Figure (5) shows a better distribution of EVs at the stations, leading to a reduction in waiting times, which are all below 2 hours in the Global Optimization scenario. Figure (6) shows the length of queues at the different stations during the day. There is a decrease in the maximum number of vehicles on standby at a station from 45 to 13. All this results in a 27% reduction in users' travel time, using the same infrastructure.

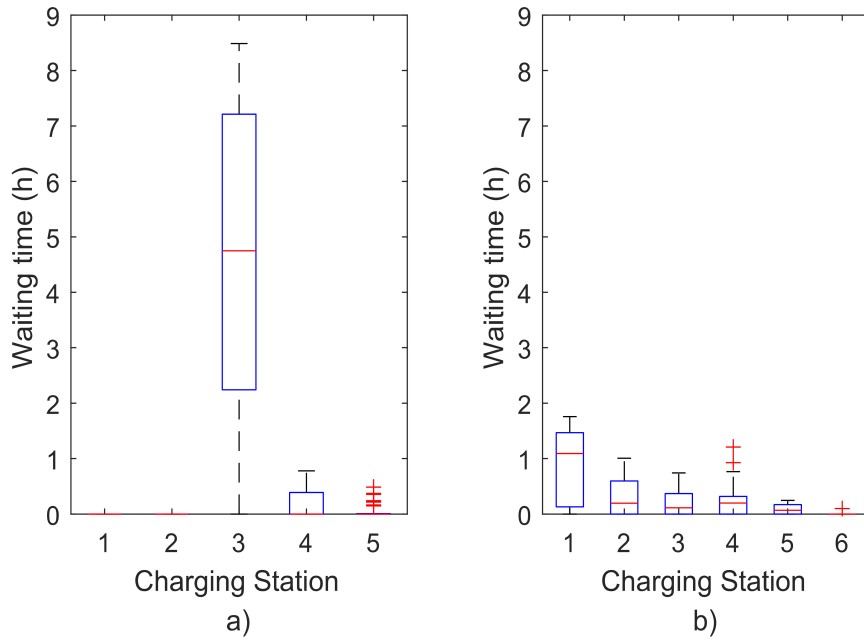


Figure 5: Box plot of EV waiting times in different charging stations, a) Without coordination b) Global optimization

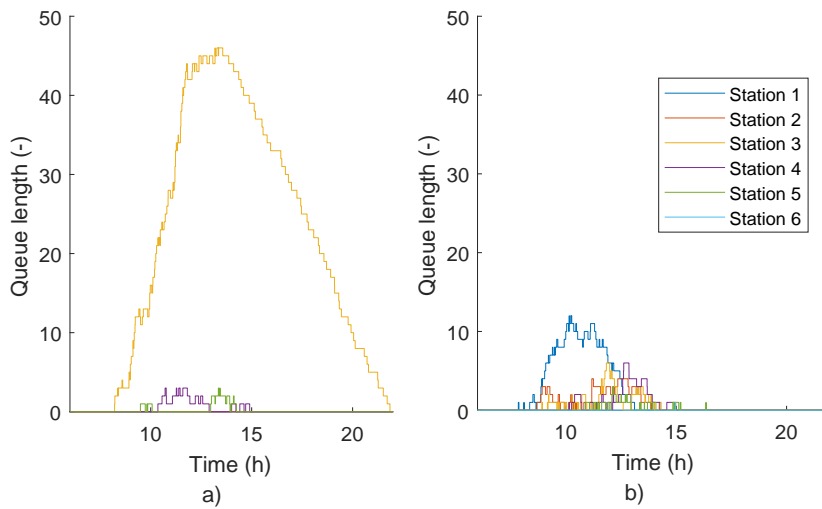


Figure 6: Queue length during the day, a) Without coordination b) Global optimization

5. Conclusion

This article propose an optimization method to minimize travel time of electric vehicle during long distance trips. The differential evolution algorithm, with the specific proposed modifications, permit to solve the non-linear mathematical problem. It brings out the benefits of

provide 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%.

In the 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.

REFERENCES

- [1] Dimitrova Z, Maréchal F. Environomic design of vehicle energy systems for optimal mobility service. *Energy*. 2014 Nov;76:1019–1028.
- [2] Csonka B, Csiszr C. Determination of charging infrastructure location for electric vehicles. *Transportation Research Procedia*. 2017 Jan;27:768–775.
- [3] Soyly T, Anderson JE, Bttcher N, Wei C, Chlond B, Kuhnimhof T. Building Up Demand-Oriented Charging Infrastructure for Electric Vehicles in Germany. *Transportation Research Procedia*. 2016 Jan;19:187–198.
- [4] Chen Z, Liu W, Yin Y. Deployment of stationary and dynamic charging infrastructure for electric vehicles along traffic corridors. *Transportation Research Part C: Emerging Technologies*. 2017 Apr;77:185–206.
- [5] Tao Y, Huang M, Yang L. Data-driven optimized layout of battery electric vehicle charging infrastructure. *Energy*. 2018 May;150:735–744.
- [6] Levinson RS, West TH. Impact of public electric vehicle charging infrastructure. *Transportation Research Part D: Transport and Environment*. 2018 Oct;64:158–177.
- [7] del Razo V, Jacobsen HA. Smart Charging Schedules for Highway Travel With Electric Vehicles. *IEEE Transactions on Transportation Electrification*. 2016 Jun;2(2):160–173.
- [8] Gusrialdi A, Qu Z, Simaan MA. Distributed Scheduling and Cooperative Control for Charging of Electric Vehicles at Highway Service Stations. *IEEE Transactions on Intelligent Transportation Systems*. 2017 Oct;18(10):2713–2727.
- [9] Qin H, Zhang W. Charging scheduling with minimal waiting in a network of electric vehicles and charging stations. In: *Proceedings of the Eighth ACM international workshop on Vehicular inter-networking*. ACM; 2011. p. 51–60.
- [10] Tan J, Wang L. Real-Time Charging Navigation of Electric Vehicles to Fast Charging Stations: A Hierarchical Game Approach. *IEEE Transactions on Smart Grid*. 2015;p. 1–1.
- [11] Yang H, Xie X, Vasilakos AV. Noncooperative and Cooperative Optimization of Electric Vehicle Charging Under Demand Uncertainty: A Robust Stackelberg Game. *IEEE Transactions on Vehicular Technology*. 2016 Mar;65(3):1043–1058.

- [12] Price K, Storn RM, Lampinen JA. Differential Evolution: A Practical Approach to Global Optimization. Springer Science & Business Media; 2006.