Optimal Charging Coordination of Electric Vehicles Using the Teaching-Learning-Based Optimization Algorithm

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Abstract. The automotive market is moving fast toward electrification. Changes in the consumer's consciousness, government policies, and regulations have been driving consumers' acceptance, and consequently the growth of electric vehicle sales. The existing barriers to such sales expansion tend to disappear with time, and it is expected that electric vehicles represent more than 30% of world sales by 2030. The participation by regions, however, should vary from country to country, and one of the main reasons is the insufficient charging infrastructure. The additional electricity demand and the unpredictable behavior of electric vehicle owners will significantly impact the electric energy distribution systems, with consequent instabilities and faults. This research work proposes a solution based on the metaheuristic Teaching-Learning-Based Optimization (TLBO) for the optimal charging of groups of electric vehicles. The proposed method aims to deliver the maximum energy possible to the batteries without violating the limits and constraints of the electric system. The TLBO is an efficient algorithm, which requires few parameters, and shows excellent exploration and exploitation characteristics. Simulation results will be shown for different charging situations and the good-quality results provided by TLBO will be discussed.

Keywords: Electric vehicles · charging · TLBO

1 Introduction

A wide and efficient transportation system is crucial for the organization of modern society. Currently, this system is driven mostly by conventional vehicles powered by internal combustion engines (ICEs). As of 2018, transport accounted for 24% of the CO_2 emissions from energy [1]. Still, according to [1], electrification technologies (including the use of hydrogen) applied to transportation systems could potentially provide significant decarbonization within decades. It is worth mentioning some important initiatives to urge governments to declare a climate emergency [2, 3] which would allow those governments to take decisive actions toward the planet's decarbonization.

Electric vehicle (EV) production has been increasing in the last few years, mostly driven by government incentives and regulations that aim to reduce pollutant emissions and greenhouse effect gases. In 2019, EV sales represented about 3% of the world market,

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and the expectation is that this share would reach 32% by 2030 [4]. This evolution will occur at variable paces in different regions. For instance, the EV sales share in China will be close to 50%, while in the US they will not surpass 30%, as shown in Fig. 1.

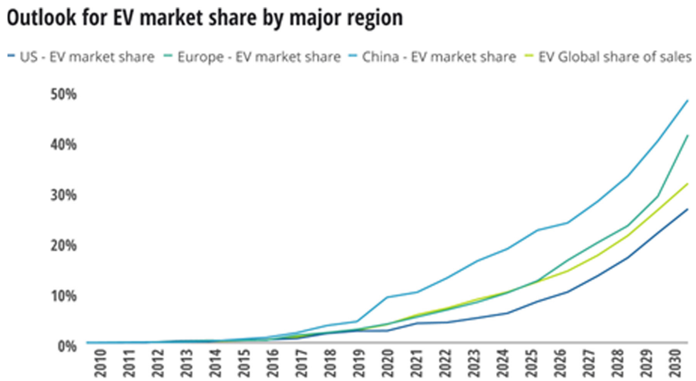

Fig. 1. Participation of EV sales in the market [4].

A successful transportation electrification transition must overcome some crucial barriers, namely, the high prices of EVs, their low autonomy as compared to ICE-based vehicles, and an insufficient number of charging stations (CSs).

EV owners will charge their vehicles in dedicated CSs located at parking lots, shopping facilities, and mainly in their homes. As far as the public CSs, appropriately located CSs should meet the consumers' needs by avoiding unnecessary trips and allowing the battery to be recharged before its minimum charge is reached. By plugging their EVs into a CS, the owners expect that the vehicles' batteries be fully charged. Moreover, the charging process would be as fast as possible.

The authors in [5] evaluated actual data from more than 76 thousand EVs in Beijing, China, for one month. Most users charge their vehicles at night. Users in transit during daylight look for parking lots and specific CSs to charge their vehicles when the state of charge (SOC) is in the range of 20–90%.

Since CSs are supplied by the electrical energy distribution networks, which may impose some limitations on the charging process, optimal coordination is needed. Poor or non-existent coordination may significantly affect the distribution system operation, by increasing power losses and impacting the quality of the service. According to [6], power losses and voltage drops may reach respectively 6% and 10.3% at peak hours, assuming a 30% EV penetration.

In [7], it is shown that the impact of EVs on household consumption is limited, however, the distribution system demand peaks are considerable. A 50% EV penetration would result in a significant increase in the demand peak, as shown in Fig. 2.

Currently, most electrical networks are not prepared to handle this additional demand. The authors of [8] observed that non-coordinated EV charging may cause overloads in electrical network equipment. These overloads reduce equipment's useful lives, leading to precocious equipment replacements.

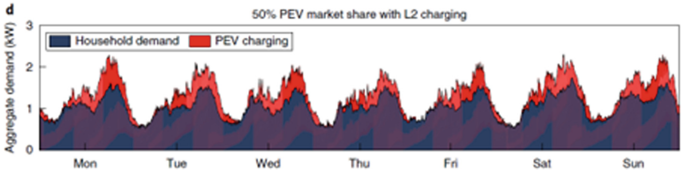

Fig. 2. Per-household average residential electricity demand for an aggregate of 200 sampled households [7].

In [9], a second-order, conic programming method was proposed for the EV coordinated charging process. CSs were connected to the IEEE 32- and 136-bus test distribution systems. The goal was to maximize the EVs' SOC and minimize the charging times. The authors show that non-coordinated charging may lead to distribution system violations, while coordinated charging do not, however, the charging process takes longer.

The EV charging process, especially considering a high EV penetration, cannot be ignored. Non-coordinated charging processes may affect their quality and efficiency as seen from both network and consumers' standpoints.

This work aims to contribute to the development of an efficient charging process, by proposing an optimal, coordinated EV charging procedure that, at the same time, guarantees the fastest charging of all EVs plugged into a CS, and respects the electrical network constraints. To reach this goal, an optimization model is proposed and solved by using the metaheuristics Teaching-Learning Based Optimization (TLBO) [10]. TLBO is an efficient and easy-to-implement metaheuristic, which does not require problem-dependent parameters.

Simulation results will be shown using small-sized cases, to show the effectiveness of the proposed procedure, as well as large ones, to show its efficiency and robustness.

2 Mathematical Model

Consider that a certain number of EVs are connected to a CS. In its turn, the CS is connected to the electric power grid through a distribution transformer, as depicted in Fig. 3. It is assumed that a measuring device is installed and sends information about the transformer's loading to a control circuit, which takes this information as well as information about the vehicles' SOC and coordinates the energy delivered to the EVs within a predetermined time period. The objectives are twofold: (1) the SOC of each EV is the highest possible, and (2) the charging of each EV is as fast as possible.

The proposed mathematical model, based on [9], is

$$\min f = \sum_{v=1}^{NV} \left(SOC_v^{max} - SOC_{v,T}\right)^2 - \sum_{t=1}^{T}\sum_{v=1}^{NV} x_{v,t} \cdot 2^{(T-t)} \tag{1}$$

$$\text{subject } to\, P_{d,t} \geq \sum_{v=1}^{NV} P_v \cdot x_{v,t},\ t = 1, \ldots, T \tag{2}$$

$$SOC_{v,t} = SOC_{v,0} + \eta \cdot \Delta t \cdot P_v \cdot x_{v,t},\ v = 1, \ldots, NV, t = 1 \tag{3}$$

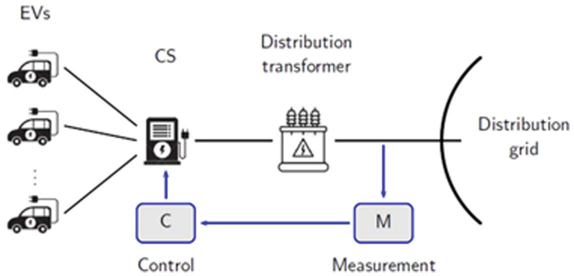

Fig. 3. Illustration of the problem.

$$SOC_{v,t} = SOC_{v,(t-1)} + \eta \cdot \Delta t \cdot P_v \cdot x_{v,t} - \beta \cdot SOC_{v,t},\ v = 1, \ldots, NV, t = 2, \ldots, T \tag{4}$$

$$SOC_{v,0} \leq SOC_{v,t} \leq SOC_v^{max},\ v = 1, \ldots, NV \tag{5}$$

$$0 \leq x_{v,t} \leq 1 \tag{6}$$

Equation (1) refers to the objective function, where NV is the number of EVs, SOC_v^{max} is the maximum state of charge of EV v, so, it corresponds to the capacity of its battery. $SOC_{v,T}$ is the state of charge of EV v at time instant T (end of the time period). $x_{v,t}$ is the parcel of P_v (charging capacity of the battery of EV v) delivered to EV v at time period t. The first term of the right-hand side is intended to charge the EVs' batteries the most possible, while the second term forces the charging process to be as fast as possible. Matrix x contains the decision variables of the problem, and its elements are within the range [0, 1], as defined by Eq. (6). Equation (2) guarantees that the power delivered to all batteries does not exceed the transformer capacity $P_{d,t}$ for each time period t. Equations (3) and (4) establish a link between two consecutive time periods, considering the charging capacity of each battery (P_v), the charging efficiency of the battery (η), and the battery self-discharge rate (β). Finally, Eq. (5) establishes the limits on the states of charge of the EVs.

3 Teaching-Learning-Based Optimization

Problems (1)-(6) can be solved by either conventional programming methods or metaheuristics. In this paper, the solution is obtained by the population-based metaheuristic Teaching-Learning-Based Optimization (TLBO), which was originally proposed by Rao, Savsani, and Vakharia [11]. TLBO is intended to find the optima of continuous functions and was inspired by the relationship dynamics in the classroom.

TLBO, as several other metaheuristics proposed in the literature, presents the ability to solve nonconvex, non-differentiable problems. Those kinds of problems can potentially pose numerical difficulties to conventional mathematical programming methods.

In TLBO the population corresponds to the class members. Each student represents a candidate solution to the optimization problem, that is, a set of decision variables. Students' grades correspond to the fitness function. In the case of a minimization problem, the fitness of each individual is the inverse of his/her grade.

The algorithm is divided into two phases, namely the Teacher phase and the Student phase. In the Teacher phase, the teacher attempts to pass his/her knowledge to the students, while in the Student phase the students share their knowledge among themselves.

Different from other existing metaheuristics in the literature, TLBO does not require problem-dependent parameters to be tuned, which is an important advantage of the method. For instance, Particle Swarm Optimization (PSO) [12] requires the tuning of inertia weight factors and acceleration constants. Also, the Firefly Algorithm (FA) [13] requires the adjustment of the light absorption and the attractiveness coefficients. The Genetic Algorithm (GA) requires the tuning of the mutation rate, the crossover probability, and the selection method [11]. TLBO does not require any such problem-specific parameters to be tuned [14] other than the population size and the number of iterations [10], which is a very interesting feature and makes its implementation much simpler.

TLBO has many advantages in addition to the need for a few parameters [14]. It is also a simple algorithm, easy to understand, computationally fast, provides high accuracy, and has good convergence ability. Moreover, TLBO is flexible, allowing the implementation of variations and improvements. The literature shows that TLBO has been used for solving several power-system-related problems, such as optimal capacitor placement in distribution systems [15], and distribution systems reconfiguration [16], among others.

Consider that the array X contains the decision variables of an optimization problem. Each individual X_i is associated with a value of the objective function, say F_i. Also, consider that (a) X_m is the mean value of all decision variables, and (b) individual X_T is elected as the teacher since it bears the best value of the objective function, F_T.

In the Teacher phase, all students are moved toward the teacher according to

$$X_i^{new} = X_i^{current} + r \cdot [X_T - (T_F \cdot X_m)], \tag{7}$$

where r is a random scalar in the range [0, 1], and the teaching factor T_F can be either 1 or 2, chosen randomly. The new individual replaces the current one if its objective function value shows improvement.

In the Student phase, a pair of students X_i and X_j is chosen arbitrarily and X_i moves according to

$$\begin{cases} X_i^{new} = X_i + r_i \cdot \left(X_i - X_j\right), \text{if} F_i < F_j \\ X_i^{new} = X_i + r_i \cdot \left(X_j - X_i\right), \text{otherwise.} \end{cases} \tag{8}$$

X_i^{new} replaces X_i in case its objective function value shows improvement. The algorithm for TLBO is described below, where the population size is N_p.

```
Algorithm - TLBO
    1. Generate the initial population X_i, i = 1, ..., N_p.
Teacher phase
    2. Compute the mean individual X_m = mean(X).
    3. Choose the Teacher X_T.
    4. Compute direction Δ = r · (X_T − T_F · X_m), where r is a
       random number in the range [0,1] and T_F is the teach-
       ing factor, randomly chosen as either 1 or 2.
    5. For each individual i, do
          a. Obtain new individual X_i^new = X_i^current + Δ, i =
             1, ..., N_p.
          b. If X_i^current is better than X_i^new, maintain X_i^current
             in the population, else, do X_i^current ← X_i^new.
Student phase
    6. For each individual X_i, i = 1, ..., N_p, do
          a. Choose an individual X_j randomly.
          b. If individual X_i is better than X_j, then do
             Best = X_i and Worst = X_j. Else do Best = X_j and
             Worst = X_i.
          c. Compute Δ = Best − Worst.
          d. Obtain a new individual X_i^new = X_i + r · Δ.
          e. If X_i is better than X_i^new, maintain X_i in the
             population, else, do X_i ← X_i^new.
    7. If the stopping criterion was met, stop. Else, go
       back to step 2.
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4 Simulation Results

The proposed method for solving problems (1)-(6) through the TLBO algorithm was implemented using GNU Octave 7.2.0 [17], in a laptop with an i5 processor and 8GB RAM. A total of three simulation cases are shown to evaluate the performance of TLBO and the quality of the results.

Table 1 shows the parameters associated with each simulation. All parameters were defined in Sects. 2 and 3. Without loss of generality, the batteries are considered 100% efficient and do not self-discharge. A maximum of 1,000 iterations was set to allow a full appreciation of the evolution of the iterative process.

4.1 Case 1

In this simulation case, the power available from the transformer P_d is less than the total power charging capacities of the batteries (150 kW). The simulation results are summarized in Fig. 4. Figures 4(a)–4(c) show that the vehicles' batteries are fully charged by time period 4. Figure 4(d) shows the evolution of the objective function along the iterations. The high values at the first iterations indicate that some constraints are violated. Afterward, TLBO converges quickly. Figure 4(e) shows a closer view of the evolution of the objective function. It is clear that 1,000 iterations are not necessary for obtaining very good quality solutions.

Table 1. Parameters for the three simulation cases.

Parameter	Case 1	Case 2	Case 3
NV	3	3	3
T	10	10	10
P_d	70	20	70
P_v	[50 50 50]	[50 50 50]	[10 5 30]
η	1	1	1
β	0	0	0
SOC_0	[15 16 25]	[80 10 10]	[80 10]
SOC^{max}	[100 100 100]	[100 100 100]	[100 100 100]
N_p	70	70	70
It_{max}	1,000	1,000	1,000

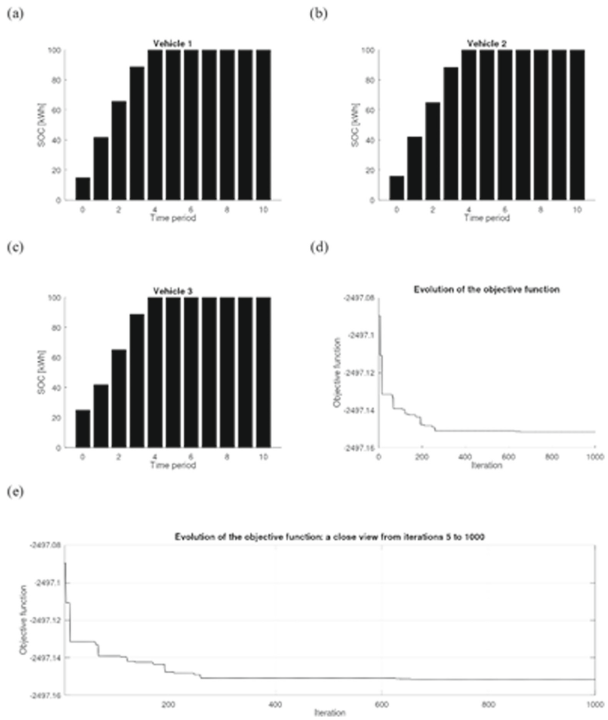

Fig. 4. Simulation results for Case 1.

4.2 Case 2

In this case, the availability of the transformer decreased from 70 kW to 20 kW. Also, two vehicles present low initial SOCs, while the third one has a high SOC from start. Figure 5 shows the simulation results. The limitation in the availability of the supplying transformer implies a longer time for the batteries to fully charge.

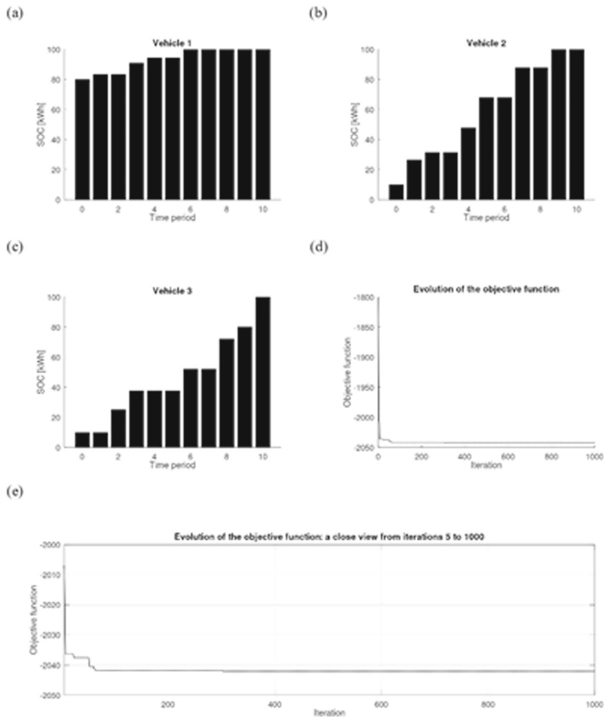

Fig. 5. Simulation results for Case 2.

4.3 Case 3

In this case, the transformer's availability (70 kW) is larger than the total charging capacity of the batteries (45 kW altogether). Once more, two vehicles present low initial SOCs, while the third one has a high SOC from start. Also, the batteries have different charging power capacities. Figure 6 shows the simulation results. The batteries from vehicles 1 and 3 end up fully charged, however, the charging rates are different. Note that vehicle 1 is fully charged before vehicle 3. Also, vehicle 2 has a small charging power capacity, so its final SOC is around 60%.

The computational times for the three cases were 124, 132, and 131 s, respectively. Note that the program was implemented in an interpreted language and that 1,000 iterations were run for each case. Considering also that, according to Figs. 4–6, all cases converged after less than half the number of iterations, the performance of the proposed method was very good regarding its computational speed.

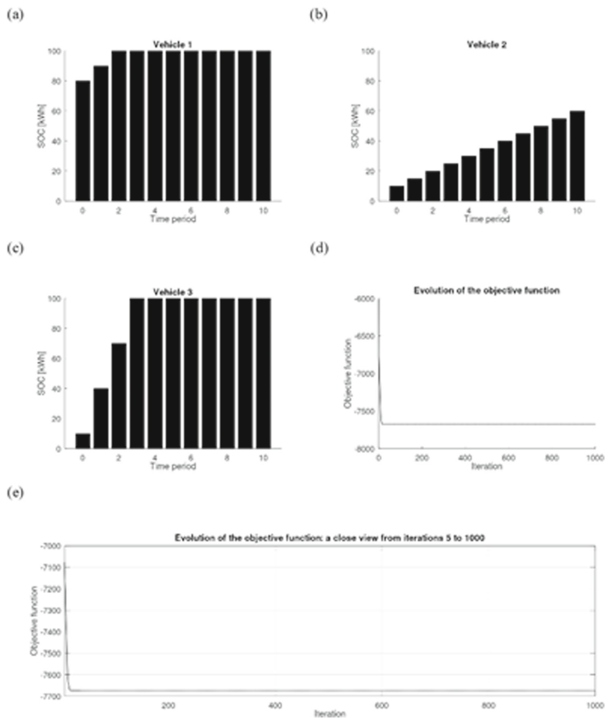

Fig. 6. Simulation results for Case 3.

5 Conclusion

The availability of charging stations is crucial to push forward the adoption of electric vehicles. Additionally, appropriate coordination of the charging processes can potentially increase the confidence of consumers. In this paper, optimal coordination of EVs' charging processes was proposed. The resulting optimization model was solved by the metaheuristic Teaching-Learning-Based Optimization. This metaheuristic showed to be easy to implement and efficient. The simulation results showed that optimal coordination can minimize the non-delivered energy to the EVs' batteries as well as the charging time. In this research, the focus was on the optimal charging coordination itself, and a constraint was added to guarantee that the charging process does not cause any violation in the distribution grid.

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