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A Cognitive Stochastic Approximation Approach to Optimal Charging Schedule in Electric Vehicle Stations

Christos D. Korkas[1], Simone Baldi[2], Panagiotis Michailidis and Elias B. Kosmatopoulos[1]

Abstract— **This paper proposes a Cognitive Stochastic Approximation (CSA)-based optimization method for charging an EV (electric vehicle) fleet, using a single, aggregate battery model. The charging station can either utilize the batteries of the parked vehicles to charge the vehicles before they leave, or can use power from the grid. The objective is to optimize the charging task with minimum energy costs, possibly taking into account price variations in the electricity price. The main advantage of the proposed approach is that it provides a nearly to optimal solution in the presence of uncertain charging/discharging dynamics. The method is evaluated through a numerical model of a grid-connected charging station. Four scenarios with different electricity price models are studied. The CSA optimization results are compared with the results obtained by a rule-based charging algorithm and by an open-loop optimal control algorithm: the results illustrate the advantages of the proposed CSA algorithm in minimizing the charging cost, satisfying the aggregate battery charge sustaining conditions and providing robust solutions in the presence of time-varying vehicle schedules.**

I. Introduction

Upcoming deployment of plug-in hybrid electric vehicles (PHEVs) and fully electric vehicles (EVs) require the integration of a huge amount of electrical storage into the electric utility grid. The overall load profile of electric system will be deeply modified due to the introduction of EV charging and discharging. With reference to the US, where the EV market is most developed as compared to other countries, it has been estimated that the total charging load of the EVs can reach 18% of the US summer peak at the EV penetration level of 30% [1]. On the other hand, an EV can also provide energy to the power grid by discharging the battery, which is known as Vehicle-to-Grid (V2G) functionality [2]. There are several approaches in literature related to modeling and charging optimization of individual EVs or EV fleets. The related studies are mostly focused on assessment of: (i) techno-economic potential of integrated EV-grid systems [3], [4], (ii) benefits related to ancillary services that EVs can provide to the grid [5], [4], and (iii) boost of RES penetration based on EV proliferation [6], [7].

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We focus on a test case study, involving a stand-alone charging station or parking lot of electric-vehicles. Owners of the charging station and EV fleet, typically aim for lower electricity cost by exploiting lower electricity prices through the day, as well as the stored energy of the parked vehicles. Regardless of whether charging management study involves the single EV level or the EV fleet level, battery of each EV can be modeled individually [4], [8], [5]. However, in order to provide numerically efficient optimization for large number of individual EVs that can scale up to integrated transport-energy systems, it is more appropriate to lump the individual batteries in a single aggregate battery with a single state-of-charge state variable [9], [10], [11]. In this paper, we adopt the aggregate battery model. The optimal time to charge and discharge must be determined combined within the charging station and vehicle owner's limitations.

This paper tackles the problem of intelligent control of battery charging/discharging in charging stations. A Cognitive Stochastic Approximation (CSA) optimization method of an EV fleet aggregate battery charging is proposed. The main idea behind CSA is a Dynamic Programming formulation, which has been shown to lead to global optima (see applications of Dynamic Programming to optimal charging of electric vehicles [12], [13] and references therein) and possibly robustness due to the closed-loop nature of the solution.

The paper is organized as follows: Section II describes the problem setting, the vehicle and station parameters as well as the charging procedure. Section III presents the case studies, the control objectives and the performance index. Sections IV and V, presents baseline charging strategies used for comparison purposes and the proposed CSA algorithm. Validation results and the robustness evaluation are presented in section VI.

II. Problem Description

In this section the basic characteristics of the problem are presented. A grid-connected charging station is considered, composed of multiple charging spots (in our numerical study we consider 12 charging spots). The charging station aims to fully charge every electric vehicle (EV) before every vehicle's departure. In this study, it is assumed that the grid can satisfy all vehicle's demands up to their maximum charger output. At each vehicle's departure time, the battery state of charge (SoC) is expected to be at a certain desirable level (in our numerical study we consider desired SoC of 100% at departure time for every vehicle). Each vehicle has the ability to discharge its battery to charge other vehicles

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(if this is beneficial for the whole system). This concept, is known as vehicle-to-grid (V2G)[1], and it is used by the charging station to charge vehicles that are planning to leave shortly thereafter, by using the stored energy of the vehicles which are leaving later on that day.

In Table I, the basic parameters of the vehicles and of the charging station are presented. We assume that the fleet of vehicles is composed of the same type of vehicles with the same battery capacity and charging/discharging efficiency. However, arrival/departure hours, and arrival capacity are stochastic, and they are determined by a Gaussian distributed random number in each variable range.

In real life implementations, the vehicle owners should be able to determine their minimum SoC at departure, furthermore, a heterogeneous fleet could be considered. These scenarios are not considered in this study for simplicity purposes.

A. EV Charging Procedure & Aggregate Battery

We study the battery cycle (charging/discharging) of EVs during a period of time (minimum a day), evenly divided into intervals. We assume that the charging or discharging power within an interval is kept unchanged. In this paper, we divide the day into 24 intervals such that the interval length 1 hour. No new arrivals neither departure are considered inside the interval (but only at the end of each interval).

Every hour, a number of cars are already plugged in the station (N_{plug}). The vehicle battery capacity and the charging station maximum output are determined in such a way that every vehicle needs 2 hours to charge fully from SoC=0%. Based of this parameter, the total number of vehicles N_{plug} is split in two separate categories:

- N_{leave}, the number of cars that are scheduled to leave during the next two hours;
- $N_{stay} = N_{plug} - N_{leave}$, the number of cars that are going to stay during the next two hours.

TABLE I

VEHICLE PARAMETERS

Parameter	Minimum	Maximum
Battery Capacity (B_{max}) (kWh)	20	20
Arrival State of Charge (%)	20	60
Arrival Time (hour)	0	22
Departure Time (hour)	Arrival+2	Next Day
Charging & Discharging Eff. ($n_{ch} - n_{dis}$) (%)	91	91
Charger Output ($P_{ch,max}$) (kW)	0	11

As mentioned in the Introduction, the plunged-in EV fleet is modeled as a single, so-called aggregate battery with the single state-of-charge (SoC_{agg}) as state variable [14], [9].

The aggregate battery model is described by the following discrete-time state equation:

$$SoC_{agg}(k) = \frac{\sum_{i=1}^{N_{stay}} (SoC_i)}{N_{stay}} \quad (1)$$

[1]We acknowledge that the feasibility of V2G is still under discussion by many experts and stakeholders. The study in this paper is just meant to check the feasibility of V2G from a control point of view.

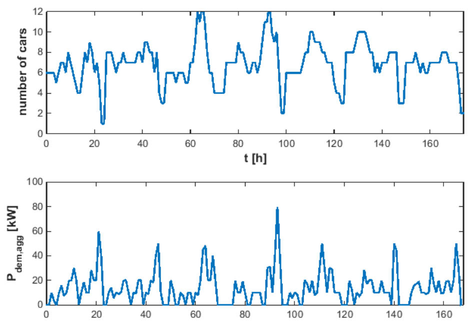

Fig. 1. Evolution of the EV number and $P_{dem,agg}$ for a week

Every moment, based on the N_{leave} and charging efficiency (n_{ch}) the power demand can be calculated as:

$$P_{dem,agg}(k) = \frac{\sum_{i=1}^{N_{leave}} ((1 - SoC_i) * B_{max})}{n_{ch} * 1hour} [kW] \quad (2)$$

$$E_{dem,agg}(k) = P_{dem,agg}(k) * 1hour[kWh] \quad (3)$$

Thus, every hour, the charging control algorithm should meet the requirements of $E_{dem,agg}(k)$, by discharging and utilizing the $SoC_{agg}(k)$ or by buying energy from the main grid ($E_{grid}(k)$).

Because of the limited charging/discharging capability of EV chargers ($P_{ch,max}$), following constraints should be satisfied:

$$P_{dem,agg}(k) <= N_{leave} * P_{ch,max}$$
$$P_{grid}(k) <= N_{stay} * P_{ch,max}$$

Also the aggregate battery should satisfy the upper and lower SoC constraints, as given by

$$0 <= SoC_{agg,min} <= SoC_{agg}(k) <= SoC_{agg,max} <= 1$$

where 0 stands for $SoC = 0\%$ and 1 stands for $SoC = 100\%$

III. CASE STUDIES & CONTROL OBJECTIVES

As described above, the charging station consists of 12 different charging spots, which are ready to be used throughout the day. The arrival and the departure of the EVs are randomly selected as in [15]. In Fig. 1, the number of the plugged-in EVs throughout a week and $E_{dem,agg}$ created based on the N_{leave} of each time step (hour), are presented. (note that the system is not reset every 24 hours, but it operates continuously).

In addition to the fluctuating EV arrival/departure schedule, we assume that dynamic pricing models are used in the interaction between grid and customers. Fig. 2 shows the four pricing models used in the case study. Roughly speaking, all four pricing models follow the same logic, i.e. larger electricity cost during peak hours (morning and midday). However, each pricing model has slightly different features. More precisely, pricing models 1 and 2 have been obtained from [9]. The logic behind these models is simple, basically piecewise constant among a couple of prices. During early morning and evening hours, the electricity is cheaper than midday, where electricity demand is higher, and therefore pricing as well. Pricing model 3 was taken from [14], and presents a finer set of pricing tariffs. Finally, the model 4 was taken from [16]. The logic is similar with model 1 and 2, with the crucial difference that late night hours are considered high demand hours.

In our case study the pricing tariffs are implemented as follows: at the beginning of each day the charging station knows which one of the four models is active. A model active at the beginning of the day will stay active for the entire day. The day after the pricing model might change and this information is communicated to the charging station 12 hours in advance.

The reason for choosing four different pricing models is the following: since the aim of this work is to develop a feedback solution that exploits information from the vehicle and from the grid, we need to develop a feedback algorithm with some robustness characteristics. In particular, the charging algorithm has to consider how to incorporate the information about the active model in order to implement different charging/discharging schedules (depending on the active model). So, having different price models makes the optimal charging problem more challenging, and testing the algorithm with different pricing models offers the opportunity to showcase robustness of the proposed charging algorithm.

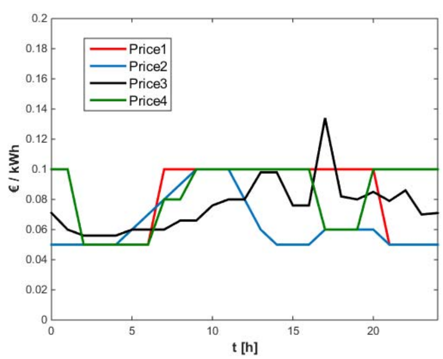

Fig. 2. Evolution of the pricing models used in the case studies

A. Control Objectives

The main objective of the proposed solution is to keep the energy cost as low as possible: this can be done, e.g. by charging the cars when the pricing is low and by using stored energy from the aggregate battery when electricity cost is high. This makes the charging problem dynamic. In addition, an extra objective is to manage the charging operation so as to satisfy the requirements of the users (SoC=100% at departure time). The two objectives are expressed by a suitable performance index:

$$Cost(k) = \sum_{k=1}^{N_t-1} \left[E_{grid}(k) * Price(k) + C_{pen}(k)\right] \quad (4)$$

where :

- $E_{grid}(k)$ = the absorbed energy from the grid for the $k_t h$ time step in [kWh].
- *Price(k)* = the electricity pricing in [€/kWh].
- $C_{pen}(k)$ = a penalty factor proportional to the difference between SoC=100% and the actual charge at departure time.
- N_t denotes the length of the experiment (e.g. N_t = 24 for a day and N_t = 168 for a week).

IV. Problem formulation and Control Strategies

The problem is formulated as an optimal control problem aiming at minimizing the index:

$$J = \sum_{k=0}^{T_f} \left[E_{grid}(k) * Price(k) + C_{pen}(k) + \rho u^2\right] \quad (5)$$

$$s.t.$$

$$x(k+1) = f(x(k)) + B * u, \quad B = [0\ I]' \quad (6)$$

where x is an augmented state, while u is an augmented input, as explained hereafter. Note that the cost (5) is a relaxed version of the cost (4), where the term ρu^2 has been introduced in order to regulate the aggressiveness of the charging strategy. The function $f(x)$ in (6) arises from the following model for the evolution of SoC_{agg}:

$$SoC_{agg}(k+1) = \quad (7)$$

$$SoC_{agg}(k) - \frac{E_{dem,agg}(k)}{B_{max}} + \frac{E_{grid}(k)}{B_{max}} + SoC_{new} \quad (8)$$

$$E_{dem,agg}(k+1) - E_{dem,agg}(k) = P_{grid} = u \quad (9)$$

Equation (7) denotes that the state of aggregate battery for the next timestep $SoC_{agg}(k+1)$ depends on the energy demand ($E_{dem,agg}$), the energy absorbed from the main grid (E_{grid}), and from the arrival of new vehicles in between time k and $k+1$, leading to the term SoC_{new}. All the variables in (7) can be measured, except the arrival of new vehicles and their initial state of battery, which is stochastic. Thus, the function $f(x)$ in (6) and by extension $SoC_{agg}(k+1)$ are uncertain. The state vector contains the battery SoC, and the demand of electricity $E_{dem,agg}$, so x= [SoC_{agg}, $E_{dem,agg}$]. The control variable u is the battery charging power, which is the power from the grid according to (9).

In this section, two strategies that will be used for comparison purposes are introduced. The first one is a simple Rule-based charging strategy; the second one is an open-loop optimization strategy based on the Matlab *fmincon* solver.

A. Rule-Based Approach

The Rule-based controller has been adopted from [14], [9]: here the charging is activated only during time steps where $E_{dem,agg}(k) > 0$. The main aim of the Rule-based is to fully charge the EVs which are leaving during the next 2 hours no matter what: if the energy stored in the aggregated battery is not enough to this purpose, the residual energy will be taken from the main grid. With reference to the cost (4), it is intuitive to understand that by doing this the Rule-based strategy does not incur in any penalty for not satisfying the requirements of the users, but it might require huge energy costs, while not exploiting the dynamics introduced by the aggregate battery.

The Rule-based controller is presented below:

if $E_{dem}(k) = 0$

do nothing

elseif $E_{dem}(k) > 0$

$$E_{grid}(k) = E_{dem,agg}(k) - E_{bat}(k)$$

end

B. Open-loop optimization strategy

The Rule-based controller is a simple strategy that does not apply any "intelligent" control action. In order to make comparisons with more intelligent optimization-based strategies, an open-loop optimization strategy was implemented, via function *fmincon* (from the Matlab Optimization Toolbox). More specifically, the *fmincon*-based charging strategy optimizes a vector of actions (24 actions for a day, 168 actions for a week, etc.) minimizing the cost (4). A multi-start approach has been adopted to minimize the chances of getting stuck in local minima. Please note that it is expected that open-loop solutions created by *fmincon* are not robust if used for different days or weeks (unless they are used in receding-horizon fashion, possibly over long horizons, which is computationally quite demanding).

C. CSA algorithm

Using dynamic programming arguments, we know that the optimal strategy u^* satisfies the Hamilton-Jacobi-Bellman (HJB) equation

$$u^* = \min_u \left\{ \frac{\partial V^*}{\partial x} \left(f(x) + Bu\right) + \Pi(x) \right\} \qquad (10)$$

where $\Pi = E_{grid} * Price + C_{pen} + \rho u^2$, and $\rho > 0$ is a design parameter to regulate the control authority.

The difficulty in solving the HJB equation in large-scale systems was known to Bellman itself, which coined the term 'curse-of-dimensionality' [17]: in order to overcome such difficulties, the CSA algorithm parametrizes the solution of the HJB equation (10) as $V^*(\chi) = \chi' P \chi$ and the optimal control strategy via $u^* = -\frac{1}{2} B' \frac{\partial V^*}{\partial \chi}$, where P is a positive definite matrix, and χ is an augmented version of the feedback vector x, as explained later. It has to be mentioned that alternative stochastic approximation-based algorithms [18], [19], [20] have been using the following parameterization $V^*(\chi) = z'(\chi) P z(\chi)$, where $z(\cdot)$ is a neural network-type approximation. However, in this specific study we have observed that $z(\chi) = \chi$ is sufficient to achieve relevant improvements (as demonstrated in Section V). With such parametrization, the problem of solving the HJB equation is recast as the problem of finding the matrix P (and thus the strategy u) that better approaches the solution of the HJB equation (10). The CSA algorithm defines the close-to-optimality index (derived from the principle of optimality [17])

$$\varepsilon(\chi, P) = V(\chi(k+1)) - V(\chi(k)) + \sum_{t=k}^{k+1} \Pi(\chi(t)) \qquad (11)$$

where $V(\chi) = z'(\chi) \hat{P} z(\chi)$, and $\hat{P}$ is an estimate of P which has to be update at every time step. The solution of the HJB equation (10) brings (11) approximately to zero: the CSA algorithm, whose steps are presented in Table II updates at every time step the strategy parametrized by $\hat{P}$ in an attempt to minimize the close-to-optimality index $\varepsilon(\hat{P})$ and to make $\hat{P}$ converge as close as possible to the solution of the HJB equation.

More about the CSA algorithm can be found can be found in Table II (the algorithm is presented in its discrete-time implementation on a calculator).

Note that the name 'cognitive' comes from step 2 of the algorithm which tries to build an approximation of the gradient.

The CSA algorithm employs a controller based on a feedback vector χ. The structure of χ vector is the following:

- $1+12$ current electricity price + electricity price in the next 12 hours
- The state of aggregate battery (SoC_{agg}).
- The power demand of N_{leave} cars ($E_{dem,agg}$).

which results basically in the fact that the control action u is a combination of feedback information from the vehicles (SoC_{agg} and $E_{dem,agg}$) and feedforward information about the electricity price. The quantities SoC_{agg} and $E_{dem,agg}$ are natural sources of feedback as they denote the current state of the system's dynamics (6). The electricity pricing both in the present and the future help to achieve a pro-active control strategy. From the feedback χ it becomes clear that a high number of states does not arise from the aggregated battery model but from the 13-states model for the electricity price. This makes an CSA approach convenient over a Dynamic Programming one.

V. RESULTS

In this section, the numerical results of the proposed algorithm are presented and compared with the Rule-based controller and the open-loop search based on *fmincon*. Table III and Table IV present the charging cost of each solution, for the four pricing schedules presented in the previous section. It can be noted, that both CSA and open-loop search offer huge cost improvements compared to the Rule-based controller. Both tables present charging/operation cost of the charging station in €. The results are validated over 7 different days in Table III and 7 different weeks in Table IV. It has to be noted that, since no penalties for not satisfying the requirements of the users has been observed, all the tables present the energy cost in € only.

CSA offers a huge improvement in terms of electricity cost, as compared with the Rule-based controller: for 1

TABLE II

CSA ALGORITHM

Initialize:

1) Set $k=0$ and initialize $\hat{P}(0)>0$ to be a positive define matrix
2) Choose a positive scalar function $a(k)$ satisfying $a(k)>0$, $\lim_{k\to+\infty} a(k)=0$, $\sum_{k=0}^{\infty} a(k)=\infty$, $\sum_{k=0}^{\infty} a^2(k)=\infty$

Step 1:
Apply the controller $\hat{u}=-\rho^{-1}B'\hat{P}(k)\chi$ for the next simulation period and calculate :

$$\varepsilon(\chi(k),\hat{P}(k))=\Delta\hat{V}(k)+\sum_{s=k}^{k+1}\Pi(\chi(s)) \tag{12}$$

$$d\hat{V}(k)=\chi'(k+1)\hat{P}(k)\chi(k+1)-\chi'(k)\hat{P}(k)\chi(k)$$

Step 2:
Construct a linear-in-the-parameters (LIP) estimator of $\varepsilon(x(t),\hat{P}(k))$ as follows :

$$\hat{\varepsilon}(\chi(k),\hat{P}(k))=\theta'\phi(\chi,\hat{P}(k)) \ ,$$
$$\theta=\arg\min_{\vartheta}\sum_{i=k-T}^{k}\left(\hat{\varepsilon}(\chi(k),\hat{P}(i))-\vartheta'\phi(\hat{P}(i))\right)^2$$

where ϕ,θ are the regressor vector and the parameters vector of the estimator and $T=min(k,T_h)$
Step 3:
Calculate the best $\hat{P}$ obtained so far from all the previously applied to the model,

$$P_{best}(k)=\arg\min\varepsilon(x(t),\hat{P}(s)), s=0,1,\ldots,k$$

Step 4:
Generate N perturbed candidates (random perturbations) of $P_{best}(k)$ as follows :

$$\hat{P}_{cand}^{(i)}=(1-a(k))\hat{P}_{best}(k)+a(k)\Delta\hat{P}^{(i)}, i=1,2,\ldots,N$$

where $\Delta\hat{P}^{(i)}$ are random block diagonal matrices where the diagonal elements are symmetric positive definite matrices satisfying $\Delta\hat{P}^{(i)}>0$
Step 5:
By utilizing step 2 estimator controller $\hat{P}(k+1)$ to be applied for the next simulation period, is :

$$\hat{P}(k+1)=\arg\min\hat{\varepsilon}\left(\chi(k),\hat{P}_{cand}^{(i)}\right), i=0,1,\ldots,N$$

Step 6:
Set $k=k+1$ and GO TO **Step 1**.

TABLE III

COST IN € FOR 1 DAY

Pricing Model	Rule-based	Open-loop	CSA
Price 1	19.52	14.14	14.15
Price 2	11.79	10.82	10.82
Price 3	17.34	12.91	13.37
Price 4	15.92	11.16	11.84

day experiments, approximately 5€ savings are observed, whereas, for 1 week experiments, we reach 25-30€. The improvements are affected by the pricing model, the different vehicle schedules of each day, the initial-arrival SoC of each car.

On the other hand, the CSA algorithm provides solutions that are very close or even equal, with the open-loop optimization: this is a hint that CSA can converge close to the global optimum strategy (or at least close to a similar local optimum).

In Fig. 3, the grid-consumption for the three strategies is presented. In a typical day, (under price model 1), both CSA and open-loop approach, avoid to utilize grid during midday, when pricing is high, and try to take advantage of low prices during morning hours. On the other hand, Rule-based does not employ such a intelligent strategy and absorbs energy when necessary.

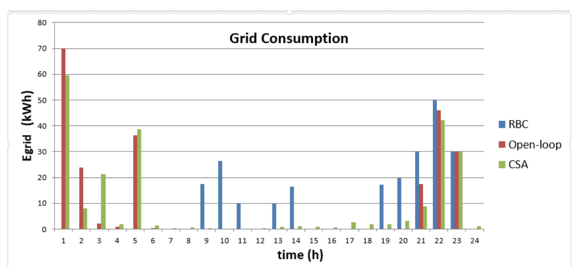

Fig. 3. Evolution of the grid-absorbed energy

A. Robustness and number of iterations

We have observed that the open-loop optimization and the CSA algorithm converge to similar optimum. However, we expect that due to their open-loop nature, the set of open-loop actions cannot be robust to different conditions

TABLE IV

COST IN € FOR 7 DAYS

Pricing Model	Rule-based	Open-loop	CSA
Price 1	127.63	95.98	96.54
Price 2	89.20	80.45	79.99
Price 3	123.64	105.07	104.85
Price 4	126.08	97.81	97.44

(different vehicle schedule, pricing models, etc.). For this reason we want to test whether the CSA algorithm has a consistent performance when different conditions than those used as training data occur. This would justify robustness of the proposed approach, and eventually its use in a learning-based fashion, with the same algorithm operating over long horizons, and sets of new data eventually used for re-training the algorithm once in a while.

In order to test robustness we keep the matrix $\hat{P}$, which was "learned" via training data,

and use it over a different week. The resulting performance was evaluated and the results are shown in Table V. We note that now CSA overcomes the open-loop optimization and, most importantly consistent improvements as compared with Table IV.

TABLE V

ROBUSTNESS EVALUATION

Pricing Model	Rule-based	Open-loop	CSA
Price 1	129.80	110.58	99.90
Price 2	93.23	91.81	81.30
Price 3	124.67	121.32	107.84
Price 4	137	128.12	111.68

Another crucial issue is the number evaluations of the fitness function (4). More specifically, in black-box optimization (where the dynamics of the model are unknown), the proposed solutions are evaluated through two parameters. The first one is the final performance, and the second is the number of fitness evaluations/iterations used by the algorithm to converge to the final solution. While the Tables III and IV have shown that the CSA algorithm is slightly further from the optimum than the open-loop algorithm, here we illustrate that CSA overcomes open-loop solutions in terms of number of iterations. With respect to Table III, *fmincon* needs around 3000 iterations to achieve the presented performance, whereas, CSA requires only around 300 iterations. In Table IV, the difference is even bigger, as *fmincon* requires around 8000 iterations, and CSA needs around 500 iterations.

VI. CONCLUSION

This work proposed an intelligent optimization approach based on Approximate Dynamic Programming for the optimal charging/discharging vehicle schedule of a grid-connected charging station. The objective of the proposed algorithm was to minimize the energy cost and respect user's requirements. Extensive simulations demonstrate that the proposed strategy can intelligently and automatically change the grid demand of the charging station, achieving relevant energy cost improvements compared to state-of the-art rule-based strategies. Furthermore, it demonstrated a robust behavior in the presence of stochastic arrival and departure times, also requiring less evaluations of the fitness function than a standard open-loop optimization strategy.

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