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Optimized Time Step for Electric Vehicle Charging Optimization Considering Cost and Temperature*

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Abstract

An optimal decentralized scheduling strategy for charging one Electric Vehicle (EV) is proposed to minimize the customer charging cost. Moreover, the EVs can offers more profit when considering the vehicle to grid feature, by discharging the EV in the grid at high peak demand the EV' owner can earn money and reduce his charging bill. Compared to existing methods, the main advantages of the proposed strategy is the considerations of an optimized time step. By doing so, the optimization problem uses a minimum number of decision variables and constraints. Then, the problem can be solved by all optimization method to reach the global optimum in reduced time. To formulate and solve a non-linear constrained optimization problem, the scheduling process takes into consideration: the time of arrival and time departure of the EV, the daily energy prices, the initial State of Charge (SoC) and the final SoC desired by the customer, the power limitations, and the temperature. The results obtained show a high impact of the optimal scheduling strategy and significant charging cost reduction compared to the uncontrolled charging and fixed time step algorithms. Moreover, the charging strategy only requires that each EV solves its optimization problem locally, therefore, its deployment requires a low computing capacity.

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Nomenclature	
i	the time slot index
N	the total number of time slot
X	the full decision vector
X_i	the decision vector value in the i^{th} time slot
P_{G2V}, P_{V2G}	the charging/discharging power decision vector
d_{G2V}, d_{V2G}	the charging/discharging duration decision vector
d_{max}	the vector of the maximum duration of each time slot
$price_{G2V_i}$, $price_{V2G_i}$	the charging/discharging electricity price of the i^{th} time slot in €/kWh
P_{G2V_i}, P_{V2G_i}	the charging/discharging power of the i^{th} time slot in kW respectively
d_{G2V_i}, d_{V2G_i}	the charging/discharging duration of the i^{th} time slot
Δt	the sampling time (constant time step)
α_1, α_2	the weighting factors for the objective function
$Pmax_{G2V_i}$, $Pmax_{V2G_i}$	the maximum charging/discharging power in the i^{th} time slot
d_{max_i}	the maximum duration for charging and discharging in the i^{th} time slot
$P_{i,Bat+}$, $P_{i,Bat+}$	the maximum accepted/delivered power by the battery
SoC_i	the state of the charge in the i^{th} time slot
T_i	the temperature in the i^{th} time slot
SoC_{mini}	the minimum value of SoC expected by the user
SoC_{max}	the maximum value of SoC expected by the user
SoC_0	the initial value of SoC
SoC_{target}	the desired final value of SoC by the user
$E_{required}$	the required energy to reach the SoC_{target}
E_{final}	the final energy value of the battery
E_0	the battery capacity
E_i	the energy of the battery in the i^{th} time slot
$\eta_{charger}$	the charger efficiency
P_{joule_i}	the power loss in the i^{th} time slot
$P_{convective_i}$	the convective power in the i^{th} time slot
mC_p	the thermal capacity of the battery
k	the thermal factor depending on the thermal inertia of the battery
T_{out}	the outside temperature
R_{th_out}	the heat transfer coefficient between the battery and the outside

1. Introduction

1.1. EVs charging context

Lithium-ion Batteries (LiBs) are widely used in electric and hybrid vehicles due to their high energy and power density [1]. This type of battery is used as a power source for traction motor of EV. Nowadays, charging EVs is mainly done simplistically. As soon as the vehicle is connected to the grid, the battery is charged by the minimal value between the available power on the grid, the maximal power accepted by the EV charger and the maximal power accepted by the battery, until it reaches a full charge. This type of charging named uncontrolled charging implementation is still in use today [2]. The improvement of charging strategies for EVs is a challenge for the next decades. Power distribution systems can be optimized, but the uncontrolled strategy used in EVs creates high peaks of power demand when considering classical daily scenarii with home to work and work to home travels [3]. In such scenario, all EVs are plug-in at similar moment to the power network and they expect to start the charging immediately whereas in most cases the charging of vehicles can be delayed. Using electricity prices as a lever to control the charging of EVs is a possible solution in a decentralized charging strategy. The user and the power network can directly obtain concrete benefits like less expensive charging, less load peaks and even network support in the case of Vehicle to Grid (V2G) feature.

1.2. Related Works

Several research studies have been conducted for developing new charging methods through centralized, and decentralized strategies. The centralized charging strategies carry out the charging of the EVs from a system level viewpoint and consider EVs present on all the nodes of the distribution system collectively [4]. These control strategies require extensive cyber-infrastructure, substantial communications, and processing resources [5]. Moreover, the centralized algorithms are more sensitive to privacy constraints, because all users data is saved in servers for real-time optimization or in the backup system for data recovery in the case of a system failure. Unlike the centralized implementation, the decentralized strategies operate at the nodal level and perform the charging of EVs present on each node locally [6]. One drawback of centralized control is the continuous change of the computed charging profile at any introduction of new EVs into the station or any demand from the Transmission Systems Operator (TSO) or the Distribution System Operator (DSO). Thus, the aggregator may need to restart again the optimization to update control signals and sometimes this operation is very expensive in terms of computation time [7]. The adoption of a decentralized control strategy can be a solution to previous drawbacks. It breaks the complexity of global optimization problem to local optimization problems at the EV level and it limits the communication between the aggregator and the EVs.

In general, the EV charging scheduling is almost focused on maximizing the aggregator profit without carefully addressing customers' needs. In [8], an unidirectional smart charging algorithm has been formulated in order to maximize the aggregator profit. The aggregator uses the capacity of the EV' batteries to participate in the regulation energy markets. The study in [9] proposes the bidirectional charging EVs while offering ancillary services (load regulation and spinning reserves) to the grid. The developed algorithm is used to maximize the annual revenues of the aggregator. Two stages of the EVs charging problem coordination have been proposed in [10], deterministic and stochastic; aiming to minimize power losses and voltage deviation when the improvements in power quality was the purpose of the study. The authors in [11] designed a smart charging strategies to operate in the unidirectional and the bidirectional mode with the consideration of the cost-benefit analysis in a distribution system. An EV charging that takes advantage of photovoltaic energy tariffs and provides ancillary services has been described in [12]; the Mixed Integer Linear Programming (MILP) is implemented to support the grid by the V2G feature and to offer ancillary services in the form of reserve. The main drawbacks of this type of scheduling is that the SoC desired by the EV' owner may not be reached in some cases at the departure time, therefore the customer would not have the required SoC to return home.

However, the EV charging scheduling from the customer's point of view is almost neglected, a few recent works studied the minimization of the EV owners charging cost. The concept of V2G and Vehicle to Home (V2H) have been exploited in the context of residential charging of one EV, [13] proposed six decentralized smart charging algorithms with the aim to minimize the charging cost of the EV' owner. In [14], a smart charging strategy has been proposed to minimize EV charging costs while maintaining acceptable distribution system voltages. The optimization decision is based on the time variations in electricity prices, the voltage variation throughout the distribution system and the cost of battery degradation caused by the charging. The authors in [15] formulated the smart charging approach as an optimization problem, aiming at minimizing the EVs charging cost considering the day-ahead electricity price, the battery degradation cost and uncertainties in EVs arrival and departure time. In [16] a coordinated charging strategy has been proposed to manage the EV fleet charging considering the charging infrustructure and the EV' users satisfaction.

In the literature various charging strategies have been proposed. Nevertheless, all of them use a constant sampling period or fixed time step defined before starting the optimization [8-16]. In the event of a fluctuation of energy prices of a few seconds within a long planning optimization window, the charging scheduling will cause an important issue with a huge number of steps. Indeed, the calculation time step is defined by the minimal duration between two changes of energy price. Therefore, the size of the decision variable vector becomes very significant, so the computation time and the complexity of the problem increase. The classical scheduling algorithms in a low computational embedded system with constant calculation time steps may not be able to carry out this optimization task because of the large number of decision variables and constraints involved in this optimization.

The objective of the paper is to transform a complicated optimization problem into a simplified one by decreasing the number of decision variables and the number of constraints. Studies have proposed advanced methods for solving such problems using reinforcement learning [17], and adaptive dynamic programming [18]. In order to be distinguished from studies that use advanced optimization methods, the proposed strategy will directly affect the mathematical modeling of the optimization problem by significantly reducing the number of decision variables and constraints. With the constraint of our industrial partner to implement such a solution on an embedded system in the electric car, our choice is turned to decentralized algorithms. With the constraint of an embedded architecture with a low computational capacity. The use of a dynamic time step greatly simplifies the optimization problem, it can change a hard problem with hundreds of decision variables and constraints to an easy problem with dozens of decision variables and constraints. Therefore the problem could be solved with all optimization methods and the convergence to the optimal solution will be easily and fast. So, the use of advanced optimization methods will not add up to much to the convergence to the optimal solution due to the simplicity of the problem.

In addition to the studies mentioned in the introduction many other optimal algorithms and strategies are available in the literature to solve the cost minimization problem, but they are tested under different conditions and assumptions: battery capacity, customers or aggregators optimization point of view, energy prices applied for aggregators (€/MWh) or customers (€/kWh), etc. However, each study is conducted in its own context and therefore it is difficult to compare the performance of different strategies.

Moreover, the LiBs health issue is related to optimizing the power scheduling of charging/discharging sequence. More specifically, the implementation of an optimized bidirectional charging with charging power equal to the fast charging power based only on the user's needs. Fast charging has a negative impact on the main considerations related to battery life objectives [19] and the power grid [20]. Charging LiBs involves many nuanced considerations and subtleties to consider conflicting objectives of maximizing the battery lifespan, reducing the charging time, and improving the charging performance.

Furthermore, optimal charging strategies do not take into account the temperature. Due to the higher sensitivity to the temperature of the LiBs compared to other type of battery chemistry [21], extreme outside temperatures such as $40°C$ and over or $-20°C$ and lower, accelerate the ageing capacity loss [22]. High temperatures increase power acceptance of the battery but the battery lifetime decreases in a short time, causing premature ageing of the LiBs [23]. On the other hand, subzero temperatures decrease the power acceptance, increasing the internal resistance of the LiBs, causing the raising of the joules power losses, decreasing the efficiency of the charging, and affecting the State of Health (SoH) of the LiBs [24, 25]. In case of cold weather when the temperature is not considered, the final SoC estimation maybe false and the battery does not reach the SoC target desired by the customer [26]. Thus, charging the battery while considering temperature is a very important issue, to get a best estimation of SoC and to conserve the lifespan of EVs batteries. Considering the outside temperature and temperature of the LiBs is a big challenge to make the EVs suitable to any climate condition and to extend the batteries lifespan.

1.3. Contributions

This article is an extension of an earlier conference paper [26], which has been significantly improved to take into account the constraint of low computational capacity of the embedded EV' system. The contribution of this paper has been capitalized in a patent [27]. The main contributions of the paper can be summarized as follows:

- A new decentralized algorithm for optimal charging of an EV;
- Low computation complexity with a dynamic time step;
- Minimization of the charging cost from the user perspective;
- Consideration of V2G feature to reduce the user cost;
- Target SoC evaluation based on temperature to avoid lower estimations like in cold temperature conditions.

The organization of the paper is as follows: the modeling of the optimization problem is given in the Section II. Section III presents the simulation results of the optimal planning strategy. Finally, Section IV addresses the conclusion of this paper and the future work.

2. Charging scheduling strategy: optimization problem modeling

The charging strategy consists of three steps: pre-processing, optimization, and post-processing, as shown in Fig. 1.

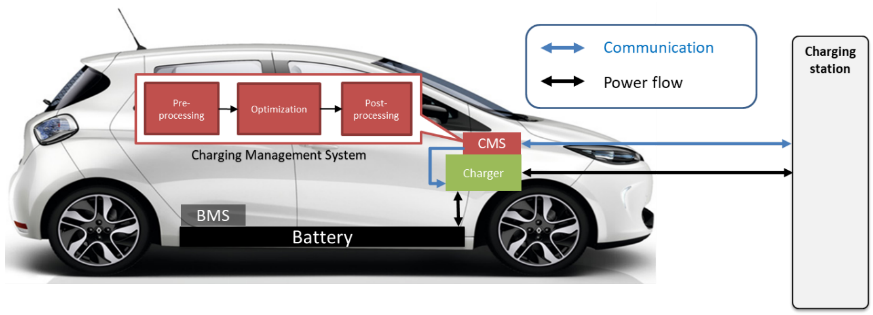

Figure 1: Decentralized charging system synoptic

2.1. Pre-processing

The pre-processing step allows, before starting the scheduling, to provide the essential data for the optimization step, namely the data collection, the subdivision of the time interval into time slots, the size of the decision vectors, as well as the determination of the upper bounds of the optimized time step. The data collection operation consists in receiving the data and parameters of the optimization problem to initiate the planning, either of the Battery Management System (BMS) or the charging station.

Fig. 1 presents the context of the contribution and the elements interacting with the Charging Management System (CMS).

The device receives from the BMS the measurement of the initial temperature, the outdoor temperature, the initial SoC, and the battery capacity.

The charging station sends the data over a maximum availability period of 24 hours. The device receives from the charging station the following information shown in Fig. 2:

- The charging energy price for the next 24 hours: $price_{G2V}$
- The maximum charging power for the next 24 hours: $Pmax_{G2V}$
- The discharging fees from V2G for the next 24 hours: $price_{V2G}$
- The maximum discharging power for the next 24 hours: $Pmax_{V2G}$

In this step, the pre-processing algorithm restricts the time base to the actual availability period of the EV on the charging station i.e. between the arrival time and departure time of the EV.

The next step is to subdivide the horizon time into a sequence of time slots. In each defined time slot, the four variables $price_{G2V}$, $Pmax_{G2V}$, $price_{V2G}$, and $Pmax_{V2G}$ have a constant value. The subdivision to time slots is the conversion of data from time scale in Fig. 2 to slot scale in Table 1.

Thus, we can conclude the number of time slots corresponding to the size of the decision vectors $N = 12$ and the duration of each time slot d_{max} shown in Fig. 3. The subdivision on time slots of the $price_{G2V}$, $Pmax_{G2V}$, $price_{V2G}$, and $Pmax_{V2G}$, can be observed in figures 2-3 and in Table 1.

For current data with a constant time step for scheduling, the maximal sampling time that can be used with optimal charging strategies is $\Delta t = 1$ hour corresponding to the minimal duration of d_{max}. Thus the size of decision vector is 24. For our strategy, the size of decision vector is 12. The difference between these two numbers mainly depends on the minimal duration that can be smaller than 1 hour in many real cases.

In case of a small variation of G2V energy prices for 10 minutes between 20:00 and 20:10 (case 2), the maximal sampling time that can be used with optimal charging strategies with constant time step is $\Delta t = 10$ minutes corresponding to a size of 144 for the decision vector. For the proposed strategy, the size of decision vector is 14.

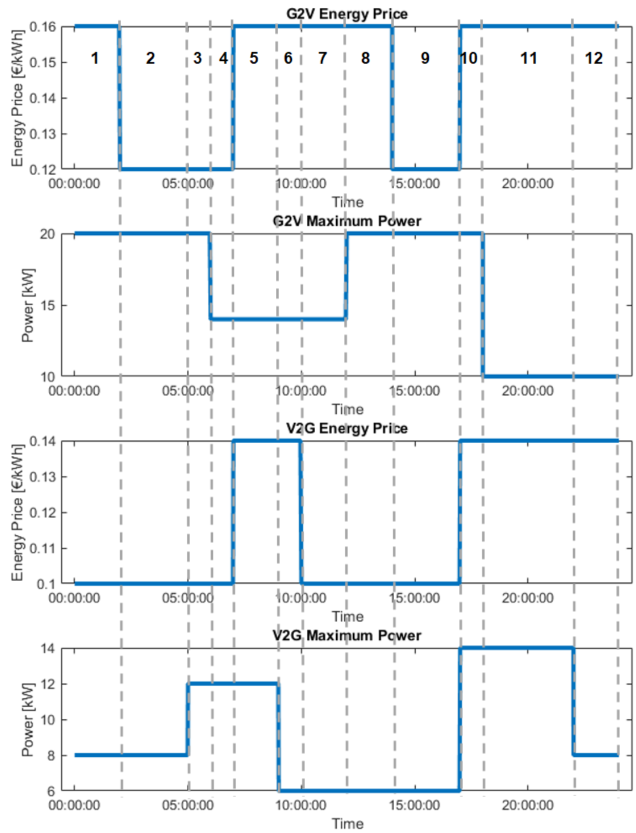

Figure 2: Subdivision on time slots case 1

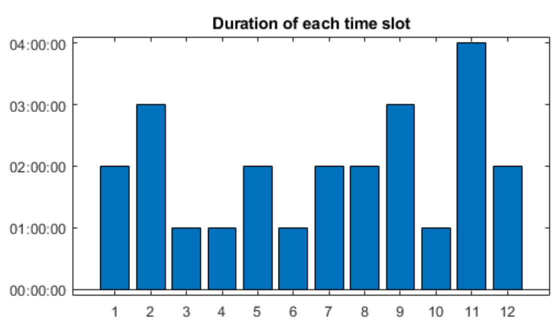

Figure 3: Duration of time slot: d_{max}

Slot	$price_{G2V}$	$P_{max_{G2V}}$	$price_{V2G}$	$P_{max_{V2G}}$	d_{max}
1	0.16	20	0.10	8	2
2	0.12	20	0.10	8	3
3	0.12	20	0.10	12	1
4	0.12	14	0.10	12	1
5	0.16	14	0.14	12	2
6	0.16	14	0.14	6	1
7	0.16	14	0.10	6	2
8	0.16	20	0.10	6	2
9	0.12	20	0.10	6	3
10	0.16	20	0.14	14	1
11	0.16	10	0.14	14	4
12	0.16	10	0.14	8	2

Table 1: Subdivision results to slot scale

A single event of a few minutes duration can penalize the whole optimization problem. To sum up, a short fluctuation of prices or maximal power can make the optimization task very difficult and even impossible (time and memory constraints) for an embedded charging scheduling system.

2.2. Optimization

This section is devoted to modeling the EV charging problem with cost minimization and temperature consideration. The modeling is done as follows:

The time horizon vector is described by $S = [1, ..., i, ..., N]$ and it contains N non equal duration time slots as defined in the previous subsection and in Figure 3. The charging and the discharging of the EV can be expressed by four decision vectors as expressed in (1).

$$X = \begin{bmatrix} P_{G2V} & P_{V2G} & d_{G2V} & d_{V2G} \end{bmatrix} \tag{1}$$

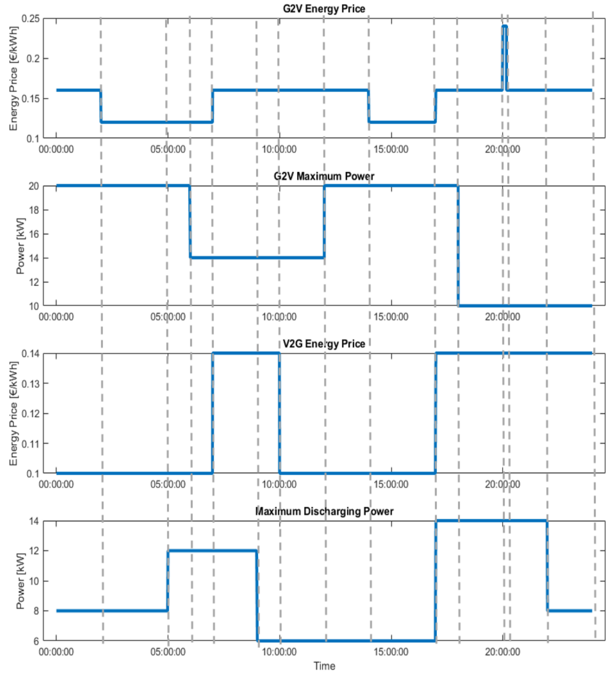

Figure 4: Subdivision on time slots case 2

With

$$\begin{aligned} P_{G2V} &= \left[P_{G2V_1}, ..., P_{G2V_i}, ..., P_{G2V_N}\right] \\ P_{V2G} &= \left[P_{V2G_1}, ..., P_{V2G_i}, ..., P_{V2G_N}\right] \\ d_{G2V} &= \left[d_{G2V_1}, ..., d_{G2V_i}, ..., d_{G2V_N}\right] \\ d_{V2G} &= \left[d_{V2G_1}, ..., d_{V2G_i}, ..., d_{V2G_N}\right] \end{aligned} \tag{2}$$

For the i^{th} time slot the vector X_i can be defined as shown in (3):

$$X_i = \begin{bmatrix} P_{G2V_i} & P_{V2G_i} & d_{G2V_i} & d_{V2G_i} \end{bmatrix} \tag{3}$$

This algorithm have two aims:

- Minimize the vehicle's charging cost through optimal grid to vehicle power flow taking into account G2V energy prices.
- To maximize the profit from selling energy from vehicle to grid considering V2G energy prices.

The objective function is composed of two objectives, a positive one C_1 and a negative one C_2. The optimization leads to minimize C_1 that refers to the EV charging cost and to maximize C_2 corresponding to the EV discharging remuneration or the economic profit of discharging EV's battery on the grid. The two objectives are expressed in (4), (5):

$$C_1 = \sum_{i=1}^{N} price_{G2V_i} \cdot P_{G2V_i} \cdot d_{G2V_i} \tag{4}$$

$$C_2 = \sum_{i=1}^{N} price_{V2G_i} \cdot P_{V2G_i} \cdot d_{V2G_i} \tag{5}$$

Where $price_{G2V_i}$ is the charging electricity price of the i^{th} time slot in €/kWh, $price_{V2G_i}$ is the the discharging electricity remuneration of the i^{th} time slot in €/kWh, P_{G2V_i}, P_{V2G_i} is the charging and the discharging power of the i^{th} time slot in kW respectively, d_{G2V_i}, d_{V2G_i} are the calculation step in hours, and i the time slot index.

The proposed optimization approach is formulated to select the optimum charging power P_{G2V} for the period of time d_{G2V}, and the discharging power

P_{V2G} for the period of time d_{V2G} that minimize the weighted sum of the two criteria. The proposed formulation of the objective function to be minimized is given as follows:

$$F(X) = \alpha_1 C_1(X) + \alpha_2 C_2(X) \tag{6}$$

where X is the decision variable, α_1, α_2 are constant positive values, given the weight for each criterion: α_1 enforces charging operation mode, α_2 leads the system to discharge the EV using the available battery power to support the grid.

The optimization problem includes linear and nonlinear constraints resulting from EV technical constraints and customer needs.

The charging power constraint related to the daily available power on the grid and the discharging power constraint related to the daily required power by the grid are expressed in (7):

$$\begin{aligned} 0 \leq P_{G2V_i} \leq Pmax_{G2V_i} \qquad & i = 1, ..., N \\ -Pmax_{V2G_i} \leq P_{V2G_i} \leq 0 \qquad & i = 1, ..., N \end{aligned} \tag{7}$$

where $Pmax_{G2V_i}$, $Pmax_{V2G_i}$ are the maximum available power on the grid and the maximum required power by the grid in the i^{th} time slot respectively.

The maximum duration of use for charging and discharging in the i^{th} time slot is formulated in (8):

$$\begin{aligned} 0 \leq d_{G2V_i} \leq d_{max_i} \qquad & i = 1, ..., N \\ 0 \leq d_{V2G_i} \leq d_{max_i} \qquad & i = 1, ..., N \end{aligned} \tag{8}$$

To allow the charging and discharging operation in the same time slot, a constraint is expressed in (9):

$$d_{G2V_i} + d_{V2G_i} \leq d_{max_i} \qquad i = 1, ..., N \tag{9}$$

The maximum power that can be accepted or delivered by the battery depends on the relation between the SoC and the battery's temperature. This power is set by the values obtained in the Powermap function:

$$\begin{aligned} &P_{G2V_i} \leq P_{i,Bat+} \qquad && i = 1, ..., N \\ &P_{V2G_i} \geq P_{i,Bat-} \qquad && i = 1, ..., N \end{aligned} \tag{10}$$

Where

$$\begin{cases} P_{i,Bat+} = Powermap(SoC_i, T_i) \\ P_{i,Bat-} = -Powermap(SoC_i, T_i) \end{cases} \tag{11}$$

The Powermap function is the internal dependence of battery power on temperature T_i of the i^{th} slot and SoC of the i^{th} slot SoC_i. It provides information on the maximum power that can be accepted by the battery or delivered to the battery. An example of Powermap is shown in Figure 5.

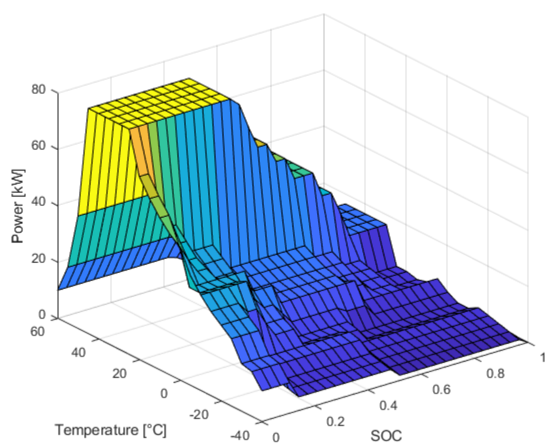

Figure 5: Lithium-ion battery power map

In order to limit the battery cycling degradation in discharging mode and to avoid customer's range anxiety in case of an emergency use of the EV, we add a SoC constraint expressed as follows:

$$SoC_i \geq SoC_{mini} \qquad i = 1, ..., N \tag{12}$$

Where SoC_{mini} is the minimum value of the SoC expected by the user, avoiding high battery Depth of Discharge (DoD) during V2G mode.

The case of overcharging is taken into account because it affects the lifetime of LiBs. Despite the fact that EV owners tend to prefer autonomy over battery life, because of the anxiety related to autonomy, which is considered one of the main obstacles to the large-scale adoption of EVs.

$$SoC_i \leq SoC_{max} \qquad i = 1, ..., N \tag{13}$$

The calculation of the required energy $E_{required}$ to reach the SoC desired by the costumer is expressed as follows:

$$E_{required} = (SoC_{target} - SoC_0) \times E_0 \tag{14}$$

SoC_0 is the initial SoC of the EV, SoC_{target} is the SoC desired by the customer, and E_0 is the capacity of the battery in kWh.

The constraint related to the final energy of the battery is:

$$E_{required} \leq E_{final} \leq E_0 \tag{15}$$

The evaluation of the energy variation of the battery at each time step can be computed as follows:

$$E_i = \eta_{charger}(P_{G2V_i} \cdot d_{G2V_i} + P_{V2G_i} \cdot d_{V2G_i}) \;\; i = 1, ..., N \tag{16}$$

Where $\eta_{charger}$ is the charger efficiency. Then, the final energy quantity in the battery can be expressed as:

$$E_{final} = SoC_0 \times E_0 + \sum_{i=1}^{N} E_i \tag{17}$$

The dynamic monitoring of the SoC is given by (18):

$$SoC_{i+1} = SoC_i + \frac{E_i}{E_0} \qquad i = 1, ..., N \tag{18}$$

The temperature calculation is a first order model expressed as follow:

$$mC_p \frac{dT}{dt} = P_{joule} + P_{convective} \tag{19}$$

The convective power is modeled by the Newton law showed in (20):

$$P_{convective_i} = \frac{T_i - T_{out}}{R_{th\_out}} \qquad i = 1, ..., N \tag{20}$$

Where T_{out} is the outside temperature and R_{th_out} is the heat transfer coefficient between the battery and the outside.

The joule power is formulated as a linear model in terms of charging and discharging power:

$$P_{joule_i} = k \times P_{G2V_i} + k \times (-P_{V2G_i}) \quad i = 1, ..., N \tag{21}$$

Where k is a thermal factor depending on the thermal inertia of the battery.

The optimization problem is solved with MATLAB optimization solver $fmincon$ with an Intel Core i7 CPU @ 2.70GHz.

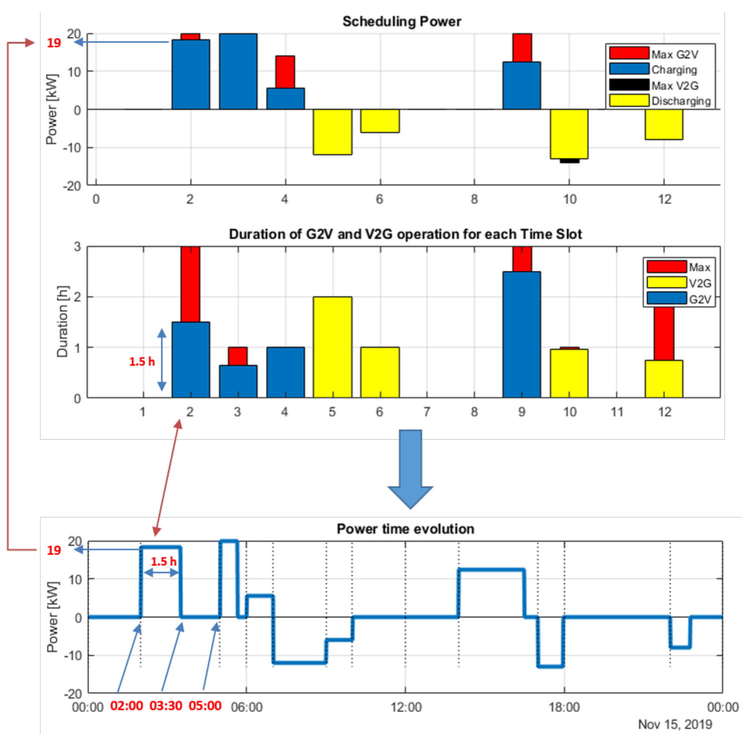

Figure 6: Data conversion to time scale

Algorithm 1 Transforming data from time slot to time scale

$d_{G2Vm} \leftarrow round(d_{G2V} \times 60)$

$d_{V2Gm} \leftarrow round(d_{V2G} \times 60)$

$d_{maxm} \leftarrow round(d_{max} \times 60)$

$t_{maxm} \leftarrow \sum_{i=1}^{N} d_{G2Vm_i} + \sum_{i=1}^{N} d_{V2Gm_i}$

$P(1) \leftarrow P_{G2V}(1)$

while $t \leq t_{maxm}$ **do**

    for $i \leftarrow 1, N$ **do**

        for $j \leftarrow 1, d_{G2Vm}(i)$ **do**

            $P(t) \leftarrow P_{G2V}(i)$

            $t = t + 1$

        end for

        for $j \leftarrow 1, d_{V2Gm}(i)$ **do**

            $P(t) \leftarrow P_{V2G}(i)$

            $t = t + 1$

        end for

        $R = d_{maxm}(i) - d_{G2Vm}(i) - d_{V2Gm}(i)$

        for $j \leftarrow 1, R$ **do**

            $P(t) \leftarrow 0$

            $t = t + 1$

        end for

    end for

end while

2.3. Post-processing

This step is used to generate the order for the charger to control the charging and discharging of the EV, respecting the scheduling carried out in the optimization stage. It consists in generating the control signal of the charge/discharge to charger by choosing a time step adapted to the communication between the CMS and the charger.

Firstly, the scheduling power obtained by the proposed strategy is transformed from the slot scale to the time scale using the Algorithm 1. The algorithm consists in processing each slot one by one separately to generate the power with the chosen time step. For example in the slot number 2, the power is 19kW (blue bar) and the duration of the slot is 1.5 hours (blue bar) as shown in Fig. 6. The output power is a constant power of 19kW that will be used from 2:00 AM to 3:30 AM and the value of zero for the remained duration until the end of the slot 5:00 AM. Secondly, when the charging power is generated then the SoC can be estimated using the equation (22)

$$SoC(t) = SoC_0 + \frac{1}{E_0}\int_0^t \eta_{charger}P(\tau)d\tau \tag{22}$$

where SoC_0 is the initial value of the SoC, E_0 is the nominal capacity in kWh and P is the charging power generated by the Algorithm 1.

Thirdly, the temperature can be estimated using the generated charging power by the equation (23):

$$T(t) = T_0 + \frac{1}{mC_p}\int_0^t (P_{joule}(\tau) + P_{convective}(\tau))d\tau \tag{23}$$

To summarize, in the post-processing step, the conversion of the optimization results from slot scale to time scale is performed, and the SoC estimation and the temperature estimation are carried out.

3. Simulations and results

The purpose of this section is to demonstrate the effectiveness of the proposed strategy. On the one hand, the results of the proposed strategy with an optimized time step have been compared to the classical approach using a fixed time step. On the other hand, the proposed strategy will be tested under an extreme outside temperature to show the effect of the temperature on the power scheduling and the final SoC. Finally, the optimized time step strategy will be tested on several daily energy price profiles to prove the effectiveness of the proposed strategy compared to the fixed time step strategy, in term of running time, the number of decision variables and the number of constraints. The initial conditions are $SoC_0 = 0.35$, $SoC_{target} = 0.7$, $SoC_{mini} = 0.1$, $SoC_{max} = 0.9$, $E_0 = 60kWh$, $\eta_{charger} = 0.9$, $P_{G2V\_Max} = 7kW$, and $P_{V2G\_Max} = -7kW$. The initial battery temperature is fixed to $20°C$.

The initial SoC and desired SoC values have been chosen considering the mean value of the used values by the EV' users in the Renault Technocentre parking. The SoC_{mini} and SoC_{max} values have been used to prevent the LiBs from high DoD and fast battery ageing and to maximize the profit. The Zoé 3^{rd} Gen has been used as an EV in the simulation with 60kWh of battery capacity and charger efficiency of 90%. We assumed a domestic charging point with a maximum charging rate of 7kW and a maximum discharging rate of -7kW.

The simulation results for the proposed scheduling strategy are presented below. The algorithm has been tested for several scenarios to validate its performance. A real French energy price profile was chosen to illustrate the charging cases. The results show two cases, the first case is the charging under an outside temperature of $20°C$, and the second case is a charging under an extreme outside temperature of $-20°C$.

For the first case, which implies a charging of the EV at night under an outside temperature of $20°C$.

The Fig. 7 shows the comparison between several charging strategies. The SoC_{target} is achieved by all strategies, however, the charging cost is different from one strategy to another. Using the uncontrolled charging, the charging starts at the moment of plug-in, neglecting the high energy prices, so the charging cost will be high and it is estimated to 2.1€. Smart charging algorithm with only G2V can shift the charging to midnight, the EV is plugged-in at 18h00,

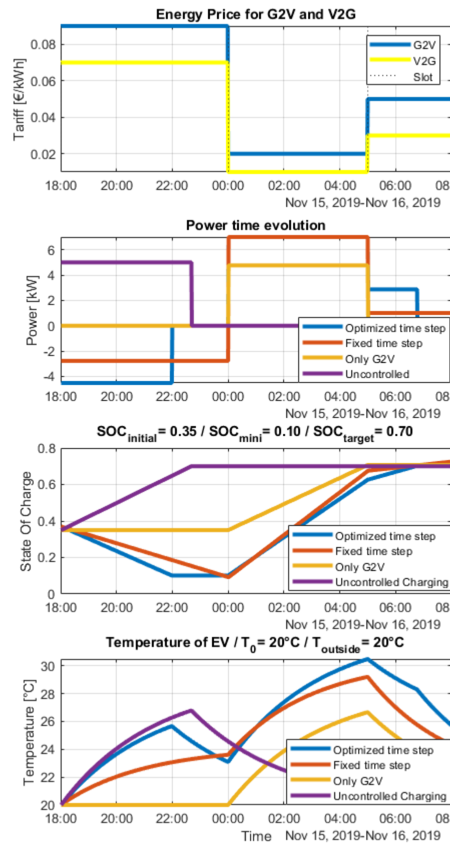

Figure 7: Charging strategies comparison under $T_{out} = 20°C$.

but the charging effectively starts until midnight when the electricity price is more attractive so the estimated charging cost is 0.47€. Using the V2G feature, the scheduling strategy, begins the discharging in the period of high V2G remuneration to maximize the profit while the SoC decreases until it reaches the minimal value of 0.1 corresponding to the SoC_{mini}. When the G2V energy price becomes cheaper, the charging begins to reach the desired SoC. The two strategies with optimized time step and fixed time step use the V2G feature, but with the proposed strategy the charging profit is 0.31€ and the executing time is 0.25 second compared to 0.28€ and 1.95 second for the classical strategy with fixed time step.

For the strategy using optimized time step, the number of decision variables is 12 and the number of constraint is 21. However, for the classical strategy using fixed time step of 10 minutes, the number of decision variables is 84 and the number of constraint is 420.

In brief, the classical strategy with fixed time step requires higher computing capacity because of the high number of decision variable and constraints compared to the proposed strategy with optimized time step that could be integrated easily to EV onboard embedded system.

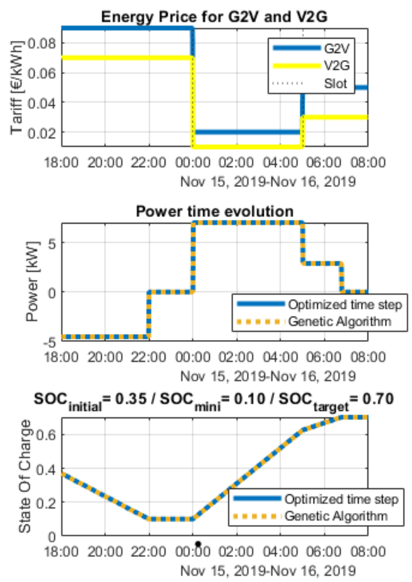

Figure 8: The impact of optimization algorithm

Fig. 8 illustrates the impact of optimization method on convergence to the optimal solution. The two charging profiles reached the targeted SoC before the departure time. Although the difference between the global methods such as genetic algorithm and the locally method based on the gradient, the two charging power profiles are the same corresponding to the optimal solution presented in Fig. 7 with the blue color. Because of the low number of decision variables and constraints (12 decision variables and 18 constraints) the genetic algorithm and the gradient method converge to the same optimal solution. In brief, the proposed method does not require the use of an advanced optimization method to converge to the optimal solution. A local optimization method may be sufficient to solve the optimization problem.

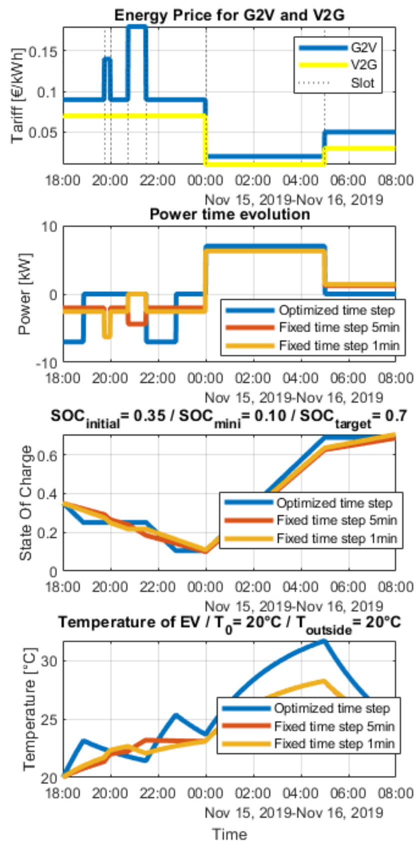

Figure 9: The impact of an extra event on power scheduling power

Fig. 9 shows the impact of an extra event such as a football match. The energy prices are directly impacted by this extra event. In order to demonstrate the advantage of the proposed optimized time step strategy and the inconvenient of the use of fixed time step, a scenario of two perturbations of 15 minutes and 45 minutes in G2V prices is used. For the fixed time step strategy, the time step should be adapted for each use case. For fixed time step strategy, the time step could be 15min or 5min or 1min. By decreasing the time step the execution time becomes greater and convergence to the optimal solution is more complicated. The main reason is the increasing of the number of decision variables from 84 for 10min to 168 for 5 minutes fixed time step and to 840 for 1 minute fixed time step. The number of constraints has been increased from 420 for 10min to 840 for 5 minutes fixed time step and to 4200 for 1 minute fixed time step. However, for the optimized time step strategy the number of constraints has been increased from 12 to 28 and the number of constraints from 21 to 49. Moreover, the execution time of the optimization problem increases as the size and complexity of the problem increases. For this case, it can be noted that the solving time is 72 seconds for 1 minute fixed time step, 2.4 seconds for the 5 minutes fixed time step, and 0.24 second for the optimized time step strategy. Furthermore, the charging profit is different for each power profile, it is estimated to 0.225€ for 1 minute fixed time step strategy, to 0.24€ for 5 minutes fixed time step strategy, 0.31€ for optimized time step strategy. To sum up, the optimized time step strategy ensures high speed convergence to optimal solution and needs low computing capacity compared to fixed time step strategies.

For the second case, the charging is done under an outside temperature of $-20°C$. The comparison between the fixed time step strategy and optimized time step strategy shows the advantage of fixed time step to follow the temperature constraint. However, it highlights the fact that the constraint evaluating process in the scheduling process is done 48 times for the fixed time step against 2 times for the optimized time step. In the case of significant variations of system inputs (energy prices and maximum powers) and long planning period the most important thing is to find a sub optimal solution in the feasible area that satisfies the constraints as quickly as possible. Therefore, the proposed strategy with optimized time step performs perfectly this task.

By applying the two power profiles defined above to the battery model, the results show a slight error between the final SoC and the SoC target. Despite the consideration of temperature in the scheduling strategy, it remains important to note that the scheduling power profiles in Fig. 10 are distinct from the effective

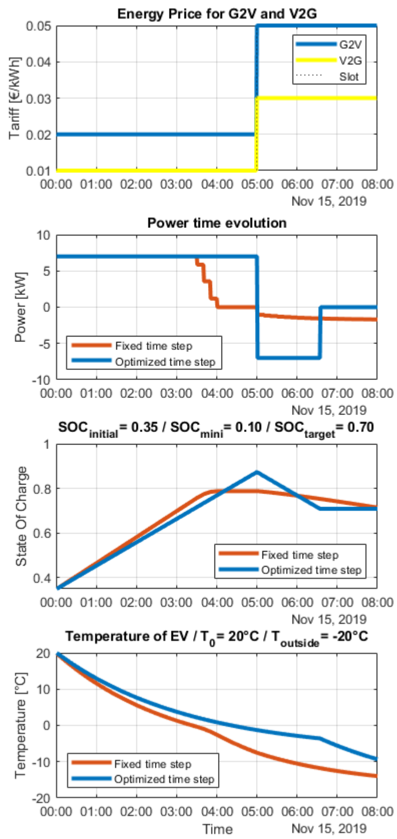

Figure 10: Charging strategies comparison under $T_{out} = -20°C$.

charging power profile in Fig. 11. Due to the rapid decrease of the battery power acceptance caused by the fast drop of the battery temperatures, the power profile is limited by the battery power restriction given by the powermap updated every minute. It is possible to overestimate the energy requirement by 5% to 15% to overcome this problem in extreme temperature.

Moreover, the proposed algorithm with optimized time step has been tested on five daily energy prices profiles and the results were compared to classical algorithms with 10 minutes and 1 minute fixed time step. The comparison has been done on several levels such as the number of the decision variables, the number of constraints, the running time and the charging cost/profit. The

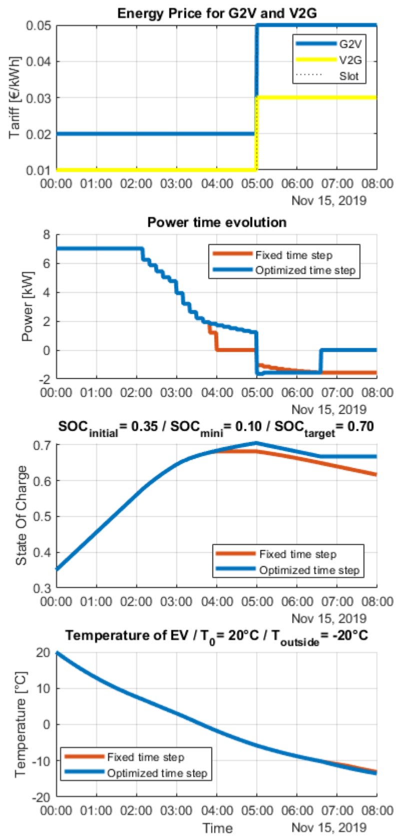

Figure 11: The simulation of battery charging with the obtained scheduling power, $T_{out} = -20°C$.

results of the study are presented in Table 2.

According to the results presented in Table 2, the algorithm with optimized time step performs the charging scheduling by using a minimal number of decision variables and the number of constraints. By subdividing the energy price profiles on optimal time slot the number of decision variables is minimized compared to the classical strategies with fixed time step. For an optimization window of 14 hours, the number of decision variables is 840, 84, for 1 minute and 10 minutes fixed time step respectively. Therefore, the executing time is very small for the proposed strategy with optimized time step compared to the strategies

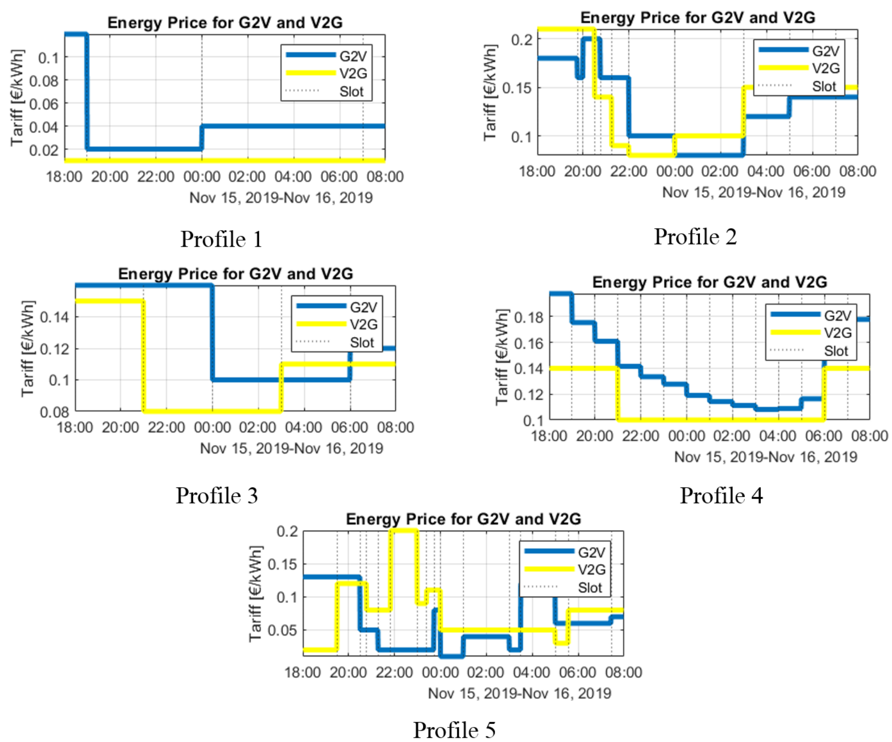

Figure 12: The used energy price' profiles

with fixed time step.

Moreover, the last column shows the charging cost (negative number) or the charging profit (positive number). The charging cost/profit value gives the information about the convergence to the optimal solution. The strategy with optimized time step has always the best value. In case of many variations in the energy price profile (profile 2 and 5) presented in Figure 12, the charging profit of the optimized time step strategy is almost double compared to the classical strategies with fixed time step. In conclusion, the optimized time step strategy converges to the optimal solution quickly and performs the charging cost minimization despite the many variations in the energy price profile.

Profile	Strategy	N^o Var	N^o const	Running time	Cost
1	1min	14x60	5x14x60	**188**	**-0.47**
	10min	14x6	5x14x6	**2.7**	**-0.41**
	Optimized	4x4	7x4	**0.3**	**-0.41**
2	1min	14x60	5x14x60	**112**	**0.15**
	10min	14x6	5x14x6	**1.6**	**0.26**
	Optimized	4x11	7x11	**0.8**	**0.41**
3	1min	14x60	5x14x60	**187**	**-1.7**
	10min	14x6	5x14x6	**2.5**	**-1.69**
	Optimized	4x14	7x14	**1.4**	**-1.63**
4	1min	14x60	5x14x60	**138**	**-1.29**
	10min	14x6	5x14x6	**1.85**	**-1.23**
	Optimized	4x5	7x5	**0.37**	**-1.22**
5	1min	14x60	5x14x60	**167**	**0.92**
	10min	—	—	—	—
	Optimized	4x16	7x16	**0.40**	**1.89**

Table 2: The result of the case study

4. Conclusion

In order to provide an economic benefit to EV users, an optimal decentralized smart charging strategy has been proposed in this work with the objective of reducing the charging cost for the EV user. When assuming the high variations in energy prices, the classic smart charging strategies can not perform the scheduling due to high number of decision variables and the high number of constraints. The added value of the proposed smart charging algorithm is the use of a dynamic optimized time step taken as a decision variable, contrary to the existing approaches that use a constant time step as a fixed parameter. The proposed algorithm can perform the power scheduling despite the high fluctuation of energy prices in a reduced time and low computational capacities such as those available on an onboard controller. Taking into account the TOU energy prices, the initial SoC, the final SoC desired by the EV user, the maximum power of the charging infrastructure, the power limitation the Li-ion battery, the initial battery temperature and the outside temperature, the smart charging strategy with optimized time step outperforms the classical strategies with a fixed time step in terms of computing time and the charging cost reduction.

Future work should include a degradation model (in scheduling) that consider the effect of the V2G feature on the degradation of Li-ion batteries, due to the large depth of discharge and long discharge time.

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