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Enhancing the Charging Process of Electric Vehicles at Residential Homes

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ABSTRACT It is essential to establish smart and efficient charging strategies for electric vehicles, due to the increase of their sales, and especially taking into account that many of these vehicles will be recharged in private parking lots, where the charging point features are limited. In this paper, we propose four different charging methods: the cheapest, the cheapest starting, the low cost, and the last period schemes, as an alternative to the traditional plug and charge method. Our objective is to find better strategies for an automatic, efficient, and scheduled electric vehicles' charging process, avoiding peak power demands, and promoting recharges at off-peak hours, where electricity prices are low. According to this, a smart charger could use our proposed methods to enhance the charging process at residential homes. To assess our proposal, we simulate the battery recharging of 1 000 vehicles per day during a full year, considering the use of domestic electrical plugs, and real electricity pricing. In Addition, three different scenarios have been simulated: 1) a regular-demand scenario; 2) a high-demand scenario; and 3) an extra-demand scenario, in which the vehicles arrive with an average battery level of only 25%. Simulation results confirm that using our charging methods, we can save between 46.9% to 75.2% in terms of electricity fee while maintaining similar battery levels after the charging process.

INDEX TERMS Electric vehicle, charging protocols, intelligent plug-charger.

I. INTRODUCTION

Recent studies on climate change warned us about the need to perform a drastic reduction in greenhouse gas (GHG) emissions [1], [2]. Most worrying cases are found in big cities, due to the air pollution levels, mainly provoked by the industry, as well as vehicles' combustion engine emissions. In fact, environmental pollution affects health very negatively, causing diseases, such as asthma, cardiorespiratory disease, or lung cancer [2], [3], and it is a common cause of shortened lifespan [4].

For this reason, governments and public sector organizations are making efforts to improve the air quality and quality of life of citizens, by proposing strategies to reduce GHG emissions (i.e., CO2, CH4, as well as pollutants, such as Nitrous oxides, dust, and smoke). These strategies also include: (i) the production of electricity through the use of renewable energy sources (e.g., solar, wind, and hydroelectric energy) [5], and (ii) encouraging the use of electric vehicles (EVs) [6]–[8].

Fortunately, thanks to the technological advances in Artificial Intelligence-based approaches, and the emerging Internet of Things (IoT), we are heading towards more advanced, developed, and efficient cities [9]. Moreover, every car-maker is currently working on electric engines or even has already a model out in the market. In fact, we can find companies that solely manufacture vehicles propelled by electric engines, such as Eve, Zytel, Little Electric Cars, or Tesla Motors. This suggests that the EV is going to be a significant player in this new scenario, since sales are progressively increasing, and they are expected to be widely deployed during the coming years. Figure 1 shows the EV sales estimation provided by different agencies and consortiums, such as the International Energy Agency (IEA) [10], [11], the Paris Declaration [12] (which tries to limit the average increase in the global temperature by 2°C), or the 'EV 30@30' campaign supported by the Clean Energy Ministerial (CEM) [13], which considers that at least 30% of vehicles sold by 2030 would include electric engines.

To promote a seamless integration of EVs into the Smart Cities, in addition to considering the specific issues related to the Intelligent Transportation Systems (ITS) [14], [15], it will be essential to equip EVs with smart and efficient charging systems, especially taking into account that most of the vehicles will be charged at residential houses, where domestic electrical installations are limited. Additionally, the recharging method currently used is the Plug&Charge (P&C) scheme, i.e., the batteries start the charging process just when the vehicle is plugged into the wall.

One of the main problems that the P&C recharging method may experience is that, in many countries, electricity pricing varies during the day, especially according to its demand. However, the P&C does not prevent users from charging their vehicles when electricity is more expensive, making EVs less attractive for potential buyers. Moreover, many people usually follow the same mobility pattern, e.g., they return home after their working day practically at the same time, and therefore, charging process can collapse the electricity grid due to the power peak demands. In essence, the traditional Plug&Charge charging method may encounter the following problems:

- The high electricity price. In most countries, the price of electricity varies along the day, and this cost remains higher, especially in high peak power demand periods, where the majority of users would try to charge their EVs.
- Possible collapse of the grid since the expected quantity of EVs in coming years and the increase of their battery capacities can greatly affect electrical grid if all these vehicles require to recharge at the same time.
- Inefficiency. Using the Plug&Charge, no efficiency parameters are taken into account. Parameters such as the price of electricity at that moment, or the quantity of energy required to fill the battery completely.
- Higher infrastructure capital expenditures (CAPEX) and operating expenses (OPEX) will be required in order to satisfy the peaks of high energy demand, especially in the near future, when the market penetration of EVs will be higher.

To properly solve the problems derived of the use of the traditional Plug&Charge method, in this paper, we propose and analyze four different charging methods, namely: (i) the Cheapest (C), (ii) the Cheapest Starting (CS), (iii) the Low Cost (LC), and (iv) the Last Period (LP). In particular, these efficient charging methods could be applied by a smart charger to maximize the recharge process, while minimizing its cost.

Our contributions in this work are the proposal of a set of battery charging strategies specially designed for EVs, and the quantification of the improvement of these strategies compared to the traditional Plug&Charge method. According to this, we present an analysis of the results obtained by the charging methods proposed, to determine the strengths and weaknesses of each one.

The manuscript is organized as follows: Section II presents some previous studies regarding EV recharging process. In Section III, we detail our four proposed methods. Section IV shows the characteristics of the simulations performed, and Section V includes the analysis of the results obtained, considering that we seek to reduce the cost of the electricity required and to optimize the final battery charge level of EVs. Finally, in Section VI, the conclusions drawn from our work are presented.

II. RELATED WORK

The interest in electric vehicles by academia has grown steadily, and the number of papers focused in EVs, especially in recent years, clearly demonstrates the increasing interest of researchers, and their desire to promote and enhance this type of vehicles.

Closely related to our work, some authors proposed new charging strategies focused on reducing the electricity cost. Wi *et al.* [16] proposed a smart EV charging algorithm based on a photovoltaic (PV) system for reducing electricity costs and determining the optimal schedules for EV charging. Their system relies on the prediction of PV power output and the electricity consumption required. Authors assessed their approach by simulating 12 EVs with a battery capacity of 24 kWh, presenting three different initial states of charge (SoC) profiles (20, 30 and 40%), and a target SoC of 80%. Additionally, all the vehicles have a fixed recharge period from 8 a.m. to 7 p.m. The results showed that their proposal is able to reduce the charging cost from 6% to 15.2% compared to the Plug& Charge method. Makkonen *et al.* [17] presented a system for smart EV charging that manages both energy storage and an energy management system (EMS). The charging system allows load shifting, enables the participation in the electricity markets, and provides a control gateway for mobile energy storages. However, authors assessed their proposal considering a single vehicle recharged from 44% to 97% battery level. Authors did not compare their approach to any other methodology, nor quantified the improvement when using their proposal. Tikka *et al.* [18] proposed an intelligent charging system aimed at minimizing the cost of the recharges. Authors demonstrated the feasibility of a simple smart charging strategy on a charging testbed, using commercially components and open source coding. To evaluate their proposal, they simulated a single vehicle recharging at home during a week and compared it with the Plug&Charge method, reducing the electricity bill up to 0.11€ per week. Authors also suggested that charging strategies targeting to minimize charging costs may not be feasible for a single customer, and additionally, electricity retailers should be interested on controlling EVs' charging processes to meet adequately electricity demand. Based on the use of emerging vehicular communications, Gharbaoui *et al.* [19] proposed a system which relies on a distributed communication infrastructure, where the vehicles can exchange useful information about their energy requirements. The approach presented allows users to minimize the charging times while

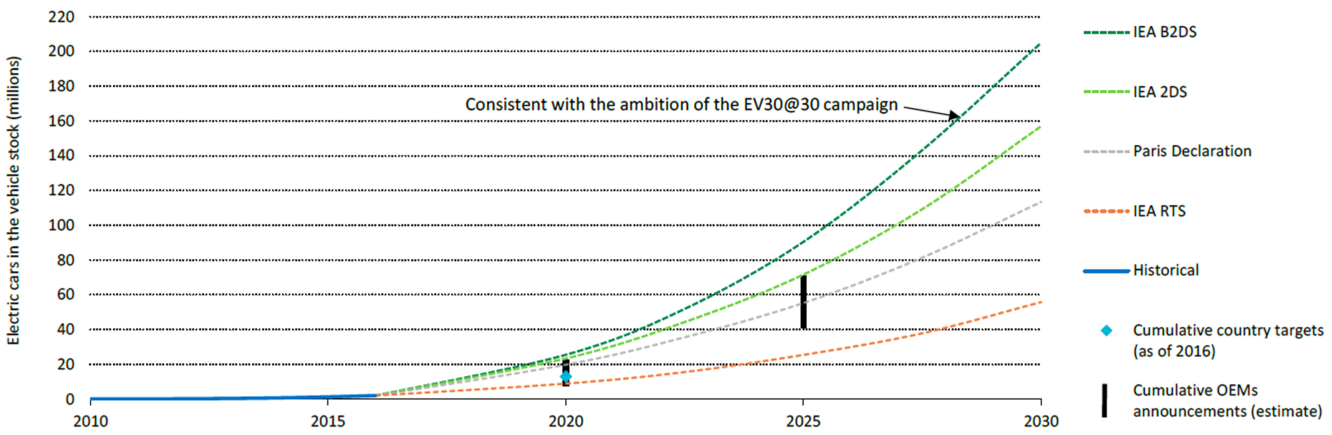

FIGURE 1. **EVs future deployment scenarios [10].**

optimizes the efficiency of the electrical infrastructure. More recently, Valdivia-Gonzalez *et al.* [20] proposed a particle swarm optimization-based (PSO) method, namely States of Matter Search (SMS), for maximizing the SoC of plug-in hybrid electric vehicles (PHEVs). To assess their proposal, they performed a 24 hours simulation of different scenarios varying the number of PHEVs (50, 100, 300, 500, and 1000). Results showed that their proposal obtains significantly better results compared to other schemes which relied on a Gravitational Search Algorithm (GSA), a Firefly Algorithm (FA), and a Genetic Algorithm (GA), respectively.

Other works, instead, promoted off-peak charges trying to mitigate the effect of charging simultaneously a high number of EVs on the electric grid, especially in peak hours. Ma *et al.* [21] created a decentralized charging control strategy, specially designed for large populations of electric vehicles. The main goal is to reduce electricity generation costs by promoting charges during overnight. In their simulations, they evaluated vehicles with two battery capacities (i.e., 10kWh and 20kWh) and a maximum charging rate of 3 kW. Mets *et al.* [22] proposed two charging strategies, a local and a global iterative strategy, with the objective of reducing the peak power demands. To do this, they simulated a set of 150 households during a period of 24 hours, and the vehicles simulated were PHEVs. More specifically, they used the Chevrolet Volt with a battery capacity of 16 kWh. Additionally, simulations considered the same specifications for every vehicle and a maximum charging rate of 4.6 kWh. Results showed that the additional power consumption ranges from 6% to 44% depending on the PHEV penetration rate, and peak loads could be reduced between 8% and 42%, compared to the business-as-usual scenario. Gan *et al.* [23] proposed a distributed protocol for managing day-ahead EVs charging schedules. The main objective is to rearrange EV charges to the overnight electricity demand valley. Authors performed a one-day simulation considering the average residential load profile in the service area of South California, and they evaluated their proposal with 10, 20, and 40 vehicles of three different types (sedan, compact, and roadster). More recently, Chen *et al.* [24] aimed at starting charges at off-peak hours, and thus optimizing the charging process while reducing high power demand peaks. In particular, and similarly to [20], they used a particle swarm optimization-based algorithm, and compared the results obtained with an uncontrolled recharge approach. Simulation results showed that the proposed algorithm not only meets EVs charging demand, but also mitigates the impact of EVs charges on the distribution network.

In the literature we can also find several works that analyzed how the growing number of EVs would affect the whole electricity demand. Particularly, Sharma *et al.* [25] analyzed the effects of EV charging in unbalanced, residential, distribution systems. For that purpose, they compared uncontrolled and smart charging schemes and simulated different scenarios throughout a day. Results showed that uncontrolled EV charging adversely affects electric grid, and therefore, controlled mode charges, through smart charging approaches, is highly recommended. Acha *et al.* [26] proposed a system to coordinate cost-effective interactions between distribution network operators, power markets, and EVs. In their simulations, they only considered two vehicle types, PHEVs with 3.12 kWh batteries and plug-in electric vehicles (PEVs) with 24 kWh batteries. They also assumed that all vehicles must be completely charged at 7 a.m. Quian *et al.* [27] presented a methodology for modeling the electricity demand of EVs in a distribution system. In particular, they compared four charging scenarios: (i) an uncontrolled domestic charging, (ii) a smart domestic charging, (iii) an uncontrolled off-peak domestic charging, and (iv) an uncontrolled public charging. According to the results obtained, authors stated that a 10% EV market penetration would increase the power demand up to 17.9%, while a 20% of EV penetration would result up to 35.8% increasing in power demand. They also determined that the starting time of the recharge process has a dramatic effect on the peak power demand. As for the simulations performed, they used statistical models to consider the arrival time and state of charge (SoC) of the vehicles. Additionally, they performed one day simulations, using two types of vehicles (the GM EV1 with a 27.19 kWh lead-acid battery and the Nissan Altra with a 29.07 kWh lithium-ion battery).

Overall, most research regarding electric vehicles focused on: (i) improving the charging strategies, (ii) optimizing the SoC, (iii) reducing electricity peaks and exploiting the overnight demand valley, as well as (iv) studying and mitigating the effect of EVs increasing electricity demand. Additionally, and similarly to other research areas, most of these works relied on simulations to assess their proposals. However, unlike our work, simulations only consider one day, a few number of vehicles, usually with the same battery capacities, and in general, authors did not quantified the improvement in terms of cost reduction, or the benefits obtained were very limited. In contrast to the previously presented studies, and to accurately appraise our proposals, our simulations included 1,000 vehicles per day and comprised a full year. In addition, our simulated vehicles have different battery capacities, following the market distribution of EV Spain sales [28]. We simulated that these vehicles started recharges with different battery levels and at different time periods. Last, but not least, we also accounted for the real electricity pricing which varies along each hour of the day and over the full year [29].

III. OUR PROPOSAL: IMPROVING EVs CHARGE STRATEGIES

The most commonly used strategy for EVs recharging is the Plug&Charge, i.e., the battery recharge process immediately starts when the user arrives at the recharging point and plugs the vehicle in the wall. However, this method is not really efficient, since it does rely on any energy efficiency or cost reduction parameters (e.g., electricity pricing, the current state of the electricity grid, the current battery level, or if the energy required has been generated in an environmentally friendly way). We consider this method as a baseline for our comparative study, since it is the most accepted and used strategy among EV users.

A. ELECTRIC CONTEXT

As we previously commented, the objective of this paper is to propose and compare four battery charging strategies that, considering additional information about the status of the battery and the time available for completing the charging process can improve the traditional Plug&Charge method. The final goal is that smart chargers can use one of our approaches to enhance the charging process, especially at residential homes.

To accurately assess our approaches, we implemented a simulator which models EVs recharges. More specifically, it is able to simulate a large number of vehicles with different battery characteristics and different charging modes.

According to the standard IEC 62196 [30], there are four different charging modes designed for EVs. They are:

- **Mode 1** is the standard mode for charging EVs at residential houses. It involves charging the batteries at 230v and a maximum current of 16 A. The process of recharging most EVs can last up to 8 hours, and therefore, it is considered a slow charge mode. In this work, we assess the different charging methods using Mode 1 since it is the mode most commonly used at residential households [31].
- **Mode 2**. This charging mode supports currents up to 32 A. Depending on the type of vehicle, the recharging process can last between 2 and 4 hours. Hence, this charging mode is known as semi-fast.
- **Mode 3**. This mode, known as fast-charge, supports currents between 32 A and 250 A. Depending on the type of vehicle, the recharging time, using this mode, can take less than 1 hour.
- **Mode 4** supports currents up to 400 A, and it is known as ultra-fast charge. It is very promising since it will extremely reduce the time required to charge EV batteries, although many types of batteries are not able to withstand the heat generated due to the amount of electricity introduced within a very short time.

Another important matter to be considered is the electricity pricing. It is worth to mention that the cost of electricity for the final user varies along the day in many countries. Examples are United States, Canada, UK, France, Portugal, Spain, Finland, Estonia, Lithuania, and Latvia [27], [29], [32]–[35]. It is very common to find high price time slots and other periods where the electricity pricing is low (typically during the night). Therefore, mainly to save money, it should be necessary to charge EVs considering this fact, i.e., encouraging users to recharge their vehicles when electricity is cheaper.

In our simulations, we considered the prices currently offered in Spain. Particularly, electricity pricing has three rates in Spain (see Figure 2): (i) the regular, (ii) the time discriminating, and (iii) the EVs rate. In addition, the price of electricity varies, daily and even along the day, in all these rates, mainly due to both the estimated demand at each hour and the cost of electricity production.

B. RECHARGING STRATEGIES PROPOSED

As previously commented, in this work we propose four different charging methods that will enhance smart chargers by enabling cheaper and more efficient EV recharges. We assume that the charging points are smart, i.e., they have communication capabilities with the vehicle and Internet access. Also, the user may inform about the scheduled departure time.

Let P represent the time period in which the vehicle could be recharged (i.e., the number of hours between its arrival and its departure), and B the time period that the vehicle needs to completely charge its battery. Moreover, $p(h)$ denotes the price of the electricity at a determined hour h, ch denotes the time instant in which electricity price is the cheapest, and l denotes the exact time when the vehicle leaves the parking lot. Finally, s and e denote the starting and ending battery charging times. Table 1 includes these parameters that will be used for the different charging methods proposed.

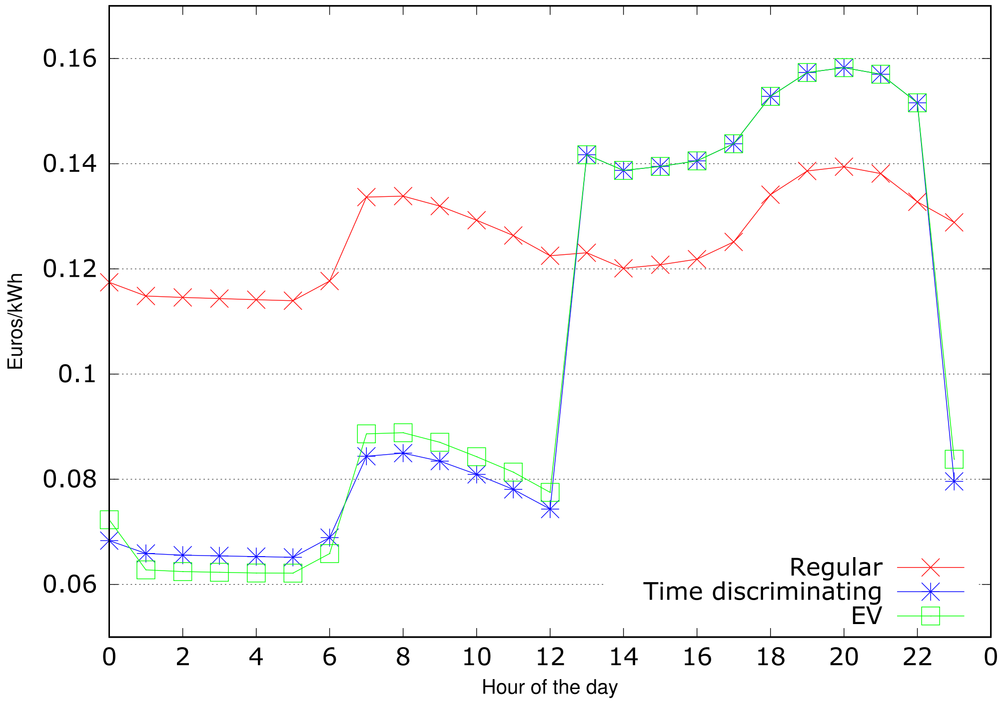

FIGURE 2. Example of electricity price in Spain on October 31, 2017 [29].

TABLE 1. Charging parameters.

Parameters	Definition	Example values
P	time period in which the vehicle could be recharged	12 hours
B	time period that the vehicle needs to completely charge its battery	6 hours
$p(h)$	price of the electricity at a determined hour	0.152 €/kWh
ch	time instant in which electricity price is the cheapest	4 a.m.
l	exact time when the vehicle leaves the parking lot	7 a.m.
s	starting battery charging time	22 p.m.
e	ending battery charging time	4 a.m.

Based on the information available including the electricity pricing, the current battery level, and the available charging time P, the smart charging system would estimate B, i.e., the time required for a complete battery recharging according to the characteristics of the battery of the vehicle and the power supplied by the recharging point. Finally, the charging method used would determine the time when the vehicle would start its recharging process.

The charging methods proposed are the following:

- **Cheapest (C)**. This charging strategy will determine s in order to allocate ch in the middle of B. According to this, the charging process period would be determined by Equation 1. Note that vehicles will be fully charged only when $(ch + B/2) < l$ is met.

$$\left[\left(ch - \frac{B}{2}\right) \cdot\cdot \left(ch + \frac{B}{2}\right)\right] \tag{1}$$

Please, refer to Table 1 for the parameter description.

- **Cheapest Starting (CS)**. The CS method will plan the start of the recharging just at the moment when electricity is the cheapest (i.e., $s = ch$), and the charging process would be determined by Equation 2. This method is more restrictive that the previous one since vehicles will be fully charged only when $(ch + B) < l$ is met.

$$[ch..\,(ch + B)] \tag{2}$$

Please, refer to Table 1 for the parameter description.

- **Low Cost (LC)**. The LC method makes that EVs start their recharges when the off-peak period begins. This recharging strategy is mainly intended for nighttime charges, and it would be determined by Equation 3. Note that we only consider negative variations in the electricity fee to the determine $max(\Delta p(h))$, i.e. when the electricity price drops.

$$[max(\Delta p(h))..(max(\Delta p(h)) + B)] \tag{3}$$

Please, refer to Table 1 for the parameter description.

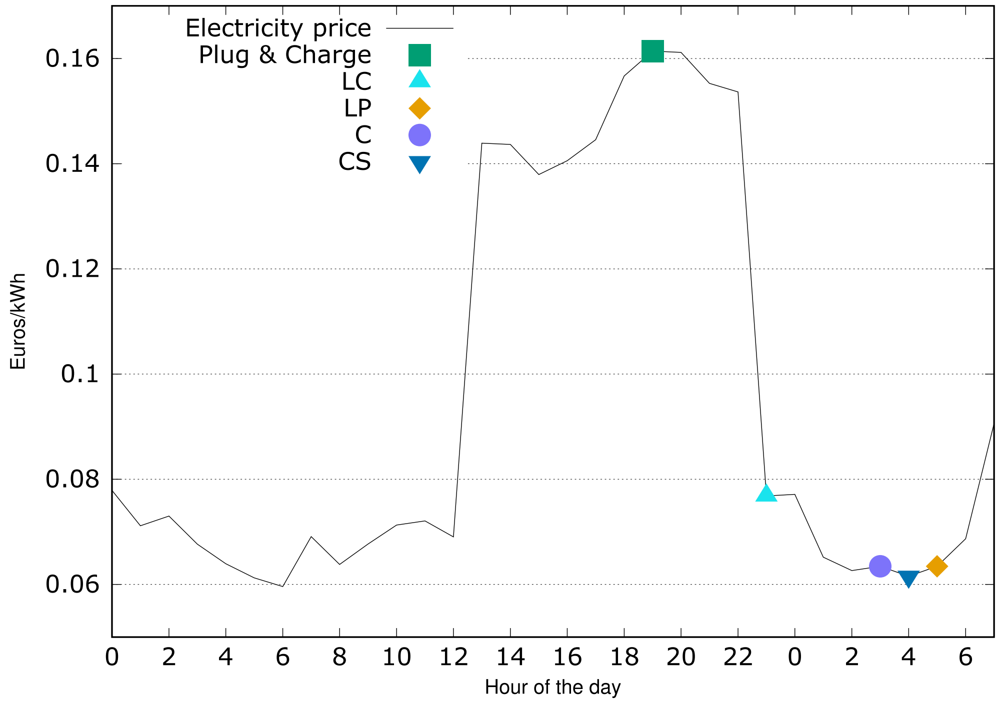

FIGURE 3. **Example that includes the electricity price and the charging starting point for the different methods (Spanish electricity pricing for EVs on January 1, 2018). To see the electricity price for additional days, please, refer to [29].**

- **Last Period (LP)**. The LP method determines that vehicles will start their recharging process during the last part of B (i.e., it ensures that the charging process will finish just before leaving the parking lot, and unlike the P&C, which starts the charging process whenever the vehicle reaches the charging point). According to this, the charging process would be determined by Equation (4). This method always allocate the charging process just before vehicles have to leave their parking lots, regardless the electricity fee. Hence, it requires to know this information to work properly. Finally, note that when $P < B$ is met, the LP will behave exactly in the same manner than the traditional P&C method.

$$[(l - B) \,..l] \tag{4}$$

Please, refer to Table 1 for the parameter description.

For the sake of clarity and better understand the operation of the proposed methods, we present the following example. Let assume we have a Nissan Leaf with a battery capacity of 24 kWh, the vehicle reaches its Mode 1 recharging point at 7:00 p.m., and leaves at 7 a.m. (i.e., $P = 12, l = 7$). Moreover, it arrived with a battery level of 75%. According to these data, the recharging process would take 2 hours ($B = 2$). Figure 3 shows the evolution of the electricity fares for EVs (y-axis) throughout the day (x-axis), and the different starting points determined by the P&C method, as well as by the proposed charging strategies.

Now, we detail the differences between the charging modes presented in this work. For example, using the traditional Plug&Charge method, the vehicle would begin to recharge immediately ($s = 19 = 7$ *p.m.*). In our example, this is exactly the time instant when the price of electricity is the highest.

In the case that the Cheapest method was used, recharging would begin at 3 a.m. since the cheapest period in which the whole recharging process fits comprises from 3 a.m. to 5 a.m. ([(4−1)..(4+1)], according to Equation (1)).

Using the Cheapest Starting method, recharging would start at 4 a.m. since this is the time when electricity is cheapest, and it would finish at 6 a.m. ([4..(4+2)], according to Equation (2)).

If we used the Low Cost method, the vehicle would start the charging process at 23 p.m. since the electricity pricing drops sharply at that time, and the off-peak period begins. According to Equation (3), the charging process would be [23..1].

Finally, if we used the Last Period recharge method, since the vehicle is going to leave at 7 a.m., the charging process would start at 5 a.m. to finish it before leaving the parking lot ([(7-2)..7], according to Equation (2)).

In this context, it is noteworthy to mention that vehicles which present a very low SOC could not be fully charged regardless of the recharging strategy used.

IV. SIMULATION ENVIRONMENT

To assess the performance of the four charging methods proposed and compare them to the traditional Plug&Charge method, we relied on simulations. More specifically, we simulated three different scenarios according to the considered

TABLE 2. EVs sales during 2016 in Spain [28].

Make and model	Battery Capacity (kWh)	Market share
Nissan Leaf	24	16.2%
Citroen C-Zero	15	15.5%
Renault Zoe	22	12.6%
BMW i3	22	10.6%
Renault Kangoo	33	10.3%
Nissan NV 200	24	9.6%
Smart fortwo	17.6	4.8%
Volkswagen Golf	24.2	4.3%
Volvo XC90	65	4.0%
BMW X5	9	3.8%
Renault Twizy 80	6.1	2.9%
KIA Soul	27	2.8%
BMW 225	7.7	2.6%

average battery level of the vehicles just before starting to recharge. The objective is to analyze the performance of our proposed methods under different energy requirements. Next, we detail the three scenarios:

- **Regular-demand scenario,** in which the vehicles' battery levels follow a Gaussian distribution with a mean (μ) of 72% and a standard deviation (σ) of 10%. These data correspond to those after one day of use, according to Qian *et al.* [27].
- **High-demand scenario,** in which vehicles present a battery level Gaussian model with μ equal to 50% and σ equal to 10%.
- **Extra-demand scenario.** We consider this scenario as very adverse. According to this, vehicles will follow a battery level distribution with μ equal to 25% and σ equal to 10%.

We consider that the three studied scenarios are representative and valid to assess our approach.

Another critical factor to account for during the simulations, is the battery capacity since EVs in the market have batteries with different capacities (see Table 2). As expected, vehicles with lower battery capacities will require less time to be fully charged than those vehicles with higher battery capacities.

With the goal of simulating the features of the EVs closer to reality, and to accurately estimate the cost of recharging EVs when using the different charging methods in each scenario along the year, we considered the model and specific characteristics of the EVs simulated. Additionally, we use a Monte Carlo method [36] to determine the different vehicles included. Hence, vehicles used in our simulations resemble the current market situation in Spain (see Table 2). The rest of parameters used in the simulations are shown in Table 3. More details are given below.

- **Number of vehicles.** We simulated a total number of 365,000 EVs, i.e., 1,000 vehicles per day along an entire year. Making this, we ensure the macro-perspective and scalability of our proposals.
- **Vehicles' arrival model.** This parameter represents the time when the vehicle arrives at residential house (i.e., at charging point). Therefore, according to the Plug& Charge method, the recharging process will start at this moment. To make simulations more realistic, the arrival of vehicles follows a Gaussian distribution with μ is equal to 1,080 minutes and σ is equal to 60 minutes, i.e., most vehicles usually reach home from 4 to 8 p.m. We considered these values according to several previous works [23]–[27].
- **Travel duration model,** which is the estimated travel time until reaching the charging point. This value follows a Weibull distribution (similarly to [37]–[42]) with $\alpha = 45$ minutes, $\beta = 1.9$, and $\gamma = 0$, i.e., most travel times require 45 minutes or less. We used these values to resemble people's life habits [43]–[45]. Particularly, this parameter allows to calculate the battery level of vehicles when they reach the charging points; we estimate these values individually since we specifically consider the consumption model of each EV.
- **Charging time model.** This parameter determines the time that the EV is parked at the charging point, i.e., it is the maximum available charging time for the vehicle. The values of this parameter follow a Gaussian distribution with μ is equal to 700 minutes and σ is equal to 150 minutes. Hence, most of vehicles stay parked from 9 to 14 hours per day.
- **Battery level model.** This parameter defines the vehicle's battery level when it arrives at its charging point. As we simulate three different scenarios (i.e., regular-demand, high-demand, and extra-demand), the values follow a Gaussian distribution with different parameters (μ is equal to 72%, 50% y 25%, respectively), while σ is 10%.
- **Charging point power.** In our simulations, as we are interested in domestic charging, we consider that all charging points support Mode 1, i.e., vehicles would charge their batteries at 230v and 16A (3.68 kWh).
- **Energy loss by heat.** During the charging process, batteries suffer from energy losses which are dissipated as heat. These losses are directly correlated to the current and voltages used in the charging, i.e., low-power charging reduces the percentage of energy lost compared to fast-charging. In our simulations, we consider that a 10% of the electricity is lost during battery charging [46].

V. SIMULATION RESULTS

This section presents the results obtained for the three different scenarios described in Section IV. The main objective is to scrutinize the performance of the charging methods proposed under different conditions.

A. FIRST SCENARIO: REGULAR-DEMAND

According to Quian *et al.* [27], the level of battery of an electric vehicle after a day of use is closely to 72% on average. Therefore, in our experiments under a regular-demand

TABLE 3. Simulation settings.

Parameters	Values
Number of vehicles	$365,000$ (1,000 * 365 days)
Vehicles' arrival model	Gaussian: $\mu = 1,080$ min., $\sigma = 120$ min.
Travel duration model	Weibull: $\alpha = 45$ min., $\beta = 1.9$, $\gamma = 0$
Charging time model	Gaussian: $\mu = 700$ min., $\sigma = 150$ min.
Battery level model	Gaussian: $\mu = 72\%, 50\%, and\ 25\%, \sigma = 10\%$
Charging Point Power	3.68 kWh (IEC 62196 Mode 1)
Energy loss by heat	10%

TABLE 4. Results obtained in the regular-demand scenario.

Metrics	P&C	C	CS	LC	LP
MegaWatts charged	2.45	2.34	1.85	2.34	2.38
price of electricity (€/vehicle per year)	349.73	139.29	104.16	161.31	148.79
difference of price compared to P&C (%)	-	-60.17%	-70.22%	-53.88%	-57.46%
energy recharged (avg. %)	27.98%	27.98%	22.08%	27.80%	27.98%
final battery level (avg. %)	99.92%	99.62%	94.03%	99.75%	99.92%
#EVs battery level <75%	637	637	27,183	871	637
#EVs battery level <50%	0				
#EVs battery level <25%	0				
starting battery level (avg. %)	71.95%				

scenario, we consider that the average battery level the vehicles before recharging is of 71.95%.

Table 4 shows the results obtained in this scenario only. In particular, we present: (i) the number of Megawatts charged when using each of the charging methods, (ii) the total amount of euros spent in charging each vehicle, (iii) the differences between each charging method and the traditional P&C, (iv) the number of vehicles whose battery level remains lower than 75%, 50%, and 25%, respectively, after the charging process, (v) the average battery level that vehicles present before starting the recharging, (vi) the average percentage of energy recharged, and finally, (vii) the average battery level that vehicles present after leaving the charging points.

As shown, the quantity of energy charged is very similar for all the methods (it ranges from 2.34 to 2.45 MW), except for the Cheapest Starting (1.85 MW). However, the differences in the electricity cost per vehicle are noticeable (from 104.16 to 349.73€). In fact, using our approaches, the cost savings range from 53.88% up to 70.22%. However, the counterpart of the method with higher saving, the CS, is that the vehicles' batteries are only charged, on average, up to 94.03% (about −5% compared to the other methods).

Regarding the EVs battery levels when vehicles leave the recharging point, results obtained in our simulations are very similar for all the methods (99.62-99.92%), except for the CS (94.03%). Additionally, we observed that there are a number of vehicles that finish their recharging process with less than 75% of battery level. This means that those vehicles have started the charging process with a lower level of their batteries, and the length of time they were at the charging point was not enough to complete the recharging process. Using the Plug&Charge, the Cheapest, and the Last Period methods, the number of vehicles with less than 75% of battery is only of 637 (out of 365,000), while using the Low Cost, this number slightly increases up to 871 vehicles. However, this problem is more remarkable when using the Cheapest Starting method since, in that case, vehicles are already plugged, but waiting without recharging until the energy pricing is the cheapest. In fact, using the CS method, this number highly increases up to 27,183 vehicles. Therefore, the CS method does not seem appropriate to be used in this scenario.

Overall, in regular-demand scenarios, i.e., where EVs present a good battery level before starting the recharging process, both the Cheapest and the Last Period exhibit the best performance (in terms of battery charged and cost savings). By contrast, the CS method does not seem a good choice since it does not guarantee that batteries are completely recharged, making it unsuitable.

B. SECOND SCENARIO: HIGH-DEMAND

The second scenario used in our simulations can be considered as high-demand since we determined that vehicles start the recharging process with an initial average battery level of 50.18%. According to Qian *et al.* [27], this battery level implies that the vehicle has been used almost two days without being recharged. Table 5 presents the results obtained in this scenario.

As shown, similarly to the results presented in Section V-A, the quantity of energy charged is very similar for all the

TABLE 5. Results obtained in the high-demand scenario.

Metrics	P&C	C	CS	LC	LP
MegaWatts charged	4.31	4.07	2.84	4.09	4.23
price of electricity (€/vehicle per year)	605.42	251.18	163.87	267.43	278.06
difference of price compared to P&C (%)	-	-58.51%	-72.93%	-55.83%	-54.07%
energy recharged (avg. %)	49.66%	47.80%	33.79%	48.48%	49.66%
final battery level (avg. %)	99.84%	97.97%	83.96%	98.65%	99.84%
#EVs battery level <75%	1,000	1,029	120,072	7,227	1,000
#EVs battery level <50%	506	506	18,774	788	506
#EVs battery level <25%	0				
starting battery level (avg. %)	50.18%				

TABLE 6. Results obtained in the extra-demand scenario.

Metrics	P&C	C	CS	LC	LP
MegaWatts charged	6.43	5.93	3.56	5.92	6.35
price of electricity (€/vehicle per year)	855.51	390.87	212.00	371.89	454.31
difference of price compared to P&C (%)	-	-54.31%	-75.20%	-56.53%	-46.90%
energy recharged (avg. %)	74.97%	69.90%	42.44%	70.44%	74.97%
final battery level (avg. %)	99.63%	94.57%	67.11%	95.10%	99.63%
#EVs battery level <75%	1,730	16,998	206,778	29,737	1,730
#EVs battery level <50%	1,000	1,000	121,912 4,410	1,000	
#EVs battery level <25%	538	538	17,004	652	538
starting battery level (avg. %)	24.67%				

methods, although it practically doubles the energy consumed in the regular-demand scenario (now, it ranges from 2.84 to 4.31 MW) due to the fact that starting battery levels are reduced from 71.95% (in the regular-demand scenario) to 50.18% (in this high-demand scenario). Again, the Cheapest Starting method does fail to meet the expectation since all the vehicles are mainly waiting for the price of electricity reaching its lowest price, making it impossible to charge their batteries fully.

The differences in the price of electricity per vehicle are even more noticeable (from 163.87€, in the case of CS, to 605.42€, as is the case of P&C). In fact, using our approaches, the cost savings range from 54.07% up to 72.93%. However, notice that the CS method charges vehicles' batteries only an 83.96% on average (about −16% compared to the other methods).

Regarding the EVs battery levels when vehicles leave the recharging point, they are very similar for all the methods (97.97-99.84%), except for the CS. In this second scenario, we observed that there are a number of vehicles that finished their recharging process even with less than 50% of battery level (506 vehicles when using the P&C, the C, and the LP charging protocols, as well as 788 and 18,774 when using the LC and the CS protocols, respectively). These considerations suggest that these vehicles remain only a few time at the charging point or their initial battery levels are quite low. Similarly that in the regular-demand scenario, the CS method does not work well, although these deficiencies are more pronounced in this scenario, i.e., when higher charges are needed.

Overall, in high-demand scenarios, i.e., where EVs require a significant amount of energy to full their batteries, the Last Period exhibits the best trade-off in performance (in terms of battery level charged and cost savings). In particular, the LP can charge the batteries exactly at the same level than using P&C, while reducing up to 54.07% the cost of recharges. By contrast, the CS method is only able to reach an average 83.96% of battery levels, in fact, using the CS, more than 120,000 out of 365,000 vehicles present battery levels lower than 75% after the recharging process.

C. THIRD SCENARIO: EXTRA-DEMAND

In this subsection, we present the results in the most exigent scenario by far. More specifically, we consider that vehicles reach the recharging points with a very low battery level on average, i.e., only 24.67%. Although this scenario could be considered as extreme, we aim to assess our proposal under a wide range of situations.

Table 6 shows the results obtained in the extra-demand scenario. As expected, the differences among the different charging methods, in terms of energy consumed, are higher in this third set of experiments (ranging from 3.56 to 6.43 MW). Compared to the regular-demand scenario, up to 162% more energy is required. Under these exigent conditions, the Cheapest Starting method works even worse

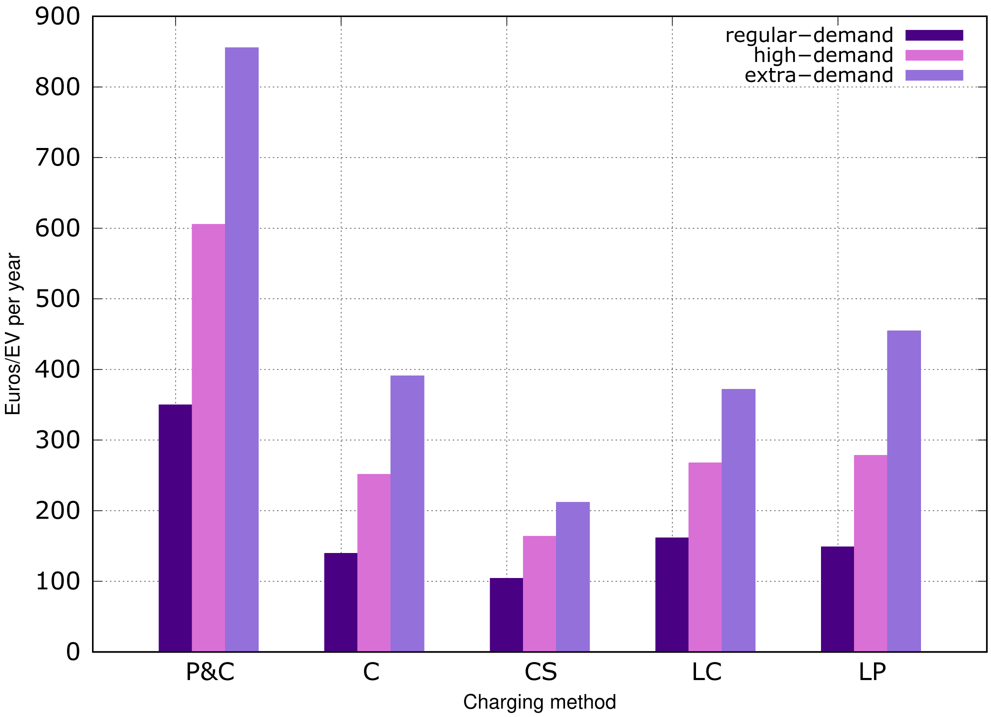

FIGURE 4. Average total euros spent to charge an EV during a full year for each charging method in the three energy demand scenarios.

since vehicles only reach the 67.11% of the battery levels (nearly −33% compared to the other methods), which is clearly unsatisfactory.

As for the price of electricity, there are significant advantages when using our proposed methods (especially the C, the CS, and the LC), compared to the traditional P&C approach. Particularly, prices range from 212.00 to 855.51€), which represent savings from 46.90% up to 75.20%.

Regarding the EV battery levels when vehicles leave the recharging point, in this third scenario, the number of vehicles that finish their recharging process without fulling their batteries increases significantly. The CS method is clearly unable to manage vehicles' charging properly in this extra-demand scenario. As shown, 206,778 (out of 365,000) remain with less than 75% of battery level. It is also noteworthy that the LP method obtains the same results, in terms of battery recharged, than the P&C method but reducing a 46.90% the electricity cost. Meanwhile, the Cheapest method is even able to reduce this cost up to 54.31%, but the number of vehicles that finish the recharging process with less than 75% of battery level increases from 1,730 when using P&C or LP to 16,998 when using the C charging method.

Although extra-demand scenarios (at least with this quantity of high energy demanding vehicles) cannot be easily found in realistic environments, we have also demonstrated the benefits of using our approaches compared to the P&C method. More specifically, our results highlighted that the Last Period charging method outperforms the rest of approaches since it clearly exhibits the best trade-off in terms of performance, battery level increasing, and cost savings.

D. OVERALL COMPARISON

To better study the differences among the charging methods, in this section, we present an overall comparison of the different charging methods under the three energy demand scenarios previously presented. Figures 4, 5, and 6 graphically depict the results obtained in terms of euros spent per vehicle, percentage of battery level after the recharging process, and electricity cost (in euros/kWh).

After having thoroughly analyzed the results obtained in the three different charging demand scenarios, relevant differences can be highlighted. As shown, the total euros spent to charge a vehicle is drastically reduced when using our proposed charging methods compared to the P&C under all circumstances, i.e., in regular, high, and extra-demand scenarios (see Figure 4).

It is noteworthy to mention that the best results were obtained by the Last Period method. It attains the same battery levels than traditional Plug&Charge in all the scenarios, but with a substantial reduction of €/vehicle in comparison to P&C. More specifically, LP reduces the electricity price: (i) a 57.46% in the regular-demand scenario, (ii) a 54.07% in the high-demand scenario, and a 46.9% in the extra-demand scenario. This is due to LP exploits the period when the electricity cost is lower to perform the recharging process. By contrast, when the period of time that the vehicle is plugged is not enough to fully recharge the battery,

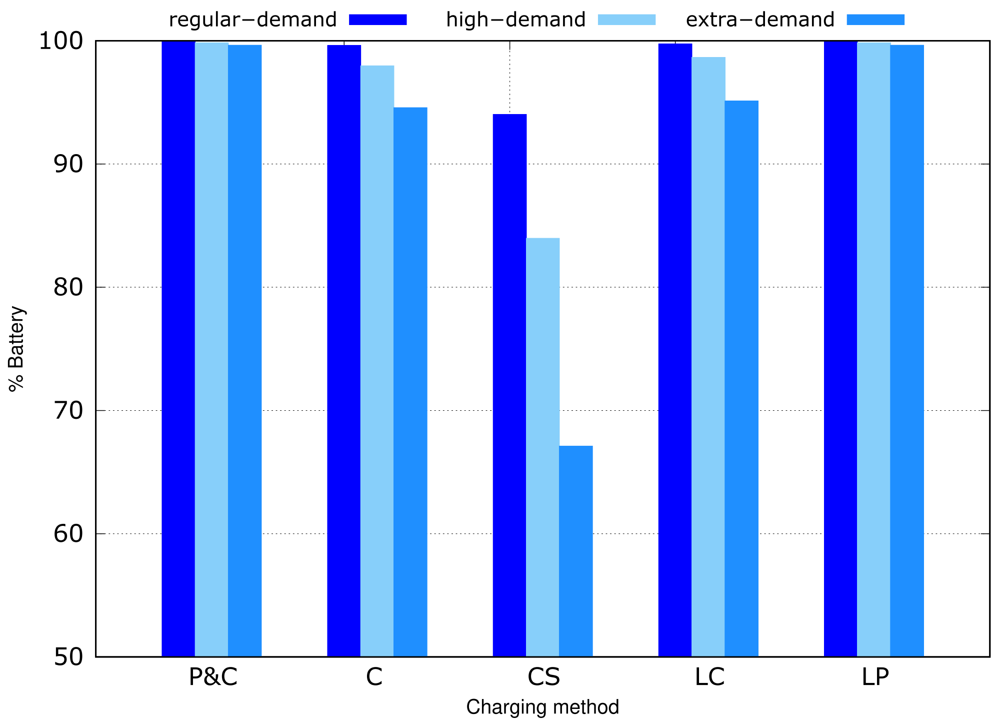

FIGURE 5. **Percentage of battery level after recharging the vehicle for each charging method in the three energy demand scenarios.**

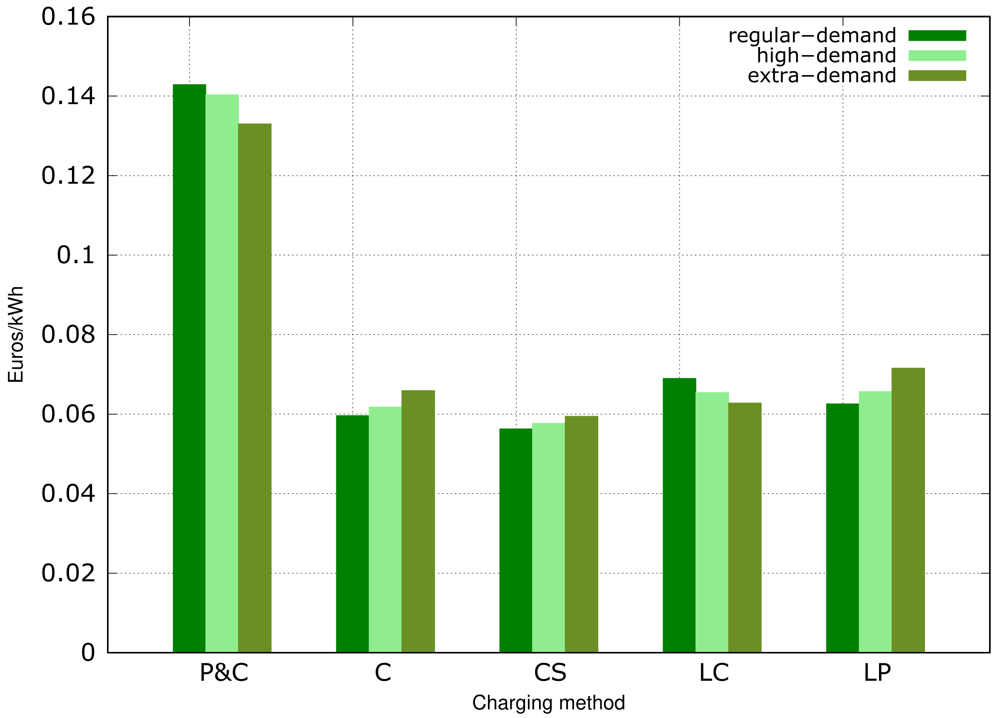

FIGURE 6. **Average euros/kWh for each charging method in the three different energy demand scenarios.**

this method behaves exactly in the same manner than P&C, i.e., the recharging process starts immediately and pricing factor does not play any significant role.

Considering that the charging mode used was Mode 1, the Cheapest Starting method should be discarded since its performance has been demonstrated unsatisfactory (in term of battery level) in all scenarios (see Figure 5), but especially in those where the vehicles demand more energy. This is due to batteries cannot be fully charged in the period between the electricity cost becomes the lowest and the time when vehicles leave the charging points. However, we consider that this method could be more promising when using more powerful charging modes (i.e., when higher currents and voltages are available), especially considering that this approach has resulted in the lowest cost in all simulations (see Figures 4 and 6). In fact, the best price-wise results were obtained in the first scenario (which we consider the most realistic), where the CS method presented an electricity cost almost three times lower than Plug&Charge).

The results obtained by our methods, in terms of battery level (see Figure 5), are very similar than those obtained by the Plug&Charge. However, the significant reduction of electricity cost (in terms of €/kWh) makes them more suitable and highly recommended. Figure 6 shows the benefits of using our proposed schemes. For example, using the LP, we can reduce the electricity cost from 52.86% to 55.71%. Additionally, it can be observed that the LC method puts the electricity cost reduction ahead of battery charge, whereas the LP ensures a good battery level despite slightly increasing the electricity cost when the energy demand also increases.

The emergence of electrical vehicles provided with higher battery capacities (e.g., more than 90 kWh) can hamper battery fully recharges, especially when vehicles arrive with low battery levels, and low power modes such as Mode 1 are used. According to this, more powerful charging points (i.e., Mode 2 or Mode 3 compliant) should be widely deployed to ensure that these type of vehicles can properly be recharged.

VI. CONCLUSIONS

The sales of EVs are increasing drastically, and we foresee that EVs are going to be a part of our daily lives in the near future. As the technologies used are continuously improving, and the batteries of this type of vehicles are gaining autonomy, it will be essential to enhance recharging methods while reducing the cost of recharging EVs.

The most common method used to recharge EVs is the well-known Plug&Charge. However, this method is not very efficient since it does not take into account any parameter for boosting efficiency. We consider that taking into account valuable information, such as electricity pricing, the current state of the electricity grid, or vehicle's battery level would definitively improve the charging process. According to this, in this paper, we propose four charging methods, namely the Cheapest, the Cheapest Starting, the Low Cost, and the Last Period. These methods seek to maximize the charge of the batteries while minimizing the cost of the electricity consumed.

To assess our approaches, we used three different scenarios (i.e., a regular-demand, a high-demand, and an extra-demand), and we simulated a total of 365,000 EVs during a full year. Simulation results showed an improvement which ranges from 46.9% to 75.2%, in terms of cost reduction of the charging process, while maintaining similar battery levels.

The study conducted demonstrates that the use of smart context-aware charging points, i.e., those chargers that adapt the charging process according to the initial vehicle battery level and the time window available to recharge the battery, is clearly convenient since the electricity cost can be drastically reduced.

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