Intelligent Participation of Electric Vehicles in Demand Response Programs

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***Abstract*—Demand Response (DR) has been proposed and implemented in recent years to enable the participation of active consumers in energy management. However, existing programs do not consider the characteristics and opportunities introduced by electric vehicles (EVs). EVs have more flexibility than traditional loads and can be used as battery energy storage systems if the vehicle-to-grid capability is available. The main contribution of this paper is the analysis of the EV user's point of view concerning different DR programs (implicit and explicit) as well as the EVs management considering different strategies. One of the most interesting strategies that have been proposed and tested is opportunity cost optimization, where the expected prices of the next days are considered. Some of the results show that DR programs with less cost are interesting for the users since also minimise the EV charging during the DR time operation. On the other hand, real-time pricing program is not interesting for the users since its performance is highly dependent on the market price.**

***Index Terms*—Charging scheduling, Demand response, Electric Vehicles (EVs), Optimization, User behaviour.**

NOMENCLATURE

Indices

CS	Index for set of charging stations t
T	Index for set of time interval t
V	Index for set of vehicles t

Parameters

$\bar{E}_v^{EV}$	Maximum energy capacity of the EV v [kWh]
$\bar{P}_c^{CS}$	Maximum power capacity of the charging station [kW]
$\bar{P}_t^{tot}$	Power limit of the system [kW]
Δ_t	Duration of time period t
C_{SP}	Strike Price [€/kWh]
C_t^{ch}	Cost of charging energy in period t [€/kWh]
C_t^{Dch}	Cost of discharging energy in period t [€/kWh]
$E_{v,tlast}^{SOC}$	Required SoC of the EV v in the departure period ($tLast$) [kWh]
$SoC_{\%(v,t)}$	State of Charge of Electric Vehicle EV in period t [%]
$tlast$	Time of departure of the vehicle
$X_{c,v,t}^{CS}$	Binary parameter for charging station usage

Variables

$AuxSOC_{tlast}^{EV}$	Auxiliar variable with information about the difference between the required SoC and the actual SoC of the EV at the departure period ($tlast$) [kWh]
CF_v	Charge Factor relating the power charge in each period t with the SoC of each EV
$E_{v,t}^{EV}$	Energy in the batteries of the EV v in period t [kWh]
$E_{v,t}^{SOC}$	State of charge of EV v in period t [kWh]
$P_{c,t}^{CS}$	Active power charge of the charging station [kW]
$P_{PeakTotal}$	Maximum total active power charge [kW]
$P_{v,t}^{ch}$	Active power charge of EV v in period t [kW]
$P_{v,t}^{Dch}$	Active power discharge of EV v in period t [kW]
P_v^{Peak}	Maximum active power charge of EV v [kW]
P_t^{tot}	Power of the system [kW]

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I. INTRODUCTION

The integration of electric vehicles (EVs) charging/discharging management in demand response (DR) programs have been widely studied recently [1]. Most of these, focus on how DR can help to mitigate the increased peak demand and the impact on the distribution system avoiding technical constraints [2]. In [3], the contributions that the DR, applied to EVs, can provide to the power system are discussed, without delving into simulations. The authors propose that this implementation should be done through an aggregator and recommend some appropriate communication systems to enable the quick transfer of information. A bi-level optimal dispatching model for a community system was developed to execute a DR program taking advantage of an EV charging station [4]. The main novelty proposed in [4] is the implementation of the DR program through the flexibility offered by EV users while their energy requirement is guaranteed at a satisfactory level. Different from the previous works mentioned, in [5], the authors provide a more detailed work, by presenting a "methodology for day-ahead energy resource scheduling for smart grids considering the intensive use of distributed generation and vehicle-to-grid

(V2G)" by proposing two different DR programs: i) "Trip reduce", allowing EV users to obtain profits by reducing their travel necessities and minimum battery state-of-charge (SoC) requirements, ii) Shifting reduction: enables EV users to formulate a collection of alternative traveling periods, for their expected travels. These two DR programs are tested by using a modified particle swarm optimisation and a mixed-integer non-linear programming optimisation. The use of these two computational intelligence techniques provides further insight into the execution times differences. The study concludes that these DR programs can "provide effectiveness regarding the reduction of the operating costs from the network operator point of view". A more specific use of DR to manage EV charging is presented in [6]. The focus lies on how a parking lot can schedule the EV charging optimizing the costs while taking advantage of DR services participation. To do this, a simulation of a real-time charging scheme is done utilizing binary optimisation. The simulation results demonstrated that the EV charging demand could be satisfied while also minimising monetary expenses. Another interesting work focusing on economic aspects is presented in [7], in which is proposed an approach to be used in house management systems, including the control of appliances and EVs. The goal is to profit from real-time prices (RTP) to reduce the energy bill. At the same time, the peak consumption limit is included in the optimization, avoiding the increase of consumption in some periods. Similar to the previous one, the authors in [8] incorporated a Time-of-Use (ToU) based DR program into the stochastic profit maximization of an energy retailer considering renewable sources and EVs, among others. Results demonstrate that the ToU-based DR program collaborates by shaving the peak load of the EVs. From the knowledge of the authors, most of the studies have analyzed consider the DR programs as part of the system in which the main goal is to optimize the operation cost considering the EVs flexibility or to avoid network constraints by considering the limits imposed by some DR programs, among others. This paper contributes to the existing literature by proposing: 1) An optimization goal focusing on the DR programs themselves, and on the adequacy of the DR programs to be used for the EVs user's perspective. 2) An analysis of different objective functions (OFs), that can be used by the EVs instead of "simple" cost optimization. Hence, this study will help to answer the research questions: What is the most appropriate DR optimization goal to increase the benefits of EV users?; and What are the implications of using price-based DR programs versus those based incentives?

II. Electric Vehicles Scheduling Methodology Considering Demand Response Programs

A. Objective functions

In this sub-section, the OFs implemented in the proposed methodology are presented. First, we use an objective function (1) to test the business as usual (BaU). Hence, the EVs are charged until the maximum capacity of the batteries, starting when the EVs arrive. This OF is used for comparison purposes.

$$\min F_{BaU} = \sum_{v=1}^{nV}\sum_{t=1}^{T}(1 - SoC_{\%(v,t)}) \tag{1}$$

In the second OF (2), the electricity cost is introduced. In this case, it is considered that the cost can be different in each period according to the tariffs defined in the DR programs (ToU, RTP, and critical peaking pricing (CPP)). Beyond the cost (C_t^{ch}), the OF includes a penalization ($M.AuxSOC_{tlast}^{EV}$) to guarantee that the EVs are charged when the EVs will departure (t_{last}) (affected by the multiplication factor M to have less importance).

$$\min F_{cost} = \sum_{v=1}^{nV}\sum_{t=1}^{T}(P_{v,t}^{ch}.\Delta_t.C_t^{ch}) + M.AuxSOC_{tlast}^{EV} \tag{2}$$

The third OF (3), not only considers the cost as the main objective but also the comfort level of the use of EVs as a secondary objective (affected by the multiplication factor M to have less importance). The comfort level can be expressed as the availability of energy $(1 - SoC_{\%(v,t)})$ in the EV in each period t. This means that, when the price of the energy is the same, the EV should be charged as soon as possible.

$$\begin{aligned}\min F_{BaU+comf} = \sum_{v=1}^{nV}\Bigg[&\sum_{t=1}^{T}(P_{v,t}^{ch}.\Delta_t.C_t^{ch}) + \\ &+ m.(1 - SoC_{\%(v,t)}) + M.AuxSOC_{tlast}^{EV}\Bigg]\end{aligned} \tag{3}$$

The fourth OF (4) considers the cost and the peak power consumption ($P_{PeakTotal}$ or P_v^{Peak}). So, it is introduced the perspective of the individual EV (OF (4)) or the perspective of an aggregator (5), that represents the OF (5). The aggregator can be a fleet operator or a parking lot/building management system. In both cases, the peak power consumption minimization is considered a secondary goal in the objective function.

$$\begin{aligned}\min F_{Cost+PeakEV} = \sum_{v=1}^{nV}\Bigg[&\sum_{t=1}^{T}(P_{v,t}^{ch}.\Delta_t.C_t^{ch}) + \\ &+ M.AuxSOC_{tlast}^{EV} + m.P_v^{Peak}\Bigg]\end{aligned} \tag{4}$$

$$\begin{aligned}\min F_{Cost+PeakEV} = \sum_{v=1}^{nV}\Bigg[&\sum_{t=1}^{T}(P_{v,t}^{ch}.\Delta_t.C_t^{ch}) + \\ &+ M.AuxSOC_{tlast}^{EV} + m.P_{peakTotal}\Bigg]\end{aligned} \tag{5}$$

In OF (6) is considered the V2G capability of EVs. This means that the EVs can discharge the energy stored in their batteries to charge other vehicles. In this work, we do not consider the option to sell energy to the network. Due to the V2G option, it is necessary to add the costs associated with the degradation of the batteries (C_t^{Dch}) in the OF. The C_t^{Dch} should also include a margin to create value for the EVs that are selling energy.

$$\begin{aligned}\min F_{cost} = \sum_{v=1}^{nV}\Bigg[&\sum_{t=1}^{T}(P_{v,t}^{ch}.\Delta_t.C_t^{ch}) + \\ &(P_t^{Dch}.\Delta_t.C_t^{Dch}) + M.AuxSOC_{tlast}^{EV}\Bigg]\end{aligned} \tag{6}$$

In OF (7), the system can maximize the opportunity cost. This OF is particularly interesting for EVs with high-capacity batteries. In that case, the EV owner should define a charging strike price and the system should consider the following rule:

$$\begin{cases} \text{If } C_t^{ch} \geq \text{Strike Price } (C_{SP}) \rightarrow & \text{The EV should charge only if necessary} \\ \text{If } C_t^{ch} \leq \text{Strike Price } (C_{SP}) \rightarrow & \text{The EV should charge as much as possible} \end{cases}$$

$$\min F_{OC} = \sum_{v=1}^{nV} \left[\sum_{t=1}^{T} (P_{v,t}^{ch}.\Delta_t.(C_t^{ch} - C_{SP})) + \right. \\ \left. + M.AuxSOC_{(EV,t_{last})} \right] \quad (7)$$

B. Optimization Constraints

The constraints related to the energy and power of EVs operation are considered. Moreover, it is necessary to include the constraints related to the charging stations (CSs) and the global operation of a set of EVs when managed by an aggregator. The energy in the batteries should be lower than the maximum capacity, as shown by (8).

$$SoC_{\%(v,t)} = \frac{E_{v,t}^{EV}}{\bar{E}_v^{EV}} \leq 1 \qquad \forall v, t \quad (8)$$

At the departure period, the SoC should be higher than the energy necessary to ensure the user's needs. When this is not possible, a penalization variable ($AuxSOC_{tlast}^{EV}$) will be positive, impacting the objective function. The required energy ($SoC_{\%(EVr)}$) can be limited in some DR programs, hence, SoC_{DRmax} represents a state of charge required for the DR program, as illustrated by (9).

$$SoC_{v,tlast} + AuxSoC_{tlast}^{EV} \geq \min\{SoC_{DRmax}; SoC_{\%(EVr)}\} \qquad \forall v \quad (9)$$

The value of the SoC should be updated considering the power charged/discharged in each EV in each period t, represented by (10). The parameter CF_v, shown by (11), relates the impact of the power charged in the SoC of the batteries in each EV, in which 60 indicates the duration of the time interval in minutes.

$$SoC_{\%(v,t)} = SoC_{\%(v,t-1)} + CF_v(P_{v,t}^{ch} - P_{v,t}^{Dch}) \qquad \forall v, t \quad (10)$$

$$CF_v = \frac{1}{\bar{E}_v^{EV}}.\frac{\Delta_t}{60} \qquad \forall v \quad (11)$$

Concerning the charging and discharging constraints, we should guarantee that the power charged and discharged in each period t should be lower than the maximum limit of the EV, as represented by (12) and (13), respectively.

$$P_{v,t}^{ch} \leq \bar{P}_v^{ch}\eta \qquad \forall v, t \quad (12)$$

$$P_{v,t}^{Dch} \leq \bar{P}_v^{Dch}\eta \qquad \forall v, t \quad (13)$$

The power charge/discharge can be limited by CS where the EV is connected, as shown by (14)–(16). The connection between the EV and CS is defined in the binary parameter $X_{c,v,t}^{CS}$. In the present formulation, it is considered that the EVs have an efficiency of 100%. The global efficiency of the process is included in the efficiency of the CS. It is also considered that each CS can supply energy to more than one EV (Multiple-port) [9].

$$P_{c,t}^{CS} = \sum_{v=1}^{nV} (P_{v,t}^{ch} - P_{v,t}^{Dch}) X_{c,v,t}^{CS} \qquad \forall c, t \quad (14)$$

$$P_{c,t}^{CS} \leq \bar{P}_c^{CS} \qquad \forall c, t \quad (15)$$

$$P_{c,t}^{CS} \geq -\bar{P}_c^{CS} \qquad \forall c, t \quad (16)$$

The CSs can be installed in a parking lot or can be managed by a fleet operator. In both cases, global power limits should be imposed, as illustrated by (17) and (18).

$$P_t^{tot} = \sum_{cs=1}^{nCS} P_{c,t}^{CS} \qquad \forall t \quad (17)$$

$$P_t^{tot} \leq \bar{P}_t^{tot} \qquad \forall t \quad (18)$$

Finally, it is necessary to define constraints related to the peak power for each EV and for global consumption. The variables $P_{PeakTotal}$ and P_v^{Peak} are used in the objective functions related to peak consumption, as illustrated by (19) and (20).

$$P_{PeakTotal} \geq P_t^{tot} \qquad \forall t \quad (19)$$

$$P_v^{Peak} \geq P_{v,t}^{Ch} \qquad \forall v, t \quad (20)$$

III. Case study and results

In the present case study, the impact of the different objective functions is analysed. The case study proposed aims to emulate weekday EV trips related to the average working schedule. The mathematical model related to the OFs has been implemented in the general algebraic modeling (GAMS) [10], and the solutions were obtained using the solver CPLEX [11]. The participants would leave their homes in the morning (6h00-8h00) and return at the end of the day (18h00-20h00). The days are divided into 24 periods, each one representing one hour. They were considered 200 EVs considering a mix of (battery electric vehicles and plug-in hybrid electric vehicles, in which each EV user charges on its individual CS, with a maximum charging capacity of 7.2kW. This is done in order to further simulate a regular home charging situation. EVs data (battery capacity, charging and discharging efficiency, V2G capability, and the maximum power of charge) were obtained from [12]. The data related to EV user profiles such as travel data (initial SoC, arrivals and departure periods, and the energy losses in between), were obtained from a simulator that effectively creates EV charging profiles as detailed in [13]. Information about the tariffs, aiming to simulate the possible hourly price programs that the users can be placed in, three different tariffs are considered. All time intervals and their electricity cost associated were taken from [14]. The overall description of these electricity costs can be seen in Table I. For the RTP program, the electricity costs were taken from [15]. The market price was considered to be 25% of the real price paid by the user (the rest of taxes, transportation, distribution fees, etc). As so, all the market spot prices were divided by 0.25 in order to obtain an approximation of the price an RTP participant would pay. In order to compare the OFs proposed for the DR programs, there are three main things to consider: the price of charging, the peak power demand, and the EV charging demand curves, i.e., how much are they ”attended” when compared to the base case, the values considered are: a total operational cost (TOC) of €2441.38 and peak power of 1147.91 MW. The outcomes are compared to the Base Line profile (case base), which will be called Non-Participant (NP). This profile aims to simulate the regular charging of an EV owner who is not enrolled in any DR program, has a single tariff plan, and charges whenever possible (BaU). Furthermore, three smart contracts are considered: the user agrees to reduce the charging power, a) charging power limitation (CPL), which establishes a maximum percentage of the charging power that can be requested during peak hours. b) Limit the maximum amount of battery charge (Maximum SoC Limitation (MSL) which restricts the maximum SoC a vehicle can have during peak hours. c) Proportional spending-charging (PSC), which is similar to CPL but the limited power varies, depending on the amount of battery used in the previous travel, during certain periods of time. These time intervals are usually the peak demand periods, helping to attend the power curves while producing savings, by reducing the amount of money spent on those segments.

A. *Economical results*

In this section, the aim is to analyse how the different OFs can lead to various economic outcomes when applied to the various DR programs. By multiplying all the computed charges (kW) by the electricity price (€/kWh) at the given period they occur (1h), the result is the TOC of supplying energy to the EVs. This will serve as the variable for the outcome comparison. The obtained results, for a case with 100% of EV SoC requirement, can be seen in Table II. ToU–OF (2) performs worst within the other combinations as well as the NP-baseline. Such is exceptionally true in the tri-hourly case, where BaU (OF (1)) forces the charges when the EV arrives. However, most EVs arrive at peak hours. Hence, from the user’s perspective, it is better to charge normally. The ToU–OFs (2)/(3) gives the same TOC outcomes seeing as both OFs limit the charge in peak periods to the lowest possible amount, taking full advantage of the price of parcels. OFs (4) and OFs (5) behave the same as the previous two cost-oriented OFs. The attending of the demand caused by them leads to the stretching of the charging power all through the off-peak time zone, never reaching the peak demand periods. This allows them to still take advantage of the different tariffs provided by the time-based program.

RTP provides the overall worst economical results, although this may vary greatly with the season, and amount of renewable energy, among other factors. Considering that the electricity prices can only be those provided by retailers (i.e.

TABLE I
DESCRIPTION OF ELECTRICITY HOURLY RATE PROGRAMS UTILISED.

Tariff Type	Periods	Time Intervals	Electricity Price (€/kW)
Single	– – – – –	0h – 24h	0.145
Bi-Hourly	*Off-Peak*	1h–7h; 23h–24h	0.099
	Peak	8h–22h	0.185
Tri-Hourly	*Off-Peak*	1h–7h; 23h–24h	0.096
	Partial–Peak	8h; 11h–17h; 22h	0.156
	Peak	9h–11h; 18h–21h	0.272

neglecting the RTP program), MSL consistently has the best outcomes across all OFs. It achieves this by implementing a massive cut during peak hours, by only allowing a very small group of vehicles to charge. This limitation forces the optimisation to take advantage of the energy price brackets, regardless of the OFs utilized. As a result, this DR program is especially effective, compared to the others, when paired with BaU by dragging the bulk of charging into the off-peak periods, taking full advantage of the peak and off-peak price differences. The couplings with the more cost-centered (2), (3), (4), and (5) do not represent significant differences from the other demand response programs pairings with these OFs, as they already avoid charging during high price periods. Finally, both CPL and PSC represent intermediary solutions, being their outcomes between the ones obtained using ToU and MSL. Despite such similarities, PSC has significantly better results in the BaU pairing. This appears to imply that proportional power cuts are better than static ones in optimisations that are not focused on avoiding charging during peak periods. As expected, reducing the required SoC of the vehicles, at departure, from 100% to 80%, results in a decrease in charging costs. This can be seen in Fig. 1, in which a summary of economic results for each OF when compared with the NP-baseline case, considering 80% of EV SoC requirement. It is observed that the BaU (OF (1)) presents the worst results (closer than the NP results), particularly the ToU DR program. However, it is important to notice that the quality of service, translated by the energy charged in the EVs, has been reduced. Finally, ToU presents the most volatile outcomes throughout its objective function pairings.

The results comparison between the use of the DR programs

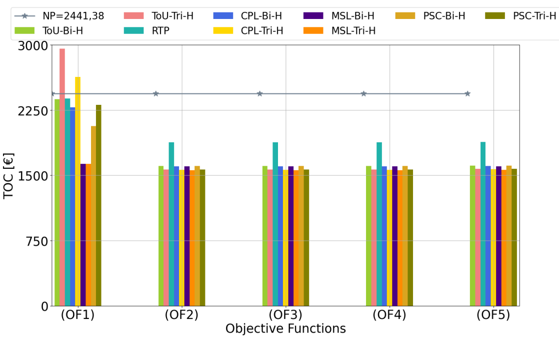

Fig. 1. TOC results compared to the Non-Participant baseline

TABLE II
TOC OF EACH OF COMBINATION FOR THE 100% SoC REQUIREMENT

	Total Operating Cost								
	ToU		RTP	CPL		MSL		PSC	
	Bi-H	Tri-H	Market Spot-H	Bi-H	Tri-H	Bi-H	Tri-H	Bi-H	Tri-H
	€	€	€	€	€	€	€	€	€
OF (1)	2464.1	3042.6	2497.67	2307.8	2715.3	1720.6	1717.8	2156.0	2393.9
OF (2)	1695.3	1651.6	1994.99	1690.3	1649.0	1690.5	1645.1	1695.3	1652.8
OF (3)	1695.3	1651.6	1996.70	1690.3	1649.0	1690.5	1645.1	1695.3	1652.8
OF (4)	1695.3	1651.6	1994.99	1690.3	1649.0	1690.5	1645.1	1695.3	1652.8
OF (5)	1696.5	1655.6	1995.30	1691.5	1653.0	1691.1	1647.4	1696.5	1656.8

TABLE III
TOC COMPARISON BETWEEN V2G DR PROGRAM AND WITHOUT V2G, WITH 100% SoC REQUIREMENT

	Total Operating Cost								
	ToU		RTP	CPL		MSL		PSC	
	Bi-H	Tri-H	Market Spot-H	Bi-H	Tri-H	Bi-H	Tri-H	Bi-H	Tri-H
	€	€	€	€	€	€	€	€	€
OF (1)	2464.10	3042.60	2434.33	2307.80	2715.30	1720.60	1717.80	2156.00	2393.90
OF (6)	-248.20	-1023.70	785.78	-250.60	-1019.40	-253.72	-1031.50	-246.60	-1013.20

without V2G and with V2G can be seen in Tables III and IV. It is possible to see that all tested DR programs provide significant profit to the EV user when paired with the OF (6). This is especially true when applied to a three-hourly tariff. It does so by utilising the larger prices during peak hours to its advantage, allocating the extra charging to the off-peak zone. Since the price requested is the maximum value within the utilised tariff, plus a battery degradation compensation, the EVs can then obtain a profitable charging/discharging operation. A high price is expected when the grid is in jeopardy and immediate action to safeguard is needed. The usage of RTP with V2G capabilities performs worse than the other OFs. The main reason is the energy prices. Despite this, there is another reason that can be cited, since the profit obtained will come from the battery degradation compensation and the difference between discharge and charge prices, which are proportional/have the same order of magnitude within the market spot prices (in RTP) and within each tariff type (all other OFs). Hence, this lower profit is also caused by the smaller difference between the lowest and highest price on the spot market, compared to the tri or bi-hourly tariff, where the price in peak periods is almost double the price in off-peak periods. The imposition between 100% of SoC requirement and 80% is also interesting. Contrasting with the observed results without V2G (Fig. 1), with SoC requirement of 80%, the results in worse economic results, i.e., in less monetary compensation for the EV owner. This is because the vehicles will have less SoC to provide to the grid during peak periods, seeing as they charge less before each travel.

Regarding the OC strategy, OF (7) aims to be applied to a more niche driver profile, with different EV use profiles during the week, alternating long travels with short ones [13]. The aim is then to determine if the OC program can obtain better results than the regular objective functions, for these types of EV profiles. This comparison is only done for the RTP program, since the charging process between (2) and (7) optimisation would be roughly the same in a tariff-based program, where it is easy to identify the line between cheap and expensive electricity prices. Hence, for this test were obtained a TOC of 69.92 and 70.63 for OF (2) and OF (7), respectively. Then, the (7) is able to obtain a better result than the (2), however, with a small difference (around 1%). The level of improvement may vary depending on the strike price (C_{SP}) chosen. Since the C_{SP} is the average value of the hourly spot prices of that day, the effectiveness of this program may be bigger on days when the market prices are more volatile. In other words, the economic improvement of the OC program, compared with other cost function approaches, can be higher when the price changes occur in short periods. Finally, this means that the OC program can demonstrate better performance in the long term and in different conditions, so more studies should be done in this regard. As a final remark, it is important to mention that the results were obtained based on real values of tariffs and spot markets. The differences obtained in the objective functions reflect these differences.

B. Peak power results

In this subsection is analysed how the peak power varies with the different OF/DR program pairings, as can be observed by Fig. 2. It is apparent that RTP displays the worst outcomes out of all the DR programs. Considering that the prices are different at all the periods and the OF gives more importance to the price instead of the peak power, the EVs charging will be scheduled as much as possible to the hour of the lowest price. This makes it so all vehicles charge at their maximum charging capabilities in the periods where the prices are lower, resulting in the peak power value being equal to the NP baseline (1147.9 kW). When paired with OF(1) or OF (2), CPL produces the best outcomes. Such leads to the conclusion that it offers the lowest power limitation during the peak time zone, resulting in a smaller charging spike in the off-peak periods. CPL combined with the peak reduction objective function OF (4) provides the best overall result, leading to a roughly 36% peak power reduction in comparison with the NP position. This is the result of the lower limitation explained previously for OF1 and OF2, which is further magnified by the peak power reduction component of the objective function.

TABLE IV
TOC COMPARISON BETWEEN V2G DR PROGRAM AND WITHOUT V2G, WITH 80% SOC REQUIREMENT

	Total Operating Cost								
	ToU		RTP	CPL		MSL		PSC	
	Bi-H	Tri-H	Market Spot-H	Bi-H	Tri-H	Bi-H	Tri-H	Bi-H	Tri-H
	€	€	€	€	€	€	€	€	€
OF (1)	2376.70	2457.96	2311.70	2280.50	2630.70	1633.25	1633.18	2068.70	2309.30
OF (6)	-181.11	-921.62	737.54	-183.50	-918.33	-186.63	-929.35	-179.17	-906.82

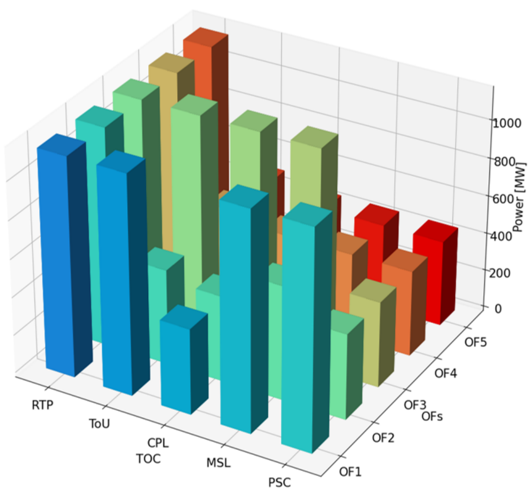

Fig. 2. Peak Power values obtained from every OFs DR program combinations for 80%

IV. CONCLUSIONS

The electric vehicles (EVs) point of view concerning different demand response (DR) programs as well as the EVs management considering different strategies have been proposed in this paper. Hence, several objective functions (OFs) are considered aiming to analyze the participation of the EVs in the DR programs. The case study proposed allows us to verify the effectiveness of each DR program with EVs and compare themselves. The results show that the DR programs are especially effective in the case of OFs with less cost since the latter already minimise the charging that could occur during the DR program's time intervals of operation. The peak power is directly correlated with how the EV demand is attended, but it has no impact on the overall total operation cost, as this peak can occur either in peak or off-peak periods; attending the EV demand may lead to the EV battery not achieving its intended required state of charge (SoC) limitations. Real-Time Pricing is a complex choice for customers, seeing as its performance depends entirely on aspects that may affect the market prices, and due to the variation, Time-of-Use (ToU) is very beneficial when paired with cost-centered OFs. This is important because the ToU program is already widely used, so the adoption of smart charging using these OFs could provide immediate benefits; Maximum SoC Limitation, Charging Power Limitation, and Proportional Spending-Charging programs are very interchangeable and really depend on the travel profile of the participant. However, the latter provides the most stable and balanced charging cut method, which most likely will be more agreeable to comfort and cost-focused users; Although the location of the max power demand (in or out of peak periods) is related to the program chosen, the reduction of this value can only be done utilising an appropriate OF to control the charging process.

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