Development of Specific Demand Response Programs for Electric Vehicles

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The growing environmental concern of modern societies has been causing an increase in the demand for electric vehicles. Although this is a positive change in many perspectives, the consequent increase in power demand may crate real problems for power systems operation. In order to contribute to the mitigation of this problem, it is imperative to explore various solutions within the scope of intelligent networks, avoiding the difficult and costly process of infrastructure reinforcement and increase in electrical generation capacity. As part of this extensive analyses, this thesis aims to access how the control of the Electric Vehicles (EVs) charging process, considering the existence of different demand response programs considering distinct objective functions in the optimisation process. In this thesis, two scenarios for the operation and management of electrical vehicles charging, are proposed. In the first scenario, the aim is to evaluate the impact that an optimised charging of EVs, utilising the proposed objective functions and demand response programs, can have. The main conclusion is that there is the possibility to reduce the cost of charging and, for the system operators, it was accessed that they can benefit from reduced power demand during peak hours. In the second scenario, we intend to study a system in which the variation in energy demand by electric vehicles can influence the production technologies necessary to satisfy all demand and, consequently, production costs. This case is interesting, especially in isolated systems such as islands. The main conclusion of this second scenario is that an aggregator can directly control the charge of an EVs, only in times of network congestion and instability, and contribute to the management of energy consumption. In this scenario, definition of consumer compensation are also studied when the consumer is willing to give up a certain percentage of energy consumption.

Keywords: Demand Response, Electrical Vehicles, Fleet Operators, Optimisation, Smart Grid

Received September 2021

1. INTRODUCTION

The need to urgently reduce the CO_2 emissions resulting from the combustion of fossil fuels is now more important than ever. Not only to avoid the more pessimist future reports on climate change, but also to comply with targets defined in the Paris agreement and the European Green Deal.
In this context, the continuous growth of Electric Vehicles' (EVs) use worldwide [1], can be seen as one of the main pillars for a more sustainable future. The transport sector is responsible for a quarter of all greenhouse gas emissions [2]. The replacement of Internal combustion Engines (ICE) for electric motors can decrease significantly the emissions of transport sector. Of course, this depends on how the energy they utilise to charge, is produced (from fossil fuels, nuclear, renewable sources, etc).
Despite this, some concerns must be scrutinised in order to accommodate the transition to the large scale utilisation of electric vehicles.
The main challenges that must be addressed is the sudden influx of new energy demand estimated to occur from the rise in utilisation of Battery Electric Vehicles (BEV). Such increase in power demand, provoked mostly by Light-Duty Vehicles (LDV) home charging [3], will have an important effect in the already sensitive peak hours. In normal weekdays, most of the EVs users arrive at home in the end of the day when the power consumption is already very high (peak hours) [4] .
The increase in Power Demand (PD) during such time intervals, if not properly addressed, may have several consequences in the overall power systems [5] :

1. Further "unflattening" of the demand curve. In other words, increase in the volatility of usage of energy during the day;
2. Need of reinforcement of the transmission and distribution grids;
3. Increase of power generation capacity;
4. Increase of ancillary services need (voltage and frequency regulation) due to the increasing volatility of large amounts of energy production/demand relation.

All of these aspects/consequences result in costs that, in the end, should be supported by the costumers [6]. Considering the time necessary to expand the transmission and distribution network imposed by the EVs increase, we can conclude that smart management solutions for EVs charge should be proposed and adopted by the power system actors.
In this context, Demand Response (DR) programs appear as one promising solution to mitigate the problem. The degree of implementation and use of DR programs worldwide, is diverse. Time-of-Use (ToU), which establishes different energy prices for different periods of the day, is already widely used in industry and households around the world [7], [8]. Direct Load Control (DLC) programs, which consists of the direct manipulation of the consumers load are only used in big energy consumers and with very specific contracts. Both ToU and DLC based programs have proven improvements in some critical areas [9], [10]:

- The difference in electricity prices, offered by ToU, aims to promote more off-peak consumption. With the same purpose but with different method, DLC forces the participants to demand less power during peak periods. Both of these lead to a more spread out energy consumption during the day, decreasing the volatility of energy usage;
- Less volatility results in the need for less ancillary services and decreases grid congestion in periods with excessive power demand;
- Both ToU and DLC provide savings for the consumer, as long as they change their energy consumption behaviours.

Although the previous two programs are already established for normal consumption, the implementation of DR for electric vehicles has yet to be subject of in depth study.
In this context, this thesis proposes two methodologies. The first methodology, or scenario, considers several DR programs, proposed by the system operator or retailer and the use of different objective functions to optimise the EVs charging, **Participant Perspective**. In the second methodology, the EVs charging is managed by an aggregator both considering the benefits for the users and for the system, **Aggregator Perspective**. This methodology was developed to be used only in emergency situations with the agreement of the EV users. Afterwards, it is assumed that the EVs charging have an impact in the generation dispatch and consequently in the total generations cost. This is particularly adapted to small and isolated systems such as the ones in islands or remote areas. The results obtained using the proposed methodologies are then illustrated, and complemented with their analyses. Finally, a summary of the most relevant findings and takeaways are provided, as well as some suggestions for future research on the matter.
In summary, the overall goal of this thesis is to help with the complex issue of accommodating the large scale integration of electrical vehicles into the grid, without it needing to suffer major alterations and/or reinforcements. It does so by proposing various methods of controlling the EV charging process. These methods mainly consist in adopting domestic and industrial demand response programs and better fitting them to the EV charging reality. The control and implementation of such programs is then done with objective functions, who are also formulated and proposed in this thesis. All of this is tested and evaluated utilising a set of realistic data (vehicle travel data, electricity price tariffs, charging power, etc) in order to access the real life viability of what is theoretically proposed.

2. STATE OF THE ART - DEMAND RESPONSE AND ELECTRICAL VEHICLES

2.1. Demand Response

2.1.1. Purpose and Definition of Demand Response in the Smart Grid Context

One of the many objectives of grid digitalization is the flattening of the demand curve [11]. In other words, the leveling of energy consumption during the hours of the day. Such can be achieved by implementing measures that aim to enhance Load Shifting (LS), Figure 1, i.e, the reduction of demand during peak periods by incentivising higher consumption in off-peak periods.

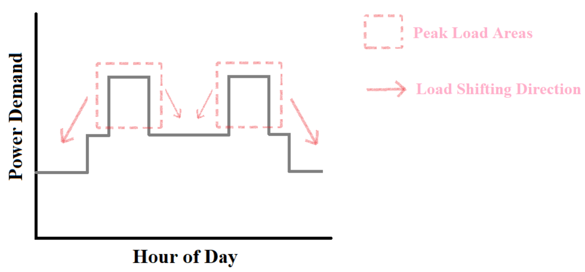

FIGURE 1. Daily Load Shifting Process visualisation

It is with this objective in mind that DR emerges as a catalyst, by motivating consumers to re-schedule their electricity demand habits [11]. Being the participation in DR programs mandatory or voluntary, the final aim is to eliminate or reduce the need for increasing the installed capacity. Such provides greater reliability to the power system, decreases grid degradation, due to lower congestion and overload, and increases market efficiency. All of this, in return, will result in financial gains for both the consumer, seeing as the expenses in grid management are reflected in energy prices, and the utilities, because they avoid these extra reinforcements. In addition to the monetary benefits, a flatter demand curve will also lead to lower carbon emission [12], by enabling a more efficient usage of the energy produced and *peak clipping* (peak demand reduction).

2.1.2. Utility/Costumer Interaction in DR Programs
Although DR promises to be one of the fundamental pillars for a more efficient power system, its benefits depend heavily in costumer participation in the proposed programs. Since the largest and most immediate benefits fall upon the utilities, it is their job to properly captivate the consumers and facilitate their integration in the technology heavy smart grid environment, required for some programs. Before delving deeper in the subject of facilitating customer participation, it is important to remember what is the point of view of each actor.
Utilities profit due to the fact that no extra power capability installation is needed to accommodate the demand. On the other hand, consumers can obtain a variety of gains, such as monetary savings or the satisfaction obtained for their help in keeping network stability and reducing CO_2 emissions. So, although this can make DR feel like an all around perfect solution, some uncertainties may arise in the consumers. These stem from the difficulty of defining the amount of load one is willing to curtail in a DR situation or the quantity of profit needed to willingly apply to a DR service. Utilities should tackle this problem by offering close assistance and monitoring to the costumers, helping them to understand the full process from the beginning to the end, and all through the length of the commitment.
This should not mean that all the work should lay in the utilities. The participants should commit to changing the electricity usage schedules as well as improving the efficiency of their domestic appliances when possible. They must also understand the overall benefits to the global energy system and how important their participation is to the improvement of their management.
Of course such problems only apply for scenarios where the participation in DR programs is not mandatory. Mandatory participation may only lead to changes in costumer bill instead of the desired load shifting, while a voluntary participation ensures a much more active role in peak demand reduction [13].

2.1.3. Demand Response Programs
In order to obtain the maximum adherence possible, it is imperative for the utilities to offer a variety of DR program options. This will help to cover the wide variety of potential costumer profiles that are expected to exist in a market as big and all-encompassing as is the energy consumption sector.
Considering that the list of already in-use DR implementations is quiet extensive, and will most likely increase proportionally to the technology evolution, it becomes important categorise them into broader groups. In order to make this aggregation, some questions can be utilised to access some key similarities between the several DR programs:

- does the utility directly control the load demand of the costumer, and if so, when?
- are the participants compelled to shift their energy usage to off-peak periods, without third party interference, i.e, through hourly tariffs and/or incentives?
- are the participants rewarded by the utilities for their change in energy usage directly or through bill savings?

The answer to such inquisitions leads most studies [14], [15] and [16], to place such programs into to two main groups, denominated **Dispatchable or Incentive-Based** and **Non-dispatchable or Time-Based**, as can be seen in Figure 2.

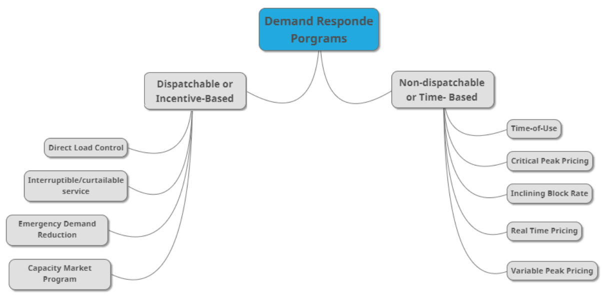

FIGURE 2. Examples of demand response programs

Dispatchable or Incentive-based Demand Response Programs (IBDRP) involve the direct control/manipulation of the costumers load in order to reduce the energy consumption either during peak periods or emergency events. Direct Load Control (DLC) and Interruptible/curtailable service (I/C) offer participants monetary compensation in exchange for a pre-specified amount of demand reduction. A slight variation to these two services can be seen in the Capacity Market Program, where participants are able to offer certain amount of demand reduction during emergency events. The definition of the amount of reduction, done in the initial contract and are not subject to short notice changes. On the other hand, programs such as Emergency Demand Reduction (EDR) compensate the participants by their measured energy reduction, only during DR events, and with short notice.

Non-dispatchable or Time Based Demand Response Programs (TBDRP) utilises period-varying prices in order to lead end users into shifting their consumption to less demand intensive periods and, consequently, flattening the overall PD curve. Time-of-Use, ToU, pre-establishes different electricity prices for different periods of the day, being the highest prices in the peak hours and the lowest during the off-peak periods. These tariff brackets are previously defined and remain un-changed for long periods of time (months, years). Critical Peak Pricing follows the same structure of ToU, but its peak price is subject to change during grid jeopardising events, which should only happen a few hours per year. Real Time Pricing (RTP) offers a more dynamic variation, being the electricity price announced to the participant in a day or hour-ahead basis. A middle term between the previous two programs is the Variable Peak Pricing *"where specific periods of electricity price fluctuations are defined in advance. The price fluctuations that occur in the defined periods, vary depending on the energy supplier and the market conditions"* [17]. Finally, Inclining Block Rate, IBR, offers a non-time based alternative, increasing the price of electricity parallel to the amount utilised by the costumer. In other words, the price per kWh increases in blocks depending on the cumulative total consumed energy. For example, the electricity costs x/kWh if the costumer uses less than 6.4kWh, and costs y/kWh ($y > x$) if the user consumes more. This can be established for kWh hourly, daily or monthly consumption.

3. DEMAND RESPONSE PROGRAMS FOR ELECTRICAL VEHICLES

3.1. Methodologies/Scenarios Scope

There where two utilised methodologies. The first, denominated **Participant Perspective**, describes the combined use of different objective functions and several demand response programs, proposed by the system operator or retailer, in order to optimise the EVs charging. The second methodology, denominated **Aggregator Perspective**, proposes an EV charging is strategy managed by an aggregator. This is done considering the benefits for both the users and for the system, and is to be used only with the consent of the EV owners and during grid emergency situations. In this Aggregator Perspective, it is assumed that the EVs charging demand is significant enough to have an influence in the generation dispatch and, as a consequence, in the generations costs. This makes this methodology specially aimed at small and isolated systems (islands or remote areas).

How each of the scenarios that will proposed fit into each of these scopes is shown in Figure 3.

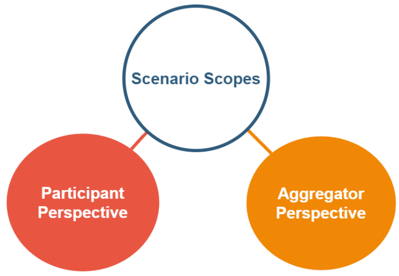

FIGURE 3. Scopes and the scenarios within them

3.2. Proposed Demand Response Programs

Inspired by existing Home/Industrial DR programs, the strategies described aim to focus solely on the EV charging prospect.

Constructed with the end goal of increasing the costumer and/or utility's benefit, these programs are:

1. **Non-Participant (NP):** the EV owner has the standard flat tariff and charges his vehicle as fast as possible without any control. This is used as a comparison tool for the other program performances;
2. **Time Of Use (ToU) [18]:** the retailer offers different electricity tariffs for different times of the day (higher prices in peak demand hours and lower prices in times of lower demand). This program is similar to the one which already exists for normal loads, but in this case it will be used to access the impact it can have on EV charging;
3. **Smart Contracts [19]:** the user agrees to reduce the charging power (**Charging Power Limitation (CPL)** and **Proportional Spending-Charging (PSC)**) or to limit the maximum amount of battery charge (**Maximum SoC Limitation (MSL)**) his BEV can have, during certain periods of time. This time intervals are usually the peak demand periods, helping to flatten the power curves while producing savings, by reducing the amount of money spent on those segments.
   - **Charging Power Limitation (CPL):** establishes a maximum percentage of the charging power that can be requested during peak hours. For example, restricts the maximum charging power to 50% of its maximum during those periods;
   - **Proportional Spending-Charging (PSC):** similar to CPL but the limited power varies, depending on the amount of battery used in the previous travel. For example, if a car used 40% of its full battery capacity in its previous travel, i.e. arrives at the charging station with 60% of its capacity, than it will only be able to charge at 40% of the maximum charging power.
   - **Maximum SoC Limitation (MSL):** re-

stricts the maximum SoC a vehicle can have during peak hours. For example, a maximum 60% of SoC can be establish for the vehicles. This means two things: if the vehicle arrives to the CS with less than 50% of its capacity, it can only charge to 50% during peak periods. If it arrives with more than 50%, than it will not charge during those periods;

4. **Real Time Pricing [20]:** similar to ToU but the prices can change daily, depending on the electricity market or other factors. The EVs can charge more or less depending on the prices and on the EV owner risk aversion/profile;
5. **Incentives [21]:** the participant will decrease his demand voluntarily in normal peak hours or in mandatory fashion during DR events. Restrictions are not implemented by direct control of the vehicle, being the costumer only complied to participate by a previously defined payment made by the company responsible for the grid functionality. In some cases, the costumer can be penalised for not fulfilling its energy consumption reduction obligations;

3.3. Methodology for Participant Focused Scenarios

3.3.1. Optimisation

A Mixed-Integer Programming approach (MIP) [22] is utilised to access the best (minimal) result for each objective function. The OF should be designed considering the charging costs and the consumer satisfaction [23]. Costumer satisfaction varies depending on charging speed, price or peak power.

3.3.2. Objective Functions

For this experiments, several objective functions were developed to possibly evaluate results. All of them were utilised when implementing the various DR profiles previously mentioned. The results from those experiments were then analysed in order to determine how the various OF/DR programs combination lead to different outcomes.
Making use of the previously established variables, the function of each of these OFs can be succinctly theorised:

- **Business as Usual (BAU)**: The main goal of this OF is to simulate the charge of EVs without control. This means that the EVs, belonging to our test group, will be charged as fast as possible;
- **Cost Minimisation (CM) [24], [25]**:Aims to minimise the overall charging cost of the vehicles, obtained by multiplying the power of charge used by every vehicle at every time interval, for the respective charging price;
- **Cost minimisation + Comfort Level (CMCL) [26], [27]**: While still taking into consideration the cost of charging, CM, it also gives importance to how close the electrical vehicle is to its total capacity during every period. In that case, the vehicles are charged faster but for the same cost, increasing the comfort level of the user;
- **Cost Minimisation + Peak Limit (CMPL)**: CM while also trying to have the least possible impact on the grid, i.e, also penalises peak power demand.
  Because it considers the global peak power of the vehicles charging, it can be used by a Fleet Operator or a parking lot manager;
- **Cost Minimisation + EV Peak Limit (CMPLEV)**: similar to CMPL but instead tries to limit the maximum demand of each vehicle;
- **Opportunity Cost (OpC):** the BEV is only mainly in off-peak hours, limiting the opposite event to the strictly necessary, i.e., if the the vehicle does not have enough battery charge to fulfil the Required SoC demanded by the participant.
  This is achieved by establishing a Strike Price and using it to modify a CM objective function;
- **Cost Minimisation + Vehicle-to-Grid (CM+V2G) [28]**: based on CM. However, in this case, discharge is allowed during peak periods or when convenient. The price received by the owner for discharging its vehicles battery energy, is the maximum price of electricity on the market day (in RTP) or in his tariff program (in the other DRPs) plus the price considered for battery degradation. Such will result in an incentive for the vehicles to give electricity back to the grid during those periods, in an effort to reduce the objective function value. This implies the existence of contracts which would allow the system operator to buy that energy. The value chosen for the battery degradation monetary compensation was 0.06/kW [29].

3.3.3. Constraints

Within the previously described experimental programs, some restrictions should be imposed, leading to different results:

1. **Minimum SoC (MinSoC):** imposes the vehicle to always have more than a certain percentage of its total battery capacity, usually around 20%, in order to avoid battery degradation,
2. **Required SoC (ReqSoC):** imposes that the vehicle should have a certain percentage of its total battery capacity, at the time of departure. This value is decided by the participants and depends on their travel needs. The charging of the vehicle beyond or below this value is penalised in the simulations.
3. **Required Kms:** similar to ReqSoC but with a minimum amount of Kms. Such can be achieved

by analysing the driving profiles of the drivers, in order to understand the kms usually used after the departure, or by simply establishing an emergency limit, taking into account the minimum distances to the nearest hospital, supermarket, school, etc. In either option, it is necessary to know the battery model, capacity, charging efficiency and if the car has an additional ICE (PHEV).;

4. **Vehicle to Grid Capability (V2G):** defines if the BEV is able to supply energy to the grid or not. This information must be supplied by the test group of vehicles utilised;
5. **Maximum Charge and Discharge of the BEVs:** imposes the maximum power charge that every individual vehicle can receive or discharge. This information is given for each vehicle in the test group. However, we need to evaluate the CS-EV relation, which will give the real maximum power charge the vehicles can demand;
6. **Maximum Charge and Discharge of the Charging Stations:** imposes the maximum amount of charge power that each charging station can dispense or receive, in total, to or from the vehicles connected to it;
7. **Maximum Power Source:** imposes a maximum power demand value, that can be requested by the overall simulated system. This value is determined by the summation of the maximum power each generator can supply in each period of simulation;
8. **Energy Balance:** establishes that the simulation must obey energy balance laws. In other words, the power supplied by the sources (generators) must be equal to the power demanded by the consumers (charging stations);

3.4. Methodology for the Aggregator Perspective Scenario

3.4.1. Event Control

The aim is to simulate an aggregator intervention in the vehicles charging process during peak hours. In other words, **the Event Control program is an aggregator controlled DLC, which is only utilised in situations where the grid is going through an emergency situation. This program is only applied with the consent of the participants** and is only aimed to be used in participants who are not actively invested in any other demand response program who restricts their charging process, i.e. the previously described Smart Contracts or V2G.

The method consists on defining the total power of the system as the summation of all the max powers each vehicle can demand, and limit it to a certain level by multiplying it by a constant.

3.4.2. Demand Reduction Compensation

In addiction to the previously described load curtailment aspect, there is the more complicated issue of **compensation pricing**. In order to reach a fair value, both parties involved, consumer and aggregators, must agree that they are benefiting from the proposed solution. This means that the determined value of compensation must ensure that retailers are not financially penalized and that the discomfort caused to the costumer is adequately remunerated. A method was utilised to address this two symbiotic counterparts, keeping in mind the aim is to develop methods that equally benefit the participants and the retailers leading to to a smoother adoption of this new methods by both parts. This method is the **Social Welfare Maximisation (SWM)** in [30], [31], with a slight modification: the energy suppliers stake in the problem is replaced by the retailers interest, as the latter would most likely be the one involved in participant procurement and negotiation.

The first step is to specify the problem mathematically. The formulation includes:

- A function to maximise: the social welfare can be defined as the sum of the normalised utilities related to the intervening parties; The **Aggregator Utility (UR)** comprises the retailer profit.

  On the other hand, the **costumer utility (UC)** can be described as the difference between a previously established satisfaction function and the product of the energy demanded and the price paid by it;
- A set of restrictions: the total EV charging power demand must be bigger than zero, and can't exceed the maximum value established by the sum of all the CS maximum power capacities or vehicle charging capabilities (which ever is bigger), and must be equal to the supplied power at every moment;
- the method utilised to execute the optimisation, based on the previously problem formulation, is the Lagragian Relaxation with the Karush-Kuhn-Tucker (KKT) conditions;

The second steps aims to further develop the previously formulation, by establishing the two missing factors: the retailer **operational costs (OC)** and the **costumer satisfaction function**.

To determine the value of the **OC** we first assume the demand curtailment is to occur at a certain hour of a certain day, and so, the retailer can represent the aggregated curve of the offers in the market, through a quadratic or linear equation. Finally it is needed that the function returns the total cost of production and not a currency amount per hourly energy ratio. So, this function is multiplied by the power demand at each point.

The only thing left to determine is the **Costumer**

Satisfaction function. Here, and based on [31], it is proposed the use of a sigmoid function as this type of functions is often used to describe costumer satisfaction [32] and [33].
Our study is only focus on the consumption of a small group of vehicles at a certain hour. As so, **this scenario is meant to be used in an island or remote system, where the EV charging process may influence the dispatch of production units and, in turn, the costs of production**. Acknowledgement of such leads to a division in this **Social Welfare Maximisation** method, depending on the comfort evaluation:

1. **SWM-A or Overall Energy Consumption Comfort**: The calculations are made by joining the daily total power that could potentially be requested by all EVs, to the total domestic consumption (contracted power). Then the sigmoids would be designed to reflect the comfort given by each MWh (megawatt-hour) consumed.
   This would be an accurate way to establish the incentive payments, if the vehicles SoC is given the same importance as other quality of living apparel (fridges, ovens, cleaning machines, etc).
   In this case, the OC are the ones calculated by the minimum square error or polynomial fitting method techniques applied to the hour offer curve.
2. **SWM-B or Participant EV Charging Comfort**: In our case, for two hundred vehicles, the maximum demand is around 2 MW. Seeing as the curves obtained for the hourly offer in Portugal usually are in the thousands of MW, this creates a dimensional problem.
   So, the sigmoids are designed to reflect the costumer satisfaction at the DR event hour and only for the participant demand and the OC function is simply the spot price multiplied by the power. So, to evaluate the maximum welfare, one establishes the costumer and retailer utilities and acquires its maximum summation value. Then establishes it as its optimum demand point and proceeds to calculate the incentive payment linked to each reduction percentage;

Finally, an alternative method is proposed to bypass the difficulties that the previous SWM method may demonstrate, utilising an **Profit Based Formula (PBF)**, based on the findings in [34]. This way requires no participant satisfaction study or function dimensioning, relaying only on data readily available to retailers/FOs. Such information consists of some previously identified variables: total demand and correspondent spot price, at event hour, before and after reduction. All of this is easily done by consulting the hourly offer curve. However, this would require a reliable knowledge of the country wide CS power summation, which may prove difficult. However, if the proper documentation is required from the owners when purchasing a charging station, this is entirely feasible.
The "fairness" of this compensation rises proportionally with the number of vehicles who participate in such control. It is also important to denote that both the retailers lost of profit and the costumers benefit, are taken into account, making this a less complex social welfare maximisation method [35, 36, 37, 38]. However, as the results show, costumer benefit is a priority, since the aim is to attract the maximum amount of participants possible.

4. RESULTS EVALUATION AND COMMENTS

4.1. Implementation

4.1.1. Scenarios

The stated scenarios, try to emulate week-day trips related to the average working schedule. Therefore, the participants would leave their home in the morning (6 to 8 am) and return at the end of the day (6 to 8 pm), being the days divided into 24 periods, each one representing one hour.
Every vehicle charges on its individual CS, with a maximum charging capacity of 7.2kW (Type 1 AC connector). This is done in order to further simulate a regular home charging situation, seeing as these are the most commonly used in LDV [1]. Vehicle data (battery capacity, charging and discharging efficiency, v2g capability and maximum power of charge) and their corresponding travel data (initial SoC, arrivals and departure periods and the energy losses in between), were obtained from [39].
The Non Participant profile is used in every scenario in order to establish a baseline for result comparison.
Being the broader picture already characterised, it is important to define the full scope of the experiments in question, by further delving into the specifics.

- **Scenario 1**: implementation of several OF/DR combinations in order to control the charging process of 200 individual vehicles, and analysis of the resulting outcome variations.
  Each participant profile is independent from the others, so their travel habits and energy usage are fairly distinct (recurrent long or short trips, or a mix).
  Each vehicle has its own uniform travel pattern. Some EVs always perform low energy travels (10%-30%), some high energy (70%-90%) and other in between (40%-60%).
  In order to evaluate the different results, a base line situation is defined and named as Non-Participant (NP), utilising BAU as the optimisation OF and the single tariff plan, in order to represent the

[1] https://pod-point.com/guides/driver/ev-connector-types-speed

normal charges one would get by not entering any DR or optimisation programs;

- **Scenario 1.1 or V2G Capability**: all technical aspects are equal to the previous scenario, but this scenario focuses on a vehicle-to-grid program an user can endeavour in, based in an appropriate objective function, **CM+V2G**. While the OFs used in Scenario 1 are used to provide optimisation to the everyday charging of EVs, CM+V2G is only activated during periods when the market price justifies it or/and the grid is in jeopardy. Such is because these time intervals are the ones the EV owner can obtain a profit, by requesting from the retailer an electricity price for his discharge larger than the one he would pay for charging;
- **Scenario 1.2 or Opportunity Cost**: the overall technical scope is in all similar to **Scenario 1**. However, for this situation, the test subjects are limited to ten BEVs who's profiles are a mix of large and small travels.
  The aim is then to understand if the OC objective function can lead to, specifically, better economic results in this subset of vehicle profiles, providing another option for the hypothetical consumer;
- **Scenario 2 or Aggregator Focused Scenario**: focuses on how an aggregator or Fleet Operator, can help to avoid damage or to facilitate the grid operations during a DR event, denominated as **Event Control**, as well as on how to define possible compensation payments in return for costumer demand reduction during peak hours, **Demand Reduction Compensation**. This simulations are adapted for a small system where the EV charging can affect the dispatch of the production units and as a consequence the price. The participation is also voluntary, i.e., this curtailments only occur if the participant consents to them;

4.1.2. Tariffs

All time intervals, and their correspondent cost of electricity, are exact replicas of the ones provided by Portugal's largest retailer [2] during the winter periods.
For the Real Time pricing program, the electricity costs were taken from the spot market of Portugal and Spain[3] on the week of 23rd to the 27th of November 2020. The market price was considered to be 25% of the price paid by the end consumer (being the rest taxes, transportation and distribution fees, etc).

4.2. Scenario 1

In order to compare the different DR programs resulting from the utilisation of the different OFs, there are three main things to consider: the price of charging, here called Total Operational Cost (TOC), the peak power demand during the five days and the EV charging demand curves obtained, i.e., how much are they "flattened" when compared to the base case, which will be called Non-Participant. 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 (Business as Usual or BAU).
The main results obtained can be summarised as: the demand response programs are especially effective in less cost focused OF, as the latter already minimise the charging that could occur during the programs time intervals of operation; Peak Power is directly correlated to how flattened the curve is, but it has no impact on the overall TOC, as this peaks can occur either in peak or off peak periods; Curve flattening may lead to the vehicle battery not achieving its intended required Soc limitations. This missing energy provides a non-significant cost reduction and cant be used as an alternative to justify the low TOC in this cases; Real Time Pricing is a complex choice for costumers, seeing as its performance depends entirely on aspects that may affect the market prices (temperature, renewable energy production); Time-of-Use is very beneficial when paired to cost centred OFs. This important because ToU is already widely used, so the adoption of smart charging using these objective functions could provide immediate benefits; Minimum SoC Reduction, 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 objective function to control the charging process.
The TOC results can be seen in Figure 4.

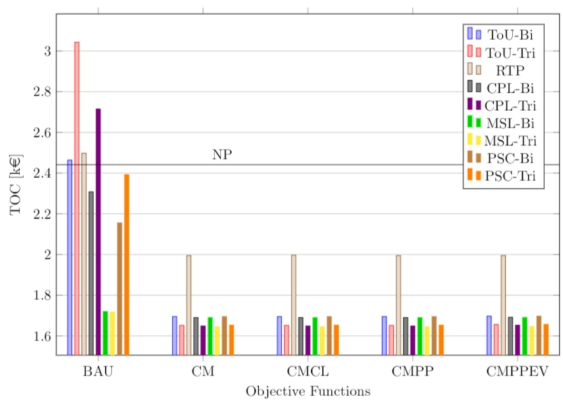

FIGURE 4. TOC results compared to the Non-Participant baseline

[2] https://selectra.pt/energia/empresas/edp/cicloshorarios
[3] https://www.mercado.ren.pt/PT/ELECTR/INFOMERCADO/INFOP/MERCOMEL/Paginas/Precos.aspx

4.3. Evaluation of the Vehicle-to-Grid Impact

The discharge prices were dimensioned to apply in situations of grid jeopardy, in order to make sure that the V2G capability can sometimes provide a profitable charging process to the EV owner. This demonstrates that the participant has incentive to help the grid during jeopardy periods. Regardless of the DRP used, the vehicle-to-grid capability mixed with its appropriate objective function, provides the best results in terms of cost and overall domestic load shifting. Such is because, although the charging power curve presents a large spike in the off peak periods (see Figure 5), its merger with the home consumption model, will lead to an overall flatter domestic curve. It is also worth mentioning that the RTP provides less profit than any other DRP, but, once again, this depends on market prices and should be subject to studies with a bigger time frame.

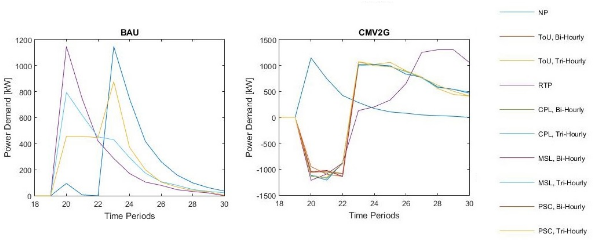

FIGURE 5. Power Demand curves for the first charging cycle in a regular charging situation and with the V2G program

4.4. Evaluation of Opportunity of Cost Function

The **Opportunity of Cost** program presents itself as a more niche pairing for the cost minimisation objective function, proving slightly more economically efficient. Despite this, the results may vary greatly with the market prices presented. The OCs relatively niche usage in vehicles with a mix of long and short travels during the week, is especially relevant in the current Covid working situation, as more and more workers adopt working from home schedule, with the occasional trip to the office. Despite all of this, the DR service provider, like the FO's, must only assign this type of optimisation to a carefully studied group of participants, which must be aware that cost reduction is the primary concern in this case and that this might lead to low battery charges at departure.

4.5. Aggregator Focused Scenario

4.5.1. Event Control

The **Event Control** shows that the interruption of vehicles charges by the FO/aggregator is a fairly simple and fast operation from a coding stand point, which would make it ideal to deal with sudden excessive demand periods. Although this curtailments during peak periods may lead to overall cost reduction to both the utilities and the consumer, most participants in this type of program are mainly concerned about their vehicles battery charge, so a monetary incentive most be provided to them in order to compensate the reduction in comfort level.

4.5.2. Demand Reduction Compensation

Three methods are proposed to calculate the compensation that must be provided for clients who participate in the demand reduction during peak periods. All of them utilise the agreggator offer curve of the hour in question. Two of them, **SWM-A and SWM-B**, utilise Social Welfare Maximisation problems, concerning, respectively,the entire electricity market/retailer/costumer and the retailer/participant relations. Both of these provide increasingly better results until the peak/optimal cut percentage, and then begin to descent. On the other hand, a **Profit Base Formula** is also proposed, which provides proportional compensation/charging cut returns. This function takes into account the lost revenue from the retailer and the increase in costumer profit.

5. CONCLUSIONS

This thesis aimed to develop several programs to help the grid accommodate the large scale usage/integration o electrical vehicles, without it needing to suffer major alterations and/or reinforcements. The need for this comes from the large increase in electrical demand that would follow such adoption.
To accomplish this two methodologies were proposed. The first, denominated **Participant Perspective**, considered several demand response programs, proposed by the system operator or retailer and the use of different objective functions to optimise the EVs charging. The second methodology, denominated **Aggregator Perspective**, puts forward an aggregator managed EV charging process, considering the benefits for booth the system and the participants. This scenario was formulated with some assumptions in mind: the programs are only done with the consent of the EV owners and the combined charging demand of all the managed electrical vehicles is significant enough to influence the generation dispatch and costs. This second condition, makes this scenario more aimed at smaller and isolated systems like islands or remote areas.
This two different perspectives were then simulated utilising realistic data (travel expenditures and periods, electricity price tariffs, charging power, etc), in order to access how they would preform in real world applications. An analyses of the simulation results shows that the suggested DR programs and objective functions can result in significant improvements when compared to the normal charging behaviour. This improvements are both to the participant, in the form of reduced charging costs, and to the overall system because

of the reduction of maximum peak demand values and the better distribution of energy consumption during the day. The energy curtailment compensation tables also produced values who would be feasible within the electricity values used, demonstrating that the proposed methods are viable. The methods also showed different pros and cons, which makes them suitable for a variety of different situations and purposes.

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