Development of Specific Demand Response Programs for Electric Vehicles

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Thesis to obtain the Master of Science Degree in

Electrical and Computer Engineering

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September, 2021

Declaration

I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

To my amazing family, friends and girlfriend, a gigantic ”thank you” for everything you give me.

Acknowledgments

The writing of this dissertation could not be done without the support and assistance of some people who I would like to bring some attention to.

First of all, I would like to show my utmost appreciation for professor Hugo Morais. His endless support and guidance are what made it possible for this thesis to exist. Thank you for all the meetings and responses to my many, many, many questions.

To Professor Rui Castro I owe my appreciation for two different reasons. In a more subject oriented note, his directives made my dissertation a much more complete and focused work. But more importantly, it was his "Renewable Energies and Decentralised Production" course which made me realise that energy engineering was my passion, and ultimately made me switch my Major. A decision I see as one of the most important moments of my life.

I would also like to quickly thank every professor who accompanied me throughout my academic path. Some of your advice and knowledge will follow me for life.

Finally, but in no way less importantly, I would like to show my appreciation for my family, friends and girlfriend. Your ears were always open to my vents and worries, and that is something that I will never forget nor can ever pay back (but I promise I'll try).

Resumo

A crescente preocupação ambiental das sociedades modernas, a diminuição do preço da tecnologia e o crescente desenvolvimento, tem vindo a provocar um aumento na procura de veículos eléctricos, sendo esperado um domínio do mercado nos próximos 50 anos.

Apesar das vantages desta mudança, o consequente aumento do consumo de energia elétrica, pode criar problemas na gestão das redes elétricas (tanto na rede de transporte como, principalmente, na rede de distribuição).

Com o intuito de contribuir para a atenuação do problema em causa, torna-se imperativa a exploração de várias soluções no âmbito das redes inteligentes, de modo a evitar o difícil e dispendioso processo de reestruturação de infrastrutura e/ou aumento de capacidade de geração elétrica.

No contexto desta extensa análise, esta tese tem como objectivo inferir os efeitos possíveis do controlo do carregamento de veículos eléctricos considerando a existência de diferentes programas de gestão da procura e a utilização de funções objetivo destintas no processo de optimização. O objetivo final é, portanto, contribuir e testar novas variantes de controlo do carregamento de veículos elétricos, destacando os diversos beneficios que podem ser obtidos pelo consumidor e pelos operadores dos sistemas elétricos.

Nesta tese são abordados dois cenários de operação e gestão do carregamento de veículos elétricos. No primeiro cenário pretende-se avaliar o impacto que o carregamento optimizado de veículos eléctricos, utilizando as funções objectivo e programas de gestão da procura propostos. A principal conclusão é que há possibilidade de reduzir o custo de carregamento dos veículos elétricos e, para os gestores de rede, apurou-se que podem beneficiar de valores de consumo mais reduzidos nas horas de pico. No cenário 2, pretende-se estudar um sistema no qual a variação da procura de energia pelos veículos elétricos pode influenciar as tecnologias de produção necessárias para satizfazer toda a procura e, consequentemente, os custos de produção. Este caso é interessante, principalmente em sistemas isolados como por exemplo em ilhas. A principal conclusão deste segundo cenário é que um agregador pode controlar diretamente a carga de um veículo elétrico, apenas em momentos de congestão e instabilidade da rede, e contribuir na gestão de consumo de energia. Neste cenário são também estudadas as formas de dimensionamento de compensação do consumidor quando este se predispõe a abdicar de uma certa percentagem de carga nas baterias dos EVs. São, de seguida, propostas variantes destinadas à compensação desta redução especificamente no carregamento de veículos elétricos.

Palavras-chave: Operadores de Frota, Optimização, Rede Inteligente, Resposta da Procura, Veículos Eléctricos.

Abstract

The growing environmental concern of modern societies, the decrease in price and the increasing development of technology, has been causing an increase in the demand for electric vehicles, with market dominance being expected in the next half a century.

Although this is a positive change in many perspectives, the consequent increase in power demand may crate real problems for the grid maintenance (both in the transportation and, mostly, in the distribution). 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/or increase in electrical generation capacity.

As part of this extensive analyses, this thesis aims to access how the control of the EVs charging process, considering the existence of different demand response programs and the utilisation of distinct objective functions in the optimisation process. The final objective is to formulate and test new ways to control the charging of electrical vehicles, demonstrating the benefits that can be obtained by the consumer and the system operators.

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 electrical vehicles, utilising the created 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 electric vehicle, 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. Subsequently, variant proposals are proposed to compensate for this reduction specifically in the charging of electric vehicles.

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

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List of Abbreviations

AC	Alternating Current
BAN	Business Area Network
BAU	Business as Usual
BEV	Battery Electric Vehicle
CM	Cost Minimisation
CMCL	Cost minimisation + Comfort Leve
CMPL	Cost Minimisation + Peak Limit
CMPLEV	Cost Minimisation + EV Peak Limit
CPL	Charging Power Limitation
CPP	Critical Peak Pricing
CM+V2G	Cost Minimisation + Vehicle-to-Grid
CS	Charging Station
DAU	Data Aggregate Unit
DC	Direct Current
DLC	Direct Load Control
DR	Demand Response
DSO	Distribution System Operator
EDR	Emergency Demand Reduction
EV	Electric Vehicle
FAN	Field Area Network
FO	Fleet Operator
HAN	Home Area Network
HEV	Hybrid Electric Vehicles
IAN	Industrial Area Network
IBDRP	Incentive-based Demand Response Programs
IBR	Inclining Block Rate
IC	Incentive Compensation
ICE	Internal Combustion Engine

ISO	Independent System Operators
KKT	Karush-Kuhn-Tucker
LDV	Light-Duty Vehicles
MIP	Mixed-Integer Programming
MDMS	Meter Data Management System
MSE	Minimum Square Error
MSL	Maximum SoC Limitation
NAN	Neighbourhood Area Network
NP	Non-Participant
OC	Operational Costs
OF	Objective Function
OpC	Opportunity Cost
PBF	Profit Based Formula
PD	Power Demand
PHEV	Plug-In Hybrid Electric Vehicles
PP	Peak Power
PS	Power System
PSC	Proportional Spending-Charging
RES	Renewable Energy Sources
RLM	Retail Benefit Maximisation
RTP	Real Time Pricing
RTO	Regional Transmission Organisations
SG	Smart Grid
SM	Smart Meters
SMUD	Sacramento Municipal Utilities District
SoC	State of Charge
SWM	Social Welfare Maximisation
TBDRP	Time Based Demand Response Programs
ToU	Time-of-Use
TSO	Transmission System Operator
UR	Aggregator Utility
UC	Costumer Utility
VPP	Variable Peak Pricing
V2G	Vehicle to Grid
WAN	Wild Area Network

List of Variables

Variables for the Participant Focused Scenario: Objective Functions

Variable	Definition
auxSOC(v,tdep)	Difference between a vehicles, **v**, total battery capacity and its state of charge [kWh] in a period of departure, **tdep**
BatteryCapacity(v)	Battery Capacity [kWh] of each vehicle, *v*
BD	Battery Degradation monetary compensation [€/kW]
ESOC(v,t)	State of charge of a vehicle [kWh], *v*, battery at each hour of simulation, **t**
MaxPrice	Maximum price of electricity [€/kWh] within a tariff program or in a day of spot market
$\mathbf{N_{departures}}$	Number of periods where vehicles start a travel
$\mathbf{N_{periods}}$	Number of periods considered
$\mathbf{N_{vehicles}}$	Number of vehicles used
Pch(v,t)	Power supplied [kW] to a vehicle, *v*, at a particular time interval, **t**
Pdch(v,t)	Power supplied [kW] by a vehicle, **v**, to the grid, at a particular time interval, **t**
PeakPower	Peak power demand [kW] from the total vehicle charge
PeakPowerEV(v)	Peak power demand [kW] for each vehicle, **v**, charge
Price(t)	Price of electricity [€/kWh] at each moment, **t**
StrikePrice	Price of electricity [€/kWh] that establishes a limit for the Opportunity of Cost program. The vehicle charges as much as possible in periods where the electricity price is bellow this Strike Price
T	Group of periods used
$\mathbf{T_{departure}}$	Group of periods where vehicles start a travel
V	Group of vehicles used

Table of variable descriptions for the objective function formulas

Variables for the Participant Focused Scenario: Constraints

Variable	Definition
CS	Group of charging stations utilised
$\mathbf{ED_{ratio}}$	Average energy expenditure for each kilometer travelled [kWh/km]
Gen	Group of generators used
$\mathbf{km_{max}}$	Average distance a vehicle can travel [km] with a full battery charge
$\mathbf{km_{needed}}$	Certain amount of kilometres [km] a vehicle should aim to be able to travel at a specific departure period
MaxChargePower(v)	Maximum power of charge [kW] the vehicle, **v**, can demand/receive
MinSoC(v)	Minimum state of charge [kWh] each vehicle, **v**, should have
$\mathbf{N_{CS}}$	Number of charging stations used
$\mathbf{N_{Gen}}$	Number of generators used
$\mathbf{P_{CS}(CS,t)}$	Power dispensed [kW] by the Charging Station, *CS*, at each period, *t*
$\mathbf{P_{CSMax}}$	Maximum power of charge [kW] a Charging Station can dispense
PD	The systems overall power demand [kW]
Pdch(v,t)	Maximum power [kW] the vehicle, **v**, can provide to the grid at each hour, **t**
$\mathbf{PD_{Max}}$	Maximum power demand [kW] value that can be requested by the overall simulated system
$\mathbf{P_{GenMax}(gen,t)}$	Maximum power [kW] that each generator, *gen*, can dispense at each period, *t*
PS	The systems overall power supply [kW]
ReqSoC	Percentage of the battery capacity a vehicle should aim to have at a specific departure period

Table of variable descriptions for the constraint formulas

Variables for the Aggregator Perspective

Variable	Definition
CPF	Costumer profit [€]
d*	Optimal power demand [MWh]
d0	Initial market electricity power demand [MWh]
d	Power Demand [kW]
$\mathbf{d_{curtailed}}$	Power demand curtailed [MWh]
dDR	Final market electricity demand after reduction [MWh]
$\mathbf{d_{max}}$	Maximum power demand [MWh]
$\mathbf{E_{reduced}}$	Total energy reduction [MWh]
$\mathbf{ep_{consumer}}$	Electricity price paid by the consumer [€/MWh]
$\mathbf{ep_{market}}$	Spot market price for electricity [€/MWh]
F(d)	Costumer satisfaction function in function of demand, d
ICH	Incentive Compensation per Hour [€]
$\mathbf{IC_{PBF}}$	Hourly incentive compensation for each kW forfeited by a participant of the Profit Based Formula [€]
$\mathbf{MaxPower_{AfterCut}(t_{emerg})}$	Maximum power demand [kW] available after the emergency limitation at the moment of the restriction,$\mathbf{t_{emerg}}$)
OC(d)	Operational cost [€] in function of demand, d
p0	Initial market electricity price [€/MWh]
pDR	Final market electricity price after reduction [€/MWh]
redux	Percentage of power limitation during emergency events
$\mathbf{R_{LostRevenue}}$	Revenue lost by the retailer caused by the reduction of demand [€]
s	Power Supply [kW]
SW	Numerical value representing the social welfare
$\mathbf{T_{Emerg}}$	Group of periods which comprise the emergency period
UC(d)	Costumer Utility in function of demand, d
UR(d)	Aggregator Utility in function of demand, d

Table of variable descriptions for the Aggregator Perspective formulas

List of Software and Hardware

Software:

Matlab	Version 2015b. Used in all simulations and to create the results graphs shown in this thesis
GAMS	Used to conduct the optimisation
Excel	Utilised to store all the data regarding the electrical vehicles and their travels

Hardware:

Lenovo Legion	NVIDIA GeForce RTX 3050, Intel Core I5 Processor, 8GB RAM

Chapter 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 Paris agreement and 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. This is emphasised in **Chapter 2**, where the state of the art of demand response programs and of electrical vehicles are described.

In this context, this thesis proposes two methodologies that will be described in **Chapter 3**. 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 generations costs. This is particularly adapted to small and isolated systems such as the ones in islands or remote areas.

In **Chapter 4**, the results obtained using the proposed methodologies are illustrated, and complemented with their analyses. Finally, **Chapter 5** summarises the most relevant findings and takeaways and suggests future research on the matter.

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 simulated 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.

Chapter 2

State of the Art - Demand Response and Electrical Vehicles

2.1 Smart Grid

This chapter describes the notion and structure of the Smart Grid (SG) as well as the relevant technology related to this concept.

2.1.1 Infrastructure

In order to access the potential future, it is important to first understand the circumstances of the present, beginning with with the description of the current state of production, transmission and distribution systems and consumption.

A glance look at the worldwide power generation patterns, shows that fossil fuels prevail as the main source for energy production [11], [12]. Despite this, the continued increase in the renewable energy technologies use has steadily provoked a decrease in the usage of those non-sustainable primary energy sources [13–15]. Although energy production is still a centralised affair, being the bulk generation made possible by large power plants, the continued adoption of Renewable Energy Sources (RES) seems to point for a future where the decentralised generation will be predominant [16–18].

Concerning the transmission and distribution systems, their are managed and operated by the transmission system operators (TSOs) and Distribution System Operators (DSOs), respectively [19].

Finally, the end consumer can be categorised as domestic, business or industrial [20], depending on the installed power, power demand and voltage level connection [15].

The growth of population and of the consumption of electricity, must be accompanied by an increase of energy production. So, in order to avoid the consequential grid reinforcement, the Smart Grid presents itself as more balanced and future oriented approach. The SG can be defined as *"an electric system that uses information, two-way, cyber-secure communication technologies, and computational intelligence in an integrated fashion across electricity generation, transmission, substations, distribution and consump-*

tion to achieve a system that is clean, safe, secure, reliable, resilient, efficient and sustainable" [21]. By replacing (or at least greatly reducing) the previous modifications with technology integration, at all voltage levels of the Power System (PS), the SG allows a more efficient monitoring and control of energy generation and consumption.

This digitisation opens the door to the consumer to behave as an active player in the PS, by modelling their consumption in accordance to some benefits they wish to earn. These can be for self gain, to the overall system stability and/or for the improvement of the climate situation. The SG also allows an easier transition to the increase of RES integration in the system as well as the development of many other new solutions such as vehicle-to-grid connections, microgrids, energy communities, etc [22].

A simplified comparison between the current power system and and the one following a Smart Grid vision [23] can be seen in Figure 2.1.

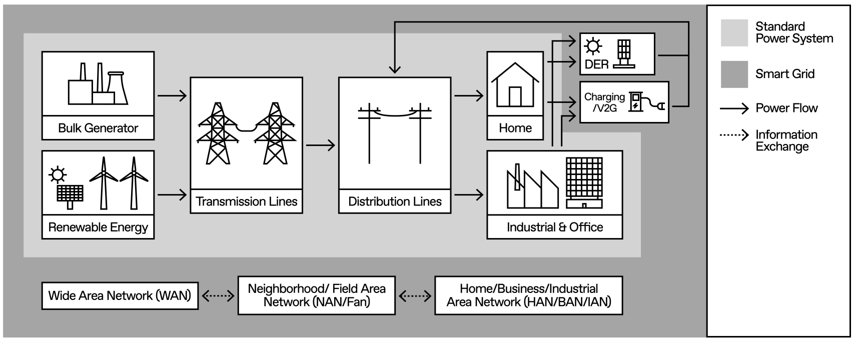

Figure 2.1: Extent of the current and future power system

Figure 2.1 shows a division of the SG into three information exchange areas, each on with a variety of standardised communication connections. These areas are a defining asset of the SG's information exchange capabilities between all power system sectors, and are described in [24], being roughly summarised as:

- **Home/Business/Industrial Area Network (HAN/BAN/IAN)**: connects several electrical appliances within a home or business/industrial building, to a dedicated smart meter. It does so trough standardised communications such as: IEEE 802.11 (WiFi), allowing cable free information exchange; IEEE 802.15.4 (ZigBee), that focuses on low cost and speed communication between devices, contrasting with the more power intensive WiFi counterpart; Power Line Communication (PLC), which make use of the already existing electrical structure, to transport information;

- **Neighbourhood/Field Area Network (NAN/FAN)**: connects several home/business/industrial smart meters to a Data Aggregate Unit (DAU). This connection, facilitates the intelligent interaction between energy transmission/distribution and the end consumer. The standards IEEE 802.11 (WiFi) and IEEE 802.16m (WiMax), who's scalable architecture allows for an easy data rate scalibillity with the available bandwidth.;

- **Wild Area Network (WAN)**: utilised to establish communication between the power system, bulk generation and the Meter Data Management System (MDMS). The MDMS stores and manages the immense amount of data acquired by the several smart meters. Such data consists mostly of energy consumption schedules, obtained from the several DAUs implemented;

The agglomerate of these three areas constitutes the Advanced Metering Infrastructure, which can be broadly defined as a system able to measure, save and analyse energy usage obtained from metering tools [25], in a scheduled manner.

2.2 Demand Response

This section aims to describe the present demand response reality by defining its purpose, explaining the relations between parties involved, describing the exiting DR programs and providing real life examples of their implementation.

2.2.1 Purpose and Definition in the Smart Grid Context

One of the many objectives of grid digitalization is the flattening of the demand curve [26]. 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, Figure 2.2, i.e, the reduction of demand during peak periods by incentivising higher consumption in off-peak periods.

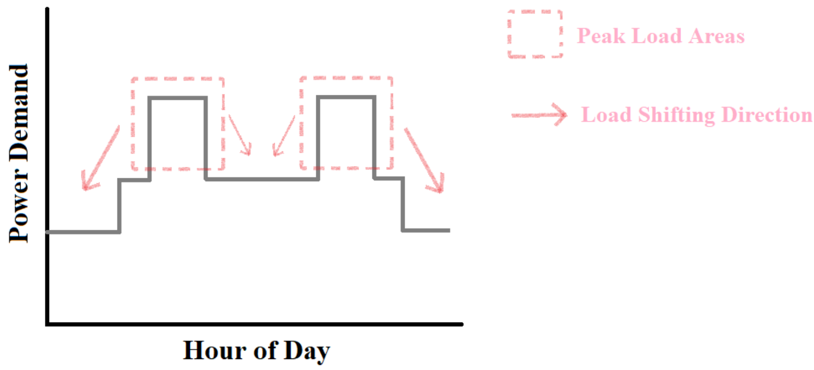

Figure 2.2: Daily Load Shifting Process visualisation

It is with this objective in mind that DR emerges as a catalyst, by motivating consumers to re-schedule their electricity demand habits [26], [27]. 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 [28], by enabling a more efficient usage of the energy produced and *peak clipping* (peak demand reduction).

2.2.2 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 includes aiding in deciding the DR program best suited to their needs and contingencies, explaining the necessary technology (metering, communication, remote controls, etc) and providing the conditions for its installation, such as providing the necessary personnel.

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 power systems and how important their participation is to the improvement of their management. Government/states/municipalities should also preform informative campaigns in order to establish the importance of responsible energy usage in climate change prevention. Such would help in further contributing to achieving the several environmental targets defined for the foreseeable future. A similar mentality which is seen towards recycling would be ideal and appropriate.

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 [29].

2.2.3 Demand Response Enablers

In [30], the author defines a smart instrument as an appliance able to communicate pertinent information and, consequently, to enable automatic or external control by the corresponding consumer, utility or other responsible third party. This control could be based on costumer preference or contractual obligation between the parties involved.

Such definition may encompass a large number of devices, which demonstrates how complex domestic/business/industrial settings can become in the future. From air conditioners to industrial power tools, anything able to be controlled/scheduled to operate in a more efficient way, may be part of an HAN/BAN/IAN.

In the this context, Smart Meters (SM) represent the front line of DR implementation thanks to their bi-directional communication: participants receive real time electricity costs (depending on the program they participate in) and utilities obtain costumer energy consumption schedules [31]. A visualisation of the SM implementation in different environments/functions can be seen in Figure 2.3.

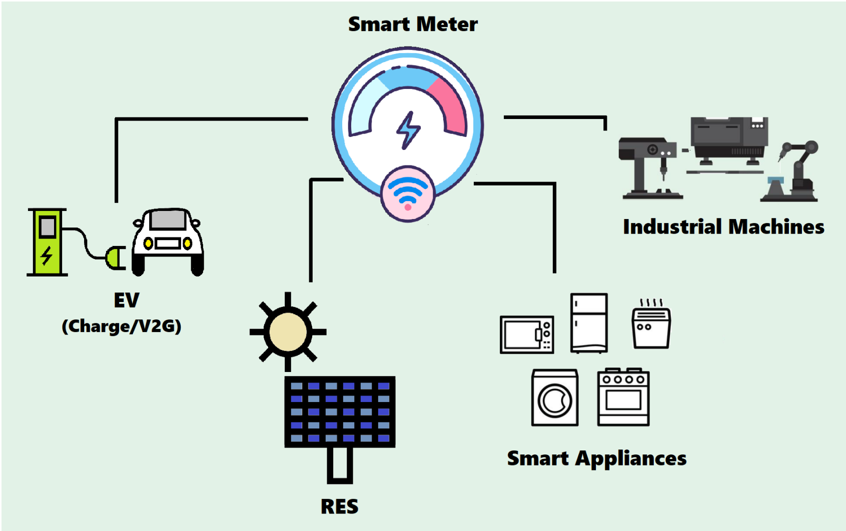

Figure 2.3: Smart Meter implementation in different appliances

In [32], the authors demonstrate the benefits of SM implementation combined with time-based DR programs. They also define the electronic structure of an SM, which can be roughly summarised as an open source hardware CPU, for easy configuration, and an integrated circuit (AS7753) which measures power by obtaining current and voltage information from dedicated sensors.

The technological depth of such a mechanism is sure to evolve in the following years, proportionally to the increase of consumer/utilities smart relation.

Another important group of devices in the DR context, are the **Control Units**. These serve as an intermediary between smart metering and costumer or utility mediation, by providing physical control of the appliances. This includes connecting/disconnecting them from the grid, power use reduction of a specific machine or an overall area-wide demand limitation. The timing of these actions can depend on several factors, such as energy price or grid contingency, according to the DR program the participant is enrolled in.

Load control switches and smart thermostats, are some examples of this type of technology, being the first one used as an on-off switch for a variety of connected loads, and the second as a controller of temperature focused appliances, adjusting their usage proportionally to the area temperature.

2.2.4 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 [20], [23] and [33], 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 2.4.

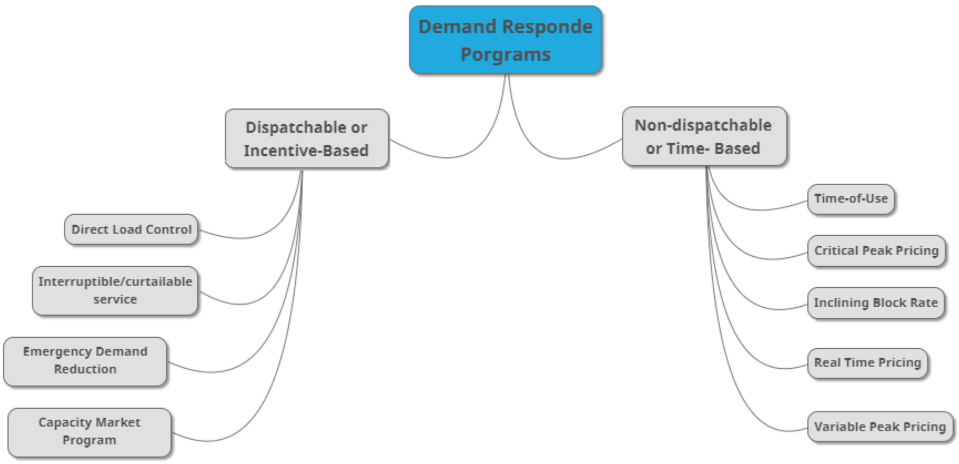

Figure 2.4: Examples of demand response programs

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 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"* [34]. 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.
In opposition to IBDRP, participation in time based programs can result in an increased costumer bill. This introduces a risk/reward factor into TBDRP which must be evaluated by each participant. An oversimplification of that ratio (left), as well as an example of resulting price/hour daily curves (right), can be seen in Figure 2.5.

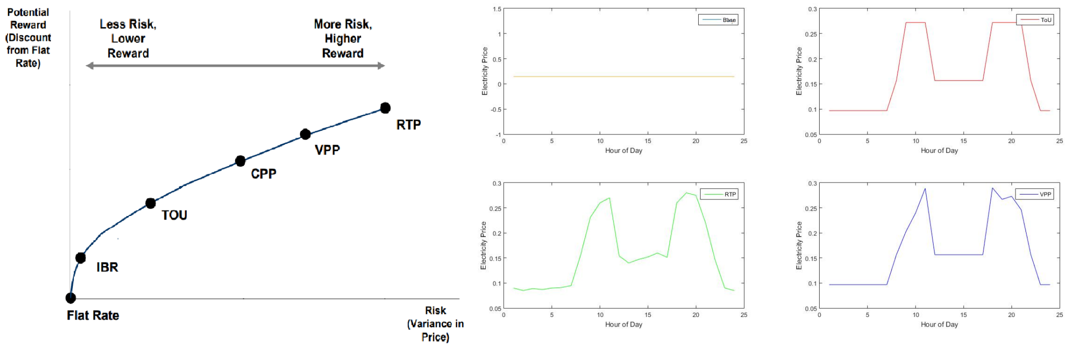

Figure 2.5: Costumer risk reward for each DR [35] (left) and generic representation of price of electricity per hour resulting from one day application of the most prominent IBRD (right). Concerning the four graphics on the right we have: the normal single tariff on the upper left, Time-of-Use on the upper right, Real Time Pricing on the lower left and Variable Peak Pricing

2.2.5 Examples of Home and Industrial Applications

The most immediately recognised DR utilisation is the ToU program, being time based tariffs already largely implemented worldwide [36]. One example is the voluntary program offered by the SMUD (Sacramento Municipal Utilities District), who's tariffs can be seen in Figure 2.6, available on the companies website[1]. In Canada, British Columbia Hydro implements Increasing Block Rate[2] dividing each year in 1-2 month periods of consumption. The tariffs implemented during the 2020 fiscal year can be seen in Table 2.1.

During a three year period, 2003-2006, Commonwealth Edison (Illinois) provided Real time pricing program [37] to roughly 1500 costumers, resulting in 15% and 3% maximum power demand reductions during peak and non-peak periods, respectively. Various implementations of Critical Peak Pricing have been evaluated, being some of them represented in Table 2.2.

[1] https://www.smud.org/en/RateInformation/TimeofDayrates/TimeofDay58pmRate/Ratedetails
[2] https://www.bchydro.com/content/dam/BCHydro/customerportal/documents/corporate/regulatoryplanning-documents/regulatoryfilings/rates/20200213bchydroresidentialincliningblockextension.pdf

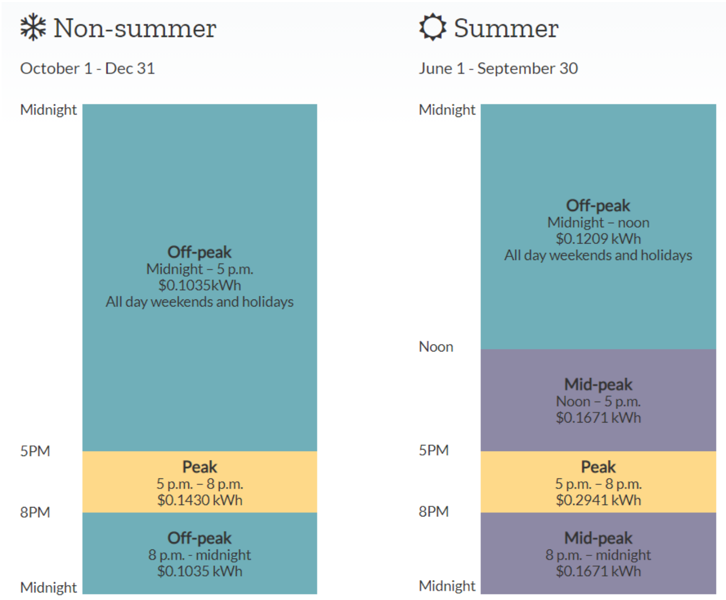

Figure 2.6: ToU tariffs graphic representation taken from the SMUD website

IBR as of April 1, 2019	Charge
Step 1 energy rate RS 1101: first 1,3450 kWh per two-month billing period (or first 675 kWh per one-month billing period)	9.45 cents per kWh
Step 2 energy rate RS 1101: all additional consumption in the billing period	cents 14.17 per kWh

Table 2.1: IBR tariffs applied by the BCH during the 2020 fiscal year

Utility Name	State	Year	Number of Participants	Peak Reduction During Critical Periods [%]
PG&E, SCE, SDG&E [38]	California	2004	226	51%
PG&E, SCE, SDG&E [38]	California	2005	199	43%
Gulf Power [39]	Florida	2000-2001	2300	44%
PSE&E [40]	New Jersey	2006-2007	1286	26%
Hydro Ottawa [41]	Ontario	2006-2007	498	25.4%

Table 2.2: Real life CPP implementation results in various utilities across the USA

Incentive-Based programs are more largely implemented, being that it requires much lower costumer participation in order to acquire savings. More than 300 Direct Load Control and 100 Interruptible/Curtailable programs are offered throughout the USA [42] with an aggregated total of more than 5.075 million participants, respectively. The most notable ones belonging to the the Southern California Edison program, resulting in an average costumer load drop of 1.7kW and 8.5kW for DLC and I/C respectively. PJM, a Regional Transmission Organisation (RTO) which serves several US states, offers an EDR program [43] with minimum reduction amount of 100kW during, at least, two hours. The New York ISO, also provides a similar program, being the participants reduction judged comparatively to their base line consumption during non-event periods.

In [44] the author shows that a variety of European countries also provide a wide range of DR programs, as can be seen in Table 2.3.

Some examples of these implementations are:

Country	Interruptible Loads Program	Emergency Demand Response	Time of Use
Austria	Yes	No	No
Belgium	Yes	No	Yes
Denmark	Yes	No	No
Finland	No	No	Yes
Germany	Yes	No	No
Italy	Yes	No	Yes
Netherlands	No	No	Yes
Poland	No	Yes	Yes
Portugal	Yes	No	Yes
Spain	Yes	No	Yes

Table 2.3: Some DR programs provided by European countries

- Germany introduced its DLC progrmas in 2013, aimed to loads connected to high or very high voltages [45];
- In Portugal[3] and Spain [4], retailers offer ToU alternatives to both domestic and industrial consumers;
- Switzerland has its ancillary services market totally opened to consumers, individual or aggregated, with relatively low participation requirements;
- Poland offers an EDR Program for loads larger than 10MW [46];

2.3 Electrical Vehicle

In this section the various types of electrical vehicles are explained. The existing charging standards implemented around the world, are also documented.

2.3.1 Types of Electrical Vehicles and Batteries

EVs can use different combinations of energy sources they to power their motors [47]. It is this fact that leads to several categories of EVs.

Hybrid Electric Vehicles (HEVs) and **Plug-In Hybrid Electric Vehicles (PHEV)** have an Internal Combustion Engine (ICE) complemented by an electric motor, in order to optimise the fuel consumption/performance of the vehicle. While HEVs obtain their electric energy purely from "regenerative braking" or from the utilisation of the ICE as generator, PHEV can charge their batteries directly from the power grid.

Hybrid vehicles can be sub categorised by how their motors supply energy to the transmission:

- Parallel Hybrid: both fuel and electric motors are connected to the transmission, resulting in the possibility that both provide energy simultaneously;

[3]https://poupaenergia.pt/tarifas-e-ciclos-horarios/

[4]https://www.endesa.com/en/blogs/endesa-s-blog/light/hourly-electricity-rates

- Series Hybrid: ICE functions as a generator, supplying the batteries and the electric motor. The latter then provides locomotive force to the transmission;
- Power-split hybrids: take advantage of the benefits of the previous two configurations by combining them;

and by degree of hybridization,

- Full Hybrid: the vehicle can function as purely electric, fossil fuel-based or mixed;
- Mild Hybrid: can only function as a mix of both engine types;

Some research has put into question the benefits of Hybrid vehicles over ICE vehicles, regarding the amount of pollution that each emit [48], [49]. Although the assessment of such claims is beyond the scope of this thesis, the ability of PHEV to demand energy directly from the grid, is not.
Finally, **Battery Electric Vehicles (BEVs)** are purely powered by internal batteries which supply the electric motors. These type of vehicles present the best alternative to the CO_2 heavy fossil fuel combustion engines, mainly when the electricity is generated by non-polluting technologies [50], [51]. The charging of these vehicles is done by connecting the EVs directly to a power source. The used standards will be presented in Subsection 2.3.3.
Some of the most relevant topics when discussing BEVs, are the battery efficiency, capacity and degradation. Although the first two aspects depend mostly on the component quality, material type and overall size, the latter is subject to much study and its rate can be optimised with different strategies, from owner behaviour to smart charging.
The comparison between several chemical composite batteries is studied in [52]. This study concludes that Li-Ion batteries are the ideal choice for BEV batteries, supporting this claim with several of this composite characteristics: moderate energy consumption, decreasing production cost, low weight, high energy storage capability and an already implemented manufacturer technology.

2.3.2 Plug-In Vehicles Charging Infrastructure

The relatively novelty mass production of EVs has lead to a lack of uniformity in charging standards across the world. This can be observed by the use of different charging modes in the most prominent EV markets, which may intensify as the number of different EV manufacturers increases.
Regardless, it is important to denote the *modus operandi* of each one. Europe adopted IEC 62196-1, describing 4 charging modes [53], [54]:

1. Mode 1: comprised of a slow charging using AC household socket. Such connection is made trough various SAE J1772-2009 standardised connectors.
   No communication exits between outlet and vehicle;
2. Mode 2: similar to Mode 1 but with the extra protection provided by an in-cable control box between the EV and the socket. Utilises VDE-AR-E 2623-2-2 connectors.
   Communication aiming to regulate the charging process, is possible;

3. Mode 3: allows slow or fast charging utilising an AC, EV-specific outlet. Communication aiming to regulate the charging process, is possible;

4. Mode 4: DC outlet which allows two categories of fast charging:

   (a) DC Level 1: voltage and current must be bellow 500V and 80A, respectively, with a power supply of 40kW;

   (b) DC Level 2: voltage and current must be bellow 500V and 200A, respectively, with a power supply of 100kW;

   The connectors to be utilised in this mode are described in IEC 62196-3.
   Communication system is included which allows battery charging management;

The Society of Automotive Engineers (SAE) defines six charging modes in SAEJ1772-2, three in AC and three in DC.
Finally, China uses the GB/T 20234-2011, similar to the European standards with some maximum current modifications.

2.4 Fleet Operators

A Fleet Operator (FO) is, in broad strokes, an aggreggator and manager of electrical vehicles. They can oversee the charging process, the vehicle-to-grid capabilities and can orchestrate the proper allocation of the EV resources in order to provide ancillary services to the power system [55]. The participants/EV owners allow the collection and organisation of their information by the FO. The fleet operator can then share that information to the grid operators, when pertinent. This allows for an optimal control within the boundaries of the established contract. Such control can be as a simple electricity request reduction, or as complex as a fully optimised charging process (Figure 2.7). Ultimately the FO aims to act as an

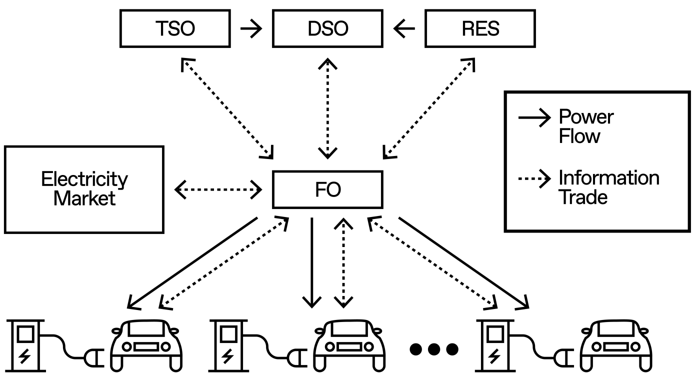

Figure 2.7: Fleet Operator interactions with the relevant entities

intermediary in the power system between consumer and the bulk generation/transportation/distributor, being the goal to obtain some benefit over its non-existence:

1. Diminish Peak Demand;

2. Flatten the overall demand curve;

3. Increase costumer savings by displacing their energy utilisation from peak to off-peak periods;

It is apparent that several sections of the power system stand to benefit from the FOs existence. Points **1** and **2** mainly relate to utilities, by preventing the necessity for generating power increases, while **3** affects only the costumer. However, 1 and 2 can also indirectly result in lower energy prices and, consequently, consumer gain.

Despite this, there are some important aspects to consider when discussing the FOs. One of these is the computing power of each individual fleet operator. This may vary according to the forms of control it will enact and the amount/type of data it will process. Aggregaters with a larger and/or more diverse fleets will process more information and deploy more prolonged and complex optimisations.

So, in order to establish the economic viability of this entity, the costs of FO computing technology and information exchanges must be juxtaposed with potential gains provided to the utilities [56].

2.5 Demand Response Applied to Electrical Vehicles

The integration of the EVs charging process in demand response programs, has been the subject of some studies in the last few years. Most of these, focus on how DR can help to mitigate the increased peak demand values and the overload conditions at the distribution system, caused by the growing EV penetration.

In [57] the authors discuss possible contributions that demand response applied to EVs, can provide to the power system, without delving into simulations. They propose that this implementation should be done through an aggregator or a fleet operator and recommend some appropriate communication systems to enable the quick transfer of information.

In an attempt to avoid infrastructure investments, [58] proposes a DR strategy as a load shaping tool. Said strategy takes into account the consumers preferences as well as the improvement in distribution transformers usage.

The authors of [59] provide a more detailed and experiment based work, by presenting a *"methodology for day-ahead energy resource scheduling for smart grids considering the intensive use of distributed generation and V2G"*. This study proposes two different DR programs:

1. **Trip reduce:** allows EV users to obtain profit by reducing their travel necessities and minimum battery SoC requirements. This agreement is made with the network operator;

2. **Shifting reduce:** enables EV users to formulate a collection of alternative travelling periods, for their expected travels. This allows the network operator to shift the charging loads by compensating the end user to shift its charging schedule;

These DR programs are tested using a case study with a 33 bus distribution network, and utilising a modified particle swarm optimisation and a non-linear programming optimisation. The use of these two computational intelligence techniques, provides further insight on the execution times differences. The study concludes that this DR programs can *"provide effectiveness regarding the reduction of the operation costs from the network operator point of view"*.

A more specific utilisation of DR in EV charging is seen in [60]. In it, the focus lies on how this programs can provide benefit for a parking station environment. To do this, a simulation of a real time charging scheme is done utilising a binary optimisation. The simulation results demonstrated that the EV charging demand could be satisfied while also minimising monetary expenses.

Lastly, [61] provides a consumer oriented perspective. These can choose which load to control and when. The impact of such a DR program on the consumer comfort is then measured utilising comfort indices in order to help utilities to better estimate consumer acceptance of these type of programs.

Chapter 3

Demand Response Programs for Electrical Vehicles

This chapter formulates the demand response programs created specifically for EV charging, describes the proposed methodology, as well as the various aspects taken into consideration, when preforming the simulations, and formulates the scenarios we aim to emulate.

3.1 Methodologies/Scenarios Scope

This section describes two utilised methodologies. The first, denominated **Participant Perspective** (Section 3.3), 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** (Section 3.4), 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).

3.2 Demand Response Opportunities

This section focuses on formulating and describing a series of demand response programs specifically created to be used in the EVs charging.

3.2.1 Proposed Demand Response Programs

Inspired by existing Home/Industrial DR programs, the strategies described in this section 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) [62], [63]:** 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 in all 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 [64], [65]:** 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):** restricts the maximum SoC a vehicle can have during peak hours. For example, a maximum 50% 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 [66], [67]:** 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 [68], [69]:** 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

This section details every component considered when preforming the simulation of the scenarios 1, 1.1 and 1.2.

3.3.1 Optimisation

A Mixed-Integer Programming approach (MIP) [70] is utilised to access the best (minimal) result for each objective function. As so, **the final aim of every objective function designed, is to minimise their final value**.

The OF should be designed considering the charging costs and the consumer satisfaction [71]. 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, $\boldsymbol{v}$, belonging to our test group ($\boldsymbol{V}$), will be charged as fast as possible. To model this behaviour we penalise the difference between the vehicles total battery capacity, **BatteryCapacity**, and its current state of charge, **ESOC**. This is done for each time period,**t**, belonging to our time frame of simulation, **T**;

$$BAU = \sum_{v=1}^{N_{vehicles}} \sum_{t=1}^{N_{periods}} BatterCapacity(v) - ESOC(v,t), v \in V, t \in T \tag{3.1}$$

- **Cost Minimisation (CM) [72], [73], [74]**: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 ,$\boldsymbol{Pch}$, for the respective charging price. The difference between the total battery capacity and its state in the departure periods, $t_{departure}$, represented by the **auxSOC**, exists only to guarantee that the vehicle has the necessary charge to execute the following travel;

$$CM = \sum_{v=1}^{N_{vehicles}} \sum_{t=1}^{N_{periods}} Pch(v,t) * Price(t) + \sum_{t_{dep}=1}^{N_{departures}} \sum_{v=1}^{N_{vehicles}} auxSOC(v, t_{dep}), \\ v \in V, t \in T, t_{dep} \in T_{departure} \tag{3.2}$$

- **Cost minimisation + Comfort Level (CMCL) [75], [76]**: While still taking into consideration the cost of charging, CM, it also gives importance to how close the BEV 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.

  The importance factor m [77] is used to attribute less importance to the comfort level when comparing with the costs. In the simulations presented in this document, m=0.001;

$$CMCL = CM + m * \sum_{v=1}^{N_{vehicles}} \sum_{t=1}^{N_{periods}} [BatteryCapacity(v) - ESOC(v,t)], v \in V, t \in T \tag{3.3}$$

- **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, ***PeakPower***. Because it considers the global peak power of the vehicles charging, it can be used by a Fleet Operator or a parking lot manager; The value of m is, again, 0.001;

$$CMPL = CM + m * PeakPower, v \in V, t \in T \tag{3.4}$$

- **Cost Minimisation + EV Peak Limit (CMPLEV)**: similar to CMPL but instead tries to minimise the maximum demand of each vehicle , **PeakPowerEV**;

$$CMPL = CM + m * \sum_{v=1}^{N_{vehicles}} PeakPowerEV(v), v \in V, t \in T \tag{3.5}$$

- **Opportunity Cost (OpC):** the BEV is only charged 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 OF. By doing so, the vehicles, belonging to our test group ($\mathbf{V_{OpC}}$), will try to charge as much as possible when energy price is below the SP, in order to make the OF value as low as possible;

$$OpC = \sum_{v=1}^{N_{vehicles}} \sum_{t=1}^{N_{periods}} Pch(v,t) * (Price(t) - StrikePrice) + \sum_{t_{dep}=1}^{N_{departures}} \sum_{v=1}^{N_{vehicles}} auxSOC(v, t_{dep}),$$
$$v \in V_{OpC}, t \in T, t_{dep} \in T_{departure} \tag{3.6}$$

- **Cost Minimisation + Vehicle-to-Grid (CM+V2G)** [78]: based on CM. However, in this case, discharge, **Pdch**, 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), **MaxPrice**, plus the price considered for battery degradation, **BD**. 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 OF value. This implies the existence of contracts which would allow the system operator to buy that energy.

$$CM + V2G = \sum_{v=1}^{N_{vehicles}} \sum_{t=1}^{N_{periods}} Pch(v,t) * Price(t) + \sum_{v=1}^{N_{vehicles}} \sum_{t=1}^{N_{periods}} Pdch(v,t) * (MaxPrice + BD)$$
$$+ \sum_{t_{dep}=1}^{N_{departures}} \sum_{v=1}^{N_{vehicles}} auxSOC(v, t_{dep}), v \in V, t \in T, t_{dep} \in T_{departure} \tag{3.7}$$

The value chosen for the battery degradation monetary compensation, BD, was 0.06€/kW [79].

3.3.3 Constraints

Within the previously described experimental programs, some restrictions should be imposed, leading to different results.
The ones theorised for the possible simulations are:

1. **Minimum SoC (MinSoC):** imposes the vehicle to always have more than a certain percentage of its total battery capacity, ***MinSoC***, usually around 20%, in order to avoid battery degradation,

$$ESOC(v,t) >= BatteryCapacity(v,t) * \frac{MinSoC(v)}{100}, v \in V, t \in T. \tag{3.8}$$

2. **Required SoC (ReqSoC):** imposes that the vehicle should have a certain percentage, ***ReqSoC***, 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.
   Such is done by imposing that each vehicles state of charge must be lower or equal then the value of required SoC, at the departure periods, $\mathbf{t_{departure}}$,

$$ESOC(v,t) <= BatteryCapacity(v) * \frac{ReqSoC}{100}, v \in V, t \in T_{departure} \tag{3.9}$$

   If a vehicle arrives from the previous travel with more than the required SoC, then it will not charge. It is also necessary to account for the fact that, considering that the energy spent on the travels is already predefined, instead of being based on the amount the car was charged before departing, some vehicles may need more charging then the ReqSoC imposes. In order to avoid errors, the EVs are analysed before optimisation. If one or more travels represent a greater energy expense than it would be possible with the desired required SoC, the vehicle in question is marked as not suitable for this restriction, and will charge as much as it needs. In other words, we are assuming two levels of required SoC options (100% and 80%), and that the vehicles who perform travels greater than 80%, would be from owners who do not wish to participate in the second level.

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).

After the travel information from the vehicle is received, the driving profile is established, as well as the approximate Energy to Distance (kWh/km) relation, $\mathbf{ED_{ratio}}$.

Afterwards, the required SoC that correlates to the amount of kms required, km_{Needed}, is easily calculated,

$$\begin{cases} BatteryCapacity = km_{Max} * ED_{ratio} \\ \frac{ReqSoc}{100} * BatteryCapacity = km_{Needed} * ED_{ratio}, \end{cases} \tag{3.10}$$

and the imposition of this restriction can be done in a the exact same way it was done for the **Required SoC**.

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. Such can be done by finding the minimum value between the maximum power the CS can dispense and the maximum power the EV in question can demand for charging, **MaxChargePower**.

   It was considered that each vehicle can discharge to the grid the same amount of power it can demand, resulting in a final equation seen in Equation 3.11.

$$\begin{cases} Pch(v,t) <= MaxChargePower(v), v \in V, t \in T \\ Pdch(v,t) >= -MaxChargePower(v), v \in V, t \in T \end{cases} \tag{3.11}$$

6. **Maximum Charge and Discharge of the Charging Stations:** imposes the maximum amount of charge power that each charging station, **CS**, can dispense or receive, in total, to or from the vehicles connected to it. This information is given for each CS, $\mathbf{P_{CSMax}}$, and is implemented with a simple pair of restrictions,

$$\begin{cases} P_{CS}(CS,t) <= P_{CSMax}, cs \in CS, t \in T \\ P_{CS}(CS,t) >= -P_{CSMax}, cs \in CS, t \in T. \end{cases} \tag{3.12}$$

   In other situation, it would be necessary to impose that the sum of the power demanded by the vehicles connected to on single CS, could not surpass the $\mathbf{P_{CSMax}}$. However, in our simulation, each CS only serves one EV, so this is not necessary;

7. **Maximum Power Source:** imposes a maximum power demand value, $\mathbf{PD_{Max}}$, that can be

requested by the overall simulated system. This value is determined by the summation of the maximum power each generator can supply, $\mathbf{P_{GenMax}}$, in each period of simulation,

$$PD_{Max} = \sum_{N_{Gen}}^{gen=1} \sum_{N_{periods}}^{t=1} P_{GenMax}(gen, t), t \in T, gen \in Gen, \tag{3.13}$$

being **Gen** the group of existing generators in the system;

8. **Energy Balance:**establishes that the simulation must obey energy balance laws. In other words, the power supplied by the sources (generators), **PS**, must be equal to the power demanded by the consumers (charging stations), **PD**,

$$\begin{cases} PS = \sum_{N_{Gen}}^{gen=1} \sum N_{periods}{}^{t=1} P_{Gen}(gen, t), t \in T, gen \in Gen \\ PD = \sum_{N_{CS}}^{cs=1} \sum_{N_{periods}}^{t=1} P_{CS}(cs, t), cs \in CS, t \in T \\ PS(t) = PD(t), t \in T. \end{cases} \tag{3.14}$$

Despite the validity and potential presented by the **Minimum Kms** restrictions, it was not utilised. The reason being that this restriction is ultimately transformed into a **Required SoC** restriction (as previously explained), so, for simulation purposes, the latter is sufficient.
The utilised restrictions were imposed to every DR program tested (when possible), in order to assess their flexibility to accommodate possible/plausible participant "assurance" requests. Th only exception to this is the **Minimum SoC** restriction, which was only applied in the V2G case, to avoid added battery degradation.

3.4 Methodology for the Aggregator Perspective Scenario

This section details every component considered when preforming the simulation of the Aggregator Focused Scenario. The **Event Control** section simply demonstrates how the controled demand reduction is done while the **Demand Reduction Compensation** establishes various methods to calculate the compensation the participants should receive for such curtailment.

3.4.1 Event Control

Aims 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. Therefore, only the juxtapositions of this type of control with ToU or Non-Participant, are studied.
The method utilised to simulate such an intervention is a fairly simple and aims to show how the maximum

power that the group of vehicles can request from the grid during an emergency, $\mathbf{MaxPower_{AfterCut}}$, can be controlled by an aggregater. 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, on minus ***redux***, during the period we wish to apply said reduction, $\mathbf{T_{Emerg}}$,

$$MaxPower_{AfterCut}(t) = (1 - redux) * \sum_{v=1}^{N_{vehicles}} MaxChargePower(v), t \in T_{Emerg}. \tag{3.15}$$

The constant ***redux*** can be defined as the normalised amount of energy we wish to cut. For example, if we want to reduce 30% of total demand, **redux** would be

$$redux = 0.3. \tag{3.16}$$

3.4.2 Demand Reduction Compensation

In addiction to the previously described load curtailment aspect (Section 3.3.1), 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. In order to address this two symbiotic counterparts, two main strategies have been theorised before, one focusing on the **Retail Benefit Maximisation (RLM)** in [80] and the other on the overall **Social Welfare Maximisation (SWM)** in [81], [82].

In the context of the present thesis, 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. So, logically, the **SWM strategy has been chosen as a basis** 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,

  $$SW = UR + UC. \tag{3.17}$$

  The **Aggregator Utility (UR)** comprises the difference between the the revenue obtained by selling an amount of electricity, s, to the consumer at a certain price, ep_{market}, and the **operational costs (OC)** resulting from the cost of the energy bought by the retailers in electricity markets,

  $$UR = s * ep_{market} - OC(s) \tag{3.18}$$

  In other words, 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,*F(d)*, and the product of the energy demanded and the price paid by it,

$$UC = F(d) + d * ep_{consumer} \tag{3.19}$$

- A set of restrictions: the total EV charging power demand must be bigger than zero,

$$d > 0, \tag{3.20}$$

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),

$$d < d_{max} = \sum_{n=1}^{N_{CS}} max(P_{CS}(n), P_{vehicle}), \tag{3.21}$$

and must be equal to the supplied power

$$d = s, \tag{3.22}$$

at every moment;

- the method utilised to execute the optimisation, based on the previously problem formulation, is the Lagragian Relaxation

$$\mathcal{L}(d, s, \lambda, \mu) = SW_t + \lambda(s - d) + \mu(d_{max} - s) \tag{3.23}$$

with the Karush-Kuhn-Tucker (KKT) conditions

$$\begin{cases} -\frac{\partial OC(s)}{\partial s} + \lambda - \mu = 0 \\ \frac{\partial F(d)}{\partial d} - \lambda = 0 \end{cases} \tag{3.24}$$

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 (F)**.
To determine the value of the **OC**, it is considered that Portugal acquires ≈55% of its annual electricity from renewable sources, as was the case in 2018 [83].
Assuming the demand curtailment is to occur at a certain hour of a certain day, the retailer can represents the aggregated curve of the offers through a quadratic or linear equation. It would then utilise a simple Minimum Square Error (MSE) program in order to find the function best fitted to that aggregated curve. Three examples (upper and lower left and upper right) of this technique applied to the MIBEL offer curve on hour 20 of the 11th of november 2020 [84], can be seen in Figure 3.2, as well as demonstration of the Polynomial Fitting method (Figure 3.2 lower right).
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.
Having established the OC determination procedure, the only thing left to determine is the **Costumer**

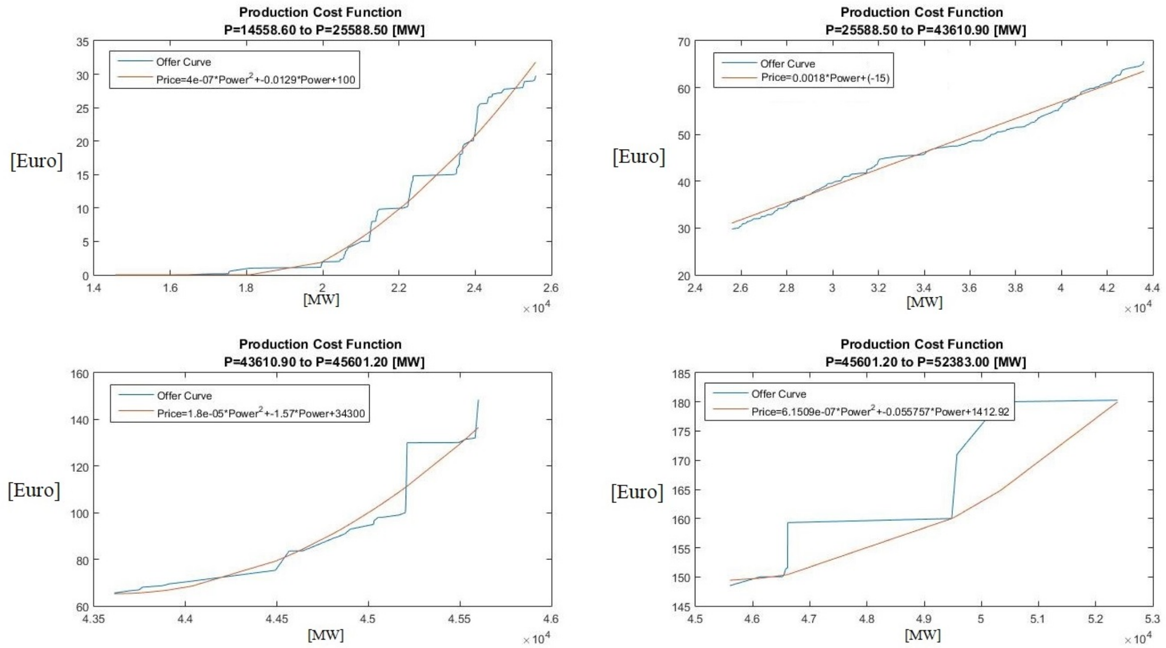

Figure 3.1: MSE technique applied to section of the offer curve at hour 20 of the 11th of November of 2020 [84] (Upper and lower left and upper right); Fitted polynomial curve (lower right)

Satisfaction function. Here, and based on [82], it is proposed the use of a sigmoid function,

$$F(d) = \frac{C}{1 + e^{-\alpha(d-\beta)}} \tag{3.25}$$

as this type of functions is often used to describe costumer satisfaction [85], [86] and [87].

A simple strategy is proposed to obtain the different function parameters:

- β: demand which results in the costumer medium satisfaction. Its value will be the power demand, before reduction, at the intended hour and day. This means we assume the costumer can have a slightly better experience by consuming a little bit more (defined by the parameter α) than the medium energy demand for the hour;
- α: can be modified in order to better fit the points were the sigmoid reaches its maximum and minimal values;
- **C**: in order to produce a satisfaction function which translates a price, this variable will entail the product of the price and the amount energy bought by the consumer,

$$C = ep_{consumer} * d. \tag{3.26}$$

Such is in order to establish that the costumer utility can be zero when he pays the price established for the amount he requires, and negative in any other case. In this way, the costumer comfort/satisfaction is tied completely to the amount of power he can demand to charge his vehicle. So, when the aggregator restricts the charging power by a certain amount (*redux*), the costumer satisfaction will be reduced. α and β were then adapted to make it so the comfort is sharply reduced by any demand curtailment.

The end result is that comfort (being able to charge with full power) is posed as the only important aspect for the costumer, and no importance is given for the potential monetary gains resulting from tariff plans and charge shifting;

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 **SWM** method, depending on the comfort evaluation:

A) **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.

The ideal demand, $d*$, calculations follow the procedures previously described in Equations 3.17 to 3.24. After that, we calculate the difference in Consumer Utility, ΔUC, with optimal demand and with the demand after curtailment, $d_{max}(1 - redux)$,

$$\Delta UC = UC(d*) - UC(d_{max}(1 - redux)), \tag{3.27}$$

Finally, the Incentive Compensation per Hour (ICH) is obtained by dividing the costumer utility variation by the demand variation, Δd, and multiplying it by the demand curtailed, $d_{curtailed}$,

$$\begin{cases} \Delta d = d * -d_{max}(1 - redux) \\ d_{curtailed} = max(PCS; P_{vehicle}) * redux \\ ICH = \frac{\Delta UC}{\Delta d} * d_{curtailed}. \end{cases} \tag{3.28}$$

B) **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, Equation 3.19, and the OC function is simply the spot price multiplied by the power,

$$OC(d) = ep_{market} * d. \tag{3.29}$$

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, $d*$ and proceeds to calculate the incentive payment linked to each reduction percentage utilising Equations 3.28;

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 [88]. 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($d0$ and $p0$) and after (dDR and pDR) 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.
Then the Costumer Profit (CPF) (participant and non-participant),

$$CPF = (p0 * d0 - pDR * dDR), \tag{3.30}$$

and the reduction in retailer profit,

$$R_{LostRevenue} = (ep_{Consumer} * d0 - p0 * d0) - (ep_{Consumer} * dDR - pDR(i) * dDR), \tag{3.31}$$

that could be obtained by this reduction, are calculated.
Finally we can obtain the proper hourly Incentive Compensation for the Profit Based Formula ($\mathrm{IC}^{\mathrm{PBF}}$) [88] results for each participant,

$$\begin{cases} E_{reduced} = \sum P_{CS} * k, \text{being k the charging cut multiplier} \\ dDR = d0 - E_{reduced} \\ \Delta D = d0 - dDR \\ IC_{PBF} = \frac{CPF + R_{LostRevenue}}{\Delta D} * E_{reduced} \end{cases} \tag{3.32}$$

As can be observed, 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 [89–92]. However, as the results show, costumer benefit is a priority, since the aim is to attract the maximum amount of participants possible.

Chapter 4

Results Evaluation and Comments

In this chapter, the results of the simulation are presented and discussed. A rational justification for each result is provided, relating them to the methodology described in Chapter 3. A schematic of the scenarios approached can be seen in Figure 4.1.

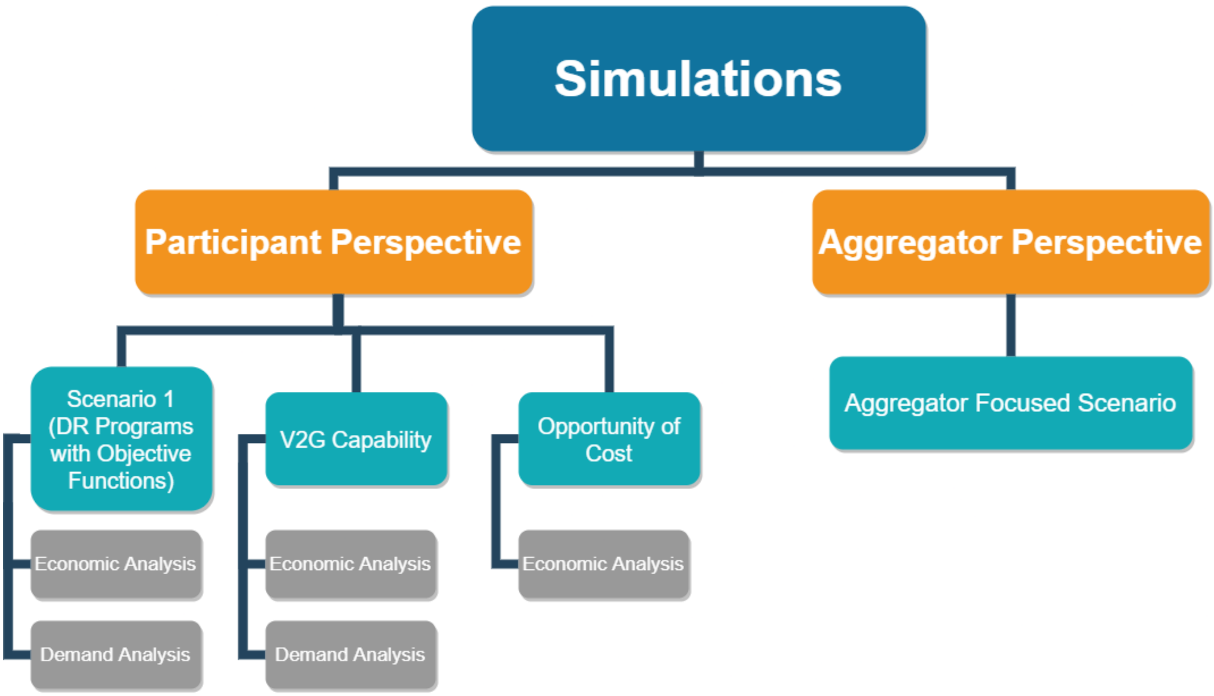

Figure 4.1: Simulated perspectives and evaluation topics

4.1 Implementation

This section defines the parts of the simulation method that are universal for all scenarios. Such includes the variables and the overall program flow.

4.1.1 Program Flow Chart

A program flow chart was designed in order to show how this files are interconnected, and work together to provide the intended simulation. This can be seen in Figure 4.2.

Each **Test ID** refers to a particular combination of DR program and tariff. For example Test ID=3 refers to the simulation of Time-of-Use in junction with the Tri-Hourly tariff, with a required SoC of 100%.

The red, round-edged rectangles signify the beginning and end of execution, while the orange ones represent either a file execution, if the lettering is in Bold, or an important command line, if not. Green diamond shape blocks represent relevant decisions and, finally, the blue trapezoid represents the outputs of the simulation.

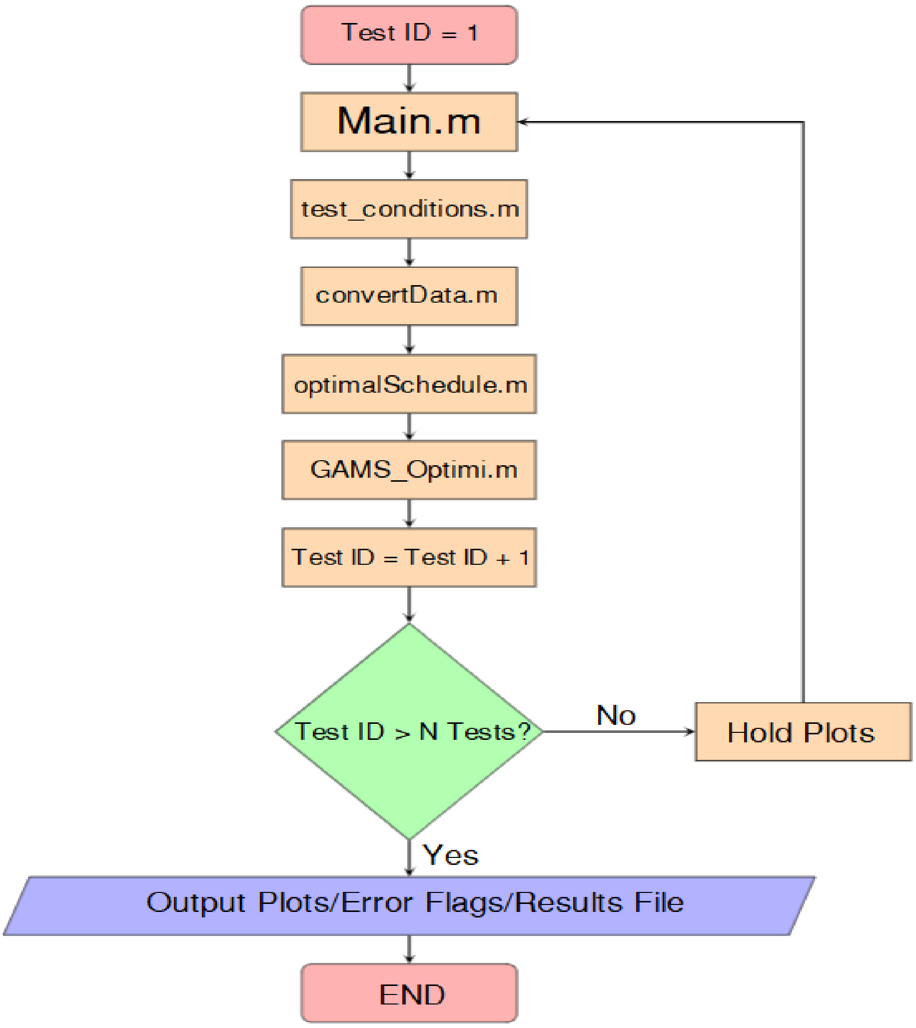

Figure 4.2: Flowchart of the simulation functioning

As for the outputs, they consist of: plots of every power demand curve resulting from each simulation (**Output Plots**); multiple **Error Flags**. During the execution of the program, various variables are verified in order to access if any of the simulations is malfunctioning. Afterwards, this flags are analysed by the coder with the aim to correct mistakes: a .docx file with the relevant results from each simulation (**Results File**).

4.2 Simulation Scenarios and Assumptions

This section aims to establish the objectives and the conditions considered in each scenario.

4.2.1 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).
The days are 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 [93].
The Non Participant profile is used in every scenario in order to establish a baseline for result comparison.
Smart Contracts and ToU are only used in scenarios 1, 1.1 and 1.2, while incentives are the focus of scenario 2.
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.
  Of these 200 EVs, 110 are eligible and take part in the required SoC restriction (55% participation rate). The other vehicles have travels which require more battery charge than 80%;
  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 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 meant to be 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;

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

- **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 OpC objective function can lead to, specifically, better economic results in this subset of vehicle profiles, providing another option for the hypothetical consumer.

  Being that each vehicle in the initial data set, demonstrates similar travel energy losses throughout the days, the sample for this scenario was obtained by creating ten "mixed driving profile" from the data available.

  Because of this changes, a new base line was obtained, utilising only the number of EVs in question;

- **Scenario 2 or Aggregator Focused Scenario**: focuses on how an aggregator, 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 meant 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.

  In the **Event Control** segment, it is considered that all participants CSs are connected to a single bus and, in direct contrast to the previous scenario, all vehicles will be bundled and controlled by a singular Fleet Operator, who will only intervene in the BEV's charging process when needed. This intervention is applied by limiting the amount of power supplied to the bus in question during the periods of time that delimit the event occurrence.

  During the five day simulation period, the bus power limitation is only applied once, in order to replicate the sparsity of DR events.

  The Non-Participant base line is the same utilised in **Scenario 1**, as the data set is the same. However, only ToU (bi and tri-hourly tariff) programs in conjunction with the BAU objective function, are used to compare to the base line. Such is done to: replicate an environment where the participant is not active, or minimally invested, in DR prevention's, only allowing the FO to affect his charging during special and infrequent situations where the grid is in an emergency state; emphasise that a client who already participates in other demand cut programs wouldn't have any motivation to also participate in this incentive based voluntary reduction; It is considered that any Fleet Operator activity regarding the participants charging process requires certain monetary compensation, regardless if this results in any sort of loss or gain to the client (uncharged battery, cost increase/decrease, etc). The amount and timing of this participant remunerations, is part of the scope of this scenario as well.

  The **Demand Reduction Compensation** scenario has the same conditions described for Scenario 1.

4.2.2 Tariffs

As part of the methodology, three different tariffs are considered, in order to simulate the possible hourly price programs the costumer can be placed in.
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.
The overall description of the various rate based programs can be seen in Table 3.3. For the Real Time

Tariff Type	Periods	Time Intervals	Electricity Prices [€/kW]
Single	—————————	0h-24h	0.1456
Bi-Hourly	*Off-Peak*	1h-7h; 23h-24h	0.09980
	Peak	8h-22h	0.18560
Tri-Hourly	*Off-Peak*	1h-7h; 23h-24h	0.0967
	Intermediate	8h; 11h-17h; 22h	0.1565
	Peak	9h-11h; 18h-21h	0.272

Table 4.1: Description of Electricity Hourly Rate Programs Utilised

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). As so, all the market spot prices were divided by 0.25 in order to obtain an approximation of the price a RTP participant would pay.

4.3 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. The discussion of this outcomes is done in the following subsections, each, with a different objective in mind. **The outcomes are compared to a base line profile, 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 values for the Non-Participant simulation outcome values can be seen in Table 4.2.

	Non-Participant	
	Single Tariff	
	TOC	Peak Power
	€	kW
BAU	2441.38	1147.41

Table 4.2: Base Case/Non-Participant values

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

4.3.1 Purely Economical Analysis

In this section, the aim is to access how the different OF's can lead to various economic outcomes when applied to the various DR programs.

By multiplying all the computed charges (kW) by the electricity price (euro/kWh) at the given period they occur (1h), the result is the Total Operational Cost (TOC) of supplying energy to the vehicles. This will serve as the variable for the outcome comparison.

It is also important to state that the price of charging from periods 116-120 were neglected, because the vehicles aim to charge the most they can before the simulations end. This leads to increased power demand during peak hours, which falsely inflate the overall cost, disrupting an objective analysis.

The obtained results can be seen in Tables 4.3 and 4.4. Figure 4.3 is also included in order to better demonstrate the contrasts in total operational cost between the Non-Participant and the other proposed profiles. Bi-H and Tri-H represent the bi-hourly and tri-hourly tariff plans, respectively, while MS-H indicates the market spot price per hour.

	Total Operating Costs								
	ToU (Time-of-Use)		**RTP** (Real Time Pricing)	**CPL** (Charging Power Limitation)		**MSL** (Maximum SoC Limitation)		**PSC** (Proportional Spending-Charging)	
	Bi-H	Tri-H	MS-H	Bi-H	Tri-H	Bi-H	Tri-H	Bi-H	Tri-H
	€	€	€	€	€	€	€	€	€
BAU (Business as Usual)	2464.1	3042.6	2497.7	2307.8	2715.3	1720.6	1717.8	2156	2393.9
CM (Cost Minimisation)	1695.3	1651.6	1995	1690.3	1649	1690.5	1645.1	1695.3	1652.8
CM+CL (Cost minimisation + Comfort Level)	1695.3	1651.6	1996.7	1690.3	1649	1690.5	1645.1	1695.3	1652.8
CM+PP (Cost Minimisation + Peak Limit)	1695.3	1651.6	1995	1690.3	1649	1690.5	1645.1	1695.3	1652.8
CM+PPEV (Cost Minimisation + EV Peak Limit)	1696.5	1655.6	1995.3	1691.5	1653	1691.1	1647.4	1696.5	1656.8

Table 4.3: TOC of each OF/DRP combinations for the 100% SoC requirement

Time of Use presents the most volatile outcomes throughout it's objective functions pairings. ToU-BAU preforms worst within the other combinations as well as the Non-Participant baseline. Such is exceptionally true in the tri-hourly case, where BAU force the charges when the EV arrives. However, most of EVs arrive at peak hours. So, from the costumer perspective, it is better to charge normally.

The ToU-CM/CM+CL give 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 parcels.

CM+PP and CM+PPEV behave the same as the previously two cost oriented OFs. The flattening of the demand curve caused by them leads to the stretching of the charging power all trough the off-peak time zone, never reaching into the peak demand periods. These allows them to still to take advantage of

	Total Operating Costs								
	ToU (Time-of-Use)		**RTP** (Real Time Pricing)	**CPL** (Charging Power Limitation)		**MSL** (Maximum SoC Limitation)		**PSC** (Proportional Spending-Charging)	
	Bi-H	Tri-H	MS-H	Bi-H	Tri-H	Bi-H	Tri-H	Bi-H	Tri-H
	€	€	€	€	€	€	€	€	€
BAU (Business as Usual)	2376.7	2957.96	2384.4	2280.5	2630.7	1633.25	1633.18	2068.7	2309.3
CM (Cost Minimisation)	1607.9	1566.97	1881.4	1602.9	1564.3	1603.2	1560.5	1607.9	1568.2
CM+CL (Cost minimisation + Comfort Level)	1607.9	1566.97	1882.8	1602.9	1564.3	1603.2	1560.5	1607.9	1568.2
CM+PP (Cost Minimisation + Peak Limit)	1607.9	1566.97	1881.4	1602.9	1564.3	1603.2	1560.5	1607.9	1568.2
CM+PPEV (Cost Minimisation + EV Peak Limit)	1611	1575.2	1881.99	1606	1572.6	1603.9	1562.8	1611.1	1576.4

Table 4.4: TOC of each OF/DRP combinations for the 80% SoC requirement

the different tariffs provided by the time based program.

Real Time Pricing provides **the overall worst economical results**, although this may vary greatly with the season, amount of renewable energy, among other factors. Because of this, a study of this program with a wider time span (one year or 6 months) is necessary to get a more accurate assessment of the RTPs benefits.

Considering that the electricity prices can only be those provided by retailers (i.e. neglecting the Real Time Pricing program), **Maximum SoC Limitation** provides **consistently 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 objective function utilised.

As a result, this DR programs 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 centred CM, CM+CL, CM+PP and CM+PPEV do not represent a 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 in avoiding charging during peak periods.

It is also fairly noticeable that the the tariff types have a major influence in most of cases, being the bi-hourly better in cases were the participants focus on the SoC of their vehicle (DRP-BAU pairings), and the tri-hourly better in every other case.

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 Table 4.4.

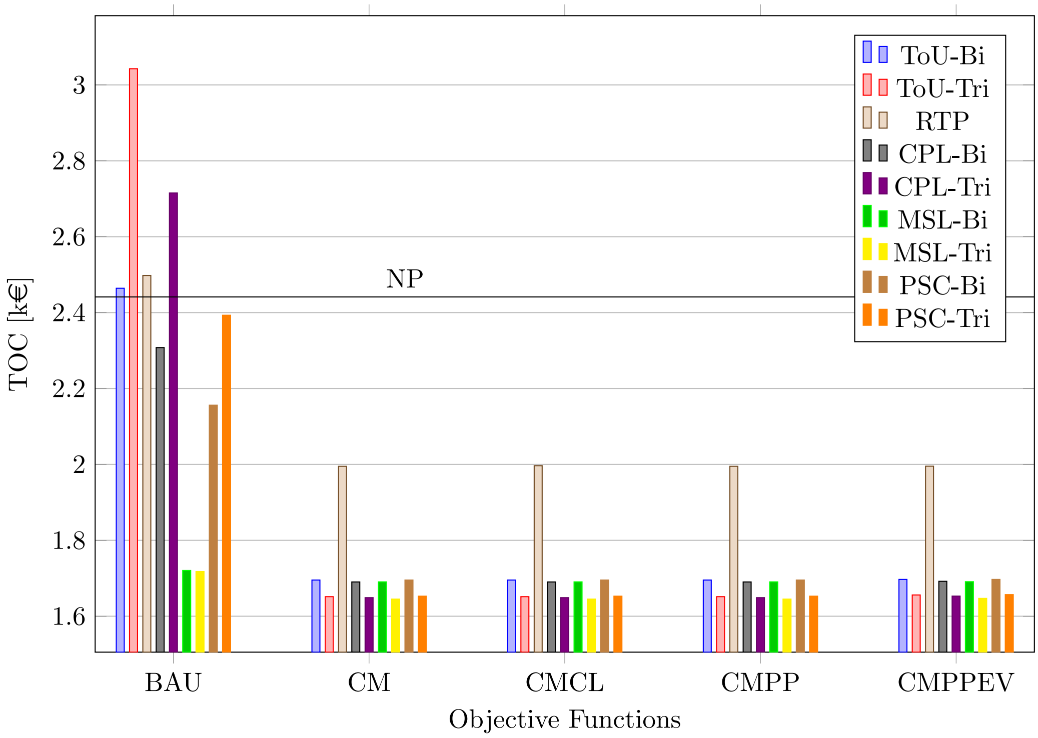

Figure 4.3: TOC results compared to the Non-Participant baseline

4.3.2 Demand Analysis

The purpose of this part of the study, is to determine how the peak power and the demand curve vary with the different OF/DRP pairings.

This can be done by summing the charge demanded by every vehicle, for each period of simulation, plotting the result, and then identifying the maximum value obtained.

The focus, unlike the previous point, relates more to the prevention of harmful events of overload to the distribution power grid. However, the contracted power is something that will ultimately affect the participant, so the his benefit is indirectly also under evaluation.

In Time-of-Use programs, tariff type has no effect in the peak power, so the separation is not emphasised here as it was in the economical evaluation.

The peak power values and a 3D visualisation of those results can be seen, respectively, in Table 4.5 and Figure 4.4.

It is apparent that **RTP** displays the **worst outcomes out of all the demand response 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 lowest price. This makes it so all vehicles charge at their maximum charging capabilities in the periods where

100% SoC Req	ToU	RTP	CPL	MSL	PSC
BAU	1147.4096	1147.4096	794.3453	1147.4096	877.9251
CM	772.4457	1147.4096	756.1485	862.359	766.7299
CM+CL	1147.4096	1147.4096	1147.4096	1147.4096	1147.4096
CM+PP	738.294444	1147.4096	684.801978	738.294444	738.294444
CM+PPEV	770.1638	1147.4096	771.1638	770.745687	771.1638
80% SoC Req	ToU	RTP	CPL	MSL	PSC
BAU	1147.4096	1147.4096	794.3453	1147.4096	877.9251
CM	821.29	1147.4096	756.5466	888.0665	761.906
CM+CL	1147.4096	1147.4096	1147.4096	1147.4096	1147.4096
CM+PP	595.727778	1147.4096	595.727778	595.727778	595.727778
CM+PPEV	662.753	1147.4096	662.753	640.0941	657.903

Table 4.5: Peak Power [kW] values for the various OF/DRP combinations

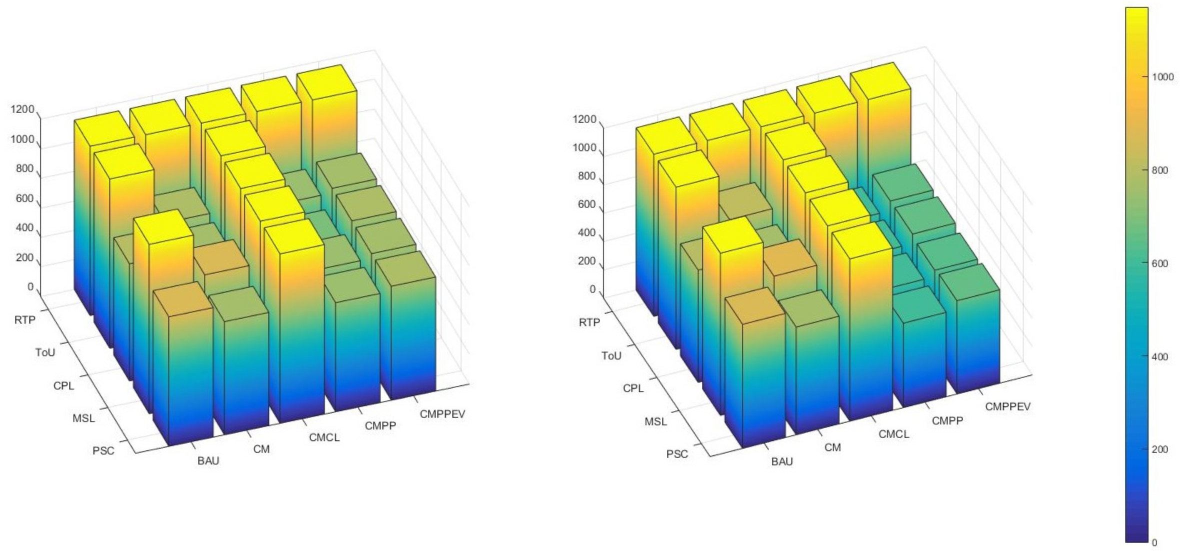

Figure 4.4: Peak Power [kW] values obtained from every OF/DRP combinations for 100% (left side) and 80% (right side) required SoC

the prices are lower, resulting in the peak power value being equal to the Non-Participant profile. This is different from tariff based programs, which have several periods of equal values where the price.

The other three DRPs present more varied responses to their pairings, having the best or worst results between each other depending on the OF used.

As so, and in order to better understand the reasons for such volatility, it is better to compare them to each other within each objective function, instead of focusing on each one individually:

- When paired with **BAU or CM**, CPL produces the best outcomes of the DRPs. 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.

  In the opposite side of the spectrum, MSL's more aggressive charging power cut, in high price periods, leads to more charging as soon as possible in BAU, and to a higher spike in CM.

PSC demonstrates a performance between the previous two.

- All DRP-**CM+CL** pairings show a maximum power demand equal to the base line, as it would be expected, since the charging is limited during peak periods by the cost component of the function, and then the maximum charging capability is demanded by the comfort component during off-peak periods.

- **CPL combined with** the peak reduction objective function **CM+PP**, provides the **best overall result**, leading to a roughly 36% peak power reduction in juxtaposition with the NP position. This is the result of the lower limitation explained previously for BAU and CM, which is further magnified by the peak power reduction component of the objective function.
  MSL, PSC and even ToU, have the same value when paired with CM+PP, suggesting that the peak limitation in this three DRPs is fully provided by the objective function.
  It is also to mention that the **CM+PPEV** performance, offers slightly worse, yet consistent results compared to the CM+PP. This makes sense, since the charging distribution of each vehicle will be equal regardless of the DR in question, in order to minimise their overall individual maximum charging power during simulation.
  Regardless of the program chosen, these two OFs result in the flattest curves, distributing the demand throughout the charging interval.

For the 80% required SoC, the results maintain roughly the same pattern concerning the peak demand, with some changes. Such is because, although the vehicles do not fully charge, they still all charge in the same periods.
In the Figure 4.5, it is possible to see an example of the first cycle of EVs charge. In the Figure we can observe that the curves change with the DRP restriction amounts and the travel profiles of the controlled vehicles.
These graphics allow a more immediate observation of the two areas of the charging process which affect not only the peak power but also the curve profile: peak period interval and off peak period interval. While the first is impacted by the limitations of both the OF and the DRP utilised, the second depends mostly on the latter.
It is possible to observe how the peak power focused objective functions, helped to mitigate the power demand peaks that occur when using BAU and CM+CL. This is achieved by spreading the charging process, resulting in a smaller peak demand. Objective functions who do not consider peak power but also neglect the comfort level (CM), also result in lower peak power values, since the optimisation spreads the charging.

4.4 Evaluation of the Vehicle-to-Grid Impact

In this section we access the outcomes obtained from utilising the proposed demand response programs in conjunction with a vehicle-to-grid capability. The aim is to access if such pairings can help the grid during an emergency event (grid technical constraints) and what would be the benefits/disadvantages to

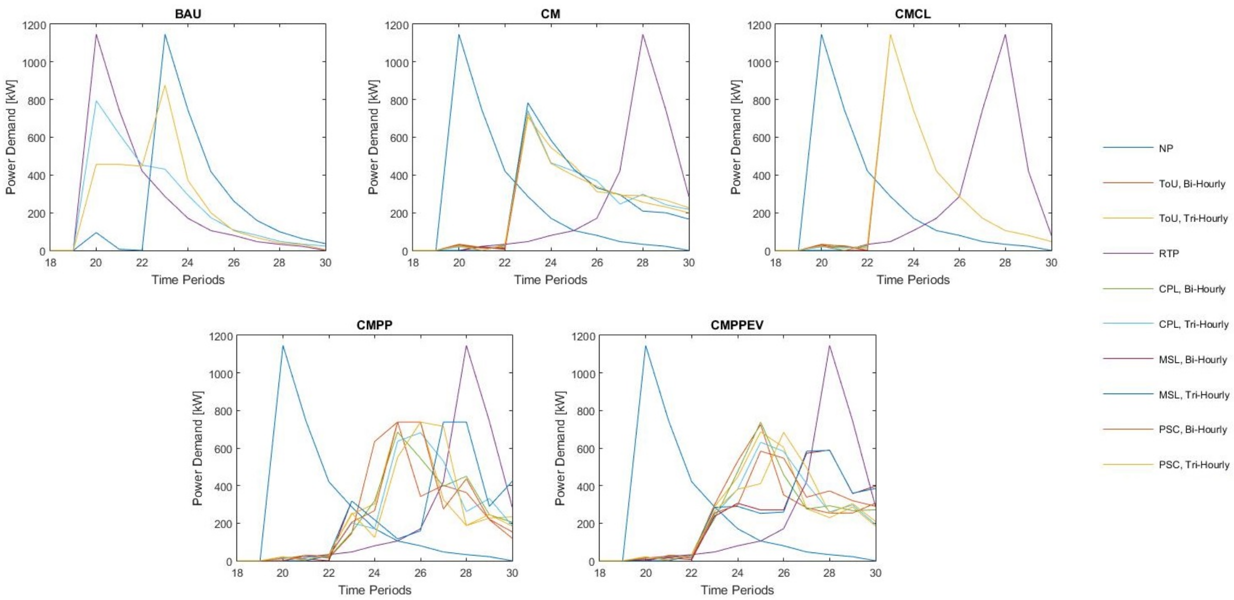

Figure 4.5: Power Demand curves for the first charging cycle, utilising different OFs. Up: a)BAU, b) CM, c) CMCL; Down: d) CMPP, e) CMPPEV

the participant. As so, this program will be referred as Vehicle-to-Grid Emergency Program (V2GEP), but the objective function will still be referred as CM+V2G, as described in Section 3.3.2.

4.4.1 Purely Economical

The results comparison between the use of the demand response programs with charging only process and with a V2G assisted one, can be seen in Tables 4.6 and 4.7. It is from these values that we can formulate some conclusions regarding the participants motivation to join a V2GEP.

It is possible to see that all tested demand response programs provide significant profit to the EV owner, when paired with a Vehicle-To-Grid capability (CM-V2G). This is especially true when applied in a three hourly tariff.

It does so by utilising the larger prices during peak hours to its advantage, selling energy back to the grid in those periods and 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 price this high can only be feasibly expected when the grid is in jeopardy and immediate action to safeguard it is needed. This is why this program was specifically designed for grid emergency situations situations and not for the every day charging procedure.

As in Scenario 1 economic results, the utilisation of Real-Time Pricing with V2G capabilities, preforms worse than the other DRPs. The main reason, of course, is the same (energy prices) and still depends on various factors that affect the market spot prices each day. Despite this, there is another reason that can be cited. Seeing as 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 DR programs). So, this lower profit is also caused by the smaller difference between the lowest and highest price in the spot market, compared to the tri or bi-hourly tariff, where the the price in peak periods is almost double the price in off-peak periods.

	Total Operating Costs								
	ToU		RTP	CPL		MSL		PSC	
	Bi-H	Tri-H	Market Spot-H	Bi-H	Tri-H	Bi-H	Tri-H	Bi-H	Tri-H
	€	€	€	€	€	€	€	€	€
BAU	2464.1	3042.6	2434.33	2307.8	2715.3	1720.6	1717.8	2156	2393.9
CM+V2G	−248.2	-1023.7	785.78	-250.6	−1019.4	-253.72	−1031.5	-246.6	−1013.2

Table 4.6: TOC comparison between vehicle-to-grid DRP and the regular charging, with 100% SoC requirement

	Total Operating Costs								
	ToU		RTP	CPL		MSL		PSC	
	Bi-H	Tri-H	Market Spot-H	Bi-H	Tri-H	Bi-H	Tri-H	Bi-H	Tri-H
	€	€	€	€	€	€	€	€	€
BAU	2376.7	2957.96	2311.7	2280.5	2630.7	1633.25	1633.18	2068.7	2309.3
CM+V2G	−181.11	-921.62	737.54	-183.50	−918.33	-186.63	−929.35	-179.17	−906.82

Table 4.7: TOC comparison between vehicle-to-grid DRP and the regular charging, with 80% SoC requirement

The imposition of a required Soc of 100% or 80% is also interesting. Contrasting with the observed results in Scenario 1, the 80% reqSoC 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 period, seeing as they charge less before each travel.

4.4.2 Peak Power

The differences in peak power values for the five day charging cycle between the normal charging process with DR programs and with the V2GEPs, can be seen in Tables 4.8 and 4.9. It is from these values that we can formulate some conclusions regarding the grid operators motivation to compensate a participant of this type of program.

Vehicle-to-Grid capability seems to provide high peak powers across all demand response programs, being some of those values worst than the Non-Participant scenario. This is because the vehicles discharge some of their SoC during periods of higher electricity demand, and so will need more charging power latter. Despite this, such peaks are pushed outside of the emergency time interval, so the energy provided to the grid will lead to a flatter demand curve overall. These curves can be seen in Figure 4.6.

Although this effect is seen throughout all DR programs, seeing as they also utilise tariff programs, it shows that the **implementation of vehicle-to-grid capabilities in EVs can be useful with demand response programs already widely used, such as ToU**.

100% SoC Req	ToU	RTP	CPL	MSL	PSC
BAU	1147.4096	1147.4096	794.3453	1147.4096	877.9251
CM+V2G	1073.447	1303.58	1034.608	1058.158	1076.238

80% SoC Req	ToU	RTP	CPL	MSL	PSC
BAU	1147.4096	1147.4096	794.3453	1147.4096	877.9251
CM+V2G	1076.3977	1303.58	1067.7923	1023.772	1045.946

Table 4.8: Peak Power [kW] values comparison between vehicle-to-grid DRP and the regular charging, with 100% (up) 80% (down) SoC requirement

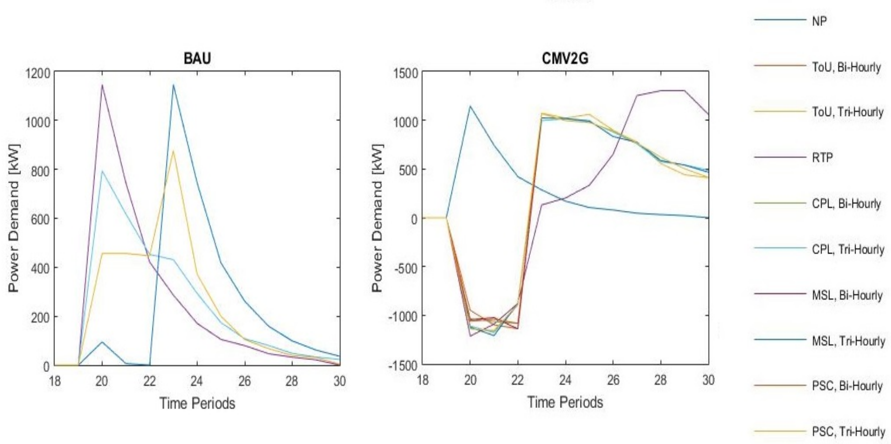

Figure 4.6: Power Demand curves for the first charging cycle in a regular charging situation and with the V2G program

4.5 Evaluation of Opportunity of Cost Function

This section will provide the results considering the different DR programs jointly with the Opportunity Cost OF. This OF aims to be applied to a more niche driver profile, with different EV use profile during the week, alternating long travels with short ones.
The aim is then to determine if this Opportunity of Cost (OpC) program can obtain better results then the regular cost centric objective functions, studied in Scenario 1, for this type of vehicles/driver profiles. Such means that the main focus of this scenario is purely economical, so the demand curve shape and the peak powers resulting from the different charging processes, will not be evaluated in this scenario.
This comparison is only done for the Real Time Pricing demand response program, since the charging process between CM and OC 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.
The results can be seen in Table 4.9.

We can see that the OpC is able to obtain a better result than the regular Cost Minimisation objective function, however, the difference is rather small (around 1%). The level of improvement may vary depending on the strike price (SP) chosen. Seeing as the SP is the average value of the hourly spot prices of that day, the effectiveness of this program may be bigger in days were the market prices are more volatile. In other words, **the economic improvement of OpC, comparing with other cost**

	Total Operating Costs
	RTP
	Market Spot-H
	€
OpC	69.92
CM	70.63

Table 4.9: TOC of each OF/DRP combinations for the 100% SoC requirement

function approaches, can be higher when the prices changes occur in short periods. Ultimately, this means that the OpC can demonstrate better performance in the long term and in different conditions, so more study should be done in this regard.

4.6 Aggregator Focused Scenario

4.6.1 Event Control

That being established, the consequences from the application of an example cut of 60% of bus power, in a single, double or triple tariffs program, can be seen in Table 4.10.
In Figure 4.7, a simple example of this cut effect on the vehicle demand curve during the five days, is demonstrated.
Although 60% might seem like a high value, compared to the usual 10-20 in domestic voluntary reduction programs, we are focus on the EV charging. So, in a case of emergency, the comfort of immediate charge is more negligible than the comfort of house heating or a refrigerator for example

	Total Operating Costs		
	ToU		NP
	Bi-Hourly	Tri-Hourly	Single tariff
	€	€	€
BAU (without cut)	2464.10	3042.60	2441.38
BAU (with cut)	2401.19	2902.35	2441.38

Table 4.10: Price comparison between normal charging process and one with a 60% power reduction during peak hour of one day

As it is immediately observable, the power limitation during peak periods may actually lead to the participants financial benefit, being that the charging process is somewhat shifted into off peak periods (depending on the amount restricted). This can be an interesting leverage tool for the FOs or/and utilities/retailers when negotiating with interested participants and it may collaterally help costumers adopt ToU as well in order to fully benefit from such events. Of course this also depends on the length of the emergency event.

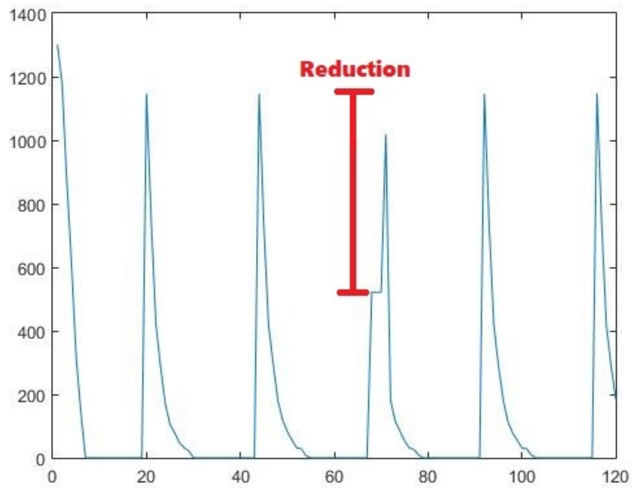

Figure 4.7: Demand Curve for the five day simulation period, suffering a 60% emergency reduction during peak hours of charging day 3

4.6.2 Demand Reduction Compensation

A) **SWM-A or Overall Energy Consumption Comfort**: The parameters utilised for simulation were obtained at hour 20 of the 11th of november 2020, being the demand in Iberian spot market 29748.9 MW/h. It is also considered that the participants charging stations can dispense no more then 7.2kW and that they are inscribed in the single tariff program with an hourly price of 145.6€/MW. Single tariff is used because participants of other hourly schemes already have an incentive to diminish their load.

The relevant curves can be seen in Figure 4.8 , and results can be seen in Table 4.11.

The Retailer cost function was obtained by approximating the offer curve of the MIBEL at the 20th hour of the 10th of november. This approximation was obtained through the Minimum Square Error method;

Charging Cut	**Individual Compensation per Hour [€]**	**Charging Cut**	**Individual Compensation per Hour [€]**
1%	0.1968	15%	0.5703
2%	0.3568	16%	0.5602
3%	0.45	17%	0.5491
4%	0.5071	18%	0.5372
5%	0.5443	19%	0.5246
6%	0.5688	20%	0.5114
7%	0.5846	30%	0.3582
8%	0.5940	40%	0.1853
9%	0.5987	50%	0.0037
10%	0.5996	60%	-
11%	0.5976	70%	-
12%	0.5933	80%	-
13%	0.5872	90%	-
14%	0.5794	100%	-

Table 4.11: Incentive Prices utilising SWM-A

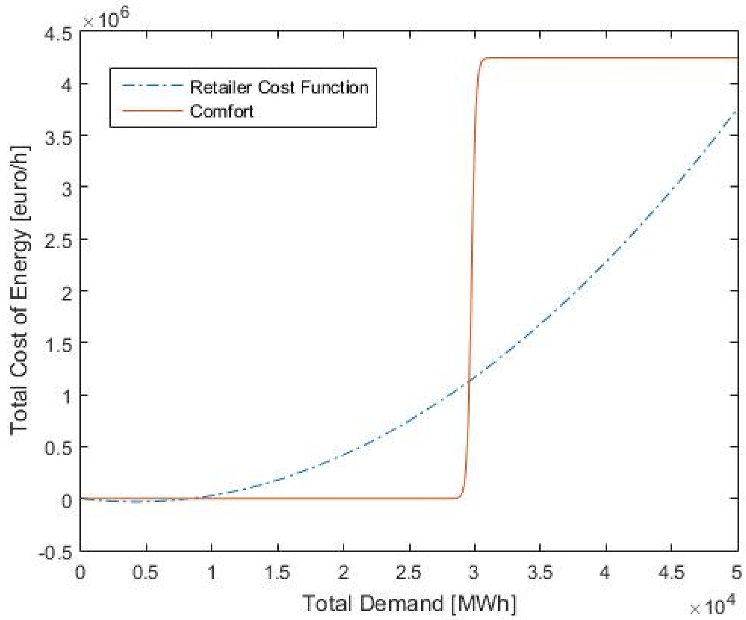

Figure 4.8: Retailer Operation Cost and Costumer Satisfaction curves

B) **SWM-B or Participant EV Charging Comfort**: In this case, the CS demand can not surpass 1.303 kW being that the maximum sum of vehicle demand, so the sigmoid was designed to reach peak costumer utility at exactly that amount. The price of electricity paid by the costumer is again 145.6€/MW.

The results are presented in Table 4.12;

Charging Cut	Individual Compensation per Hour [€]	Charging Cut	Individual Compensation per Hour [€]
1%	-	15%	0.7064
2%	-	16%	0.6919
3%	-	17%	0.6763
4%	-	18%	0.66
5%	0.0356	19%	0.6433
6%	0.1306	20%	0.6262
7%	0.2808	30%	0.4460
8%	0.4519	40%	0.2580
9%	0.5915	50%	0.0668
10%	0.6766	60%	-
11%	0.7168	70%	-
12%	0.7296	80%	-
13%	0.7280	90%	-
14%	0.7191	100%	-

Table 4.12: Incentive Prices utilising SWM-B

C) **Profit Based Formula (PBF)**: The offer curve of the Iberian Market on hour 20 of the 11^{th} of november, 2020 is again utilised. The registered amount of EVs in Portugal is considered to be 90.532 [94], all of them with a maximum charging capacity of 7.2kW (very conservative simulation parameters). The spot price before EV demand reduction was 38.45 €/MW.

The value of compensation for each participant at various power cuts can be seen in Table 4.13.

Charging Cut	Individual Compensation per Hour [€]	Charging Cut	Individual Compensation per Hour [€]
1%	0.0196	15%	0.2938
2%	0.0392	16%	0.3133
3%	0.0588	17%	0.3329
4%	0.0783	18%	0.3525
5%	0.0979	19%	0.3721
6%	0.1175	20%	0.3917
7%	0.1371	30%	0.5875
8%	0.1567	40%	0.7834
9%	0.1763	50%	0.9792
10%	0.1958	60%	1.1750
11%	0.2154	70%	1.3709
12%	0.2350	80%	1.5667
13%	0.2546	90%	1.7626
14%	0.2742	100%	1.9584

Table 4.13: Incentive Prices utilising PBF

It is important to point out that the programs which try to balance the aggregator and the consumer welfare, SWM-A and SWM-B, have an optimal charging cut. From that point on, the compensation to the participant is diminished. This occurs because too much charging cut leads to less energy sold and so, less revenue to the retailer which will result in less incentive for the aggregator to enforce this DR. SWM-B also has a minimum charging cut ($\approx 5\%$) under which the consumer gets no compensation from. When the compensation value no longer is beneficial to the participant (zero or bellow), this was marked with ”-” in Tables 4.11 and 4.12.

On the other hand the PBF shows a more linear relation between charging cut and compensation, which may be simpler for the consumer to understand and see the benefits in. It also has the highest incentive price values of the three presented options, but these are only applied for much larger cut percentages than in SWM-A and B. For example, SWM-A has a maximum compensation of 0.5996 €/h for 10% cut and SWM-B offers a maximum incentive of 0.7296 €/h for a 12% reduction. On the other hand, PBF has a maximum compensation of 1.9584 €/h for a full demand curtailment (100%), but it only provides the participants with 0.1958 €/h and 0.2350 €/h for 10% and 12% reductions, respectively.

This approaches present different pros and cons. In order to further discuss them, we will call SWM-A and B **Concave Compensation** , since the ”compensation/cut percentage” relation mimics a concave function, and PBF will be denominated **Linear Compensation**. Concave compensation programs give the participant the assurance that their demand has a very low chance of being severely curtailed. However this results in lower monetary gain. By contrast, the Linear compensation program offers higher incentives which come at the cost of a larger charging cut. For the aggregator, the choice between the two should depend on the particular system needs. For example, if this programs are to be used in a location which often experience grid emergency situations, the Linear programs should be chosen as they would allow greater demand cuts.

Chapter 5

Concluding remarks

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. In the Participant Perspective, the various objective function/DR programs pairings where tested for a five days period. The results were then compared to a base case (the participant charges normally and is not enrolled in any program) and to each other, in terms of charging costs, demand curve "flatness" and peak demand values. For the Aggregator Perspective, three energy curtailment compensation (amount to be payed for the participant for each kW curtailed each hour of the emergency duration) tables were calculated, using the three different methods proposed.

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. A more in depth look into these conclusions is done in the **Discussion** Section.

5.1 Discussion

From all the previously obtained results, some main conclusions are important to highlight, as they appear to be the most important ones in the scope of this thesis.

The first set of conclusions comes from the **Participant Perspective**. From the **Scenario 1**, one can infer that: the DRP 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 can´t 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.

In the analysis of the **V2G capability**, the discharge prices were dimensioned to apply in situations of grid jeopardy. This makes it so the V2G capability is able to 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, 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.

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 OpCs 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.
Finally, the **Aggregator Perspective** also provides several insights. 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. In the **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.
Some broad, more generic, assumptions also arrive from the study of the aggreagtor scope:

- FO can be a separate entity or an integrated division of retailers. This can only be decided by intense economical studies concerning the profitability of such as an independent entity;

- FOs must establish the connection between utilities and interested costumers, as well as control the charging of the vehicles as necessary. They must also access if the costs of communication apparel and costumer compensation can be covered by the maintenance savings provided by the utilities, in order to establish a feasible company model. If such is not the case, the FO must establish a contract with utilities were the avoidance of extra generation costs must be balanced.

5.2 Future Research

From the initial scenario 1 ramifications proposed, only the testing within a complex, multiple bus, RES integrated, grid scenario, was not materialised in these experiments. This comes from the immense increase in program complexity that would result from such modifications. The planning and implementation time is the main issue.
It is also important to study the Real Time Pricing program in a larger time scale, in order to more accurately ascertain its effects on the participant charging.
Taking this into account, there are some important aspects relating to future research:

- Utilising similar (or improved) methodology on a scenario focused on the day time charging of vehicles, for example, in a company setting. The resulting possible savings should be analysed to access if its implementation would be beneficial to large vehicle parking receptacles.

  In this context, a V2G scenario would also be of interest, especially when paired with renewable energies;

- Repetition of the studied scenarios and the one established in the previous point, taking into account the effect of renewable energies on the hourly price;
- Studies about battery degradation that may occur or be avoided by the implementation of this smart control methods;
- Ancillary services that can be provided by these types of charging controls;

Bibliography

[1] M. Woodward, *Electric Vehicles: Setting Course for 2030 (http://www-cs-faculty.stanford.edu/ un-o/abcde.html)* (website accessed in 2020).

[2] F. Cuenot, *et al.*, *CO2 Emissions From Cars: the facts* (2018).

[3] *Global EV Outlook 2019 (https://www.iea.org/reports/global-ev-outlook-2019)* (website accessed in 2020).

[4] A. Robinson, P. T. Blythe, M. C. Bell, Y. Hübner, G. A. Hill, *Analysis of electric vehicle driver recharging demand profiles and subsequent impacts on the carbon content of electric vehicle trips* (2013).

[5] N. Powell, *et al.*, *Impact Analysis of Mass EV Adoption and Low Carbon Intensity Fuels Scenarios :Summary Report* (2018).

[6] EIA, *Electricity Explained: factors affecting electricity price* (2020).

[7] J. Torriti, M. G. Hassan, M. Leach, *Demand response experience in Europe: Policies, programmes and implementation* (2010).

[8] M. H. Albadi, E. F. El-Saadany, *Demand response in electricity markets: An overview* (2007).

[9] S. Feuerriegel, D. Neumann, *Integration scenarios of Demand Response into electricity markets: Load shifting, financial savings and policy implications* (2016).

[10] EDF, *Time-of-Use Electricity Pricing: Savings When They Matter* (2014).

[11] *Where does electricity come from (https://www.world-nuclear.org/nuclear-essentials/where-does-our-electricity-come-from.aspx)* (website accessed in 2020).

[12] *Fossil fuel energy consumption (https://data.worldbank.org/indicator/EG.USE.COMM.FO.ZS)* (website accessed in 2020).

[13] *Electricity Mix (https://ourworldindata.org/electricity-mix)* (website accessed in 2020).

[14] D. Gielen, *et al.*, *Global Energy Transformation: A roadmap to 2050* (2020).

[15] *Electricity Information: Overview (https://www.iea.org/reports/electricity-information-overview)* (website accessed in 2020).

[16] D. Grosspietsch, M. Saenger, B. Girod, *Matching decentralized energy production and local consumption: A review of renewable energy systems with conversion and storage technologies* (2019).

[17] A. M. Adil, Y. Ko, *Socio-technical evolution of Decentralized Energy Systems: A critical review and implications for urban planning and policy* (2016).

[18] J. Schulz, V. M. Scharmer, M. F. Zaeh, *Energy self-sufficient manufacturing systems–integration of renewable and decentralized energy generation systems* (2020).

[19] J. Hu, H. Morais, T. Sousa, S. You, R. D'hulst, *Integration of electric vehicles into the power distribution network with a modified capacity allocation mechanism* (Energies 10 (2), 2017).

[20] P. Siano, *Demand response and smart grids—A survey* (2014).

[21] R. Anderson, R. Ghafurian, H. Gharavi, *Smart Grid The Future of the Electric Energy System* (2018).

[22] J. Soares, H. Morais, T. Pinto, F. Lezama, *Survey on complex optimization and simulation for the new power systems paradigm* (Complexity, 2018).

[23] R. Deng, Z. Yang, M.-Y. Chow, J. Chen, *A survey on demand response in smart grids: Mathematical models and approaches* (2015).

[24] B. Alohali, K. Kifayat, Q. Shi, W. Hurst, *Group authentication scheme for neighbourhood area networks (NANs) in Smart Grids* (2016).

[25] H. S. Farmad, S. Biglar, *Integration of demand side management, distributed generation, renewable energy sources and energy storages* (2012).

[26] T. Logenthiran, D. Srinivasan, K. Vanessa, *Demand side management of smart grid: Load shifting and incentives* (2014).

[27] Y. Wang, W. Saad, N. B. Mandayam, H. V. Poor, *Load shifting in the smart grid: To participate or not?* (2015).

[28] D. Violette, M. Shober, *Carbon Dioxide Reductions from Demand Response Impacts in Three Markets Prepared for: Advanced Energy Management Alliance* (2014).

[29] I. H. Rowlands, I. M. Furst, *The cost impacts of a mandatory move to time-of-use pricing on residential customers: an Ontario (Canada) case-study* (2011).

[30] *Smart Home (https://www.smartgrid.gov/the_smart_grid/smart_home.html)* (website accessed in 2020).

[31] P. Palensky, D. Dietrich, *Demand side management: Demand response, intelligent energy systems, and smart loads* (2011).

[32] L. I. Minchala-Avila, J. Armijos, D. Pesántez, Y. Zhang, *Design and implementation of a smart meter with demand response capabilities* (2016).

[33] F. Shariatzadeh, P. Mandal, A. K. Srivastava, *Demand response for sustainable energy systems: A review, application and implementation strategy* (2015).

[34] *Dynamic Electricity Prices (https://www.eurelectric.org/media/2453/dynamic-pricing-final.pdf)* (website accessed in 2020).

[35] G. Dutta, K. Mitra, *Dynamic Pricing of Electricity: A Survey of Related Research* (2015).

[36] A. Anisie, F. Boshell, *Innovation landscape brief: Time-of-use tariffs* (2019).

[37] *Evaluation: Energy-Smart Pricing Plan (https://assets.fiercemarkets.net/public/smartgridnews/2006-espp-evaluation.pdf)* (website accessed in 2020).

[38] K. Herter, P. McAuliffe, A. Rosenfeld, *An exploratory analysis of California residential customer response to critical peak pricing of electricity* (2007).

[39] S. Borenstein, M. Jaske, A. Rosenfeld, *Dynamic pricing, advanced metering, and demand response in electricity markets* (2002).

[40] D. Violette, J. Erickson, M. Klos, *Final Report for the myPower Pricing Segments Evaluation* (2007).

[41] J. Strapp, C. King, S. Talbott, *Ontario Smart Price Pilot Final Report* (2007).

[42] M. Lee, *et al.*, *Assessment of demand response and advanced metering* (2013).

[43] *Emergency Demand Response in PJM and NYISO (https://www.naesb.org/pdf2/dsmee061807w2.pdf)* (powerpoint accessed in 2020).

[44] DREAM-GO, *Identified Short and Real-Time Demand Response Opportunities and the Corresponding Requirements and Concise Systematization of the Conceived and Developed DR Programs* (2017).

[45] S. E. D. Coalition, *Mapping demand response in Europe today* (2014).

[46] SEDC, *Explicit Demand Response in Europe* (2017).

[47] *Types of Electric Vehicles: A brief overview of EV options (https://www.evgo.com/why-evs/types-of-electric-vehicles/)* (website accessed in 2020).

[48] *UK briefing: The plug-in hybrid con (https://www.transportenvironment.org/publications/uk-briefing-plug-hybrid-con)* (website accessed in 2020).

[49] P. Plötz, S. Á. Funke, P. Jochem, *Empirical fuel consumption and CO2 emissions of plug-in hybrid electric vehicles* (2018).

[50] E. Helmers, M. Weiss, *Advances and critical aspects in the life-cycle assessment of battery electric cars* (2017).

[51] R. K. Lattanzio, C. E. Clark, *Environmental Effects of Battery Electric and Internal Combustion Engine Vehicles* (2020).

[52] C. Iclodean, B. Varga, N. Burnete, D. Cimerdean, B. Jurchiş, *Comparison of different battery types for electric vehicles* (2017).

[53] D. Sbordone, *et al.*, *EV fast charging stations and energy storage technologies: A real implementation in the smart micro grid paradigm* (2015).

[54] P. Blockx, *et al.*, *Beyond the plug and socket: Towards safe standardized charging infrastructures* (2013).

[55] J. Hu, H. Morais, T. Sousa, M. Lind, *Electric vehicle fleet management in smart grids: A review of services, optimization and control aspects* (2016).

[56] R. J. Bessa, M. A. Matos, *Economic and technical management of an aggregation agent for electric vehicles: a literature survey* (2012).

[57] M. C. Falvo, G. Graditi, P. Siano, *Electric vehicles integration in demand response programs* (2014).

[58] S. Shao, M. Pipattanasomporn, S. Rahman, *Demand response as a load shaping tool in an intelligent grid with electric vehicles* (2011).

[59] J. Soares, H. Morais, T. Sousa, Z. Vale, P. Faria, *Day-ahead resource scheduling including demand response for electric vehicles* (2013).

[60] L. Yao, W. H. Lim, T. S. Tsai, *A real-time charging scheme for demand response in electric vehicle parking station* (2016).

[61] S. Shao, M. Pipattanasomporn, S. Rahman, *Grid integration of electric vehicles and demand response with customer choice* (2012).

[62] D. R. Katrina Jessoe, *Commercial and Industrial Demand Response Under Mandatory Time-of-Use Electricity Pricing* (2015).

[63] S. Zhao, Z. Ming, *Modeling demand response under time-of-use pricing* (2014).

[64] X. Wanga, *et al.*, *Blockchain-based smart contract for energy demand management* (2011).

[65] H. Mortaji, S. H. Ow, M. Moghavvemi, H. A. F. Almurib, *Load Shedding and Smart-Direct Load Control Using Internet of Things in Smart Grid Demand Response Management* (2017).

[66] S. Widergren, C. Marinovici, T. Berliner, A. Graves, *Real-time pricing demand response in operations* (2012).

[67] Z. P.Faria, *Demand response in electrical energy supply: An optimal real time pricing approach* (2011).

[68] P. Khajavi, H. Abniki, A. B. Arani, *The role of incentive based Demand Response programs in smart grid* (2011).

[69] M. Yu, S. H. Hong, Y. Ding, X. Ye, *An Incentive-Based Demand Response (DR) Model Considering Composited DR Resources* (2019).

[70] L. A. Wolsey, *Mixed Integer Programming* (2008).

[71] J. Soares, T. Pinto, F. Lezama, H. Morais, *Survey on complex optimization and simulation for the new power systems paradigm* (2018).

[72] S. Hatami, M. Pedram, *Minimizing the Electricity Bill of Cooperative Users under a Quasi-Dynamic Pricing Model* (2010).

[73] S. Tiptipakorn, W.-J. Lee, *A Residential Consumer-Centered Load Control Strategy in Real-Time Electricity Pricing Environment* (2007).

[74] P. Du, N. Lu, *Appliance Commitment for Household Load Scheduling* (2011).

[75] N. Li, L. Chen, S. H. Low, *Optimal demand response based on utility maximization in power networks* (2011).

[76] H. Goudarzi, S. Hatami, M. Pedram, *Demand-side load scheduling incentivized by dynamic energy prices* (2011).

[77] Z. Song, *The evaluation of parameter m in the big m method of linear programming* (2015).

[78] M. A. Ortega-Vazquez, *Optimal scheduling of electric vehicle charging and vehicle-to-grid services at household level including battery degradation and price uncertainty* (2011).

[79] W. Kempton, J. Tomić, *Vehicle-to-grid power fundamentals: Calculating capacity and net revenue* (2005).

[80] Y. Chai, *et al.*, *Incentive-based demand response model for maximizing benefits of electricity retailers* (2019).

[81] N. Hajibandeh, M. Ehsan, S. Soleymani, M. Shafie-khah, J. Catalao, *Modeling price-and incentive-based demand response strategies in the renewable-based energy markets* (2017).

[82] H. Takano, A. Kudo, H. Taoka, A. Ohara, *A basic study on incentive pricing for demand response programs based on social welfare maximization* (2018).

[83] APREN, *Electricity Generation by Energy Sources in Mainland Portugal* (2016).

[84] OMIE, *Curvas agregadas de oferta e demanda (https://www.omie.es/pt/market-results/daily/daily-market/aggragate-suply-curves?scope=dailydate=2020-11-20hour=20)* (website accessed in 2020).

[85] R. Mu, Y. Zheng, K. Zhang, Y. Zhang, *International Journal of Computational Intelligence Systems* (2021).

[86] K. Shyamala, C. Padmasini, *Mtanh-Attention-BiLSTM model for prediction of Automobile Export Customer Satisfaction.* (2021).

[87] X. Wang, Y. Qu, C. Wu, *Research on Maximal Covering Problem Based on Cost and Customer Satisfaction Degree* (2015).

[88] K. R. Gadham, T. Ghose, *Demand response program using incentive and dis-incentive based scheme* (2020).

[89] M. Parvania, M. Fotuhi-Firuzabad, M. Shahidehpour, *Optimal demand response aggregation in wholesale electricity markets* (2013).

[90] N. Mahmoudi, *et al.*, *A bottom-up approach for demand response aggregators' participation in electricity markets* (2017).

[91] T. M. Hansen, R. Roche, S. Suryanarayanan, A. A. Maciejewski, H. J. Siegel, *Heuristic optimization for an aggregator-based resource allocation in the smart grid* (2015).

[92] L. K. Panwar, S. R. Konda, A. Verma, B. K. Panigrahi, R. Kumar, *Demand response aggregator coordinated two-stage responsive load scheduling in distribution system considering customer behaviour* (2017).

[93] H. Morais, T. Sousa, J. Soares, P. Faria, Z. Vale, *Distributed energy resources management using plug-in hybrid electric vehicles as a fuel-shifting demand response resource* (2015).

[94] IMT, *Veículos eletricos matriculados acumulado e por ano* (2019).