UNIVERSIDAD PONTIFICIA COMILLAS

ESCUELA TÉCNICA SUPERIOR DE INGENIERÍA (ICAI)

OFFICIAL MASTER'S DEGREE IN THE ELECTRIC POWER INDUSTRY

Master's Thesis

What is the economic value of PEV aggregation in the balancing market?

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Madrid, 2014-2015

IIT - Institute for Research in Technology

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Summary

Electric vehicles (EVs) are likely to play an important role in the coming future. Along with reducing emissions and fostering energy efficiency to meet decarbonisation objectives of our society, EVs will strongly interact with power systems. Indeed, apart from yielding environmental benefits, EVs could provide services to power systems while complying with the mobility needs of EVs owner. Recent research on EV integration led to the birth of new potential actors, namely aggregators who would manage a vehicle fleet and act as an intermediary between EVs owner, system operator and electricity markets. Among the different services that an Aggregator could provide, ancillary services have been put forward; the aggregator would manage a virtual power plant taking into account the information regarding EVs owners' mobility needs and connection schedule to the grid.

Many aspects of aggregation have already been studied, from the range of services that could be provided to the impact on networks operations and incremental investments required to deal with EVs. However a research gap has been identified regarding the added economic value of the aggregator charging strategy. Considering a vehicle fleet in which every single car would be optimally charged independently from each other, will the aggregator managing the whole fleet in a coordinated way obtain better results? Would the optimal strategy of a single EV owner having full access to electricity markets yield the same results as the aggregator? If the aggregator achieves to charge EVs in a cheaper way, where does the difference come from? These are the main questions that will be answered in this Master's Thesis, analysing particularly balancing markets and the effect of different price mechanisms on the results obtained.

To this end, a mathematical formulation of the optimal purchases in different markets to meet the driving needs of EV owners has been developed. The simulation presents in a first step the optimal strategy of an aggregator and the one of an independent EV owner before to obtain the economic value of aggregation by comparing the outcome of both strategies. Optimization models have been developed using GAMS, a modelling software for mathematical programming.

The results coming from the simulation are clear, the aggregator coordinating a vehicle fleet achieves better results than EV owners charging their car independently, both under single price and dual price imbalance mechanisms. Economic benefits of aggregation are higher when the balancing market is designed with a dual price system instead of a single price one. Benefits in balancing markets stem from imbalances netting possibility of aggregation. Indeed, when charging an EV independently, the netting opportunity disappears, giving rise to higher charging costs than under aggregation scheme.

As for secondary objectives, the impact of capacity charges on optimal day-ahead purchases has been assessed along with an estimation of balancing costs due to the uncertainty of EV owner's behaviour, i.e. unforeseen events that entail driving the car when it should have been connected to the grid.

Resumen

La creciente importancia de normativas ambientales en nuestra sociedad para mitigar el calentamiento del planeta y la contaminación atmosférica requiere un cambio progresivo de los medios de transporte actuales. En este contexto, los coches eléctricos aparecen como una buena alternativa para reducir emisiones y mejorar la eficiencia del sector del transporte.

Además de reducir la contaminación atmosférica, los coches eléctricos podrían apoyar a la red eléctrica y proveer distintos servicios al operador del sistema como servicios auxiliares o reservas. Como consecuencia de ello, la investigación realizada en las últimas décadas ha destacado la importancia de un nuevo agente que actuaría como intermediario entre los mercados eléctricos, el operador del sistema y los propietarios de coches eléctricos. Este agente conocido como agregador se encargaría de proveer servicios al operador del sistema así como de cargar los coches eléctricos bajo su control. Con las informaciones proporcionadas por los usuarios de coches eléctricos (horas de conexión a la red, energía requerida para conducir) el agregador se ocuparía de gestionar un "generador virtual" producto de los distintos vehículos conectados a la red bajo su control. No hay dudas de que los agregadores desempeñarán un papel importante en un futuro próximo.

Muchos aspectos de la agregación ya han sido estudiados, entre ellos los distintos servicios que se podrían ofrecer al operador del sistema y el impacto en las redes debido al aumento de coches eléctricos. Sin embargo, se ha identificado una falta de información sobre el valor económico de agregar coches eléctricos en el mercado de los desvíos bajo distintas regulaciones. Considerando una flota de vehículos en la que cada vehículo se cargaría de forma óptima y aislada, ¿Coordinar la carga de todos los vehículos juntos da mejores resultados? ¿Cuál es la estrategia más rentable para cargar coches eléctricos? ¿La de un agregador o da lo mismo la de un propietario de coche eléctrico teniendo acceso a los mercados? ¿Si hay beneficios agregando coches, de dónde vienen?

En este documento, se pretende demostrar el valor económico de la estrategia de carga del agregador así como evaluar el impacto del sistema de precios del mercado de los desvíos (sistema de precios simétricos o asimétricos) sobre el valor de la agregación.

El análisis se centrará fundamentalmente sobre las compras óptimas de energía en los mercados para alcanzar los requerimientos de los propietarios de coches, comparando la estrategia de un agregador con la de propietarios de coches optimizando sus compras solos.

Por ello, una formulación matemática de cada estrategia ha sido desarrollada en GAMS, un programa de optimización matemática.

Los resultados obtenidos son unívocos, agregar la carga de coches eléctricos permite ahorrar dinero en el mercado de los desvíos, y eso sucede con ambos sistemas de precios (simétricos y asimétricos).

Además del valor económico de la agregación en el mercado de los desvíos, se ha estudiado el impacto del coste de la capacidad contratada en casa sobre las compras óptimas de energía en los mercados. También, una estimación de los costes de desviaciones ha sido realizada.

Acknowledgment

I would like to express my gratitude to my supervisors Tomás Gómez San Roman and José Pablo Chaves Ávila for guiding me through the elaboration of this master's Thesis. By sharing their knowledge and valuable experience in the power sector, they have encouraged me to complete my work.

I am especially thankful to José Pablo who has always helped me with enthusiasm whenever I needed it.

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CHAPTER IV: Deviation costs and optimal capacity

CHAPTER V: Conclusions

CHAPTER I: Introduction

I – 1. Context

Transport is driving the world we live in. It is one of the essential links between people across the globe which fostered trade and led to globalisation. More importantly, it is a crucial vector for the evolution, development and progression of modern societies. Indeed, it seems difficult to imagine how would be the world without transport. This catalyst for massive production, mobility of goods and employment opportunities is also one of the greatest tools to stimulate economic efficiency and resources optimal management. By bringing the opportunity to link markets worldwide, overall welfare was given a chance to increase significantly.

Automobile has come a long way since 1768 when Nicolas-Joseph Cugnot, a French inventor, build the first self-propelled vehicle capable of human transportation. Nowadays, the internal combustion engine (ICE) is absolutely dominating the transportation market. However, due to recent environmental concerns, climate change and atmospheric pollution regulations are threatening the well-established status of the ICE.

Why should we worry about the environment? This question may seem a bit redundant, nonetheless having clear ideas and basic key figures related to the transport sector is an imperative to understand the way energy companies and governments are moving nowadays, but also to explain the motives driving this Master's thesis.

Environmental impacts are externalities that affect public goods, i.e. damages created by an agent affect another one who bears the costs of the harm produced. The culprit does not take these extra costs into consideration, therefore an externality arise and resources allocation is not efficient anymore.

The short-term problem: atmospheric pollution

Air pollutants mainly emanate from combustion processes and have adverse effects on human health, crops and ecosystems. The common ground for all those adverse effects are anthropogenic emissions. When released in the air, these pollutants may be dispersed in the atmosphere by wind and remain there for a couple of days causing damages on diverse population.

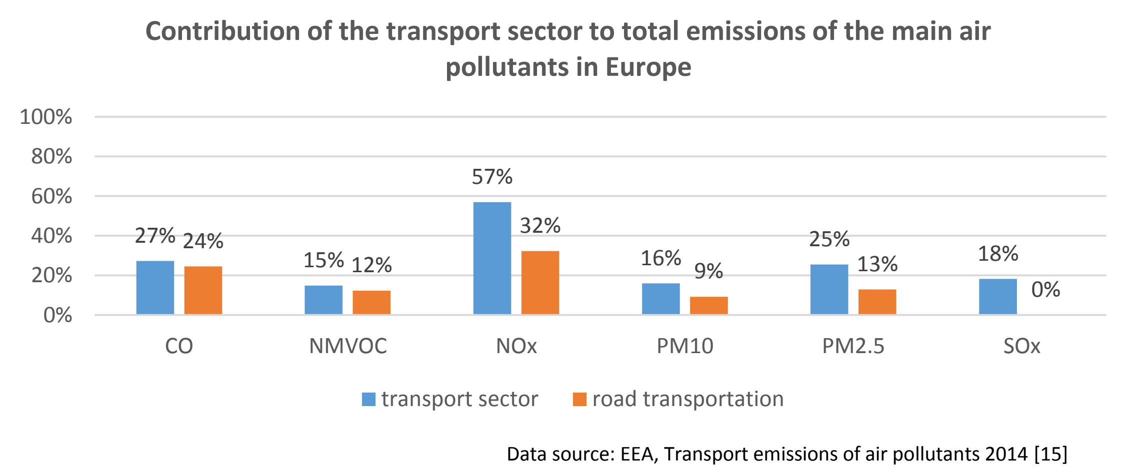


Figure 1 - Contribution of the transport sector to total emissions of the main air pollutants in Europe

Figure 1 depicts the contribution of the transport sector to the atmospheric pollution in Europe. NOx emanating from cars tailpipes is a major concern regarding road transportation and is likely to persist for decades. Emerging countries such as China see their vehicle fleet growing fast, with around 23 million vehicles sold in 2014. At this alarming pace, internal combustion engine (ICE) still has fruitful years ahead and drives us safely to a more polluted environment. Of course, as time goes by ICE technology will be cleaner and more efficient, but we will still inexorably burn fuel and emit pollutants. Only looking at the small progress made by ICE engines over a century we can conclude that a technological change is needed.

The long-term problem: climate change

Climate change cannot be denied and human activity is the most important factor driving it.

Earth's average temperature has been changing constantly through time, and without the help of humanity. These temperatures variations are quite clear in figure 2. The question is not about having lower or higher temperatures than past records, but more about why what is happening right now is different than before.

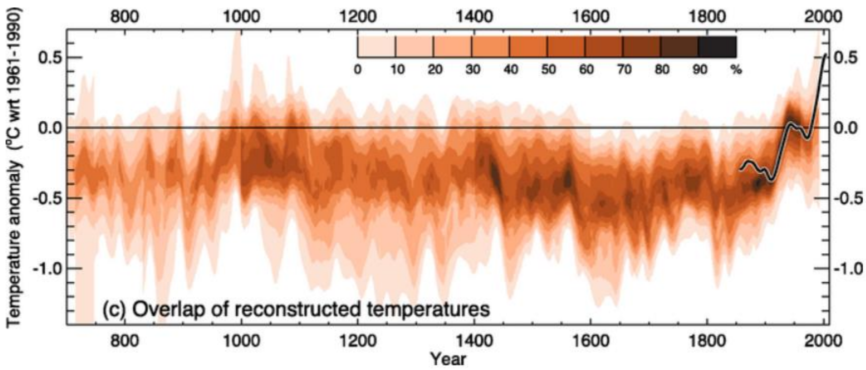


Figure 2 - Temperature of Planet Earth over the last centuries [16]

The current change of temperature we are experiencing is different because its pace is much faster than usual. According to the NASA [1], the temperature has increased in the past century ten times faster than the average rate of ice-recovery warming. Still according to the NASA [1], *"The forecasted rate for the next century is at least 20 times faster."*

Another striking aspect supporting the anthropogenic climate change theory is how temperature has been increasing since the industrial revolution. It can be seen quite easily in figure 2. In May 2015, CO_2 concentration in the atmosphere is estimated to 400 ppm, that is to say 48% more than pre-industrial time (271 ppm).

As a matter of facts, transport appears as the second largest emitting sector of CO_2 after power industries hence the importance of developing effective solutions for reducing the impact of transport on the environment. The transport sector is composed of the different means of transportation, namely aviation, marine and automotive transportation. An important figure to have in mind is that around 75% of CO_2 emissions of the transport sector come from road transportation. This alarming percentage finds its roots in the underdevelopment of alternative energy sources for transportation which hampers the progress towards cleaner options. The drastic dependency of that sector on crude oil is well represented by the fact that crude oil derived products account for 95% of total energy used for the transportation sector worldwide [2].

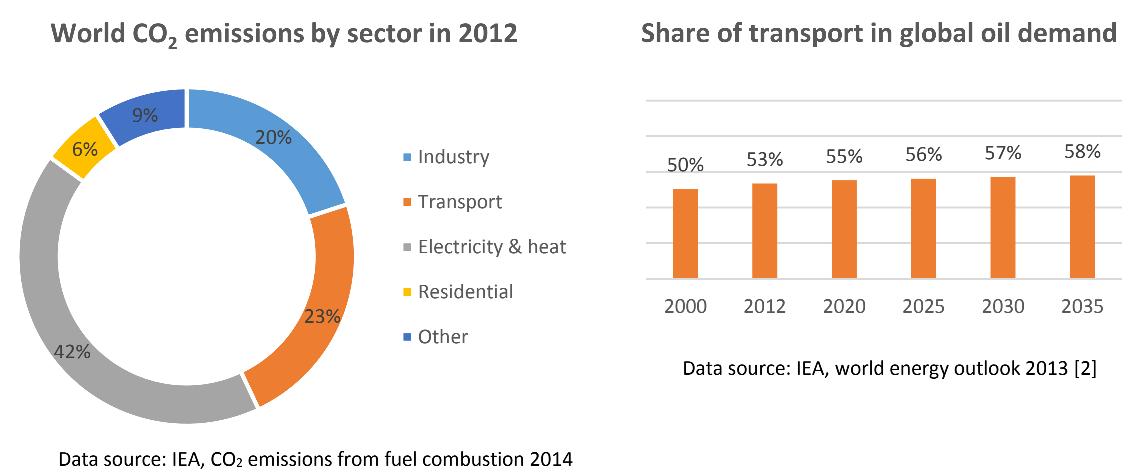


Figure 3 - World CO2 emissions by sector and share of transport in global oil demand

High dependency on crude oil is at the essence of the transportation problematic and represents the main barrier against a technological change. At a global scale, one barrel of crude oil out of two is used for transportation and this trend is not likely to change in the following years as shown in figure 3. The dominance of oil & gas industries in the world top ten largest companies by revenue tells a lot about it. Indeed, this podium is made up of eight companies of the oil industry! The inertia of the current transportation system is so huge that few chances are given to new technologies to challenge the existing one. How to compete with ICE engines and infrastructures in place when considering the stratospheric economies of scale already in place? The capital intensiveness of the whole system is tremendous from the implementation across the world of fuelling stations to service facilities and spare part manufacturers. Breaking the deadlock on the transportation problem will not be easy but it is a necessity.

Several solutions have been proposed to do so, electric vehicles among them. This led us to the last part of this introduction in which a quick review of the current situation, benefits and drawbacks of electric vehicles is presented.

Benefits of electric vehicles (EVs) are plural, mainly EVs are more efficient than ICE and less polluting. A popular reasoning about EVs is that we are just moving emissions from tailpipes to electricity plants. This is not wrong, but even if we emit more at the electricity production level, GHGs emissions would decrease if ICE vehicles are replaced by EVs. In 2008, WWF published a life cycle analysis of electric vehicles versus ICE vehicles in "The end of the oil age" [3]. Back then, the conclusion of that study was already that *"even based on today's relatively carbon-intensive energy mix, the electrification of automotive transport can deliver an immediate reduction of greenhouse gases, an improvement in urban air quality and noise levels, and significantly lower operating costs."* No need to say that as time goes by, the power sector will become cleaner and cleaner and thus implementing EVs will be more and more beneficial. Efficiency of ICE is also quite low when compared to EVs. Indeed, electric motor are between 80% and 85% more efficient than an ICE. According to the US Department of Energy [4], only between 14% and 30% of the fuel is put to use for moving the vehicle, the rest being lost mainly due to inefficiencies of the engine and the drivetrain. Diesel engines are doing a bit better with a 23% average but still far worse than electric motors. Indeed, still according to the US department of energy [5], the efficiency of electric vehicles is between 59% and 62% (electricity to wheels power). Of course, EV is a really young technology and is susceptible to better a lot in the coming years.

Primary energy efficiencies		Fuel (ICEV)	Electricity (EV)
Plant to tank	Plant efficiency	83%	40%
	Transmission and Distribution		92%
Tank-to-Wheels		23%	60%
Plant-to-Wheels		19%	22%

Figure 4 - Electricity to wheels vs Fuel to wheels efficiency comparison

However, electric vehicles are not without defaults, the main one being batteries: price, charging time, life duration. Hydrocarbon fuels are much more energy dense than the better batteries developed and a tank can be filled almost instantly. Currently, the best Tesla's electric cars can handle around 450 km autonomy which is not bad despite the longer charging time than using fuel. An interesting statistic delivered by Eurostat revealed that Europeans do an average of 30km to 40km per day across all modes of transport. This survey is thus demonstrating that most of the mobility requirements for daily transportation needs are perfectly achievable with electric vehicles. One of the main barriers to technological change is thus psychological, we could perfectly see an EV as a cell phone we need to charge during the night. The driving pattern of a vehicle owner is not so relevant, in a night the battery could be fully charged.

In conclusion, electric vehicles appear as an effective solution for cutting CO_2 emissions and even better, emissions would be reduced independently of the production mix of the power system according to [3]. Indeed, the electricity pathway is cleaner than the fuel one for any given source. Highly dependent on liquid hydrocarbon fuel, electricity could help diversifying energy sources of the transport sector. By burning less fossil fuels, emissions of short-term air pollutant are directly reduced (such as NOx) along with long-term ones (CO_2). Much work needs to be done to escape the ICE status quo, for instance regarding the installation of charging infrastructure across a country or the improvements of batteries and reduction of their costs. The growth of mobility in non-developed countries is tremendous, adopting, improving and developing cleaner technologies for transports is therefore crucial, the transport sector already being the second biggest responsible for CO_2 emissions worldwide.

I – 2. Motivation

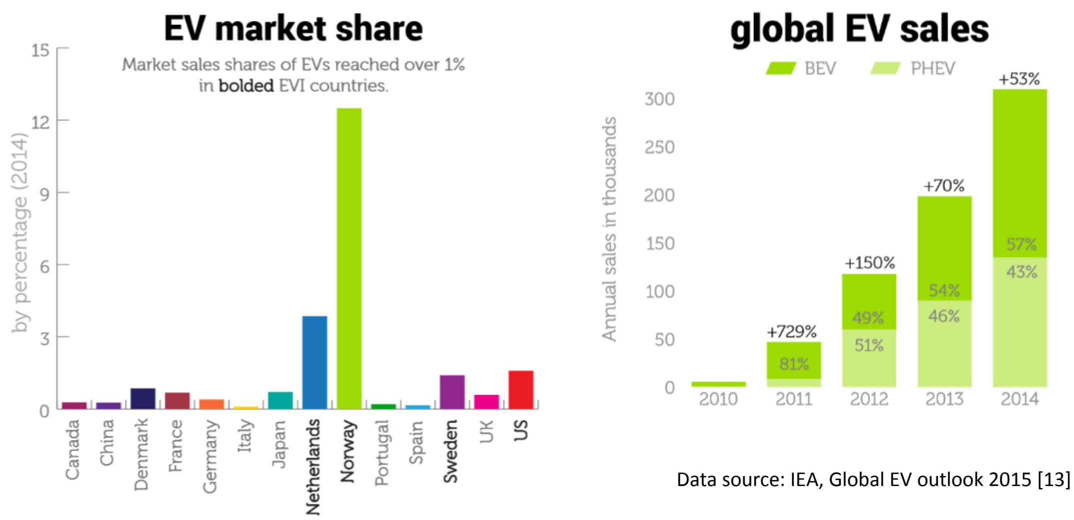


Figure 5 - Electric vehicles market share & sales

Given the aforementioned background, PEVs are likely to play an important role in the future to reduce the environmental impact of human mobility. As shown by figure 5, every year sales of EVs are growing and there is no doubt that mankind will use electric vehicles. Indeed, EVs appear as a good option for fostering efficiency and as a good substitute for conventional combustion engine vehicles. Adopting plug-in electric vehicles (PEVs) entails reducing pollution but not only: recent research on EVs integration revealed that they could also be used as a flexible source of energy providing services to the electrical system.

In that promising context, a lot of ideas and new concepts are emerging, in particular the concept of aggregators. This new agent would gather a portfolio of electric car owners and manage the charging schedule of EVs under his control. Being a cornerstone between electricity markets, the system operator and PEVs owner, aggregators could represent a genuine and profitable business for the future while reducing the bill of consumers charging their PEVs.

Integrating EVs in our electric systems may not be an easy task but it is deemed beneficial and essential. In the face of the current situation, every single contribution to an efficient integration of PEVs is welcomed; and helping moving aside a given integration model or on the contrary encouraging it is of crucial importance to implement PEVs as efficiently as possible in our lives. A general motivation driving this Master's thesis is thus to pave the way to a cleaner transportation system and to lessen the cost of motorized mobility to public health and society. More precisely, the main motive behind this Thesis is to analyse and find all the benefits that aggregation could bring regarding EVs integration.

This master's thesis is part of the Utility of the Future project [6], which is a joint project between IIT-Comillas and MIT seeking to determine the future of the provision of electricity services. Different topic such as distributed energy resources integration or new business models will be studied in this multi-year project among which electric vehicles play an important role.

I – 3. Thesis objectives

The main goal of this Master's thesis is to assess the optimal charging strategy of a vehicle fleet through participation in electricity markets (day-ahead and balancing markets). Understanding the economic value of EVs aggregation in balancing markets, estimating the added economic value of the aggregator's business, the savings that could be generated for consumers represent the main task to conduct. Therefore, this master's thesis will consist in a techno-economic study aiming at obtaining optimal purchases of electricity in different markets while complying with the inherent technical constraints of electric vehicles. More specifically, the following points will be studied:

- Obtaining the optimal charging schedule of a PEV fleet considering the day ahead market
- Assess the impact of capacity charge
- Assess the impact of the uncertainty of consumer's behaviour in the balancing market
- Assess the economic value of an aggregator in the balancing market
- Analyse the effect of imbalance prices: Dual price/Single price

I – 4. Approach

In order to achieve the objectives proposed, this thesis has been divided into two parts:

1. A qualitative one defining the different concepts and background necessary for a good understanding of the study to be conducted
2. A quantitative one presenting a mathematical analysis and several case studies

For the quantitative part of this Thesis, optimization models have been developed with GAMS, simulating the optimal strategies for charging EVs under different schemes. The General Algebraic Modelling System (GAMS) is a mathematical programming and optimization software widely used for developing economical models, which suits the objectives of this Thesis perfectly. The input and output data management for the different models is handled with Microsoft Excel through macros programmed in VBA. Excel is also the interface for running the different models and simulations. Figure 6 presents the global interaction between the software used.

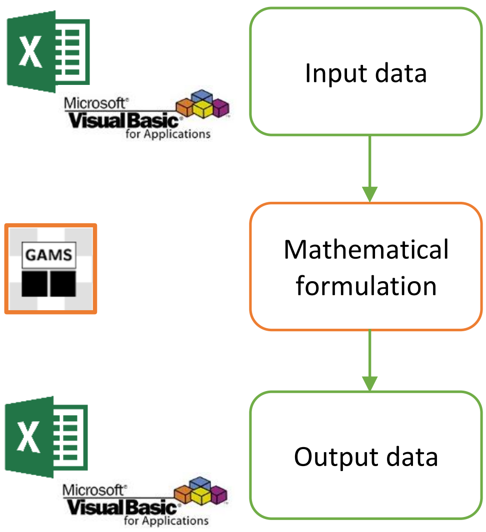


Figure 6 - Interaction between the different software used for the Thesis

I – 5. Document organization

This document is organized around 5 chapters, each one of them contributing to the research objectives. The first chapter presents the context of this master's Thesis, the objectives pursued and the overall methodology followed. Chapter 2 will provide the necessary background for a good understanding of the work conducted: general conceptual ideas and key figures.

Chapter 3 and 4 are dedicated to the thesis objectives. Chapter 3 is the most important one dealing with the economic value of aggregation whereas chapter 4 tackles secondary objectives. In both chapters, a first part will present the methodology followed and a second one the mathematical formulation of the problems. Then, several case studies are proposed to explain and analyse the impact of different factors on the results obtained with optimization models.

Finally, chapter 5 will close this dissertation summarizing the work done and the main results obtained before to propose future work.

CHAPTER II: PEV general framework

II – 1. Global market structure [7]

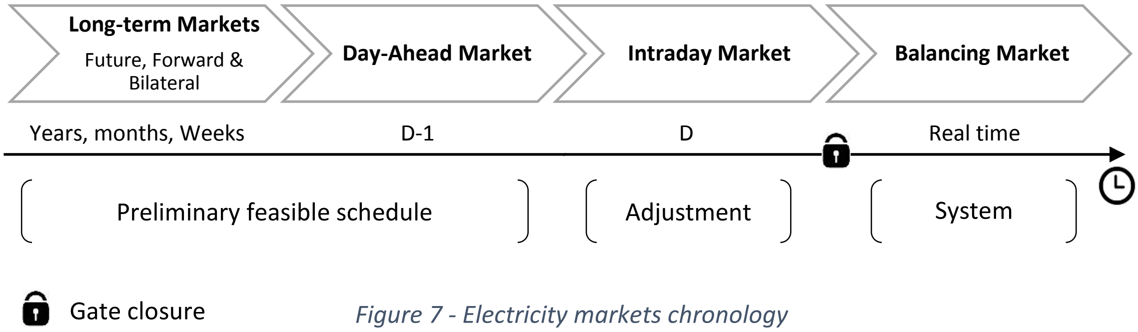
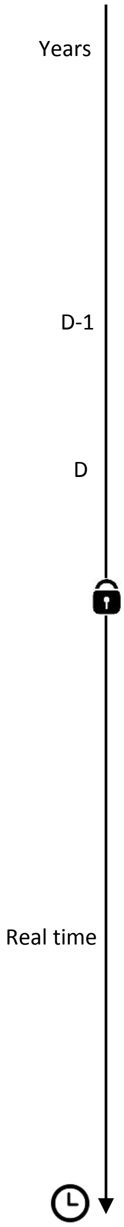


Figure 7 - Electricity markets chronology

In liberalized paradigm, the electricity business is conducted through a succession of several markets, in which agents buy and sell energy but also services related to system security (such as ancillary services). The chronology of these successive markets is presented in figure 7.



Long-term markets allow producers and consumers to hedge their position along with bringing opportunities to speculate and arbitrate. Long-term markets operate prior to the day-ahead market. The day before electricity delivery (D-1), both agents that have bilateral contract and those who do not go through the market operator and submit their offers. The ones having bilateral contracts declare the quantity of energy traded for the following day while the others send their bids to the market operator. After clearing the auction, the market operator obtains a preliminary schedule for the following day. Then, the SO checks that the schedule resulting from the market operator is technically feasible. If it is not the case, and transmission constraints arise, the SO solves them in the least costly manner to provide a feasible schedule.

In order to correct any deviations from the first feasible program that might appear before real time (schedule changes of a generating unit with respect to the DAM, error in weather forecasts…), other transaction processes have been put in place to allow market participants or the SO to modify and adapt their planning. This is done through the intraday market, where agents can adjust their positions with respect to the day-ahead schedule by submitting additional bids. The moment when trading and adjustments are over is called ‘’gate closure’’. Until gate closure, market agents are allowed to balance their positions and correct their deviations without any type of intervention of the SO. At gate closure, market participants should have submitted their balancing bids (upwards and downwards) for the balancing market run by the SO. The purpose of this auction is to find the least costly approach for the SO to fix imbalances in real time. After gate closure, the final production schedule is set for all market participants and only the SO can act to adjust any deviation.

Once the market is closed (after gate closure), the SO takes the control of the system. His duty is to ensure that supply matches demand at every single moment. Reserve markets provide tools for the SO to fix imbalances and maintain system stability (Ancillary Services). Indeed, in real time there is no time to submit deviations to an auction since every single system imbalance must be corrected at once. Therefore, in most systems the SO contracts in the long-term additional ancillary services, such as very short-termed reserves that might be necessary for responding to specific contingencies.

II – 1.a) Balancing market

As the name suggests itself, balancing markets are designed as a tool for balancing electricity production and consumption in real time. As electricity cannot be economically stored, the SO is in charge of meeting production and demand at every single moment: this is real time operation. In order to maintain this equilibrium, the SO must have under his control energy reserves to make the necessary adjustments. Indeed, a variety of incidents may disrupt the established schedule such as transmission lines outages or generating plants contingencies. The SO has at its disposal three types of reserves: primary reserves, secondary and tertiary. In case of an imbalance and once primary reserves and secondary reserves have been used (automatic reserves controlled by the SO), the SO asks generators and consumers to quickly modify their operating schedule so as to restore the equilibrium between demand and supply. That is the moment when the balancing market is required (tertiary reserves). Through a mechanism where market agents offer to increase or decrease their production/consumption along with declaring their technical and financial conditions, the SO can modify their consumption or injection schedules. The SO compensates for any imbalances by ranking offers according to economic precedence, taking into account technical constraints expressed by agents and selecting the cheapest offers to put the system back to equilibrium.

The time limit to send a bid for participating in the different markets is commonly called “gate closure”. Gate closure is different from one country to another, mainly depending on the kind of market in place and on the flexibility of the electric system of the country. For instance, a nuclear plant needs much more time to start than a CCGT unit. With a more specific view on the balancing market, gate closure can be a rolling time limit with a specific time interval which depends on the country (example: for England and Wales, half hour interval). It can also be a fixed deadline at specific hours during the day as it is the case for Spain or France.

An important point related to balancing markets is the concept of balance responsible party (BRP). Balance responsible parties are market agents who committed to manage their imbalances within a certain perimeter. In case of having deviated from their foretold schedule, they will have to pay for the imbalances generated. For instance, if a BRP falls short of energy due to a plant outage or a demand increase, the imbalance arising between his original schedule and what really happens will be charged by the SO to that BRP. All market agents are compelled to be a BRP or to go through one (such as an aggregator with a BRP status).

Balancing markets are designed for providing security of supply with a market approach. Energy is bought by the SO according to a market criteria, which should be sound an efficient. As the objective of the balancing market is security of supply, the price mechanism of that market should not encourage agents to deviate from their schedule. That is why balancing markets prices are usually higher than day-ahead or intraday market prices, so as to minimize the energy needed to compensate for imbalances.

Pricing methodologies, positive and negative imbalances

There are two main electricity pricing mechanisms in balancing markets: dual-pricing and single-pricing systems. In a single price balancing market, the same price is used to settle both positive and negative imbalances whereas in a dual-price market, positive and negative deviation are priced differently. In dual pricing markets, agents are always penalized when they deviate from their schedule whereas in single price markets, agents are not penalized if they are deviating in accordance to system needs. The concept of positive and negative imbalances is depicted in figure 8.

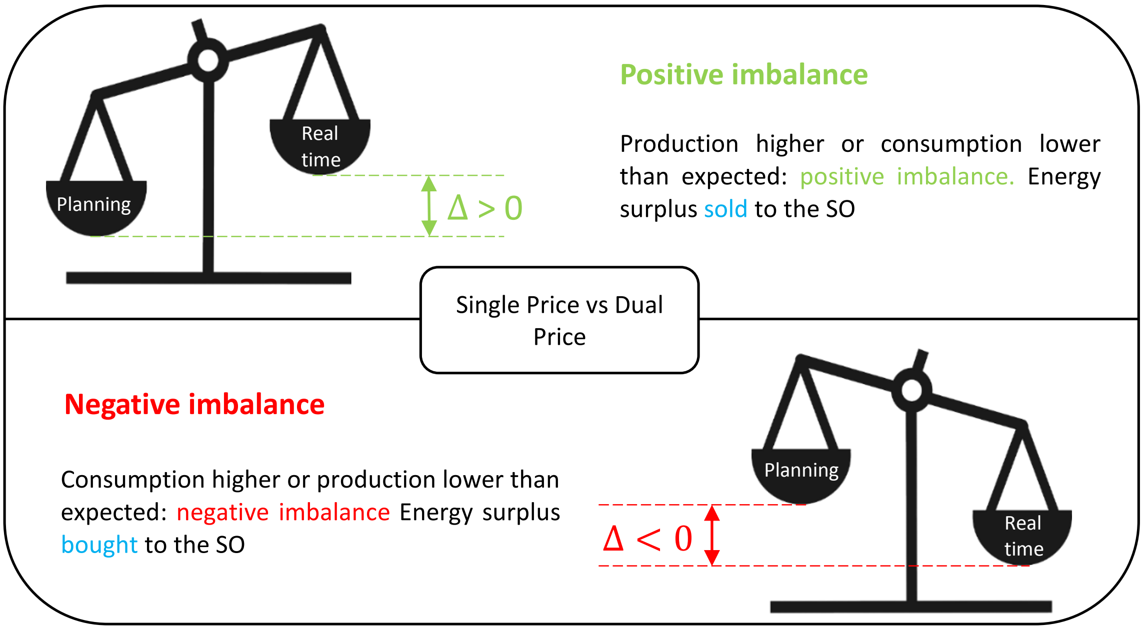


Figure 8 - Positive and negative imbalances

		System imbalance		
		positive	**null**	**negative**
BRP imbalances	**positive**	min (pDA ; pDW)	pDA	pDA
	negative	pDA	pDA	max(pDA ; pUW)

Table 1 - Imbalance pricing applied in Spain

In Spain, a dual pricing imbalance mechanism is applied as shown in table 1 where the different parameters are defined as:

- pDA : Day-ahead market price
- pDW: volume weighted average price downward of the activated bids from deviation management
- pUW: volume weighted average price upward of the activated bids from deviation management

In a single price system, the price is calculated depending on the system imbalance:

- If the system needs energy the single price is the upward price.
- If the system has a surplus of energy, the single price is the downward price.

II – 2. Electric vehicles

This section will provide briefly the basics about electric vehicles. The literature can sometimes be confusing since several acronyms are used to refer to different car types, hence the need to clarify the nomenclature for a good understanding of the work conducted in this Thesis. Another crucial point when talking about electric vehicles is the battery. A summary of relevant information regarding batteries and charging modes is provided below.

II – 2.a) Vehicle types

There exist different types of vehicles:

- **ICEs**: Internal combustion engines
    - This is the classic car burning fuel (gasoline, diesel …)
- **EVs**: Electric vehicles, sometimes called BEVs (battery electric vehicles)

- They are powered by electric motors only, charging their batteries when connected to the grid
- **HEVs**: Hybrid electric vehicles
    - An ICE and an electric motor propel the car but they cannot be plugged-in to charge their batteries
- **PEVs**: Plug-in electric vehicles
    - Regroup all vehicles with an electric motor that can be plugged to the grid for charging (even hybrid ones)
- **PHEVs**: Plug-in hybrid electric vehicles
    - They possess two motors, an ICE and an electric one and can be plugged to the grid

Only plug-in electric vehicles (PEVs) are considered in this Master's Thesis which encompass all cars able to connect to the grid for charging. Batteries may also be charged with regenerative braking systems improving the overall efficiency of the car.

II – 2.b) Batteries & charging process

Today, batteries are the core problem of electric vehicles: price, technical characteristics including autonomy, life span and rate of charge. The necessary time to fully charge a battery can range between 20-30 minutes to around an entire day. The charging time is usually the object of a separation in two charging mode:

1. **DC-fast charging**

Around half an hour is needed to fully charge the battery providing direct current and thus avoiding the conversion of alternative current (AC) to direct current (DC) done by the on-board equipment of the car. A tremendous amount of power is needed to do fast charging (for instance Tesla is currently rolling out charging station across the world of 120kW)

2. **AC-Slow charging**

The average time to charge completely a depleted battery is around 8 hours. Slow charging is often associated to home charging and a power capability around 3 kW. The on-board equipment of the vehicle converts AC to DC.

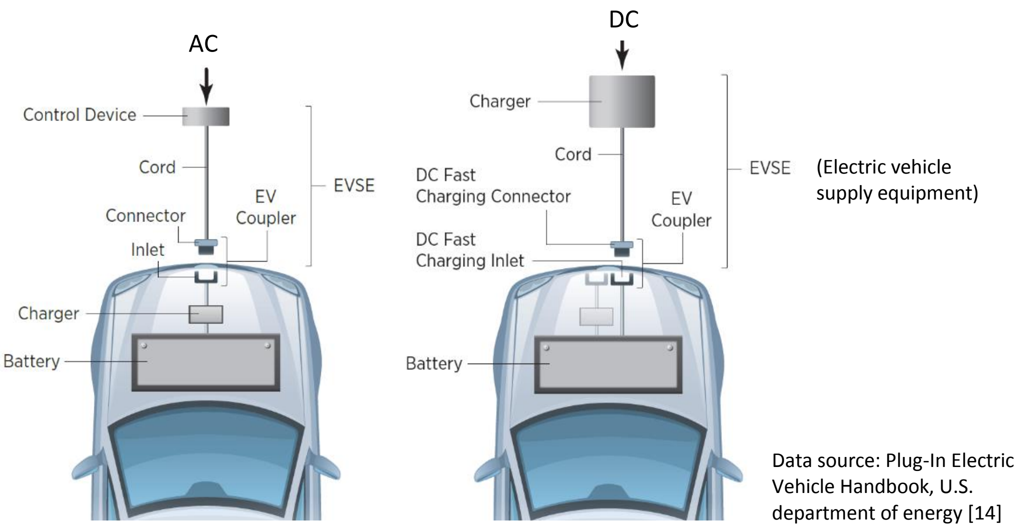


Figure 9 - Fast charging/slow charging

As shown by figure 10, today's cost per kWh of batteries is really high (around 300€/kWh). In fact, batteries represent the biggest cost of an electric vehicle. If we take the Tesla model S 85 which has a battery of 85kWh, the cost of the battery is currently around 25.500€!

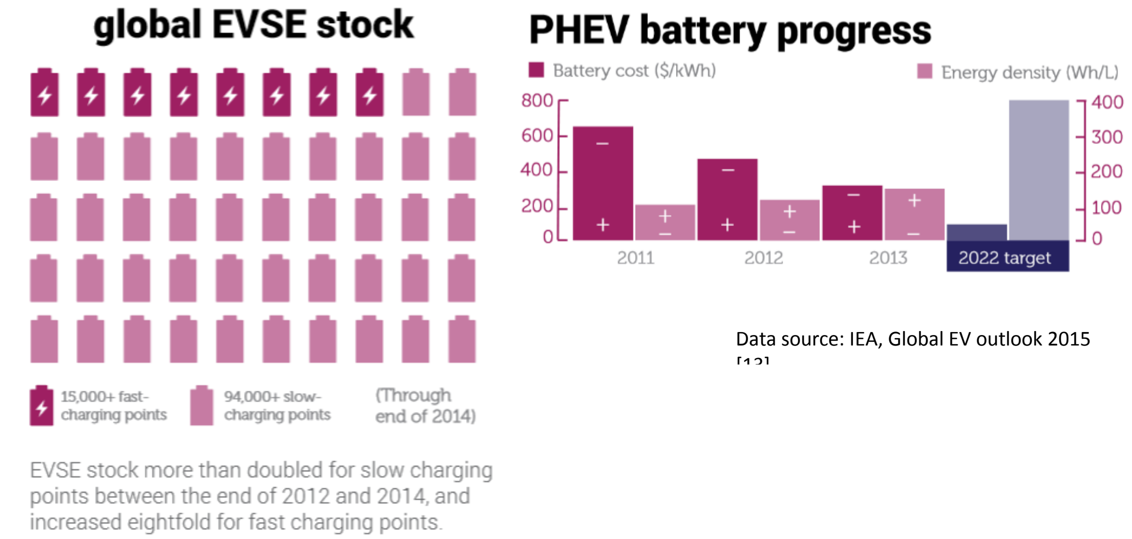


Figure 10 - EVSE stock and battery prices evolution

Bidirectional vs unidirectional flows

When talking about bidirectional flows for batteries, it is understood that batteries can behave as generators injecting power into the grid on top of its storage functionality. This is also commonly referred as vehicle to grid capabilities (V2G). On the opposite, when talking about unidirectional flows, it is considered that the battery can only be charged and cannot provide electricity to the grid. An important technical characteristic of batteries is their maximum rate of charge which limits the amount of energy that can be charged during a time period. The effect of the maximum rate of charge of a battery on market operations will be latter developed in this Thesis. Usually when considering bidirectional flows, i.e. injection of electricity into the grid from batteries, the maximum rate of charge of batteries is equal to the maximum rate of discharge since the energy is going through the same equipment, the only difference being in opposite direction. The maximum discharge rate for grid purposes has nothing to do with the discharge rate from driving needs since two different controller are used, one for each.

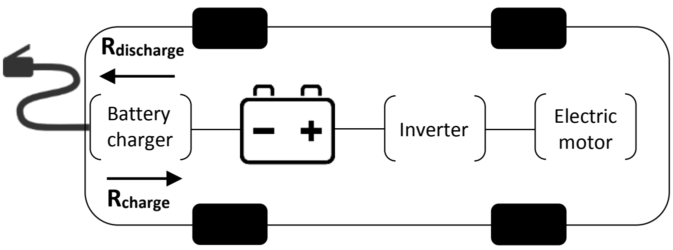


Figure 11 - Schematic view of a battery charger

The battery rate of charge is also commonly called the charging rate (C-rate). This technical parameter of batteries defines the charging and discharging rate in function of its total capacity. For instance a battery of 10 kWh with a C-rate of one can deliver a power of 10 kW. A C/2 rate would therefore represent a 5kW power capability.

II – 2.c) Charging modes

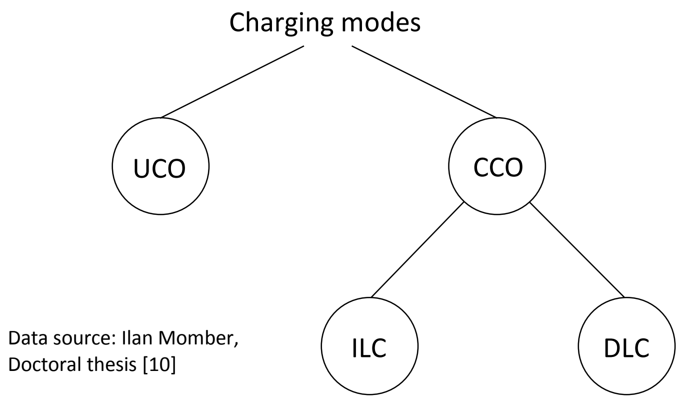


Figure 12 - Charging modes

There are mainly two charging modes: Uncontrolled charging (UCO) and Controlled charging (CCO). Uncontrolled charging is the conventional way of charging devices, i.e. plug-in a device and directly start withdrawing energy from the grid. It is also called dumb charging. It is assumed that there is no incentive whatsoever to drive the way of charging an electric vehicle in an efficient way for the system (no price differentiation along the day or other signals).

On the contrary, controlled charging refers to a “smart” way of charging vehicles by controlling when and how much to charge. CCO are divided into two subgroups: Indirect load control and direct load control. Technically speaking, a mere controllable switch would do the job for cutting the load when required.

- Indirect load control (ILC)

  ILC commonly refers to a price signal mechanism which drives the charging schedule of a vehicle in response to those prices. This is beneficial for power systems since charging during high prices hours (meaning higher loads in the network) would be avoided and thus network reinforcements and investments will be lower. Conversely, low prices hours which technically are off-peak hours will be preferred for charging vehicles.

- Direct load control (DLC)

  DLC is directly setting the load to charge at a given moment with a controller. This could be used to respond to DSOs’ needs to reduce loads in given areas and adapting the charging to the system. Aggregators could also use DLC to optimize the charging of a portfolio of EVs.

II – 3. Aggregation of electric vehicles

What is an aggregator? What services and benefits could an aggregator provide to power systems or to PEV owners? Who are the agents interacting with an aggregator? This section will provide some background needed for a good understanding of the study conducted on the economic value of aggregation.

It is usually considered that 3 different types of agent will have a stake in aggregation of PEVs:

- **The distribution system operator** (DSO) which is in charge of the distribution grid (medium and low voltage). The DSO's work encompasses different activities such as network expansion planning, operation of the grid (maintaining voltage levels…), maintenance…
- **PEVs owners** who will require electricity for charging their cars connecting to the grid either in their houses or to supply points.
- **The aggregator,** a new agent in charge of managing the charging of a vehicle fleet under his control.

In that context, the aggregator would be the interface between electricity markets and PEV owners, buying energy on behalf of its customers to provide them with the energy required for their mobility needs. In the end an aggregator would be some kind of electricity retailer exposed to markets prices variability and its vehicle fleet requirements & uncertainties.

Several possibilities are contemplated regarding the charging of a PEV fleet. A first approach could be to charge PEVs only according to users' preferences and try to reduce their energy bills. A second one would be to charge vehicles in function of the power system needs to reduce the impact of the penetration of PEVs on the system or provide some services (such as ancillary ones, supporting the integration of intermittent generation sources (solar, wind…)). Finally, it could also be a combination of both. In any cases, the benefits of aggregation for power systems or consumers rely heavily on the charging strategy of the vehicle fleet.

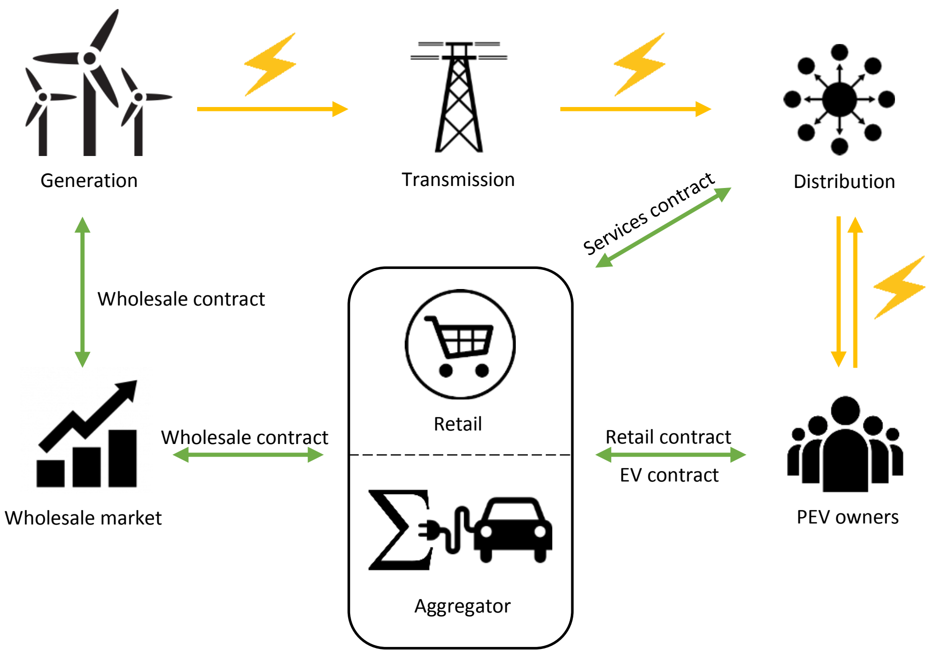


Figure 13 - Aggregator role in the power system

Figure 13 presents the probable interactions of the aggregator with all other agents. The aggregator business could be implemented in several ways, bundled with a retailer function or as a totally new independent entity dealing only with electric vehicles. In any cases, the aggregator business should be fully unbundled from vertical activities and be set as a competitive activity. In the literature, the acronym PEVSA may be encountered standing for PEV Supplier-Aggregator.

		Aggregation make sense?
Economies of scale	Charge controller, batteries…	yes
Economies of scope	Bringing together different services to reduce costs	yes
Entry barriers	Minimum amounts of energy required to trade in markets	yes
Information asymmetry	Consumer understanding, knowledge, bounded rationalities	yes
Transaction costs	Information research cost, negotiation & decision cost, monitoring cost	yes
Provide services to the system	Ancillary services, storage and backup power to accommodate renewable production intermittency…	yes
Economies in the charging strategy	A PEV owner charging its car alone with access to markets would obtain the same results as the aggregator?	**?**

Figure 14 - Aggregation advantages

It is quite straightforward to see that aggregation is beneficial for diverse reasons, mainly to address bounded rationalities. Indeed normal individuals do not have time for everything and would not bother optimizing their charging schedule to respond to system needs because they do not care or simply lack information to do so. In that case, an aggregator taking care of all this work is recommendable. Furthermore, current regulation restrict access to energy markets with a minimum amount tradable that could not be reached by a single individual charging his own vehicle. By aggregating several vehicles, it makes economic sense to trade aggregated volumes of energy since those volumes are big enough to recover market fees. Economies of scale, scope and transactions costs reduction are appearing with any growing business, therefore developing aggregation businesses will necessary present advantages when growing bigger and bigger. Regarding services that could be provided to the system, a more detailed explanation is proposed in the state of the art part of this Thesis.

The relevant question for this Master's Thesis is the following one: Can an aggregator charge a vehicle fleet in a least cost manner than PEV owners charging their vehicles independently? Are there economies possible in the charging strategy of an aggregator with respect to the one of a single individual having access to energy markets? If such economies exist, where do they come from?

All these questions will be answered through this Thesis and backed by a mathematical simulation.

II – 4. State of the Art

This section presents a review of the literature used for the development of this Master Thesis organized around three topics: PEV aggregation, Battery degradation and charging strategies optimization models.

II – 4.a) PEV aggregation

Bessa and Matos [8] review economic and technical problems related to the aggregation of electric vehicles, present possible benefits that could arise from aggregating the charging of PEVs and key concepts. A key finding common to a lot of studies is that smart-charging would avoid higher investments needs in networks infrastructures, prevent higher energy losses and network congestion as well as reducing CO_2 emissions. EVs aggregation could also help maintaining the system more stable. This could be done through vehicle-to-grid (V2G) whereby a vehicle connected to the grid would provide energy to the network. The car would require a bidirectional charger, but V2G services could also be provided with unidirectional ones. Indeed by increasing or lowering consumption, an electric vehicle could respond to some DSOs needs.

Among the different services that aggregation of PEVs could provide, the main ones are:

- Peak power
  - EVs could be used as a peak power resource to supply electricity during high demand hours: this could be done to supply electricity to the system or for personal use at home assuming having time differentiated contract.
- Ancillary services
  - Ancillary services are needed for ensuring security of supply and quality of supply. Some examples of ancillary services are: load shedding, voltage control, black-start capability, spinning reserves, frequency control…
  - Aggregators of EVs could be paid for the availability of a given capacity (€/MW) synchronized to the grid and also for the energy provided (€/MWh)
  - Inherent characteristics of EVs make them attractive for ancillary services: distributed location & fast response, automation possible.
- Storage and renewable energy
  - Storage and backup power provided by EVs could help further integrating intermittent renewable generation.
- Other services possible
  - Reactive power management, load curtailment, peak shaving

As stated in [8], all aforementioned services are becoming interesting from a network perspective if provided by a large fleet of EVs although some could be provided by individual vehicles like demand response. Therefore aggregation appears essential for reaching a minimum power capacity to trade in markets or establish contract with power utilities (at least 1 MW).

From a business model point of view, several concepts have been proposed, one being an aggregator fully in charge of managing batteries (deterioration costs, cycling, replacement…) while complying with the driving needs of his clients. Another one could be to split benefits of aggregation to clients through direct payments or additional battery warranty.

II – 4.b) Battery degradation

The battery is the core of V2G applications. Indeed, charging and discharging batteries to provide services to the system will accelerate its degradation and reduce its lifespan. Although battery degradation does not represent the main focus of this Master' Thesis, it has been taken into consideration when developing the optimization models of this study. Usually, it is considered that a battery needs to be replaced after losing 20% of its initial capacity although each manufacturer sets its recommendations. The linear formulation as well as basic assumptions of batteries degradation used in this Thesis are coming from [9] . The main ideas developed in this paper with regards to battery degradation are the following ones:

1. The battery degradation coefficient depends on:
    a. Driving patterns
    b. Battery type
2. Considering a driving pattern of 25 miles per day (40km/day) 330 days a year:
    a. Around 20% of the capacity of the battery will be deteriorated after 5 years of utilisation for V2G and mobility purposes. This last assumption gives us the battery degradation coefficient.

The linear formulation of the cost of battery degradation appears conceptually as follow:

$$\frac{battery\ cost\left[\frac{€}{kWh}\right]\times Degradation\ coefficient\times energy\ flows\ in\ and\ out\ of\ the\ battery[kWh]}{0{,}2}$$

The above equation is divided by 0,2 because it is considered that a battery needs to be replaced after losing 20% of its initial capacity.

II – 4.c) Charging strategies optimization models

Several PEV coordination models have been proposed by Momber [10] in his doctoral Thesis under different charging strategies: DLC and ILC. For direct load control, the model underlying assumption is a contract between the aggregator and the PEV owner giving right to the aggregator of exercising DLC. Under this scheme, the aggregator decides when and how much to charge in function of market prices. Under ILC, a bi-level optimization model was proposed. The upper level characterizes the optimal strategy of the aggregator regarding market bids and retail prices while the lower level focuses on the minimization of mobility costs, i.e. the determination of the cheaper way for PEV owners to charge their vehicles.

Apart from coordination strategies of electric vehicles, Momber [10] provides a global view of aggregation and a complete literature review regarding relevant topics for this Master Thesis such as battery degradation, assumptions on mobility behaviour and PEV aggregators' role. This doctoral Thesis represents the main source of information used to develop this Master Thesis and the starting point for the mathematical formulations proposed.

II – 4.d) Conclusion on the state of the art

Many aspects of aggregation have already been studied, from the range of services that could be provided to the impact on networks operations and incremental investments required to deal with EVs. However a research gap has been identified regarding the added economic value of the aggregator charging strategy. Understanding the added value of the aggregator charging strategy and analysing which factors have an influence on the benefits of aggregation has not already been studied to the author's deepest knowledge. What is the impact of imbalance prices on the benefits of aggregation? What is the impact of capacity charges or battery degradation when considering V2G? Does the value of aggregation depends on the size of the PEV fleet? What happens when grid to battery efficiency is considered?

This master's Thesis aims to shed some light on the aforementioned questions and will try to provide a rational and comprehensive analysis backed by mathematical models to assess the value of PEV aggregation.

CHAPTER III: Aggregation economic value

III – 1. Comparison methodology

The purpose of this section is to present the methodology followed to assess the economic value of plug-in electric vehicle aggregation. Roughly speaking, this value is obtained as the difference in the results of two optimization models:

- One representing the optimal strategy of an aggregator charging a vehicle fleet under his control (model 3)
- The other characterizing the optimal strategy of PEV owners charging their car independently (model 2)

The global process of this study is illustrated by figure 15 and detailed below. Before further explaining the methodology followed, let us define the major assumptions of this comparison.

III – 1.a) General assumptions

The basic assumptions underlying the different models elaboration are the following one:

1. The value of aggregation is only estimated for the balancing market
2. Perfect information is assumed:
    a. Market Prices
    b. Daily information of PEV behaviour
3. The aggregator is a price taker
4. PEV owner optimizing their energy purchases for charging their vehicles have access to the different markets.

Arbitraging in the DAM has not been considered in this study, but it could represent a good opportunity for an aggregator to make additional profits (see later figure 16). A major assumption is that all the models are deterministic: market prices are known in advance whereas in real life, those prices would have to be estimated for the BM and the DAM. In both models considering balancing markets, all deviations are known in advance for the rest of the day, therefore the aggregator having perfect information regarding the behaviour of its clients can optimize in a better way the charging of its vehicle fleet. In reality, those deviations are revealed throughout the day, giving the aggregator less flexibility to plan the charging of the vehicles under his control. For instance if at 9 a.m. a PEV owner informs the aggregator that he is going to disconnect his car from the grid at 8 p.m., the latter knowing that fact can adapt the charging schedule of this particular car and all the others composing its fleet accordingly since 9 a.m. in the morning. If the aggregator does not have that information before real time, his playing ground to cope with that deviation is much smaller and thus, he will likely incur in higher costs to deal with it. Therefore, real-time communication between the aggregator and its clients appears as a concern of interest to reduce imbalance costs.

The assumption considering the aggregator as a price taker has a simple and rational explanation: a maximum fleet of 1500 PEV is considered in this study which represents a daily consumption of 30 000 kWh if each vehicle is charged for a 100 km every day (consumption around 20kWh/100km). Now, if this amount is compared to the daily amount of energy traded in spot markets, it appears insignificant. Indeed, taking a look at the hourly energy demand of the Iberian market the third of June 2015, it can be seen that it lies between roughly 23 GWh and 35 GWh. Several orders of magnitudes separate the aggregator consumption from the global daily consumption, thus, for an aggregator to have influence on prices, it would require a very large vehicle fleet.

Finally, in order to compare the charging strategy of a PEV owner on its own and the one of an aggregator, full access to markets is assumed for single PEV owners. By unrestricted access to markets is meant that a single PEV owner can buy energy or sell it in the different markets without minimum energy thresholds or entry barriers (such as market participation fees).

III – 1.b) Global process

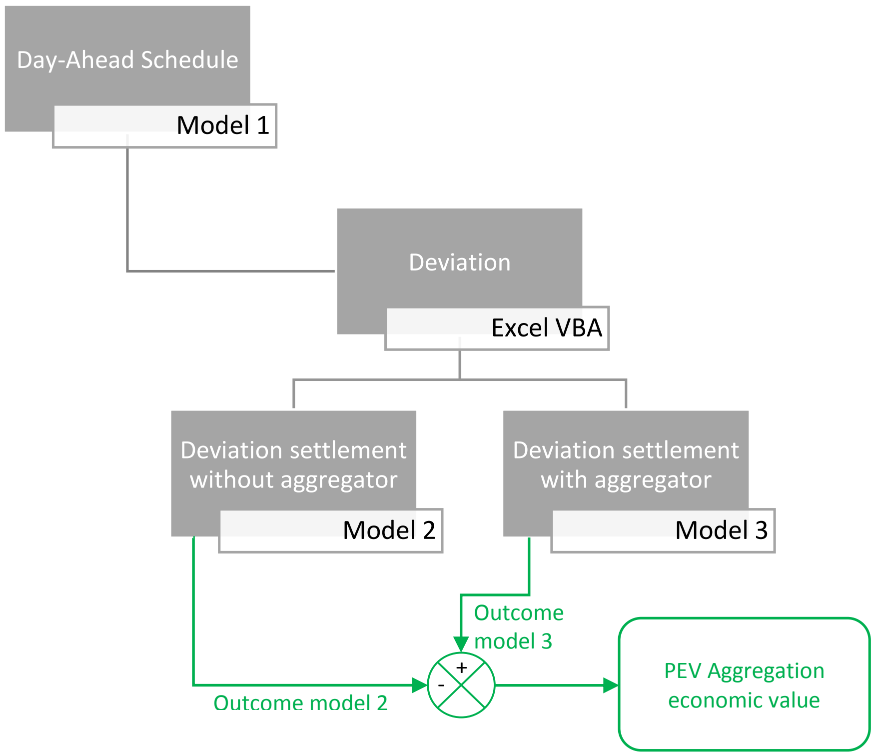


Figure 15- Comparison global process

As explained earlier, the economic value of aggregation in balancing markets is obtained as the difference in results coming from model 3 and 2. Four different steps have been designed to get to the final outcome:

1. Day-Ahead schedule
2. Deviation simulation
3. Deviation settlement without aggregator
4. Deviation settlement with aggregator

The first step is to establish the day-ahead schedule, i.e. the energy to buy for charging PEVs in the day-ahead market. No differentiation is made in this first step between an aggregator charging several vehicles at the same time or a PEV owner charging his own vehicle. The main rationale behind this is that optimal purchases are the same for an agent charging one vehicle or another one charging a thousand cars. Indeed, if we consider that all batteries are depleted at the beginning of the day, the optimal hours to buy electricity will be the same in both cases, i.e. the cheapest hours of the DAM. In reality there are possible synergies between the PEVs constituting the vehicle fleet of an aggregator which were not taken into account in this study for the DAM. Let us consider a simple example with two electric vehicles. If the price variation of the DAM was to be really high along a day and allowed to recover the cost incurred in transferring energy from one vehicle battery to the other, a situation as the one depicted in figure 16 could arise.

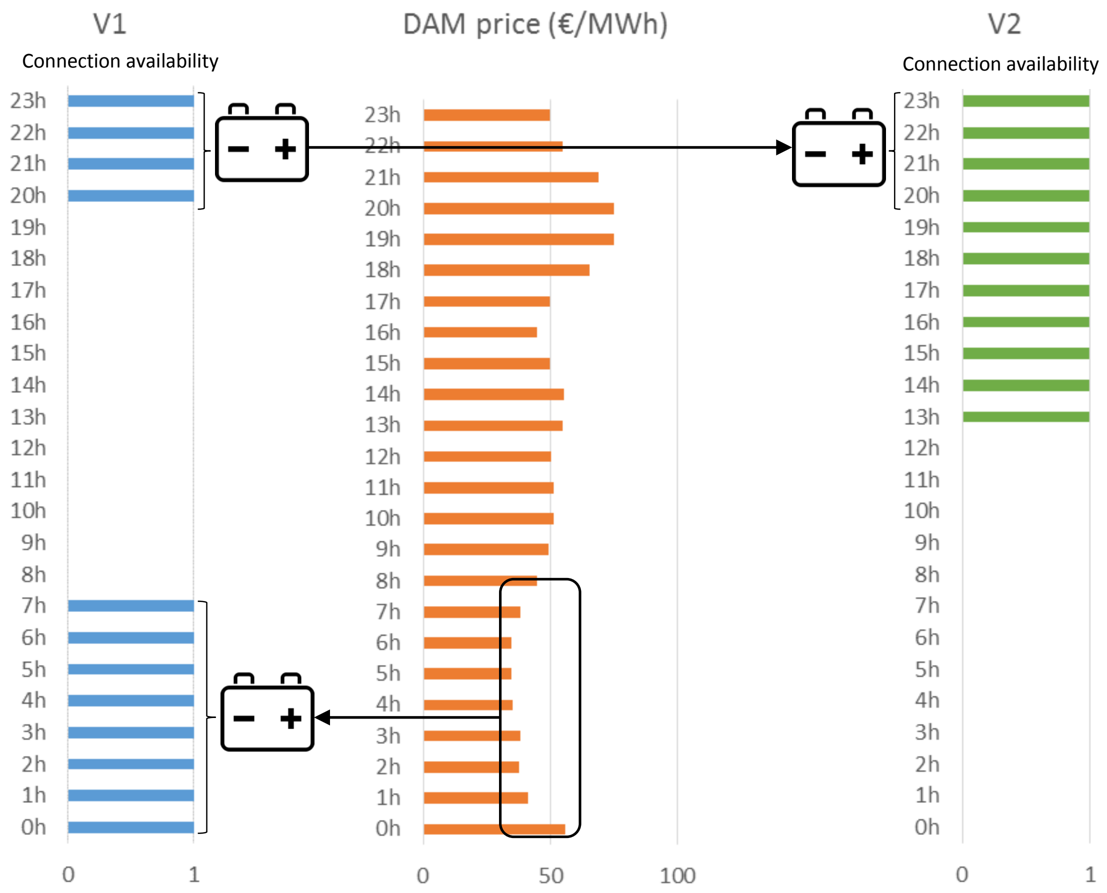


Figure 16 - Day-ahead benefits of aggregation

If the connection availabilities to the grid of two cars offer some complementarities, a car (v1) could charge more energy than needed and later transfer that surplus of energy bought at a cheaper price to another vehicle (v2). This is possible only if the price differential of the DAM is enough to recover the transfer of energy between both PEVs.

As aforementioned, this study emphasizes on the value of aggregation in the BM. Thus, arbitraging in the DAM has not been considered as it lies outside the scope of this thesis. In order to conduct a rigorous comparison of both models considering aggregation and no aggregation (model 2 and 3), a common base is needed to see if one provides better results than the other. Having a different day-ahead schedule for the aggregator model and the PEV owner one does not make much sense since it would result in a flawed comparison between two models under distinct initial conditions.

The common base for comparing the two different approaches is an already established day-ahead schedule consisting of the optimal purchases in the DAM for charging the vehicles the following day.

The second step of this study is the deviation simulation: the optimal DA schedule obtained with model 1 is altered by a random deviation simulation to account for the uncertainty of PEVs owners' behaviour in real time. This altered DA schedule is then used as input data for running models 2 and 3. Those two last models depict the optimal strategy to cope with deviations in real time, i.e. imbalances arising from a higher consumption of energy than foreseen or the opposite. Finally the difference between the two last models, one considering aggregation the other not considering it, gives the value of aggregation in balancing markets.

III – 2. Day-Ahead schedule

The day-ahead schedule (purchases of electricity in the DAM for charging batteries the next day) is obtained according to PEVs owner preferences:

- Connection status of the vehicle to the grid (hours of connection)
- Energy to be charged in the battery for the following day

The first requirement represents the number of hours that a PEV owner is going to connect his car to the grid along the day. It could be three, four or ten hours depending on the life style of the owner. The second one depicts the daily energy needs for the personal mobility of the PEV user. The amount of energy to be charged for a day according to user preferences is assumed to be reached the last hour of connection to the grid of this same day. Let us define a small example to fully grasp how user preferences are defined:

- A PEV owner wants to charge his car to be able to drive 50km the next day
- He is leaving his house at 8 o'clock in the morning and will plug his car since midnight.

The distance requirement is converted in energy requirement with a simple product. For instance, the Tesla model S 85 has a battery of 85 kWh for an autonomy of 265 miles (~425 km). Therefore, 50 km would represent a charge of $(50 \times 85) \div 425 = 10kWh$.

As it will be seen later in the presentation of the different models and equations, the battery state of charge of each vehicle is subject to a minimum energy requirement defined by the PEV owner. That is, in this small example to have a minimum of 10 kWh in the battery for 8 o'clock in the morning. Whatever happens between midnight and 8 a.m. does not really matter as long as the car is charged for the user leaving at 8 a.m. From 8 a.m. until the rest of the day, driving discharges of the battery are not simulated, all models focus only on optimal purchases and the requirement of energy set by the user for the next day.

Five different profiles of preferences have been defined for this study, each one having its own connection availability and energy requirements for the next day. Connection availability is an extremely important parameter for charging electric vehicles. Indeed, the more flexibility available, i.e. the higher number of hours connected to the grid, the cheapest it will be to charge the vehicle. Prices of the DAM are changing every hour, and are usually lower during the night. Therefore if a PEV is plugged-in during the night, the cost for charging the car battery will be lower than if the vehicle was only connected during the day when prices are normally higher. Figure 18 shows quite well the price volatility of the DAM along a single day, highlighting the importance of the connection availability to the grid. Connection to the grid is conditioned by several factors, mainly by the habits of PEV owner. Most people work during the day and would connect their vehicle during the night when coming back to their house. Therefore connection availability from 21h until 7h the following day seems reasonable and probable. If charging infrastructures were available at working places, connection availability could almost be extended the whole day.

The energy to charge in a car battery, i.e. the energy to buy in the DAM, depends on the driving patterns of PEVs owner. An interesting statistic delivered by Eurostat revealed that Europeans do an average of 30km to 40km per day across all modes of transport. If we consider a typical rate of charge of 3kWh and an average consumption of 20kWh to drive 100 km with a PEV, less than 3 hours and half are needed to charge a battery for 50 km autonomy. Consequently, a single night connected to the grid is more than enough to meet most people daily needs.

Another crucial parameter when talking about charging electric vehicles is the maximum rate of charge of batteries. Globally speaking, the maximum amount of energy that can be charged in a car battery during a single hour is limited by two factors: the house contracted capacity and the maximum rate of charge of the battery itself. The optimal house capacity to contract considering average driving patterns and PEV owner connection habits is detailed in part IV – 2 of this Master's thesis.

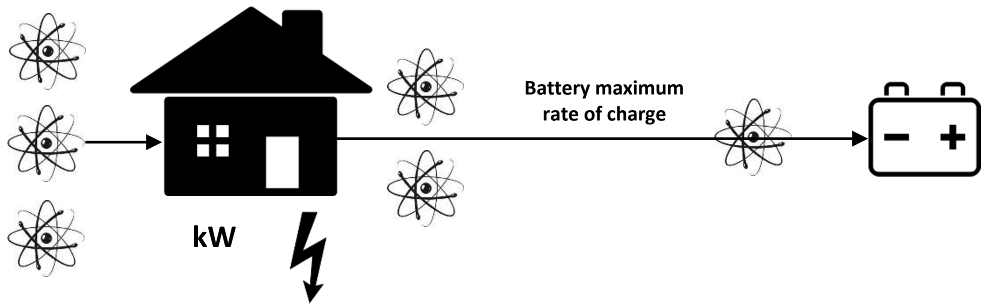


Figure 17 - Factors limiting the battery rate of charge

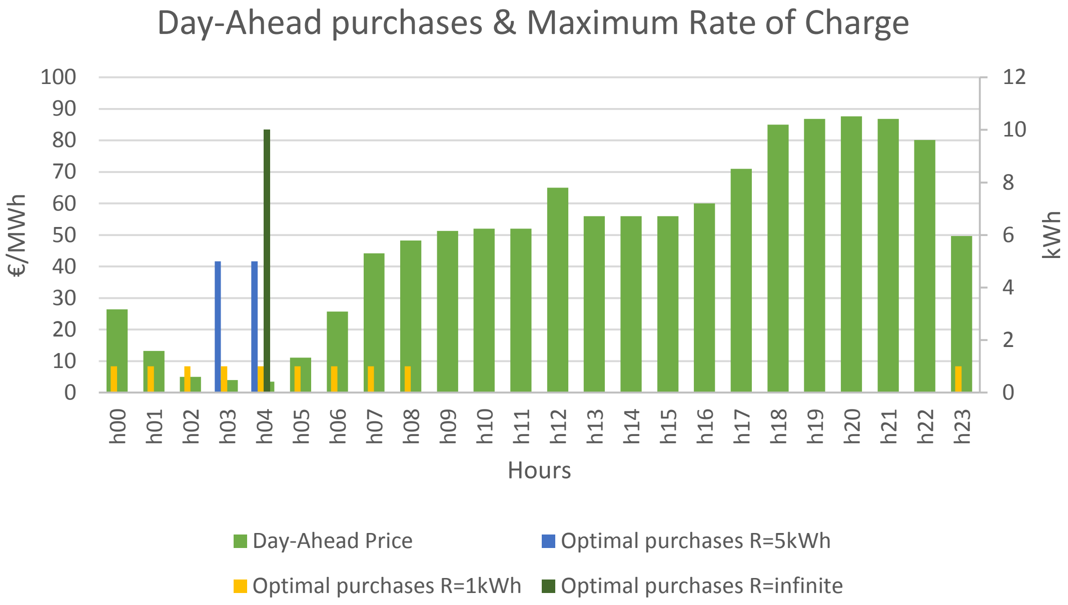
Figure 17 illustrates the different elements having an effect on the final maximum rate of charge of a car battery. The house capacity is the first element restricting the maximum rate of charge of a car battery. Let us imagine that the house capacity contracted is 3 kW and that the battery maximum rate of charge is 7 kW. Since a power of 7 kW is not available when plugging-in the EV to the house, the real maximum rate of charge of the battery will in that case be reduced to 3 kW, i.e. the capacity contracted and not the technical maximum of the battery itself.

The rate of charge is one of the most important feature of car batteries because of the correlation between the following parameters:

- Market prices
- Connection availability to the grid
- Maximum rate of charge of the battery

Indeed, the higher the rate of charge the better since in one hour more energy can be charged in a battery, the objective being to make the most of low prices hours of the DAM. With unlimited house capacity and car rate of charge, it is easy to see that the optimal strategy would be to charge the vehicle at the cheapest hour of the day.

Graph 18 depicts a simple example of the optimal purchases to reach 10 kWh in a battery considering different maximum rate of charge and having a PEV connected to the grid the whole day.



	R=1kWh	*R=5kWh*	*R= infinite*
DA energy cost	0,2310 €	0,0373 €	0,0345 €

Figure 18 - Day-ahead purchases and rate of charge limitation

As shown by table 18, the energy cost incurred for charging 10 kWh with a rate of charge of 1kWh is roughly the sextuple of having a battery with a 5kWh rate of charge. Usually the rate of charge of car batteries is not the most limiting factor regarding charging time or optimal purchases in the DAM. It is rather the available power at home that restricts the charging rate of batteries. Houses circuits normally deliver a power around 3 kW which means that in ten hours, 30kWh can be charged in the battery. As aforementioned, electric vehicles consume around 20kWh/100km. Considering a charge for driving 300 km, it would take around 3 minutes to do it at a filling station with petrol. To be able to charge an EV in 3 minutes, it would require a connection of 1200kW to obtain the same charging time! This is obviously a tremendous amount of power, therefore, when talking about fast-charging, the charging time is usually of 30 min with powerful infrastructures delivering around 120kW.

III – 3. Deviation simulation

To compute the benefits of aggregation in the balancing market, deviations from the DA schedule have been simulated. BMs only exist to correct real-time imbalances (higher or lower energy consumption than expected). Therefore, if no deviations from the initial DA schedule appear, apart from doing arbitraging, there would be no need to participate in BMs since no more energy would be needed to charge PEVs according to PEVs owners' day ahead plan. Without deviations, i.e. imbalances with respect to previous commitments, the balancing market is useless.

For electric vehicles, deviations have a special meaning. Imbalances arise due to the uncertainty of people behaviour when using their car in real life. Indeed, although a PEV user would like his car ready for a certain hour the next day, unexpected events may crop up and alter the DA planning. A simple example to illustrate the latter is set out below:

- A PEV was supposed to be connected to the grid at 10 a.m. and is eventually not connected during that hour.
- Energy had been bought in the DAM for the PEV during that hour.

This change of planning is affecting the balance between supply and demand in real time. As explained earlier, it is the responsibility of the SO to maintain the equilibrium between production and consumption at all time. In this example, the PEV owner is not consuming the energy it should have consumed at 10 a.m., thus, a surplus of energy is appearing: the vehicle owner is creating a positive imbalance for the system. A second effect arising when disconnecting a car from the grid is an implicit one: the car is used for driving. Therefore, when driving, the battery is discharging itself. If a battery is discharged due to unforeseen mobility needs, the energy required to charge the car according to the day-ahead plan will be higher since extra energy was used for driving. In that case, the initial schedule obtained with optimal DAM purchases will be altered and more energy will be bought to compensate for driving unforeseen needs: the PEV owner is creating a negative imbalance for the system.

Technically speaking, deviations have been simulated in excel via the build-in programming tool in Visual Basic. How so? Basically, disconnection and connection are generated randomly to affect the initial DA schedule along with changes in the amount of energy to be charged if desired. Furthermore, when a car was supposed to be connected to the grid according the DA planning and is not in real time, a discharge of the battery is produced to simulate unexpected driving needs.

III – 3.a) Uncertainty of PEV owner behaviour

Behavioural changes are simulated according to a percentage α of deviation defined for the whole comparison between the charging strategy of an aggregator and the one of a PEV owner on its own. This percentage is affecting the connection schedule as well as the energy requirements for charging the car.

The global procedure to obtain those deviations is illustrated by figure 19. The VBA code will not be detailed in this report since it does not provided added value for the understanding of the approach followed. However, the code is provided in the annexes of this report.

First, the deviation percentage α is defined for the simulation. Then, for each PEV, the total number of hours of connection to the grid of the DA schedule is calculated. By multiplying this number by the percentage α, the total number of connection/disconnection deviations for the whole day is obtained. The question now is how to distribute this amount of connection/disconnection through the day. In general terms, people are unlikely to change their plan in the middle of the night. Therefore a distribution of possible changes through the day has been considered to try to reflect as much as possible reality. This distribution is presented in figure 20.

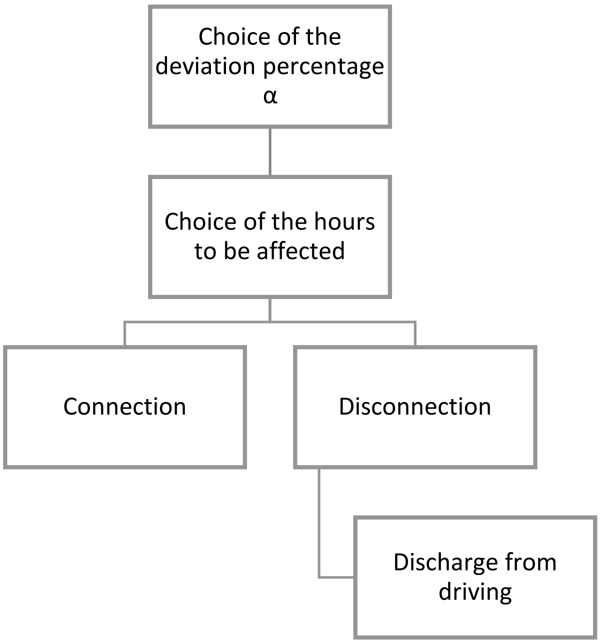


Figure 19 - Deviation simulation process

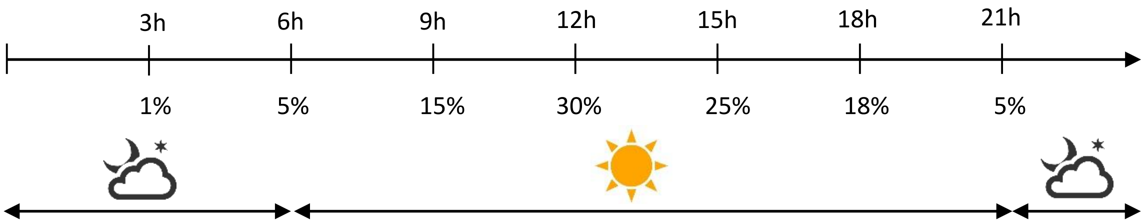


Figure 20 - Deviation distribution through the day

When affecting the connection parameter of a car to the grid, first an hour of the day is chosen randomly according to this distribution. From that hour to the last one of the current day, connections and disconnections will be applied randomly by an exact amount of the total number of connections/disconnections deviations calculated as a function of α. If a car was initially connected to the grid in the DA program, it is disconnected and a discharge of 3 kWh of the battery is generated to simulate driving needs. Currently, electric cars consume around 20kWh/100km. The aggregator model and the one without aggregation being scaled on a half hour basis; a 3kWh discharge represents a 15 km trip in half an hour. Conversely, when the car is initially not connected to the grid in the DA program, the deviation simulation connects it to the grid.

III – 4. Imbalance settlement with and without aggregator

The deviation settlement or imbalance settlement represents the last step of this comparison between aggregation and no aggregation. Both models (2 and 3) are scaled on half hour basis to better account for deviations along the day: connection and disconnection may be generated for half hours period by the deviation simulation. Another reason for scaling those models on a half hour basis is that in several countries imbalance prices change every 30 minutes. This is the case of France for instance.

For the model not considering aggregation (model 2), every single vehicle composing the fleet is charged independently from the others. Therefore, no interaction is possible between the different vehicles to reduce imbalances. When charging a car under this scheme, the only possibility for a vehicle to correct its imbalances is to interact with the balancing market: sell or buy energy.

Conversely, the aggregation model considers the possibility to reduce imbalance costs by netting deviations of energy consumption among the whole vehicle fleet. For example if two cars deviate from their schedule at the same moment, one positively (consuming less energy than expected) and the other negatively (consuming more energy than expected), the overall deviation could be zero, one deviation compensating the other. In that case, no need to buy or sell energy in the balancing market which usually penalizes agents with respect to their DA schedule (buying energy in the balancing market is always more expensive or equal to the DA price under dual imbalance pricing). Therefore, with aggregation, the cost of mitigating imbalances could be reduced. This is actually the objective of this master thesis, to estimate how much an aggregator could reduce the costs of charging EVs.

The aggregation model has been developed with the following assumptions:

- The aggregator receives all the information regarding its clients driving needs and connection to the grid. The balancing model is deterministic, all deviations are known in advance.
- The aggregator takes into account all the information provided by PEV owners to manage a "virtual power plant" made of its EV fleet: the number of cars connected during a given hour and the energy available is known.

III – 5. Decision models

III – 5.a) Day-ahead schedule

$$\textbf{\textit{Objective Function}}: \quad Min \sum_{h,v} e_{h,v}^{DA} . p_h^{DA} \qquad (1)$$

$$\textbf{\textit{Subject to}}: \left\{ \begin{array}{lll} \forall(h,v) & b_{h,v} = b_{h-1,v} + \eta_v . e_{h,v}^{DA} + i_v^{SOC} \; [if \; h = 0] & (2) \\ \forall(h,v) & b_{h,v} - b_{h-1,v} \leq \overline{R}_v . c_{h,v} & (3) \\ \forall(h,v) & \underline{B}_{h,v} \leq b_{h,v} \leq \overline{B}_v & (4) \\ \forall(h,v) & e_{h,v}^{DA} \geq 0 \; ; \quad b_{h,v} \geq 0 & (5) \end{array} \right\}$$

SETS

h Hours [0h – 23h]
v Vehicles

PARAMETERS

p_h^{DA}	Hourly day-ahead market price	[€/kWh]
η_v	Grid to battery efficiency of the vehicle v	[p.u.]
i_v^{SOC}	Initial state of charge of the vehicle v	[kWh]
$\overline{R}_v$	Maximum rate of charge of the vehicle v	[kWh]
$c_{h,v}$	Connection status of the vehicle to the grid 1 means that the vehicle is connected, 0 that it is disconnected	[0/1]
$\overline{B}_v$	Maximum battery state of charge	[kWh]
$\underline{B}_{h,v}$	Minimum battery state of charge	[kWh]

VARIABLES

$e_{h,v}^{DA}$	Energy to buy in the day-ahead market in the hour h for the vehicle v	[kWh]
$b_{h,v}$	Battery state of charge during the hour h of the vehicle v	[kWh]

MODEL EXPLANATION

The objective of the DA market model is to buy electricity in the least-cost manner possible while complying with PEV owner's requirements. Therefore the objective function (1) is the minimisation of the energy to buy for each PV in the DAM. The second equation depicts the battery balance through time. The battery state of charge in an hour is equal to the energy that was in the battery the hour before plus the energy bought during that hour and the addition of the initial state of charge of the battery. The energy bought in the DAM is reduced by the grid to battery efficiency. Equation (3) ensures the charging limitation of the battery during an hour with respect to the previous one. If the vehicle is connected to the grid, the vehicle can be charged by a maximum amount of the maximum rate of charge, else the state of charge of the battery from an hour to the other remains the same. The fourth equation defines the bounds of the battery state of charge. The lower bound is defined by the PEV owner who might want is car ready for a certain hour with a certain amount of energy available in his battery. Finally, equations (5) define positive variables.

III – 5.b) Deviation settlement without aggregator

OBJECTIVE FUNCTION

$$Max \sum_{h,v} \left[(Q_{h,v}^{\uparrow} + [c_{h,v}.\delta_{h,v} + (1 - c_{h,v})].e_{h,v}^{DA}).p_h^{BM+} - Q_{h,v}^{\downarrow}.p_h^{BM-} - e_{h,v}^{DA}.p_h^{DA} \right] - \frac{\sum_v \left[B_v^{cost}.B_v^{deg}.\sum_h \left(Q_{h,v}^{\uparrow} + Q_{h,v}^{\downarrow} + c_{h,v}.(1 - \delta_{h,v}).e_{h,v}^{DA} \right) \right]}{0,2} \quad (1)$$

SUBJECT TO

$$\forall (h,v) \qquad b_{h,v} = b_{h-1,v} + \eta_v.\left(Q_{h,v}^{\downarrow} + c_{h,v}.(1 - \delta_{h,v}).e_{h,v}^{DA}\right) - \frac{Q_{h,v}^{\uparrow}}{\eta_v} - L_{h,v}^{driving} + i_v^{SOC} \quad (2)$$

$$\forall(h,v) \qquad \underline{B}_{h,v} \leq b_{h,v} \leq \bar{B}_v \tag{3}$$

$$\forall(h,v) \qquad 0 \leq Q^{\downarrow}_{h,v} \leq (\frac{\bar{R}_v}{\eta_v} - e^{DA}_{h,v}).c_{h,v}.\left(1-\delta_{h,v}\right) \tag{4}$$

$$\forall(h,v) \qquad 0 \leq Q^{\uparrow}_{h,v} \leq y_{h,v}.c_{h,v} \tag{5}$$

$$\forall(h,v) \qquad y_{h,v} \leq \bar{B}_v.\delta_{h,v} \tag{6}$$

$$\forall(h,v) \qquad -b_{h-1,v} + y_{h,v} \leq 0 \tag{7}$$

$$\forall(h,v) \qquad b_{h-1,v} - y_{h,v} + \bar{B}_v.\delta_{h,v} \leq \bar{B}_v \tag{8}$$

$$\forall(h,v) \qquad b_{h-1,v} \leq \bar{B}_v \tag{9}$$

$$\forall(h,v) \qquad 0 \leq Q^{\uparrow}_{h,v} \leq \bar{R}_v.\eta_v.c_{h,v}.\delta_{h,v} \tag{10}$$

SETS

h	Half hours	[1-48]
v	Vehicles	

PARAMETERS

p^{DA}_h	Day-ahead market price during the period h	[€/kWh]
p^{BM+}_h	Balancing market price for positive imbalance during the period h	[€/kWh]
p^{BM-}_h	Balancing market price for negative imbalance during the period h	[€/kWh]
$e^{DA}_{h,v}$	Energy bought in the day-ahead market for the vehicle v during the period h	[kWh]
η_v	Grid to battery efficiency of the vehicle v	[p.u.]
i^{SOC}_v	Initial state of charge of the vehicle v	[kWh]
$\overline{R}_v$	Maximum rate of charge/discharge of the vehicle v	[kWh]
$c_{h,v}$	Connection status of the vehicle to the grid during the period h 1 means that the vehicle is connected, 0 that it is disconnected	[0/1]
$\overline{B}_v$	Maximum battery state of charge of the vehicle v	[kWh]
$\underline{B}_{h,v}$	Minimum battery state of charge of the vehicle v during the period h	[kWh]
B^{cost}_v	Battery replacement cost of the vehicle v	[€/kWh]
B^{deg}_v	Battery degradation coefficient of the vehicle v	[p.u.]
$L^{driving}_{h,v}$	Battery discharge due to driving needs of the EV owner	[kWh]

VARIABLES

$Q^{\downarrow}_{h,v}$	Energy bought in the BM during the period h for the vehicle v	[kWh]
$Q^{\uparrow}_{h,v}$	Energy sold from the battery in the BM during the period h for the vehicle v	[kWh]
$b_{h,v}$	Battery state of charge during the period h of the vehicle v	[kWh]
$\delta_{h,v}$	Binary decision variable of buying (0) or selling (1) electricity in the BM	[0/1]
$y_{h,v}$	Auxiliary variable to linearize the product $b_{h,v}.\delta_{h,v}$	[kWh]

MODEL EXPLANATION

The model aims to reduce the maximum possible the cost of imbalances of a PEV owner without aggregator. Imbalances occur when a PEV owner had bought energy in the DAM at a certain hour and eventually is not connected the day d at this specific moment. Therefore the PEV is not consuming the energy it should have been consuming hence incurring in a positive imbalance. The objective function (1) is a maximization because theoretically, by selling energy to the SO contained in a car battery, a profit could potentially arise. A car owner could try to make money by arbitrating in the balancing market if circumstances are favourable to do so. The objective function is divided into two parts: the first one deals with the energy to buy or sell in the balancing market as well as the energy already bought in the DAM. The second part depicts the cost arising from the degradation of batteries due to the flows of energy going in and out when charging or discharging the vehicle, i.e. selling or buying energy in the markets.

$$Max \boxed{\sum_{h,v}\left[\left(Q^{\uparrow}_{h,v} + \left[c_{h,v}.\delta_{h,v} + (1-c_{h,v})\right].e^{DA}_{h,v}\right).p^{BM+}_{h} - Q^{\downarrow}_{h,v}.p^{BM-}_{h} - e^{DA}_{h,v}.p^{DA}_{h}\right]} - \boxed{\frac{\sum_{v}\left[B^{cost}_{v}.B^{deg}_{v}.\sum_{h}\left(Q^{\uparrow}_{h,v} + Q^{\downarrow}_{h,v} + c_{h,v}.(1-\delta_{h,v}).e^{DA}_{h,v}\right)\right]}{0,2}}$$

Before having a detailed explanation of the equations, the relationship between δ_h , c_h and e^{DA}_h will be fully analysed. Indeed, the correlation between the two parameters c_h & e^{DA}_h and the binary decision variable δ_h is not easy to understand at first glance. An important point to have in mind is that energy coming from the DAM (e^{DA}_h) is an input data for this model. Therefore, two decisions can be made regarding e^{DA}_h : either to charge it in the PEV battery or to sell it in the balancing market. The decision to charge or sell this energy depends on whether the vehicle is connected to the grid (c_h), the decision to buy or sell energy in the BM (δ_h) and the energy requirement for driving. When the PEV is not connected to the grid the day d during a period h and electricity had been bought in the DAM for this same exact period, the energy purchased cannot be charged in the car battery. Therefore, the only option for the PEV owner is to sell that energy in the BM. On the other hand, when the car is connected to the grid, the decision to sell or charge e^{DA}_h will depend on the binary decision variable to buy or sell energy in the BM. All the possibilities are summarized in the figure 21 presented below.

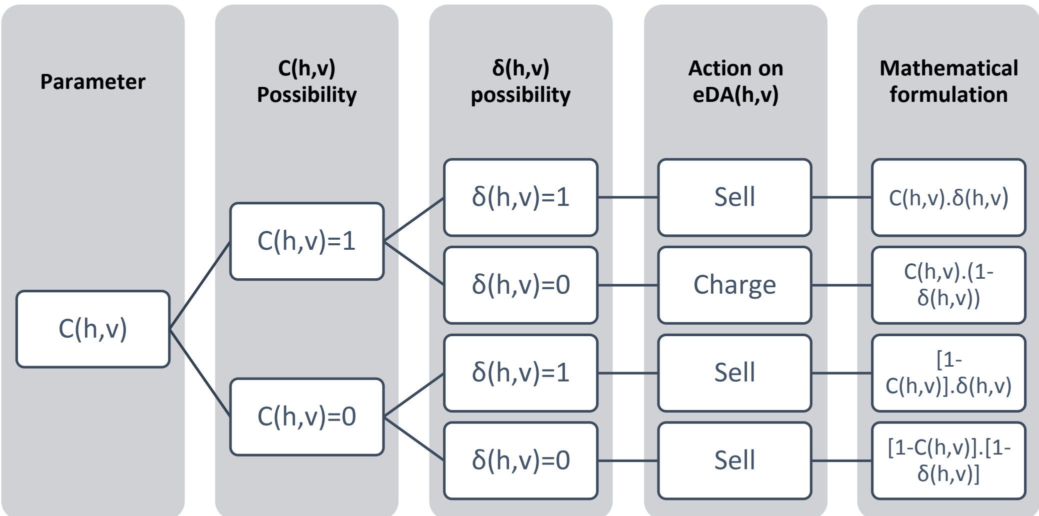


Figure 21 - PEV owner possible strategies

It can be easily seen that the energy already bought in the day-ahead market will be sold in the balancing market in three cases. The DA energy to be sold can be mathematically formulated as follow:

$$[\, c_{h,v}.\,\delta_{h,v} + (1 - c_{h,v}).\,\delta_{h,v} + (1 - c_{h,v}).\,(1 - \delta_{h,v})].\,e_{h,v}^{DA}$$

This formulation can be further reduced to:

$$[c_{h,v}.\,\delta_{h,v} + (1 - c_{h,v})].\,e_{h,v}^{DA}$$

This last formulation can be seen in the objective function. Similarly, the DA energy to be charged in the battery can be mathematically formulated as follow:

$$c_{h,v}.\,(1 - \delta_{h,v}).\,e_{h,v}^{DA}$$

This formulation can be found in the battery state of charge equation (2) and in the objective function dealing with battery degradation costs.

The first part of the objective function is quite straightforward, the different amount of energy bought or sold are multiplied by their respective prices to obtain the different energy costs or profits. The second part of the objective function dealing with battery cost deserves a more detailed explanation. It is assumed that 20% of the initial battery capacity is lost at the end of a 5-year lifetime and that batteries need to be replaced when losing 20% of their initial capacity. The battery degradation coefficient is computed for a day since the model is designed on a daily basis:

$$B_v^{deg} = \frac{0{,}2}{5 \times 365} = 0{,}000109589\ of\ initial\ capacity\ lost\ per\ day$$

Conceptually, the degradation cost is obtained as follow:

$$\frac{battery\ cost\left[\frac{€}{kWh}\right] \times B_v^{deg} \times energy\ flow\ in\ and\ out\ of\ the\ battery[kWh]}{0{,}2}$$

The second equation depicts the battery balance through time. The battery state of charge in a certain hour is equal to the energy that was in the battery the hour before plus or less the energy bought in the different markets during that hour. It can be noticed that if the PEV is not connected to the grid, the energy bought in the DAM will not be charged in the battery. The energy bought or sold in the different markets is affected by the grid to battery efficiency and the initial state of charge of the battery is also taken into account in equation (2). Discharge from driving also form part of this equation, due to deviation of the PEV owner from his initial schedule. Indeed, when a PEV owner is not connected to the grid when he should have been (according to the day-ahead schedule) it is assumed that the car was used for driving and a discharge of 3kWh of the battery is generated. The initial state of charge i_v^{SOC} is only added when h=0.

Equation (3) defines the bounds of the battery state of charge. The lower bound is defined by the PEV owner who might want is car ready for a specific hour with a certain amount of energy available in his battery.

Equation (4) expresses the limitation of the quantity of energy to be bought in the BM. Energy can be bought if and only if the PEV is connected to the grid (ensured by $c_{h,v}$). Another important point is that energy cannot be bought or sold at the same moment, i.e. the battery cannot be physically charged and discharged at the same moment. This is ensured by the binary decision variable of buying or selling energy $\delta_{h,v}$. If the vehicle is connected to the grid, the vehicle can be charged by a maximum amount of the rate of charge Therefore that maximum amount is technically the difference between the maximum rate of charge increased by the grid to battery efficiency and the energy already bought in the DAM.

Equations (5) (6) (7) (8) and (9) are a linearization of the following equation:

$$\forall(h\,,v) \qquad 0 \leq Q^{\uparrow}_{h,v} \leq \boldsymbol{b_{h-1,v}} \,.\, \boldsymbol{\delta_{h,v}} .\, c_{h,v}$$

The maximum energy that can be sold in the BM during the period h is the energy that was in the battery the period before if the PEV is connected to the grid. The product $\boldsymbol{b_{h-1,v}} \,.\, \boldsymbol{\delta_{h,v}}$ needs to be linearized, $\delta_{h,v}$ being the binary decision variable to buy or sell in the BM and $b_{h-1,v}$ the variable representing the state of charge of the battery. The linearization process is explained in annexes.

III – 5.c) Deviation settlement with aggregator

OBJECTIVE FUNCTION

$$Max \sum_h \left[Q_h^{\uparrow}.p_h^{BM+} - Q_h^{\downarrow}.p_h^{BM-} - \sum_v \left(e_{h,v}^{DA}.p_h^{DA} \right) \right] - \frac{\sum_v \left[B_v^{cost}.B_v^{deg}.\sum_h \left(\xi_{h,v}^{\downarrow} + \xi_{h,v}^{\uparrow} \right) \right]}{0,2} \quad (1)$$

SUBJECT TO

$\forall(h,v) \quad b_{h,v} = b_{h-1,v} + \eta_v.\xi_{h,v}^{\downarrow} - \frac{\xi_{h,v}^{\uparrow}}{\eta_v} - L_{h,v}^{driving} + i_v^{SOC}\ [if\ h=0]$ (2)

$\forall(h\,,v) \quad \underline{B}_{h,v} \leq b_{h,v} \leq \bar{B}_v$ (3)

$\forall(h\,,v) \quad 0 \leq \xi_{h,v}^{\downarrow} \leq \frac{\bar{R}_v}{\eta_v}.\left(1-\delta_{h,v}\right).c_{h,v}$ (4)

$\forall(h\,,v) \quad 0 \leq \xi_{h,v}^{\uparrow} \leq \eta_v.\bar{R}_v.\delta_{h,v}.c_{h,v}$ (5)

$\forall h \quad \sum_v \left(\xi_{h,v}^{\downarrow} - \xi_{h,v}^{\uparrow} \right) = \sum_v \left(e_{h,v}^{DA} \right) + Q_h^{\downarrow} - Q_h^{\uparrow}$ (6)

$\forall h \quad 0 \leq Q_h^{\downarrow} \leq \sum_v \left[\left(\frac{\bar{R}_v}{\eta_v} - e_{h,v}^{DA} \right).c_{h,v}.\left(1-\delta_{h,v}\right) \right]$ (7)

$\forall h \quad 0 \leq Q_h^{\uparrow} \leq \sum_v \left(y_{h,v}.c_{h,v} + e_{h,v}^{DA} \right)$ (8)

$\forall(h\,,v) \quad y_{h,v} \leq \bar{B}_v.\delta_{h,v}$ (9)

$\forall(h\,,v) \quad -b_{h-1,v} + y_{h,v} \leq 0$ (10)

$\forall(h\,,v) \quad b_{h-1,v} - y_{h,v} + \bar{B}_v.\delta_{h,v} \leq \bar{B}_v$ (11)

$\forall(h\,,v) \quad b_{h-1,v} \leq \bar{B}_v$ (12)

$\forall h \quad 0 \leq Q_h^{\uparrow} \leq \sum_v \left[\eta_v.\bar{R}_v.c_{h,v}.\delta_{h,v} \right] + \sum_v \left(e_{h,v}^{DA} \right)$ (13)

SETS

h Half hours [1-48]
v Vehicles

PARAMETERS

p_h^{DA}	Day-ahead market price during the period h	[€/kWh]
p_h^{BM+}	Balancing market price for positive imbalance during the period h	[€/kWh]
p_h^{BM-}	Balancing market price for negative imbalance during the period h	[€/kWh]
$e_{h,v}^{DA}$	Energy bought in the day-ahead market for the vehicle v during the period h	[kWh]
η_v	Grid to battery efficiency of the vehicle v	[p.u.]
i_v^{SOC}	Initial state of charge of the vehicle v	[kWh]
$\overline{R}_v$	Maximum rate of charge/discharge of the vehicle v	[kWh]
$c_{h,v}$	Connection availability of the vehicle v to the grid during the period h	[0/1]
$\overline{B}_v$	Maximum battery state of charge of the vehicle v	[kWh]
$\underline{B}_{h,v}$	Minimum battery state of charge of the vehicle v during the period h	[kWh]
B_v^{cost}	Battery replacement cost of the vehicle v	[€/kWh]
B_v^{deg}	Battery degradation coefficient of the vehicle v	[p.u.]
$L_{h,v}^{driving}$	Battery discharge due to driving needs of the EV owner	[kWh]

VARIABLES

$Q_h^{\downarrow}$	Energy bought in the balancing market during the period h	[kWh]
$Q_h^{\uparrow}$	Energy sold in the balancing market during the period h	[kWh]
$\xi_{h,v}^{\downarrow}$	Energy to charge in the vehicle v during the period h	[kWh]
$\xi_{h,v}^{\uparrow}$	Energy to discharge in the vehicle v during the period h	[kWh]
$b_{h,v}$	Battery state of charge during the period h of the vehicle v	[kWh]
$\delta_{h,v}$	Binary decision variable of buying (0) or selling (1) electricity in the BM	[0/1]
$y_{h,v}$	Auxiliary variable to linearize the product $b_{h,v} . \delta_{h,v}$	[kWh]

MODEL EXPLANATION

The model defines the optimal strategy of an aggregator to charge its vehicle fleet. The general idea is to consider the energy available as a whole and distribute it across the vehicle fleet optimally. PEVs' imbalances are optimized globally, taking advantage of synergies arising with the vehicle fleet. Imbalances occur when a PEV owner had bought energy in the DAM for a certain hour and is eventually not connected the day d at this specific moment. Therefore the PEV owner is not consuming the energy he said he would hence the imbalance. The objective function (1) is a maximization because theoretically, by selling energy to the SO contained in the batteries, a profit could be made. The aggregator could try to make money by arbitrating in the balancing market if circumstances are favourable to do so. The objective function is divided into two parts: the first one deals with the energy bought or sold in the balancing market as well as the energy already bought in the DAM. The second part depicts costs arising from batteries degradation due to the flows of energy going in and out when charging or discharging the batteries.

The only difference with the previous model is that here, energy is bought or sold for the whole vehicle fleet at the same time, and vehicles charging strategies are not independent from each other's anymore. Assumptions for the degradation of batteries are exactly the same as for the model without aggregator.

The second equation depicts the battery balance through time. The battery state of charge in a certain hour is equal to the energy that was in the battery the hour before plus or less the energy to charge or discharge during that hour. The energy charged is reduced by the grid to battery efficiency, the energy discharged is increased by this same grid to battery efficiency and the initial state of charge of the battery is also taken into account. Discharge from driving also form part of this equation, due to deviation of the PEV owner from his initial schedule. Indeed when a PEV owner is not connected to the grid when he should have been (according to the day-ahead schedule), it is assumed that the car was used for driving and a discharge of 3kWh of the battery is generated.

Equation (3) defines the bounds of the battery state of charge. The lower bound is defined by the PEV owner who might want his car ready for a certain hour with a certain amount of energy available in his battery.

Equation (4) expresses the limitation of the energy to be charged in a vehicle v during the period h. Energy can be charged if and only if the PEV is connected to the grid (ensured by $c_{h,v}$). Another important point is that energy cannot be charged or discharged at the same moment in the battery, this is ensured by the binary decision variable of charging or discharging energy $\delta_{h,v}$. The maximum amount that can be charged is the maximum rate of charge increased by the grid to battery efficiency.

Equation (5) depicts the limitation of the energy to be discharged in a vehicle v during the hour h. Explanations for this equation are the same than for equation (4) except that the energy to be discharged is reduced by the grid to battery efficiency.

Equation (6) represents the energy balance of the aggregator every hour. The energy available during a period h for charging and discharging vehicles is equal to the energy already bought in the DAM plus the energy to buy in the BM less the energy to sell in the BM.

Equation (7) ensures that the energy bought by the aggregator during a period h is lower or equal to the maximum rate of charge of the vehicles connected if it is decided to buy energy with those vehicles ($\delta_{h,v}$).

Equations (8) (9) (10) (11) and (12) are a linearization of the following equation:

$$\forall h \qquad 0 \leq Q_h^{\uparrow} \leq \sum_v \left(\boldsymbol{b_{h-1,v}} \cdot \boldsymbol{\delta_{h,v}} \cdot c_{h,v} + e_{h,v}^{DA} \right)$$

The maximum energy to be sold in the BM during a period h is the energy available in the PEVs' batteries the period before if the PEVs are connected to the grid plus the energy previously bought in the DAM.

Equation (13) complements the previous linearized equation: the maximum energy to be sold in the BM during a period h is bounded by the maximum rate of discharge. Indeed, when there is more energy in a battery than the maximum rate of discharge, this surplus cannot be sold during a single period h.

III – 6. Detailed case study – 3 vehicles

Why an Aggregator is obtaining better results coordinating the charging of a vehicle fleet when compared to the optimal charging schedule of each vehicle independently? This is precisely the object of this small case study considering three vehicles to fully grasp from where stems the added economic value of aggregation in the balancing market.

As aforementioned, three vehicles have been considered for this case study, each one of them having a distinct profile as set out in table 2. To simplify the understanding of this case study, battery degradation has not been considered nor energy efficiency when charging or discharging the batteries. By perfect energy efficiency when charging an EV battery is understood that the *grid to battery efficiency* is set to 1 which technically means that the energy bought or sold in the different markets is charged or discharged by the exact same amounts in the battery. This case study will be fully detailed, presenting input data and models results before to explain the rationale behind the models outcome. A single day was considered using prices data from the Spanish power system of the 1st January 2014. The corresponding market prices are available in the chart below.

Ideal case – 3 vehicles

Deviation		10%		
Discharge from driving		3kWh		
Vehicle type		1	2	3
Connection to the grid		0h-7h 21-23h	0h-8h 18h-23h	0h-6h 19h-23h
Battery max rate of charge	[kWh]	3	3	3
Grid to battery efficiency	[p.u.]	1	1	1
Battery max state of charge	[kWh]	85	85	85
Battery max autonomy	[km]	450	450	450
Battery initial state of charge	[kWh]	0	0	0
Kilometres to charge	[km]	40 [7,56kWh]	30 [5,67kWh]	60 [11,33 kWh]
Battery degradation coefficient	[%]	0,000109589	0,000109589	0,000109589
Battery replacement cost	[€/kWh]	0	0	0

Table 2 - detailed case study, PEVS input data

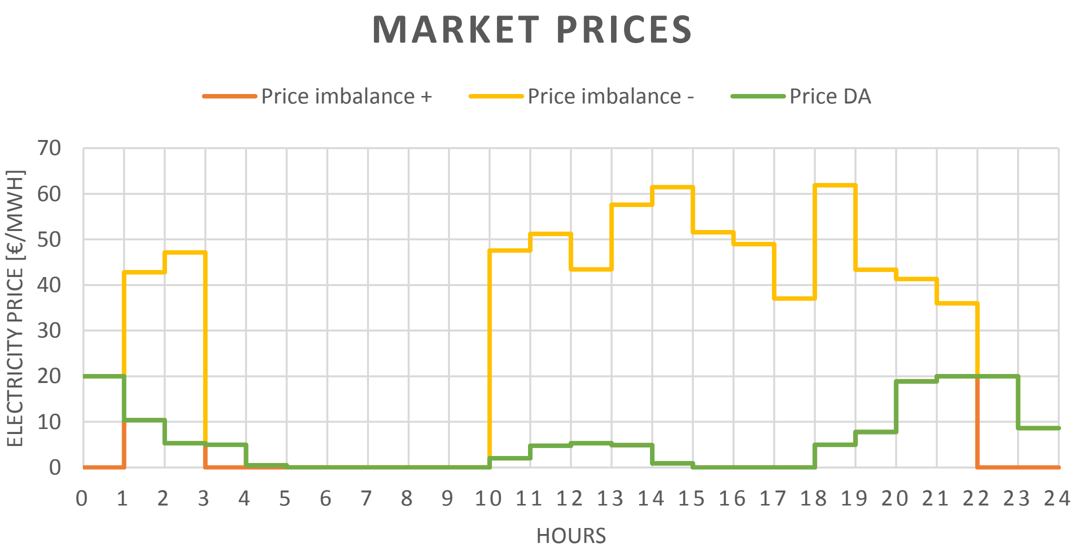


Figure 22 - Detailed case study, market prices

III – 6.a) Day-Ahead schedule

Input data									Optimization Results							
Connection				Min Battery SOC				pDA	DA Energy bought				Battery SOC			
	v1	v2	v3		v1	v2	v3			v1	v2	v3		v1	v2	v3
0h	1	1	1	0h	0	0	0	20,02	**0h**	0,00	0,00	0,00	**0h**	0,00	0,00	0,00
1h	1	1	1	1h	0	0	0	10,34	**1h**	0,00	0,00	0,00	**1h**	0,00	0,00	0,00
2h	1	1	1	2h	0	0	0	5,35	**2h**	0,00	0,00	0,00	**2h**	0,00	0,00	0,00
3h	1	1	1	3h	0	0	0	5	**3h**	0,00	0,00	2,33	**3h**	0,00	0,00	2,33
4h	1	1	1	4h	0	0	0	0,5	**4h**	0,00	0,00	3,00	**4h**	0,00	0,00	5,33
5h	1	1	1	5h	0	0	0	0	**5h**	1,56	0,00	3,00	**5h**	1,56	0,00	8,33
6h	1	1	1	6h	0	0	0	0	**6h**	3,00	0,00	3,00	**6h**	4,56	0,00	11,33
7h	1	1	0	7h	0	0	0	0	**7h**	3,00	2,67	0,00	**7h**	7,56	2,67	11,33
8h	0	1	0	8h	0	0	0	0	**8h**	0,00	3,00	0,00	**8h**	7,56	5,67	11,33
9h	0	0	0	9h	0	0	0	0	**9h**	0,00	0,00	0,00	**9h**	7,56	5,67	11,33
10h	0	0	0	10h	0	0	0	2	**10h**	0,00	0,00	0,00	**10h**	7,56	5,67	11,33
11h	0	0	0	11h	0	0	0	4,75	**11h**	0,00	0,00	0,00	**11h**	7,56	5,67	11,33
12h	0	0	0	12h	0	0	0	5,35	**12h**	0,00	0,00	0,00	**12h**	7,56	5,67	11,33
13h	0	0	0	13h	0	0	0	4,9	**13h**	0,00	0,00	0,00	**13h**	7,56	5,67	11,33
14h	0	0	0	14h	0	0	0	0,9	**14h**	0,00	0,00	0,00	**14h**	7,56	5,67	11,33
15h	0	0	0	15h	0	0	0	0	**15h**	0,00	0,00	0,00	**15h**	7,56	5,67	11,33
16h	0	0	0	16h	0	0	0	0	**16h**	0,00	0,00	0,00	**16h**	7,56	5,67	11,33
17h	0	0	0	17h	0	0	0	0	**17h**	0,00	0,00	0,00	**17h**	7,56	5,67	11,33
18h	0	1	0	18h	0	0	0	5	**18h**	0,00	0,00	0,00	**18h**	7,56	5,67	11,33
19h	0	1	1	19h	0	0	0	7,8	**19h**	0,00	0,00	0,00	**19h**	7,56	5,67	11,33
20h	0	1	1	20h	0	0	0	18,9	**20h**	0,00	0,00	0,00	**20h**	7,56	5,67	11,33
21h	1	1	1	21h	0	0	0	20	**21h**	0,00	0,00	0,00	**21h**	7,56	5,67	11,33
22h	1	1	1	22h	0	0	0	20	**22h**	0,00	0,00	0,00	**22h**	7,56	5,67	11,33
23h	1	1	1	23h	7,56	5,67	11,33	8,6	**23h**	0,00	0,00	0,00	**23h**	7,56	5,67	11,33

Table 3 - Detailed case study, DAM results

$$\boldsymbol{Objective\ Function}: \quad Min \sum_{h,v} e_{h,v}^{DA} . p_h^{DA} = 0{,}01317\ €$$

The day-ahead model outcome is pretty easy to understand. The detailed assumptions of this simulation can be found in section III – 1.a), however it is important to remind that this model is deterministic, market prices are known and what happens when the car is not connected is not simulated (driving patterns and discharge of the battery from driving the car).

As shown by the market prices chart, from 5 to 10 a.m., hourly prices of the day-ahead market are null. Therefore, when cars are plugged-in during those hours, the model decides to buy the maximum amount of energy possible to reach the target defined by the EVs owners (Min battery SOC). As explained earlier, the point in time to reach the user required charge is defined as the last hour of connection defined by the user. The maximum amount of energy that can be bought during a single hour is limited by the maximum rate of charge of the batteries (3kWh). No energy is bought during the last hours of the day since prices are higher. The objective function being a minimisation of the cost of buying energy in the DAM, its value represents an expense.

III – 6.b) Deviation simulation

Input data for balancing market models

	Connection				Discharge from driving				Energy bought in the DA		
	v1	v2	v3		v1	v2	v3		v1	v2	v3
0h	1	1	1	**0h**	0	0	0	**0h**	0	0	0
0h30	1	1	1	**0h30**	0	0	0	**0h30**	0	0	0
1h	1	1	1	**1h**	0	0	0	**1h**	0	0	0
1h30	1	1	1	**1h30**	0	0	0	**1h30**	0	0	0
2h	1	1	1	**2h**	0	0	0	**2h**	0	0	0
2h30	1	1	1	**2h30**	0	0	0	**2h30**	0	0	0
3h	1	1	1	**3h**	0	0	0	**3h**	0	0	1,167
3h30	1	1	1	**3h30**	0	0	0	**3h30**	0	0	1,167
4h	1	1	1	**4h**	0	0	0	**4h**	0	0	1,5
4h30	1	1	1	**4h30**	0	0	0	**4h30**	0	0	1,5
5h	0	1	1	**5h**	3	0	0	**5h**	0,778	0	1,5
5h30	1	1	1	**5h30**	0	0	0	**5h30**	0,778	0	1,5
6h	1	1	1	**6h**	0	0	0	**6h**	1,5	0	1,5
6h30	1	1	1	**6h30**	0	0	0	**6h30**	1,5	0	1,5
7h	1	1	0	**7h**	0	0	0	**7h**	1,5	1,333	0
7h30	1	1	0	**7h30**	0	0	0	**7h30**	1,5	1,333	0
8h	0	1	0	**8h**	0	0	0	**8h**	0	1,5	0
8h30	0	1	0	**8h30**	0	0	0	**8h30**	0	1,5	0
9h	0	0	0	**9h**	0	0	0	**9h**	0	0	0
9h30	0	0	0	**9h30**	0	0	0	**9h30**	0	0	0
10h	0	1	0	**10h**	0	0	0	**10h**	0	0	0
10h30	0	0	0	**10h30**	0	0	0	**10h30**	0	0	0
11h	0	0	0	**11h**	0	0	0	**11h**	0	0	0
11h30	0	0	0	**11h30**	0	0	0	**11h30**	0	0	0
12h	1	0	0	**12h**	0	0	0	**12h**	0	0	0
12h30	0	0	0	**12h30**	0	0	0	**12h30**	0	0	0
13h	0	0	0	**13h**	0	0	0	**13h**	0	0	0
13h30	0	0	0	**13h30**	0	0	0	**13h30**	0	0	0
14h	0	0	0	**14h**	0	0	0	**14h**	0	0	0
14h30	0	0	0	**14h30**	0	0	0	**14h30**	0	0	0
15h	0	0	1	**15h**	0	0	0	**15h**	0	0	0
15h30	0	0	0	**15h30**	0	0	0	**15h30**	0	0	0
16h	0	0	1	**16h**	0	0	0	**16h**	0	0	0
16h30	0	0	0	**16h30**	0	0	0	**16h30**	0	0	0
17h	0	0	0	**17h**	0	0	0	**17h**	0	0	0
17h30	0	0	0	**17h30**	0	0	0	**17h30**	0	0	0
18h	0	1	0	**18h**	0	0	0	**18h**	0	0	0
18h30	0	1	0	**18h30**	0	0	0	**18h30**	0	0	0
19h	0	1	1	**19h**	0	0	0	**19h**	0	0	0
19h30	0	1	1	**19h30**	0	0	0	**19h30**	0	0	0
20h	0	0	1	**20h**	0	3	0	**20h**	0	0	0
20h30	0	1	1	**20h30**	0	0	0	**20h30**	0	0	0
21h	1	1	1	**21h**	0	0	0	**21h**	0	0	0
21h30	1	1	1	**21h30**	0	0	0	**21h30**	0	0	0
22h	1	1	1	**22h**	0	0	0	**22h**	0	0	0
22h30	1	1	1	**22h30**	0	0	0	**22h30**	0	0	0
23h	1	0	1	**23h**	0	3	0	**23h**	0	0	0
23h30	1	1	1	**23h30**	0	0	0	**23h30**	0	0	0

Table 4 - Detailed case study, deviation simulation outcome

Input data emanating from the deviation simulation are presented in table 4. A deviation of 10% has been considered for this case study, thus the first vehicle (v1) will see its connection schedule altered by an amount equivalent to:

[10%] × [11 hours connected in the DA schedule] =1.1 hour ≈ 2 half hours

As it can be verified in the input data table, v1's two periods affected by the deviation simulation are at 5 a.m. and 12 a.m.

Three interesting hours are highlighted in green in the above table. At 5 o'clock in the morning the first vehicle (v1) is disconnected from the grid by the deviation simulation and thus a discharge of 3kWh has been generated because it is assumed that the EV owner drove his car during that half hour. Another interesting point is that energy had been bought in the DAM for that particular hour. A direct effect of that deviation is that the energy bought will not be charged in the battery since v1 is not connected to the grid at that moment: a positive imbalance for the system arise at 5h (energy not consumed).

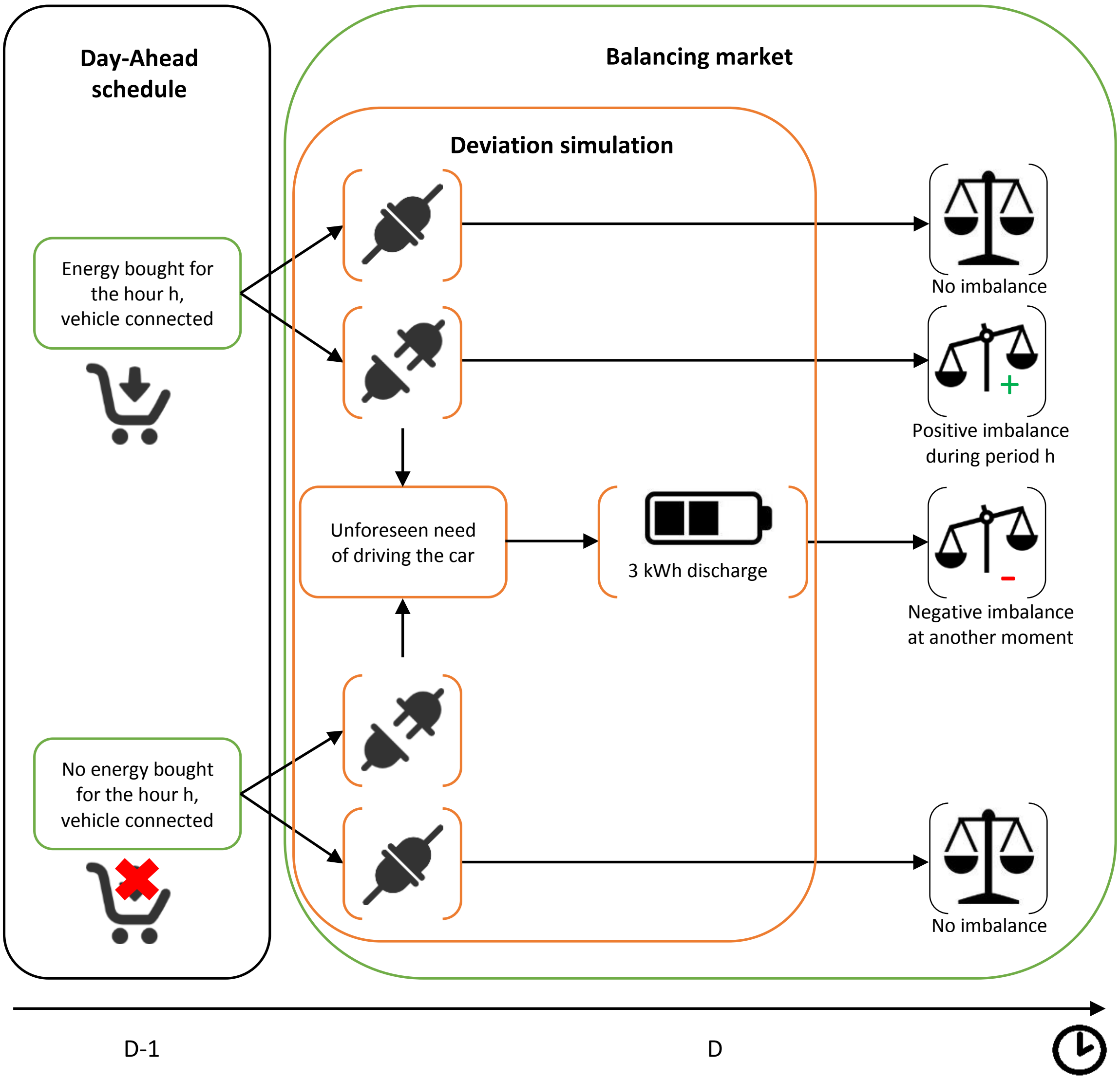


Figure 23 - Imbalance possibilities

A second interesting hour is 8 o'clock at night. The second vehicle (v2) is disconnected from the grid and thus a battery discharge is generated by the deviation simulation due to unforeseen need of driving the car. In that hour no energy was bought in the DAM, therefore there is no imbalance for the system arising in that particular hour. However, in order to compensate for the energy discharged from the battery and reach the EV user target (5.67 kWh in that case), more energy will have to be bought at another moment: a negative imbalance will arise sooner or later.

Finally at 11 p.m., another disconnection and discharge is generated for v2 which means that even more energy will have to be bought at another moment following previous explanation. A summary of the imbalances created in function of the day-ahead schedule is proposed in figure 23. Here, the importance of information regarding deviations appears clearly. Given that the maximum energy that can be charged in a battery in 30 minutes is 1.5 kWh (due to the maximum rate of charge of the battery of 3kW), if the aggregator does not know that a car owner is going to deviate from his initial schedule beforehand, he will be unable to meet the energy requirements of the user for midnight since when losing 3kWh between 23h an 23h30, the remaining time (30 minutes) is not enough to compensate for a 3kWh discharge (only 1.5 kWh can be charged in 30 minutes). Of course, as this model is deterministic and everything is known since the beginning of the day, the aggregator has plenty of time to cope with that deviation in the least cost manner.

A simulation considering only one vehicle and moving through the day by three hours steps has been developed to assess the aforementioned effect of having information later and not being able to adjust the charging schedule of a car since the first hour of the day. This is the objective of section IV -1.

III – 6.c) Imbalance settlement without aggregator

Let us now examine how the model without aggregator responds to the imbalances artificially created by the simulation. A first interesting result is the positive value of the objective function. The objective function being a profit maximisation, a positive result means that money is earned charging the 3 vehicles. This profit is due to arbitraging in the balancing market due to low prices for negative imbalances during the morning (grey zone of table 5) and high prices for positive imbalances during the evening (yellow zone). Therefore, each vehicle charges more energy than necessary at the beginning of the day to take advantage of high selling prices at the end of the day.

Now, let us come back to 5 a.m. when energy had been bought in the DAM for v1 but will not be charged in the battery since the car is not connected. The following equation coming from the objective function will be explained to understand what happens here:

$$(Q^{\uparrow}_{h,v} + [c_{h,v}.\delta_{h,v} + (1 - c_{h,v})].e^{DA}_{h,v}).p^{BM+}_{h}$$

Price of the BM for positive imbalances

Energy sold in the balancing market from the battery

Decision to sell energy from the battery in the BM (δ=1) or to buy energy in the BM (δ=0)

Connection of the EV to the grid (connected when c=1)

Energy bought in the DAM

As the energy bought in the DAM cannot be charged nor given to another vehicle since aggregation is not considered in this model (each vehicle manages its charging schedule independently), the DAM electricity bought is a sunk cost. The best decision that can be made is thus to sell that energy in the BM. As $c_{5h,v1} = 0$, the sale of $e^{DA}_{5h,v1}$ is directly enforced by the above equation independently of the value of δ and without going through the battery: it is a mere financial transaction. Here no energy was sold at 5h in the BM from v1's battery ($Q^{\uparrow}_{5h,v1} = 0$).

Model results

	Energy bought in the BM				E sold in BM from battery				Battery SOC		
	v1	v2	v3		v1	v2	v3		v1	v2	v3
0h	0	0	0	**0h**	0	0	0	**0h**	0	0	0
0h30	0	0	0	**0h30**	0	0	0	**0h30**	0	0	0
1h	0	0	0	**1h**	0	0	0	**1h**	0	0	0
1h30	0	0	0	**1h30**	0	0	0	**1h30**	0	0	0
2h	0	0	0	**2h**	0	0	0	**2h**	0	0	0
2h30	0	0	0	**2h30**	0	0	0	**2h30**	0	0	0
3h	1,5	1,5	0,333	**3h**	0	0	0	**3h**	1,5	1,5	1,5
3h30	1,5	1,5	0,333	**3h30**	0	0	0	**3h30**	3	3	3
4h	1,5	1,5	0	**4h**	0	0	0	**4h**	4,5	4,5	4,5
4h30	1,5	1,5	0	**4h30**	0	0	0	**4h30**	6	6	6
5h	0	1,5	0	**5h**	0	0	0	**5h**	3	7,5	7,5
5h30	0,722	1,5	0	**5h30**	0	0	0	**5h30**	4,5	9	9
6h	0	1,5	0	**6h**	0	0	0	**6h**	6	10,5	10,5
6h30	0	1,5	0	**6h30**	0	0	0	**6h30**	7,5	12	12
7h	0	0,167	0	**7h**	0	0	0	**7h**	9	13,5	12
7h30	0	0,167	0	**7h30**	0	0	0	**7h30**	10,5	15	12
8h	0	0	0	**8h**	0	0	0	**8h**	10,5	16,5	12
8h30	0	0	0	**8h30**	0	0	0	**8h30**	10,5	18	12
9h	0	0	0	**9h**	0	0	0	**9h**	10,5	18	12
9h30	0	0	0	**9h30**	0	0	0	**9h30**	10,5	18	12
10h	0	0	0	**10h**	0	0	0	**10h**	10,5	18	12
10h30	0	0	0	**10h30**	0	0	0	**10h30**	10,5	18	12
11h	0	0	0	**11h**	0	0	0	**11h**	10,5	18	12
11h30	0	0	0	**11h30**	0	0	0	**11h30**	10,5	18	12
12h	0	0	0	**12h**	0	0	0	**12h**	10,5	18	12
12h30	0	0	0	**12h30**	0	0	0	**12h30**	10,5	18	12
13h	0	0	0	**13h**	0	0	0	**13h**	10,5	18	12
13h30	0	0	0	**13h30**	0	0	0	**13h30**	10,5	18	12
14h	0	0	0	**14h**	0	0	0	**14h**	10,5	18	12
14h30	0	0	0	**14h30**	0	0	0	**14h30**	10,5	18	12
15h	0	0	0	**15h**	0	0	0	**15h**	10,5	18	12
15h30	0	0	0	**15h30**	0	0	0	**15h30**	10,5	18	12
16h	0	0	0	**16h**	0	0	0	**16h**	10,5	18	12
16h30	0	0	0	**16h30**	0	0	0	**16h30**	10,5	18	12
17h	0	0	0	**17h**	0	0	0	**17h**	10,5	18	12
17h30	0	0	0	**17h30**	0	0	0	**17h30**	10,5	18	12
18h	0	0	0	**18h**	0	0	0	**18h**	10,5	18	12
18h30	0	0	0	**18h30**	0	0	0	**18h30**	10,5	18	12
19h	0	0	0	**19h**	0	0,333	0	**19h**	10,5	17,67	12
19h30	0	0	0	**19h30**	0	1,5	0	**19h30**	10,5	16,17	12
20h	0	0	0	**20h**	0	0	0	**20h**	10,5	13,17	12
20h30	0	0	0	**20h30**	0	1,5	0,667	**20h30**	10,5	11,67	11,33
21h	0	0	0	**21h**	1,5	1,5	1,5	**21h**	9	10,17	9,833
21h30	0	0	0	**21h30**	1,5	1,5	1,5	**21h30**	7,5	8,667	8,333
22h	0	0	0	**22h**	0	0	0	**22h**	7,5	8,667	8,333
22h30	0	0	0	**22h30**	0	0	0	**22h30**	7,5	8,667	8,333
23h	0	0	1,5	**23h**	0	0	0	**23h**	7,5	5,667	9,833
23h30	0,056	0	1,5	**23h30**	0	0	0	**23h30**	7,556	5,667	11,33

Table 5 - Detailed case study, BM model outcome without aggregation

$$Max \sum_{h,v}\left[(Q^{\uparrow}_{h,v} + [c_{h,v}.\delta_{h,v} + (1-c_{h,v})].e^{DA}_{h,v}).p^{BM+}_{h} - Q^{\downarrow}_{h,v}.p^{BM-}_{h} - e^{DA}_{h,v}.p^{DA}_{h}\right] = 0{,}159472€$$

Apart from the energy bought for arbitraging purposes at the beginning of the day, the amount of electricity purchased during those low prices hours also encompasses the necessary energy to compensate for the discharges created due to the unforeseen mobility needs of PEVs users in real time.

	V1	V2	V3
Day ahead cost	0€	0€	0,01316667€
Balancing market profit	0,04302222€	0,08615€	0,0303€

Table 6 - Results of the deviation settlement without aggregation

Simulation global energy balance without aggregation

	Purchases DA			Purchases BM			Sales BM			Discharge			Battery SOC			Connection		
	v1	**v2**	**v3**	**v1**	**v2**	**v3**	**v1**	**v2**	**v3**	**v1**	**v2**	**v3**	**v1**	**v2**	**v3**	**v1**	**v2**	**v3**
0h	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
0h30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
1h	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
1h30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
2h	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
2h30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
3h	0	0	1,17	1,5	1,5	0,33	0	0	0	0	0	0	1,5	1,5	1,5	1	1	1
3h30	0	0	1,17	1,5	1,5	0,33	0	0	0	0	0	0	3	3	3	1	1	1
4h	0	0	1,5	1,5	1,5	0	0	0	0	0	0	0	4,5	4,5	4,5	1	1	1
4h30	0	0	1,5	1,5	1,5	0	0	0	0	0	0	0	6	6	6	1	1	1
5h	0,78	0	1,5	0	1,5	0	0	0	0	3	0	0	3	7,5	7,5	0	1	1
5h30	0,78	0	1,5	0,72	1,5	0	0	0	0	0	0	0	4,5	9	9	1	1	1
6h	1,5	0	1,5	0	1,5	0	0	0	0	0	0	0	6	10,5	10,5	1	1	1
6h30	1,5	0	1,5	0	1,5	0	0	0	0	0	0	0	7,5	12	12	1	1	1
7h	1,5	1,33	0	0	0,17	0	0	0	0	0	0	0	9	13,5	12	1	1	0
7h30	1,5	1,33	0	0	0,17	0	0	0	0	0	0	0	10,5	15	12	1	1	0
8h	0	1,5	0	0	0	0	0	0	0	0	0	0	10,5	16,5	12	0	1	0
8h30	0	1,5	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	1	0
9h	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	0
9h30	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	0
10h	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	1	0
10h30	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	0
11h	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	0
11h30	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	0
12h	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	1	0	0
12h30	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	0
13h	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	0
13h30	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	0
14h	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	0
14h30	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	0
15h	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	1
15h30	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	0
16h	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	1
16h30	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	0
17h	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	0
17h30	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	0	0
18h	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	1	0
18h30	0	0	0	0	0	0	0	0	0	0	0	0	10,5	18	12	0	1	0
19h	0	0	0	0	0	0	0	0,33	0	0	0	0	10,5	17,7	12	0	1	1
19h30	0	0	0	0	0	0	0	1,5	0	0	0	0	10,5	16,2	12	0	1	1
20h	0	0	0	0	0	0	0	0	0	0	3	0	10,5	13,2	12	0	0	1
20h30	0	0	0	0	0	0	0	1,5	0,67	0	0	0	10,5	11,7	11,3	0	1	1
21h	0	0	0	0	0	0	1,5	1,5	1,5	0	0	0	9	10,2	9,83	1	1	1
21h30	0	0	0	0	0	0	1,5	1,5	1,5	0	0	0	7,5	8,67	8,33	1	1	1
22h	0	0	0	0	0	0	0	0	0	0	0	0	7,5	8,67	8,33	1	1	1
22h30	0	0	0	0	0	0	0	0	0	0	0	0	7,5	8,67	8,33	1	1	1
23h	0	0	0	0	0	1,5	0	0	0	0	3	0	7,5	5,67	9,83	1	0	1
23h30	0	0	0	0,06	0	1,5	0	0	0	0	0	0	7,56	5,67	11,3	1	1	1

Table 7 - Detailed case study, global energy balance without aggregation

Table 7 shows the final results of the different components of the battery state of charge equation presented below, i.e. the energy balance of batteries through time:

$$\forall(h,v) \quad b_{h,v} = b_{h-1,v} + \eta_v.\left(Q^{\downarrow}_{h,v} + c_{h,v}.\left(1-\delta_{h,v}\right).e^{DA}_{h,v}\right) - \frac{Q^{\uparrow}_{h,v}}{\eta_v} - L^{driving}_{h,v} + i^{SOC}_v\,(if\ h=0)$$

Battery state of charge

Connection of the EV to the grid (connected when c=1)

Energy bought in the DAM

Discharge from unforeseen need of driving the car (3kWh)

Initial state of charge

Grid to battery efficiency

Energy bought in the BM

Decision to sell energy from the battery in the BM (δ=1) or to buy energy in the BM (δ=0)

Energy sold in the balancing market from the battery

III – 6.d) Imbalance settlement with aggregator

Now let us study the effect of charging vehicles together, with the same input data as the one used for the model without aggregation. A first striking element when looking at the outcome of the model with aggregation is the value of the objective function: it is higher than without aggregation.

	Aggregation	No Aggregation	Difference
Value of the objective function	0,184972€	0,159472€	0,01317€

Table 8 – Results of the deviation settlement with and without aggregation

Where does that difference stem from?

At 5 o'clock in the morning, the aggregator has more possibilities regarding the energy bought in the DAM for v1 than the owner of the vehicle facing alone the same situation. Indeed the aggregator can either:

- Sell that electricity in the balancing market
- Charge it in another vehicle battery under his control

In that particular case, the second option was chosen as shown by the model results. The energy bought in the DAM for v1 ($e_{5h,v1}^{DA}$) was passed to v2 since this one is not charging its battery at 5 a.m. and is connected according to the DA schedule. This avoid having to buy energy later at a higher price in the BM compared to the DAM price for v2, hence a difference arising in the final result between aggregation and no aggregation.

Of course, this value is not much since the different behaviours of the distinct cars composing the fleet need to be complementary. In that particular case, it's a casualty that v2 was not charging and connected when v1 should have been doing so. Indeed most people would have their car connected during the night and charging at the same time since they would take advantage of low prices hours. They would not only buy energy at the same moment during the lowest prices hours of the day but also in amounts equal to their maximum rate of charge. That last fact is of utmost importance because in that case there are few possibilities to pass a positive imbalance to other vehicles since all vehicles are already charging at the maximum of their respective capabilities. Let us also not forget that a deviation during the night is much less likely to occur than one during the day.

As in the previous model without aggregation, the aggregator takes advantage of the arbitraging profit potential of the day due to the sufficient price differential between markets appearing between different hours and the flexibility that its vehicle fleet offers. Therefore, once again vehicles are charged more than necessary during the morning (grey zone of table 9) and discharged at the end of the day (yellow zone) when prices for positive imbalances are high.

Model results

	Charge +			Charge -			Battery SOC			purchases BM	Sales BM
	v1	v2	v3	v1	v2	v3	v1	v2	v3		
0h	0	0	0	0	0	0	0	0	0	0,00	0,00
0h30	0	0	0	0	0	0	0	0	0	0,00	0,00
1h	0	0	0	0	0	0	0	0	0	0,00	0,00
1h30	0	0	0	0	0	0	0	0	0	0,00	0,00
2h	0	0	0	0	0	0	0	0	0	0,00	0,00
2h30	0	0	0	0	0	0	0	0	0	0,00	0,00
3h	1,5	1,5	1,5	0	0	0	1,5	1,5	1,5	3,33	0,00
3h30	1,5	1,5	1,5	0	0	0	3	3	3	3,33	0,00
4h	1,5	1,5	1,5	0	0	0	4,5	4,5	4,5	3,00	0,00
4h30	1,5	1,5	1,5	0	0	0	6	6	6	3,00	0,00
5h	0	1,5	1,5	0	0	0	3	7,5	7,5	0,72	0,00
5h30	1,5	1,5	1,5	0	0	0	4,5	9	9	2,22	0,00
6h	1,5	1,5	1,5	0	0	0	6	10,5	10,5	1,50	0,00
6h30	1,5	1,5	1,5	0	0	0	7,5	12	12	1,50	0,00
7h	1,5	1,5	0	0	0	0	9	13,5	12	0,17	0,00
7h30	1,5	1,5	0	0	0	0	10,5	15	12	0,17	0,00
8h	0	1,5	0	0	0	0	10,5	16,5	12	0,00	0,00
8h30	0	1,5	0	0	0	0	10,5	18	12	0,00	0,00
9h	0	0	0	0	0	0	10,5	18	12	0,00	0,00
9h30	0	0	0	0	0	0	10,5	18	12	0,00	0,00
10h	0	0	0	0	0	0	10,5	18	12	0,00	0,00
10h30	0	0	0	0	0	0	10,5	18	12	0,00	0,00
11h	0	0	0	0	0	0	10,5	18	12	0,00	0,00
11h30	0	0	0	0	0	0	10,5	18	12	0,00	0,00
12h	0	0	0	0	0	0	10,5	18	12	0,00	0,00
12h30	0	0	0	0	0	0	10,5	18	12	0,00	0,00
13h	0	0	0	0	0	0	10,5	18	12	0,00	0,00
13h30	0	0	0	0	0	0	10,5	18	12	0,00	0,00
14h	0	0	0	0	0	0	10,5	18	12	0,00	0,00
14h30	0	0	0	0	0	0	10,5	18	12	0,00	0,00
15h	0	0	0	0	0	0	10,5	18	12	0,00	0,00
15h30	0	0	0	0	0	0	10,5	18	12	0,00	0,00
16h	0	0	0	0	0	0	10,5	18	12	0,00	0,00
16h30	0	0	0	0	0	0	10,5	18	12	0,00	0,00
17h	0	0	0	0	0	0	10,5	18	12	0,00	0,00
17h30	0	0	0	0	0	0	10,5	18	12	0,00	0,00
18h	0	0	0	0	0	0	10,5	18	12	0,00	0,00
18h30	0	0	0	0	0	0	10,5	18	12	0,00	0,00
19h	0	0	0	0	0	0	10,5	18	12	0,00	0,00
19h30	0	0	1,5	0	1,5	0	10,5	16,5	13,5	0,00	0,00
20h	0	0	0	0	0	1,5	10,5	13,5	12	0,00	1,50
20h30	0	0	0	0	1,5	1,5	10,5	12	10,5	0,00	3,00
21h	0	0	0	1,5	1,5	1,5	9	10,5	9	0,00	4,50
21h30	0	0	0	1,5	1,5	1,5	7,5	9	7,5	0,00	4,50
22h	0	0	1,5	1,167	0,333	0	6,333	8,667	9	0,00	0,00
22h30	0	0	0	0	0	0	6,333	8,667	9	0,00	0,00
23h	0	0	1,5	0	0	0	6,333	5,667	10,5	1,50	0,00
23h30	1,222	0	0,833	0	0	0	7,556	5,667	11,33	2,06	0,00

Table 9 - Detailed case study, BM model outcome with aggregation

$$\textbf{\textit{Objective function}}: Max \sum_h \left[Q_h^{\uparrow} . p_h^{BM+} - Q_h^{\downarrow} . p_h^{BM-} - \sum_v \left(e_{h,v}^{DA} . p_h^{DA} \right) \right] = 0{,}184972€$$

Energy sold in the balancing market

Energy bought in the balancing market

III – 7. Case study – [500/1000/1500] PEVs – Dual price

In the previous case study considering 3 PEVs, the economic value of aggregation has been explained in details: where does the added economic value comes from, how coordinated charging schedules of PEVs interact with each other.

This new case study proposes to see the influence of different parameters on the benefits obtained by the aggregator with a dual price BM. Three small cases have been developed, each one of them considering respectively [500/1000/1500] PEVs, comparing the difference in profits between aggregation and no aggregation:

1. **First case**: **Perfect conditions** : no battery degradation (battery replacement cost = 0€/kWh), perfect grid to battery efficiency ($\eta_v = 1$)
2. **Second case**: **G2B** : no battery degradation (battery replacement cost = 0€/kWh), G2B efficiency ($\eta_v = 0{,}94$)
3. **Third case: G2B + battery degradation** : battery replacement cost = 300 €/kWh, G2B efficiency ($\eta_v = 0{,}94$)

Five different standard car profiles have been defined around the daily average mobility needs in Europe (40km) for the three cases, computing PEVs' optimal charging schedules of January 2014 with Spain markets prices. In each of the three cases, the same number of PEVs of each type is considered. For instance when 500 PEVs are introduced as input data in the simulation, there are 100 PEVs of type 1, 100 PEVs of type 2 and so on. In green are highlighted the parameters that are going to change in the 3 small cases according to previous explanations.

Dual price case Parameters						
Deviation		10%				
Discharge from driving		3kWh				
Market prices used		Spain January 2014				
Vehicle type		1	2	3	4	5
connection availability		0h-7h 21-23h	0h-8h 18h-23h	0h-6h 19h-23h	0h-9h 22h-23h	0h-5h 19h-23h
battery max rate of charge	[kWh]	3	3	3	3	3
grid to battery efficiency	[p.u]	1	1	1	1	1
battery max state of charge	[kWh]	85	85	85	85	85
battery max autonomy	[km]	450	450	450	450	450
battery initial state of charge	[kWh]	0	0	0	0	0
kilometres to charge	[km]	40	30	60	45	75
battery degradation coefficient	[%]	0,000109589	0,000109589	0,000109589	0,000109589	0,000109589
battery replacement cost	[€/kWh]	0	0	0	0	0

Table 10 - Input data for the BM dual price case

III – 7.a) [500/1000/1500] PEVs – Perfect conditions

All graphs hereinafter present the final results of the simulation explained in this chapter, i.e. the optimal charging schedule of PEVs after imbalances settlement under aggregation and no aggregation. First, daily results of the aggregator and the ones without aggregator are presented for [500/1500] PEVs, before to see more precisely the profit difference between both strategies.

Figure 24 - Daily profit from charging 500 PEVs - Perfect conditions

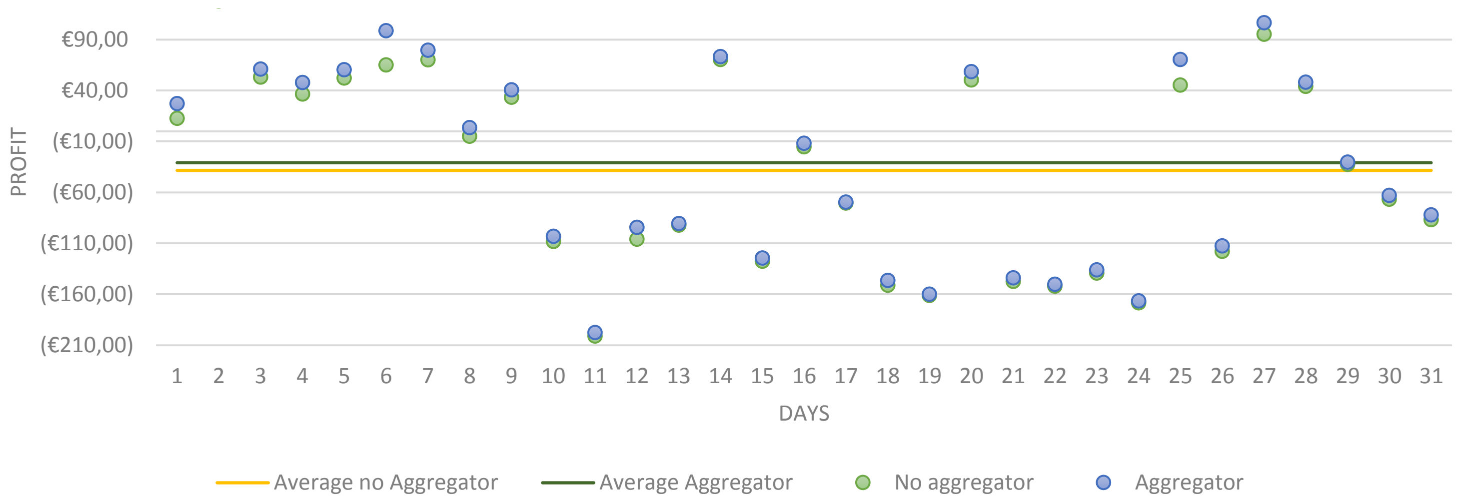


Figure 24 presents the daily results of the simulation for charging 500 PEVs. As it can be seen, some days a profit is made charging 500 vehicles while other days charging car is costly. Market prices of January 2014 are quite often null during the night hence a profit arising from arbitraging at the end of the day. The aggregator always obtain equal or better results than the same fleet with vehicles charged independently from each other's.

Figure 25 shows the daily results of the simulation for charging 1500 PEVs. Profits and costs increase when coordinating more vehicles as well has the difference between aggregation and no aggregation.

Figure 25 - Daily profit from charging 1500 PEVs - Perfect conditions

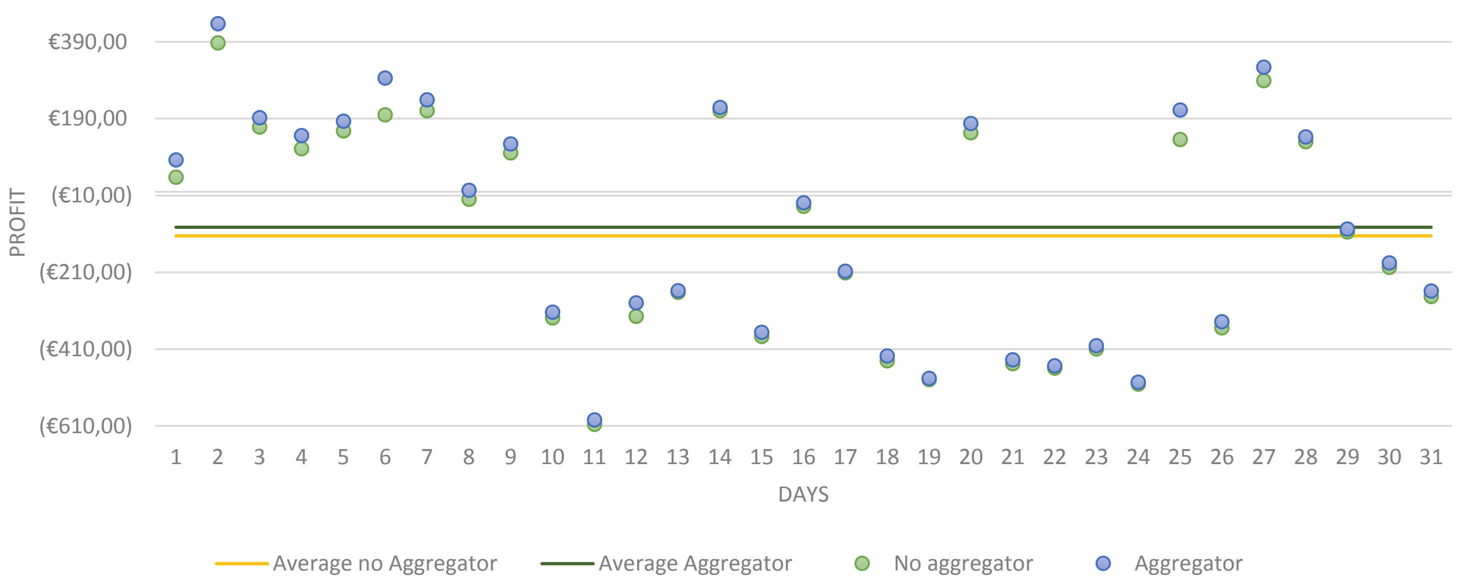


Figure 26 - Aggregation/no aggregation profit difference - 500 PEVs - Perfect conditions

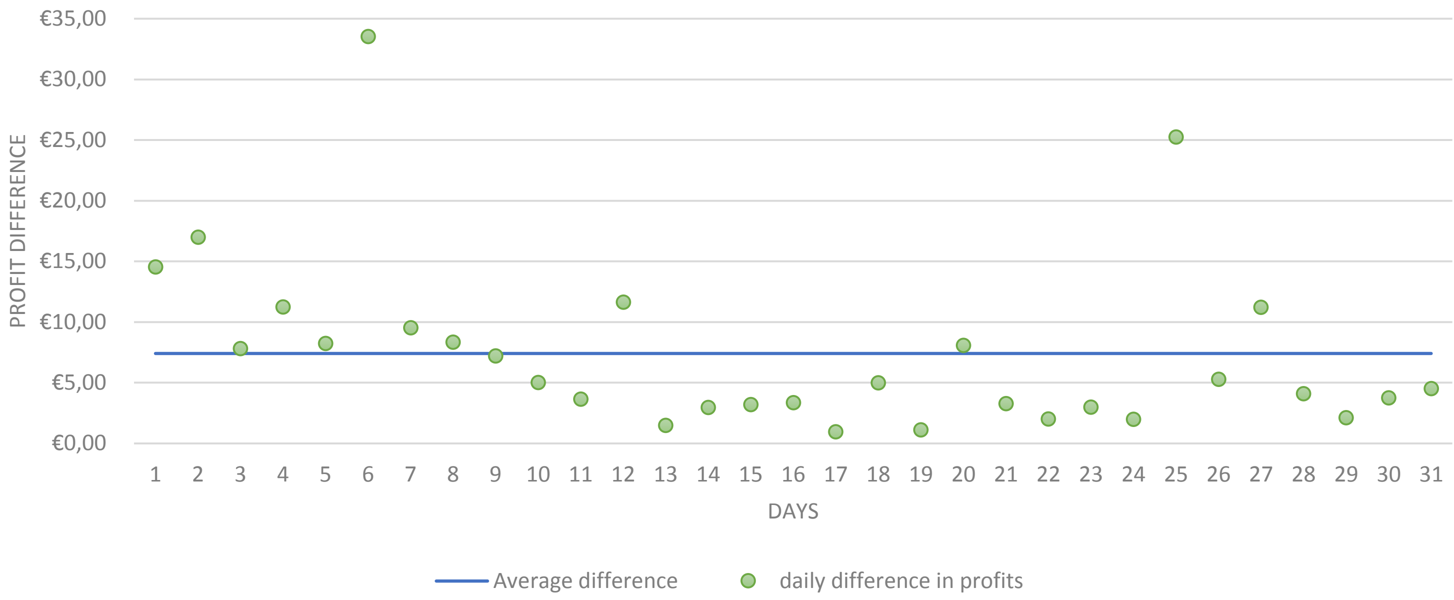
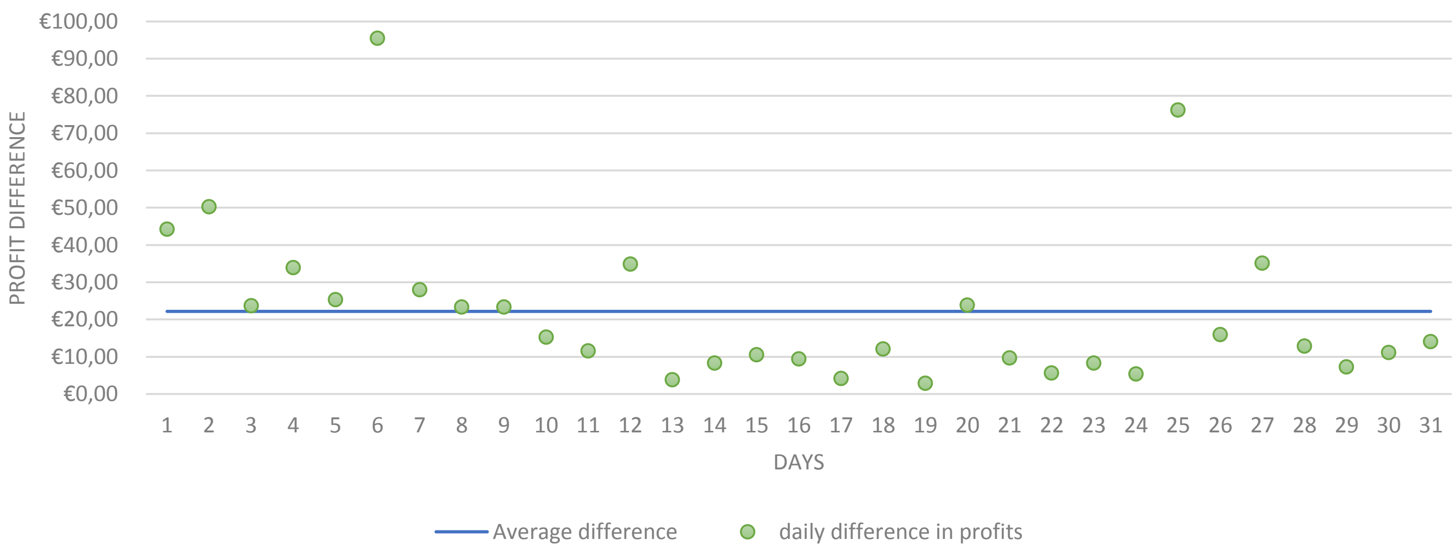
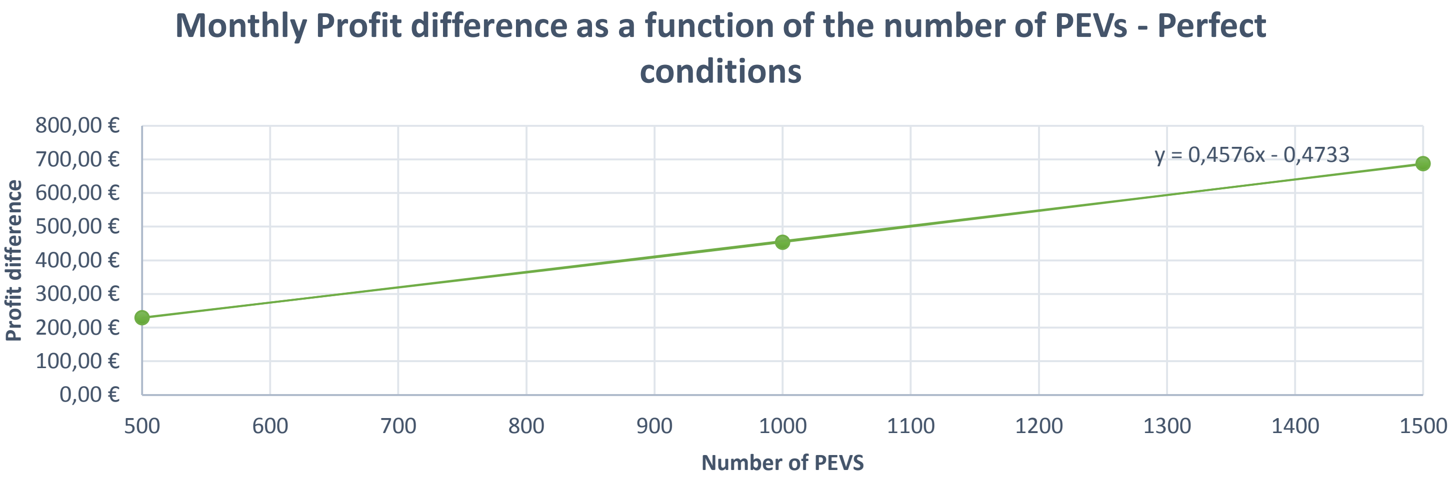


Figure 26 and 27 present respectively the daily difference in profits obtained between aggregation and no aggregation for the month of January 2014 with 500 and 1500 PEVs. As it can be seen, the difference is always positive meaning that the aggregator strategy is always achieving better results than the one without coordination. The difference in profits increases with the number of vehicles due to more synergies available among the vehicles of a bigger fleet.

Figure 27 - Aggregation/no aggregation profit difference - 1500 PEVs - Perfect conditions





Number of PEVs	*Monthly difference in profits between Aggregation and no Aggregation*
500	229,88 €
1000	454,04 €
1500	687,49 €

Figure 28 - [500/1000/1500] PEVs – Perfect conditions results

As it can be seen in graphs 26 & 27 and in the summary table, the aggregator is always achieving better results than when the exact same vehicle fleet is charged without aggregation. The profit is increasing linearly with the number of vehicles. The difference obtained is not stratospheric, but it must be kept in mind that no arbitrage was considered in the day-ahead market and that the same distribution of deviations has been applied for the 5 vehicle types (see figure 20). This explains why the curve of profits as a function of the number of PEVs is almost perfectly linear.

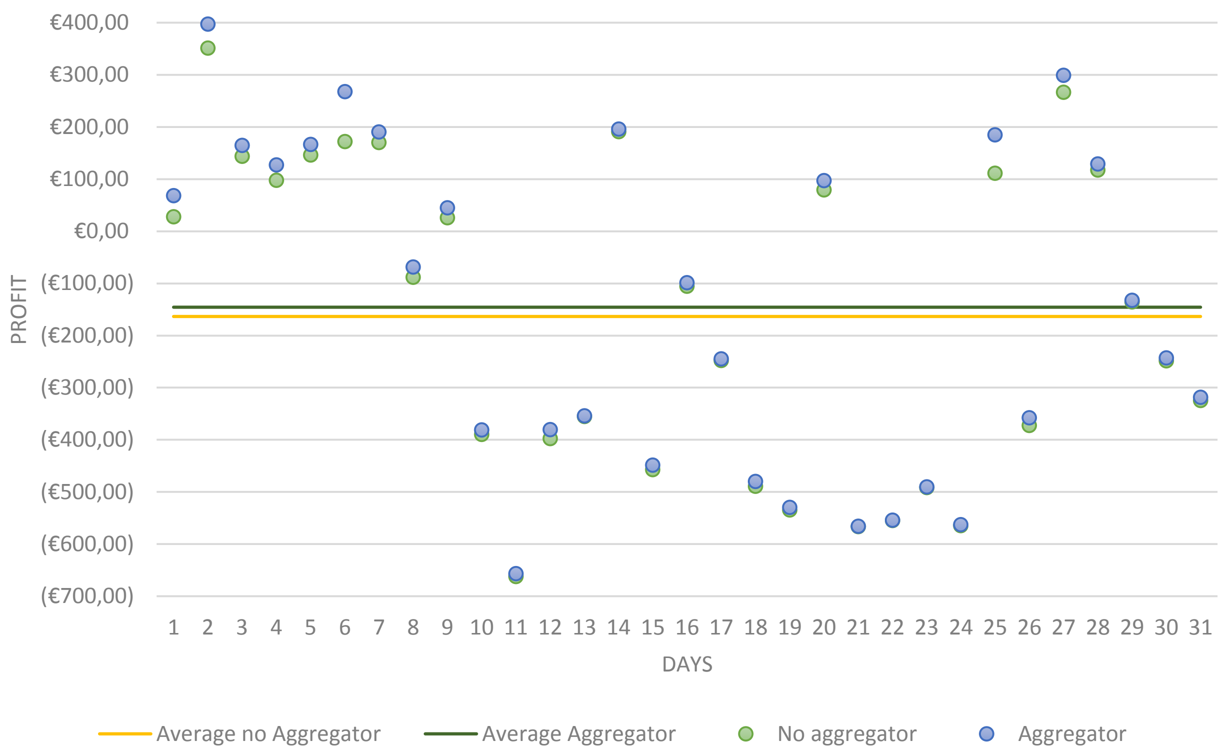
III – 7.b) [500/1000/1500] PEVs – Grid to battery efficiency

In this case the grid to battery efficiency is set to 0,94. It means that the energy bought or sold in different markets is not charged or discharged by the exact same amounts in the battery. When selling energy from a car battery, more energy will be discharged than what will be sold. Similarly, when buying energy in electricity markets, more energy will be bought than what is going to be charged. As it can be expected, the difference in profits is lower due to this new constraint which leads to less arbitraging in the BM as price differences get smaller.

Number of PEVs	*Monthly difference in profits between Aggregation and no Aggregation*
500	180,81 €
1000	364,89 €
1500	550,35 €

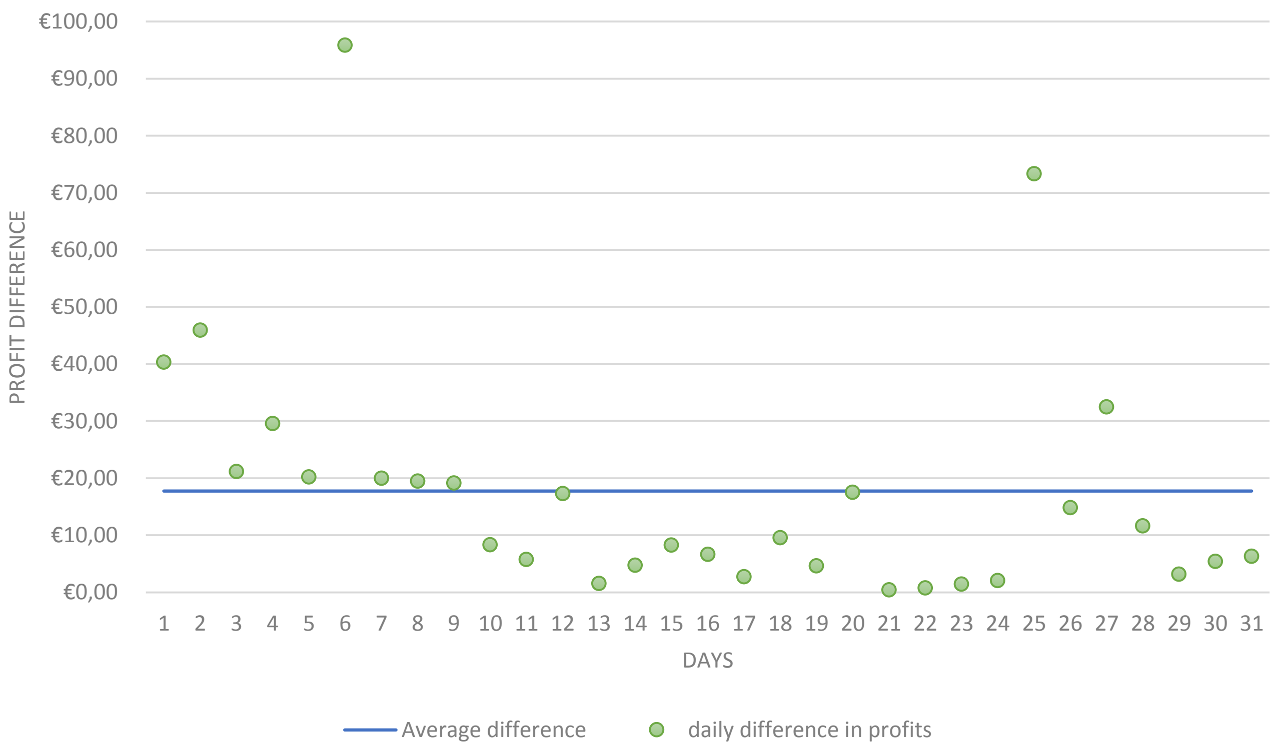
Figure 29 - [500/1000/1500] PEVs – G2B results

Figure 30 - Daily profit from charging 1500 PEVs - G2B efficiency



When comparing figure 26 and 27 with figures 30 and 31, it can be seen than the profit difference between aggregation and no aggregation is lower, and that daily costs incurred for charging PEVs are higher due to the grid to battery efficiency restriction.

Figure 31 - Aggregator/no Aggregator profit difference - 1500 PEVs - G2B efficiency



III – 7.c) [500/1000/1500] PEVs – G2B efficiency & battery degradation

		Normal DA purchases			10% more DA purchases		
		ideal	G2B	G2B + Battery costs	ideal	G2B	G2B + Battery costs
Monthly difference	**500 PEV**	229,88 €	180,81 €	31,33 €	204,05 €	168,63 €	108,56 €
	1000 PEV	454,04 €	364,89 €	64,38 €	416,18 €	334,08 €	216,25 €
	1500 PEV	687,49 €	550,35 €	92,35 €	620,19 €	499,40 €	326,17 €

Figure 32 - [500/1000/1500] PEVs – Global results

In this last case considering battery costs (300€/kWh) and grid to battery efficiency (set to 0,94), battery flows going in and out of the battery are penalized in the objective function. Therefore, due to this new strong restriction, the profit difference is going down between aggregation and no aggregation due to less arbitraging in the BM. Considering batteries fixed costs in operations is quite controversial and subject to debate. Some will think that a battery is bought to be used without limits, others will think that battery degradation should be taken into consideration for operations.

When considering battery degradation, the choice of the energy flows going in and out of the battery to be penalized in the objective function is crucial. In that simulation, all physical flows going in and out of the battery have been included in the battery degradation equation. Battery degradation is not the core of this Master's Thesis and lies out of scope of the work conducted. Nonetheless, having some thought about battery degradation when charging PEVs is important.

Finally another case was computed buying 10% more energy than required in the DAM to compensate for imbalances in real-time. If we compare normal day-ahead purchases results with 10% more day-ahead purchases results, it can be seen that the difference between aggregation and no aggregation is lower when buying 10% more for perfect conditions and grid to battery efficiency but higher when considering battery degradation with respect to normal day-ahead purchases.

For ideal and G2B efficiency cases, the difference in profits obtained is smaller due to lower needs of buying electricity in the BM for independent PEVs owners since they bought more energy than necessary in the DAM. Buying energy in the BM being quite expensive with respect to the DAM price, the difference in profit decreases.

As for the case considering G2B efficiency and battery costs, profit difference increases due to the fact that the aggregator has more possibilities to manage surpluses of energy than independent PEV owners. Indeed when a car is disconnected in real time and energy had been bought in the DAM, the aggregator has the possibility to:

- Directly sell that energy in the BM without going through any battery: a mere financial transaction is occurring.
- Charge it in a car battery and later sell it during high prices hours.

III – 8. Case study – Dual price versus Single price

The objective of the case study is to analyse the influence of the balancing market price mechanism on the benefits of the aggregator charging strategy. The same input data as for the perfect conditions case study of section III – 7.a) have been used. In this section, results have been computed with Spain single BM prices of January 2014 and will afterwards be compared with the ones obtained in section III – 7.a) with dual prices.

Figure 33 - Daily profit from charging 1500 PEVs - perfect conditions - single price

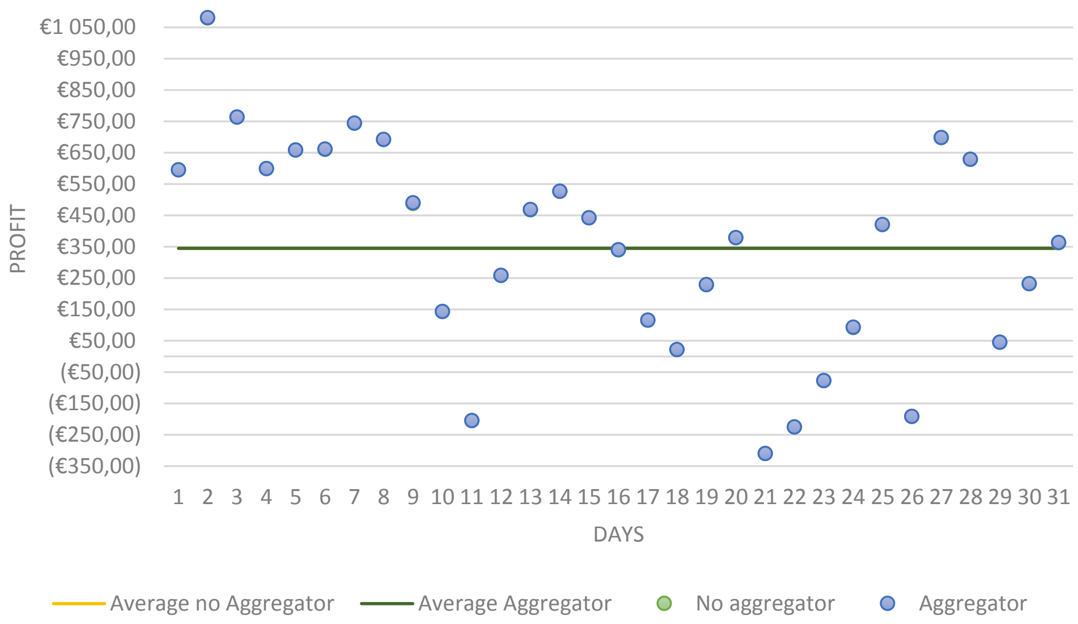
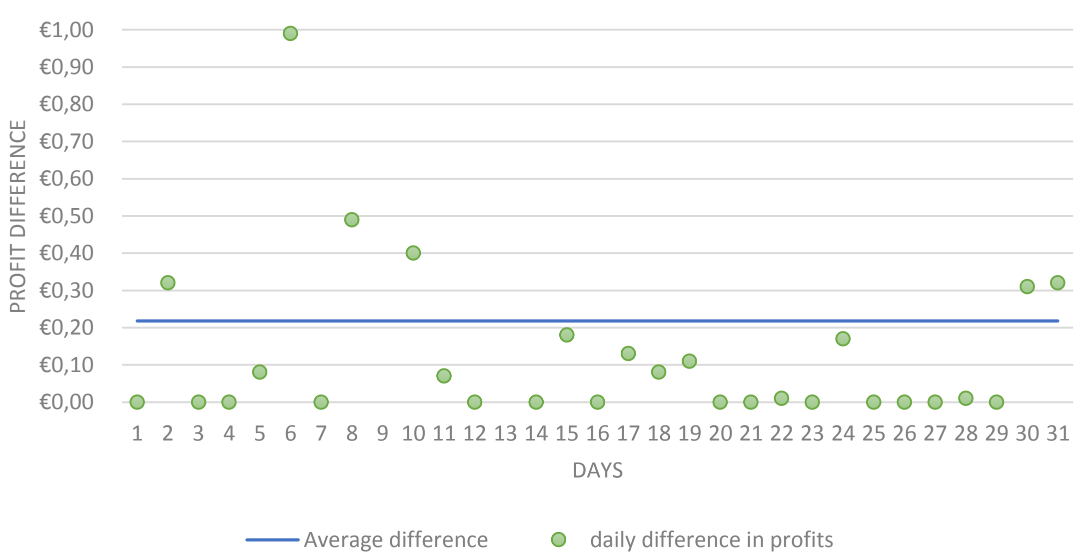


Figure 34 - Aggregator/no Aggregator profit difference - 1500 PEVs - perfect conditions - single price



	Dual price			Single price		
	Monthly profit		**Difference in profits**	**Monthly profit**		**Difference in profits**
	Aggregator	No aggregator		Aggregator	No aggregator	
500 PEV	-960,58 €	-1 190,46 €	229,88 €	3 591,46 €	3 589,20 €	2,26 €
1000 PEV	-1 899,58 €	-2 353,62 €	454,04 €	7 135,57 €	7 130,88 €	4,69 €
1500 PEV	-2 872,53 €	-3 560,02 €	687,49 €	10 705,06 €	10 698,31 €	6,75 €

Table 11 - Dual price versus Single price results – January 2014

It can be noticed in table 11 that the difference in profits between aggregation and no aggregation is lower when having a single price BM than a dual price one. The daily difference in profits between aggregation and no aggregation presented in figure 34 is quite often null or really small. This is due to the fact that the playing ground of the aggregator is smaller when the BM is designed with a single price system than with a dual price mechanism. Indeed, with a single price BM, a PEV incurring in an imbalance is not necessarily penalized. If the system needs energy and the PEV deviates positively from its schedule, it will not be penalized. Similarly, if the system has a surplus of energy and a PEV is consuming more than expected, it will not be penalized. Under a dual price scheme, deviations are always penalized or at least with the same remuneration of the DAM no matter the energy balance of the system (see table 1).

As for monthly profits, with a dual price system, the price for selling energy being much lower than with a single price one, arbitraging possibilities are lower, hence the huge difference between monthly profits of both BM pricing mechanisms. The difference of daily profits along the month of January 2014 is quite huge as shown in figure 33. Table 12 presents results obtained after computing the simulation for the month of June with Spanish market prices when prices in the morning are much higher than in January. Indeed January prices of Spain in 2014 were quite often null during the first hours of the day.

	Dual price			Single price		
	Monthly profit		**Difference in profits**	**Monthly profit**		**Difference in profits**
	Aggregator	No aggregator		Aggregator	No aggregator	
1000 PEV	-13 659,95 €	-13 833,95 €	174,51 €	-7 439,03 €	-7 441,46 €	2,43 €

Table 12 - Dual price versus Single price results - June 2014

CHAPTER IV: Deviation costs and optimal capacity

IV – 1. Deviation costs - Rolling optimization through the day

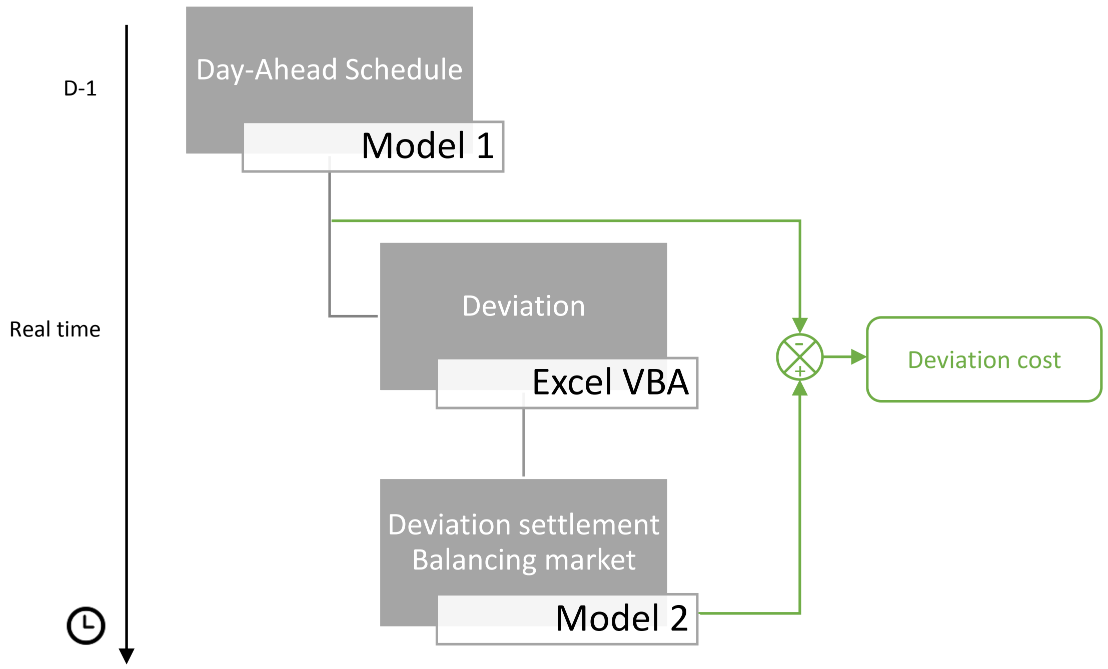


Figure 35- Deviation costs global process

The purpose of this section is to provide an estimation of imbalances costs of a single EV. The estimation has been done with a rolling model through the day, i.e. deviations from the day ahead schedule are not deterministic anymore and appear on a rolling basis of three hours steps.

Figure 35 depicts the methodology followed to estimate deviation costs. Imbalance costs are obtained as the difference between the results of the second and the first model. The first model provides the optimal energy purchases in the DAM according to the PEV owner mobility needs: connection availability of the PEV to the grid, number of kilometres the user wants to do the next day and the hour when the car should be ready. This simulation does not differ a lot from previous one, the only difference being that for balancing markets, deviations from the DA schedule will not be known since the beginning of the day and will occur as time goes by. Under that scheme, decisions taken in previous hours (already past hours) affect the ones to come if a deviation occurs: every three hours, the PEV owner may change its original schedule for the rest of the day, only disposing of the remaining hours of the day to adapt his charging schedule.

IV – 1.a) Rolling optimization algorithm

The simulation has been developed for a single vehicle which is going to see its day-ahead schedule altered in real time by a percentage for the whole day. The deviation simulation is programmed in excel and the balancing market visual basic macro is in charge of saving past decisions coming from the BM model outcome and introducing them as input data for next model resolution. Details of the code will not be explained, but an overall explanation will be provided. From the percentage of deviation desired for the whole day is obtained a deviation matrix. This deviation matrix is the core of the deviation simulation for running the balancing market model. Figure 36 presents how the deviation matrix interacts with the balancing market model.

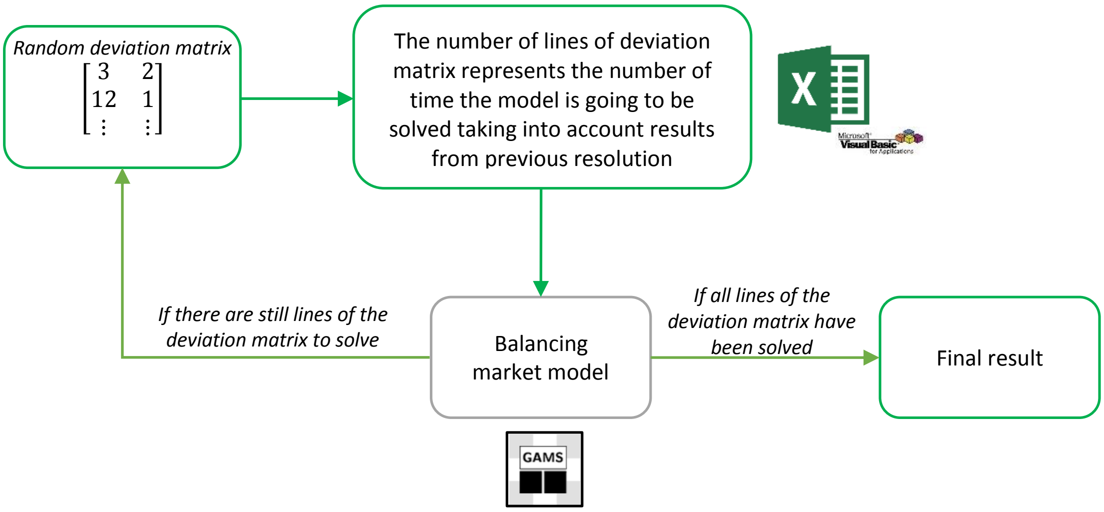


Figure 36 - Deviation matrix and BM model

Generation of the random deviation matrix

Let us assume that the percentage of deviation chosen for the simulation is 10% and that the PEV owner is connected to the grid 11 hours according to the DA schedule. The balancing market model being defined on a half-hour basis, the number of half hours to be affected according to the deviation percentage is obtained as follow:

[10%] × [11 hours connected in the DA schedule] =1.1 hour ≈ 2 half hours

As in the previous deviation simulation, connection and disconnection will be generated along with discharge in the battery due to unforeseen driving needs. Before to do so, it must be decided when to operate those modifications. The same distribution as in previous deviation simulation has been used (see figure 20). First, an hour is randomly chosen according to that distribution, let us say 6h for example. Then, as two half hours need to be modified for the whole day, it is randomly chosen to affect one or two half hours from 6h to the last hour of the day. If the deviation simulation chooses to affect only one half hour out of the two, the above process is repeated again. Let us imagine that in the next loop, the hour chosen according to the distribution is 18h. To complete the number of modifications needed for the whole day, as one half hour modification has already been assigned from 6 a.m., and the total for the day is two half hours modification, only one half hour will be affected from 18h until the rest of the day. The resulting deviation matrix would be in that case:

$$\begin{bmatrix} 6 & 1 \\ 18 & 1 \end{bmatrix}$$

The first column represents the hour chosen according to the distribution and the second one the number of modification to operate from that hour until the rest of the day. The balancing market model will be executed as many times as the number of lines of the deviation matrix, applying in every resolution the number of modification associated. Once a line of the matrix is solved by the model in GAMS, decisions are saved and passed as input data before to solve the next line of the matrix.

IV – 1.b) Rolling balancing market model

OBJECTIVE FUNCTION

$$Max \sum_{h} - e_h^{DA}.p_h^{DA} - \left(Q_h^{\downarrow} + e_h^{pr\downarrow}\right).p_h^{BM-} + \left(Q_h^{\uparrow} + e_h^{pr\uparrow} + [c_h.\delta_h + (1 - c_h)].e_h^{DA}\right).p_h^{BM+}$$

SUBJECT TO

$$\forall h \quad b_h = b_{h-1} + \eta.[e_h^{DA}.c_h.(1-\delta_h) + Q_h^{\downarrow} + e_h^{pr\downarrow}] - \frac{Q_h^{\uparrow} + e_h^{pr\uparrow}}{\eta} - L_h^{driving} + i^{SOC} \quad (2)$$

$$\forall h \quad -\bar{R}.c_h - L_h^{driving} \leq b_h - b_{h-1} \leq \bar{R}.c_h \quad (3)$$

$$\forall h \quad \underline{B}_h \leq b_h \leq \bar{B} \quad (4)$$

$$\forall h \quad 0 \leq Q_h^{\downarrow} \leq \left(\frac{\bar{R}}{\eta} - e_h^{DA}\right).c_h.(1-\delta_h).\Psi_h \quad (5)$$

$$\forall h \quad 0 \leq Q_h^{\uparrow} \leq y_h.c_h.\Psi_h \quad (6)$$

$$\forall h \quad y_h \leq \bar{B}.\delta_h \quad (7)$$

$$\forall h \quad -b_{h-1} + y_h \leq 0 \quad (8)$$

$$\forall h \quad b_{h-1} - y_h + \bar{B}.\delta_h \leq \bar{B} \quad (9)$$

$$\forall h \quad b_{h-1} \leq \bar{B} \quad (10)$$

SETS

h	half hours	

PARAMETERS

$\bar{R}$	Battery maximum rate of charge /discharge	[kWh]
$\bar{B}$	Maximum battery state of charge	[kWh]
$\underline{B}_h$	Minimum battery state of charge	[kWh]
i^{SOC}	Battery initial state of charge	[kWh]
η	Grid to battery efficiency	[p.u.]
e_h^{DA}	Energy bought in the day-ahead market	[kWh]
p_h^{DA}	Day-ahead market price	[€/MWh]
$e_h^{pr\downarrow}$	Energy bought in the balancing market in previous model resolution	[kWh]
$e_h^{pr\uparrow}$	Energy sold from the battery in the BM in previous model resolution	[kWh]
p_h^{BM-}	Balancing market price for negative imbalance	[€/MWh]
p_h^{BM+}	Balancing market price for positive imbalance	[€/MWh]

$L_h^{driving}$	Discharge from driving the PEV during the hour h	[kWh]
c_h	Connection status of the PEV to the grid 1 is connected, 0 disconnected	[0/1]
Ψ_h	Energy trading authorization	[0/1]

VARIABLES

b_h	Battery state of charge during the hour h	[kWh]
$Q_h^{\downarrow}$	Energy bought in the balancing market	[kWh]
$Q_h^{\uparrow}$	Energy sold from the battery in the balancing market	[kWh]
δ_h	Binary decision variable for buying or selling energy in the balancing market 1 is selling, 0 is buying	[0/1]
y_h	Auxiliary positive variable for linearizing the product $b_{h-1} . \delta_h$	[kWh]

MODEL EXPLANATION

The model aims at reducing the maximum possible the cost of imbalances of a PEV owner. The objective function (1) is a maximization because theoretically, by selling energy to the SO, a profit could potentially arise. A car owner could try to make money through arbitrage in the balancing market if circumstances are favourable to do so.

A detailed explanation of the relationship between δ_h , c_h and e_h^{DA} is provided in section III - 5.b). Two decisions can be made regarding e_h^{DA} : either to charge it in the PEV battery or to sell it in the balancing market. The decision to charge or sell this energy depends on whether the vehicle is connected to the grid (c_h) and the decision to buy or sell energy from the battery in the BM (δ_h). When the PEV is not connected to the grid the day d during a period h and electricity had been bought in the DAM for this same exact period, the energy purchased cannot be charged in the car battery. Therefore, the optimal decision for the PEV owner is to sell that energy in the BM. On the other hand, when the car is connected to the grid, the decision to sell or charge e_h^{DA} will depend on the binary decision variable to buy or sell energy in the BM.

The overall formulation of the objective function is pretty simple and consist in a profit maximisation. The energy to sell less the energy to buy in the different markets multiplied by the corresponding prices gives the profit. As the model is progressing through the day and does not see all deviations at once, decisions that have been taken in previous resolution affects the current ones, hence the presence of two new parameters $e_h^{pr\downarrow}$ and $e_h^{pr\uparrow}$. Those parameters are past decisions of buying or selling energy in the BM which are saved by the deviation simulation and updated after the resolution of each line of the deviation matrix.

The second equation depicts the battery balance through time. The battery state of charge in a certain hour is equal to the energy that was in the battery the hour before plus or less the energy bought in the different markets during that hour. It can be noticed that if the PEV is not connected to the grid, the energy bought in the DAM will not be charged in the battery as previously explained. The energy bought or sold in different markets is affected by the grid to battery efficiency and the initial state of charge of the battery is also taken into account in equation (2). Discharge from driving also form part of this equation, due to deviations of the PEV owner from his initial schedule. Indeed, when a PEV owner is not connected to the grid when he should have been, it is assumed that the car was used for driving purposes and a discharge of 2kWh of the battery is generated. The initial state of charge i_v^{SOC} is only added when h=0.

Equation (3) describes the charge limitation of the battery during an hour with respect to the previous one. If the vehicle is connected to the grid, the vehicle can be charged or discharged by a maximum amount of the rate of charge, else, if the PEV is disconnected, the state of the battery during a certain hour may be reduced by an amount of the discharge from driving. The fourth equation defines the bounds of the battery state of charge. The lower bound is defined by the PEV owner who might want his car ready for a specific hour with a certain amount of energy available in his battery.

Equation (5) expresses the limitation of the quantity of energy to be bought in the BM. Energy can be bought if and only if the PEV is connected to the grid (ensured by c_h). Another important point is that energy cannot be bought or sold at the same moment, i.e. the battery cannot be physically charged and discharged at the same moment. This is ensured by the binary decision variable of buying or selling energy δ_h. The maximum amount that can be bought is technically the difference between the maximum rate of charge increased by the grid to battery efficiency and the energy already bought in the DAM. The trading authorization parameter Ψ_h ensures that past hours from previous model resolution cannot be affected by current model execution. Ψ_h is updated before the resolution of each lines of the deviation matrix, for instance with the following deviation matrix:

$$\begin{bmatrix} 6 & 1 \\ 18 & 1 \end{bmatrix}$$

When solving the first line, $\Psi_h = 0$ from 0h to 5h30 and $\Psi_h = 1$ from 6h to the rest of the day.

Equations (6) (7) (8) (9) and (10) are a linearization of the following equation:

$$\forall h \quad 0 \leq Q_h^{\uparrow} \leq \boldsymbol{b_{h-1}} \,.\, \boldsymbol{\delta_h} \,.\, c_h . \Psi_h$$

The maximum energy that can be sold in the BM during the period h is the energy that was in the battery the period before if the PEV is connected to the grid and energy can be traded ($\Psi_h = 1$). The product $\boldsymbol{b_{h-1}} \,.\, \boldsymbol{\delta_h}$ needs to be linearized, δ_h being the binary decision variable to buy or sell in the BM and b_{h-1} the variable representing the state of charge of the battery.

IV – 1.c) Case study – Deviation costs estimation

Deviation costs have been computed every day of 2014 with Spanish market prices and a rolling period of three hours. A deviation from the DA-schedule of 15% has been applied every single day of the year after calculating the optimal purchases in the DA market. Table 13 summarizes the input data used to conduct calculations.

Deviation	15%	
Discharge from driving needs	2	[kWh]
Connection availability	0h-7h 20h-23h	
Battery max rate of charge	3	[kWh]
Grid to battery efficiency	0,94	[p.u]
Battery max state of charge	85	[kWh]
Battery max autonomy	450	[km]
Battery initial state of charge	0	[kWh]
Kilometres to charge	50	[km]

Table 13 - Input data for the deviation costs estimation

Figure 37 - PEV charging - Day-Ahead costs

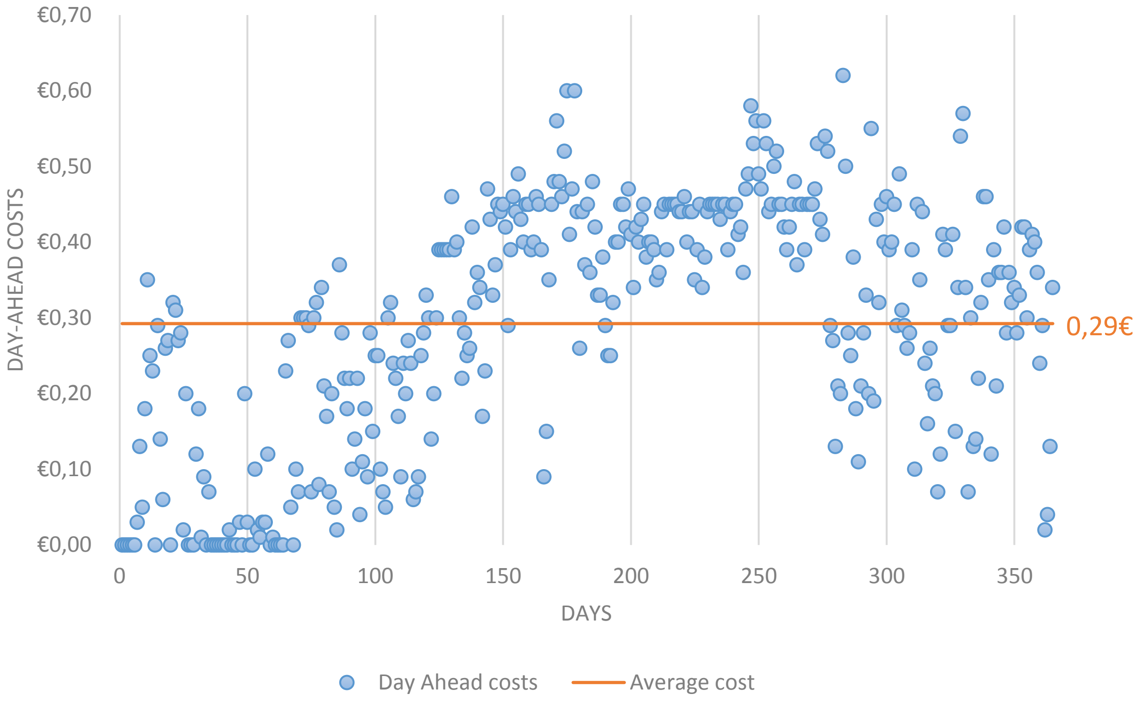
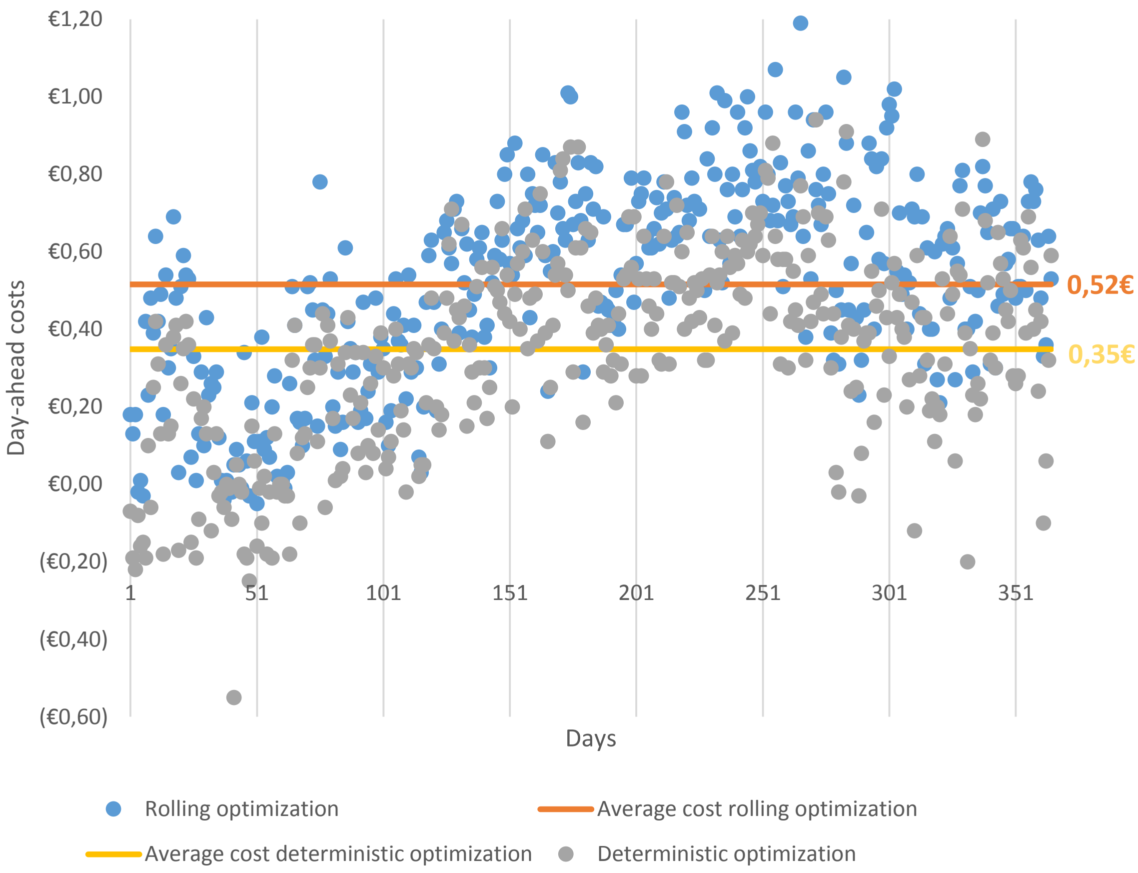


Figure 38 - PEV charging - Day-Ahead & Balancing costs



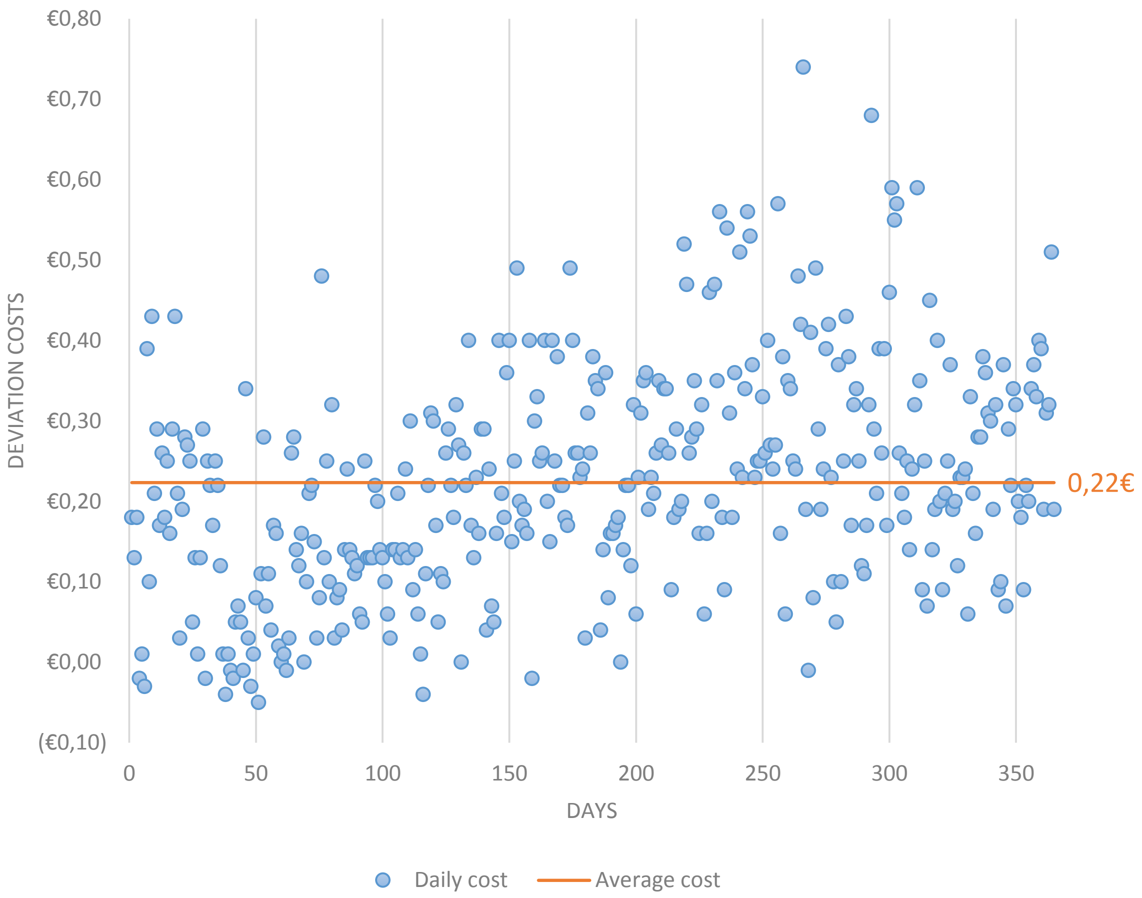


Figure 39 - PEV charging - deviation costs

The average deviation costs obtained for 2014 with the simulation are of 0,22€ (figure 39) which represents almost 76% of the day-ahead cost of charging the electric vehicle (figure 37). Deviation costs account for an important part of the total charging cost of an electric vehicle (figure 38). Also, it can be seen that the cost of charging a PEV is quite volatile along a year in figure 38. When comparing the results obtained with a rolling optimization and a deterministic optimization as in section III, it can be seen in figure 38 than instead of having an average daily cost of 0,35€ charging the PEV, it costs 0,52€ to charge the vehicle with the rolling optimization. This is due to the fact that when having information regarding deviations later during the day, less hours remains to cope with those deviations and thus, the charging schedule can be adapted in a less flexible way than when having perfect information since the beginning of the day.

	DAILY AVERAGE OF DAY-AHEAD AND BALANCING COSTS
ROLLING OPTIMIZATION	0,52 €
DETERMINISTIC OPTIMIZATION	0,35 €

Table 14 - Deterministic vs rolling optimization results

IV – 2. Optimal capacity to contract

All previous models dealt with energy purchases but did not considered the optimal in home contracted capacity. In order to have an idea of the optimal capacity to contract for charging an EV buying energy in the DAM, a simulation has been conducted with average driving patterns for a whole year.

The simulation analyses the trade-off between the maximum energy that can be bought in an hour at a certain price due to the capacity restriction and the cost of contracting more capacity. As explained earlier, a higher capacity means that more energy can be bought during a single hour and therefore more energy can be charged in the battery during low price hours.

The model only considers energy purchases in the day-ahead market and the PEV owner average daily mobility requirements.

OBJECTIVE FUNCTION

$$Min \quad \left[\sum_h \left(\frac{b_h - b_{h-1}}{\eta} . p_h^{DA} \right) + CAP \, . \, p^{CAP} \right]$$

SUBJECT TO

$$\forall(h) \quad b_{h-1} \leq b_h \tag{2}$$

$$\forall(h) \quad \underline{B}_{23h} \quad \leq \ b_h \tag{3}$$

$$\forall(h) \quad \frac{b_h \ - \ b_{h-1}}{\eta} \ \leq CAP . c_h \tag{4}$$

$$\forall(h) \quad CAP \quad \leq 10 \tag{5}$$

SETS

h	hours	[0h – 23h]

PARAMETERS

$\underline{B}_{23}$	Minimum battery state of charge	[kWh]
η	Grid to battery efficiency	[p.u.]
p_h^{DA}	Day-ahead market price	[€/kWh]
p^{CAP}	Capacity price	[€/kW/d]
c_h	Connection status of the PEV to the grid 1 is connected, 0 is disconnected	[0/1]

VARIABLES

b_h	Battery state of charge during the hour h	[kWh]
CAP	Capacity to contract	[kW]

The objective function is divided into two parts:

1. The energy component
2. The capacity component

The energy component is the sum of the energy bought in the DAM multiplied by its corresponding price every hour of the day. The energy bought during an hour h is defined as follow:

$$\frac{b_h - b_{h-1}}{\eta} = energy\ bought\ in\ the\ DAM\ during\ the\ hour\ h$$

In fact this equation can be seen as the battery state of charge (BSOC) through the day, the energy contained in the battery during an hour h is equal to the BSOC the hour before more the energy bought for that hour reduced by the grid to battery efficiency.

The capacity component of the objective function is nothing more than the capacity to contract multiplied by its corresponding price.

Equation (2) ensures that the battery does not discharge itself from an hour to the other.

Equation (3) defines the energy to reach in the battery for the last hour of the day. This energy corresponds to the requirements in kilometres of the PEV owner.

Equation (4) is the maximum rate of charge limitation due to the capacity contracted, i.e. the maximum energy that can be charged in the battery during one hour.

Equation (5) limits the capacity to contract to 10 kW. Contracting more than 10 kW would require special equipment to cope with the power capability and is usually not common for domestic purposes.

IV – 2.a) Case study – Optimal capacity

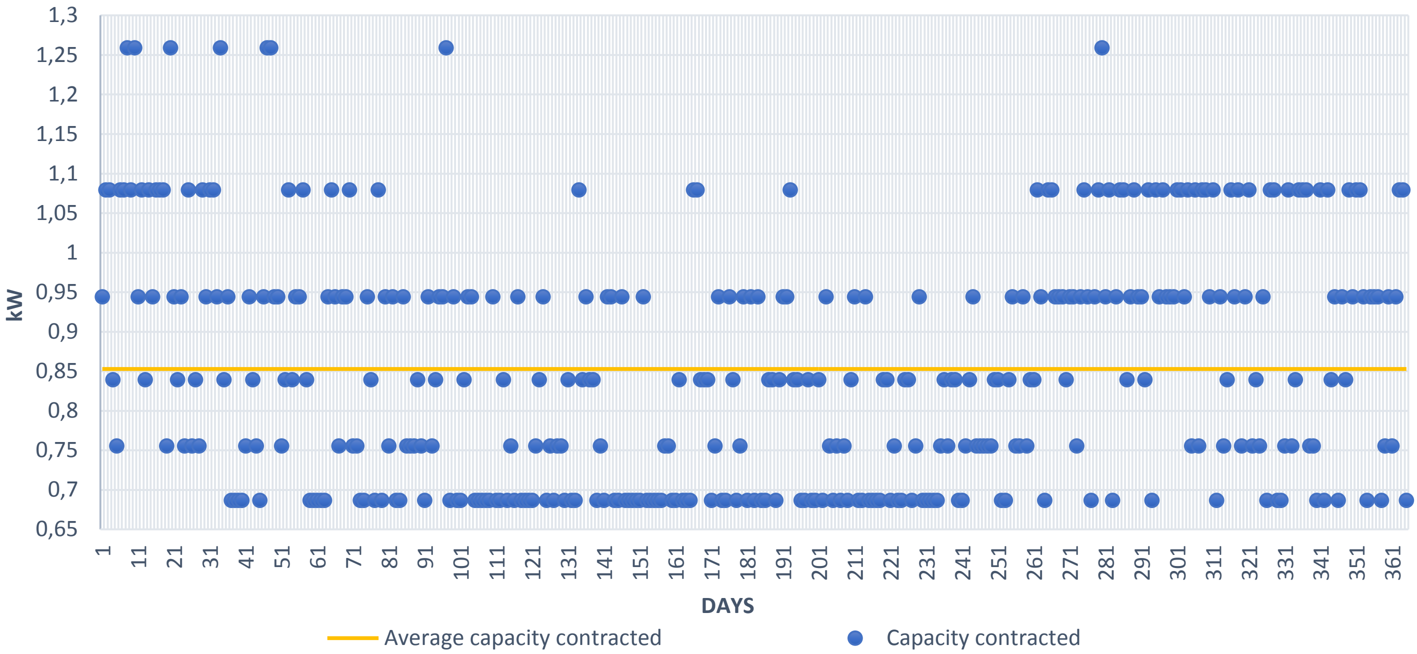
The purpose of this case study is to have an idea of the optimal capacity required to supply the average mobility needs of an electric vehicle along a year. First the optimal daily capacity is computed for a whole year, then an example of the optimal day-ahead purchases as a function of the contracted capacity is presented to analyse the impact of capacity on DA charging strategy.

The daily optimal capacity has been computed for a whole year with Spanish day-ahead market prices of 2014. The battery characteristics are the ones of Tesla model S:

- 450 km autonomy for 85kWh battery capacity which represents a consumption around 19kWh/100km.

The average distance travelled every day was set to 40 km which is converted in a minimum amount of energy to reach in the battery of 7,56 kWh every day by midnight. The daily car connection to the grid is set to 0h-7h and 21h-23h. This profile is considered as standard, since average mobility needs in Europe are around 40 km per day. Capacity prices [42€/kW/year] are coming from Iberdrola [11], one of the five major electricity companies in Spain.

Figure 40 - Optimal daily capacity along the year



The first striking element when looking at the results obtained is that there are 5 optimal daily capacities to contract along the year and not a different one every day: 0,69 kW / 0,76 kW/ 0,84 kW / 0,94 kW / 1,08 kW / 1,26 kW. The rationale behind this outcome is logical since those numbers are multiples of the amount of energy to charge every day of the year (7,56 kWh). Contracting 1,26 kW means that the battery would be charge in 6 hours (7,65 ÷ 1,26). Contracting 0,69 kW means that the battery would be charge during the 11 hours of connection of the car. As the model is defined by hour steps, it tries to define the optimal capacity also in hour steps.

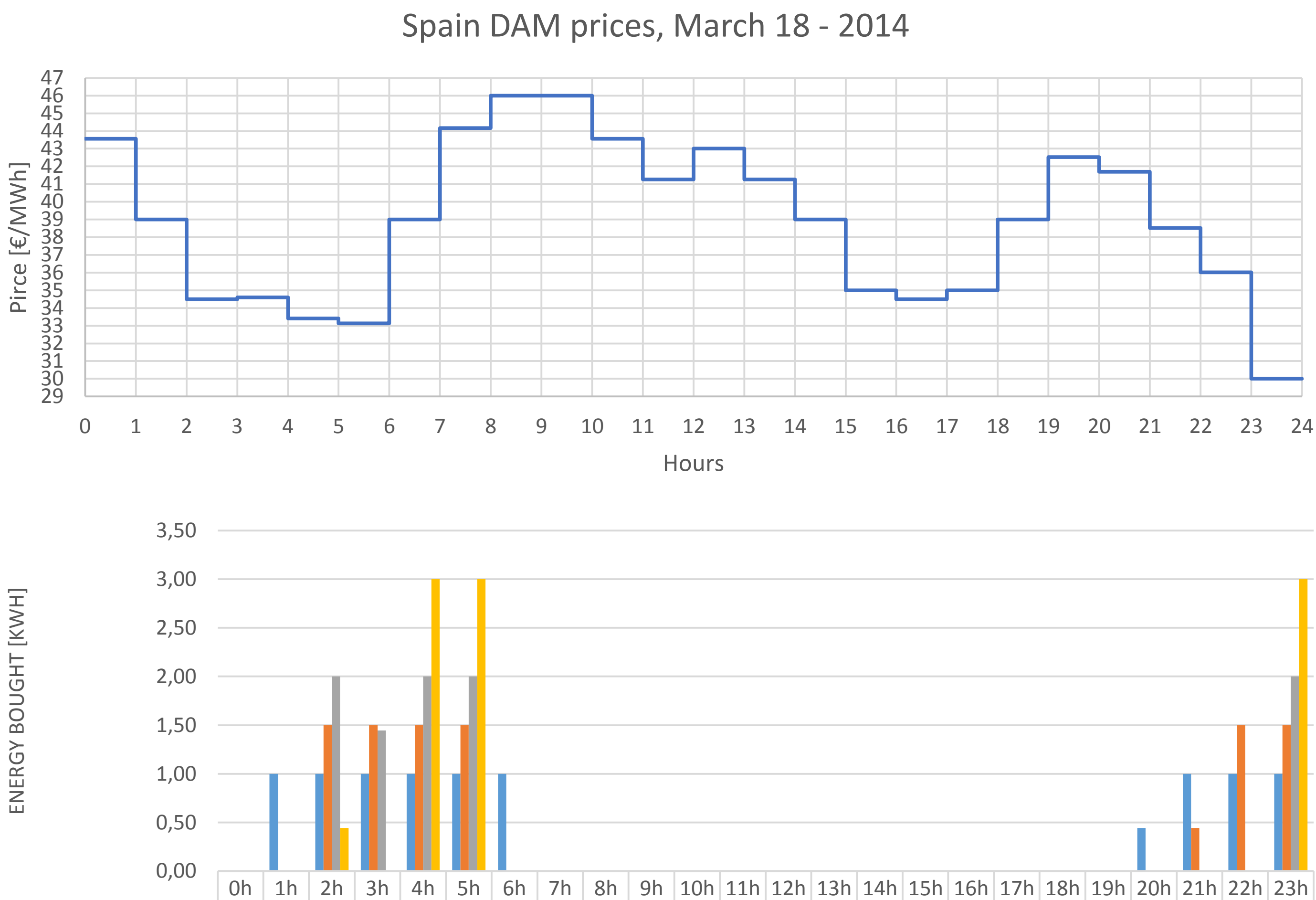
Looking at the results in figure 40 it can be concluded that the optimal capacity to contract for charging purposes with average mobility needs is not a lot and roughly around 0,85 kW (average value). In real life, the exact optimal capacity cannot be contracted due to technical characteristics of the grid. The distributor will propose to choose among some capacities which will not fit perfectly the driving needs of the PEV owner. However, this tool provide a good estimation of the required capacity as function of the daily average distance travelled and the connection habits of an electric car owner. In addition, this computation would need to consider the house load profile if the EV is charged directly from the house.

Capacity effect on optimal daily purchases

The effect on optimal purchases in the DAM of the house capacity contracted has been analysed considering a single EV and a single day of 2014 with Spain DAM prices of March 18. Input data used to conduct this simulation are shown in table 15. Four different capacities have been considered: 1 kW, 1,5 kW, 2kW, 3kW.

Input data		
Connection availability	0h-7h 20h-23h	
Grid to battery efficiency	1	[p.u]
Battery max state of charge	85	[kWh]
Battery max autonomy	450	[km]
Battery initial state of charge	0	[kWh]
Kilometres to charge	50	[km]

Table 15 - Input data for the capacity effect on optimal DA purchases



	0h	1h	2h	3h	4h	5h	6h	7h	8h	9h	10h	11h	12h	13h	14h	15h	16h	17h	18h	19h	20h	21h	22h	23h
1 kW contracted		1,00	1,00	1,00	1,00	1,00	1,00														0,44	1,00	1,00	1,00
1,5 kW contracted			1,50	1,50	1,50	1,50																0,44	1,50	1,50
2 kW contracted			2,00	1,44	2,00	2,00																		2,00
3 kW contracted			0,44		3,00	3,00																		3,00

Figure 41 - DAM purchases as a function of the contracted capacity

CAPACITY CONTRACTED	ENERGY COST
1 KW	0,33668€
1,5 KW	0,31958€
2 KW	0,31203€
3 KW	0,30492€

Table 16 - Energy cost results

The higher the capacity contracted the lower the number of hours needed to charge the vehicle. When more capacity is available, more energy is bought during low prices hours, reducing the energy cost component of charging the EV. The energy costs of charging the vehicle in function of the contracted capacity are summarized in table 16.

CHAPTER V: Conclusions

V – I. Main findings

The main results of this master's Thesis are summarized below, analysing the proposed objectives of section I - 3.

- **Obtaining the optimal charging schedule of a PEV fleet considering the day-ahead market.** The optimal charging schedule in the DAM of a PEV fleet has been computed with a mathematical optimization model forming part of a wider study on aggregation in balancing markets. The DAM model outcome has been used as a preliminary deterministic schedule for balancing markets models. For a standard PEV profile with 50km daily mobility needs , the average daily cost of charging the car buying energy in the Spanish DAM for 2014 was estimated to 0,29 c€.

- **Assess the impact of the uncertainty of consumer's behaviour in the balancing market.** A deviation simulation has been elaborated in visual basic to account for PEV owners unexpected needs of driving their car. These unexpected events originate imbalances for the system which must be settled in the balancing market. Deviations are simulated by altering the preliminary schedule obtained with the day-ahead market model. Then they are introduced in balancing market models as input data, accounting for the uncertainty of consumer's behaviour in real-time. In addition, an estimation of imbalances costs has been conducted for a single vehicle with a rolling optimization model through a whole year. The results obtained show that the cost of imbalances is significant when compared to the day-ahead cost of charging a PEV (around 75% of the day-ahead cost) and that having information regarding PEV owners' behaviour is really important. Indeed, when comparing the cost of charging a car with a deterministic model and a rolling optimization through the day, deterministic results are far better than the ones obtained with a rolling optimization (33% better on average terms).

- **Assess the economic value of an aggregator in the balancing market.** This objective has been achieved by comparing the outcome of two balancing markets models: one considering aggregation, the other not considering it. Results are clear, the charging strategy of an aggregator is always better or equal to the charging strategy without aggregation. Benefits in balancing markets stem from imbalances netting possibility of aggregation. Indeed, when charging an EV independently, the netting opportunity disappears, giving rise to higher charging costs than under aggregation scheme. The higher the number of PEVs under aggregation, the higher the benefits of aggregation. This has been demonstrated running the simulation for [500/1000/1500] PEVs showing that the difference in profits between aggregation and no aggregation increase linearly with the number of vehicles aggregated. Under perfect conditions, benefits of aggregating 1000 PEVs in the Spanish BM for the month of January 2014 have been estimated to 454€. It has also been demonstrated that benefits of aggregation are lower when considering grid to battery efficiency and battery degradation cost, due to less possibilities of making money through arbitrage in the BM. Compared to perfect conditions, adding G2B efficiency reduces benefits of aggregation of around 20% and if battery degradation is added, benefits are reduced of around 86% (with batteries current replacement cost (300€/KWh)).

- **Analyse the effect of imbalance prices: Dual price/Single price.** Under a single price balancing mechanism, benefits of aggregation appear to be lower than with a dual price market. Indeed, under a single price market, benefits of aggregation are of a few euros per months (around 3€ for charging 1000 PEVs under perfect conditions whereas under a dual price market it is around 454€). However, charging electric vehicles in a single price balancing market is less costly than in a dual price one. Indeed, much more money can be made through arbitrage as deviations from the day-ahead schedule are not always penalized. The important point here is that benefits of aggregation appear both under a dual price and a single price BM.

- **Assess the impact of capacity charge.** An estimation of the optimal capacity needed for using an electric vehicle at home has been conducted, seeking the best trade-off between capacity cost and energy purchases savings in the day-ahead market. Indeed, a higher contracted capacity permits to buy more energy during low price hours, therefore reducing the energy cost component of charging an electric vehicle. For average mobility needs in Europe (40km/day), the optimal capacity needed for charging an electric vehicle (without considering other domestic energy needs) is around 0,85 kW taking into account the assumptions of the model proposed.

- **Additional points.** Information is crucial for the aggregator to achieve the best charging schedule possible for its fleet: market prices, connection status of the fleet to the grid, possible unexpected driving needs of a client. Indeed, benefits of aggregation stem from the optimal management of all this information to handle a "virtual power plant" and bid in an optimal way in electricity markets. It is noteworthy that battery degradation due to energy flows coming in and out of batteries have a strong impact on optimal bids in electricity markets due to the current high price of batteries. Although benefits of the aggregator charging strategy are not tremendous, they are not only limited to optimal bids in energy markets. Indeed, this is only a part of the iceberg, and as detailed in this master's Thesis, the aggregator could provide additional services to the grid, reach economies of scale and scope overcoming participation market fees, reduce transaction costs and address bounded rationalities.

V – 2. Future work

The work presented in this master's Thesis is limited and subject to many simplifying assumptions. Improving, developing and extending the models presented along this report may be a good start for future work, more specifically:

- **Increase the number of PEVs** considered in simulations to several thousands to see the impact of having a really large vehicle fleet under aggregation (1500 PEV being the maximum considered in this master's Thesis). Along with increasing the number of vehicles, it would be interesting to **define several deviation distributions** for different vehicle charging profiles (truck driving during the night, household PEV used during the day…). **Increasing the number of vehicle types** is also important to assess the impact of a wide range of PEV behaviours on aggregation.

- **Develop a PEV aggregation rolling optimization model through the day for imbalances settlement in balancing markets**. Indeed it would be interesting to assess the impact of not having information about changes in PEVs schedule since the beginning of the day when considering deviations from the day-ahead schedule.

- **Include markets price forecasts** in the models developed to assess the effect of imperfect information regarding markets prices on the optimal charging strategy of the aggregator.

- **Consider arbitraging in the DAM.** Indeed, arbitrage was not considered in the DAM in this master's Thesis. Playing with batteries in the DAM could generate additional profits for the aggregator.

Figures and tables

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Annexes

Deviation simulation VBA code

```
Sub deviationPEV()

    'desactivate screen updating
    Application.ScreenUpdating = False

    nPEV = ThisWorkbook.Sheets("Dahead").Cells(9, 10).Value
    compteur = 1

    'scale initial hourly connection and Energy bought in DA to half-hour vector
    ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
    Dim Chour(0 To 23) As Byte 'initial hourly connection vector
    Dim Chalf(0 To 47) As Byte 'half-hour connection vector
    Dim ehour(0 To 23) As Variant 'initial hourly connection vector
    Dim ehalf(0 To 47) As Variant 'half-hour connection vector

    For v = 1 To nPEV
        For i = 0 To 23
            Chour(i) = ThisWorkbook.Sheets("Data2GAMS").Cells(i + 2, v + 1).Value
            Chalf(2 * i) = Chour(i)
            Chalf(2 * i + 1) = Chour(i)
            ehour(i) = ThisWorkbook.Sheets("ResultsDA").Cells(i + 2, v + 1).Value / 2
            ehalf(2 * i) = ehour(i)
            ehalf(2 * i + 1) = ehour(i)
        Next i
        Range(ThisWorkbook.Sheets("Data2GAMS2").Cells(157, v + 1), ThisWorkbook.Sheets("Data2GAMS2").Cells(204, v + 1)).Value = Application.
WorksheetFunction.Transpose(ehalf)
        Range(ThisWorkbook.Sheets("Data2GAMS2").Cells(208, v + 1), ThisWorkbook.Sheets("Data2GAMS2").Cells(255, v + 1)).Value = Application.
WorksheetFunction.Transpose(Chalf)
    Next v
    ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''


    'Generation of connection deviations and discharges from unexpected driving needs for each vehicle v of  type t
    ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
    For t = 1 To 5

        nPEVt = ThisWorkbook.Sheets("Dahead").Cells(9, 4 + t).Value
        'Find the original number of half hour connections
        ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
        firsth = CInt(Left(ThisWorkbook.Sheets("Dahead").Cells(11, 4 + t).Value, 2))
        Secondh = CInt(Left(ThisWorkbook.Sheets("Dahead").Cells(12, 4 + t).Value, 2))

        If ThisWorkbook.Sheets("Dahead").Cells(15, 4 + t).Value <> "" Then
            starth2 = CInt(Left(ThisWorkbook.Sheets("Dahead").Cells(15, 4 + t).Value, 2))
            finishh2 = CInt(Left(ThisWorkbook.Sheets("Dahead").Cells(16, 4 + t).Value, 2))
        Else
            starth2 = 0
            finishh2 = 0
        End If

        Halfhconnection = (finishh2 - starth2 + 1 + Secondh - firsth + 1) * 2
        ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''


        'set parameters
        ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
        Dim parameters(0 To 7)
        For y = 0 To 7
            parameters(y) = ThisWorkbook.Sheets("Dahead").Cells(18 + y, 4 + t).Value
            parameters(0) = ThisWorkbook.Sheets("Dahead").Cells(18, 4 + t).Value / 2
        Next y
        ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''


        'Define the number of modification to operate on connection vector
        ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
        Dim Nmodifmax As Variant 'maximum number of modification to operate for the whole day
        alpha = CInt(Left(ThisWorkbook.Sheets("Deviation").Range("P5").Value, 2)) / 100
        Nmodifmax = CInt(Halfhconnection * alpha)
        ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
```

```
    For v = compteur To nPEVt + compteur - 1

        'initialize vectors to change
        ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
        Dim discharge(0 To 47)
        Dim choosen(0 To 47) As Boolean 'vector to do the random drawing and see if smth has already been picked
        For k = 0 To 47
            discharge(k) = 0
            Chalf(k) = ThisWorkbook.Sheets("Data2GAMS2").Cells(208 + k, v + 1).Value
            choosen(k) = False
        Next k
        ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''


        'initialize the boolean vector to false
        ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
            Dim vector(1 To 100) As Boolean 'vector to do the random drawing and see if smth has already been picked
            For x = 1 To 100
                vector(x) = False
            Next x
        ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''


        'copy parameters
        Range(ThisWorkbook.Sheets("Data2GAMS2").Cells(366, 1 + v), ThisWorkbook.Sheets("Data2GAMS2").Cells(373, v + 1)).Value = Application.WorksheetFunction.Transpose(parameters)
        ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
        For f = 1 To Nmodifmax

            'choose an integer number between 1 and 100 that has not already been picked
            ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
            Do
                Randomize
                random = CInt(Rnd() * 99) + 1
            Loop Until vector(random) = False
            ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''


            'Define % of chances
            ''''''''''''''''''''''''''''''
            If (random = 1) Then
                H = 0
                vector(1) = True
            ElseIf (random = 2) Then
                H = 3
                vector(2) = True
            ElseIf (random <= 7) Then
                H = 6
                For x = 3 To 7
                    vector(x) = True
                Next x
            ElseIf (random <= 17) Then
                H = 9
                For x = 8 To 17
                    vector(x) = True
                Next x
            ElseIf (random <= 47) Then
                H = 12
                For x = 18 To 47
                    vector(x) = True
                Next x
            ElseIf (random <= 72) Then
                H = 15
                For x = 48 To 72
                    vector(x) = True
                Next x
            ElseIf (random <= 90) Then
                H = 18
                For x = 73 To 90
                    vector(x) = True
                Next x
            ElseIf (random <= 100) Then
                H = 21
                For x = 91 To 100
                    vector(x) = True
                Next x
            End If
            ''''''''''''''''''''''''''''''
```

```vb
            'choose the hour affected randomly between lower and upperbound included
            Do
                Randomize
                random = CInt((47 - H) * Rnd()) + H
            Loop Until choosen(random) = False
            choosen(random) = True

            'find the last half hour connection
            Lastconnection = ThisWorkbook.Sheets("Data2GAMS2").Range(ThisWorkbook.Sheets("Data2GAMS2").Cells(208, v + 1), ThisWorkbook.Sheets("Data2GAMS2").Cells(255, v + 1)).Find(1, SearchDirection:=xlPrevious, LookIn:=xlValues, LookAt:=xlWhole).Row - 208

            If (random > Lastconnection) Then
                Chalf(random) = 1
                If discharge(random) = 3 Then discharge(random) = 0
            ElseIf (random = Lastconnection) Then
                Chalf(random) = 0
                If discharge(random) = 3 Then discharge(random) = 0
            Else
                If Chalf(random) = 0 Then
                    Chalf(random) = 1
                    If discharge(random) = 3 Then discharge(random) = 0
                Else
                    Chalf(random) = 0
                    discharge(random) = 3
                End If
            End If

        Next f

        Range(ThisWorkbook.Sheets("Data2GAMS2").Cells(208, 1 + v), ThisWorkbook.Sheets("Data2GAMS2").Cells(255, 1 + v)).Value = Application.WorksheetFunction.Transpose(Chalf)
        Range(ThisWorkbook.Sheets("Data2GAMS2").Cells(259, v + 1), ThisWorkbook.Sheets("Data2GAMS2").Cells(306, v + 1)).Value = Application.WorksheetFunction.Transpose(discharge)


        'Change Bmin(h) vector, the minimum energy that must be charged in the battery during the hour h
        ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
        'convert initial km in kWh
        b = ThisWorkbook.Sheets("Data2GAMS").Cells(53, v + 1).Value
        '* (1 + alpha)
        'reset Bmin(h) vector to 0
        Dim bmin(0 To 47) As Variant
        For w = 0 To 47
            bmin(w) = 0
        Next w

        Lastconnection = ThisWorkbook.Sheets("Data2GAMS2").Range(ThisWorkbook.Sheets("Data2GAMS2").Cells(208, v + 1), ThisWorkbook.Sheets("Data2GAMS2").Cells(255, v + 1)).Find(1, SearchDirection:=xlPrevious, LookIn:=xlValues, LookAt:=xlWhole).Row - 208

        For w = Lastconnection To 47
             bmin(w) = b
        Next w
        Range(ThisWorkbook.Sheets("Data2GAMS2").Cells(310, v + 1), ThisWorkbook.Sheets("Data2GAMS2").Cells(357, v + 1)).Value = Application.WorksheetFunction.Transpose(bmin)

        ''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''

    Next v

    compteur = compteur + nPEVt

  Next t

  'Activate screen updating
  Application.ScreenUpdating = True


End Sub
```

Linearization of non-lineal products with binary variables [12]

Let us consider the following product where x is a positive variable and δ a binary variable:

$$x.\delta$$

A way to linearize this product would be to define a new positive auxiliary variable $\boldsymbol{y}$ and replace the product $\boldsymbol{x}.\boldsymbol{\delta}$ by $\boldsymbol{y}$ in corresponding equations following the logic below:

$$\delta = 0 \Rightarrow y = 0$$
$$\delta = 1 \Rightarrow y = x$$

This logic can be translated as follow, where M is the upper bound of x:

$$y \geq 0$$
$$y \leq M.\delta$$
$$-x + y \leq 0$$
$$x - y + M.\delta \leq M$$
$$x \leq M$$