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Home energy management system with multiple assets and multiple value pockets, a utopia?

Author: **Lucien HALKIN**
Supervisor: **Emmanuel DE JAEGER**
Readers: **Nabil BOUCHAIR, Cathy CRUNELLE, Jean-Pierre RASKIN**
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Abstract

Historically, large power plants dominated electricity production. These plants, while easy to control for grid balance, emitted significant amounts of carbon emissions. Today, the development of renewable energy sources is increasing, bringing control challenges due to their intermittent nature and decentralized setup. The rise of domestic photovoltaic panels has introduced a bidirectional electricity flow for some consumers, creating prosumers who both produce and consume electricity.

Previously, electricity consumption involved limited appliances with minimal flexibility. Today, the electrification of assets, particularly in transportation with electric vehicles, has increased. Moreover, prosumers who both produce and consume electricity can now decide to use their own production when it is necessary to charge an asset. Residential demand side flexibility is now more viable due to the increased number of assets and bidirectional electricity flow. Due to these changes in production and consumption, new pricing programs have been developed to meet today's needs of prosumers who both produce and consume electricity.

For consumers, and especially prosumers who both produce and consume electricity, it becomes difficult to manage the recharging of all these electrical assets under various pricing programs. This is why the development of home energy management systems, which are tools that manage all these constraints simultaneously, has become crucial. This study aims to evaluate multiple assets and flexibility mechanisms together, comparing the results with simpler ones. The assets and types of pricing were chosen to correspond to the case of a consumer from Flanders in Belgium. The residential system is composed of a house with photovoltaic panels and an electric vehicle under capacity pricing.

Simulations are based on the control of the battery charge of the electric vehicle. Three simple controllers, each based on a control technique of its own, are used. The Self-Consumption controller maximizes the use of local photovoltaic electricity, the Peak-Shaving controller smooths the power consumption, and the Load-Shifting controller moves the recharge to nighttime. A controller called Multi-Pocket is designed for this study. It integrates the control logic of the three simple controllers with additional specifications in order to adapt to the constraints of the capacity pricing of the Flemish household. This household is simulated with each of the four controllers by integrating all the system variable parameters into the simulation. Those parameters vary the type of household consumption, the driving profile of the electric vehicle, the technical parameters of the electric vehicle, and the photovoltaic installation specifications.

We compare the results of the controllers with profit generated and the self-consumption factor as key performance indicators. Controllers were grouped into two categories that follow similar trends. The Peak-Shaving and Load-Shifting controllers are adapted for workers with high

mileage who commute every day of the week by car. They are particularly suitable for individuals with low household consumption, where an oversized photovoltaic installation is desirable but not necessary. An electric vehicle with standard parameters is sufficient. In contrast, the Self-Consumption and Multi-Pocket controllers are suitable for flexible hybrid workers who park their cars at home several days a week. High domestic consumption is not a disadvantage and is even more advantageous during the summer. An oversized photovoltaic installation and an electric vehicle with robust technical parameters are important. Self-Consumption and Multi-Pocket controllers are much more profitable than Peak-Shaving and Load-Shifting. From this result, it is concluded that a strategy focused on maximizing the consumption of free electricity from photovoltaic production yields significant profit. Conversely, a strategy based on minimizing power peaks to comply with capacity pricing is less successful.

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Contents

Acronyms

RES Renewable Energy Sources

CE Carbon Emissions

EV Electrical vehicule

PV Photovoltaic

DSF Demand Side Flexibility

LBE Laborelec

TSO Transport System Operator

HEMS Home Energy Management System

BESS Battery Energy Storage System

ESyPAC Energy Systems Performance Assessment and Comparison

EPL Ecole Polytechnique de Louvain

HV High Voltage

BRP Balance Responsible Parties

DSO Distribution System Operator

IEA International Energy Agency

EU European Union

CAISO California Independent System Operator

FGU Flexible Generation Units

DLR Dynamic Line Rating

TOU Time-of-Use

CPP Critical Peak Pricing

RTP Real-Time Pricing

LP Linear Programming

MINLP Mixed Integer Linear Programming

PSO Particle Swarm Optimization

SC Self-Consumption

PS Peak-Shaving

LS Load-Shifting

MP Multi-Pocket

FPS Federal Public Service

KPI Key Performance Indicator

RFE Random Forest Estimator

Nomenclature

Symbols

P_{nom}	Nominal power of the PV installation	kWp
$E_{baseload}$	Annual energy consumption of the house	kWh
E_{PV}	Annual energy production of the PV installation	kWh
P_{EV}^{max}	Maximum power charge of the EV	kW
P_{EV}^{min}	Minimum power charge of the EV	kW
P_{EV}^{c}	Comfort power charge of the EV	kW
P_{EV}^{PV}	Power charge of the EV from the PV production	kW
E_{EV}	Capacity of the EV	kWh
C_{EV}	Consumption of the EV	kWh/km
FD	Full day : Number of day per week of work-home round-trip	day
HD	Half day : Number of half-day per week of work-home round-trip	day
d	Distance of the commute	km
d_c	Comfort distance	km
C_{total}	Annual cost of the electricity bill	€
π	Annual economical profit	€
t_d	Departure time of the next trip	s
Δt_d	Recharge time needed at P_{EV}^{max} to complete the next trip	s
Δt_n	Night recharge range from 11 p.m. to 7 a.m.	s
$\eta_{inverter}$	Inverter yield	
α_{PV}	Peak power coefficient	
β_{SC}	Annual system self-consumption factor	
$\eta_{EV,charge}$	Charge efficiency of the EV	
SOC_{EV}^{max}	Maximum state of charge of the EV	
R_{SW}	Summer/Winter ratio of baseload consumption	
R_{DN}	Day/Night ratio of baseload consumption	
SOC_m	Minimal SOC of multi-pocket algorithm	
SOC_t	Transport SOC of multi-pocket algorithm	
SOC_c	Comfort SOC of multi-pocket algorithm	

1 Introduction

Society's energy landscape is rapidly evolving due to the urgent need to address climate change caused by human activities. There is a global shift towards reducing fossil fuel dependency, marked by the increased development of Renewable Energy Sources (RES) to cut Carbon Emissions (CE) [1]. These RES are intermittent and decentralized, posing new challenges. The electrification of various assets, such as Electric Vehicles (EV) and household appliances, is transforming energy consumption [2].

Maintaining a balanced power grid is crucial, requiring a constant equilibrium between electricity production and consumption. Flexibility mechanisms from production actors have traditionally managed this balance. Now, new flexibility mechanisms on the consumption side are emerging to improve grid stability [3].

Historically, large power plants dominated electricity production. These plants, while easy to control for grid balance, emitted significant amounts of CE. Today, the development of RES is increasing, which allows for zero CE but poses control challenges due to their intermittent nature and decentralized setup [4]. The rise of domestic Photovoltaic (PV) panels has introduced a bidirectional electricity flow for some consumers, creating prosumers who both produce and consume electricity, thereby providing them with new flexibility opportunities [5].

Previously, electricity consumption involved limited appliances with minimal flexibility. Today, the electrification of assets, particularly in transportation with EVs, has increased. This electrification boosts the potential for flexibility. Moreover, prosumers can now decide to use their own production when it is necessary to charge an asset. Residential Demand Side Flexibility (DSF) is now more viable due to the increased number of assets and bidirectional electricity flow, enhancing consumer flexibility control [5].

Therefore, residential DSF is becoming an important subject of investigation to develop flexibility. The research and development center of the Engie group in Belgium, Laborelec (LBE), has already conducted research on the value creation of the control of residential asset charging. As a retailer, Engie is the direct intermediary with the consumer through the contracts offered. These contracts contain new pricing methods to meet today's needs of prosumers.

For consumers, and especially prosumers, it becomes difficult to manage the recharging of all these electrical assets under various tariffs. This is why the development of Home Energy Management Systems (HEMS), which are tools that manage all these constraints simultaneously, has become crucial.

This study, conducted in collaboration with LBE, seeks to answer the question: Home energy management system with multiple assets and multiple value pockets, a utopia?

LBE's previous studies focused on single assets with multiple flexibility mechanisms or multiple assets with one mechanism. This study aims to evaluate multiple assets and flexibility mechanisms together, comparing the results with simpler ones. The assets and types of tariffs were chosen to correspond to the case of a consumer from Flanders in Belgium. The residential system is therefore composed of a house with PV panels and two assets, an EV and a residential Battery Energy Storage System (BESS). Simulations will be carried out over a year using LBE's Energy Systems Performance Assessment and Comparison (ESyPAC) tool, based on Python, for a case study in Flanders, Belgium.

This work is structured in four parts. First, we will define and explain in greater depth the terms mentioned in this introduction in a chapter dedicated to the state of the art. The next chapter will detail the methodology used, setting the precise framework of the study based on a Flemish household. It will revisit all the parameters and the control logic behind the algorithm designed for this study. We will conclude by explaining the two major sets of simulations performed. The fourth chapter presents the results of the implemented algorithm. These results will be compared to those of algorithms already implemented within ESyPAC. At the end of each chapter, corresponding user scenarios will be provided. The report concludes with a summary of the insights provided by the results and prospects for improvement.

2 State of Art

To properly understand the upcoming chapters, a state-of-the-art overview is provided in the following pages. First, the foundations are laid by referring to the various players in the electricity market in Section 2.1. The main problem related to the rapid development of RES and the growing need for flexibility to avoid energy waste is then discussed in Section 2.2. In addition to defining and classifying flexibility, we explain how each actor can generate it. The following section focuses on one actor: the end consumer and the residential DSF related to them. The end consumer is subject to pricing programs designed to activate their flexibility, which become increasingly complex, as explained in Section 2.3. With the massive electrification of society and increasingly complex pricing, it becomes difficult for the consumer to manage everything simultaneously. This challenge has led to the emergence of the HEMS concept in recent years, which is reviewed in Section 2.4. Finally, terms developed by LBE in connection with these four sections are defined in Section 2.5.

2.1 Electricity Market and Actors

The organisation of the electricity market and the different actors involved are explained in this section. Their roles in the market and the links between them come from the course *LELEC2520 Electrical Power Systems* taught at the "Ecole polytechnique de Louvain" (EPL) [6].

This organisation and actors involved are displayed in the Figure 1. This diagram shows on the left the actors involved in electricity production and its transmission on high-voltage (HV) lines. To its right are end consumers who consume this electricity. In the middle, are the market intermediaries and actors in local distribution. This historical structure with the production from left to right is changing because of RES development as will be explained in the Section 2.2.

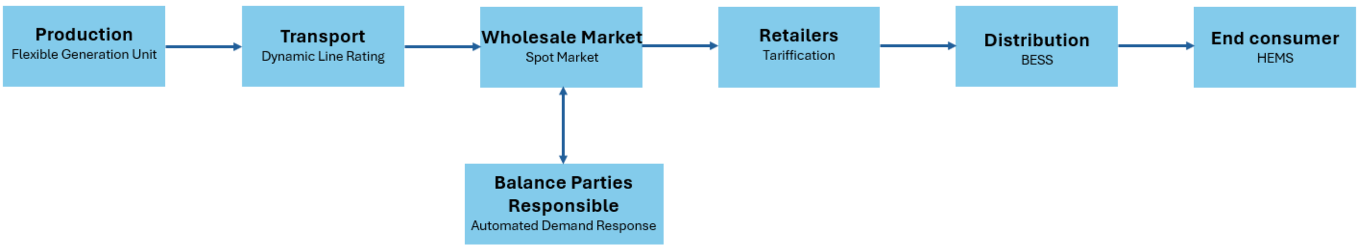


Figure 1: Electricity market structure and actors with their names, connections, and flexibility mechanisms. On the right, actors linked to production; in the middle, market intermediaries; and on the left, end consumers. Historical structure in transition due to RES development.

Production

The production takes into account all forms of electricity production. This includes fossil fuel-based production units such as coal/gas and nuclear power plants. RES complement the mix with hydroelectric dams, wind farms, and photovoltaic panels. Producers can be large centralized plants or smaller distributed generators. To balance demand, units are activated based on their cost. From the cheapest (RES, then nuclear) to the most expensive (gas, then coal).

Transport

TSO serves as the intermediary between electricity production and the market, acting as both a physical and commercial link. Since the TSO is responsible for the HV transmission network, it operates as a natural monopoly. Competition would be impractical due to the high cost of the HV network. This entity therefore defines the transmission prices and transports the electricity between the production, the large companies, and the wholesale market, ensuring that the market is balanced.

Wholesale market

The wholesale market is the interface between the production and the demand side. The producers sell portions of their capacity at a power rate. Those portions are sorted by prices. Retailers and energy-intensive companies make offers that can be accepted depending on the remaining market demand. This mechanism ensures a balance between supply and demand.

Balance Responsible Parties

Balance Responsible Parties (BRP) play a crucial role in maintaining the balance between electricity supply and demand of a part of the network. They are entities like producers, large consumers or retailers that are responsible for managing a "balancing group" in their local area. A balancing group is an account that tracks the electricity generated, consumed, bought, and sold by the BRP. The primary responsibility of a BRP is to ensure that the amount of electricity produced or procured matches the amount consumed by their customers.

Retailers

Retailers in the electricity market act as intermediaries between the wholesale market and end consumers, including households and small businesses in the tertiary sector. They purchase electricity from producers or on the wholesale market and resell it to them. Retailers are responsible for customer service, billing, and offering a range of contracts of varying lengths with different types of conditions.

Distribution

Distribution System Operators (DSO) are responsible for managing the low and medium-voltage networks that deliver electricity from the transmission system to end consumers, including homes, commercial, and small industrial users. Similar to the TSO, the DSO is a natural monopoly because it is impractical to have parallel distribution networks. Unlike the TSO, DSOs operate in more regional markets, meaning that a DSO can vary from one region to another.

End consumer

End consumers are the final users of electricity, including residential households, commercial businesses, and industrial facilities. They play a crucial role in the electricity market as their consumption patterns directly influence supply-demand dynamics.

This traditional structure is undergoing significant changes. The rapid expansion of RES and the widespread adoption of PV installations in households, enabling them to generate their own electricity (known as prosumers), are transforming the market landscape. This transformation involves the emergence of the concept of flexibility, which will be described in the next section.

2.2 Flexibility: Why We Need It and What It Is ?

This section will address the issue of flexibility. By asking the question at first what causes this need for flexibility. In a second step, a definition of flexibility will be given as well as the different categories and mechanisms that result from it.

2.2.1 Development of RES

The shift from fossil fuels to cleaner, more sustainable energy sources is fueling a substantial increase in the global deployment of RES. According to the International Energy Agency (IEA), the share of RES in global electricity generation rose from 25.1% in 2018 to 30.2% in 2023, driven largely by advances in solar and wind technologies [7]. The global capacity of solar energy alone increased by over 26% in 2022, marking one of the fastest-growing segments in the energy market [8]. This transition not only advances climate goals but also decreases reliance on volatile fossil fuel markets.

The European Union (EU) has established ambitious targets for renewable energy under its Green Deal, with the aim of achieving climate neutrality by 2050. This ambition is justified, as in 2020, the share of RES in the EU's gross final energy consumption reached 22.1%, surpassing the initial target of 20% [9]. Countries such as Germany and Spain have led the way, with Germany generating nearly 33% of its electricity from wind and solar in 2020 [10]. The EU reports that wind and solar power have been the primary drivers, accounting for over 20% of the EU's electricity production in 2020 [10].

Belgium has been progressing towards its renewable energy targets, in alignment with the EU's directives. As of 2020, RES accounted for approximately 13% of Belgium's total energy consumption [9]. Owing to the rise in wind and PV production, this figure increased to 28.2% in 2023 [11]. The Belgian offshore platform reported that wind power, particularly offshore wind farms, has been a major contributor to this growth, with Belgium ranking among the top five for highest offshore wind capacities in Europe [12]. Solar power installations have also seen a steady increase, representing nearly one-tenth of the total production at 9.5% in 2023 [11].

The development of RES, particularly domestic PV production, is a positive aspect; however, the initial grid was designed based on the structure explained in Figure 1 from the previous section. It was not designed with end-consumer production in mind, leading to curtailment issues discussed in the next subsection.

2.2.2 Waste of Energy and Inverter Tripping

This section explains the temporal mismatch between RES production and end-user consumption. This phenomenon is observed both at the scale of large RES units, such as wind farms, and smaller installations like PV panels by prosumers, which is commonly referred to as the "Duck Curve." A specific case study from Belgium is presented at the end of this subsection.

Negative electricity prices have been observed in the electricity market, particularly in countries that have extensively developed RES, mainly due to wind energy. For instance, in Germany, negative prices were recorded for 146 hours in 2017 as a result of high wind output coinciding with periods of low demand [13]. This oversupply situation leads to curtailment; for instance, Germany curtailed approximately 4% of its renewable electricity generation in the first half of 2022 due to grid bottlenecks. As a result, around 5.4 TWh of renewable energy was wasted, highlighting the challenges of integrating intermittent RES into the grid [14].

The "Duck Curve," depicted in Figure 2, illustrates the challenge of integrating high levels of PV generation into the grid. The curve, named for its shape, shows a significant drop in net load (load minus wind and PV generation) during midday when solar output peaks, followed by a steep rise in the evening as solar generation drops off and demand increases. This pattern creates significant overgeneration issues during midday. This curve was created by the California Independent System Operator (CAISO) to highlight the overgeneration of PV panels during midday and the curtailment that this implies [15].

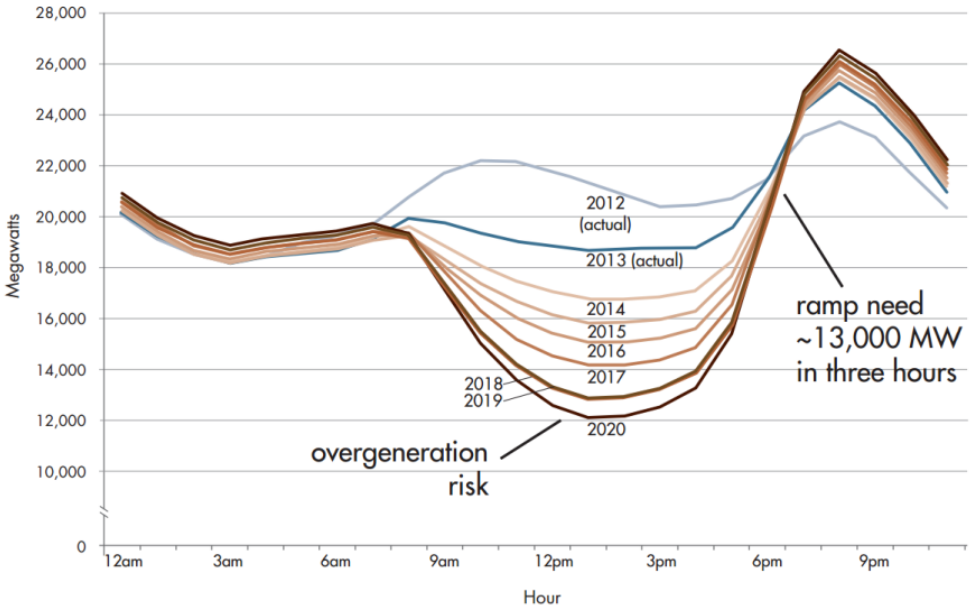
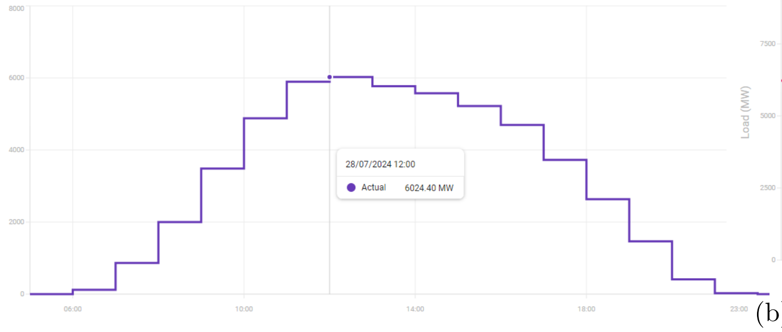


Figure 2: Net load curve [MW] over time [h] observed by CAISO, shaped like a duck. The "belly" represents the period of lowest net load, corresponding to the maximum PV generation. The belly deepens as PV installations increase from 2012 to 2020. The "neck" represents the steep rise in net load as solar power decreases and demand increases rapidly. This figure highlights the risk of overgeneration from PV panels during midday and the resulting need for curtailment.

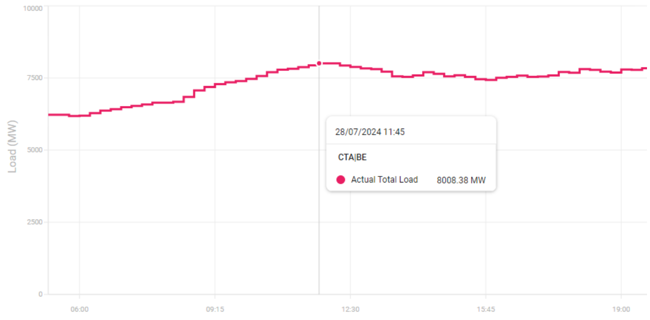
This issue of PV overgeneration also occurs in Belgium, particularly in Flanders due to a higher concentration of rooftop solar installations, though the problem is also present in Wallonia. The overgeneration from domestic PV installations leads to local oversupply on the electricity network. DSOs temporarily disconnect inverters from PV installations to prevent damage and network saturation.

Fluvius, the primary Flemish DSO, received over 5,042 complaints from prosumers in 2023 regarding inverter reconnection delays after curtailment [16]. In Wallonia, the non-profit association *BeProsumer* recorded a map of inverter tripping incidents due to grid saturation, with 3,000 cases reported in 2023 [17].

Figure 3 illustrates the PV production and total consumption on a sunny Sunday, July 28, 2024, in Belgium, as tracked by *entsoe* [18][19]. It highlights the phenomenon of PV overgeneration and subsequent inverter tripping. At that time, domestic PV production covered more than 75% of total consumption. As mentioned in 2.2.1, PV production covered 9.5% of consumption in 2023. Nuclear power plants, which remain the dominant source covering 41.3% of consumption, cannot be shut down, leading to negative pricing and energy waste [11]. These negative prices can be profitable to a user with dynamic pricing as will be explained in Section 2.3.2.



(a) PV production [MW] over time [h] from 6 a.m. to 10 p.m., with a peak of 6,024.40 MW at 12 p.m.



(b) Total load [MW] over time [h] from 6 a.m. to 10 p.m., with a peak consumption of 8,008.38 MW at 11:45 a.m.

Figure 3: PV production and total consumption in Belgium on Sunday, July 28, 2024 [19]. PV production covered more than 75% of total consumption at 12 p.m. Nuclear power plants could not be shut down, resulting in negative pricing of -46.43 €$/MWh$ and subsequent energy waste.

The same source reports that electricity prices in Belgium were negative from 10 a.m. to 6 p.m. on that Sunday, with a peak negative price of -46.43 €$/MWh$ at 2 p.m.

These extreme negative prices are primarily due to lower total consumption on a Sunday. With a peak of PV production at 6,943.15 MW and consumption at 9,788.27 MW on Monday, July 30, 2024, the most negative price recorded was -0.03 €$/MWh$.

To mitigate energy waste and prevent inverter tripping, the concept of flexibility will be defined in the next subsection, with strategies outlined for each market player to generate it.

2.2.3 Flexibility at All Times and Levels

This subsection covers the definition of flexibility and a way to categorize it. This classification comes from the study *"Flexibility: Literature review on concepts, modeling, and provision methods in smart grids"* which gives a state of art of the flexibility concept [20]. Flexibility mechanisms for the different actors are given at the end of this subsection.

Definition

To tackle the problems mentioned in sub-sections above, the electricity market can no longer rely on a balance control coming only from large production units, as it has historically been. The decentralization of smaller RES units also requires a rethinking of the system. This problem led to the intensification of the concept of flexibility within the electricity grid.

Flexibility is defined for power systems by IEA as «*the extent to which a power system can modify electricity production or consumption in response to variability, expected or otherwise*» [21].
Belgian TSO (Elia) categorizes 3 types of flexibility according to the response time to adjust power generation or consumption. The **ramping flexibility** adjusts on a minute-by-minute basis, **fast flexibility** responds within 15 minutes, and **slow flexibility** makes adjustments within a 5-hour timeframe [3].

Classifications

Hussain et al. (2023) provide several ways to categorize flexibility, the one based on *the action level in the electricity market* is used to make links with Section 2.1 [20]. The authors divide flexibility into two main categories: system side flexibility and the DSF. The next paragraph will provide a complete explanation of it.

System side flexibility refers to the actors producing and transporting electricity on the grid. Within this category, there are two distinctions.

- **Flexibility for power** : short-term equilibrium between power supply and demand for maintaining frequency stability.
- **Flexibility for energy** : medium to long-term equilibrium between energy supply and demand for demand scenarios over time.

DSF concerns local or regional demands. It is also divided into two parts.

- **Flexibility for transfer capacity** : short to medium-term ability to transfer power between supply and demand, where local or regional limitations may cause bottlenecks resulting in congestion costs.
- **Flexibility for voltage** : short-term ability to keep the bus voltages within predefined limits.

This spatial and temporal categorization of flexibility is shown in Figure 4 below.

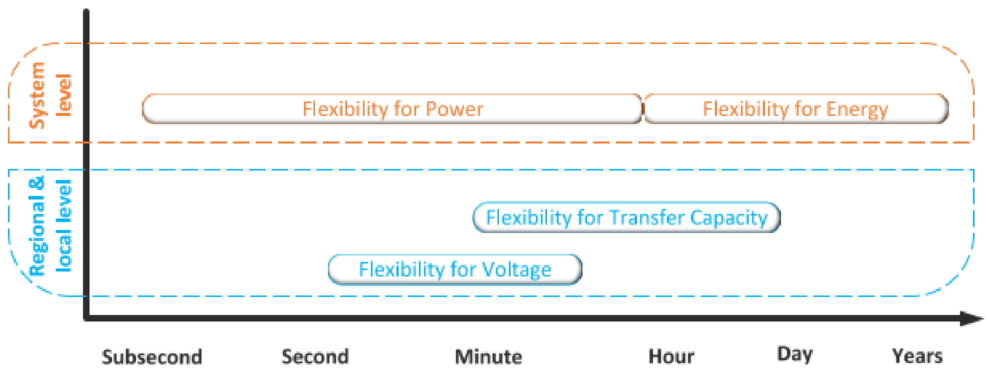


Figure 4: Flexibility classification in terms of space (local/regional to system level) and time (second to years) proposed by [20]. At system level, flexibility for power is a short-term equilibrium for frequency stability and flexibility for energy a long-term for scenarios. At local/regional level, flexibility for transfer capacity is a medium-term ability to transfer power to resolve bottlenecks and flexibility for voltage a short-term to keep bus voltages within limits.

Flexibility mechanism for each actor

With this categorization, it is now possible to locate in which category each actor detailed in Section 2.1 belongs. An example of flexibility solution is given for each of them.

At the system level, the production and the transport player are responsible for the flexibility for energy and for power respectively. Here are mechanisms that they could use.

- **Production** : Flexible Generation Units (FGU) like gas power plants or combined cycle plants can start up in a short amount of time ($\approx 15min$) to equilibrate production and consumption. These production units have high ramp rates and operate efficiently at minimum load [22]. FGU provides a fast flexibility response.

- **Transport** : A way to improve the flexibility of the market and the integration of RES production is by using Dynamic Line Rating (DLR). DLR allows transmission lines to operate closer to their actual thermal limits by continuously adjusting their capacity based on real-time environmental conditions such as temperature, wind speed, and solar radiation. By using DLR, TSO can safely increase the line's capacity during favorable conditions, effectively using existing infrastructure more efficiently [22]. DLR is a ramping flexibility mechanism.

At regional and local levels, or DSF flexibility, BRP and DSO can generate the two types of flexibility. End consumers can have an influence on the flexibility for voltage only.

- **Balance Responsible Parties** : To balance supply and demand quickly, these large consumers could use automated demand response to adjust their own demand. For example, industrial facilities equipped with smart meters and automated control systems that can reduce consumption during peak periods or increase it during times of surplus generation [23]. This automated response is a fast flexibility technique.

- **Distribution** : Integrating BESS into the distribution network to store excess electricity during low demand and high RES production periods and discharge it during consumption peaks adds flexibility to the market. For example, installing community battery storage systems in neighborhoods with high solar penetration. Energy delivered by BESS is instantaneous and belongs to ramping flexibility tools.

- **End consumer** : By the time, manner, and quantity that they consume electricity, they can bring a lot of flexibility to the network. This is part of the DSF called residential DSF, which will be fully explained in the next section.

Wholesale markets and retailers are the remaining actors in the market. They are more difficult to categorize thanks to the Hussain et al. categorization because they do not physically produce or consume energy. Nevertheless, some flexibility mechanisms are also possible for them and are detailed below.

- **Wholesale market** : By its bid/offer mechanism, the wholesale market contributes intrinsically to flexibility. More sophisticated markets that integrate RES better are a solution. For example, the spot market facilitates trading of electricity on the same day as delivery, providing flexibility to adjust for real-time changes in supply and demand [24].

- **Retailers** : The creation of residential DSF hinges on them through the contracts they offer. They already offer flexibility with bi-hourly pricing. Other tariff schemes now exist to address the integration of RES and develop flexibility; they will be explained in Section 2.3.2.

Now that the flexibility mechanisms for different actors have been listed, detailed according to the level of action (system side and DSF), the category to which they belong (flexibility for power, energy, transfer capacity and voltage), and the time spectrum where their action is possible (short, medium, long term and ramping, fast, slow). A focus will be done in next sub-section on part of the DSF that is only related to the end consumer, called residential DSF.

2.3 Demand Side Flexibility with Pricing Activation

This section provides a comprehensive overview of residential DSF and its two main forms. For one of these forms, we explain how it can be initiated through pricing programs.

2.3.1 Controllable or Not?

According to Elia, the residential DSF can be defined as "*the capability of electricity consumers to adjust their power consumption patterns in response to external signals, such as market prices or incentives.*"[25]
This subsection focuses on the consumer side of the electricity supply chain, as detailed in Figure 1, and explores the flexibility solution wanted for this work.

In **explicit** DSF, electrical assets can provide ancillary services and participate in day-ahead, intraday, and balancing markets. Asset owners sell flexibility to aggregators.
This type of DSF allows asset owners to receive financial incentives for their responsiveness, encouraging greater involvement in the program [26].

Implicit DSF requires consumers to adjust their electricity usage in response to price signals. These programs encourage customers to shift their electricity consumption to periods with lower prices, thereby reducing their overall electricity costs [26].
Participation is voluntary, meaning consumers can choose not to respond to price signals if they deem it unnecessary. The disadvantage is that this type of DSF is less controllable than the explicit one.

The different pricing programs that can activate this implicit form of DSF are detailed in the following subsection.

2.3.2 Pricing Programs for Implicit DSF become Complex

This section analyzes different pricing strategies that can be imposed on end consumers to encourage behavior changes, thereby activating residential DSF.
Yan et al. (2018) have reviewed residential pricing programs, and their results are presented in the next lines [27].

The primary goals of electricity pricing programs are to reduce overall energy consumption and shift portions of the peak load to off-peak hours. Initially implemented in the industrial sector, where energy costs constitute a significant portion of production expenses, these programs have been extended to residential areas due to advancements in infrastructure and the widespread adoption of smart meters. Smart meters enable real-time monitoring of electrical energy consumption, facilitating the effective implementation of these tariffs in homes.

Now, we explain those pricing models, including Time-of-Use (TOU) pricing, Critical Peak Pricing (CPP), and Real-Time Pricing (RTP), providing detailed descriptions and analyzing the pros and cons of each approach observed by the authors. These models are illustrated in Figure 5 below.

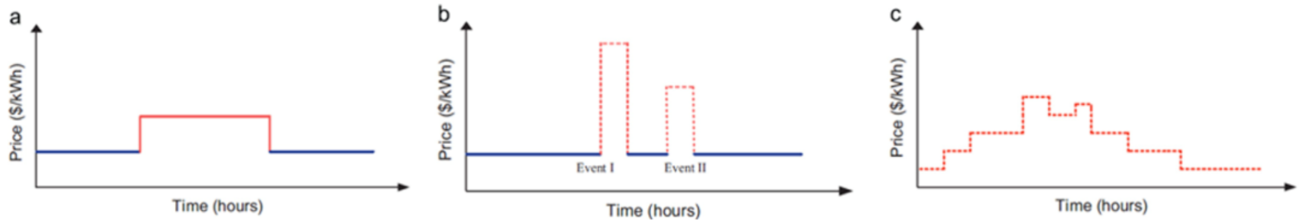


Figure 5: Pricing programs [$/kWh] over time [h]. a) TOU, b) CPP, and c) RTP. The TOU chart represents peak/off-peak pricing, which is easy to use, leading to higher user participation and increased awareness of energy savings. CPP is an event-driven tariff program with higher prices than TOU, effective for peak shifting but not for improving energy consumption efficiency or reducing CE. Under RTP, electricity prices vary continuously, making it difficult for consumers to participate, however, when combined with HEMS, it has the potential to deliver benefits.

Time-of-Use

The most common TOU program features peak and off-peak pricing, as illustrated in Figure 5.a). This pricing pattern typically remains consistent throughout each season (prices are updated annually), providing predictable and stable rates for consumers. One key benefit is its ease of use. Since the pricing remains constant within each season, consumers can easily understand and plan their daily electricity consumption. This predictability leads to a higher participation ratio in TOU programs, with a consistent percentage of consumers adhering to the pricing structure daily. A significant issue is the shifting of peak load. The demand peak often occurs immediately after the high-priced peak hours end and the lower-priced off-peak hours begin as shown in Figure 6.
Pricing models belonging to the TOU category will be used throughout this work.

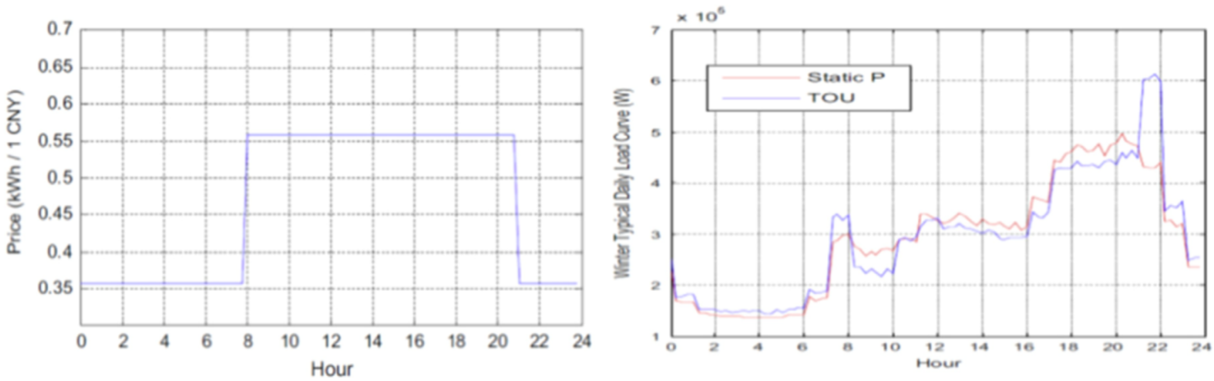


Figure 6: a) Peak/off-peak price [kWh/CNY] over time [h] b) Comparison of power generated [W] over time [h] under TOU pricing (blue) and static pricing (red). The demand peak occurs right after the price drops from peak hours to off-peak hours. The shifted peak is higher than the static price ones in red. The TOU pricing model could lead to significant power peaks in the grid.

This shifted peak is often higher than those seen with static pricing. Widespread adoption of this pricing model could lead to significant power peaks in the grid, which we aim to avoid. On the positive side, studies have shown that overall energy consumption decreases, indicating that TOU pricing successfully raises awareness about energy usage among consumers.

Critical Peak Pricing

CPP is an event-driven tariff program that uses high electricity prices when the system is severely constrained, such as during cold winter or warm summer periods, for a limited number of hours, as shown in Figure 5.b). Day-ahead CPP values are delivered to consumers through social media such as newspaper, text messages, and websites. Since severe system constraints do not occur daily, prices do not follow daily, monthly, or other regular updates. CPP may be imposed and values are higher than TOU pricing values. Because of efficient communication about prices, it is easy to use and visualize incentives. Moreover, it is highly effective for shifting peaks because events are infrequent, and households are willing to participate in ensuring system reliability. However, CPP is not an effective program for improving energy consumption efficiency or reducing CE. Because this event-driven tariff is not applied daily, it makes it difficult for consumers to plan their consumption.

Real-Time Pricing

Under the RTP program, electricity prices vary continuously in response to wholesale market prices. Prices are available to the public an hour or sometimes one day ahead (Figure 5.c)). Negative electricity prices explained at the end of subsection 2.2.2 could be used in this type of pricing. Due to difficulties in manually responding to time-differentiated prices, customers find it challenging to participate in these pricing programs. However, studies have shown that RTP signals, when combined with automation in end-use systems like HEMS, have the potential to deliver even greater benefits to both operators and consumers.

These pricing models, and their evolution into more complex versions such as RTP, complicate usage for the end consumer. The use of automation tools like HEMS, introduced in the next section, becomes essential to manage these complexities.

2.4 HEMS

Among all the actors and mechanisms specific for each of them listed in Section 2.2.3, HEMS seem to be one of the most promising solutions for end consumers. This will allow them to manage their implicit DSF (Section 2.3.1) with all the complexity that comes with it. Including the management of pricing (Section 2.3.2) and the optimization of all possible value pockets (Section 2.5).

In response to the growing relevance of this subject, Han et al. (2023) reviewed numerous studies on HEMS [28]. The study panel covers an extensive historical range, starting with foundational studies in 1979 and continuing through to the latest findings. They have developed a categorization based on system architecture, objectives, and resolution methods, which will be detailed in the following subsections.

2.4.1 Architecture of the Study System

A typical HEMS structure is composed of five main components. A **central controller** that complements the given objectives and meets user-defined specifications and preferences. It processes usage data, forecasts uncertainties, and provides optimization strategies for the household. **Sensing and measuring devices** manage real-time grid information to achieve objectives and offer utilities the ability to predict load demand more accurately. The **user interface** is software that acts as an interface between the controller, sensors, smart meter, and the appliances of the HEMS, displaying relevant information. **Energy generation and storage devices** include residential RES production systems like PV panels, wind turbines, or biomass, coupled with a domestic BESS. The fifth component is the **appliances or assets**, as previously mentioned.

The first three components are integral to the HEMS but are less relevant for this research, as we are simulating a HEMS system rather than implementing it. The last two components are crucial at this stage because all related parameters must be considered in the simulation tool.

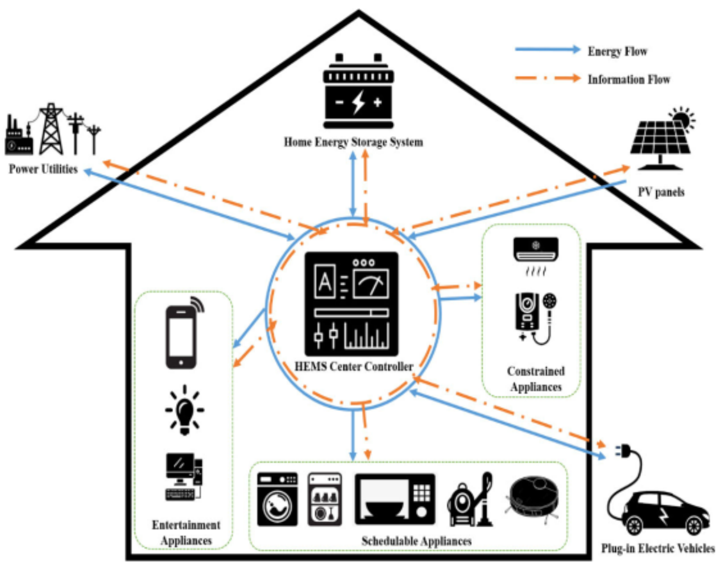


Figure 7: Architecture of a representative HEMS with energy and information flow. Information flow managed by the central controller, user interface, and sensing devices will not be covered in this work. Energy generation, storage devices, and appliances exchange energy, and this energy flow will be simulated in the study.

Appliances are the essential building blocks of HEMS, and knowing their behavior and how they work is crucial to getting the most flexibility out of them. Figure 7 shows these five components of the HEMS, with appliances categorized as entertainment, schedulable, or controllable. The EV appliance is represented separately because its behavior is significantly more complex than that of the other appliances.

The next subsection looks at how to write these components in mathematical form and what the system should be for.

2.4.2 Objectives and Constraints

Once the assets and energy generation components of our system are defined, the constraints are established as well. Load constraints are primarily built on the consumption curves for electrical appliances. Sometimes, due to a lack of specific information, an average constant consumption profile is applied to model the load. For energy generation, the production curve is utilized.

It remains to establish the system's goals, namely the objectives of our system.
Cost is the most common objective, as it primarily motivates residents to minimize electricity expenses while considering available electricity prices and RES generation. **Load profiling** is another common objective aimed at altering the peak-to-valley structure. This can make the household microgrid beneficial for HEMS users as well as public utilities by generating fewer peaks. Recently, **user comfort** has become an important consideration, as discomfort caused by unwanted interruptions, long wait times, and strict usage schedules has influenced limited participation in programs by residents.

The study references all research related to these objectives and provides the associated objective functions. Additionally, it lists the authors who focus on single-objective approaches and those who explore multi-objective methods. Finally, it presents the optimization methods that address these constrained objectives, as discussed in the next subsection.

2.4.3 Optimisation Methods

Finally, with the problem fully established, it remains to determine the appropriate method of resolution to obtain the final results. The authors list these methods and provide the pros and cons of each.

The most well-known methods are mathematical approaches such as linear programming (LP) and mixed-integer linear programming (MINLP). The advantage of these methods is their low computational resource requirements. A second family of methods includes nature-inspired meta-heuristics such as particle swarm optimization (PSO). These methods allow the integration of uncertain information, such as weather forecasts. Methods based on artificial intelligence and predictive control models are also detailed.

With this review of state-of-the-art HEMS systems, the reader now has most of the information needed to approach the next chapters. A final section will cover the concepts and work conducted at LBE within the framework of the DSF study known as value creation.

2.5 Value Creation

This research is conducted within the Renewable and Urban Department of the company LBE. The potential benefits of residential flexibility have been extensively studied and well-documented through LBE's research. As a result, they have defined concepts such as value pocket, value stacking, and multi-pocket, which are outlined in this section.

2.5.1 Value Pocket

A value pocket is defined as the value derived from the load management of a residential electric appliance [29]. To determine the value created by this load management, the simulation always involves both a controlled and an uncontrolled case to assess the value generated. A value pocket is based on three components.

- **System and asset**: The system includes the user's baseload and RES production, to which an electrical asset is added. The assets most studied by LBE include an EV, a water boiler, a residential BESS, and HVAC. The system is comparable to the architecture described in Subsection 2.4.1.
- **Tariff**: This refers to the contract chosen by the end users with their retailer, as explained in Section 2.1. It may or may not favor a particular use case.
- **Use case**: The use case refers to the load control algorithm applied to the asset. It represents the desired goal, similar to the objectives explained in Subsection 2.4.2. It can be:
  - **Self-Consumption (SC)**: The aim is to consume as much of the local RES production as possible.
  - **Peak-Shaving (PS)**: The purpose is to generate the fewest power peaks possible.
  - **Load-Shifting (LS)**: The goal is to shift consumption to a time when demand is lower and production availability is higher.

The value created is derived from the difference between the uncontrolled and controlled cases. The indicators can be of various types.

- **Economical**: Profit is calculated based on the tariff, providing insight into the economic value created.
- **Self-consumption**: Self-consumption rate represents the portion of local production consumed on-site (i.e., not injected into the grid).
- **CE emitted**: The CE emitted by the asset's consumption.

Figure 8 illustrates this concept by representing all the elements together.

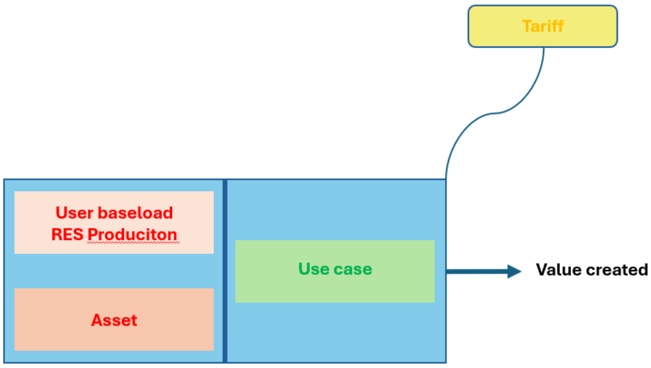


Figure 8: Representation of a value pocket concept used by LBE. The most studied assets (red box) are an EV, a water boiler, a residential BESS, and HVAC. The use case (green box) represents the load control algorithm. The tariff (yellow box) refers to the contract chosen by the end users with their retailer. The value created is the difference between the uncontrolled and controlled cases (economic, self-consumption).

The next subsection explains two ways to optimize the value of multiple pockets simultaneously.

2.5.2 How to Take Advantage of Several Value Pockets at Once

With this concept defined, we want to determine whether managing several value pockets simultaneously can generate more value than focusing on a single value pocket. The concepts of value stacking and Multi-Pocket aim to answer this question.

Value Stacking

Each value pocket generates value from a specific use case. By stacking use cases on the same asset, it's possible to maximize the resulting value (Figure 9.a)). Incompatibilities may arise between use cases. This question was investigated in the work carried out by Adam in 2022 [29].

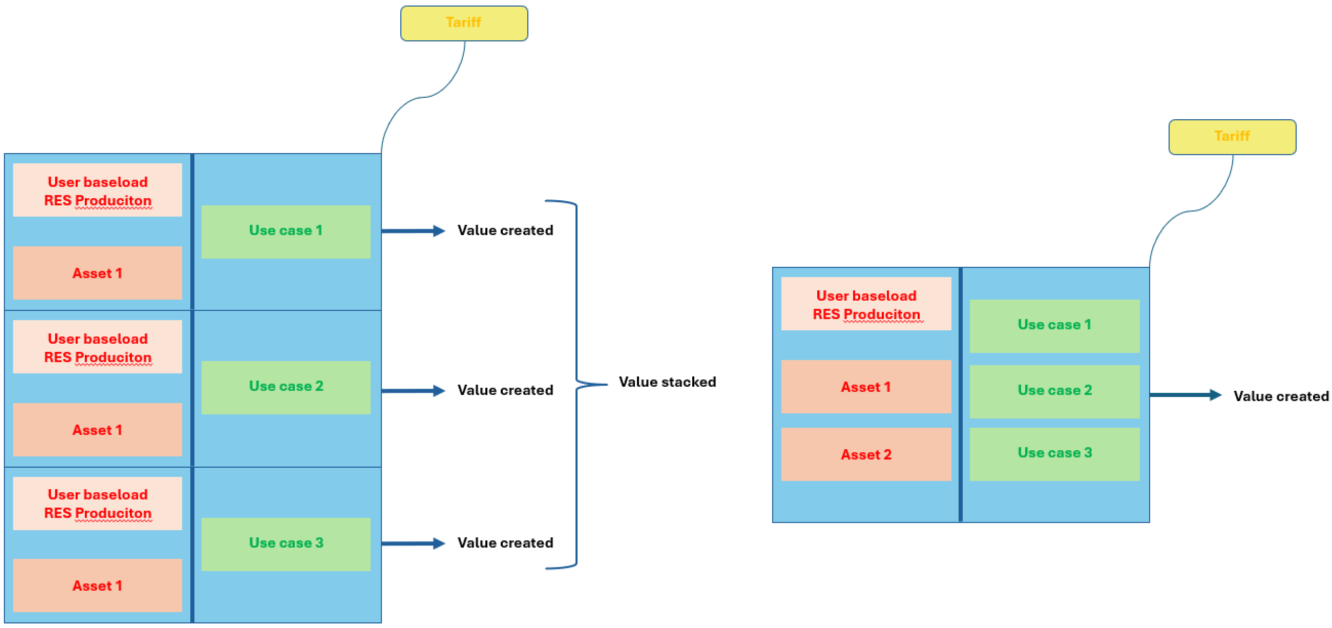


Figure 9: a) Stacking of value pockets; b) Multi-Pocket. Value stacking refers to the stacking of different use cases on the same asset to maximize the resulting value; however, incompatibilities may exist. MP involves several assets and use cases. This study attempts to compare the value created by MP with that of a single value pocket.

Multi-Pocket

One question remains regarding value creation from residential assets. It is to know if we play on several assets and use cases at the same time, in other words doing Multi-Pocket (MP) as shown in Figure 9.b), how much value we create? If so, can we create more value than with a single pocket?

With this explanation of the Multi-Pocket concept, all elements necessary for understanding the following chapters are now defined. The next chapter presents the methodology used in this work.

3 Methodology

This chapter is dedicated to the methodology used. First , we give a precise definition of our case study, namely a Flemish household. Ensuite, on revient sur tous les paramètres utilisés en entrée de nos simulations. We review the choices and justifications of the values taken for each. Finally, we explain our two families of one-value pocket and multi-pocket simulation by explaining the used controllers and the control logic of the Multi-Pocket algorithm.

3.1 Goals Pursued by the Flemish Household

To begin this chapter on methodology, we will explain in detail our case study for a Flemish household. The simulation tool and functions used are also covered. Finally, we ensure that our study aligns with the theme of HEMS.

3.1.1 Typical Flanders Case

As explained at the end of Section 2.5, the aim is to study the value created with a multi-pocket configuration. The question is, therefore, which assets, use cases, and pricing should be chosen to define our system. The Flemish region was chosen for its unique pricing program and the significant role Engie plays as a retail company. The following sections explain the various elements that make up an MP configuration, as illustrated in Figure 9 for this Flemish household.

The residential system includes PV production, placing it in the context of a prosumer facing congestion problems, as discussed in Subsection 2.2.2. LBE is based in Belgium, where the proportion of electric cars in the car fleet was 2.8% in 2023 [30]. This percentage is well below Norway's 20%, but favorable tax policies for company car access are rapidly evolving the market [31]. In 2023, the number of electric cars nearly doubled, with a growth rate of 93.6%, and 80.8% of these EVs were company cars [30]. The choice of an EV, with all its advantages for generating flexibility, is therefore a natural one. To handle the intermittency of PV production, a household BESS was intended to be added to the system, but it could not be integrated, as will be explained at the end of Chapter 5. This PV production and EV asset are represented in red in Figure 10.

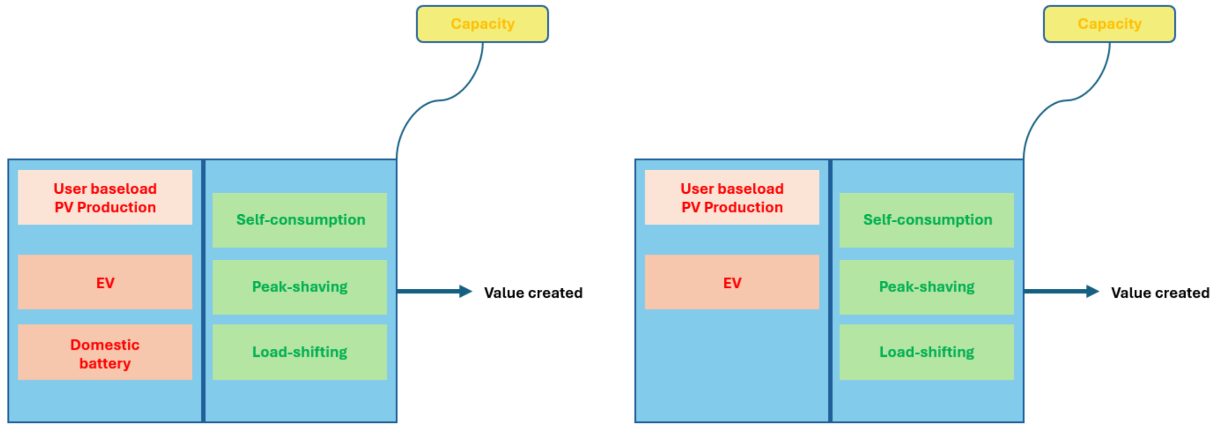


Figure 10: Multi-pocket configuration studied in this work: a) Complete configuration with EV and domestic BESS assets; b) First configuration studied with EV asset to understand the possible value created from the EV.

As previously explained, the choice was made to study a Flemish household. Flanders has a nearly unique pricing program, the capacity pricing shown in yellow in Figure 10. Its functioning is explained in detail in Subsection 3.2.4.

A use case is selected to maximize PV production utilisation through self-consumption. Considering the importance of minimizing power peaks in capacity pricing, we use peak-shaving. Finally, a use case for load shifting is integrated by using night charging. Although night pricing is expected to disappear in the coming years, the benefits that can still be derived from it led to its inclusion in our MP algorithm, as explained in Section 3.3.3.

This Flanders case is illustrated in Figure 10.a). From a methodological standpoint, the first study focused on the residential system with only the EV, as this asset is more complex and to understand all the possible value created from the EV. This initial system is shown in Figure 10.b). The configuration shown in Figure 10.a), which represents the complete configuration, has not been studied and is reserved for future research.

The next subsection discusses in detail the simulation tool and the time series used in it.

3.1.2 Simulation Tool and Time Series

The system is simulated over a period of one year, from January 1, 2019, 12:00 a.m. to January 1, 2020, 11:45 p.m. The time interval is set to a stepsize of 15 minutes. The time series data for user baseloads and PV production comes from anonymized Engie customers.

The simulation tool is based on Python. LBE has developed a Python tool called ESyPAC that simulates a virtual home. This virtual home can integrate a baseload, PV production, electrical appliances, and pricing. Controllers can be used for electrical assets to simulate desired charging behavior. These controllers are defined as functions within Python. Three built-in controllers are used for EV charging. Each simulates one of the three use cases defined for our Flanders case. The MP controller integrates these three use cases into a single controller. It was developed for this study and will be explained in detail in Subsection 3.3.3.

As output, this tool provides various information, such as the injection every quarter of an hour in kW and kWh from the house and assets. From this information, it calculates the total cost under the chosen pricing.

This configuration and these tools define our case study for HEMS. The next subsection explains how this research fits within the broader context of other HEMS studies.

3.1.3 Link with Objectives and Methods of HEMS Review

This section revisits the characteristics of an HEMS system as set out in Section 2.4 to demonstrate that our study is well suited to this field of research.

In our case, the two components of energy generation and appliances are represented by PV production and the EV. The assets in our system align well with those typically encountered in a HEMS architecture, as illustrated in Figure 7.

The use cases are similar to the most common objectives listed in Section 2.4.2. The cost minimization objective is reflected in the self-consumption and peak-shaving use cases. SC allows to use at minimum the paying electricity from the network. PS, by limiting peaks, ensures that the bill is minimized under capacity pricing, which will be explained shortly. The purpose of load profiling is achieved through peak-shaving by nature, as well as by load-shifting, as will be explained later.

Among the methods specified in Section 2.4.3, the one used in the simulations for this research is a heuristic method.

With our case study now precisely defined and clearly situated within the HEMS field of study, we will explain the parameters and assumptions used in our simulation tool in the next section.

3.2 Data Input and Parameters

In this section, PV production series, EV technical parameters, user and trip profiles, and tariffication values will be examined. For PV and EV, a distinction will be made between fixed and variable parameters. Additionally, each parameter involves a choice among possible values. This choice is made to avoid an excessive number of variables that could significantly increase simulation time.

3.2.1 PV Profiles

In the following lines, the tilt angle and azimuth angle of a PV installation are explained. Additionally, the principle of oversizing a PV installation is explained.

Fixed

The tilt angle is the angle between the panel and the roof. In Belgium, the optimal tilt angle for maximum annual solar energy production is typically around 30-35 degrees [32]. The azimuth is the angle that determines the horizontal orientation of the PV panel and is crucial for maximizing solar energy capture throughout the day. South-facing panels generally receive the most sunlight throughout the day, corresponding to an azimuth angle of 0 in our profile names.

Based on these factors, we use the series CSV file *PV_slope_35_azimuth_0* to maximize PV production. This file contains production data for every quarter-hour in kWh and is provided by LBE. A similar profile could also be found on the internet.

Variable

The nominal power, P_{nom}, of the PV installation is calculated as $P_{nom} = \alpha_{PV}(\frac{E_{baseload}}{E_{PV}\eta_{inverter}})$ with $\eta_{inverter} = 0.92$.

α_{PV} is the peak power coefficient and can take the values: $\alpha_{PV} \in \{0.75, 1.25\}$. This represents the case where a user has chosen to undersize or oversize their PV installation. Indeed, oversizing a PV system allows it to capture more energy during sub-optimal sunlight conditions, such as cloudy days.

The following section explains the EV parameters.

3.2.2 EV Characteristics

The technical values of the EV are presented in the tables below. Justification for the selected value or set of values is provided for each parameter. For some parameters, potential improvements are suggested to increase the realism of the simulation but were not implemented due to time or computational power limitations.

Fixed

C_{EV} is the consumption of an average sedan model on the market. P_{EV}^{min} is the minimum power accepted for the recharge of an EV from the IEC 61851-1 protocol. Stating that it's possible to achieve SOC_{EV}^{max} equal to one is somewhat idealized. In reality, car manufacturers limit the state of charge to a value below one to increase longevity. The maximum achievable value

	P_{EV}^{min}	C_{EV}	$\eta_{EV,charge}$	SOC_{EV}^{max}
EV	1.38	0.15	0.82	1

Table 1: EV fixed parameters.

decreases over the years. However, for a simulation based on one year of use, this assumption is acceptable.
Finally, assuming a constant value for $\eta_{EV,charge}$ is a significant simplification. In reality, it's a function of power. At low power, efficiency may be reduced due to constant losses in the battery management system and power converters. These losses become proportionally less significant compared to the amount of energy transferred at high power. Using a variable value depending on the charging power would improve the model's accuracy.

Variable

	P_{EV}^{max}	E_{EV}
EV	$\{3.7, 7.4\}$	$\{43.125, 71.875\}$

Table 2: EV variable parameters.

The IEC 61851-1 protocol also defines the maximum single-phase AC charging power, which is reflected in the value for P_{EV}^{max}. An average value of E_{EV} for a sedan is 57.5 kWh. Multiplying this value by 0.75 or 1.25 accounts for the case of an EV with a small or large battery.

With the technical parameters of PV and EV defined, the next subsection provides the user-related parameters.

3.2.3 User Profile

A user by his consumption behavior of his electrical assets has a great impact on the final value created. This subsection presents the different user profiles considered for use of the EV and his home.

Trip

There are 5 driving profiles that are all built the same way. Each line of the CSV file includes the time of departure from home and return to home, the distance of the trip and the motive for the trip.

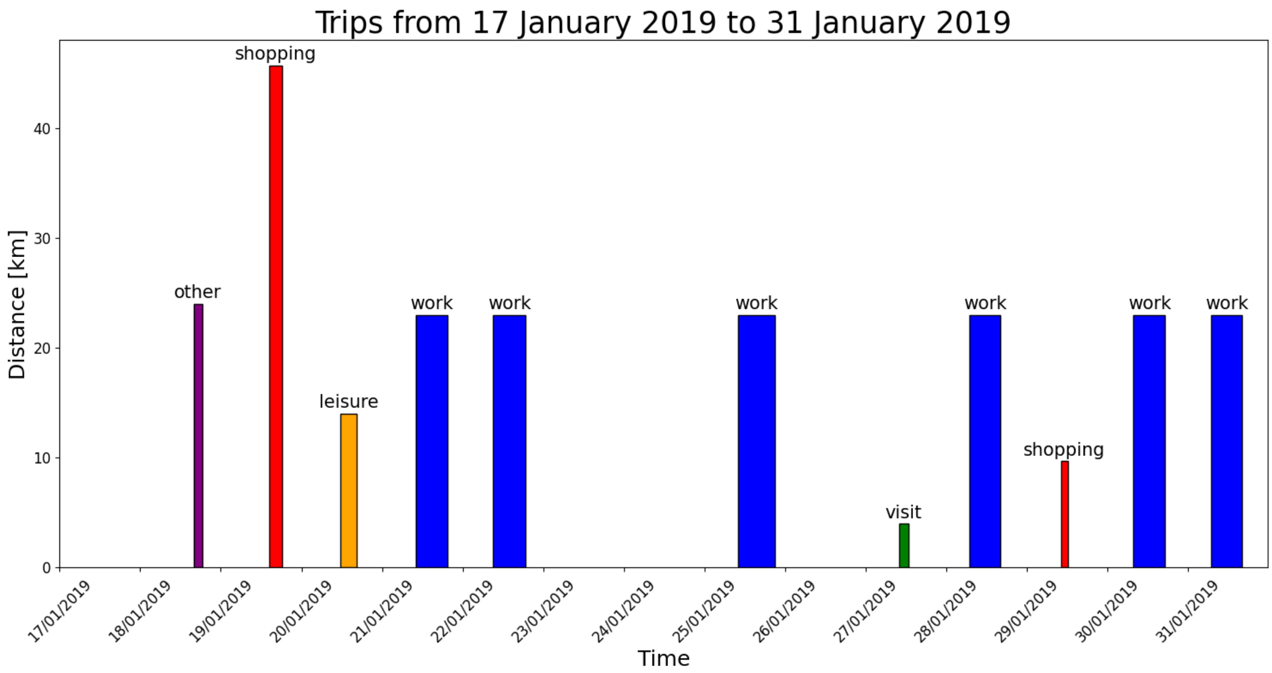


Figure 11: Representation of the H23 trip profile CSV file from 17 January 2019 to 21 January 2019. Each line in CSV file is a trip with a time of departure from home and return to home, the distance of the trip and the motive (work, visit, shoping, leisure, other)/

There are 5 types of trips: work, shopping, leisure, visit and others. Figure 11 is a graphical representation of a trip profile. The width of each stick represents the time that the car is not at home because of the trip and the height the distance of this trip. The maximum trip is 300 km. This distance limit represents the hypothesis that any journey must be feasible without intermediate recharge. The total capacity of the EV is about 350 km, the choice is to take a slightly lower value for safety.

Panel of trip

The 5 profiles are different in the number of days of the week that the user goes to work with his EV, which is called Full Day (FD). This parameter allows to take into account a potential use of teleworking. H capital letter is used for the name of trip profile corresponds to a hybrid worker who can work from home. Trip profile name with the letter O means that the worker must be on-site for the 5 days of the week. The distance of the commute in km d, also differs between trip profiles. The value chosen are coherent for a Belgian worker. The table below summarizes the different possible combinations.

FD \ d	23	46
2	**H23**	**H46**
5	**O23**	**O46**

Table 3: Trip profile function of the distance of the commute and the number of days of the week that the user goes to work with his EV (Full Day).

Profiles H46 and O23 represent an annual distance of 15 000 km which is a total distance representative of an average driver in Belgium. H23 and O46 are profiles under and above this average value.

Finally, a particular profile that does not represent a large part of the population but is interesting for its potential recharge behavior is used. This corresponds to the S23 profile where the user uses his car to get to work for half a day per week and the other half of the day his vehicle is parked at home. The letter S means that this corresponds to a special category of workers.

Baseload

Baseload file is a 15 min stepsize file representing the consumption of the house in kWh. This consumption is the sum of the consumption of all basic electrical appliances like lighting, washing machine, dishwasher, use of electrical outlets, etc. This consumption doesn't take into account the EV consumption.

There are 8 user baseload profiles available. In order to understand the differences between them, 3 indicators were used for the characterization. Annual energy consumption of the house ($E_{baseload}$) allows to know if it's a large or small consumer. Summer/Winter ratio (R_{SW}) represents the seasonal tendency where the summer period is defined from April to September. Day/Night ratio (R_{DN}) shows the daily consumption with a day starting at 7 a.m. and finishes at 7 p.m. The heat map below (Figure 12) allows to see the trend of each user for the 3 indicators.

To limit the simulation calculation time, a choice was to select 4 users who would be different from each other and would capture a maximum of available information. The four profiles are as follows:

- User 1: **User D**: Small daily consumer: 3354 [kWh]
- User 2: **User N**: Small nightly consumer: 3422 [kWh]
- User 4: **User W**: Middle winter consumer: 4449 [kWh]
- User 7: **User S**: Big summer consumer: 5335 [kWh]

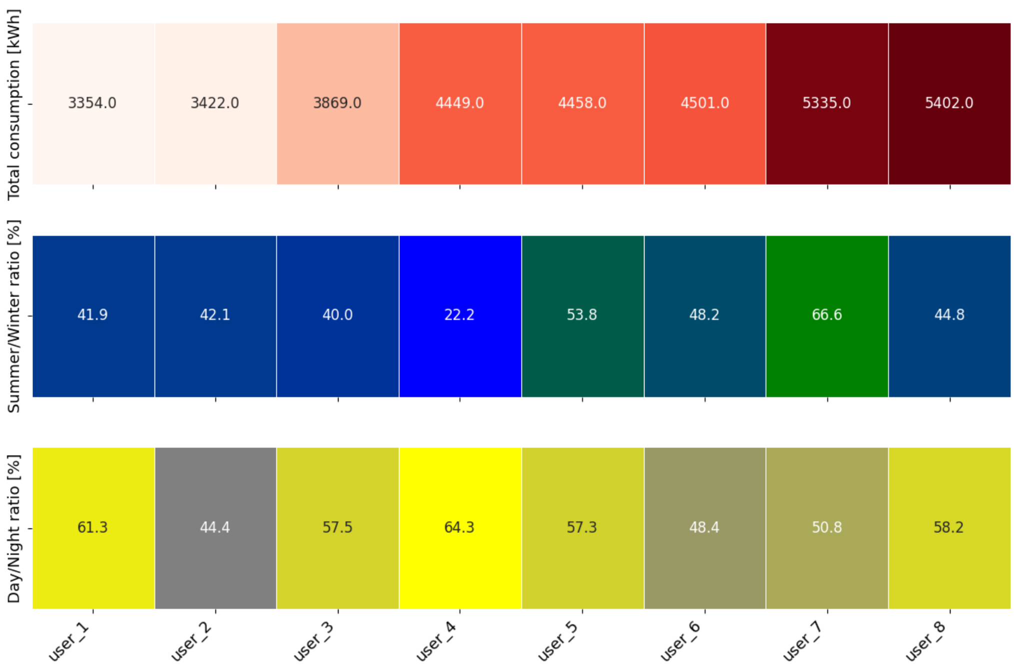


Figure 12: Analysis of each 8 user profiles using $E_{baseload}$, R_{SW} and R_{DN}. We choose 4 user profiles that capture the maximum of the available information. A small daily consumer (User D), a small nightly consumer (User N), a middle winter consumer (User W) and a big summer consumer (User S).

3.2.4 Tariffication

Tariffication is used to obtain the annual cost of electricity used. There are different possible pricing programs as explained in Subsection 2.3.2. One that is used for our Flanders case (Section 3.1.1) is the TOU detailed this subsection. This part explains on the one hand which actors are present on the invoice and what type of invoice we have chosen for our Flemish Household. On the other hand, we explain the reason and the functioning of the capacity pricing introduced by Flanders.

Electricity market actors prices on invoice

The prices used are taken from the *Easy fixed 1 year* invoice attached in the Appendix A. It comes from the Engie retailer. This bill offers fixed prices related the Flemish region dated from December 2023 and valid for a period of one year corresponding to our case study defined in the Section 3.1.2. We have no choice to use fixed prices given that we need to know the prices in advance to integrate them into the simulation. Monthly variable and dynamic tariff are also offered by Engie but are unusable because of this. In the following lines are presented the actors implicated in this total cost and prices noted with a letter p that is used in the following Subsection 3.3.1.

In this invoice, the actors listed in Figure 1 involved in tariffication are those located at the end of the transport chain except for transport, just before the final consumer, namely retailers and distribution entities. Retailers as Engie imposes tariff, they are presented inside the red box on the first page of the invoice of the Appendix A. The word tariff in this study is not to be confused with tariffication which is used to describe the total cost of the electricity consumed. Tariff corresponds only to the contract established with the retailer. Tariff cost is one of the cost takes into account in the tariffication and is noted as $p_{tariff,conso}$ or $p_{tariff,inj}$. DSO entities assume the regional distribution costs, in the case of Flanders this is the capacity distribution as explained in the next subsection. The different distributors are shown on page 2 of the invoice. The one chosen for our case study is *fluvius antwerpen* is in the second red box. The only TSO on the market also claims a cost to the end consumer related to the management of the HV network where transit the electricity. This cost is included in the DSO cost $p_{distribution}$ on the invoice. Finally, the state taxes this electricity consumption with the price p_{taxes}.

In our simulations, the two tariffs used are those called *Normal* and *Bihoraire* in the first red box of the invoice. They are translated by *Base* and *Peak-offpeak* in Figures 13 and 14 that represent the simulations performed, as it will be detailed in the following section.

Capacity distribution to spread user consumption

Flanders has introduced capacity distribution pricing since 1 January 2023. The idea is that the end consumer in addition to paying for his electricity consumption (kWh) will also pay for the peaks of electrical powers (kW) that he generates when he consumes the electricity from network. The aim is to encourage consumers to distribute their consumption throughout the day. The goal is to force him to avoid a behavior where he charges all his electrical assets at the same time, when returning from work for example. This behaviour is expressed by a high electrical power called power peaks. This is even more relevant now that large, energy-intensive electrical appliances such as EV and heat pumps are entering households and may overload the network. In addition, this daily dispatch allows to consume electricity during sunny hours from the PV production sometimes waste as explained on the Figure 3a. This pricing is almost unique to

Flanders. Only countries such as Germany, Norway, and Sweden have similar mechanisms or are exploring them.

From a practical point of view, the Flemish DSO are responsible for reflecting this in their distribution costs. There is a classic price based on the amount of energy consumed (kWh) over the year $p_{distribution}$. The second price for peak power is based on the average of the 12 monthly peaks of the year. Specifically, digital meters every 15 minutes of the day record the energy consumed by the household from the network called quarter-hourly power. It records the highest quarter-hourly power of the month for the 12 months of the year and averages these 12 values. Finally, multiply this quantity (kW) by the price p_{peak}. It is noted that if the monthly peak is less than 2.5 kW then it is replaced by this limit value. For analog meters, not able to measure this quarter-hourly power, each monthly peak is set at 2.5 kW.

Values for prices of capacity distribution are given in the second red box in the invoice of Appendix A. Obviously, the only distribution pricing used is the capacity because all simulations are simulate a Flemish case as illustrated in yellow on Figure 10. All these prices will be used in the total cost formula of the next Section 3.3.1.

3.3 Simulations

The purpose of this section is to present the two main simulations and the Key Performance Indicator (KPI) used to analyse and compare the results. For each simulation, its functioning and purpose results will be presented.

3.3.1 Simulation Output and KPI

The interest of the ESyPAC tool is that it allows to obtain all the exchanges of energy consumed and produced by the residential system for each time step according to the control decided. Thus, for the Flanders case depicted in Figure 10.b), ESyPAC generates for every quarter-hour the energy consumed by our home (e_{home}) from the user baseload and the EV (e_{EV}). As well as the energy produced by our PV (e_{PV}) installation, all expressed in kWh.

From these values we can determine 4 global values of our system,

- **Total consumption**: $e_{tot} = e_{home} + e_{EV}$
- **Gross production**: $e_{prod} = e_{PV}$
- **Net injection**: $e_{inj} = e_{tot} - e_{prod}$
- **Self-consumption**: $e_{\mathrm{SC}} = \begin{cases} e_{tot} & \text{if } e_{tot} < e_{prod} \\ e_{prod} & \text{if } e_{prod} < e_{tot} \end{cases}$

It is possible to obtain the equivalent of these 4 global values in term of power by multiplying them by 4. From these global values, two interesting KPIs can be extracted: the global self-consumption factor over the year β_{SC} and the annual economic profit π. These indicator are calculated as :

Annual self-consumption factor : Self-consumption factor β_{SC} is obtain as $\beta_{SC} = \frac{\sum^{\text{Year}} e_{\mathrm{SC}}}{\sum^{\text{Year}} e_{\mathrm{tot}}}$

Annual economical profit : To determine the profit we need to first calculate the total cost. The total cost of tariffication explained in the section above is calculated with the formule below. All prices note with a p letter are in $\frac{€}{kWh}$ except if it's explicitly mentionned.

$$C_{total} = \sum^{\text{Year}} c_{stepsize} \quad + \quad C_{peak} \quad + \quad C_{fixed}$$

- Tarrif cost: $c_{stepsize} = \begin{cases} e_{inj}(p_{tariff,conso} + p_{taxes} + p_{distribution}) & \text{if } e_{inj} > 0 \\ e_{inj}(p_{tariff,inj}) & \text{if } 0 < e_{inj} \end{cases}$
  - Tariff prices:
    * Base:

p_{conso}	p_{inj}
0.21678	0.05113

Peak-offpeak:

	p_{conso}	p_{inj}
Day	0.22957	0.06683
Night	0.19391	0.01108

  - Taxes: $p_{taxes} = 0.05237$
- Distribution cost: $C_{peak} = \sum^{12} \min(2.5, \max_{month}(e_{inj}))p_{peak}$ where $e_{inj} > 0$ is in kW

– $p_{peak} = 3.3359\,[\frac{€}{kW}]$ $\qquad p_{distribution} = 0.03742$

- Fixed cost : C_{fixed} : This cost includes annual costs related to administrative or meter fees. It is not detailed here because it is constant to all simulations and this subtracts when calculating profit.

Finally, the economic KPI used is the profit between a case where the EV is not controlled and the case where it is controlled : $\pi = C_{total,uncontrolled} - C_{total,controlled}$

These KPIs will be used in the rest of this section and in the results chapter.

One Pocket simulations are presented in detail in the next subsection.

3.3.2 One Value Pocket

The purpose of the one value pocket simulation is to determine the value created by one value pocket as defined in 2.5.1. In practice, 3 simulations are run separately and correspond to each of the use case of our typical Flanders case stated in Section 3.1.1. For each pocket of value, the tariff that maximizes the created value will be used. The purpose being to simulate the most favorable case. Figure 13 illustrate those 3 simulation case.

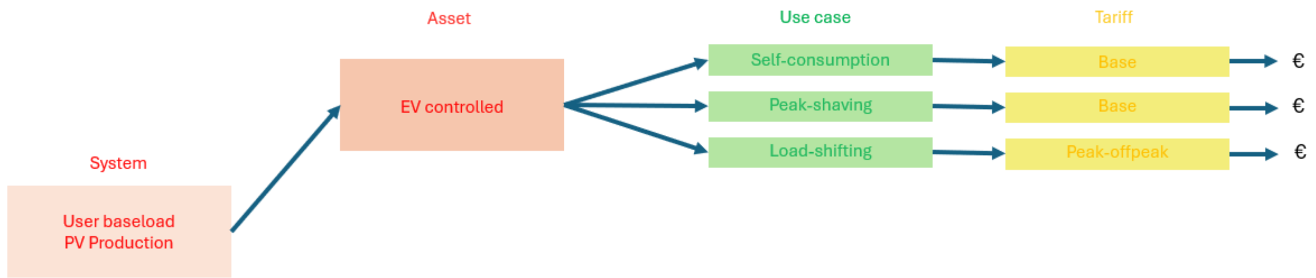


Figure 13: Diagram of the three one value pocket simulations with the system and asset, use case and tariff used corresponding to Flemish household defined in Section 3.1.1. For each pocket of value, the tariff that maximizes the created value will be used.

The goal of this simulation is to obtain the economic profit created by each value pocket. The final indicator used to assess value creation is therefore economical. With this profit for each use case determined by an advantageous tariff, reference values are obtained. These reference values will be used as a comparison value. They will help to judge whether the value created by the Multi-Pocket control algorithm described in the next subsection will be more profitable than a one pocket case. In addition, it will help to know whether the use of a more complex control is worthwhile.

3.3.3 Multi-Pocket

It is here that the core of research work was carried out. As recalled in Section 2.5.2, the purpose is to know the value released in multi-pocket configuration. To do this, it was first necessary to analyze the one value pocket simulation results in order to have an idea on how to design the algorithm. Then, with resources used from Laborelec the idea was to introduce two new parameters to the controller. The next subsection explain this.

Use cases priority

The use of financial profit allowed to determine which use case behavior prioritized more than another in the construction of the algorithm.

	Self-Consumption	Peak-Shaving	Load-Shifting
π	261.06	90.34	81.15

Table 4: Profit of the 3 value pocket controllers. Self-Consumption is the highest then Peak-Shaving and Load-Shifting is the lowest.

Table 4 show the three profits with Self-Consumption is the highest then Peak-Shaving and Load-Shifting is the lowest. Priority use of electricity produced locally via PV production is to be taken into account first within our algorithm. Peak-Shaving generates slightly more value than Load-Shifting and is integrated with a bit more importance within the algorithm. The diagram (Figure 14) below summarizes the situation.

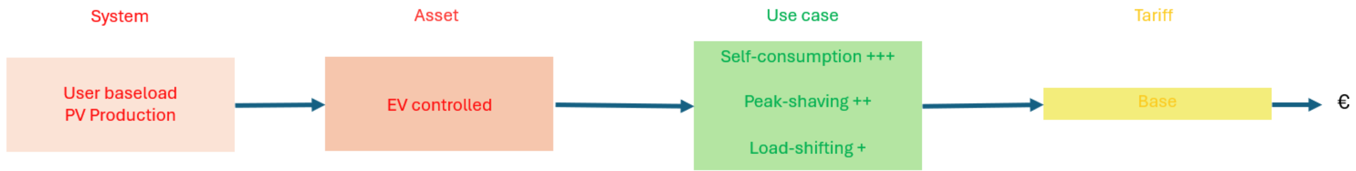


Figure 14: Diagram of the three one value pocket simulations with the system and asset, use case and tariff used. With profits of the Table 4. We know that we must use the Self-Consumption use case first, then with slightly more importance the Peak-Shaving and finally the Load-Shifting.

Multi-Pocket algorithm

The main idea of the algorithm is to divide the battery capacity of the EV into 3 levels of State Of Charge (SOC). Then, the charging rules are different depending on the SOC slice in which EV battery is. The levels of state of charge are defined as,

- SOC_m: **Minimal SOC**: minimum level of recharge to ensure emergency trips. These emergency trips are a round trip to the hospital, a last minute grocery shopping, etc. It is fixed at 50 km in view of the density and size of Belgium.
- SOC_t: **Transport SOC**: It corresponds to the SOC required for the next trip.
- SOC_c: **Comfort SOC**: This is a level of state of charge introduced. Its usefulness will be explained in the lines below in the recharge rules.
- SOC_i: **Instaneous SOC**: It represents the energy level contained in the battery for the instaneous quarter-hour i.

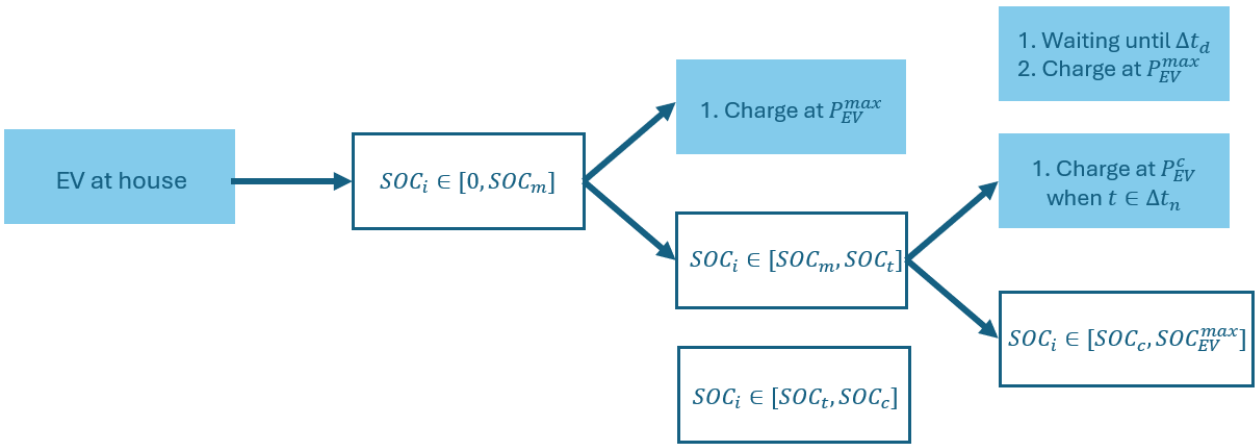


Figure 15: Logical diagram of the control inside the multi-pockets algorithm.

Before explaining the charging rules others physical quantity as to be defined. t is the current time, t_d is the departure time of the next trip, Δt_d represents the recharge time needed at maximum power charge P_{EV}^{max} to complete the next trip, Δt_n is the night recharge range from 11 p.m. to 7 a.m.

The charging rules are as follows:

- $SOC_i \in [0, SOC_m]$: EV is charge at $\mathbf{P_{EV}^{max}}$ even though this can handle peaks, it is not possible to not have this quantity of energy in the EV. If there is PV production at this time, the power taken on the network may be less than P_{EV}^{max} because the production allows to reach a part of this charging power.
- $SOC_m < SOC_t$ or $SOC_t < SOC_c$: Most of the time, SOC_c is greater than SOC_t (except for a very long next trip) so the first inequality is often invalidated before the second one.
  1. $t_d - t > \Delta t_d$
     - True : Waiting and go to condition 2.
     - False : Stop of the algorithm here and charge at $\mathbf{P_{EV}^{max}}$ because there is no enough time left to charge at a power below P_{EV}^{max}.
  2. $t \in \Delta t_n$
     - True : Stop of the algorithm and charge of the EV at $\mathbf{P_{EV}^{c}}$
     - False : Waiting and go to condition 3.
  3. $P_{EV}^{PV} \geq P_{EV}^{min}$
     - True : Stop of the algorithm and charge of the EV at $\mathbf{P_{EV}^{PV}}$
     - False : Waiting.
- $SOC_i \in [SOC_c, SOC_{EV}^{max}]$
  1. $P_{EV}^{PV} \geq P_{EV}^{min}$
     - True : Stop of the algorithm and charge of the EV at $\mathbf{P_{EV}^{PV}}$
     - False : Stop of the algorithm, the EV is not charged.

At the end either a charging power is obtained for the EV or no charging is carried out.
A logical diagram of the recharge control algorithm is shown in Figure 15.

Power and distance comfort

As shown in the previous section, the parameters called "comfort", comfort power (P_{EV}^{c}) and comfort state of charge (SOC_c) are the two parameters introduced for the algorithm. SOC_c is based on a comfort distance d_c whose relationship with the SOC_c is given by $SOC_c = \frac{d_c C_{EV}}{SOC_{EV}^{max}}$. They allow the use of night recharge to add a safety margin between the state of charge of transport SOC_t and the state of charge maximum SOC_{EV}^{max}. The idea with this safety margin is to avoid falling too quickly into the SOC_t because the EV is charged at maximum power charge P_{EV}^{max} in this one, this increases the risk of power peaks. The choice of numerical values for these parameters is presented in the table below,

d_c	100	150	200	250		
P_{EV}^{c}	1.4	1.85	2.775	3.7	4.625	5.55

Table 5: Numerical value for the two comfort parameters, comfort distance (d_c) and comfort power (P_{EV}^{c}).

To determine these numerical values of P_{EV}^{c} the following choices were made. The minimal value is the minimum power charge P_{EV}^{min}, the rest of the values are multiples of $P_{EV}^{max} = 3.4$ times $\{0.5, 0.75, 1, 1.25, 1.5\}$. For comfort distance ($d_c$) , with a maximum distance of 400 km that can be travelled with the EV, these lower values are chosen.

The choice of used a large panel of numerical values will be refined. In the next chapter, a discussion of optimal values for these two parameters will explain this.

The last subsection of this methodology chapter gives all the elements used to analyse the results of simulations.

3.3.4 Result and Analysis

Now that the context is set (Section 3.1), the data input and parameters explained (Section 3.2) and the two batteries of simulations presented in the lines above, the way in which simulation results have been used remains to be explained. A reminder of the parameters and the presentation of the analysis of the simulation results will be presented in the following lines.

Summary table of parameters

The following two tables summarize the fixed and variable parameters values used in the simulations and explained in Section 3.2.

Table 6, resume the fixed parameters.

PV Profile	$\boldsymbol{\eta_{inverter}}$	$\mathbf{P_{EV}^{min}}$	$\mathbf{C_{EV}}$	$\boldsymbol{\eta_{EV,charge}}$	$\mathbf{SOC_{EV}^{max}}$	$\mathbf{SOC_m}$	$\boldsymbol{\Delta t_n}$
PV_slope_35_azimuth_0	0.92	1.38	0.15	0.82	1	50	7AM to 7PM

Table 6: Fixed parameters of the simulations and a color code. Orange for PV production, grey for EV and blue for Multi-Pocket algorihtm.

Table 7, resume the variable parameters.

α_{PV}	$\mathbf{P_{EV}^{max}}$	$\mathbf{E_{EV}}$	**Trip**	**User**	$\mathbf{d_c}$	$\mathbf{P_{EV}^{c}}$
0.75	3.7	43.125	H23	D	100	1.4
1.25	7.4	71.85	H46	N	150	1.85
			O23	W	200	2.775
			O46	S	250	3.7
			S23			4.625
						5.55

Table 7: Variable parameters of the simulations with their possible values and a color code. Orange for PV production, grey for EV and blue for multi-pocket algorihtm. Multiple colours are used for trip and user to help in the results chapter graphs. Two light azure backgrounds represent values not used for final simulation for comfort power P_{EV}^{c}, this will be explain in the next chapter.

Global simulation results

As explained in the Section 3.3.1, the ESyPAC tool generates for each quarter-hour the e_{home},e_{EV}, e_{PV} energy quantities from which we obtain e_{tot}, e_{prod}, e_{inj}, e_{SC} and their equivalents in power units.

Nevertheless, what interests us in the end are the global values of profit (π) and self-consumption factor (β_{SC}) determined from these values. More precisely, the value of these two KPI according to the variables parameters used for one of the simulations launched from one of the two simulation set : One value pocket or Multi-Pocket.

For example, a line of the final result file for a simulation of the One value pocket is display on the Table 8 below.

α_{PV}	P_{EV}^{max}	E_{EV}	Trip	User	π	β_{SC}
0.75	3.7	43.125	H23	D	138.28	22.19

Table 8: Result line of one of the one value pocket simulation. The variable parameters, the economical profit (π) and annual self-consumption factor (β_{SC}) are the column names. A row corresponding to one simulation of One Value Pocket.

The two comfort parameters are added for the Multi-Pocket simulations as shown in the Table 9 bellow.

α_{PV}	P_{EV}^{max}	E_{EV}	Trip	User	d_c	P_{EV}^{c}	π	β_{SC}
0.75	3.7	43.125	H23	D	100	1.4	155.43	20.25

Table 9: Result line of a of Multi-Pocket simulation set. This line is the same as in the previous table but with the comfort power (P_{EV}^{c}) and comfort distance (d_c) added.

In total, the one pocket simulation set has three subsets of 160 simulations each. These 3 subsets correspond to the 3 use case in green shown in Figure 13. The 160 simulations correspond each to a set of different parameters represented by the 5 first columns presented in the Table 7. In total, for the one pocket simulation set 460 simulations have been done.

For the multi-pocket set there are 2560 simulations in total because of the two added parameters P_{EV}^{c} and d_c. As will be explained later, the two values for P_{EV}^{c} of 4.625 and 5.55 were not retained in this set. They are on a light blue background to mark this difference in the Table 7.

Sensitivity analysis

With those number of simulations, it would be impossible to represent the two KPIs according to each variable parameter. The number of graphs to analyze would be too large. Therefore, a sensitivity analysis is performed to determine between the 5 or 7 variable parameters, which are the most important and make a parameter selection.

To do this, we use the Random Forest Estimator (RFE) from the scikit-learn python library. Its functioning is explained in Appendix B. RFE is an ensemble methods of machine learning models that helps us to understand which features contribute the most to the prediction process. In our case, it allows us to know which parameter influences the more the profit π or self-consumption factor β_{SC}.

Box plots

Once the important parameters have been determined, the KPI will be plotted on the y-axis with two variable parameters with one on the x-axis and the other as a color map of a box plot. Each of these box plot contains the minimum, first quartile (Q1), median, third quartile (Q3), and maximum. The points next to each box represent a simulation of the set considered.

Mean and Extreme Values Tables

In the analyses using box plots, it may be necessary to obtain the mean value of a KPI as a function of two parameters. To avoid overloading the figure, these means are provided in the tables in Appendix C, D, E, F. Additionally, the same approach was taken for the ten maximum and minimum profit values obtained for the three subsets of the one pocket and multi-pocket simulations, which can be found in the tables in in Appendix G, H, I, J. We have included more tables than those referenced in the text. The reason is that the reader may wish to know one of these values for a better understanding of the work.

4 Results

In this chapter, the results of two simulation sets, one for one value pocket and another for multi-pocket, will be presented. For each set, sensitivity analyses will be conducted, followed by a more in-depth studies of the important parameters.
A comparison will then be made between the two case studies. This will help identify a set of parameters for which one control strategy is more appropriate than another. Ultimately, the goal is to establish ideal user profiles and common scenarios where one control strategy is preferable to another. Additionally, this chapter will address the potential for value creation in multi-pocket configurations, as explained in Section 2.5.2.

4.1 One Value Pocket

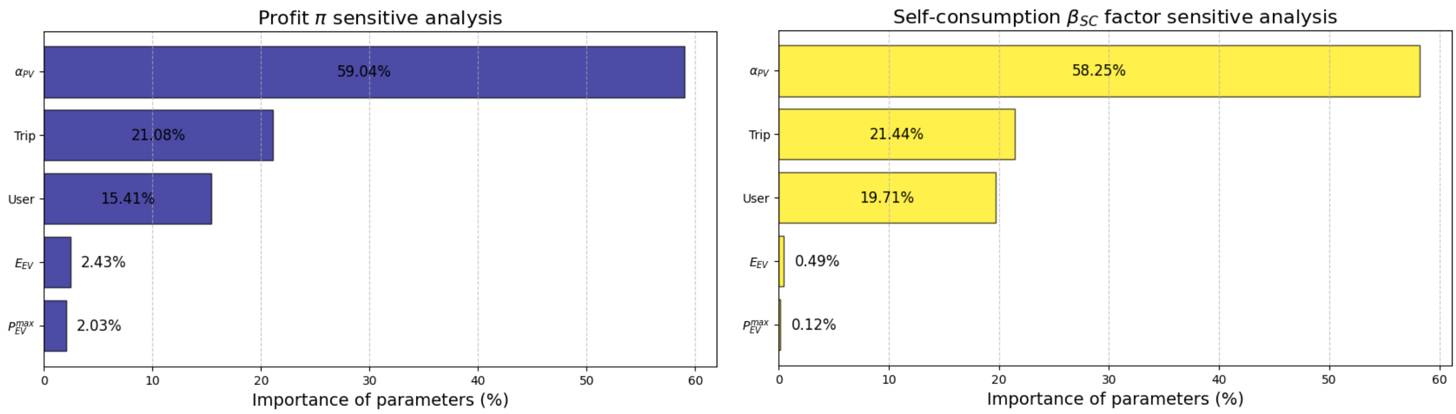
As mentioned at the end of Section 3.3.4 and illustrated in Figure 13, the one value pocket simulation set consists of three subsets of 160 simulations, each corresponding to one of the three use cases: self-consumption, peak-shaving, and load-shifting. These three sets of simulations will be presented in the following subsections.

4.1.1 Self-Consumption

As highlighted in Section 2.5.1, the purpose of self-consumption is to maximize the consumption of locally produced electricity, which in our Flanders case is the PV production (Section 3.1.1). This section first presents the results of the one value pocket simulation, focusing on the self-consumption use case, which will be referred to as SC to avoid repetition. Sensitivity analyses will be presented, highlighting the relevant parameters, followed by interpretations of those.

Sensitivity analyses

As shown in sensitivity analyses (Figure 16), the most important parameter for profit is the coefficient α_{PV}, with an importance of 59.04%. This is logical, as the variation in α_{PV} determines whether the PV installation is undersized or oversized. The EV controller maximizes the use of PV production; therefore, α_{PV} is crucial for this value pocket. The next two most significant parameters are trip and user profiles, each with values around 20%. These parameters highlight how the timing and amount of energy a user consumes and how he uses his car are decisive. The technical parameters related to the EV, E_{EV} and P_{EV}^{max}, have little influence on profit. The car is almost exclusively charged when PV production is available, so the user has limited control over the charging power. Finally, the self-consumption factor sensitivity analysis β_{SC} (Figure 16b) closely mirrors the profit analyse, leading to similar conclusions. This is logical because the purpose of the EV controller is to maximize self-consumption. The value created, as represented by both KPIs, pursues the same objective.



(a) Profit sensitivity analysis.

(b) Self-consumption factor sensitivity analysis.

Figure 16: Sensitivity analyses of SC simulations. α_{PV} is the most important; the SC controller maximizes the use of PV production, making an oversized PV installation preferable. Trip and user profiles are the next most important parameters; the timing and amount of energy a user consumes and how he uses his car are decisive. E_{EV} and P_{EV}^{max} are less important; the car is charged when PV production is available, so the user does not choose the charging power. (b) is similar to (a) because the EV controller maximizes self-consumption.

To observe trends across different values within the same parameter, some of them are presented below. The color code used to represent these values follows the color sets defined in Table 7. A graph representing the two KPIs according to user and trip parameters is presented below, allowing observation of the differences between various types of consumers.

User and Trip

Figures 17 and 18 bellow give the following interpretations :

- **The bigger the consumer is the bigger the benefits** : The bigger the annual baseload of a consumer, the more π and β_{SC} will be important. Users being located from left to right (from user D to user S) in ascending order of baseload. The step-by-step structure of the two graphs below and the average values shown in the Tables 12 and 31 prove it.
- **More profitable to be a hybrid worker** : Whatever the KPI, it is more profitable to have the car 3 days week at home to allow use of PV production.
- **Half day worker auto-consumes more but not earn more than an onsite** : Because the car is present half days the special trip profile self-consumes more than the onsite ones. However, the profit is the same or slightly less for S23 than O23 and O46. Indeed, profit is a difference with an uncontrolled case that by the presence of the car during the half days self-consumes already without a control being necessary.
- **Commute of 23km is better than 46km for teleworkers to self-consume** : We see that β_{SC} is slightly better for the commute of 23km because the PV production may not be sufficient to cover all the commutes of 46km.

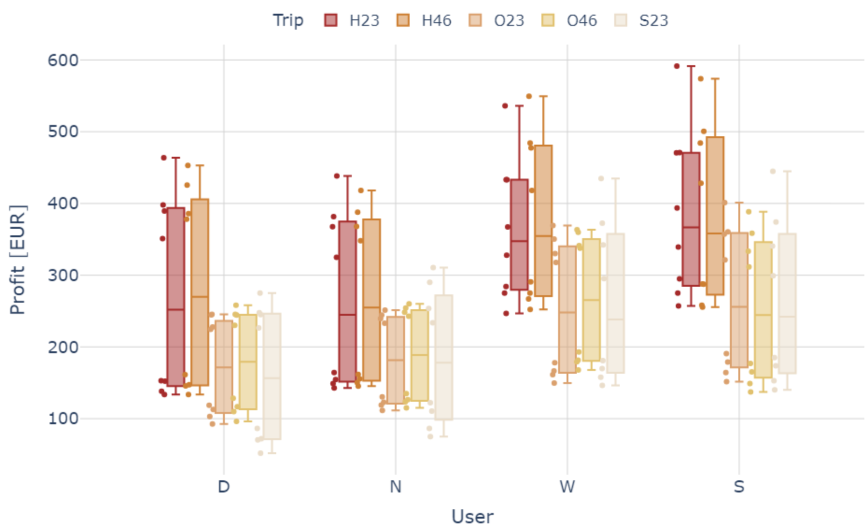


Figure 17: Profit π [€] in function of user and trip of SC simulations. Bigger the consumer is (from D to S) bigger the profit is. More profitable to be a hybrid worker (H) than an on-site ones (O).

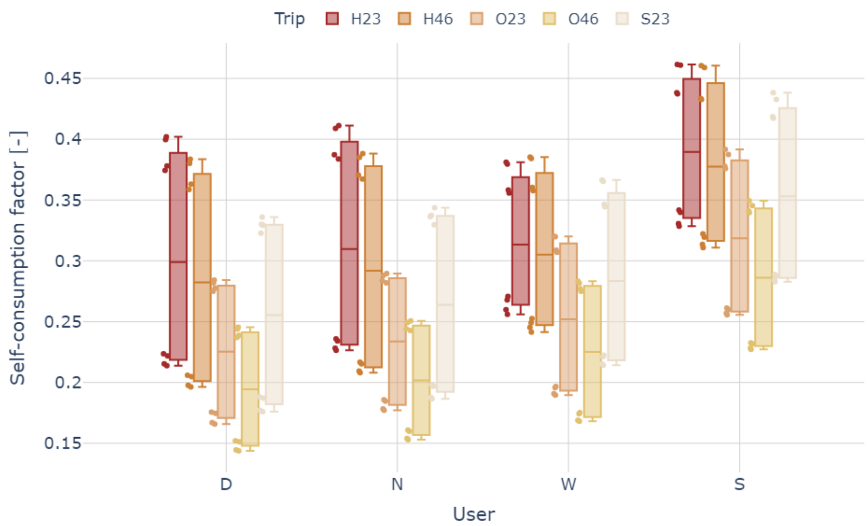


Figure 18: Self-consumption factor β_{SC} in function of user and trip of SC simulations. Half day worker (S) self-consumes more but not earn more than an onsite (O) because the car is already present in uncontrolled case. Short commute (23km) is better than long (46km) for teleworkers (H) to self-consume.

PV peak power and User

In view of the importance α_{PV} observed in Figure 16, we plot it with user in Figures 19 and 20 bellow.

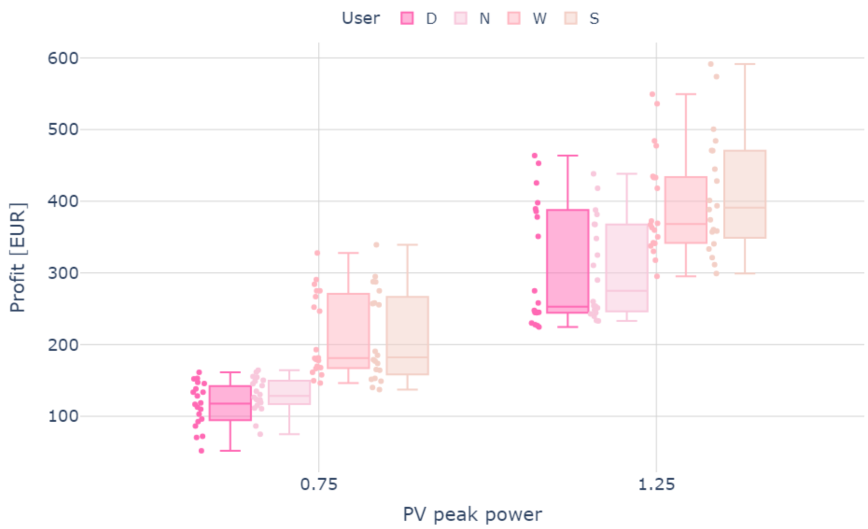


Figure 19: Profit π [€] in function of α_{PV} and user of SC simulations. Oversized PV installation (α_{PV}=1.25) is more desirable to generate bigger profit.

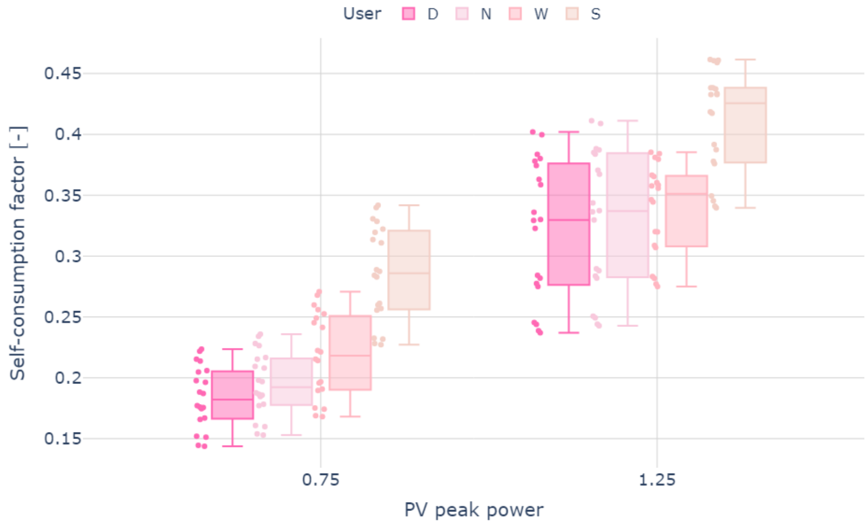


Figure 20: Self-consumption factor β_{SC} in function of α_{PV} and user of SC simulations. Oversized PV installation (α_{PV}=1.25) is more desirable and a summer consumer (S) self-consume more since the majority of its consumption comes at the peak of his seasonal PV production.

From this figure we can give the following observations :

- **Oversized PV installation is more desirable** : For both KPI, it's better to have an oversized PV installation because it's free electricity for π. Inevitably, a larger PV installation allows to cover a larger portion of consumption and therefore self-consume more.
- **Summer consumer is better than winter for self-consumption**: As observed in Figure 17 the big consumers are favored regardless of the KPI. Nevertheless, the present plot shows that a summer consumer will self-consume more than a winter. This is normal since the majority of its consumption comes at the peak of his seasonal PV production.

EV variables parameters

Although the importance of the parameters related to EV observed in Figure 16 is very small, the Figures 21 and 22 below allows us to observe which value is preferable for both parameters.

The conclusions in this regard are :

- **Large capacity is better for achieving high results** : For both KPIs, the results as a function of E_{EV} do not change significantly between the two capacity values. However, the median profit is slightly higher for a capacity of 71.875 compared to 43.125. Additionally, the third quartile (Q3) has a higher value distribution for the capacity of 71.875, indicating that the upper 25% of the data points are more profitable for this higher capacity.
- **High maximum power charge profitable for profit only** : An increase of P_{EV}^{max} leads to a slightly better profit median value. This seems counterintuitive under an unfavorable pricing for power peaks, but it allows to take full advantage of the PV production peak of the middle day.

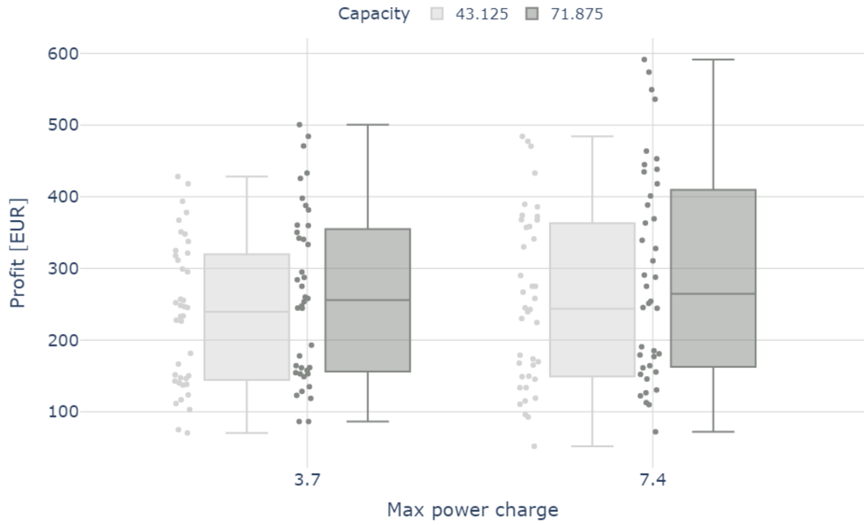


Figure 21: Profit π [€] in function of P_{EV}^{max} and E_{EV} of SC simulations. Big E_{EV} is better for achieving high results, Q3 has a higher value distribution for high values (71.875). High P_{EV}^{max} (7.4) leads to a slightly better profit median value. Counterintuitive under capacity pricing but it allows to charge more with the PV production peak of the middle day.

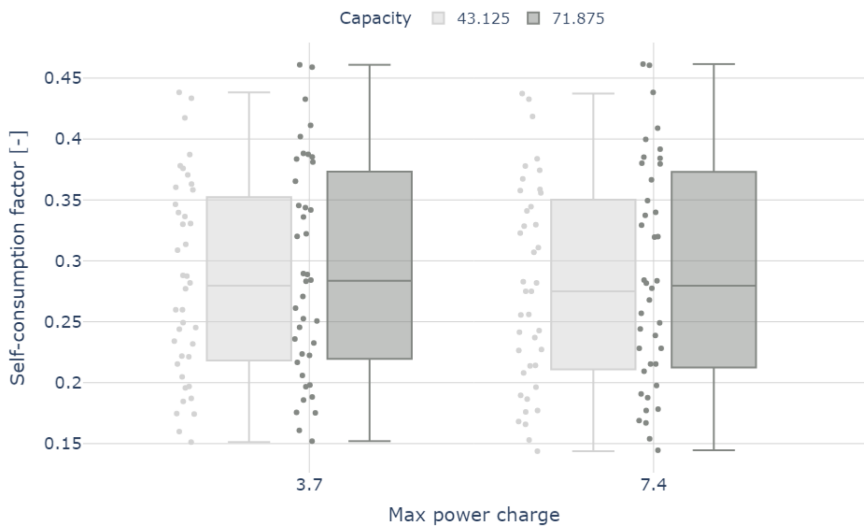


Figure 22: Self-consumption factor β_{SC} in function of P_{EV}^{max} and E_{EV} of SC simulations. Big E_{EV} is better for achieving high results, (Q3) has a higher value distribution for high values (71.875).

This last analyse closes the results of the first one pocket simulation on the SC controller maximizing self-consumption. The next subsection presents the second subset with the PS controller.

4.1.2 Peak-Shaving

The second simulation subset of the one value pocket simulation set (Figure 13) is for the use case of PS. This approach aims to minimize power peaks, as discussed in Section 2.5.1. This strategy is particularly useful for capacitive pricing, as explained in Section 3.2.4.

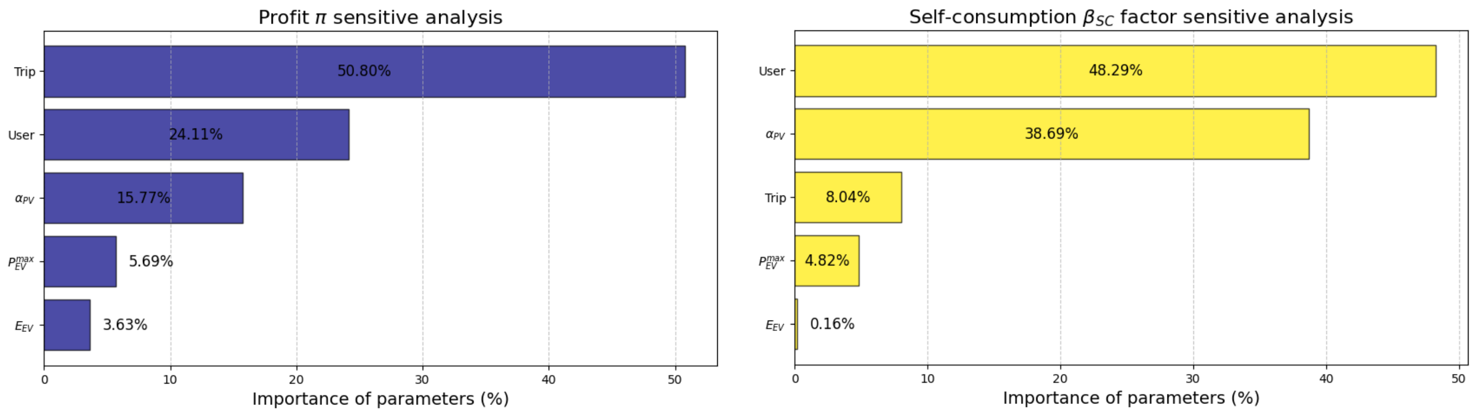
As with the SC use case, sensitivity analyses will be presented, followed by more detailed analyses of important parameters.

Sensitivity analyses

This time, the most important factor for profit is the trip, with an influence of 50.8%, as shown in Figure 23a. The user parameter is the second most significant, with about half the influence of the trip. This indicates that usage patterns are critical in limiting peaks. Finally, α_{PV} is important but much less so than in the case of SC. P_{EV}^{max} appears to be slightly more significant.

Unlike the SC case, the sensitivity graphs for the two KPIs differ significantly. In the β_{SC} sensitivity analysis, α_{PV} is more than twice as important as it is for profit. Regarding user influence, only the user baseload is significant, while the trip influence is only 8.04%. The EV controller's goal is to avoid peaks, rather than to maximize PV production consumption. As a result, the two sensitivity analyses are less correlated, and only house production and consumption influence the self-consumption factor.

Among all the sensitivity analyses in the one value pocket set, this is the case where P_{EV}^{max} is the most important, with values of 5.69% and 4.82%, respectively. This is not surprising, given the importance of power in the EV controller. Nevertheless, considering that capacity pricing is based on power peaks (Section 3.2.4), one might have expected this parameter to have greater importance in the other two subsets as well.



(a) Profit sensitivity analysis. (b) Self-consumption factor sensitivity analysis.

Figure 23: Sensitivity analyses of PS simulations. The most important parameter for (a) is the trip, followed by the user. α_{PV} is important but less so than in the case of SC; usage is critical in limiting peaks. For (b), α_{PV} is more than twice as important as in (a), and only the user baseload is significant for user influence. The sensitivity graphs differ between the KPIs because the PS controller's goal is to avoid peaks rather than to maximize PV production consumption.

User and Trip

The pattern of the user and trip in Figures 24 and 25 is quite different than for the SC case of Figures 17 and 18. On the one hand, the earnings are smaller with an average around 100€ for profit and 0.18 for β_{SC} as illustrated on those and detailed in Table 18 and 19. On the other hand, the differences between the different values by parameter are less marked. Following observations are made :

- **Bigger the annual mileage is, the more it's beneficial for profit** : Except for O23 and pairs (user W, O23) and (user S, H46). The more distance the trip profile contains over the year, the more the profit generated with the PS controller is big. This makes sense because a high-mileage driver has to charge more his vehicle resulting in more power peaks in the uncontrolled case.
- **Hybrid driving profile with a commute of 23km are better to self-consume** : As shows the Figure 25, the profile H23 by its presence at home at the same time as PV production allows to self-consume more. The H46 profile with its greater home presence should have a larger factor than O23 but the PV installation is not large enough to cover all its consumption which explains this anomaly. This explanation is also valid for S23 which has the same annual mileage base as H46.
- **Summer consumer self-consume the most so pay less** : It is clear from the Figure 25 that the summer consumer because of the peak of seasonal PV production auto-consumes more than the other three who are in the same value range. This summer self-consumption leads to a lower cost both for the controlled and uncontrolled case which explains why this user has the least profit π.
- **Can be better to not use PS controller for profit generated by half day worker** : The profit generated in the case of the S23 trip profile is very low or negative for the pair (user S, S23). This is because the controller to avoid peaks charges longer and at lower power than the uncontrolled case. These longer durations are made in advance of the next trip and therefore often at times without PV production. Whereas the uncontrolled case charges at full power just before leaving (departure are mainly during the possible sunny hours of a day), using more free electricity.

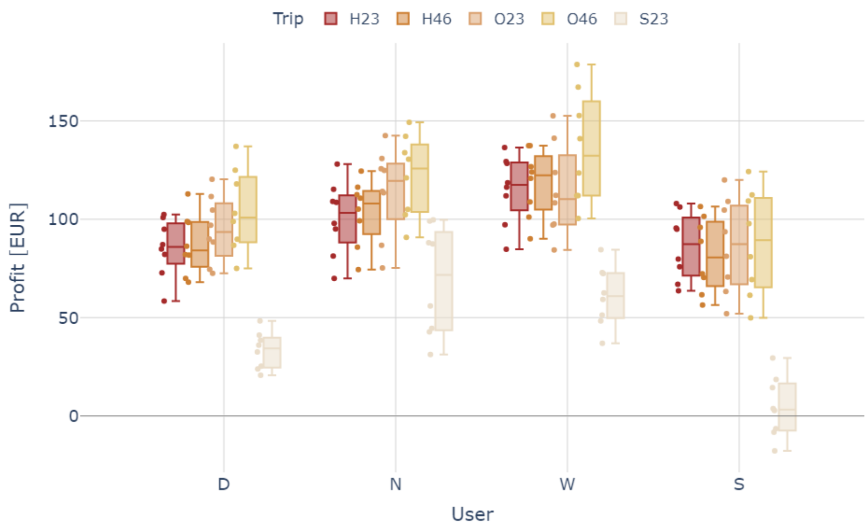


Figure 24: Profit π [€] in function of user and trip of PS simulations. Bigger the annual mileage (O46, O23) is, the more it's beneficial for profit because a high-mileage driver has to charge more his vehicle resulting in more power peaks in the uncontrolled case. Summer consumer (S) self-consume the most for the controlled and uncontrolled case which explains why this user has the least profit. Can be better to not use PS controller for profit generated by half day worker (S23) because uncontrolled case charges more during sunny hours with free electricity.

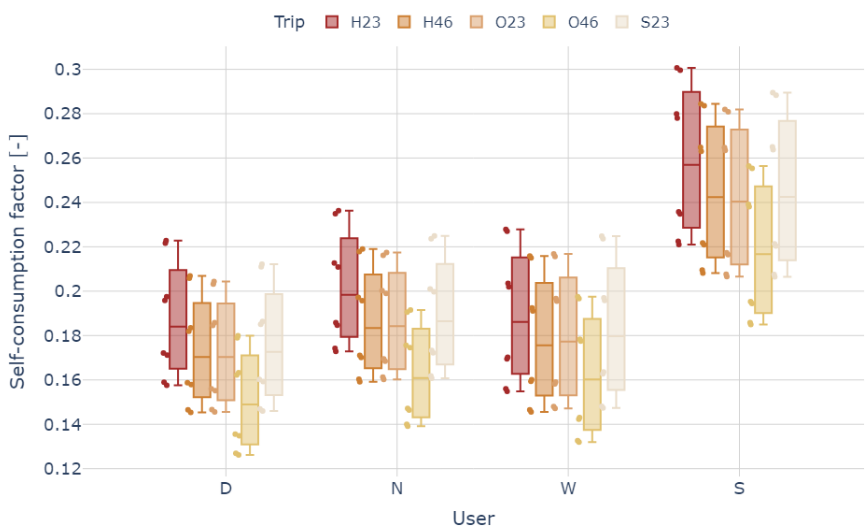


Figure 25: Self-consumption factor β_{SC} in function of user and trip of PS simulations. Hybrid driving profile with a commute of 23km (H23) are better to self-consume, PV installation is not large enough for large commute (H46).

PV peak power and User

Although the importance of the parameter α_{PV} is less than in the case SC, this parameter remains the second most important parameter in the sensitivity analysis of β_{SC} in Figure 23b. This is why it is shown in the following graph.

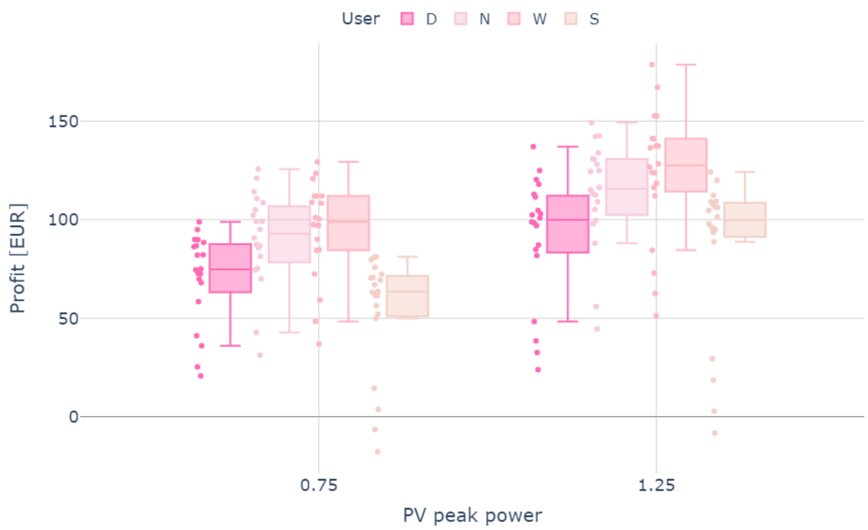


Figure 26: Profit π [€] in function of α_{PV} and user of PS simulations. Oversized PV installation (α_{PV}=1.25) is more desirable for high profit.

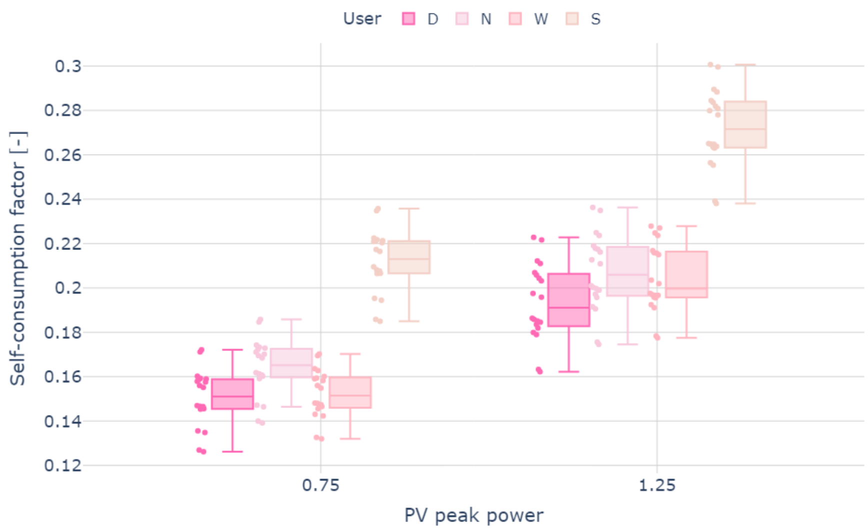


Figure 27: Self-consumption factor β_{SC} in function of α_{PV} and user of PS simulations. Oversized PV installation (α_{PV}=1.25) is more desirable for self-consumption.

From these graphs we conclude :

- **Oversized PV installation is more desirable** : For both KPI and for the same reason as it was for SC case, it's better to have an oversized PV installation.

EV variables parameters

As explained above, among the three subsets, it is for this case that the importance of technical parameters related to the EV and especially P_{EV}^{max} are the most important. Only the sensitivity analysis for profit is shown because the analysis about β_{SC} does not bring new informations.

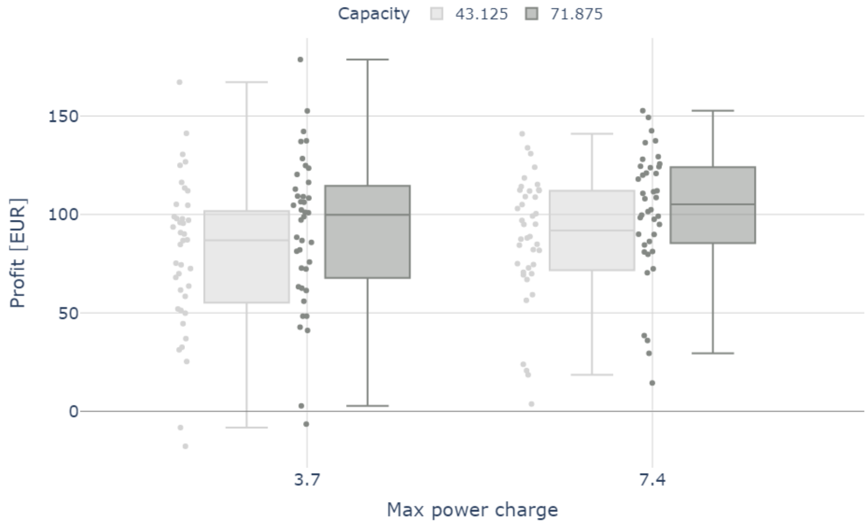


Figure 28: Profit π [€] in function of P_{EV}^{max} and E_{EV} of PS simulations. Better a large capacity (E_{EV}) and max power charge (P_{EV}^{max}) because a large E_{EV} allows to charge anticipatively and avoid peaks whereas high max power charge ($P_{EV}^{max} = 7.4$) allows for higher power charging when there is PV production.

This graphs indicates that :

- **Better a high capacity and maximum power charge** : Figure 28 reveal that it's better to have a large capacity and max power charge to generate more profit. The bigger the capacity is, the better it's possible to charge the EV battery anticipatively and avoid peaks. The earnings are slightly higher in case $P_{EV}^{max} = 7.4$. The reason is probably that although a large maximum power charge generates larger peaks, it also allows for higher power charging when there is PV production.

It is this last analysis that closes the results for the PS controller. The next subsection covers the latest controller for one value pocket simulations.

4.1.3 Load-Shifting

Load-shifting is the final use case and subset of the one value pocket set. The goal is to shift consumption to a more suitable time (Section 2.5.1). The relevance of this study is not directly tied to the typical Flanders case (Section 3.1.1) but rather to its application in the multi-pocket algorithm explained in Section 3.3.3.

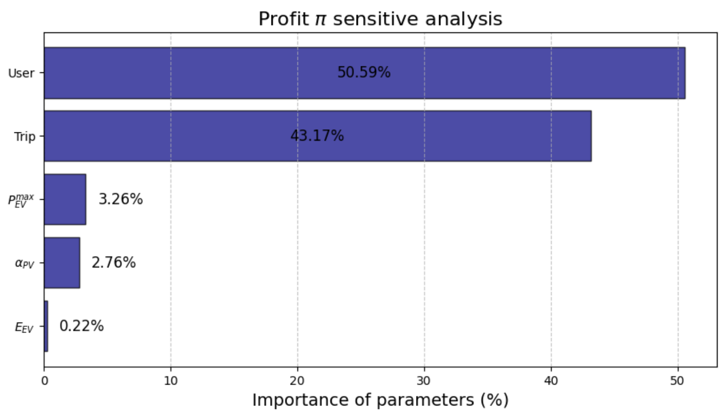
As with the other two subsets, sensitivity analyses will be followed by a detailed examination of important parameters.

Sensitivity analyses

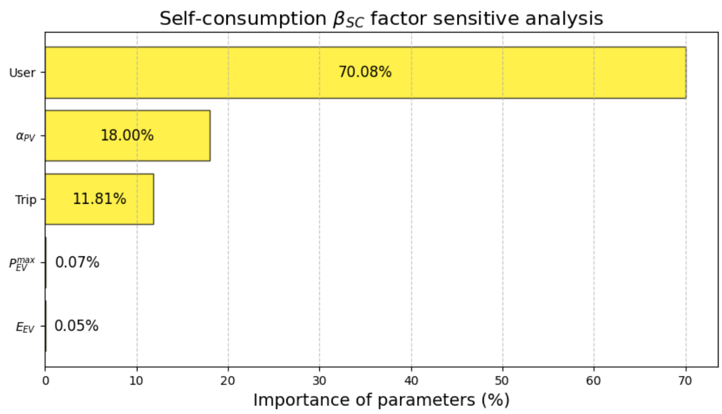
Among the three one value pocket cases, sensitivity analyses show the importance concentrated in the fewest parameters.

In the case of profit, more than 90% of the importance is shared by the user and trip profiles, with the user at 50.59% and trip at 43.17%. The influence of α_{PV} is 2.76%, the lowest value observed. P_{EV}^{max} again has a low value of 3.26%, and the importance of E_{EV} is negligible. These values can be explained by the night charging of the EV, which leads to minimal use of the PV installation. Therefore, user behavior is the primary determinant in this case.

This rationale, where the EV controller does not consider PV production, also applies to the sensitivity analysis of β_{SC}. Indeed, the importance of the trip parameter is only 11.81%. As a result, only the user baseload, with a high importance of 70.08%, and the PV installation, with an α_{PV} of 18%, significantly contribute to self-consumption.



(a) Profit sensitivity analysis.



(b) Self-consumption factor sensitivity analysis.

Figure 29: Sensitivity analyses of LS simulations. For (a), more than 90% of the importance is shared by the user and trip. For (b), the user has high importance, followed by α_{PV}. The importance is primarily shared by two parameters in each analysis. This can be explained by the night charging of the EV, which leads to minimal use of the PV installation, making user behavior the primary determinant.

Future analyses of two parameters for this LS case presents a much narrower distribution box. This is because the two parameters for each KPI, as explained above, capture the majority of the importance.

User and Trip

This narrower distribution is evident in the user and trip graphs of Figures 30 and 31 below. It is a little more extensive and grouped in two clusters for β_{SC} thanks to α_{PV} and its two possible values. This graph is more similar to the one presented for the PS case in Figures 24 and 25 than for the SC case in Figures 17 and 18. The few differences are explained in the following points:

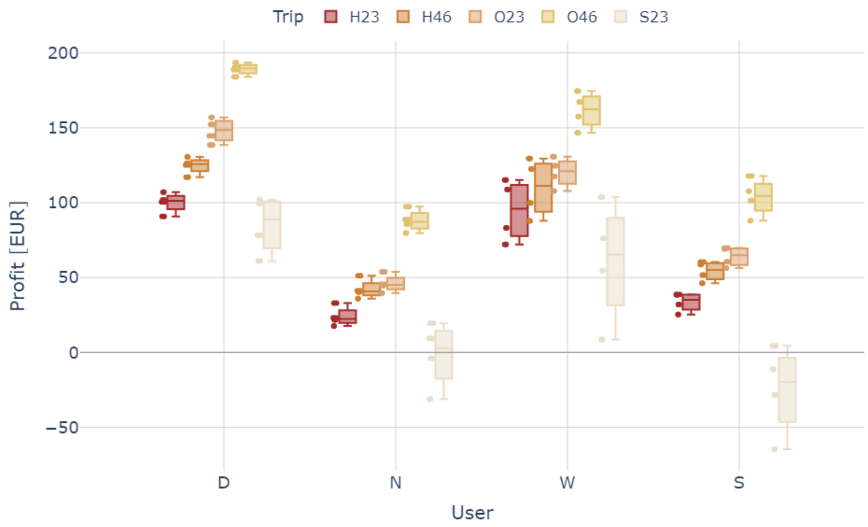


Figure 30: Profit π [€] in function of user and trip of LS simulations. Bigger the annual mileage (O23, O46) is the more it's beneficial for profit, even more than in the PS. Daily (D) and winter (W) users do not generate more profit than summer (S). It's because LS control is unfavourable for them, it forces them to use a night charging instead of their summer PV production. Magnitude of profit is lower for night-time consumer (N) because LS simulation is under peak off-peak pricing, benefiting for them. Consequently, the initial uncontrolled price is already lower than other users.

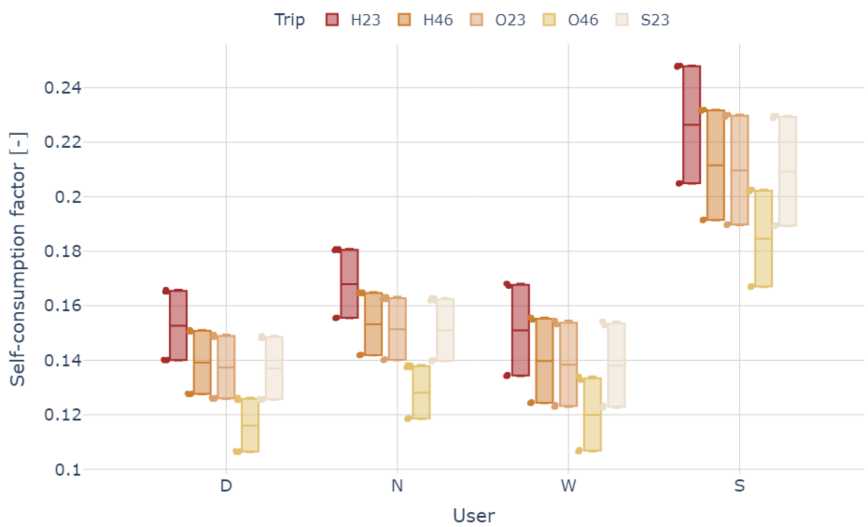


Figure 31: Self-consumption factor β_{SC} in function of user and trip of LS simulations.

- **Bigger the annual mileage is the more it's beneficial for profit** : Even more than in the case of PS where exceptions were present, here the staircase pattern shows that the more you drive better is to use the LS control. The reason is similar, the night charging is economically cheaper than the basic tarification of the uncontrolled case. More a user drives, the more this difference will be marked.

- These conclusions are exactly the same as found on Figures 24 and 25 for PS case explained in Section 4.1.2.
  - **Hybrid driving profile with a commute of 23km are better to self-consume**
  - **Summer consumer self-consume the most so pay less**
- **Daily and winter user generate more profit** : Figure 30 shows that daily and winter users generate more profit than the two others. In fact, they do not generate more profit but rather because this control is unfavourable for the summertime user because it forces to use a night charging for the EV instead of the free energy of the PV production during the day. For the night user, it is explained in the next point.
- **Night tarification benefits night-time consumer** : Figure 30 have lower values for the small night user N. This subset of simulation is carried out under peak off-peak pricing, benefiting night consumers. Consequently the initial price of the uncontrolled case of user N is already lower than other users. EV night controller is still profitable but the order of magnitude of the gain is lower.
- **Can be better to not use PS controller for profit generated by half day worker** : For pairs (user N, O23) and (user S, S23), it would be better to not use the LS controller to avoid negative profit. The controller imposes a night charging preventing this trip profile from using PV production during afternoon after his half days of work.

PV peak power and User

The last important parameter in the LS case is α_{PV} for β_{SC}. The following points will be highlighted :

- **Oversized PV installation is more desirable for self-consumption** : Same as for the two other cases but this time only for β_{SC}, it's better to have an oversized PV installation for self-consumption.

There is an inconsistency in the results where the user 2 who is a night consumer has a self-consumption factor β_{SC} slightly higher per intake than the daily consumer. However, this is not significant in view of the low difference values.

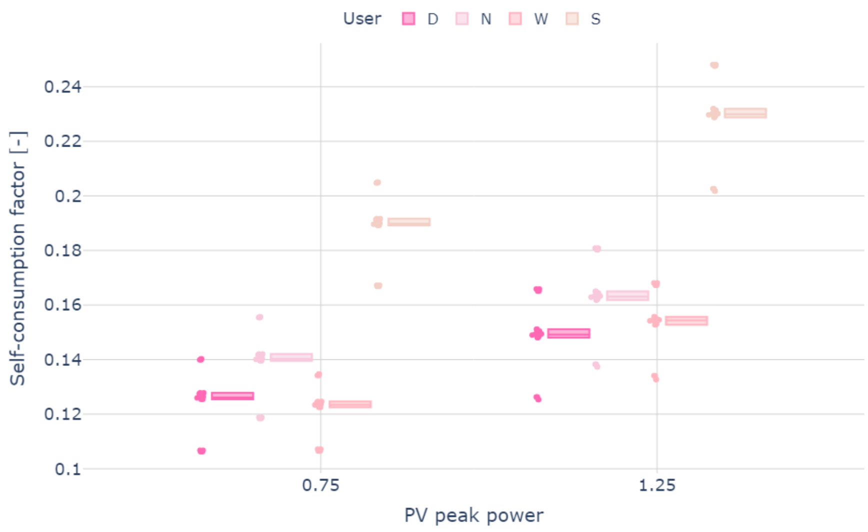


Figure 32: Self-consumption factor β_{SC} in function of α_{PV} and user of LS simulations. Better to have an oversized PV installation (α_{PV}=1.25) for self-consumption.

Given the low importance of EV-related variables parameters (Figure 29), it was not considered necessary to further analyse them in this case.

This analysis closes the section on the results of the one value pocket set simulations. There are common trends between cases such as the preference for a large α_{PV}. Differences are also present especially for the trip and users parameters. We will discuss these convergences and divergences in detail in the Section 4.3 devoted to the comparison of the two sets of simulations.

The subsections regarding the one value pocket simulations are now completed. The results of the MP controller developed for this study are presented in the next section.

4.2 Multi-Pocket

It's time to present the results of the multi-pocket simulation set to determine the potential value that can be generated and to address the question raised in Section 2.5.2. The idea behind MP control is to prioritize the three use cases: SC, PS, and LS, as schematically shown in Figure 14. The control logic, which introduces two new comfort parameters (P^c_{EV} and d_c), is explained in Figure 3.3.3.

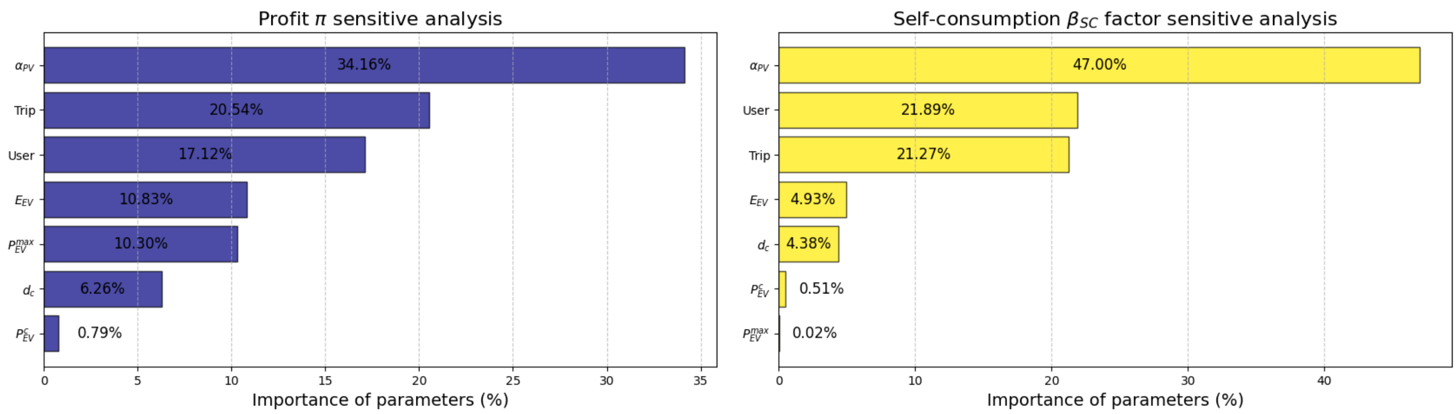
To analyze all simulations related to each choice of variable parameters listed in Table 7, we will perform sensitivity analyses followed by more detailed analyses, as done previously.

Sensitivity analyses

These sensitivity analyses share similarities with the one-pocket SC analyses shown in Figure 16. Indeed, α_{PV} is the most important parameter for both KPIs, followed by the trip and user profiles with similar importance. This is logical since the SC use case is prioritized within the MP algorithm, as seen in the profit comparisons in Table 4.

Regarding profit, the technical parameters related to the EV, E_{EV} and P^{max}_{EV}, with values of 10.83% and 10.30%, are of significant importance. This is twice the values obtained in the one pocket results observed in Section 4.1. Surprisingly, the parameters specific to the MP controller have the least importance, with 6.26% and 0.79% for d_c and P^c_{EV}, respectively.

Importance is shared among a smaller number of parameters for β_{SC}, with α_{PV}, user, and trip having values of 47%, 21.89%, and 21.27%, respectively. The parameters related to energy capacity are more important than those representing power. E_{EV} and d_c, which determine SOC_c, have an importance of 4.93% and 4.38%, while P^c_{EV} and P^{max}_{EV} have values of less than 1%.



(a) Profit sensitivity analysis. (b) Self-consumption factor sensitivity analysis.

Figure 33: Sensitivity analyses of MP simulations. These analyses share similarities with the SC analyses shown in Figure 16. α_{PV} is the most important parameter for both KPIs, followed by trip and user with similar importance. This is logical since the SC use case is prioritized within the MP algorithm. For (a), EV technical parameters are of significant importance, being twice the values obtained for the other controllers. MP parameters have the least importance. For (b), importance is shared among α_{PV}, user, trip and parameters related to energy capacity are more important than those representing power.

With the same 3 important parameters as for the 3 one value pocket cases, the same two-parameter analyses will be presented with an additional one on comfort parameters.

User and Trip

The graphs of both KPIs according to the user and trip profiles of the MP controller are similar to the SC case presented in the Figures 17 and 18. The points of interest are :

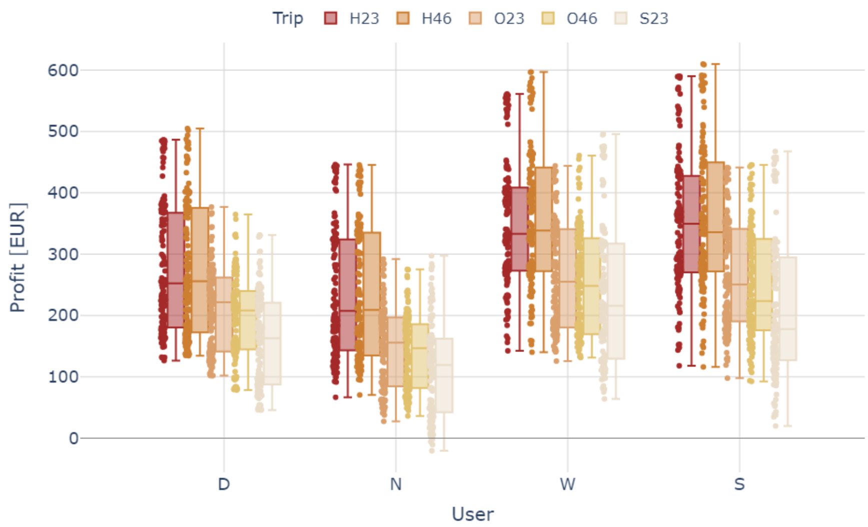


Figure 34: Profit π [€] in function of user and trip of MP simulations. Big consumer (W,S) are advantages for profit while summer no longer exceeds as it was the case for SC controller in Figure 17. Half-day worker (S23) has the lowest profit because of SOC_m and SOC_c introduced in MP algorithm. Daily consumer (D) profit is above the nightly (N) despite that this one has a slightly higher annual baseload.

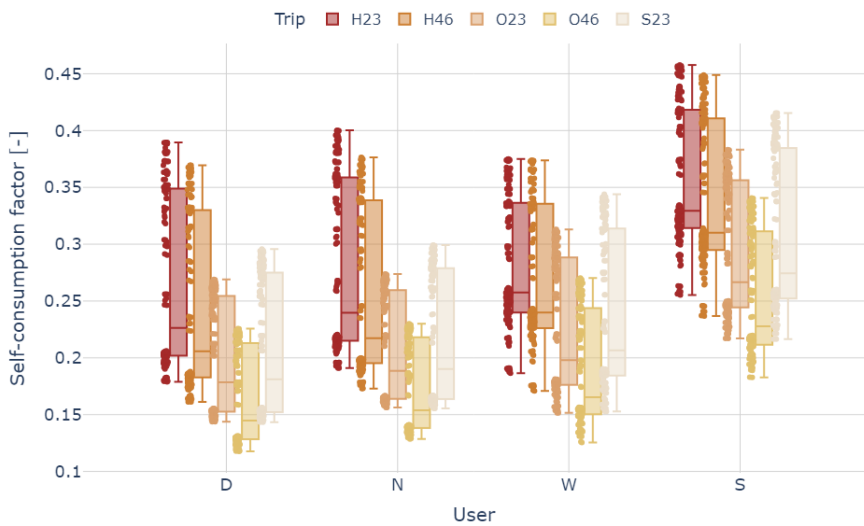


Figure 35: Self-consumption factor β_{SC} in function of user and trip of MP simulations. Positively skewed distributions of self-consumption factor β_{SC}. Among the other variable parameters, the value of some leads to a low factor clustering while other parameters lead to large factor values with possible high values.

- **Big and daily consumer are advantages for profit** : The trend observed in graph 17 is similar but the staircase structure is no longer observed. Table 31 shows that both high-end consumers (summer and winter) generate the same profit, while summer no longer exceeds. In addition, the daily consumer is above the nightly despite that this one has a slightly higher annual baseload.

- These conclusions are exactly the same as found on the Figures 17 and 18 for SC controller explained in Section 4.1.1.
  - **More profitable to be a hybrid worker**
  - **Commute of 23km is better than 46km for teleworkers to self-consume**
- **Half-day worker has the lowest profit** : This trip profile has the lowest values or even negative for some simulations of nightly user. Having defined SOC_m and SOC_c for which the advance recharge from the grid is allowed means that at times we pay more than in the uncontrolled case.
- **Positively skewed distributions of self-consumption factor** : The distribution of β_{SC} for the different simulations is positively skewed or right-skewed which means that most data points are concentrated near the lower values, while the upper values are more spread out. This means that among the other variable parameters, the value of some leads to a low factor clustering β_{SC} for the lower half while other values lead to factors β_{SC} larger with possible high values for the upper half.

PV peak power and User

With the use of PV production as a priority within the MP algorithm, we have Figures for the coefficient α_{PV} and user profiles almost identical to the one of the case SC.

From those Figures 19 and 20 of the Section 4.1.1 the following conclusions have been drawn :

- **Oversized PV installation is more desirable**
- **Summer consumer is better than winter for self-consumption**

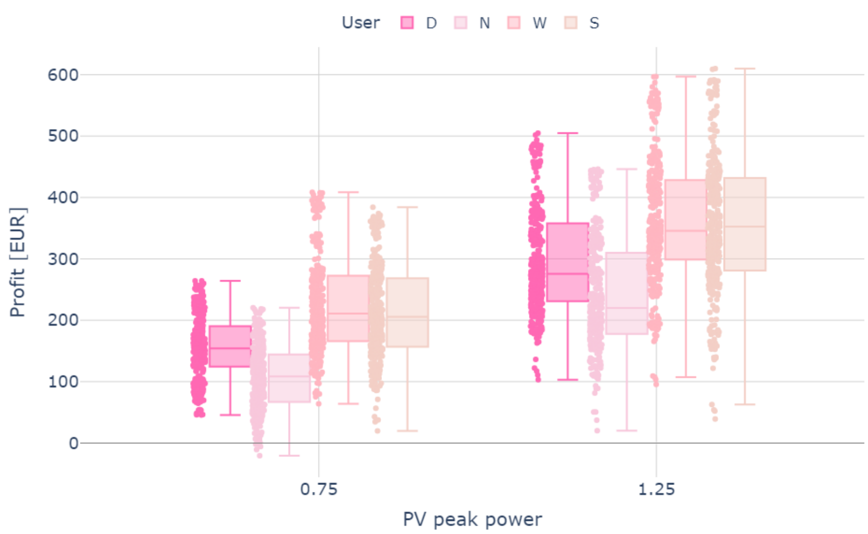


Figure 36: Profit π [€] in function of α_{PV} and user of MP simulations. Observations are the same as for SC controller and corresponding analysis of Figure 19.

Negative values observed in figure above for night user are associated with half-day worker (S23), as explain in the analysis just before.

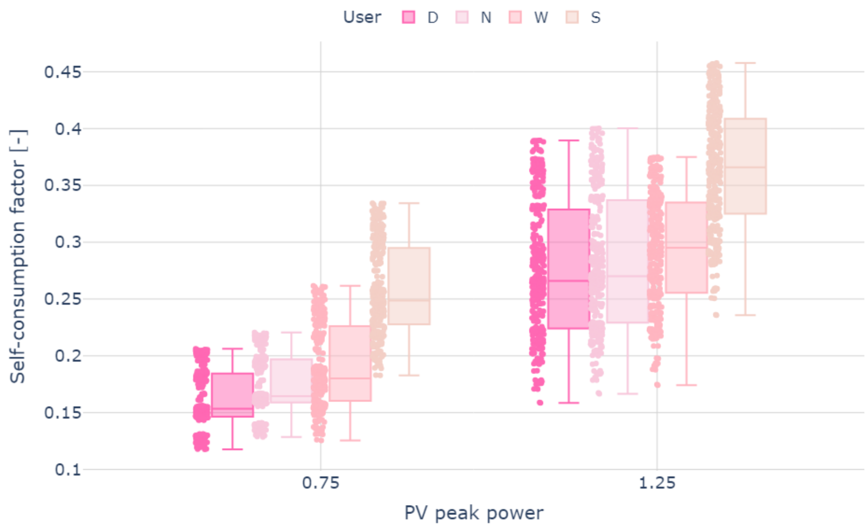


Figure 37: Self-consumption factor β_{SC} in function of α_{PV} and user of MP simulations. Observations are the same as for SC controller and corresponding analysis of Figure 20.

EV variables parameters

It's for MP case that the EV variables parameters are the most importants. Only profit has decided to be presented for the lower importance of these in the self-consumption sensitivity analysis (Figure 33b) and because it does not lead to other conclusions.

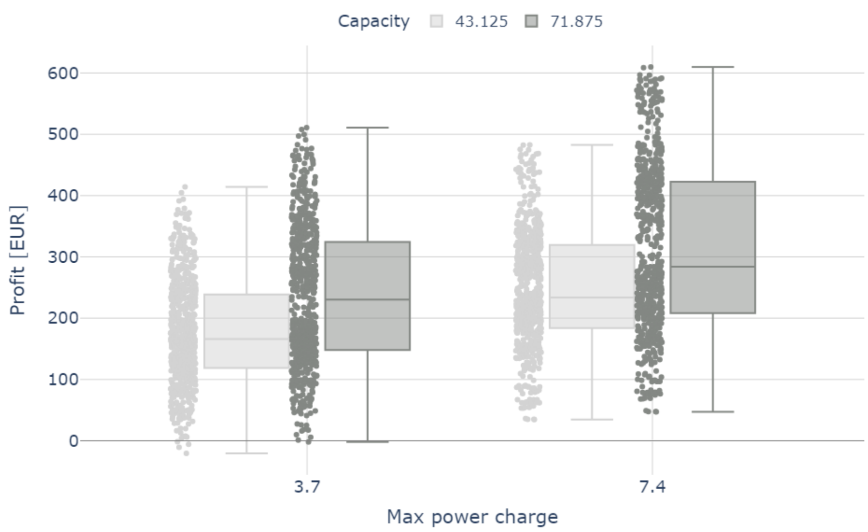


Figure 38: Profit π [€] in function of P_{EV}^{max} and E_{EV} of MP simulations. Better a large EV capacity (E_{EV}) because a larger comfort state-of-charge (SOC_c) is loaded at small comfort power (P_{EV}^{c}). Once reached, larger amount of energy can be charged via PV production. It's also better a high maximum power charge (P_{EV}^{max}), because when EV is charging with PV production (P_{EV}^{PV}), it's not possible to go beyond this P_{EV}^{max} and therefore $P_{EV}^{max} = 3.7$ could waste energy.

This figure above leads to these findings :

- **Better a large EV capacity** : As for the Peak-Shaving case with the Figure 28, it's better to have big capacity to generate more profit. This bigger capacity allows for a larger tranche of comfort state-of-charge (SOC_c) that is loaded at comfort power (P^c_{EV}). In addition, a larger amount of energy can be charged via PV production only. This results in a slower drop into the minimum state-of-charge (SOC_m) that is charged at maximum power and uses of more free energy.

- **Better a high maximum power charge** : Here too the reason is the same as in the case of Peak-Shaving. It may seem meaningless that with the capacity pricing we generate more profit with a more important maximum power charge (P^{max}_{EV}) but this is the case. Indeed, as explained in the charging rules of the Section 3.3.3. When charging at PV power (P^{PV}_{EV}) you cannot go beyond this P^{max}_{EV} and therefore if the PV production is larger you waste energy. In addition, this peak is a local production peak and is therefore not included in the billing.

Confort distance and power

This last analysis concerns the parameters used only in the case of the MP control. As shown by the sensitivity analysis in Figure 33, it is mainly the parameter d_c which has influence. The significance of P^c_{EV} is less than unit for both KPI.

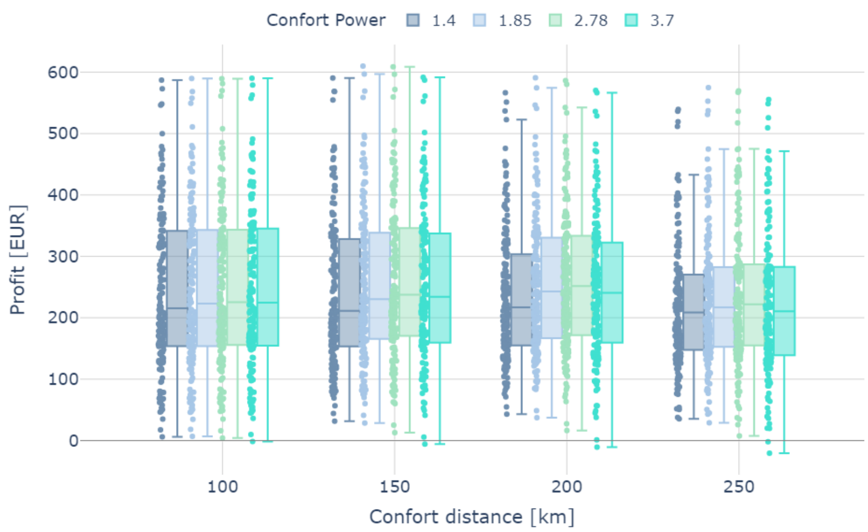


Figure 39: Profit π [€] in function of d_c and P^c_{EV} of MP simulations. There is a optimum value of comfort distance (d_c) for profit because a distance too small gives a safety margin too low before falling into the minimum state-of-charge (SOC_m), increasing the risk of generating power peaks. A distance too large reduce the amount of free electricity that can be charged via PV production.

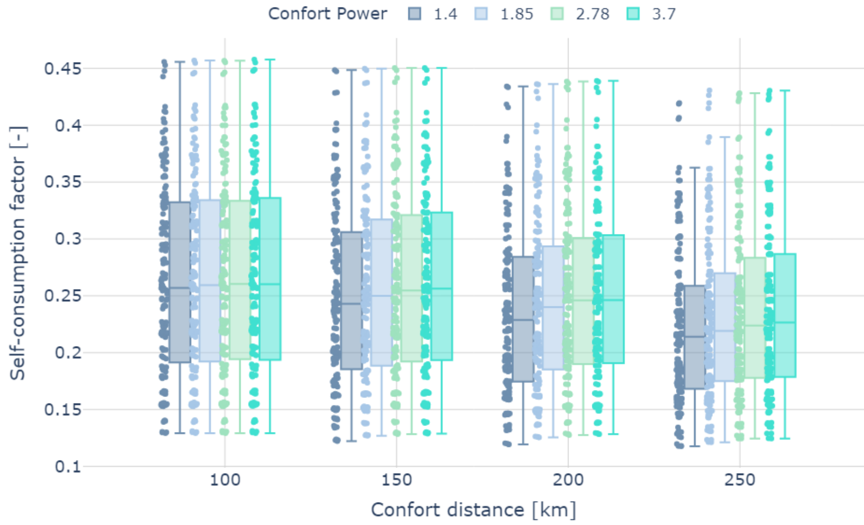


Figure 40: Self-consumption factor β_{SC} in function of d_c and P_{EV}^c of MP simulations. Smaller comfort distance (d_c) is better for self-consumption to have the largest proportion of the battery available to be charged via PV production.

The points of interest highlighted by this Figure are :

- **Optimum value of comfort distance for profit** : Figure 39 shows that the distances of 150 km and 200 km generate the highest profits. The Table 36 of the average values confirms that apart from the pair (100, 1.4) the most important profits are located between the 100 km and 250 km limits. This is logical, a distance too small would result in more potential of the battery being charged with PV production but at the same time the safety margin before falling into the minimum state-of-charge (SOC_m) is low and the risk of generating power peaks is greater. On the other hand, a confort distance too big means that too large part of the battery is charged at night, reducing the amount of free electricity that can be charged via PV production after reached comfort state-of-charge SOC_c.
- **Smaller comfort distance is better for self-consumption** : If the goal is just to self-consume, then it is better to impose a low distance in order to have the largest proportion of the battery available to be charged via PV production.

Even if the importance of P_{EV}^c is very low, a simulation was run with two extra power values (4.625 kW and 5.55 kW) present on an azure blue background in the Table 7. This simulation shows also an optimum of confort power between 2,775 kW and 3,7 kW. This helped to remove doubt about the need for larger values for P_{EV}^c in the simulation.

This analysis of the parameters introduced in this work closes the sections devoted to the presentation of results. We will now compare the one value pocket results with those of the multi-pocket ones in the next section to try to answer the question of the Subsection 2.5.2.

4.3 Multi-Pocket Creates more Value than Single Pocket?

After presenting the results of the 4 controllers with sensitivity analysis for both KPI π and β_{SC} as well as a descriptive analyses of important parameters. It remains to compare the 3 use case from the one pocket simulation with each other and with the MP algorithm result developed for this work.

A general comparison will be made to confirm the trend that Self-Consumption and Multi-Pocket cases are more favourable than Peak-Shaving and Load-Shifting. This trend has already been observed in the Table 4 and in the KPI values encountered in the detailed analyses graphs above.

We will compare Peak-Shaving and Load-Shifting by proposing ideal users who have variable parameter values that give the higher profit and self-consumption factor. Finally, we propose a common scenario for these two control techniques. The same will be done to judge the Self-Consumption and Multi-Pocket case. Moreover, to better discern the potential of these two we will analyze the sets of parameters that lead to the most higher profit.

4.3.1 Self-Consumption is the Best Behavior under Capacity Pricing

In this subsection we compare the techniques of control of EV recharging: Self-Consumption, Peak-Shaving, Load-Shifting and Multi-Pocket defined in Subsections 3.3.2 and 3.3.3. The results detailed in the two previous sections are analyzed according to their average profit values, self-consumption factor (β_{SC}) and the power peaks generated to close this part with an interesting finding.

Figures 41 and 42 allows us to compare our 4 control strategies with the same box plot as before and with the mean value at the centre represented by a red dot. Each box represents the distribution of profit π and self-consumption factor β_{SC} for the 160 simulations for each subsets of the one pocket set and uncontrolled case. The 2560 simulations of the Multi-Pocket set are also presented. The uncontrolled case is not present for profit being given that each profit comes from the difference of each case with this uncontrolled.

Figures 41 clearly shows that Self-Consumption and Multi-Pocket control based on maximum use of PV production either with the β_{SC} most important (Figure 42) are the ones that create the most value. The profit generated is more than twice as high than Peak-Shaving and Load-Shifting.

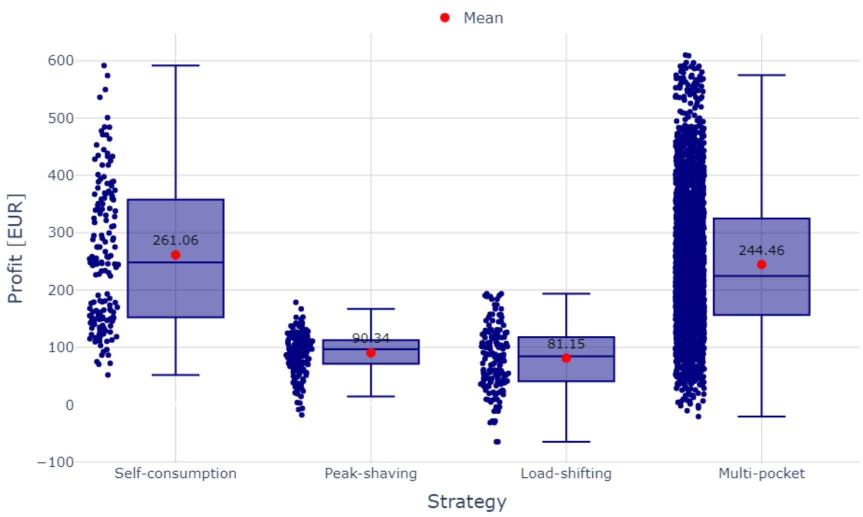


Figure 41: Comparison of the distributions of the profit (π) obtained for each simulation of each control strategy. The mean value of these profits for each strategy is the value above the red dot in each box. Self-Consumption then Multi-Pocket based on maximum use of PV production generated more than two times more value than Peak-Shaving and Load-Shifting.

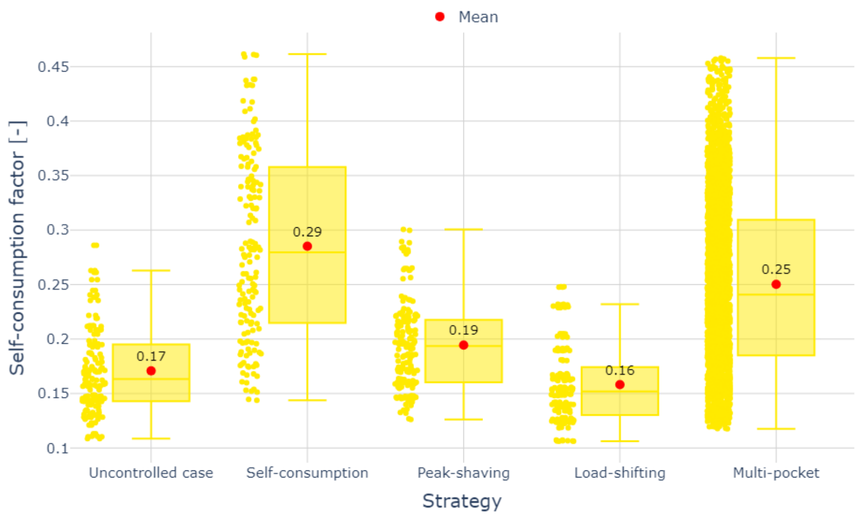


Figure 42: Comparison of the distributions of the self-consumption factor (β_{SC}) obtained for each simulation of each control strategy. The mean value of for each strategy is the value above the red dot in each box. Strategies based on maximum use of PV production, Self-Consumption and Multi-Pocket have the larger β_{SC} factor. The uncontrolled case (β_{SC}=0.17) and the Peak-Shaving (β_{SC}=0.19) and Load-Shifting (β_{SC}=0.16) controls have similar average values.

Figure 43 represents the average of 12 power peaks observed for each month of the year crucial for the calculation of capacity pricing explain in Section 3.2.4. It highlight that no matter the control, the average of peaks will be lower than the uncontrolled case. In addition, the three one pocket cases have about the same average of power peaks while the MP controller has the lowest average with a value of 6.51 kW. This highlights that the introduction of the comfort state-of-charge (SOC_c) plays its role of security well and allows to generate less important peaks as defined in Subsection 3.3.3.

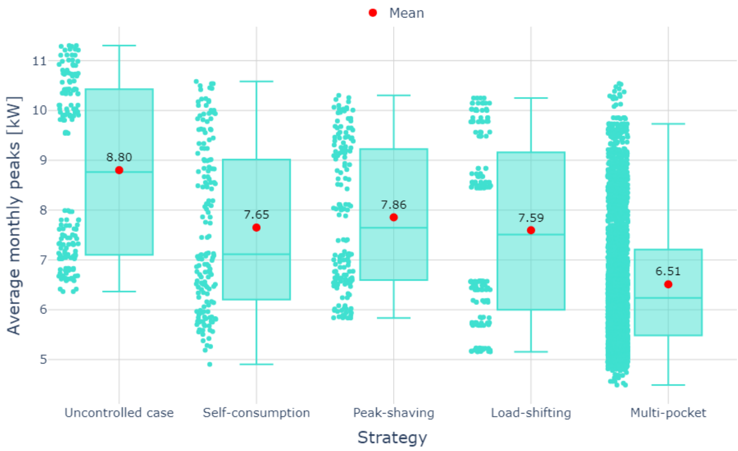


Figure 43: Comparison of the distributions of the average of monthly power peaks [kW] obtained for each simulation of each control strategy. The mean value of these average of monthly power peaks for each strategy is the value above the red dot in each box. The three one pocket cases have about the same average of power peaks while uncontrolled case give the worst (8.8 kW). Multi-Pocket controller has the lowest value (6.51 kW) highlights that the confort state-of-charge (SOC_c) plays its role of security to generate less peaks as defined in Subsection 3.3.3.

These figures allow us to draw an important point. All those simulations are carried out under the capacity pricing. The logical behind force you to use a behavior that minimizes the peaks of powers. Yet, we see that despite an average of peaks at 7.59 kW, the Load-Shifing case has an average profit of 81.15 €. The Self-Consumption case has a slightly higher peaks average of 7.65 kW and generates a 3 times greater profit with a value of 261.06 €. In addition, the Multi-Pocket case which generates the smallest average peaks of 6.51 kW still does not manage to exceed the Self-Consumption control with its lower profit of 244.46 €. In fact, the averages of the profits of the different strategies follow exactly the pattern of the self-consumption factor averages (β_{SC}).

This leads to the finding that it is economically more profitable to use a control which may generate more power peaks but at the same time will use the maximum PV production. Generated peaks but use free electricity is preferable than smoothing the peaks and not fully use PV production.

This interesting result explains why two groups can be distinguished based on the highest profits or in other words the maximum use of PV production. Consequently, the two groups of controllers PS,LS and SC,MP are compared in the next two subsections.

4.3.2 PS and LS Control for Standard High Mileage Workers

The first comparison is therefore between the two one pocket Peak-Shaving and Load-Shifting cases, which are the two control techniques producing the least profit. The average value of the profits of the Peak-Shaving simulations is 90.34 € whereas for the Load-Shifting case it is 81.15 €. The PS distribution is concentrated around the median while the LS is more extensive and shows greater variability as illustrated in Figure 41. This slightly higher profit value can again be explained by the fact that the PS case self-consumes more than the LS which privileges a night consumption where there is no PV production as shown in Figure 42.

An Ideal and unfavourable consumer for each case will be established in the following lines. The aim is to know which type of control technique should be recommended or not to which type of consumer.

Ideal user for Peak-Shaving control

By reviewing conclusion bullets in Subsection 4.1.2 about the Figures 24, 25, 26, 27, 28. Knowing that, these trends are confirming using the Tables 40 and 41 of 10 minimum and maximum simulations profits for PS, we can conclude.

The ideal consumer for PS control has a **high annual mileage**. He does **not need to telework** as he will not benefit from having his vehicle at home on certain days of the week. If he has the choice, it would be interesting for him to take an EV with **a large capacity** but this choice is **not decisive**. It is with a **nightly or wintry** house consumption that he will **see the most result** by contribution to his initial situation. An oversized PV installation is **preferable**.

However, he must choose not to make his EV controllable if he is a summer consumer with a driving profile where **he drives half days** to work and with an EV having **a low** P_{EV}^{max}**.**

Ideal user for Load-Shifting control

Again, from the same type of figures but from Section 4.1.3 of Load-Shifting results and Tables 42 and 43 on the extreme values of the LS case, is proposed.

The LS control will suit for a consumer with a **high annual mileage** that can make **every day of the week** if he wants the commute from his home to his place of work. His EV **does not** need to present **the largest technical values**. A house **with or without PV production** where the consumption of the devices is done **during the day** and/ or **mainly during winter** is preferable.

Finally, it is preferable to not control a user **working half days** who has **night and/or summer** house consumption.

Scenario

In conclusion, for both cases it is preferable to have a high annual mileage and the presence of the vehicle at home some days of the week does not matter. For small consumer, a nightly consumer will prefer the Peak-Shaving control while a daily consumer will take the Load-Shifting controller. Large values of technical parameters for the EV and an oversize of the PV production is more important for the PS case.

The same analysis is given for the Multi-Pocket and Peak-Shaving controllers in the next subsection.

4.3.3 SC and MP Controllers for Highly Electrified Flexible Workers.

It remains to compare the two techniques that prioritise the use of PV production in the control of EV recharge. It turns out to be a winning choice as explained at the end of Section 4.3.1. Self-Consumption case performs better than the Multi-Pocket controller implemented for this study with an average profit value of 261.06 € against 244.46 € as shown in Figure 41. The main reason is the loss in self-consumption linked to the introduction (detailed in this Subsection 3.3.3) of minimum state-of-charge (SOC_m) and comfort state-of-charge (SOC_c) which are recharged with the electricity of the grid as shown in Figure 42. Finally, the distribution of these profits is a little wider for the MP case with a greater dispersion for values above the median leading to slightly higher extreme values as it will be explained later.

Ideal user for Self-Consumption control

For this last case of the one pocket set, we use the higlights of the Section 4.1.1 and the Tables 38 and 39 of the minimum and maximum values.

The ideal consumer for Self-Consumption control is someone who works remotely several days per week with **his vehicle during the day at home**. It can have a commuting distance **up to 50 km** without that being unfavourable. If he wants to achieve the most important profit it is important that he has an EV with a **large capacity and maximum power of recharge**. **The larger the residential consumption**, the better is but he must have **an oversized PV production**. To achieve the higher profits it is preferable to be a summer consumer.

Ideal user for Multi-Pocket control

Finally, the Section 4.2 and the important points drawn from Figures 34, 35, 36, 37, 38, 39, 40, including this time the comfort distance (d_c) and power (P^c_{EV}) parameters. In addition, Tables 44 and 45 allow to give this ideal user.

The perfect consumer for this control works remotely several days a week and has his **vehicule parked at home during the day**. He can have a commute that **goes up to 50 km**. His EV must have **the highest technical parameters**. A **comfort distance too large** as 250 km is **to be avoided** if he wants to get the higher results it must be 150 km. An **oversized PV** installation is **absolutely necessary**. The **more he consumes** with his domestic assets, the more control will be **favourable**. To achieve the best profits it is preferable to be a summer consumer. For **a small consumer** it is better to be a **daytime consumer**.

A consumer who is not in favour of this control has a **nightly small household consumption**. His house is equipped with a **undersized PV installation**. He uses his EV to perform **half-days of work** and this EV has **a low maximum charging power**.

Scenario

For these two techniques using PV generation, there are points of convergence and an common ideal consumer profile can be given. He has a commute up to 50 km and can work from home leaving his EV parked during the daytime at home. He has a large domestic consumption with an oversized PV installation. If this consumption is small and he consumes during the day he will prefer the Multi-Pocket control. An EV with large parameters is desirable especially for the Multi-Pocket control.

At the end of the previous subsection it's recommended for a small night consumer to use the Peak-Shaving control and the Load-Shifting for a daily. This is true only if the Self-Consumption and Multi-Pocket controls are not taken into account. Indeed, the Tables 18 and 25 of average profit values for the two small consumers with control PS and LS give an average that is never more than 120 €. Whereas for the SC and MP cases, in Tables 12 and 36 the average profit is never less than 120 €. Therefore, it is better to use SC and MP controls even for small consumers if they are available.

Finally, it has already been mentioned above that the Self-Consumption control outperforms the Multi-Pocket control. However, as shown Tables 10 and 11 below. The 5 most economically profitable MP simulations have a higher profit than the simulations with the higher profit of the SC case. This performance is due to the controller design for this study because the self-consumption factor β_{SC} for MP simulations is lower than the ones of SC simulations. So these higher profits are not due to free electricity from PV production but through the implemented Multi-Pocket control logic. This result should be taken with a grain of salt because the differences of profit of those high profit simulations are small. Moreover, there is still a 15€ difference in the average of the profits of the two cases as recalled in Figure 41.

α_{PV}	P_{EV}^{max}	E_{EV}	Trip	User	β_{SC}	π
1.25	7.4	71.875	H23	S	0.4615	591.4591

Table 10: Variables parameters set of Self-Consumption simulation giving the highest profit.

α_{PV}	P_{EV}^{max}	E_{EV}	Trip	User	d_c	P_{EV}^{c}	β_{SC}	π
1.25	7.4	71.875	H46	S	150.0	1.850	0.4375	609.8838
1.25	7.4	71.875	H46	S	150.0	2.775	0.4416	608.6346
1.25	7.4	71.875	H46	W	150.0	1.850	0.3643	596.9876
1.25	7.4	71.875	H46	W	150.0	2.775	0.3658	596.4081
1.25	7.4	71.875	H46	S	150.0	3.700	0.4408	591.7487
1.25	7.4	71.875	H46	S	200.0	1.850	0.4296	590.7640

Table 11: Variables parameters sets of Multi-Pocket simulations giving the 6 highest profits.

5 Conclusion

The development of RES with prosumers and the electrification of Belgian society have created a need for residential DSF. As consumers contend with increasingly complex pricing, HEMS have emerged. This flexibility is called value creation and is studied via the optimization of value pockets on electrical assets.

This work aims to answer the question: Home energy management system with multiple assets and multiple value pockets, a utopia?
This conclusion provides satisfactory answers to this question. Nevertheless, only one asset was considered, and the introduction of a second would answer the whole question.

The study simulates a Flemish household under capacity pricing (unfavorable to peak power) with an EV and a PV installation over a year. The results depend on the parameter values from this system and the EV recharge controller. The Multi-Pocket controller designed separates the EV battery into segments and charges one of them up to a limit (d_c) at a fixed power (P^c_{EV}) during the night to avoid power peaks. This controller is compared to a Self-Consumption controller that maximizes the use of local PV electricity, a Peak-Shaving controller that smooths power consumption, and a Load-Shifting controller that moves the recharge to nighttime. The key performance indicators used in this study are profit (π) and the self-consumption factor (β_{SC}).

The important parameters for each control case were determined through sensitivity analyses. Based on that, further analysis of important parameters has led to trends. As a result, the controllers were grouped into two categories that follow similar trends. The Peak-Shaving and Load-Shifting controllers are adapted for workers with high mileage who commute every day of the week by car. They are particularly suitable for individuals with low household consumption, where an oversized PV installation is desirable but not necessary. An EV with standard parameters is sufficient.
In contrast, the Self-Consumption and Multi-Pocket controllers are suitable for flexible hybrid workers who park their cars at home several days a week. High domestic consumption is not a disadvantage and is even more advantageous during the summer. An oversized PV installation and an EV with robust technical parameters are important.

The average profits generated by each control technique are 261.06 € for SC, 244.46 € for MP, 90.34 € for PS, and 81.15 € for LS. The same trends are observed, with Self-Consumption and Multi-Pocket controllers being much more profitable than Peak-Shaving and Load-Shifting. From this result, it is concluded that a strategy focused on maximizing the consumption of free electricity from PV production yields significant profit. Conversely, a strategy based on minimizing power peaks to comply with capacity pricing is less successful. The greater importance of the comfort power (d_c), which determines the proportion of rechargeable battery via PV production in the Multi-Pocket algorithm, compared with comfort power (P^c_{EV}), confirms this conclusion. Finally, the MP controller underperforms economically on average compared to the SC controller. However, in extremely favorable cases, it generates a higher profit (609.88 € versus 591.46 €) while consuming a smaller share of PV production ($\beta_{SC} = 0.4375$ versus $\beta_{SC} = 0.4615$).

These conclusions should be considered in light of the simplifications and idealizations introduced by certain parameters. The trip profiles used include all journeys planned in advance for an entire year. However, some trips, such as shopping or visits, are less predictable in practice. In addition, O46 and H23 profiles are further from reality. The more distant the workplace is, the more a worker will want to work remotely on certain days of the week if they have the opportunity. Conversely, if they live close to their workplace, they will want to come to the site more often. Moreover, the higher EV capacity value (71.85 kWh) corresponds to a premium car, which is less common in the current vehicle fleet.

To go further and fully answer the question, one perspective is to introduce a domestic BESS within the Flemish household. An analysis of the proportion of time spent in the different state-of-charge bands of the algorithm suggests that the potential of PV production is not being exploited for almost 75% of the time. During 20% of the time, the vehicle is on the road or has a full battery. For 54% of the time, it is parked at home, but the PV power generated is less than the minimum charging power. It should be noted that within this 75%, there is time when there is no PV production, at night, for example. However, this is still a large amount of free energy that could be stored in a BESS to be discharged at night into the EV instead of using the network's night recharge, as it does in the Multi-Pocket algorithm. For example, taking the most favorable case with a profit of 609.88 € and a BESS usage cost of 0.274 € per kWh, the cost of storing 20% of the annual PV production of this favorable case would be 365.44 €, bringing the final profit to 244.45 €. Indeed, the advantage of the EV is that its primary function is mobility. There is no cost of energy storage; we just take advantage of its large battery to recharge at the right time. This example illustrates the complexity of the concept of multi-pocket value creation. It reminds us how profitable it remains to consume the electricity produced by PV panels directly in assets.

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A

Electricity Bill

EASY Fixe 1 an

Prix fixes électricité pour les contrats conclus en Décembre 2023
Pour les particuliers en Région Flamande
Prix, 6% de tva comprise(12)

Composition du prix de votre énergie(9)

- Energie fournie (ENGIE)
- Coûts de réseaux (Gestionnaire de réseau)
- Impôts, charges et tva (Gouvernement)

Vos avantages

- Un prix fixe pendant 1 an quelle que soit l'évolution du marché de l'énergie
- Une électricité 100 % verte
- Un compteur digital? Un aperçu de votre consommation via le Smart app

Services gratuits

- Service client 5 étoiles en ligne et par téléphone
- Facture par la poste ou par e-mail
- Réductions chez nos partenaires

Prix d'énergie Fixe - 1 an

Redevance fixe(1)
61,48 €/an

Prix par kWh (€cent/kWh)				
Type d'usage	Normal	Bihoraire Heures pleines	Bihoraire Heures creuses	Exclusif Nuit
+ Consommation(2)	21,678	22,957	19,391	19,391
− Injection(3)	5,113	6,683	1,108	

Coûts énergie verte & cogénération(5) (€cent/kWh)
+ 2,241

Partage de l'énergie (15)	
Coût administratif	121 €

EASY Fixe 1 an

Prix fixes électricité pour les contrats conclus en Décembre 2023
Pour les particuliers en Région Flamande
Prix, 6% de tva comprise[12]

Coûts de réseaux (distribution et transport)[6]

Région Flamande	Compteur digital				
	Distribution**				
Gestionnaire du réseau de distribution	**Tarif capacitaire** moyenne des pics mensuels*	**Total tarif-kWh**	**Total tarif-kWh** exclusif nuit	**Tarif gestion de données** régime de mesure : quart-horaire	**Tarif gestion de données** régime de mesure : mensuel/annuel
	€/kW/an	€cent/kWh	€cent/kWh	€/an	€/an
FLUVIUS ANTWERPEN	40,0309	3,74193	2,60192	14,53	13,39
FLUVIUS LIMBURG	37,6491	3,94475	2,81516	14,53	13,39
FLUVIUS WEST	41,0824	3,81831	2,72467	14,53	13,39
GASELWEST	48,7615	4,98204	3,36755	14,53	13,39
IMEWO	43,5071	4,01029	2,82576	14,53	13,39
INTERGEM	39,0604	3,65582	2,59558	14,53	13,39
IVEKA	45,0292	4,21339	2,89091	14,53	13,39
IVERLEK	43,6742	3,88562	2,77610	14,53	13,39
PBE	53,0580	3,64580	2,89941	14,53	13,39
SIBELGAS	48,1157	4,57544	3,22842	14,53	13,39

Cette liste de prix comprend les tarifs du réseau de distribution incluant déjà les coûts de transport.

Région Flamande	Compteur analogique				
	Distribution				
Gestionnaire du réseau de distribution	**Tarif capacitaire** terme fixe	**Total tarif-kWh**	**Total tarif-kWh** exclusif nuit	**Tarif gestion de données** régime de mesure : mensuel/annuel	**Tarif prosumer (7)**
	€/an	€cent/kWh	€cent/kWh	€/an	€/kW/an
FLUVIUS ANTWERPEN	100,0746	5,70831	4,56830	13,39	38,56
FLUVIUS LIMBURG	94,1280	6,08459	4,95500	13,39	41,11
FLUVIUS WEST	102,7034	6,10955	5,01591	13,39	41,28
GASELWEST	121,9000	7,40908	5,79459	13,39	50,05
IMEWO	108,7666	6,23503	5,05050	13,39	42,12
INTERGEM	97,6472	5,76780	4,70756	13,39	38,97
IVEKA	112,5720	6,37959	5,05710	13,39	43,10
IVERLEK	109,1906	6,12534	5,01581	13,39	41,38
PBE	132,6484	6,47113	5,72474	13,39	43,71
SIBELGAS	120,2888	6,93899	5,59198	13,39	46,87

Cette liste de prix comprend les tarifs du réseau de distribution incluant déjà les coûts de transport.

B

Random Forest Estimator

Following explanation of the RFE comes from the site of *scikit-learn* package site scikit [33].

The RandomForestRegressor is a versatile tool within the scikit-learn library that can be employed as a Random Forest estimator to perform regression tasks. As an ensemble learning method, it operates by constructing a multitude of decision trees during training time and outputting the mean prediction (regression) of the individual trees. This approach allows for enhanced prediction accuracy and robustness, as it mitigates the risk of overfitting commonly associated with individual decision trees.

In practice, the Random Forest Regressor works by randomly selecting features and data samples to build each decision tree in the ensemble. At each node, the algorithm chooses a feature and a threshold that best splits the data into two subsets. The data is recursively split, and the process continues until the nodes reach a stopping criterion, such as a minimum number of samples or a maximum depth. The predictions from all trees are then averaged to produce the final output, offering a balance between bias and variance.

A key advantage of this method is its ability to determine the most important features in a dataset, as indicated by the relative decrease in predictive performance when a particular feature is removed. This makes it especially useful in scenarios where understanding the influence of individual features on the prediction is critical.

For each regression task, RandomForestRegressor employs the scikit-learn Python library, optimizing based on the data and feature importance analysis. By default, features that are highly correlated or less impactful are excluded, helping to refine the model and focus on the most significant predictors. This method is particularly beneficial when dealing with complex datasets where non-linear relationships between variables exist.

C
Mean Value SC

Trip	H23	H46	O23	O46	S23
User					
D	243.52	255.36	168.64	175.83	181.01
N	265.36	266.80	181.46	188.19	185.32
W	362.84	376.75	252.84	265.45	262.48
S	386.67	384.55	265.71	252.56	263.85

Table 12: Mean Profit EV (User, Trip)

Trip	H23	H46	O23	O46	S23
User					
D	0.30	0.29	0.23	0.19	0.26
N	0.31	0.30	0.23	0.20	0.26
W	0.32	0.31	0.25	0.23	0.29
S	0.39	0.38	0.32	0.29	0.36

Table 13: Mean Auto Conso EV (User, Trip)

User	D	N	W	S
α_{PV}				
0.75	116.21	130.04	212.51	211.08
1.25	307.96	304.82	395.63	410.25

Table 14: Mean Profit EV (α_{PV}, User)

User	D	N	W	S
α_{PV}				
0.75	0.18	0.19	0.22	0.29
1.25	0.32	0.33	0.34	0.41

Table 15: Mean Auto Conso EV (α_{PV}, User)

C_{EV}	43.125	71.875
P_{EV}^{max}		
3.7	235.54	263.01
7.4	255.23	290.47

Table 16: Mean Profit EV (P_{EV}^{max}, C_{EV})

C_{EV}	43.125	71.875
P_{EV}^{max}		
3.7	0.28	0.29
7.4	0.28	0.29

Table 17: Mean Auto Conso EV (P_{EV}^{max}, C_{EV})

D Mean Value PS

Trip	H23	H46	O23	O46	S23
User					
D	85.43	87.26	94.87	104.18	33.28
N	100.64	103.56	114.21	121.88	68.59
W	115.37	118.28	114.65	135.95	61.01
S	86.35	81.68	86.80	88.17	4.57

Table 18: Mean Profit EV (User, Trip)

Trip	H23	H46	O23	O46	S23
User					
D	0.19	0.17	0.17	0.15	0.18
N	0.20	0.19	0.19	0.16	0.19
W	0.19	0.18	0.18	0.16	0.18
S	0.26	0.24	0.24	0.22	0.25

Table 19: Mean Auto Conso EV (User, Trip)

User	D	N	W	S
α_{PV}				
0.75	70.66	90.34	94.81	53.48
1.25	91.34	113.21	123.29	85.55

Table 20: Mean Profit EV (α_{PV}, User)

User	D	N	W	S
α_{PV}				
0.75	0.15	0.16	0.15	0.21
1.25	0.19	0.21	0.20	0.27

Table 21: Mean Auto Conso EV (α_{PV}, User)

C_{EV}	43.125	71.875
P_{EV}^{max}		
3.7	80.00	92.09
7.4	87.96	101.30

Table 22: Mean Profit EV (P_{EV}^{max}, C_{EV})

C_{EV}	43.125	71.875
P_{EV}^{max}		
3.7	0.20	0.20
7.4	0.19	0.19

Table 23: Mean Auto Conso EV (P_{EV}^{max}, C_{EV})

E
Mean Value LS

Trip	H23	H46	O23	O46	S23
User					
D	65.83	78.90	79.90	118.95	-14.68
N	23.85	42.11	45.94	87.93	-1.57
W	94.77	109.92	120.12	161.51	60.75
S	33.55	54.22	63.91	103.71	-25.00

Table 24: Mean Profit EV (User, Trip)

Trip	H23	H46	O23	O46	S23
User					
D	0.15	0.14	0.14	0.12	0.14
N	0.17	0.15	0.15	0.13	0.15
W	0.15	0.14	0.14	0.12	0.14
S	0.23	0.21	0.21	0.18	0.21

Table 25: Mean Auto Conso EV (User, Trip)

User	D	N	W	S
α_{PV}				
0.75	135.12	45.64	116.65	54.74
1.25	123.77	33.67	102.19	37.42

Table 26: Mean Profit EV (α_{PV}, User)

User	D	N	W	S
α_{PV}				
0.75	0.13	0.14	0.12	0.19
1.25	0.15	0.16	0.15	0.23

Table 27: Mean Auto Conso EV (α_{PV}, User)

C_{EV}	43.125	71.875
P_{EV}^{max}		
3.7	75.25	75.25
7.4	87.05	87.05

Table 28: Mean Profit EV (P_{EV}^{max}, C_{EV})

C_{EV}	43.125	71.875
P_{EV}^{max}		
3.7	0.16	0.16
7.4	0.16	0.16

Table 29: Mean Auto Conso EV (P_{EV}^{max}, C_{EV})

F Mean Value MP

Trip User	H23	H46	O23	O46	S23
D	276.95	280.21	210.83	197.17	160.34
N	236.21	236.88	147.41	139.66	113.26
W	349.50	359.95	263.68	253.94	236.09
S	347.83	355.97	263.64	249.03	210.69

Table 30: Mean Profit EV (User, Trip)

Trip User	H23	H46	O23	O46	S23
D	0.27	0.25	0.20	0.17	0.21
N	0.28	0.26	0.21	0.17	0.22
W	0.28	0.27	0.23	0.19	0.24
S	0.36	0.34	0.29	0.26	0.31

Table 31: Mean Auto Conso EV (User, Trip)

User α_{PV}	D	N	W	S
0.75	155.40	107.17	223.72	213.42
1.25	294.80	242.20	361.55	357.45

Table 32: Mean Profit EV (α_{PV}, User)

User	D	N	W	S
α_{PV}				
0.75	0.16	0.17	0.19	0.26
1.25	0.28	0.28	0.29	0.37

Table 33: Mean Auto Conso EV (α_{PV}, User)

C_{EV}	43.125	71.875
P_{EV}^{max}		
3.7	177.93	237.80
7.4	247.06	315.06

Table 34: Mean Profit EV (P_{EV}^{max}, C_{EV})

C_{EV}	43.125	71.875
P_{EV}^{max}		
3.7	0.24	0.26
7.4	0.24	0.26

Table 35: Mean Auto Conso EV (P_{EV}^{max}, C_{EV})

d_c	100.0	150.0	200.0	250.0
P_{EV}^{c}				
1.400	244.57	242.07	236.30	219.57
1.850	247.20	256.00	256.18	232.73
2.775	248.43	260.07	261.98	236.49
3.700	244.82	252.79	248.42	223.77

Table 36: Mean Profit EV (P_{EV}^{c}, d_c)

d_c	100.0	150.0	200.0	250.0
P_{EV}^{c}				
1.400	0.26	0.25	0.24	0.22
1.850	0.27	0.26	0.25	0.23
2.775	0.27	0.26	0.25	0.24
3.700	0.27	0.26	0.25	0.24

Table 37: Mean Auto Conso EV (P_{EV}^{c}, d_c)

G Extreme SC values

α_{PV}	P_{EV}^{max}	E_{EV}	Trip	User	β_{SC}	π
0.75	7.4	43.125	S23	D	0.1760	51.8660
0.75	3.7	43.125	S23	D	0.1871	70.5003
0.75	7.4	71.875	S23	D	0.1772	72.1294
0.75	3.7	43.125	S23	N	0.1968	75.0111
0.75	3.7	71.875	S23	D	0.1882	86.3057
0.75	3.7	71.875	S23	N	0.1980	86.5074
0.75	7.4	43.125	O23	D	0.1659	92.5776
0.75	7.4	43.125	O46	D	0.1438	96.3215
0.75	3.7	43.125	O23	D	0.1746	102.9829
0.75	7.4	71.875	O46	D	0.1446	109.7440

Table 38: Variables parameters sets of SC simulations giving the 10 smallest profits.

α_{PV}	P_{EV}^{max}	E_{EV}	Trip	User	β_{SC}	π
1.25	7.4	71.875	H23	S	0.4615	591.4591
1.25	7.4	71.875	H46	S	0.4604	573.8879
1.25	7.4	71.875	H46	W	0.3842	549.4258
1.25	7.4	71.875	H23	W	0.3796	536.0507
1.25	3.7	71.875	H46	S	0.4590	500.6257
1.25	7.4	43.125	H46	S	0.4327	484.3451
1.25	3.7	71.875	H46	W	0.3853	484.1319
1.25	7.4	43.125	H46	W	0.3578	477.3166
1.25	3.7	71.875	H23	S	0.4610	470.9911
1.25	7.4	43.125	H23	S	0.4373	470.4460

Table 39: Variables parameters sets of SC simulations giving the 10 largest profits.

H

Extreme PS values

α_{PV}	P_{EV}^{max}	E_{EV}	Trip	User	β_{SC}	π
0.75	3.7	43.125	S23	S	0.2204	-17.7453
1.25	3.7	43.125	S23	S	0.2884	-8.3064
0.75	3.7	71.875	S23	S	0.2213	-6.4454
1.25	3.7	71.875	S23	S	0.2895	2.8160
0.75	7.4	43.125	S23	S	0.2065	3.7737
0.75	7.4	71.875	S23	S	0.2075	14.3951
1.25	7.4	43.125	S23	S	0.2638	18.6087
0.75	7.4	43.125	S23	D	0.1460	20.6417
1.25	7.4	43.125	S23	D	0.1850	23.8838
0.75	3.7	43.125	S23	D	0.1593	25.2844

Table 40: Variables parameters sets of PS simulations giving the 10 smallest profits.

α_{PV}	P_{EV}^{max}	E_{EV}	Trip	User	β_{SC}	π
1.25	3.7	71.875	O46	W	0.1975	178.6907
1.25	3.7	43.125	O46	W	0.1966	167.1882
1.25	7.4	71.875	O46	W	0.1784	152.6869
1.25	3.7	71.875	O23	W	0.2168	152.5926
1.25	7.4	71.875	O46	N	0.1756	149.2423
1.25	7.4	71.875	O23	N	0.2003	142.5575
1.25	3.7	71.875	O46	N	0.1915	142.1199
1.25	3.7	43.125	O23	W	0.2156	141.2422
1.25	7.4	43.125	O46	W	0.1775	141.0000
1.25	3.7	71.875	H46	W	0.2159	137.4088

Table 41: Variables parameters sets of PS simulations giving the 10 largest profits.

I

Extreme LS values

α_{PV}	P_{EV}^{max}	E_{EV}	Trip	User	β_{SC}	π
1.25	3.7	71.875	S23	S	0.2297	-64.7045
1.25	3.7	43.125	S23	S	0.2297	-64.7045
1.25	3.7	71.875	S23	N	0.1629	-31.2421
1.25	3.7	43.125	S23	N	0.1629	-31.2421
1.25	7.4	43.125	S23	S	0.2288	-28.2961
1.25	7.4	71.875	S23	S	0.2288	-28.2961
0.75	3.7	43.125	S23	S	0.1896	-11.3692
0.75	3.7	71.875	S23	S	0.1896	-11.3692
1.25	7.4	43.125	S23	N	0.1619	-3.8929
1.25	7.4	71.875	S23	N	0.1619	-3.8929

Table 42: Variables parameters sets of LS simulations giving the 10 smallest profits.

α_{PV}	P_{EV}^{max}	E_{EV}	Trip	User	β_{SC}	π
0.75	7.4	71.875	O46	D	0.1062	193.5767
0.75	7.4	43.125	O46	D	0.1062	193.5767
0.75	3.7	43.125	O46	D	0.1067	190.4484
0.75	3.7	71.875	O46	D	0.1067	190.4484
1.25	7.4	71.875	O46	D	0.1254	188.7694
1.25	7.4	43.125	O46	D	0.1254	188.7694
1.25	3.7	43.125	O46	D	0.1263	184.0056
1.25	3.7	71.875	O46	D	0.1263	184.0056
0.75	7.4	43.125	O46	W	0.1065	174.5818
0.75	7.4	71.875	O46	W	0.1065	174.5818

Table 43: Variables parameters sets of LS simulations giving the 10 largest profits.

J

Extreme MP values

α_{PV}	P_{EV}^{max}	E_{EV}	Trip	User	d_c	P_{EV}^{c}	β_{SC}	π
0.75	3.7	43.125	S23	N	250.0	3.700	0.1586	-20.5894
0.75	3.7	43.125	S23	N	200.0	3.700	0.1633	-10.5988
0.75	3.7	43.125	S23	N	150.0	3.700	0.1648	-5.6775
0.75	3.7	71.875	S23	N	250.0	3.700	0.1643	-2.0676
0.75	3.7	43.125	S23	N	100.0	3.700	0.1658	-1.7427
0.75	3.7	71.875	S23	N	200.0	3.700	0.1644	1.2677
0.75	3.7	43.125	S23	N	100.0	2.775	0.1658	4.3085
0.75	3.7	71.875	S23	N	150.0	3.700	0.1658	5.8568
0.75	3.7	43.125	S23	N	100.0	1.400	0.1654	6.0013
0.75	3.7	43.125	S23	N	100.0	1.850	0.1660	6.7486

Table 44: Variables parameters sets of MP simulations giving the 10 smallest profits.

α_{PV}	P_{EV}^{max}	E_{EV}	Trip	User	d_c	P_{EV}^{c}	β_{SC}	π
1.25	7.4	71.875	H46	S	150.0	1.850	0.4375	609.8838
1.25	7.4	71.875	H46	S	150.0	2.775	0.4416	608.6346
1.25	7.4	71.875	H46	W	150.0	1.850	0.3643	596.9876
1.25	7.4	71.875	H46	W	150.0	2.775	0.3658	596.4081
1.25	7.4	71.875	H46	S	150.0	3.700	0.4408	591.7487
1.25	7.4	71.875	H46	S	200.0	1.850	0.4296	590.7640
1.25	7.4	71.875	H46	S	150.0	1.400	0.4288	590.4472
1.25	7.4	71.875	H23	S	100.0	3.700	0.4577	590.2504
1.25	7.4	71.875	H23	S	100.0	1.850	0.4569	589.5778
1.25	7.4	71.875	H23	S	100.0	2.775	0.4568	589.3090

Table 45: Variables parameters sets of MP simulations giving the 10 largest profits.

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
École polytechnique de Louvain
Rue Archimède, 1 bte L6.11.01, 1348 Louvain-la-Neuve, Belgique | **www.uclouvain.be/epl**