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Optimization of EV dynamic tariffs in hybrid PV and storage charging stations

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Abstract

As a response to growing concerns about the excessive consumption of fossil fuels, the introduction of electric vehicles (EV) is being encouraged. The massive increase in the number of EVs results in a disorganised increase in load and a need for charging infrastructure for these new EVs. It is, therefore, necessary to develop intelligent load management strategies and invest in charging infrastructure. This dissertation analyses the use of dynamic tariffs in the context of electric vehicle charging. To this end, a program was developed to optimise dynamic tariffs that maximise the operator's profits in various existing photovoltaic (PV) and energy storage (ES) contexts. Subsequently, the impact of dynamic tariffs, PV and ES in the operation of EV charging stations is analysed.

Resumo

Como resposta às crescentes preocupações com o consumo excessivo de combustíveis fósseis, está a ser incentivada a introdução de electric vehicles (EV). O aumento maciço do número de EVs resulta num aumento desorganizado da carga e na necessidade de infra-estruturas de carregamento para estes novos EVs. É, portanto, necessário desenvolver estratégias inteligentes de gestão de carga e investir em infra-estruturas de carregamento. Esta dissertação analisa a utilização de tarifas dinâmicas no contexto do carregamento de veículos eléctricos. Para tal, foi desenvolvido um programa de otimização de tarifas dinâmicas que maximizam os lucros do operador em vários contextos de photovoltaic (PV) e energy storage (ES) existentes. Posteriormente, é analisado o impacto das tarifas dinâmicas, PV e ES na exploração de postos de carregamento EV.

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Filipe Lobo

“Shut up and let’s do this!

Monkey D. Luffy

Contents

List of Figures

List of Tables

Abbreviations and Symbols

BL	Bi-level
CPP	Critical Peak Pricing
CS	Charging station
DT	Dynamic tariffs
EPSO	Evolutionary particle swarm optimization
ES	Energy storage
EU	European union
EV	Electric vehicle
GA	Genetic algorithm
IRES	Intermittent renewable energy sources
LL	Lower-level
LP	Linear programming
MIBEL	Iberian electricity market
MILP	Mixed integer linear programming
MM	Mathematical model
MPPT	Maximum power point tracking
PSO	Particle swarm optimization
PV	Photovoltaic
RES	Renewable energy resource
RTP	Real-Time Pricing
SC	Self-consumption
SS	Self-sufficiency
TOU	Time-of-Use
UL	Upper-level
V2G	Vehicle-to-Grid

Chapter 1

Introduction

1.1 Context

The increasing popularity of electric vehicles (EV) has sparked a global shift towards sustainable transportation, driven by environmental concerns [1], government initiatives, and technological advancements. EVs have become one of the most popular choices for eco-conscious consumers, offering zero-emission transportation and reduced dependence on fossil fuels [2].

The European Union (EU) has set ambitious goals to achieve carbon neutrality by 2050, aiming to eliminate the contribution of greenhouse gas emissions to the atmosphere. As part of this vision, the EU has announced plans to phase out combustion engine cars, accelerating the transition to electric mobility. This commitment highlights the urgency to establish adequate charging infrastructure to support the widespread adoption of EVs.

However, the lack of sufficient charging stations (CS) remains a significant obstacle to the seamless integration of EVs into daily life. The limited availability of charging infrastructure leads to concerns about range anxiety and inhibits the convenience and practicality of EV ownership. Expanding and optimizing the charging network is crucial to overcome this challenge, ensuring EV drivers have reliable access to charging facilities wherever they go [3].

The cost of photovoltaic (PV) cells, which convert sunlight into electricity, has steadily decreased in recent years. This cost reduction, coupled with improvements in battery technology, has made PV systems an increasingly attractive solution for powering EV CSs. The evolution of battery technology has enhanced energy storage (ES) capabilities, enabling CSs to store surplus energy and provide a consistent power supply, even during periods of low sunlight or high demand.

The convergence of these factors - the popularity of EVs, the EU's commitment to carbon neutrality, the phase-out of combustion engine cars, the lack of charging infrastructure, the decreasing cost of PV cells, and the advancements in battery technology - creates a compelling context to explore and optimize the integration of PV-powered CSs. By leveraging renewable energy sources and improving the accessibility and reliability of charging infrastructure, the transition to electric mobility can be accelerated, contributing to a more sustainable and greener future.

1.2 Motivation

Several key factors drive the motivation behind this research. Firstly, charging EVs with PV energy has the potential to reduce their carbon footprint significantly. By leveraging renewable energy sources like solar power, EV charging can align with sustainability goals and contribute to reducing greenhouse gas emissions, helping combat climate change. However, it is essential to ensure the environmental benefits of EV charging with PV and ES by considering the life cycle analysis of all of this systems and considering factors like production, recycling, and end-of-life management of PV and ES components.

Secondly, there is a pressing need to make CSs more economically viable and less dependent on fossil fuels. Integrating PV systems into charging infrastructure offers an opportunity to reduce operational costs by utilizing abundant and increasingly affordable solar energy. By tapping into this renewable resource, CSs can minimize their reliance on traditional grid power and create a more sustainable economic model for EV charging. This economic viability benefits CS operators and encourages wider adoption of EVs by making charging more affordable and attractive to consumers.

Additionally, enhancing the SS of CSs by adopting ES is crucial. ES enable CSs to store excess PV-generated electricity and utilize it during low solar generation or high-demand periods. This increased self-sufficiency reduces the negative impact on the grid by minimizing the additional load imposed by CSs. CSs can optimize their operations and contribute to grid stability by effectively managing their energy supply and demand [4]. Furthermore, research in this area could explore the optimal sizing and integration of ES systems to maximize their benefits for CS operators and the grid.

By focusing on these motivations, this dissertation explores strategies and solutions that maximize the utilization of PV energy for EV charging. It seeks to establish the economic viability of CSs by reducing reliance on fossil fuels, optimizing ES systems, and creating a more sustainable charging infrastructure. By promoting the integration of PV and ES technologies, the research aims to facilitate the transition towards a greener and more efficient transportation ecosystem while minimizing the environmental impact of EV charging.

1.3 Objectives

The primary objective of this master's dissertation is to optimize EV DT in hybrid PV and storage CSs. Specifically, the aim was to develop a mathematical model (MM) and apply meta-heuristic optimization techniques to determine the optimal tariff structures that maximize the utilization of renewable energy resources (RES) while minimizing the cost for EV owners. While it may increase total costs for EV owners, it offers EV owners that react to DT the opportunity to pay less.

This research addresses three key challenges: the high penetration of intermittent renewable energy sources (IRES), the introduction of massive and disorderly EV charging and the lack of investment in EV charging infrastructure. Successfully tackling these challenges is crucial for promoting the sustainable integration of EV and RES into the energy network.

This work focuses on developing intelligent charging management strategies for EVs by combining direct ES control and DTs as inducers. The objective is to optimize the availability of charging points and benefit the energy supplier. These strategies will be based on predicting various variables, such as the availability of charging points, energy consumption, market prices, and occupancy. The developed methods will be flexible enough to accommodate different realities and objectives, enabling efficient charging management in diverse scenarios.

This research encourages user cooperation with the electricity grid by developing effective charging management strategies. This cooperation can be fostered by providing users with load-balancing benefits, including monetary incentives, prize draws, and rewards for frequent users. Additionally, increasing transparency and empowering users in the charging process have proven effective motivators.

Overall, this research seeks to optimize EV DTs in hybrid PV and storage CSs, considering the integration of RES, load balancing, user cooperation, and supplier benefits. The strategies developed will consider predictive variables and be adaptable to different contexts and objectives, contributing to a more sustainable and efficient charging infrastructure for ESs.

1.4 Document Structure

This dissertation is structured as follows:

- Chapter 2 provides an overview of the current state of the art in RES for electric vehicle (EV) CSs, including a detailed exploration of PV systems, ES technologies, and charger technologies. It also discusses the concept of DTs, focusing on their applications in grid usage, smart homes, and EVs. Additionally, the chapter examines existing approaches for optimizing EV electricity tariffs, including MM and meta-heuristic algorithms.

- Chapter 3 outlines the methodology employed in this research. It describes the program used for simulation and optimization and presents the formulation of the problem, including both the initial formulation and the proposed new formulation. The chapter further elaborates on the implementation details, including the power mixed integer linear programming (MILP) model and the heuristics used for optimization.

- Chapter 4 presents the results obtained from case studies and illustrative examples. It evaluates the performance of the optimized EV DTs in terms of profit, investment plans, self-consumption (SC) and SS.

- Chapter 5 concludes the dissertation by summarizing the capabilities of the program, results obtained, and what can be inferred from these results, discussing their implications, and suggesting avenues for future work. It highlights this research's contributions to DTs for EV and offers recommendations for further development on this project.

Chapter 2

State of the Art

2.1 Renewable Energy Resources for Electric Vehicle Charging

RES is crucial in achieving a sustainable, low-carbon transportation system. In the context of EV charging stations, integrating RES technologies, such as photovoltaic (PV) systems, ES, and advanced charger technologies, has garnered significant attention. PV systems convert sunlight into electricity, offering a clean and RES for EV charging. ES technologies, such as batteries, enable the capture and storage of excess energy generated by PV systems, allowing for its utilization during periods of low solar irradiance. Charger technologies have also evolved to manage the charging process efficiently, considering factors like power flow, grid constraints, and user preferences. Some even allow more complex operations like Vehicle-to-Grid (V2G).

2.1.1 Photovoltaic systems

PV systems have witnessed remarkable advancements, making them an attractive option for EV CSs. Technological innovations, such as higher conversion efficiencies, reduced costs, and improved reliability, have increased the viability of PV systems. Integrating PV panels with EV charging infrastructure allows for direct utilization of solar energy, reducing dependence on the grid and decreasing carbon emissions. Furthermore, advanced techniques, such as maximum power point tracking (MPPT) algorithms and smart grid integration, optimize PV system performance and enhance its integration with the charging infrastructure.

There is a PV technology that is particularly interesting for this application. Solar Carport, oftentimes called a solar port, is a dual-purpose, stand-alone structure that provides shelter for vehicles while generating clean, renewable energy from the sun. Solar ports integrate PV panels into their design, allowing EVs parked beneath them to charge directly from solar energy. These structures offer an innovative solution for sustainable EV charging, providing environmental benefits and vehicle shade.

2.1.2 Energy Storage

ES technologies complement PV systems by capturing and storing excess energy generated during high solar irradiance periods. Batteries, in particular, have gained prominence due to their ability to store and discharge energy as per demand. Lithium-ion batteries, for instance, offer high energy density, longer lifetimes, and rapid charging capabilities, making them suitable for EV charging applications. There is also the possibility of using second-life batteries to reduce the environmental impact of battery production and disposal [5]. Additionally, emerging technologies like flow and solid-state batteries hold promise for future ES advancements, offering advantages such as longer cycle life and increased safety and lower costs.

2.1.3 Chargers

Charger technologies have evolved to cater to the specific requirements of EV CSs. Intelligent chargers incorporate features like bidirectional power flow, demand response capabilities, and V2G functionality. Bidirectional chargers allow EVs to consume energy from the grid and supply excess energy back to the grid or to other electrical loads. This bidirectional power flow capability facilitates integrating EVs into the grid as distributed energy resources. V2G technology enables EVs to act as mobile ES units, offering grid support services and participating in energy market transactions. Demand response capabilities enable chargers to respond to grid demand and price fluctuations, optimizing the charging process and contributing to grid stability [6].

2.2 Dynamic Tariffs

DTs are pricing strategies that determine optimal selling prices for products or services by easily and frequently adjusting prices based on various factors [7]. This approach is widely used in airlines, hospitality, and retail industries. In modern systems, DTs plays an essential role, dynamically adapting prices to achieve different objectives, such as maximizing profits, preserving supply during shortages, maximizing customer satisfaction, or improving system efficiency.

As an emerging area of focus, DTs draw contributions from various knowledge sectors, including operational research, management science, marketing, computer science, and economics. However, obtaining a large volume of sales data to understand consumer behaviour and price variation remains a challenge in certain areas, particularly those with emerging businesses or legislation limiting DT implementation.

In the context of EV charging, DTs present unique challenges. As an emerging business, most Western countries' pricing legislation often lacks the flexibility for exhaustive application of price variation. Nevertheless, theoretical work studying and formulating mathematical models and real-case implementations within legal boundaries contribute to advancing the understanding and implementation of DTs for EV charging [8] [9].

2.2.1 Grid Usage

DTs have been explored for grid usage optimization, managing electricity consumption and balancing supply-demand fluctuations. Time-of-Use (TOU) and Critical Peak Pricing (CPP) tariffs incentive consumers to shift their electricity usage to off-peak periods or reduce consumption during peak hours. Real-Time Pricing (RTP) tariffs provide price signals based on instantaneous supply and demand conditions, allowing consumers to make informed decisions regarding their electricity usage [10].

2.2.2 Smart Homes

DTs are used in smart homes to optimize energy consumption patterns. By incorporating data from smart meters, weather forecasts, and occupancy sensors, DTs can adjust electricity prices based on individual household requirements and preferences. This enables homeowners to schedule energy-intensive tasks, such as EV charging, during low prices and high renewable energy availability [11].

2.2.3 Electric Vehicles

DTs for EV charging are approached through different models based on Pricing Scheme Type, Pricing Scheme Implementation, and Addressed Flexibility. These models consider various factors, such as objectives, available technologies, and operational requirements.

All DT approaches assume users will make decisions that maximize their profit, preferring the cheapest options that satisfy their charging needs. The objective of DTs is typically to maximize social benefit, considering utilities gained by users minus the energy cost.

The operator's objective may vary, including objectives to reduce environmental impact [12], reduce the impact on the electricity grid [13].

2.2.3.1 Pricing Scheme Type

Pricing Scheme Types categorize how prices are structured from the user's perspective (Figure 2.1):

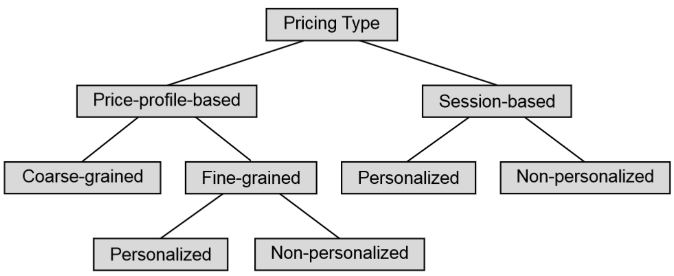

Figure 2.1: Categorization regarding pricing type [14]

- **Price-profile-based:** Price-profile-based sets prices for different scheduling time intervals, the most common being different prices per unit of energy. Fine-grained price profiles define individual prices for small intervals, typically 5 minutes to 1 hour. Coarse-grained price profiles define constant prices for larger intervals, such as daily or day and night prices. Fine-grained price profiles can be personalized or non-personalized. If non-personalized, users can all have the same price per unit of energy. If personalized, different users can have different prices per unit of energy. For example, different prices can be offered based on the amount of energy the user intends to buy.

- **Session-based pricing:** In session-based pricing, prices are set per charging session. In this Pricing Type, the user cannot access billing data for particular time intervals or billing subsections. Like the fine-grained price, these can also be personalized or non-personalized. If non-personalized, users are priced the same if they order the same amount of power in the same period. An example of a case where prices would be customized might be a model that works by auctions. The auction result may be different for two users, even if they are requesting the same amount of energy in the same period.

2.2.3.2 Pricing Implementation

Pricing Implementation categorizes the strategies used to implement, the main strategies can be divided into the following categories DTs (Figure 2.2):

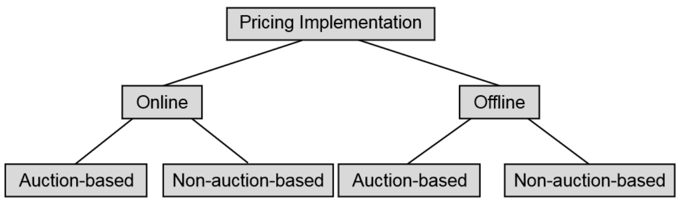

Figure 2.2: Categorization regarding pricing implementation [14]

- **Offline:** Offline approaches determine prices for a long planning horizon (at least 24h). They depend on knowledge, or good predictions, of the number of EVs they intend to charge during the planning horizon and how much they intend to charge. Auction-based cases are completely dependent on user inputs since to plan the next day, users need to define the amount of energy they want to obtain and during which period. Offline approaches without auctions should rely primarily on the forecast.

- **Online:** Online pricing mechanisms do not depend on knowing the demand for a long planning horizon as they only plan for the immediately following period or do not use any type of forecast in planning. They can deal better with unforeseen events, however, they have their challenges, namely the allocation of permanent resources to deal with unforeseen events.

2.2.3.3 Addressed Flexibility

The benefit of using DTs for EV charging is that it allows us to use the flexibility of the users(Figure 2.3). The best result will be achieved when the is access to full user flexibility, so it is necessary to categorize what types of flexibility exist and how can they be used to improve the management of electric charging, and how that type of flexibility can be accessed.

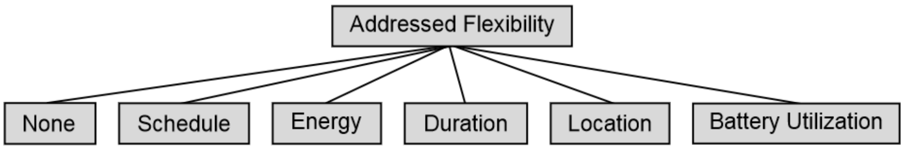

Figure 2.3: Categorization regarding addressed flexibility [14]

- **No flexibility:** It is possible to approach this problem without considering the issue of flexibility, that is, without expecting user reactions to price changes. One approach that does this, is to adjust the minimum price in each period according to the cost of operation by ensuring that the customer charging requirements cover the operation costs and that these charging requirements are not affected by the price.
- **Flexibility in the schedule:** In this type of flexibility, is assumed that it's not important to users how much they charge over time as long as they get the amount of energy they need when they pick up their car. This knowledge can be implemented in strategies to coordinate the charging of EVs unevenly according to available resources, such as renewable production and price on the energy market.
- **Flexibility in the amount of charged energy:** While it is normally preferable to charge the battery completely, users may be satisfied with an amount that deviates somewhat from their desired amount. So they might be satisfied with a different amount of energy if it means a lower price. This can be useful when the price of energy is very high, there is a lot of demand, or renewable generation is low [15].
- **Flexibility in the charging duration:** There is a minimum charging time associated with the amount of energy the user wants to charge, however, often the customer is willing to leave their vehicle charging for a longer period. By offering different tariffs depending on the total charging time, one can use strategies that maximize the self-consumption of renewable energy and purchase energy from the market in periods when it is cheaper. This is one of the types of flexibility with more potential, as it allows for more complex smart charging models.
- **Flexibility in location:** This type of flexibility consists of the possibility of changing the user's CS. It is particularly useful for load balancing over multiple charging sites. Implementing it can be done simply by offering a lower price at the locations where the load is to be moved.

- **Flexibility in battery utilization:** This flexibility consists of making the batteries available for bidirectional charging. With this flexibility, there can store energy in some EVs to use later to charge other EVs, or even supply energy to the grid. The use of the batteries results in some damage so not all users are willing to allow the use of their battery for these applications, especially while there is no absolute data on the impact of this type of operation on battery deterioration. Models using this kind of flexibility have many more variables to consider, as different levels of battery use should result in different tariffs.

2.2.4 Benefits

DTs for EV charging can provide a range of benefits:

- **Improved utilization of charging infrastructure:** DTs incentivize EV owners to charge during low-demand and cheaper electricity periods, optimizing the utilization of charging infrastructure and reducing the need for additional investments.
- **Reduced strain on the electricity grid:** DTs help smooth out demand for electricity, reducing peak demand and the need for expensive peak generation capacity, improving grid stability.
- **Cost savings for EV owners:** Charging during low-price periods enables EV owners to save money on their electric bills.
- **Increased adoption of EVs:** DTs can make EV ownership more attractive by reducing upfront and ongoing costs.
- **Reduced greenhouse gas emissions:** By encouraging EV adoption and reducing strain on the grid, DTs contribute to reducing greenhouse gas emissions.
- **Environmental sustainability** Allows a more efficient use of self-generation, encouraging the use of RES.

2.2.5 Challenges

While DTs have several potential benefits, there are also challenges and drawbacks to implementing such pricing strategies:

- **Difficulty in predicting demand:** Accurate demand predictions are essential for optimizing DTs, but predicting demand fluctuations and tariff response can be challenging, especially with the lack of data.
- **Potential for increased costs for consumers:** DTs can lead to higher prices during periods of high demand, which may be disadvantageous for consumers with limited flexibility in their schedules [16].

- **Complexity:** Implementing DTs may require advanced technology like smart meters and data analysis in cloud computing, which could pose challenges for some businesses.
- **Consumer confusion:** DTs can confuse consumers who may not understand how prices are adjusted, leading to frustration and mistrust.
- **Regulatory challenges:** DTs may face regulatory hurdles in some jurisdictions due to price manipulation or fairness concerns.

2.2.6 Conclusion

Overall, DTs offer both benefits and challenges for consumers and businesses. Careful consideration of potential drawbacks and the role of technology is crucial when implementing such pricing strategies. Due to the generalist nature of the study to be carried out, this dissertation will not go into several of these issues. The pricing type is non-personalised, fine-grained, and price-profile-based, it has chosen to implement the set of users as a single entity, so the chosen pricing type cannot be customised, and the tariffs are defined for smaller periods to be able to take advantage of hourly energy prices and also self-generation. The price implementation chosen is offline and non-audition-based as it allows better optimisation of tariffs when there is a good forecast and gives more control to the operator to ensure the economic viability of the charging operation. The aim is to analyse the economic impact of DTs, so the only the form of flexibility used is scheduling flexibility in which users change the period in which they will charge the car. Other forms of flexibility require multiple charging stations or more precise modelling of the technologies used.

2.3 Optimising electric vehicle electricity tariffs

Efficiently optimising EV electricity tariffs requires developing and applying suitable mathematical models and optimisation techniques. This subsection explores the approach mostly commonly used in the literature: mathematical models and meta-heuristics. The importance of forecasting EV-related variables is also discussed.

2.3.1 Mathematical models

MMs provide a structured framework for tariff optimisation, allowing for the formulation and solution of complex optimisation problems. Two widely utilised mathematical models in the context of EV DTs are MILP and bi-level (BL) models.

2.3.1.1 MILP

Linear Programming (LP) is a powerful optimisation technique that can handle various constraints and decision variables in tariff optimisation problems. By formulating the problem with LP, it becomes possible to optimise EV electricity tariffs while considering factors such as renewable energy availability, grid constraints, and user preferences. The LP formulation enables the determination of the optimal tariff structure that maximises renewable energy utilisation and minimises costs for EV owners. Using MILP, discrete and binary decision variables can be used in the formulation, allowing you to use more accurate and complex models.

2.3.1.2 Bi-level models

BL models address the hierarchical nature of tariff optimization, where decision-making occurs at multiple levels [17]. In the context of EV electricity tariffs, the BL framework involves optimizing the tariff structure at the upper level and considering the response of EV owners at the lower level. By capturing the interaction between the tariff provider and the EV owners, BL, models enable the identification of optimal tariffs that align with the preferences and behaviours of EV users [15].

2.3.2 Meta-heuristics

Meta-heuristic optimization techniques offer alternative approaches to solving complex optimization problems when an exact solution is complicated. In the context of EV DTs, meta-heuristics provide practical tools to search for near-optimal solutions within a reasonable computational time. Three commonly employed meta-heuristics for tariff optimization are genetic algorithm (GA), particle swarm optimization (particle swarm optimization (PSO)), and hybrid GA and PSO optimization.

2.3.2.1 Genetic algorithms

The process of natural selection and evolution inspires GAs. They employ operators such as selection, crossover, and mutation to iterative search for optimal or near-optimal solutions in an ample solution space. GA-based optimization can effectively handle complex search spaces and objective functions, making them suitable for some tariff optimization problems.

2.3.2.2 Particle swarm optimization

Particle swarm optimization is a population-based optimization technique that simulates the collective behaviour of a swarm of particles moving towards an optimal solution. By iteratively updating the position and velocity of particles based on their individual and global best-known positions, PSO explores the solution space to find the optimal or near-optimal tariffs. PSO is known for its simplicity and efficiency in solving optimization problems.

2.3.2.3 Hybrid GA and PSO optimization

Hybrid optimization techniques combine the strengths of multiple algorithms to enhance search capability and convergence speed. The hybridization of genetic algorithms and particle swarm optimization can leverage their complementary characteristics, improving performance in finding optimal or near-optimal tariff structures. By integrating the exploration capability of GA and the exploitation ability of PSO, hybrid optimization approaches can overcome limitations and achieve better results in complex tariff optimization problems [10] [9]. For this thesis, evolutionary particle swarm optimization (EPSO) [18] is used, a hybrid optimization technique developed at Inesc-tec, where the work was carried out.

2.3.3 Forecast of Electric Vehicles Variables

Forecasting EV-related variables, such as EV charging demand, renewable energy generation, and electricity prices, is crucial for accurate tariff optimization. Accurate forecasts provide valuable insights into future conditions and help make informed decisions regarding tariff structures. Forecasting techniques, including time series analysis, machine learning algorithms [19], and statistical models, predict these variables based on historical data and relevant factors [20]. Proper forecasting of EV variables enables the development of robust and adaptive tariff optimization strategies [21]. As forecasting is not the focus of this thesis, real data will be used as forecasts, and the only prediction made is users' response to dynamic tariffs.

Chapter 3

Methodology

This chapter elucidates the methodology employed to examine the impact of DTs in conjunction with various PV and ES configurations.

To analyze these diverse scenarios, a dedicated program was employed to optimize DTs and encourage desirable consumer behaviour by leveraging their scheduling flexibility.

The program considers the 2015 PV production from PVGIS [22], the 2022 iberian electricity market (MIBEL) market prices, the energy consumption of a grocery store throughout 2022, and the occupancy and energy consumption data of an EV CS in the same grocery store throughout 2022.

Running for a year with this comprehensive dataset, the primary goal is to compare results obtained from several scenarios, facilitating a comprehensive understanding of the optimal combination of PV production levels and battery storage capacity for EV CSs. Additionally, this investigation aims to shed light on the impact of DTs on the overall operation of these CSs and how it interacts with ES and PV systems.

The program developed was built on top of an existing program provided by Inesc-Tec, therefore, a description of this program is given in order to isolate the work developed in this dissertation.

3.1 Program Description

The program takes as inputs the energy market price data, photovoltaic (PV) generation, electric vehicle (EV) occupancy, and store load forecasts for each hour. Its core objective is to optimize battery operation and DTs to influence EV users' behaviour, thereby maximizing the operation's profitability.

The key inputs include energy market prices, EV occupancy, and PV production forecasts. The program's outputs encompass the determined tariffs for each period, the optimal battery operation strategy, the energy transactions involving buying and selling to the grid, the projected occupancy for each period, and the anticipated profits.

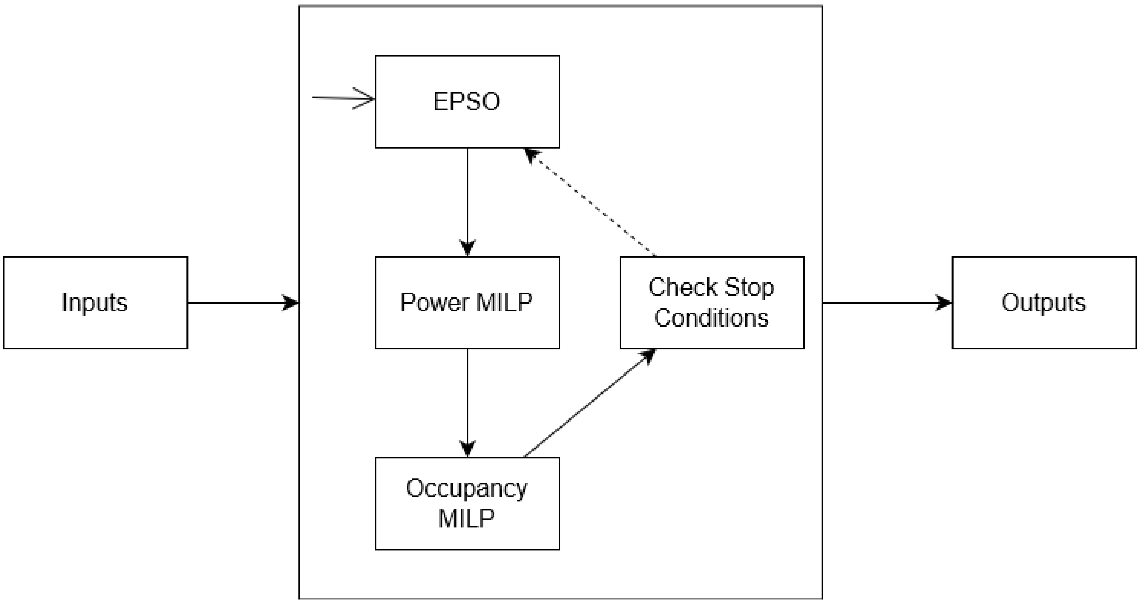

Figure 3.1: Program description

The program operates in a cycle visualised in the figure 3.1. It starts by organising the information received. Then, in the EPSO, it creates particles with a random tariff and velocity for each period. To improve the convergence of the program, the initial positions of the particles are corrected so that the initial average of the rates corresponds to the desired final average. After having the particles, the occupancy response of each particle is calculated. This gives us the load associated with the electrical load. Once all the loads and the power generated are known, the battery operation is optimised. Then, the income and expenditure associated with each particle are calculated. If the stop conditions are met, the outputs are obtained and optimised for the next day. Otherwise, the fitness of each particle is used to update the particles, and the cycle is repeated.

3.2 Formulation

This section presents the formulation of the hybrid meta-heuristics and MILP problem, describing the parameters and decision variables involved in the optimization process.

In table 3.1 are the parameters, and in table 3.2 are the decision variables used in the formulation.

3.2.1 Formulation of the starting program

The formulation of the starting program, which served as the basis for the optimization program, consists of a BL optimization problem.

3.2.1.1 Upper-level problem

Objective:

Table 3.1: Parameters

S = 1,...,T	set of time intervals
$t \in S$	index for time interval
π_t^b	buying price
π_t^s	selling price
Δt	time interval duration
λ_t^{min}	minimum tariff
λ_t^{max}	maximum tariff
λ^{avg}	tariff average (€/min)
r^{lim}	tariff transition rate limit
P_t^{avg}	forecast average EV consumption
P_t^s	other consumption
P_t^{RES}	renewable power generated
P^{limit}	transformer power limit
O^{max}	maximum occupancy number of charging vehicles
$O_t^{flex\ min}$	minimum occupancy flexibility for period t
$O_t^{flex\ max}$	maximum occupancy flexibility for period t
O_t	forecast occupancy for period t
SoC^{min}	minimum state of charge
SoC^{max}	maximum state of charge
E_t^{max}	battery energy capacity
η^{charge}	battery charging efficiency
$\eta^{discharge}$	battery discharging efficiency
$P_t^{bat\ max\ charge}$	maximum battery charging power
$P_t^{bat\ max\ discharge}$	minimum battery charging power

Table 3.2: Decision Variables

λ_t	dynamic tariff
O_t^r	response occupancy
P_t^{in}	imported power
P_t^{out}	exported power
P_t^r	power load of electric vehicle charging
P_t^{net}	net power
δ_t	1 if importing energy, 0 if exporting energy
P_t^{bat}	battery power
SoC_t	state of charge
E_t	battery energy
$P_t^{bat\ charge}$	battery charging power
$P_t^{bat\ discharge}$	battery discharging power
α_t	1 if the battery is charging, 0 if the battery is discharging

$$max \sum_{t=1}^{T} (\lambda_t \cdot O_t^r \cdot 60 - \pi_t^b \cdot P_t^{in} + \pi_t^s \cdot P_t^{out}) \cdot \Delta t \tag{3.1}$$

Subject to:

$$\lambda_t^{min} \leq \lambda_t \leq \lambda_t^{max}, \forall t \in S \tag{3.2}$$

$$\frac{1}{T} \sum_{t=1}^{T} \lambda_t = \lambda^{avg} \tag{3.3}$$

$$\frac{|\lambda_t - \lambda_{t+1}|}{\lambda_t} \leq r^{lim}, \forall t \in 1, \ldots, T-1 \tag{3.4}$$

$$P_t^r = O_t^r \cdot P_t^{avg}, \forall t \in S \tag{3.5}$$

$$P_t^{net} = P_t^r + P_t^s - P_t^{RES}, \forall t \in S \tag{3.6}$$

$$P_t^{net} = P_t^{in} - P_t^{out}, \forall t \in S \tag{3.7}$$

$$P_t^{in} \leq P^{limit} \cdot (\delta_t), \forall t \in S \tag{3.8}$$

$$P_t^{out} \leq P^{limit} \cdot (1 - \delta_t), \forall t \in S \tag{3.9}$$

$$\lambda_t, P_t^{in}, P_t^{out} \geq 0, \forall t \in S \tag{3.10}$$

$$\delta_t \in 0, 1, \forall t \in S \tag{3.11}$$

The objective function 3.1 maximises the operator's profits by considering the revenues from charging electric vehicles, the costs of buying energy from the grid and the profits from selling energy to the grid. Constraint 3.2 limit tariff values to prevent extreme price fluctuations during specific periods. By doing so, it maintains a more predictable and steady pricing structure. Constraint 3.3 defines an average tariff value applicable throughout the day, introducing a balancing mechanism. A decrease in a tariff must compensate for an increase in another period. The occupancy response model assumes a constant total occupancy hence the importance of not inflating tariffs in all periods. To avoid abrupt changes in tariffs, Constraint 3.4 limits the variation between two consecutive periods, safeguarding against unexpected price fluctuations for users. Constraint 3.5 determines the electric vehicle charge based on the occupancy level determined by the lower-level (LL). Constraint 3.6 determines the energy exchange with the grid. Constraint 3.7 determines the energy balance and calculates the energy to be exported or imported from the grid. Constraints 3.8 and 3.9 indicate the maximum energy capacity that can be imported and exported from and to the grid. Constraint 3.10 ensures that the relevant variables remain positive, preventing any invalid solutions from being considered. Finally, Constraint 3.11 dictates that a specific variable must be binary, allowing for discrete choices and optimizing decision-making processes within the tariff management system.

3.2.1.2 Lower-level problem

Objective:

$$min \sum_{t=1}^{T} (\lambda_t \cdot O_t^r \cdot 60) \tag{3.12}$$

Subject to:

$$0 \leq O_t^r \leq O^{max}, \forall t \in S \tag{3.13}$$

$$O_t^{flex\ min} \leq O_t^r \leq O_t^{flex\ max}, \forall t \in S \tag{3.14}$$

$$\sum_{t=1}^{T} O_t = \sum_{t=1}^{T} O_t^r \tag{3.15}$$

The objective function 3.12 minimises the total costs of charging consumers by intelligently allocating occupancy to periods with the most affordable tariffs. This optimisation process accounts for the defined limits, ensuring a cost-effective solution while adhering to necessary restrictions using optimal response mechanisms. Constraint 3.13 protects against exceeding the physical limits of charging points. By imposing this constraint, the system prevents any potential issues related to overloading or straining charging infrastructure, promoting the overall reliability and safety of the charging process. Constraint 3.14 restricts the occupancy to calculated flexibility limits using the Chebyshev with historical data and practical considerations. This data-driven approach helps maintain consistency and compatibility with past charging patterns. Constraint 3.15 ensures that the total occupancy obtained on this new solution day remains the same as in the estimated occupancy.

3.2.2 Current Formulation

Incorporating the battery into the system introduced an additional layer of decision-making to manage the battery's operation effectively. To address this, a MILP problem was included at the upper-level (UL). The MILP works with the UL's objectives and adopts an objective function derived from the initial UL objective function.

By integrating the MILP into the UL, the system can optimize the battery's operations efficiently, enhancing overall efficiency and performance. The derived objective function ensures an alignment between the UL's goals and the battery's optimal operation, resulting in well-coordinated decision-making.

The MILP also optimizes power transits, addressing power transit optimization.

The UL equations not related to power and LL also remain the same.

3.2.2.1 Upper-level problem

Objective:

$$max \sum_{t=1}^{T} (\lambda_t \cdot O_t^r \cdot 60 - \pi_t^b \cdot P_t^{in} + \pi_t^s \cdot P_t^{out}) \cdot \Delta t \tag{3.1}$$

Subject to:

$$\lambda_t^{min} \leq \lambda_t \leq \lambda_t^{max}, \forall t \in S \tag{3.2}$$

$$\frac{1}{T} \sum_{t=1}^{T} \lambda_t = \lambda^{avg} \tag{3.3}$$

$$\frac{|\lambda_t - \lambda_{t+1}|}{\lambda_t} \leq r^{lim}, \forall t \in 1, ..., T-1 \tag{3.4}$$

UL MILP:

Objective:

$$min \sum_{t=1}^{T} (\pi_t^b \cdot P_t^{in} - \pi_t^s \cdot P_t^{out}) \cdot \Delta t \tag{3.16}$$

Subject to:

$$P_t^r = O_t^r \cdot P_t^{avg}, \forall t \in S \tag{3.5}$$

$$P_t^{net} = P_t^r + P_t^s - P_t^{RES} + P_t^{bat}, \forall t \in S \tag{3.17}$$

$$P_t^{net} = P_t^{in} - P_t^{out}, \forall t \in S \tag{3.7}$$

$$P_t^{in} \leq P^{limit} \cdot (\delta_t), \forall t \in S \tag{3.8}$$

$$P_t^{out} \leq P^{limit} \cdot (1 - \delta_t), \forall t \in S \tag{3.9}$$

$$SoC^{min} \leq SoC_t \leq SoC^{max}, \forall t \in S \tag{3.18}$$

$$SoC_t = E_t / E_t^{max}, \forall t \in S \tag{3.19}$$

$$E_t = E_{t-1} + (\eta^{charge} \cdot P_t^{bat\ charge} - \eta^{discharge^{-1}} \cdot P_t^{bat\ discharge}) \cdot \Delta t, \forall t \in \{2, ..., T\} \tag{3.20}$$

$$P_t^{bat} = P_t^{bat\ charge} - P_t^{bat\ discharge}, \forall t \in S \tag{3.21}$$

$$P_t^{bat\ charge} \leq P^{bat\ max\ charge} \cdot (\alpha_t), \forall t \in S \tag{3.22}$$

$$P_t^{bat\ discharge} \leq P^{bat\ max\ discharge} \cdot (1 - \alpha_t), \forall t \in S \tag{3.23}$$

$$P_t^{bat\ discharge} \leq P^{bat\ max\ discharge} \cdot (\delta_t), \forall t \in S \tag{3.24}$$

$$P_t^{in}, P_t^{out}, P_t^{bat}, P^{bat\ charge}, P^{bat\ discharge} \geq 0, \forall t \in S \tag{3.25}$$

$$\delta_t, \alpha_t \in \{0, 1\}, \forall t \in S \tag{3.26}$$

Objective function 3.16 plays a pivotal role in minimizing the costs associated with purchasing energy from the grid. It accomplishes this by summing up the expenses incurred from buying energy and subtracting the profits earned from selling energy back to the grid. To address power transactions involving the battery, 3.17 operates similarly to Constraint 3.6, encompassing battery-related power transactions for comprehensive management. Constraint 3.18 assumes significance in setting limits on the battery's state of charge, as this helps mitigate battery degradation and ensures optimal performance and longevity. The relationship between the state of charge and the energy stored in the battery is established by Constraint 3.19, where the state of charge represents the ratio of the energy stored in the battery to its maximum energy capacity. Maintaining a sequential flow of energy stored in the battery is the objective of Constraint 3.20. It calculates the current energy stored based on the preceding period's energy, incorporating energy charged and energy discharged and accounting for energy losses by considering the efficiency of each process, defined by their respective yields. Constraint 3.21 combines charging and discharging power to streamline calculations into a single variable, facilitating their use in other equations. To ensure appropriate charging and discharging operations, Constraint 3.22 limits the battery's charging power, while Constraint 3.23 restricts the discharging power. These two constraints rely on a binary variable to ensure that only one of the two variables is nonzero at a given time. Preventing the battery from discharging back to the grid is the purpose of Constraint 3.24, maintaining a unidirectional energy flow. Constraint 3.25 guarantees that relevant variables remain positive. Lastly, Constraint 3.26 mandates that relevant variables be binary, enabling discrete choices.

3.2.3 Lower-level problem

Objective:

$$min \sum_{t=1}^{T} (\lambda_t \cdot O_t^r \cdot 60) \tag{3.12}$$

Subject to:

$$0 \leq O_t^r \leq O^{max}, \forall t \in S \tag{3.13}$$

$$O_t^{flex\ min} \leq O_t^r \leq O_t^{flex\ max}, \forall t \in S \tag{3.14}$$

$$\sum_{t=1}^{T} O_t = \sum_{t=1}^{T} O_t^r \tag{3.15}$$

3.3 Implementation

This section delves into specific details of the implemented methodology.

Due to the BL nature of the problem, a non-linear method is necessary. The chosen approach involves utilizing in the UL the EPSO algorithm, known for its effectiveness in solving such problems. EPSO combines two established optimization techniques in the meta-heuristic family: evolutionary computing and particle swarm optimization.

The LL MILP and the auxiliary UL MILP were implemented using PuLP in Python and solved with the CBC solver.

3.3.1 Dynamic Tariffs and EPSO

This component receives the following inputs: maximum and minimum tariffs in each period and the average tariff for the entire day. For the EPSO part, the inputs consist of the maximum number of generations, the number of particles, the mutation rate, and the communication probability.

The program starts by generating 25 random particles, each comprising a position (tariff value) between the specified limits and a speed (positive or negative value) limited by the difference between the maximum and minimum tariffs.

A particle position correction algorithm was introduced to address difficulties in reaching a solution that respects the average tariff constraint. This algorithm scales the particle's position values by a scaling factor, the desired average position divided by the current average position. This correction may need multiple iterations until the expected average value is achieved. This addition significantly improved the program's efficiency, leading to more reliable results with fewer generations.

The two MILPs are then executed to determine the particle's fitness, and if the stop conditions are not meet the process continues for the next generation.

3.3.2 MILPs

The LL MILP utilizes the optimal response to the tariffs to allocate EVs to the cheapest periods, minimizing consumer charging costs. It takes as inputs the tariff for each period obtained from the particles, the original occupancy data, and flexibility forecasts obtained using the Chebyshev interval. The new occupancy is used to determine the load of EV charging.

The UL MILP takes as input the battery's charging and discharging limits, maximum ES capacity, charging and discharging efficiencies, upper and lower state of charge limits, initial state of charge, and minimum acceptable state of charge at the end of the last period. Additionally, it receives the previous day's final state of charge and the new EV charging load resulting from occupancy adjustments in response to DTs. This MILP primarily aims to optimize the battery's operation based on the inputs. To do this, it ends up calculating all the system's power flows.

Chapter 4

Results

4.1 Case Studies

This study used a maximum tariff of 0.15€/min and a minimum tariff of 0.01€/min with an average tariff of 0.10€. For EPSO, the maximum number of generations is 100, with a mutation rate of 40% and a communication probability of 80%. For the battery, the maximum charge it can charge or discharge per period is 50%, and the charging and discharging efficiency is 95%. To reduce the wear and tear of the battery, limits have been set for the state of charge, minimum limit 20%, maximum limit 80%. At the end of each day, the state of charge should be at least 50%. To emulate an extra load associated with the CS, energy consumption data from a grocery store was used to simulate the consumption of a convenience store that could be associated with the CS. The energy market data is from MILP from 2022, the PV production data is from PVGIS and is from 2015. The occupancy data is from 2022 data from CSs associated with a grocery store. This case study is not intended to study a specific case but something that works for different types of CSs.

To be able to study various PV and ES installation scenarios and how they interact with dynamic tariffs, simulations of 1 full year of operation were carried out for all combinations of a set of PV and ES values. The values used for PV installation range from 0 to 500kWp with intervals of 50kWp. These values were used because with 500 kWp a very high self-sufficiency is achieved, and with higher values, many days have no possible solution due to the limit of power transmission with the grid. The values used for ES installation range from 0 to 100kWh with intervals of 100kWh. With 1000kWh of energy storage, it is already achieved that the battery does not reach the state of charge limit in many days, so the benefits of a larger battery would be negligible. Several mesh grids show various results as a function of the PV and ES installed.

For investment studies is considered a horizon of 25 years as this is the expected lifetime of the PV[23]. The battery has a lower estimated lifetime, so a reinvestment in the year 13 is considered. The battery price is 280€ per kWh, the PV price is 750€ per kWp. The profit from the loading operation is assumed to be constant over the years.

4.2 Illustrative Examples

In this section are included some of the studies that can be done with the data acquired from the program developed using the data obtained from the case studies indicated above.

4.2.1 Optimization Analysis

Before proceeding to the more advanced studies, it was found that the optimisation algorithm is performing logical decisions that lead to the optimal operation of the system.

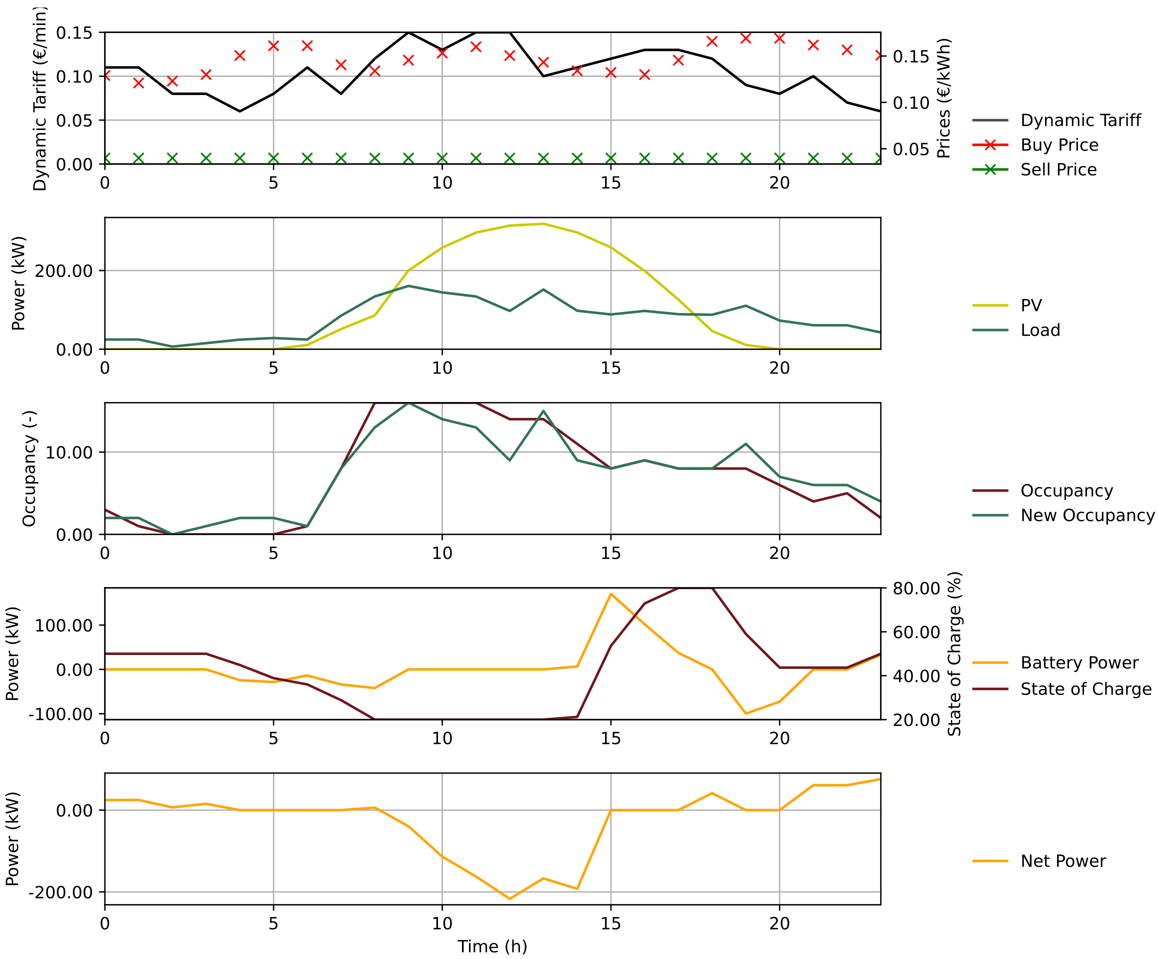

Figure 4.1: One Day Analysis ES 500kWh PV 350 kWp

Figure 4.1 presents a set of graphs that allow us to analyse what decisions are made during optimisation. The case used is 350kWp of installed PV and 500 kWh of ES. The first shows the DTs for each of the 24 hours of the day, together with the market prices. The second shows the final total load and PV production. The third shows the initial occupancy and the final occupancy obtained by optimisation. The fourth one shows the electrical power leaving and entering the battery and the state of charge of the battery. The fifth shows the energy exchanges with the electricity grid.

It can be seen that the algorithm prefers to increase tariffs in periods with higher occupancy, even if these periods coincide with peak generation. The battery power only starts to be utilised when market prices start to rise and is discharged as much as possible before the solar surplus period starts in which the battery can charge from the surplus PV power. It chooses to only charge at the end of the surplus period, although this is indifferent as the energy sales prices are constant. Charges fully, discharging at the end of the day when prices are highest and recharging at the last hour, which has a lower price, to reach the minimum final charge required.

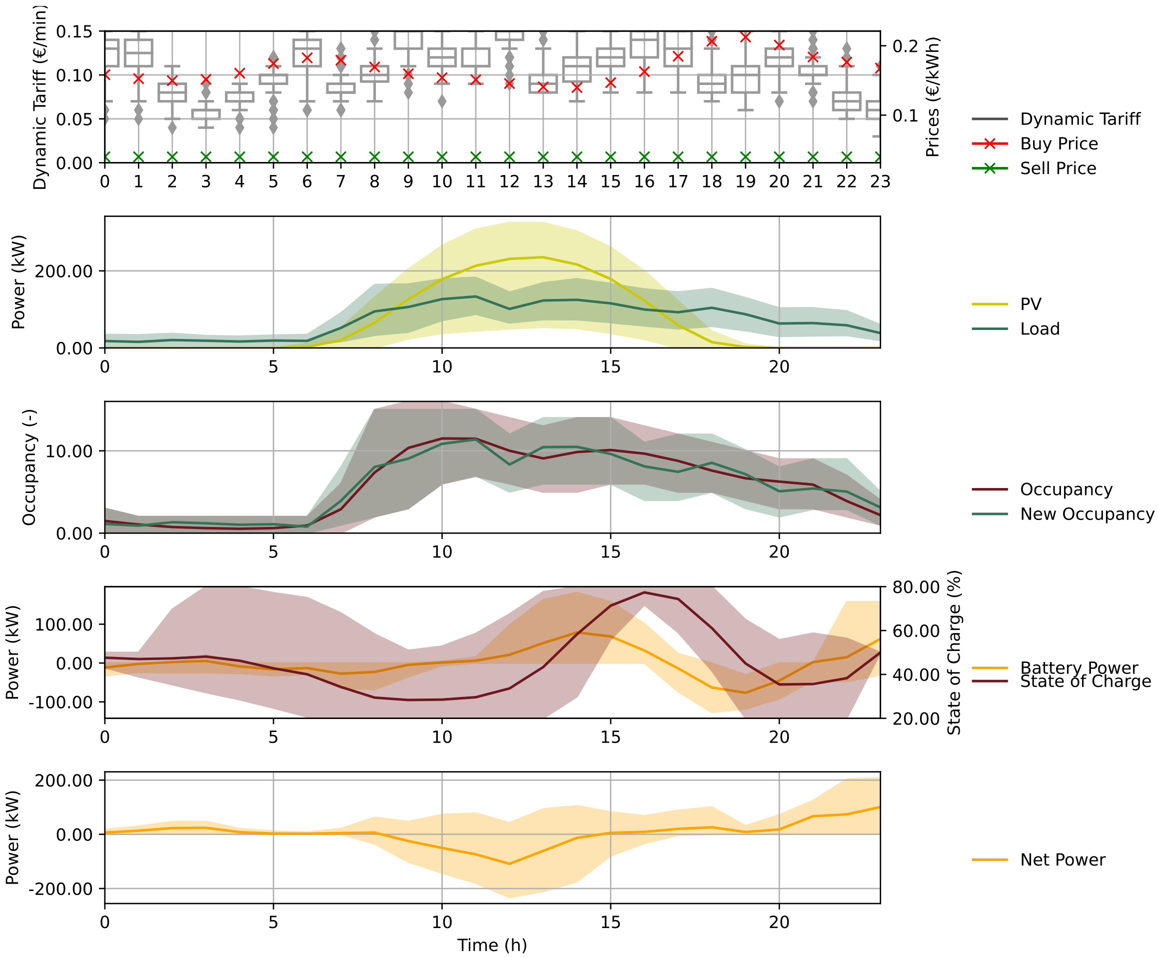

Figure 4.2: Year Analysis ES 500kWh PV 350 kWp

Figure 4.2 presents the same set of graphs as figure but for one year of operation. The case used is 350kWp of installed PV and 500 kWh of ES. The buy and sell price is the average values. Dynamic tariffs are in boxplots of the quadrants. The remaining values are present with the median on the line and the shaded space represented da values between 20% and 80%.

We were able to verify some general trends. Tariffs are higher during periods of higher occupancy and lower during periods of lower occupancy. The battery discharges before having a surplus of PV generation and charges again with the PV surplus. There are a considerable number of days when you choose to charge early in the morning due to lower buy prices.

4.2.2 Total Profit

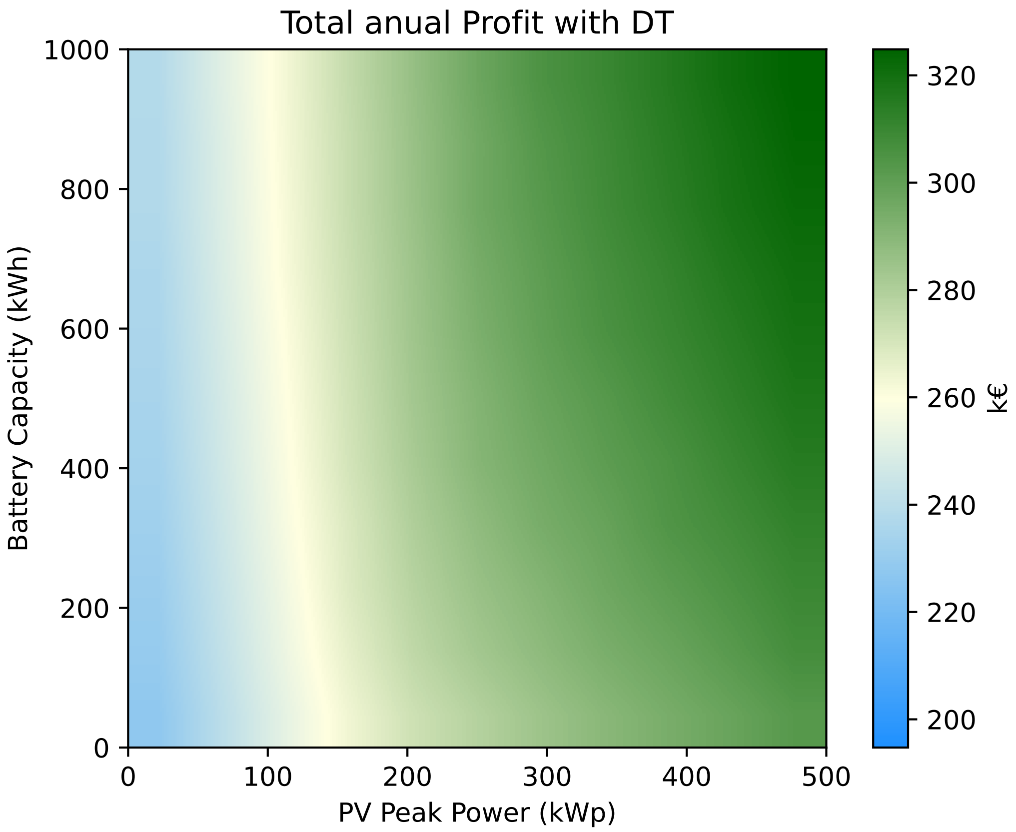

Figure 4.3: Total anual profit with DT

The figures 4.3 and 4.4 are graphs showing the total profit from the EV charging operation for one year of operation of the CS as a function of the installed PV capacity and the installed ES capacity. Figure 4.3 in the case with DT and figure 4.4 in the case without DT. In these figures, we can see that profit is ever-increasing with an ever-diminishing impact with the installation of PV, whereas the effect of ES is more felt when there is a surplus in the cases with higher PV.

Figure 4.5 represents the increase in profits when DT is used, compared to the case where it is not used, obtained by directly subtracting the total profits of the two cases. With the figure 4.5, we can conclude that the difference between the case with constant tariff and with DT is quite constant, which does not suggest a great synergy between dynamic tariffs and PV and ES.

4.2.3 ROI

$$ROI = \frac{\sum_{j=1}^{n} \frac{P_j}{(1+a)^j}}{\sum_{j=0}^{n-1} \frac{I_j}{(1+a)^j}} \tag{4.1}$$

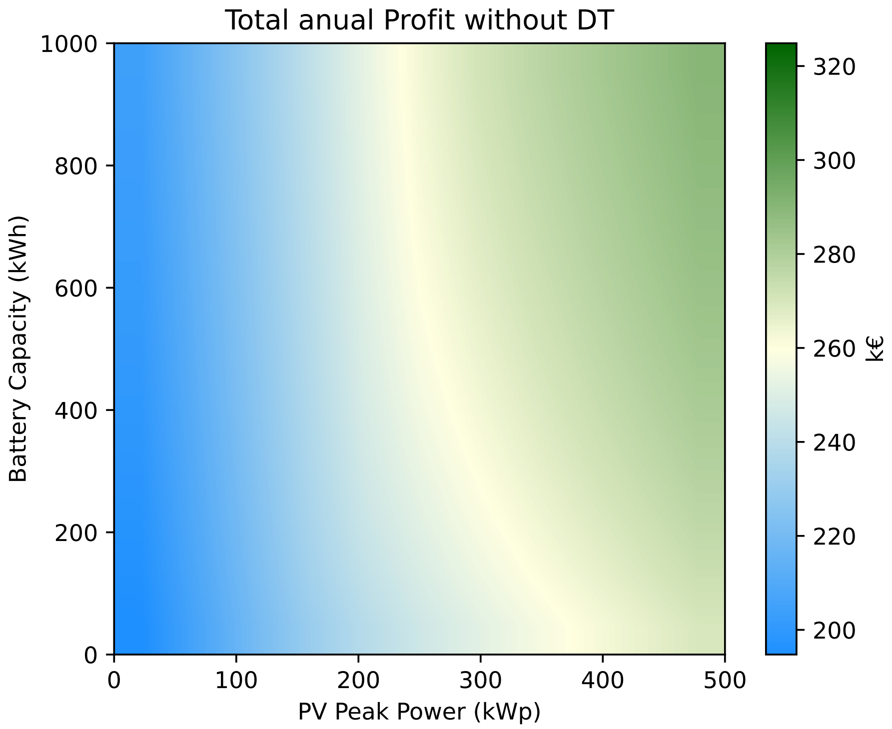

Figure 4.4: Total anual profit without DT

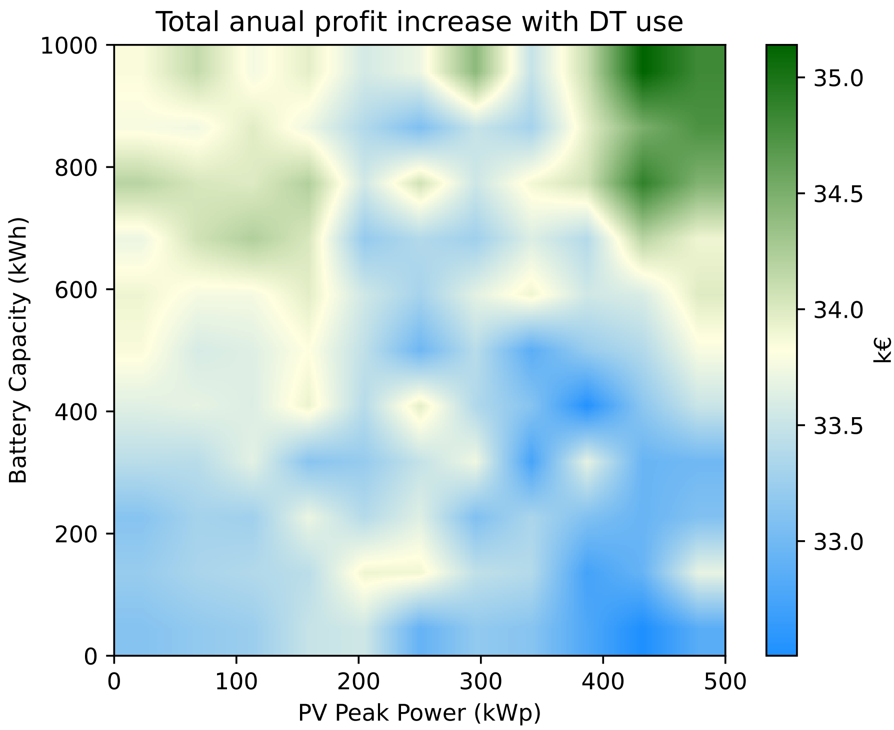

Figure 4.5: Total anual Profit incrise with DT use

Equation 4.1 is used to calculate the ROI for the results shown. P_j represents the cash flow for period j in the profit category. I_j represents the cash flow for period j in the investment category. a is the discount rate or interest rate used for present value calculations. n is the number of periods for which cash flows are considered.

This formula is used to calculate the ROI by comparing the present value of cash flows from profit to the present value of cash flows from investment. The discount rate a is used to calculate the present value of cash flows at different time periods.

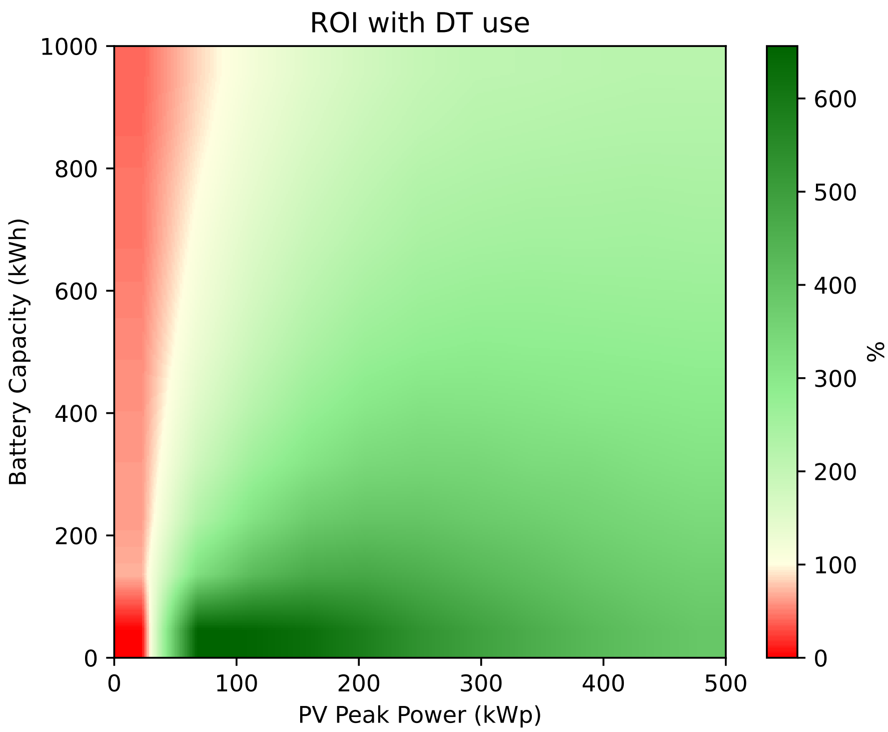

Figure 4.6: ROI with DT use

Figure 4.6 presents the ROI for each combination of PV and ES when using DT. Figure 4.7 does the same but for the case without DT. Values in red never return the investment. The investments are the installation of PV and ES, and the returns are the increased profit of the EV charging operation. It should be noted that The case with DT and the case without DT have different base profit values.

Both ROIs have similar behaviours. We can observe that the highest ROI occurs when only a small amount of PV is invested. This is expected because the energy produced is almost completely consumed which translates into a simple reduction of the energy that needs to be purchased from the grid. As PV increases there starts to be more surplus energy, the surplus is bought by the grid at a lower price, so it has a lower return. Despite this, it still has a fairly high return. Investment in batteries always has a negative impact compared to investment in PV alone. This

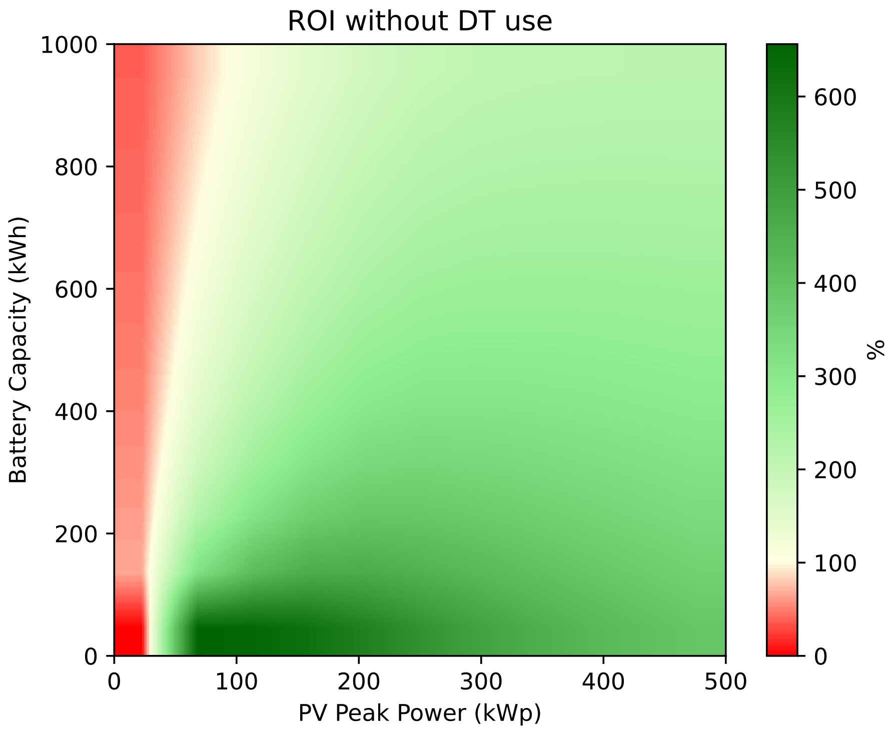

Figure 4.7: ROI without DT use

negative impact is less felt as the surplus increases, due to the ability of the ES to capitalise on the surplus energy from the PV and not just on market price variations.

In the figure 4.8 we can see the difference between the two ROIs. In general, using DT results in a higher ROI, but not always. In cases with high PV and low ES the ROI decreases. Recall that ROI only takes into account the profits obtained over and above the profits of the operation without PV and ES.

4.2.4 Net Present Value

$$NPV = \sum_{j=1}^{n} \frac{P_j}{(1+a)^j} - \sum_{j=0}^{n-1} \frac{I_j}{(1+a)^j} \tag{4.2}$$

The equation 4.2 is used to calculate the NPV. NPV represents the difference between the present value of cash inflows and outflows. P_j represents the net cash inflow during period j, which is made of profits from EV charging operation and energy sells to the grid. I_j represents the net cash outflow during period j, which includes investments in PV and ES and or costs incurred during the project or investment. a is the discount rate or required rate of return used to discount future cash flows back to their present value. n is the number of periods for which cash flows are considered.

The NPV is used to determine whether an investment or project is expected to be profitable or not. If the NPV is positive, the acquisition is expected to generate more cash inflows than outflows

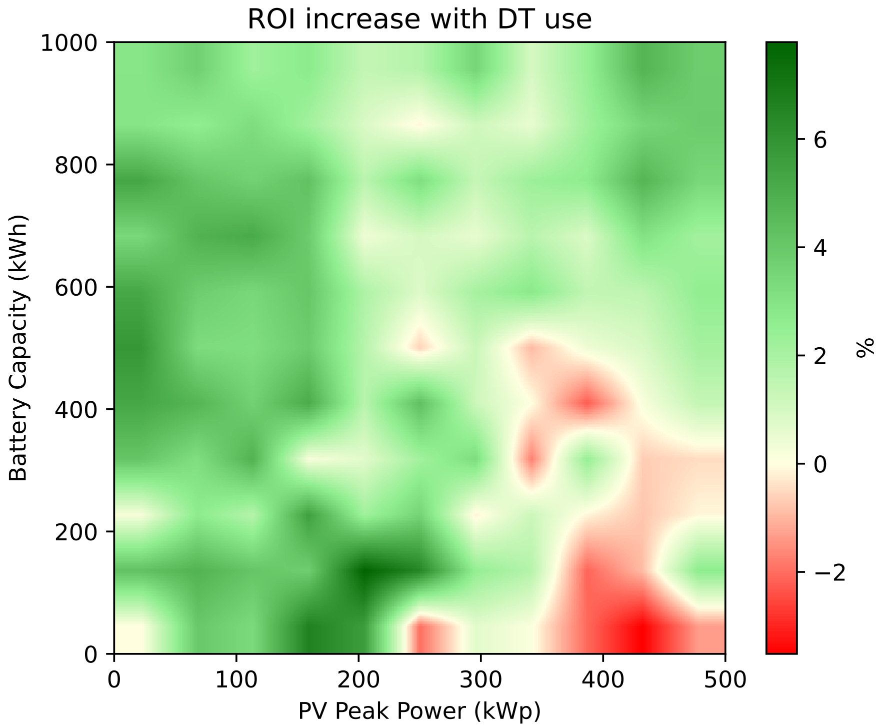

Figure 4.8: ROI increase with DT use

and is considered financially viable. On the other hand, if the NPV is negative, the investment is unlikely to be profitable.

These NPVs consider as an inflow of the extra profit compared to the case without ES and PV. In figure 4.9 that uses DT, the base profit is 228 and in figure 4.10 that does not use DT, the base profit is 195.

Both show similar behaviour. Investing in the battery without investing in PV never returns the investment. In general, investing in ES reduces NPV, so there is no financial incentive to do so. Investing in PV is always positive, but increasingly less impactful. ES has a less negative impact in cases with PV due to the surplus of PV, which is reused by ES.

Figure 4.11 shows the difference between the two NPVs. It is important to remember that NPVs have different base profit values. Consequently, this figure having negative values does not mean that the operation with DT is less profitable than the operation without DT. It means that the investment in PV and ES is more valuable in the case where no DT is used than in the case where the same investment is made in the case where DT is used.

It can be observed that the tendency is to have a higher NPV in the case with DT. However, this may not be the case. Because dynamic tariffs can take advantage of lower solar peak hour grid prices, investing in PV without ES is more profitable when dynamic tariffs are not used.

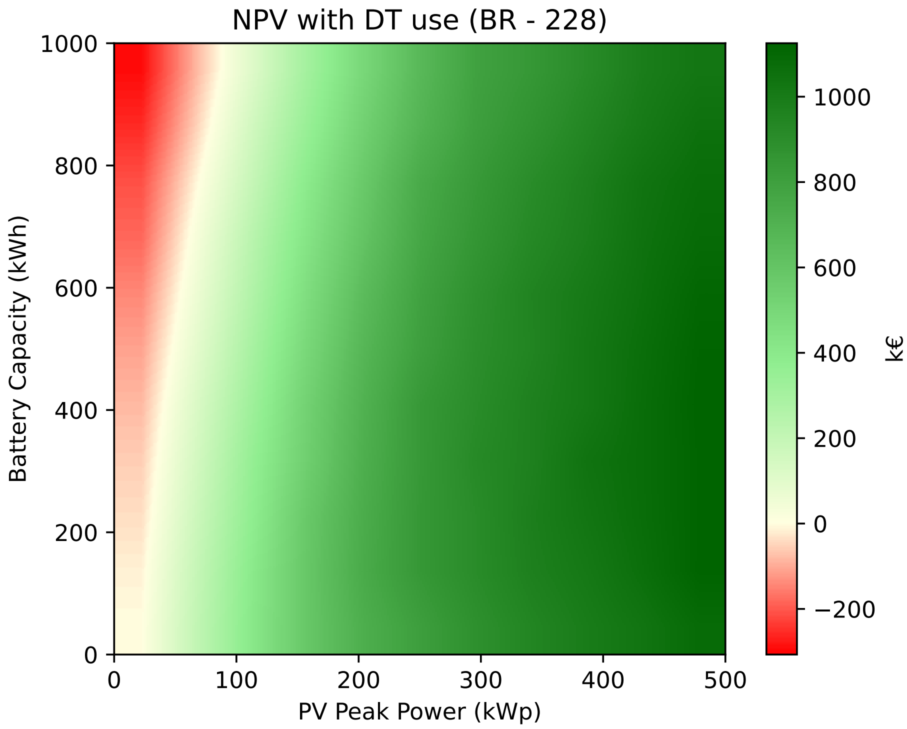

Figure 4.9: NPV with DT use

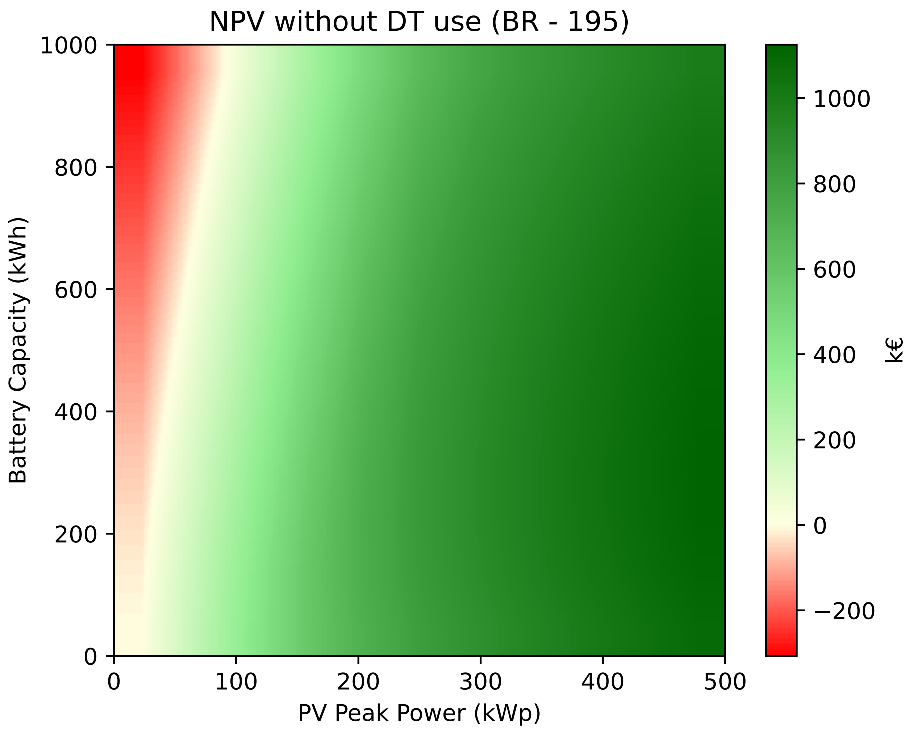

Figure 4.10: NPV without DT use

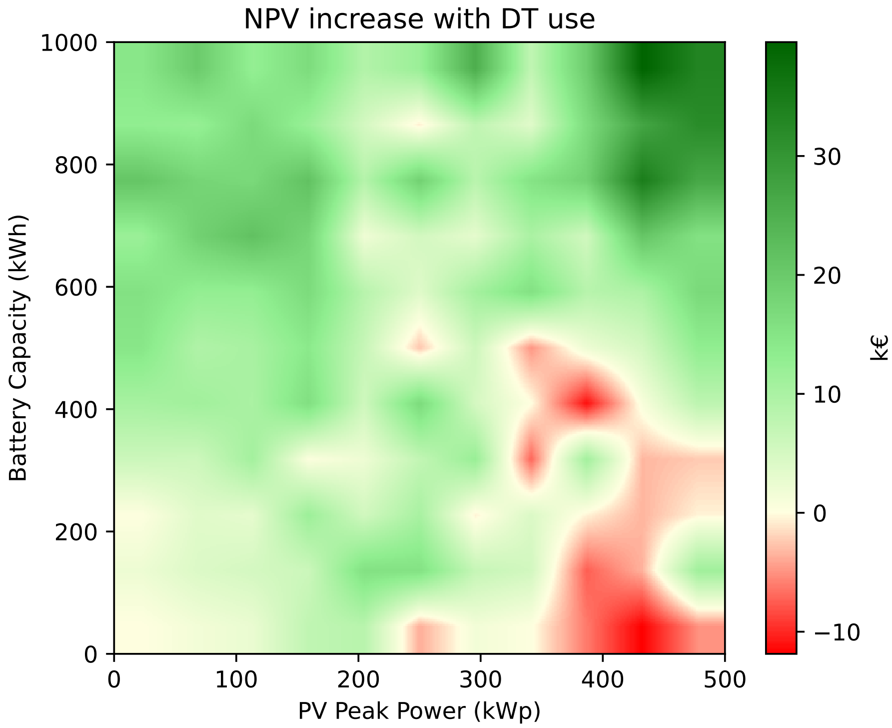

Figure 4.11: NPV increase with DT use

4.2.5 Self Consumption

$$SC = \frac{\sum_{t=1}^{n} P_t^{RES} - \sum_{t=1}^{n} P_t^{out}}{\sum_{t=1}^{n} P_t^{RES}} \tag{4.3}$$

The equation 4.3 represents the calculation of the SC ratio used in the context of renewable energy systems. The variables P_t^{RES} and P_t^{out} represent the power generated from renewable energy sources and the power exported at each time step t from 1 to n. The equation determines the ratio of consumed renewable energy to the total renewable energy generated.

As usual, the 4.12 and 4.13 figures representing respectively the CS for the case with DT and without DT are similar. As expected, when we have a smaller PV the SC is total. As PV increases, we have a surplus that is exported to the network, and the presence of ES allows us to use the surplus in other periods, thus increasing SC. It should be noted that the losses in charging and discharging the battery are considered consumptions that also increase SC.

Figure 4.14 shows the difference between the figures in SC. Dynamic tariffs appear to have a predominantly negative impact on SC. This is due to the objective of DT being purely economic. Moving consumption to periods with cheaper energy and increasing prices when occupancy is higher is preferable. In the case with high ES and DT this does not happen because the need to buy energy from the grid is almost nil, so the tariffs help to utilise the surplus further.

The 4.15 figure is the version of the figure 4.14 but without charging the battery from the grid. There is a greater increase in self-consumption because tariffs cannot prioritise from the grid.

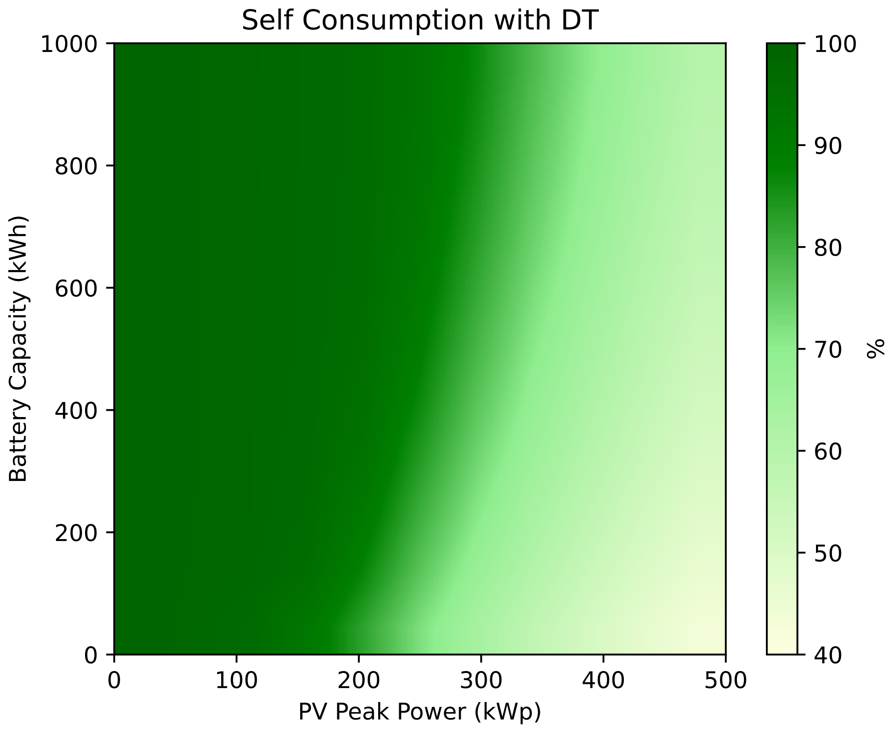

Figure 4.12: NPV with DT use

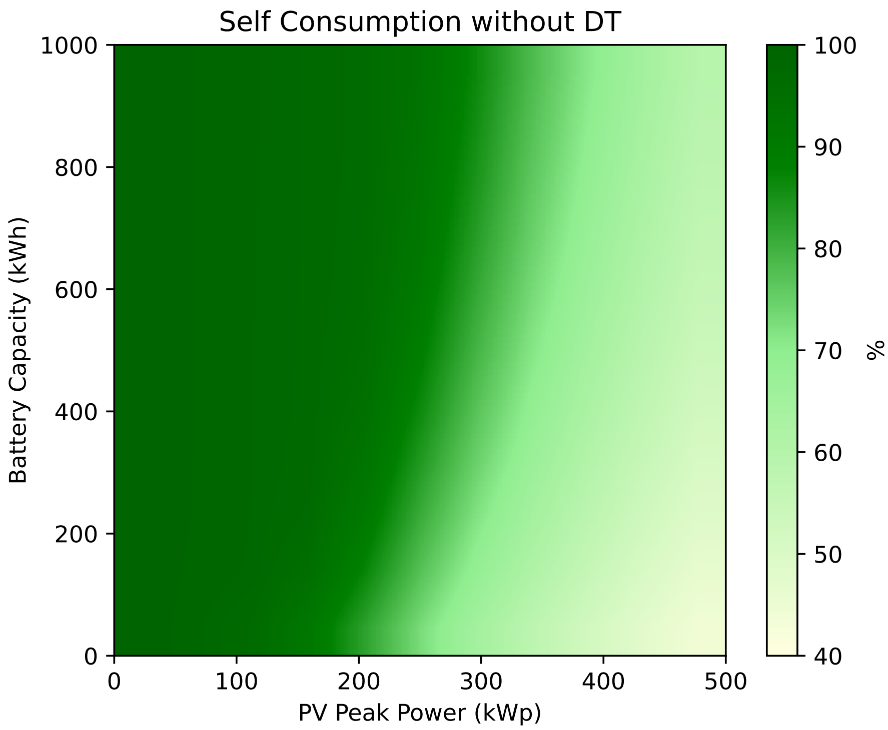

Figure 4.13: NPV without DT use

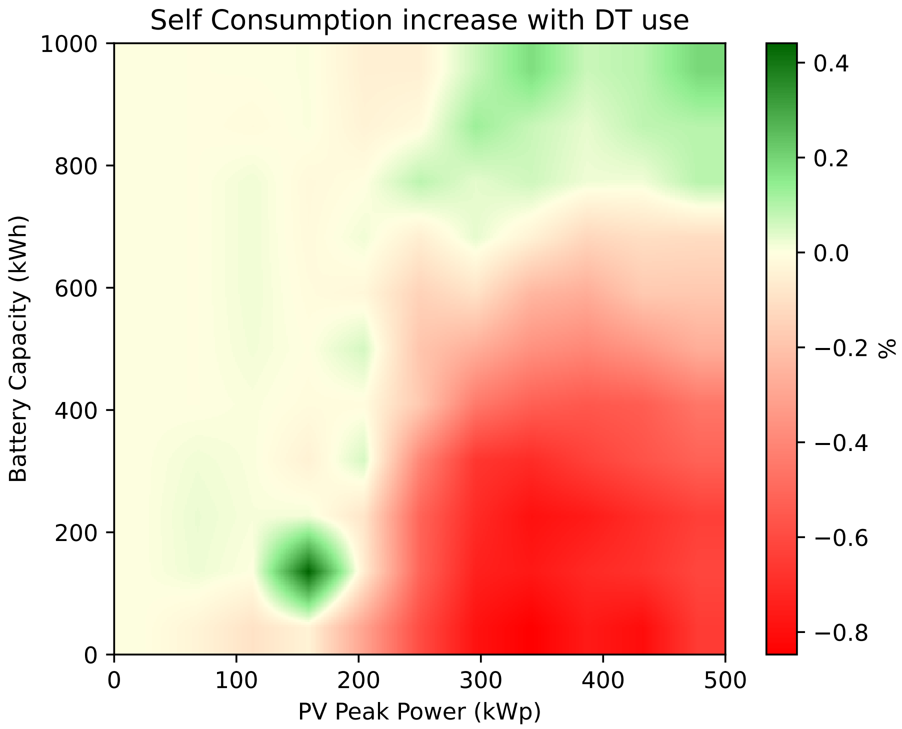

Figure 4.14: SS increase with DT use

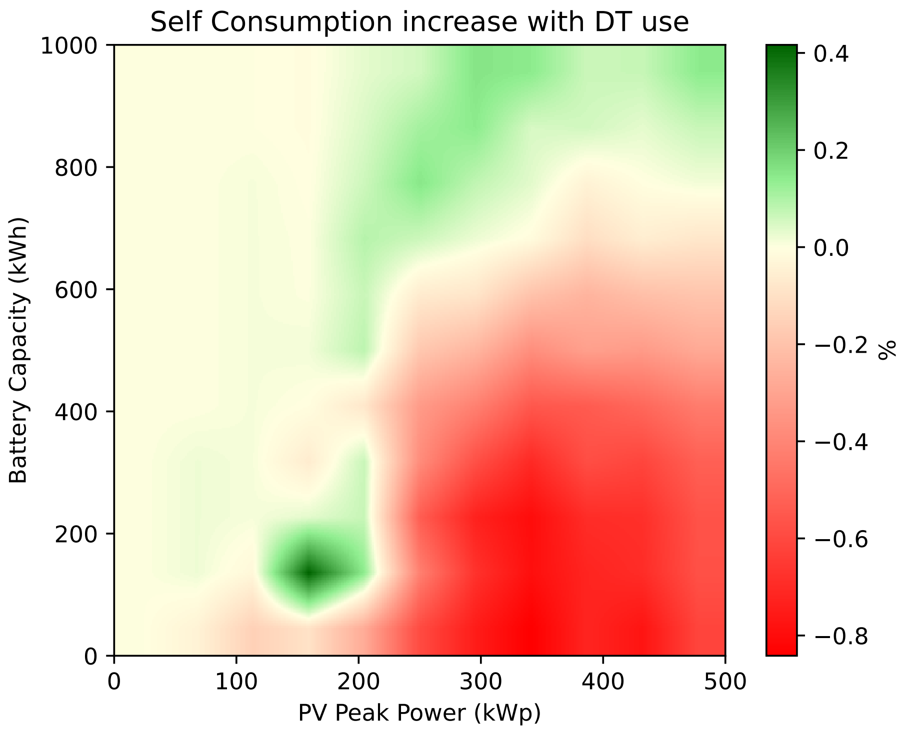

Figure 4.15: Self Sufficiency increase with DT use

When not charging from the grid, it improves a little as with self-consumption, but with a more negligible difference. As the battery cannot charge from the grid, charging through surplus PV is maximized.

4.2.6 Self Sufficiency

$$SS = 1 - \frac{\sum_{t=1}^{n} P_t^{in}}{\sum_{t=1}^{n} P_t^{load}} \tag{4.4}$$

The equation 4.4 for SS calculates the SS ratio, which represents the degree to which a system meets its energy demand through local generation rather than relying on imported power.

In this equation, the variables are SS is the SS ratio, P_t^{in} represents the power imported at each time step t from 1 to n, P_t^{load} means the power demand (load) at each time step t from 1 to n. The equation calculates the self-sufficiency ratio by subtracting the fraction of imported power from 1 and then dividing it by the total power demand. This equation determines the degree of energy independence for a given system by evaluating the share of energy needs that are fulfilled by local generation.

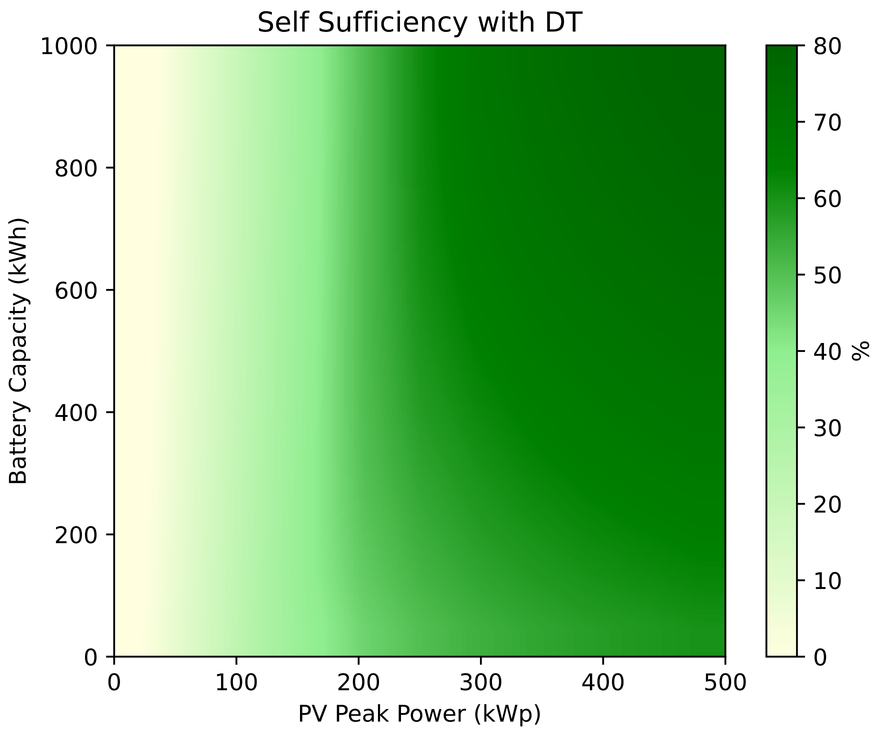

Figure 4.16: Self Sufficiency with DT use

Figures 4.16 and 4.17 represent respectively SS for the case with DT and for the case without DT As usual, the figures are similar. SS starts at 0 when there is no PV and increases with increasing PV. When the surplus grows, the ES shows its value increasing the SS significantly.

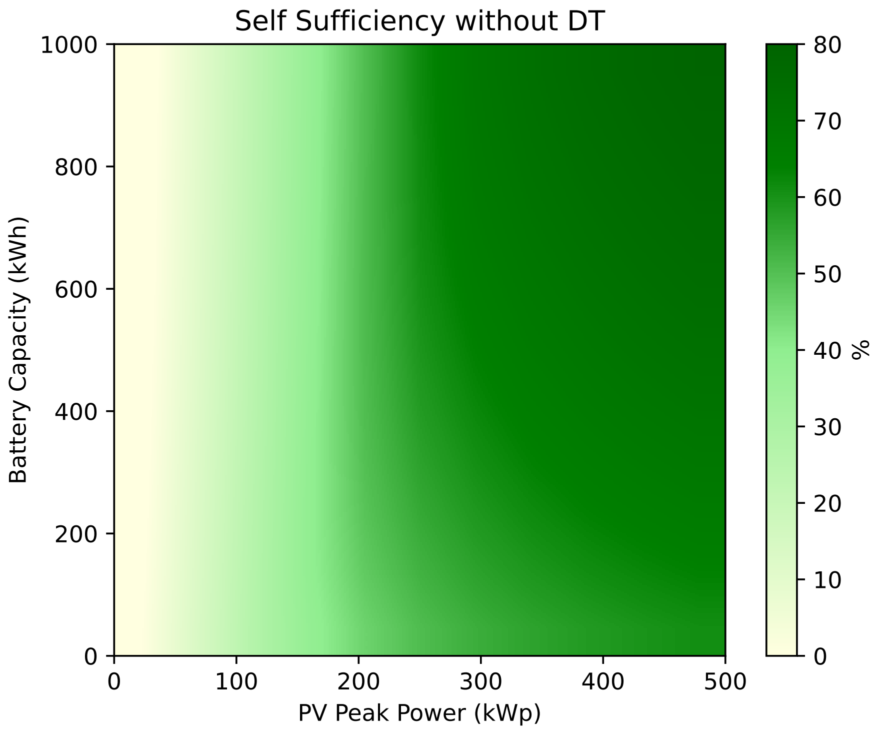

Figure 4.17: Self Sufficiency without DT use

With maximum PV, the SS stays at 60% due to the consumption outside the hours of total solar production, but with ES, it manages to raise the SS to close to 80%.

As usual, the 4.18 figure is the difference between the two previous ones. Again the difference is negligible. In this case, the impact of DT is even worse because DT tends to move the load to the periods of best occupancy and lowest prices during the night. It hurts almost all combinations of PV and ES

The 4.19 figure is the version of the figure 4.18 but without charging the battery from the grid. Again the difference is negligible. When not charging from the network, it improves a little as with self-consumption, but with a more negligible difference. Again, as the battery cannot charge from the grid, charging through surplus PV is maximized.

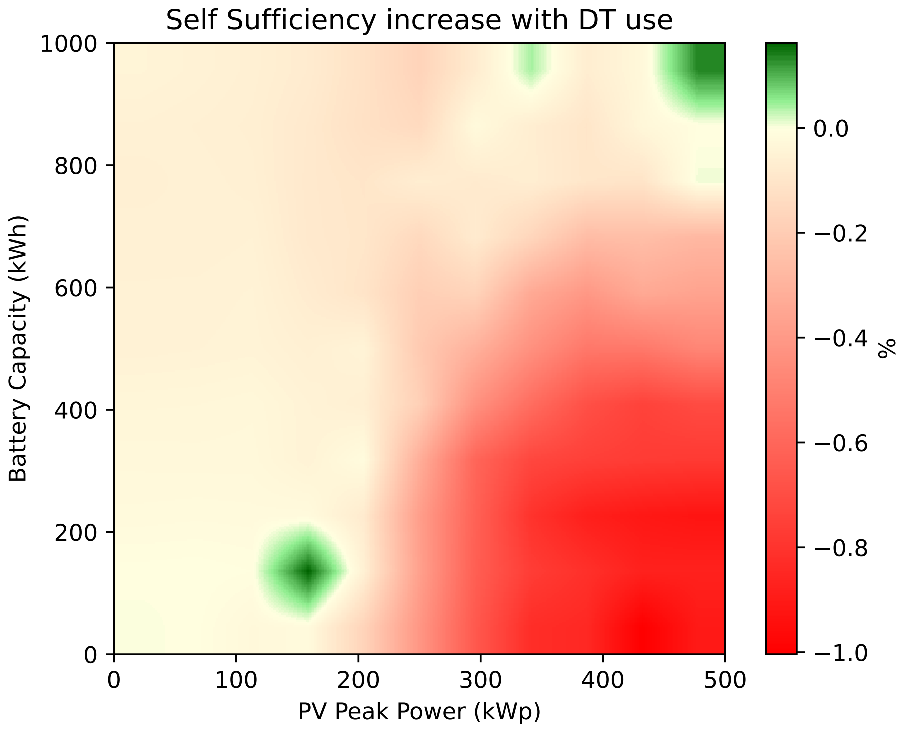

Figure 4.18: Self Sufficiency increase with DT use

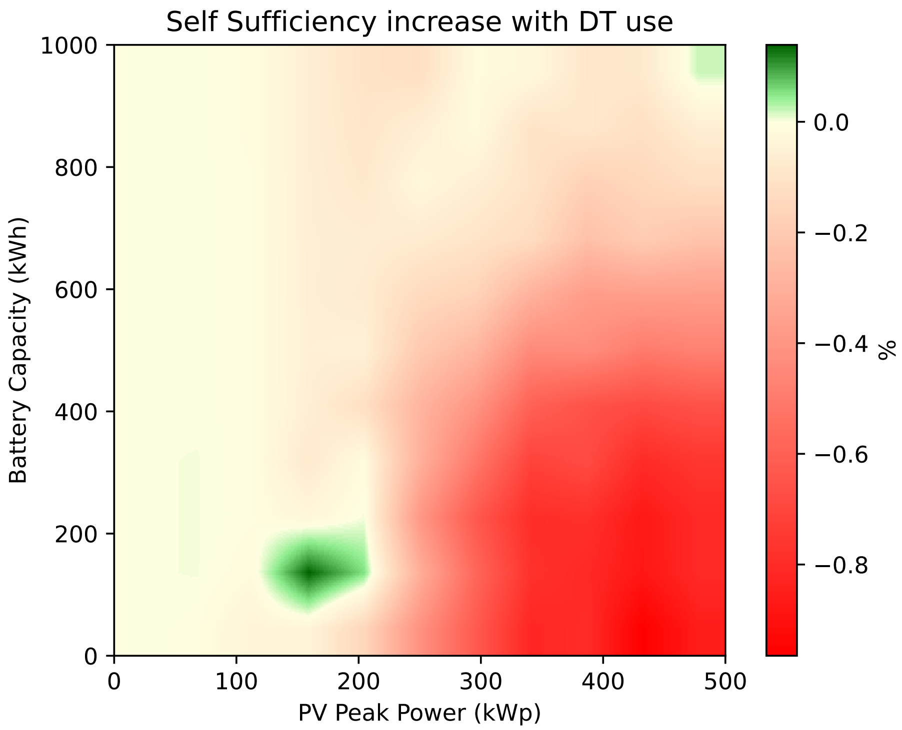

Figure 4.19: Self Sufficiency increase with DT use

Chapter 5

Conclusions and Future Work

5.1 Conclusions

DTs offer an effective strategy to enhance the financial sustainability of a glscs without imposing significant financial burdens on the consumers. The installation of a battery system becomes less advantageous when there is no surplus of PV generation. The combination of DT, glspv systems, and ES may not yield substantial benefits when used in conjunction. However, each of these components individually offers numerous advantages.

One of the most direct methods to enhance profitability is by introducing additional costs for consumers with limited flexibility in their choices. Consequently, it is essential to establish mechanisms that control price increase, preventing them from reaching exorbitant levels for consumers. Excessive cost escalation can slow the transition to EV, adversely affecting the long-term revenue potential of charging infrastructure. Moreover, CS can strategically be associated with other services that stand to benefit from increased consumer traffic. These services may be negatively impacted despite the enhanced profitability of the charging operation.

The implementation of DT must align with the reality of each EV charging facility. CSs primarily serving long-distance travelers may not derive significant benefits from daily tariffs determined the day before, as users may require more time to adapt their behavior to these tariffs. In this case, it is better to use dynamic tariffs determined at least one week in advance.

Through the incorporation of DTs, CSs can optimize their financial performance and facilitate cost-effective charging for EV users. PV systems and ES systems contribute to sustainability and grid independence, fostering a more environmentally friendly and resilient energy ecosystem in the process.

5.2 Future Work

In light of this research, there are several avenues for future exploration:

1. Test a case where the revenues obtained from EV users must remain constant. Investigate how to maintain steady revenues while optimizing charging operations.

2. Improve the accuracy of the forecasts used in the optimization process. Enhanced forecasts will lead to more precise decision-making and optimize the charging station's performance.

3. Utilize the developed tool to create a more advanced case study tool for real investment research. This enhanced tool could offer more in-depth analysis and facilitate investment decisions for stakeholders.

4. Experiment with objectives beyond total profit maximization. Consider objectives such as environmental sustainability, reducing grid dependency, offering grid services, and modifying occupancy for other purposes. Exploring these diverse objectives will help create charging solutions aligned with broader sustainability and societal goals.

5. Develop a tool that pre-defines dynamic tariffs and battery operation for future charging station installations. A user-friendly tool that pre-determines these parameters will streamline charging station development and ensure optimized performance from the outset.

The comprehensive investigation of these future work areas will further advance the sustainable integration of EV charging stations with renewable energy sources and dynamic tariff systems, ultimately contributing to a more eco-friendly and efficient transportation landscape.

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