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Design and Testing of Online and Offline Optimization Algorithms for Vehicle-to-Grid (V2G) Industrial Applications

TESI DI LAUREA MAGISTRALE IN
AUTOMATION AND CONTROL ENGINEERING -
INGEGNERIA DELL'AUTOMAZIONE

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Abstract

Due to the future widespread adoption of electric vehicles (EVs) it is crucial to take advantage of the possibilities offered by Vehicle to Grid (V2G) technologies. Many studies on V2G were already performed in domestic environments but the increasing number of sells in EVs market suggest that there is the need to examine also how V2G can be implemented from the companies' point of view.

Following these motivations this thesis presents an innovative algorithm designed to optimize the utilization of Vehicle-to-Grid (V2G) technology in industrial landscapes, with the aim of advancing the transition towards a more sustainable future. The algorithm maximizes revenues and minimizes costs while also reducing wasted energy and so carbon dioxide (CO2) emissions, contributing to environmental preservation.

The algorithm incorporates three optimizers: the negotiation optimizer, Model Predictive Control (MPC), and the SOC updating optimizer. Through these three algorithms after an agreement in between the employees and the company, the optimal State of Charge (SOC) profile and control actions for each vehicle are generated.

Through extensive testing, the algorithm consistently delivered optimal results, showcasing its efficacy and adaptability in diverse scenarios. Companies by implementing this algorithm can achieve multiple benefits, including financial gains and environmental preservation, leading to a more sustainable future.

Key-words: Electric Vehicles, Vehicle to Grid, Energy consumption optimization, Renewable energies, SOC control, control techniques (MPC), advanced control strategies (Receding Horizon, Shrinking Horizon), optimization techniques (linear programming, quadratic programming).

Abstract in italiano

Il continuo aumento delle vendite di veicoli elettrici rende imperativo trovare nuovi modi per integrare il loro utilizzo nella società ed uno di questi è sfruttare al massimo le potenzialità della tecnologia Vehicle to Grid. Molti studi sono già stati effettuati sul V2G, però ci si è sempre fermati ad esaminare scenari domestici. È quindi necessario andare oltre e studiare anche una possibile applicazione negli ecosistemi aziendali.

Per le precedenti motivazioni questa tesi presenta un algoritmo innovativo progettato per ottimizzare l'utilizzo della tecnologia Vehicle-to-Grid (V2G) in contesti industriali, con l'obiettivo di promuovere la transizione verso un futuro più sostenibile. L'algoritmo massimizza i ricavi e minimizza i costi, riducendo allo stesso tempo lo spreco di energia e quindi le emissioni di anidride carbonica (CO_2), contribuendo alla salvaguardia dell'ambiente.

L'algoritmo incorpora tre ottimizzatori: l'ottimizzatore di negoziazione, il Model Predictive Control (MPC) e l'ottimizzatore di aggiornamento SOC. Attraverso questi tre sottoprogrammi, dopo un accordo tra dipendenti e azienda, vengono generati il profilo ottimale dello stato di carica (SOC) e le azioni di controllo per ciascun veicolo. Attraverso un'ampia serie di test, l'algoritmo ha costantemente fornito risultati ottimali, dimostrando la sua efficacia e adattabilità in scenari diversi. Le aziende che implementano questo algoritmo possono ottenere numerosi vantaggi, tra cui guadagni finanziari e la conservazione dell'ambiente, contribuendo a un futuro più sostenibile.

Parole chiave: Veicoli elettrici, Vehicle-to-Grid, ottimizzazione del consumo energetico, energie rinnovabili, controllo dello stato di carica (SOC), tecniche di controllo (MPC), strategie di controllo avanzate (Receding Horizon, Shrinking horizon), tecniche di ottimizzazione (programmazione lineare, programmazione quadratica).

Contents

1 Introduction

As the world races towards a sustainable future, Vehicle-to-Grid (V2G) technology has emerged as an effective method to link transportation sector and energy systems. V2G enables electric vehicles (EVs) to become active participants in energy ecosystems by permitting bidirectional power flow between the grid and the vehicles.

Beyond their primary role as eco-friendly modes of transportation, EVs with V2G techniques can store surplus energy and feed it back into the grid when needed. This dynamic interaction between EVs and the grid unlocks a wide range of possibilities for optimizing energy consumption, enhancing grid stability, and maximizing the utilization of renewable sources.

As it can be seen in the following plot, according to the International Energy Agency, recent years have seen a rapid growth in EVs sales, and due to the "Net Zero Emissions by 2050 Scenario" the IEA forecasts that EVs will cover the 60% of new car market in 2030 [1].

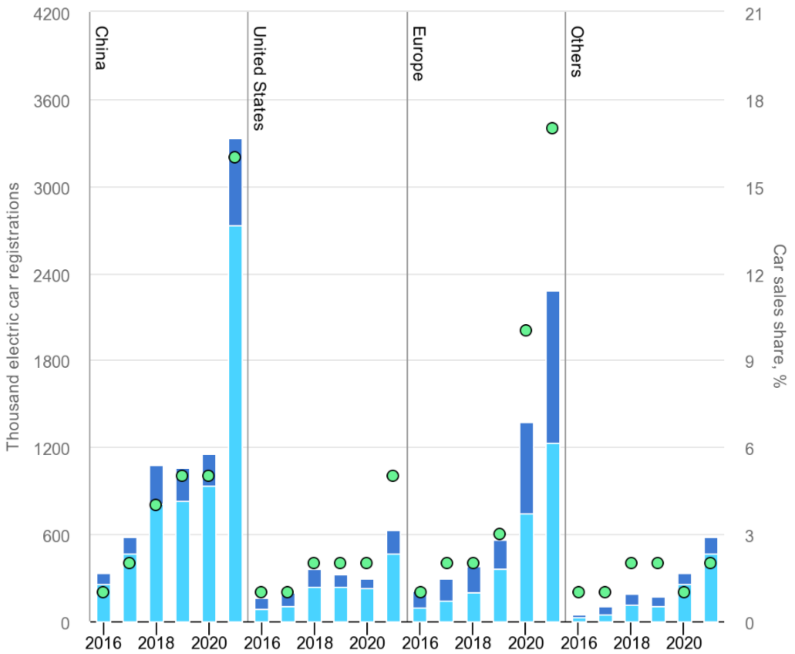

Figure 1-1: Electric car registrations and sales share in China, United States, Europe and other regions, 2016-2021 [1]

Because of this future widespread adoption of EVs, it is interesting to delve into the companies' point of view on V2G.

In the industrial environment V2G can provide many advantages, such as:

- **Generation of incomes**: energy can be stored and sold in another moment with the best rate.
- **Reduction of the energy costs**: similarly, energy can be stored in the vehicles when is cheap and utilized later.
- **Company's sustainability**: wasting less energy is another key advantage.

But how can V2G be utilized from a company's perspective?

EVs can be simply seen as batteries, and so used as flexible energy resources. Following the previous considerations EVs can be utilized to optimize the company's energy management. In order to do so it is crucial to find a method to absorb the fluctuations of the power produced by renewable resources or the variations in the company's daily energy consumption.

In this industrial context V2G cannot be utilized without the participation of the vehicle owners: the employees. Thus, a payment must be guaranteed to them for the sharing of their vehicle's battery. This arises the necessity of a negotiation at the beginning of the day in between the company and the employees.

The negotiation outputs will be: the payment of each user (employee), the available space on every EV for V2G operations, and the optimal State of Charge (SOC) profile of the batteries of each vehicle during the day. However, this negotiation is based on the predictions of energy production/consumption at the beginning of the day, which are not accurate.

As a matter of fact, considering a working day of 10 hours (8:00-17:00) the energy production/consumption forecasts are subjected to unpredictable uncertainties; thus the initial predictions will surely be wrong. For these issues it is crucial to update these predictions and to generate new optimal SOC profiles each hour.

In a nutshell this thesis aims to propose a strategy for the successful implementation of V2G in the business landscape through an optimization/control algorithm.

This algorithm is divided into three main components:

1. **Negotiation optimizer**: through the iteration of linear optimization an agreement is reached in between the company and the users and an equivalent battery's optimal SOC profile is computed.
2. **SOC updating optimizer**: a similar but simpler optimizer with respect to (1) is used to update the equivalent's battery optimal SOC profile at every hour.
3. **MPC algorithm**: during the hourly window in between two subsequent predictions, the SOC of each vehicle is controlled by an MPC with receding and shrinking horizon strategies.

This thesis presents the above strategy, initially showcasing a simple yet realistic case to illustrate the key features of the solution's algorithm. The simplified scenario revolves around a situation where the energy production exceeds consumption throughout the day, and three employees are involved in V2G operations.

Following the exposition of results in this simplified case, a dedicated chapter delves into thoroughly testing the algorithm's robustness and limitations. This analysis includes variations of the power profiles, adjustment of the number of users, and manipulation of the uncertainty levels in power forecasts. At the end of the testing chapter, also an economic analysis of the benefits of the algorithm is reported.

Through these comprehensive tests, the thesis provides a full evaluation of the algorithm's robustness, performance, and limitations across different scenarios. This detailed analysis serves to validate the algorithm's efficacy and provides essential insights for its practical implementation in real-world industrial settings.

2 State of the Art

This opening section contains a discussion on the principal studies regarding V2G technology and its applications, highlighting the lack of studies focused on industrial environments.

Up to now, V2G research has made notable progress, focusing on three fundamental aspects:

- the physical integration of EVs batteries with the power grid,
- economic analyses,
- the optimization of V2G operations.

Regarding the physical aspects, research has addressed the technical challenges of connecting vehicle batteries to the grid [2,3], validating the feasibility of the V2G concept [4], and identifying potential services [3].

Other studies focus on the role of Aggregators in maximizing the benefits of Vehicle-to-Grid. Those studies highlight the necessity of Aggregators for effectively integrating a fleet of battery vehicles into the grid as Distributed Energy Resources (DERs) [5, 6, 7]. Aggregators can be shortly described as operators which sign V2G contracts with the final costumers, to reach a significant energy storage capacity in order to enter in the energy market.

These studies also propose aggregation models and emphasize the Information Technology (IT) potential in managing control signals and communication flows between different agents involved, such as the PHEV owner, the Aggregators, and the Transmission System Operator (TSO) [5].

Instead, economic analyses of V2G technology have been extensively discussed in the literature. Researches by Kempton and Tomic [8] evaluated the revenue and costs associated with V2G use in various EV types. In this examination different models of electric vehicles were considered to assess the economic viability of V2G. Remaining on the same line analyses by Zhong and Cruden [9] were also conducted within the context of specific electricity markets, such as the UK. Moreover, further studies on V2G involve collaborations between organizations like National Grid and Ricardo and are focused on UK V2G's market [10].

Recently more attention has been directed towards optimizing V2G operations, however vehicles were studied in limited environments. These scenarios often considered cases in which vehicles were charged only with energy generated by renewable resources [11] (photovoltaic panels, wind turbines), or in which the possibility of selling back the energy to the grid was not considered [12]. In these studies, the predictions regarding the production of renewable energy didn't take into account the variability of those predictions, which obviously are subjected to the unpredictability of the natural sources.

Furthermore, most studies have been confined to domestic settings, focusing primarily on task scheduling rather than SOC level control. Outside of these domestic domains researchers have explored the potential of smart parking lots [13], where vehicles were charged minimizing costs with respect to energy rates and EVs' batteries were used for grid stability.

It is important to highlight the main State of Charge models which were taken as reference in the thesis. Noticeably as presented in figure 2-1 models influence the computing time, so the right trade-off in between accuracy and complexity must be found.

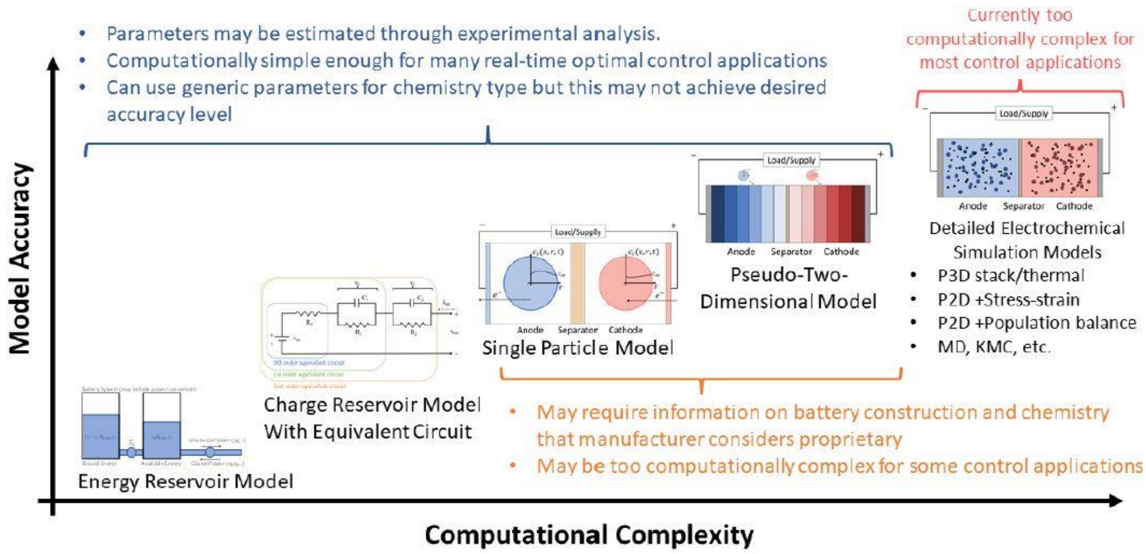

Figure 2-1: Illustration of the trade-off between model accuracy and complexity [14]

The details of all the models are presented in [14]. Most of the literature regarding the control of V2G used the Energy Reservoir Model (ERM) to minimize the computational times and maintain a high-level perspective on the problem.

In this thesis the same approach is adopted, so EV's batteries are characterized by the previous ERM SOC model to not overcomplicate the scenario.

In conclusion the existing literature highlights the lack of investigations into V2G technology within industrial contexts, where the scale and complexity of energy management differ significantly from domestic settings. Industrial environments present unique opportunities for companies to participate in energy markets by selling excess energy back to the grid, contributing to their sustainability goals and generating additional revenue streams.

3 Case study description

The following chapter aims to perform an accurate analysis on industrial applications of V2G, so a discussion on the main features of the company must be done, with the target of setting the initial parameters of the general problem. Let’s consider a realistic company’s ecosystem and reduce it to the main components/characteristics of our interest.

3.1. The industry

To properly assess the industrial scenario, several features of the problem must be considered. The representation of an average industry can be simplified by focusing on the physical size of the building, the presence of a solar plant, and the daily energy consumption.

For instance, let's consider an average building with an area of 1000 square meters located in northern Italy. The geographical location is crucial as it determines the number of peak sun hours that the solar panels are exposed to. In this case, an average value of 4.5 hours per day can be considered for Northern Italy.

The photovoltaic panel's production is directly influenced by the number of peak sun hours. Taking into account that 400W panels are considered standard as of 2022, we can use this output value for our calculations. To determine the daily energy production of a single solar panel, we can multiply the panel's output by the peak sun hours:

4.5 hours x 400W (output) = 1.800 kWh per day

Suppose there is an available space of 800 square meters on the company's building roof. It would allow the installation of a solar plant composed of 350 panels (each with dimensions of 2x1 square meters). Based on these figures, the company's daily energy generation can be estimated at 630 kWh per day.

Moving on to the daily energy consumption parameters, research by ENEA [15] suggests that a medium-sized company utilizes approximately 1,600,000 kWh of energy annually. Using this value as a reference, the daily energy consumption for our industrial scenario can be estimated at around 420 kWh per day.

By dimensioning the problem in this manner, the baseline parameters for the average industry are established, including the physical dimensions of the building, the solar plant's capacity, the daily energy generation from solar panels, and the daily energy consumption of the industry. These considerations provide a starting point for further analysis and exploration of the potential benefits and challenges associated with integrating V2G technology into this environment.

3.2. The charging stations:

The choice of the right charging stations is needed for dimensioning the problem, because the constraints related to the charge of the EVs depend on the stations' characteristics. There are several types of charging stations available to meet the diverse charging needs of EVs, but they can be gathered into: level 1, level 2, and level 3.

3.2.1. Level 1 Charging: 120-Volt

Charging Speed: 5 to 8 km Per Hour
Locations: Home, Workplace & Public

Level 1 charging stations, also known as trickle chargers, provide the slowest charging rate. They typically utilize a standard household outlet (120V AC) and are convenient for overnight charging at home or in residential settings. Level 1 charging stations work well with plug-in hybrid vehicles (PHEV). PHEV have small batteries with capacity up to 25 kWh and so they are not very suitable for needs of this thesis' case of study.

3.2.2. Level 2 Charging: 208-Volt to 240-Volt

Charging Speed: 20 to 130 km Per Hour
Locations: Home, Workplace & Public

Level 2 charging stations offer faster charging speeds compared to Level 1. These stations require a dedicated circuit with a higher voltage (usually 240V AC) and provide more power to charge the EV. Level 2 chargers are commonly found in public charging stations, workplaces, and commercial areas, enabling efficient charging within a few hours. These chargers have a power output which ranges from 3.3 kW to 25 kW, depending on the station and EVs' characteristics.

3.2.3. Level 3 Charging: 400-Volt to 900-Volt (DC Fast Charge & Supercharging)

Charging Speed: 5 to 32 km *Per Minute*
Locations: Public

DC Fast Charging, also known as Level 3 or quick charging, is the fastest charging option available. These charging stations utilize direct current (DC) to deliver a significant amount of power directly to the EV's battery, enabling rapid charging. DC Fast Charging stations can charge an EV to approximately 80% capacity in just 30 minutes, making them ideal for long-distance travel or when quick charging is needed. These stations are commonly located along highways, at rest stops, and in busy urban areas.

Considering these different levels of chargers, the right choice for the modelling of our industrial ecosystem would be the Level 2 charger, because it has the right trade-off in between speed and costs. Moreover, it would be unnecessary to have DC fast chargers, because of the 10-hour window in which the algorithm works.

3.3. The employees' EVs

In this thesis electric vehicles are considered only as batteries, because their function of transportation is not modelled. Once the vehicles are connected to the charging stations, they are not usable until the end of the day. So, the meaningful parameters relatable to these vehicles are their number, their battery capacity, and the SOC value at their arrival.

The number of vehicles and the initial SOC value will be chosen later to perform a clear analysis of the main problem.

Instead, it is interesting to look at the typical parameters of EVs' batteries. Battery capacities in EVs can vary significantly depending on the model and technology used. In general, smaller and more affordable electric vehicles tend to have battery capacities ranging from around 20 kWh to 40 kWh, providing a driving range of approximately 160 to 320 km. Mid-range EVs typically have battery capacities between 40 kWh and 60 kWh, offering a range of 320 to 480 km. Larger and higher-end electric vehicles, including SUVs and luxury models, often have battery capacities exceeding 60 kWh, allowing for ranges over 480 km. Following the previous data, the battery capacity will be modelled in between 40 kWh to 60 kWh according to the average values of the previous discussion.

As discussed before in the state-of-the-art chapter, the model used for the SOC profiles of the batteries will be the ERM one.

The Energy Reservoir model uses kilowatt-hours (kWh) to describe the SOC level of the battery of the vehicles:

$$SOC(k+1) = SOC(k) + \frac{\eta}{Q} * E_u \tag{3-1}$$

As described in (3-1) the value of SOC (in % of battery's capacity Q) at time k+1 is the value at time k plus a factor that depends on the efficiency η of charge/discharge, which for simplicity will be assumed to be constant, and it depends also on the energy exchanged with the vehicle E_u. However, in further discussions the SOC value of the vehicles will be utilized not as a percentage but as already multiplied by Q, so in kWh.

There are other models like the Charge Reservoir Model, which describe the model at a lower level, but they add unnecessary complexity to the system, including the availability of parameters.

4 Simplified N=3 problem

In this chapter a simplified case of study is derived from choosing some realistic values from the discussion of chapter 3. This problem will be used later in the analysis of the proposed solution algorithms.

Consider a scenario where a company has a photovoltaic plant and N level 2 charging stations, all equipped with Vehicle-to-Grid (V2G) technology. In this system, the company has N employees, and each employee owns an electric vehicle with a battery capacity ranging from 40 to 60 kWh. The employees offer a portion of their vehicle's battery capacity for V2G operations, and in return, they receive a compensation in kilowatt-hours (kWh), which is negotiated based on the agreed terms. For the sake of clarity, let's assume N=3 initially, but later this number will be increased during testing.

The primary objective of this setup is to generate an optimal charging profile for each vehicle. These profiles must minimize costs, maximize revenues, and effectively manage the uncertainty associated with energy generation/consumption forecasts, which are not 100% accurate. To streamline the analysis, we consider a 10-hour window within the workday and a sampling time of one hour. By optimizing the SOC profiles of the EVs within this timeframe, the system can efficiently utilize the available renewable energy from the photovoltaic plant, while considering the varying energy demands and the requirements of the electric vehicles owned by the employees.

The optimization process takes into account factors such as electricity prices, forecasted energy generation from the photovoltaic plant, and the individual vehicle's charging needs. By strategically managing the charging and discharging of the vehicles, the system can balance energy supply and demand, ensuring cost-effective operations and maximizing the utilization of renewable energy resources. This approach helps to create a win-win situation, benefiting both the company, which can reduce energy costs and potentially generate additional revenue from V2G operations, and the employees, who receive compensation for participating in the V2G program while contributing to a more sustainable energy ecosystem.

4.1. Power generation/consumption

Initially, a scenario of "energy surplus" will be considered, this context will be used as an example during the presentation of the algorithms, later also scenarios of energetic deficit and a mixed deficit/surplus will be reported in testing. By sticking to the values reported in chapter 3 it can be considered an average daily energy production of 630 kWh. Instead, the daily energy consumption can be supposed to be around 420 kWh. So, a probable power profile calculated at 8:00 of production Ppv and consumption $Pload$ may be:

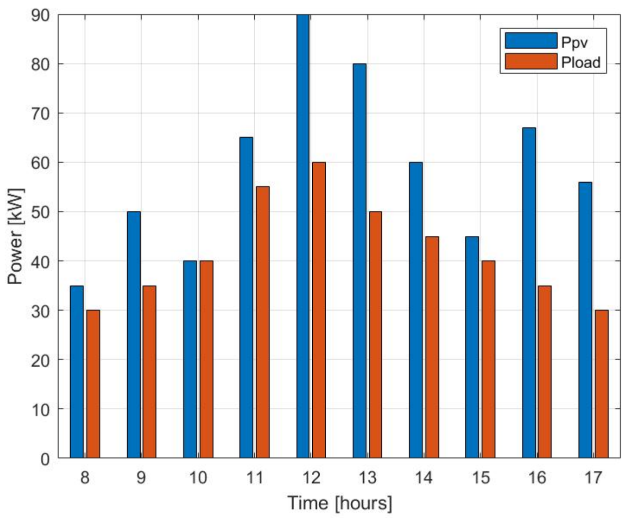

Figure 4-1: Hourly power generation/consumption

Now these power profiles are not 100% correct due to the uncertainties of the predictions. Logically the forecast's accuracy is decreasing with time, so the initial hours' predictions are very close to the real situation, but the final hours' ones are far from the real values.

In order to proceed in the analysis, the uncertainties must be modelled. The uncertainties' amplitude grows, as said before, with the distance of the value on the prediction horizon. Therefore, the uncertainties are generated by multiplying an "uncertainty index" β by the distance on the horizon of the prediction and by the value of the prediction at 8:00. As an example, by speaking of Ppv:

$$uncertainty\ at\ time\ jj = (Ppv(8{:}00, ii) * \beta * (jj + ii)) * (-1)^{ii+jj};$$

Where jj is the distance of the prediction from 8:00, and ii is the index of the hour at which the prediction is calculated.

For example, by taking the prediction value of Ppv at hour 13:00, calculated at 10:00 has the value of $jj = 6$ while $ii = 3$. This because hour 8:00 has as index ii=1 and proceeding on the horizon 10:00 has index $ii = 3$, while 13:00 has index 6, therefore $jj = 6$. Instead, β is fixed to the value 0.02 in the full analysis until testing, in which cases with a higher value of uncertainties will be treated. It's important to say that this is one way to generate the uncertainties, but any other methodology could be used to compute them.

After this discussion, it is clear that there is the need to generate new accurate predictions at each time instant (at the beginning of every hour). The new plots will have a shorter horizon because forecasts are limited to 17:00, and it will be different with respect to the previous one because of the improved accuracy of the predictions. Working in this way the following matrices are generated:

Table 4-1: Power produced forecasts at each hour.

Time/ Prediction:	**8:00**	**9:00**	**10:00**	**11:00**	**12:00**	**13:00**	**14:00**	**15:00**	**16:00**	**17:00**
Ppv1	35	50	40	65	90	80	60	45	67	56
Ppv2		54	36	72.8	77.4	92.8	49.2	54	52.26	69.44
Ppv3			40.8	63.7	91.8	78.4	61.2	44.1	68.34	54.88
Ppv4				74.1	75.6	94.4	48	54.9	50.92	70.56
Ppv5					93.6	76.8	62.4	43.2	69.68	53.76
Ppv6						96	46	55.8	49.58	71.68
Ppv7							63.6	42.3	71.02	52.64
Ppv8								56.7	48.24	72.8
Ppv9									72.36	51.52
Ppv10										73.92

Table 4-2: Power consumed forecasts at each hour.

Time/ Prediction:	**8:00**	**9:00**	**10:00**	**11:00**	**12:00**	**13:00**	**14:00**	**15:00**	**16:00**	**17:00**
Pload1	30	35	40	55	60	50	45	40	35	30
Pload2		37.8	36	61.6	51.6	58	36.9	48	27.3	37.2
Pload3			40.8	53.9	61.2	49	45.9	39.2	35.7	29.4
Pload4				62.7	50.4	59	36	48.8	26.6	37.8
Pload5					62.4	48	46.8	38.4	36.4	28.8
Pload6						60	35.1	49.6	25.9	38.4
Pload7							47.7	37.6	37.1	28.2
Pload8								50.4	25.2	39
Pload9									37.8	27.6
Pload10										39.6

4.2. Energy rates

Being connected to the national grid, the company has the flexibility to buy any lacking energy or sell any surplus energy back to the grid. To regulate these transactions, it is imperative to establish the pricing for each kilowatt-hour (kWh) bought from or sold to the grid, which varies based on the time of consumption or injection.

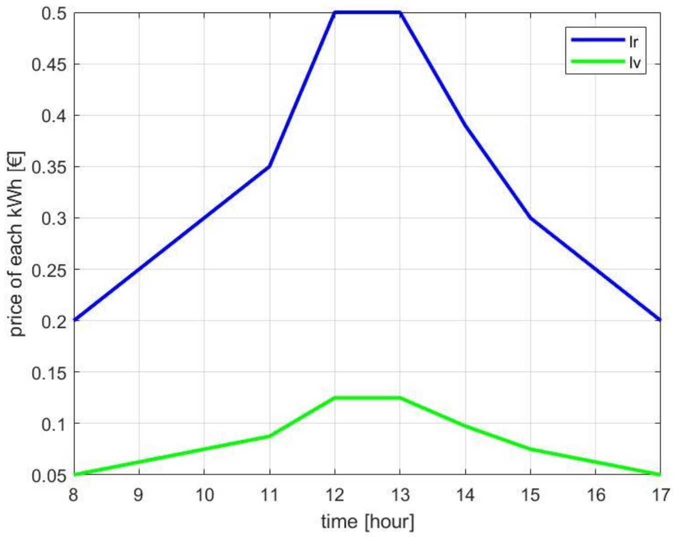

Figure 4-2: Price of each kWh in € for each hour

In this regard, the energy rates are carefully considered to ensure optimal financial outcomes. Two distinct profiles are taken into account: lr, representing the price profile for energy purchased from the grid, and lv, representing the price profile for energy sold to the grid.

The above rates are considered by looking at the real energy tariffs and are slightly exaggerated to underline the results of the algorithm. Moreover, as an assumption the grid pays the bought energy as ¼ of the price for the bought one.

4.3. The employees' model

To encourage employees' participation in V2G operations, it is necessary to offer remuneration that satisfies their expectations. The model representing the employees, referred to as users, consists of three key factors:

1. **Behaviour**: Each user has a unique behaviour pattern that represents their willingness to engage in V2G operations. To establish the users' behaviour, they are modelled in this way: each user i (i=1, …, N) associates a minimum price (Y_i) per kilowatt-hour with the amount of energy (X_i) requested by the company for storage. These price associations reflect the users' expectations and the compensation required to incentivize their active involvement in V2G operations. For instance, we can consider three distinct types of users: one with a linear behaviour (U1), one with a parabolic behaviour (U2), and one with a logarithmic behaviour (U3). These patterns capture their preferences and response to varying incentives.
2. **Battery capacity**: The capacity of the electric vehicle battery plays a significant role in determining the maximum energy that can be stored or discharged during V2G operations. For the three users mentioned above, their respective maximum capacities ($Capmax$) are as follows:
   - $U1.Capmax = 60\ kWh$
   - $U2.Capmax = 50\ kWh$
   - $U3.Capmax = 40\ kWh$
3. **Initial SOC value**: The state of charge at the start of V2G operations also impacts the users' participation and energy storage/discharging capabilities. The initial SOC values for the three users are:
   - $U1.SOCi = 41\ kWh$
   - $U2.SOCi = 24\ kWh$
   - $U3.SOCi = 36kWh$

By considering these factors, the company can tailor its remuneration and engagement strategies to align with the users' behaviours, battery capacities, and initial SOC values. The users, in order to participate in V2G operations, must communicate at their arrival the maximum capacity and the initial SOC of their EV. This personalized approach enhances the attractiveness of V2G participation, facilitating employee engagement and efficient energy management within the organization.

Setting the behaviours for the N=3 case, all the users accept offers from the company which are superior to their minimum request, which for U1, U2 and U3 is modelled in this way:

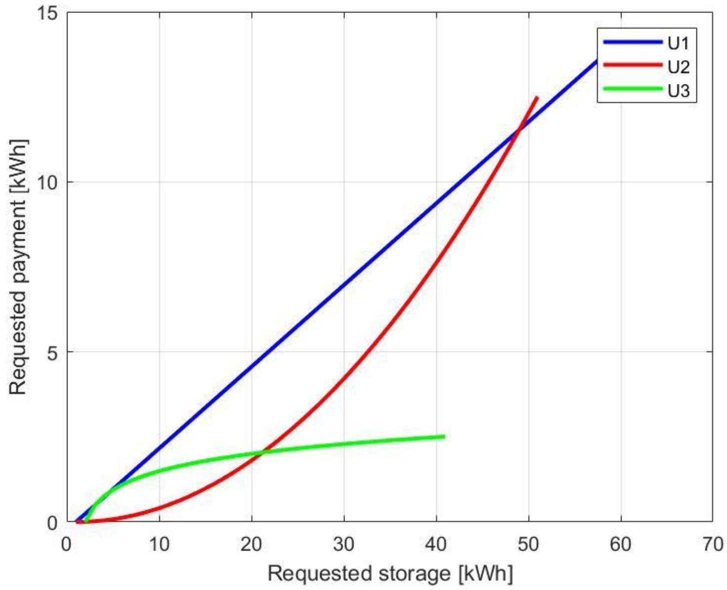

Figure 4-3: Users' model in N=3 case

As it can be seen from the plot the users' model starts from zero, this allows the negotiation algorithm to "leave out" maybe a too expensive user from the negotiation simply by offering to him 0 kWh of payment for 0 kWh of storage.

5 Solution algorithm

It is necessary to build an algorithm that creates and manages the State of Charge profiles of the vehicles. The algorithm must also find an agreement between the company and the users. Moreover, as explained in the previous chapters the optimal profile cannot be calculated only at the beginning of the day because of the uncertainties of the power predictions. So, at each time instant new predictions and control actions must be computed. How to do this?

The proposed solution is divided into 3 components:

1. **Negotiation optimizer**: through linear optimization offers are generated for the user's participation in V2G operations. These offers can be accepted or refused by the users until all of them find an agreement with the company, or until a defined number of failed negotiations is reached. This optimizer also generates the optimal SOC profile of an equivalent battery, a profile which is based on the power predictions at 8:00. The limit of this first algorithm is represented by the fact that it does not consider the uncertainties of the predictions and by the fact that it cannot figure out the optimal SOC profile of each vehicle.
2. **SOC updating optimizer**: To counter the prediction's uncertainties a similar but simpler optimizer with respect to (1) is used to update the optimal SOC profiles. At each hour this optimizer is launched, and it calculates the optimal equivalent SOC profile utilizing updated predictions. However also this algorithm is based on linear programming and so it cannot calculate the individual SOC profiles of the EVs. Its output will be used as a reference of the MPC.
3. **MPC algorithm**: it is used to fulfil the shortages of the two previous optimizers. MPC has as aim to follow the equivalent battery's SOC profile given by the SOC updating optimizer and to compute the optimal control sequence for each EV. MPC in this way solves the problem of the division of the equivalent SOC profile into the single EVs. Moreover, by applying the Receding Horizon strategy at every time instant the control action is computed and implemented, countering the uncertainties of the predictions. The Shrinking Horizon strategy is instead utilized in the last samples of the

operating window to reduce the dimension of the prediction and control horizons of the MPC.

Let's discuss these three optimizers in detail, having in mind that the target of the analysis is minimize costs and maximize incomes. For the creation of these algorithms MATLAB was used, the code is not presented to simplify the visualization.

5.1. Negotiation optimizer

By looking at the main problem as presented, it is clear that there is the need of a negotiation in between the company and the users (employees). The skeleton of the negotiation algorithm will be a simplified bidding structure, in which the company generates the offers in kWh (payment) for the V2G action's battery space (storage) on the vehicles. The EVs' batteries in this situation are considered as one equivalent battery, with the maximum capacity equal to the sum of the capacities of the EVs and the initial SOC value equal to the sum of the initial SOC values of the single EVs. One of the outputs of the negotiation will be the optimal SOC profile of this equivalent battery, a profile which minimizes the costs/maximizes the revenues.

Algorithm 1 Negotiation Algorithm:

1: The company generates an initial offer for each single user. In these initial offers the payment in kWh is very small with respect to the storage portion of the EV's battery requested.

2: The users evaluate their offer, and if they consider it inadequate, they respond with a counteroffer, in which the payment is slightly higher than the minimum one they would accept.

3: Based on the counteroffer, through interpolation linear models of the users are generated.

4: Using a negotiation function and the generated models, the optimal way to manage the energy and minimize costs is calculated. Additionally, offers are computed for the users.

5: The offers are then presented to individual users (the offer is lower than what the company could offer).

6: Each user re-evaluates his offer, and it responds with a counteroffer, and the process restarts from step 3.

7: The algorithm repeats until all users accept the offer or until a maximum number of cycles (30) is reached.

Now the fundamental features of the previous steps will be explained in detail.

5.1.1. The initial offer

This offer is a "dummy" operation performed by the company to obtain a counteroffer from the users, which is necessary for the creation of the linear generated models. The initial offer proposes a very small Y_i associated with the request of the full capacities of the EVs batteries. Following this procedure leads to the failure of the first interaction because the offer is below the expectations of the users, which refuse it and generate a counteroffer.

5.1.2. Acceptance/refusal of offers

The users accept offers which are above their behaviour's model and refuse ones below it. If an offer is refused a counteroffer is generated in this way: the user fixes the value of X_i and requests a payment value above the curve of its behaviour. This because the users are interested in obtaining the highest payment possible from the company.

Instead, if user i accepts its offer, the counteroffer of user i is the accepted offer.

5.1.3. The generated model

As it is reported in point 3 of Algorithm 1 a linear model of the behaviour of the users is generated from their counteroffer. The counteroffers can be represented as simply points in the Xi, Yi plot (the same used before in the representation of users' models). Then, a line is drawn in between the origin of the plot and the counteroffer value, this line will be used as the generated model of the user i.

5.1.4. The negotiation function

In step 4 of Algorithm 1 the negotiation function was introduced, let's talk deeply about it. This function has in input:

- The generated linear model of the single users.
- The minimum value of SOC reachable for each vehicle
- The energy price profiles lr, lv.
- The generated/consumed power profiles Ppv and $Pload$.
- The ERM battery model.

The aims of the negotiation function are to:

- Fix the values of Xi for each user (battery space).
- Fix the values of Yi for each user (payment).
- Find the optimal SOC profile for the equivalent battery.
- Find the profiles of the energy sold and bought from the national grid.

This formulation reduces this initial problem to a linear optimization problem, because all the relationships in between the variables are linear. MATLAB's linear programming can be used to solve this negotiation.

5.1.5. Linear programming

Linear programming is a mathematical optimization technique used to find the best possible outcome in a mathematical model with linear relationships. It involves maximizing or minimizing a linear objective function, subject to a set of linear equality or inequality constraints.

In linear programming, the objective function represents the goal to be optimized, whether it is maximizing profit, minimizing costs, or achieving a certain target. The constraints define the limitations or restrictions on the variables that influence the objective function. These constraints can represent resource availability, capacity constraints, or any other relevant restrictions.

Linear programming is the mathematical problem of finding a vector x that minimizes the function:

$$\min_{x}\{f^T x\}$$

Subject to the constraints:

$$Ax \leq b$$

$$Aeqx = beq$$

$$lb \leq x \leq ub$$

Solving a linear programming problem involves finding values for the decision variables that optimize the objective function while satisfying all the constraints. Various algorithms and methods, such as the Simplex method or interior point methods, are used to solve linear programming problems and determine the optimal solution.

5.1.6. Decision variables

Following the previous explanation and going back to the negotiation problem, its decision variables and its constraints must be fixed:

- $Eneed$: total energy storage space on the batteries necessary for V2G operation

Then for each user i (i=1, …, N with N number of users):

- X_i: storage requested on vehicle of user i. [kWh]
- Y_i: payment proposed for user i. [kWh]

Instead, for each time instant k (k=1, ….,10):

- Er: energy bought from the grid at time instant k. [kWh]
- Ev: energy sold to the grid at time instant k. [kWh]
- Eu: energy exchanged with the vehicles at time instant k. Eu is positive when energy flows from users to the company and negative vice versa. [kWh]
- SOC: value of the equivalent battery's SOC at time instant k. [kWh]

5.1.7. Assumptions

Before proceeding it is important to make some assumptions:

- Let's suppose that by contract the minimum value of the SOC of each EVs cannot be under $SOCMIN = 10\ kWh$. Moreover, let's set the minimum value of SOC of the equivalent battery $SOCMINeq$ equal to $N * SOCMIN$.
- At the beginning of the day users must communicate to the company their value of SOC at the arrival ($SOC_i(0)$) and the maximum capacity of the battery of their EV ($U(i).CAPmax$).
- The equivalent battery's maximum capacity $CAPeq$ is equal to the sum of the single $U(i).CAPmax$.
- Let's also assume that equipped Level 2 charging stations can charge a maximum of 25 kWh on the EVs in one hour.
- However, the most important assumption is that the EVs at the end of the day must have a SOC value which is equal to the initial one plus the payment promised after the negotiation.

By means of simple calculations we can set the following useful variables:

- $sumX = \sum_{i=1}^{N} X_i$
- $sumY = \sum_{i=1}^{N} Y_i$
- $Crete = \sum_{k=1}^{10} lr(k) * Er(k)$ → cost of the energy bought from the grid in €
- $Gven = \sum_{k=1}^{10} lv(k) * Ev(k)$ → revenue of the energy sold to the grid in €
- $diff(k,j) = SOC\{j\} - SOC\{k\}$ → difference between the equivalent SOC values at time k and j.

5.1.8. Constraints

Having settled the previous assumptions and variables we can proceed with the constraints. MATLAB allows the use of a simple and intuitive way to define constraints for linear optimization, without the need of writing them in matrix form. That's why the following constraints are not reported in that form:

- $SOCMIN \leq X_i \leq U(i).CAPmax$
- $0 \leq Y_i \leq U(i).CAPmax - U(i).SOCi$
- $0 \leq Eneed \leq CAPeq - SOCMINeq$
- $0 \leq Ev \leq \infty$
- $0 \leq Er \leq \infty$
- $-N * 25 \leq Eu \leq N * 25$
- $SOCMINeq \leq SOC \leq CAPeq$
- $SOC(k+1) = SOC(k) - Eu$

  → this derives from ERM model's equation 3.1.
- Energy balance constraint:
  $Er(k) + Ppv(k) * 1[hour] + Eu(k) = Pload(k) * 1[hour] + Ev(k)$

  →Ppv and $Pload$ are supposed to be constant, so the energy generated/consumed in a 1h window is equal to the multiplication in between the power and the time window.
- $Eneed \geq diff\ (k,j)$

  → $Eneed$ is defined as the total energy storage needed for V2G operations, so it must be >= to the maximum difference in between every equivalent's battery SOC value.
- $SOC(1) = SOCIeq$

  → where $SOCIeq$ is initial SOC of the equivalent battery and so the sum of the $SOC_i(0)$.
- $SOC\ (10) = SOCIeq + sumY$
- $sumX >= Eneed$

Moreover, the linear optimizer first behaviour would be to use the cheapest users at their maximum and to not use the expensive ones. To avoid this, users firstly are ordered from the cheapest to the most expensive one and an additional constraint the is introduced:

- $-2.5 * N \leq X_i - X_{i+1} \leq 2.5 * N$

→ Through this constraint the distance between the requested storage in between two adjacent users is limited.

5.1.9. Objective function

The linear programming's objective function is the following one:

$$\min Crete - Gven$$

Therefore, the optimizer minimizes the difference between the total costs and the total revenues. Writing in this way the objective function is useful because at the same time it minimizes the total cost while maximizing the total revenue.

5.1.10. Negotiation's outputs example

As we can see the steps 4-5-6 of the algorithm are a while cycle, which terminates only when all users accept the offers or when a maximum number of cycles is reached. In detail we can see that utilizing previous data, the first output values of the negotiation function are:

$Eneed$= 82.646

Table 5-1: First cycle results

	U1	U2	U3
X (kWh)	35.049	27.549	20.049
Y (kWh)	4.936	8.0829	4

However, these offers are accepted only by two users, U1 refuse its offer because it is too low. The offers must be re-generated.

The second cycle produces these values:

$Eneed$= 89.589 kWh

Table 5-2: Second cycle results

	U1	U2	U3
X (kWh)	22.819	30.319	36.452
Y (kWh)	4.5181	4.8925	4

The same situation as before is presented in this second cycle.

The algorithm repeats until cycle 11 which finds the following solution:

$Eneed$= 90.007 kWh

Table 5-3: Last cycle results

	U1	U2	U3
X (kWh)	22.502	30.002	37.502
Y (kWh)	5.6706	4.753	2.5698

All the 3 users accept the offers generated for them, with an expected revenue of 19.00€. If the algorithm wouldn't have been used the expected revenue would have been 14.70€. It must be said that the revenues are 'expected' and not the real ones, because the predictions on which the algorithm works are the ones at 8:00 and so they are incorrect by definition. Later by applying the full algorithm the real revenues are computed.

The final cycle's optimal SOC profile (SOCF) of the equivalent battery is the following one:

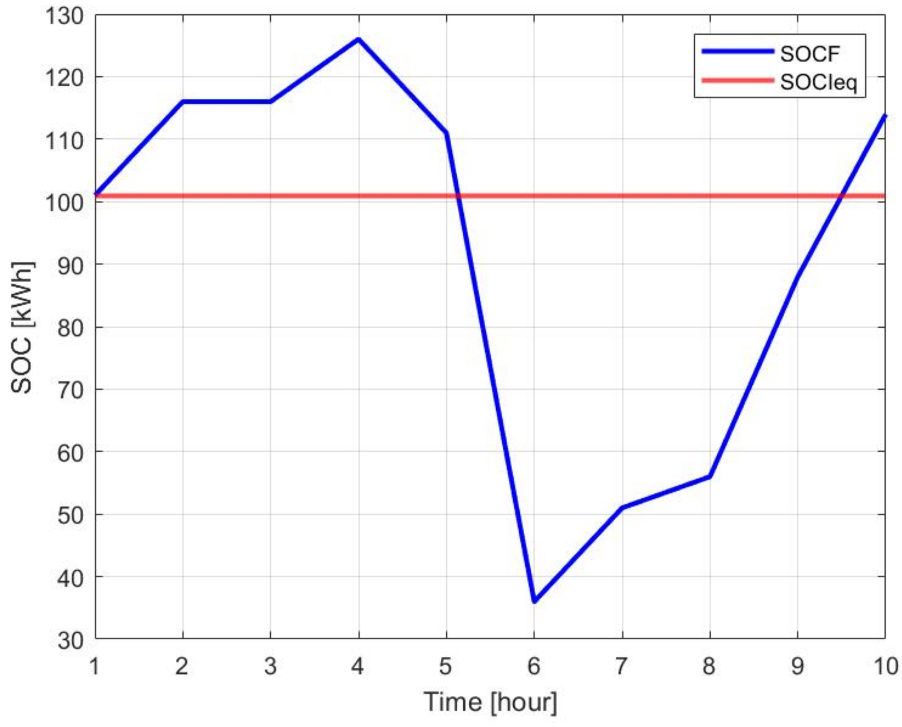

Figure 5-1: hourly optimal SOC profile at 8:00

As it can be seen from the previous figure 5-1 the equivalent SOC profile remains inside all the imposed constraints. The profile reported in figure 5-1 suggests that the optimizer, at the beginning of the day, stores the surplus energy in the EVs' batteries, later this energy is sold when the energy rates are more convenient.

Moreover, the profile of SOCF is also coherent with the assumption that at the end of the day the batteries must have a SOC value equal to the initial one plus the kWh of payment.

Instead by looking at the hourly management of energy, the optimal profiles of the bought and sold energy are:

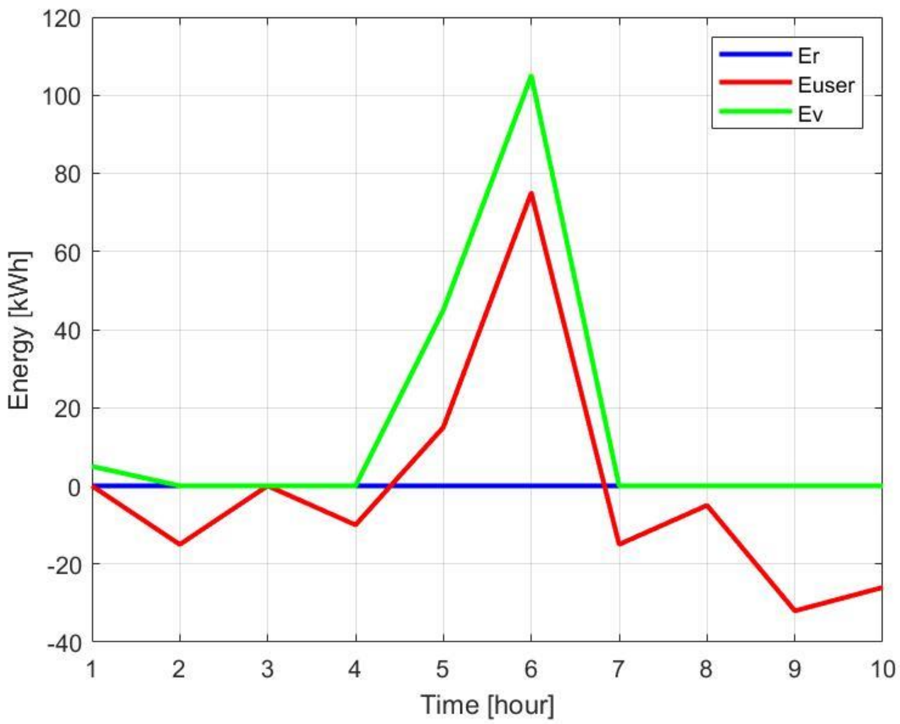

Figure 5-2: Energy management in N=3 surplus scenario

Being in an energy surplus scenario, the Energy bought from the grid Er always has a value equal to zero. The $Euser$ plot is negative when the energy is charged into the EVs and positive when discharged from them.

These results highlight that the algorithm is well functioning because it charges the vehicles when the energy price is low and sells the energy later, when the energy rates are more convenient. At the end of the day, it can be seen how the algorithm utilizes the energy in excess produced from the photovoltaic system to bring the vehicles to the agreed SOC level.

In conclusion, in a scenario where the produced energy is greater than the consumed one, and with N=3 users, the negotiation algorithm is able to compute the best SOC profile for the equivalent battery, and to find the best way to manage the energy flows in between the company and the grid.

5.2. SOC updating optimizer

The previously discussed in Chapter 4.1 the problem relative to the uncertainty of the predictions must yet be solved. The solution calculated at 8:00 cannot be correct for the full duration of the 10 hours. This leads to the need of a recalculation of the optimal SOC profile for the equivalent battery and of the $Er, Ev, Euser$ profiles. The recalculation is performed at each hour by a lighter optimizer, which is almost equal to the negotiation one, but maintains only the portions relative to the calculus of the equivalent SOC profile and of the energy management. Moreover, this SOC updating optimizer must work with a shrinking horizon, due to the fact that every time it is called the time window for which has to generate the profiles is smaller (w). The values of $Eneed$ and of the X_i, Y_i are no more decision variables but are fixed to the ones decided in the negotiation, so the inputs of the optimizer will be:

- $Eneed, X_i, Y_i$
- The minimum value of SOC reachable for each vehicle
- The energy price profiles lr, lv.
- The generated/consumed power profiles Ppv and $Pload$.
- The number w equal to the remaining hours until 17:00

The aims of the negotiation function are to:

- Find the optimal SOC profile for the equivalent battery.
- Find the profiles of the energy sold and bought from the national grid.

5.2.1. Assumptions

At each hour new predictions of generated/consumed power are available.

As for the previous optimizer, let's suppose that minimum value of the SOC of each EVs cannot be under SOCMIN=10 kWh.

At the beginning of the hour the value of the SOC of each vehicle is known.

The maximum capacity $CAPeq$ of the equivalent battery is determined by the sum of each individual $U(i).CAPmax$, as mentioned earlier. I t is assumed also that the Level 2 charging stations installed can charge the electric vehicles (EVs) up to a maximum of 25 kWh per hour. Furthermore, the crucial assumption is that by the end of the day, the EVs must have a state of charge (SOC) value that is equal to the initial SOC plus the payment agreed upon during the negotiation.

The same variables are used:

- $Crete = \sum_{k=1}^{10} lr(k) * Er(k)$ → cost of the energy bought from the grid in €
- $Gven = \sum_{k=1}^{10} lv(k) * Ev(k)$ → revenue of the energy sold to the grid in €
- $diff(k,j) = SOC\{j\} - SOC\{k\}$ → difference between the equivalent SOC values at time k and j.

5.2.2. Constraints

The constraints are almost the same as the previous optimizer, only the ones needed for the computation of Xi and Yi are not used:

- $0 \le Ev \le \infty$
- $0 \le Er \le \infty$
- $-N * 25 \le Eu \le N * 25$
- $SOCMINeq \le SOC \le CAPeq$
- $SOC(k+1) = SOC(k) - Eu$
  → this derives from ERM model.
- $Er(k) + Ppv(k) * 1[hour] + Eu(k) = Pload(k) * 1[hour] + Ev(k)$
  → Ppv and $Pload$ are supposed to be constant, so the energy generated/consumed in a 1h window is equal to the multiplication in between the power and the time window.
- $Eneed \ge diff\ (k,j)$
  → $Eneed$ is defined as the total energy storage needed for V2G operations, so it must be >= to the maximum difference in between every equivalent battery's SOC value.
- $SOC(1) = SOCIeq$
- $SOC\ (10) = \ SOCIeq + sumY$

5.2.3. Objective function

The objective function remains the same of the previous optimizer. This because the target of the SOC updating optimizer is always minimize the costs and maximize the revenues.

5.2.4. SOC updater's results

Utilizing the values of the N=3 example, here there are reported the optimal SOC profiles for the equivalent battery calculated at different hours:

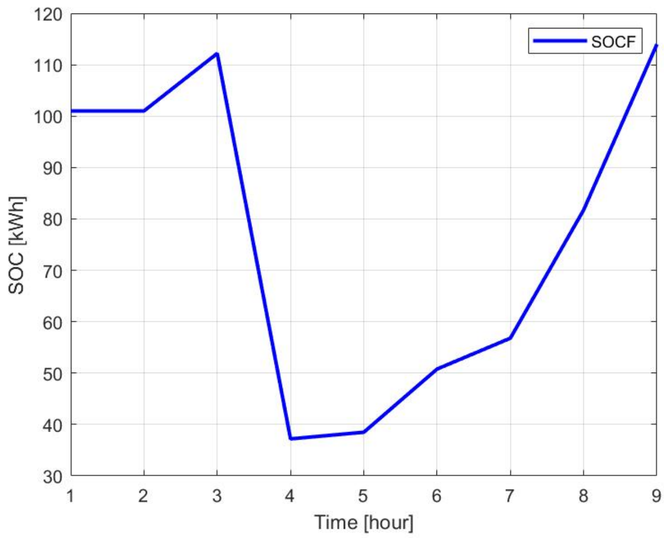

Figure 5-3: equivalent battery's SOC profile calculated at hour 9:00.

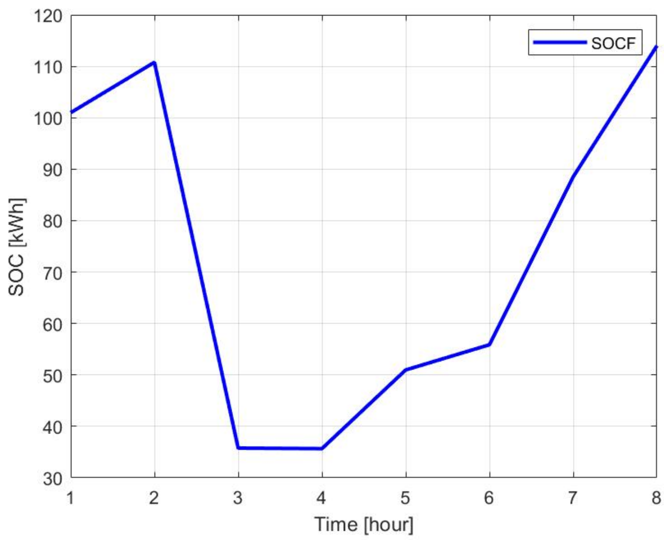

Figure 5-4: equivalent battery's SOC profile calculated at hour 10:00.

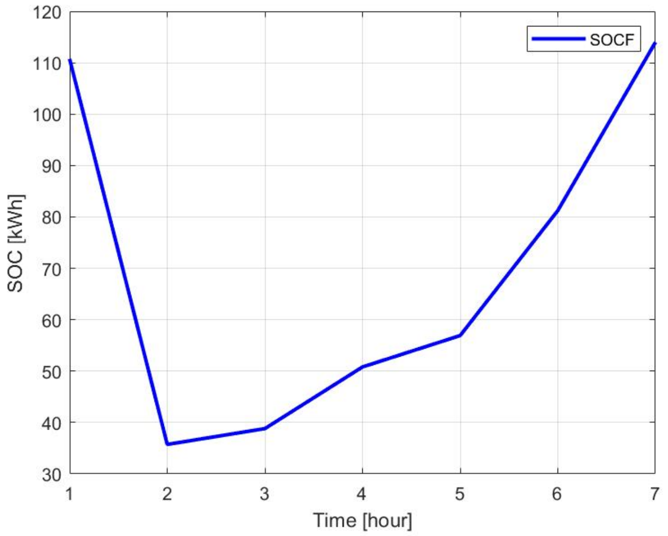

Figure 5-5: equivalent battery's SOC profile calculated at hour 11:00.

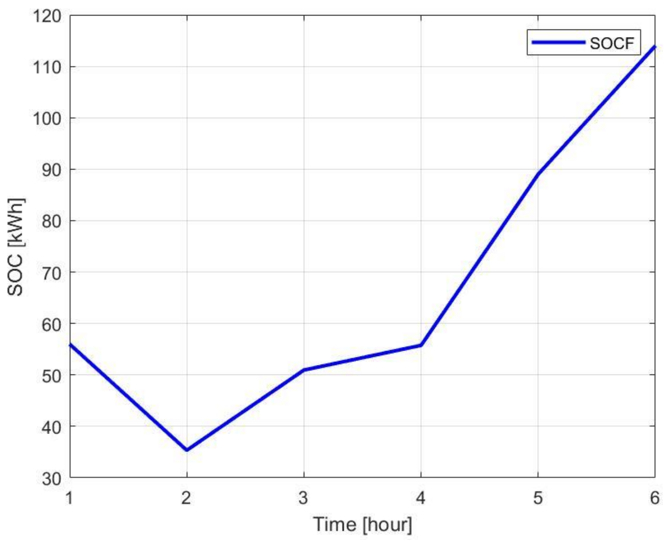

Figure 5-6: equivalent battery's SOC profile calculated at hour 12:00.

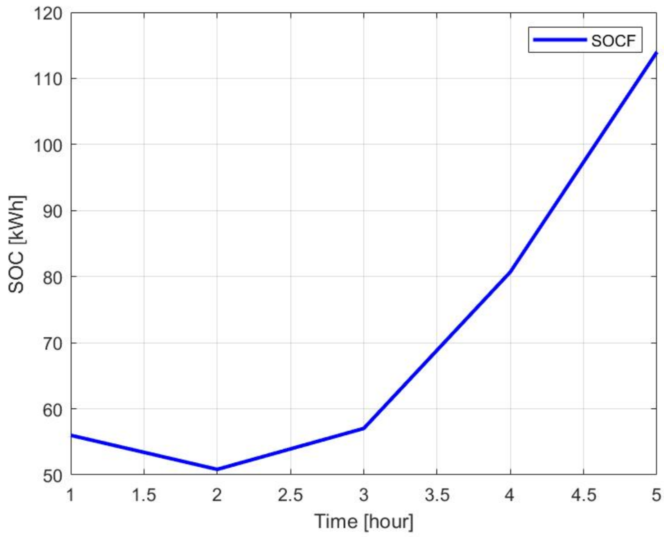

Figure 5-7: equivalent battery's SOC profile calculated at hour 13:00

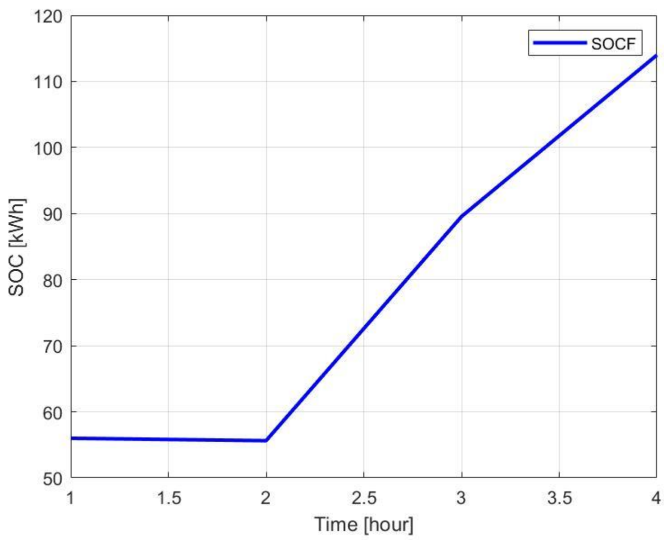

Figure 5-8: equivalent battery's SOC profile calculated at hour 14:00.

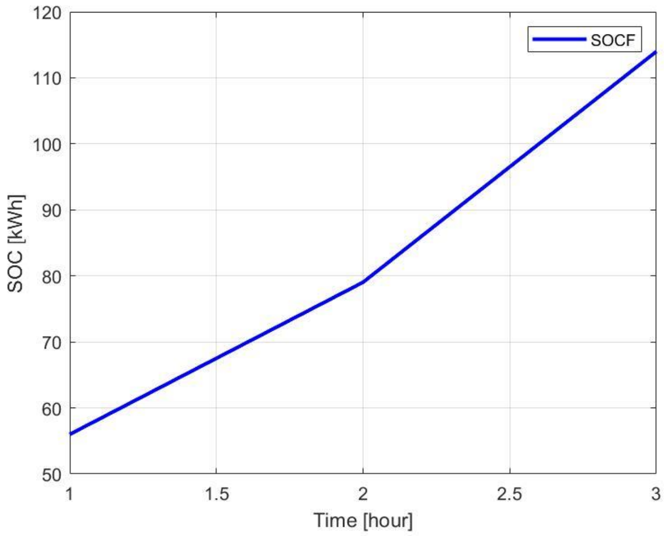

Figure 5-9: equivalent battery's SOC profile calculated at hour 15:00.

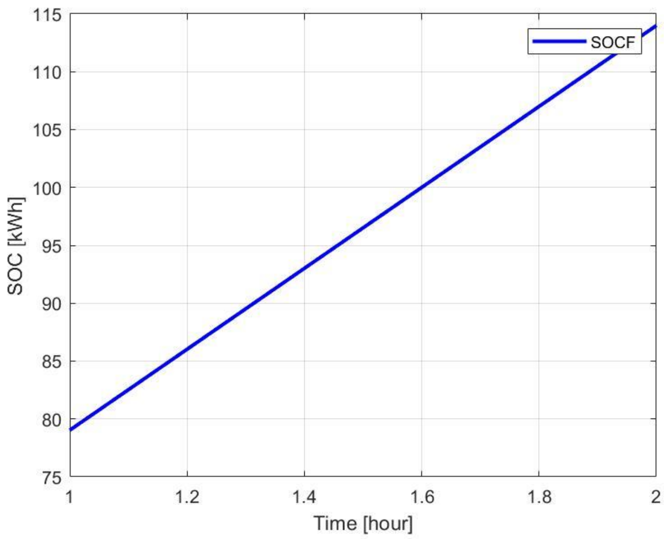

Figure 5-10: equivalent battery's SOC profile calculated at hour 16:00.

All these previous figures confirm the well-functioning of the optimizer which is able to provide at the beginning of each new hour the correct reference for the MPC, in function to the power predictions.

5.3. Model Predictive Control with Receding/Shrinking Horizon

Having obtained the preceding optimal SOC profiles for the equivalent battery, it is now imperative to compute the single EV's optimal profiles for each hour. This operation cannot be performed with linear optimization techniques because with a great number of users the number of the decision variables will be very high, leading to high complexity and high computational times. Moreover, for each hour a smart control of the energy exchanged in between the company and the users is needed.

The best fitting solution for this problem is MPC (Model Predictive Control) strategy.

MPC is a control strategy that uses a mathematical model of the system to optimize future control actions. It solves an optimization problem at each time step to determine the best control input sequence over a finite time horizon, considering system dynamics and constraints. Utilizing the Receding Horizon strategy, the first element of the control sequence is implemented, and then the process is repeated at the next time step, using updated measurements and predictions. Shrinking Horizon strategy is instead utilised in the last samples of the 10-hour time window to reduce the prediction and control horizons of the MPC. In this way MPC provides a systematic approach to handle complex systems, handle constraints, and optimize control performance in real-time.

According to [16] the most important features of MPC are:

- The problem is formulated as an optimization one, so different goals can be considered.
- Constraints on the state and on the output can be included in the optimization.

The main ingredients of MPC are:

- A model of the system.
- A cost function J is needed.
- An optimization algorithm which computes the future optimal control sequence.
- Constraints on input, output and state.
- Prediction horizon: sets how far we predict the control sequence.
- Moving horizon window: a time-dependent window from t_k to $t_k + Tp$. The value of t_k increases with the hours while Tp remains constant until the number future hours on which future has to be predicted (h) is smaller than Tp, then it shrinks following Tp=h.

- The Receding Horizon (RH) principle: At each time step k, an optimization problem is solved using the available process information, to determine the optimal future control sequence [u(k), ..., u(k+N-1)]. Then only the first element of this control sequence, $u^0(k)$, is applied. At the next time step k+1, a new optimization problem is solved using the process information at time k+1, considering the prediction horizon [k+1, k+N].
- Shrinking Horizon principle: MPC with shrinking horizon refers to a variation of the traditional MPC approach where the prediction horizon is dynamically adjusted or shortened as time progresses.

In essence, the objective of MPC is to compute the future steps of the control variable u to optimize the future plant output y. The optimization is performed using the information available at the beginning of a fixed time window. To understand why MPC algorithms fit well our problem a typical day of functioning of the full algorithm can be considered.

Considering the N=3 simplified model, the day begins at 8 o'clock in the morning. The negotiation generates the first SOC profile of the equivalent battery. This profile is used as a reference for the MPC which has as object to minimize the distance in between the plant output and this profile. The MPC always plans the EVs charges and discharges in the next 4 hours. However only the plan for the first hour is implemented. At 10:00 the previous forecasts become obsolete and the $u^0(9)$ has already been applied, the new equivalent SOC profile generated by the SOC updating optimizer must be used as a new reference. MPC algorithm computes the new control sequence and only $u^0(10)$ is applied. The process repeats in this way every fresh hour until 14:00, when the control horizon starts following the shrinking horizon strategy and so it shrinks from the value of 4 to the number of the remaining time steps on the horizon. MPC then continues working with the shrinking horizon technique until 17:00.

5.4. MPC theory

5.4.1. State-space formulation

In detail an MPC algorithm must be built with the aim of following a given reference. In order to do that, the augmented system strategy is used.

The problem of having multiple EVs connected to the same grid, whose control follows a single equivalent's battery optimal SOC profile as reference, is clearly a situation in which the plant must be modelled as a MISO system. By fixing the number of vehicles N and utilizing ERM model, the plant becomes:

$$\begin{cases} x_1(k+1) = A_1 * x_1(k) + B_1 * u_1(k) \\ x_2(k+1) = A_2 * x_2(k) + B_2 * u_2(k) \\ \dots\dots\dots \\ x_N(k+1) = A_N * x_N(k) + B_N * u_N(k) \\ Y(k) = x_1(k) + x_2(k) + \dots . + x_N(k) \end{cases} \quad (5\text{-}1)$$

As shown in (5-1) the states represent the SOC values of each vehicle and Y represents the unique output, equal to the sum of each vehicle's SOC and so equal the SOC of the equivalent battery.

The state-space formulation can be written as:

$$x_m(k + 1) = A_m x_m(k) + B_m u(k) \quad (5\text{-}2)$$

$$y(k) = C_m x_m(k) \quad (5\text{-}3)$$

Where:

- $\boldsymbol{xm(k)}$ is a Nx1 vector which contains all the single states of the EVs.
- $\boldsymbol{u(k)}$ is a Nx1 vector which contains all the inputs of the EVs.
- $\boldsymbol{Am}$ is an identity matrix of dimension NxN.
- $\boldsymbol{Bm}$ is also an identity matrix of dimension NxN but it is multiplied by the charge efficiency η (fixed to 0.9).
- $\boldsymbol{Cm}$ is a ones vector of dimension 1xN.

Here, u represents the total manipulated/input variable, y represents the process output, and x_m represents the state variable vector. It is important to note that the plant model in equations (5-2) has u(k) as its input. To align with our design purpose of following a given reference, we need to modify the model to include an embedded integrator.

In a general state-space model, there is a direct term from the input signal u(k) to the output y(k) given by:

$$y(k) = C_m x_m(k) + D_m u(k) \quad (5\text{-}4)$$

However, considering the principle of receding horizon control, where current plant information is required for prediction and control, we assume that the input u(k) does not directly affect the output y(k) simultaneously. Hence, in the plant model, we set $D_m = 0$.

We need to perform some calculations to build the right MPC structure for the reference tracking. In order to do that let's follow the computations reported by [16].

By taking a difference operation on both sides of equation (5-2), we obtain:

$$x_m(k+1) - x_m(k) = A_m\big(x_m(k) - x_m(k-1)\big) + B_m\big(u(k) - u(k-1)\big) \quad (5\text{-}5)$$

Let's define the difference of the state variable:

$$\Delta x_m(k+1) = x_m(k+1) - x_m(k) \quad (5\text{-}6)$$

$$\Delta x_m(k) = x_m(k) - x_m(k-1) \quad (5\text{-}7)$$

and the difference of the control variable:

$$\Delta u(k) = u(k) - u(k-1) \quad (5\text{-}8)$$

In this way the increments of the variables $x_m and\, u$ are defined. The initial state space equation (5-5), by applying the previous (5-6, 5-7, 5-8) equations will then be:

$$\Delta x_m(k+1) = A_m \Delta x_m(k) + B_m \Delta u(k).$$

Now the input of the state space model is $\Delta u(k)$. Moreover it must be settled a new state variable vector:

$$x(k) = [\Delta x_m(k)^T \;\; y(k)]^T$$

The output equation (5-3) will be transformed into:

$$y(k+1) - y(k) = C_m\big(x_m(k+1) - x_m(k)\big) = C_m \varDelta x_m(k+1)$$
$$= C_m A_m \varDelta x_m(k) + C_m B_m \varDelta u(k).$$

Finally, the complete state space model is:

$$\begin{bmatrix} \varDelta x_m(k+1) \\ y(k+1) \end{bmatrix} = \begin{bmatrix} A_m & o_m^T \\ C_m A_m & 1 \end{bmatrix} \begin{bmatrix} \varDelta x_m(k) \\ y(k) \end{bmatrix} + \begin{bmatrix} B_m \\ C_m B_m \end{bmatrix} \varDelta u(k)$$
$$y(k) = \begin{bmatrix} o_m & 1 \end{bmatrix} \begin{bmatrix} \varDelta x_m(k) \\ y(k) \end{bmatrix}$$

Where o_m is a zeros vector of dimension $N * n1$, and n1 is the number of states.

The form of the obtained state space variable is the classical one, the state space model can be rearranged in this way:

$$\begin{cases} x(k+1) = \ Ax(k) + Bu(k) \\ \quad\quad\;\; y(k) = Cx(k) \end{cases}$$

However:

$A = \begin{bmatrix} A_m & o_m^T \\ C_m A_m & 1 \end{bmatrix}$ $\quad B = \begin{bmatrix} B_m \\ C_m B_m \end{bmatrix}$ $\quad$ C=$[o_m \quad 1]$ $\quad x(k) = \begin{bmatrix} \varDelta x_m(k) \\ y(k) \end{bmatrix}$

This final formulation is called the augmented model.

The next step is the calculus of the predicted system's output by using the values of the future control sequence as adjustable variables. This prediction must be defined inside an optimization window. Let's assume being at time k_j with an optimization window of length Np. At time k_j the state $x(k_j)$ is measurable for the definition of the problem. The control sequence is denoted by:

$$\varDelta u(k_j), \varDelta u(k_j+1), \ldots, \varDelta u(k_j + Nc - 1)$$

Nc is the control horizon, and it defines the number of control actions to be calculated. Np instead is the prediction horizon, and it defines the number of state predictions.

In the problem's analysis they will be settled Nc=Np=4. Note that when the remaining time steps on the horizon are less then Nc, following the shrinking horizon principle the value of Np and Nc is fixed equal to the remaining time steps on the horizon.

For example, as reported in [17] in a situation with a window of 10-time steps, and with a control horizon of n=3, MPC operates until time instant 7 with an unchanged control horizon =3, then the n value decreases as in figure 5-11:

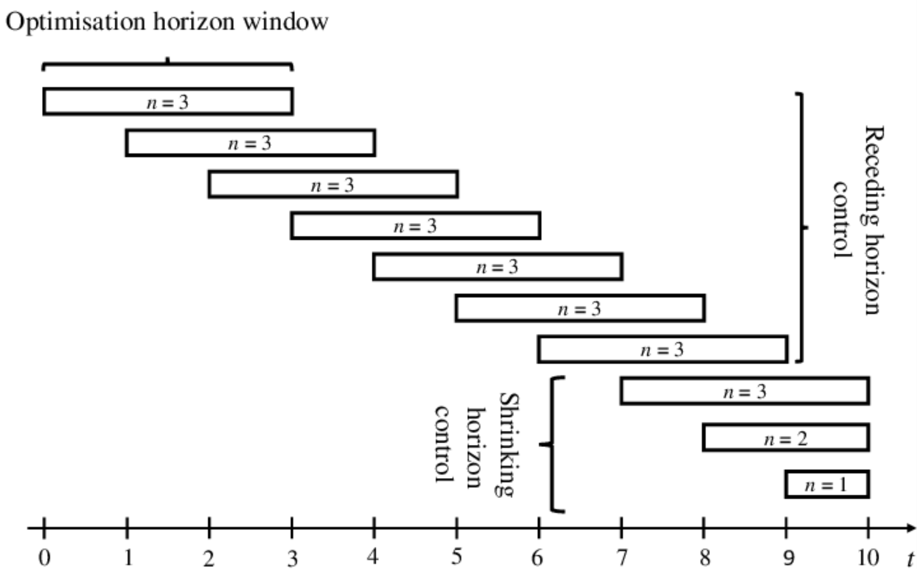

Figure 5-11: Hybrid receding-shrinking horizon control scheme, with a maximum horizon length of 3. [17]

In the thesis' case with Np=Nc=4 the same hybrid Receding/Shrinking horizon is followed. Therefore, when the time instant 6 is reached, the MPC changes its prediction and control horizons to follow the shrinking horizon principle.

Going back to the state space manipulations, the state predictions at time k_j will be:

$$x(k_j + 1 \,|k_j), x(k_j + 2 \,|k_j), \ldots, x(k_j + Np|k_j)$$

In detail we can calculate:

$$x(k_j + 1 \,|k_j) = Ax(k_j) + B\Delta u(k_j)$$

$$x(k_j + 2|k_j) \ = \ Ax(k_j + 1|\, k_j) + B\Delta u(k_j + 1)$$

$$= \ A^2 x(k_j) \ + \ AB\Delta u(k_j) \ + \ B\Delta u(k_j + 1)$$

$$\dots\dots$$

$$x(k_j + Np|k_j\,) \ = A^{Np} x(k_j) + A^{Np-1} B\Delta u(k_j) + A^{Np-2} B\Delta u(k_j + 1)$$

$$+ \dots + A^{Np-Nc} B\Delta u(k_j + \ Nc - 1)$$

For the predicted output values the same process can be followed:

$$y(k_j + 1 \,|k_j) = CAx(k_j) + CB\Delta u(k_j)$$

$$y(k_j + 2|k_j) = CA^2 x(k_j) + CAB\Delta u(k_j) + CB\Delta u(k_j + 1)$$

$$y(k_j + 3|k_j) = CA^3 x(k_j) + CA^2 B\Delta u(k_j) + CAB\Delta u(k_j + 1)$$

$$+ CB\Delta u(k_j + 2)$$

$$\dots$$

$$y(k_j + Np|k_j) = CA^{Np} x(k_j) + CA^{Np-1} B\Delta u(k_j) + CA^{Np-2} B\Delta u(k_j + 1)$$

$$+ \dots + CA^{Np-Nc} B\Delta u(k_j + \ Nc - 1).$$

The following vectors can be defined:

$$Y = [\ y(k_j + 1\,|k_j) \quad y(k_j + 2|k_j) \quad y(k_j + 3|k_j) \quad \dots \quad y(k_j + Np|k_j)\ ]^T \text{(5-9)}$$

$$\Delta U \ = \ [\Delta u(k_j) \quad \Delta u(k_j + 1) \quad \Delta u(k_j + 2) \quad \dots \quad \Delta u(k_j + Nc - 1)\ ]^T \ \text{(5-10)}$$

Utilizing (5-9,5-10) the plant's output can be finally written as:

$$Y \ = \ Fx(k_j) \ + \ \Phi\Delta U$$

Where:

$$F = \begin{bmatrix} CA \\ CA^2 \\ CA^3 \\ \dots . \\ CA^{Np} \end{bmatrix}; \qquad \Phi = \begin{bmatrix} CB & 0 & 0 & \dots & 0 \\ CAB & CB & 0 & \dots & 0 \\ CA^2B & CAB & CB & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ CA^{Np-1}B & CA^{Np-2}B & CA^{Np-3}B & \dots & CA^{Np-1}B \end{bmatrix}$$

Those F and Φ matrices will be also useful in the definition of the constraints of the problem because of the augmented model.

5.4.2. MPC's objective function

In a predictive control system, considering a set-point signal $r(k_j)$ at sample time k_j, the goal is to minimize the difference between the predicted output and the set-point signal within a prediction horizon. To achieve this objective, the design aims to find an optimal control vector ΔU. This vector is determined by minimizing an error function between the set-point and the predicted output, ultimately seeking the best possible match.

Let's assume that the vector of data which contains the information of the reference is:

$$R_s^T = [1\ 1\ 1 \dots 1]r\left(k_j\right)$$

The cost function J is defined as:

$$J = (Rs - Y)^T(Rs - Y) + \Delta U^T \bar{R} \Delta U$$

The first term of the cost function is linked to the target of minimize the distance in between the set-point signal and the predicted output, while the second term reflects the consideration given to ΔU. $\bar{R}$ is a diagonal matrix defined as $\bar{R} = r_\omega I_{NcxNc}$.

r_ω is a tuning parameter fixed to 0.001 in our problem and it is responsible for the closed-loop performance.

The target of MPC is to find the optimal ΔU that will minimize J, where J is:

$$J = (R_s - Fx(k_j))^T\ (R_s - Fx(k_j)) - 2\Delta U^T \Phi^T\ (R_s - Fx(k_j)) + \Delta U^T\ (\Phi^T \Phi + \bar{R})\Delta U.$$

5.4.3. MPC's constraints

The peculiarity of MPC is the fact that it accepts constraints on the state and on the control variable, but how to consider them in the augmented system? It can be said that:

$$\Delta u_{min} \leq \Delta u(k) \leq \Delta u_{Max}$$
$$\Delta x_{min} \leq \Delta x(k) \leq \Delta x_{Max}$$
$$y_{min} \leq y(k) \leq y_{Max}$$

Where:

$$\Delta U_m = \begin{bmatrix} \Delta u_{min} \\ \Delta u_{min} \\ \Delta u_{min} \\ \dots. \\ \Delta u_{min} \end{bmatrix}; \qquad \Delta U_M = \begin{bmatrix} \Delta u_{Max} \\ \Delta u_{Max} \\ \Delta u_{Max} \\ \dots. \\ \Delta u_{Max} \end{bmatrix};$$

$$X_m = \begin{bmatrix} \Delta x_{min} \\ \Delta x_{min} \\ \Delta x_{min} \\ \dots. \\ \Delta x_{min} \end{bmatrix}; \qquad X_M = \begin{bmatrix} \Delta x_{Max} \\ \Delta x_{Max} \\ \Delta x_{Max} \\ \dots. \\ \Delta x_{Max} \end{bmatrix};$$

$$Y_m = \begin{bmatrix} y_{min} \\ y_{min} \\ y_{min} \\ \dots \\ y_{min} \end{bmatrix}; \qquad Y_M = \begin{bmatrix} y_{Max} \\ y_{Max} \\ y_{Max} \\ \dots \\ y_{Max} \end{bmatrix};$$

$$Y(k) = \begin{bmatrix} y(k+1) \\ y(k+2) \\ \dots \\ y(k+N-1) \\ y(k+N) \end{bmatrix};$$

It is important to keep in mind that we are operating in a MISO situation.

Therefore, the dimension of Δu_{min}, Δu_{Max}, Δx_{min}, Δx_{Max} is Nx1, while y_{min} and y_{Max} are 1x1.

5.4.4. The final MPC formulation

As a recap of the last theory steps, reported also in [16], the final formulation of the problem is the following:

State space representation:

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) \\ y(k) = Cx(k) \end{cases}$$

Where:

$$A = \begin{bmatrix} A_m & o_m^T \\ C_m A_m & 1 \end{bmatrix} \quad B = \begin{bmatrix} B_m \\ C_m B_m \end{bmatrix} \quad \text{C}=[o_m \quad 1] \quad x(k) = \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix}$$

With the objective of:

$$\min_u J = (R_s - Fx(k_j))^T \, (R_s - Fx(k_j)) - 2\Delta U^T \Phi^T \, (R_s - Fx(k_j)) + \Delta U^T \, (\Phi^T \Phi + \bar{R})\Delta U$$

Subjected to:

$$X_m \le X(k) \le X_M$$
$$U_m \le U(k) \le U_M$$
$$Y_m \le Y(k) \le Y_M$$

Being formulated like this, the problem is a quadratic programming one, which can be solved with MATLAB quadratic programming tools.

5.5. MPC MATLAB application

Quadratic programming (QP) involves the optimization of an objective function while considering bounds, linear equality, and inequality constraints. It is a mathematical problem that aims to find a vector x that minimizes or maximizes a quadratic function:

$$\min_{x}\{\frac{1}{2}x^T Hx + f^T x\}$$

Subject to the constraints:

- $Ax \leq b$ (Inequality constraint)
- $Aeqx = beq$ (Equality constraint)
- $lb \leq x \leq ub$ (Bound constraint)

In MATLAB quadratic programming is performed through the function:

$$\varphi = quadprog(H, f, A, b, Aeq, beq, lb, ub)$$

It has already been said that the objective of the MPC problem is to find the optimal ΔU that will minimize J, where J is:

$$J = \left(R_s - Fx\left(k_j\right)\right)^T (R_s - Fx(k_j)) - 2\Delta U^T \Phi^T (R_s - Fx(k_j)) + \Delta U^T\ (\Phi^T \Phi + \bar{R})\Delta U$$

The corresponding values of H and f would be:

$$H = 2 * (\Phi^T \Phi + \bar{R}) \qquad\qquad f = 2 * \Phi^T\ (R_s - Fx(k_j))$$

The first term of the objective function is excluded because it does not depend on the vector ΔU. Notice that the problem's control variable is Δu(k) and the state is x(k), so all the constraints must be elaborated to be coherent with this formulation.

The constraints which have to be inserted in this last study are:

a) The battery of EV_i can be used only for the negotiated portion X_i
b) At the end of the day the SOC level of EV_i must be equal to the initial one plus the negotiated payment Y_i

The first constraint can be written as a constraint on the output value. Let's assume that once each X_i is decided the SOC value of each vehicle i cannot exceed the boundaries:

$$SOC_i(0) - \frac{X_i}{2} \leq SOC_i \leq SOC_i(0) + \frac{X_i}{2} \qquad \rightarrow \qquad Y^{min} \leq SOC_i \leq Y^{Max}$$

Where $SOC_i(0)$ it is the vehicle's i initial SOC value.

The (b) constraint instead, dictates that:

$$SOC_i(10) = SOC_i(0) + Y_i$$

Notice that this constraint is seen by the MPC starting from a distance of Nc but inserting the constraint at the 9th time instant is simpler and it has the same effect.

The constraints, to be implemented in MATLAB must have a matrix formulation like:

$Ax \leq b$ (Used for constraints of type (a))

$Aeqx = beq$ (Used for constraints of type (b))

Starting from the inequalities, they can be written as:

$$Y^{min} \leq Fx(k_j) + \Phi \Delta U \leq Y^{Max}$$

Which is the same as writing:

$$\begin{cases} \Phi \Delta U \leq Y^{Max} - Fx(k_j) \\ -\Phi \Delta U \leq Y^{min} + Fx(k_j) \end{cases}$$

So, it is simple to build matrix A and vector b:

$$A = \begin{bmatrix} \Phi\Delta U \\ -\Phi\Delta U \end{bmatrix}; \qquad \text{b}=\begin{bmatrix} Y^{Max} - Fx(k_j) \\ Y^{min} + Fx(k_j) \end{bmatrix};$$

Through this constraint it is assured the used of maximum X_i kWh on the battery of EV_i.

By following what said before on constraint (b) at every time instant k different from the 9th one Aeq is a zero matrix with dimensions (N*Nc)x(N*Nc) and beq is a null vector of dimensions (N*Nc)x1.

Only when the time reaches the 9th hour (on a 10-hour working day) the first N elements on Aeq's diagonal become equal to 1. The same happens for the first N elements of beq which instead take the value:

$$beq(1,1) = x_1(0) + Y_1 - (2 * (x_1(8) + u_1(8)) - x_1(8))$$

$$beq(2,2) = x_2(0) + Y_2 - (2 * (x_2(8) + u_2(8)) - x_2(8))$$

……………………………………………

$$beq(N,N) = x_N(0) + Y_N - (2 * (x_N(8) + u_N(8)) - x_N(8))$$

It's important also to model the shrinking horizon principle and so include MATLAB instruction for the shrinking of the control and prediction horizons when the number of remaining steps to calculate is lower than 4.

By utilizing these constraints and instructions the problem can be formulated for the N=3 case, the results are reported in the following chapter 5.6.

5.6. Simplified N=3 energy surplus scenario's results

Let's now focus on the energy surplus scenario with N=3. The MPC with receding horizon strategy produces the following results:

- Let's start with the MPC which works at 8:00 with the initial predictions:

In the figure 5-12 the three different plots represent respectively:

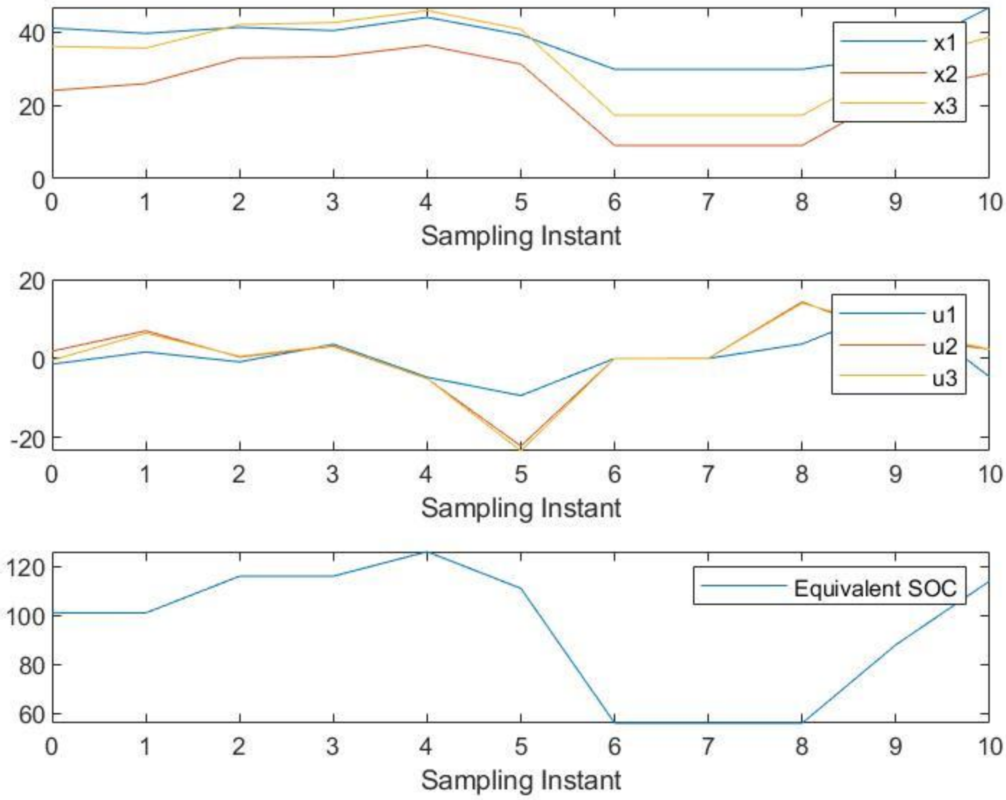

Figure 5-12: MPC results at 8:00

- The forecasted profile of the SOC the vehicles EV1, EV2, EV3
- the predicted control sequence which contains the control variables of each EV at every time instant
- the equivalent battery forecasted profile.

The three predictions are generated through receding horizon strategy, which is applied on all the 10-hour working window seeking robustness with respect to the uncertainties of the power forecasts. This because if from hour 9:00 the power forecasts are not available the process would follow the calculations performed at

8:00. Moreover, considering all the complete window assures the respect of the constraint on the final value.

Let's recall the final outputs of the negotiation:

	U1	U2	U3
X (kWh)	22.502	30.002	37.502
Y (kWh)	5.6706	4.753	2.5698

As it can be seen in figure 5-12 the SOC level of each vehicle respects the constraints imposed in the negotiations and by the MPC, which were:

- The initial SOC value is coherent referring to the ones fixed for the N=3 case (EV1→41 kWh, EV2→24 kWh, EV3→36 kWh).
- The difference in between two subsequent states is never greater than 25 kWh, nor smaller than – 25 kWh, which is the maximum energy delivered by the charging stations.
- The final state of the EVs is equal to the initial state plus the respective promised payment (EV1→46.67, EV2=28.75, EV3=2.57)
- The SOC value of each EV never exceeds the boundaries (5-11) imposed by the negotiation:

$$SOC_i(0) - \frac{X_i}{2} \leq SOC_i(k) \leq SOC_i(0) + \frac{X_i}{2} \quad (5\text{-}11)$$

$$\rightarrow 29.75 \leq SOC_1 \leq 52.25$$

$$\rightarrow 9 \leq SOC_2 \leq 39$$

$$\rightarrow 17.25 \leq SOC_3 \leq 54.75$$

The predicted SOC profile of the equivalent battery is similar to the one generated by the negotiation, but it is not equal because that the negotiation didn't consider the uncertainties and the constraints of the maximum usage of the vehicle's battery imposed by the X_i.

Proceeding with the receding horizon principle one should obtain the desired results, however the forecasts that were imposed in chapter 4.1 are such that the initial SOC value of the vehicles at hour h is different to the one predicted at the previous time instant, so the "initial" SOC value is far from the optimal one, because of the uncertainty of the prediction at hour h-1. This can be solved by applying a receding horizon technique in which it is implemented not only the first element of the command sequence, but also the second one. In this way the next plots are obtained:

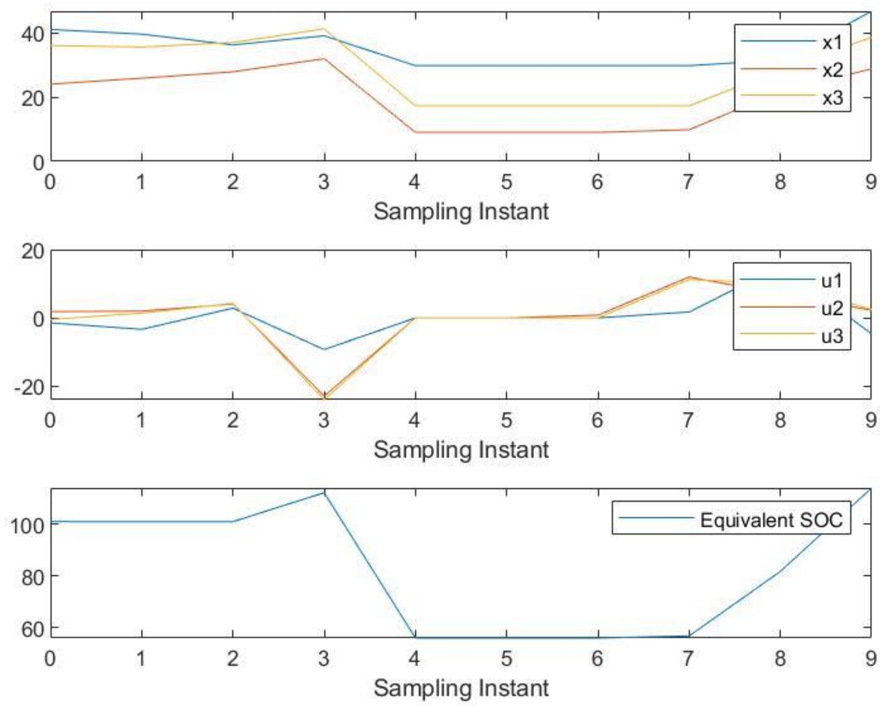

Figure 5-13: MPC results at 9:00

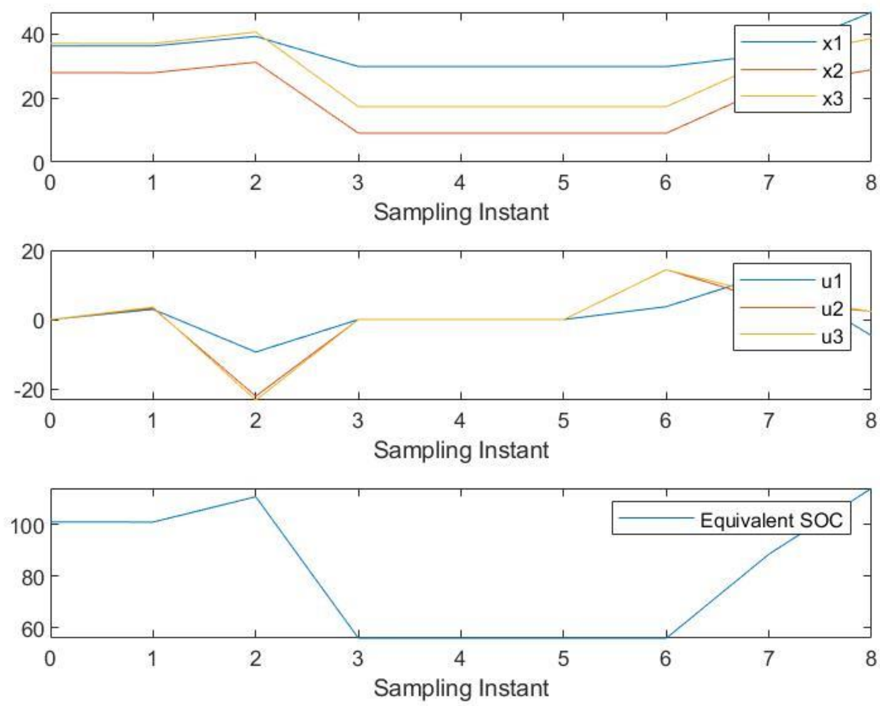

Figure 5-14:MPC results at 10:00

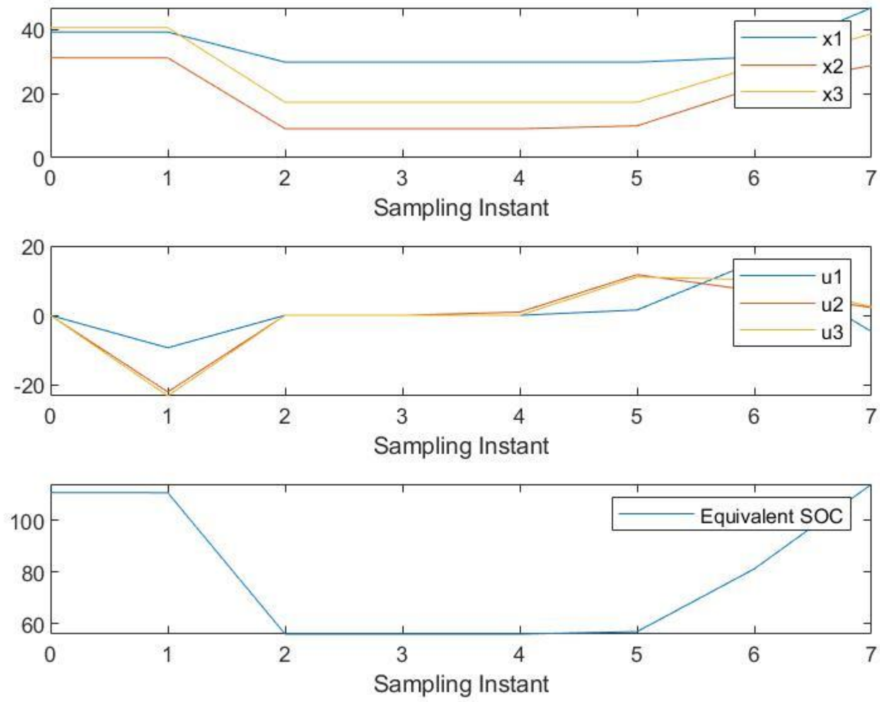

Figure 5-15: MPC results at 11:00

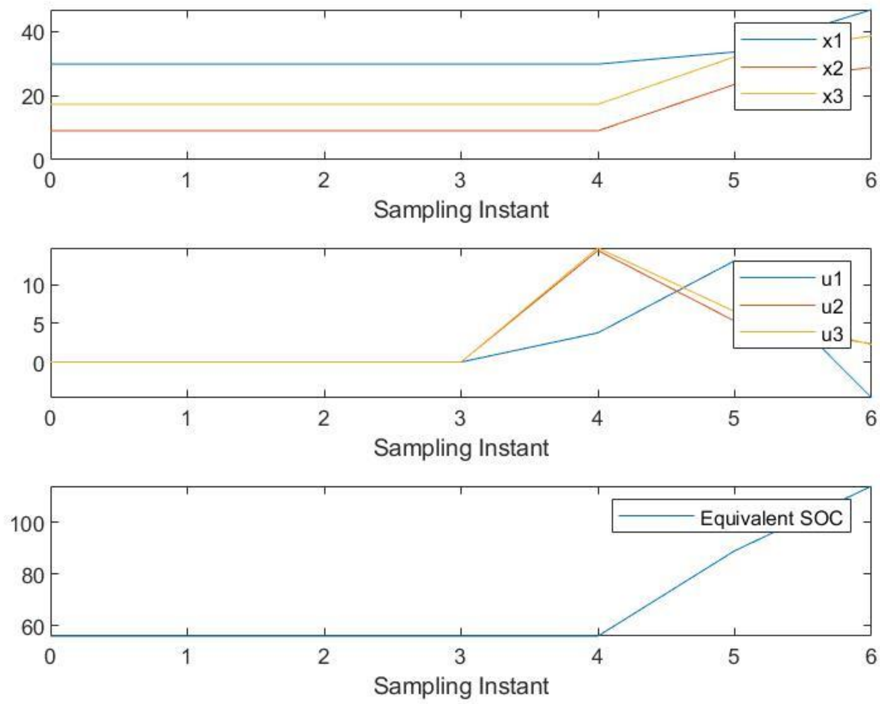

Figure 5-16: MPC results at 12:00

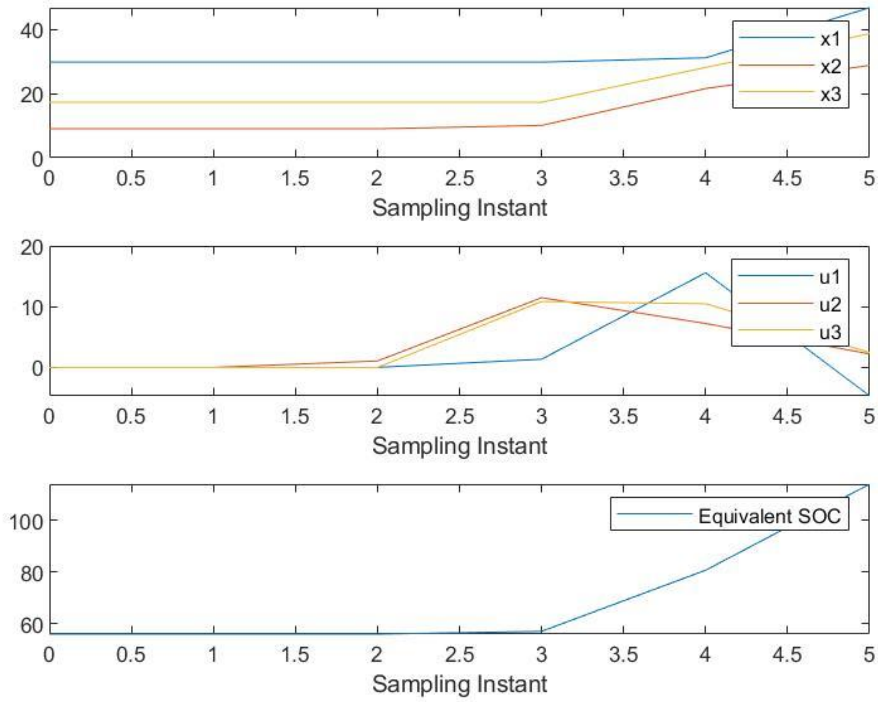

Figure 5-17:MPC results at 13:00

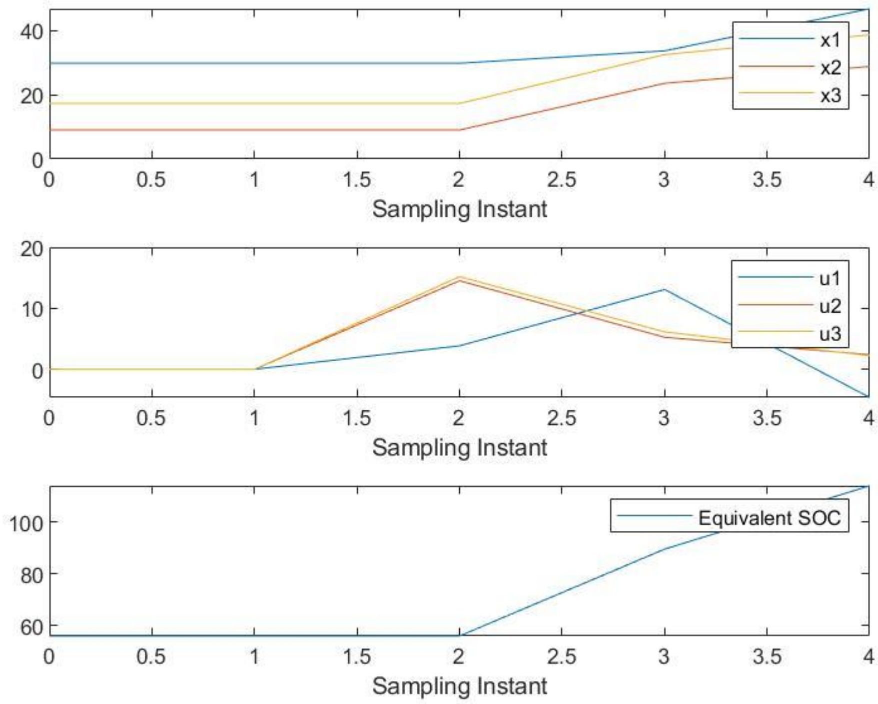

Figure 5-18:MPC results at 14:00

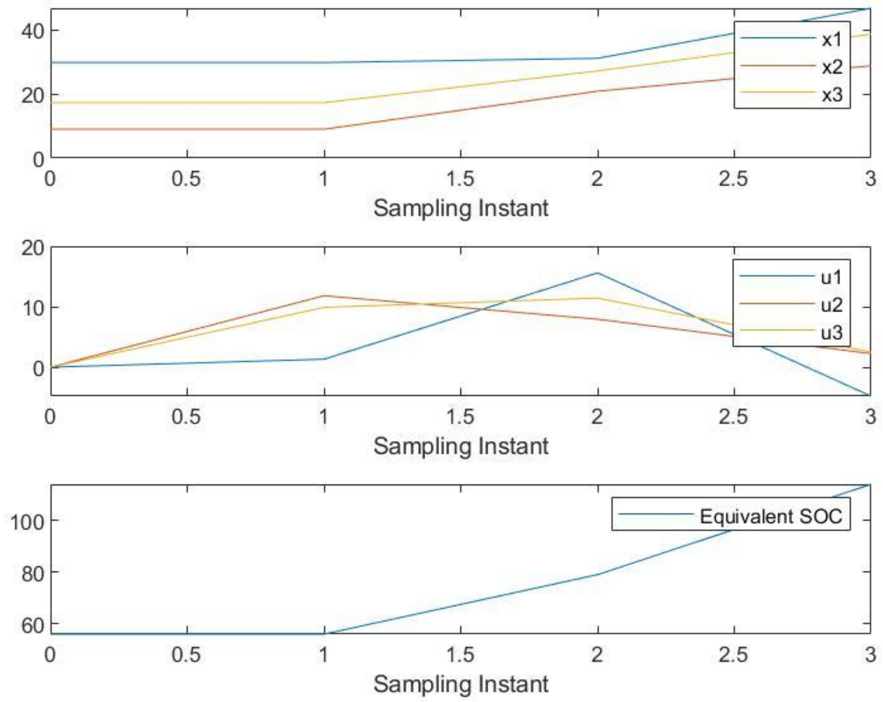

Figure 5-19:MPC results at 15:00

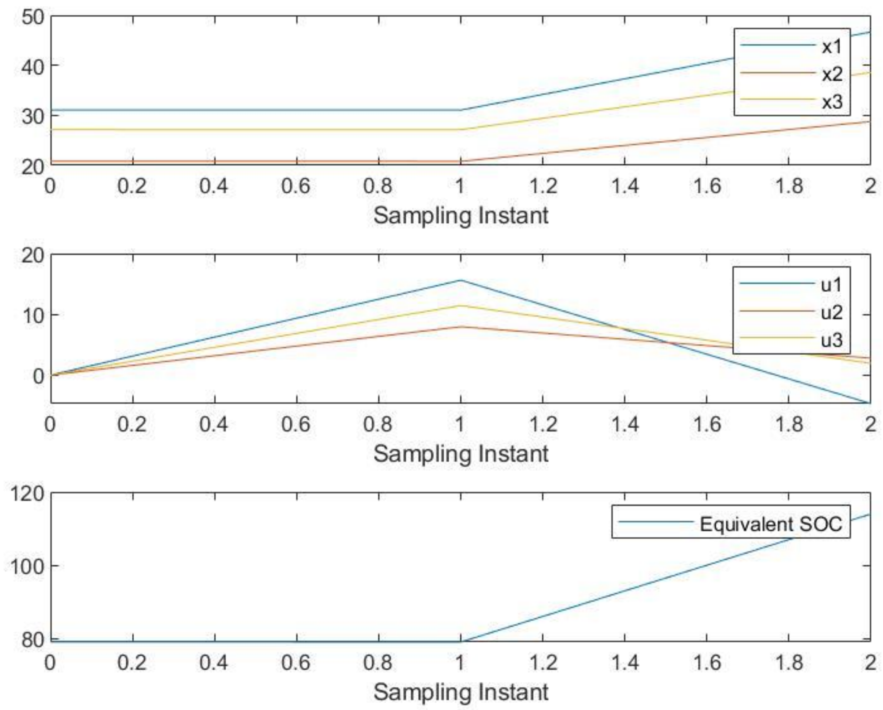

Figure 5-20: MPC results at 16:00

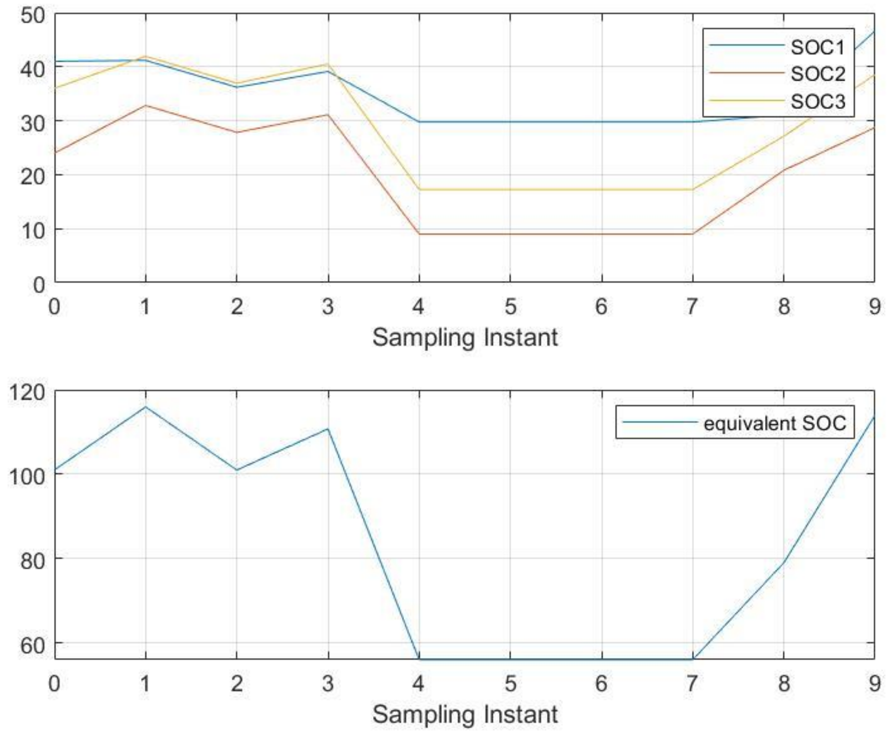

Figure 5-21: Final Receding Horizon results

5.7. Final comments on N=3 energy surplus scenario

Figure 5-21 reports the final profile of the SOC of each EV and the SOC profile of the equivalent battery. As it can be seen it respects all the constraints imposed in the previous chapter demonstrating the effectiveness of the full algorithm, starting from the negotiation to the MPC with receding/shrinking horizon.

MPC with the hybrid receding/shrinking horizon strategy was a perfect choice for the problem because it allowed to the optimal division of the optimal equivalent SOC profile in every EV. Moreover, the usage of MPC reduced drastically the complexity of the formulation of the problem, which could be also solved by linear optimization but the number of the variables of the constraints would be enormous.

It is easy also to calculate via some mathematical operations the bought/sold energy management:

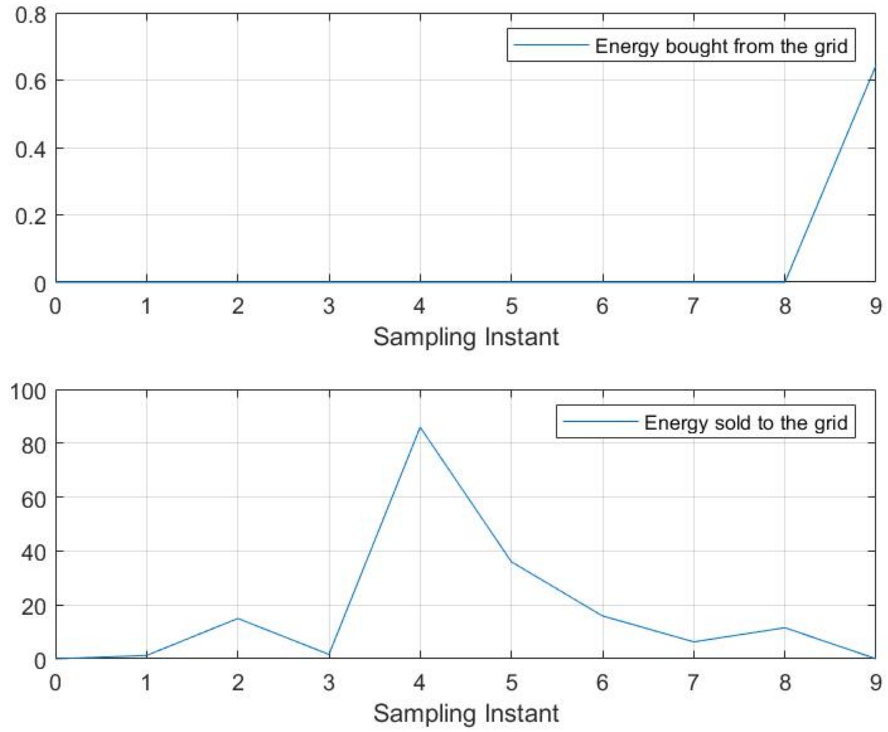

Figure 5-22: Final energy management

By applying the lr and lv rates, the revenue of the sold energy during the day is equal to 19.33 €, while the cost of the bought energy is 0.13€. In the end the total revenue would be of 19.20€. If the full algorithm was not used the revenue would only be of 16.55€.

Obviously by increasing the values of the study such as the number of users and setting more convenient rates the income of this scenario increases drastically. However, also by using these simple values the problem results are the same: an optimal energy management and the single optimal SOC profiles are obtained, providing more incomes and less outcomes.

6 Testing

To ensure the effectiveness and robustness of the algorithm outlined in Chapter 5, it is crucial to conduct testing. Initially, it is beneficial to generate different scenarios of power generation and consumption to evaluate the algorithm's performance and robustness in different conditions. This includes establishing values for a "deficit" scenario, where the energy generation is lower with respect to consumption, as well as a "mixed deficit/surplus" scenario, where the energy generation fluctuates between deficits and surpluses. By examining the algorithm's behaviour in these scenarios, its ability to handle varying energy dynamics can be assessed.

Furthermore, the testing target can be expanded by increasing the number of vehicles, denoted as N, and correspondingly scaling up the dimensions of the power profiles. This enables an evaluation of how the algorithm scales with a larger fleet of electric vehicles and assesses how the computational times vary in more demanding scenarios. So, by analysing the algorithm's response under increased vehicle count and larger power profiles, the system's scalability and adaptability can be tested.

Another crucial aspect of testing involves exploring the algorithm's tolerance for uncertainty in energy generation forecasts. It is important to examine the algorithm's behaviour when subjected to escalating levels of uncertainty in the energy predictions. By gradually increasing the uncertainty values, the algorithm's ability to adapt and make optimized decisions in the presence of greater unpredictability can be evaluated. This provides insights into the algorithm's robustness and reliability under varying levels of forecast accuracy.

Through comprehensive testing encompassing diverse power scenarios, increased vehicle counts, and augmented uncertainty levels, a comprehensive understanding of the algorithm's capabilities and limitations can be obtained. This iterative testing approach allows for refinements and improvements to be made to ensure the algorithm's efficiency, effectiveness, and adaptability in managing charging profiles and optimizing energy utilization within the V2G system.

6.1. N=3 deficit scenario

Let's define a deficit scenario simply by inverting the values of the predictions of generated and consumed power. The first powers forecast at 8:00 will be:

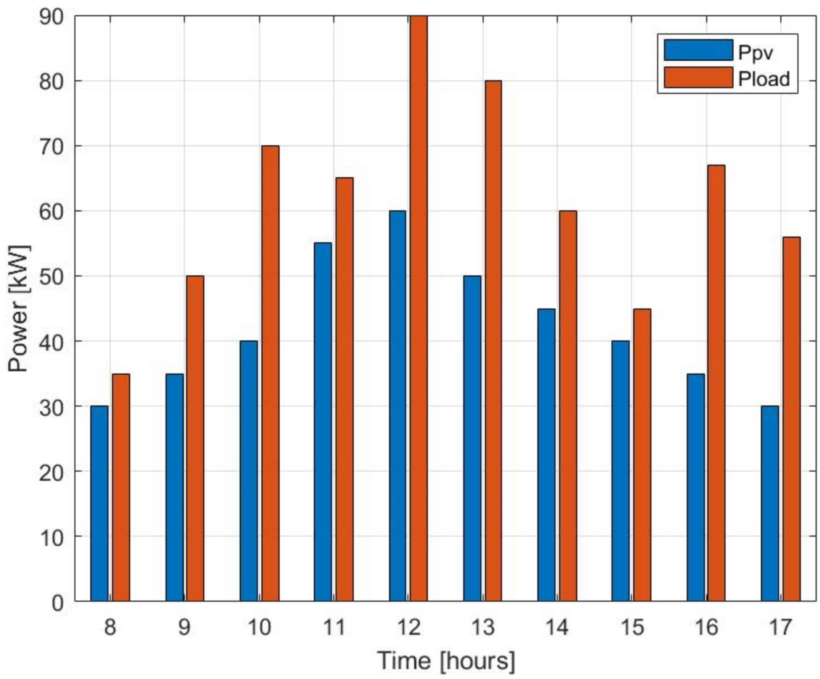

Figure 6-1: Power profiles in deficit scenario forecasted at 8:00

In every time instant the power consumed is higher than the generated one, logically the algorithm should provide an energy management in which energy is stored when its cost is low and used when its cost is high. The energy rates remain the same as the surplus scenario:

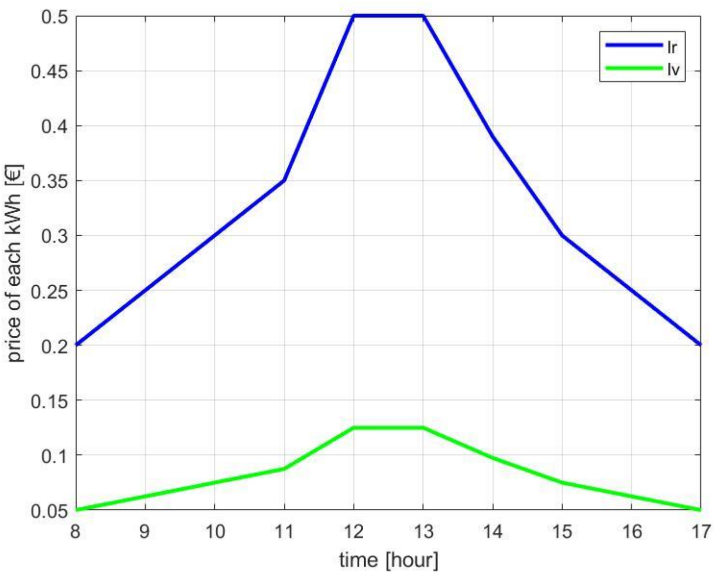

Figure 6-2: Energy rates

Also, the users are modelled in the same way they were modelled for the surplus scenario.

The negotiation, after 7 cycles sets the following results:

- The users' payment and requested storage are:
  Eneed=97.5 kWh; Expected cost=48.8384€;

Table 6-1: Negotiation's final results deficit scenario

	U1	U2	U3
X (kWh)	25	32.5	40
Y (kWh)	6	5.5453	2.5084

- The initial optimal SOC profile of the equivalent battery is:

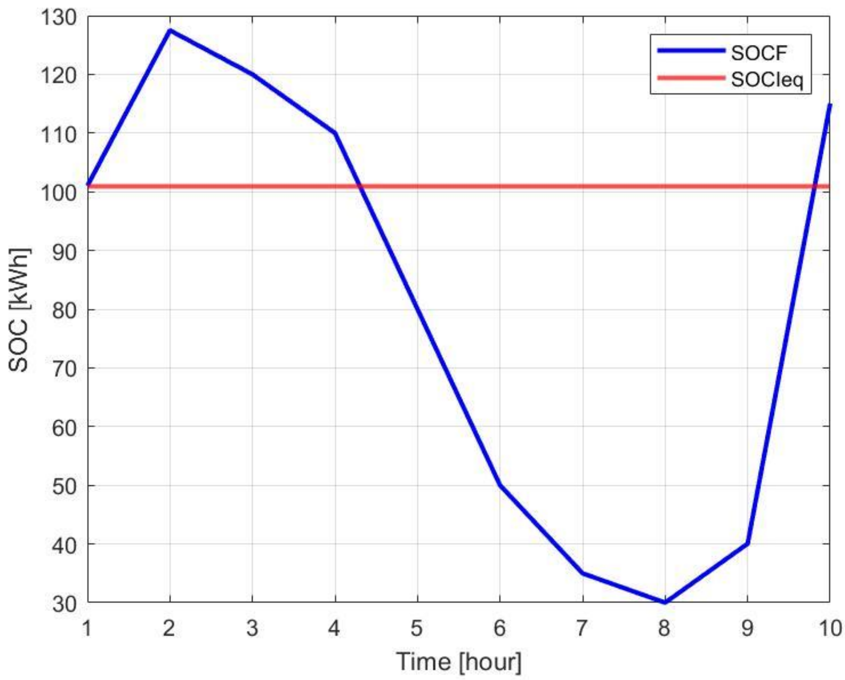

Figure 6-3: Optimal SOC profile generated at 8:00 in deficit scenario.

As expected, the equivalent battery is charged at the beginning and at the end of the day when the energy rates are cheaper.

Then through the work of the MPC and of the SOC updating optimizer we obtain the following results:

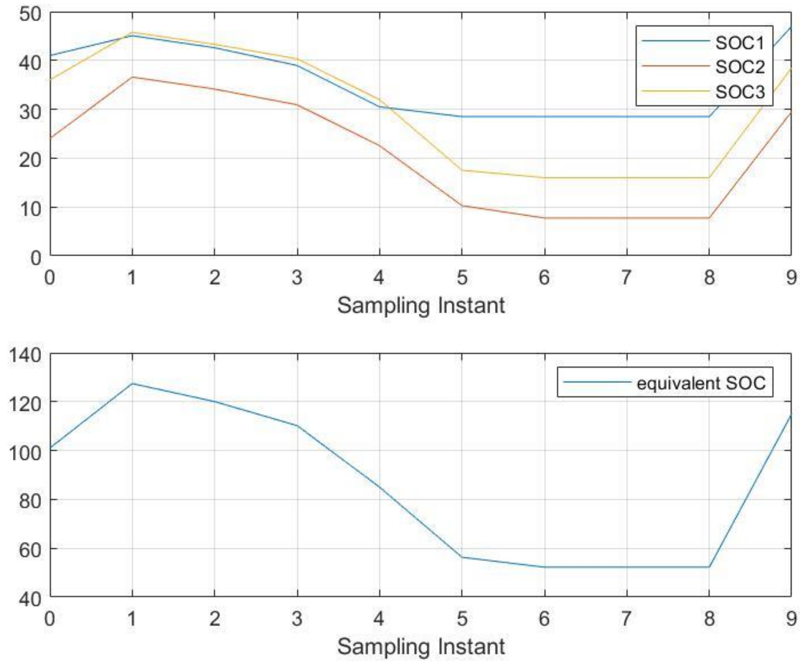

Figure 6-4: Final SOC profiles with MPC utilizing RH in deficit scenario.

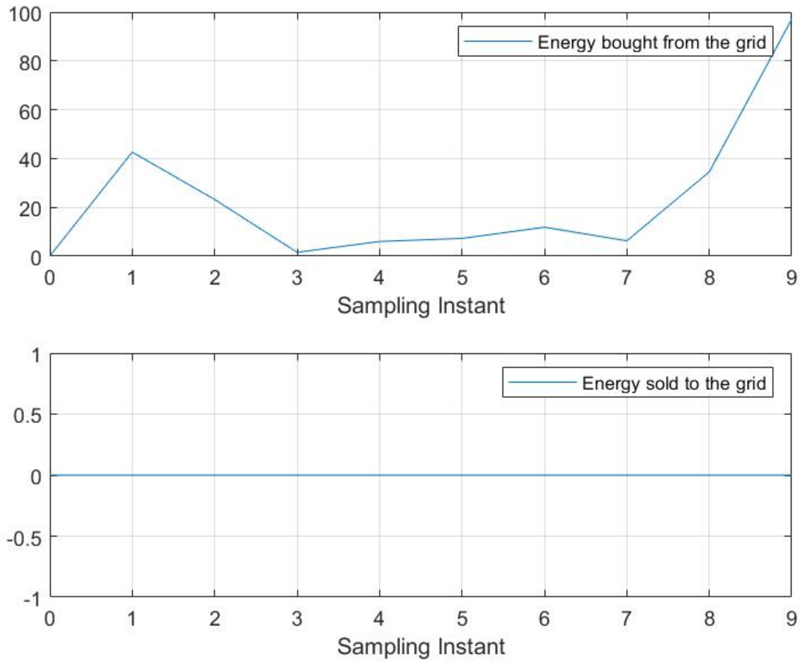

Figure 6-5: Final energy management in deficit scenario.

6.1.1. Comments on the N=3 deficit scenario results

The SOC profile for each individual EV is effectively distributed, ensuring that all the constraints for each vehicle are satisfied. However, the energy management aspect is primarily influenced by the energy purchased from the grid. As anticipated, all the energy generated is consumed promptly at the time of its production.

In the absence of the algorithm, the energy procured from the grid would amount to a cost of 75.41 €. However, by leveraging the comprehensive algorithm described in the thesis, the cost is significantly reduced to 59.39€. It is important to note that the final cost exceeds the expected value at 8:00, which was estimated at 48.8384€. This discrepancy can be attributed to the impact of uncertainties, which cause the cost to escalate by almost 10€.

Despite the deficit situation, the algorithm has demonstrated its ability to function optimally, achieving favorable outcomes. It effectively manages the SOC profiles of individual EVs and ensures compliance with their respective constraints. Moreover, the algorithm enables efficient energy utilization, resulting in substantial cost savings. These results emphasize the algorithm's efficacy and its capability to handle challenging scenarios, making it a valuable tool for energy optimization within V2G systems.

6.2. N=3 mixed deficit/surplus scenario

Let's define a mixed surplus/deficit scenario in which the first powers forecast at 8:00 will be:

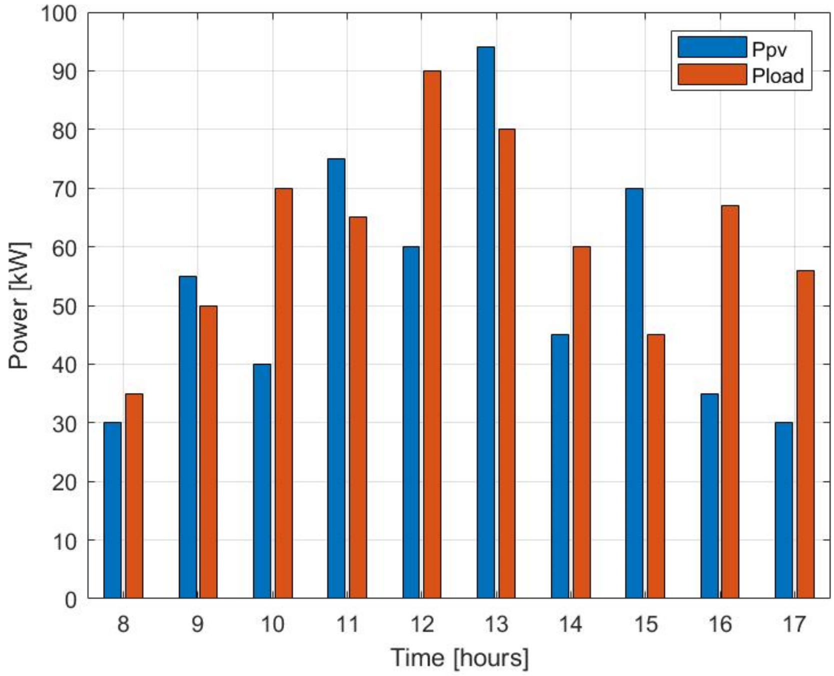

Figure 6-6: Power profiles at 8:00 in mixed scenario

The energy rates remain the same as the surplus scenario:

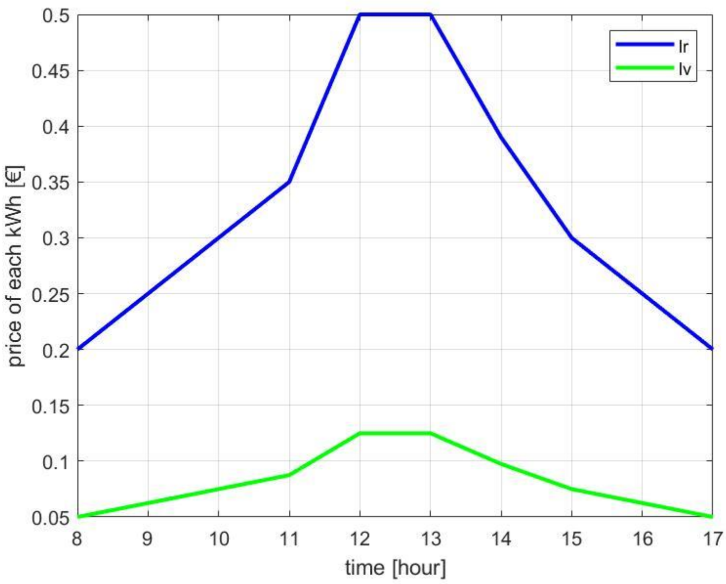

Figure 6-7: Energy rates

The users are modelled in the same way they were modelled for the surplus scenario.

The negotiation, after 11 cycles fixes the values:

- The users' payment and requested storage are:
  Eneed= 60.718 kWh; Expected cost= 18.3436€.

Table 6-2: Negotiation's results mixed scenario.

	U1	U2	U3
X (kWh)	12.739	20.239	27.739
Y (kWh)	3.2103	2.1271	2.3804

- The initial optimal SOC profile of the equivalent battery is:

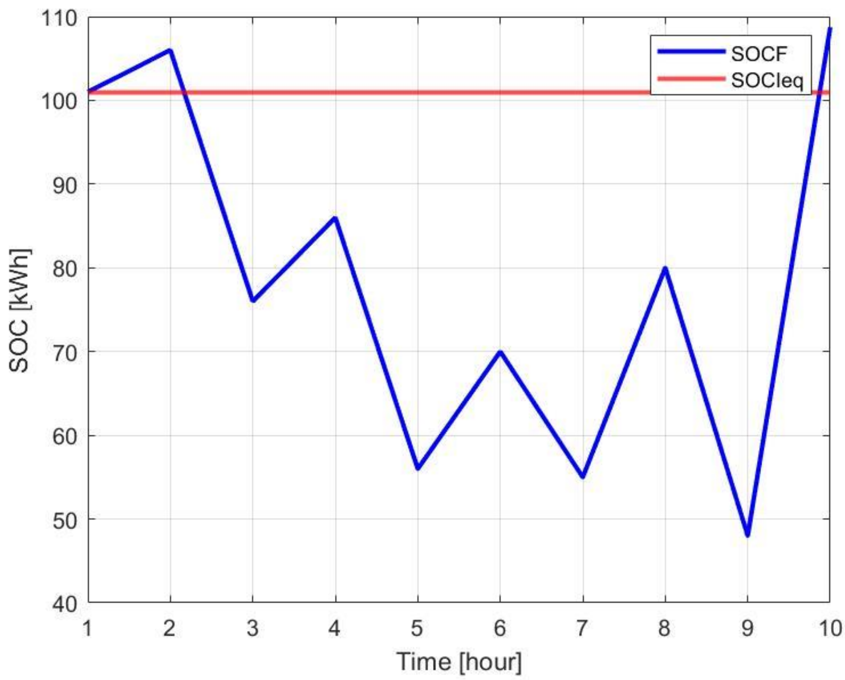

Figure 6-8: Optimal SOC profile at 8:00 in mixed scenario.

The equivalent battery's SOC profile reacts to the fluctuations of deficit/surplus generating this profile in which charges and discharges continuously alternate.

Then through the work of the MPC and of the SOC updating optimizer we obtain the following results:

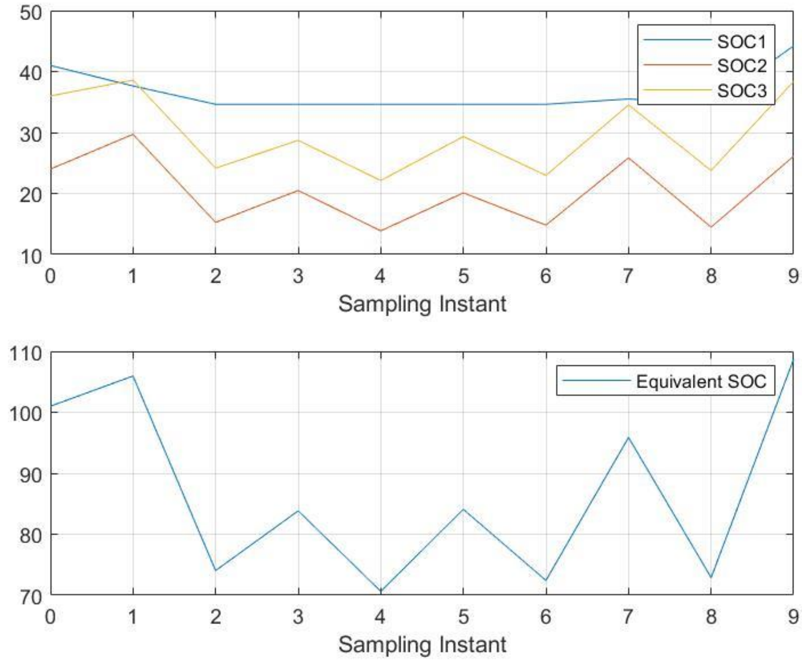

Figure 6-9:MPC results in mixed scenario.

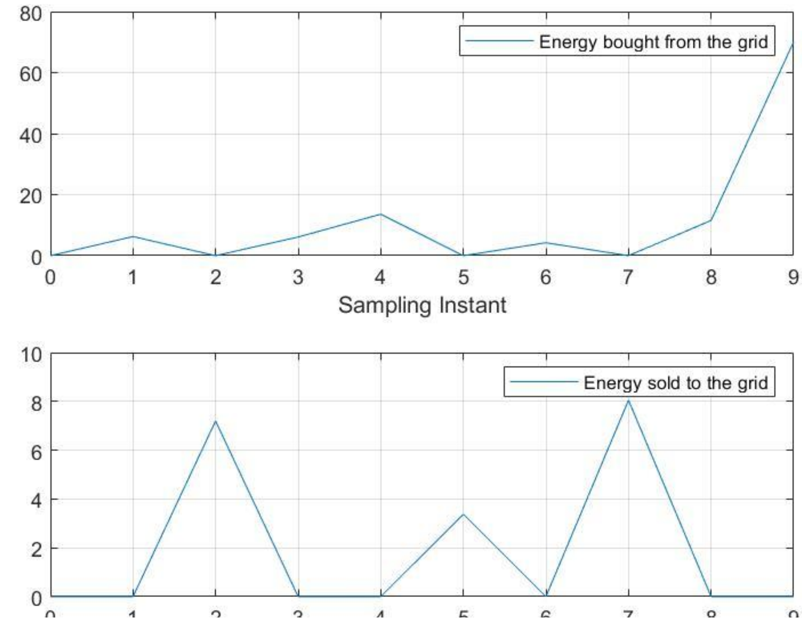

Figure 6-10: Final energy management in mixed scenario.

6.2.1. Comments on the results

The SOC profiles for each individual EV demonstrate a well-divided allocation, ensuring that all the constraints for each EV are satisfactorily met. Among the EVs, EV1 exhibits a more relaxed behavior since it has tighter constraints, while EV2 and EV3 closely follow the fluctuations of the power profiles. This distinction arises from the greater available capacity in their batteries, which the MPC can effectively utilize.

The energy management strategy aligns with the SOC profiles, facilitating the buying and selling of energy as deemed convenient. Without the implementation of the algorithm, the energy purchased from the grid would have a cost of 41.68€, considering also the revenue from sold energy. However, by utilizing the full algorithm proposed in the thesis, the cost is significantly reduced to 26.28€.

These findings highlight the algorithm's ability to function optimally even in fluctuating scenarios. It successfully manages the SOC profiles of individual EVs, ensuring compliance with constraints, and dynamically adapts the energy management strategy to maximize efficiency. By significantly reducing the energy cost through intelligent decision-making, the algorithm demonstrates its effectiveness contributing to the optimization of V2G systems.

6.3. N=10 surplus scenario

Building upon the foundation of the surplus scenario with N=3 vehicles, it becomes intriguing to expand the system by increasing the number of vehicles to N=10. This expansion necessitates the enlargement of the entire N=3 scenario, starting from the power profiles themselves. For instance, the power profiles can be multiplied by a factor of 4 to accommodate the larger fleet. This scaling adjustment results in a more comprehensive and intricate plot that captures the dynamics of the system with the increased vehicle count.

This leads to the following figure 6-11:

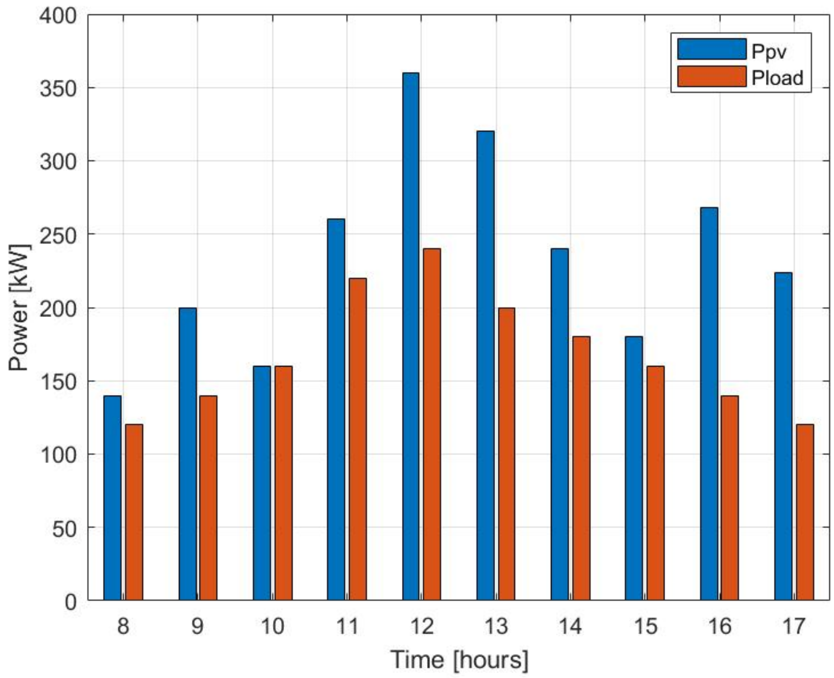

Figure 6-11: Power profiles forecasted at 8:00 in N=10 case

As mentioned earlier, the energy profiles can be derived from the N=3 scenario by multiplying the PV power generation (Ppv) and the load power consumption ($Pload$) by a factor of 4. This scaling allows us to simulate a larger-scale scenario while maintaining the same characteristics and trends observed in the smaller scenario.

The energy rates remain the same, changing them would not add further complexity to the problem.

The negotiation's outputs, after 11 cycles are:

- The users' payment and requested storage are:

$$Eneed = 367\ kWh; \qquad Expected\ revenue = 154.0974€.$$

Table 6-3: N=10 negotiation's results

	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10
X(kWh)	10	35	60	46.2	21.2	46.2	71.2	46.2	21.2	10
Y(kWh)	2.5	6.43	2.92	2.33	5.33	11.2	3.03	2.33	5.33	1.79

- The initial optimal SOC profile of the equivalent battery is:

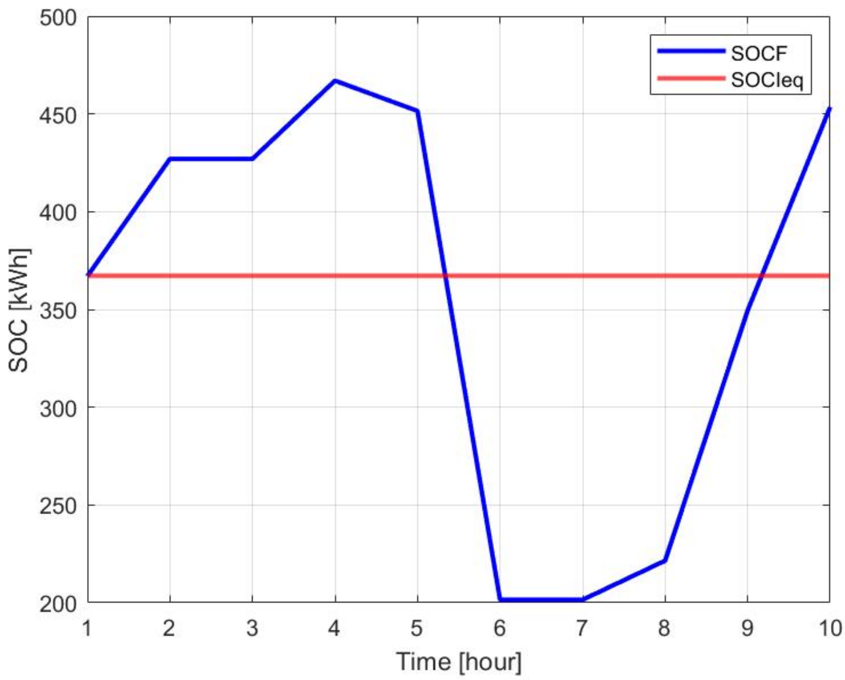

Figure 6-12: Optimal SOC at 8:00 for N=10 case

It can be noticed that the plot is equal to the N=3 scenario with augmented amplitude.

The MPC computes the next values:

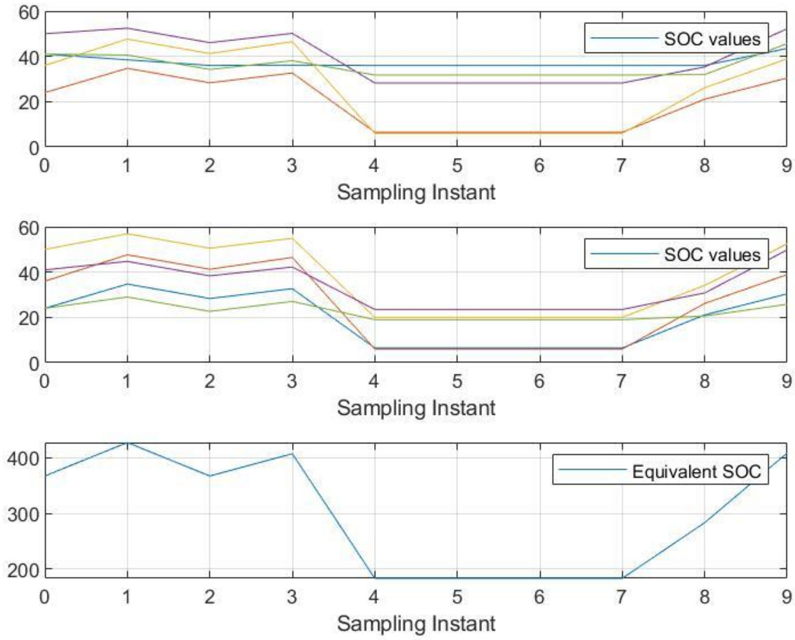

Figure 6-13: MPC results for N=10 case

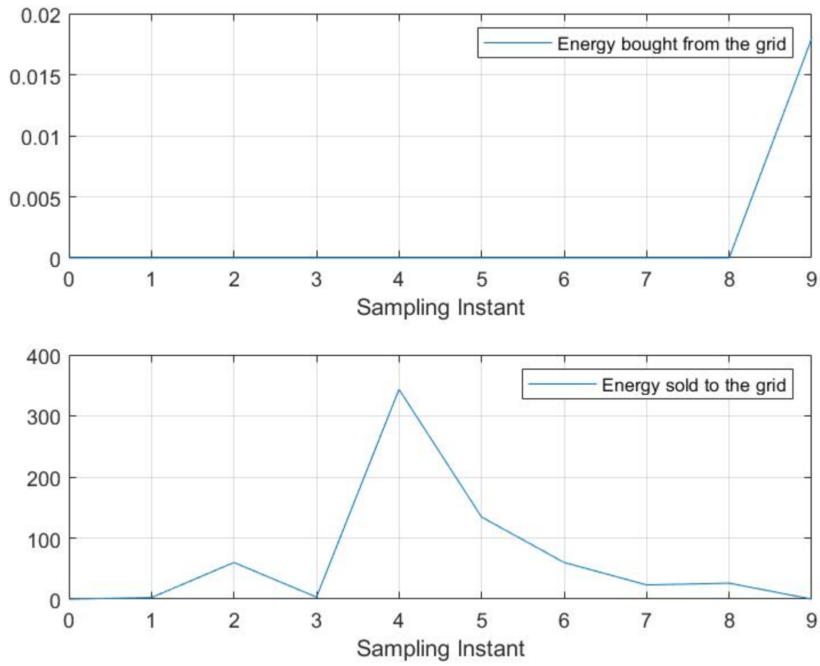

Figure 6-14: Final energy management for N=10 case

6.3.1. Comments on the results

Since the number of the users was too big to have a clear vision, the figure 6-13 plot was divided into two subplots, one containing the final SOC profiles of users from 1 to 5 one containing the profiles of users 6 to 10.

The algorithm's performance in this extended scenario remains effective in achieving the desired outcomes.

However, it is worth noting that there is a slight difference in computational times compared to the N=3 case. This disparity is not attributed to the Model Predictive Control (MPC) algorithm itself, which operates swiftly, but rather to the negotiation algorithm. With a greater number of users, the negotiation algorithm requires slightly more time to identify the optimal offers for each participant.

The negotiation algorithm utilizes linear programming, which, due to the increased number of decision variables and constraints, imposes a higher computational load on MATLAB compared to the MPC algorithm. As a result, the computational time for the extended scenario is approximately 15 seconds, doubling the time required for the N=3 case.

While the current computational times are within reasonable limits, there is potential for improvement in future iterations of the algorithm. By optimizing the implementation of the negotiation algorithm or exploring alternative algorithms, it may be possible to reduce the computational time and enhance the efficiency of the overall solution.

Nonetheless, it is important to emphasize that the slightly increased computational times do not compromise the effectiveness or reliability of the algorithm. The algorithm remains a valuable tool for managing and optimizing V2G operations in an industrial environment, providing insightful solutions that maximize the benefits for both the company and the participating EV owners.

6.4. N=50 "Mixed" Scenario

Let's increase again the number of the users, and coherently the amplitude of the power profiles. By applying the algorithm to a scenario in which N=50 the power profiles of the N=3 "mixed deficit/surplus" case can be multiplied for a factor of 20 to be consistent with the number of the EVs. The following power profiles at hour 8:00 are obtained:

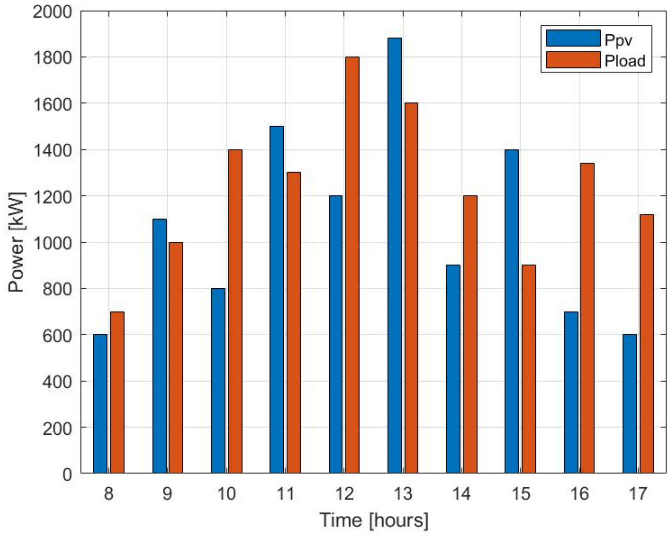

Figure 6-15: N=50 power profiles forecasted at 8:00

In this case 50 users are created with random variables, however all these variables are coherent with the assumptions formulated in Chapter 3. The equivalent battery's SOC profile calculated by the negotiation optimizer at 8:00 is:

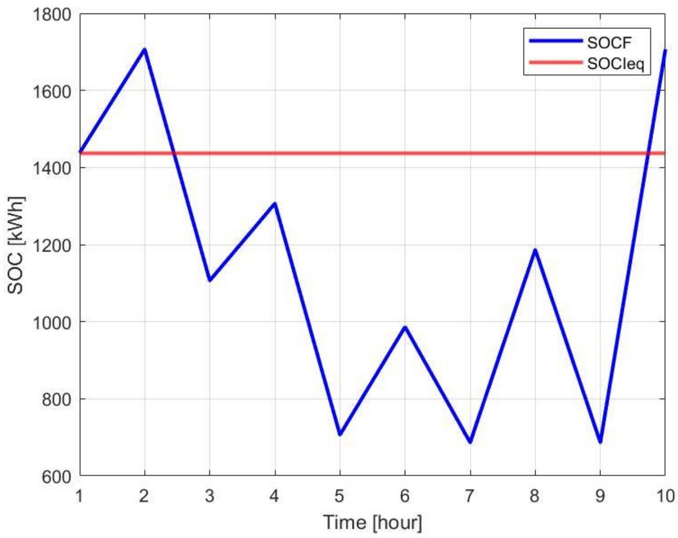

Figure 6-16: Equivalent battery's optimal SOC profile calculated at 8:00

The MPC effectively manages also in this case the division of the equivalent battery's SOC profiles into the single EV SOC profiles, generating these plots:

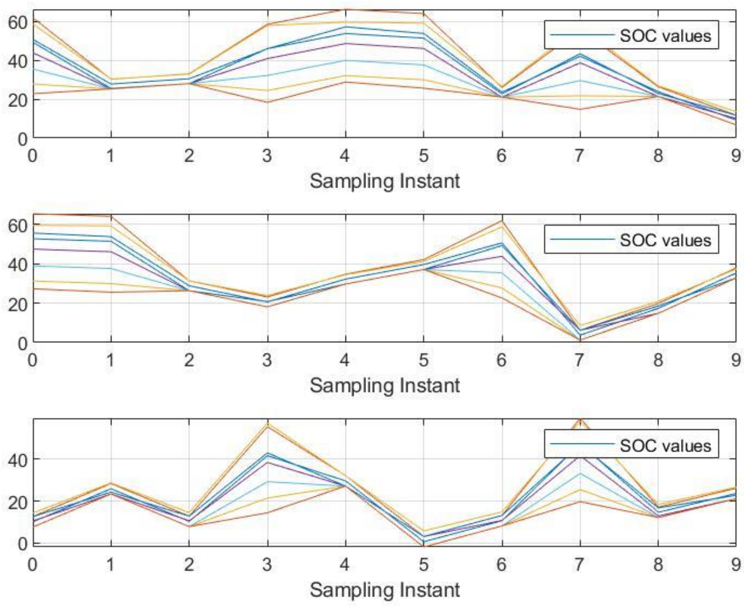

Figure 6-17: Result SOC profiles of vehicles 1-30

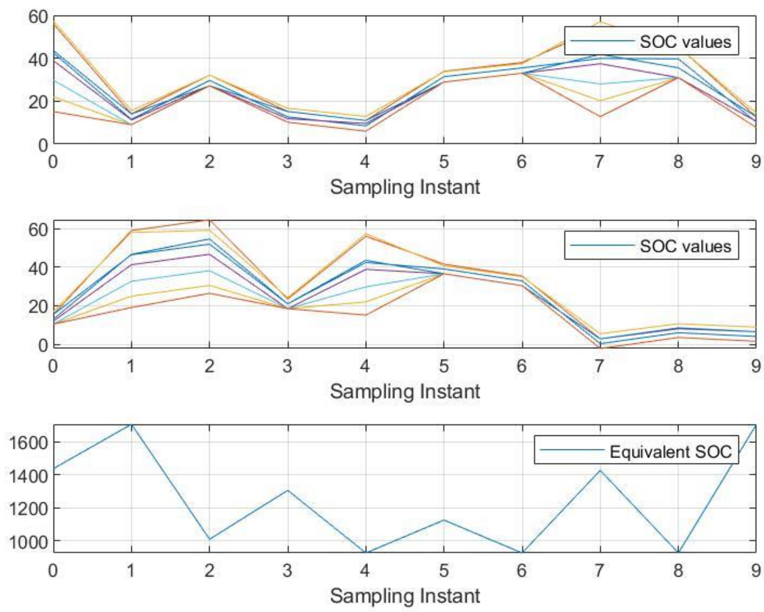

Figure 6-18: Result SOC profiles of vehicles 31-50 and of the equivalent battery

Instead, the energy management operated by MPC during the day is the one in figure 6-19:

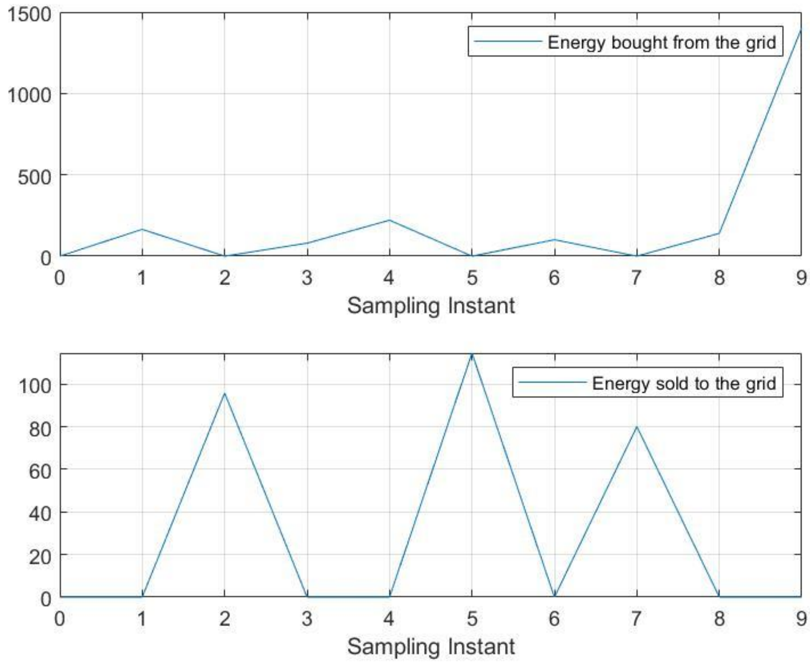

Figure 6-19: Final energy management for N=50 case

6.4.1. Comments on N=50 results

After the N=10 case the testing of the algorithm continued also with the N=50 case. This test aimed to assess the scalability and performance of the algorithm under more demanding conditions.

As expected, the computational time increased proportionally with the number of users. However, it is crucial to highlight that despite the longer computational times, the efficiency and effectiveness of the algorithm remained unchanged. The algorithm successfully managed the complex decision-making process and delivered optimal solutions for V2G operations, even with larger user populations.

By maintaining the energy rates fixed for the N=3 case, the algorithm permits a saving of almost 40€ with respect to a situation in which it is not applied.

The results of these tests demonstrated the algorithm's robustness and capability to handle industrial-scale scenarios with a significant number of participants. While the computational time may continue to increase as the number of users grows, the fundamental efficiency and reliability of the algorithm were not compromised.

6.5. N=100 “deficit” scenario

As an ultimate proof of the effectiveness of the algorithm it’s useful to report also the results of a computationally expensive scenario in which N=100. Setting a situation of energy deficit, the negotiation converges with an agreement of all the users in 12 cycles. The single EVs SOC profiles are managed by the algorithm in this way:

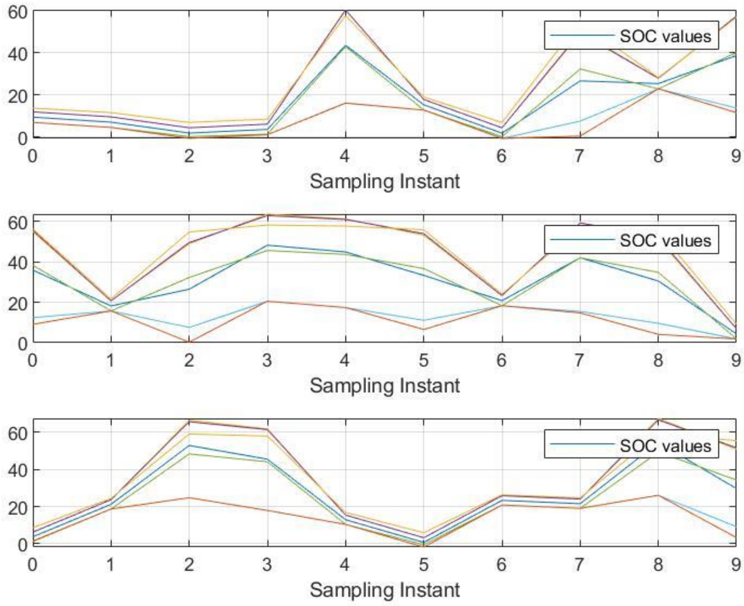

Figure 6-21: N=100 SOC profiles of EVs 1-30

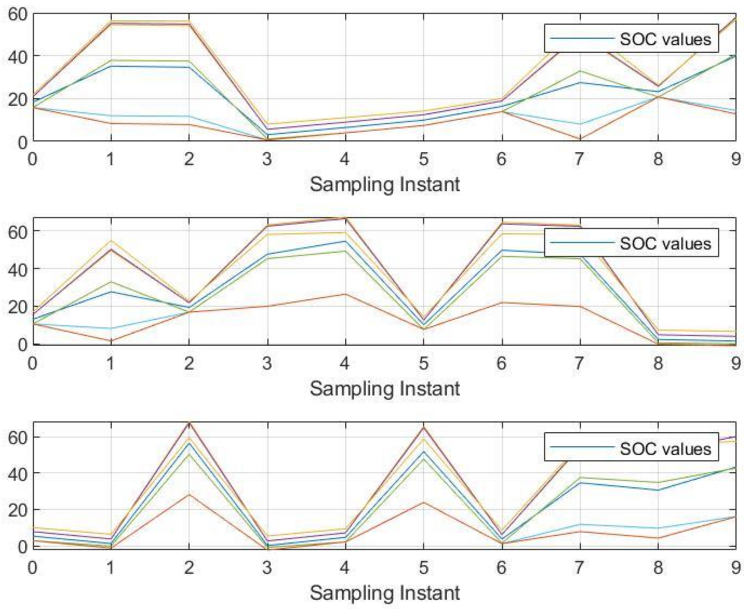

Figure 6-20: N=100 SOC profiles of EVs 31-60

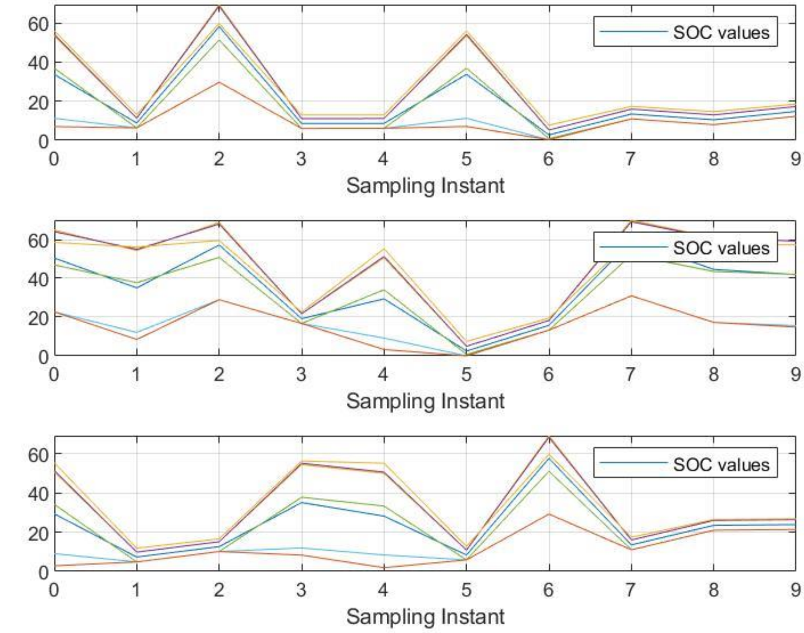

Figure 6-23: N=100 SOC profiles of EVs 61-90

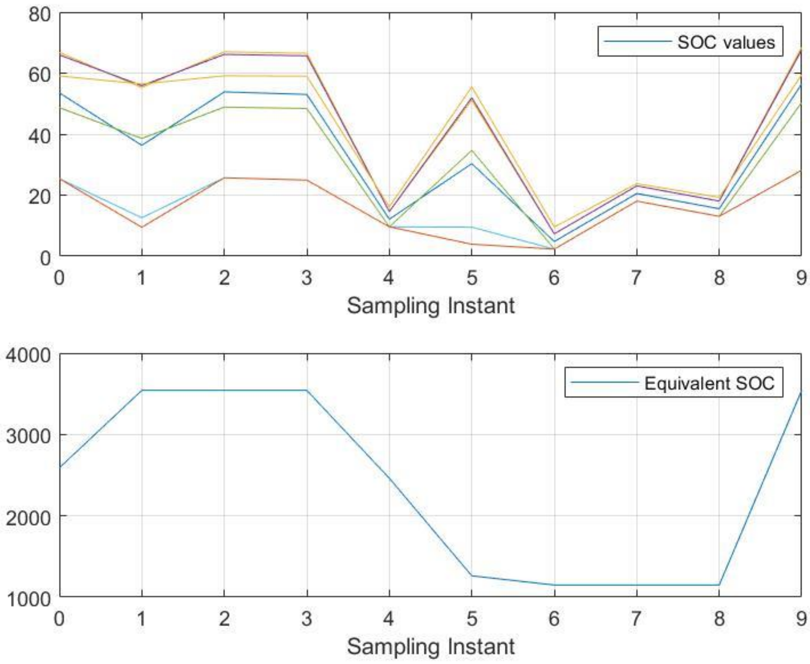

Figure 6-22 N=100 SOC profiles of EVs 91-100 and of the equivalent battery.

The algorithm performs well also with this great value of N. The computational times are around 30s due to the high number of the decision variables both in negotiation and in the MPC. The energy cost utilizing the algorithm amounts to 2345€ instead of 2852€.

6.6. N=3 with variable uncertainties

In addition to the aforementioned tests, there is another fundamental aspect to explore: the algorithm's capability of handling increased uncertainties in power generation and consumption forecasts. As outlined in chapter 4.1, these uncertainties are modelled using an uncertainty index denoted as β, which was fixed to the value 0.02.

The key question is: How does this uncertainty index β impact the computation of optimal State of Charge profiles of the equivalent battery performed by the SOC updating optimizer? Moreover, what is the threshold value of β beyond which the computation becomes infeasible?

Investigating these aspects is useful to evaluate the algorithm's ability to adapt and provide reliable solutions under varying levels of uncertainty in power forecasts. The uncertainty index β serves as a measure of the uncertainty magnitude, influencing the adjustment of the equivalent SOC profiles to accommodate these uncertainties.

By increasing systematically the value of β, it can be observed how the algorithm responds and how the results change. This analysis sheds light on the algorithm's ability to handle higher levels of uncertainty and provides insights into the practical limitations.

Furthermore, the determination of the upper limit of β, if present, is a critical aspect to consider. This threshold signifies the point beyond which the algorithm's performance may deteriorate, making the computation of equivalent SOC profiles impractical or unreliable. Identifying this limit will contribute to defining the algorithm's operational boundaries and guiding decision-making regarding acceptable levels of uncertainty in power forecasts.

Understanding the relationship between the uncertainty index β and its impact on the computation of optimal equivalent SOC profiles is vital for assessing the algorithm's practicality and reliability in real-world scenarios. By thoroughly investigating this aspect, we can gain valuable insights into the algorithm's performance under varying degrees of uncertainty, enabling informed decision-making and ensuring the algorithm's successful application in practical industrial environments.

6.6.1. Search of the β limit in N=3 surplus scenario

Let's set the pseudocode of an algorithm for an iterative test:

Algorithm 2 β test algorithm:

Set β=0.05
Run the full algorithm
while β **<=2 do**
β= β+0.05
Run the full algorithm
end while

A comprehensive series of tests was conducted to investigate the impact of changing the uncertainty index β on the algorithm's performance. These tests yielded insightful findings regarding the behaviour of the equivalent battery's SOC profiles of the vehicles as β was varied.

As β increased, a noticeable effect on the final single SOC values of the EVs calculated by the Model Predictive Control (MPC) algorithm was observed. Specifically, the SOC profiles of the vehicles became flatter and smoother compared to the profiles generated with β=0.02.

As the uncertainty index β increased, the fluctuations in power generation and consumption forecasts had a more pronounced impact on the energy trading dynamics between the vehicles and the grid. The algorithm cleverly adjusted the sold and bought energy profiles to accommodate the heightened uncertainties, effectively absorbing the excess variability introduced by higher β values.

Tests were conducted until a β value of 2 which means extremely wrong predictions (an uncertainty of 200% only for the prevision with position index=1), limit over which it is not realistic to study.

In figure 6-20 and figure 6-21 are reported the results of a test with β=1.5. In this test the variability of the prediction is very high, it is an unrealistic situation.

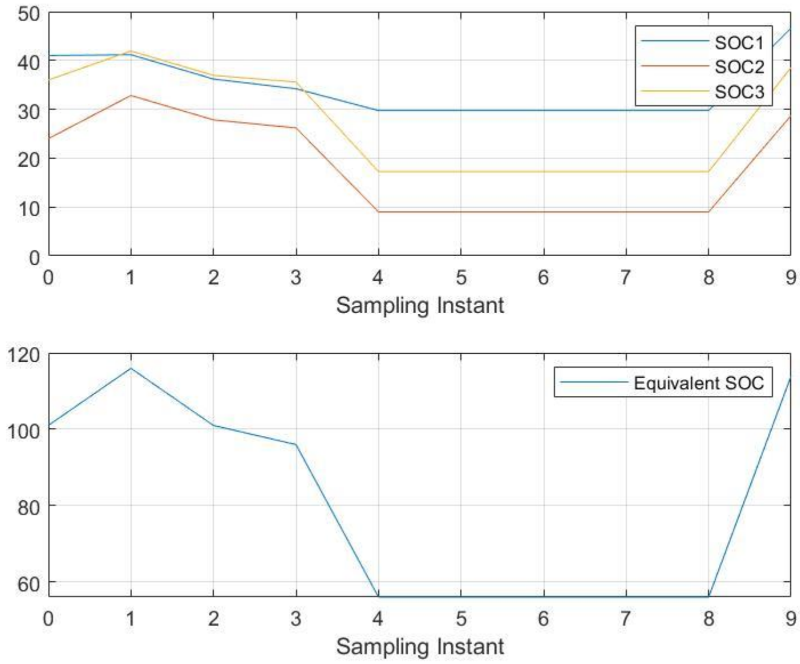

Figure 6-24: β=1.5 MPC results

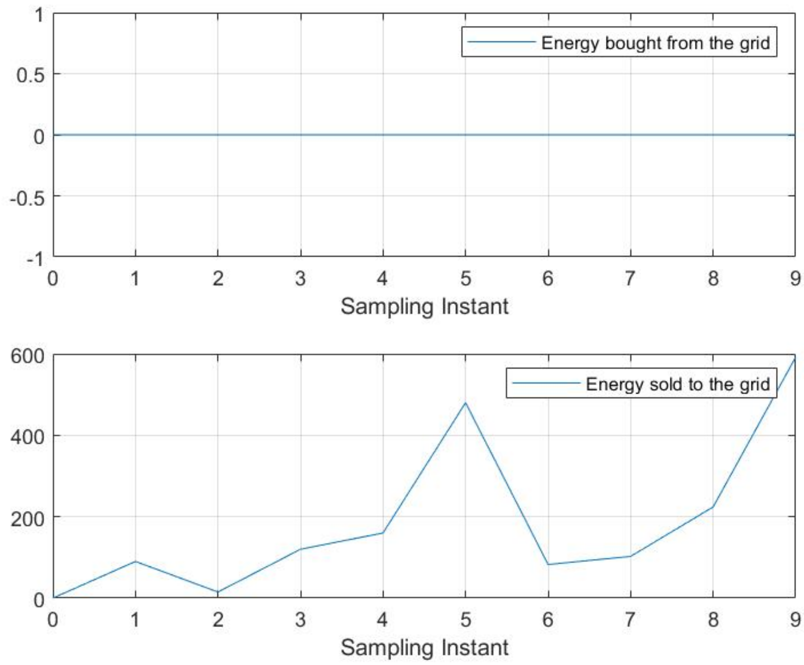

Figure 6-25: β=1.5 energy management

As said before the profiles of the SOC values of the EVs are smoother with respect to the N=3 β=0.02 scenario. This may be due to the fact that the sign of the uncertainties is depending on the index of the prediction, so it is varying alternatively in between two subsequent predictions.

In the quest to determine the upper limit of β, it was found that the algorithm did not yield a definitive threshold (under β=2). This outcome is attributed to the algorithm's adaptability and ability to counteract variations by adjusting the profiles of sold and bought energy. This finding highlights the algorithm's versatility, as it can operate effectively under diverse uncertainty conditions and consistently provide optimal solutions.

This discovery is particularly significant for the algorithm's practical applicability. It demonstrates that the algorithm is capable of handling a wide range of uncertainty levels, ensuring reliable and efficient V2G operations in industrial environments.

7 Economic analysis of performed tests

It is interesting to look at the economic results of the application of the thesis' algorithm Let's consider the tests in chapter 6 and let's perform other ones. The economic results of all those tests are reported in table 6-4.

Table 7-1: Economic analysis

Scenarios:	**Bought energy cost [€]**	**Sold energy revenue [€]**	**Total revenue(+) / cost(-) [€]**	**Revenue(+) / Cost(-) without the algorithm [€]**	**Profit due to the use of algorithm**
N=3 surplus	0	+18.3	+18.3	+14.7	19.6%
N=3 deficit	-59.39	0	-59.39	-75.41	21.2%
N=3 mixed	-29.05	+1.57	-27.48	-41.68	34%
N=10 surplus	0	+148	+148	+124.6	15.8%
N=10 deficit	-216.9	0	-216.9	-285.2	23.9%
N=10 mixed	-119.73	+20.64	-99.09	-137.12	27.7%
N=50 surplus	0	+674.86	+674.86	+623.1	7.7%
N=50 deficit	-1178	0	-1178	-1426	17.4%
N=50 mixed	-539	+57	-482	-685.6	29.6%
N=100 surplus	0	+1373	+1373	+1246	9.24%
N=100 deficit	-2345	0	-2345	-2.852	17.7%
N=100 mixed	-1073	+112	-961	-1371	29.9%

The benefits of the application of the algorithm are evident when examining Table 6-4. Across various scenarios, positive effects are consistently observed. In the surplus scenario with N=3, the algorithm leads to a substantial 19.6% increase in revenue. Similarly, in the deficit scenario, costs are reduced by a 21.2%. However, it is the mixed case that reaps the greatest advantage, achieving a remarkable 34% reduction in costs.

Expanding the scope to the N=10 scenario with a larger user base, significant improvements are still witnessed. Revenues rise by 15.8% in the surplus scenario, while costs experience a notable reduction of 23.9% in the deficit scenario. In the mixed scenario for N=10, costs are lowered by a 27.7%.

Further analysis in the N=50 scenarios demonstrate the algorithm's continued effectiveness. A surplus scenario yields a revenue increase of 7.7%, while a deficit scenario generates savings of 17.4%. The mixed case stands out with savings of 29.6%.

It’s interesting to note how the revenue percentages for the N=100 scenarios are similar to the N=50 cases. This is due to the fact that the N=100 case is generated the same way as cases N=50.

The N=50 and N=100 surplus scenarios hold the smallest profit of among all the tests. This happens because the vehicles’ batteries are saturated quickly and so the exceeding energy is sold as soon as produced.

Nevertheless, the most significant advantages are observed in the mixed cases, where a substantial amount of charge/discharge activity occurs. This finding is crucial as mixed scenarios closely resemble real-world conditions compared to other cases.

As a conclusion it can be said that the more the vehicles are involved in the energy exchanges the higher is the profit.

8 Conclusions and future developments

8.1. Conclusions

This thesis presents an innovative algorithm designed to optimize the utilization of Vehicle-to-Grid (V2G) technology in industrial landscapes. The significance of this algorithm lays in advancing the transition towards a more sustainable future, future which will be characterized by the widespread adoption of V2G and electric vehicles (EVs) across nations.

Implementing the solution proposed, companies can achieve multiple benefits that extend beyond mere financial considerations. This because while the algorithm maximizes revenues and minimizes costs from a monetary point of view, its impact extends to the reduction of carbon dioxide (CO2) emissions, contributing to environmental preservation.

The findings of this study demonstrate the effectiveness of the proposed algorithm which enforces three optimizers: the negotiation optimizer, Model Predictive Control (MPC), and the SOC updating optimizer. Together, these optimizers enable the generation of optimal state of charge profiles for each electric vehicle connected to the charging stations.

The negotiation optimizer facilitates effective communication and agreement between the EV owners and the company, enabling the choice of the right offers for the employees.

Instead, the SOC updating optimizer ensures the creation of the optimal equivalent battery's SOC profiles at every hour, accounting for uncertainties and dynamically adjusting the energy flows. These profiles are generated at the beginning of every hour and are perfect to be used as a reference for the MPC.

By incorporating MPC, the algorithm finds the best way to perform energy exchange between the EVs and the power grid. This is achieved through receding horizon strategy for which at each hour the optimal control sequence is generated but then only the first two elements of that sequence are applied. MPC was chosen to reduce the complexity of the operation, which without MPC had to be performed with linear programming which would have meant very high computational times.

Testing proved the robustness of the complete algorithm. Initially the power profiles were altered, testing the algorithm in different energy scenarios. This examination provided valuable insights into how the algorithm performs in diverse scenarios, highlighting its capability to optimize energy flows under varying demand profiles.

Subsequently, the testing was expanded to assess the algorithm's scalability by increasing the number of users involved in V2G operations. Also, the results of these tests were optimal, the algorithm reacted well to the increasing number of users, only the computational times were lightly affected.

It is possible to claim that negotiation itself is quite fast (for N=3 cases around 7 seconds of computation on a modern laptop of medium level), but also MPC control execution takes from 5 to 20 seconds (depending on the size of the problem) with a sampling time of one hour.

Finally, the thesis studied the algorithm's response to increased uncertainties in power forecasts. Introducing varying levels of uncertainty, the algorithm's ability to adapt and optimize energy trading activities was tested under more challenging and volatile conditions. The algorithm also surpassed this test, moreover the limit to the uncertainties dimension wasn't found.

Speaking of numbers, the algorithm provides savings which vary from 7.7% to 34% in the different scenarios, depending on the engagement of the batteries in the energy management. As a matter of fact, the lowest savings are related to "surplus" scenarios where the EVs batteries are rapidly saturated and so they are not further usable. Instead, the best results are obtained in the "mixed" cases (savings on average of 30%) where the batteries are continuously charged and discharged.

In a nutshell the thesis proposed and tested a solution algorithm, which it demonstrated to be effective and resilient providing optimal results in each scenario it was tested in. Furthermore, the economic analysis proved how the algorithm is more effective in dynamic cases such as the mixed scenarios, which are closer to the reality with respect to the other cases.

8.2. Further developments

The limitations of this thesis primarily lie in the assumptions made during the formulation of the general problem. Future studies can explore alternative approaches by challenging the foundational assumptions. For instance, one branch of investigation could involve considering scenarios where the number of charging stations is insufficient to accommodate all users' EVs. This would necessitate adjusting the problem formulation to address this constraint.

Additionally, in Chapter 3.3, an assumption was made that once connected to the charging stations, vehicles cannot disengage from V2G activities. Exploring the case where vehicles are allowed to disconnect from the charging stations would be interesting. In this situation the users are obliged to communicate their parking durations, and this introduce new constraints to the problem and provides valuable insights. This dynamic factor would add complexity to the optimization process, but it would better reflect real-world scenarios.

Linked to the previous assumption is the fact that EVs were solely considered as energy storage devices, neglecting their primary transportation function. Further studies can focus on integrating constraints related to the energy utilized for transportation purposes by the vehicles. This would provide a more comprehensive analysis of the overall energy dynamics and optimize the utilization of EVs in both mobility and grid services.

Moreover, the battery model used in this thesis was simplistic yet effective. However, exploring more complex battery models would contribute to a deeper understanding of the scenarios. This could lead to studying battery degradation in V2G operations and potentially adjusting the optimizer's objectives to minimize battery degradation while maximizing other performance metrics.

The final development would be to apply the thesis algorithms to a real company ecosystem to see the results that can be achieved not only in simulation but also in the real world.

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Variable	Description	SI unit
SOC	State of Charge	kWh
Ppv	Power generation	kW
Pload	Power consumption	kW
N	Number of users	/
X	Requested space on EVs' battery for V2G operations	kWh
Y	Payment for the users	kWh
η	Charge/discharge efficiency	/
U(i).Capmax	Maximum capacity of the EV of user i	kWh
U(i).SOCi	Initial value of SOC of the EV of user i	kWh
Er	Energy bought from the grid	kWh
Ev	Energy sold to the grid	kWh
Eu	Total energy exchanged with the users	kWh
Eneed	Total energy needed for V2G operations	kWh
SOCMIN	Fixed minimum value of SOC	kWh
SOCMINeq	Minimum SOC value of the equivalent battery	kWh
$\boldsymbol{SOC_i(0)}$	Initial SOC value of EV i	kWh
SOCIeq	Initial SOC value of the equivalent battery	kWh
sumX	Total requested space on the EVs	kWh
sumY	Total payment promised to the users	kWh
Crete	Total cost of the bought energy	€
Gvend	Total revenue of the sold energy	€

Acknowledgments