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TESI DI LAUREA IN INGEGNERIA GESTIONALE

A Model Predictive Control scheme for the optimal management of an innovative energy system

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Thanks

Abstract

This work present a hybrid charging station for electric vehicles composed of a photovoltaic panels, battery, a complete hydrogen system based on a fuel cell, electrolyzer, and tank as an energy storage system, grid connection, and fast charging units for Electric Vehicles. The utilization of this system allows to develop a sustainable mobility with a low impact on environment. But the very target of the work is the Energy Management System, the control systems that regulate the energy exchange between the different elements in these facilities. It is necessary in this type of systems because the solar power fulfills the energy to photovoltaic panels and his behaviour is different from the demand of the electric vehicles, so an energy storage system and a technique of control are needed. In this case the system is optimized by Model Predictive Control, making decisions on two principal variables: the state of charge of the battery and the level of hydrogen in the tank.

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Chapter 1

Introduction

One of the major growing concerns of this era is environmental sustainability. Recently with the climate change there is the need to transform the production of the energy by fossil fuel and coal to a clean production by renewable sources such as solar, hydroelectric and wind-energy. So the potential to create green energy that is both ecologically benign and financially operative is the primary argument. Another necessity is to change the actual source of the transport fuelling in a more sustainable and eco-friendly fuel. Thanks to this solution the greenhouse gas emissions of the vehicles can decrease but the main problem is that the population must adapt to it, buying new electric vehicles (EVs) which surely are not inexpensive. In spite of that many countries around the world have registered an increase in EVs on the road compared to 2019 [?]. The greenhouse gas emissions are divided mainly in these two types of pollution although they are not alone, how one can see in Fig 3.7.

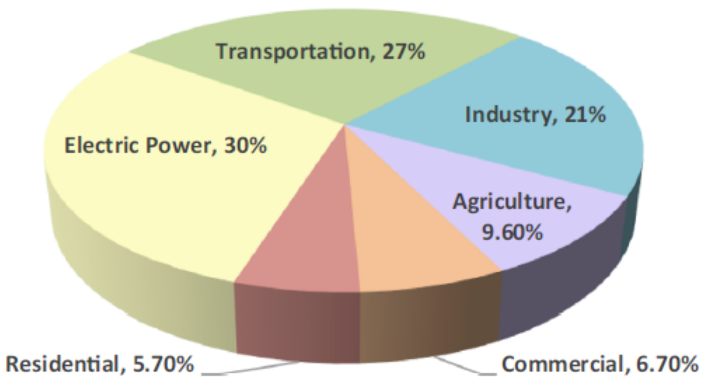

Figure 1.1: Greenhouse gas emission by sector in 2020

The carbon dioxide (CO_2) is the main greenhouse gas and a lot of measures and policies are studied and applied to reduce it. The first sector in which the governments intervene is that of the transportation because of the highest quantity of CO_2 emitted and the growing number of vehicles. Indeed recently the European Union has approved a law on the prohibition to buy internal combustion engine starting from 2035 [2]. If the Governments want to electrify the majority of the transportation, as a consequence also to increase the capacity of the power systems is important but paying attention to the environment. If the pollution of the transportation decrease but the emissions of the production of energy increase the results are not good how one can hope. So the best solution is to look for new sustainable power systems but it is not much easy for several problems: there is the need to invest in the research and development because at the moment there is not the suitable infrastructure to satisfy the energy demand in a sustainable way [7].

This project combines two different goals with the utilization of the photovoltaic panels that use a renewable energy (solar) and this energy is used to power the electric vehicles. All that has a significant impact on the environment because it functions over two important sides: less energy is required from the normal grid (which utilizes the fossil fuels and coal in majority) and the number of internal combustion engine decrease, so the (CO_2) emissions of the transportation decrease. Furthermore this system is hybrid because an hydrogen (H_2) system composed of electrolyzer, H_2 tank and a fuel cell is used to stock the energy. The main variable which refer to level of energy (for the H_2 system) is the percentage of hydrogen in the tank. It will be converted in energy thanks to fuel cell. The photovoltaic panels are a good idea because of their facility to be installed in a small land but it can be good only for a little system with a small power demand. The problem is that a great land and a lot of photovoltaic (PV) panels are needed to satisfy the growing request of energy. An other problem is the place where they are installed: for example, a system in the extreme north of the Europe will not provide the power needed by electric vehicles because of the lack of solar radiation. In this work, a small-scale system is studied and it is composed of a PV panels, energy storage system and the charging stations for electric vehicles. It is generally a good way to satisfy a little part of the energy demand of the transport. The data of photovoltaic panels are taken from the Spain. This type of system increases the self-consumption and autonomy thanks to the Energy Storage System (ESS) which allows to stock the energy and give to the system more flexibility. When needed there is the grid that satisfy the demand of the EVs. Furthermore in this case the energy in excess can be sold to the grid in a peak time, if the storage system is full and there is not request by electric vehicles. In the case of the photovoltaic panels and the energy storage system can not satisfy the demand of electric vehicles, the power can be bought from the grid. An important concern is about the differences between the irradiation of the sun (which represents the power absorbed by photovoltaic panels) and the request of the fast charging stations (or rather the EVs demand): their usually behaviour is different among themselves and this means that without a good Energy Management System (EMS) and an Energy Storage System the efficiency decreases. The EMS is referred to an optimal management of energy systems to take the best possible decision in every moment considered. It is very important because it allows not to waste energy and money. In this case an optimal control technique is used to manage the system. A control technique is a way to control the systems, it has as objective that of determine the optimal evolution of the control variables for a dynamic system which can be subject to constraints. The technique utilized in this work is the Model Predictive Control: it is based on the solution of an optimal problem every time interval to manage the system in optimal way and it repeats this scheme until the end of the time considered. It will be explained better in the next chapters. Looking at the solution of the optimal problem, there is always a function which must be optimized, generally called cost function. Considering that the energy has a price (which can change during the day) of sale and purchase different among themselves (usually the price of the energy bought is greater than the price of energy sold), the function which must be optimized (the cost function) in this model can be considered exactly as the money spent by the system. When the batteries and the hydrogen tank are full, the energy in excess can be sold to the grid and so there is a gain of money. The cost of the problem is quantified thanks to the price of energy. If the management system work well it will spend a very little quantity of money and all the renewable energy will be used to fulfill the electric vehicles.

Chapter 2

State of the art

As previously mentioned in the introduction, the governments have studied the problem of greenhouse gas emissions for years [4] and the first idea is to electrify the transport. However this change has been faced with some problems: one of these is to meet the demand and the supply of the energy that increase considerably and it has a negative effect on pollution on the side of the energy production. Furthermore the demand may be not satisfied because of the growing number of electric vehicles, so now there is the need to build new sustainable plants which function with renewable energy. The increasing number of EVs has an impact on the customers which have to buy new cars and to adapt to a new system of recharge of the vehicles. In the paper [?] the relation between two car-sharing/ride-hailing mobility services and electric vehicles adoption was studied underlining that there is a positive relationship between new mobility usage (both car-sharing and ride-hailing) and desire to purchase electric vehicles in the future. The conclusion of the paper is that there is not causal effects of these services on the adoption of electric vehicles, but the survey highlights that new mobility services are an important predictive indicator for future vehicle preference. At the highest levels of usage of new mobility services there is a higher probability that the customers probably would consider to purchase EVs. The studies on the field of eco-friendly energy production in recent years increased but further research is necessary to have an appropriate efficiency and a better utilization of small land in which build new systems. In the paper [5] a system with the same components of the system studied in this work was analyzed and optimized with the same technique control and it was simulated for 25 years. The main difference between the system analyzed in this work and the system of the paper mentioned, is the focus of the projects: the paper previously mentioned does an evaluation of an investment for each device utilized during 25 years, whereas the objective of this work is to study the Model Predictive Control applied to the hybrid energy system, so the time considered is also different. That paper obtained some positive results but only the PV power and the power supplied by the batteries are not sufficient to fulfill the charging stations: the help of the grid is needed. However the MPC-technique was compared with a simple EMS strategy and some improvements were seen such as the efficiency and the cost due to management of the system. MPC-technique as an EMS in hybrid power systems combining renewable resources and ESS has been applied in several studies: in [8] an overview of the state of the art of the application of the MPC in micro-grids is presented. It describes also some types of MPC to be applied at microgrids which are divided into two levels and three layers control structure: primary, secondary and tertiary. The primary control stabilizes system frequency and voltage and shares loads with the fast response. The secondary control offsets the deviations of frequency/voltage derived from the primary control, whereas the tertiary control concerns the power flow among microgrid clusters, or between microgrids and upstream grid with additional functions like power planning and economic optimal scheduling. Another similar system was studied with the same components but with a different optimization technique [10]: in this case the multi-agent particle swarm optimization (MAPSO) algorithm was applied, which combines the multi-agent system (MAS) and the mechanism of particle swarm optimization (PSO) in order to overcome the shortcomings of traditional PSO. In this method, each agent competes and cooperates with its neighboring agents, and it obtains high-quality solutions through self-learning. It was applied in Shanghai, China with three scenarios analyzed to test the performance of the model: grid-connected photovoltaic/ battery energy storage/ electric vehicle charging station (PBES), without the PV panels and then without grid connection. The results of that paper are that the PBES is the most cost-effective solution and the result accuracy of MAPSO algorithm, compared to the only PSO, is better. The recent growth of this kind of studies is due to the recently large-scale penetration of the electric vehicles but it needs an higher efficiency in the power systems. In order to achieve the objective to reduce the greenhouse gas emissions it represents the opportunity to have more and more sustainable power system. At the state of the art there are two architectures of charging stations for EVs: alternating current (AC) and direct current (DC) charging systems (Fig. 2.1).

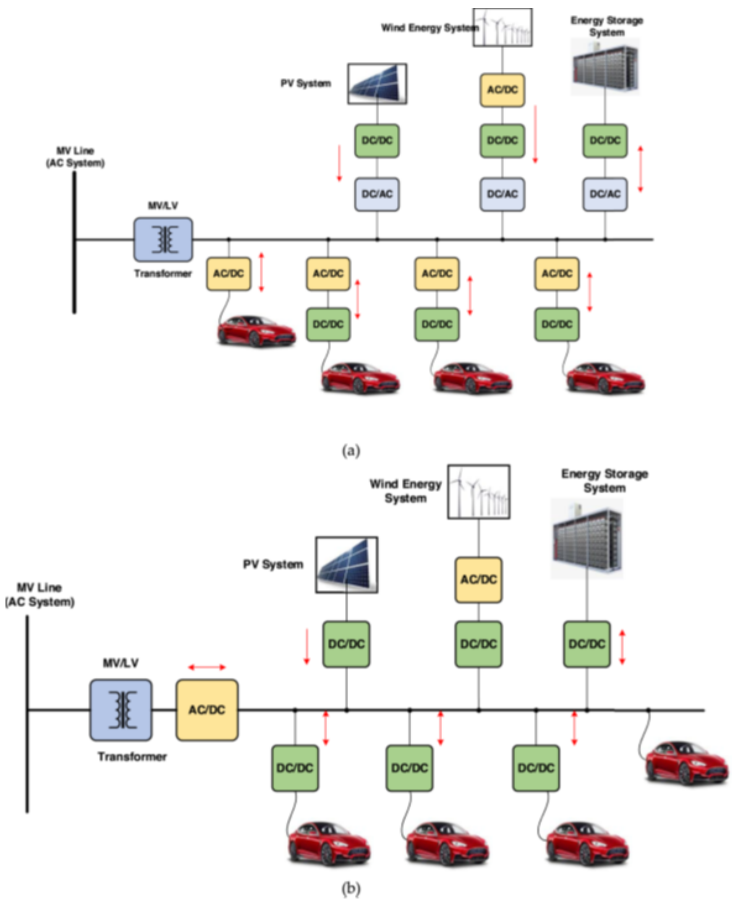

Figure 2.1: EV charging stations integration with the grid. a) AC charging system. b) DC charging system. [7]

It represents the scheme of AC and DC charging systems. In AC charging systems the secondary side of a MV-LV distribution transformer acts as a common AC bus which is connected to the EV charger. The MV-LV is necessary to make suitable the energy for the electric vehicles. It can be on the main bus or on every side which fulfill the power and it is the main different structural feature between the AC and DC systems. AC charging consist of AC/DC converters which are part of the charger, whereas, in DC-fast charging systems, a common AC/DC converter is connected to the MV-LV distribution transformer. In this type of connection, an AC bus rated at 400-480 V is connected to an AC/DC converter. These power electronic converters provide rectifications, power factor correction, voltage control, isolation and DC power to the EV port. The AC-bus architecture comprises of various power conversion stages, communicating with DC loads and sources [7]. The DC-bus charging architecture is usually lower in cost and size and provides better dynamic performance than AC-bus charging stations but it is challenging to develop power converters for DC charging stations as DC current does not have natural zero-crossings, or rather the instantaneous point at which there is no voltage present (important for systems that send digital data over AC circuits and so very important for this system). Other works such as [9] focused the study on the behaviour of the EV-battery charging management because it is still a problem to understand and to forecast how much energy is necessary to satisfy the demand of the vehicles. In this paper an optimization algorithm to coordinate the charging of EVs has been developed and implemented using a Genetic Algorithm (GA). This methodology has been applied to an existing residential low voltage system obtaining that a smart charging schedule for EVs allow to have a flattening load profile and less peak load. Another paper [6] speaks about a novel and comprehensive mechanism for the energy management of a Hybrid Micro-grid System. The suggested hybrid microgrid system consist of Photovoltaic cell and fuel cell with batteries and supercapacitor, AC loads and electrolyzer cell. The energy management system utilized in that case is the Maximum Power Point Tracking (MPPT) which is a technique used with variable power sources to maximize energy extraction as conditions vary. The technique is most commonly used with photovoltaic (PV) solar systems, but can also be used with wind turbines, optical power transmission and thermophotovoltaics. In this system the energy is distributed among the sources and the main control variable is the state of charge of the batteries. The conclusion of this paper is that the hybrid system managed by MPPT overcomes the difficulties of each device and provides sufficient power to the load. The PV panels provide the primary electricity, while the fuel cell makes up for any power shortage. A distributed MPC based energy scheduling problem for islanded multi-microgrids (MMGs), an isolated mode, is presented in the paper [3]. Its objective is to achieve supply-demand balance through energy coordination and reduce battery degradation for its extended cycle life. The effectiveness of proposed scheme is verified with a case study based on three interconnected MMGs.

Chapter 3

Model and optimal control of hybrid charging stations for electric vehicles

The considered system, as described in the introduction, is composed of photovoltaic panels, the energy storage system which is divided in two parts and the charging stations for EVs. It is a grid connected system, so it can be powered by the normal grid when needed. Every device carries out its function and has its dynamic: the photovoltaic system uses the irradiation of the sun and transforms it to useful energy which goes to the charging stations or to the storage system. It function through more photovoltaic cells connected among themselves and thanks to a physic reaction they can convert the photons (taken by radiation solar) to a direct current. Then the energy must go to inverter which make suitable the electric current to the system. In the Fig.3.1 is illustrated a simplified scheme of the process of the photovoltaic panels.

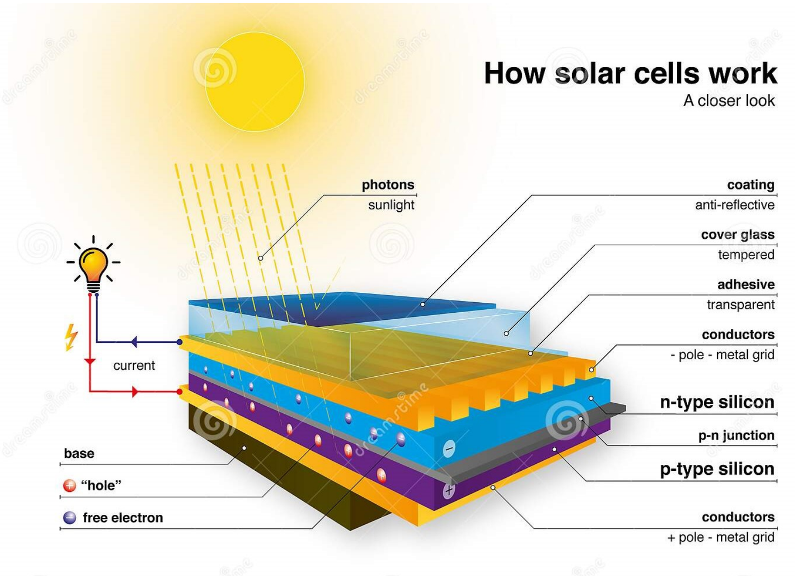

Figure 3.1: Photovoltaic panels scheme

The cells are composed of three layers of silicon: type n, type $p-n$ and type p. The first layer reacts with the photon and the electron flow of the radiation solar rejecting the negative charge to the outer. The last layer allows to convert it to suitable energy. In order to store the energy this system is composed of a simple battery energy storage system (BESS) which has a maximum capacity and gives it to the charging stations when needed and of a hydrogen system which is composed of electrolyzer (EZ), fuel cell and a hydrogen tank. The EZ is a device which converts the water to hydrogen thank to a process called electrolysis: it allows to obtain hydrogen and oxygen at the gaseous state from the water via passage of the electricity. It happens only in the electrolytic cells contained in the electrolyzer. In the cell two different metals are contained: one is anode and the other is cathode. When the electric current powers the EZ the water molecules (H_2O) separate in hydrogen where there is the cathode and in oxygen where there is the anode. The Fig.3.2 provides a good explanation of the process.

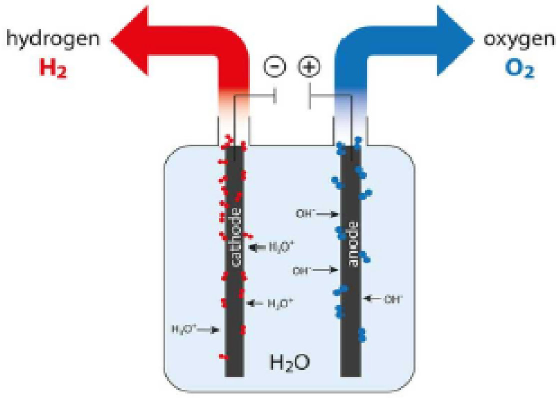

Figure 3.2: Electrolysis of the water

The entire hydrogen system allows to store the energy through the H_2 tank: the electrolyzer can be powered by PV panels, produces H_2 by the water thanks to its electrolysis and it is used to fulfill the fuel cell which can give energy to the charging stations or to sell it to the grid. The fuel cell allows to produce energy only thanks to the contact between H_2 and air (and so oxygen). This process does not need the combustion process or fulfill of energy. For that reason also this storage system is eco-friendly and powered by renewable energy. The H_2 tank allows to store the energy in the form of hydrogen. It is a good vector of energy because of the utilization with the fuel cell which can produce clean energy. The level of H_2 and the state of charge of the battery represent how much energy is contained in the storage system and therefore how much energy the system can deliver to the charging stations or sell to the grid. The electric vehicles charging stations in this model are seen only as a demand of energy which would be satisfied by PV panels. That demand is the simulation of the request energy by users of electric vehicles.

All the devices are connected to a common bus, more precisely to a medium-voltage direct current (MVDC) bus through Z-source converters (ZSC) which is a type of power inverter, or rather a circuit that converts direct current to alternating current. It functions as a buck-boost inverter without making use of DC-DC converter bridge due to its unique circuit topology [?]. DC/DC ZSC is used for PV and hydrogen system and DC/AC Z-source inverter (ZSI) integrating BES for the grid connection. There is also communication line to receive the decisions by EMS. In the figure 3.3 the system just described is represented.

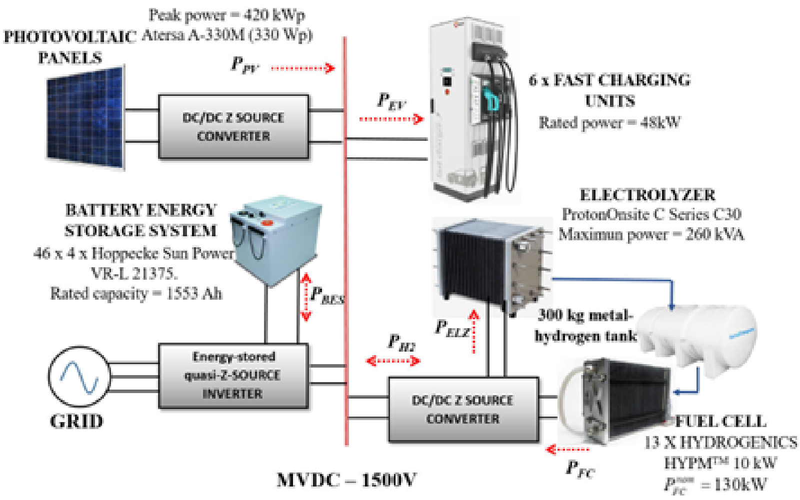

Figure 3.3: Hybrid charging stations for EVs

The dynamic of the analyzed system is expressed in discrete-time equations and this type of problem is easier to solve than the continuous-time problems that use the differential equations, which in some cases are very difficult to solve. So in this case there are not the differential equations but there are the equations based on the previous interval time and it simplifies the problem solution. In this system there are some power variables: the power of PV panels and of the charging stations are seen as constraints, one is a source of energy and the other is a demand of energy, they can not be modified and both they will be described better in the next sections; the power of the storage system, included the batteries and the H_2 system are the main variables because they are controllable and they allow to optimize the system; the power of the grid is calculated thanks to the energy balance and it allows to have an idea on the cost of managing the energy system. It represent the electricity exchanged between the studied system and the normal grid: if its sign is negative the level of energy decreases and the power is sold to the grid, if its sign is positive the energy is purchased by the grid. There are not only power variables but also some values which represent the level of the energy inside the system. They are the state of the charge of the batteries (SOC) and the level of hydrogen (LOH) in the tank and both they are expressed in percentage. Furthermore thanks to these variables one can understand and verify how much energy the system contains and can deliver to the charging stations to satisfy the demand of electric vehicles. The aim of the control of the system is utilize mainly the power of the PV panels to fulfill the EVs. In order to achieve that result is needed an energy storage system because of the different behaviour of supply-demand of electricity and the energy management system allows to not waste the power and to increase the efficiency of the system. The variables of the system can be divided in state (x vector) and control (u vector) variables such as follow:

$$x = [P_{grid} \quad P_{bat,disc} \quad P_{bat,ch} \quad P_{fc} \quad P_{ez} \quad P_{ev} \quad P_{pv} \quad SOC \quad LOH] \tag{3.1}$$

$$u = [P_{bat} \quad P_{H_2}] \tag{3.2}$$

So, the decisions of the control technique are taken based on the power inside the system. The other variables are referred to a respective device which has a dynamic different than others. The MPC algorithm take decisions based on these two variables, P_{bat} and P_{H_2}, which correspond to the power that the system can deliver in every time. The state equation of the dynamic system is composed of two equations which describes the state of the charge of the battery and the level of hydrogen in the tank. They are linear and they allow to update the variable values at the next step. Both these variables depend on other variables such as the power delivered by BESS ($P_{bat,disch}$)or by H_2 system (P_{fc}). Accordingly with this the discrete-time linear equations that represent level of energy in the system are two:

$$SOC_{bat}(t+1) = SOC_{bat}(t) - \frac{\eta_{bat} T_s}{C_{max}} P_{bat}(t) \tag{3.3}$$

$$LOH(t+1) = LOH(t) - 100 \cdot \frac{\eta_{H2} T_s}{V_{max}} P_{H2}(t) \tag{3.4}$$

where:

- t is the current time instant.
- T_s is the sample time in hours.
- η_{bat} is the efficiency of the battery.
- C_{max} is the maximum battery capacity.
- V_{max} is the maximum hydrogen tank capacity.
- $P_{bat}(t)$ is the power of the battery at time t, expressed in kW.
- $P_{H2}(t)$ is the power of the hydrogen system at time t, expressed in kW.

These two variables depend on the two powers of the storage system, respectively the SOC depends on the P_{bat} and the LOH on the P_{H2}. The last two power variables are the control variables and the dynamic of the respectively two devices will be explained. But if the problem is stated in terms of continuous and binary variables the following equations can be considered:

$$P_{bat}(t) = P_{bat,disc}(t) - P_{bat,ch}(t) \tag{3.5}$$

$$P_{H2}(t) = P_{fc}(t) - P_{ez}(t) \tag{3.6}$$

The efficiencies of the components can be broken down depending of the sign of the respective power as follows:

$$\eta_i = \begin{cases} \eta_{ch} & P_i < 0 \\ \frac{1}{\eta_{disc}} & P_i \geq 0 \end{cases} \tag{3.7}$$

Where i is referred to the device utilized (so it can be equal to bat or H_2).

It means that if the power of the device i (battery or hydrogen system) is negative, the power is injected in the bus and the appropriate efficiency is the η_{ch}. If the power is positive it is not injected but consumed and therefore the correct efficiency is η_{disc}. In the case of the H_2 system the state of charging corresponds to fuel cell and discharging to electrolyzer. Considering these equations, the system can be rewritten as follows:

$$SOC_{bat}(t+1) = SOC_{bat}(t) + \frac{\eta_{bat,ch}T_s}{C_{max}}P_{bat,ch}(t) - \frac{T_s}{\eta_{bat,disc}C_{max}}P_{bat,disc}(t) \tag{3.8}$$

$$LOH(t+1) = LOH(t) + 100\frac{\eta_{ez}T_s}{V_{max}}P_{ez}(t)\sigma_{ez}(t) - 100\frac{T_s}{\eta_{fc}V_{max}}P_{fc}(t)\sigma_{fc}(t) \tag{3.9}$$

Where $\sigma_{ez}(t)$ and $\sigma_{fc}(t)$ are two binary variables which indicate the energized state of the electrolyzer and of the fuel cell respectively. If the electrolyzer is working at time instant t, $\sigma_{ez}(t)$ will be '1', if is not working will be '0' (it's the same for the fuel cell). Looking at equations 3.5 and 3.6 one can see that if the storage system is charging (or the electrolyzer is working) the energy level will increase. On the contrary if the storage system is discharging (or the fuel cell is working) the energy level will decrease. Those energy levels are defined as a coefficient between the actual capacity and the maximum capacity of each storage device. In order to simplify the equations, one can define these constants which all have the unit of measurement of $(kWh)^{-1}$:

$$K_{bat,ch} = \frac{\eta_{bat,ch}}{C_{max}} \tag{3.10}$$

$$K_{bat,disc} = \frac{1}{\eta_{bat,disc}C_{max}} \tag{3.11}$$

$$K_{ez} = \frac{\eta_{ez}}{V_{max}} \tag{3.12}$$

$$K_{fc} = \frac{1}{\eta_{fc}V_{max}} \tag{3.13}$$

They are some constants which simplify the equations, they do not change the dynamic system. Replacing these constants in the equations (3.1) and (3.2) one can obtain:

$$SOC_{bat}(t+1) = SOC_{bat}(t) + K_{bat,ch}T_sP_{bat,ch}(t) - K_{bat,disc}T_sP_{bat,disc}(t) \tag{3.14}$$

$$LOH(t+1) = LOH(t) + 100K_{ez}T_sP_{ez}(t)\sigma_{ez}(t) - 100K_{fc}T_sP_{fc}(t)\sigma_{fc}(t) \tag{3.15}$$

Finally the energy balance must be formulated as follows:

$$P_{pv}(t) + P_{grid}(t) + P_{bat}(t) + P_{fc}(t) - P_{ez}(t) - P_{ev}(t) = 0 \tag{3.16}$$

Where $P_{pv}(t)$, $P_{fc}(t)$, $P_{ez}(t)$ are only positive values, whereas $P_{grid}(t)$ and $P_{bat}(t)$ are positive or negative depending on the defined sign criterion. The powers of photovoltaic panels and EVs are taken as inputs, they can not be controlled during the solving of the problem but they must be balanced throughout the storage system, deciding on the control variables. The total net power can be considered as the difference between the generation and consumption power and it can be defined as a measurable disturbance $d(t)$. So the following equations is valid:

$$d(t) = P_{generation}(t) - P_{consumption}(t) = P_{pv}(t) - P_{ev}(t) \tag{3.17}$$

And the equation (3.14) can be rewritten:

$$P_{grid}(t) + P_{bat}(t) + P_{fc}(t) - P_{ez}(t) + d(t) = 0 \tag{3.18}$$

The main equations of this model are the dynamic of the system and the energy balance, but they both depend on the behaviour of storage system, divided in batteries and hydrogen system and on the inputs that are the irradiation of PV panels and EVs demand of electricity. In the next sections all the components of the system with their dynamics are explained with more details.

All the components have practical limits which are the landmarks of the model and of its formulation on Matlab. They refer for example to efficiency of every component of the system or their maximum capacity and they are listed in the table 1:

Parameter	Representation	Unit	Value
Battery charging efficiency	$\eta_{bat,ch}$	%	90
Battery discharging efficiency	$\eta_{bat,disc}$	%	95
Maximum battery capacity	C_{max}	kWh	17,6
Electrolyzer efficiency	η_{ez}	Nm^3/kWh	0,23
Fuel cell efficiency	η_{fc}	kWh/Nm^3	1,32
Maximum hydrogen capacity	V_{max}	Nm^3	7

Table 1: Components parameters

The table highlights that there are two different efficiencies for the charging of the battery and for the discharging of it although there is only one component in this storage system.

3.1 Photovoltaic system

The power of photovoltaic panels is the principle source of energy of the system. It is considered as constraint given by Matlab file. It contains a lot of meteorological variables but the only suitable to have an idea of the power supplied to the charging stations or to the storage system is the irradiation of the sun. These data refer to a week of July and they are taken every 5 minutes as represented in the figure 3.4:

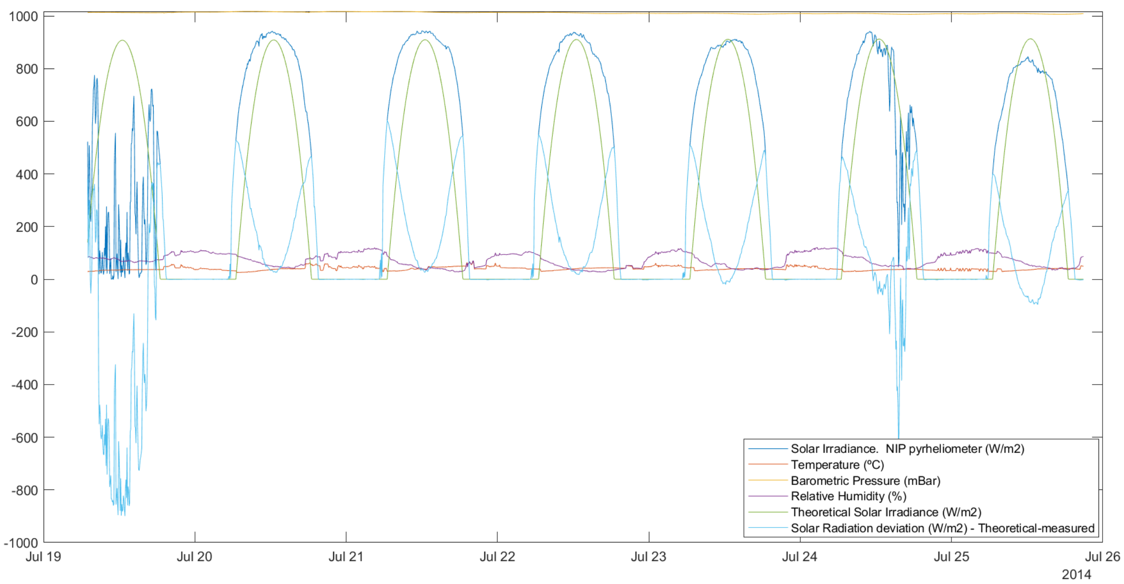

Figure 3.4: Photovoltaic panels data

The energy absorbed, which is the principle variable of the PV system, by photovoltaic panels is the sun irradiation. Its evolution is naturally the same of the sun, so it has the peaks at the middle of the day. The barometric pressure is at standard conditions, or rather 1 Bar (1000 $mBar$ as reported in the last image). The data are taken in Spain.

3.2 Charging stations for electric vehicles

In the proposed work the charging stations fulfill the electric vehicles, so the request of the charging stations can be seen as the demand of the EVs users. This demand is taken by Matlab file and simulated on Matlab to plot it and have a better idea on what is the demand which must be satisfied by this system. In the Fig. 3.5 one can see that all the peaks are near at the end of the day, approximately starting at 5 p.m. at greatest value and decreasing to zero in the night and in the morning. Comparing it to the solar radiation it is clear that it is necessary to have an energy storage system to have a serviceable system fuelled by renewable energy. The EMS plays a fundamental role in the gain of efficiency. This plot is view in the Fig. 3.5, also in this case the data are taken every 5 minutes:

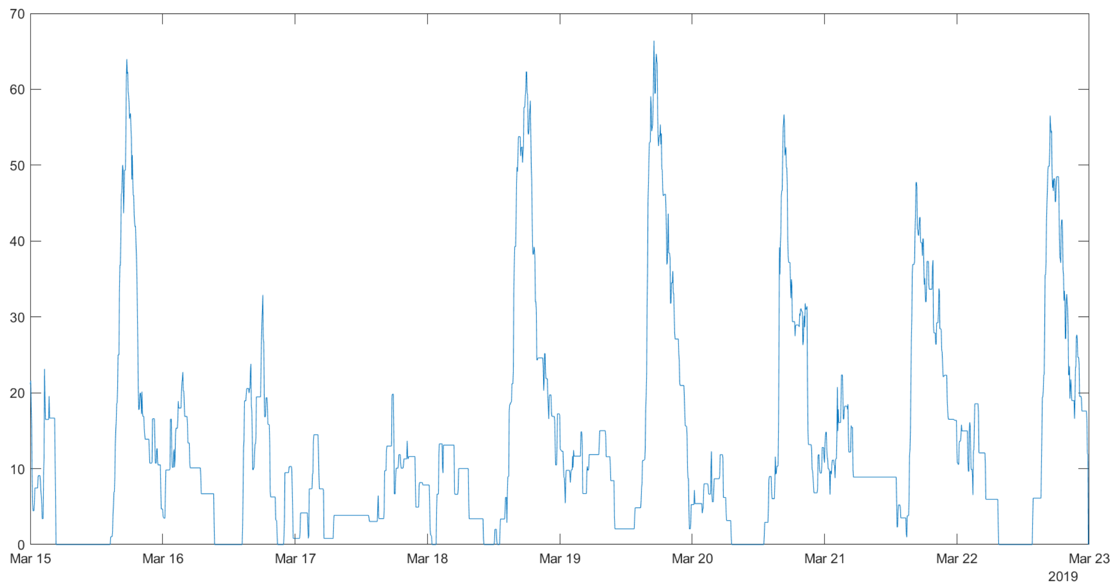

Figure 3.5: Electric vehicles demand

3.3 Energy storage system

The energy storage system is fundamental for this model because of the differences between the dynamics solar radiation and the demand of the electric vehicles: it allows to control ad manage the power in the devices. Therefore the efficiency of the utilization of the renewable energy increases, objective of the work. It is composed by two parts which have different behaviour and it is better separate them to describe their dynamics in the best way possible.

3.3.1 BESS

The battery energy storage system is the easiest way to store the energy. The state of charge is one of the variables controlled by EMS. It can be calculated with an energy balance between the energy delivered ad absorbed by the BESS. The maximum charge and discharge power of the BESS (P_{bes}) can be calculate using:

$$P_{bes}{}^{max,disc}(t) = min(P_{bes}{}^{nom}, \frac{E_{bes}{}^{nom}}{\Delta t} \cdot (\frac{SOC(t) - SOC_{min}}{100})) \tag{3.19}$$

$$P_{bes}{}^{max,char}(t) = min(P_{bes}{}^{nom}, \frac{E_{bes}{}^{nom}}{\Delta t} \cdot (\frac{1 - SOC(t)}{100})) \tag{3.20}$$

where:

- $P_{bes}{}^{max,disc}$ is the maximum discharge power in a sample time.
- $P_{bes}{}^{nom}$ is the nominal power of the BES.
- SOC_{min} is the minimum batteries SOC allowed (in this case 20%).
- $P_{bes}{}^{max,char}$ is the maximum charge power in a sample time.
- $\frac{E_{bes}{}^{nom}}{\Delta t}$ represents the maximum theoretical power the battery could provide assuming full capacity is discharged in a single sample time ($E_{bes}{}^{nom} = 50$ $[kWh]$ capacity).

These equations mean that the charge and discharge power can not be greater that $P_{bes}{}^{nom}$ for clear technical reasons. At every interval time the $SOC(t)$ is calculated (starting from the first value which is set equal to 50%) thanks to equations 3.1 which calculate the next step and then, with 3.17 and 3.18, the power delivered by the batteries is calculated: if it is lower than nominal power it can be chosen for the specific sample time. This loop is repeated until the end of the time considered (1 day in this case). Furthermore one can note that all the parameters in the equations (3.17) and (3.18) are fixed whereas the only variable that can change is $SOC(t)$.

3.3.2 Hydrogen system

The level of hydrogen in the tank $LOH(t)$ is the other control variable in the EMS and just as the $SOC(t)$ it can be calculated through two equations of hydrogen system: one for the electrolyzer and one for the fuel cell. It represents the level of the energy of the hydrogen system. But in this case there are two different equations because it refers to electrolyzer for the "charge" and to fuel cell when the energy is needed by charging stations or sell to the grid. The mentioned equations are the following:

$$P_{H2}{}^{max,gen}(t) = min(P_{fc}{}^{nom}, U_f \cdot \eta_{them} \cdot \eta_{stack} \cdot \frac{E_{H2}{}^{low} \cdot LOH(t)}{\Delta t \cdot 100}) \tag{3.21}$$

$$P_{H2}{}^{max,abs}(t) = min(P_{ez}{}^{nom}, B \cdot q_{H2}{}^{nom} + A \cdot \frac{M_{H2}{}^{nom}}{\Delta t} \cdot \frac{100 - LOH(t)}{100}) \tag{3.22}$$

where $P_{H2}{}^{max,gen}(t)$ and $P_{H2}{}^{max,abs}(t)$ are respectively the maximum power generated and absorbed by H_2 system and there a lot of fixed parameters which are defined in table 2.

Parameter	**Representation**	**Unit**	**Value**
Fuel cell nominal power	${P_{fc}}^{nom}$	kW	1.5
FC utilization factor	U_f	%	85
Fuel cell Thermodynamic efficiency	η_{them}	%	60
Stack efficiency	η_{stack}	%	95
Lower calorific H_2	${E_{H2}}^{low}$	kWh/kg	33.31
Electrolyzer nominal power	${P_{ez}}^{nom}$	kW	1
Nominal H_2 flow in the EZ	${q_{H2}}^{nom}$	kg/s	1.1810e-05
Maximum capacity of EZ	${M_{H2}}^{nom}$	kg	0.5
Constant EZ model	A		-10.800
Constant EZ model	B		82.872,93

Table 2: Fuel cell and electrolyzer parameters

The basic concept of these two equations is the same of the BESS system: the generated power by hydrogen system can not be greater than the nominal fuel cell power (and it is the same for the electrolyzer with absorbed energy). Every sample time the energy absorbed or delivered is calculated and it is compared with the respective fuel cell or electrolyzer nominal power. Then the lower value is taken. Also in this case there are only fixed parameters except for the $LOH(t)$ which is calculated with equation 3.2.

3.4 The Model Predictive Control scheme

The system illustrated in the previous chapter is optimized through an optimal control technique, but first of all identify the type of problem is necessary: it is a dynamic problem, the equations which describe the dynamic of the system are expressed in discrete-time and they are not linear. The variables can assume continuous values. The difficulty of the resolution of it, can be found in the satisfaction of the constraints and in the behaviour of the single components, which have own properties and evolution. Furthermore the main equations depend on this components evolution, so it is a type of problem difficult to resolve. The optimal control techniques, in general, have the aim to determine the optimal evolution of the control variables for a dynamic system which is limited by constraints. The most general case of a state representation is:

$$x(t+1) = f(x(t), u(t), w(t), t) \quad t = 1, ..., N \tag{3.23}$$

Where the vector x is the state variable, u vector contains the control variables and w is a stochastic disturbance, independent between different step time. There is a correspondence with the studied problem and the general form as following:

$$x = [P_{grid} \quad P_{bat} \quad P_{fc} \quad P_{ez} \quad P_{ev} \quad P_{pv} \quad SOC \quad LOH] \tag{3.24}$$

$$u = [P_{bat} \quad P_{H2}] \tag{3.25}$$

$$w = d \tag{3.26}$$

The functions f which connect one time instants to the next one are the equations of SOC_{bat} and LOH, so the equations 3.14 and 3.15, that both depend on the power of the batteries and of the hydrogen system respectively. The variable d is calculated as seen in the 3.17 and it is not stochastic but is a data of energy demand by electric vehicles, simulated on Matlab and shown in the Fig.3.4. Thanks to the energy balance (3.16) can be calculated the P_{grid} which is the power that allows to obtain a numerical idea on the effective cost of managing the system.

In the easier cases of the discrete-time problems a control law based on the state variables can be found for the control variables. In this study finding this law is not possible because of the difficulty of the problem resolution, so the Model Predictve Control (MPC) is applied. It is a control technique applied only in the case of system represented in a discrete time and when the problem is very difficult to resolve, so when the general optimal control techniques are not usable. This happens when: the analytic solution does not exist or the constraints are applied on the state and on the control variables which are not exploitable with dynamic programming. The MPC is based on the on-line resolution, at every sample time, of a optimization control problem composed on a K_p range time. This optimal control problem is like a mathematical planning problem with finite horizon (horizon made of K_p sample time) which is initialized in real time with the measure of the state and it produces a numerical solution. The model predictive control technique does not find a mathematical law which can solve the problem but it is able to return a numerical control solution which must be applied to the system. The MPC is highly utilized in the industrial field and it consists of a real time resolution of optimal control problems. It is based on the prediction of the state of the system in a determined future horizon. Actually, MPC does not refer to a particular control approach, but rather to a set of control approaches that take full advantage of the system model under specific constraints to gain the control signals or commands through minimizing predefined cost functions or objective targets. The optimization is performed over the prediction horizon by minimizing a cost function. It is also named Receding Horizon Control (RHC) because it is based on the concept of the receding horizon: at time $k = 0$ it solves a problem, based on the measure $x(0)$, considering a horizon that finishes at instant $k = k_p$ and it returns the control $u(0)$. Then it applies $u(0)$ to the system, it measure $x(1)$ and it solves the optimization problem until to $k = K_p + 1$ which returns the control $u(1)$. This procedure is iterated until the end of the total problem how illustrated in the Fig.3.6

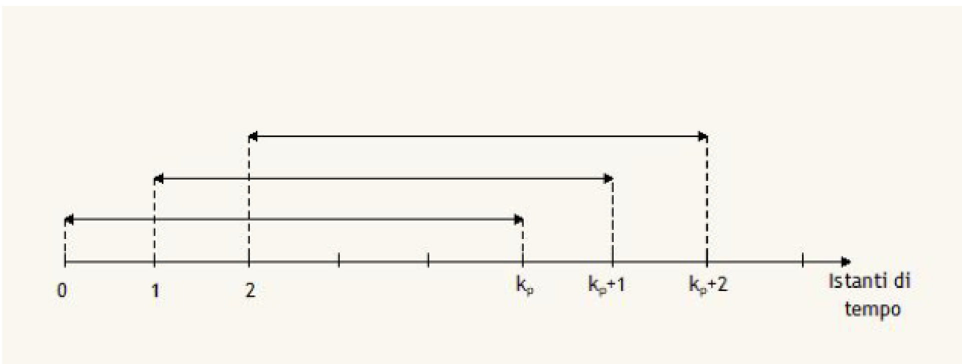

Figure 3.6: MPC general scheme

There are two levels of application of MPC to microgrids: converter level and grid level. The former produces a switching signal to drive the power converters while the latter determines the commands to control the loads. However, these two levels have a similar control structure and design a procedure based on the common MPC architecture: predictive model, cost function and solving algorithm are three key ingredients of MPC. Taking the one-horizon prediction, for instance, Fig.3.7 shows the general principle of converter-level MPC. The predictive model is obtained from the discretization of RLC circuit dynamics through state variable acquirement that can be achieved by either measurement or estimation of voltage/current/power.

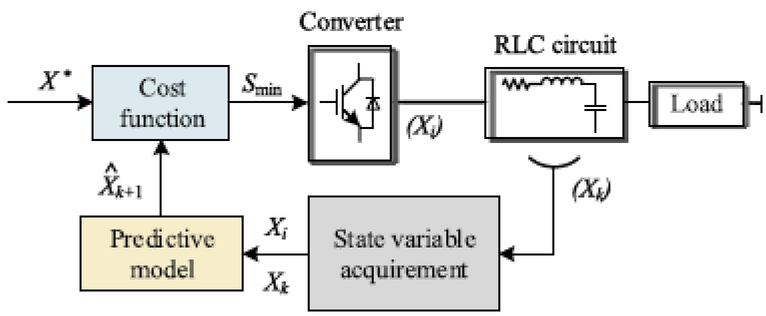

Figure 3.7: MPC converter level

Similar to converter-level MPC, the grid-level MPC also consists of predictive model, cost function and solving algorithm. However, gridlevel MPC aims to control system-level operating statuses (for example ESS capacity or among networked microgrids). Fig.3.8 illustrates the general diagram of grid-level MPC.

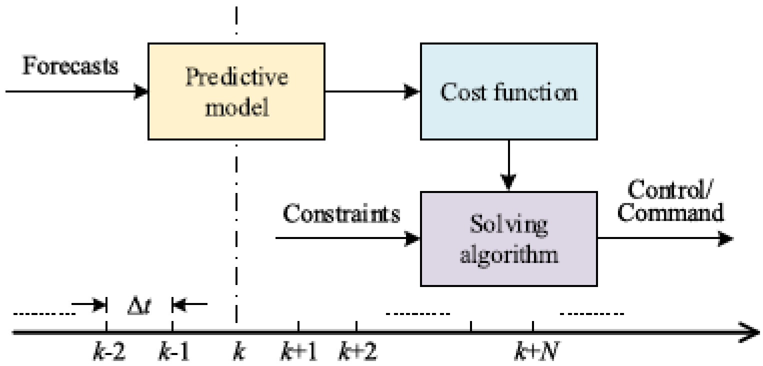

Figure 3.8: MPC grid level

As shown, the predictive model is built upon the system states with possible forecasts, which formulates an expression for the future state prediction usually on the basis of current/past states. In the proposed study, the MPC grid level is applied considering as cost function the price of energy multiplied for the quantity of the power sold or bought to the grid. Looking at the last two figures 3.7 and 3.8 and accordingly to the explication of the two scheme levels, one can note that the level of this work is a grid level which allows to control the powers evolution, in particular the power of the battery and of the hydrogen system are controlled. The concept of MPC can be explained better through this scheme: at every instant k the following optimization problem is solved, also called Finite-Horizon Optimal Control Problem (FHOCP) which can be formalized, in the general case, as following:

$$minJ(k) = \sum_{h=k}^{k+k_p-1} g(x(h), u(h)) + g^F(x(k+k_p)) \tag{3.27}$$

such that

$$x(h+1) = f(x(h), u(h)) \quad h = k, \ldots, k+k_p-1 \tag{3.28}$$

$$u^{min} \leq u(h) \leq u^{max} \quad h = k, \ldots, k+k_p-1 \tag{3.29}$$

$$x^{min} \leq x(h) \leq x^{max} \quad h = k+1, \ldots, k+k_p \tag{3.30}$$

$$x(k+k_p) \in X^F \tag{3.31}$$

Where:

- h is the current time instant and corresponds to t of the studied case.
- k_p is the prediction time horizon.
- $J(k)$ is the function which must be minimized; it is composed of the cost of every stage and the final cost at the end of the prediction horizon.
- the constraint 3.28 represents the dynamic of the system and it corresponds at equations 3.14 and 3.15.
- the constraints 3.29 and 3.30 are the lower and upper bounds of the control and state variables.
- the 3.31 is the constraint of the final state, it indicates the admissible final state.

It means that the equation 3.28 predicts the system in the time range $k-k_p$ based on $x(k)$, so the FHOCP solution considers the evolution system in the range evaluated. The constraint 3.28 represents the dynamic of the system, so in this case the general equations 3.14 and 3.15 correspond to it and they are based on the dynamic of the components. So the evolution of the system is based on the state of charge of the battery and the level of hydrogen which represent the level of energy stored in these two storage system. But they depend on the dynamic of the components such as electrolyzer, fuel cell and battery. Their evolution is described in the following equations: 3.19 and 3.20 represent the dynamic of the discharging and charging powers of the battery respectively, 3.21 returns the maximum value of the fuel cell, the 3.22 refers to the electrolyzer. The choice of k_p has a great impact on the problem resolution: an high value means an higher predictive capacity but there are more decision variables, so is more difficult to resolve. This needs a compromise on the value of k_p, which in this study is set equal to 5 hours. The upper and lower bounds are the nominal power of each storage device, so the battery (charged and discharged), the electrolyzer and the fuel cell. In the table 1 and in the table 2 are indicated all the nominal powers of each device. In this case there is not a constraint on the admissible final state and there is not the cost of the final state but only the cost of every stage. The energy balance 3.18 is another constraint which serves the purpose of respecting the energy conservation of the system: the sum of all the powers delivered and absorbed must be equal to zero. Thanks to it to calculate the power of the grid (P_{grid}) is possible and it allows to have an idea about the cost of the management of the system, considering the energy sold and purchased. The cost function 3.27 can be written like this:

$$minJ(k) = \sum_{t=k}^{k+k_p-1} (P_{pur}(t+k) \cdot P_{grid,pur}(t+k) + P_{sale}(t+k) \cdot P_{grid,sale}(t+k) + \\ + P_{stor}(t+k) \cdot P_{bat,stor}(t+k) + P_{stor}(t+k) \cdot P_{H_2,stor}(t+k)) \tag{3.32}$$

Where:

- P_{pur} is the price of purchased energy.
- P_{sale} is the price of sold energy.
- P_{store} is the price of the stored energy.

A consideration on the sign of the powers must be done accordingly with the assumption done at the start of the chapter: the powers are considered positive if injected in the bus and negative if the opposite happens. So, $P_{grid,pur}$ is the purchased power, therefore it is taken only when the power of the grid is positive. It means that the value $P_{pur}(t+k) \cdot P_{grid,pur}(t+k)$ will increase the cost function which must be minimized. Naturally the sign of the $P_{grid,sale}$ is the opposite. About the price of the storage, it can be considered as an incentive to not sale always the unused power by charging stations and store it in the storage system. Indeed the powers $P_{bat,stor}$ and $P_{H_2,stor}$ are always negative values because they are not injected in the bus. As a consequence they will decrease the cost function and it has a positive effect.

Only for the first simulation and in order to validate the system, the prices are assumed constants equal to the average of the very energy price market, which varies during the day, taken by [1] and are different among themselves: P_{pur} is equal to 0,5 €$/kWh$, P_{sale} is equal to 0,2 €$/kWh$ and P_{store} to 5 €$/kWh$. The big difference between the stored power and the other is due to the highest importance of storing energy in the studied system. It is important because in order to be more sustainable to utilize the power provided by PV panels is better than utilize the power of the normal grid.

Chapter 4

Matlab system model

The system described in the previous chapter is simulated on Matlab through the dynamic equations that describe the entire system and the dynamics of the single components. Furthermore the energy balance is very important because that equation serves to conserve the energy maintaining the sum of all the powers equal to zero (equation 3.18).

4.1 Model code

In order to simplify the model and to have an easier operating method to solve it, a division of the code in more function is needed. All the described functions are connected between themselves thanks to the definition of the inputs of every function. Then the connection is completed with the recall of these inputs in the function in which are request. The first of them gathers all the functions of the system, included those serve the purpose to plot the obtained results. There is not the cost calculation because it is included in the optimization function, such as the constraints of the optimization code. Furthermore in this part of the model some inputs and all the parameters are defined, such represented in the Fig. 4.1:

```
function EVCS_Simulator11
close all
%Definition of the parameters
p = parameterInitialization;
% Define inputs for open-loop test
PbatAux = 500*sin(2*pi/12*[1:p.finalTime/p.Ts]');
Pdis_bat = -min (0,PbatAux); % Negative values of PbatAux mean "discharging"
Pch_bat = max (0,PbatAux); % Positive values of PbatAux mean "charging"
P_ez=zeros(p.finalTime/p.Ts,1);
%P_fc=zeros(p.Ts,1);
P_fc=-min(0,300*sin(2*pi/12*[1:p.finalTime/p.Ts]'));

% optimization problem
x0 =[0      0      0    0    0    0    10          10]; % Initial conditions

%load('results.mat');
[x,Pdec,vt]=recedingHorizonControl(x0,p);

save('results.mat','x','p','vt');
plotResultsOptimized(x,p,vt);
end
```

Figure 4.1: General function of the model

The defined inputs $P_{bat,aux}$, P_{ez} and P_{fc} are powers of the battery, electrolyzer and fuel cell which are considered fixed in order to validate the model. It is done with an open-loop test, so without the part of optimization and it serves the purpose to validate the model written on Matlab. There are also the initial conditions of the state vector which allow to start the optimization problem: all the powers are equal to zero but the system is loaded, so the state of charge and level of hydrogen is 100 %. The function "$recedingHorizonControl$" is the main part of the optimization in which other functions needed to complete and optimize the system are defined. At the end there are the functions that save the result and they plot it. In the second part of the code the part of optimization will be described and explained.

The second function serves the purpose of setting the parameters that do not change in all the equations. They are for example the maximum capacity of the hydrogen tank or of the battery, the constants of the hydrogen model, the sample time or the efficiencies of the components (Fig.4.2 and Fig.4.3). All they are written in the table 1 and in table 2. The equations 3.10 - 3.13 are constant, they are written starting from the efficiency of the battery or of the H_2 system and also these are defined in this function.

```
function  p = parameterInitialization
% returns a structure p with all parameters
p.Np = 5; % Prediction Horizon
p.Ph=5;
p.eta_ch_bat=0.9;
p.eta_dis_bat=0.95;
p.C_max_bat=20; % [kWh] is the maximum battery capacity
p.eta_ez=0.23; % [Nm^3/kWh]
p.eta_fc=1.32; % [kWh/Nm3]
p.V_max=7; % [Nm^3] is the maximum H2 capacity
p.P_nom_bat=50; %[kW]
p.Enom_bat=3*p.P_nom_bat; %[kWs]
p.Ts=1/12; %[h]  sample time
p.finalTime = 24; % (h) Final simulation time
p.SOCmin=5; % [%]
p.Pfc_nom=1.5; %[kW]
p.Uf=0.85;
p.eta_therm=0.6;
p.eta_stack=0.95;
p.EH=33.31; %[kWh/kg]
p.Pez_nom=1; %[kW]
p.MH2=5; %[kg]
p.deltat=3600; %[s/h]
p.qH2=1.1810e-05; %[kg/s]
p.B=1.5*p.Pez_nom/p.qH2;
p.A=-1.5*p.deltat*p.Pez_nom/p.MH2;
```

Figure 4.2: Parameters initialization part 1

```
% to Simplify the equations
p.Kch_bat=p.eta_ch_bat/p.C_max_bat;
p.Kdis_bat=1/(p.eta_dis_bat*p.C_max_bat);
p.K_ez=p.eta_ez/p.V_max;
p.K_fc=1/(p.eta_fc*p.V_max);

p.evFactor=1;
p.pvFactor=1;

p=loadData(p);

% define power purchase and power sale (assumed as a constants for ease)
p.PricePur = 0.5*ones(p.finalTime/p.Ts,1);   % 0,5 [$/kWh]
p.PriceSale = 0.2*ones(p.finalTime/p.Ts,1);

p.PricePur = (5-20*p.mean_evData.Var1/1000)/10;
p.PriceSale = 0.8*p.PricePur ;
p.PricePur=p.PricePur(1:p.finalTime/p.Ts);
p.PriceSale=p.PriceSale(1:p.finalTime/p.Ts);

p.PriceBatStorage = 10*ones(p.finalTime/p.Ts,1);
p.PriceH2Storage = 10*ones(p.finalTime/p.Ts,1);
p.PriceBatNStorage= 10*ones(p.finalTime/p.Ts,1);
p.PriceH2NStorage= 10*ones(p.finalTime/p.Ts,1);
```

Figure 4.3: Parameters initialization part 2

Both the prices of the energy purchased and sold to the grid are assumed constants in order to validate the system and they are set equal to the average of the daily price. If the lines 81-84 are commented (as the line 77 for example) they are not considered by Matlab simulation and the prices will be considered constants. If these lines are not commented they are considered in the simulations and the prices are variables during the day as in the Fig.4.4. The price of the storage is considered always constant. It is a fake price, considering the sign of the power stored: it would be an incentive to store the energy in the system. In this part also the function which loads the inputs of the EVs and PV panels is defined.

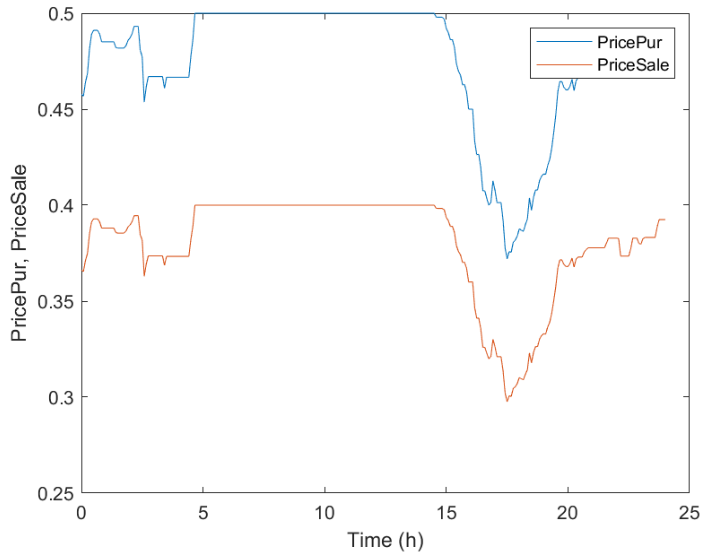

Figure 4.4: Daily prices of the energy sold and purchased

The third function of the code serves exactly the purpose to load the data vector of electric vehicles request and of solar radiation. They will be extracted in the first function of the parameters and in other functions in which these powers are needed Fig. 4.5

```
function p=loadData(p)
%Load ev and solar data

solar_rad = load('solarRad.mat');
fields(solar_rad)

ev_dataT = load('evData.mat');
ev_dataTT = timetable(ev_dataT.vt',ev_dataT.vdEV');
%mean_evData = retime(ev_dataTT, "hourly", "mean");

evRange = timerange("15-Mar-2019 00:00:00","20-Mar-2019 00:00:00");
p.mean_evData = ev_dataTT(evRange,1);

solarRadT = struct2table(solar_rad);
solarRadTT = table2timetable(solarRadT);
%mean_solarRad_tot = retime(solarRadTT,"hourly","mean");

solarRange = timerange("20-Jul-2014 00:00:00","25-Jul-2014 00:00:00");
p.mean_solarRad_tot = solarRadTT(solarRange,:);
end
```

Figure 4.5: Loading the EVs and PV data

Inside the fourth function there is the open-loop test of the system without the part of optimization. It validates the Matlab code which models the system. It is called "*systemSimulator*" and it corresponds to the entire dynamics of the system. There are all the equations written in the third chapter with other equations in addict needed to complete all the constraints of the system. The equations addicted serve the purpose, for example, to not take the negative value of the power of the battery if it is charging. Therefore they do not change the dynamics of the system but they allow to respect the limits of the signs of the powers. Also the EV data and the solar radiation data are updated again to be defined in the energy balance. A division in 4 images is needed to see the fourth function, from row 77 to 166 (Fig.4.6 - Fig.4.9).

```
77  function [x] = systemSimulator(p,u)
78  % Inputs:     p -> structure of system paremeters
79  %             u -> System inputs (power diverted to battery, EZ, etc)
80  %             x -> State vector containing the power flows computed, SoC
81  %                  and LoH
82  % Outputs:    x-> Updated state
83  
84  % Extract inputs
85  uPdis_bat = u(:,1);
86  uPch_bat = u(:,2);
87  uP_ez = u(:,3);
88  uP_fc = u(:,4);
89  
90  
91  %Intialization
92  SOC_bat = 0.5*ones(p.finalTime/p.Ts,1); % Initial SoC of BES
93  LOH     = 50*ones(p.finalTime/p.Ts,1); % Initial Level of H2 Tank
94  
95  %load ev and solar data
96  
97  solar_rad = load('solarRad.mat');
98  fields(solar_rad)
```

Figure 4.6: System simulator part 1

In the Fig.4.6 the first part of the function is represented. The inputs are extracted and they change the name: every column of the input vector u is associated to new variable which will be recalled in the following equations. For this function, the input is the vector of control variables, already defined in this study (equations 3.24 and 3.25) but not optimized. One can note that the two control variables P_{bat} and P_{H_2} are a linear combination of the four components of the input vector (P_{bat} is the difference between the first two and P_{H_2} between the last two).

```
99   ev_dataT = load('evData.mat');
100  ev_dataTT = timetable(ev_dataT.vt',ev_dataT.vdEV');
101  %mean_evData = retime(ev_dataTT, "hourly", "mean");
102  
103  evRange = timerange("15-Mar-2019 00:00:00","20-Mar-2019 00:00:00");
104  mean_evData = ev_dataTT(evRange,1);
105  
106  solarRadT = struct2table(solar_rad);
107  solarRadTT = table2timetable(solarRadT);
108  %mean_solarRad_tot = retime(solarRadTT,"hourly","mean");
109  
110  solarRange = timerange("20-Jul-2014 00:00:00","25-Jul-2014 00:00:00");
111  mean_solarRad_tot = solarRadTT(solarRange,:);
112  
113  % dynamic system
114  for t=1:p.finalTime/p.Ts
115  
116      Pdis_bat_max= min(p.P_nom_bat,(p.Enom_bat/p.deltat)*...
117          (SOC_bat(t,1)-p.SOCmin)/100);
118      Pch_bat_max= min(p.P_nom_bat,(p.Enom_bat/p.deltat)*...
119          (1-SOC_bat(t,1)/100));
120  
121      Pch_bat(t,1)  = min(uPch_bat(t),Pch_bat_max);
122      Pdis_bat(t,1) = min(uPdis_bat(t),Pdis_bat_max);
123  
124      P_bat(t,1)=Pdis_bat(t,1)-Pch_bat(t,1);
```

Figure 4.7: System simulator part 2

In the Fig.4.7 the data from Matlab tables are updated: they contain one week of data, but the Matlab model stops to simulate at the first day. Then the equations of the battery system are written: previously the variable P_{bat} is separated in $P_{dis,bat}$ and $P_{ch,bat}$ to calculate the maximum possible value of the power at every time, accordingly to equations 3.19 and 3.20 that describe the dynamic of the battery. In order to obtain the true value of the power a new passage composed of new equations is needed. The equations are written in the rows 121-122 of the Matlab model. They mean that the system take the minimum value between the input (the variables $P_{dis,bat}$ and $P_{ch,bat}$) and the maximum value that it can assume (it is like a constraint). Once the powers of discharging and charging battery are defined, they are subtract between themselves to obtain the control variable P_{bat}. Therefore the battery power P_{bat} can be positive or negative depending on the direction of the power: if it is charging is positive, if it is discharging is negative. At the end the $SOC(t+1)$ is updated and it depends on the previously value of SOC and the efficiencies of charging and discharging. The state of the charge can vary between 0 and 100 %. The same concept of the minimum value between the input extracted and the maximum value admissible, is also valid for the hydrogen system and it is written in the rows 135-136 of the model (Fig.4.8).

```
126        % Update SoC
127        SOC_bat(t+1,1)=SOC_bat(t,1)+p.Kch_bat*p.Ts*Pch_bat(t,1)-...
128            p.Kdis_bat*p.Ts*Pdis_bat(t,1);
129
130        % Update H2 subsystem state
131        P_fc_max= min(p.Pfc_nom,p.Uf*p.eta_therm*p.eta_stack*...
132            (p.EH*LOH(t,1))/p.deltat*100);
133        P_ez_max= min(p.Pez_nom,p.B*p.qH2+p.A*(p.MH2/p.N)*(100-LOH(t,1))/100);
134
135        P_fc(t,1)=min(uP_fc(t),P_fc_max);
136        P_ez(t,1)=min(uP_ez(t),P_ez_max);
137
138        P_H2(t,1) = P_ez(t,1)-P_fc(t,1);
139
140        if P_fc(t,1)>0
141            sig_fc=1;
142        else
143            sig_fc=0;
144        end
145
146        if P_ez(t,1)>0
147            sig_ez=1;
148        else
149            sig_ez=0;
150        end
```

Figure 4.8: System simulator part 3

For the H_2 system it is different because it is composed of two components. In this case the equations must be different because they are composed of two components that can not work simultaneously: in the last figure, the equations 3.8 and 3.9 are got back, or rather if the electrolyzer is working the σ_{ez} will be equal to 1 and if it is not working the σ_{ez} will be equal to 0. The same concept is valid for the fuel cell: σ_{fc} will be equal to 1 if the fuel cell is working and it is equal to 0 if is not working. Naturally if the σ_{ez} is equal to 1, the σ_{fc} can not be equal to 1 but it must be 0. Or rather the two devices of the hydrogen system can not work simultaneously. Being a percentage, the level of hydrogen can not be negative, so the value of LOH can vary between 0 and 100 %.

```
        LOH(t+1,1)= LOH(t,1)+100*p.K_ez*p.Ts*P_ez(t,1)*sig_ez-...
            100*p.K_fc*p.Ts*P_fc(t,1)*sig_fc;
        LOH(t+1,1)=max(0,LOH(t+1,1));
        % update pv and ev data
        P_pv(t,1) = mean_solarRad_tot.vd(t,1);
        P_ev(t,1) = 20*mean_evData.Var1(t);

        % energy balance
        P_grid(t,1)= -P_pv(t,1)-P_bat(t,1)-P_fc(t,1)+P_ez(t,1)+P_ev(t,1);


        n=size(P_grid,1); %Number of values computed
    end
    x=[P_grid P_bat P_fc P_ez P_ev P_pv SOC_bat(1:n,1) LOH(1:n,1)];
    end
```

Figure 4.9: System simulator part 4

4.2 MPC code

The concept explained in the chapter 3 about the optimization problem is written on Matlab with a particular function which allows to define the constraints and to set the cost function. It corresponds, on Matlab, to "$fmincon$": in general it is a nonlinear programming solver which finds the minimum of the function specified by:

$$min f(x)\, such\, that = \begin{cases} c(x) \leq 0 \\ ceq(x) = 0 \\ A \cdot x \leq b \\ Aeq \cdot x = beq \\ lb \leq x \leq ub \end{cases} \tag{4.1}$$

where:

- $f(x)$ is the cost function that returns a vector (it can be nonlinear) and it is the function which must be minimized.
- $c(x)$ and $ceq(x)$ are the nonlinear constraints of inequality and of equality respectively; they are functions that return vectors that express the nonlinear constraints.
- A and Aeq are matrices, composed of constants of the linear constraints.
- b and beq are vectors.
- lb and ub are the lower and upper bounds.

The cost function corresponds to the equation 3.32 which must be minimized. There are some different versions of the $fmincon$ function on Matlab: in this case the version with the nonlinear constraints is needed and a specific function on Matlab is needed to define it. The main "constraint" is the dynamic system written in the function "$systemSimulatorAtTimet$". But the cost function and the nonlinear constraint are defined in other Matlab function and they are recalled in the optimization section ("$recedingHorizonControl$"). The nonlinear constraint allows to respect the limit of the H_2 storage and the battery capacity, indeed these two variables are represented as percentage. Instead the upper and lower bounds must be defined inside this function. Before to explain the Matlab code, to repeat the control and state vectors is necessary.

$$x = [P_{grid} \quad P_{bat} \quad P_{fc} \quad P_{ez} \quad P_{ev} \quad P_{pv} \quad SOC \quad LOH] \tag{4.2}$$

$$y = [P_{bat} \quad P_{H2}] \tag{4.3}$$

The control vector now is called y and not u as in the theoretical explication. So, the y_1 corresponds to P_{bat} and y_2 to P_{H2}. The function "*optimoptions*" returns options with specified parameters set using one or more name-value pair arguments. It is recalled in the $fmincon$ because it represents how the optimization problem is solved. The number "3000" refers to how many iterations are done. The function previously described is initialized and set in the "$recedingHorizonControl$" which is represented in the Fig.4.10. The constraints which must be defined in this function are the nonlinear constraint recalling another function and the upper and lower bounds: they are written through the Matlab function "*repmat*": it returns an array containing N_p copies of the first vector in the row and column dimensions. The size of lb and ub is a $(N_p \times 2)$ matrix. The same concept is valid for y_0 (initial value of the control variable): it has the same dimensions of the bounds but with zero as values.

```
206 function [xSto,Pdec,vt]= recedingHorizonControl(x0,p)
207 % Optimization model initialization
208 A = [];
209 b = [];
210 Aeq = [];
211 beq = [];
212 lb=repmat([-p.P_nom_bat -p.Pez_nom],[1,p.Np]);
213 ub=repmat([ p.P_nom_bat  p.Pfc_nom],[1,p.Np]);
214 % update the value of P_grid that change with  time
215 x=x0;
216 xSto = x0;
217 vt=0;
218 % Define optimization problem
219 opts=optimoptions('fmincon', 'MaxFunctionEvaluations',3000);
220 y0 = repmat([0 0],[1,p.Np]); % Initial values
221 for t = 1:p.finalTime/p.Ts - p.Np
222     vt=[vt t];
223     fprintf('Time = %d\n',t)
224 
225     [y,fval] = fmincon(@(y)fun(y,t,p,x),y0,A,b,Aeq,beq,lb,ub,[],opts);
226 
227     % Get only the first 2 values of the solution
228     P_bat = y(1);
229     P_H2  = y(2);
230 
231     uk = [P_bat, P_H2];
232     Pdec(t,:) = uk;
233     % Apply input
234     [x] = systemSimulatorAtTimet(x,p,uk,t);
235     xSto =[xSto; x];
236 end
```

Figure 4.10: Definition of the optimization problem

A, b, Aeq and beq are not defined because there is not inequality/equality constraints on the system. In the lines 215-218 the initialization of the problem starts with the definition of the initial state values, x_0, at every starting time of the problem, therefore the value of P_grid that change with time is updated. The variable vt serves only the purpose to returns the time vector.

The dynamic of the system repeated in the function "$systemSimulatorAtTimet$", the cost function and the nonlinear constraint are sufficient to proceed with the solving of the problem. The limits defined in this function are the lower and upper bounds that are technical limits of the components. Then the state and the control variables are updated recalling the function "$systemSimulatorAtTimet$". The problem with the starting points y_0 (assumed equal to zero) is also initialized. With the function "$fmincon$", the vector P_{dec} is calculated. It is the control vector u defined in the equation 4.3 (and now called y). The function "$fprintf$" is written only to display the results and to validate the model. The variable P_{H2} is defined as the difference between the P_{fc} and P_{ez}. Then to get only the first two values of the solution is needed and it is written in the lines 227 - 232: the new vector of solutions u_k (it refers to value of u at the instant k) is defined equal to P_{dec} which is the control vector of the system. In order to apply the input, the function of the dynamic of the system is recalled. Then $xSto$ serves the purpose to storage the values of the state vector x. The function previously mentioned is illustrated in the Fig.4.11.

```
function   [x] = systemSimulatorAtTimet(x,p,uk,t)
% extract control signal
P_batk = uk(1);
P_H2k  = uk(2);
if P_H2k>0
    P_fck=P_H2k;
    P_ezk=0;
else
    P_fck=0;
    P_ezk=-P_H2k;
end

if P_batk>0
    Pdis_batk=P_batk;
    Pch_batk=0;
else
    Pch_batk=-P_batk;
    Pdis_batk=0;
end
% Extract state
P_grid = x(1);
P_ev   = x(5);
P_pv   = x(6);
SOC_bat= x(7);
LOH    = x(8);
```

Figure 4.11: Definition of the optimization problem part 2

The definition of P_{H_2k} can be explained with the following equation accordingly to the definition 4.3:

$$P_{H2k} = \begin{cases} P_{fck}, & P_{ezk} = 0 \qquad if\ y_2 > 0 \\ P_{ezk}, & P_{fck} = 0 \qquad if\ y_2 \leq 0 \end{cases} \tag{4.4}$$

It means that if fuel cell is working, the electrolyzer can not take energy and it is the same in the opposite case: when the electrolyzer works, the fuel cell can not give the energy to the system. Just like for P_{H2k}, also P_{batk} must be specified better always considering the definition 4.3:

$$P_{batk} = \begin{cases} P_{ch,batk} & if\ y_1 > 0 \\ P_{dis,batk} & if\ y_1 \leq 0 \end{cases} \tag{4.5}$$

The addiction of the k refers to the instant resolution of the problem, the variable definition do not change. The power of the battery is easier than P_{H2} to be defined because there are not two devices that work but there is only the battery which can take or give the power. It will be updated in the new function "$systemSimulatorAtTimet$" (Fig.4.11) which takes as input the solution of $fmincon$, or rather P_{dec}, and it resolves the same problem of "$systemSimulator$" but with a "$forcycle$" composed on K_p instants. When it finishes, it restart from the next instant and it resolves always the same problem but with a different control input every starting time. The vector of uk is control vector, equal to y. The other parts of this function are all equal to the equations of "$systemSimulator$" illustrated in the Fig.4.7,4.8, 4.9. It represents the dynamic of the system and it is repeated because it is recalled in the optimization function "$recedingHorizonControl$". The cost calculation needs another function divided in the model in two images (Fig.4.12 and 4.13).

```
% Function that obtains the cost of operation
function  costo = fun(y,t,p,x)

% calculate the total cost
costo=0;
for k=0:p.Np-1
    P_pv = p.mean_solarRad_tot.vd(t+k,1)/1000;
    P_ev = -20*p.mean_evData.Var1(t+k)/1000;

    uk=[y(2*k+1) y(2*(k+1))];
    [x] = systemSimulatorAtTimet(x,p,uk,t+k);

    P_bat = x(2);
    P_fc = x(3);
    P_ez = x(4);
    P_H2  = P_fc-P_ez;
    %penCost=0; % Penalization in case SOC or LOH limits are exceeded
    P_grid = -P_pv-P_bat-P_H2-P_ev;
    if P_grid>0 % If energy is purchased from the grid
        costo = costo + p.PricePur(t+k)*P_grid;

    else % if it is sold
        costo = costo + p.PriceSale(t+k)*P_grid;
```

Figure 4.12: Cost function

```
        if P_bat<0  % if the battery is charging
        costo = costo + p.PriceBatStorage(t+k)*P_bat;
        else
            costo = costo + p.PriceBatNStorage(t+k)*P_bat;
        end

        if P_H2<0 % if the EZ is working
            costo = costo + p.PriceH2Storage(t+k)*P_H2;
            else
            costo = costo + p.PriceH2NStorage(t+k)*P_H2;
        end
    end
    %disp(costo)
    end
```

Figure 4.13: Cost function

In the first part the input of the cost function are updated. They are the state vector x which is given by the dynamic of the system and the control vector u_k. The EVs and PV data are uploaded. The cost is calculated updating the variables that determine the P_{grid} value at every time instant that the MPC problem is resolved: if P_{grid} is positive the power level increase, so the energy is purchased by the grid, if P_{grid} is negative the the power is sold to the grid. So the system can have an earn in the peaks moment of the sun radiation. But it is not the only part of the cost: the storage of the energy must be incentivized to make it suitable in a next moment if needed by the charging stations. It is done accordingly with the negative sign of the power which is not injected in the bus and the positive sign of the cost. Therefore it decreases the cost function which must be minimized and so it is a positive aspect. Whereas if the power is injected in the bus the powers are positive and it increases the cost. It serves to encourage further the storage. In the optimization problem there is also the constraint c (Fig.4.14) which is utilized to respect the limit of the percentage of the SOC ad LOH (naturally they must be inside the interval 0-100 %).

```
364 % Restricciones
365 function [c,ceq] = mycon(y,t,p,x)
366 c=-1000;
367 for k=0:p.Np-1
368     uk=[y(2*k+1) y(2*(k+1))];
369     [x] = systemSimulatorAtTimet(x,p,uk,t+k);
370     SOC = x(7);
371     LOH = x(8);
372     c = max([c 1*SOC*(SOC-100) 1*LOH*(LOH-100)]);
373      if SOC<0 || SOC>100 || LOH<0 || LOH>100
374         c=1;
375     end
376 end
377 ceq = [];
378 end
```

Figure 4.14: Constraint function

In the line 372 the maximum value between c (set equal to -1000), the SOC and LOH both changed of the sign are defined. It is written because in addiction to the line 373, for sure the constraint of the percentage, which must be included in the interval 0-100 %, will be respected. Remember the equation 4.1, the constraint $c(x)$ is respected if the value of c is negative. So, if the level energy exceed the 100 % or it is negative, the value of c is equal to 1 and the constraint is not respected and the problem can not be solved.

At the end of the code there is the function "*plotResultsOptimized*" that allows to evaluate if the system simulation is correct and how the evolution of the power evolves (Fig. 4.15 and 4.16).

```
function plotResultsOptimized(x,p,vt)

vt = vt*p.Ts;
Pgrid=x(:,1);
Pbat =x(:,2);
Pez  =x(:,3);
Pfc  =x(:,4);
Pev  =x(:,5);
Ppv  =x(:,6);
P_grid2= -Ppv-Pbat-(Pfc-Pez)-Pev;
figure("Name",'Power in the system')

plot(vt,Pgrid,...
     vt,Pbat,...
     vt,Pez,...
     vt,Pfc,...
     vt,Pev,...
     vt,Ppv, ...
     vt,P_grid2)
xlabel('Time (h)')
legend('Pgrid','Pbat','Pez','Pfc','Pev','Ppv','P_grid2')
hold off
```

Figure 4.15: Function to plot the model of the system

```
figure
plot(vt,Pbat )
xlabel('Time (h)')
ylabel('Pbat')
%legend('SoC','LOH')
figure
plot(vt,Pfc-Pez )
xlabel('Time (h)')
ylabel('PH2')
figure
plot(vt,x(:,7),...
    vt,x(:,8) )
xlabel('Time (h)')
ylabel('SoC (%), LOH (%)')
legend('SoC','LOH')
end
```

Figure 4.16: Function to plot the model of the system

Chapter 5

Results

In order to provide a good idea on the work three cases are studied:

- **scenario 1** does an evaluation with the prices of energy constant and it validates the model.
- **scenario 2** considers the daily variation of the energy (Fig.4.4) and it is the case closest to the reality.
- **scenario 3** assumes that the demand of energy by charging stations will double, considering the increasing number of EVs.

The sample time of the simulation is taken equal to 5 minutes, such as the EV and PV data in order to simplify the model and to equalize the sampling time of the data and the sampling time of the model. In order to obtain meaningful results, the first prediction horizon is set to 12 h. It is set so high because the highest goodness of the results is tested. For example, with a prediction horizon set equal to 4 h, the power grid is more utilized than in the proposed case and it highly affects the renewable energy utilization, which is the scope of the work. As a consequence the battery is not utilized as though in the following results. The evolution of the powers in the system are plotted for one day (Fig. 5.1) considering that in the first simulation the prices of the energy are set constants in order to validate the proposed model. More cases are developed changing the energy price profile and other cases with a larger EVs demand or PV panels production. All the powers are expressed in the unit of kWh.

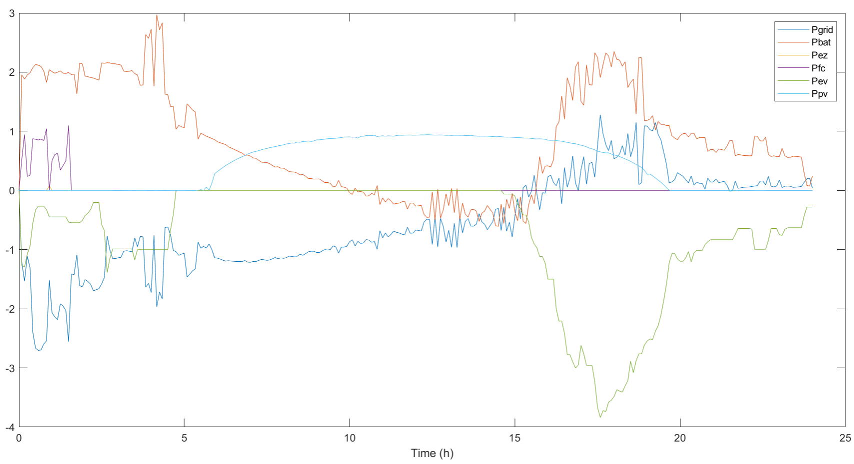

Figure 5.1: Evolution of the different powers, scenario 1

The image with the plotted results underlines that, at the start of the day, when there is not solar power, the battery ad the fuel cell can both satisfy the request of electric vehicles which is small. Remember that a positive sign of the power means the power is injected in the bus whereas a negative value of the power means the opposite. Accordingly with this, the EVs demand is always negative. So, at the starting time the power of the grid is negative and so the energy is sold to the normal grid. When the solar power increases, the energy delivered by the storage system is less needed and it allows to charge it for a few moment because the power demand is very low. In the peak time of the request of power by charging stations, the photovoltaic panels, the grid and the battery are all necessary to satisfy the demand. One can see that the main contribution is given by the battery. In spite of that the clean energy is not sufficient, the help of the grid is needed. This result underlines the importance of the storage system which contains renewable power, with the fuel cell less utilized than the battery. Indeed only in the first hours the H_2 system fulfills the charging stations, when there is not injection of the solar power. To focus on the evolution of the two control variables (Fig.5.2) and on the respective level of energy (Fig.5.3) can be interesting to understand and analyze the system.

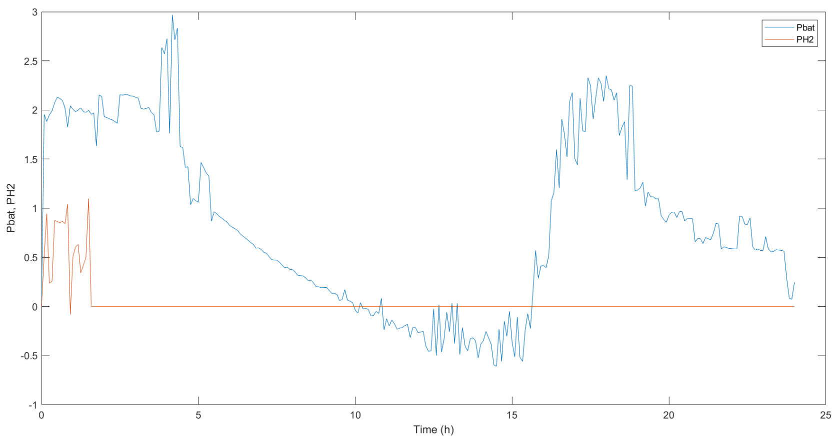

Figure 5.2: Evolution of H_2 and battery powers, scenario 1

Also the two variables of the level of energy of the system are plotted to see if it can satisfy the constraints and if it coincides to the powers evolution.

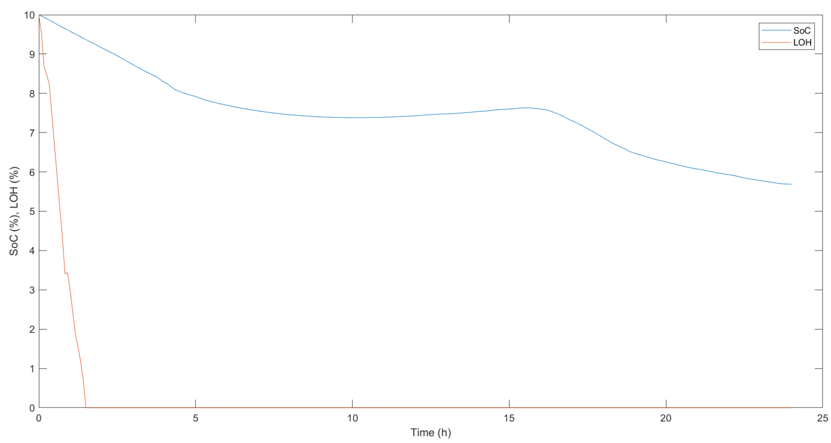

Figure 5.3: Evolution of SOC and LOH, scenario 1

It is clear that the level of hydrogen decreases always very fast and after two or three hours it is equal to zero, whereas the state of charge of the battery decreases slowly. In a little interval time in the middle of the day it increases without exceed the 85% of SOC. The component of storage system most utilized is the battery, whereas the H_2 system is less utilized. It means that the hydrogen system is normally utilized when it contains energy but if it is empty, to charge it is not convenient. Whereas the battery is charged as soon as the request of the EVs is not high and the PV panels can satisfy it. It allows to utilize the stored energy in the future. The reason behind this behaviour can be found in the efficiencies of the two storage system and in the highest number of components of the hydrogen system: the transition in the electrolyzer, then in the H_2 tank and finally in the fuel cell maybe represents an obstacle and an efficiency drop. Therefore to utilize this storage system is not convenient.

The second proposed scenario considers the daily variation of the price of the energy, resulting as in the Fig.5.4

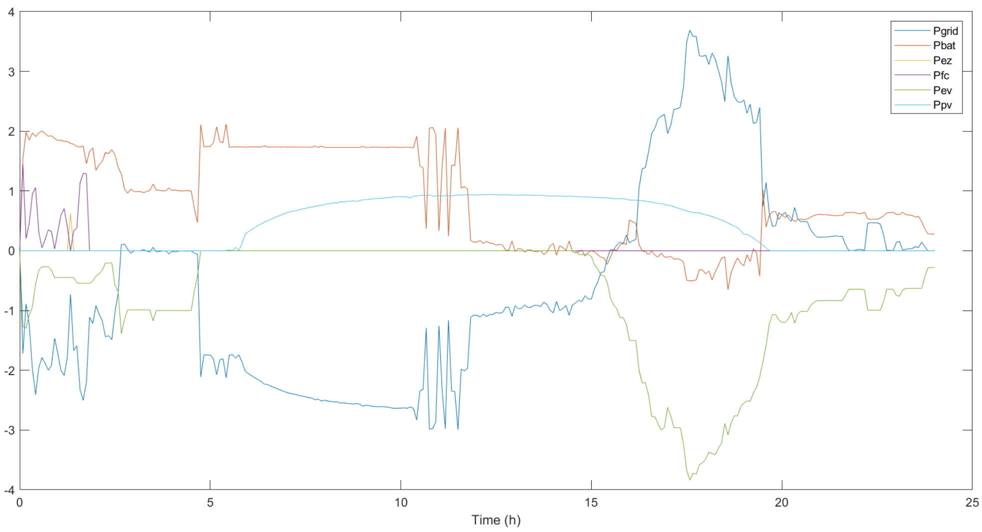

Figure 5.4: Evolution of the power with the variation of the price, scenario 2

In order to understand better the evolution of the powers in this case, remember the Fig.4.4 with the prices behaviour. After 15 hours there is a decrease of the price and it coincides with the peak of demand of energy: the result naturally is the highest utilization of the P_{grid} in this moment to satisfy the EVs request. Their demand is satisfied by the grid and also by the PV panels. Moreover in that interval time to recharge the battery can be useful. It has an effect on the utilization of the battery which is utilized at the end of the day, when there is not solar energy, the price is increasing and the demand of power can be satisfied by it. The battery is less utilized when the price is lower but when it is highest the BESS fulfills the grid because there is not demand by EVs in that interval time. Moreover the PV panels "sell" the power to the grid. The evolution of SOC and of LOH is illustrated in the Fig.5.5.

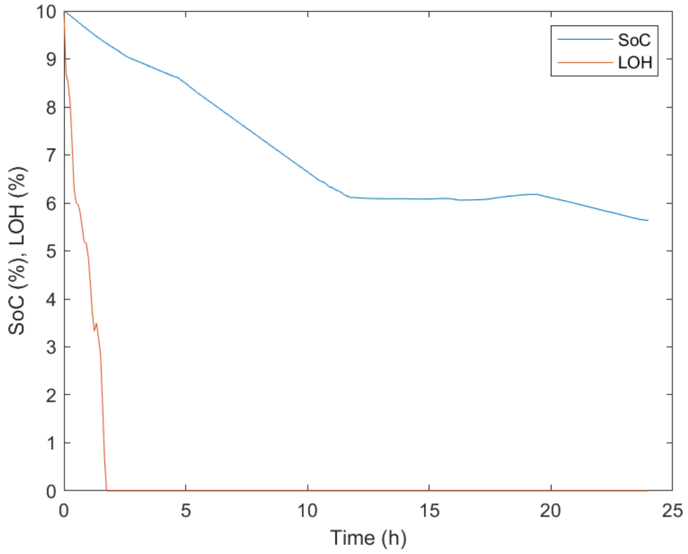

Figure 5.5: Evolution of SOC and LOH with the variation of the price, scenario 2

There are not a lot differences with the previous case: the level of hydrogen decreases very fast whereas the battery is more utilized than before, so the state of charge decreases faster. Also in this case it can be compared to the behaviour of the powers in the Fig.5.7

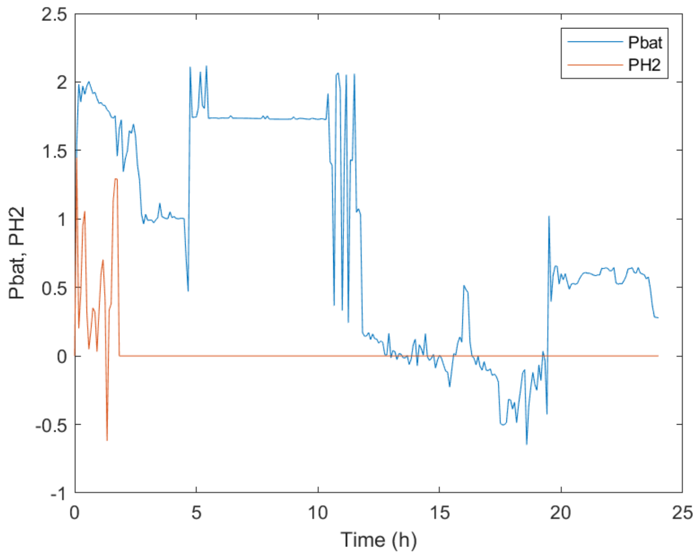

Figure 5.6: Evolution of SOC and LOH with the variation of the price, scenario 2

The evolution is surely more irregular than in the first case and it is due to the changing price of energy. Also it is seen that the battery is utilized for more time but in the first part but it never is completely discharged. When the price goes down the battery is charged because now it is more convenient take the energy from the grid. Then with the increasing price, is once more utilized to fulfill the electric vehicles. Moreover there is the solar power which can fulfill the charging stations until the 19 hours. Accordingly with the increasing sales of EVs and with the new rules that encourage the utilization of them, the last scenario is simulated with a doubled electric vehicles demand of energy (Fig.5.7).

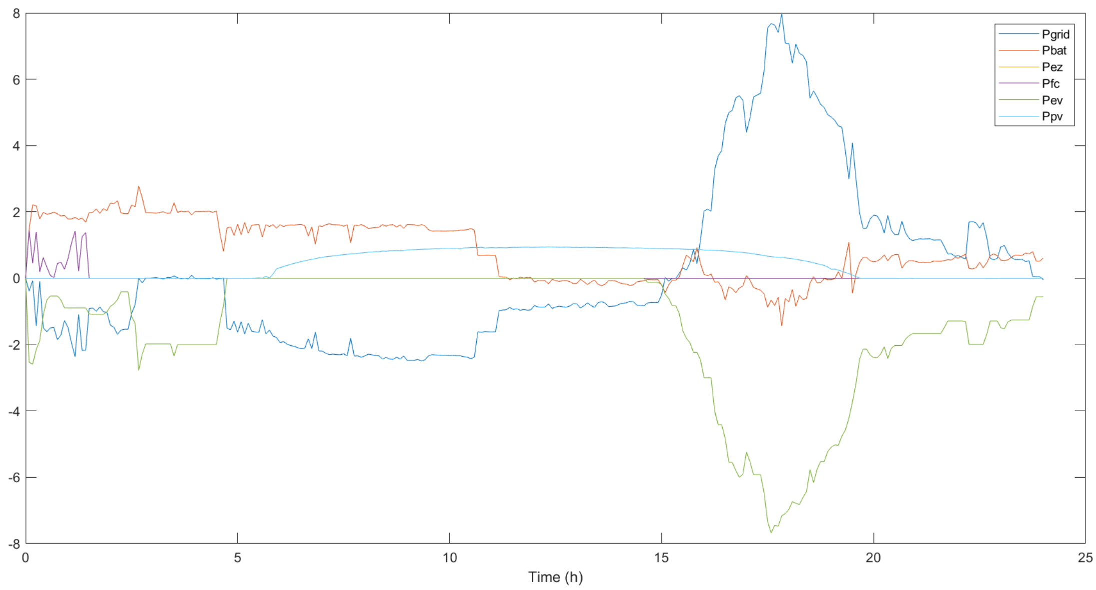

Figure 5.7: Evolution of powers with doubled demand, scenario 3

When the price go down there is a large utilization of the grid because it also charges the battery which will be utilize in a next time. For the other features it remains the same type of behaviour, with the fuel cell utilized only at the starting time because it is completely charged. Also the evolution of the powers of the battery and of the fuel cell is equal to the scenario 2.

Chapter 6

Conclusions

The obtained results have proved that a small-scale system powered by solar energy which fulfills the electric vehicles is a good solution to decrease the pollution. It has been tested in three scenarios and also with the doubled demand of energy it can satisfy the request. The optimal control is fundamental to manage an energy system and to increase its efficiency. The storage system play a very important role that allows to take different decisions in every time: sell the energy to the grid if it is inside the system in excess, buy it when is needed or store it if the storage system is empty. The proposed system can decreases the CO_2 emissions on two sides: it can sells the renewable energy to the grid and it can fulfills the EVs.

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