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Implementing supervised learning techniques to design a decentralized control strategy for Electric Prosumer Communities

Relatore : Prof. Spertino Filippo

Correlatori[1] : Prof. Damien Ernst

Raphael Fonteneau

Frédéric Olivier

Candidato: Marulli Daniele

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[1] Université de Liège

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Con questo lavoro va a concludersi, almeno idealmente, una fase della mia vita.

Ho riflettuto a lungo prima di decidere se inserire, come è consuetudine, una sezione dedicata ai ringraziamenti. Il motivo è legato proprio alle formalità: chi mi conosce sa quanto poco io vi sia propenso in certi contesti. Quando un atto diviene usanza, si corre il rischio di perderne il valore che sta all'origine. Non volevo ringraziare solo perché è uso comune, senza dar conto al significato dietro il gesto, senza l'entusiasmo di chi invece lo compie genuinamente. Perciò ci ho pensato, e sono giunto alla conclusione che sento davvero ciò che vado a dire.

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Sono lieto di non avercela fatta da solo.

Abstract

This work is dedicated to Electricity Prosumer Communities (EPC) and their challenges. The first pages of the work introduce briefly the reasons that are bringing the shape of the traditional grid to change. A description of the concepts and of the technologies associated with the figure of the prosumer is provided, in order to better understand its role. After this introductory part, we formalized a mathematical model to describe the dynamics of the community, such as power production, energy storage and power exchanges between the prosumers. The challenge involved in the control of the EPC is then contextualized, discussing the differences between centralized and decentralized schemes. The design of a distributed control mechanism has been then investigated, focusing the attention on the possibility to resort on machine learning approaches in order to try to achieve a common goal for the community. An alternative decentralized strategy, easier to implement and based on simple control rules, has been also formulated. We presented finally a case study, analyzing the characteristics and the limits of the developed control strategies. The results are then discussed and conclusions are drawn.

Contents

Chapter 1

Introduction

We live in a world that seems to go, now more than ever, towards an energy crisis. The old traditional power grids have been used in conditions that are a lot different from the ones they were originally designed for, causing great stress and deterioration to the system. In their current state, they are not adequate to fit the future needs of the society [1]. This is not the only the reason of why it is needed to change the way we conceive the electricity sector. Relying only on large power stations, far from the place where the electricity is consumed, brings to a huge waste of energy due to transmission losses (transmission and distribution losses represents about the 8% of the world output [2], only in the United States they cost $70 to $120 billion a year [3]). Besides transmission losses, wide-scale power outages leave million of peoples and services without electricity every year (see Table 1.1). Improving the traditional grid can help to reduce them but it is not enough.

Largest power outages			
Location	**Date**	**People affected**	**Duration**
India	30-31 July 2012	620 millions	From 1 to 2 days
India	2 January 2001	230 millions	3 hours
Bangladesh	1 November 2014	150 millions	10-12 hours
Pakistan	26 January 2015	140 millions	10 hours
Java-Bali	18 August 2005	100 millions	7 hours
Brazil	11 March 1999	97 millions	4 hours
Brazil and Paraguay	10-11 November 2009	87 millions	5 hours
Turkey	31 March 2015	70 millions	8 hours
Northeast America	14-15 August 2003	55 millions	From 1 to 2 days
Italy	28 September 2003	230 millions	12 hours

Table 1.1: 10 biggest black-outs in history[1](8 are in the last 15 years).

Global warming and the resulting climate change (Fig. 1.1) have been accepted as undisputed facts by now even if they are, sometimes, underestimated. The increasing greenhouse gases emissions have been implicated as the main cause of global warming, thus the energy sector could play a crucial role in confining it. The environment is asking to make big changes in the way we produce most of the energy we consume, shifting to a cleaner power generation portfolio. Moreover, many conventional technologies and fossil fuels involved in the electricity production are not considered anymore much affordable. The recent improvements and results achieved with renewable sources are astonishing but it is still not enough.

These and other relevant problems requires drastic changes in the electric power industry. A better integration of renewables along the grid, smarter ways of managing it, reducing the energy consumption: many solution have been suggested in the last years. Some of them are very promising, some are more difficult to put in place. Most of them, however, cannot be implemented continuing to use the current traditional power grids: a re-design is needed. A re-design of the electrical grid that has more and more been proposed usually involves the introduction of a smaller, and smarter, type of network inside the grid, the so-called "*microgrid*".

[1]Source: Wikipedia

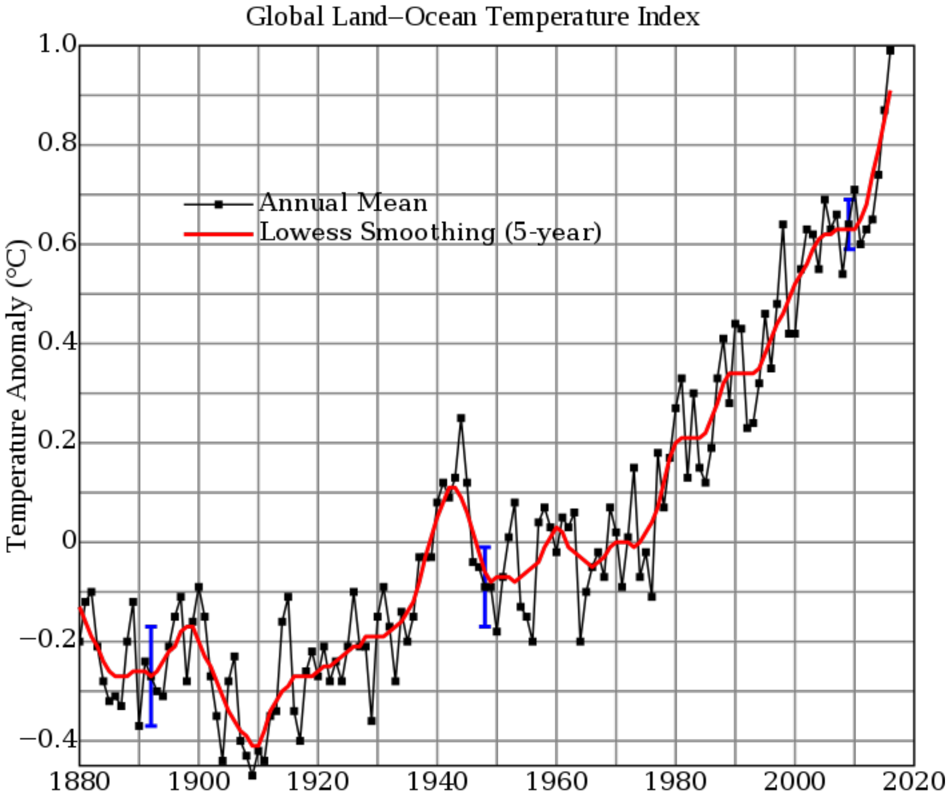


Figure 1.1: Global mean surface-temperature change respect to the '51-'80 mean[2].

The U.S. department of energy defines the microgrid as "*a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A microgrid can connect and disconnect from the grid to enable it to operate in both grid-connected or island-mode*" [4]. Creating a microgrid offers many key advantages: the generating units are usually located near the place where the energy will be consumed, reducing the losses due to transmission; small, renewable energy generators, can be integrated more easily in a microgrid, making it an eco-friendly concept; a smaller grid is easier to be monitored and managed than the traditional ones; their architecture allows in some cases to serve the loads even when the transmission grid is down (island mode). However, they presents shortcomings too and developing a stable and reliable microgrid is not easy. Something that shares many similarities to the concept of the microgrid is a *Electric Prosumer Community*, a group of people ("prosumers") that consumes and produce electricity at the same time, gathered together to achieve some common goals.

[2]Source: NASA

Controlling such an interconnected system, where many elements are involved, is a real challenge. Variables like electricity prices, energy demand or potential production are difficult, if not impossible, to predict and even if some of them are known, we would need to find a way to define the optimal approach to adopt in real-time (how much energy to produce, to consume or to store). Starting from these arguments we thought about how supervised learning machine techniques and pattern recognition could be implemented to control a small microgrid. Electric Prosumer Community, machine learning techniques and some of the challenges associated with their development are the main subject of this work and they will be investigated in the next chapters.

1.1 Outline

The thesis is structured as follows:

- Chapter 2 gives a quick insight into the concept of the EPC, presenting some of the technologies available to produce and store the energy, describing their advantages and their drawbacks;
- Chapter 3 provides a simplified mathematical formalization of the community, required for the design of a control scheme. A decentralized approach that relies on imitative learning techniques is then discussed;
- Chapter 4 describes a method to solve the optimal power flow in a low-voltage distribution network, in order to obtain a learning set for the training of the supervised learning model;
- Chapter 5 presents a case study that compares the performances of the supervised learning algorithm with those of another, simpler, decentralized control scheme and with the optimal strategy;
- Chapter 6 concludes and analyzes what could be future researches in the context of control schemes for EPCs.

Chapter 2

The electric prosumer community

A *prosumer* is somebody that can both consume and a produce a certain good. In the energy sector, it is often used to indicate consumers (households, businesses, communities, organizations, etc.) that rely on microgeneration systems to produce electricity and/or combine these with energy management systems, energy storage and electric vehicles [5]. The technologies that revolve around the idea of the electricity prosumer have seen, in the last decades, an outstanding process of growth and improvements. The recent large availability of generating units that offer different sizes at ever lower prices, the increasing potential of storage technologies and the proliferation of smart meters devices are helping the figure of the prosumer to spread around the globe.

Single renewable generators managed by prosumers that act individually are too small to compete on the market and their supply is unpredictable or inappropriate to satisfy efficiently the demand profile [6]. However, better results can be achieved when prosumers located in the same area that have the same goals and motivations are gathered together as a community. This group of people is what is called an **Electric Prosumer Community** (EPC).

Many drawbacks and challenges are encountered at various levels of the concept, from the development of solid regulations to the expedients to make it an economically advantageous alternative to traditional strategies. Co-ordinating efficiently the interests of every member of the community can be difficult and disagreements among members are very likely to occur [7]. The following sections present some popular technologies to produce and store energy, along with some goals likely to be pursued by the community.

2.1 Generation

The revolution brought by renewable energies has already passed its early stage and it has started to be taken seriously by almost everyone. Even though most of the estabilished goals are not yet reached, the transition to a low-carbon economy seems, now, less distant than before. The total installed power capacity associated to renewable sources reached 2 millions of MW at the end of 2016 [8] providing, in the same year, the 24.5 % of the global electricity production [9]. Renewables are breaking records after records. In March and April 2017, renewable generation surpasses nuclear in the U.S., for the first time since 1984 [10]. One month later (May 2017) in Italy, renewable sources produced more than the 87% of the total demand of one day [11]. And these are just some of the recent milestones hit by renewables.
Even if they are not the only available option, renewables and eco-friendly generators have become one of the first things that comes to mind when people talk about small distributed generating units and thus, when discussing about microgrids and electric prosumer communities.
The most promising and widespread technologies for current microgeneration systems are:

- Solar PV panels;
- Micro-wind turbines;
- Micro Combined Heat and Power (micro-CHP);
- Fuel cells;
- Microturbines;

They and some of their characteristics will be now introduced.

Solar photovoltaic

Solar photovoltaic (PV) panels are usually considered as the front face of the "*renewable revolution*". The electric capacity of solar PV installed has been, in 2016, bigger than any other generation technology [12] (the total capacity has crossed the 300 GW [13]). Residential solar PV systems are now as much as 70% cheaper than in 2008 [14]. In Germany, prices for a typical 10 to 100 kWp PV residential rooftop-system were around 14,000 $€/kWp$ in 1990. At the end of 2016, such systems cost about 1,270 $€/kWp$. As regards the Energy Payback Time of a solar photovoltaic system, it is strongly dependent from the location: in the Northern Europe it is less than 3 years, while in the South it is around 1.5 years (in Sicily a new PV installation has a PBT of 1 year) [15].

Parameter	**Value**	**Reference**
European Union / Worldwide		
PV market	7.3 / 77.3 GW	IHS
Cumulative installation	106 / 320 GW	IEA+IHS
PV power consumption	114.4 / 333 TWh	BP
PV electricity share	3.4 / 1.3 %	BP
Worldwide		
Record solar cell efficiency: III-V MJ / mono-Si / multi-Si / CIGS / CdTe	46.0 / 26.7 / 21.9 / 21.7 / 21.0 %	Green and al.
Germany		
Price PV rooftop system	≈ 1500 €/kWp	BSW
LCOE PV power plant	≈ 0.08 €/kWh	ISE & Agora

Table 2.1: Data about photovoltaics installation [15]

There is also a less popular type of solar panels that integrates PV panels with solar collector, called PV/T collector. Besides the merit of producing additional thermal energy, the presence of the solar collector decreases the temperature of the above PV panels, increasing their electrical efficiency. The main shortcoming is in their price, since they are more expensive than traditional solar PV systems.

Small wind Turbines

In the last decade, the interest in wind turbines has continued to increase enormously worldwide. Competition in the market and better performances reduced the capital costs, making them a competitive alternative to produce electricity, even when compared with traditional power plants. Promising new designs are characterized by rotors much larger than before, since the capacity factor increases with the size. Large scale wind farms, both onshore and offshore, can provide exceptional results when placed in the right location, but their range of size and power usually do not fit the requirements and the resources of an EPC. Residential and smaller users needs can be tackled with smaller systems that work with the same principles. These *small wind turbines* or *micro-wind turbines*, whose power ratings are around few kW, can help to satisfy (at least partially) the domestic demand, especially if installed together with other generating units. Despite their potential, small wind turbines present many shortcomings: the efficiency of these devices is smaller then the one of common wind turbines, the problem of noise production becomes very relevant inside a neighborhood and suburban locations offer, in most of the cases, only low wind speed with high turbulence. These characteristics make small wind turbines difficult to get accepted by the public opinion [16].

Micro-CHP

Cogeneration is the production at the same time of two forms of energy, usually electricity and heat. It is an old concept and it can be found applied even in early power plants. The recent growing interest by consumers (and investors) in sustainability gave an additional boost to cogeneration because, even when it does not involve renewable energy sources, it represents a very efficient way to reduce carbon emissions. Moreover it allows to save an incredible amount of money. Combined heat and power system can be also designed at smaller scales (Micro-CHP), making it an attractive option to implement in EPCs. Another advantage of cogeneration is that it can be applied with a wide range of (renewables and non-renewables) generation systems [17].

Microturbines

Among the distributed generation technologies that do not rely on renewable sources, there is one that fits very well the characteristics of the EPCs: microturbines. Microturbines are basically small versions of the combustion turbines that can be found in power plants. Their output can go from 10 kW to a few hundred of kW [18]. The main advantages are the tolerable costs, the good efficiency, the easy installation and a high reliability. A wide range of models with different features are available on the market. Most of them are powered by fuels like natural gas or diesel and, unlike PV panels or wind turbine, can be started whenever it is needed.
The use of fuel in microturbines becomes more efficient when the device is integrated in a co-generation (CHP) system, achieving efficiency up to 80%. In this case, the thermal energy produced by the turbine is no more entirely wasted, but it can be used for heating.

Fuel cells

Another option to generate power inside an EPC is represented by fuel cells. Fuel cells are devices that convert the chemical energy of a fuel into electrical energy [19] and can be easily integrated into CHP systems. They are usually compared to batteries since the conversion is performed by electrochemical processes, but they differ in the fact that fuel cells require a fuel to flow through them. There are a lot of different fuel cells and most of them represents an eco-friendly option to generate energy with a good efficiency. Their market is growing rapidly, researchers are developing more and more technolgies. Among the current available fuel cells, phosphoric acid fuel cells (PAFC), molten carbonate fuel cells (MCFC), and solid oxide fuel cells (SOFC) are the most recommended ones for an EPC [1].

Other technologies

What has been presented in this section is only a small part of the available technologies for distributed generation (DG). Many other techniques used to produce electric energy in large power plants can be applied also at smaller scales. Sustainable alternatives such as small hydroelectric plants, geothermal energy or biomass resources can be feasible option in some cases. Each one is characterized by advantages and disadvantages and it is not possible to affirm which one is the best, since it depends on countless parameters. A good suggestion on how to produce energy in the community is to rely on more than just one technology: hybrid systems are a good method to compensate for the shortcomings of one technology with the advantages of another one, increasing the production reliability.

2.2 Storage

Renewable distributed generators are far from perfection. Many flaws that are often ascribed to these technologies are, for example, the lack of high reliability, the limited power quality and the difficulties to predict and organize the production. An expedient that helps to mitigate these problems is the integration in the network of efficient energy storage systems (ESS). Besides the benefits that they offer to renewable generators, they are however a powerful tool to manage energy in a clever way. EES can be classified according to the form of energy they involve: we can have electrochemical, thermal, chemical, electrical or mechanical devices.

Electrochemical batteries are what is popularly associated to the concept of energy storage, due to their presence in many common applications. Batteries store energy under the electrochemical form and saw their origin at the beginning of the 19th century. Since then, countless technologies appeared, increasing the capacity, the power density, the lifetime, etc. The last decades saw new remarkable improvements, making batteries less expensive and more suitable for residential usage [19] - [20].

Even though batteries are very popular, the 96% of the electrical storage capacity installed in the world is represented by another kind of system: the pumped hydroelectric energy storage (PHES) [19]. PHES uses the gravitational energy of a reservoir of water located at a certain elevation. When electrical power is required, the water is sent to a lower reservoir, flowing through a turbine that produce electricity. Depending on the case, some communities could implement smaller PHES system for seasonal storage.

Many other technologies are available for EES, such as compressed air energy storages (CAES), flywheels and supercapacitors, but they still present major shortcoming and are suited only for particular applications. A summary of the characteristics of some of the energy storage technologies is presented in Tab. 2.2.

Type	**Energy Density** Wh/kg	**Power Density** W/kg	**Response Time**	**Cycling Times**
Flywheel	5-30	400-1500	1 s	Above 20,000
Compressed air	30-60	-	1-10 min	Above 100,000
Lead-acid	30-50	75-300	10 s	2000
Lithium-ion	75-200	150-300	10 s	10,000
Sodium-sulfur	100-250	100-230	10 s	2500-6000
Supercapacitor	5-10	5-10	1 s	100,000

Table 2.2: Energy storage technologies [20]

2.2.1 Electric Vehicles

There is another element, besides renewables, that promises to help the shift to a cleaner environment and the building of a more sustainable future: Electric Vehicles (EVs). Besides the effects that they can have on the automotive industry, EVs can be a powerful tool into the pocket of the electric grid, providing or storing power upon request when plugged in: this concept is called Vehicle-to-Grid power (V2G) [21]. Utility fleets seem to have a good economic potential as ancillary service for the power grid [22], but also individual vehicles could be exploited if used as storage devices in an EPC. Their implementation in a microgrid is more difficult than the common battery's one, but they still can provide interesting features and additional capacity [23].

2.3 Demand

The cleanest energy is the one that you do not use, we all know it. Reducing the energy consumption would be probably the most efficient way to contrast pollution and global warming, but it is not always feasible in practice. Many studies and projections state that, even in the best case, the global demand will continue to increase due to economic and population growth. One of the key points of an EPC is trying to satisfy the internal demand of the prosumers in an efficient way in terms of economic cost and sustainability. Not an easy task since forecasting future demand and production is extremely difficult and in some cases, impossible. But when more consumers join together in the same community it is possible to coordinate and to organize some of the energy consuming tasks. Some of the demand could be shifted to times of the day when energy is cheaper or when renewable sources are available; other expensive energy tasks could be coordinated in order to reduce the peak demand. Another interesting prospect is the possibility to purposely consume more energy if there is some risk of overvoltages in the community or to help frequency control for the main grid. This approach is called "demand management" (from the demand-side).

2.4 A goal-oriented community

The concept itself of a community of multiple electric prosumers implies that they intend to pursue a set of mutual goals. Since EPCs are still in their early state and since there is a lack of regulations, it is not perfectly clear what the policy of a community could be. The objective of the community can be, for example, to maximize the consumption of "green" power produced by the distributed generators, to minimize the exchanges with the feeder or to optimize the overall revenues of the entire community [25]. Whatever the goal is, however, there are very few studies that analyze the energy sharing between prosumers and there seems to exists no techniques yet to identify proumers that do not act as agreed [26]. Investigating further on these aspects is crucial for the development of new successful EPCs.

Chapter 3

A control scheme for the community

Since their conception, microgrids have been deeply examined in literature (see for example [27] - [29]) and many challenges and shortcomings have been detected. Monitoring and controlling the network can be extremely difficult, becoming an interesting argument for research. The dynamics of electric power system are complex even at smaller scales, due to all the parameters that have effect on the system. The safety of the network is not the only thing that matters, the economic side of the problem is much relevant too. If the concept of the microgrid is juxtaposed to the one of a prosumer community, with some specific goal to reach while operating the grid, the difficulty increases. Being able to optimize the behavior of each generating unit, load and storage in a microgrid is a crucial step for the spread of EPCs along the main grid. It requires taking into account variables like electricity prices, demand and production forecast, real-time availability of storage and, last but not least, the safety of the grid. This work is focused exactly on this: designing a way to control the prosumers' operation inside the community, trying to ensure the safety of the grid while pursuing a common objective.

3.1 Formalising the prosumer community

To describe and to deal with the control challenges, we need first to formalize a simplified model of the prosumer community dynamics and then use it in the design of a decentralized control scheme.

We consider a low-voltage distribution network composed by $N \in \mathbb{N}$ buses, where one bus is the *root connection* (the point of connection between the community and the power system), while the remaining $N - 1$ buses are the $N_{pro} \in \mathbb{N}$ prosumers' dwellings inside the EPC. The number of branches in the network is $L \in \mathbb{N}$, with R_l and X_l as, respectively, the resistance and the reactance of the $l-th$ branch ($l \in \{1, \ldots, L\}$). Let's consider a linear network like the one in Fig.3.1.

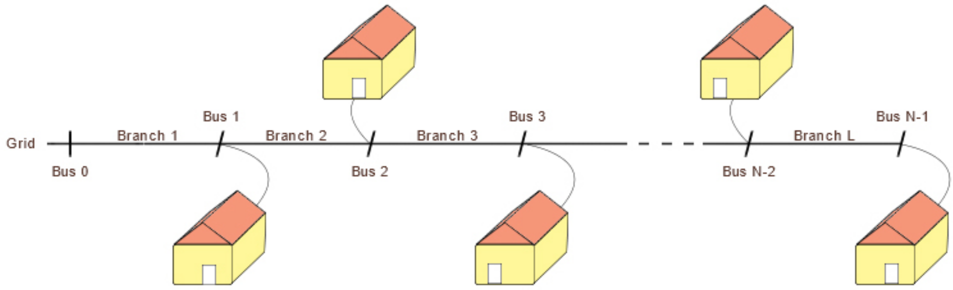


Figure 3.1: Simplified representation of the electric prosumer community

As previously stated, each prosumer $i \in \{1, \ldots, N_{pro}\}$ inside the community can consume, produce or store electricity. We associate a generation capacity $X_{pr,i}$, a storage capacity $X_{batt,i}$, a storage charging efficiency $\eta_{ch,i}$ and a storage discharging efficiency $\eta_{dis,i}$ to each bus $i \in \{1, \ldots, N-1\}$. If prosumer i has no generation/storage device installed, they are set to zero.
We consider the community behavior over a set of discrete time steps $t \in \{1, \ldots, T\}$ with $T \in \mathbb{N}$ as the time horizon. Please note that all the quantities are assumed to be in per unit and all the power related variables assume the average value over the time interval Δt between two time steps. At each time step $t \in \{1, \ldots, T\}$ the prosumer $i \in \{1, \ldots, N-1\}$ consumes the active power $P^t_{load,i}$ and the reactive power $Q^t_{load,i}$. The load consumption depends on the electrical appliances located and used inside the dwelling and, in the context of this work, we consider that it can not be purposely modulated by the control system. What can be directly controlled is the power production (active $P^t_{pr,i}$ and reactive $Q^t_{pr,i}$) and the power exchanged with the batteries (stored $P^t_{ch,i}$ or drawn $P^t_{dis,i}$). The power produced is capped by the maximal potential that the device allows:

$$P^t_{pr,i} \leq P^{t,max}_{pr,i} \tag{3.1}$$

$$\left|Q^t_{pr,i}\right| \leq Q^{t,max}_{pr,i} \tag{3.2}$$

If, for example, the prosumer has installed wind turbines or photovoltaic panels, the potential production $P^{t,max}_{pr,i}$ at timestep t will depend mainly by the weather condition at that

time.
The battery at bus i is characterized at every time step by the energy stored S_i^t. The two variables related to the power exchanged with the batteries, $P_{ch,i}^t$ (power charging the battery) and $P_{dis,i}^t$ (power discharging the battery), are both always positive values. The net power exchanged with the device can not exceed a limit ($P_{batt,i}^{t,max}$) that depends on the the storage device. Moreover, the power exchanged with the battery can not cause its state of charge to go to values smaller than 0% or higher than 100%. The battery dynamics are described in the following equations:

$$|P_{ch,i}^t - P_{dis,i}^t| \leq P_{batt,i}^{t,max} \tag{3.3}$$

$$0 \leq S_{batt,i}^t + \eta_{ch,i} P_{ch,i}^t \Delta t - \frac{P_{dis,i}^t}{\eta_{dis,i}} \Delta t \leq X_{batt,i} \tag{3.4}$$

We need to consider that part of the power that the prosumer injects in the battery and extracts from it will be wasted due to losses. Eq. 3.4 takes into account the losses appearing in charge and discharge process through, respectively, parameters $\eta_{ch,i}$ and $\eta_{dis,i}$.
The previous equations are related to the "internal" balance of power of a single prosumer. Not always this balance is equal to zero. There are many occasion in which the power installed or stored in a single dwelling is not enough to satisfy the load, there are times when it produces more than it can consume or store, or times when it is more convenient to sell energy instead of storing it. To study the power exchanges with the rest of the grid, we denote with $P_{\delta,i}^t$ and $Q_{\delta,i}^t$ the power injected into the distribution network from prosumer i at time t.

$$P_{\delta,i}^t = P_{pr,i}^t + P_{dis,i}^t - P_{ch,i}^t - P_{load,i}^t \tag{3.5}$$

$$Q_{\delta,i}^t = Q_{pr,i}^t - Q_{load,i}^t \tag{3.6}$$

Eq. 3.5 and 3.6 are the active and reactive power balances at bus i at time t. The power injected into the distribution network from prosumer i at time t will be therefore the sum of the power produced and the power discharging the battery minus the power consumed by the appliances and by the battery. When these variables are different from zero it means that the prosumer i has a surplus (if $P_{\delta,i}^t > 0$) or a deficit of power (if $P_{\delta,i}^t < 0$).
In these cases, the difference needs to be balanced. This can happen balancing the surplus/deficit of another prosumer inside the community or it is balanced by the feeder (the main grid). If both the options are available, we need to understand which one is more

profitable (depending on electricity price) and safe (depending on voltages along the microgrid). The control of the power production and the usage of the batteries is a crucial element to reduce overvoltages, line overloadings, network losses and costs.
Discussing costs and revenues is not easy because there is still no specific regulatory or policies about prosumers. As what regards the exchanges with the main grid it is reasonable to think that gathering more prosumers inside the same community could led to more advantageous tariffs for them or even to compete as bidders in market auctions. Also, it will be interesting to see how tariffs on internal power exchanges between two prosumers will be managed. The tariff could be fixed for the community or could change for each prosumer, depending on their consumption, their capacity and other factors. Several models have been predicted and only a future legislation will say which one will be applied.
In our formalization we assume that the exchanges between prosumers are not associated to any expense (internal energy costs zero to other prosumers) while the energy exchanged by a prosumer with the retailer is characterized by a price c^t_{el}, fixed no matter which prosumer sells it/buys it, depending only by time t. This implies that in some scenarios it could be convenient to consume the self-generated power or to consume external power and to store the self-generated one in order to use it in the future.

3.2 Decentralized control scheme

Once the prosumer community has been introduced in term of main variables and dynamics, we can talk about the control scheme for an EPC. Like other systems composed by multiple agents, there are two main control strategies, a centralized and hierarchical mechanism or a distributed scheme.
A *centralized control scheme* indicates that all the data possessed are gathered together and sent to a central entity that computes the orders and coordinates the prosumers' actions.

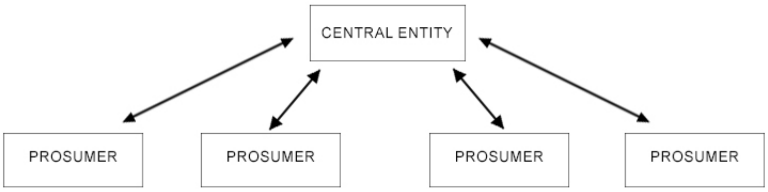


Figure 3.2: Centralized control scheme.

In order to achieve good results, this entity should have a detailed model of the network, efficient communication devices and an equipment able to receive, store and process the information. The latter is called "Microgrid Central Controller" (MGCC) and plays a fundamental role in the control structure. The main shortcoming of building and maintaining all the machinery involved in the centralized strategy is that it can be very delicate and expensive. Each prosumer should send anytime a big amount of data to this central entity, such as potential production and demand forecasts, state of the storage devices, voltages at their buses, etc. Since current smart meters technologies appeared on the market, privacy concerns for the single prosumer are rised due to the sharing of personal consumption information with other people [30]. We still do not know how a future regulation will treat this matter once the figure of prosumers will spread, therefore it is interesting to investigate possible designs for decentralized control schemes that do not require the individual to share too much information.

With "*decentralized control scheme*" we imply that each single prosumer in an EPC takes autonomous decisions on its own behavior and on how to interact with the rest of the network.

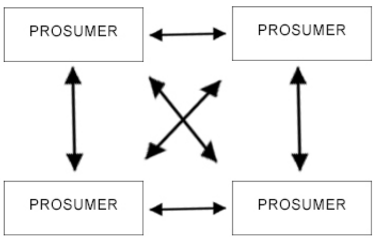


Figure 3.3: Decentralized control scheme.

We want to investigate how to design distributed control schemes that may contribute to reach (at least partially) the objectives of the community. More specifically, we want to avoid that prosumers share privacy-related information so we decided that they can compute their actions relying only on their own data and measurements. This means to decide, for example, how much power to inject in the grid or in the battery without knowing if the community needs it. This is not an easy task, since a partial knowledge of the state of the network makes difficult for the prosumer to compute cost-effective decisions. Not only the revenues are difficult to maximize, but unappropriate actions can cause overvoltages, undervoltages or overloadings inside the network, undermining the safety of the micro-grid.
Our strategy is to resort to supervised learning techniques that may extract from simulated optimal solutions decision making patterns to be applied at the level of the single prosumer.

3.3 Supervised learning algorithm

Supervised learning (SL) methods are a branch of machine learning that has its roots in statistics world. SL can be implemented in many fields, areas and problems with good results. Their task is the definition of a function used to predict the optimal output value Ψ associated to a set of inputs ψ (usually a vector).
The choice of inputs and outputs depends on the problem. A classical example is when applied to the handwriting recognition problem: in the simplest case, if an image of an handwritten character is given to the function as input, its output will be its guess of which character it is. When the outputs are some sorts of labels (as the character in the handwriting recognition case), we call it a *classification problem* otherwise, if the outputs consist of continuous variables, it is a *regression problem*.
Each problem involving Supervised Learning includes, indeed, a training process, that is performed using a data-set of samples that contains inputs and outputs, in groups of input-output pairs.
The first thing to do is, therefore, defining these training examples, thinking about what kind of inputs should be used to guess the output we want. The inputs should be measurable, independent and relevant to the output choice. This step is essential for the efficiency of the implementation. Once the shape of the inputs and outputs is determined, we need to construct a set (sufficiently big to provide enough information but either not too large) of input-output pairs. The outputs need to be the exact value that we want to be associated to the input if they were provided to the function in the real world. For the handwrit-

ting recognition, this learning set would be a large set of different handwritten characters, each one paired to the character we know it represents (the *label*). When the training set of data is defined, it is analyzed through a learning algorithm: it examines these data, tries to learn from them a pattern in the association between input and output and define the structure of the learned function. The goal is to get a function that is now able to predict a output (close to the one we expect) when a new input (even unseen in the learning set) is provided.

Literature is full of SL methods and algorithm to apply to several problems. One popular family of SL techniques is the branch of the *tree-based* methods, simple to apply and suitable for both classification and regression problems [31].

This family of methods shares the concept at the base: they try to split the input-output pairs in smaller and smaller groups in order to develop a decision tree as the algorithm to select the final output. Once the tree is constructed, it will consist in a certain number of decision nodes (depending on the complexity of the problem): at each node it evaluates the attribute analyzed at that node and, starting from the top to bottom, the algorithm will arrives to the output (a label, if it is a classification problem, or a value, if it is a regression one). A representation of a generic (very simple) decision tree is shown in fig. 3.4.

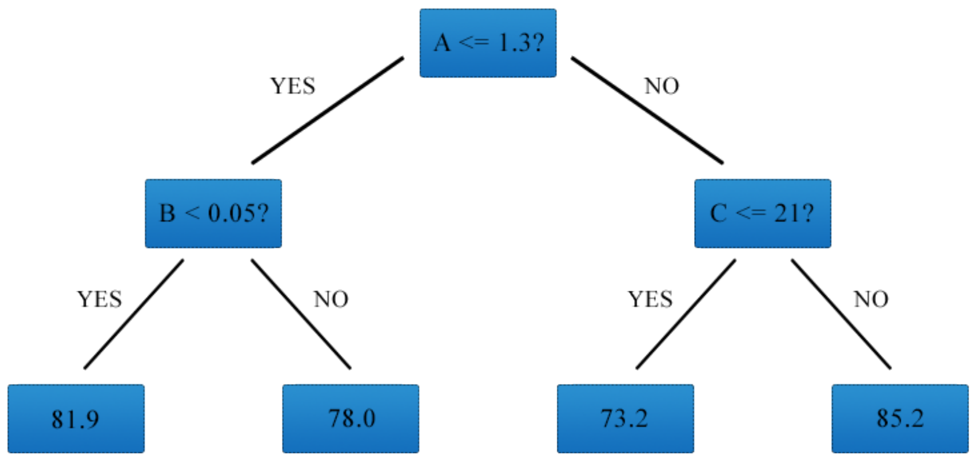


Figure 3.4: A representation of how a very simple decision tree constructed by SL works.

Some common tree-based methods are: CART (Classification and Regression Trees) [32], Tree Bagging and Random Forest [33]. The accuracy of these models depend on the particular problem on which they are applied, but in several cases the results are slightly the same. The model used in the development of the decentralized control strategy is another tree-based method called Extremely Randomized Trees. The next sections will treat the development of the decentralized strategy.

3.3.1 Estimators

As we said before, supervised learning algorithms give as result functions (we call them "*estimators*" from now on) that should be able to predict an output as answer to some input. In our case we want to use these estimators to predict the current optimal strategy for a prosumer.
In the model of the microgrid we have formalized in the previous sections, a prosumer, in a decentralized scheme, can take decisions about four different variables: how much active power to produce, how much reactive power to produce, how much charging the battery, how much discharging the battery (consumption is not directly controlled). So we decided to develop four different estimators to take these decisions for the prosumer. These four estimators are called $\mathcal{R}_P, \mathcal{R}_Q, \mathcal{R}_C$ and $\mathcal{R}_D$ and they are dedicated, respectively, to the optimal levels of active power production, reactive power production, power charging the storage device and power discharging the storage device. Each estimator is constructed to take as input a vector of data related only to the local prosumer i at timestep t. The choice about which data should be relevant for the estimators fell upon current electricity price, voltage at the bus, consumption, potential productions and state of charge of the batteries.

Training

The training of estimators in the supervised learning problem is performed passing to the model a set of data containing several samples of (input,output) pairs. The estimator, observing this data, extracts from them a strategy to predict what should be the output to associate to a certain input. This samples need to contain the *optimal* strategy for each prosumer in configurations similar to real-world conditions.
To find the decision making patterns to be applied locally by the prosumers, the four estimators $\mathcal{R}_P, \mathcal{R}_Q, \mathcal{R}_C$ and $\mathcal{R}_D$ are trained extracting data from the solution of optimal power flow problems, solved by a centralized "*omniscient*" scheme, set in the same network that the estimators would deal with. Several methods exist to solve such problems. One of them, suited for our case, is described in chapter 4. This centralized controller has a perfect knowledge at any time of the problem and it can thus detect the decisions that optimizes the global objective of the EPC over the entire time period.

Solving one such problem provides a time series of data, corresponding to the evolution of all the indicators over the time horizon:

$$[\Xi_0^*, \dots, \Xi_{T-1}^*] \tag{3.7}$$

From this time series of data, one can extract a series of local data, i.e. relative to one single prosumer (i):

$$\left[\Xi_1^{(i),*}, \dots, \Xi_T^{(i),*}\right] \tag{3.8}$$

where $\forall t \in \{1, \dots, T\}$, $\forall i \in \{1, \dots, N-1\}$,

$$\Xi_i^{t,*} = \begin{pmatrix} P_{pr,i}^{t} & Q_{pr,i}^{t} \\ P_{pr,i}^{max,t} & Q_{pr,i}^{max,t} \\ P_{Load,i}^{t,} & Q_{Load,i}^{t,} \\ P_{ch,i}^{t} & P_{dis,i}^{t} \\ S_{batt,i}^{t} & c_{el}^{t} \\ \left|\underline{\mathbf{v}}_i^t\right| & arg(\underline{\mathbf{v}}_i^t) \end{pmatrix}, \tag{3.9}$$

From these extractions, we generate the following learning sets:

- To generate a learning set dedicated to how to predict the optimal level of active power production, we process the whole variables $\Xi_i^{t,*}$ into the following set of (input, output) pairs:

$$\mathcal{L}^P = \left\{\left(\psi_{P,i}^t, \Psi_{P,i}^t\right)\right\}_{i=1,t=1}^{i=N-1,t=T} \tag{3.10}$$

where, $\forall t \in \{0, \dots, T-1\}$, $\forall i \in \{1, \dots, N\}$,

$$\psi_{P,i}^t = \left(i,\, t,\, c_{el}^t,\, \left|\underline{\mathbf{v}}_i^t\right|,\, arg(\underline{\mathbf{v}}_i^t),\, P_{Load,i}^t,\, Q_{Load,i}^t,\, P_{pr,i}^{max,t},\, Q_{pr,i}^{max,t},\, S_{batt,i}^{t}\right) \tag{3.11}$$

$$\Psi_{P,i}^t = P_{pr,i}^t \tag{3.12}$$

Where:

  - i : id number of the bus considered;
  - t : time-step considered;
  - $\left|\underline{\mathbf{v}}_i^t\right|$: magnitude of the voltage at bus i at time step t;
  - $arg(\underline{\mathbf{v}}^t)$: phase of the voltage at bus i at time step t;

- c_{el}^{t} : electricity price at time step t;
- $S_{batt,i}^{t}$: level of charge of the storage of bus i at time step t;
- $P_{Load,i}^{t}$, $Q_{Load,i}^{t}$: active and reactive power consumption at bus i at time step t;
- $P_{pr,i}^{max,t}$, $Q_{pr,i}^{max,t}$: maximal active and reactive production potential at bus i at time step t;

- To generate a learning set dedicated to how to predict the optimal level of reactive power production, we process the whole variables $\Xi_i^{t,*}$ into the following set of (input, output) pairs:

$$\mathcal{L}^Q = \left\{\left(\psi_{Q,i}^t, \Psi_{Q,i}^t\right)\right\}_{i=1,t=1}^{i=N-1,t=T} \tag{3.13}$$

where, $\forall t \in \{0,\dots,T-1\}$, $\forall i \in \{1,\dots,N-1\}$:

$$\begin{aligned}\psi_{Q,i}^t = &= \psi_{P,i}^t\\ \Psi_{Q,i}^t = &= Q_{pr,i}^t\end{aligned}$$

- To generate a learning set dedicated to how to predict the optimal level of power injected into the battery, we process the whole variables $\Xi_t^{(i),*}$ into the following set of (input, output) pairs:

$$\mathcal{L}^C = \left\{\left(\psi_{C,i}^t, \Psi_{C,i}^t\right)\right\}_{i=1,t=1}^{i=N-1,t=T} \tag{3.14}$$

where, $\forall t \in \{0,\dots,T-1\}$, $\forall i \in \{1,\dots,N-1\}$:

$$\begin{aligned}\psi_{C,i}^t = &= \psi_{P,i}^t\\ \Psi_{C,i}^t = &= P_{ch,i}^t\end{aligned}$$

- To generate a learning set dedicated to how to predict the optimal level of power extracted from the battery, we process the whole variables $\Xi_i^{t,*}$ into the following set of (input, output) pairs:

$$\mathcal{L}^D = \left\{\left(\psi_{D,i}^t, \Psi_{D,i}^t\right)\right\}_{i=1,t=1}^{i=N-1,t=T} \tag{3.15}$$

where, $\forall t \in \{0,\dots,T-1\}$, $\forall i \in \{1,\dots,N-1\}$:

$$\begin{aligned}\psi_{D,i}^t = &= \psi_{P,i}^t\\ \Psi_{D,i}^t = &= P_{dis,i}^t\end{aligned}$$

The optimal power flow simulations from which the learning sets should be obtained are set in scenarios similar to those that the actual network could deal with. With the word "*scenario*" we denote the entire set of variables that can not be modulated through the operation of the microgrid (electricity prices, sun radiation, loads, etc.). The set of network data included in the input $\psi^t_{P,i}$, $\psi^t_{Q,i}$, $\psi^t_{C,i}$, $\psi^t_{Q,i}$ of the estimators $\mathcal{R}_P, \mathcal{R}_Q, \mathcal{R}_C$ and $\mathcal{R}_D$ could be different from the one presented. Data like the voltage or the power production at the neighbors' buses have been neglected in order to avoid privacy concerns. Information like the period of the year (contained in the value of t) or the phase of the voltage could seem, instead, useless, but preliminary tests showed that they can help the quality of the predictions.

3.3.2 Post-processing the prediction

Once the estimators are trained they can be used to try to predict the decision of the single prosumer when it dinamically interacts with other prosumers and the retailer. The idea is to provide to the estimators $\mathcal{R}_P, \mathcal{R}_Q, \mathcal{R}_C$ and $\mathcal{R}_D$ local measurements referred to a prosumer i (the same inputs vector used to train them) and to use their predictions to control the choices of that prosumer. Since there are no constraints to the values that an estimator provides as output, its prediction could lead to impracticable or dangerous actions when applied in real-world condition. Therefore a partial post-processing of the outputs is needed to *correct* them. We denote with $\mathcal{R}^{P*}_{i,t}$, $\mathcal{R}^{Q*}_{i,t}$, $\mathcal{R}^{C*}_{i,t}$ and $\mathcal{R}^{D*}_{i,t}$ the preliminary predictions made by the estimators associated to the input of bus i and time step t.
The outputs suggested to the prosumer at that time step are corrected to $P^t_{pr,i}$, $Q^t_{pr,i}$, $P^t_{ch,i}$ and $P^t_{dis,i}$ as follows.

- For the active power production level:

if $\mathcal{R}^{P*}_{i,t} \geq P^{max,t}_{pr,i}$

$$P^t_{pr,i} = P^{max,t}_{pr,i}$$

else if $\mathcal{L}^P\left(in^{i,t}\right) \leq P^{min,t}_{pr,i}$

$$P^t_{pr,i} = P^{min,t}_{pr,i}$$

else $P^t_{pr,i} = \mathcal{R}^{P*}_{i,t}$

If the predicted active power production is bigger than the maximum power it could produce, the suggested power will be the maximum potential one. If the predicted active power production is smaller than the minimum power it could produce (typically zero) the suggested power will be the minimum. Otherwise the suggested active power production will be exactly the predicted one.

- For the reactive power production level:

  if $\mathcal{R}^{Q*}_{i,t} \geq Q^{max,\,t}_{pr,\,i}$

  $Q^{t}_{pr,\,i} = Q^{max,\,t}_{pr,\,i}$

  else if $\mathcal{L}^{Q}\left(in^{i,t}\right) \leq Q^{min,\,t}_{pr,\,i}$

  $Q^{t}_{pr,\,i} = Q^{min,\,t}_{pr,\,i}$

  else $Q^{t}_{pr,\,i} = \mathcal{R}^{Q*}_{i,t}$

If the predicted reactive power production is bigger than the maximum reactive power it could produce, the suggested power will be the maximum potential one. If the predicted reactive power production is smaller than the minimum power it could produce (it can also be negative) the suggested power will be the minimum. Otherwise the suggested reactive power production will be exactly the predicted one.

As regard the power exchanged to the batteries, we need not only to cap the maximum and the minimum suggested power, but also to be sure that they do not bring the state of charge of the storage over forbidden levels.

- For the power injected in the battery:

  if $\mathcal{R}^{C*}_{i,t} \geq P^{max}_{batt,\,i}$

  $P^{t}_{c,\,i} = P^{max,\,t}_{pr,\,i}$

  else if $\mathcal{R}^{C*}_{i,t} \leq 0$

  $P^{t}_{ch,\,i} = 0$

  else $P^{t}_{ch,\,i} = \mathcal{R}^{C*}_{i,t}$

  if $S^{\,t}_{i} + P^{t}_{ch,\,i}\eta_{ch,i} \geq X_{batt,\,i}$

  $P^{t}_{ch,\,i} = \frac{X_{batt,\,i} - S^{t}_{i}}{\eta_{ch,\,i}}$

- For the power drawn from the battery:

  if $\mathcal{R}^{D*}_{i,t} \geq P^{max}_{batt,\,i}$

  $P^{t}_{dis,\,i} = P^{max,\,t}_{pr,\,i}$

else if $\mathcal{R}_{i,t}^{D*} \leq 0$

$P_{dis,i}^{t} = 0$

else $P_{dis,i}^{t} = \mathcal{R}_{i,t}^{D*}$

if $S_i^t - \frac{P_{dis,i}^t}{\eta_{dis,i}} < 0$

$P_{dis,i}^t = S_i^t \eta_{dis,i}$

It is important to notice that post-processing the output values does not prevent the risk of incurring in under-voltages or over-voltages.

Chapter 4

The Power flow analysis

The study and operation of any interconnected electric power system require to perform a numerical analysis to determine the electrical state of the network starting from parameters that are known: this computation is called *power flow analysis* or *load-flow study*.
Power flow analysis allows to compute currents, real and reactive power flowing in the branches, losses, voltages at the buses. It is used not only to analyze the operation of networks that already exist, but is a powerful method also to find what configurations lead to critical conditions or to design new power systems. Moreover it can be included in other methods to perform unit commitment, economic dispatch or to determine the *optimal power flow*, the most efficient configuration of the system.
This chapter presents a formulation of the problem and a method to solve it when applied to an EPC.

4.1 AC Power flow equations

Defining and solving the power flow equations of the power system are the main tasks in the load flow study.
One of the data required to perform a load flow study is the nodal admittance matrix $\mathbf{Y}_{BUS}$.
In a system of N buses, $\mathbf{Y}_{BUS}$ is a $N \times N$ matrix such that:

$$\mathbf{V}\mathbf{Y}_{BUS} = \mathbf{I} \tag{4.1}$$

Eq. (4.1) is the matrix form of the well-known Ohm's Law. $\mathbf{Y}_{BUS}$ can be constructed knowing how the buses are connected between them and what is the admittance of each branch inside the system.
There are four different variables associated to each bus $i \in \{0, \ldots, N-1\}$: the active

power injection P_i, the reactive power injection Q_i, the voltage magnitude V_i and the voltage phase θ_i. Depending on the type of the bus i, the variables that are assumed to be known are:

- if the bus i is the slack bus, the voltage magnitude V_i and phase θ_i;
- if the bus i is a P-V bus, the voltage magnitude V_i and the active power injection P_i;
- if the bus i is a P-Q bus, the active power P_i and reactive power Q_i injections;

The purpose of the analysis is to evaluate the remaining:

- $N_{P-V} + N_{P-Q}$ voltage phases;
- N_{P-Q} voltage magnitudes;

The total unknowns are thus $N_{P-V} + 2N_{P-Q}$.
For each bus $i \in \{0, \ldots, N-1\}$ we can write the following power balance equations:

$$P_i = \sum_{j=0}^{N-1} V_i V_j \left(G_{ij} cos\left(\theta_i - \theta_j\right) + B_{ij} sin\left(\theta_i - \theta_j\right)\right) \tag{4.2}$$

$$Q_i = \sum_{j=0}^{N-1} V_i V_j \left(G_{ij} sin\left(\theta_i - \theta_j\right) - B_{ij} cos\left(\theta_i - \theta_j\right)\right) \tag{4.3}$$

Where:

- G_{ij} is the real part of the element corresponding to the ith row and jth column in the Y_{BUS};
- B_{ij} is the imaginary part of the element corresponding to the ith row and jth column in the Y_{BUS}.

We have therefore a set equations that we can use to find the unknown variables. Once the values of these variables are found, the evaluation of the remaining parameter of interest (i.e.: current in the branches, power losses, etc.) becomes trivial, using other theoretical relationships such as:

$$\mathbf{I}_i = \left(\frac{P_i + jQ_i}{V_i}\right)^* \tag{4.4}$$

4.2 Optimal Power Flow in an EPC

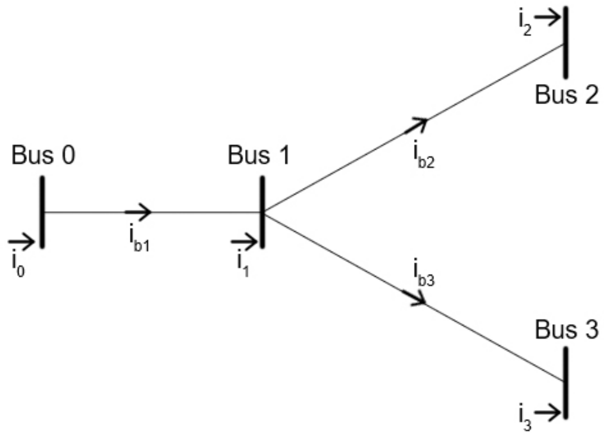
The power flow study can be implemented in an optimization problem to look for the best way to operate a power system while respecting the network operating limits and other constraints. This problem is commonly referred as the Optimal Power Flow (OPF).
From problem to problem, the term "best" can change very much. It depends on what the operator is trying to achieve: it can be optimizing the revenues, maximizing the use of green energy, etc.
The set of equations described in Section 4.1 involves non-linear relationships. The resulting optimizational problem is non-linear and non-convex, increasing exponentially the computational cost required to solve the OPF, especially with large interconnected power systems. There are many methods to solve it and multiple approaches have been developed to decrease the complexity of the problem (i.e. "Direct Current Power Flow" [34] and "Fast Decoupled Load Flow" [35]). The assumptions that most of these models require, however, do not always fit with low-voltage (LV) distribution networks.
An interesting method with good convergence properties that well matches with LV networks is the one developed by Fortenbacher and al. [36]. In this paper, the authors recast the non-linear power flow equations into a linear problem, relying on assumptions that are common to most LV networks. This linear problem is iteratively solved, updating each time the voltages at the buses with a combined forward backward sweep technique (FBS) [37]. This method is called Forward-Backward Sweep Optimal Power Flow (FBS-OPF) and it will be used, in the context of this work, to represent a centralized "ominiscient" control strategy and to create the learning sets used by SL model presented in Section 3.3. Its formulation will now be resumed and explained.

4.2.1 The FBS-OPF algorithm

Let's consider a low-voltage distribution network with a weakly meshed radial structure similar to the one formalized in the previous chapter, composed by $N \in \mathbb{N}$ buses, where the first bus is the Point of Common Coupling (PCC) between the main grid and the microgrid, while the remaining $N - 1$ buses are the $N_{pro} \in \mathbb{N}$ prosumers' houses of the electricity prosumer community. Every relationship that follows is written for a generic time step t and are valid $\forall t \in \{1, \ldots, T\}$ with T as the time horizon of the problem. The topology of the network is mapped by the bus-injection to branch current matrix $\mathbf{M}_f \in \mathbb{R}^{L \times N}$ defined in [37]. It links the vector $\underline{\boldsymbol{i}}^t \in \mathbb{R}^{N \times 1}$ of the bus current injections to the vector $\underline{\boldsymbol{i}}_b^t \in \mathbb{R}^{L \times 1}$ of the branch currents through the Kirchhoff's Current Laws.

$$\underline{\boldsymbol{i}}_b^t = \boldsymbol{M}_f \, \underline{\boldsymbol{i}}^t \tag{4.5}$$

For example, if we consider the following simple network:



We can write:

$$\boldsymbol{i}_{b1} = \boldsymbol{i}_1 + \boldsymbol{i}_2 + \boldsymbol{i}_3$$
$$\boldsymbol{i}_{b2} = \boldsymbol{i}_2$$
$$\boldsymbol{i}_{b3} = \boldsymbol{i}_3$$

From eq. 4.5 we have that M_f is equal to:

$$\mathbf{M}_f = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

The formulation of the FBS-OPF requires also the introduction of another matrix, indicated with $\mathbf{M} \in \mathbb{R}^{L \times N-1}$ that is obtained deleting the first row from $\mathbf{M}_f$. To convert the traditional OPF into a linear problem we need now to make some approximations about voltages, currents and losses.

Approximating the voltages

If we consider a generic branch $l \in \{1 \ldots L\}$ we can write, according to Ohm's Law, that the voltage drop in the line is:

$$\Delta \underline{v}_l^t = [R_{d1} + j X_{dl}] \; \underline{i}_{bl}^t \tag{4.6}$$

Merging eq. 4.6, 4.4 and 4.6 we can write in a matricial form:

$$\Delta \underline{\boldsymbol{v}}^t = \boldsymbol{M}^T [\boldsymbol{R}_d + j \boldsymbol{X}_d] \, \boldsymbol{M}_f \, \underline{\boldsymbol{V}}_{df}^t \left[\boldsymbol{P}_{gen}^t + j \boldsymbol{Q}_{gen}^t\right]^* \tag{4.7}$$

where:

- $\boldsymbol{R}_d = diag\{R_{d1} \ldots R_{dL}\} \in \mathbb{R}^{L\times L}$ is the resistance matrix;
- $\boldsymbol{X}_d = diag\{X_{d1} \ldots X_{dL}\} \in \mathbb{R}^{L\times L}$ is the reactance matrix;
- $\underline{\boldsymbol{V}}^t_{df} = diag\left\{\frac{1}{\underline{v}^t_0} \ \ldots \ \frac{1}{\underline{v}^t_N}\right\} \in \mathbb{R}^{N\times N}$ is nodal line to neutral voltages matrix.

Eq.(4.7) presents a complex relationship. To linearize it, the authors of the paper [36], decide to assume that nodal voltage angles are small and resistances in the network are way bigger than its reactances. This assumptions is usually true for LV networks. We can approximate then Eq.(4.7) as:

$$\boldsymbol{v}^t \approx \boldsymbol{v}_s + \left[\boldsymbol{M}^T\boldsymbol{R}_d\boldsymbol{M}_f\left|\underline{\boldsymbol{V}}^t_{df}\right| \quad \boldsymbol{M}^T\boldsymbol{X}_d\boldsymbol{M}_f\left|\underline{\boldsymbol{V}}^t_{df}\right|\right]\begin{bmatrix}\boldsymbol{P}^t_{gen}\\ \boldsymbol{Q}^t_{gen}\end{bmatrix}$$

The matrix $\left[\boldsymbol{M}^T\boldsymbol{R}_d\boldsymbol{M}_f\left|\underline{\boldsymbol{V}}^t_{df}\right| \quad \boldsymbol{M}^T\boldsymbol{X}_d\boldsymbol{M}_f\left|\underline{\boldsymbol{V}}^t_{df}\right|\right]$ is called $\mathbf{B}^t_v$ and $\boldsymbol{v}_s \in \mathbb{R}^{L\times 1}$ is the slack bus voltage vector.

Approximating the currents in the branches

Another assumption that we can make for LV networks is that reactive power injections are usually small if compared with active power injections. Assuming that, we express current in the branches as:

$$\boldsymbol{i}^t_b \approx \boldsymbol{M}_f\left|\underline{\boldsymbol{V}}^t_{df}\right|\boldsymbol{P}^t$$

The product $\boldsymbol{M}_f\left|\underline{\boldsymbol{V}}^t_{df}\right|$ is denoted as $\mathbf{B}^t_r$.

Approximating the losses

The power losses are approximated as linear piecewise function:

$$\mathbf{P}_{Loss} \approx max\{\mathbf{L}^t_0\mathbf{P}^t, -\mathbf{L}^t_0\mathbf{P}^t, \mathbf{L}^t_1\mathbf{P}^t + \mathbf{b}^t, -\mathbf{L}^t_1\mathbf{P}^t + \mathbf{b}^t\}$$
$$\mathbf{Q}_{Loss} \approx max\{\mathbf{L}^t_0\mathbf{Q}^t, -\mathbf{L}^t_0\mathbf{Q}^t, \mathbf{L}^t_1\mathbf{Q}^t + \mathbf{b}^t, -\mathbf{L}^t_1\mathbf{Q}^t + \mathbf{b}^t\}$$

Where:

- $\mathbf{L}^t_0 = diag\{i^{0,t}_0, \ldots, 1^{0,t}_l\}\mathbf{R}_d\mathbf{M}_f\left|\underline{\mathbf{V}}^t_{df}\right|$

- $\mathbf{L}_1^t = diag\{i_0^{0,t} + i_0^{1,t}, \ldots, i_l^{0,t} + 1_l^{1,t}\}\mathbf{R}_d\mathbf{M}_f \left|\underline{\mathbf{V}}_{df}^t\right|$
- $\mathbf{b}^t = -\left[r_{d1}i_0^{0,t}i_0^{1,t}, \ldots, r_{dl}i_l^{0,t}1_l^{1,t}\right]$
- $i^{0,t} = 0.25\mathbf{M}_f\mathbf{P}^{max,t}$
- $i^{1,t} = 0.75\mathbf{M}_f\mathbf{P}^{max,t}$

A graphic representation of the loss approximation for a two bus system is showed in Fig. 4.1.

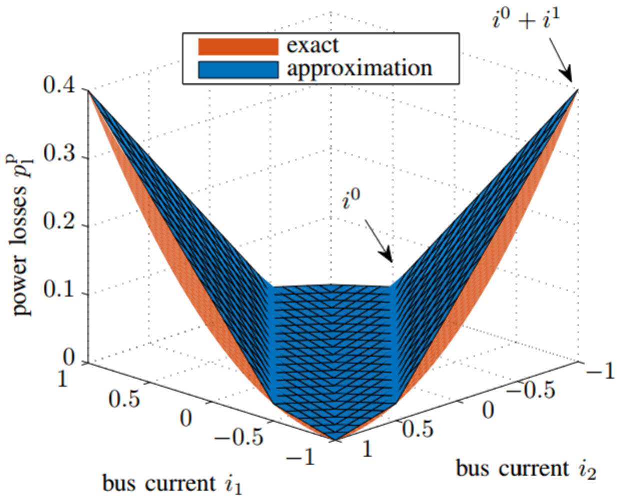


Figure 4.1: Example of the loss approximation in a line between two buses [36].

Battery dynamics

If there are storage devices in the network, we need to introduce additional equations to model their dynamics. A possible way to describe the time-varying level of charge of the battery at bus $i \in \{1, \ldots, N-1\}$, $\forall t \in \{2, \ldots, T\}$ is:

$$S_{batt,i}^{t} = S_{batt,i}^{t-1} + \eta_{ch,i}P_{ch,i}^{t-1} - \frac{P_{dis,i}^{t-1}}{\eta_{dis,i}}$$

Where $\eta_{ch,i}$ and $\eta_{dis,i}$ are the efficiency of the battery for the charge and discharge processes. The initial charge of the battery, $S_{batt,i}^{1}$, is usually fixed to 0.

Power balance

The most important constraint of the OPF problem is to satisfy the power balance inside the network, expressed as:

$$\sum_{i=0}^{N-1} P_{gen,i}^{t} - \sum_{j=1}^{L} P_{los,j}^{t} - \sum_{j=1}^{L} Q_{los,j}^{t} - \sum_{i=0}^{N-1} P_{load,i}^{t} = 0$$

Network physical limits

Any solution proposed by the optimization problem must respect the physical limits. These constraints can be written as:

$$\begin{gathered}
-\mathbf{i}_b^{max} + \mathbf{B}_r^t \mathbf{P}_{load}^t \leq \mathbf{B}_r^t \mathbf{P}_{gen}^t \leq \mathbf{i}_b^{max} + \mathbf{B}_r^t \mathbf{P}_{load}^t \\
\mathbf{v}^{min} \leq \mathbf{v}^t \leq \mathbf{v}^{max} \\
\mathbf{P}_{pr}^{min,t} \leq \mathbf{P}_{pr}^t \leq \mathbf{P}_{pr}^{max,t} \\
\mathbf{Q}_{pr}^{min,t} \leq \mathbf{Q}_{pr}^t \leq \mathbf{Q}_{pr}^{max,t} \\
0 \leq \mathbf{P}_{ch}^t \leq \mathbf{P}_{batt,ch}^{max} \\
0 \leq \mathbf{P}_{dis}^t \leq \mathbf{P}_{batt,dis}^{max} \\
S_{batt,i}^{t=1} = S_{batt,i}^{in} \\
S_{batt,i}^{min} \leq S_{batt,i}^{t} \leq x_{batt,i} \\
\eta_{ch,i} P_{ch,i}^{T} \leq x_{batt,i} - S_{batt,i}^{T} \\
\frac{P_{dis,i}^{T}}{\eta_{dis,i}} \leq S_{batt,i}^{T}
\end{gathered}$$

Where:

- $\mathbf{i}_b^{max}$ is the vector of the maximal admissible currents in the branches;
- $\mathbf{v}^{min}$ and $\mathbf{v}^{max}$ are the vectors of the minimal and maximal admissible voltages at the buses;
- $\mathbf{P}_{pr}^{min,t}$ and $\mathbf{P}_{pr}^{max,t}$ are the vectors of the minimal and maximal level of active power production at the buses;
- $\mathbf{Q}_{pr}^{min,t}$ and $\mathbf{Q}_{pr}^{max,t}$ are the vectors of the minimal and maximal level of reactive power production at the buses;
- $\mathbf{P}_{batt,dis}^{max}$ is the vector of the maximal admissible power exchanged with the batteries;

The first equation makes sure that the current along each branch is below a safety value. The second one prevents overvoltages and undervoltages. The other ones are similar to those previously seen, related to power production and batteries dynamics.

The feeder

Since we use the same kind of variables both for the prosumer and the feeder, we need to fix to zero the variables related to batteries and consumption of the first bus (the root connection).

$$P^t_{Load,0} = 0$$
$$Q^t_{Load,0} = 0$$
$$P^t_{ch,0} = 0$$
$$P^t_{dis,0} = 0$$

Objective Function

The objective of the optimization problem is to minimize the costs (or maximize the revenues) encountered, over the entire time period, exchanging power with the main grid. If c^t_{el} is the price of the electricity and P^t_0 is the power exchanged with the grid at time $t \in \{1, \ldots, T\}$ (positive if sold to the feeder, negative if bought from it), the objective function of the optimization problem can be written as:

$$min \sum_{t=1}^{T} c^t_{el} P^t_0$$

LP-OPF

The assumptions and approximations introduced until now define the formulation of a Linear Programming of the Optimal Power Flow (LF-OPF) problem:

$$\underset{\mathbf{y}}{\text{minimize}} \quad \sum_{t=1}^{T} c_{el}^{t} P_{0}^{t} \tag{4.8}$$

subject to $\quad \forall t \in \{1, \dots T\}:$

$$\mathbf{P}_{gen}^{t} = \mathbf{P}_{pr}^{t} + \mathbf{P}_{dis}^{t} - \mathbf{P}_{ch}^{t} \tag{4.9}$$

$$\sum_{i=0}^{N-1} P_{gen,i}^{t} - \sum_{j=1}^{L} P_{los,j}^{t} - \sum_{j=1}^{L} Q_{los,j}^{t} - \sum_{i=0}^{N-1} P_{load,i}^{t} = 0 \tag{4.10}$$

$$\mathbf{B}_{v}^{t} \begin{bmatrix} \mathbf{P}_{gen}^{t} \\ \mathbf{Q}_{gen}^{t} \end{bmatrix} - \mathbf{v}^{t} = \mathbf{B}_{v}^{t} \begin{bmatrix} \mathbf{P}_{load}^{t} \\ \mathbf{Q}_{load}^{t} \end{bmatrix} - \mathbf{v}_{\mathbf{s}} \tag{4.11}$$

$$\mathbf{P}_{los}^{t} - \mathbf{L}_{0}^{t}\mathbf{P}_{gen}^{t} \geq -\mathbf{L}_{0}^{t}\mathbf{P}_{load}^{t} \tag{4.12}$$

$$\mathbf{P}_{los}^{t} + \mathbf{L}_{0}^{t}\mathbf{P}_{gen}^{t} \geq \mathbf{L}_{0}^{t}\mathbf{P}_{load}^{t} \tag{4.13}$$

$$\mathbf{P}_{los}^{t} - \mathbf{L}_{1}^{t}\mathbf{P}_{gen}^{t} \geq -\mathbf{L}_{1}^{t}\mathbf{P}_{load}^{t} + \mathbf{b} \tag{4.14}$$

$$\mathbf{P}_{los}^{t} + \mathbf{L}_{1}^{t}\mathbf{P}_{gen}^{t} \geq +\mathbf{L}_{1}^{t}\mathbf{P}_{load}^{t} + \mathbf{b} \tag{4.15}$$

$$\mathbf{Q}_{los}^{t} - \mathbf{L}_{0}^{t}\mathbf{Q}_{gen}^{t} \geq -\mathbf{L}_{0}^{t}\mathbf{Q}_{load}^{t} \tag{4.16}$$

$$\mathbf{Q}_{los}^{t} + \mathbf{L}_{0}^{t}\mathbf{Q}_{gen}^{t} \geq \mathbf{L}_{0}^{t}\mathbf{Q}_{load}^{t} \tag{4.17}$$

$$\mathbf{Q}_{los}^{t} - \mathbf{L}_{1}^{t}\mathbf{Q}_{gen}^{t} \geq -\mathbf{L}_{1}^{t}\mathbf{Q}_{load}^{t} + \mathbf{b} \tag{4.18}$$

$$\mathbf{Q}_{los}^{t} + \mathbf{L}_{1}^{t}\mathbf{Q}_{gen}^{t} \geq +\mathbf{L}_{1}^{t}\mathbf{Q}_{load}^{t} + \mathbf{b} \tag{4.19}$$

$$-\mathbf{i}_{b}^{max} + \mathbf{B}_{r}^{t}\mathbf{P}_{load}^{t} \leq \mathbf{B}_{r}^{t}\mathbf{P}_{gen}^{t} \leq \mathbf{i}_{b}^{max} + \mathbf{B}_{r}^{t}\mathbf{P}_{load}^{t} \tag{4.20}$$

$$\mathbf{v}^{min} \leq \mathbf{v}^{t} \leq \mathbf{v}^{max} \tag{4.21}$$

$$\mathbf{P}_{pr}^{min,t} \leq \mathbf{P}_{pr}^{t} \leq \mathbf{P}_{pr}^{max,t} \tag{4.22}$$

$$\mathbf{Q}_{pr}^{min,t} \leq \mathbf{Q}_{pr}^{t} \leq \mathbf{Q}_{pr}^{max,t} \tag{4.23}$$

$$0 \leq \mathbf{P}_{ch}^{t} \leq \mathbf{P}_{batt,ch}^{max} \tag{4.24}$$

$$0 \leq \mathbf{P}_{dis}^{t} \leq \mathbf{P}_{batt,dis}^{max} \tag{4.25}$$

$$S_{batt,i}^{\,t=1} = S_{batt,i}^{\,in} \tag{4.26}$$

$$S_{batt,i}^{\,min} \leq S_{batt,i}^{\,t} \leq x_{batt,i} \tag{4.27}$$

$$S_{batt,i}^{\,t} = S_{batt,i}^{\,t-1} + \eta_{ch,i}\, P_{ch,i}^{t-1} - \frac{P_{dis,i}^{t-1}}{\eta_{dis,i}} \tag{4.28}$$

$$\eta_{ch,i}\, P_{ch,i}^{T} \leq x_{batt,i} - S_{batt,i}^{\,T} \tag{4.29}$$

$$\frac{P_{dis,i}^{T}}{\eta_{dis,i}} \leq S_{batt,i}^{\,T} \tag{4.30}$$

Where $\mathbf{y}$ is the set of variables of the optimization problem:

$$\mathbf{y} = \{\mathbf{y}^1, \ldots, \mathbf{y}^T\} \tag{4.31}$$

$$\forall t \in \{1, \ldots, T\} :$$

$$\mathbf{y}^t = \{\mathbf{v}^t, \mathbf{P}^t_{pr}, \mathbf{Q}^t_{pr}, \mathbf{P}^t_{ch}, \mathbf{P}^t_{dis}, \mathbf{P}^t_{los}, \mathbf{Q}^t_{los}, \mathbf{S}^t_{batt}\}, \tag{4.32}$$

FBS algorithm

The matrices $\mathbf{L}^t_0, \mathbf{L}^t_1, \mathbf{B}^t_r$ and $\mathbf{B}^t_v$ depend on the bus voltages $\underline{\mathbf{v}}^t$, that are initially unknown. The way to get around it, as presented in [36] is to set first the voltages to **1** pu and then to solve iteratively the LP-OPF. After each iteration h, the currents are calculated in the forward stage and the voltages updated in the backward stage. The new voltages are used to evaluate the matrices $\mathbf{L}^t_0, \mathbf{L}^t_1, \mathbf{B}^t_r$ and $\mathbf{B}^t_v$ for the next iteration, until the difference between the values of $\underline{\mathbf{v}}$ of two consecutive iterations is below a certain threshold of tolerance.

The presented FBS-OPF problem, optimizes the control strategy over all the simulated period, knowing at each step the future and past prices of electricity, the future and past load consumption and the future and past potential power production. Thanks to this information, it is able to decide how to produce, store, buy and sell the electricity in the most efficient way. This is obviously an idealistic situation, since in real world, future is extremely difficult to predict. However, the results obtained simulating realistic scenarios and solving them with this centralized "omniscient" controller, can be useful to look for a decision making pattern and to produce a learning set for a SL model as the one presented in the chapter 3.

Chapter 5

Case study

In this chapter we check how the SL algorithm performs on a simulated test network in different scenarios of load consumption, potential production and electricity prices. We will tackle the operation of this EPC through these scenarios controlled with:

a) the Supervised Learning algorithm (Section 3.3);

c) the centralized optimized strategy (Section 4.2);

b) an alternative decentralized control strategy (it will be presented in Section 5.5);

The simulation part has been performed using Julia [41] language, involving the use of GUROBI [42] as solver for the FBS-OPF and the Extremely Randomized Trees [43] (using the Scikit-learn [44] library) for the machine learning approach.
We will compare the results to have an idea on the quality of the performance.

5.1 Test network

The control schemes are simulated on a linear network composed by the root connection and N_{pro} prosumers similar to Fig.5.1. Each branch linking two buses has the same length, the same resistance and the same reactance. The simulations are performed over a period representing an entire year, with one time-step per hour.

In summary:

- The number of buses N is 15;
- The number of prosumers N_{pro} is 14;

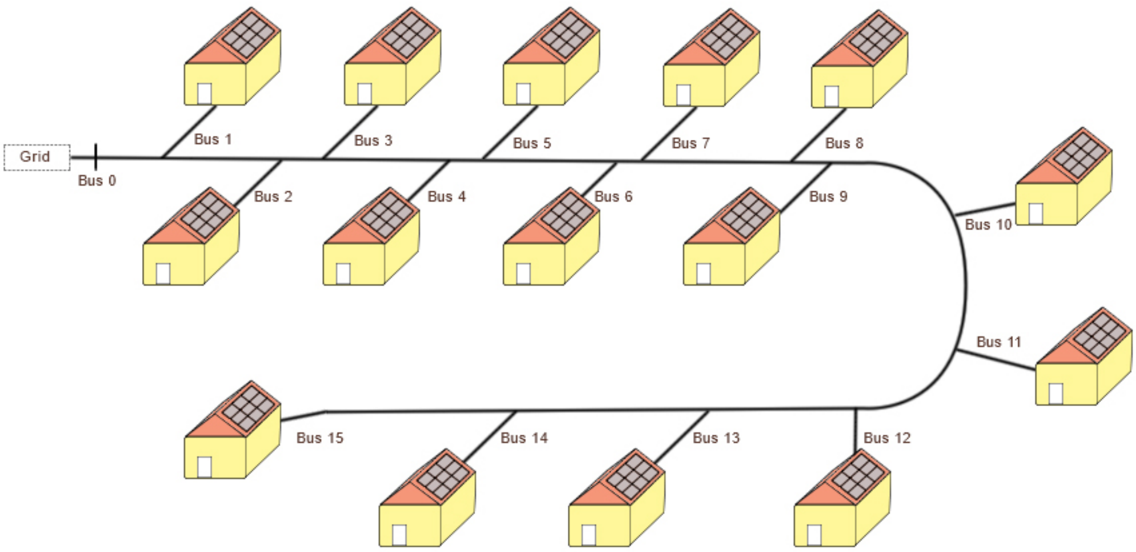


Figure 5.1: Representation of the electric prosumer community simulated in the case study.

- The number of branches L is 14;
- Δt is 1h;
- The time horizon T is 8760;
- The line resistance $R_{d1} = R_{d2} = \ldots = R_{dL}$ is 0.025 Ω;
- The line reactance $X_{d1} = X_{d2} = \ldots = X_{dL}$ is 0.005 Ω;
- The nominal voltage of the network is 400 V;
- The maximum admissible voltage v^{max} is 1.10 pu;
- The minimum admissible voltage v^{min} is 0.90 pu;
- For the feeder, $P_{pr,0}^{max,t}$= 1 MW, $P_{pot,0}^{min,t}$ = -1 MW, $Q_{pr,0}^{max,t}$ = 1 MW, $Q_{pr,0}^{min,t}$ = -1 MW $\forall t \in \{1, \ldots, T\}$;

Each prosumer inside the community is defined by an identification number (its position along the network), the number of occupants of the associated dwelling, the PV and storage installed capacity. These information are resumed in Table 5.1.

Id	**Number of occupants**	**PV installed capacity** kW_p	**Storage installed capacity** kWh
1	1	2	2
2	1	2	2
3	2	3	2
4	2	3	2
5	2	3	2
6	3	3.5	5
7	3	3.5	5
8	3	3.5	5
9	4	5	6
10	4	5	6
11	4	5	6
12	4	5	6
13	5	7	8
14	5	7	8

Table 5.1: Dwellings characteristic inside the community

All the values are then converted in the per unit system.

5.2 Test scenarios

As we said before, we denote the entire set of external variables that can not be modulated through the operation of the microgrid with the word *"Scenario"*. It basically represents the environment in which the network will go to operate. To create a complete scenario that can be used to test the control schemes we need, after defining the characteristic of the test network, to specify the load profiles, maximal production potentials and electricity prices over the entire period of time. Three different scenarios named *S1, S2* and *S3*, are generated as follows.

5.2.1 Load profiles

Domestic eletricity demand can vary widely depending on the number of occupants, on the type and number of the appliances and on their usage. Defining a realistic profile of daily consumption for a certain dwelling is not immediate. The generation of the load profiles of each prosumer are obtained using the model described in [38]. The model allows to produce the load profile of a customized dwelling in a day, setting the number of residents of the house, specifying the type of day (weekday or weekend), the month and what are the appliances inside. Once these parameters are set, the model ran an algorithm to determine, at each hour of the day, the active occupancy (how many occupants are present and awake), the occupant activity, the appliance use, the sharing of appliances, etc., taking into account also month of the year and the type of day (weekday or weekend day). An example of the output is provided in the figure below. To obtain the set of $P^t_{Load,i}$ and $Q^t_{Load\,i}$ $\forall t \in \{1, \ldots 8760\}$, $\forall i \in \{1, \ldots N-1\}$ the model has been processed several times, obtaining weekdays and weekend days for every month of the year. The domestic appliances associated to a dwelling have been selected randomly, with only some basic post-correction in order to get a reasonable configuration. The model also provides a mean power factor for the appliances, in order to obtain the reactive power associated to the active power values.

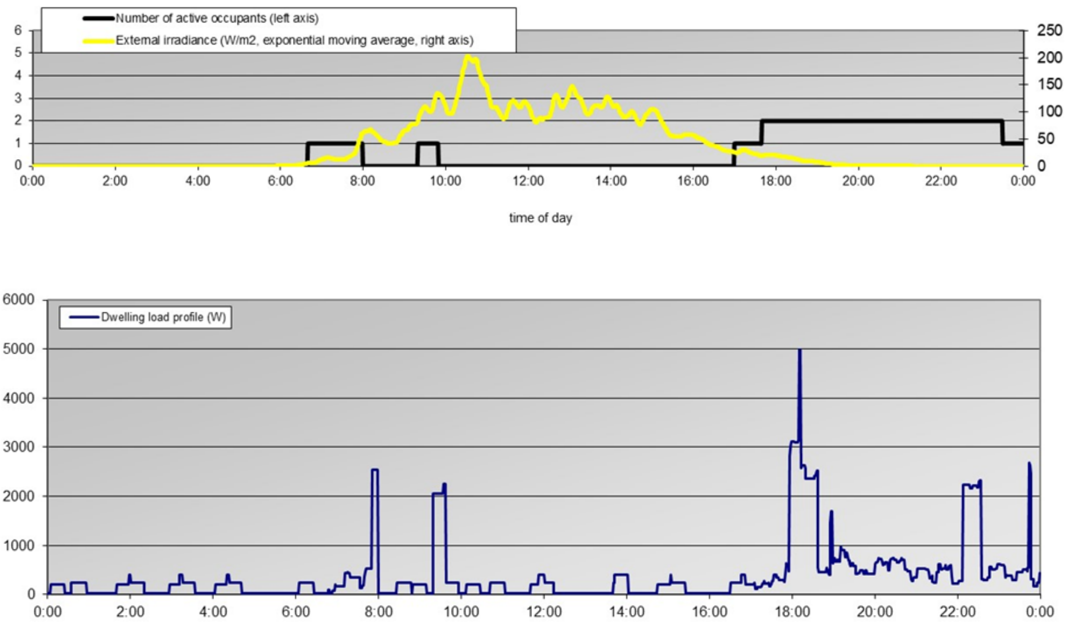


Figure 5.2: Active occupancy (top) and load profile (bottom) for a dwelling with 2 occupants along a weekday in the month of April.

5.2.2 Sun radiation profiles

The sets of maximal production potential $P_{pr,i}^{max,t}$, $\forall t \in \{1, \dots 8760\}$, $\forall i \in \{1, \dots N-1\}$ are obtained using real solar radiation data evaluated in W/W_p and multiplying them for the nominal power of the PV panels installation of each prosumer. Potential production will be, obviously, subjected to great fluctuation from one hour to the other and the control algorithm should try to exploiting them as best as it can. An example of the solar radiation in the three scenarios on the same month (June) is showed in Fig. 5.3.

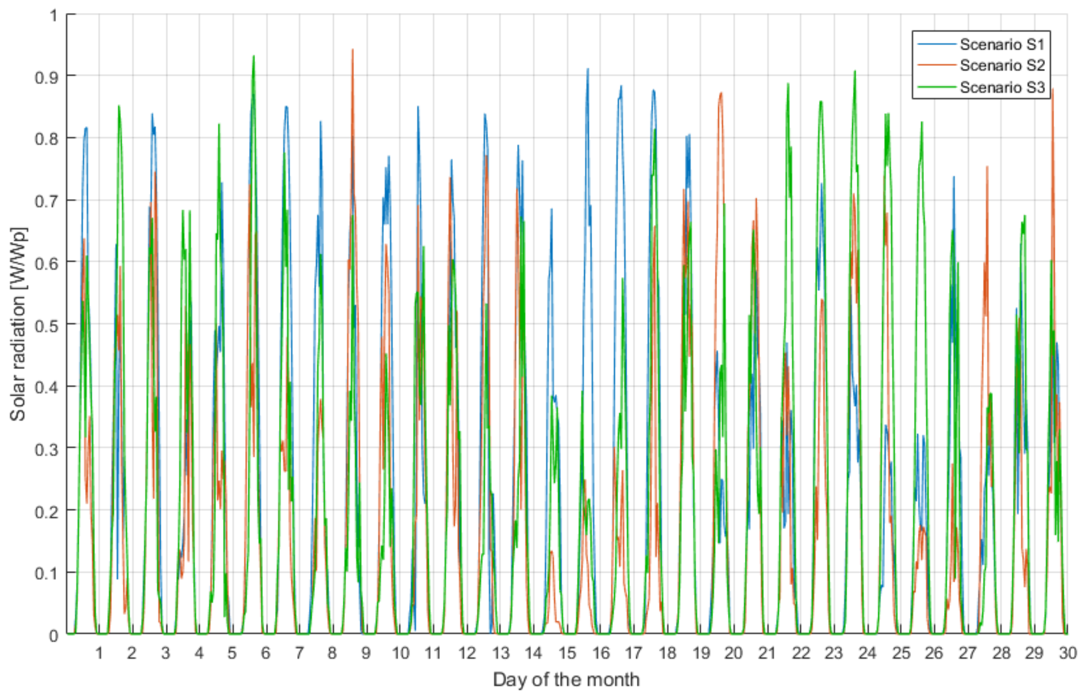


Figure 5.3: Sun radiation in the three scenario on the same month.

5.2.3 Electricity prices

The time series of price vectors c_{el}^{t} for $t \in \{1, \dots 8760\}$ used in the scenarios are equal to the prices set on the EPEX SPOT Belgium Day-Ahead Market [39] in past years. Each scenario is related to a specific year. The average daily price over the year in the three scenarios is showed in Fig. 5.4.

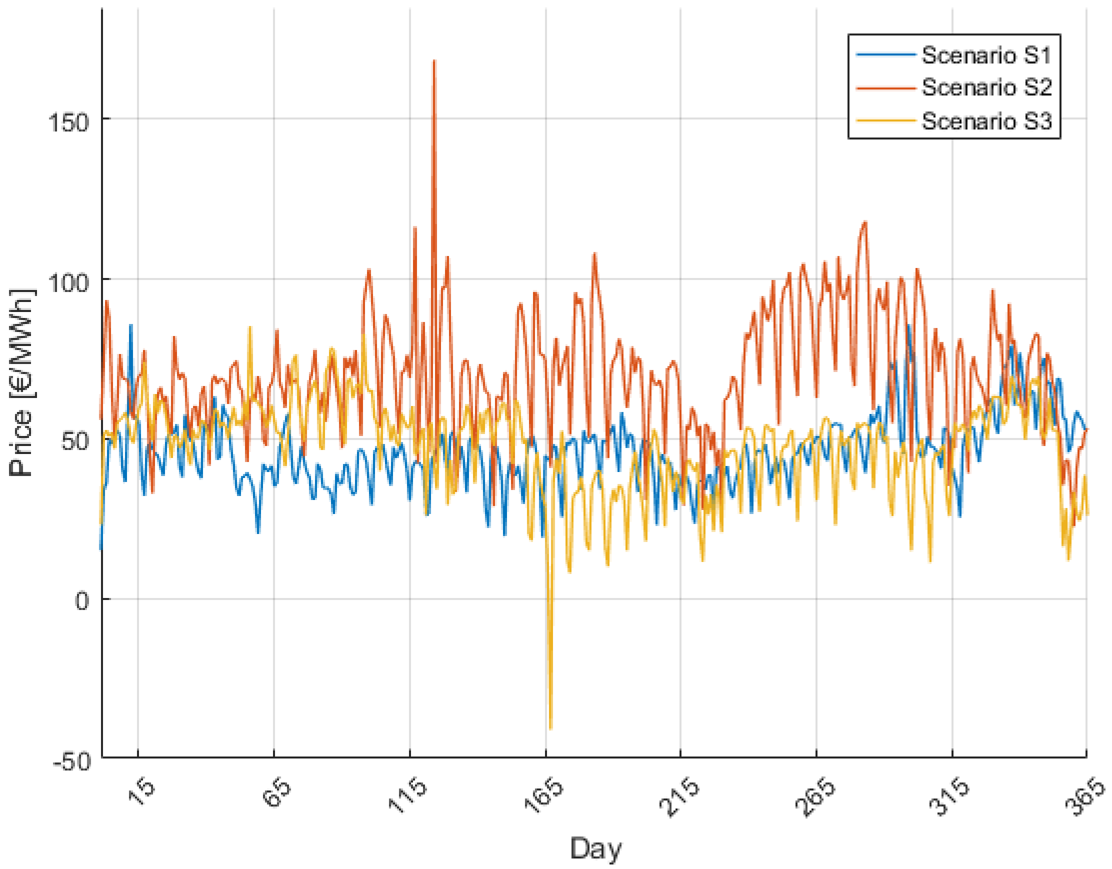


Figure 5.4: Average daily price for electricity in the test scenarios

5.3 Learning set

Due to the nature of the imitative techniques used in the SL algorithm, we must produce also an appropriate learning set, as described in Section 3.3, before using it in the decision making process. Two additional scenarios, $S4$ and $S5$ are generated in the same way of the test ones (the average daily prices of the training scenarios are showed in Fig. 5.5). The two resulting power flow problems are solved using the FBS-OPF algorithm presented in Section 4.2 and the outputs (the optimal strategies) are processed to obtain the learning sets as described in Section 3.3.

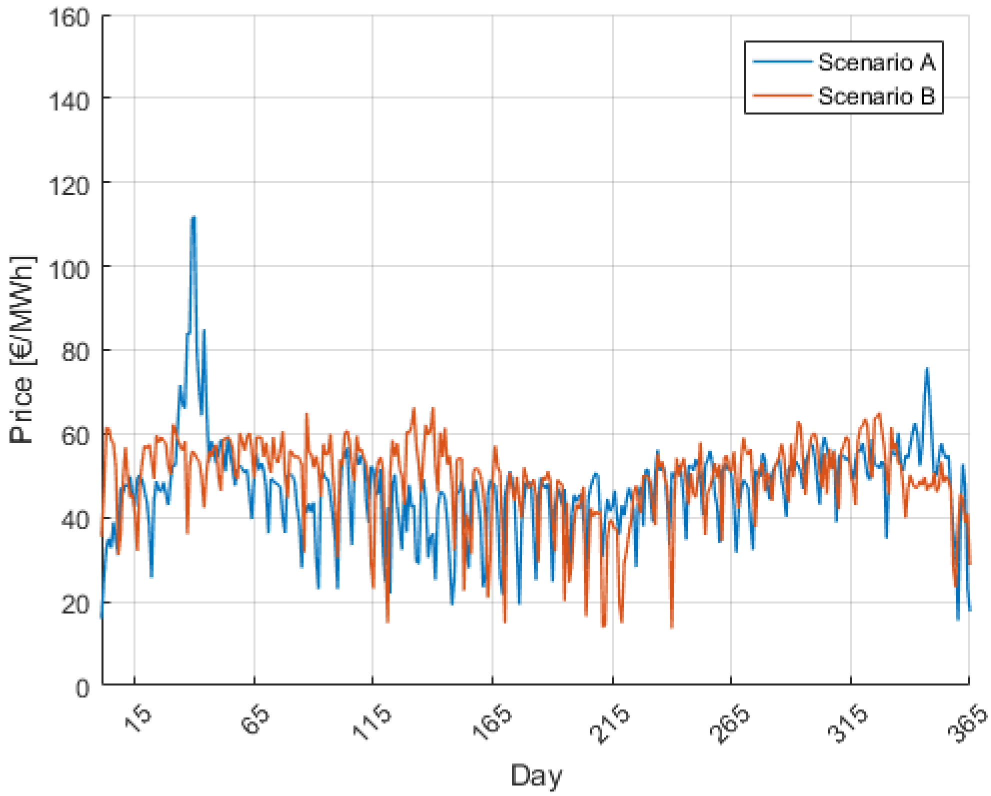


Figure 5.5: Average daily price for electricity in the training scenarios

5.4 Implementing the SL algorithm

Once the training scenarios are solved and the optimal behavior of the EPC is found using the FBS-OPF algorithm, a learning set is extrapolated as previously explained. The learning set is passed to the SL algorithm and the resulting estimators have been obtained, ready to be used to control the prosumers' behavior.
The logical steps for implementation of the Supervised Learning are one last time summarized below.

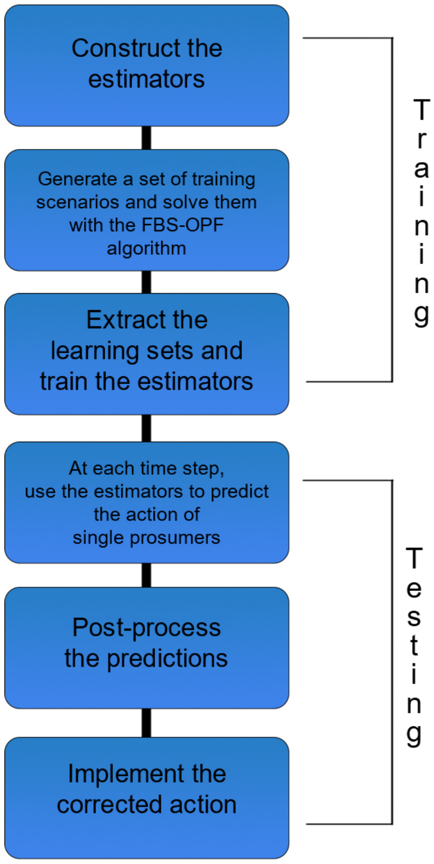


Figure 5.6: A summary of the steps followed to use the SL model controlling the prosumer's actions

5.5 "Rule of thumb" algorithm

To validate the results and to get an idea of how good or bad the performances of the SL algorithm can be, it is useful to compare the results obtained in the test scenarios with those achievable with other methods. Another alternative method to design a decentralized control strategy is to define a set of predetermined, thresholds-based decision rules that each prosumer has to follow, a sort of checklist based on experience and common sense. This set of rules is designed so that it should ensure first the safety of the system and then try to restrain the overall costs of the community. We grouped these rules in the form of an algorithm and we denote it as "Rule of Thumb" (RT) algorithm. The inputs that the algorithm take are the same as the estimators so that they can work with the same amount of knowledge about the network. The algorithm is used by each prosumer i at each time step t and it can be expressed, for example, in the following form:

---

if $|\underline{\mathbf{v}}_i^t| \leqslant 0.91pu$

$P_{pr,i}^t = P_{pr,i}^{max,t}$

$Q_{pr,i}^t = Q_{pr,i}^{max,t}$

$P_{dis,i}^t = S_i^t \, \eta_{d,i}$

$P_{ch,i}^t = 0$

else if $|\underline{\mathbf{v}}_i^t| \geqslant 1.09pu$

$P_{pr,i}^t = 0$

$Q_{pr,i}^t = -Q_{pr,i}^{max,t}$

$P_{ch,i}^t = \frac{X_{batt,i} - S_i^t}{\eta_{c,i}}$

$P_{dis,i}^t = 0$

else

$P_{pr,i}^t = P_{pr,i}^{t,max}$

$Q_{pr,i}^t = 0$

if $c_{el}^t \geqslant c_{el}^+$

$P_{ch,i}^t = 0$

if $P_{pr,i}^t \geqslant P_{Load,i}^t$

if $S_i^t \geqslant 0.3 \, X_{batt,i}$

$P_{dis,i}^t = \left(S_i^t - 0.3 \, X_{batt,i}\right) \eta_d^{(i)}$

else

$P_{dis,i}^t = 0$

else

$P_{dis,i}^t = S_i^t \, \eta_d^{(i)}$

else if $c_{el}^t \leqslant c_{el}^-$

if $P_{pr,i}^t \geqslant P_{Load,i}^t$

if $P_{pr,i}^t - P_{Load,i}^t \leqslant \left(X_{batt,i} - S_i^t\right) \eta_c^{(i)}$

$P^t_{ch,i} = \frac{P^t_{pr,i} - P^t_{Load,i}}{\eta_c^{(i)}}$

else

$P^t_{ch,i} = \frac{X_{batt,i} - S^i_t}{\eta_c^{(i)}}$

else

if $S^t_i \geqslant 0.3\ X_{batt,i}$

$P^t_{dis,i} = \left(S^t_i - 0.3\ X_{batt,i}\right)\eta_d^{(i)}$

else

$P^t_{ch,i} = \frac{0.3\ X_{batt,i} - S^t_i}{\eta_c^{(i)}}$

if $P^t_{ch,i} > P^{max}_{batt,i}$

$P^t_{ch,i} = P^{max}_{batt,i}$

if $P^t_{dis,i} < P^{max}_{batt,i}$

$P^t_{dis,i} = P^{max}_{batt,i}$

The first step is to check if there is a risk of over-voltages or under-voltages at the bus and, in this case, to orient the actions of that prosumer to avoid it: if the voltage is too low it injects into the grid everything it can (maximum power production and fully discharge of the storage), if the voltage is too high it consumes everything it can (fully charge of the battery and minimum power production).

In the case where the safety of the grid seems ensured, the production is always set to the maximum value. The rest of the decisions variables are imposed as follows and are based mainly on the retail price of the electricity at that time step.

We define two thresholds values c^+_{el} and c^-_{el} (arbitrarily, based on the values seen in real data) to determine if the electricity price is "high" or is "low" (in the current case study they are set to 2 and 0.5 times the average price of the training scenarios). The algorithm is designed to keep the battery always with a minimum SoC of 30% and to discharge the battery totally only when there is a deficit of power production and the electricity price is very high. When the prosumer has a production surplus, it injects it into the network or into the battery depending on the price.

Using this kind of algorithm is certainly a rough method to take decisions and it is oriented to favor the single prosumer more than the entire community, but it is still a reasonable way to control the action of the prosumer when there are not other strategies. Lastly, it has the advantage of being very easy to implement in a logic controller.

5.6 Results

Scenarios *S1, S2* and *S3* have been simulated on the test network controlled with the three control strategies (FBS-OPF algorithm, "rule of thumb" algorithm and "Supervised learning" algorithm). The index used to compare the performance of the three schemes is the overall costs that the community suffers during the year (that is also the objective function of the FBS-OPF).

The numerical results are showed in Table 5.2. The centralized controller obviously achieves the best result in every scenario. The costs encountered with the SL algorithm in scenarios *S1* and *S3* are lower then the ones suffered with the RT algorithm. In scenario *S2* the SL emerge as the worst one among the three strategies.

Overall costs			
Scenario	S1	S2	S3
FBS-OPF algorithm	1105.54 €	2121.16 €	1837.80 €
SL algorithm	2711.44 €	7832.43 €	5123.09 €
RT algorithm	5143.32 €	6501.94 €	5807.77 €

Table 5.2: Overall costs encountered with the three algorithms

A deeper insight of the strategies' behaviors can be gained looking at the prosumers' decisions and at the electrical state of the network during the year.
The key reason why PV panels production requires to be controlled is that, in some cases, generating too much power and injecting it in the network leads to overvoltages or overloadings. When this happens, the inverters of the PV units need to be disconnected and the prosumer wastes the solar radiation that he could have harness. A partial curtailment of the total production, in order to prevent the disconnection, would be in these cases a better alternative for the prosumer. The RT algorithm does not provide this option (when there is risk of overvoltages it set the production to zero), unlike the FBS-OPF and the SL algorithms. The percentages of the total potential production that has actually been produced is showed in Table 5.3.

Curtailments over the year			
Scenario	S1	S2	S3
FBS-OPF algorithm	7.01%	11.20%	9.69%
SL algorithm	11.13%	32.78%	14.80%
RT algorithm	11.91%	13.46%	15.12%

Table 5.3: PV production respect to total potential production.

Another relevant difference between the control scheme can be observed in the use of the storage systems. The FBS-OPF algorithm expects that the prosumers exchange power with the batteries very often, with at least one storage system inside the community that stores or release energy most of the time steps, in order to buy energy whenever it is affordable and sell it when it is expensive. The other two algorithms take instead much less advantage of the presence of the storage, charging and discharging them in a less efficient way.

Discussing the results

Huge differences between the FBS-OPF algorithm and the two decentralized control schemes were expected, since it has much more data about the problem and each prosumer action is oriented to optimize the global objective. Batteries play a crucial role in the centralized strategy: thanks to the knowledge of future prices and demand, storage can be used to manage perfectly well the energy, optimizing the purchases and avoiding to waste potential production when possible.
The optimal behavior is impossible to formalize or to mimic perfectly. The results obtained by the SL algorithm in the scenario *S1* can be considered, thus, more than acceptable, especially if compared with the RT algorithm. In the other two scenarios, the decisions taken by the algorithm based on machine learning brought to worse results. In scenarios $S2$ and $S3$ it has suggested many times to curtail the production even when it was not needed (one third of the total potential production is not harnessed in the scenario $S2$) and to use the batteries in an inappropriate way. The set of inputs of the estimators contains many variables, so it is possible that unexpected values of some of the variables inside the input vector misled the predictions of the estimators about what was the optimal behavior to suggest. RT algorithm was able to perform better than SL in the case of scenario $S2$ since it is programmed to no undertake irrational choices even when the environment takes unexpected configuration (prices too high or too low, extraordinary demand, etc.) .
The contrasting performances in the three cases are probably linked to the fact that scenario *S1*, in terms of prices and solar radiation profiles, is similar to the two training scenarios, while scenarios *S2* and *S3* present many differences in potential production, load profiles and electricity prices from the data used in the learning set. The "*quality*" of the learning set has, indeed, critical effects on methods based on imitative learning.
A better, more complex, post-processing of the predictions made by the estimator could be implemented, maybe adding some extra check, similar to those of the RT algorithm to verify that the actions are not obviously illogical, in order to avoid results like the one

seen in scenario $S2$. Testing other SL methods, different from tree-based models, for the SL control strategy can be interesting too. However, imitative learning models have their limits and are not suited to manage very unexpected inputs.
The simulations performed demonstrate however that a decentralized control scheme that uses only local measurements, designed relying on supervised learning techniques, can produce very good results, better than those obtained with predetermined strategies, if the samples it is trained with are able to reproduce the environment in which it will be used.

Chapter 6

Conclusion

This work presented some of the main aspects that revolve around the concept, quite recent, of the Electric Prosumer Communities. It pointed out several times what are the reasons for them to spread worldwide and what could be the challenges that they offer. A snapshot of the technologies associated to distributed generation and energy storage has been provided, demonstrating that many solutions are available to shift from being a consumer to becoming a prosumer. The attention was then moved on the control strategies of a community, in particular on decentralized schemes. A simplified mathematical framework has been presented in order to better contextualize the problem. Power flow analysis and optimal power flow problems have been briefly introduced. We formulated one possible method to find what are the optimal actions of each prosumer when all the external variables, such as potential production, consumption and electricity price are known at every instant. We tried to design a decentralized control scheme using a machine learning approach (more specifically, regression trees) to mimic, at an individual level (using local measurements only), the optimal behavior observed in the centralized solution. Another decentralized control strategy that follows predetermined procedures has been developed to make some comparisons. The control schemes were then tested on a case study in three different scenarios.

As expected, decentralized control schemes are penalized respect to centralized strategy when it comes to pure efficiency. A deeper and wider knowledge of the network is essential to manage adequately the community and to understand what would be the appropriate behavior of single prosumers. Finally, knowing about the simultaneous actions of every prosumers gives the central entity a better insight of the situation, making it possible to put in place cost-effective strategies. Hierarchical control mechanisms require however expensive machinery and sharing personal information such as consumption habits and it is not so easy to find the optimal strategy with so many unpredictable parameters. The re-

sults suggest that a decentralized control scheme relying supervised learning can provide interesting results, but revealed some of its limits. Some expedient that can improve this SL control strategy have been proposed.
This thesis work was however performed using several simplifications. The mathematical model used for the community and for the power flow analysis involved many assumptions in order to reduce the computational cost of the problems and discrete event simulation can rarely model adequately the dynamics of electric power system, therefore the results of the case study need to be seen in the right perspective.
What is for sure is that developing more and more sophisticated methods to tackle the control challenge of microgrids and EPCs is an essential step to make them spread. Designing new decentralized schemes relying on more advanced machine learning techniques, such as Reinforcement Learning (RL), could lead to interesting results, due the ability of those method to self-improve, even when addressing unexpected scenarios [45].

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