Tesis Doctoral
Ingeniería automática, electrónica y de telecomunicación

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A Cristina, por el tiempo robado y por hacerme feliz.
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Resumen

La irrupción de los sistemas de generación distribuidos en los sistemas eléctricos dan lugar a nuevos escenarios donde los consumidores domésticos (usuarios finales) pueden participar en los mercados de energía actuando como *prosumidores*. Cada prosumidor es considerado como un nodo de energía con su propia fuente de generación de energía renovable, sus cargas controlables y no controlables e incluso sus propias tarifas. Los nodos pueden formar agregaciones que serán gestionadas por un agente denominado *operador del sistema*.

La participación en los mercados energéticos no es trivial, bien sea por requerimientos técnicos de instalación o debido a la necesidad de cubrir un volumen mínimo de energía por transacción, que cada nodo debe cumplir individualmente. Estas limitaciones hacen casi imposible la participación individual, pero pueden ser salvadas mediante participaciones agregadas.

El agregador llevará a cabo la ardua tarea de coordinar y estabilizar las operaciones de los nodos de energía, tanto individualmente como a nivel de sistema, para que todo el conjunto se comporte como una unidad con respecto al mercado. Las entidades que gestionan el sistema pueden ser meras comercializadoras, o distribuidoras y comercializadoras simultáneamente. Por este motivo, el modelo de optimización sobre el que basarán sus decisiones deberá considerar, además de las tarifas agregadas, otras individuales para permitir facturaciones independientes. Los nodos deberán tener autonomía legal y técnica, así como el equipamiento necesario y suficiente para poder gestionar, o delegar en el operador del sistema, su participación en los mercados de energía. Esta agregación atendiendo a reglas de negocio y no solamente a restricciones de localización física es lo que se conoce como *Virtual Power Plant*.

La optimización de la participación agregada en los mercados, desde el punto de vista técnico y económico, requiere de la introducción del concepto de *virtualización dinámica del almacenamiento*, para lo que será indispensable que los nodos pertenecientes al sistema bajo estudio consten de una batería para almacenar la energía sobrante. Esta virtualización dinámica definirá particiones lógicas en el sistema de almacenamiento para dedicar diferentes porcentajes de la energía almacenada para propósitos distintos. Como ejemplo, se podría hacer una virtualización en dos particiones lógicas diferentes: una para la participación en el mercado energético del *day-ahead*, y la otra para el programa de *demand-response*. Así, el sistema podría operar y satisfacer ambos mercados de manera simultánea con el mismo grid y el mismo almacenamiento. El potencial de estas particiones lógicas es que se pueden definir de manera dinámica, dependiendo del contexto de ejecución y del estado, tanto de la red, como de cada uno de los nodos a nivel individual.

Para establecer una estrategia de participación se pueden considerar apuestas arriesgadas que reportarán más beneficios en términos de compra-venta, pero también posibles penalizaciones por no poder cumplir con el contrato. Por el contrario, una estrategia conservadora podría resultar menos beneficiosa económicamente en dichos términos de compra-venta, pero reducirá las penalizaciones. La inclusión del concepto de *perfiles de intención dinámicos* permitirá hacer pujas que sean arriesgadas, cuando existan errores de predicción potencialmente pequeños en términos de generación, consumo o fallos; y pujas más conservadoras en caso contrario.

El operador del sistema es el agente que definirá cuánta energía utiliza para comercializar, cuánta para asegurar autoconsumo, cuánta desea tener disponible para participar en el programa de demand-response etc. El gran número de variables y de situaciones posibles hacen que este problema sea muy costoso y complejo de resolver mediante métodos clásicos, sobre todo teniendo en cuenta que pequeñas variaciones en la toma de decisiones pueden tener grandes implicaciones económicas incluso a corto plazo.

En esta tesis se ha investigado en el concepto de virtualización dinámica del almacenamiento para permitir una participación simultánea en múltiples mercados. La estrategia de optimización definida permite participaciones simultáneas en diferentes mercados que pueden ser controladas con el objetivo de optimizar el beneficio potencial, el riesgo potencial, o incluso una combinación mixta de ambas en base a otros criterios más avanzados marcados por el know-how del operador del sistema.

Se han desarrollado algoritmos de optimización para el mercado del day-ahead, para la participación en el programa de demand-response y un algoritmo de control para reducir las penalizaciones durante la operación mediante modelos de control predictivo. Se ha realizado la definición e implementación de un componente estocástico para hacer el sistema más robusto frente a la incertidumbre inherente a estos sistemas en los que hay tanto peso de una componente de tipo *forecasing*. La formulación de esta capa se ha realizado mediante *chance-constraints*, que incluye la posibilidad de combinar diferentes componentes para mejorar la precisión de la optimización. Para el caso de uso presentado se ha elegido la combinación de métodos estadísticos por probabilidad junto a un agente inteligente basado en una arquitectura de *codificador-decodificador* construida con redes neuronales compuestas de Gated Recurrent Units.

La formulación y la implementación utilizada permiten que, aunque todos los algoritmos estén completamente desacoplados y no presenten dependencias entre ellos, todos se encuentran completamente engranados ya que las ejecuciones consideran tanto el escenario actual como la estrategia seleccionada. Esto permite la definición de un contexto mucho más amplio en la ejecución de las optimizaciones y una toma de decisiones más consciente, real y ajustada a la situación que condiciona al proceso.

Además de las pertinentes pruebas de simulación, parte de la herramienta ha sido probada en un sistema real compuesto por 40 nodos domésticos, convenientemente equipados, durante un año en una infraestructura implantada en la isla alemana de Borkum. Esta experiencia ha permitido extraer conclusiones muy interesantes sobre la implantación de la plataforma en entornos reales.

Abstract

The emergence of Distributed Energy Resources (DERs) in the electricity system involves new scenarios in which domestic consumers (end-users) can be aggregated to participate in energy markets, acting as *prosumers*. Every prosumer is considered to work as an individual Energy Node (EN), which has its own renewable generation source, its controllable and non-controllable energy loads, or even its own individual tariffs to trade. The nodes can build aggregations which are managed by a System Operator (SO).

The participation in energy markets is not trivial for individual prosumers due to different aspects such as the technical requirements which must be satisfied, or the need to trade with a minimum volume of energy. These requirements can be solved by the definition of aggregated participations.

In this context, the aggregators handle the difficult task of coordinating and stabilizing the prosumers' operations, not only at an individual level, but also at a system level, so that the set of ENs behaves as a single entity with respect to the market. The SOs can act as a trading-distributing company, or only as a trading one. For this reason, the optimization model must consider not only aggregated tariffs, but also individual tariffs to allow individual billing for each EN. The EN must have the required technical and legal competences, as well as the necessary equipment to manage their participation in energy markets or to delegate it to the SO. This aggregation, according to business rules and not only to physical locations, is known as Virtual Power Plant (VPP).

The optimization of the aggregated participation in the different energy markets requires the introduction of the concept of Dynamic Storage Virtualization (DSV). Therefore, every EN in the system under study will have a battery installed to store excess energy. This dynamic virtualization defines logical partitions in the storage system to allow its use for different purposes. As an example, two different partitions can be defined: one for the aggregated participation in the Day-Ahead (DA) market, and the other one for the Demand Response Program (DRP).

There are several criteria which must be considered when defining the participation strategy. A risky strategy will report more benefits in terms of trading; however, this strategy will also be more likely to get penalties for not meeting the contract due to uncertainties or operation errors. On the other hand, a conservative strategy would result worse economically in terms of trading, but it will reduce these potential penalties. The inclusion of Dynamic Intent Profiles (DIPs) allows to set risky bids when there exist a potential low error of forecast in terms of generation, load or failures; and conservative bids otherwise.

The SO is the agent who decides how much energy will be reserved to trade, how much to EN self consumption, how much to DRP participation etc. The large number of variables and states makes this problem too complex to be solved by classical methods, especially considering the fact that slight differences in wrong decisions would imply important economic issues in the short term.

The concept of DSV has been studied and implemented to allow the simultaneous participation in multiple energy markets. The simultaneous participations can be optimized considering the objective of potential profits, potential risks or even a combination of both considering more advanced criteria related to the SO's know-how.

DA bidding algorithms, DRP participation optimization and a Penalty Reduction (PR) operation control algorithm have been developed. A stochastic layer has been defined and implemented to improve the robustness inherent to *forecast-dependent* systems. This layer has been developed with Chance Contraints (CC), which includes the possibility of combining an intelligent agent based on a *encoder-decoder* arquitecture built with Neural Networks (NNs) composed of Gated Recurrent Units (GRUs).

The formulation and the implementation allow a total decouplement among all the algorithms without any dependency among them. Nevertheless, they are completely engaged because the individual execution of each one considers both the current scenario and the selected strategy. This makes possible a wider and better context definition and a more real and accurate situation awareness.

In addition to the relevant simulation runs, the platform has also been tested on a real system composed of 40 ENs during one year in the German island of Borkum. This experience allowed the extraction of very satisfactory conclusions about the deployment of the platform in real environments.

Glossary

Cap_k Capacity of the battery installed in node k (kWh).

Con_{max} Maximum setpoint which a node can inject into the network (kW).

Con_{min} Maximum setpoint which a node can consume from the network (kW).

$DA(t)$ Baseline set by DA algorithm at time t (kW).

$FDR - P_{\text{max-load-increase},k}(t)$ Maximum setpoint allowed for the System Operator to perform an increase maneuver (kW).

$FDR - P_{\text{max-load-reduction},k}(t)$ Maximum setpoint allowed for the System Operator to perform a reduction maneuver (kW).

FS_k Observed fixed setpoint due to failures of the node k.

$F_{st}(t)$ Stochastic factor, result of the Disturbance Mitigation Layer at t.

$PR(t)$ Summatory of all the setpoints of the participant nodes at time t.

$P_{BASE}(t)$ Aggregated setpoint of the baseline at time t (kW).

$P_{DR_n}(t)$ Aggregated setpoint of the pipe baseline at time t (kW).

$P_{GRID}(t)$ Aggregated setpoint of the grid at time t (kW).

$P_{\text{bat-max-charge},k}$ Maximum setpoint to charge the battery of node k at time t (kW).

$P_{\text{bat-max-discharge},k}$ Maximum setpoint to discharge the battery of node k at time t (kW).

$P_{\text{charge},k}(t)$ Charge power (kW) for node k at time t.

$P_{\text{load-increase-limit}}$ Power limit fixed by the System Operator which the node k can increase the consumption with a maneuver (kW).

$P_{\text{load-reduction-limit}}$ Power limit fixed by the System Operator which the node k can reduce the consumption with a maneuver (kW).

$P_{bat,k}(t)$ Setpoint of the battery of node k at time t (kW).

$P_{ex,k}(t)$ Setpoint of node k at time t.

$P_{gen,k}(t)$ Forecasted generation power for node k as time t (kW).

$P_{load,k}(t)$ Forecasted load power for node k as time t (kW).

SOC State of Charge.

T_s Sample time.

$\eta_{\text{charge},k}$ Charge efficiency for node k.

$\eta_{\text{discharge},k}$ Discharge efficiency for node k.

ψ_{gen_k} Generation Neural Network agent in the Disturbance Mitigation Layer for node k.

ψ_{load_k} Load Neural Network agent in the Disturbance Mitigation Layer for node k.

$\text{Price}_{inj,k}(t)$ Consumption price (€/kWh) of node k at time t.

$\text{Price}_{inj,k}(t)$ Injection price (€/kWh) of node k at time t.

$\varphi^{-1}_{gen_{k,t}}(\delta)$ Result of applying the Chance-Constrained models for generation for the node k at t, with a risk factor of $(1-\delta)$.

i Intrahour sample time execution index, from 0 to 5.

r_k Reliability Factor for node k.

t Sample time index.

t_{DR_n} Sample time of the nth execution of the DR algorithm.

Acronyms

AGG-DA Aggregated Day-Ahead.

AI Artificial Intelligence.

API Application Programming Interface.

AS Ancillary Service.

BESS Battery Energy Storage System.

BRNN Bidirectional Recurrent Neural Network.

CAES Compressed Air Energy Storage.

CC Chance Contraints.

CC-MPC Chance Contraint Model Predictive Control.

CDF Cumulative Distribution Function.

CNN Convolutional Neural Network.

DA Day-Ahead.

DAM Day-Ahead Market.

DER Distributed Energy Resource.

DES Distributed Energy Storage.

DG Distributed Generation.

DIP Dynamic Intent Profile.

DL Deep Learning.

DML Disturbance Mitigation Layer.

DR Demand Response.

DRF Django Rest Framework.

DRP Demand Response Program.

DSO Distribution System Operator.

DSV Dynamic Storage Virtualization.

ECDF Empirical Cumulative Distribution Function.

ED Encoder-Decoder Model.

EMP Energy Management Platform.

EMS Energy Management System.

EN Energy Node.

ESO Electricity System Operator.

ESS Energy Storage System.

EU European Union.

FDR Fast Demand Response.

FES Flywheel Energy Storage.

FF Feed Forward.

GAN Generative Adversarial Networks.

Genco Large generation plant.

GRU Gated Recurrent Unit.

IoT Internet of Things.

IP Intent Profile.

ISO Independent System Operator.

JSON JavaScript Object Notation.

KPI Key Performance Indicator.

LSTM Long-Short Term Memory.

MILP Mixed Integer Linear Programming.

MIQP Mixed Integer Quadratic Programming.

ML Machine Learning.

MLD Mixed Logic Dynamic.

MO Market Operator.

MPC Model Predictive Control.

MS Market Settlement.

MSE Mean Squared Error.

NLP Natural Language Processing.

NN Neural Network.

ORM Object-Relational Mapping.

P2P Peer to Peer.

PA Profile Accuracy.

PDDR Price Driven Demand Response.

PDF Probability Distribution Function.

PHES Pumped Hydro Energy Storage.

PR Penalty Reduction.

PV Photovoltaic.

ReLU Rectified Linear Unit.

RES Renewable Energy Resource.

REST REpresentational State Transfer.

RNN Recurrent Neural Network.

RTB Real Time Balancing.

SaaS Software as a Service.

SG Smart Grid.

SMES Superconducting Magnetic Energy Storage.

SMPC Stochastic Model Predictive Control.

SO System Operator.

SQL Structure Query Language.

TES Thermal Energy Storage.

TSO Transmission System Operator.

VPP Virtual Power Plant.

Contents

1 Introduction

With great power comes great responsibility

BEN PARKER

The world, as we know it, is totally dependent on electricity and power systems. However, the industry has not been in the need of defining a total revolution regarding the way the energy is generated, transported and consumed. This is due to the good relation between the economic and reliability factors presented by classical electrical systems.

The big picture of electrical systems has somehow evolved more slowly than other disciplines in which external agents, such as the leading digital revolution, have forced fast and vertiginous changes. In addition, making any revolution in this field is usually extremely complicated, since power systems are involved in almost any critical system, as well as some inherited technical impediments, such as the need to work in the continuous spectrum.

Figure 1.1 shows a simplified version of a classic electrical system. The *primary energy* (energy which is directly harvested from natural resources) is generated in central power plants and it is distributed to end-users through some energy transmission systems called power lines. This energy is converted before and during the transmission stages so that it could be usable to end-users. Some examples of energy conversion technologies could be the hydrocarbon molecules in the coal (chemical stored energy $\rightarrow$ heat), turbines (heat $\rightarrow$ motion $\rightarrow$ electricity) or even the electric circuit with a battery (chemical energy $\rightarrow$ electricity).

The transmission system contains a set of substations which act as switching points with different functions. The substations can be classified as:

- *Step-up Transmission Substation*: It uses large power transformers to distribute the electrical power to distant locations by increasing the voltage.
- *Step-down Transmission Substation*: These substations change the transmission voltage to subtransmission voltage and prepare the eletric power to be distributed.

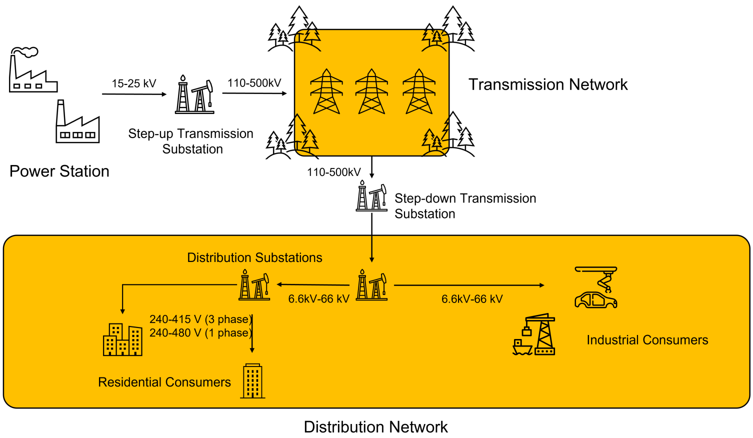

Figure 1.1 Example of a classic electrical system.

- *Distribution Substation*: These substations are located near the end users. Distribution nodes perform the final conversion from subtransmission voltage to end-user levels.
- *Underground Distribution Substation*: They are distribution substations located underground.

The relation between the amount of voltage and the different power lines can be found in [1].

There are many more functions that can be accomplished by substations, such as making interconnections between the electrical systems of more than one utility, or measuring electric power qualities flowing the circuit. More specific low-level technical information about the facilities in the electric system can be found in [2].

The utilities have historically been responsible for the stability and availability of the network. There are many different reasons why electricity shortages may happen. A very intuitive example could be a sudden demand increase that could make the demand of energy be larger than the supply availability. It can be solved by implementing reserve capacity systems. However, a sudden decrease in demand can also affect the frequency of the system and result in a massive power blackout. A blackout, also defined as power outage, is the loss of power supply from the electrical grid to an end-user. Massive blackouts cause large financial losses since they compromise the availability of critical systems which usually depend on electricity. Power system blackouts can be due to dynamic or static stability loss, voltage collpase, voltage instability in transmission networks, or inappropiate load shedding [3], among others.

Many different contingency systems exist to ensure the network availability, but the increase in electricity consumption worldwide, as well as its centralized management, have triggered new challenges that have begun to be addressed by research and industry. A clear example of a change in the paradigm is the concept of *reserve capacity*, which was previously mentioned in this thesis. The more energy is consumed, the more capacity

Table 1.1 Increases in EU final energy consumption from 2014 to 2016 in .

Sector	**Million tonnes of oil equivalent (Mtoe)**	Percentage increase
Transport	15.0	4.3 %
Industry	0.9	0.4%
Residencial	19.8	7.4%
Services	9.1	6.4%

is needed to ensure the network availability. It implies a potential waste of energy which will be stored only to be used in case of any disaster, but this amount of energy will be effectively useless during most of the time.

The energy consumption is continuously increasing, so the centralized Energy Management System (EMS) will become more and more complex, in terms of capacity and stability, in the future. The European Union (EU) is targeting to limit the primary energy and the final energy consumption with some success, but it remains impossible to reduce it in the near future. Table 1.1 shows the latest trend of final energy consumption in the EU [4]. Thus, a decentralization of energy and industrial processing becomes mandatory [5]. The development of *economies of scale* is the key concept that revolutionizes the way energy is generated, distributed and consumed.

Global warming and climate change are two issues which humanity is most concerned about nowadays. The use of non-renewable fossil fuels, such as coal, oil or natural gas, are the driving actors to accelerate the negative effects of these worrying problems through the release of CO_2 [6]. Although it has been demonstrated that increasing the proportion of renewable energy production for a country decreases its CO_2 emissions [7, 8], there is still a considerable larger percentage of use of non-renewables. In 2020, the EU countries' target was 20% of final energy consumption from renewable sources [9]. It has been established a new binding renewable energy target for the EU for 2030 of at least 32% according to the *directive 2018/2001/EU* [10]. Energy and market trends show what the near future will look like, but there is still a long way to go in that direction.

The use of Renewable Energy Resource (RES) implies modularity and decentralization, which makes power systems more stable with respect to size issues. However, descentralized systems present new challenges in terms of aggregation for larger energy volumes, communication and network problems or failure resistance. Energy grids must become more intelligent to overcome these difficulties autonomously as much as possible. This is what is commonly defined as *Smart Grid (SG)*.

1.1 Virtual Power Plants, Smart Grids and Distributed Energy Resources Management

The transition towards a low-carbon economy implies an increasingly important role for renewable resources as well as for consumers, who will act as nodes of a decentralized power system. The nodes of a power system can be added according to business rules

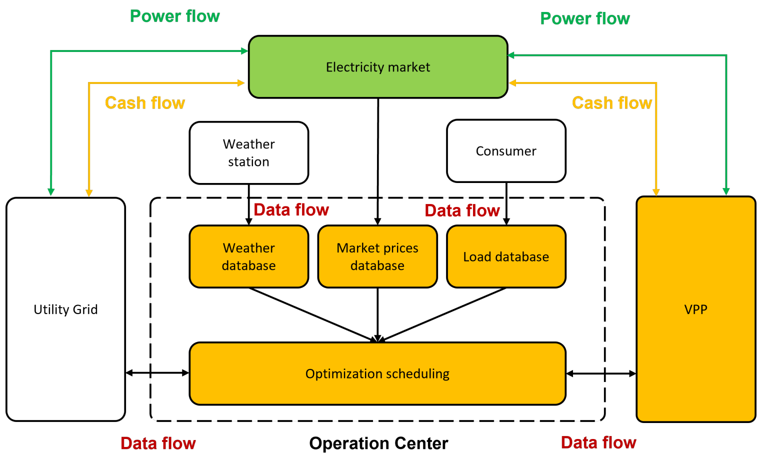

Figure 1.2 Schematized figure of VPP operation framework. Source: Slightly modified version from [12].

and not only to physical locations by defining a VPP. The concept of VPP appears in [11] with the following meaning: *a flexible collaboration of independent and market-oriented entities that provide an efficient energy service required by consumers without necessarily owning the corresponding assets*.

According to [12], the typical characteristics of VPPs are:

- Environmental protection and renewability
- High efficiency by managing internal DERs and controllable loads effectively.
- Synergy and interactivty through the EMSs.
- Improved balance because the end-users become active participants in the energy system.

The operational framework of a generic VPP is defined in figure 1.2. This figure shows the data, power and cash flows belonging to the different parts of the VPP, as well as how they are integrated to make profitable the operation of this VPP in any energy market.

There are several agents which compose VPPs, each of them with different roles:

- Electricity suppliers: They buy electricity from generators and sell it to consumers.
- Consumers: They pay the bills to the electricity suppliers. Nowadays, with the concept of prosumage (prosumer with storage), their role is changing. Prosumers are able not only to consume but also to supply their excess energy to reduce the bills or to earn some incomes.
- Transmission System Operator (TSO): These operators are paid for long-distance transport of the electricity and for ensuring the stability of the system.
- Distribution System Operator (DSO): The business of DSOs are electricity mid-distance transport and its delivery to consumers.

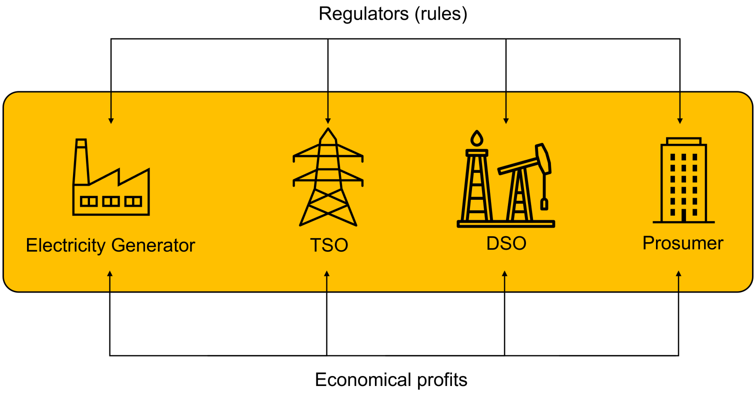

Figure 1.3 Stakeholders involved in the electricity system.

- Regulators: They set the rules and oversee the operation of the market.

Figure 1.3 describes the flow of income and outcome in the chain of electricity stakeholders.

SGs can be divided into three main categories: *generation, transmission and distribution* [13]. The first two are mainly managed by power generators and TSOs, roles usually performed by utilities. Generation and transmission SGs are implemented without many differences between them. However, the distribution SGs are more heterogeneous due to the different stakeholders involved.

Since prosumers will actively manage their energy, it becomes mandatory to find new business models. SGs have revolutionized the energy sector and their importance in a near future will even be more evident with the democratization of the use of intelligent agents.

1.2 Electricity markets: Retail and Wholesale

The role of the agents involved in the energy industry has been in continuous evolution. These structural changes have affected the field of the production and the distribution of the electricity. There are two main types of markets: Wholesale and Retail.

- Wholesale: This is the first market where the electricity is produced and sold.
- Retail: Distribution agents, mostly DSOs, buy the energy from the Wholesale and offer and deliver the electricity over the retail market.

DSOs are responsible for the retail market since they have a monopoly on the sale of energy to all consumers connected to their networks, unless there is a market organization in charge of this management[14].

Figure 1.4 shows the complete picture of both energy markets. The acronyms and the definitions of the agents are available in the following subsection.

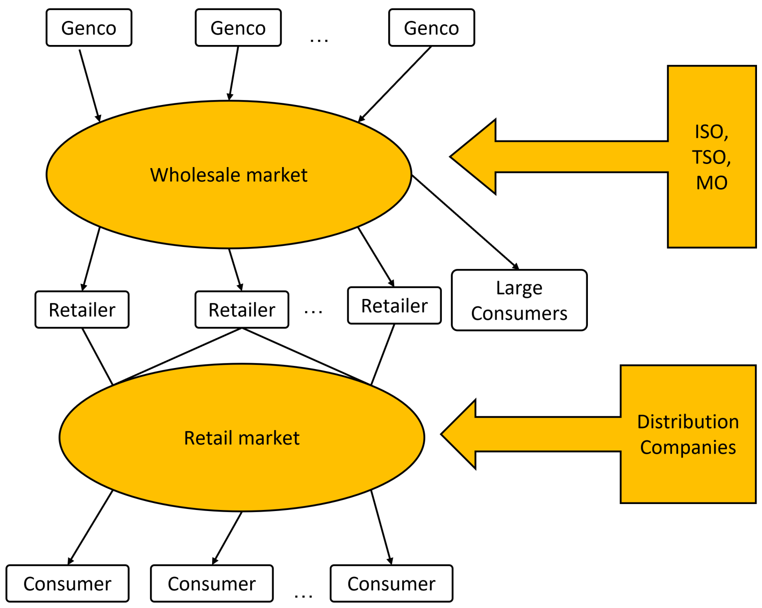

Figure 1.4 Market with retail competition (Source [14]).

1.2.1 Wholesale Competition

There are two main ways to participate in the wholesale market. The first one is through sales contracts between individual buyers and sellers. The second one is by bidding in an global market, seeking a balance between large volumes, low prices and bidding better than competitors.

The Large generation plants (Gencos) compete to sell electricity. Independent System Operators (ISOs) have two main roles: to manage the market fairly and efficiently, and also to be responsible for the reliability of the transmission system. They must be institutionally independent from any other market participant. Some Market Operators (MOs) may appear to facilitate the transaction between buyers and sellers, and the TSO. As it was mentioned in previous sections, TSOs are the responsible for the stability of the system.

1.2.2 Retail Competition

Retailers buy large amounts of electricity in bulks at the wholesale and resell this electricity to their customers. Thus, the electricity prices for the retail market are higher than the prices for the wholesale market, because there are additional charges to purchase and transport the energy to the end-user.

It is very important to regulate the price of the electricity in the retail market. Each DSO constitutes a local monopoly with customers in its distribution networks which can end up in abusive situations.

The strategy considered to exploit the full potential of the algorithms in this dissertation is related to the bids in the wholesale market. The target operators of the presented platform are SOs acting as a DSO. This SO can develop a profitable business model to operate in the retail market to get the best from the smart infrastructure, by using the capacity of its distribution grid and the context where the market participation will be executed. This context is defined in terms of possible prices, energy generation and energy consumption, as well as the possible faults of the system.

1.3 Current Challenges in the operation of Virtual Power Plants

The hetereogeneous nature of a VPP implies the appearance of different challenges related to its optimal operation.

One of the most important challenges in the operation of DERs is the optimal management of uncertainty. Uncertainties are caused by the intermittent nature of renewables and loads, as well as the price volatility of energy markets. This strongly affects the estimation accuracy of the variables during the operation of a VPP. According to [15], there are three main types of uncertainties:

- Market Price Uncertainty: Prices are volatile and, in most of the scenarios, it is necessary for participants to forecast the real price before the start of the operation as some markets operate with bidding systems.
- Load Demand Uncertainty: The larger the number of prosumers in the VPP is, the more problems related to intermittent peaks of demand may arise. There will be more unexpected connections and the demand profile may differ from the predicted one.
- Renewable Power Uncertainty: Renewable generation sources, such as photovoltaic and wind power, depend on external agents which can introduce uncontrollable uncertainties. SOs must be able to reach the difficult achievement of compensating these potential deviations, at the optimization stage, before operation. Thus, the use of intelligent agents to help the SOs in the decision-making process becomes a necessity.

However, uncertainties are not the only problem to be solved in the field of VPPs. The reference [16] addresses an in-depth review of microgrid and VPP problems during operation from different perspectives, such as reliability, stability, or control and automation:

- Formulation type and objective function.
- Solving method.
- Reliability.
- Reactive power.
- Control and automation.
- Emission.
- Stability.
- Demand Response.

- Multi-Objective.

More details on the current state of the art of these challenges can be found in the chapter Literature Review. The only ones which are out of the scope of this thesis are those classified in *reactive power* and *stability*. The others have been covered theorically or empirically in this dissertation.

1.4 Thesis Motivation

The optimal management of VPPs must handle a large number of variables with complex models. Experts are able to intuit the selection of one of the best solutions most of the times, but this might not be enough for some business models, or not even enough for problems in which the decision must be taken before gathering all the necessary information, and the solution is based on forecasts. The problem becomes more difficult when the VPP is involved in different services and these must be coordinated and synchronized. The solution must not only be efficient, but also robust and technically possible. This will involve various technical skills from different disciplines so that the research could result in a product which is close to the industry.

1. Expert SOs need help in handling the difficult problem of optimizing the operation of the VPP. This help is necessary to optimize the bids before participating in markets, as well as to control the grid at the operation stage.
2. It is economically beneficial to have multi-purpose VPPs to run better business models. It is possible to achieve the multi-purpose without impacting other services.
3. The combination of several disciplines makes it possible to build incredible intelligent agents. In addition, it is necessary to demonstrate that the theory can be applied in the field of research. Research leads to innovation, and both are the key to create a better future. In this thesis, several disciplines have been combined, such as electrical, control and software engineering, to build and deploy a real platform which meets the time constraints, the computational complexity and the necessary standards to be served as a service.

1.5 Research Objectives

The main objective of this thesis is to develop an intelligent agent which helps and improves the VPP operator's performance when participating in multiple markets simultaneously. The proposed VPP considers different ENs with photovoltaic generation, non-regulable loads and an energy storage system composed of a battery which acts as a buffer. The dissertation has the following specific objectives:

1. To improve the operation of VPPs in energy markets to obtain the benefits of not wasting clean energy by operating optimally with the excess energy in these energy markets.

2. To present and develop the concept of DSV and dynamic Intent Profiles (IPs) for VPPs to offer multiple simultaneous energy services at the same time.
3. To develop an optimal economic management model by using Chance Contraint Model Predictive Control (CC-MPC), to ensure optimal and flexible solutions for the operation of the VPP where there are some problems related to a possible lack of accuracy in the forecastings.
4. To implement a scalable and robust platform to be deployed and tested in real environments.

1.6 Dissertation Layout

The optimal operation of VPPs implies different challenges which were not present in classical power systems. Decentralization means distributed environments so better communications and more robust solutions in terms of failures are needed. This dissertation defines an approach to solve the difficult task of setting the optimal operation of a VPP and of providing multiple services by participating in several markets simultaneously by controlling individual nodes, called prosumers.

The dissertation is structured in eight chapters. In the **first chapter**, an introduction to the electricity system and electricity markets is provided to set the context of the research.

In the **second chapter** there is a literature review which focuses on four main aspects: DERs state of the art, important aspects related to Day-Ahead Market (DAM) participations, several operation strategies to operate VPPs in energy markets, as well as some literature about intelligent agents.

The system model and operating strategies are defined in the **third chapter**. In addition, the key concepts which are necessary to define the strategies have also been defined.

The **fourth chapter** presents the implementation of strategies for multiple services and simultaneous participation in different energy markets. A reconfigurable multilevel dynamic control strategy for operating the grid by a Mixed Logic Dynamic (MLD) is proposed. The use of IPs, together with the DSV, improves the profitability of the operation as well as it reduces the potential penalties at operation time. The Model Predictive Control (MPC) for DA and DRP optimizations is solved as Mixed Integer Linear Programming (MILP). The PR algorithm to control the operation is solved as Mixed Integer Quadratic Programming (MIQP).

In order to reduce the impact of deviations in forecasts, the inclusion of CC is detailed in **the fifth chapter**. Deterministic approaches have a strong dependency on forecast systems and the inclusion of chance constraints adds an extra flexibility, which improves most of the scenarios that the VPP may present. The CC factor is calculated as a combination of statistical methods and Artificial Intelligence (AI). The AI agent has been developed with an encoder-decoder architecture.

The **sixth chapter** shows the results of a real pilot. The application was run and deployed in a real environment, integrated with physical devices. This experience demonstrated that it is possible to deploy a platform as the one proposed in the other chapters.

The **seventh chapter** defines the details of the software: the architecture, the software model and the implementation details regarding deploying the algorithms as a service.

The **last chapter** summarizes the main conclusions. In addition, the main contributions and future research lines are also explained.

1.7 Publications

This dissertation yielded several publications from different parts of the research process, the software implementation and the pilot. Part of the work was developed within the framework of Netfficient (H2020 project), so it was necessary to filter all the outputs that involved third-party companies or research centers. This limitation reduced the number of possible publications to three valuable papers: one for an international congress and two for different international journals with a high impact factor.

1.7.1 Analysis of Data Generated by an Automated Platform for Aggregation of Distributed Energy Resources

The paper [17] published the analysis of the data generated during the pilot operation deployed in the island of Borkum. The analysis of real data raised valuable conclusions about the feasibility and robustness of the strategy implemented for participating in simultaneous energy markets.

- Congress: International Conference on Optimization and Learning
- Book: Optimization and Learning
- Publisher: Springer International Publishing
- Date: February, 2020

1.7.2 Chance Constraints and Machine Learning integration for uncertainty management in Virtual Power Plants operating in simultaneous energy markets

The paper [18] presented the DML implementation and the promising results of the combined Machine Learning (ML) and CC-MPC strategy to trade off the optimal DA participations and the potential penalties at the operation stage. The feed-forward disturbance compensation layer for the CC strategy with the encoder-decoder architecture was presented and assessed.

- Journal: International Journal of Electrical Power & Energy Systems
- Volume: 133
- Publisher: Elsevier
- Date: December, 2021

1.7.3 Intent Profile Strategy for Virtual Power Plant Participation in Simultaneous Energy Markets With Dynamic Storage Management

The paper [19] published the approach of using strategies based on DIPs combined with DSV to optimize the bids for simultaneous energy markets not only according to economical indicators, but also according to some risk factors. The publication includes case studies with satisfactory conclusions in non-ideal scenarios where it can be concluded that the combination of DIPs and DSV optimizes the participation at both bid and operation times and they improve the flexibility of the powerful two-stage hierarchical formulation methodology present in the current state of the art.

- Journal: IEEE Open Access
- Volume: 10
- Publisher: IEEE
- Date: February, 2022

2 Literature Review

It really matters whether people are working on generating clean energy or improving transportation or making the Internet work better and all those things. And small groups of people can have a really huge impact.

LARRY PAGE

2.1 Introduction

Clean and distributed energy systems are becoming more and more important. Climate change and its consequences have become one of the major concerns worldwide. The developed countries must lead the society towards the transition from non-renewable energy generation sources to low-carbon ones, sharing a weighted responsibility with the developing countries playing a secondary role. The scenario in these countries is more problematic, since they have to balance the lack of having a regular access to electrical power with this shared responsibility [20].

According to [21], energy sources replace each other in a regular fashion. Oil replaced coal as well as coal replaced biomass. The next turn is for clean energy to success. Renewable energy accounted for 30.7 % of gross final electricity consumption, 19.5 % of energy consumption for heating and cooling, and 7.6 % of transport fuel consumption in the whole EU [22] by the end of 2017. The analysis of these data yields different possible interpretations since these volumes might seem to be not enough, but the trend is that these percentages are dramatically increasing. The share of renewable energy in gross final energy use in the EU has doubled since 2005. It reached 17.6 % in 2017, 18.0 % in 2018 and it increased further to the 22.1% in 2020 according different reports of the European Environment Agency. Thus, the EU reached its headline target (20%) for 2020. The current energy target has been set to 32% for 2030 [23]. Figure 2.1 shows EU and Member State shares of renewable energy sources and two trajectories with the objectives which were set for the year 2020 by the Renewable Energy Directory and the Renewable

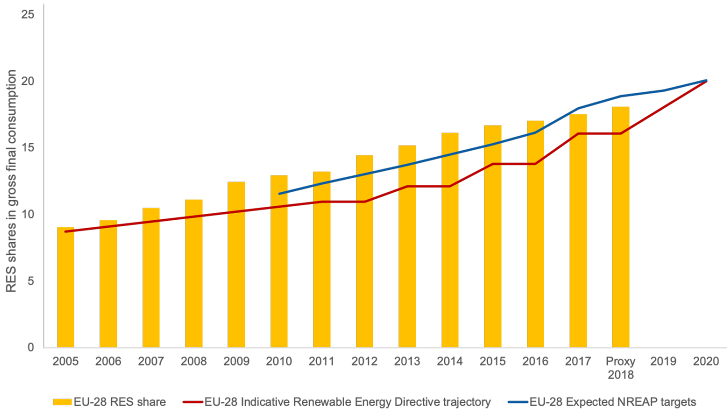

Figure 2.1 Progress towards renewable energy source targets at Member State and EU-28 levels (source [23]).

Energy Action Plan. Although this figure shows the aggregated data of all the countries, the report also presents disaggregated information per country.

However, the success of DERs is not only related to their clean nature. Distributed systems are positioned as the perfect alternative also in the energy generation field since the centralized ones always require higher investments in infrastructures as well as in control systems, and they also present higher maintenance costs as well.

The main objective of the development and deployment of DERs for the end-users is self-consumption. However, participating in energy markets can also be profitable if several prosumers participate in an aggregated way with the appropriate feed-in tariff [24]. In section 2.3, the two energy markets participations which are in the scope of this dissertation have been defined. Despite the fact that only DA and DRP participations have been considered, the proposed solution is open to the inclusion of other services for simultaneous operations.

In section 2.3.3 different strategies for the optimal management of microgrids and VPPs are presented. Finally, the last objective is to get intelligent agents involved in the process of working with classical deterministic methods to get the best from both approaches. Section 2.4 describes which are the state-to-art techniques in artificial intelligence.

2.2 Distributed Energy Resources

VPPs have traditionally had many different means of producing energy with a clearly decreasing trend of the use of non-renewable ones. Their environmental negative effects and the finite fossil fuel reserves are among the main driving factors which will inevitably put an end to the use of non-renewable generation sources. In fact, the World Energy Council has predicted that the global power output will increase from 23% as it was in 2010 to 34% in 2030 [25]. Moreover, according to the International Energy Agency, by

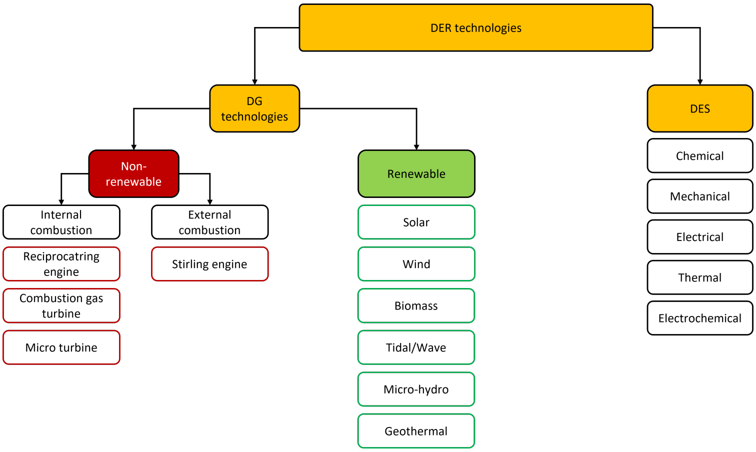

Figure 2.2 DER technologies (source [27]).

2040, the total renewable electricity generation will be equal to that of the coal and natural gas-based electricity generation [26].

2.2.1 Technologies

DERs can be installed at consumers' houses or at electric utility facilities, which reduces physical and electrical distances between the generation and the load. This reduces the losses, minimizes carbon emissions, and reschedules the establishment of new large generators and transmission lines [27]. In fact, the losses have a huge impact on the optimal economic dispatch and they determine the network configuration since they can behave as bottlenecks [28].

Another important advantage to consider is the fact that it is possible to provide remote locations with power by using DERs, where it is too expensive or impossible to build transportation lines from primary generators working as standalone power systems [29, 30].

DERs are composed of Distributed Generations (DGs) units as well as Distributed Energy Storages (DESs). Figure 2.2 shows the different technologies of these components. Renewable DGs units in general, and photovoltaic generation with chemical storage units in particular, are the DGs technologies in the scope of the study.

The use of Photovoltaic (PV) generation units has been increasing due to the continuous an dramatically decrease of the investment costs. In fact, the cost of solar panels has dropped by nearly 50% since 2014 [31]. In addition, it is a well known technology which has been implemented for almost one century, after the first discovery of the photovoltaic effect present in semiconductor materials two centuries ago. Table 2.1 summarizes a brief hitsorical timeline of the development of photovoltaic technology for electricity generation.

One of the Key Performance Indicators (KPIs) to assess DGs technologies is *efficiency*. Efficiency can be defined as the amount of potential energy that becomes electricity. Most of the renewable generation sources present a low efficiency, as it can be seen in table 2.2. Despite its low maximum theoretical efficiency limit (33% according to [33]), PV generation is the most widely spread technology installed at prosumers' due to its

Table 2.1 Brief historical timelines of the development of photovoltaic technology (source: [32]).

Year	Event
1839	Discovery of photovoltaic effect by Alexandre-Edmund Becquerel
1876	Demonstration of photovoltaic effect on selenium bar by William Grylls Adams and Richard Evans Day
1883	Construction of the first solar cell by using the semiconductor selenium with gold by Charles Fritts
1941	Patent for p-n junction solar cell using semiconductor silicon was applied by Russel Shoemaker Ohl for Bell Telephone Laboratories
1954	First practical silicon solar cell with an efficiency of 6% was constructed by Daryl M. Chapin, Callvin S. Fuller and Gerald L. Pearson for Bell Laboratories.

Table 2.2 Comparison between the efficiencies of renewable generation sources (source: [34]).

Solar	Minimum Efficiency	Maximum Efficiency
Solar	14%	33%
Wind	24%	55%
Geothermal	10%	20%
Hydro	-	90%
Biomass	20%	25%

affordable investment costs, the size of the installs and its independence in terms of location requirements.

2.2.2 Applications

DERs can be used for different purposes depending on commercial, technical or environmental considerations.

Standalone

A standalone power system does not need any connection to the utility grid. In addition, it can work autonomously. Sometimes, these systems are very important in remote areas with no available connection or when the cost of transporting the power is not cost effective. In addition, an ordinary power system can also work in this mode due to economical reasons and disconnect on demand to perform its business models. Standalone systems usually combine different DER technologies to generate reliable power. Operating and designing a standalone power system is a hard problem to solve, from small power systems such as 3 kWh/day housing units [35] to medium-large power systems [36, 37, 38].

Peak Shaving

The randomness and volatility of renewable energy has a big impact in the stability of power systems. DERs, and their DESs can aliviate the peak load regulation pressure, and effectively achieve a load translation in time and space [39]. Since the stability of a power system depends on the equilibrium between supply and demand, DERs can solve the two main concerns: when the power supply is higher than the demand and vice versa, by increasing or decreasing their power setpoints commanded to the utility grid.

Standby Power

Standby power is ready-to-use electrical power without any current allocation in markets or stored for some consumption. Implementing DERs in a VPP allows the availability of power when the power supply is interrupted temporarily. However, the standby power can also be used to trade with markets or to participate in energy markets offering some services such as peak shaving or Demand Response (DR). The main purpose of storing energy will depend on economical or technical factors, which will be defined by the SO according to a established business model.

Load Curtailment

Load curtailment defines operations where there is a need of an unusual reduction in the consumption of a power system due to problems with the system stability or market requirements. It is somehow the opposite to peak shaving and both are related to DR actions. This reduction can be voluntary, based on incentives and penalties; or mandatory, to avoid a possible massive blackout.

Demand Response

DR defines the process of decreasing the amount of power required by customers from the utilities to strategically reduce the cost of energy, to ensure the stability of the system or for other market requirements.

2.2.3 Storage Methods

RESs present a big issue related to their reliability and steadiness due to the large and sudden load variations, so the storage of energy becomes necessary. Thus, it is necessary to convert the energy to other forms, such as chemical or mechanical energy among many others to store electrical energy. A broad categorization of different methods of Energy Storage Systems (ESSs) is:

- Mechanical: Pumped Hydro Energy Storage (PHES), Compressed Air Energy Storage (CAES) or Flywheel Energy Storage (FES).
- Chemical: Fuel cell and electrolyzer.
- Electro-chemical: Battery Energy Storage System (BESS).
- Electro-static: Ultracapacitor, supercapacitor.
- Electro-magnetic: Superconducting Magnetic Energy Storage (SMES).
- Thermal: Sensible Thermal Energy Storage (TES), latent TES, thermochemical TES or pumped TES.

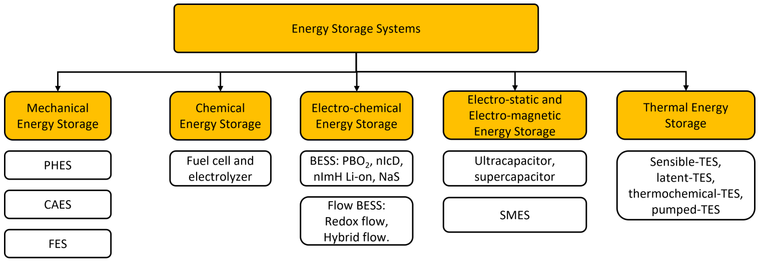

Figure 2.3 Methods of energy storage according to form of energy (source [40]).

A very exhaustive review of the different ESSs in more detail can be found in the source reference of this categorization [40]. Figure 2.3 shows the relation between the different ESSs and the form of energy to be stored.

Moreover, another important issue to be considered when providing a grid with storage is the size of the pool of storage devices. On the one hand, undersized ESS would imply non optimal operations with markets. On the other hand, oversizing implies high capital costs which strongly affect the end revenue [41].

2.3 Energy Market Participation

Storing energy has an implicit limit related to the nature of this commodity. The management of this limitation through the intelligent control of the controllable loads of a system is one of the main researches in the field, taking advantage of the continuous improvements in storage technologies [42, 43]. Currently, around 40 per cent of the electricity is consumed by buildings [44] and the population trend around the world shows that this could go even higher [45]. Thus, implementing a solution to that end will result in a huge impact for the society. Several algorithms have been developed in the literature for the smart management of the load by using approaches for individual control systems, but it becomes necessary to provide solutions for aggregated optimizations which, consequently, will also remove bid-volume barriers for the prosumers. Two different reviews about current energy markets can be found in [46, 47].

In this dissertation, the focus is set on two main market participations: DAM and DRP. The first one is the main arena to trade power by buyers and sellers to be delivered on the following day. Secondly, DRPs are used by operators as resource options to balance the supply and the demand in the power system.

2.3.1 Day Ahead Market Participation

The DAM allows its participants to buy or sell energy from wholesale market, based on biddings set the day before. Thus, the offer is planned to be bid in the DAM depending on some selected strategy according to a SO or an Energy Management Platform (EMP)

Figure 2.4 depicts the process of DAM from the perspective of the Electricity System Operator (ESO).

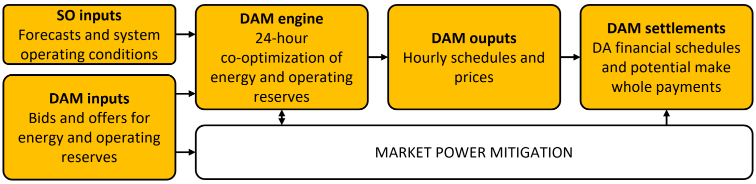

Figure 2.4 DAM process.

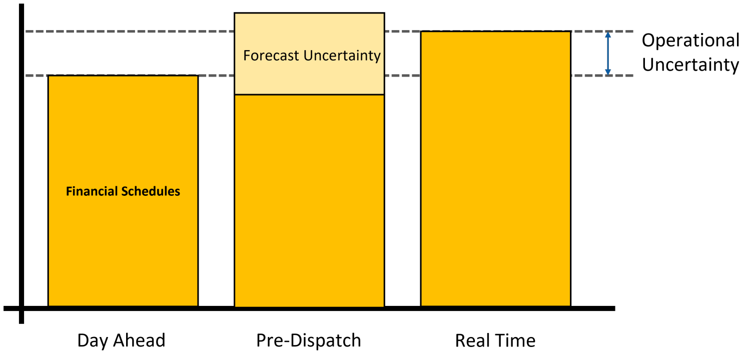

Figure 2.5 DA market and real time balancing integration steps.

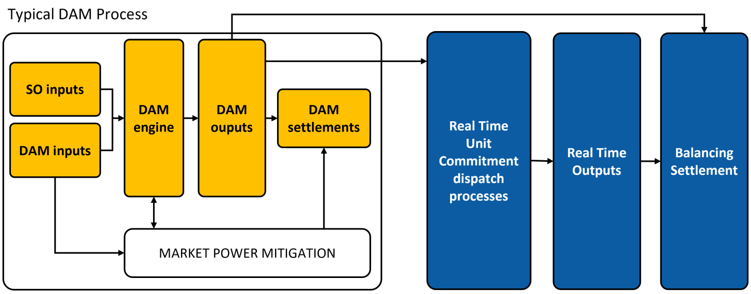

Figure 2.6 Full picture of DA market and real time balancing integration.

The participation in DA implies signing an hourly contract which must be fullfilled during the following day. Thus, it is very important to define a contingency plan for mitigating the penalties during the operation.

Figure 2.5 shows how it is somehow necessary to consider uncertainties to optimize the participation of the grid in the DAM. In addition, an optional step (known as *pre-dispatch*) is defined to adjust the participation on Real Time Balancing (RTB) and to make the grid more resilient to deviations.

In figure 2.6 it can be observed the whole picture of the operation with DAM. Settlement prices are the price that end-consumers pay for the energy. DAM settlements are based on DA schedules, while RTB settlements are based on actual metered quantities for energy, and on real-time schedules for operating reserves.

In this dissertation, uncertainties are handled by the implementation of DIPs, DSV and the inclusion of a stochastic component to build a Stochastic Model Predictive Control (SMPC). Otherwise, performing a profitable participation, or not, will strongly depend on the forecast uncertainties.

2.3.2 Demand Response Programs

DRPs allow the economic and environmental optimization of energy resources involving customers and utilities [48].

Power systems must always avoid system imbalances, defined as the difference between electricity supply and demand [49]. These differences cause deviations of system frequency and, consequently, a lower-quality electricity supply. The use of renewable resources such as photovotaics introduces uncertainties whose participants cannot manage in bid time before market clausures. Uncertainties are defined as “any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system” [50]. One of the main techniques to mitigate deviations are DR services. DR is defined by the Federal Energy Regulatory Comission as “changes in electric usage by demand-side resources from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” [51].

Participating in energy markets implies bidding in advance, which results in a fixed contract based on forecasts. The deviations which appear from these forecasts, due to uncertainties, could make impossible for one individual EN to meet its expectations in terms of injection during some hours, incurring in hard penalties. DR can be used by aggregators to reduce loads during peak hours, when the energy is often more expensive so that some economical benefit could be obtained from the operation by using a load shifting approach [52].

Sometimes, there are some DRPs, such as Time of Use programs, where market operators incentivize some load-change operations to reduce any imbalances presented in the rest of the power system, so microgrids can be actors in this balance process and get some economic incomes for it. This concept is known in the literature as Price Driven Demand Response (PDDR) [53], since the most important reason to modify the electricity usage is due to these market incentives.

According to [54, 55], there are two main types of programs: time-based programs, and incentive-based ones, summarized in figure 2.7.

- Time of Use: These programs empower the reduction of loads during load peak times to enable the power grid to meet consumer’s needs without requiring more costly backup infrastructures [56].
- Real Time Pricing: These programs are based on giving responses to limiting situations for local distribution system capacity, based on the marginal price of energy in each one [57].
- Critical Peak Pricing: This concept is a means of controlling the energy demand and alleviating the tight balance, not only inside but also outside the home [58].

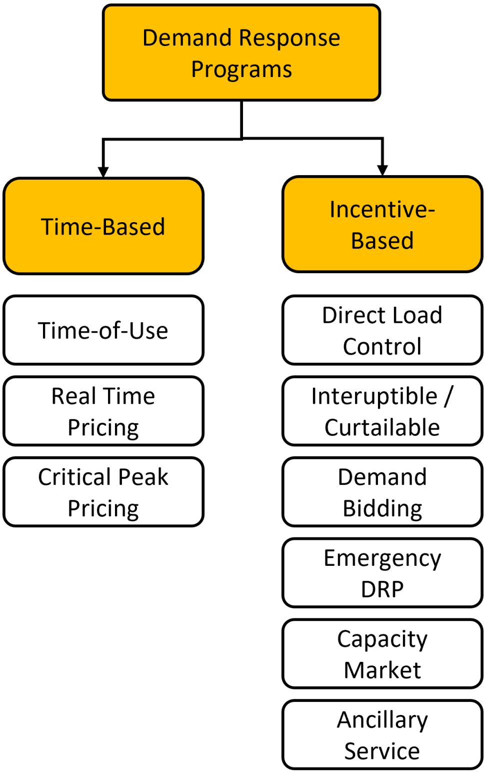

Figure 2.7 DRPs classification.

- Direct Load Control: SOs can manage the set of controllable loads in a grid to avoid exceeding the threshold of the supply capacity or the threshold of the thermal requirements of the system [59].
- Interruptible / Curtailable Service: This incentive-based DRPs penalize those customers who do not perform load reductions, but they receive a discount or bill credit in exchange for agreeing to reduce the load during system contingencies [55].
- Demand Bidding: These programs are more focused on large consumers, incentivizing them to change their energy consumption pattern and to reduce their peak loads [60].
- Emergency DRP: This type of DRP could be classified in a third category of reliability-based programs. It demands load reductions to leverage the stress on the electric grid during periods of increased demand or problems with weather forecasting [61].
- Capacity Market Program: In this type of programs, when the system contigencies arise, consumers have the duty to offer load reductions but they are also subject to penalties when not curtailing when directed [55].

- Ancillary Service (AS): There are occasions when the curtailment of load is much faster than the ramping of thermal and hydropower plants [62]. DR resources can provide the grid with the necessary technical requirements to participate in ASs and to be incentived for this participation.

2.3.3 Operation Strategies

Nowadays, the irruption of DERs in the energy system is a fact. Affordable prices for clean energy technologies, external factors such as governmental incentives, new policies to enhance the participation in energy markets or the liberalization of the electricity [63] have enforced the concept of prosumage [64]. Prosumages (producer-consumer with storage) have now the possibility to participate individually in energy markets, but this participation may be restricted due to infrastructure requirements or to low bid volume limitation. In this context, the aggregators handle the difficult task of building a VPP [65] with different prosumages to participate in energy markets such as DA, RTB, DRP or AS, among others.

In [66], a review of hierarchical control strategies to operate microgrids is presented. This type of strategies have also been developed for the optimization of the bidding for DAM, by the use of a hierarchical MPC [67, 68, 69]. In this line, [70, 71] describe different two-layer models to handle the optimal bid for DA as well as a strategy to control the penalties. The work presented in [72] defines a stochastic scenario-based model comparing different DA bidding and PR control strategies with the objective of reducing network costs. Other strategies including stochastic approaches such as the use of meta-heuristics [73], genetic algorithms [74] or Stackelberg game [75] have also been explored.

Attractive tariffs and reductions in energy bills are key to get the end-users involved in energy markets. In [76], it is highlighted that consumers are sensitive to cost savings and more than 80% of them considered the possibility of using automatic controls for some domestic appliances schedule. In this line, [77] defends *customer empowerment* as a way to allow consumers, prosumers and utilities to modify the terms of business deals through incentives and disincentives. Thus, it is necessary to explore new business models [78, 79] to get the equilibrium between a profitable operation for utilities as well as for individual prosumages.

It is also important to consider Peer to Peer (P2P) communication in the bidding optimization and control strategy to share the excess energy between nodes. Related to this concept, [80] presents a hierarchical P2P model to reduce the total operation cost and [81] defines an auction mechanism for P2P local Energy Trading using Bayesian Game Theory, by optimizing each prosumer's bid.

Multi-service approaches encourage the allocation of a VPP total capacity in different markets simultanously to improve the economical operation profits. However, sharing the capacity allocation increases possible potential penalties, so operational strategies should be both optimal in profit and resilient to possible deviations. In [82], a multi-service energy storage management is defined by using Portfolio Theory. Several interesting concepts can be highlighted from the former reference, such as the fact of basing the decisions for bidding on the relation between risk and return. In addition, some interesting use cases are also presented.

Another important issue to consider is the fact that renewable sources are weather-dependent, so they often produce rapid changes in power output, resulting in unscheduled ramping events. These ramping events present scheduling challenges for utilities operating within hourly or sub-hourly electricity trading markets [83, 84, 85] For instance, in the case of PV generation, the passing of clouds can imply a fluctuation about up to 80% of power variation per minute [86, 87]. The reliability and resiliency of power systems can be enhanced with the use of modern technologies oriented to the self-healing of the network [88], or by implementing interesting stochastic solutions based on SMPCs [89].

2.4 Intelligent Agents

Nowadays, talking about AI inevitably implies thinking about ML or NNs. It is absolutely true that NNs are an important field regarding intelligent agents, but there are many other types of intelligence depending on the scope of the agent, its nature, its technology, etc. To start classifying the different types of agents, it is necessary to define the concept of *intelligence* first.

There are many different ways of defining AI, depending on what we expect from an intelligent agent. According to [90], it can be expected from machines:

- To act humanly: This approach is related to Turing Test or, as Allan Turin called it, The Imitation Game [91]: If a human interrogator cannot conclude from a test, with written answers, if the interviewed is a human, or not, this artificial agent can be considered intelligent.
- To think humanly: This approach is related to the field of cognitive science [92], which brings together computer models from AI and experimental techniques from psychology. It is necessary to understand how a human brain works to express some theory about artificial brains.
- To think rationally: This approach is probably the first one found by humans when Greek philosophers started defining the propositional logic. It is possible to extract conclusions following some argument structures, called syllogisms, starting with correct premises. This approach is the most difficult one to implement since it is almost impossible to formalize the whole informal state space and knowledge into formal rules.
- To act rationally: The agents act to achieve the best outcome, or the best expected outcome in case of uncertainties.

So, what does *intelligence* mean? It can be defined as *the ability which an agent has to solve some problems with some percentage of success*. The level of intelligence is directly related to its specificity, and not related to the number of different tasks it would accomplish. Thus, having multiple intelligences, as humans have, does not make an artificial agent better in performing its tasks. Most of the times, a more complex intelligent system is defined by a combination and integration of several individual agents which are more focused on their specific tasks. The path towards the general intelligence is in its first steps and the state of art of the current technology and research is nowadays far from the end.

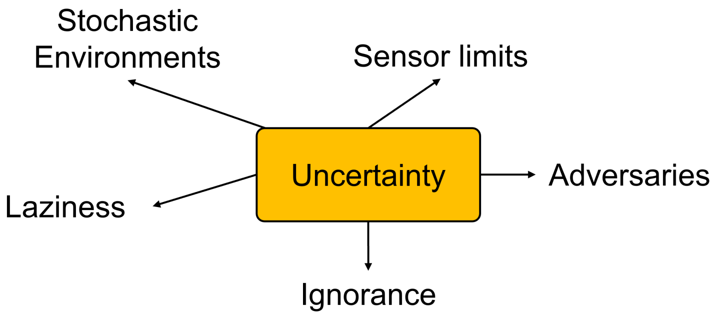

Figure 2.8 Different uncertainty sources.

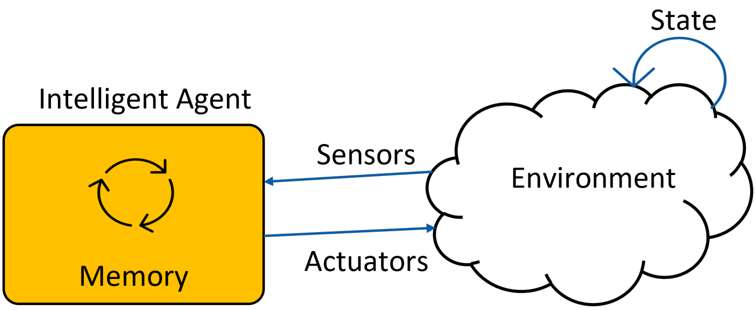

Figure 2.9 Perception-Action Cycle.

Generally speaking, AI can also be broadly defined as the technique to manage uncertainty, "what you do when you do not know what to do". Figure 2.8 shows a mindmap about possible sources of uncertainties.

A complete scenario of a classical problem is defined in figure 2.9. The observable portion of the whole environment affecting the problems, as well as the actors, is the state. Metaphorically, the intelligent agents get the information with sensors and perform actions through actuators. These actions change the environment, not only the states. This is known as the perception-action cycle [93].

2.4.1 Problems classification

It is possible to classify the problems into several types regarding different considerations. For instance, the poker game would be defined as a *partially observable, stochastic, discrete and adversarial problem*. The different classifications are defined as follows:

Fully vs Partially Observable

In fully observable problems, it is possible to gather the necessary information to reach the optimal decision. This does not implies that the success of the agent only depends on its decisions, but it has everything it needs to decide optimally. For example, a card game with all cards up and uncovered.

In partially observable problems, the agent has to make use of its memory to make the best decision. In this type of problems, anything which can be observed is considered to belong to the environment state. For example, poker.

Deterministic vs Stochastic

The concept of being deterministic or stochastic is similar to the classical meaning. A problem is considered to be deterministic when the resulting state after executing one action, or not executing anyone at all, depends only on the action itself.

Stochastic problems are those where any movement or action can be conditioned to external agents, stakeholders or new variables which make impossible the exact and precise resulting state. This state does no only depend on the action of the agent.

Discrete vs Continuous

Discrete problems are those with a finite number of actions and a finite number of possible variables to consider before executing an action. The problems with a vast range of possible scenarios, such as the agents which play chess, are also considered finite. Continuous problems are those related to infinite possibilities for actions and states, such as autonomous driving or the optimization of energy market participations.

Benign vs Adversarial

In benign problems, the objective of the environment, which also includes opponents, has not any conflict with the objective of the agent. Hazard or stochastic problems can be examples of challenging benign problems. In adversarial problems, the environment (opponent) will try to defeat the agent. It is more difficult to make good decisions in this type of problems.

2.4.2 Neural Networks and Machine Learning

Although NN and ML are not the only concepts in this field, they have become more and more important as the capacity of computation in the industry has increased. ML is strongly based on Bayesian Networks, presented in a Thomas Bayes's posthumous publication in 1763 [94].

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{2.1}$$

where:

- P(A|B): likelihood of event A to occur, given that B ocurred (conditional probability).
- P(B|A) is the conditional probability of B given A.
- P(A) and P(B) are the probabilities of observing A and B respectively.

In the 20^{th} century, except for the AI winter from 1980s through the 2000s due to a lack of funding, ML has been widely studied and developed. However, the real rise was in the

2010s, when Deep Learning (DL) became feasible. The requirements to train and develop NNs now are lower and it is possible for most of research centers to work with them.

ML is mostly an empirical field. Theory remains behind the practice and research is getting more promising conclusions from experiments than from theoretical development. This is possible due to the large number of applications and frameworks which have been built over ML and to the huge amount of data which some datasets have stored. These fast improvements and discoveries, without a solid theory in the background, may lead us think about another AI winter [95]: a hibernation of the research in the field while theory is catching up the state of art of the empirical results.

The most important features of NNs are the following [96]:

- NNs can learn and model non-linear and complex relationships, which is very useful for real life problems.
- They can generalize and infer unseen relationships on unseen data.
- They do not impose any restrictions on the input variables, and they adapt better to *heteroskedasticity*, when the data present high volatility and non-constant variance.

Universality in Neural Networks

Universality defines a property which NNs present if they are able to approximate any continuous function. There are many attempts to prove the universality property of NNs from different perspectives. In [97], it is proved that multilayer perceptrons are universal assuming the use of sigmoid activation functions, which have been deprecated by the widespread use of Rectified Linear Unit (ReLU) ones. Nevertheless, the use of sigmoid functions is not necessary since [98, 99] proved that only some type of activation functions make NNs not universal. Other examples of more complex architectures such as Convolutional Neural Networks (CNNs) [100] or Recurrent Neural Networks (RNNs) [101] have also been proved to be universal function approximators.

2.4.3 Neural Networks Classification

There is a large number of architectures, and the state of the art is increasing extremely fast. Researchers and industry are continuously discovering new advanced architectures for specific use cases. In this subsection, most of the main accepted architectures for different purposes are defined.

Simple Perceptron and Multilayer Perceptron

Simple perceptron is the very first and most simple structure of NNs, which consists of two layers: input and output. The input layer receives the network inputs, performs the calculations and provides the result to the subsequent layers, as it is shown in figure 2.10. The output layer produces the final result according to the results of previous layers and other elements of the network definition, such as the activation function.

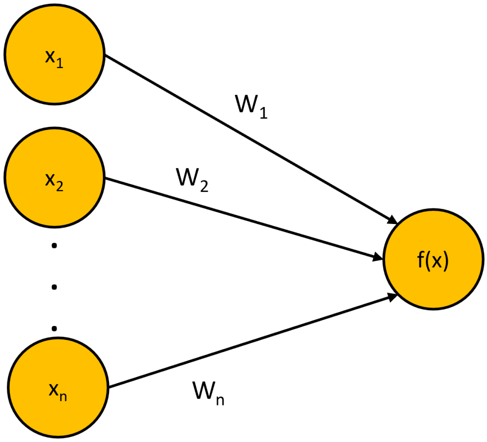

Figure 2.10 Simple Perceptron.

Simple perceptrons can be formulated as:

$$f(x) = \Big(\sum_{i}^{n} x_i * w_i\Big) + b \tag{2.2}$$

where x is a vector with input values, n is the length of the inputs, w_i is the weight of each neuron and b the bias of the function.

Multilayer perceptrons are NNs with one or more hidden layers. The hidden layers are those internal and private layers which are not visible to the external systems, which increase the depth of the network. The deeper the NN is, the more versatile it is and the better approximations it is supposed to present. However, the Universal Approximation Theorem [102] states that any continuous function can be approximated with one single hidden layer. In addition, deeper NNs may overfit the dataset, resulting in worse general inferences than others with less deep agents.

Figure 2.11 represents a sample of a multilayer perceptron agent. This figure shows a fully-connected network. Having all the neurons connected is not required, and the different ways of setting these connections for layers and neurons, in addition to other aspects such as the customization of the training process, will set the differences among the following more complex architectures.

Convolutional Neural Networks

CNNs are the state-of-art in applications such as voices interfaces, Natural Language Processing (NLP) and computer vision. They work better than fully-connected NNs with visual information due to their two main types of layers: convolutional and pooling layers.

The convolutional layers, with a kernel covolving different subsections of the data, are used to extract the high-level features from the images. The layer applies a set of different filters which gives more depth to the data.

The pooling layers are responsible for reducing the spatial size of the convolved feature. The main advantages of using these layers are the reduction of the computational power

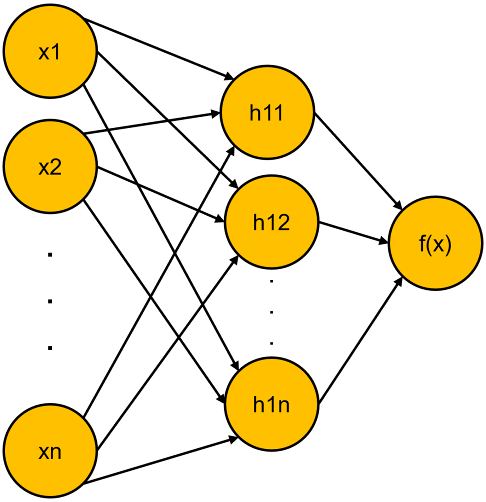

Figure 2.11 Multilayer Perceptron.

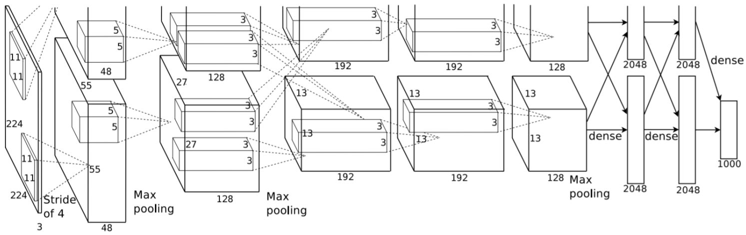

Figure 2.12 Sample of a deep CNN presented in [103] with an extremely good performance on image classification.

required to process the data, as well as the extraction of the dominant features which are rotational and positional invariant.

Thus, by combining layers of these two types, the network has deeper and deeper layers (but with reduced dimensions), so that the data can be analysed from the most specific features to the more general ones.

In figure 2.13, a graphic example of the analysis of an image classification by a CNN is represented.

In this type of NNs, the use of *dropout layers* [104] usually improves the final results. The main purpose of these layers is the reduction of the connections between layers and neurons when training. These connections have a probability of being retained during the training process. This increases the variability and reduces the complexity of the network since there are fewer connections after performing the dropout. In addition, they prevent the overfitting with the training data, so the network is able to better infere in more challeging situations. Figure 2.14 has two samples of networks with and without dropout.

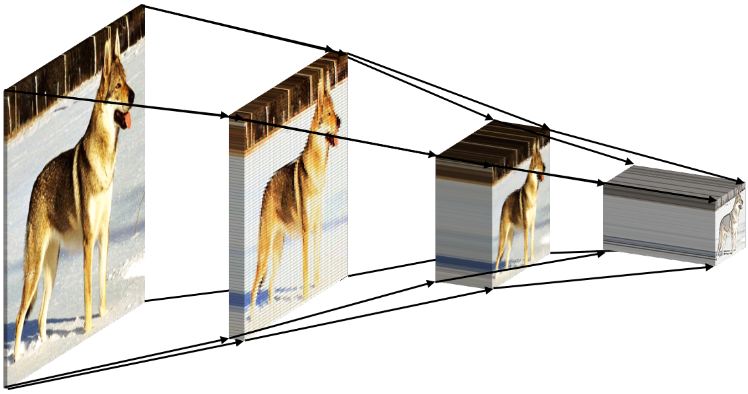

Figure 2.13 Graphical scheme of the transformation process of an image in a CNN.

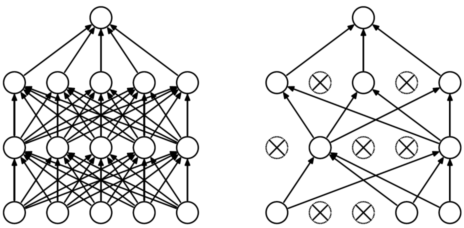

Figure 2.14 Standard NN (left) and NN after applying dropout (right), source [104].

Autoencoders

Autoencoders are a special type of NNs whose output values are as similar as possible to the input ones. The hidden layers are narrower than the input and output layers, so the network must find a compressed version of the data, by actually learning the identity function [105]. Basically, the autoencoders reduce the data dimensions by ignoring the noise in the data. These networks are built with one or more hidden layers acting as the encoder, and other ones acting as a decoder. They are used with different purposes such as image noise reduction or data compression with loss. Figure 2.15 shows a schematized sample of a noise reductor system.

Recurrent Neural Networks

RNN are especially useful in problems with ordered data, such as NLP, machine translation, speech recognition or financial time series. Their output depends on the previous output and the current input values, establishing connections between neurons along a temporal sequence with a feedback loop [107]. Figure 2.16 shows a schematized version of the most simple version of a RNN. There are other more complex versions of RNNs, such as Long-Short Term Memory (LSTM) or GRU.

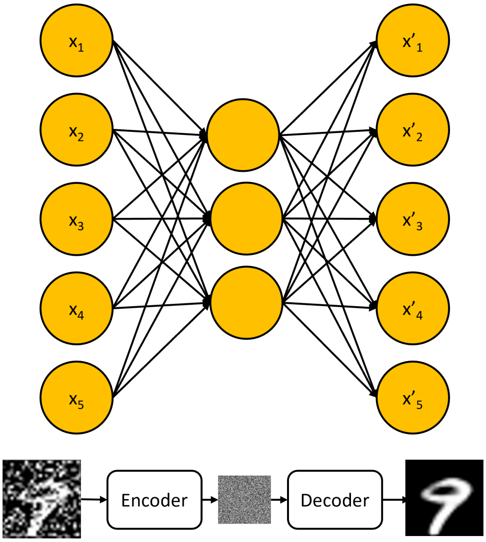

Figure 2.15 Noise reductor autoencoder sample with a sample of a number from MNIST database [106].

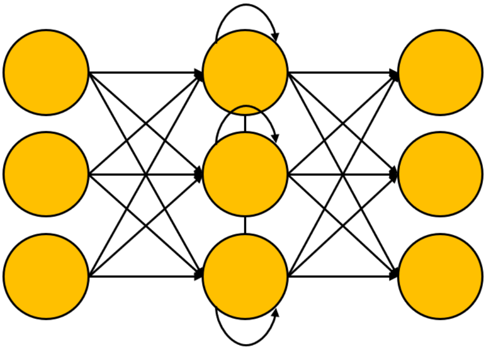

Figure 2.16 Schematized figure of a simple recurrent neural network.

Long Short Term Memory Networks

LSTMs is a classical type of RNN that can use their feedback connections to consider recent input events in form of activations [108]. They have two types of memory, one short-term memory for short-time patterns, and another one to understand the noisy and incomprehensible input sequences. This architecture improves some vanishing gradient problems which come with the standard RNN.

LSTM layers are composed of one or more LSTM units. Figure 2.17 shows the architecture of a LSTM unit in detail. It can be splitted in different parts for a better understanding:

- State (blue section): State of the cell without many interactions with the rest of elements.

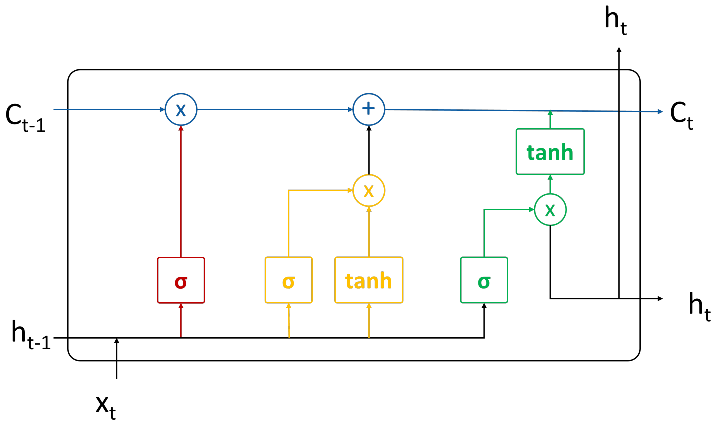

Figure 2.17 Long Short Term Memory Neural Network cell scheme.

- Forget Gate (red section): This sigmoid layer decides which information is not useful anymore during the training process and removes it from the state.
- Input Gate (orange section): It is composed of a sigmoid layer which determines the information to be added, and a *tanh* layer to create the new candidate to update the state.
- Output Gate (green section): These sigmoid and *tanh* layers build the final output of the cell, which results in the input of the following cell in the network.

In the scheme, C_t represents the value of the cell, h_t defines the value of the hidden layer and x_t is the input data, all of them at their corresponding sample times. The elements with a 'plus' symbol perform bitwise plus operations, and the others with a 'cross' symbol perform bitwise product operations.

LSTMs have become very useful in time-series forecasting, speech processing or NLP as advanced RNN architectures.

Gated Recurrent Unit Networks

GRUs were first introduced in [109]. The cells in this architecture have two gates: the update and the reset gate.

In the scheme, h_t defines the value of the hidden layer, r_t represents the value of the reset cell, z_t defines the value of the update cell and x_t is the input data, all of them at their corresponding sample times. The elements with a 'plus' symbol perform bitwise plus operations, while the others with a filled circle perform the Hadamard product operation.

Figure 2.18 shows the scheme of a GRU unit. The cell can be splitted in the following sections:

- State (blue section): State of the cell.
- Reset Gate (red section): Used to determine how much of the past information must be forgotten.

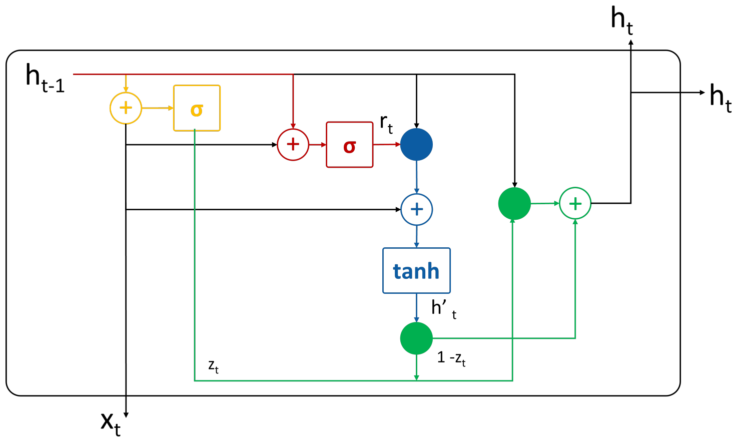

Figure 2.18 Gated Recurrent Unit cell scheme.

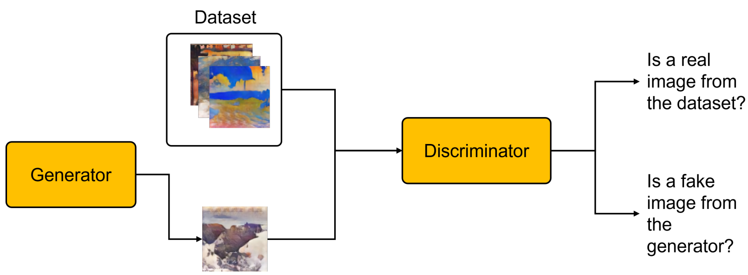

Figure 2.19 Generative adversarial network scheme.

- Update Gate (orange section): Used to determine how much of the past information is passed along to the future.
- Final memory (green section): Section to calculate the outputs of the GRU cell.

Generative Adversarial Networks

Generative Adversarial Networkss (GANs) represent one of the most important improvements in the field of NNs. These networks are defined by a framework composed of two different NNs which are involved in an adversarial process, a zero-sum (minimax two-player) game where the gain of one agent is the loss of the other [110, 111]. The two networks are in continuous improvement in a simultaneous training.

Figure 2.19 shows a schematized version of a GAN. There is a generative model, which fakes data according to the original distribution; and a discriminative model, which estimates the probability that a sample comes from the training data rather than other from the generative model. Thus, the training procedure for the generative model is to maximize the probability of the discriminator making a mistake.

Figure 2.20 Realistic artificial faces built by a generative adversarial network.

The applications of GANs are infinite. GANs are able to perform image-to-image translations, such as the creation of very realistic images from sketches [112]. Furthermore, they can also be used for inspirational purposes in contexts where there is a strong need of creativity such as indoor design [113] or generating cartoon characters [114] with impressive results. In addition, they are very useful for these data-driven problems where the dataset is not very large, by increasing the number of samples to improve the training of the intelligent agent.

In figure 2.20, it can be observed how well GANs work in the creation of realistic artificial faces [115].

Neural Networks in the scope of this dissertation

The main objective of the AI agent in this dissertation is to mitigate the negative effects of the disturbances given by the forecast services. These disturbances imply *uncertainty*, which usually results in penalties during the operation stage since the optimization might not be accurate enough.

This scenario is a clear example of the application of time series forecasting since the objective of the intelligent agent is to predict future disturbances based on the past behaviour. In the field of time series forecasting, the use of LSTM and GRU architectures are an increasing trend in the state of the art, as well as the use of *encoder-decoder* architectures. The intelligent agent is based on a *encoder-decoder* architecture composed of GRUs to get the advantages of both techniques and to improve the final results. The full definition of the NN can be found in section Neural Network Disturbance Mitigation Service.

3 System model and Optimal Operation Strategy definition

We will make electricity so cheap that only the rich will burn candles

THOMAS A. EDISON

This chapter describes in detail the system under study, its model and the strategies considered to optimize and to control the operation of a VPP. The VPP is composed of ENs of different nature, such as domestic or commercial buildings, or even facilities with a storage unit and a RES to allow the active management of their electricity.

Most of the following approaches and formulations have been tested in a real environment on the island of Borkum (Germany), during a 4-year project that ended in a successful pilot [17]. The case study in this pilot consisted of 40 households equipped with energy storage units including Li-Ion batteries, HESS systems and second-life vehicle batteries. The conclusions and main findings drawn from this operation can be found in chapter 6.

The main objectives of the approach can be summarized as follows:

- To enable domestic prosumers to participate in the wholesale energy market by aggregating operations with other ENs in the same business grid (VPP, in this case). All the DERs act as a single instance.
- To give the prosumers a roadmap with the best operation according to a fixed business model, or to give them the possibility to delegate the energy management to an external operator, for instance a TSO. This implies optimal bidding and penalty reduction techniques.
- The Intelligent Management and the improvement of the operation of a VPP, by helping the SOs in the decision-making process to participate in energy markets.

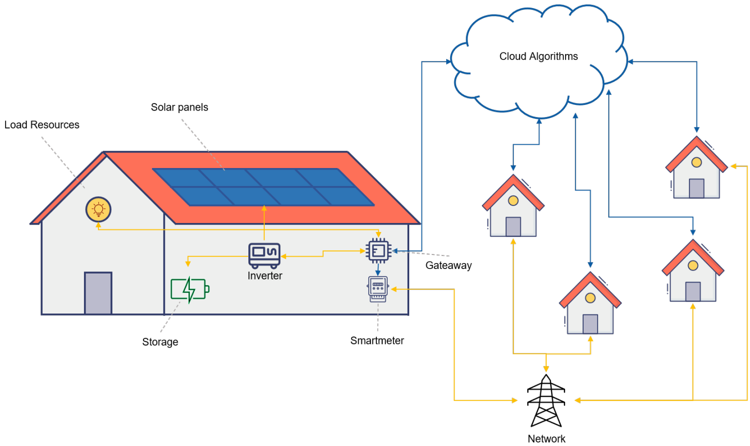

Figure 3.1 Energy Node definition and integration in the grid.

3.1 System Definition

The following subsections define the basic concepts which must be considered in the study of the strategies developed in the designed models.

3.1.1 Energy Node

In the proposed implementation, every EN is composed of PV panels, a battery with an inverter, and a homeLynk (for stand-alone use). Figure 3.1 depicts the grid definition by detailing a single EN and its relations with other ENs in the grid.

The homeLynk is a logic controller which allows the connection of households to different protocols for different purposes such as home automation or energy meetering. During stand-alone or offline modes, the EN has not connection to the grid, so an intelligent device is needed to manage the ENs during the sample times when the EMP cannot send them the control commands. The homeLynk will work together with the inverter, whose buffer stores the optimal commands. The commands, also named *setpoints*, are defined considering the state after the last execution of the PR algorithm. In offline mode, the homeLynk and the inverter execute the following setpoints with a timer, so that the EN can be kept in the pool of ENs in the optimization, without affecting the aggregated optimization. The buffer of the inverter where the setpoints are stored is finite, but this limitation does not affect the formulation. The size will depend on the short-term horizon of the PR algorithm implementation. The minimum size which the buffer must have is the value of the control horizon, to store as many setpoints as possible. The proposed system stores 18 sample times. Thus, because each sample time lasts 10 minutes, the system is able to store and provide up to 3 hours of actions, which is the maximum time to operate in offline mode without affecting the aggregation. After these 3 hours, the EN enters in standalone mode and it is pulled out from the aggregation.

Table 3.1 Nodes Definition.

Config Param	Unit	Value
Capacity	kWh	5kWh
Battery Max Charge Power	kW	2.3 kW
Battery Max Discharge Power	kW	4.6kW
Max State of Charge	Percentage	100%
Min State of Charge	Percentage	15%

The framework is flexible enough to allow different storage units, different RESs, or even different loads per unit with minor changes and without affecting the mathematical model or the platform.

3.1.2 Storage

ENs are modeled with a single storage unit with some technical specifications. The use of several storage systems would imply a specific controller to manage the optimal energy allocation and availability. Furthermore, each technology presents its own degradation, efficiency, etc. and the development of control systems at such a low level is beyond the scope of this dissertation.

Table 3.1 defines the main technical specifications and values considered for most of the case studies which will be presented.

3.1.3 Status

The ENs in the grid can be in different modes depending on their availability, the presence of work problems etc. These modes are very important for the optimization. For instance, the PR algorithm can deal with *offline nodes* as they were working ideally, so that they stay in the pool without affecting the aggregation. These modes are defined regarding different states:

- Online: EN is available without any issue.
- Offline: Although it is not possible to establish a connection with the EN, there is no reason why the EN could have some malfunction errors. Most of the times this is related to network connection issues or due to an insufficient data transmission speed. The EN is supposed to be operating with the stored setpoints so it can be maintained in the pool of working ENs of the PR algorithm.
- Standalone: The EN has been pulled out manually from the pool, or more than 3 hours have passed (18 sample times) without any successful connection. As a result, this EN cannot be operated and it is not considered in the aggregation.
- Read-Only: The EN is able to send the telemetry data, but it cannot be commanded. The node has a frozen setpoint and it cannot be changed. A model is developed in 4.2.3 to enhance the robustness and to be able to maintain these nodes in the pool.

3.1.4 Reliability Factor

The weight in the participation of each EN in the aggregation is different depending on a factor related to their reliability. A customizable *back-window* interval has been defined to calculate this factor when the EN is evaluated.

The reliability factor r_k for an EN can be calculated as:

$$r_k = \sum_{i}^{t} \frac{(P_{ex,k}(i) - P_{ex_{real},k}(i))^2}{t-i} \tag{3.1}$$

where $t-i$ is a non-empty back-window time interval from time t to current sample time; $P_{ex,k}(i)$ is the setpoint commanded by the PR algorithm for the EN k in sample time i ; and $P_{ex_{real},k}(i)$ the real power exchange executed by the EN k in sample time i.

This factor is calculated after every sample time during operation stage. The weight in the participation of the EN is inversely proportional to its reliability factor. By limiting the impact of ENs presenting problems during the operation, which means a low accuracy, the uncertainties will be reduced. The ENs with a higher accuracy have more impact in the optimization so that the aggregation may not be affected by the ones with problems. The reliability factor is normalized by using the *softmax function* to weight the EN participation.

$$r'_{ki} = \frac{\exp(r_{ki})}{\sum_j \exp(r_{kj})} \tag{3.2}$$

where *exp* is the function to calculate the exponential value with the base set to *e*.

3.2 Forecasts

Forecasts are one of the most important factors involved in both the optimization and control models. The forecast layer will generate the following forecast outputs:

- Consumption and injection energy prices Price$_{inj,k}(t)$, Price$_{inj,k}(t)$: They are used to optimize the consumption / injection profile in the optimization layer.
- Generation $P_{gen,k}(t)$: Forecast of generation given an EN.
- Load $P_{load,k}(t)$: Forecast of consumption given an EN.

The sample time unit for the generation and load profiles will depend on whether the forecast is an input for the optimization (which means a 1-hour sample time) or for the operational layer (10-minute sample time).

3.3 Baseline and Piped Baseline

The optimal *baseline* is defined as the aggregated bid-profile, per hour, for a VPP participation in the DAM. The main objective of the PR algorithm during the operation stage is to follow this baseline, overcoming uncertainties, deviations and the partipation of the grid in other energy markets. SOs need to take the control of the VPP at the execution

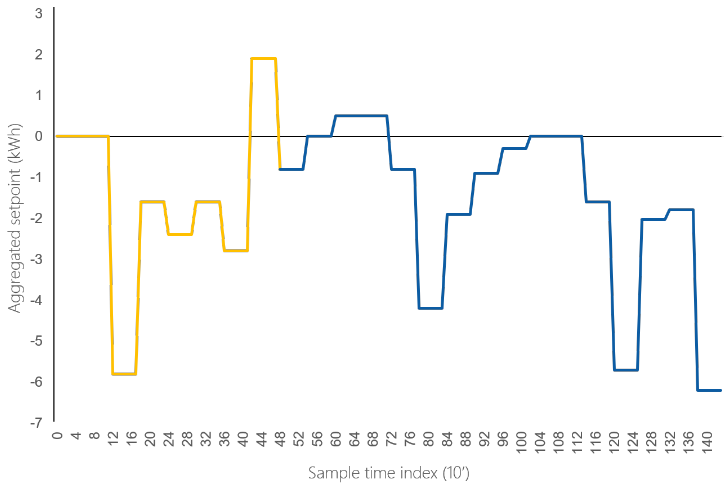

Figure 3.2 Piped Baseline with a DR call at 8 am..

time to follow this baseline in terms of both aggregated energy injection and consumption. Given a baseline, positive values define the sample times when the VPP must inject power into the network, and the negative ones when it must consume.

The concept of *piped baseline* allows the progressive updating of the baseline as the grid participates in new markets, such as DRP. The proposed DR algorithm modifies the baseline using the shift-load approach [116] to optimize the new scenario with new prices, grid constraints and EN statuses as the SO may request some changes in the load and generation profile to avoid imbalances. In sections 2.3.2 and 4.3 more details about these challenges and current existing solutions can be found.

The Piped Baseline can be formulated as:

$$P_{GRID}(t) = \begin{cases} P_{BASE}(t) & t < t_{DR_1} \\ P_{DR_n}(t) & t_{DR_n} < t < t_{DR_{n+1}} \end{cases} \tag{3.3}$$

where t is a 24-value array, one for each hour in the day; $P_{GRID}(t)$, the aggregated setpoint of the grid at time t; $P_{BASE}(t)$ the aggregated setpoint of the baseline at time t; t_{DR_n},the sample time of the nth execution of the *DR* algorithm; $P_{DR_n}(t)$, the aggregated setpoint of the pipe baseline at time t.

Since the DR request may occur at any time between two PR executions, it is necessary to track the executed profile to the time of the last DR call, and append this DR solution to the projection in the future of the new optimization. At this time, any previous baseline becomes inactive and there will only be one active baseline which is the one given by the last DR call. This allows the PR algorithm to satisfy the active baseline at every execution time.

In figure 3.2 it can be observed a simulation in which a DR call happened at 4 am. PR algorithm tracked the default baseline until this hour, but after this call, the active profile will be the DR solution, which has slight and optimal changes from the original one.

3.4 Profile Accuracy

Profile Accuracy (PA) is a KPI defined to evaluate the PR execution. It is defined by:

$$PA = \sum_{t=1}^{t=24} \|DA(t) - PR(t)\| \tag{3.4}$$

This simplification allows comparison between different baselines and executions without having to consider the asymetric and non linear penalties that the difference between them could imply. That is, a measure of the difference between of the ideal profile generated during the optimization of the bids for DA and the real operation.

3.5 Intent Profiles

In this section, the new concept of IP is introduced. It can be defined as *specific strategies for operating simultaneous energy markets, according to the relation between potential penalties and potential risks of having baseline deviations* [19]. For instance, the potential profit of the DA optimization implementing a Conservative IP when running the algorithms will not be as high as using a Risky one, but the overall system will be more resilient to forecast deviations. Thus, penalties will be lower.

There is no discrete categorization of IPs, as the number of possible states in the state space is infinite. Defining the optimal IPs configuration is out of the scope of this dissertation, but it is one of the most interesting research and innovation lines to be accomplished in the near future. In the context of this dissertation, three different IPs have been defined according to the behavior patterns observed in the results presented in [17]: *Risky IPs, Conservative IPs and Mixed IPs*. The Mixed IP is developed by using the concept of DSV presented in section 3.6. Thus, SOs decide when to take risks or to be conservative by using different Mixed IPs, depending on their know-how.

3.6 Dynamic Storage Virtualization

DSV empowers the use of storage units as energy buffers when operating simultaneous energy markets. The objective function of the optimization problem is to get the best performance for the VPP when participating as a single agent, which would result in certain losses for individual ENs. Thus, the business model must compensate the affected ENs with incentives to set the economic equilibrium among each VPP EN. Figure 3.3 depicts different IPs working with the concept of DSV.

DSV enables the system not only to set different size storage allocations for each service, but also to set battery *SOC*s at certain levels at some time checkpoints according to the behavior of the grid. The system under consideration is similar to the one defined in 3.1, with a PV panel and a battery for energy storage.

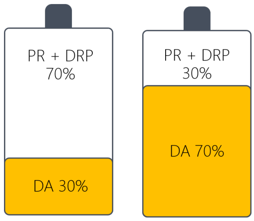

Figure 3.3 Conservative IP (left) and Risky IP (right).

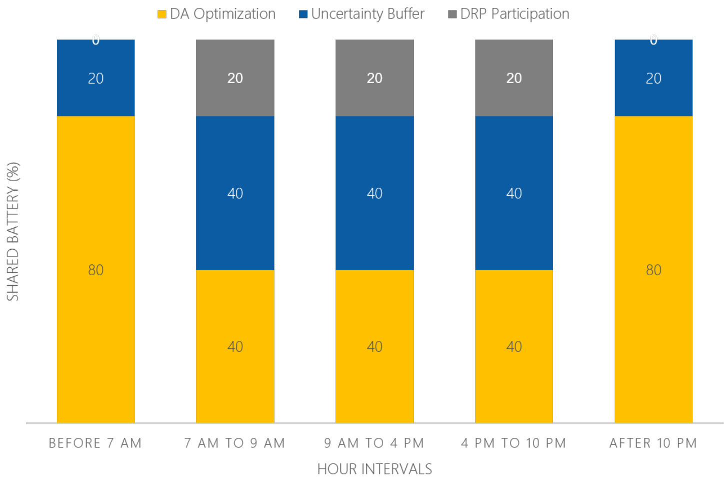

Figure 3.4 Dynamic Battery Virtualization with Mixed IP.

Let us consider the Mixed IP to be split into five different time regions as it is shown in figure 3.4:

- Before 7 am. Grid behavior is very predictable because there is not any generation or load power. Real power setpoints must remain near to forecasted ones since there is less activity at homes during these night hours and only constant loads might be working (fridge, heating etc.). Risky IPs are recommended for this kind of time regions.
- From 7 am to 10 pm there are three time regions when Conservative IPs are recommended. The first region, from 7 am to 9 am, presents a high risk of uncertainties due to the ordinary early home activity. This is the time when the end-users make their lives at home and may plug in some unexpected very energy-demanding appliances. During the second one, from 9 am to 4 pm, the forecasts for PV generation are very high, so any problem in the forecast results would imply large differences between real and forecasted values at execution time. The last region, from 4 pm to 10 pm, is similar to the one from 7 am to 9 am because the endusers arrive home and the demand profile becomes less predictable again.

- After 10 pm, the time region is similar to the one before 7 am, so Risky IPs are recommended again.

The hours limiting the different time regions are considered as *soft checkpoints*. These guidelines are not fixed and their only purpose is illustrative. They are meaningful in depicting the strategy which SOs can consider to operate the VPP, and how they mix the different IPs from a full-day perspective. Soft checkpoints are not stored nor processed in any algorithm execution.

Knowing the environmental factors of the VPP, if possible, makes easier to set more accurate IPs. The previous Mixed IP is representative of a smart grid fully located in Borkum, Germany [17], but it may differ from other VPPs.

The use of IPs makes the DSV independent of any algorithm execution and also decoupled from any energy service. Nevertheless, it is not recommendable to change the IP configuration after DA time without having a major reason, such as a massive breakdown or important issues with forecast service, so that it could be possible for the VPP to meet the commitment during the operation stage. Although the framework makes it possible, these advanced operational decisions are under SOs' responsibility.

3.6.1 Individual or aggregated Intent Profiles

IP can be defined individually for each EN, but they can also be defined at grid level (aggregated IPs). SOs can select the most appropriate mode depending on their business models, and how the end-users will be billed. In the context of this dissertation, the IPs have been defined at a grid level so that it would be easy to see the effect of applying the different strategies.

3.7 Framework Definition: A general overview

The following subsections provide a high-level overview of the entire platform. Figure 3.5 depicts a full overview of the platform with all the integrations. The first step to start working with the platform is to select the target markets and the configuration of the grid. In this dissertation, the platform has been orientated to be used for DAM as well as to participate in DRP. The operation in multiple markets is achieved by developing a hierarchical multi-model which is composed of independent models that can be integrated with low decoupling. The DA optimization algorithm uses the intelligent forecast services to improve its accuracy when optimizing. The optimal result given by this algorithm is tracked by the PR algorithm at the operation stage. There is another algorithm integration with the tracking process: The results of the DR participation. This algorithm modifies the previous baseline so that the PR algorithm can track the new baseline and reduce the penalties in the new scenario. The inclusion of more energy market participations is beyond the scope of this dissertation, but it is possible as the platform is open to new integrations and enhancements. All the services have in common the intelligent use of the battery, as it is shown in section 3.6.

Figure 3.6 defines a single execution of the algorithm for a DA participation. It details the layer of the operations before the gates closure, called *optimization layer*. The rest of

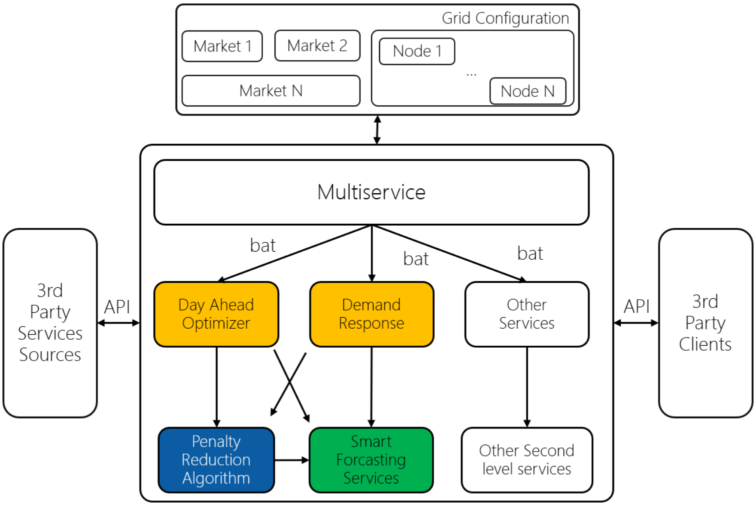

Figure 3.5 Platform General Overview.

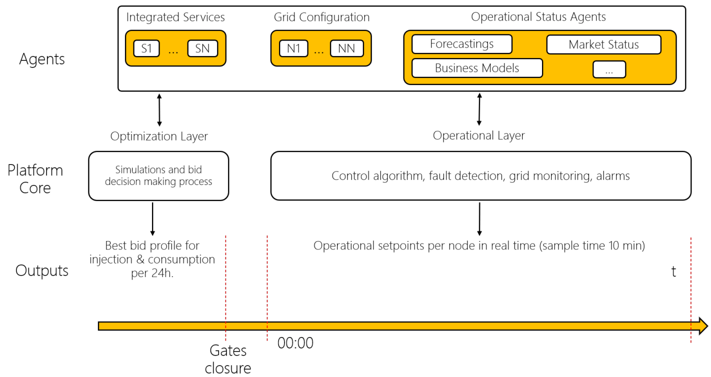

Figure 3.6 2-stage hierarchical framework execution example.

the actions are executed at the operation stage, and they belong to the *operational layer*. In this dissertation, since DRP participation is also proposed and implemented, during the execution of the operational layer, different calls to the DR algorithm may occur, which will update the baseline according to new contract constraints, building the previously defined *piped baseline*.

The SO can execute different simulations with several IPs, grid configurations or even considering different forecasting services. Nevertheless, this is only a help in the complex decision making process of bidding and, if the SOs have other considerations they can submit the profile according to their needs.

4 Optimal Virtual Power Plant multi-service participation

Technology has really enabled the sharing economy to not only become a major trend, but (also to) continue to grow and be successful

Leah Busque

The multi-service proposed in this dissertation is composed of a DA individual bidding optimization with participation in DRP. The strategy consists of two stages. The first stage optimizes the strategy for bidding in DA. The second stage consists of a control strategy to mitigate deviations and potential penalties (PR layer). DRP integration takes place during PR execution and modifies the proposed baseline in DA by the use of the piped baseline concept (see section 3.3).

4.1 Bidding Optimization for Day-Ahead Market Participation

The first stage is defined by an optimization algorithm that generates the optimal *baseline*. Figure 4.1 depicts a sample of a baseline. Positive values define sample times when the VPP is supposed to inject power into the network, and negative values when the VPP is supposed to consume.

The optimization problem is formulated as a MILP based on MPC. This algorithm receives the forecast of energy prices (injection and consumption) and the forecasts of every EN load and renewable source generation. The model also receives the grid topology as well as the physical limitations of every EN, such as storage capacity, charge / discharge efficiencies, etc. The specification of these parameters can be found in section 3.1 in detail.

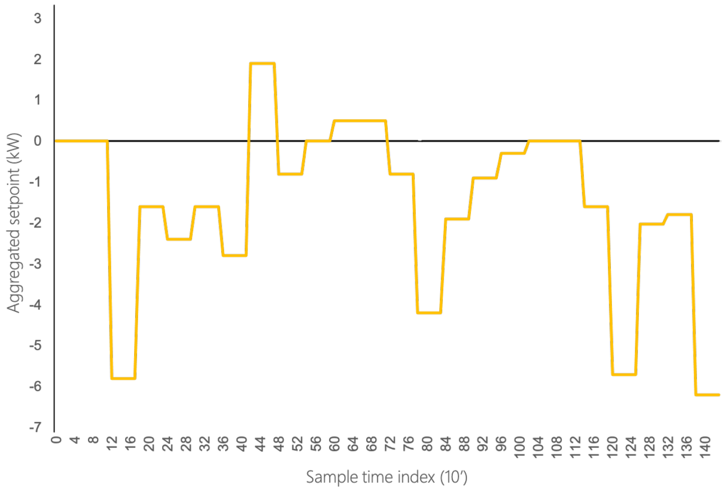

Figure 4.1 Example of an optimal grid profile (baseline) for a day with good generation and a low energy-demanding VPP.

4.1.1 Mixed Logic Dynamic Systems

MLD systems were introduced in the literature as *a framework for modeling and controlling systems described by interdependent physical laws, logic rules, and operating constraints. These are described by linear dynamic equations subject to linear inequalities involving real and integer variables* [117]. In this dissertation, the MLD system also includes boolean variables for solving problems with non-linerarity.

In [117] a generalized MLD definition through the following linear relations is presented as:

$$x(t+1) = A_t x(t) + B_{1t} u(t) + B_{2t} \delta(t) + B_{3t} z(t) \tag{4.1}$$

$$y(t) = C_t x(t) + D_{1t} u(t) + D_{2t} \delta(t) + D_{3t} z(t) \tag{4.2}$$

$$E_{2t} \delta(t) + E_{3t} z(t) \leq E_{1t} u(t) + E_{4t} x(t) + E_{5t} \tag{4.3}$$

where x is the state of the system, y is the output vector, u is the command input (which can be continuos or binary on/off commands), $\delta \in 0{,}1$ and $z \in \mathbb{R}$ represent respectively auxiliary logical and continuous variables.

MLD systems are solved through MILP or a MIQP, depending on the type of objective function used in the algorithm. In this dissertation, MILP has been used to optimize bids in DA and DR. A MIQP implementation has been chosen to solve the PR optimization.

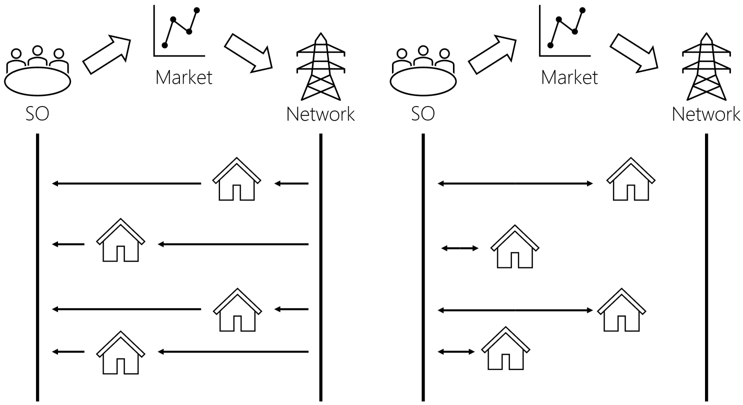

Figure 4.2 SO types. On the left, an energy producer SO; on the right, a market participant-producer SO.

4.1.2 Optimization Scenarios

The framework considers four different scenarios for optimizing the VPP participation in DAM depending on network costs and the type of SO [118].

- Aggregated Billing, with P2P.
- Aggregated Billing, without P2P.
- Individual Billing, with P2P.
- Individual Billing, without P2P.

Individual billing is formulated for SOs playing the role of energy-producer, whereas *aggregated billing* is defined for those working as market participant-producer. Figure 4.2 depicts the different types of scenarios. At the operational level, the main difference between the two modes is that the former requires the forecasting of consumption and injection prices for every node, and the latter only requires the forecasting of the prices of the VPP. In fact, individual billing option makes more flexible business models possible with custom agreements for each client.

The framework enables SOs to set a P2P cost to consider some network transmission costs in the optimization too. This cost will reduce transmission actions between nodes and reinforce the operations with the external network. P2P prices must also be provided individually, or for the grid, depending on the mode. Energy transmission always implies a cost, so P2P modes enable more accurate optimizations for those cases when the SOs know the real cost or when they have a good enough estimation.

4.1.3 Algorithm inputs

The algorithm receives different inputs depending on the mode to be executed:

- 24-hour injection and consumption market price forecast. These prices are provided from external forecast services for every EN or for the whole grid depending on the optimization mode.
- 24-hour P2P forecast, which is optional depending on the optimization mode. It can be constant, but also specified for every hour and every EN.
- 24-hour load and generation power forecast of every EN.
- Grid topology in terms of physical limitations of every EN, such as storage capacity, charge / discharge efficiency, batteries maximum charge / discharge power and the limitation of the nodes and grid in terms of the maximum allowed power in the connection point to the network.

4.1.4 Simulations and submissions

DA algorithm is prepared to be run as many times as needed to create different profile optimizations. The SO can perform the optimizations with different topologies of the grid such as including or excluding specific nodes. They can even optimize with different available IPs to extract the necessary conclusions. The results are not definite so that the SO might be able to build their desired profile, which will be used as the baseline to be tracked by the PR algorithm.

Some systems are more stable and predictable than others with respect to their future behaviour. In these cases, the know-how of the SO could be expendable and the DA requests can be configured with the option of *autosubmit* so that the solution of the DA algorithm will be automatically registered as the optimal baseline for the operation stage.

4.1.5 Objective and Cost function

The objective of the problem is to optimize the aggregated Market Settlement (MS) for all the ENs during a full day. Considering this, the objective function can be defined as:

$$\max \sum_{i=1}^{i=t_{end}} \mathrm{MS}(t_i) \tag{4.4}$$

where t_{end} is the last operation hour. This value can differ from 24, depending on daylight saving events. For the purpose of this paper, t_{end} = 24.

The MS is defined in this context by the revenue of selling energy to the network and the cost of consumption. Considering this, MS is given by:

$$\mathrm{MS}(t) = \sum_{k=1}^{N} \mathrm{MS}_k(t) \tag{4.5}$$

$$\mathrm{MS}_k(t) = \begin{cases} (Price_{inj,k}(t) - PP2P_k(t)) * P_{ex,k}(t) \\ \qquad \text{for } P_{ex,k}(t) >= 0 \\ \\ (-Price_{con,k}(t) - PP2P_k(t)) * P_{ex,k}(t) \\ \qquad \text{for } P_{ex,k}(t) < 0 \end{cases} \tag{4.6}$$

Most of the times, t_{end} will be 24 because the optimization is supposed to be executed for a full day. However, in most of the countries there are two special days every year when daylight saving events happen. In these days, the country changes its time zone so these days can have some more, or less, hours, depending if the event sets the clock back or forward. In other words, in most of the cases, there is one 23-hour day in late winter (or early spring) and one 25-hour day in autumn. Thus, rigid implementations would make the system out of order twice a year. The proposed platform considers this issue and it is stable and robust even for these corner cases. Special days are dynamically calculated so that the validations will not fail and it will be checked if the algorithm call is done with the appropriate number of values in these special days, and 24 values for ordinary ones.

4.1.6 Linear State Space Model

The dynamic of the state variables is given by the equation 4.7:

$$\begin{aligned} SOC_k(t+1) = SOC_k(t) &+ \frac{P_{\text{charge},k}(t) * \eta_{\text{charge},k} * T_s * 100}{Cap_k} \\ &+ \frac{P_{\text{discharge},k}(t) * T_s * 100}{\eta_{\text{discharge},k} * Cap_k} \end{aligned} \tag{4.7}$$

where $SOC_k(t)$ represents the state of charge in percentage; $P_{\text{charge},k}(t)$ and $\eta_{\text{discharge},k}$ are the power charge and discharge respectively given a node k; T_s defines the sample time; Cap_k the capacity of the battery; $\eta_{\text{charge},k}$ and $\eta_{\text{discharge},k}$ are the efficiencies given a node with values from 0 to 1, where 1 is the ideal scenario.

4.1.7 Model Specification

The receding horizon of the MPC model is 24, with a sample time of 1h. The implementation of the algorithm is prepared to use a different horizon considering daylight saving events, depending on the event (start or end of the daylight saving time) and the timezone.

The variables are built dynamically depending on the number of ENs. They can be grouped and defined as:

- $\left[P_{DA}(1)...P_{DA}(nh)\right]$ - Continuous variables for aggregated power
- $\left[P_{bat,1}(1)...P_{bat,1}(t), P_{bat,k}(t)(1)...P_{bat,K}(nh)\right]$ - Continuous variable for each EN. One per sample time and EN.
- Profit. Continuous variable to optimize the profit in the formulation
- $\left[L1(1)...L1(nh)\right]$ Continuous variable to linearize the problem, one per sample time.
- $\left[L2(1)...L2(nh)\right]$ Integer (binary) variable to linearize the problem, one per sample time

where nh is the horizon and K is the number of ENs participating in the aggregation. Thus, the number of variables is $(3+K)*nh+1$.

There are more details about the linearization process involving the variables in L1 and L2 in [119]. This transformation is necessary due to the different possitive or negative nature of the prices for consumption and injection.

4.1.8 System Constraints

The optimization problem is subject to the system constraints, defined as follows:

Power Battery physical limits

These limits are related to the physical limitations that the batteries and the nodes present for charging and discharging, which may imply a bottleneck in the optimization. Thus,

$$P_{bat,k}(t) \leqslant P_{\text{bat-max-discharge},k} \tag{4.8}$$

$$P_{bat,k}(t) \geqslant P_{\text{bat-max-charge},k} \tag{4.9}$$

$$P_{bat,k}(t) \leqslant Con_{max} - P_{gen,k}(t) + P_{load,k}(t) \tag{4.10}$$

$$P_{bat,k}(t) \geqslant Con_{min} - P_{gen,k}(t) + P_{load,k}(t) \tag{4.11}$$

where $P_{\text{bat-max-discharge},k}$ and $P_{\text{bat-max-charge},k}$ are the physical limits of the battery; Con_{max} and Con_{min} define the maximum and minimum connection limits of a node; $P_{gen,n}(t)$ and $P_{load,n}(t)$ represent the forecasted generation power and the forecasted load power respectively given a sample time and an EN. All values of generation and load for nodes correspond to long-term forecasts.

State of charge limits

The SOC of every EN is individually limited so that the batteries can participate with the appropriate and real storage specifications. In addition, setting the batteries with a maximum and a minimum SOC enhances their life cycle.

Thus,

$$P_{bat,k}(t) > P_k(SOC_{init,k}) - P_k(SOC_{max,k}) - P_{bat,k}(t-1) \tag{4.12}$$

$$P_{bat,k}(t) < P_k(SOC_{init,k}) - P_k(SOC_{min,k}) - P_{bat,k}(t-1) \tag{4.13}$$

where

$$P_k(SOC)$$

is the result of applying the following unit conversion function from percentage to kW for a given EN:

$$P_k(SOC) = \frac{SOC * \text{Cap}_k}{100 * T_s} \tag{4.14}$$

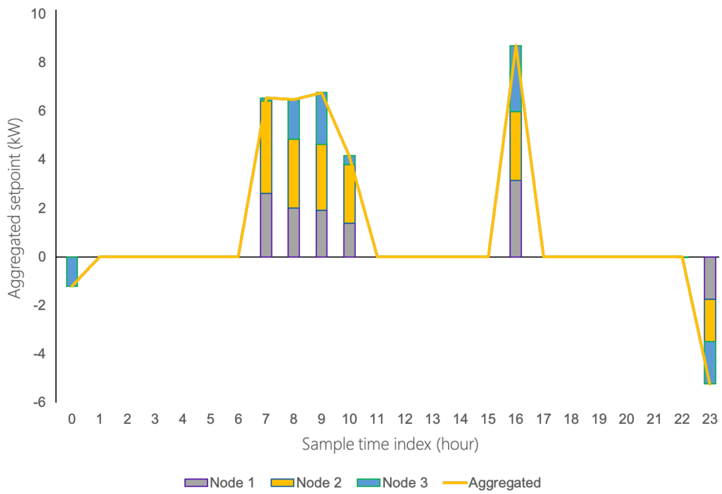

Figure 4.3 Profile optimization without P2P.

where T_s defines the sample time and Cap_k the capacity of the battery.

Aggregation limits

Finally, the aggregated power exchange of the grid can be defined as:

$$P_{GRID}(t) = \sum_{k=1}^{K} P_{bat,k}(t) + P_{gen,k}(t) - P_{load,k}(t) \tag{4.15}$$

4.1.9 Cases of Study

Evaluation of the different Day Ahead model versions

The four different modes generate slightly different solutions, especially due to the required inputs of the forecast of prices. The aggregated result will remain almost the same, but the individual setpoints will differ due to P2P cost or the different tariffs that each EN can have signed.

Having a P2P cost will penalize the EN energy transmission and reinforce the operation with the network. Furthermore, having different tariffs implies that there might be ENs that would prefer to participate or not, depending on their own future bills.

The following case study has been developed to illustrate these scenarios. The comparison has been made between the modes *individual without P2P* and *individual with P2P*. To simplify the example, the P2P cost is 0.2 €/kWh for every sample time. This cost is the only difference between both simulations since the topology of the grid or any node specification remains the same.

Figures 4.3 and 4.4 represent the aggregated profile together with the individual contributions to the grid of each of the three nodes considered for the experiment.

The optimization without P2P costs results in a more aggresive baseline than the other. Due to the fact that using the network implies some costs, the ENs prefer to save energy for

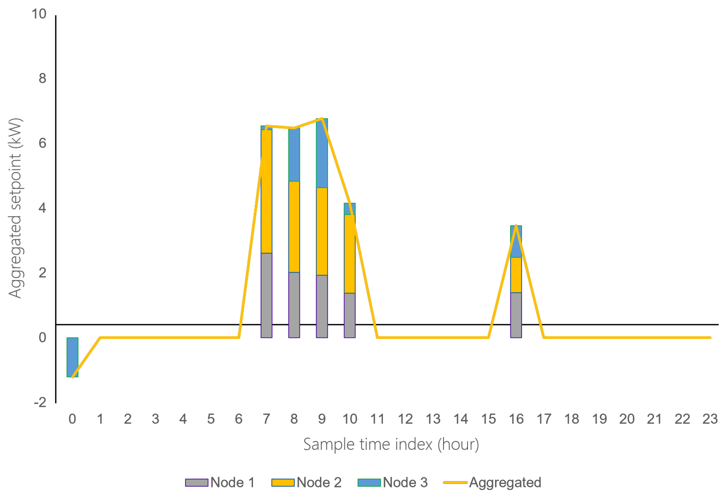

Figure 4.4 Profile optimization with P2P.

self-consumption, as well as for operations which are much more economically interesting. It can also be observed that not only the peaks are reduced, but also the sample times in which one node, at least, decides to operate.

Intent profiles evaluation

This case study presents the benefits of implementing IPs. SOs have more control over the optimization with the use of IPs, depending on their business cases. In this subsection some advanced strategies are also presented by using dynamic IPs. It is very important to have a deep knowledge about the operation of the grid where the IPs are going to be executed, which allows better economic operations. In the following subsections, the performance of IPs will be studied in terms of MS, penalties and *SOC* use.

To reduce the complexity, all nodes have been defined with the same specifications: 5 kWh of capacity, 2.3 kW and 4.6 kW for max power charge and max power discharge respectively. *SOC*s between 15% and 100%. Consumption prices were got from an external price forecast service. To reduce energy transactions, injection energy prices have been set at 80% of consumption prices.

Figure 4.5 shows three different IPs:

- Risky IP: Represented with a dotted and red curve. Capacity for DA optimization 70%, 30% for deviation mitigation and DRP participation.
- Conservative IP: Represented with a green curve. Capacity for DA optimization 40%, 60% for deviation mitigation and DRP participation.
- Mixed IP: Represented with a dashed and orange curve. Conservative between 7 am and 22 pm, and risky during other hours.

It can be observed in figure 4.9 that the Risky IP schedules the *SOC*s of the batteries closer to their limits (in comparison with the information shown in 4.10), with more

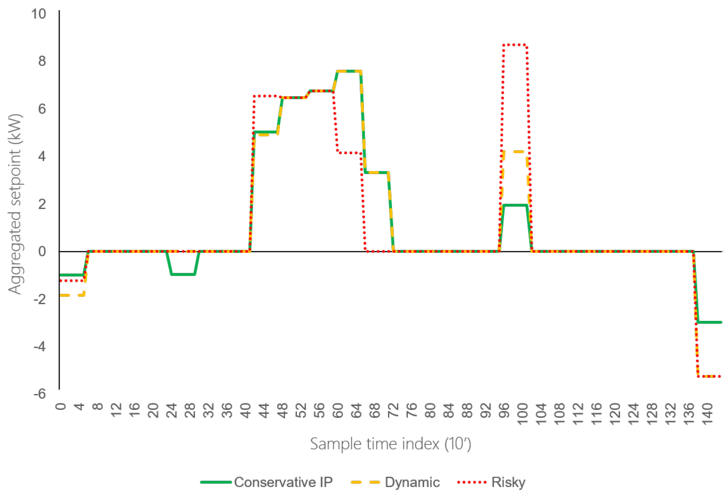

Figure 4.5 Intent profile comparative.

aggressive charge/discharge actions, which will result in a more profitable optimization (see subsection 4.1.9 for more details).

For the development of this case study, the IPs have been applied to all nodes (*aggregated IPs*), but it is also possible to apply *individual IPs* to single nodes with the developed model, as it was defined in section 3.6.1.

Analysis of the results given different Intent Profiles

The assessment of the results has been defined as the MS difference in relation to the best PA in every analysis for each IP. The PA is a KPI defined in section Profile Accuracy. First, optimality in ideal scenarios has been analyzed. Later, several non-ideal scenarios (with high deviations in forecasts) have been simulated to evaluate the resilience of the different IPs.

Considering the previous optimizations and the profit definition presented in 4.5, Risky IP is the highest ranked. Conservative IP performs a 3.97% worse than Risky IP, but Mixed only a 1.85%. Using more complex VPPs, with more nodes and a higher aggregated capacity, the differences will be more evident.

Figures 4.6, 4.7 and 4.8 depict three complete executions considering that there is not any generation. In Risky IP, there is more exchange of energy than in the others, but the batteries get empty faster. One of the most important features of the framework is the freedom that the SO has to decide how to combine the executions.

Three complete-day executions have been run for every IP, defining different load and generation profiles from that forecasted for ENs. The executions have been summarized in table 4.1.

Conservative IP is more resilient to the forecast deviations in all simulations and, consequently, the best option to mitigate penalties. On average, Mixed IP is the second one and Risky is clearly the worst. Thus, Risky IPs present more potential profits but also more potential penalties, as it has been referenced previously in this dissertation.

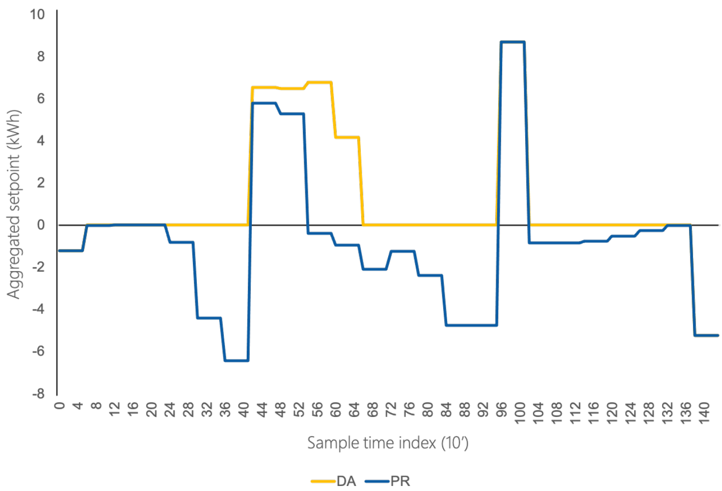

Figure 4.6 Full day simulation for Risky IPs without any generation.

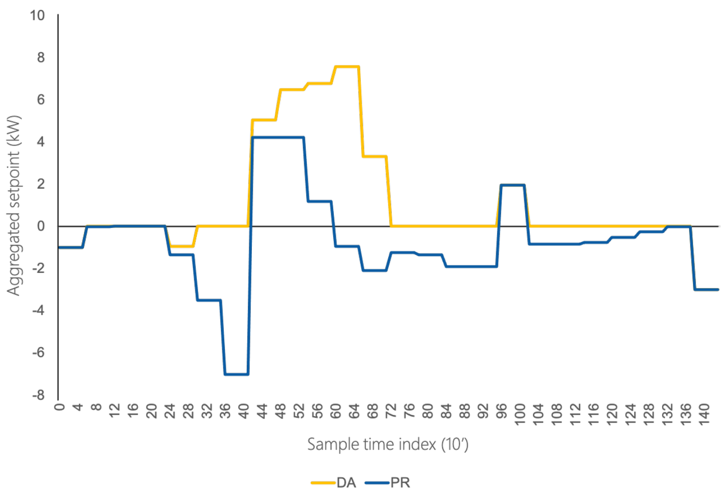

Figure 4.7 Full day simulation for Conservative IPs without any generation.

Evolution of the State of Charge values given different Intent Profiles

Figures 4.9, 4.10 and 4.11 show the *SOC* values at every sample time for the different profiles. It can be observed how Mixed IP has much more margin of capacity to operate multi-service, whereas the MS remains considerably acceptable.

Having batteries with more flexible *SOC*s makes possible more integrations with other services and also more possibilities in scenarios where penalties in the control layer will be worth it, if incentives in the other services compensate them.

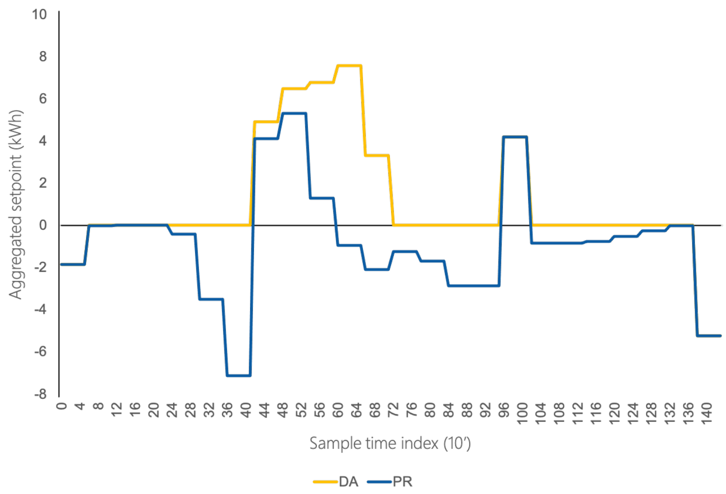

Figure 4.8 Full day simulation for Mixed IPs without any generation.

Table 4.1 Relative deviation compared with best execution.

	Risky	**Mixed**	**Conservative**
No Load	27.8 %	0% (best)	0% (best)
No Gen	5.3 %	5.3%	0% (best)
No Load, no Gen	9.4 %	9.4 %	0% (best)
Avg deviation	14.16 %	4.9%	0% (best)

4.2 Penalty Reduction Optimization

This second stage is an operational control layer. The system generates all the optimal setpoints for every EN so that the aggregated profile meets as much as possible the contracted baseline to reduce operation penalties.

A 10-minute sample time has been chosen for the case study presented in this dissertation, but this interval is configurable. The control strategy is formulated as a Mixed-Integer Quadratic Programming optimization problem based on MPC. This approach has been proposed and implemented in the literature with satisfactory results such as the research of García-Torres et al., who proposed an advanced control algorithm to operate renewable energy microgrids minimizing the penalties due to deviations by using this approach in [120].

The result is a set with the following 18 setpoints of every EN. The EMP(Energy Management Platform) sends the setpoints to the corresponding homeLynk and they are stored in the inverter, overwriting all the existing ones. The inverter will apply the first setpoint from the internal queue at every sample time until the queue is empty. With

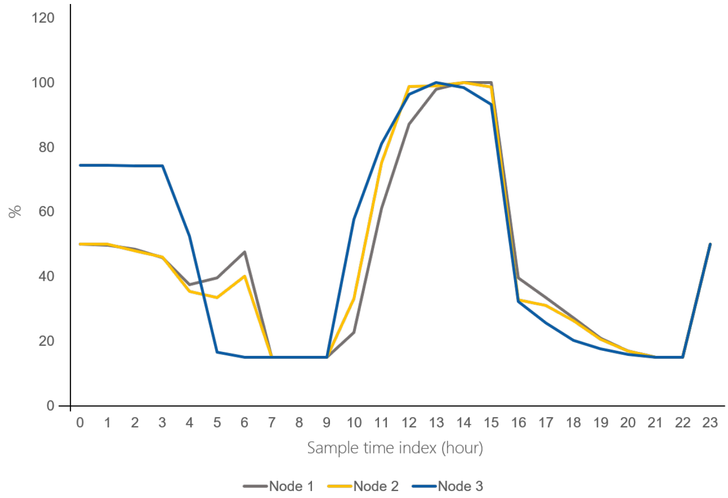

Figure 4.9 *SOC* evolution for a Risky IP execution.

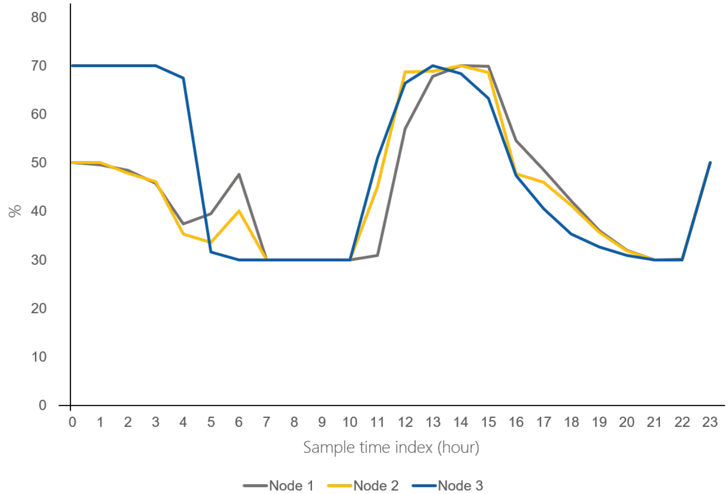

Figure 4.10 *SOC* evolution for a Conservative IP execution.

these 18 setpoints, the ENs can work correctly even with network failures until entering standalone mode. In addition, the PR algorithm can deal with these *offline nodes* as if they were working as expected, so it is possible to maintain them in the pool. There are four different EN statuses that can be managed by the system, as it is described in subsection 3.1.3.

Most of the issues which may appear during the control stage are related to data, since the platform is executed remotely and any problem gathering every node *SOC*, setpoints and short-term forecasts will imply wrong results of a PR execution.

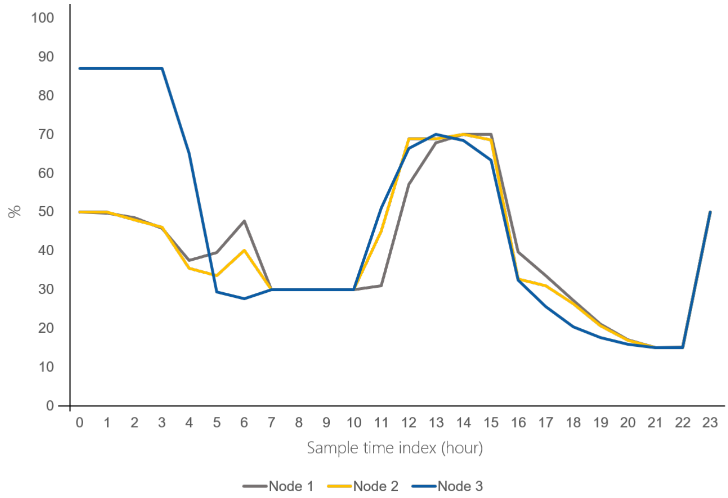

Figure 4.11 *SOC* evolution for a Mixed IP execution.

4.2.1 Objective and cost functions

The function to be optimized is the difference between the DA profile and the new schedule. Some deviations may occur due to the unavoidable uncertainties in this kind of problems, such as a low accuracy in forecasts for generation or load profiles or the appearance of unexpected malfunction errors. However, the platform is designed to mitigate most of these uncertainties by the use of DSV and IPs.

Given this, the objective function is as follows:

$$\min \sum_{t_i}^{t_{i+18}} DA(t) - PR(t) \tag{4.16}$$

where $DA(t)$ is the baseline set by the DA algorithm and the $PR(t)$ is the summatory of each individual EN setpoints.

In this stage, the sample time is 10-minute, not for one hour as it was in the previous stage. All the setpoints of generation and load for EN correspond to a short-term forecast. These values will be more accurate than the ones obtained during bid time the day before. These forecast values must be provided at every PR step so that they could be refreshed to improve the control performance.

4.2.2 System Constraints

The optimization problem is subject to the system constraints, defined as follows:

Grid constraints

These constraints define the power flow equations, enabling the aggregated optimization of all EN participation at every sample time to reduce the deviations related to the current baseline in execution.

$$P_{GRID}(t) = \sum_{k=1}^{K} P_{ex,k}(t) + \sum_{k=1}^{K} P_{gen,k}(t) - \sum_{k=1}^{K} P_{load,k}(t) - P_{Base}(t) \tag{4.17}$$

where $P_{ex,k}(t)$ is the setpoint of the node k at time t.

The baseline can be modified by DR calls, as it is described in 4.3. In that case, the constraint is slightly changed since the baseline to meet is not the DA one, but the last DR baseline result. The constraint 4.17 is a generalization of 4.18.

$$\begin{aligned} P_{GRID}(t) = {} & \sum_{k=1}^{K} P_{ex,k}(t) + \sum_{k=1}^{K} P_{gen,k}(t) \\ & - \sum_{k=1}^{K} P_{load,k}(t) - P_{DRn}(t) \end{aligned} \tag{4.18}$$

Energy node constraints

The first two equations define the exchange limits for every node. The following two constraints establish the unavoidable physical limits related to the battery.

Finally, the last two ones determine EN *SOC*s in different optimization sample times.

$$P_{ex,k}(t) \leqslant Con_{max,k} - P_{gen,k}(t) + P_{load,k}(t) \tag{4.19}$$

$$P_{ex,k}(t) \geqslant Con_{min,k} - P_{gen,k}(t) + P_{load,k}(t) \tag{4.20}$$

$$P_{ex,k}(t) \leqslant P_{\text{bat-max-discharge},k} \tag{4.21}$$

$$P_{ex,k}(t) \geqslant -P_{\text{bat-max-charge},k} \tag{4.22}$$

$$SOC_k(t) \leqslant SOC_{max,k}(t) - SOC_k(t-1) \tag{4.23}$$

$$SOC_k(t) \geqslant SOC_{min,k}(t) - SOC_k(t-1) \tag{4.24}$$

4.2.3 Fault Detection Enhancement

Several strategies have been designed and implemented to enhance the system robustness by considering some fault detection problems: the intrahour equilibrium and the management of non controllable nodes. The former improves these scenarios where there are deviations in time gaps shorter than one hour, which would result in deviations of the mean power supplied, or consumed, for this given hour. The latter maintains the ENs with *read only* status in the pool of available nodes in case it would be interesting for the operation.

Intrahour equilibrium strategy

In this dissertation, *intrahour equilibrium strategy* refers to a strategy to solve issues related to the multi-time intrinsic feature by interpolating deviations for intervals of time of less than one hour (which is the DA sample time unit) and, consequently, minimizing the impact in the following executions. There are two ways to perform the intrahour equilibrium: the *average power* mode and the *energy* mode.

At every sample time in average power mode, the PR algorithm calculates the accumulated average power which the VPP has operated during the current hour. If the average power differs from the commitment in DA, all the following 10-minute sample times within the same hour must compensate for this deviation as much as possible.

Due to the fact that the deviation penalties, when the VPP is supposed to inject energy into the power system, are much higher than the ones in consumption, the intrahour equilibrium is only activated for sample times when the commitment in DA is for injecting power.

$$P_{ref}(t_i) = \begin{cases} \dfrac{DA(t) - \sum_{j=0}^{i-1}\sum_{k=1}^{K} P_{real,k}(t_j) * T_s}{\dfrac{1}{T_s} - i} \\ \qquad \text{for } DA(t) > 0 \\ DA(t) \\ \qquad \text{for } DA(t) \leq 0 \end{cases} \tag{4.25}$$

where i is defined in the natural interval of 0-5 since T_s is defined every 10 minutes. The number of available sample time depends on the PR algorithm execution time.

Figure 4.12 shows a full-day simulation with deviations. The series shown in blue color represents the average power for the VPP to exchange during the same hour, but it can be observed in red color that the real setpoints, which were actually commanded to the EN, are slightly different. The shape of the chart representing this second series is characteristic of a system which has lost its generation source. Consequently, the optimization algorithm will try to reduce the deviations without success since errors do not converge.

Two different models have been implemented for running this enhancement, depending on the SO needs.

- Energy Mode: The SO indicates the amount of energy that the grid has injected or consumed from the network during the current hour in the inputs of the PR algorithm. This mode is very conveninent for smart grids with ENs composed of a smart-meter that can be queried in real time.
- Power Mode: It is activated by default. The system tracks the real power executed by each EN and creates a new virtual baseline for the current hour to be optimized in the current execution.
- Off: The intrahour enhancement can be completely deactivated. It is not recommended, unless the SO has strong knowledge about the actions which they are

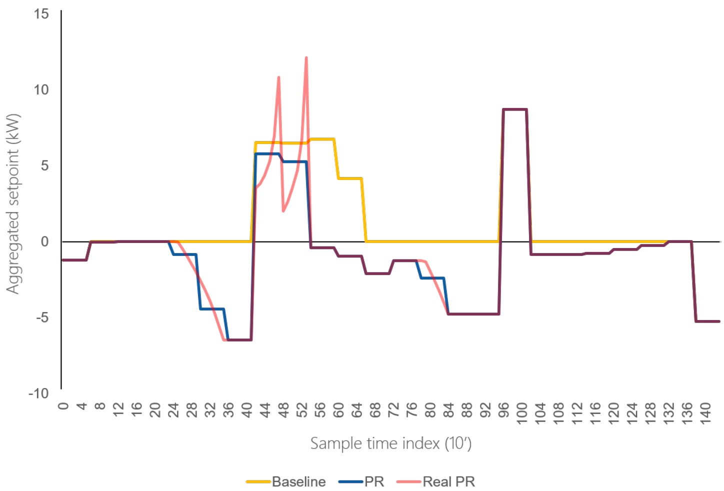

Figure 4.12 Comparison between power mean and real setpoints.

performing. In most of the scenarios, having this enhancement activated will improve the overall optimization. In section 4.2.3 there is a case study to illustrate its importance.

It is important to remark the strong dependency that exists when the *power mode* is activated. In this framework, every algorithm remains absolutely decoupled from others, being coordinated by the powerful role of the storage system. This means that not only every execution of the algorithms are independent, but also several steps of the same algorithm will not present any dependency from others. Having *power mode* activated implies that the virtual baseline will depend on previous executions, and it would not be possible to run algorithms in the real environment without affecting the following steps. This is not an actual problem for operation since each PR execution will be executed only once in a real environment. To solve this issue, it can be deployed other entrypoint in the Application Programming Interface (API) of the system only for simulation purposes with an implementation which does not interfere with the operation of the smart grid. There is more information about the software architecture and the implication of new developments in chapter 7.

Intrahour enhancement can be activated or deactivated in every sample time by setting the request. By default, power mode is enabled since this is the best option for most of the times, according to the research. However, the platform gives the operator the freedom to switch it on, or off, depending on their context.

Non controllable nodes

There are some occasions when the ENs are not controllable although they are able to send the telemetry (read-only status, see 3.1.3). However, it would be profitable to maintain these nodes even without controlling them, but adapting the VPP to compensate their behavior. Two clarifying scenarios could be:

- The read-only EN is generating much energy and its load profile is not very demanding. The excess energy can be saved by other EN.
- There is a DR action and the VPP needs the inclusion of more ENs.

The model to adapt the VPP to read-only nodes is defined as:

$$P_{bat_{total},k}(t) = P_{bat_{bat},k}(t) + P_{bat_{network},k}(t) \tag{4.26}$$

$$P_{bat_{total},k} = FS_k - P_{gen,k}(t) + P_{load,k}(t) \tag{4.27}$$

where FS_k is the observed fixed setpoint due to failures of the node.

$$SOC(t) = \begin{cases} SOC(t-1) - P_{bat} * T_s \\ \quad \text{for } SOC_{min} < SOC(t) < SOC_{max} \\ \\ SOC_{min} \\ \quad \text{for } SOC(t) \leqslant SOC_{min} \\ \\ SOC_{max} \\ \quad \text{for } SOC(t) \geqslant SOC_{min} \end{cases} \tag{4.28}$$

$$P_{bat_{bat},k}(t) = \begin{cases} \dfrac{-(SOC(t-1) - SOC(t))}{T_s} \\ \quad \text{for } P_{\text{bat-max-charge},k} \\ \qquad < P_{bat_{bat},k}(t) \\ \qquad < P_{\text{bat-max-discharge},k} \\ \\ P_{\text{bat-max-charge},k} \\ \quad \text{for } P_{bat_{bat},k}(t) \leqslant P_{\text{bat-max-charge},k} \\ \\ P_{\text{bat-max-discharge},k} \\ \quad \text{for } P_{bat_{bat},k}(t) \geqslant P_{\text{bat-max-discharge},k} \end{cases} \tag{4.29}$$

Considering that the real power exchange is the difference between the fixed reference and the power battery that applies to network, it can be concluded that:

$$RS_k(t) = FS_k - P_{bat_{network},k}(t) \tag{4.30}$$

Substituting with 4.26:

$$RS_k(t) = FS_k - (P_{bat-total}(t) - P_{bat_{bat},k}(t)) \tag{4.31}$$

The value of $RS_k(t)$ is the real setpoint that the read-only EN is actually performing. PR algorithm considers this value and it adapts the setpoints of the other nodes so that the aggregation could adapt the operation.

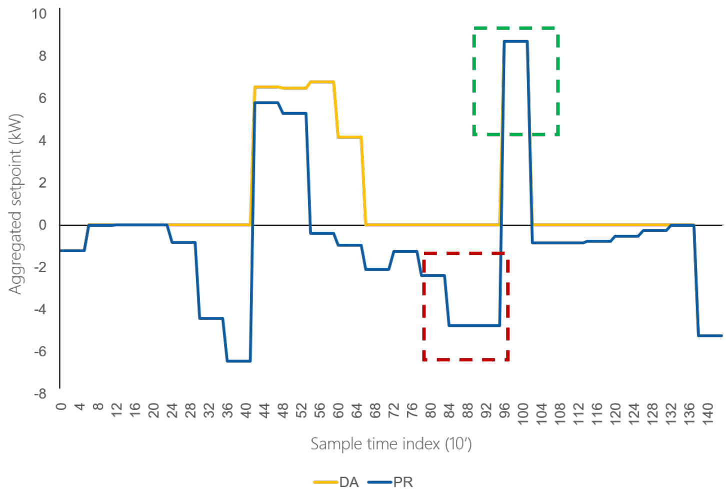

Figure 4.13 Complete day simulation without generation in any node.

Meeting injection

It is extremely important to consider that deviation penalties when the VPP is supposed to inject power are much higher than the ones in consumption [121]. PR algorithm is able to consider more deviations in consumption sample times to meet as much as possible during injection ones. This is possible because of the intrinsic receding horizon of the MPC formulation.

The main type of actions which can be commanded are two:

- Inject-to-consume: Actions needed when the grid has more stored energy than optimal. It could be anti-intuitive to assimilate the fact that having an excess of clean renewable energy could imply problems, but there are some systems which cannot drop energy. Thus, they would not be able to store the amount of energy needed resulting in additional unexpected energy injection actions.
- Consume-to-inject: The energy is bought before-hand in sample times when the grid is not injecting to meet the commitment in following injection sample times.

Figure 4.13 depicts a complete-day execution where the real values for generation have been submitted as 0 during operation time, instead of the forecasted values. Due to this scenario, the batteries get empty, so meeting high injection sample times remains complicated. Physical limits of ENs and batteries make impossible faster charge actions to meet the injection profile. However, there can be found many sample times with *consume-to-inject* actions located before every injection peak. In these sample times, the VPP consumes more energy than needed to store it and use it for injection.

The area delimited by the red slashed line is an example of *consume-to-inject* action. The green one is the injection peak which has been successfully satisfied.

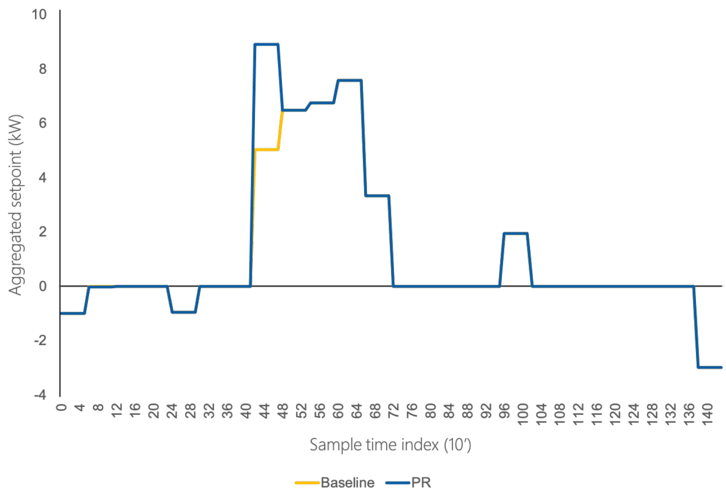

Figure 4.14 Execution with Intrahour Equilibrium Off.

The importance of the injection meeting enhancement during operation

The design and the implementation of this fault detection enhancement is extremely important. It can be observed in 4.14 and 4.15 the difference between the accuracy of the two simulations. In this simulation, the forecast values for generation and load are set without any disturbance in relation with the real ones during the control stage, except for the steps 42 and 43. In these steps, the real generation was 5kW higher than forecasted for each node. The grid is not able to compensate these deviations during the following four sample times that still belong to the same hour. Thus, the injected energy in the grid for this sample time (equivalent to the mean of the power since the tracking sample time is of one hour) is much higher.

The PA is 2.77 with the enhancement activated and 23.45 otherwise. Then, the grid without the enhancement activated presents 88.2% less deviations than the other in terms of absolute deviations considering this case study. This is possible due to the fact that the grid was able to absorb the impact of the deviations during its control stage.

As it can be observed, the deviations happened during only one hour have a big impact for the rest of the day, which means that not having the optimal *SOC* in each node compromises the contract for the rest of the day.

4.3 Demand Response Program Integration

In this section a DR model is presented based on MPC and MILP. This model is integrated with the reconfigurable multilevel dynamic model for the microgrid optimal operation. DR adds more flexibility to the decoupled system since it generates a new profile which overrides the scheduled actions for the nodes in the grid, in the interval of time between a DR execution and the end of the day. This last profile is considered to be the active one,

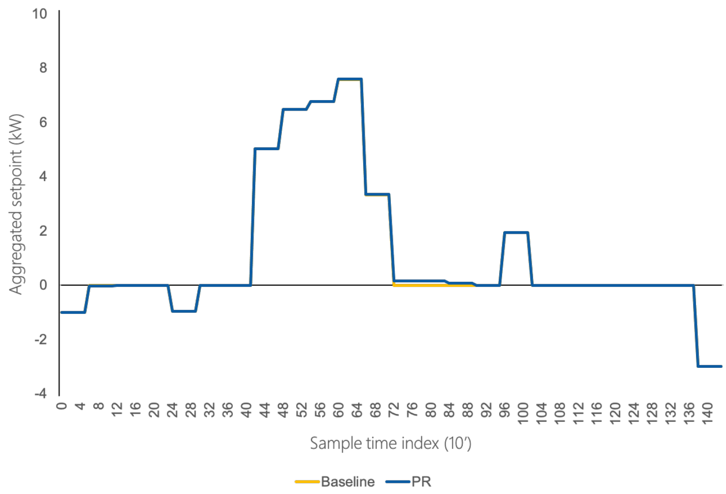

Figure 4.15 Execution with Intrahour Equilibrium On.

while the previous ones are all deactivated. The resulting grid profile which is operated at the end of the day will be the conjunction of all the active ones, which was defined as piped-baseline in 3.3. The algorithm is designed to handle real operation simulations so that the operator could be able to simulate different scenarios to assess how the grid would perform after every optimization. Once the DR action is approved, the profile must be explicitly submitted to the multilevel dynamic model.

The DR algorithm has been designed as an expansion of DA formulation, but absolutely decoupled and independent. SOs can run this algorithm every time that the market makes an offer for an increase or reduction of the consumption from the network. This optimization needs the updated forecast measures and the current VPP state (ENs availability, individual *SOC*s, etc.). The VPP will try to satisfy the new scenario by modifying the commands of the following hours which were not scheduled to inject, avoiding the impact on injection sample times so that high penalties would be reduced. If it is possible for the VPP to allocate the changes, the algorithm will generate and persist the new baseline in the database, or *no solution* otherwise. Only if the injection profile is not compromised, DR applies.

4.3.1 Objective and Cost function

The objective function is defined as:

$$\max \sum_{t_{DRn}}^{t_{end}} \mathrm{MS}(t) \tag{4.32}$$

where MS is similar to the equation defined in 4.5, but only with the sample times that are between the time of execution and the end of the day.

The DR service can be called with different *intervals* depending on the TSO's needs. An interval is defined as:

- Init hour.
- End hour.
- Incentive price.
- Load offset (positive or negative) to be reduced or incresed during interval time.

4.3.2 Specific System Constraints

Profile limits

In order to ensure the optimal performance by reducing penalties, it is necessary for the aggregation to maintain the values of the won bids on the day before, and to limit *conversions*. A conversion is defined as the change from consumption mode to injection mode, given a sample time. The only allowed conversion is during the DR interval and only if feeding compensation is enabled, as it is explained in the next subsection. Thus,

$$P_{DRn}(t) = P_{GRID}(t)\forall t \in P_{GRID}(t) \geq 0 \tag{4.33}$$

$$P_{DRn}(t) \leq 0\forall t \in P_{GRID}(t) \leq 0 \tag{4.34}$$

Feeding compensation vs No-Feeding compensation

Feeding compensation occurs when the DR optimization changes the value of a previous established command for one hour from a negative value to a positive value. This means a change from a consumption command to an injection one. This should be forbidden since the bid was not won for this sample time during the day before, so the VPP would not be allowed to inject. Nevertheless, this flexibility enables new economic operations and agreements between the TSO and the SO, as well as potential benefits for prosumers.

Disabling feeding compensation constraints are given by:

$$P_{DRn}(t) = \max(0, P_{GRID}(t))\forall t \in \{t_{DR_n} \ldots 24\} \tag{4.35}$$

where t is an array with $24-t$ values; $P_{GRID}(t)$, the aggregated setpoint of the grid at time t; t_{DR_n} the sample time of the n^{th} execution of the DR algorithm; $P_{DR_n}(t)$, the aggregated setpoint of the pipe baseline at time t.

4.3.3 Fast Demand Response (Maneuvers)

DR algorithm integrates a system of Fast Demand Response (FDR) to participate in the DRP under the SO's criteria. The system generates one maneuver for consumption increase and other manuever for consumption reduction, for each of the following two hours, at every PR step (every 10 minutes). This value depends on three factors: the capacity of the node, the current *SOC* of the EN and a security value that the SO fixes to avoid large maneuvers that would imply future large deviations in PR.

$$FDR - P_{\text{max-load-reduction},k}(t) = \min(SOC_{max,k} - SOC_k(t), P_{\text{load-reduction-limit}}) \tag{4.36}$$

$$FDR - P_{\text{max-load-increase},k}(t) = \min(SOC_k(t) - SOC_{min,k}, P_{\text{load-increase-limit}}) \tag{4.37}$$

where $FDR - P_{\text{max-load-reduction},k}(t)$ and $FDR - P_{\text{max-load-increase},k}(t)$ are the allowed maneuvers for reduction and increase; and $P_{\text{load-reduction-limit}}$ and $P_{\text{load-increase-limit}}$ are the limits fixed by the SO.

This mode does not work as the other DRP participation, since the system will not generate a new baseline to be tracked, so the operation may not be optimal. However, the SO can consider to change manually the automatic operation of the system because of their know-how. This kind of manual algorithm tweakings give more control over the grid under operation and solves possible differences between the system model and the reality.

4.4 Conclusions

In this chapter, the implementation and integration of different strategies for the simultaneous participation in different energy markets have been presented. In addition, some case studies have also been explained to describe the functionalities and features of them. It can be seen how the system is robust and flexible, which will allow the inclusion of more services and new possibilities. The use of DSV to share the capacity and the stored energy between different market participations has been already addressed in the literature, but the contributions of the model presented in this chapter are mainly the following key points:

- The SO has all the control over the platform. Running simulations do not imply their submissions, so SOs can draw all the necessary scenarios to see the required possibilities to make a decision at bid time. During the control stage, it is also possible to control which are the nodes that will belong to the operational grid. It is also possible to add and remove dynamically ENs at every sample time.
- Possibility to adopt dynamic strategies, depending on the risk level that the SO would like to take. It is also possible to adopt a mixed strategy to make the operation more profitable when the risk of forecast deviations is low, and to take a more conservative one otherwise.
- Integration between different services by using the concept of piped baseline, which makes the PR algorithm independent from any other service participation. It is possible to operate in several services with different targets and commitments, and the PR algorithm is only responsible for reaching this commitment. The modification of the baseline will depend on some business criteria and market incentives, but these decisions are under the control of the SO.

- Fault detection models integrated to enhance operation and reduce penalties. This improves the decision making process and makes the platform aware of potential penalties to fix them in time.

It can be observed in chapter 6 that the system performed very well in real situations, even with strong difficulties. However, the presented strategy still has a strong dependency on the accuracy of the forecasts due to its deterministic nature. In the following chapter, a stochastic component will be added to the model to mitigate this issue. Thus, it will be possible to create some situations that may stochastically violate the original constraints for the bidding optimization, depending on the historical forecast errors for generation or consumption. This stochastic behavior performs better than the deterministic approach in most of the cases. In any case, the model can be switched from deterministic to stochastic and vice versa with a single parameter in the algorithm call.

5 Chance Constraint Optimization

A stochastic process is about the results of convolving probabilities-which is just what management is about, as well.

Anthony Stafford Beer

The best deterministic optimization algorithms which rely on forecasts (provided as inputs or calculated as state transitions, for example) must consume extremely high accurate services since their optimality absolutely depends on these external agents. Any small deviation ocurred during the prediction horizon can imply high deviations from the optimal solution.

This situation is even worse when considering non-controllable forecasts such as prices or energy generation. There are other forecasts such as user loads (end-user consumption) which can be partially controllable, for example, through the use of smart domestic appliances. However, it is imposible to take an absolute control over the end-user consumption because the final decision will rely on them, since they are the people who will be billed accordingly to an established business model. Nevertheless, the duty of the EMP is to ensure that these deviations do not imply economical or technical issues for the grid exploitation and stability. The smart system must be able to overcome all the deviations from all the nodes by offering a general, aggregated and fair solution.

This chapter presents the inclusion of stochasticity into a deterministic MPC to improve the performance of the smart agent when dealing with these unavoidable deviations. The stochastic component defines the uncertainties so that they could be explicitly included in the model. The resultant SMPC is more robust to generation and load forecast deviations by including some allowed constraint violations based on some probability criteria.

There are several approaches which allow the inclusion of stochastic components in deterministic linear problems. Bordons et al. present a deep and complete literature and study about uncertainties in microgrids in [69, Chapter 7], as well as the possibilities which actually exist to implement SMPC solutions in this field. In this dissertation, the CC-MPC is the chosen technique over the others, like scenario-based techniques.

The participation in energy markets implies *bidding in advance*, which results in a fixed contract based on forecasts. The deviations which may appear from these forecasts, due to uncertainties, could make it impossible for some individual ENs to meet their own expectations in terms of consumption or injection during some hours and, incurring thus in hard penalties. Consequently, the SO of the VPP is responsible for compensating these deviations with power from other ENs in the pool so that the aggregated participation is accurate and the VPP will not be penalized. Since the generation in DERs strongly depends on weather, they often produce rapid changes in power output, resulting in unscheduled ramping events. These type of issues can trigger some system imbalances that must be controlled before ending in a massive blackout.

Uncertainties often arise due to sudden disturbances in the generation forecast and to the errors introduced by the lack of accuracy from the demand side owing to their complicated patterns of energy use [122]. Disturbances have two components: one deterministic and other stochastic. It is possible to consider Feed Forward (FF) compensation of future diturbances [89] in the forecasts presenting a low stochastic influence. In addition, it is also possible to mitigate the stochastic component by the integration of CC models with probabilistic constraints. These models are designed to improve the deterministic ones in the majority of possible scenarios. According to [123], the probabilistic constraints *"help to model feasible decisions when the latter are taken prior to observing uncertainty and both decisions and uncertainty are involved in a constraint structure of an optimization problem."* A deep study of analytical properties of dynamic CC problems was published in [124], and many works in the literature deal with the combination of uncertainty and CC, such as [125, 126, 127, 128]. The CC models can be built based on theorical and analytical concepts, but also combined with data-driven methods, including ML techniques [129] to avoid conservative sampling.

Several different approaches to the application of CC models can be found in the chapter *Uncertainties in Microgrids* in [69]. The analytical-based stochastic MPC approach has been the one considered among all the proposed method for the purpose of this dissertation. The implementation of a DML(Disturbance Mitigation Layer) to deal with the disturbances improves the overall operation of the aggregation.

The use of CC to mitigate the effect of uncertainties has been widely studied in the fields of multi-market participation [130], distribution network planning [131] or power supply [132]. There is an increasing trend in the use of data-driven solutions, ML techniques and big data [133, 134, 135], which are proposed to solve uncertainty issues in complex systems [136, 137, 138].

The following sections define some concepts about stochastic programming and CC-MPC, as well as the details of the implementation. Finally, some results show the benefits of using stochastic approaches to solve problems of accuracy in forecast services.

5.1 Disturbance Mitigation Layer

The DML is an extra layer implemented in the optimization problem to manage the uncertainties that the load and generation forecast services may present. Although the forecasts come from external sources, it is possible to model their behavior with historical data, as well as to know how they used to work in the past to foresee the future. This enables a preprocessing of the inputs and the execution of a more realistic optimization by compensating for their future deviations. This can be achieved with stochastic approaches such as CC implementations. These formulations are based on the assumption that they work better than deterministic solutions in almost all possible situations. It is possible to model the historical uncertainties with classical probabilistic methods or by using other approaches such as machine learning.

The proposed DML defines the stochastic component with a CC model and an Encoder-Decoder Model (ED) for Multistep Time Series Forecasting to predict uncertainties in load and generation forecasts. The composition of the stochastic component and its inclusion in the optimization problem have also been defined. The goal of this stochastic layer is to generate a combined factor of both methods: the CC component and the NN service [18].

The proposed DML defines the stochastic component with a CC model and an ED to predict uncertainties in load and generation forecasts. The composition of the stochastic component and its inclusion in the optimization problem have also been defined in this dissertation. The goal of this stochastic layer is to generate a combined factor of both methods: the CC component and the NN service.

There are different situations when the models must be reset, such as those when there is a replacement of the forecast system, a change in the specification of some assets, or the inclusion of new ones. In these cases, when the amount of past data is not enough to provide an accurate model, the DML does not affect the operation. Thus, the affected nodes participate in the optimization in a deterministic way, while the others whose models are available can properly handle the disturbances stochastically.

There is a first mitigation system which is intrinsic to the formulation of the problem and its DSV: The system reserves a certain capacity in the battery for uncertainties. Thus, depending on the strategy to operate with the markets, it would have a bigger impact on the disturbance mitigation. However, this might not be enough and other mitigation systems may be needed.

5.1.1 Disturbance Mitigation Layer formulation in the framework

Disturbances can be mitigated by the use of FF compensations when their behaviour is hypothetically well known. In fact, having a good accurate estimation of the disturbance will improve the operations since the disturbance is not measurable at optimization time. Thus, a forecast of the disturbance is necessary to compensate for the lack of accuracy. Some constraints must be redefined to include the stochastic component. A detailed formulation about the inclusion of CC in an MPC is presented in [89]. In the context of the model presented in this dissertation, the constraints which should be redefined are the ones related to the *SOC* limits of the ENs in the VPP, so from (4.12) and (4.13) the problem can be redefined as:

$$P_{bat,k}(t) > P_k(SOC_{init,k}) - P_k(SOC_{max,k}) - P_{bat,k}(t-1) + F_{st}^{-}(t) \tag{5.1}$$

$$P_{bat,k}(t) < P_k(SOC_{init,k}) - P_k(SOC_{min,k}) - P_{bat,k}(t-1) - F_{st}^{+}(t) \tag{5.2}$$

where $F_{st}(t)$ is the stochastic factor, the result of the DML at a certain sample time. This term is defined as:

$$F_{st}(t) = \left[f_{c1}\left(\varphi^{-1}_{gen_{k,t}}(\delta), \psi_{gen_k}(t)\right) - f_{c2}\left(\varphi^{-1}_{load_{k,t}}(\delta), \psi_{load_k}(t)\right)\right] \tag{5.3}$$

$$F^{+}_{st}(t) = \begin{cases} F_{st}(t) & \text{for } F_{st}(t) \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{5.4}$$

$$F^{-}_{st}(t) = \begin{cases} F_{st}(t) & \text{for } F_{st}(t) \leq 0 \\ 0 & \text{otherwise} \end{cases} \tag{5.5}$$

where f_{c1} and f_{c2} are functions to combine the results, depending on some selected criteria; $\varphi^{-1}_{gen_{k,t}}(\delta)$ and $\varphi^{-1}_{gen_{k,t}}(\delta)$ are the results of applying the CC models for PV and load respectively for each EN and sample time, with a risk factor of $(1-\delta)$; ψ_{gen_k} and ψ_{load_k} define the NN models for a given EN. f_{c1} and f_{c2} have been defined in this case study as a simple linear combination of both services. The definition of more complex combination functions is possible, but out of the scope of this paper.

The following subsections describe the implementation of each component in the stochastic factor.

Stochastic Component Service

The stochastic component has been developed as a customizable optimization feature which can be deactivated on demand at each optimization run. In the implementation, the stochastic factor is given by an isolated service which obtains both the CC and the NN method and calculates the result by a simple linear combination of both (f_{c1} and f_{c2}). The combination of each participant is under the SOs' criteria. The pseudocode in the algorithm 1 outlines the implementation of how the stochastic component service obtains the stochastic factor.

5.1.2 Chance Constrained Disturbance Mitigation Service

CC are used to solve problems where uncertainties may exist and the constraints have to be satisfied in the vast majority of cases, but not necessarily in all of them. This can be formally written as:

$$\begin{aligned} &\text{minimize} && f(x,\xi) \\ &\text{subject to} && P(g(x,\xi) \leq 0) \geq 1-\varepsilon \end{aligned}$$

where P is the probability of the expectation so as not to violate these constraints.

According to [89], the information about the prediction error can be modeled by the Probability Distribution Function (PDF) by comparing historical data with their respective predictions. The Cumulative Distribution Function (CDF) can be deduced from the

Algorithm 1 Calculate Stochastic Component

$\delta \leftarrow 0.95$
$D^{CC}_{gen} \leftarrow \emptyset, D^{CC}_{load} \leftarrow \emptyset$
$D^{NN}_{gen} \leftarrow \emptyset, D^{NN}_{load} \leftarrow \emptyset$
$nodes \leftarrow EN_1..EN_k$
for n in nodes **do**
  for t in [1..24] **do**
    $D^{CC}_{gen} \leftarrow append(D^{CC}_{gen}, \varphi^{-1}_{gen_{k,t}}(\delta))$
    $D^{CC}_{load} \leftarrow append(D^{CC}_{load}, \varphi^{-1}_{load_{k,t}}(\delta))$
  end for
  $D^{NN}_{gen} \leftarrow \psi_{gen_k}(t)$
  $D^{NN}_{load} \leftarrow \psi_{load_k}(t)$
  $F_{gen} \leftarrow f_{c1}(D^{CC}_{gen}, D^{NN}_{gen})$
  $F_{load} \leftarrow f_{c2}(D^{CC}_{load}, D^{NN}_{load})$
end for
return $F_{load}(t) - F_{gen}(t) \forall t \in [1..24]$

where D^{CC}_{gen}, D^{CC}_{load} are two lists of results from the CC algorithm (with 24 values each, one solution per sampling time), with a risk of violation of the constraint of $(1 - \delta = 0.05)$. D^{NN}_{gen} and D^{NN}_{load} are the results (24 values each) of the ED model, F_{gen} and F_{load} the result of combining both aproaches.

previous comparison to describe the cumulative distribution of the disturbance. This function can generally be defined as:

$$F_X(x) = P(X \leq x), \forall x \in \mathbb{R} \tag{5.6}$$

The stochastic factor in the MPC is included in the formulation by combining the CC and the NN components. The steps to build the CC component are defined in the following subsections.

The approach to collect the data to build the CDF will depend on the nature of the system to be operated. In the case study presented, the uncertainties in the generation forecast for PV panels are very different depending on the hourly correlation with respect to the working day. Forecast systems are less likely to present deviations in the intervals of time when there is no solar radiation than in others in the central hours of the day. Consequently, in order to build better solutions, it is necessary to create 24 different models per EN.

The data to be gathered are the historical deviations between forecasts and actual values per EN. In case that the platform has different sources of forecast, it is also possible to indicate which the source is and to build different models for each one. Thus, one model is built for each tuple of forecast source, EN and sample time.

The size of the data is not important in terms of performance since the models are built and stored only once. It is possible to rebuild these models according to the SO's know-how since the source of the forecast service may have changed, or the VPP may present some new developments from a specific date, which could affect the accuracy of the following forecasts.

Cumulative Distribution Function Definition and implementation

A CDF function can be defined by giving values within the domain of the model function in systems where the model can be formulated and is well known. Consequently, when defining the CC model, CDF^{-1} can be calculated, if it exists.

However, when working with real systems in real environments, the model to be used is a data-driven one. In fact, this is the real problem in this context, when the disturbance model is very hard to formulate by means of classical methods, and the system tries to compensate the disturbances with additional actions.

Consequently, an Empirical Cumulative Distribution Function (ECDF) is necessary to be formulated based on historical data to build the model with its inverse. The only difference between this function for PV forecast, and the implementation of the CC model for loads, is the predictor component. The predictor is the agent which fetches the disturbances from the database. The implementation of ECDF^{-1} must interpolate the results obtained from the extrapolation of the $\mathrm{ECDF}(\delta)$ resolution for each historical data saved at the given sampling time. After building the models, all of them must be executed with the appropriate risk of violation of the constraints. In this dissertation, $(1-\delta) = 0.95$. In the implementation, `pv_pred` is the disturbance predictor of PV.

Code 5.1 Implementation of CC model.

```
from scipy.interpolate import interp1d
from statsmodels.distributions.empirical_distribution \
 import ECDF

def build_pv_cc_model(en, t, fc='default'):
  model = lambda x: x
  disturbances = set(pv_pred.get_all(en, t, fc))
  if not len(disturbances):
    return lambda x: 0
  elif len(disturbances) == 1:
    return lambda x: disturbances[0]
  else:
    ecdf = ECDF(disturbances)
    keys = sorted(disturbances)
    return interp1d([ecdf(v) for v in keys], keys,
             fill_value="extrapolate")
```

The implementation of ECDF^{-1} must interpolate the results obtained from the extrapolation of the $\mathrm{ECDF}(\delta)$ resolution for each historical data saved at the given sampling time.

After building the models, all of them must be executed with the appropriate risk of violation of the constraints. In this paper, $(1-\delta) = 0.95$.

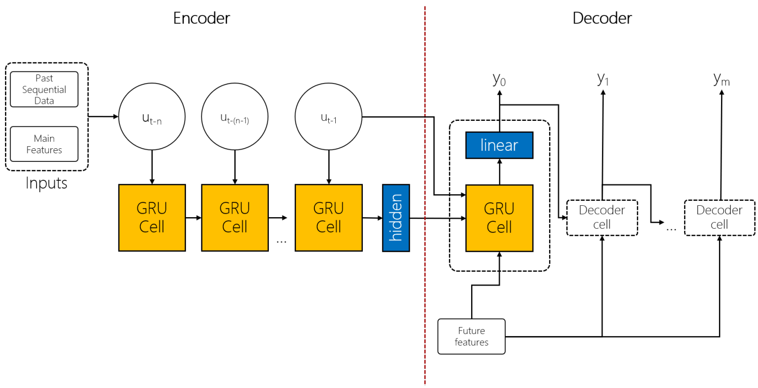

Figure 5.1 Encoder-Decoder Architecture.

5.1.3 Neural Network Disturbance Mitigation Service

In recent times, the number of possible applications for NNs and their impact on society has been increasing in fields such as classification, clustering, pattern recognition and prediction. In the field of time series, the current state of the art shows that RNNs present better results than traditional NNs. RNNs can be built by two main approaches: LSTMs or GRUs. It is possible to establish forward and backward dependencies between RNN layers by means of building Bidirectional Recurrent Neural Networks (BRNNs). Although the backward dependency may seem not to make sense in forward predictions, this combined strategy is widely being used successfully in NLP. Finally, one of the most accepted aproaches are attention layers. This architecture consists of an encoder-decoder which sets not only dependencies between the different features, but also between features of different sample times.

In this dissertation, an ED architecture is defined and implemented. The encoder is defined with an unidirectional GRU layer and the decoder cell are defined as GRU cells.

Neural Network Model Definition

The definition of a GRU cell can be found in [139]. Figure 5.1 shows the full architecture of the NN.

The inputs are defined with two different types of data:

- Past Sequential data: Last 24 values of disturbances in the forecast service and other step-dependent features such as the daily correlation or weather factor.
- Main Features: Features which remain the same for the whole prediction: categorical data, averages and EN identifier.

Logit functions are those which perform logistic regression with outputs from 0 to 1 (regression probability). These functions are widely used in the last layer of NNs and they take as inputs the outputs of other deeper layers in the network for use cases such as pattern detection or information classification, for example. The output of the encoder is the result of its last hidden layer without applying any logit function. Thus, the decoder

Table 5.1 Encoder-Decoder Hyperparameters.

	Encoder - Decoder
Optimizer	AdamW
Learning Rate	0.001
Loss Function	MSE
Sequence Length	72
Input Feature Length	5 (one of them with 24 values)
Hidden Size	300
Output Size	24

receives the raw values of this hidden layer, as well as the previous and future features. The output of this layer is the sequence of 24 values with the forecasted disturbance error to fix the original forecast profile.

There are other settings as important as the architecture or the data when working with NNs: hyperparameters, optimizers, etc. In the proposed case study, table 5.1 defines the best settings found for the NN after iterating over different configurations.

The hyperparameter that had the most important impact on the accuracy of the network in this case study was the optimizer. Tests showed that AdamW [140] was the best optimizer, presenting better performance in forecasts since it reduces the overfitting. It is an improved implementation of Adam optimizer.

5.2 Results

The prices of the imbalances are traditionally calculated by considering different complex criteria depending on the state of the power system [141, 142, 143]. In addition, power systems can be split in different zones and each one can have its own approach to penalize the imbalances. However, there is a clear pattern: the incentives to respond to the demands of energy markets to fix deviations, as well as the penalties for not meeting the commitment, are always higher than regular prices, as it can be observed in different zones such as Belgium [144] or the Nord Pool in the North of Europe [145]. In this paper, the assessment of the results will be presented considering that the price per kWh in penalties is higher than regular prices, and the evaluation will be performed in terms of relative savings and improvements.

The forecasts can be divided into two main categories: *pessimistic and optimistic*. Pessimistic forecasts are those which generally predict a lower power generation, or a higher power load, than real values. Optimistic forecasts are just the opposite. Figure 5.2 depicts a sample of each type of forecast.

Most of the time, the forecast might not show any clear trend but, precisely in these cases, the effects of the disturbances are less critical for the optimization. They are still important, but some sample times with overestimations can, to some extent, compensate for other understimated forecasts. Optimistic forecasts have the advantage of generating

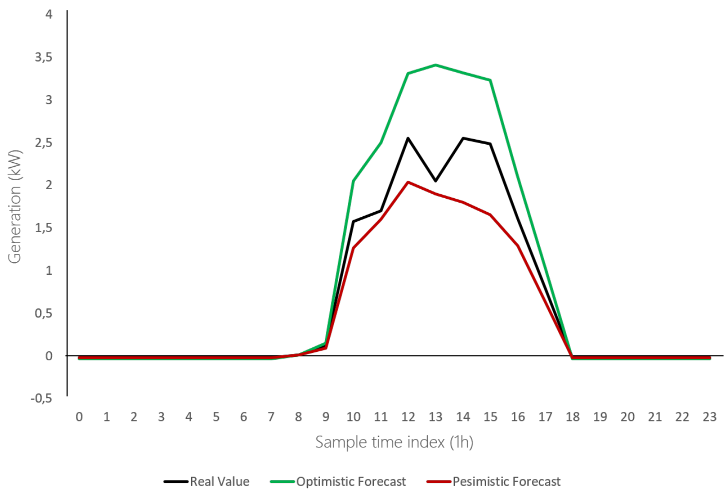

Figure 5.2 Pessimistic generation forecasting (red) vs Optimistic generation forecasting (green) vs Real generation values.

more profitable DA bids, but a worse performance in the operation and, consequently, more potential penalties. Pessimistic ones have the disadvantage of generating less profitable DA bids, but also present a worse operation performance. In this case, ENs are supposed to generate less energy, so the grid is prepared to handle this volume of expected energy. Consequently, the batteries can be filled up, causing penalties due to the deviations.

5.2.1 Disturbance Predictors

The CC disturbance predictor is built with the models of each EN and sample time, pre-calculated and *cached in-memory* to be executed faster. The 24 results of each node are combined with those obtained from the ED disturbance predictor.

The ED disturbance predictor receives the last 24 values of the disturbances of a node, as well as some pre-processed features related to the day of the execution and the weather. The data to train the NN has been downloaded from the London Datastore Repository [146], and processed to add some weather criteria to build the disturbances. This dataset contains data collected from 20 substations and 10 domestic premises over 480 days with a sample time of 10 minutes.

Figure 5.3 shows a sample of a disturbance forecast run with both methods.

5.2.2 Case Study: DML Performance Assessment

The best possible scenario to use the DML is with the mitigation of deviations of pessimistic forecasts. The optimization will be more profitable than in the optimistic forecasts since the real values, in generation or load, will be lower than expected, so the variable defined to optimize the revenues can be maximized with a higher value. In addition, penalties will be lower due to the fact that the fixed forecasts are more accurate than the other ones with errors.

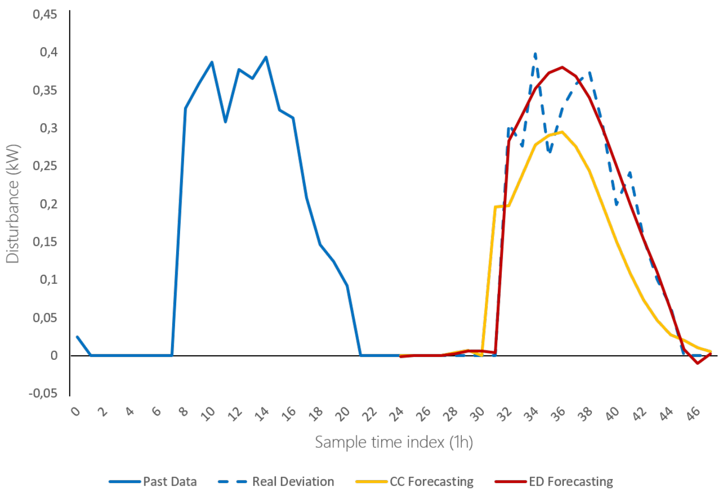

Figure 5.3 Sample of disturbance forecasting with CC and ED.

The main objective of the DML is to reduce the penalties without a dramatic impact in the revenue. The market settlement may be slightly lower at the time of optimization, so the optimization might seem to be more profitable without the activation of the DML. However, the problem arises when the grid is being controlled at operation time, since the penalties also turn to be much higher.

The penalty reduction algorithm implemented to control the grid considers that the penalties for not meeting the commitment at the time of injection are much higher than those applied during the consumption sample times. The system is capable of fixing future deviations in injection sample times by modifying its aggregate consumption profile. It is achieved by performing *consume-to-inject* actions up to 3 hours after the last operation time, which is the time interval of the receding horizon. This asymmetrical control technique improves the accuracy of the profile in injection times compared to consumption ones [17].

In table 5.2, the assessment of several 15-day simulations with full-day operations in the VPP is presented, having the DML deactivated (deterministic model) or with partial or total layer activation. Real and optimized profiles are compared by their Mean Squared Error (MSE). All the studied scenarios have been run with the same forecasting error, storage and load conditions. The control algorithm has the same configuration and implementation. The only difference between the optimizations is the activation of the DML, or the execution of the optimization with the DML deactivated.

The columns with $\overline{\Delta}$ values represent the average of the relative value of MSE with respect to the deterministic approach for every day, according to the following equation:

$$\overline{\Delta} = \sum_{d=1}^{15} \left(\frac{\text{Stochastic}(d)}{\text{Deterministic}(d)} - 1 \right) * 100 \tag{5.7}$$

Table 5.2 Different executions with the complete/partial activation, or deactivation, of the DML.

DML	MSE	MSE_{inj}	MSE_{con}	$\overline{\Delta_{mse}}$	$\overline{\Delta_{inj}}$	$\overline{\Delta_{con}}$
Deactivated (deterministic)	955.82	391.39	564.43	-	-	-
Fully activated (stochastic)	933.25	381.73	551.52	-11.85%	-11.10%	-7.93%
Only CC activated (stochastic)	938.14	384.34	553.80	-9.67%	-8.92%	-7.42%
Only NN activated (stochastic)	955.82	391.39	564.43	-11.92%	-7.61%	-8.42%

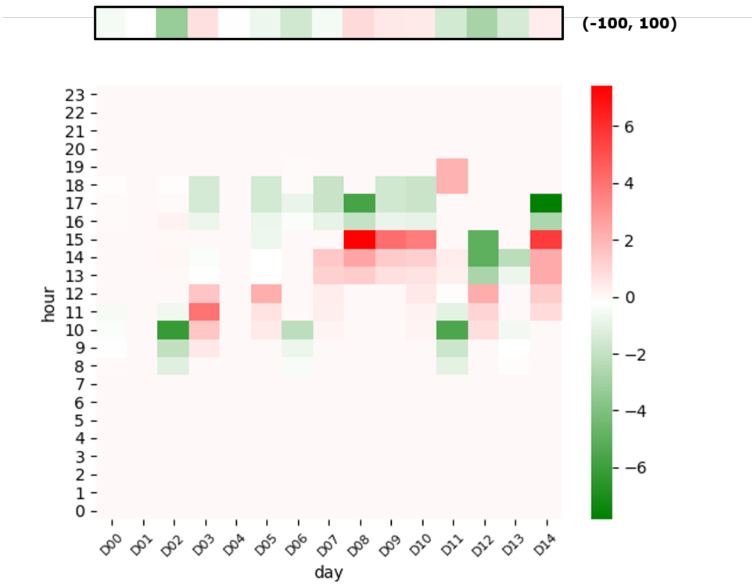

Figure 5.4 Heatmap with the cardinal differences between the MSE with deterministic and stochastic versions of the problem. The top horizontal bar shows the average improvement for the whole day.

where *opt* corresponds to the three different analysed stochastic optimizations: *CC*, *NN*, or combined.

In figure 5.4, a heatmap showing the differences between the deterministic execution and the stochastic one is shown. It can be observed how the central hours are more sensitive to uncertainties since solar panels focus their activity in the time interval from 12 pm to 16 pm approximately, so PV forecast generation may be less accurate. In addition, pessimistic PV forecasts cause that the batteries tend to get filled more than they should, so it is common for them to overflow and, consequently, to result in penalties during these central hours.

In this figure, it can also be seen in the top row that 10 days out of 15 presented less deviations and worked better with the stochastic optimization. The days whose deviations

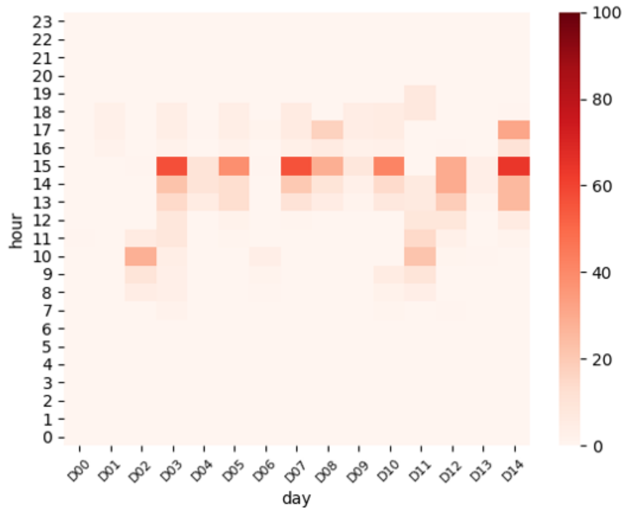

Figure 5.5 Heatmap with the deviations from the contract in the deterministic approach.

were reduced presented a total improvement of 35.45 kWh, with 24.68% of improvement on average for each day. On the contrary, the days which increased their deviations performed 12.88 kWh worse with 3.96% of increase on average for each day.

The simulations executed show that the VPP is less operable when the battery charges are near their limits. According to figure 5.5, most of the deviations happened around the central hours since the storage virtualization is not capable enough absorbing the impact of the uncertainties due to the fact that the storage cannot work as a buffer. Thus, minimal deviations in the DML predictions may impact on the optimization at the control stage if the forecasting errors are persistent during peak hours. However, it can also be observed that the stochastic optimization improves the overall performance of the optimization for the majority of the cases.

5.2.3 Disturbance Mitigation Layer Robustness

The accuracy of forecast systems improves when several sources contribute to the prediction. In fact, the higher the number of sources is, the better the worst case works. In practice, individual methods may have a significantly worse performance than any multi-source method in the worst case, and a slightly similar performance in the best one [147].

The disturbance predictor in the DML defined in this paper has two different sources, but the addition of other sources does not present any difficulty. The combination of different forecasts will provide the aggregation DML with independence, which implies a more robust system by limiting the impact of the disturbance predictors in the optimization problem.

It can be seen in section 5.2.2 how the single activation of the ED component of the DML would provide better results than also activating the CC one, for the given case study.

However, this makes the optimization more dependent on ED errors, resulting in a less robust system for the majority of the executions.

5.3 Conclusions

One of the most important problems regarding the use of renewables is the presence of uncertainties. The lack of accuracy in the forecast services can lead to instabilities in the system or to sanctions for not fulfilling the commitment signed at the time of bidding, before starting the operation stage. In many scenarios, the forecast sources are external, which cannot receive feedback from the EMS to improve their accuracy. Therefore, the operation of VPPs must be improved by modelling the potential disturbances and optimizing the bids to compensate them. A stochastic DML implementation on a MPC problem to mitigate the deviations is proposed. The resulting SMPC model improves the overall revenue of the grid by reducing the penalties at operation time. This implies that, although the optimization earnings could be lower than the ones when not applying the mitigation layer, the results show that the reduction of penalties will compensate these lower revenues.

The results show that the implementation of the DML reduces the average error between the optimized profile and the operated one 11.85% with respect to the deterministic approach in the case study presented. In fact, the average error on injection (the one which implies the highest penalties) was also reduced in 11.1%, which generates large savings. It can also be obtained from the results that partial DML activation can be profitable as well, since the CC component improves the results in 9.67%, whereas the NN component improves them in 11.92%.

These findings open new lines of research such as the implementation of a more intelligent CC component, or the development of even more accurate NNs for building more intelligent disturbance predictors. The approach of combining both components in the DML as well as the analysis of adding several more components to build a more robust stochastic agent are interesting subjects of study.

6 The Pilot. Analysis in a real environment

Experiment is the expected failure to deliberately learn something

SCOTT BERKUN

This chapter describes the findings and conclusions drawn from Netfficient, an H2020 project (grant agreement No 646463). The key points of Netfficient's mission were:

- Improve the state of the art in storage solutions.
- Strengthen the management of distribution grids.
- Develop a central EMP.

Netfficient was a 4-year project with 2-year piloting period. Very valuable data were generated during these two years which allowed interesting conclusions to be drawn not only about DERs implementations, but also about the possibility of individual small-scale agents to participate in energy markets.

6.1 Pilot Description

The services tested at Netfficient, among those presented in this dissertation, were the DA and PR. The VPP deployed consisted of an aggregation of 40 ENs with the system specifications defined in 3.1.

Different KPIs have been analyzed during the operation of the grid in the following sections. The frequency of the DA algorithm execution is once a day, the day before the operation. The sampling time of the PR algorithm was of 10 minutes, so PR algorithm is executed 6 times per hour. It is run just after all the information is gathered from the devices and the data from the short-term forecast services are updated.

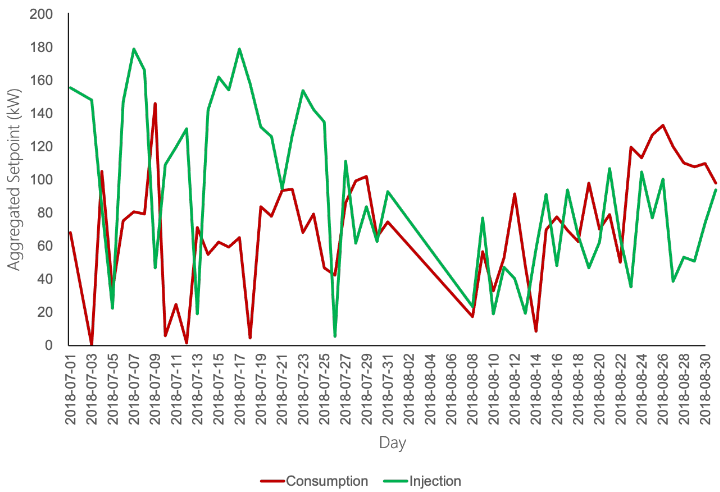

Figure 6.1 Aggregated Power Injection profile (green) vs Aggregated Power Consumption profile per day (red).

The system has been running for 24 months. The time interval used for the analysis in this chapter is a 2-month interval of the last and mature stage of the deployment. In this time interval, the EMP worked successfully in 56 days, considering a success that 25% of the hours did not present any failure for any node. In fact, there were 40 days with more than 80% of the hours without any failure in any EN.

In that context, the days belonging to that time interval operated simultanously with 10.6 ENs per hour on average. Several approaches have been studied to assess the results, considering three main different aspects: *generic operational information, real performance testing and robustness assessment*.

6.2 Generic Operation Information

Figure 6.1 depicts the aggregate profiles of injection power and power consumption per day. One of the first questions to solve could be related to the fact that the first days have significantly higher aggregated injection power setpoints compared to the consumption ones. However, after a few days both profiles reach a balance. There are two main reasons for this:

- July 2018 was better for power generation than August 2018, so there is more excess energy and the grid injects more power into the grid.
- Borkum is a holiday place. As a result, the load profiles of the houses are significantly lower than expected, which also provoque the storage of excess energy until the batteries are full.

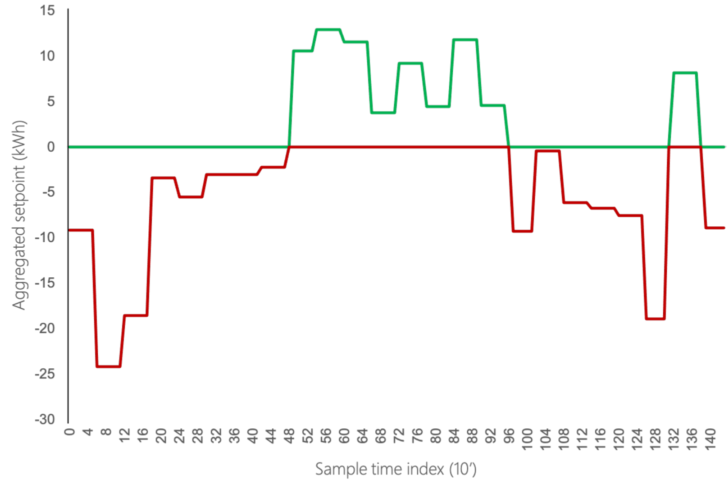

Figure 6.2 Real DA optimization for a single day (August 25^{th}, 2018).

Figure 6.3 Forecast of energy price per hour to participate in DA.

Nevertheless, the main important concept extracted from figure 6.1 is *self-consumption*. The injection actions are only scheduled when the individual ENs do not present difficulties in being able to operate by themselves through self-consumption.

The aggregated profile for August 25^{th} 2018 is described in figure 6.2 as a representative example of an individual day. As previously defined in this dissertation, negative values imply that the aggregated grid consumes power from the network, and the positive ones define sampling times of power injection.

Considering that the batteries start the day of operation at the 50% of their capacity, it

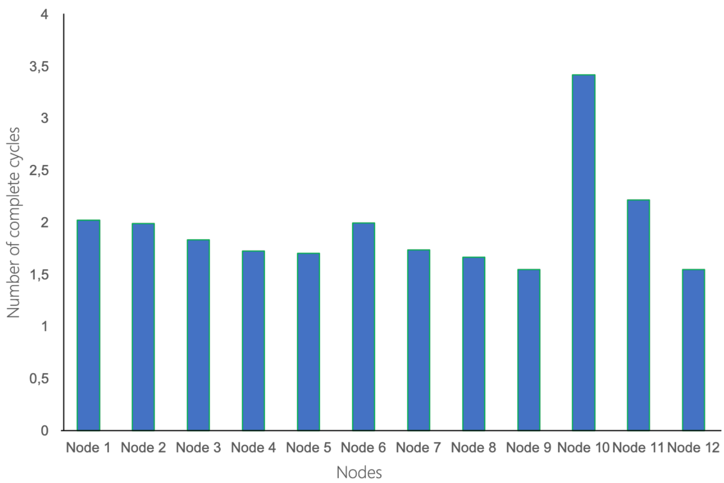

Figure 6.4 Number of complete battery cycles for each participant node.

can be observed how the main intention of the grid is to consume energy during the first hours to store it, since prices are cheaper and the batteries are not full. During these hours, the only bottlenecks are physical constraints, such as the maximum power load limit of the batteries, which have been modelled in the system.

Figure 6.3 shows the forecast profile of the prices of energy consumption and injection. In this case study, prices have been set with the same quantity for purchasing and selling electricity. Relaxing the problem facilitates the assessment of other core features of the algorithms and the platform.

It can be observed how, as the trend of the price is increasing and the price is becoming more expensive, the grid reduces the aggregate consumption. During the central hours of the day, when the energy generation is much higher than consumption, the grid is always trying to inject prioritizing self-consumption, but getting the benefits of higher prices and anticipating the low price of electricity during the last hours of the day. During these last hours, it can be observed that the ENs performs an *inject-to-consume* action to obtain some profit and to set the batteries at 50% at the beggining of the following day. Setting the *SOC* of the batteries to 50% at the beginning of every day is a parameter with a huge impact in an overall multiservice integration, but it is not a strong constraint.

Another important aspect to consider is related to the number of the cycles performed to the battery. The use of batteries as buffers will force them to be charged and discharged more often than usually, resulting in more battery cycles. These operations have been demonstrated to have a negative impact on battery lifecycles and their capacity. Figure 6.4 shows how many cycles the system made for optimal market participation.

Adding battery cycle minimization to the optimization algorithm could be an interesting line of future research, by including battery degradation in the optimization function.

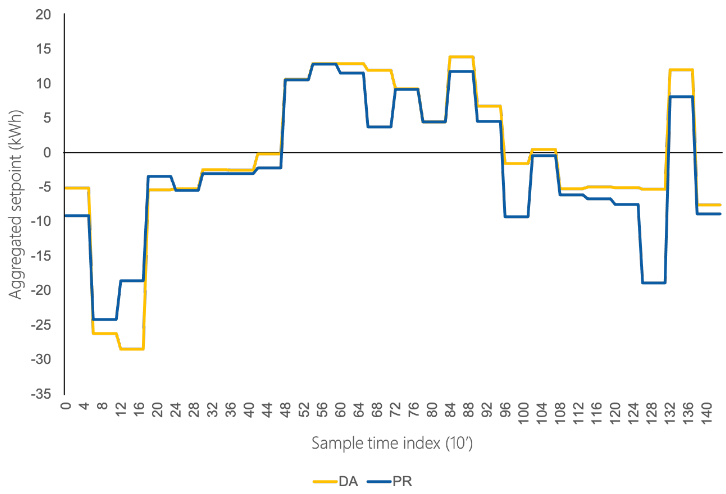

Figure 6.5 DA optimization vs real execution.

6.3 Performance Testing

This section discusses the performance of the system on August 25th 2018. Figure 6.5 shows the complete execution for this day. The deviations which can be observed are due to different reasons.

Firstly, there were 16 communication errors (in total). This issue is not relevant in this scenario because of the robustness of the platform and the stability of the system. The platform is prepared to handle massive ENs failures and this amount of errors is not sufficient to generate any deviation in the aggregated profile.

However, there is an intrinsic issue related to the deterministic optimization problems: the differences between the forecast profiles, for generation and load values, and the actual profiles during the operation stage. The stochastic model had not been developed at the time of the pilot execution and, therefore, this improvement was not tested. This development would have considerably improved the performance, as it can be seen in chapter 5.

Related to the lack of accuracy in the generation forecast, it is important to remark that this day was extremely poor in generation [149]. It was rainy and cloudy the entire day as it can be seen in table 6.1 during the hour when the photovoltaic panels were supposed to generate far more energy.

The lack of accuracy of forecast services has a huge impact on the overall platform execution, but the robustness of the system based on battery buffering helps the system to reach the commitment, by mitigating the deviations and penalties.

PA for this day, which was defined in 3.4, was 1.01. This means that the system worked very well, even considering that there were many communication errors and high forecast deviations. Figure 6.6 shows the evolution of the system through the 2-month interval time.

Table 6.1 Weather status during main hours for photovoltaic generation for August 25th, 2018. Source [148].

Time	Temperature	Humidity	Condition
03:00 PM	16.33 C	59%	Cloudy
04:00 PM	15.7 C	67%	Cloudy
05:00 PM	14.3 C	63%	Cloudy
06:00 PM	14.97 C	59%	Cloudy
07:00 PM	13.32 C	72%	Rain
08:00 PM	12.65 C	62%	Cloudy
09:00 PM	12.3 C	62%	Cloudy
10:00 PM	11.99 C	58%	Cloudy
11:00 PM	11.32 C	62%	Cloudy

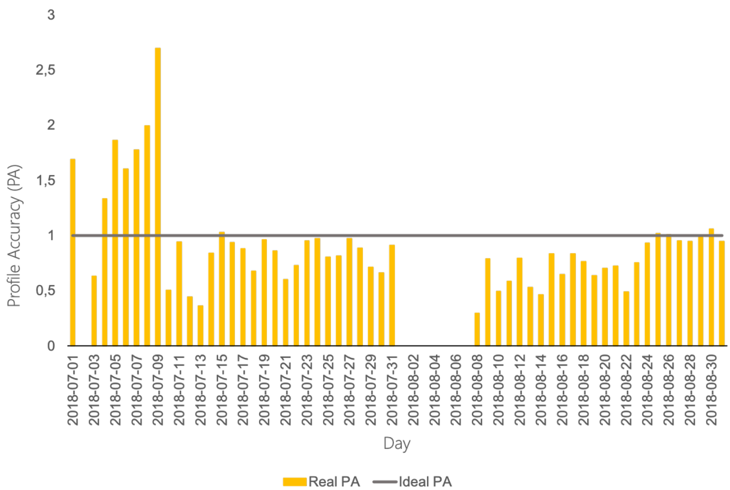

Figure 6.6 PA factor for every day during the 2-month sample time.

To fully understand the figure 6.6 it is important to highlight that due to some problems, as well as the tunning of different parameters in the forecast algorithms, the forecasts were pessimistic about generation during the first days of July. This implied that the real injection was much higher than the forecasted profile defined in DA. Due to this, the grid stored more energy than needed and the batteries were filled up. This may not be a real problem, as the inverters can be configured not to inject when the batteries are full and there is still generation in the photovoltaic panel. In this case study, the decision was to inject all the excess energy, even if it meant not meeting the contract, due to the testing purposes of these scenarios, as well as to stress the sytem.

Figure 6.7 Injection sample times prioritized over consumption sample times.

Nevertheless, the platform worked very well even in such a hostile situation. August 2018 was a bad month for generation, which implied lack of accuracy in generation. In addition, it should be considered that the selected IP was Risky to get the best possible profit from the operation. It can be observed how, even with this aggressive IP, the last week of the 2-month time interval was much better than the previous ones, since the intelligent services and the infrastructure were improved with new developments.

Another important key question that can be extracted from the pilot is that the strategy defined in the subsection 4.2.3, about the priority of meeting when injecting power, actually worked and reduced penalties. In figure 6.7 it can be observed how the execution of August 25^{th} carried out two clear *consume-to-inject* actions, represented with dashed areas in the figure. The red dashed areas represent the sample times when the grid consumed more than the commitment to meet, as much as possible, the contract in sample times for power injection.

It can also be observed how the injection target of the first green dashed area was achieved during the first following two hours. The main reasons for failure after those two hours are both the errors in the forecast of user consumption and deviations in the short-term forecast algorithm for generation. In the second *consume-to-inject* action, the bottlenecks are physical constraints. It is physically impossible to charge the batteries faster. Finally, at 20:00 PM the generation forecast was not accurate enough, so the system tried to meet the commitment without success. Nevertheless, a penalty minimization was achieved.

6.4 Robustness Assessment

During this pilot, the system was stressed to assess how it would work in real environments where there were poor connections and many network errors. Several hardware failures

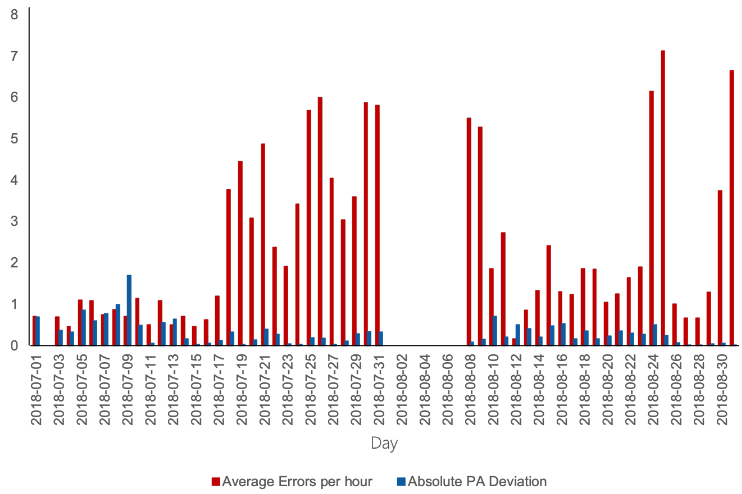

Figure 6.8 Average errors per hour / PA absolute deviation..

were also solved. The criteria for including them in the development of the final product were based on different priorities according to the severity of the issue, and its frequency of ocurrence.

It can be observed how the number of connection errors is independent of the absolute deviation of PA. In fact, the absolute deviation of PA decreases with time. In addition, not all errors were due to real problems in the grid because some of them were explicitly forced to test the system under limiting and stressful conditions. It can be observed that the system works better in the last days, even with a higher average of errors per hour.

Most of these errors are temporary, such as some delays or network problems. The main feature of the developments in this context was the ability of the inverter to store the 18 following setpoints from the last execution. This enabled the system to work temporarily offline (see subsection 3.1.3).

7 Framework as a platform

Why is more important than how.

SECOND LAW OF SOFTWARE ARCHITECTURE

Software Engineering can be defined as *the systematic approach to the development, operation, maintenance and retirement of software* in accordance with IEEE[150]. Any valuable software development must meet different standards without losing the focus on the end user [151, 152, 153]. This chapter details design decisions, the software architecture, tools and models that have been built to serve the algorithms as a service.

The platform has been implemented in python with Django Framework and the python scientific stack (Numpy, Scipy, Pandas, Scikit among others), and it is served through a secure REpresentational State Transfer (REST) API. It is prepared to run asynchronously all the algorithms, making the platform more robust and resilient against network delays or computational issues. The software which has been chosen to solve the algorithms is CPLEX, using its Python API available for the three main operating systems.

The main reason why CPLEX was chosen is its natural integration with MATLAB (used to prototype the algorithms) so that both implementations can provide the same approximations when solving the equations. Developing in MATLAB is faster than developing in Python when working with mathematical problems, and this way of proceeding makes the development experience better and more reliable.

The other powerful reason was the fact that CPLEX works very well with sparse matrices. This type of matrices only stores indices and values of non-zero cells. Due to the shape of the matrices in these optimization problems, there is a huge difference in both space and processing time between this type and the classical one (dense matrices) since any cell that does not belong to the constraint specification will be empty. As an example, the coefficient matrix size considering a problem with only three nodes for the first versions of Aggregated Day-Ahead (AGG-DA) is larger than 4GB. This slows down the process of working in workstations with less than 8GB of RAM and it is absolutely non-scalable. However, the sparse version was a bit larger than 100MB. A good implementation based on a good design and supported by powerful tools are the key elements to make the implementation of powerful services possible.

The platform is not agnostic regarding this decision, so changing the solver may involve some code refactor. Nevertheless, the architectural pattern organizes these potential changes in the last layer, reducing the impact when changing the solver.

7.1 Design Patterns and Software Architecture

It is essential to treat the development process like any classical engineering discipline to build robust and solid platforms, which implies repeatability, rigor and effective analysis [154]. Software Engineering is not only coding, but it also involves working with high levels of abstraction, designing solutions considering end users and business engagement as well as dealing with the latest concepts of continuous delivery and continuous integration. Delivering quality software is impossible without defining the software architecture, technology stack integrations, or even the test plan to find future failures.

In software design literature there are many universally accepted design patterns. A design pattern can be vaguely defined as *a bundle of design decisions* [155]. More precisely, they are often a set of standard solutions for various well-known scenarios. There are different fields of application for design patterns such as object-oriented programming [156], agile methodology [157], or even for complete architectures (Big Ball of Mud, Unitary Architecture or Client-Server Architecture) [154, Part II]. The irruption of Internet of Things (IoT) has exploited the deployment and aceptation of decentralized architectures, where each device may have enough power to perform Extract, Load and Transform actions, relaxing the computational requirements of the central server in distributed environments.

One of the main classifications regarding architecture is related to deployment: *monolithic* (systems that have been designed to be run in a single deployment unit, most of the times for unique users) and *distributed* (many units and users connected simultaneously by remote protocols). The second approach faces new challenges that were not present in monolitic designs, such as network reliability, network administration permission issues, the need of more secure firewalls, protocols and authentication systems or even new business models to build profitable solutions.

The concept of cloud computing involves distributed architectures for scalable platforms. The most widespread one is the Client-Server architecture, also called Two Tier. The simplest scenario is composed of a server node and different nodes working as clients, such as browsers, mobile apps or IoT devices. The possibilities in this architecture are not limited, since the participant nodes can act as server and client simultaneously, and dynamically change their role depending on the use case. Nevertheless, complex environments do not need complex architectures most of the times, and the best option is usually to keep it simple and straightforward (KISS principle).

Figure 7.1 shows several of the main actors in cloud environments. There are many more, but these concepts have been selected due to their importance and the relevancy in relation to the developed platform. The figure shows how the requests find the entrypoint through the Load Balancer. This node, which can also be multiple or belong to a hierarchy [158] automatically distributes the incoming traffic across different instances depending

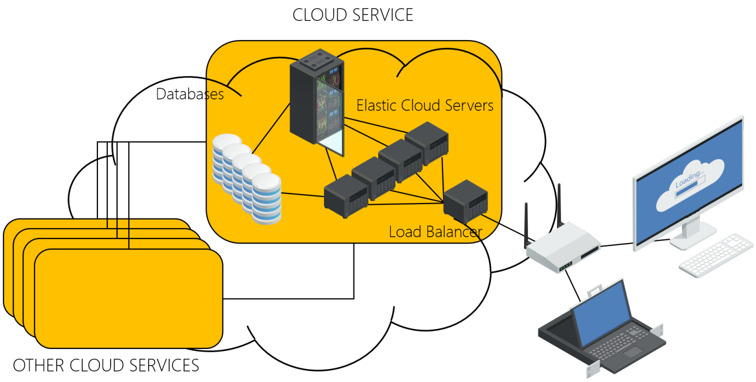

Figure 7.1 Example of a Cloud Computing Software as a Service (SaaS) with elastic servers with different servers for business logic, databases and the concept of load balancer.

on a defined balancing criteria. These instances are created to parallelize server requests and to send the response faster. Despite their server nature in this sample architecture, the balancers can also act as individual clients regarding other servers where other services may require specific licences or stronger security restrictions. They can also be in the need of being considered as critical legacy applications which must be isolated from the new layers. The flexibility of the cloud allows communication between platforms from different decades and requirements for systems that have compatible internet protocols.

In this example, the four central instances improve the system scalability for a large number of requests per second. Elastic cloud computing enhances resource parallelization and dynamic infrastructure scaling, improving investment and maintenance costs for relatively large platforms [159]. There are two main possibilities for scaling an infrastructure: *vertical scaling* (by adding more power to the infrastructure, such as RAM or CPU, to an existing machine) or *horizontal scaling* (by adding more machines into the pool of resources). The scalability could be done manually if the traffic peak pattern were correctly identified and the volume of traffic were not very large. However, most of the times an algorithm will be needed to handle the scale changes optimally. The latest approaches in the literature are the use of smart agents developed with reinforcement learning [160].

7.2 Platform Definition

Amongst the different architectures present in the literature [154, Part II], it has been chosen a mixed Service-Based Architecture, which is distributed, combined with a strong sense of layer isolation in the implementation of each service. It could be considered that each service has been designed by using the Layered Architecture, which is monolithic. The reason why this hybrid architecture has been chosen rather than others is to combine the simplicity of layered implementation with the flexibility of the service-base. The former improves scalability if necessary, and the smart agent can be deployed in different instances (depending on the service, as it is shown in the figure 7.2). The latter reduces possible deployment issues and maintenance costs, since bugs and enhancements will be easier to close.

The following subsections explain the contributions of every architecture to integrate the hybrid version.

7.2.1 Layered Architecture Component

Figure 7.2 shows in its first column a theoretical approach of layered architecture, differentiating the presentation and database layers from the application business logic. Persistence layers are often abstractions to automate database query building.

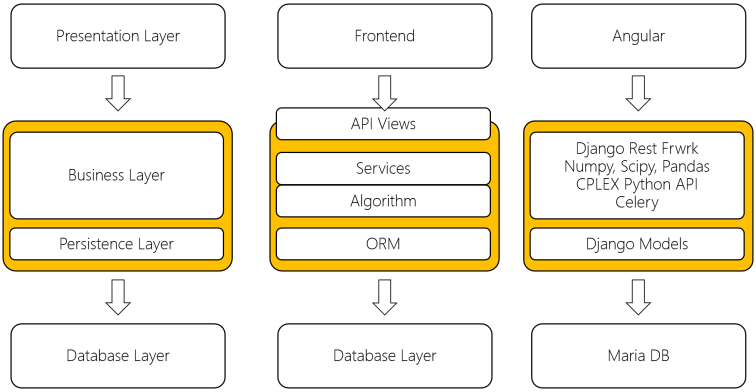

Figure 7.2 Application of Layered Architecture to framework development.

In the second column, it can be observed the equivalence between theory and actual implementation whereas the use of the different technologies in the different layers is shown in the third column.

The services are accessible through a secure API REST and they can be consumed from front-end applications, such as native mobile apps, progressive web applications, other servers or IoT devices able to make REST requests. The API is built using Django and Django Rest Framework (DRF). Django is a high-level Python web framework for building platforms with a clean and pragmatic code design. The main feature of Django is its Object-Relational Mapping (ORM), placed in the persistence layer. The ORM is the interface between the database and Python objects and vice versa. DRF is a library built on Django which exposes the endpoints and the services through the API with its APIViews by using JavaScript Object Notation (JSON). The JSONs are deserialized using the DRF serializers and built into Python objects. Figure 7.3 shows in detail the entire flow of an algorithm call from a client. Asynchronous execution is explained in the section 7.4. This separation is necessary to avoid the dangerous concept of *coupling*, defined as the degree of interdependence between software modules.

The flow of a sample request is as follows:

1. The system receives the request to the URL exposed through the ApiView.

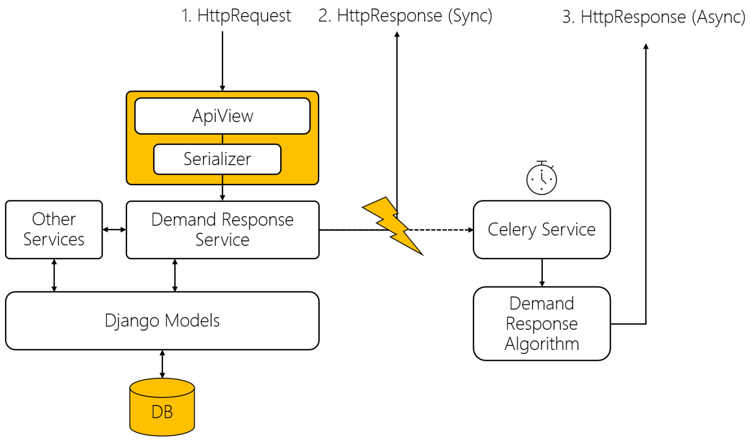

Figure 7.3 Algorithm execution flow over the Layered Architecture.

2. The ApiView creates the serializer and validates it. After validating the data according to the API definition, the serializer creates Python objects from the received JSON.
3. The ApiView goes one level deeper and calls the main service once the data is transformed.
4. The main services can call other auxiliary services at the same level or work with the models and the persistence layer. The system send the data to a queue to solve the algorithm asynchronously once the mathematical problem is fully built to be solved.
5. The algorithm layer solves the instance of the problem during its turn in the queue, and stores the solution in the database.

7.2.2 Service-Based Architecture Component

Service-based architectures are generally distributed architectures where the main important concept for designing, implementing and performing the functionality of the platform is the service itself. Components tend to be more isolated, leading to more decoupled, testable and easier-to-maintain software.

Figure 7.4 shows a sample service-based architecture composed of different nodes with independently deployed services, but working with the same information source. Achieving this ideal scenario is not trivial since there are usually strong dependencies between the services. In these cases, design patterns help to decrease the decoupling, but sometimes there would be inevitable relations. There is no universal solution in the dilema of duplicating the code to improve the isolation or maintaining the dependency; thus, a contextualization becomes necessary for analysts to be able to choose the best option.

The framework has been designed to have isolated but synchronized services. It has also been explained that even several executions of the same algorithm are also completely independent from each others.

According to [154, Chapter 13], in most cases there is not more than one instance per service unless some scalability or fault tolerance issues are detected. Another important aspect mentioned in this reference is the small number of services that usually share a context: between 4 and 12, with an average of around 7.

There are currently 4 different services that can be deployed in different nodes:

- *Management Service*: Unit to maintain settings and grid information. This service is used to perform creating, reading, updating and deleting operations on the grids, energy nodes, storages and users stored in the platform. These operations are commonly known as *CRUD* operations.
- *Day Ahead Service*: This service unit contains the four implemented versions of DA algorithms. Simulation, submission and parameter tweaking for this service. It also manages the DIP at optimization time.
- *Penalty Reduction Service*: Contains the functionalities related to PR algorithm and the activation / deactivation of the extra-optimizations.
- *Demand Response Service*: This service performs the optimizations related to the participation in the DRP.

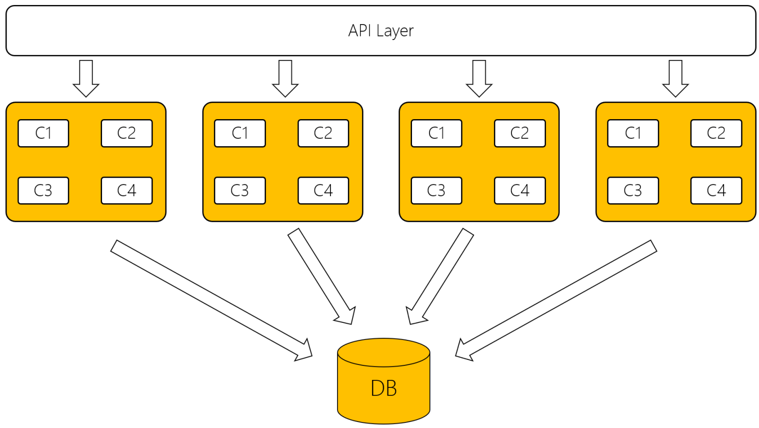

Figure 7.4 Application of Service-Based Architecture to framework development.

7.3 Software Model Design

The proposed model is a conceptual design to show the big picture. This design was thought to get the benefits of relational databases and non relational databases, depending on the nature of the stored data.

Relational databases are digital databases which are organized by tables which can present relations to other tables and constraints regarding either data or relations. They are very well structured. In addition, the information must meet the definition in terms of number of fields, types and validations. The data is managed by using Structure Query Language (SQL) queries, but the syntax can be slightly different depending on the database distribution (for example: Oracle DB, MySQL DB or Microsoft SQL). They can be used to manage transaction-oriented applications and they support ACID transactions (Atomicity, Consistency, Isolation, Durability).

Non-relational databases, also called NoSQL, emerged in early 2000s, and they are usually grouped into four categories: key-value stores, graph stores, column stores and document stores. Some of the most popular ones are MongoDB, DocumentDB Cassandra or Redis. They work with semi-structured data (XML, JSON) and they are prepared to handle large amount of data. Their use has enormously increased since the irruption of data analysis and artificial intelligence in the industry.

NoSQL databases are mainly used to store information with many records that are supposed to be stored only once and read multiple times. The information can be updated or deleted but it is not supposed to change in the future. On the other hand, relational databases are designed for storing smaller databases with more volatile information. However, a table can handle several million rows, depending on the distribution.

Figure 7.5 describes the conceptual proposal of the platform model. All the entities are presented in a relational representation. The implementation may differ from design due to technological limitations, but the key point in this struture is the use of a hybrid database system to store and manage the information.

The items stored in the relational database have an orange background color. They are mainly configuration items for the grid, energy nodes etc. Django ORM is transparent when choosing the SQL database. The one selected for the platform was Maria DB, an open source relational database very similar to MySQL, but with the enhancements from community contributions.

The elements located in NoSQL databases have a grey background color. They are mainly measurements and algorithms executions. MongoDB is the selected NoSQL database engine, a document-based database integrable with Django that fits the needs of this architecture.

The use of NoSql database is necessary due to the amount of data that will be stored. In the data age, storing information is very important for smart agents and big data analysis since it adds some extra value to the platform. For example, a full day performance for 40 nodes (considering only the 144 steps of the PR algorithm) will create 103,680 records for short time forecast generation, and the same amount for load forecast. This would make a SQL database inoperable in a few months, or even less, if larger grids, or different simultaneous grids, were operated.

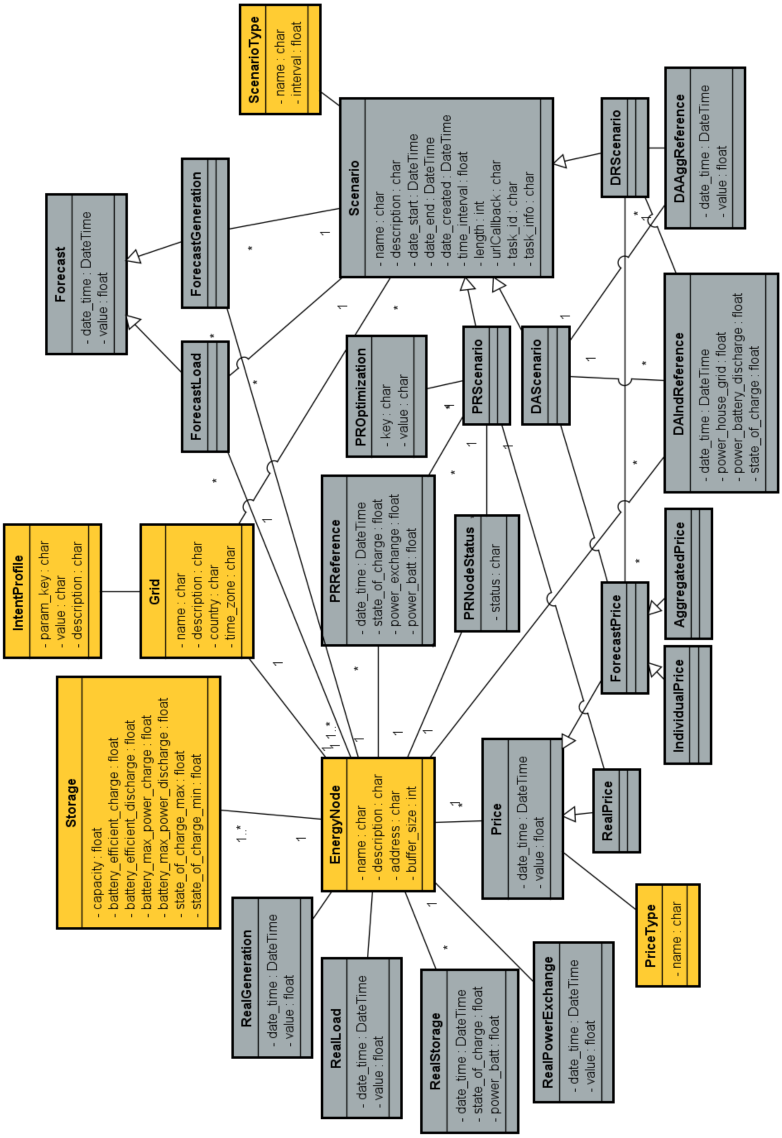

Figure 7.5 Application proposed model detailing SQL entities (orange) and NoSQL entities (gray).

7.4 Asynchronous Execution

Depending on the complexity and magnitude of the optimization, solvers can find some difficulties in sending a robust response in the appropriate time. According to [161], user's perception and expectations are more important than considering absolute times. In [162], Jakob Nielsen published the following rules regarding response times, which have remained about the same for thirty years. His work in this publication is a classical reference in the field of usability, but the conclusions have been considered to be state-of-the-art until now.

- *0.1 seconds*: The user's perception is of instantaneous reaction.
- *1.0 seconds*: The user's flow of thought is uninterrupted, even though the user may notice the delay. No actual feedback is needed to keep the user's attention.
- *10 seconds*: If the response lasts more than 10 seconds, the most possible issue will be the loss of their attention. It is necessary to develop some feedback techniques to successfully retain the user's attention.

Nevertheless, numerical problem solving depends not only on the complexity or magnitude, but also on the instance of the problem. Solving some instances of the PR algorithm have taken more than 12 times more than other with the same number of variables and constraints. This behaviour can sometimes be observed when the PR algorithm tries to minimize the penalties of the aggregated power for a sample time with a target value of 0, due to the fact that the numerical aproximation method needs many more iterations to find the optimal solution.

Since these corner cases cannot be predicted, the resolution process is solved asynchronously using Celery. According to their official documentation [163], *Celery is an asynchronous task queue/job queue based on distributed message passing*.

Figure 7.3 depicts the call flow and Celery execution. The response is made as soon as the input data is captured, transformed and persisted in the database so that the service consumer could receive feedback and see if the response was successful or any error ocurred. The platform offers an API endpoint to check the status of the task, and to verify if it is waiting, being processed, finished or cancelled. The results can be retrieved using this pulling system, by sending GET requests repeatedly until it is finished. However, to reduce traffic, the server will publish the results to a callback address, implementing a more efficient push communication.

7.5 Remote Solvers

The use of sparse matrices described at the beginning of this chapter makes possible the secure remote execution of solvers. The process of solving the problem could be a bottleneck for large problems over simultaneous massive grid management on real-time platforms. Owing to this, more solver units may be required to parallelize algorithm executions.

This can be accomplished by sending a compressed, encrypted and serialized versions of the matrices by using https protocol from the unit where the platform is deployed to the unit hosting the solver installation. A plugin has been developed to decrypt and extract the matrices on destination side, and to build the inputs for the solver. The information is sent via https, which implies end to end encryption. After that, the solution is sent back by using the same procedure of compression-decompression.

The main advantage is that the core information is not sent to any external unit. Even if the requests were intercepted by malicious software and the matrices compromised, it would be impossible to do reverse engineering to get the model since the constraints are shuffled in each execution and the only source of knowledge will not be deployed outside the secure limits of central servers. In other words, the matrices by themselves are not more relevant than the result.

8 Conclusions

A theory that explains everything, explains nothing

KARL POPPER

8.1 Closing Remarks

The simultaneous participation in multiple energy markets presents several problems that must be solved by intelligent agents due to the complexity of the context situation. VPPs are a flexible and powerful solution to meet the hard requirements of energy markets, with the additional incentive of using clean energy. Battery virtualization adds an extra level of flexibility to operate and enhance the participation in more markets without incurring penalties in the others. SOs can define different strategies, which this dissertation has defined as IP. The IPs allow to set the energy allocation for every service depending on some criteria based on potential earnings and potential penalties.

The development of a platform of such complexity which implements DSV and dynamic IPs is possible and profitable. Several scenarios have been presented in which it has been demonstrated that Mixed IPs perform better than Conservative IPs in terms of profit, but they have the huge advantage of being more resilient to deviations than Risky IPs. It is important to consider that the differences between the performance of each strategy would be much higher in scenarios with larger batteries and more nodes than those in the case studies. Thus, IPs will be determinant for the operation of the grid and their possible business models.

8.2 Contributions

The main contributions of this dissertation can be highlighted in the following points:

1. The introduction of a new stochastic MLD for the economic dispatch of VPPs with DERs systems when participating in multiple energy markets. Integration with the

DAM and participation in the DRP simultanously. Both algorithms draw a baseline tracked by a PR algorithm operating in short sample times of approximately 10 minutes.

2. The introduction of the concepts of DIP and DSV and their integration with the strategies to operate in multiple markets. This integration allows riskier, more conservative or even more intelligent dynamic strategies based on the forecasts and the status of the components of the VPP.
3. The development of a CC-MPC in which the stochastic component is integrated through a weighted decision of the implementations of chance constraints and a forecast error predictor implemented with neural networks.
4. The decoupling of the multiple participation in different markets by using storages as central communication agents and by giving the SO full control of the optimization and operation of the VPP.
5. The sucessful deployment of the platform in a real environment to analyze the achievements in real scenarios.
6. The integration of different services by using the piped baseline concept to make the PR algorithm independent of any optimization at the control stage. The PR algorithm is only responsible for achieving its commitment without having any concern related to multiple participations, and only with the context awareness of both the current and the near future situations.

8.3 Future Studies

Considering the research presented in this dissertation, new fields have been opened to be explored:

- To build an intelligent layer for the automation of the definition of IP based on past forecast deviations, penalties or failures related to past EN participations.
- The integration with smart domestic appliances can help end-users with the schedule and the automation of controllable loads, which would result in better optimizations for the participations in DRP. The integration with the PR algorithm would allow the platform to send the apropriate commands to the domestic appliances to reduce future penalties, as well as to perform automatic DR actions. Prosumers must be able to set some comfort parameters to define the schedules and limits of the automation. This allows new formulas to be included in new business models depending on the availability of the consumers' regulable loads.
- Remuneration mechanisms (business model) to set not only attractive billing systems for customers, but also profitable operations for SOs.
- To develop an intelligent layer to automatically select the optimal ENs, as well as their configurations, to participate in the different services depending on their specifications, historical operation information such as errors or availability, and the services that the optimization may involve.

In addition, it might be interesting to explore other approaches, such as platform decentralization and horizontal scalability, splitting the way in which the problem is built and solved. The software architecture is prepared so that it would be easy to add new intelligent layers to improve the SOs' decision making process. The improvement of the human-machine interaction is also a necessity since, although AI is revolutionizing the world we know, the combination of human and artificial intelligences is currently vastly more powerful. The research presented in this dissertation opens many other lines of research, all of them in search of a more intelligent world with the ultimate goal of reaching what is known as *general artificial intelligence*.

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