Universidade de Vigo

EIDO International Doctoral School

José Luis Crespo Vázquez

DOCTORAL DISSERTATION

Optimization of a wind and storage power plant participating in the electricity market: a data-driven stochastic approach

2018

Universidade Vigo

International Doctoral School

José Luis Crespo Vázquez

DOCTORAL DISSERTATION

OPTIMIZATION OF A WIND AND STORAGE POWER PLANT PARTICIPATING IN THE ELECTRICITY MARKET: A DATA-DRIVEN STOCHASTIC APPROACH

Supervised by:

Dr. Camilo José Carrillo González
Dr. Eloy Diaz Dorado

2018

Universidade Vigo

Universidade Vigo

International Doctoral School

Camilo José Carrillo González and Eloy Diaz Dorado,

DECLARE that the present work, entitled "Optimization of a wind and storage power plant participating in the electricity market: a data-driven stochastic approach", submitted by José Luis Crespo Vázquez to obtain the title of Doctor, was carried out under their supervision in the PhD programme "Research in Technologies and Advanced Processes at the Industry".

Vigo, 19 July 2018

The supervisors,

Dr. Camilo J. Carrillo González　　Dr. Eloy Diaz Dorado

Universidade Vigo

PREFACE

This thesis was written under the part-time PhD program in the Department of Electrical Engineering of the University of Vigo (Spain).

Firstly, I would like to thank my supervisors, Prof. Camilo J. Carrillo and Prof. Eloy Díaz Dorado, for giving me the opportunity to complete my doctoral studies under their guidance. I greatly appreciate the freedom provided in the choice of the research topics and their understanding of what a part-time doctoral program means.

I would also like to thank the personal of the experimental wind farm of Sotavento, who kindly provided us with real-world information and data.

Some of the research developed in this work was done at the Department of Mechanical and Industrial Engineering and the Department of Electrical and Computer Engineering at Northeastern University. I want to thank Prof. Md. Noor-E-Alam and Prof. Jose A. Martinez for their helpful insights in the research topics and their support during my stay in Boston.

I would also like to thank my friends for providing me with invaluable moments helping to reset a quite often stuck mind.

Finally, I thank my family for their unconditional support, and especially to my wife and my son, who also invested a huge amount of time in this thesis.

ABSTRACT

In recent years, as a result of a growing concern about the effects of climate change, the decarbonization of the electric power generation sector has been promoted. As a result, generation technologies based on renewable resources, mainly wind and solar, have undergone a strong development that has led them, today, to be considered mature generation technologies in a position to compete with traditional generation sources in the electricity markets. Thus, these technologies have achieved significant quotas of presence in the generation mix of many countries, which together with its inherent variability, poses a serious challenge in terms of guaranteeing the reliability and safety of the electrical system.

This integration of renewable generators in the electrical systems of many countries has evolved from both the technical and the market points of view. Thus, in the technical aspect, specific regulations to increase the requirements of telemetry and remote control and to regulate the behavior of wind and solar generators concerning voltage regulation have been developed by the system operator to guarantee the reliability and safety of the system. Regarding the integration of this type of generators in the electricity market, the most usual trend was to allow them to deliver all the generated energy at a price that would allow them to offset the high original costs. Recently, progress is being made towards an effective participation in the electricity markets and there are currently countries that already allow these generators to participate even in the adjustment markets and ancillary services.

In this environment, the focus of this thesis is on the integration of a renewable generator in the electricity market. Specifically, in the problem faced by an operator of a wind farm when deciding how to participate in it. The main characteristic of this decision-making problem has its origin in the structure of the electricity market in which a large part of the decisions to be made by the operator of a generation plant have to be made in advance with respect to the moment of effective participation in the market. Thus, the decision-making problem should take into account the uncertainty associated with important parameters such as energy prices or the availability of the renewable resource.

At the same time, the field of applied mathematics driven by the extraordinary advances in computing capacity available and easily accessible, puts at the disposal of engineering a wide range of tools that can not be wasted. In particular, this thesis aims to apply two areas of applied mathematics to very specific problems. Thus, on the one hand, the decision-making problem is modeled as an optimization problem under uncertainty. More specifically, a stochastic approach will be applied to deal with the uncertainty associated with certain parameters of the problem such as wind resource availability or energy prices. This stochastic approach will require defining a set of scenarios, with an associated probability of ocurrence, that represent possible realizations of the parameters affected by the uncertainty.

On another hand, a data-driven approach is used to define these scenarios, that is, information will be extracted from the available data. To carry out this task, machine learning tools, both supervised and unsupervised, are proposed.

In this thesis, the Iberian electricity market (Spain and Portugal) will be used as the inspiration for the proposed models. Chapter 2 presents a conceptual description of the said market with the sole objective of contextualizing the problems that will be developed in later chapters. In addition, in chapter 3, the mathematical tools that will be used throughout the thesis are described, both in terms of optimization problems and data analysis tools. The goal is to make this document as self-contained as possible. In Chapters 4, 5, and 6 different cases of a wind farm with storage that participates in different markets, both energy and regulation, are dealt with. Finally, in chapter 7 some relevant conclusions are drawn and future lines of work are established.

RESUMEN

En los últimos años, como consecuencia de una preocupación creciente por los efectos del cambio climático, se ha promovido la descarbonización del sector de la generación de energía eléctrica. Como resultado, las tecnologías de generación basadas en fuentes renovables, principalmente eólica y solar, han experimentado un fuerte desarrollo que las ha llevado, a día de hoy, a ser consideradas tecnologías de generación maduras en disposición de competir con las fuentes de generación tradicionales en los mercados eléctricos. Así, estas tecnologías han conseguido importantes cuotas de presencia en el mix de generación de muchos países, lo que unido a su inherente variabilidad constituye un serio reto en lo que se refiere a garantizar la fiabilidad y seguridad del sistema eléctrico.

Esta integración de generadores renovables en los sistemas eléctricos de muchos países ha ido evolucionando tanto desde el punto de vista técnico como desde el de mercado. Así, en el aspecto técnico, se ha desarrollado, por parte del operador del sistema, reglamentación específica para aumentar las exigencias de telemedida y telecontrol o para regular el comportamiento de generadores eólicos y solares frente a huecos de tensión, con el fin de garantizar la fiabilidad y seguridad del sistema. En cuanto a la integración de este tipo de generadores en el mercado eléctrico, en un principio la tendencia más habitual era permitir que éstos entregasen toda la energía generada a un precio que les permitiese compensar los elevados costes de inversión. Posteriormente, se avanzó hacia una participación más efectiva en los mercados de electricidad y, actualmente, hay países que ya permiten que estos generadores participen, incluso, en los mercados de ajuste y servicios auxiliares.

En este entorno, el foco de esta tesis se pone en la integración de un generador renovable en el mercado eléctrico. En concreto, en el problema que afronta un operador de un parque eólico, a la hora de decidir cómo participar en el mismo. La característica principal de este problema de toma de decisiones tiene su origen en la estructura del mercado eléctrico en el que buena parte de las decisiones a tomar por el operador de una planta de generación tienen que ser tomadas con antelación respecto al momento de participación efectiva en el mercado. Así, el problema de toma de decisiones ha de plantearse teniendo en cuenta la incertidumbre asociada a parámetros importantes del mismo como pueden ser los precios de la energia o la disponibilidad del propio recurso renovable.

Por otro lado, el campo de las matemáticas aplicadas traccionada por los avances extraordinarios en la capacidad de computación disponible y fácilmente accesible, pone a disposición de la ingeniería una amplia oferta de herramientas que no pueden ser desperdiciadas. En particular, en esta tesis se plantea unir dos áreas de la matemática aplicada y aplicarlos a un problema muy concreto. Así, por un lado se plantea el modelo de toma de decisiones como un problema de optimización bajo incertidumbre. Más concretamente, se aplicará un enfoque estocástico para tratar la incertidumbre asociada a ciertos parámetros del problema como disponibilidad de recurso eólico o precios de la energía. Este enfoque estocástico exigirá definir un conjunto de escenarios, con una probabilidad asociada, que representen realizaciones posibles de los parámetros afectados por la incertidumbre.

Para definir estos escenarios se utilizará un enfoque basado en datos, es decir, se extraerá información de los datos disponibles. Para llevar a cabo esta tarea, se plantea la utilización de herramientas de aprendizaje automático tanto supervisado como no supervisado.

En esta tesis, se utilizará el mercado eléctrico ibérico (España y Portugal) como inspirador de los modelos planteados. En el capítulo 2 se presenta una descripción conceptual de dicho mercado con el único objetivo de contextualizar los problemas que se desarrollarán en capítulos posteriores. Por un lado se describen los mercados de energía, gestionados por el polo español del MIBEL y en los que se negocian la mayoría de los intercambios de energia que se producen. Ejemplos de estos mercados de energía son el mercado diario y las diferentes sesiones del mercado intradiario. Por otra parte se describen los mercados de ajuste, gestionados por los operadores del sistema español y portugués, y que tienen por finalidad el garantizar que la operación del sistema se realice de forma segura y eficiente. Por último, se describe en detalle el mercado de balance, el cual tiene una gran importancia en el caso de los generadores basados en energías renovables. En este mercado, los generadores compran y/o venden energía para compensar sus desvíos con respecto a los compromisos adquiridos en los mercados de energía.

En el capítulo 3, se describen las herramientas matemáticas que se utilizarán a lo largo de la tesis con el objetivo de hacer este documento lo más auto-contenido posible. Se presenta, por un lado, el concepto de optimización matemática como marco idóneo en el que plantear problemas de toma de decisiones. A partir del planteamiento general de un problema de optimización se presentan las estructuras del problema más habituales. Así se introducen los conceptos, por ejemplo, de programación lineal, convexa y no lineal. Además, se presentan dos enfoques para tratar problemas de optimización bajo incertidumbre, estocástico y robusto. En este tipo de problemas bajo incertidumbre, los datos de entrada a los mismos no son conocidos con exactitud. En particular, en esta tesis, se plantea un enfoque estocástico para incorporar la incertidumbre asociada a ciertos parámetros de los problemas considerados en la toma de decisiones. Bajo este enfoque, la incertidumbre se modela definiendo una serie de escenarios posibles de realización del paramétro afectado por la incertidumbre y asignándole a cada uno de esos escenarios una probabilidad de ocurrencia. Por otro lado, en este mismo capítulo, se hace una introducción a las técnicas de aprendizaje automático supervisado y no supervisado que se utilizarán en esta tesis. En concreto, estas técnicas se utilizarán para analizar datos históricos disponibles y extraer de ellos tanta información como sea posible para definir los escenarios y su probabilidad asociada que serán utilizados para resolver los problemas planteados. Por un lado, y dentro de las técnicas de aprendizaje no supervisado, se presenta el concepto de clustering. El objetivo del clustering es el de agrupar los puntos que forman parte del conjunto de datos dado en un cierto número de clusters. Se busca así representar un conjunto de datos original con una serie de puntos representativos del mismo. Por otro lado, y dentro de las técnicas de aprendizaje supervisado, se presenta el concepto de redes neuronales y, más en particular, una especialización de las mismas, denominadas redes neuronales recurrentes, para extraer información de conjunto de datos que forman parte de una secuencia.

Los capítulos 4, 5 y 6 plantean diferentes casos de un parque eólico con almacenamiento que participa en diferentes mercados, tanto de energía como de regulación y consituyen el núcleo de esta tesis. En estos tres capítulos, el parque eólico considerado es el parque eólico experimental de Sotavento, ubicado en Galicia, en el noroeste de España, y que amablamente ha proporcionado datos reales relativos a las predicciones de generación y a la generación en tiempo real del mismo. Además, los datos relativos a parámetros del mercado eléctrico, tanto precios como requisitos de regulación se han descargado de la página web de Red Eléctrica de España (www.esios.ree.es), en dónde se encuentran a disposición de cualquiera que quiera consultarlos.

En primer lugar, en el capítulo 4 se considera que el parque eólico con almacenamiento participa en el mercado diario, en el mercado de regulación secundaria y en el mercado de balance. El objetivo de este capítulo es el de desarrollar un modelo determinístico del problema y utilizar dicho modelo para evaluar el coste de no disponer de información exacta cuando se resuelve el problema. El modelo planteado es un problema de optimización convexo con variables binarias y los datos de entrada afectados por la incertidumbre son los precios en los tres mercados considerados, la energía eólica disponible y los requerimientos de regulación en tiempo real que serán exigidos por el operador del sistema. El planteamiento para evaluar el coste de la incertidumbre consiste en resolver el problema con unos datos de entrada fácilmente extraíbles de los datos disponibles y comparar el resultado obtenido con el que se obtendría en el utópico caso de haber conocido esos datos con exactitud. Así, por ejemplo, los datos de precios se calcularán como una media horaria de los precios de la última semana y los datos de energía eólica disponible son datos de previsión reales proporcionados por el propio operador del parque eólico de Sotavento. En el caso de la cantidad de regulación exigida por el operador del sistema se consideran varios casos. Por un lado, se analizan los requisitos más habituales extraídos de los datos históricos disponibles y, por otro lado, se considera una generación aleatoria de estos requisitos de regulación. Se lleva a cabo una simulación de los ingresos netos que obtendría el parque eólico durante un año en los casos reales propuestos y se comparan con los ingresos que se obtendrían si la información disponible fuese perfecta. Se observa que la influencia de la incertidumbre en la energía eólica disponible y en los requisitos de regulación del operador del sistema es similar y representa entre un 2% y un 4% de los ingresos obtenidos en el caso de información perfecta dependiendo del sistema de almacenamiento considerado. Por el contrario, la influencia de la incertidumbre en los precios es pequeña en comparación con las otras dos fuentes de incertidumbre. Durante la simulación también se concluye que la presencia de almacenamiento añade poco valor si sólo se participa en el mercado diario mientras que proporciona un aumento considerable de los ingresos netos si se considera también la participación en el mercado de regulación secundaria.

Una vez evaluado el coste de la incertidumbre en el problema, en el capítulo 5 se plantea incorporar la incertidumbre en la energía eólica disponible y en los requisitos de regulación exigidos por el operador del sistema al problema de toma de decisiones. Para ello, y tomando como base el modelo determinístico desarrollado en el capítulo anterior, se propone un enfoque estocástico. Bajo este enfoque, los parámetros afectados por la incertidumbre se modelan como un conjunto de escenarios posibles a los que se le asigna una determinada probabilidad de ocurrencia. Más específicamente, se plantea un modelo estocástico en dos etapas. El objetivo de este modelo es el de optimizar las decisiones tomadas en la primera etapa, que serán las que serán implementadas, pero teniendo en cuenta las posibles realizaciones de la incertidumbre y sus efectos en las variables de la segunda etapa. Una vez planteado el problema de toma de decisiones como un problema de optimización estocástico en dos etapas, se plantean una serie de hipótesis para definir escenarios. Por un lado, los escenarios que modelan la incertidumbre asociada a la disponibilidad del recurso eólico se definen a partir de predicciones reales disponibles por el operador del parque eólico de Sotavento. En lo relativo a los requisitos de regulación se plantean diferentes posibilidades. En primer lugar, se utilizan redes neuronales para llevar a cabo una predicción de dichos requisitos en función de los datos ya conocidos de los días precedentes. Por otro lado, se realiza un clustering unidimensional de los datos históricos de un año y se plantean dos hipótesis para definir escenarios para un día completo. Un enfoque diferente es realizar un clustering multidimensional sobre el histórico de datos diarios. El último enfoque considerado consiste en tomar como escenarios los datos conocidos de los últimos días. Para evaluar todas las posibilidades planteadas se simula durante dos meses los ingresos netos obtenidos en cada una de ellas y se comparar con los que se obtendrían en el caso de información perfecta. La conclusion más importante es que el clustering multidimensional consigue reducir de una manera significativa el coste de la incertidumbre asociada a los requerimientos de regulación.

En el capítulo 6, se considera que el parque eólico con almacenamiento participa únicamente en el mercado diario, intradiario y de balance. En este caso, se tiene en cuenta la incertidumbre asociada a los precios de la energía en todos los mercados y a la disponibilidad del recurso eólico. El planteamiento para definir escenarios que modelen la incertidumbre asociada a esta última es análogo al empleado en el capítulo 5. Por el contrario, para modelar la incertidumbre asociada a los precios en los diferentes mercados se plantea un enfoque totalmente basado en técnicas de aprendizaje automático. Se comparan en este capítulo dos propuestas para definir escenarios. Por un lado, un clustering multidimensional que defina patrones de precios diarios englobando a todos los mercados. A su vez, y teniendo en cuenta el número de datos diarios asignados a cada cluster se define una probabilidad desde un punto de vista frecuentista de cada uno de esos patrones. Por otro lado, y utilizando los mismos patrones definidos en el clustering, se extrae información de la secuencia temporal de ocurrencia de esos patrones. Así, mediante el uso de una red neuronal recurrente basada en celdas del tipo LSTM, se realiza una predicción de con qué probabilidad puede ocurrir cada uno de los patrones definidos en función de los datos más recientes de precios disponibles. Los modelos planteados se comparan entre sí y contra la situación de información perfecta y se concluye que el segundo enfoque obtiene mejores resultados comparados con el enfoque frecuentista, lo que parece razonable al extraer información no sólo de los precios si no también de la secuencia diaria de éstos.

Por último, en el capítulo 7 se extraen algunas conclusiones relevantes y se establecen futuras líneas de trabajo. En particular, se concluye que la utilización de un enfoque estocástico basado en datos es adecuado para tratar problemas en los que existe incertidumbre asociada a los datos de entrada y cuyo proceso de decisión se repite de una manera continuada. En esta tesis, las simulaciones se realizaron para un mínimo de dos meses. Por otro lado, la utilización de técnicas de aprendizaje automático y, en especial, combinando técnicas de aprendizaje supervisado y no supervisado se presenta como un enfoque interesante para extraer información de los datos disponibles. En cuanto a las líneas de trabajo futuras se plantea, por un lado, desarrollar modelos de decisión multietapa que se ajusten a la estructura de toma de decisiones en el mercado eléctrico. Por otro lado, parece interesante seguir explorando técnicas de aprendizaje automático que sean capaces de extraer información de los datos disponibles, suministrando así valiosa información de entrada al problema.

CONTENTS

List of figures

List of tables

List of acronyms

W&SPP	Wind and Storage Power Plant
ESS	Energy Storage System
WF	Wind Farm
DAM	Day-Ahead Market
IDM	Intraday Market
PM	Pool Market
RM	Reserve Market
SO	System Operator
MO	Market Operator
MIBEL	Iberian Electricity Market
REE	Spanish System Operator
REN	Portuguese System Operator
OMIE	Spanish Market Operator
OMIP	Portuguese Market Operator
UC	Unit Commitment
ED	Economic Dispatch
LSTM	Long Short-Term Memory
NN	Neural Network
RNN	Recurrent Neural Network
PI	Perfect Information
RI	Real Information
AWE	Available Wind Energy
VRRG	Variable Renewable Resources Generator

GENCO	Generation Company
PFP	Provisional Feasible Program
AD	Agent Deviation
NABE	Net Amount of Balance Energy
BE	Balance Energy

CHAPTER 1

1 Introduction

In this chapter, the motivation of this research is exposed. A research statement is exposed in order to define the interest of the proposed research problem and the approaches followed to handle it. At the end of the chapter, the main contributions of this thesis are highlighted and a list of the work published as a result of this research is provided.

1.1 Motivation

In recent years, as a result of a growing concern about the effects of climate change, the decarbonization of the electric power generation sector has been promoted. As a result, generation technologies based on renewable resources, mainly wind and solar, have undergone a strong development that has led them, today, to be considered mature generation technologies in a position to compete with the traditional generation sources in the electricity sector. Thus, these technologies have achieved important quotas of presence in the generation mix of many countries. As an example, the generation mix of Spain is shown in Figure 1.

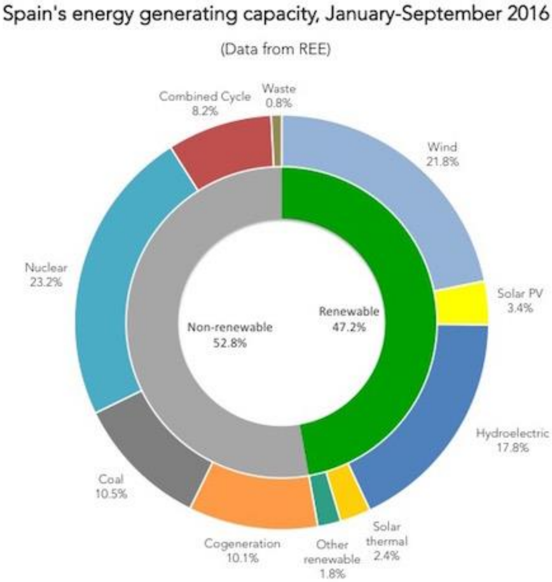
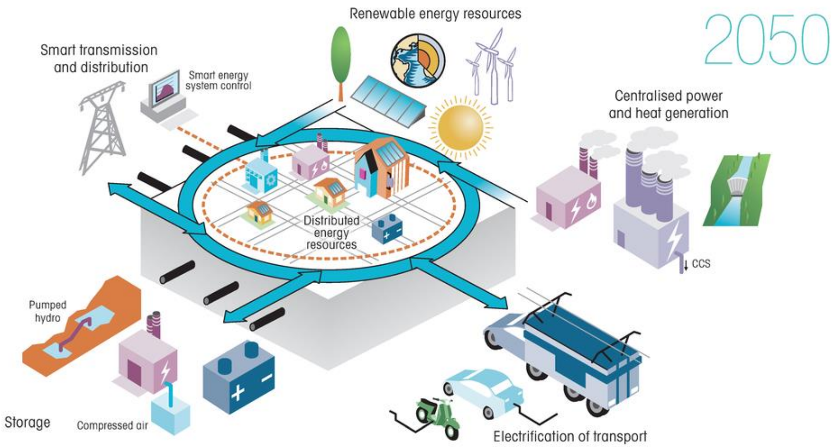


Figure 1.- Generation mix in Spain

The share of renewable generation in the capacity mix is expected to continue to increase in several countries, which poses new challenges to effectively integrate them in both the power system and the electricity market. On one hand, from the power system point of view, that integration deals with keeping the system running in a safe and reliable way. On another hand, from an electricity market

point of view, it is necessary to develop market mechanisms that take into account the characteristics of renewable generation.
Moreover, new agents in the power system are expected to become relevant in the near future such as electric vehicles, prosumers, storage systems, active distribution networks operators, and probably others that we can not even imagine at present. An illustration of the coming power system is shown in Figure 2.



.

Figure 2.- Power system of the future. Source: International Energy Association.

As a consequence, the power system will become a game field with a huge number of participants seeking at achieving their own objectives where massive amounts of data will be also available to help these participants to decide how to interact with each other.
In this context, the motivation of this thesis is to propose and explore data-driven decision-making frameworks that can be used, eventually, by agents taking part of the challenging power system of the near future.

1.2 Research statement

Power systems are becoming more and more complex with many agents aiming at achieving their own goals while interacting with each other in an intensive data environment.
In this context, power systems are also experiencing a strong concurrence among agents wishing to sell/buy energy, power, and services in the electricity markets. Thus, there is an actual need to develop decision-making tools that can help

agents to make optimal decisions as to how to participate in those markets. One important feature of these decision-making problems is that decisions have to be made in an uncertain environment, i.e., the input data is not known when the problem is to be solved.
A renewable energy-based generator will be considered in this thesis. In particular, a wind farm is proposed due to the important presence of this kind of renewable generators in the generation mix of many countries. Moreover, energy storage technologies are seen as a key technology to facilitate the massive integration of renewable energy systems in the power systems by increasing the power system flexibility and adaptability to fluctuations of renewable energy generation. This need is thus pushing the technological development of more and more competitive electrical storage systems. The possibility of adding storage capacity to the wind farm is also worth studying in order to evaluate the benefits of increasing the manageability of the wind generation.

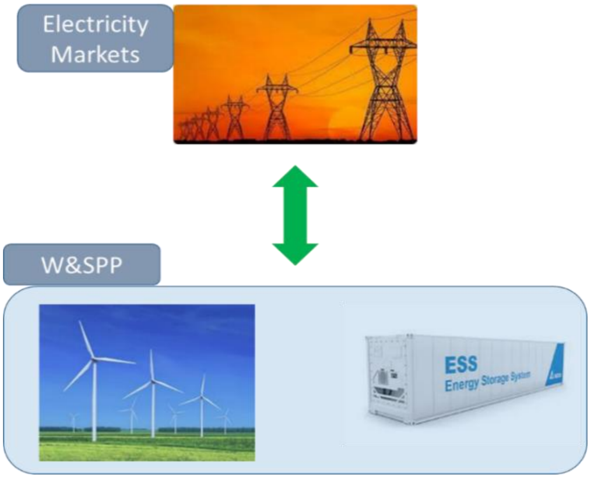


Figure 3.- Wind and storage power plant

Thus, the research problem to be handled in this thesis deals with the proposal of decision-making frameworks for a wind and storage power plant, as shown in Figure 3, participating in the electricity market. This decision-making problem occurs in an uncertain environment. In this particular case, uncertainty concerns, for example, the availability of wind energy and the market prices. In Figure 4, a one-week long forecast of available wind energy is shown. In this figure, the red line shows the actual value of available wind energy with respect to the interval forecast. It can be seen how the uncertainty increase with the time span of the forecast. On another hand, in Figure 5, the volatility of energy prices in the day-ahead market is shown.

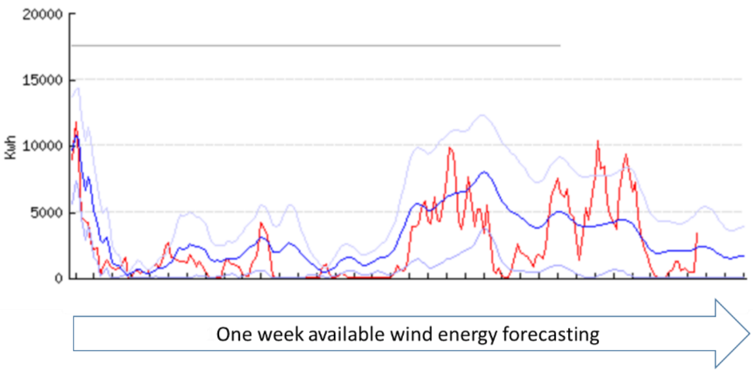


Figure 4.- Available wind energy forecast

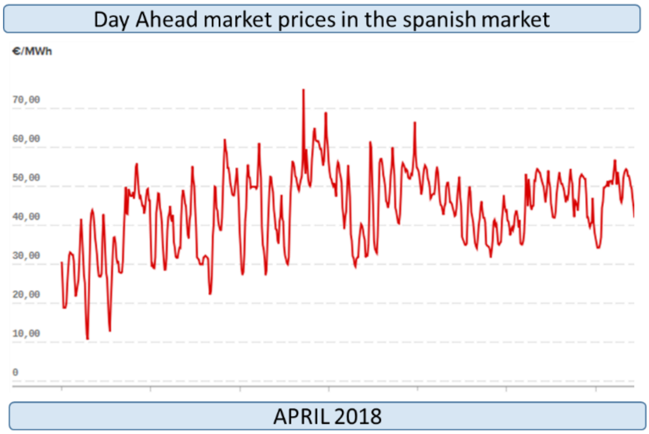


Figure 5.- Day-ahead market prices

To tackle this problem, this thesis proposes to apply mathematical tools to build a decision-making framework under uncertainty. More specifically, stochastic programming is proposed to model the uncertainty in the decision-making problem while several machine learning techniques are leveraged to supply meaningful data to the decision-making problem.

Thus, the first objective of the thesis is to develop optimization models in an environment of uncertainty in order to decide the operational strategy of a wind farm in the electricity markets and assess the suitability of having storage capacity.

The second objective is to propose and validate strategies for the use of available data that can provide meaningful input data to the optimization models developed. In particular, machine learning techniques will be used, both supervised and unsupervised.

Real world data is used throughout the thesis. In the one hand, market data is downloaded from the site of Red Eléctrica de España [1], where a vast amount of data concerning prices and other parameters of the Spanish electricity system and market are publicly available. On another hand, an experimental wind farm located in Northwestern Spain [2] has kindly provided us with real data concerning wind energy availability. A picture of the experimental wind farm is shown in Figure 6. The availability of real-world data is used throughout the thesis twofold: firstly, as a source of historical data from where extract information on how to model uncertainty, and secondly to evaluate the quality of the proposed methods to handle such uncertainty.

Figure 6.- Experimental wind park of Sotavento

This research has been raised at the intersection between very broad fields: electricity markets, optimization under uncertainty, and machine learning techniques as shown in Figure 7.

The approach of the thesis is to pool these three areas to generate decision-making frameworks based on mathematical models of optimization that together with data analysis strategies, are useful to decide the operation of a generator based on renewable energy and equipped with storage that participates in one or more of the available electricity markets. This decision-making problem is strongly affected by uncertainty which should be included in the modeling of the problem. Machine learning techniques are leveraged in order to extract as much information as possible out of the available data and provide the decision models with valuable information concerning the uncertain parameters.

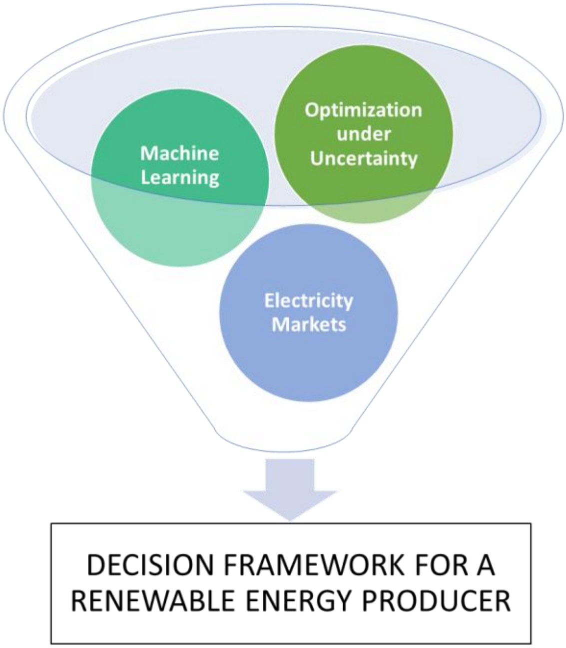


Figure 7.- Areas of knowledge relevant for this thesis

1.3 Contributions

At the higher level, this thesis shows the effectiveness of leveraging machine learning techniques to extract information out of available data that can be used in decision-making models under uncertainty, in particular, for a wind and storage power plant participating in several electricity markets. More specifically, the most important contributions of this thesis are the following:

- Development of a deterministic optimization model to evaluate the cost of the uncertainty concerning the available wind energy and the parameters of the electricity market in the decision-making problem of a wind and storage power plant that participates in the day-ahead, balancing, and reserve markets.
- Development of a two-stage stochastic model of the wind storage power plant participating in the day-ahead, balancing, and reserve markets.
- Development of a two-stage stochastic model of the wind and storage power plant participating in the pool market, i.e., day-ahead, intraday, and balancing markets.
- Proposal of unsupervised machine learning techniques, specifically monovariate and multivariate clustering, to analyze historical data of the requirements of participation in the reserve market by the system operator.
- Development of a framework combining multivariate clustering and recurrent neural networks to generate scenarios modeling the uncertainty associated with pool prices.
- Evaluation of the proposed strategies through simulation and comparison with the ideal case of perfect information.

1.4 Thesis Outline

The rest of this thesis is organized as follows.

- **CHAPTER 2**. In this chapter, the Iberian electricity market is described in detail in order to understand the models that are proposed in this thesis. Both electricity and adjustment services markets are explained. The balancing market is given a special attention because of its relevancy when dealing with renewable-based generators.

- **CHAPTER 3**. In order to make this work as self-contained as possible, a basic introduction to mathematical tools that will be used in the next chapters is given. In one hand, the concept of an optimization problem, from a mathematical point of view, is presented. An optimization framework is used in the next chapters to model several decision-making problems of a W&SPP participating in electricity markets. On another hand, some machine learning techniques are presented. In particular, clustering and neural networks. A data-driven approach is followed to generate meaningful input data to the optimization problems, and the presented machine learning techniques are used to extract information out of available data. Moreover, a short review of the applications of optimization theory to kind of problems arising in the power systems is also presented in this chapter.

- CHAPTER 4. A deterministic model of a wind-storage power plant is developed in this chapter. This model is used to evaluate the cost of uncertain parameters when the wind-storage power plant takes part in both day-ahead and reserve markets. Uncertainty in available wind energy, regulation requirements, and energy and power prices is considered.

- CHAPTER 5. The decision-making problem under uncertainty, both in available wind energy and regulation requirements, of a W&SPP participating in day-ahead, and regulation markets, is modeled by a two-stage stochastic problem. Several approaches are proposed and evaluated to generate meaningful scenarios modeling the uncertainty.

- CHAPTER 6. The participation of the wind and storage power plant participating in the pool market, i.e., in day-ahead, intraday, and balancing markets, is modeled as a two-stage stochastic problem. Uncertainty in both available wind energy and market prices is considered. A hybrid approach, using clustering to define price patterns and recurrent neural networks to extract information from the temporal sequence of such patterns, is proposed to generate scenarios for day-ahead, intraday, and balancing market prices.

- CHAPTER 7. In the last chapter, a set of conclusions and future work directions are discussed.

1.5 List of publications

As a result of this research work, several papers were published in scientific journals and international conferences.

Research Papers:

- *J. L. Crespo-Vazquez, C. Carrillo, and, E. Diaz-Dorado, "Evaluation of the Uncertainty in the Scheduling of a Wind and Storage Power Plant Participating in Day-Ahead and Reserve Markets", Energy Procedia, vol. 136, pp. 79–84, 2017.*

- *J. L. Crespo-Vazquez, C. Carrillo, E. Diaz-Dorado, J. A. Martinez-Lorenzo and, Md Noor-E-Alam, "Evaluation of a data-driven stochastic approach to optimize the participation of a wind and storage power plant in day-ahead and reserve markets", Energy, vol. 156, pp. 278–291, 2018.*
  JCR, Energy & Fuels : 18 / 97 (Q1); (I.F. 2017 : 4.908).

- *Jose L. Crespo-Vazquez, C. Carrillo, E. DÍaz-Dorado, Jose A. Martinez-Lorenzo, Md Noor-E-Alam, "A machine learning based stochastic optimization framework for a wind and storage power plant participating in the energy pool market", Applied Energy, accepted for publication.*
  JCR, Energy & Fuels : 8 / 97 (Q1); (I.F. 2017 : 7.900).

Oral Presentations in International Conferences:

- *"Evaluation of the Uncertainty in the Scheduling of a Wind and Storage Power Plant Participating in Day-Ahead and Reserve Markets", J.L. Crespo-Vazquez, C. Carrillo, E. Diaz-Dorado, 4th International Conference on Energy and Environment Research, ICEER, Porto, Portugal, July 2017.*

- *"Leveraging machine learning approaches to optimize the participation of a wind and storage power plant in the electricity market", Md. Noor-E-Alam, J.L. Crespo-Vazquez, Jose A. Martinez-Lorenzo, C. Carrillo, E. Diaz-Dorado, INFORMS Anual Meeting, Phoenix, USA, November 2018.*

CHAPTER 2

2 Overview of electricity markets.

The goal of this chapter is to make it clear the structure of the market associated with the power systems in a liberalized environment. The Iberian peninsula case, comprising Spain and Portugal, is chosen as a reference and presented in detail. A special consideration is given to the so-called balancing market because of its important influence in the operation of renewable energy based generators.

2.1 Introduction

An electrical system can be viewed as a set of agents that interact in an organized manner. The ultimate goal of the system is that the power generators supply the electric power demand of the consumers in an efficient, reliable, and safe manner. Thus, in an electrical system, it is necessary to define a set of activities and services to be carried out by different agents.

The main activities within an electrical system are the following: generation, transport, distribution, and commercialization. Traditionally, these activities have been vertically integrated and under the responsibility of a single operator, resulting in a monopolistic regime. When in some countries it is decided to liberalize the electricity sector, it is necessary to define who and how each of the aforementioned activities will be carried out. The most usual approach has been to liberalize generation and commercialization activities, while transport and distribution have remained as regulated activities.

In a liberalized framework, it becomes important to define which agents perform the regulated and unregulated activities and how each of them will be rewarded for the services rendered to the system. This is how the concept of the electricity market appears in the context of a liberalized electric system.

Below, a flavor of the operation of the Iberian electricity market is given in order to provide the necessary background to understand the models developed in chapters 4, 5, and 6.

2.2 Iberian electricity market

Since 1998, the year in which the Spanish and Portuguese governments began talks and studies to progressively eliminate the barriers and promote the development of the Iberian Electricity Market, there have been a series of events that, gradually, have been laying the foundations of the construction and development of what can now be called the Iberian Electricity Market. As a result, the Iberian Electricity Market (MIBEL) was created and it is working since July 1st, 2007.

Under the MIBEL a bunch of several markets is run [3]. These markets are operated by several entities as shown in Figure 8. In the one hand, the electricity markets are operated by the Spanish and Portuguese market operators, OMIE and OMIP respectively. The first one, the Spanish pole, is in charge of the day-ahead and the intraday markets which will be presented shortly. In another hand, the adjustment services markets are operated by the Portuguese (REN) and the Spanish (REE) system operators.

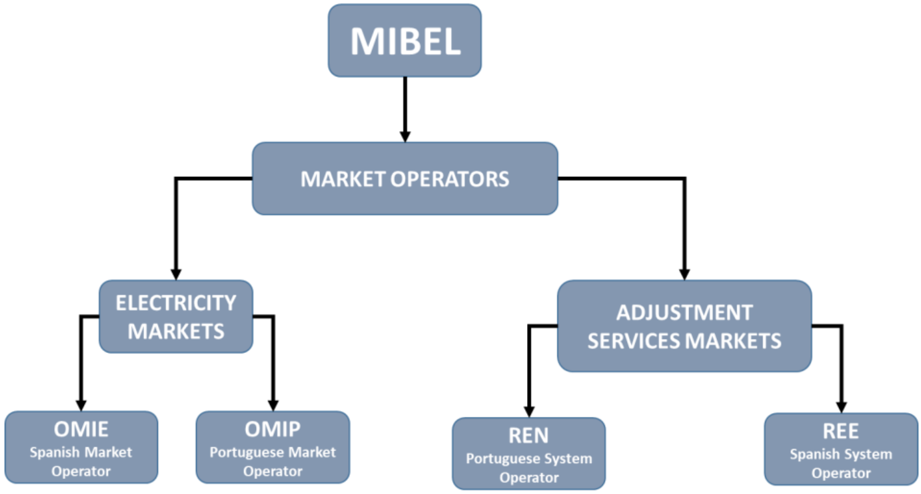


Figure 8.- MIBEL and market operators

Thus, the Iberian market can be split into two main markets: an electricity market where most of the energy exchanges among generators and consumers are traded and a sequence of activities, most of them remunerated under market mechanisms, aimed at keeping the whole power system operating efficiently and safely.

Around both, market and system operators, a bunch of agents plays their role in the whole system as it is shown in Figure 9. On the one hand, the generation companies (GENCO) provides energy that can be sold either through the market operator or through bilateral contracts with large consumers. The GENCOs are also an important player in the ancillary services market which aims at keeping the power system operating in a reliable and safe way as it will be explained shortly. It is to note that with the ongoing increase on the presence of distributed generation technologies, an equivalent role may be played by aggregators of distributed generation assets. On another hand, large consumers and retailers buy huge amounts of energy to be consumed by themselves or sold to end-users respectively. Large consumers also can participate in the ancillary services market. End users are also becoming generators which can consume their own generated electricity. A growing interaction of this self-consumption agents with the system is expected and thus, likely by aggregating agents, the participation in ancillary services would become also possible.

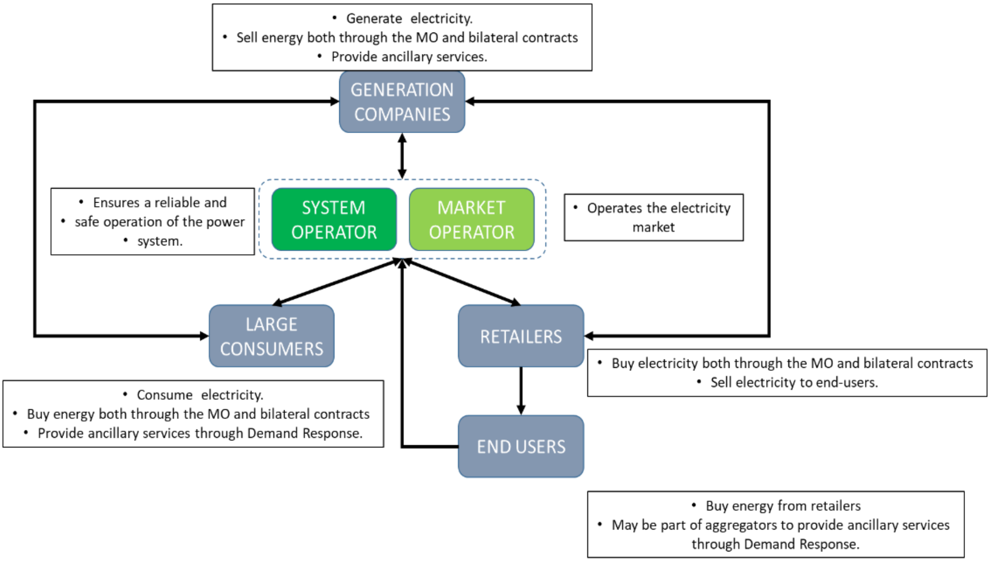


Figure 9.- Power market agents.

A qualitative introduction to these markets is presented in the rest of this chapter. At first, the pool market is described as that market where most of the energy is traded. Afterward, the adjustment services markets are described and lastly, the balancing market is presented in detail. A chart showing this markets and their temporal sequence is represented in Figure 11.

2.2.1 Pool Market

The pool market includes the day-ahead market, the intraday markets, and the balancing market [4]. The day-ahead market is the main electricity contracting market in the Iberian Peninsula and works 365 days a year. As in the rest of the European Union, it is a marginal market in which the price and the volume of hiring in each hour are established from the point of equilibrium between supply and demand. Every day, until 12:00 a.m., electricity purchase and sale offers are received for the following day. These offers are then processed with an algorithm called EUPHEMIA [5] , which is used in most of the European countries. Once the process is over, OMIE communicates publicly the prices and energy that will be produced and purchased in each of the hours of the next day in the Iberian market.

Once the day-ahead market has been cleared, the adjustment markets (also called intraday markets) are carried out, allowing buyers and sellers to make offers to buy and sell electric power to adjust their programs based on their best forecasts of what will happen in real time. The market operator is also in charge of managing the bilateral contracts between generators and large consumers.

2.2.2 Adjustment services market

In order to guarantee a reliable and safe operation of the power system, the system operator (SO) is entrusted to manage the so-called adjustment services which include: management of technical constraints and ancillary services [6].
The provision of these services is awarded through an adjustment services market. The system operator is in charge of managing and liquidating said markets. Although these adjustment services are essential to guarantee the safety and quality of supply, their influence on the cost of electricity supply is very limited as shown in Figure 10 [7]. The operation of the adjustment services markets is described in detail in reference [8].

- Solution of technical constraints

The process of solving technical constraints aims at guaranteeing that the energy exchanges resulting from the electricity market can be undertaken under safe and reliable conditions. This process is executed once the sessions of the day-ahead market and each of the intraday market sessions have been closed. In addition, existing bilateral contracts and forecasted international exchanges that have been communicated to the system operator are also taken into account. In addition, prior to the solution of the technical constraints, the generation plants have had to submit to the system operator their offers to participate in this service, i.e., their offers to increase or decrease their generation and/or consumption in order to solve the technical constraints as to the SO requirements. With all this information, the process consists of two well-differentiated phases. In the first phase, the generation plants are rescheduled based on different scenarios that contemplate different contingencies that would affect the operation of the system. In this phase, the redispatches up, i.e, requiring more energy, are settled based on the specific offer submitted by the generators, while the redispatches down are settled based on the daily market price. In the second phase, new reprogramming is carried out in order to balance the global generation and demand programs. In this phase, an order of merit is followed between the offers submitted to upload and download. The settlements are made based on the specific offers to upload and download.

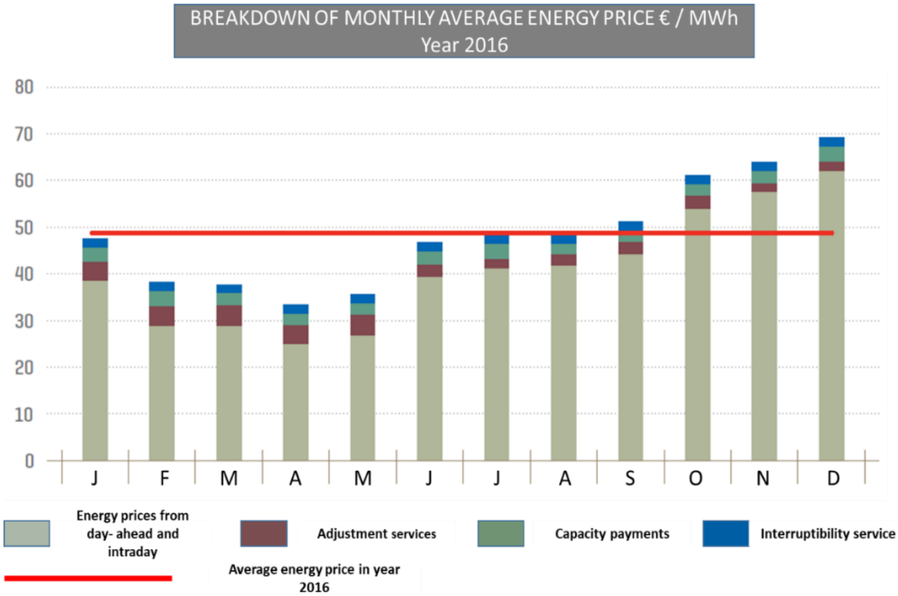


Figure 10.- Influence of adjustment services on energy price.

As a result of this process of solution of technical constraints, a *provisional feasible program* (PFP) is obtained. In this program, a set of agents and their respective amount of energy to be supplied/consumed in each hour of day D is established. From this PFP a set of markets is defined to guarantee a safe and reliable operation of the system when approaching real time.

➢ Ancillary services

Ancillary services are necessary to ensure the safety, quality and, reliability of electricity supply. There are several kinds of ancillary services as follows:

- Frequency regulation.

First of all, there exist ancillary services aimed at keeping the frequency of the system in the allowed threshold. These services are thus called frequency regulation services. Within this service, several levels of regulation are defined:

primary, secondary, and tertiary regulation. The primary regulation automatically corrects instantaneous imbalances between generation and demand. It is provided by the speed regulators of the generators themselves and their time horizon is 30 seconds. This service is mandatory for all generators although it is not rewarded. Secondary regulation also aims at guaranteing the generation-demand balance but, in this case, the time horizon extends from 30 seconds to 15 minutes. This service is awarded through competitive mechanisms between the generators willing to offer it and consists of two concepts: availability (regulation band) and utilization (energy). Thus, each generator offers a quantity of power that will be available to the system operator to be used eventually. A regulation band is assigned to each generator with minimum cost criteria. As a result of this procedure, a marginal price of the regulation band is established for each hour. Generators with regulation band allocation will have to provide the energy that the system operator may require in real time. This energy is valued at the marginal price of the tertiary regulation energy.
Finally, among the services linked to frequency regulation, tertiary regulation is defined. The objective of this regulation is to restore the secondary regulation availability. Thus, it is defined as the maximum variation of power that a generator can provide in 15 minutes and be maintained for at least 2 hours. It is a mandatory offer service and, if necessary, it is assigned based on the offers received, with the price of the service being fixed by the last offer assigned in each direction, up and down, in each hour.

- Deviations management.

Another complementary service is linked to the management of deviations. This service aims at providing the system operator with flexibility to resolve generation-demand imbalances without putting the availability of secondary and tertiary regulation reserves at risk. Thus, this deviation management market will be executed in the case that expected imbalances are important.

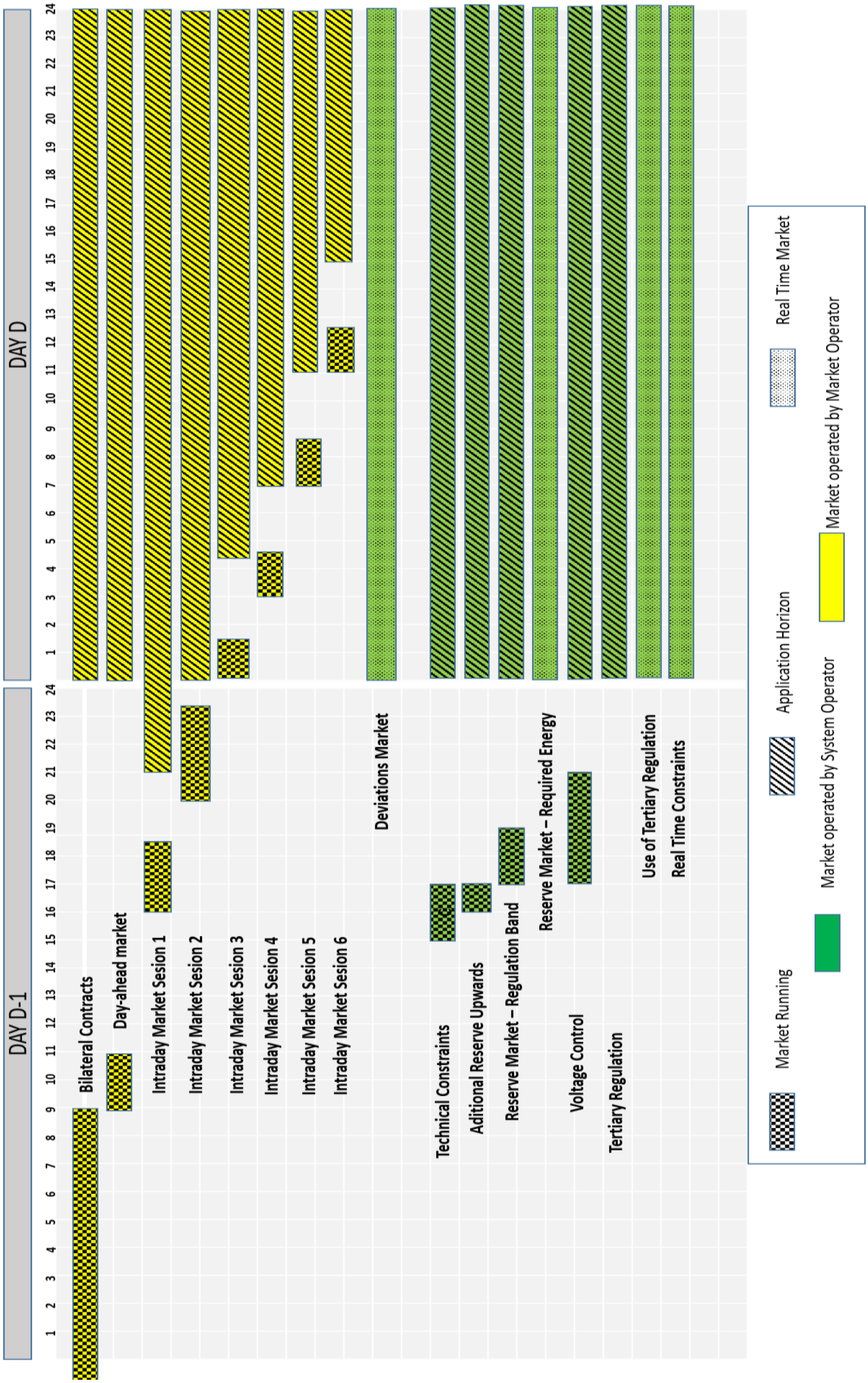


Figure 11.- Sequence of markets operated by SO and MO

- Voltage regulation.

Voltage in the nodes of the transport network is another important parameter within the electrical system. This voltage must be maintained within the appropriate limits to guarantee that the supply is carried out in the required safety, reliability and quality conditions. Certain generators, transport companies, and certain consumers can provide this complementary voltage regulation service.

- Blackstart capabilities.

Finally, there is a complementary service linked to the ability of certain generators to replenish the supply in the event of a national or regional disturbance. These generators must be able to start without external power supply after a zero of general voltage and keep generating in a stable manner throughout the process of replacement of the service.

2.2.3 Balancing market

In the Spanish case, there exists one more mechanism to deal with the variability of renewable resources generators. This mechanism aims at setting a price, which may constitute a penalty or not, to the excess or lack of delivered energy with respect to the programmed energy in every hour for a given agent. Although this mechanism is referred to as *balancing market*, it is not an actual market. Instead, the prices of the deviations are calculated from the prices of energy in other markets as it will be explained shortly.
Due to the importance of this mechanism in the integration of renewable energy resources in the electrical system, it is explained in detail. A full description may be found in [9].
Firstly, the deviations incurred by a renewable energy generator have to be defined. Thus, the programmed energy for a given generator in each hour of day D depends on the commitments acquired in the day-ahead market, on the updatings made by the agent in the corresponding intraday market session, and on the adjustments made by the system operator in the real-time constraints market. By adding up all these three components, a certain amount of energy is programmed for that generator in a given hour. Had the generator fail to follow the programmed energy, it would be incurring in a deviation which will be handled by the balancing market.

A deviation is considered positive when either the agent is producing more energy or consuming less energy than programmed. Conversely, a deviation is considered negative when either the agent is producing less energy or consuming more energy than programmed. Thus, the deviation in which an agent incurs in every hour is referred to as *agent deviation* (AD) and, is defined as to equation (1).

$$Agent\_Deviation_h = Delivered\_Energy_h - Programmed\_Energy_h \qquad (1)$$

As it was explained before, the system operator run a set of markets in order to guarantee the stability of the system. All these markets aim at matching the unbalances between generation and demand in every moment. The net amount of energy that the systems needs for balance purposes in every hour (NABE) is defined as to equation (2)

$$Net\_Amount\_Balance\_Energy_h = \sum_{m,d} Balance\_Energy_{h,m,d} \qquad (2)$$

In the equation (2), subindex *m* stands for the considered market, i.e, either secondary or tertiary regulation or deviations market. On another hand, subindex *d st*ands for the direction of the regulation, either upwards or downwards, that is needed. The *balance energy* (BE) is the amount of energy required for regulation in a given hour, in a given market and in a given direction, i.e, upwards or downwards. It is important to highlight that the regulation requirements may be demanded in fractions of an hour so it is possible to have, in the same hour, periods (minutes) when energy for regulation upwards is needed and periods when regulation downwards is required. Thus, the NABE represents the aggregated needs of regulation requirements in a given hour in the considered markets.

In order to define the prices of the deviation that will be applied to the power agent in each hour, both magnitudes, NABE and AD need to be compared as represented in Figure 12, i.e., actual deviation of the considered agent and actual balancing needs of the system has to be compared.

Thus, when the deviation of the agent is favorable to the balance needs of the whole system, the price of the deviation will be that of the day-ahead market, i.e, no penalty is applying. This is the case, for example, when the agent is deviating upwards, for example by producing more energy than programmed, and the system is needing extra energy for regulation. In this case, the agent will be paid at the same price as if it would have committed that excess of energy in the DAM. A similar case arises when the agent is deviating downwards, for example by producing less energy than programmed, and the system is needing to reduce energy for regulation. In this case, the agent just needs to buy energy at the DAM price, which is equivalent to return the money it got in the DAM back.

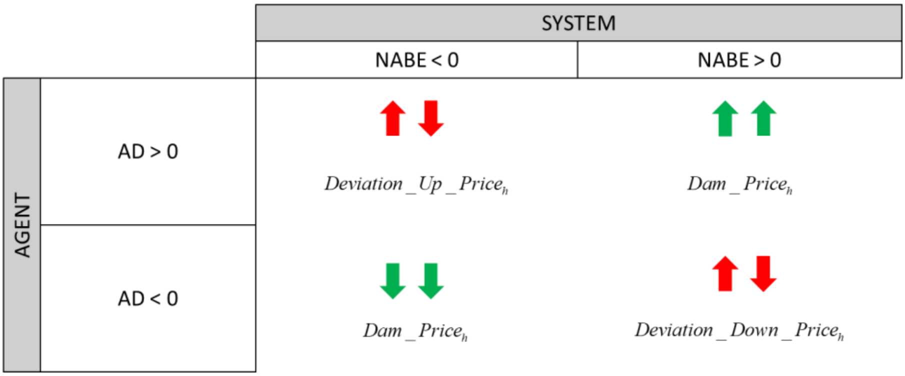


Figure 12.- Prices in the balancing market

On another hand, it may happen that the agent and the system do not match their deviation and regulation needs respectively. In this case, the deviation of the agent needs to be compensated. Thus, the SO needs to use regulation capabilities from the ancillary services markets. The cost of using these regulation capabilities should be taken into account to calculate the deviation price to be faced by the agent.

The equations (3) and, (4) define the deviation prices, both upwards and downwards, that apply to the deviations with respect to the programmed energy when the deviation and the systems needs are opposite.

In case the agent is deviating upwards and the system needs to reduce energy, the SO will need to increase the requirements of regulation downwards. The SO may get this regulation from the frequency regulation markets, both secondary and tertiary, and/or from the deviations market. The deviation price applied to the agent takes into account the weighted average price of the regulation costs and cannot be smaller than the DAM price as stated in the equation (3).

$$Deviation\_Up\_Price_h = \min\left(\frac{\sum_m (Balance\_Energy_{h,m,down} \times Marginal\_Price_{h,m,down}}{\sum_m Balance\_Energy_{h,m,down}}, DAM\_Price \right) \quad (3)$$

Analogously, if the agent is deviating downwards and the system needs regulation upwards, the SO will need to increase the requirements for regulation upwards. In this case, the price applied to the deviation will be the weighted average of the regulation upwards prices. The deviation down price is defined with a max function in order to avoid that it may be lower than the DAM price as to equation (4).

$$Deviation\_Down\_Price_h = \max\left(\frac{\sum_m (Balance\_Energy_{h,m,up} \times Marginal\_Price_{h,m,up}}{\sum_m Balance\_Energy_{h,m,up}}, DAM\_Price \right) \quad (4)$$

2.3 Conclusions

The structure of the Iberian electricity market was presented in this chapter. The market is split into two groups of submarkets, i.e., electricity or pool market, which operates under the control of a market operator, and an .adjustment market running under control of a system operator. In the first market, the majority of energy is traded while in the second one a set of services are traded in order to guarantee a reliable and safe operation of the system. The balancing market is also presented in detail. This market plays an important role in the case of renewable energy generators and consequently will also play an important role in the rest of this thesis.

CHAPTER 3

3 Mathematical Background

In order to make this thesis as self-contained as possible, this chapter sets the mathematical background to follow the rest of the chapters. It aims at introducing some basic concepts to those not familiar with mathematical programming and machine learning concepts. In the first place, some introductory knowledge of mathematical optimization is exposed in order to develop an intuition on how to translate a decision-making problem into mathematical terms. Moreover, two approaches are presented to introduce uncertainty in the decision-making problem: stochastic and robust approaches. Lastly, several machine learning techniques are described.

3.1 Introduction

A decision-making problem is often modeled as an optimization problem where the best decision among a set of feasible or possible ones is to be identified. This problem comprises two equally important aspects. In one hand, the optimization problem itself and, on another hand, the input data to that optimization problem. In this chapter, the mathematical background needed to understand the basic concepts used in this thesis to handle both, optimization problem formulation and input data definition, is presented. Thus, in section 3.2 an optimization problem, from a mathematical point of view, is defined. An optimization framework is chosen for the rest of this thesis to model the decision-making problems we will be dealing with. In this section, the structure of an optimization problem and the importance of that structure in the tractability of the problem is highlighted. Moreover, the concept of optimization under uncertainty, which will play a crucial role in the rest of the thesis, is also introduced.
For the second task, a data-driven approach is proposed. Thus, in section 3.3, several machine learning techniques, both supervised and unsupervised, are presented. These tools aim at extracting as much information as possible out of the available data in order to feed to the optimization problem input data as meaningful as possible.

3.2 Optimization.

A decision-making problem can be written as a mathematical optimization problem. In this section, firstly, a few definitions concerning the concept of a mathematical optimization problem are exposed. Secondly, some approaches to model the uncertainty in the optimization problem are presented.

3.2.1 Definition

An optimization problem aims at finding the best solution among a set of feasible ones. Thus, this problem can be expressed mathematically as to equation (5) as follows:

$$\begin{aligned} &\textit{minimize} && f_0(x) \\ &\textit{subject to} && f_i(x) \le b_i \qquad i=1,....,m \end{aligned} \tag{5}$$

Where the variable $x \in \mathbb{R}^n$ is called the *decision or optimization variable.* While the functions f_0, f_i are real and defined in $\mathbb{R}^n$. The function f_0 is called the *objective function* and the functions f_i define the so-called *constraints* of the problem.
A vector $x^* \in \mathbb{R}^n$ is called *optimal,* or *solution* of the problem, if it has the smallest objective value among all vectors satisfying the constraints as defined in the equation (6) as follows:

$$\forall z \in \mathbb{R}^n,\ f_1(z) \leq b_1, \ldots\ldots, f_m(z) \leq b_m \Rightarrow f_0(z) \geq f_0(x^*) \tag{6}$$

Depending on the characteristics of the objective function and constraints, several classes of optimization problems may be defined. The structure of the problem is of paramount importance when dealing with the tractability and solvability of the problem. Thus, for example, if the condition (7) holds for all functions involved, objective and constraints, the resulting problem is called a *linear problem*.

$$f_i(\alpha x + \beta y) = \alpha f_i(x) + \beta f_i(y) \quad \forall x, y \in \mathbb{R}^n, \forall \alpha, \beta \in \mathbb{R} \tag{7}$$

In this case, a linear problem can be expressed as follows:

$$\begin{aligned} &minimize && \sum_{i=1}^{n} c_i x_i \\ &subject\, to && \sum_{i=1}^{n} a_{j,i} x_i \leq b_j \qquad j = 1, \ldots\ldots, m \end{aligned} \tag{8}$$

Being x_i the i-th component of the vector $x \in \mathbb{R}^n$ and, c_i, $a_{j,i}$, $b_j \in \mathbb{R}$.
A linear program can be also expressed in matrix form resulting in a more compact notation as follows:

$$\begin{aligned} &minimize && c^T x \\ &subject\, to && Ax \leq b \end{aligned} \tag{9}$$

Where $c \in \mathbb{R}^n$, $b \in \mathbb{R}^m$ and, $A \in \mathbb{R}^{m \times n}$.

Linear programs have been studied for a long time. As a result, algorithms to solve linear programs, such as simplex or interior point based methods, have reached a remarkable mature status. Currently, linear programs of several millions of variables and constraints can be solved in a reasonable amount of time on a personal computer.

Analogously, a *convex optimization problem* is defined if all the functions involved in the problem are convex [10]. A function is convex if the condition (10) holds, which can be interpreted as a relaxation of the linearity condition.

$$\begin{aligned} & f_i(\alpha x+\beta y) \le \alpha f_i(x)+\beta f_i(y) \quad \forall x, y\in\mathbb{R}^n, \forall \alpha,\beta\in\mathbb{R} \\ & \alpha,\beta \ge 0 \;\; and \;\; \alpha+\beta=1 \end{aligned} \tag{10}$$

As it happens for linear programs, a local optimum of a convex problem is guaranteed to be also a global optimum.

An example of a real convex function in $\mathbb{R}^2$ and the explanation of the convexity condition in a real function in $\mathbb{R}$ are shown in Figure 13.

Although the maturity of convex problems solvers is not as remarkable as that of linear programs, an acceptable level of performance can be achieved for certain structures of convex problems, such as those with conic or semidefinite constraints [10]. In those cases, problem sizes of hundreds of thousands of variables and constraints may be tractable.

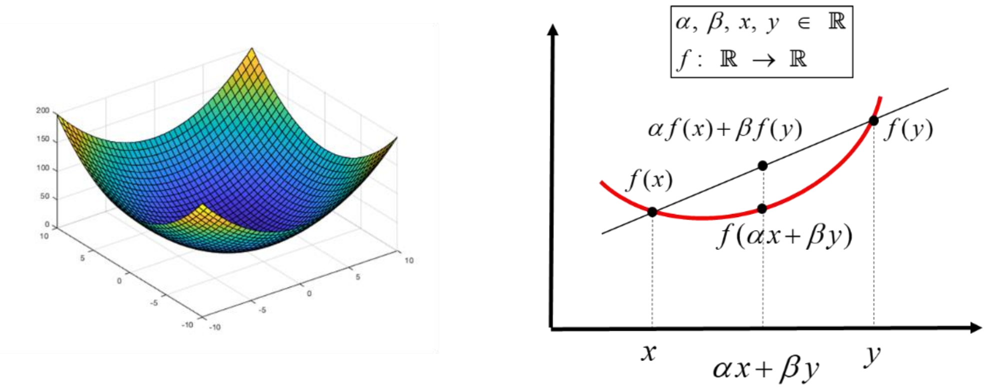


Figure 13.- Example of convex functions. Representation of the convexity condition.

Traditionally, when either the objective function or some of the constraints are nonlinear, the problem is referred to as a *nonlinear problem*. In this case, with the aforementioned exceptions of certain types of convex problems, there are not effective ways to solve these problems in a general way [11]. This kind of problems use to be handled by heuristic techniques and problem-customized methods.

It is also possible, and interesting, to define optimization problems where some variables are discrete, for example, binary or integer variables. This kind of variables have a great interest from a modeling point of view in many real-world applications of optimization theory. An optimization problem with some of the variables being discrete is referred to as a *Mixed Integer Problem*.

If a linear program is generalized to include discrete variables, the resulting problem is called a *Mixed Integer Linear Program*. Although there exist solvers able to handle these problems efficiently, the tractable sizes are considerably reduced with respect to the continuous linear situation.

In the case of *Mixed Integer Nonlinear* problems, the addition of discrete variables puts additional complexity onto the nonlinear program making quite challenging to solve them.

3.2.2 Optimization under uncertainty

Decision-making processes are inherently made under uncertain conditions. Moreover, we claimed that most of decision-making problems may be represented as mathematical optimization problems. Thus, it looks plausible that approaches to handle uncertainty in the decision process be considered which we have not done so far.

Without loss of generality, and for sake of simplicity, a decision-making problem that can be modeled as a linear problem is considered as being affected by uncertainty. All the concepts and ideas presented in this subsection are straightforwardly generalized to nonlinear programs. Thus, let’s consider the linear program written in matrix form as an equation (9). In this problem, vectors c and b, and matrix A are the input data. If the input data is perfectly known, the optimization problem is *deterministic* and solving the problem guarantees to have the best possible action. On another hand, it may happen, and actually often does, that the input data is not certainly known. Two approaches are presented to handle this uncertainty: stochastic and robust approaches.

- Stochastic programming

A first approach to deal with uncertainty in the input data is to assume that the input data is describable through probability distributions. This approach has been deeply treated in the literature. In this section, we aimed at introducing the basic concepts of stochastic programming that are used in coming chapters. All the concepts in this section can be found in [12], [13], and [14]. These references can be also used for further reading and deeper understanding of stochastic optimization.
Given the probability distribution of the uncertain input data, a straightforward approach is to calculate the expected value of the uncertain parameters and solve the resulting *deterministic equivalent* problem.
A more interesting approach is to represent the uncertain input data as a set of scenarios with an associated probability of occurrence. Thus, a stochastic optimization problem can be formulated which takes into account what may happen in every scenario weighted by the corresponding probability of occurrence. As a result, the solution of the problem is the best action taken into account the possible realizations of the uncertain input data. Depending on the number of considered scenarios, the size of the problem may become very large. This issue will lead to important subjects on the stochastic programming theory as scenario reduction techniques or decomposition techniques to solve huge problems. These questions are out of the scope of this introductory section but it is interesting to build the intuition on the size issues of stochastic problems, and that there are a theory and tools, both from the modeling and the algorithmic points of view, which deal with that problem [15].
Given the inherent structure of an optimization problem where some decisions have to be made in a given moment taking into account uncertainties about the future, the so-called *two-stage stochastic problems* can be defined.
The following equation (11) states a generic objective function of a two-stage stochastic minimization program:

$$minimize \ f(X) + \mathrm{E}\left[g(X,Y,\xi)\right] \qquad (11)$$

In the equation (11), X is the set of the so-called *first stage* variables, also known as *here-and-now* decisions. Y is the set of *second stage* variables, or *wait-and-see* decisions, while ξ is the set of random variables. These random variables are modeled as a set of plausible scenarios with an associated probability of occurrence. The operator E calculates the expected value of the function *g* for the considered scenarios. First-stage decisions are the actual decisions of the decision making problem which have to be implemented at the time of solving the optimization problem. On another hand, second stage decisions are made once the random variables take values, i.e, in a particular scenario. Second stage decisions are not actually implemented but just taking into account into the optimization process.

Thus, the interpretation of the objective function of a two-stage stochastic problem is to find a set of first stage decisions that are optimal taking into account several scenarios, with an associated probability of occurrence, which model the uncertainty about the future.

Uncertainty may also affect input data in the constraints. For example, if considering a linear program, matrix *A* and/or vector *b* may be uncertain. Such an uncertainty is also included in the scenario definition. The resulting problem replicates the constraints of the deterministic version of the problem which have to be respected in all the considered scenarios.

Lastly, given the intrinsic temporal relationship among first-stage and second-stage decisions variables, a special case of constraints need to be added to the two-stage stochastic problem. These constraints are called *non-anticipativity constraints* and they guarantee that first-stage decisions are considered in the second-stage process., i.e, second-stage decisions are calculated once first-stage decisions have been already made and for a given scenario representing one realization of random variables.

Thus, a common structure of a two-stage stochastic program is shown in Figure 14:

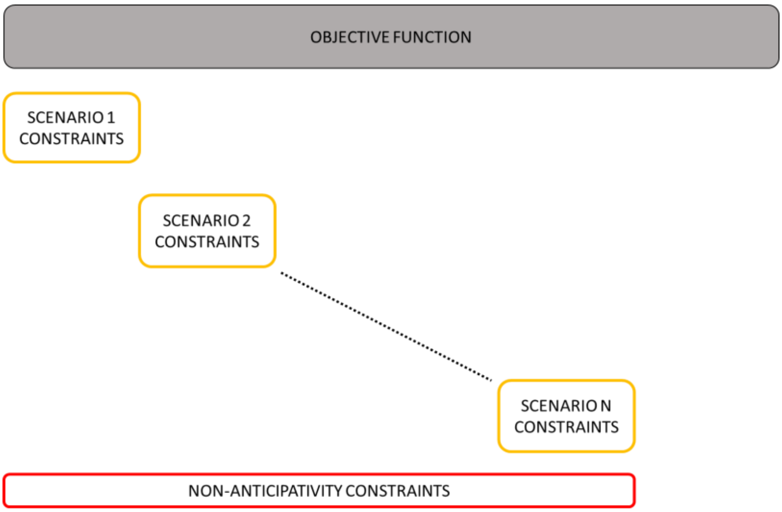
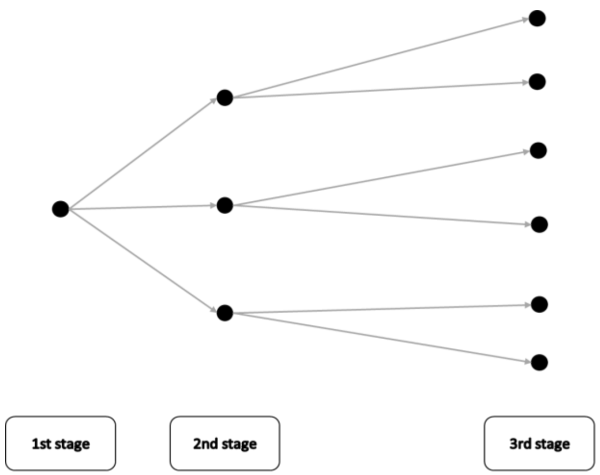


Figure 14.- Typical structure of a two-stage stochastic program

A generalization of the two-stage problem is to consider more than one decision point. It is possible to think about decision-making problems where decisions are made in several time slots in such a way that new decisions depend on past decisions, past realizations of random variables and plausible future scenarios of the uncertain parameters. This approach leads to the so-called *multi-stage stochastic problems*. In this problem, a scenario tree is defined to model the uncertainty along the time span of the problem and a policy is proposed to define the optimization actions that will be taken in every time spot as a function of past decisions and past random realizations.
A representation of a 3-stage stochastic program is shown in Figure 15, which may be straightforwardly generalized to any n-stage stochastic problem. In this figure, $x^{(k)}$ represents the decisions made in stage *K* while $w^{(k)}$ represents the actual realization of the uncertainty after the decision in stage *k* is made but before the decision in stage *k+1* is made.



$x^{(1)}$ $\quad x^{(2)} = f(x^{(1)}, w^{(1)})$ $\quad x^{(3)} = f(x^{(1)}, w^{(1)}, x^{(2)}, w^{(2)})$

Figure 15.- Scenario tree for a 3-stage stochastic problem.

- Robust optimization

A different approach to deal with uncertain data when modeling a decision making task as an optimization problem is the so-called *robust optimization* framework [16]. Under this approach, an uncertain-but-bounded model of input data is used. Thus an *uncertainty set* is defined as that of allowable values for the

input data. A solution to a robust optimization problem is required to be robust feasible, i.e, it has to satisfy the constraints whatever be the values taken by the uncertain parameters as long as they fall into the uncertainty set. This approach, although originated around 1970, just started to be developed fast since 20 years ago.
The definition of the uncertainty set is really important to get to meaningful solutions. If the uncertainty set is too big, the problem will be really robust but the optimal value may be seriously damaged. On another hand, if the uncertainty set is too small, there is a risk of the problem to not be as robust as desired. Thus, how to define a meaningful uncertainty set is an important modeling issue for a given problem.

3.2.3 Application of optimization to power systems problems

The utilization of optimization theory to approach kind of problems appearing in the vast area of power systems has been ubiquitous. In this section, some of these problems are presented and some literature review of research papers dealing with them is provided.

3.2.3.1 Introduction

The utilization of optimization theory is ubiquitous to face power systems problems. The goal of this section is to provide some examples of how the optimization theory is applied to solve different kinds of problems arising in the study of power systems. These problems are classified considering two criteria. The first one has to do with who is facing the problem, i.e., problems can be faced by the system operator, by the market operator or by any agent or group of agents producing and/or consuming electricity. In particular, just renewable resource-based generators are considered in this section. The second one has to do with the time scale concerned by the problem.

	TIME SCALE			
	CYCLE SCALE	SECONDS – MINUTES	HOURS - DAYS	MONTHS - YEARS
MARKET / SYSTEM OPERATOR	Stability	Power Quality	Economic Dispatch Unit Commitment	Capacity Planning
AGENT RENEWABLE ENERGY GENERATOR	Power Quality	Power Quality Regulation Market	Bidding Strategy Market Participation	Investment Decisions

Figure 16.- Problems in power systems

In Figure 16 several problems arising in power systems are presented. Those problems in the millisecond time scale, such as stability or power quality problems are not considered in this section. Instead, problems with a time span of several minutes up to several years and faced by both system operator and renewable energy generator companies are presented.

3.2.3.2 Unit Commitment problem.

First, the unit commitment problem, usually referred to as UC problem, deals with the decision that the system operator has to make in order to assign which power generation units will be on/off and the actual value of power to be delivered by those decided to be online in a given time step. These decisions are to be made while respecting several constraints such as power balance, capacity limit, minimum up and down times, ramping constraints, etc.
This problem results to be highly complex because of several reasons. On the one hand, the number of variables and constraints used to be high, and often nonlinear. Moreover, its discrete nature implies the existence of binary and/or integer variables which leads to mixed-integer optimization problems structure. On another hand, it appears an inherent uncertainty linked with data concerning the load in the system, the available renewable generation or the power plants reliability. Thus, optimization under uncertainty frameworks has been treated extensively in the research community to solve this problem. For example, the unit commitment problem taking into consideration the uncertainty in the generation from renewable resources and the challenge of the presence of electric vehicles is considered in [17]. In this work, a robust approach is proposed.

Similarly, the uncertainty in load and wind generation are considered under a robust multistage approach in [18], and the UC problem considering nodal load uncertainty is cast as a multistage robust problem in [19]. A multistage approach is also proposed in [20] considering the uncertainty in the wind and solar generation. A two-stage mixed-integer linear stochastic program is proposed to schedule the operation of a set of natural gas-fired power plants in [21]. In this problem, the first stage variables represent the day-ahead scheduling while the second stage variables represent real-time operations in every scenario modeling the uncertainty related to natural gas prices and gas availability. A two-stage stochastic model is also proposed in [22] for the UC problem considering uncertainty in both load and wind power generation.

3.2.3.3 Planning and investment decisions

Another application of optimization frameworks under uncertainty is aimed at solving long-term decision problems. In the scope of power systems, these problems have to do with investment decisions both from a system operator and from an independent operator points of view. In the first case, the system operator needs to make decisions in order to take the best actions to guarantee that the power system will keep on working reliably and safely under the foreseeable changes concerning, for example, a long-term variation of the demand, raising of generation from renewable resources, etc.

In the second case, an existing or a potential generator may have to make decisions concerning new investments in either existing power plants or new generation assets. These long-term decision problems are highly affected by uncertainty and they have also been treated extensively by the research comunity.

For example, a transmission expansion planning problem is modeled as a mixed-integer nonlinear optimization problem in [23]. In this problem, uncertainties associated with load and wind power generation are considered. A transmission expansion problem is also solved in [24]. In this work, a multiobjective and multiyear formulation is proposed and the uncertainty concerning the availability of generation units, transmission lines, wires, and transformers are handled by a MonteCarlo simulation approach. In [25], a framework for transmission and wind power expansion planning is modeled as a stochastic bi-level optimization problem. In this problem, a set of scenarios is defined to model the uncertainty on load and wind generation.

An equivalent problem to the transmission expansion can be defined for the distribution network. A two-stage stochastic problem is proposed to decide the

size of several energy storage systems to be installed in the distribution network In [26]. Both generation and demand uncertainties are considered.
A scenario-based stochastic optimization approach to find the best alternative for location, size and operational strategy of the distribution network assets such as lines, transformers, generators, etc, under uncertainty in demand and renewable generation is proposed in [27].
A model for evaluating investment decisions in renewable projects under uncertainty is proposed in [28]. The types of uncertainty considered include the price of electricity, regulatory policies, technological progress and weather conditions among others.

3.2.3.4 Operations and participation in the power market.

The operational problems dealing with the participation of generator agents in the electricity markets is another broad area of application of optimization theory. In particular, the problems considered in this thesis fall into this category. For example, the scheduling problem of a thermal power producer participating in a pool-based electricity market is considered in [29]. A price taker assumption is made and uncertainty in the electricity price is taken into account. This uncertainty is modeled by scenarios and thus a stochastic mixed integer linear programming approach is proposed. The scheduling problem of a gas-fired generator is considered in [30]. A data-driven risk-averse stochastic approach is proposed to optimize its participation in real-time market.
Recently, operational problems concerning renewable energy based generators have become very popular in the research community. In particular, problems concerning solar power plants and wind farms have received a lot of interest. In those cases, an extra issue arises when dealing with this kind of problems: both wind energy and solar irradiation are not known when the solution to the problem needs to be found. Thus, an optimization under uncertainty framework should be considered.
It is in this framework where this thesis actually falls. In the next chapters, specific problems of a wind farm participating in power markets under uncertainty are proposed and a detailed literature review is also provided.

3.3 Machine learning techniques

Machine learning is a broad concept that embraces a good number of techniques to extract information from a certain set of data. This section is not aimed at providing an overview of machine learning concepts, algorithms, and/or

techniques at all. Instead, the goal of this subsection is to present the concepts that will be used later in this thesis.
With this goal in mind, the machine learning techniques are split into two main groups: unsupervised and supervised learning.

3.3.1 Unsupervised learning.

Unsupervised learning is a machine learning problem where a labeled dataset is not available. Among all the unsupervised learning problems, we focus on the one called *clustering*.
In a clustering problem, the input is a set of arrays representing something, for example, a picture or a time sequence of data, and the goal of the machine learning task is to find groups of points in the dataset which are similar to each other. The output of the machine learning problem is a set of groups, referred to as *clusters*, defined by a *centroid* and a set of data points assigned to each cluster. An example of a clustering problem is shown in Figure 17.

Figure 17.- Clustering over a 2-dimension dataset

While keeping in mind the dataset available and the goal of the clustering techniques, a description of the problem from a mathematical point of view and the presentation of two of the most popular algorithms to solve such a problem are presented in the following:

3.3.1.1 Clustering

Firstly, let's introduce the concept of *probabilistic distance* among two discrete probability distributions. This distance can be defined by the following equation (12).

$$d_r(F,\hat{F}) = \left(\min_{y_{i,j} \in [0,1]} \left\{ \sum_{i=1}^{N} \sum_{j=1}^{M} y_{i,j} \cdot \left\| z_i - \hat{z}_j \right\|^r \;/\; \sum_{j=1}^{M} y_{i,j} = p_i \;,\; \sum_{i=1}^{N} y_{i,j} = q_j \right\} \right)^{\frac{1}{r}} \tag{12}$$

In this equation, F and $\hat{F}$ are two discrete probability distributions. z_i represents datapoints in *F* (*N* elements) and p_i is the probability associated to each of them; analogously, $\hat{z}_j$ and q_j stand for elements in $\hat{F}$ (out of *M* elements) and the corresponding probability. The probabilistic distance is defined as a minimization problem in variables $y_{i,j}$ which weights all the distance among points of both distributions. The assignment of these weights have to maintain the probabilities of occurrence of every data points, i.e., the total assignment of weights associated with one point has to match its probability in its own distribution.

In general, a clustering technique aims at finding a discrete distribution with smaller support than the original one minimizing a probabilistic distance between them. Thus, in a clustering problem, F is the original discrete distribution with N elements, whereas $\hat{F}$ is the target discrete distribution with M elements. These *M* elements correspond to the number of clusters aimed at representing the original distribution, thus becoming the decision variables. Hence, the clustering problem can be set as the following optimization problem (13):

$$\underset{\hat{z}_1,\ldots\ldots,\hat{z}_M}{\text{minimize}} \left\{ \left(\min_{y_{i,j} \in [0,1]} \left\{ \sum_{i=1}^{N} \sum_{j=1}^{M} y_{i,j} \cdot \left\| z_i - \hat{z}_j \right\|^r \;/\; \sum_{j=1}^{M} y_{i,j} = p_i \;,\; \sum_{i=1}^{N} y_{i,j} = q_j \right\} \right)^{\frac{1}{r}} \right\} \tag{13}$$

Following, two algorithms to solve the clustering problem are presented. These algorithms are called *k-means* and *k-means++*.

3.3.1.1.1 *K-means* algorithm

The clustering problem cast as an optimization problem as to equation (13) is a non-convex NP-hard problem. To deal with this situation, a local optimum of this optimization problem can be found by modifying the problem to perform a hard assignment of data points to each cluster, i.e, each point of the original dataset can be only assigned to one cluster. To do so, constraints need to be rewritten as stated in (14) and decision variable $y_{i,j}$ will become a binary variable.

The clustering problem just defined may be solved by applying the k-means algorithm to the original dataset. In the k-means algorithm, the Euclidean distance is considered (i.e., *r* = 2).

$$\underset{\hat{z}_1,\dots\dots,\hat{z}_M}{minimize} \left\{ \left(\underset{y_{i,j} \in \{0,1\}];q_j \geq 0}{min} \left\{ \sum_{i=1}^{N} \sum_{j=1}^{M} y_{i,j} \cdot \left\| z_i - \hat{z}_j \right\|^r \ / \ \sum_{j=1}^{M} y_{i,j} = 1 \,, \ \sum_{i=1}^{N} y_{i,j} = q_j \cdot N \right\} \right)^{\frac{1}{r}} \right\} \quad (14)$$

Thus, the k-means algorithm proposes the next sequence of operations to solve the problem by finding a local optimum. This sequence is represented in Figure 18.

Step 1 : Initialize the cluster centers.
In this first step, the number of clusters needs to be defined.

Step 2 : Assign observations (data points) to each cluster based on a minimum distance criteria

$$Z_i \leftarrow \underset{j}{argmin} \ \| \ \hat{z}_j - z_i \ \|_2^2$$

Step 3 : Revise/update cluster centers as mean of assigned observations.

$$\hat{z}_j \leftarrow \frac{1}{n_j} \sum_{i:z_i = j} z_i$$

Equivalently,

$$\hat{z}_j \leftarrow \underset{z}{argmin} \sum_{i:z_i = j} \| \ \hat{z} - z_i \ \|_2^2$$

Step 4 : Repeat 2 and 3 until convergence.

Thus, the k-means algorithm can be seen as an alternating minimization algorithm or a coordinate descent algorithm which guarantees local convergence.

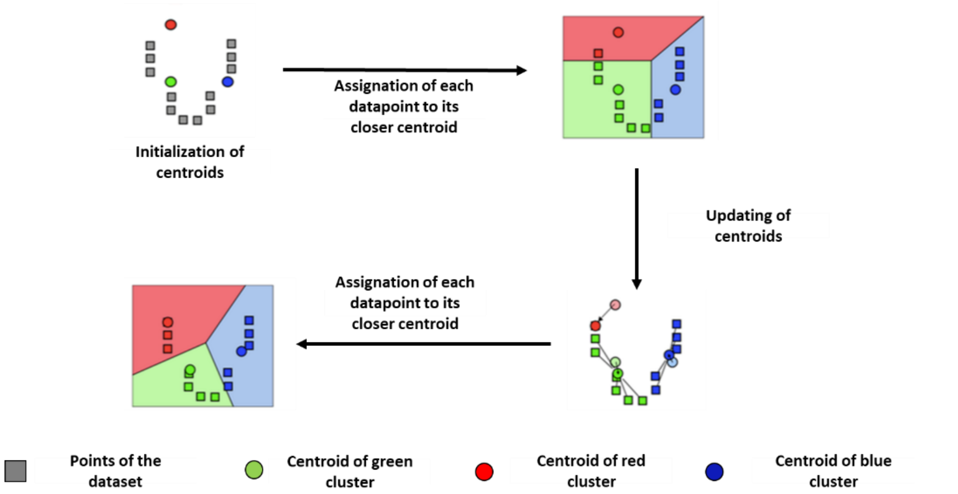


Figure 18.- Iterative process in the k-means algorithm

A common issue for non-convex problems is the strong dependence on the initialization concerning the quality of the local minimum obtained. In order to handle this issue, a step forward may be given.

3.3.1.1.2 K-means ++

This algorithm focuses on the initialization step of the *k-means* algorithm. It aims at finding a good guessing for the first set of centroids that will be used in the first iteration of the *k-means* algorithm. The steps of this algorithm are shown in Figure 19.

Step 1: Choose a cluster center out of the whole dataset randomly.
Step 2: Calculate the distance from every point of the data set to the defined centroid.
Step 3: Choose the second centroid as the farthest point to the first centroid.
Step 4: Calculate the distance from every point to its closest centroid.
Step 5: Choose the third centroid as the data point with the biggest distance computed.

Step 6: Repeat sequence until all the necessary clusters is defined.
Step 7: Run a k-means algorithm with the defined clusters as an initialization step.

Although it is computationally more expensive to initialize the k-means in this way, it is usually worth due to faster convergence and better local optimum obtained.

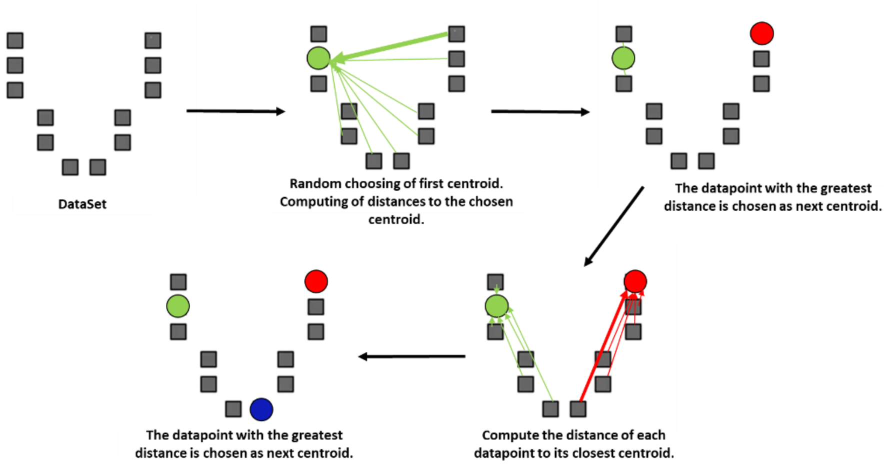


Figure 19.- K-means++ initialization

3.3.2 Supervised learning. Neural Networks.

Unlike *unsupervised machine learning* problems, a *labeled dataset* is available when dealing with *supervised learning* problems. A labeled dataset is made up of a set of input data and the known corresponding output. Thus this pair input/output is used to train the model and found a good representation of the underlying model.
The most popular techniques for supervised learning are *statistical learning algorithms*, *support vector machines* (SVM), and *neural networks*.
In this subsection, the focus is put on neural networks in order to provide a brief introduction to a vast area of knowledge that will be applied to some specific problems in coming chapters.
Firstly, the concept of *feedforward neural network* is explained. Afterward, the limitations of this concept are stated and a new architecture is presented to overcome such limitations, the *recurrent neural networks*.

3.3.2.1 Feedforward neural networks

Firstly let's introduce the concept of *perceptron*. The perceptron is the basic unit over which a feedforward neural network is built.

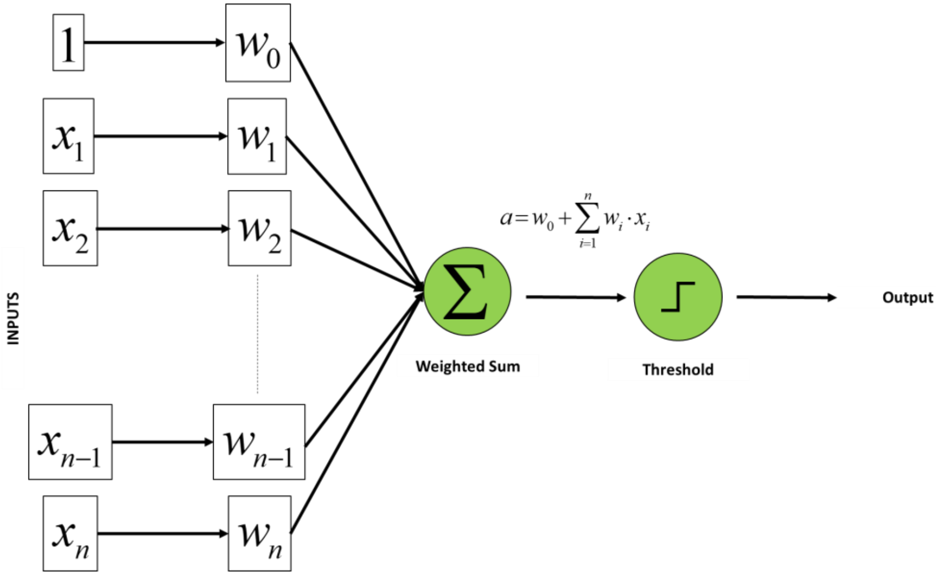


Figure 20.- Structure of a perceptron.

The simplest perceptron, also referred to as McCulloch-Pitts neuron [31], is represented in Figure 20. A n-dimension array is the input of a perceptron. Each component of the array is assigned a *weight.* A weighted sum of the inputs plus a constant value called *bias* is calculated and fed into a so-called *activation function*. In the most simple case, a step function is defined as the activation function. The perceptron defined in this way is a binary classifier, i.e., given an input, the perceptron assign it to one of the two possible outputs.

Obviously, given the simplicity of the model, it is expected that a single neuron can only make simple decisions.

In order to model more complex situations, a generalization of the neuron concept is given by the *multilayer feedforward neural networks* as shown in Figure 21.

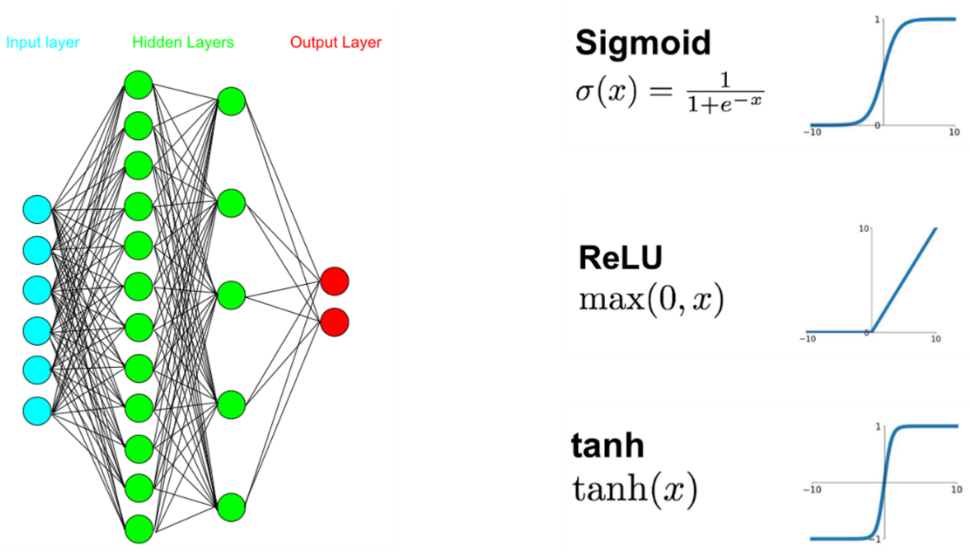


Figure 21.- Feedforward NN and several activation functions.

Three kinds of layers are defined in a multilayer feedforward neural network. On one side, an *input layer* is defined as in the case of the simple perceptron. On another side, an *output layer* with as many neurons as needed is defined. Between these two layers, an arbitrary number of *hidden layers* is added in order to provide the network with the desired modeling capabilities. The neural network thus defined uses to be *fully connected*, i.e., all the neurons are connected with all the neurons of the next layer.

The way this network works is a generalization of that of the simple perceptron. Thus, each neuron of the first hidden layer calculates the weighted sum of all the inputs and applies to it as an activation function. Several activation functions can be used, being the sigmoid the most popular. Several activation functions are shown in Figure 21. The output of each neuron is connected to every neuron in the next layer which will repeat the process. This flow of information from input to output is the reason why these networks are referred to as *feedforward* nets.

The modeling capabilities of a feedforward neural network, once the structure of the net is defined, is given by the definition of the weights and bias on every neuron and layer. In a supervised learning framework, where a labeled dataset is available, the process of deciding which weights and bias are the best to model a given problem is called the *training of the neural network*.

A labeled dataset is a set of pairs input/output. This dataset is also referred to as *training set*. The training of the neural network is an iterative process where the first step is to initialize the weights and bias of the whole network. Then, the first input of the training set is fed into the network and the output is calculated as to the process explained before. The calculated output of the network is compared with the actual output and thus an error can be calculated. Once the error is calculated a process to update the weights and bias is defined and the process starts it over with another sample of the training set. This iterative process ends when the error is smaller than a predefined threshold.
Usually, a *batch* of elements of the training set is fed into the network in every iteration for stability reasons of the training process. Moreover, the whole training set can be used more than once during the training process. Every time the dataset is used is referred to as an *epoch*.
The idea of the training process is that in every iteration the weights and bias be updated in a way that minimizes the error function. This minimization problem is highly non-linear due to the presence of the activation functions. Most of the algorithms used to face this problem belongs to the family of Gradient Descent algorithms: Stochastic gradient descent, Adam, Nesterov accelerated gradient, and others.
All these algorithms need at some point to calculate the gradient of the error, i.e, how the error depends on the weights and bias in order to update them for the next iteration. The most popular algorithm used to calculate this gradient is called *backpropagation* algorithm [32].

- Recurrent Neural Networks.

The *recurrent neural networks (RNN)* include loops in the structure of the network, allowing information of one-time step to persist and condition the next steps [33]. In Figure 22, an RNN is represented. The utilization of this structure has been extremely successful in problems involving sequence data such as speech recognition, language modeling and translation, image captioning, etc.
The unfold representation of the loop makes it clearer why this structure is naturally used to model sequence data.

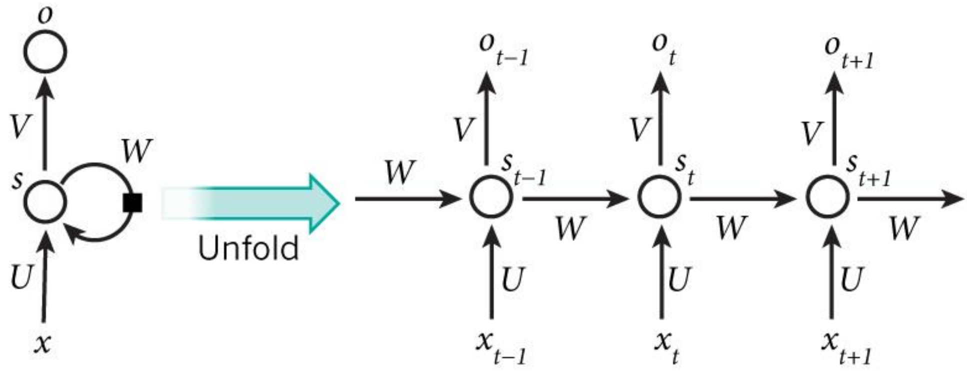


Figure 22.- Recurrent Neural Network.

In every time step, it is possible to have as many layers as needed. Moreover, in every time step not just the output of that neuron is calculated but also the so-called *hidden state,* which is passed to the next time step and will be concatenated with the input in that time step. That is the mechanism to pass information from one time step to the next. It is to note, that the weights and bias, i.e.,the parameters of the net, are shared among all the time steps.

The training process of an RNN is quite similar to that of a feedforward neural network. In this case, the backpropagation algorithm used in the feedforward case is modified in order to better fit the structure of the RNN. The resulting algorithm is called *backpropagation through time (BPTT)* [34].

There are cases where the time sequence of input data may be quite long. In theory, RNN is capable of learning under such conditions but, in practice, its performance is rather poor. This is due to the fact that the gradient tends to either vanishes or go to infinite when the error is propagated through long sequences.

To overcome this limitation, researchers have proposed RNN featuring more complex neurons. The goal of this more complex neurons, also called *cells* in this context, is to provide each time step with the capability to decide what information is to be passed to the next cell, deleted or updated. One of the most popular cells is the *Long Short-Term Memory (LSTM)* [35]. In Figure 23 is shown a simple RNN in the upper figure and an RNN featuring LSTM cells in the bottom figure [36].

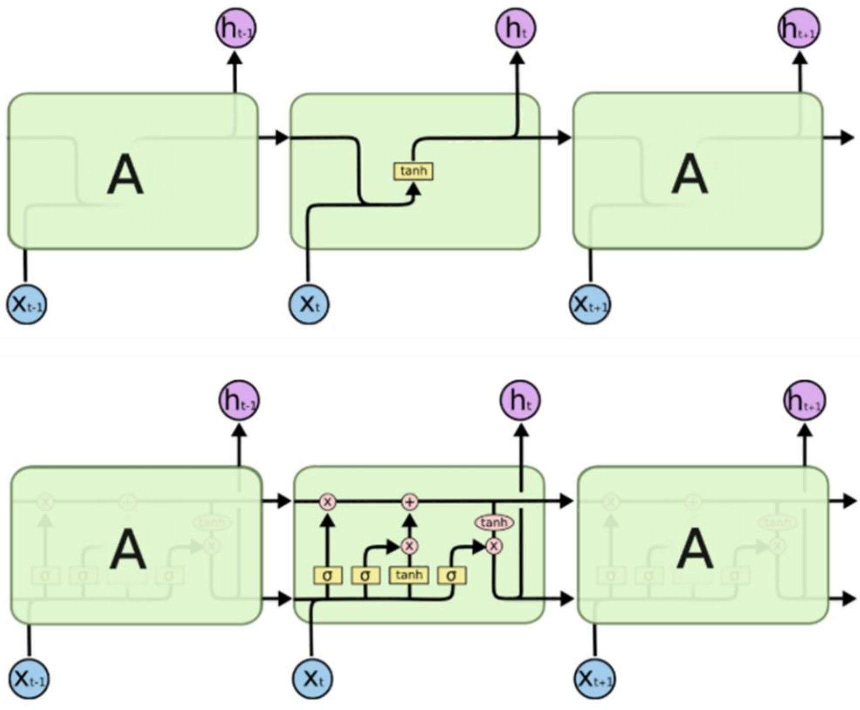


Figure 23.- Upper: Simple RNN; Bottom: LSTM-RNN

The key aspect of the LSTM cell is that one more output to the cell is added, the so-called *cell state*. This cell state run through the entire chain and it is controlled by three gates that are able to add or remove information in it depending on the current input and past cell states.

3.4 Conclusions

A set of mathematical concepts and tools were presented in this chapter. The concepts are presented in a not formal way in order to give a qualitative introduction to those not familiar with optimization and machine learning. The goal is to give the reader a basic knowledge of the tools that are used in the coming chapters. Thus, firstly, the concept of an optimization problem from a mathematical point of view is introduced. The importance of including ways to

consider uncertainty in the input data is also highlighted and two approaches to handle it are presented: stochastic and robust optimization.
Machine learning is a vast area of knowledge in the applied mathematics world. It has shown a great power to deal with huge amounts of data and extract valuable information out of them. In this chapter, clustering techniques, as an example of unsupervised learning, and neural networks, as an example of supervised learning, were presented. Both techniques are used in coming chapters.

CHAPTER 4

4 Evaluation of the uncertainty in the scheduling of a wind and storage power plant participating in day-ahead and reserve markets.

One of the main problems faced by a renewable energy based power plant operator when deciding its strategy to participate in the power markets is that data concerning both renewable energy availability and market parameters are not known when the decisions are to be made. In this chapter, an agent consisting of a wind farm and an energy storage system is considered and a methodology to evaluate how much does it cost the uncertainty associated with available wind energy, market prices, and regulation requirements is proposed. For such a goal, the decision-making problem of such a plant participating in day-ahead and reserve markets is modeled as a Mixed Integer Convex program. A real-world case of a wind farm located in northwestern Spain is studied and several simulations are performed over one year in order to show, in one hand, the importance of participating in reserve markets, and in another hand, the effects of uncertainty. Some results of the work described in this chapter were published in [37].

4.1 Introduction

One way to overcome the drawbacks associated with the use of renewable energy resources is to use energy storage systems (ESS) to be able to manage the generation from renewable energy resources appropriately [38]. With this idea, a wind farm (WF) as a renewable energy source and an ESS is considered in this chapter.The resulting system will be referred to as a Wind and Storage Power Plant (W&SPP). The traditional way to operate a system of this kind is to consider such a system participating in the day-ahead energy market (DAM) following the strategy of buying energy during low price periods to be sold during peak hours. Several authors have reported the lack of economic feasibility for such a strategy [39], proposing a more comprehensive participation in the electricity markets instead. In particular, [40] shows that the participation of a pump-hydro energy system (PHES), which is a particular case of ESS, in the reserve market (RM) is mandatory to get economic feasibility. The advantages of operating jointly a wind farm and a pump hydro plant as ESS in the DAM are shown in [41]. Not too much research attention has been devoted to the modeling of RM in the short term scheduling problem of a wind farm [42]. For example, [43] models the participation of a hydro-pump power system in the RM without considering the uncertainty effects in the results, [44] discusses two strategies for a wind farm to bid under uncertainty in both DAM and RM and [45] proposes an adjustable interval approach to handle the wind power uncertainty in the problem of scheduling of a wind farm operating in both markets. However, several papers have studied the impact of the uncertainty of wind power availability in different kind of problems. Just to name a few, [46] proposes a stochastic Mixed Integer Linear Programm to asses the impact of the wind uncertainty on ESSs and thermal units scheduling in Unit Commitment problem and; [47] considers several scenarios to propose a two-stage optimization problem of a wind-ESS system while also considering demand response capabilities.
Two main questions are to be answered in this chapter. On the one hand, what is the influence of the uncertainty in the net income achievable by a W&SPP participating in both DAM and RM and, on another hand, what are the benefits of including an ESS in such a system.

Thus, the main contributions of this chapter are:

- Develop a deterministic model of a W&SPP participating in DAM, RM, and BM. Imbalances and regulation capabilities both upwards and downwards are allowed in both modes of operation and in both markets.

- Evaluate the increase in the net income that a W&SPP can get by participating in the RM.
- Evaluate the cost of the uncertainty peculiar of several parameters in the model such as market prices, available wind energy, and requirements of regulation by the system operator (SO) in the RM.

4.2 Nomenclature

Parameters

T Number of periods.

l_t Duration of each period.

$\hat{P}_t^{wind}$ Available wind power in time t.

E_0^{ess} Initial energy stored in the ESS.

η_{in} Charging efficiency of the ESS.

η_{out} Discharging efficiency of the ESS

$\overline{E}^{ess}$ Maximum energy stored in the ESS .

$\overline{P}^{ess}$ Maximum power to/from ESS.

$SOC_t^{\min}$ Minimum state of charge of ESS

β_t^{dam} Energy price in the DAM.

$\lambda_t^{bm,up}$ Energy price of deviation up in BM.

$\lambda_t^{bm,dw}$ Energy price of deviation down in BM.

$\varphi_t^{bm}, \gamma_t^{bm}$ Auxiliary parameters.

γ_t^{rm} Price of power reserve.

$\beta_t^{rm,up}$ Energy price under regulation up.

$\beta_t^{rm,dw}$ Energy price under regulation down.

$\beta_{desv,t}^{rm,up}$ Price of energy not supplied for regulation up.

$\beta_{desv,t}^{rm,dw}$ Price of energy not supplied for regulation down.

$\pi_t^{rm,up}$ Ratio of reserves required for regulation up.

$\pi_t^{rm,dw}$ Ratio of reserves required for regulation down .

$R_t^{rm,up}$ Ratio between reserve up and total reserve.

Continuous Variables

P_t^{wind} Wind power used in time t.

E_t^{ess} Energy stored in time t.

$P_t^{ess,in}$ Power entering the ESS in time t.

$P_t^{ess,out}$ Power delivered by the ESS in time t.

SOC_t State of charge of ESS in time t.

P_t Power to/from W&SPP in time t.

$\hat{P}_t^{dam}$ Power offered in the DAM for every hour of day D.

P_t^{dam} Power actually delivered/taken in time t in the DAM.

Δ_t^{bm} Participation in the BM.

$\Delta_t^{bm,up}$ Deviation up in BM.

$\Delta_t^{bm,dw}$ Deviation down in BM..

$\hat{P}_t^{rm}$ Total power committed in the RM.

$\hat{P}_t^{rm,up}$ Power committed for regulation up.

$\hat{P}_t^{rm,dw}$ Power committed for regulation down.

$\hat{E}_{t,reg}^{rm,up}$ Energy required by SO for reg. up.

$\hat{E}_{t,reg}^{rm,dw}$ Energy required by SO for reg. down

$E_t^{rm,up}$ Energy actually offered for reg. up.

$E_t^{rm,dw}$ Energy actually offered for reg. down.

$D_t^{rm,up}$ Deviation in regulation up.

$D_t^{rm,dw}$ Deviation in regulation down.

Binary Variables

u_t 1 if ESS is charging. 0 otherwise.

All parameters and variables representing power are expressed in MW. Accordingly, all parameters and variables representing energy are expressed in MWh. As to market prices, euros are considered as the currency.
The remaining of this chapter is organized as follows. Firstly, the considered system and the power market it is involved in, are described. Afterward, the mathematical model to describe the aforementioned problem is developed. Lastly, a real-world application of the developed model is presented and some conclusions are discussed and highlighted.

4.3 Description of the system and electricity markets.

The considered system puts together a wind farm and an energy storage system operating as a single unit. Such a system is called a Wind and Storage Power Plant and interacts with the utility as a single unit, selling or buying energy to/from the grid while allowing internal power flow from the WF to the ESS. The objective of this system is to increase the manageability of the wind farm in an attempt to get a dispatchable generation unit.
The mechanisms of the market described in this chapter refer to those of the Iberian electricity market which has been already introduced in Chapter 2. In particular, in this chapter, the W&SPP is considered to participate in day-ahead, balancing, and reserve markets. Thus, on the one hand, the W&SPP operator will send its offer to participate in the DAM in the morning of day D-1 (being D the day when the energy will be delivered). This offer consists of the hourly amount of energy that the power agent is willing to sell or buy at the corresponding price at that hour. It is possible to deliver a different amount of energy with respect to what was committed in the DAM in every time slot. This situation is handled by the balancing market (BM) as already explained in Chapter 2. On another hand, the W&SPP is also allowed to participate in the reserve market. Also during day D-1, the W&SPP operator will place its offer to participate in the RM. This offer consists of an amount of power that the W&SPP is able to supply or consume in each hour of day D and which is therefore available for regulation tasks, which is called *the regulation band*. During day D the SO will require some percentage of the power committed in the RM to be actually delivered by the W&SPP. Regulation requirements can be either upwards or downwards. Let's define both kinds of regulation for generating mode of operation. Specifically, regulation upwards means to be able to supply a surplus of energy and regulation downwards means to supply less energy for regulation goals. With a similar reasoning, in importing mode, regulation upwards is defined as importing less energy and, conversely, regulation downwards is to import more energy for

regulation tasks. In both cases, regulation upwards aims at raising the frequency of the system while regulation downwards aims at decreasing it.
The operation in these markets is shown in Figure 24. Decisions on how much to offer in both DAM and RM are made in day D-1. These decisions are made in an uncertain environment. For example, market prices, available wind energy, and regulation requirements by SO are not known in day D-1. Thus, the influence of the uncertainty affecting these parameters needs to be studied.

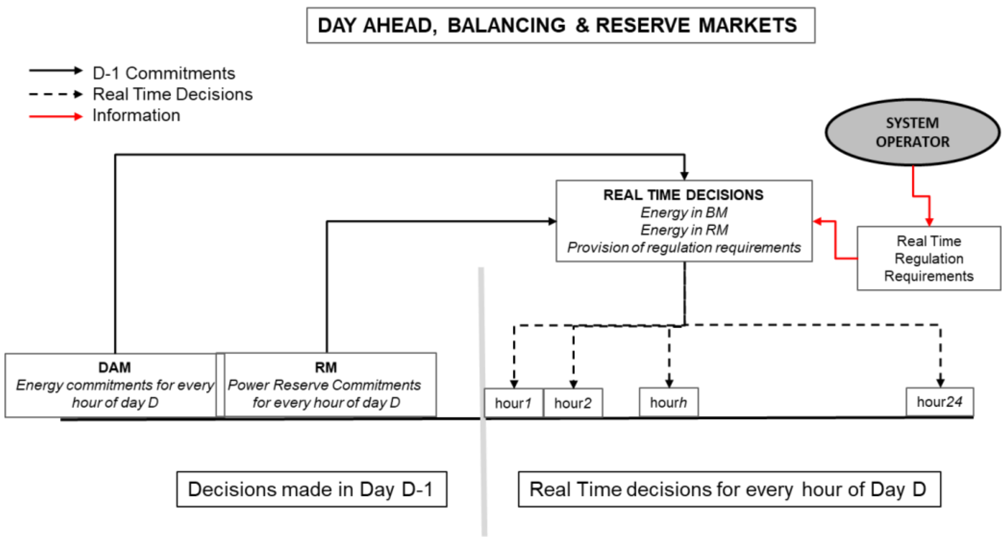


Figure 24.- Participation in DAM, BM, and RM

4.4 Description of the deterministic model.

In this section, the mathematical model of the W&SPP participating in the electricity markets described above is presented. The W&SPP is supposed to be a price taker agent meaning that it is not able to influence the market price no matter how much power/energy it offers. Another assumption is that all the parameters are supposed known when decisions are made, thus resulting in a deterministic model. All the functions taking part to the model are convex or affine functions while continuous and binary variables are used, so a Mixed Integer Convex Program is developed and applied. Firstly, the model for a W&SPP participating only in the DAM and BM is presented. Secondly, the participation in the RM is added to the model.

4.4.1 W&SPP participating in DAM.

The first case to be considered is the W&SPP participating in the DAM and BM. In this situation, imbalances are allowed in both modes of operation: selling (exporting) and buying (importing) power. The objective function aims at maximizing the net income of the operation of the system as stated by the equation (15).
All the subindexes *t* in this chapter refers to $t = 1, ..., T$:

$$maximize \quad l_t \cdot (\sum_t \beta_t^{dam} \cdot \hat{P}_t^{dam} + \sum_t \lambda_t^{bm,up} \cdot \Delta_t^{bm,up} - \sum_t \lambda_t^{bm,dw} \cdot \Delta_t^{bm,dw}) \tag{15}$$

It is important to note that in the DAM, it is equivalent to talk about power and/or energy because the time step considered is one hour. In the equation (15), the first term accounts for the net income due to selling and buying energy in every hour of day D corresponding to DAM. The second and third terms account for the penalties resulting from not matching the commitments taken in day D-1 for participation in the DAM, which is handled in the BM. It is to note that unbalances upwards always are a positive income. On the other hand, imbalances downwards always are a negative income. For example, if the system is exporting power and decides to export more than committed, the extra power will be paid at deviation up price, and if it decides to sell less power it will have to return the money corresponding to that power difference at deviation down price. An analogous reasoning should be made for the case where the system is importing power. The imbalance in the DAM is defined in such a way that it will be considered an imbalance up when it is positive and an imbalance down when it is negative, no matter the mode of operation as in the following equation (16). That definition allows us to avoid the use of binary variables, which is common in this problem [48] while considering separately the imbalances up and down, governed by equations (17) and (18). Thus, the objective function can be rewritten as (19). There are other modeling proposals to avoid the use of binary variables to model the deviations in DAM [49]. Our model generalizes it in the way that is is also valid for the cases where DAM prices are zero.

$$\Delta_t^{bm} = P_t^{dam} - \hat{P}_t^{dam} \tag{16}$$

$$\Delta_t^{bm,dw} = max\left\{-\Delta_t^{bm}, 0\right\} = [\Delta_t^{bm}]^- \tag{17}$$

$$\Delta_t^{bm,up} = max\left\{\Delta_t^{bm}, 0\right\} = [\Delta_t^{bm}]^+ \tag{18}$$

$$minimize \quad l_t \cdot (-\sum_t \beta_t^{dam} \cdot \hat{P}_t^{dam} - \sum_t \lambda_t^{bm,up} \cdot [\Delta_t^{bm}]^+ + \sum_t \lambda_t^{bm,dw} \cdot [\Delta_t^{bm}]^-) \tag{19}$$

This objective function is not linear because (17) and (18) represent convex functions. As a consequence, a typical linear solver cannot be used to handle this problem. For this reason, a convex problems modeling software, such as CVX is proposed to tackle this problem [50]. This software counts on a set of rules to accept a problem as convex. The equation (19) will not be accepted by CVX as a valid convex function because the difference between convex functions is not generally convex. However, in our case, equation (20) always holds [49], thus making equation (19) actually convex. An intuition on why this is so, is shown in Figure 25.

$$\lambda_t^{bm,dw} \geq \lambda_t^{bm,up} \tag{20}$$

$$\varphi_t^{bm} = \frac{\lambda_t^{bm,dw} - \lambda_t^{bm,up}}{2} \tag{21}$$

$$\gamma_t^{bm} = \frac{\lambda_t^{bm,dw} + \lambda_t^{bm,up}}{2} \tag{22}$$

To overcome this situation, the objective function needs to be represented in a more convenient way to be handled by convex programs modeling software. To do so, the difference of the two m*ax* functions appearing in the equation (19) is equivalently expressed as the sum of a linear function plus an absolute value function [51]. For such a transformation, two auxiliary parameters are defined according to equations (21) and (22).

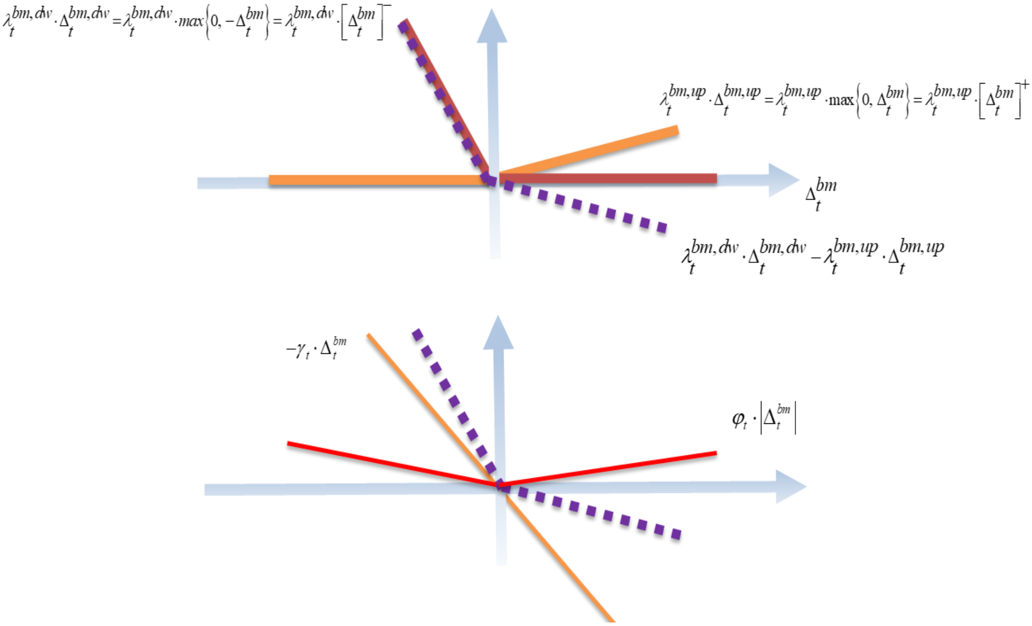


Figure 25.- Transformation of the difference of two *max* - functions

Thus, the objective function may be rewritten as equation (23), where the difference between convex functions is substituted by a convex function (absolute value function) multiplied by a constant (CVX will accept it as convex as long as the constant is greater than zero) summed to a linear function.

$$\textit{minimize} \quad -\sum_t \beta_t^{dam} \cdot \hat{P}_t^{dam} + \sum_t \varphi_t^{bm} \cdot \left|\Delta_t^{bm}\right| - \sum_t \gamma_t^{bm} \cdot \Delta_t^{bm} \tag{23}$$

The next step is to include the model of the W&SPP and the DAM into the optimization problem. To do so, a set of constraints is defined.

$$E_t^{ess} = E_0^{ess} + l_t \cdot \sum_{\tau=1}^{t} \eta_{in} P_\tau^{ess,in} - l_t \cdot \sum_{\tau=1}^{t} \frac{1}{\eta_{out}} P_\tau^{ess,out} \tag{24}$$

Equation (24) sets the energy stored in the ESS in every time step as a function of the initial conditions, the power entering and leaving the ESS and the efficiency of charging and discharging processes.
Equation (25) limits the wind power to that available in the wind farm. Also related with the ESS, equation (26) requires to have the same energy stored at the

beginning and at the end of the period under study (one day in our case) while equations (27), (28), and (29) limits the maximum and minimum energy stored in the ESS.

$$P_t^{wind} \leq \hat{P}_t^{wind} \tag{25}$$

$$E_0^{ess} = E_T^{ess} \tag{26}$$

$$E_t^{ess} \leq \overline{E}^{ess} \tag{27}$$

$$SOC_t = E_t^{ess} / \overline{E}^{ess} \tag{28}$$

$$SOC_t \geq SOC_t^{\min} \tag{29}$$

Constraints (30) and (31) ensure that the power can not enter and leave the ESS at the same time while setting the maximum power that can enter/leave the ESS. The power balance of the systems is defined in the equation (32). Lastly, equation (33) makes the connection between the W&SPP and the power market and equation (34) sets some non-negative constraints.

$$P_t^{ess,in} \leq \overline{P}_t^{ess} \cdot u_t \tag{30}$$

$$P_t^{ess,out} \leq \overline{P}_t^{ess} \cdot (1-u_t) \tag{31}$$

$$P_t = P_t^{wind} + P_t^{ess,out} - P_t^{ess,in} \tag{32}$$

$$P_t = P_t^{dam} \tag{33}$$

$$P_t^{ess,out} \, ; \, P_t^{ess,in} \, ; \, E_t^{ess} \geq 0 \tag{34}$$

4.4.2 W&SPP participating in DAM and RM.

In this case, the objective function also takes into consideration incomes from the RM.

$$minimize \quad -\sum_t \beta_t^{dam} \cdot \hat{P}_t^{dam} + \sum_t \varphi_t^{bm} \cdot \left|\Delta_t^{bm}\right| - \sum_t \gamma_t^{bm} \cdot \Delta_t^{bm} - IRM \tag{35}$$

$$\begin{aligned} IRM = & \sum_t \gamma_t^{rm} \cdot \hat{P}_t^{rm} + \sum_t \beta_t^{rm,up} \cdot E_t^{rm,up} - \sum_t \beta_t^{rm,dw} \cdot E_t^{rm,dw} - \\ & \sum_t \beta_{desv,t}^{rm,up} \cdot D_t^{rm,up} - \sum_t \beta_{desv,t}^{rm,dw} \cdot D_t^{rm,dw} \end{aligned} \tag{36}$$

The objective function (35) includes the income coming from the participation of the W&SPP in the RM as to equation (36). The first term of this equation accounts for the incomes due to the power commitment in the RM, i.e., the offered regulation band. If the SO requires the W&SPP to supply reserve up, that will involve an extra income no matter the system is either in generation or consumption mode. On the other hand, the supply of regulation downwards will produce an extra negative income. The last two terms of (36) accounts for the cost of deviating from the regulation requirements ordered by the SO.
In this model, all the constraints (24)-(34), except equation (33), still applies. However, several constraints have to be added to account for the participation in the RM.

$$\hat{P}_t^{rm} = \hat{P}_t^{rm,up} + \hat{P}_t^{rm,dw} \tag{37}$$

$$\hat{P}_t^{rm,up} \leq \overline{P}^{ess} \tag{38}$$

$$\hat{P}_t^{rm,dw} \leq \overline{P}^{ess} \tag{39}$$

$$\frac{\hat{P}_t^{rm,up}}{\hat{P}_t^{rm}} = R_t^{rm,up} \tag{40}$$

Equation (37) sets the total regulation band as the sum of both regulation up and down. In this model, it is considered that the maximum power capacity eligible for RM corresponds to that of ESS. This is defined in equations (38)-(39). The meaning of this assumption arises as an attempt by SO of just counting on “manageable” capacity, thus excluding the wind power as available for regulation requirements. It is also needed to set the ratio between the regulation up and the total regulation band offered. This ratio has to follow the ratio assigned for the whole system [52] as to equation (40).

$$\hat{E}_{t,reg}^{rm,up} = l_t \cdot \pi_t^{rm,up} \cdot \hat{P}_t^{rm,up} \quad (41)$$

$$\hat{E}_{t,reg}^{rm,dw} = l_t \cdot \pi_t^{rm,dw} \cdot \hat{P}_t^{rm,dw} \quad (42)$$

$$E_t^{rm,up} \le \hat{E}_{t,reg}^{rm,up} \quad (43)$$

$$E_t^{rm,dw} \le \hat{E}_{t,reg}^{rm,dw} \quad (44)$$

$$D_t^{rm,up} = \hat{E}_{t,reg}^{rm,up} - E_t^{rm,up} \quad (45)$$

$$D_t^{rm,dw} = \hat{E}_{t,reg}^{rm,dw} - E_t^{rm,dw} \quad (46)$$

Constraints (41)-(46) sets the energy actually required by the SO, the energy actually delivered by the W&SPP in the RM and the deviation in the RM. It is important to note that the following equation (49) always holds. This means that the system can follow requirements up and down in the same hour.

$$l_t \cdot P_t = l_t \cdot P_t^{dam} + E_t^{rm,up} - E_t^{rm,dw} \quad (47)$$

$$\hat{P}_t^{rm,up}; \hat{P}_t^{rm,dw}; P_t^{rm,up}; P_t^{rm,dw}; E_t^{rm,up}; E_t^{rm,dw} \ge 0 \quad (48)$$

Lastly, the equation (47) sets the energy balance between the system and the market and several nonnegative constraints are defined in (48).

$$\pi_t^{rm,up} + \pi_t^{rm,dw} \le 1 \qquad \forall t \in T \quad (49)$$

4.5 Method to evaluate the influence of the uncertainty.

The scheduling problem of a W&SPP participating in DAM and RM is a decision-making problem under uncertainty. When the decisions are to be made in day D-1, data concerning availability of wind energy, regulation requirements in the reserve market, and prices of energy and reserves are not known. To evaluate the effect of the uncertainty in these parameters of the problem a perfect information hypothesis is proposed in order to be used as the upper bound of the net income achievable.

- Perfect information hypothesis:

Under this hypothesis, the optimization problem is solved considering perfect knowledge of uncertain parameters. In this case, available wind energy in day D, energy prices, and regulation requirements from SO are supposed to be known and fed into the model. With this assumption, an upper bound on the achievable net income by the W&SPP is calculated as explained in the following Figure 26.

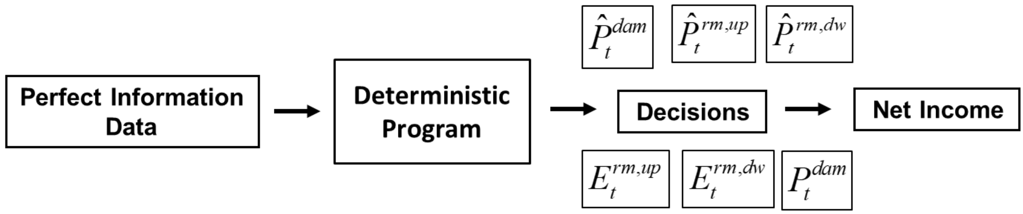


Figure 26.- Perfect information hypothesis.

- Real information hypothesis:

The reality is that in day D-1 data concerning available wind energy, energy prices, and regulation requirements by SO for day D are not known. In order to solve the proposed deterministic problem, some values have to be assigned to those parameters. Once the uncertain parameters are defined, the deterministic problem can be solved and the participation in the DAM and RM is defined. When day D comes, all the guessed parameters take actual values, i.e., uncertainty is revealed. Thus, in real time, decisions to accommodate to these actual values are to be made as shown in Figure 27.
It is important to note that these actions concerning the actual participation in the balancing market and the actual provision of regulation services are computed as an optimization problem. The optimization problem is solved for the 24 hours of day D at the same time as if we knew the actual values of available wind energy and regulation requirements at the same time. This is equivalent to a real-time optimization technique because the operation of the ESS is also decided in day D-1.

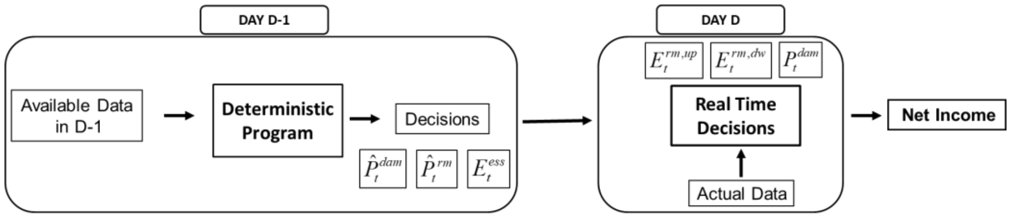


Figure 27.- Real information case.

Depending on the values considered to model uncertainty, the net income under RI hypothesis will be different and by comparing it with the net income under PI, the cost of the uncertainty may be evaluated.

4.6 Case study

This case study is focused on a wind farm located in Northwestern Spain [2]. The objective of this study is threefold. First, to compare the operation of the system when it just participates in the DAM and when participating in both DAM and RM. Secondly, to analyze in each case the effects of having storage capabilities in the net income of the W&SPP, and lastly to evaluate the cost of the uncertainty linked to several parameters in the models: market prices, available wind energy, and regulation requirements made by the SO in the RM.

In order to evaluate the influence of the storage and the influence of the uncertainty, a simulation period of one year is considered. It means that the optimization problem will be solved once per day for a whole year.

To perform this simulation, actual data concerning available wind energy, both forecast and real-time, is kindly provided by the WF operator. On the other hand, market data, both prices and regulation requirements, are downloaded from the Spanish System Operator website [1], since they are publicly available.

To evaluate the cost of uncertainty the perfect information case is considered as benchmark . Thus, firstly, the deterministic problem is solved as if all the data were actually known. This will be referred to as a perfect information case (PI) and it is an upper bound for the net income achievable. Secondly, the same problem is solved with forecast and/or estimated values for the uncertain parameters which correspond to the real information (RI) case. The decisions made are evaluated in real time with the actual values of the uncertain parameters. Thus, the actual net income is computed. By comparing both results of the net income, the influence of the uncertainty can be derived.

4.6.1 Treatment of uncertain parameters

In this subsection, the procedures to forecast/estimate the uncertain parameters are explained. Firstly, the energy and power market prices are estimated through a moving average approach to calculate the prices for day D based on the prices of recent days. Secondly, the available wind energy for day D is directly obtained from forecasts provided by the WF operator. Lastly, regulation requirements by SO are estimated by analyzing historical data.

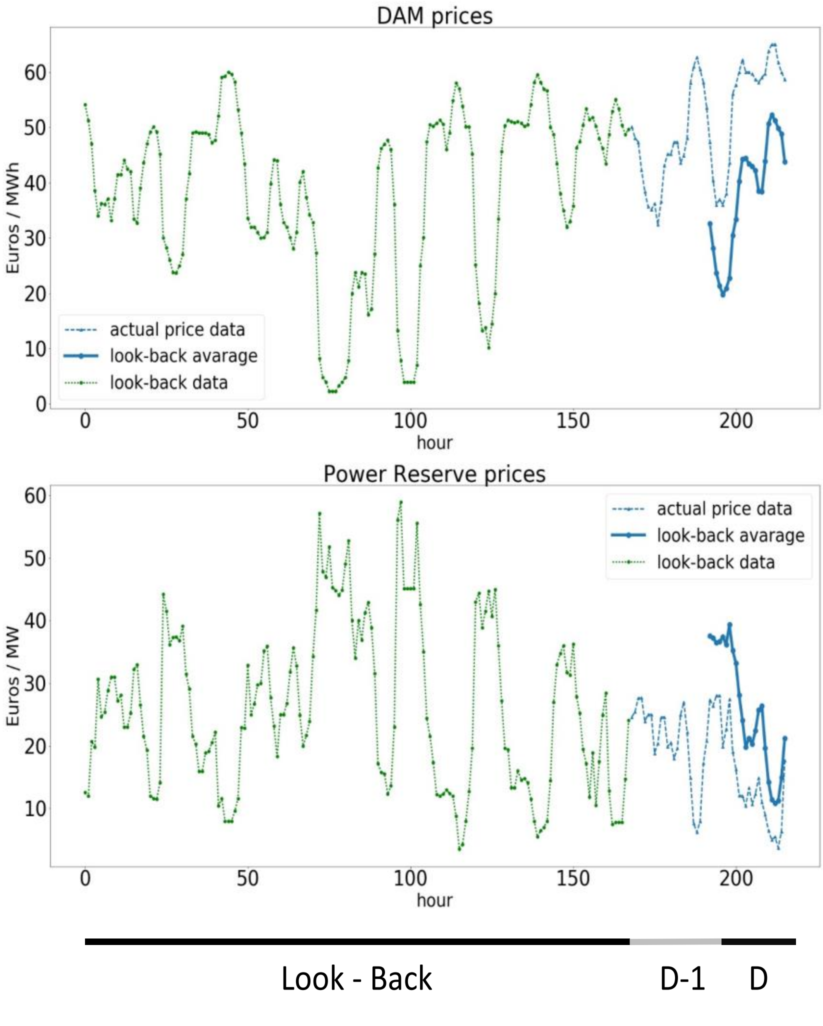


Figure 28.- Estimation of market prices.

4.6.1.1 Market prices

The W&SPP operator does not know the market prices when it has to make the decisions concerning its participation in DAM and RM.
In this chapter, a *look-back* approach is proposed to feed energy and power prices data to the deterministic optimization problem that has to be solved in day D-1. This approach will consider as the forecast prices for day D an hourly average of the prices that occurred during several days before D-1. This period is referred to as *Look-Back*. In particular, a look-back period of one week is considered in this work. The same strategy is deployed for all the prices involved in DAM and RM. An example of this approach for one day and, for DAM and RM regulation band prices, is shown in Figure 28.

4.6.1.2 Available wind energy

The wind farm operator relies on available wind energy forecast for day D to make its offers to participate in DAM and RM. Thus, in day D-1, a forecast for the available wind energy in every hour of day D is available. This forecast is used to solve the deterministic problem. The decisions made are evaluated in day D with actual data of available wind energy.
One year of data is represented in Figure 29. Every point of the scatter plot is one hour of the year under simulation. The forecast available wind energy and the actual available wind energy can be read for each point in the vertical and horizontal axis respectively.

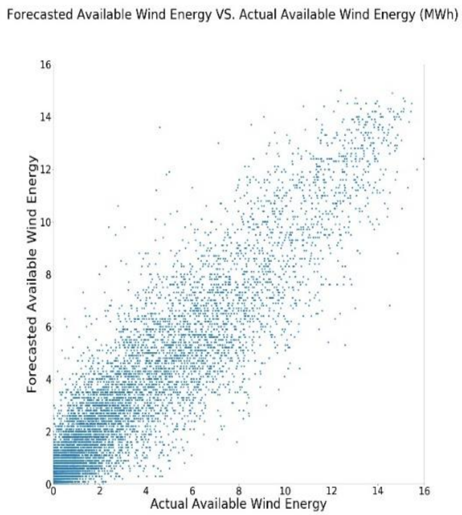


Figure 29.- Forecast available wind energy vs. actual available wind energy

4.6.1.3 Regulation requirements

The percentage of the reserve committed in the RM that will be actually required by the SO to perform regulation tasks is not known in day D-1. To estimate this parameter two approaches are proposed. Firstly, a one year of hourly data for regulation requirements, both up and down, are represented in Figure 30 (Left). From this figure, three deterministic cases will be considered. The first one considering that all the reserve committed will be required for regulation down. Second, that just a small fraction of the reserve committed is required for regulation up and down, and lastly, all the reserve committee is required for regulation up. The three cases are highlighted with a red dot in Figure 30 (left).

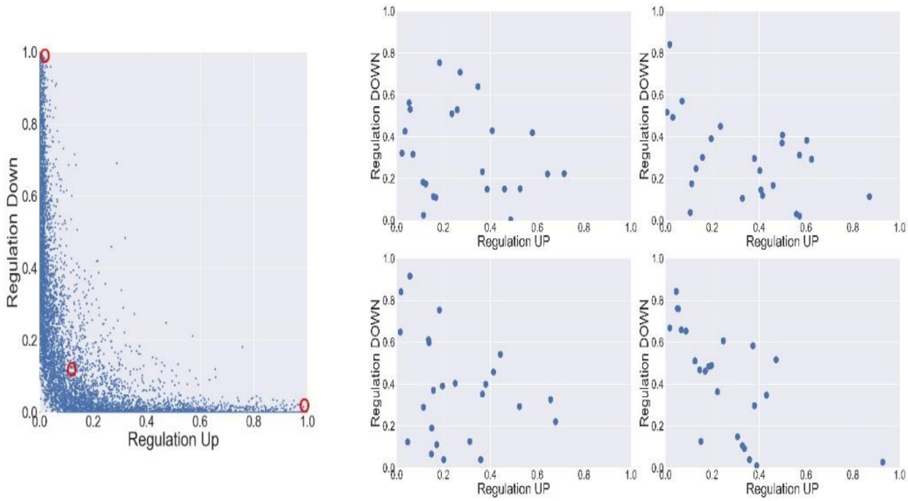


Figure 30.- Regulation requirements estimation.

The second approach is shown in Figure 30 (Right). Under this approach, the regulation requirements for every hour of every day are generated randomly. All the points generated should respect equation (49).

4.6.2 W&SPP participating in DAM .

The first considered case is that of the W&SPP only allowed to participate in the DAM. In this case, both available wind energy and, DAM and BM prices are not known when decisions are to be made. In Table 1, the yearly net income achievable by the W&SPP under several simulation cases is presented. Several

ESS, varying both power and energy capacity, are considered for simulation. All the systems are evaluated under several hypotheses concerning the knowledge of the uncertain parameters. Under perfect information hypothesis (PI) a perfect knowledge of the uncertain parameters is assumed. On another hand, under real information hypothesis (RI) the uncertain parameters are estimated as explained earlier. By analyzing the results, the influence of the uncertainty may be evaluated.

Table 1.- Net income participating in DAM for several ESS and uncertainty cases

NET INCOME (k€ / YEAR) - DayAhead Market

ESS POWER	ESS CAPACITY				Uncertainty Case	
	No Storage	**1 MWh**	**2 MWh**	**5 MWh**	**Available Wind Energy**	**DAM Prices**
No Storage	1326.6					
1 MW		1329.1	1331.4	1336.2	**PI**	**PI**
2 MW		1329.1	1331.6	1338.2		
5 MW		1329.1	1331.6	1339.1		
No Storage	1258.5					
1 MW		1260.1	1263.2	1268.1	**RI**	**PI**
2 MW		1261	1263.5	1270		
5 MW		1261	1263.5	1271		
No Storage	1326.6					
1 MW		1328.1	1329.3	1331.9	**PI**	**RI**
2 MW		1328.1	1329.6	1333		
5 MW		1328.1	1329.6	1334		
No Storage	1258.5					
1 MW		1259.9	1261.2	1263.8	**RI**	**RI**
2 MW		1259.9	1261.4	1264.9		
5 MW		1259.9	1261.4	1265.9		

Thus, under PI, it will be considered a perfect knowledge of the available wind energy in the day D and, DAM and BM prices. That is the ideal situation and the results will be an upper bound on the net income achievable by the system. The operation strategy under this assumption is to arbitrate between the hour of day D with the highest price and the hours with the lowest one. If the ratio energy capacity/power of the ESS is greater than one, the strategy will be to fill the ESS in decreasing order of arbitrage prices. On the other hand, it makes no sense to add power to the ESS above the energy capacity. Under RI considerations, the W&SPP operator counts on available wind energy forecasts to take decisions concerning how much energy is to be sold/bought during day D. During real-time operation, the W&SPP will have to deviate to accommodate the actual wind energy available. It is to note that the influence of the uncertainty in the market prices is small. In contrast, wind energy forecast error in the net income is more important, inducing the cost of uncertainty a reduction in the net income by a 5% with respect to that achievable under PI.

4.6.3 W&SPP participating in DAM and RM .

If the W&SPP is also allowed to participate in the RM, one more source of uncertainty appears. In day D-1, when decisions are to be made, the amount of regulation that the SO will require in day D is not known. As already explained, several cases to estimate these regulation requirements are considered.
In order to evaluate the uncertainty associated with each of the unknows parameters, several simulations are run considering different levels of knowledge of these uncertain parameters as it can be seen in Table 2 . As to the ESS, only one system with 2 MW of power and 2 MWh of capacity is considered.

Table 2.- Net income participating in DAM and RM.

NET INCOME (k€ / YEAR) - DayAhead & Reserve Markets

ESS		Uncertainty Case		
NO STORAGE	**2 MW / 2 MWh**	**Available Wind Energy**	**Market Prices**	**Regulation Requirements**
1326.6	2022.5	**PI**	**PI**	**PI**
1258.5	1954.4	**RI**	**PI**	**PI**
1326.6	2019.3	**PI**	**RI**	**PI**
1326.6	1972.5	**PI**	**PI**	**RI - Deterministic I ***
	1917.6			**RI - Deterministic II ****
	1935.6			**RI - Deterministic III *****
	1963.9			**RANDOM**
1258.5	1928.7	**RI**	**RI**	**RI - Deterministic I**
	1856.8			**RI - Deterministic II**
	1905.3			**RI - Deterministic III**
	1918.6			**RANDOM**

* Reg UP = 0.1 and Reg DOWN = 0.1
** Reg UP = 1 and Reg DOWN = 0
*** Reg UP = 0 and Reg DOWN = 1

By analyzing the results obtained, two main outcomes are to be highlighted. Firstly, the participation of the W&SPP in the RM greatly increases the net income of the system. This increase comes, primarily, from the selling of capacity in the RM. For example, for the ESS simulated and under PI, the net income increases by almost 50% when participating in RM. Secondly, and similarly to the case where the W&SPP is only allowed to participate in the DAM, the influence of the uncertainty in the market prices is small. Uncertainty in available wind energy and regulation requirements have similar effects on the achievable net income. In this case, both available wind energy and regulation requirements reduce the net achievable income by 3.5%.

4.7 Conclusions

A convex deterministic model is developed to model the participation of a W&SPP in both DAM and RM. This model avoids the use of binary variables to model the participation in the BM and it is successfully used to optimize the operation of such a plant participating in the particular case of the Spanish electricity market. In such a case, it is shown that adding an ESS to a WF just participating in the DAM may not be economically feasible. On another hand, the net income increases sharply if the W&SPP is allowed to participate in the RM as considered in this work.

As to the influence of the parameters affected by uncertainty in the net income achievable by the W&SPP, it is important to note that even a simple approach is enough to reduce the effects of the uncertainty concerning market prices. The effectiveness of the approach to estimate market prices comes from that it respects the daily pattern of prices. Although the price estimation is not accurate, the daily pattern is well represented and thus, the decisions made are close to those made under PI hypothesis. Uncertainty concerning available wind energy and regulation requirements have similar effects on the net income achievable. The reduction in the net income because of this uncertainty ranges from 2-4% depending on the ESS considered.

As a consequence, in order to reduce the effects of uncertainty, more effort should be done to get better forecasts of available wind energy and better estimates of regulation requirements. Optimization approaches under uncertainty may also be useful to handle the intrinsic uncertainty in those parameters. Another improvement would be to consider longer optimization periods, for example, one week long, allowing for more profitable arbitrage strategies.

CHAPTER 5

5 A data-driven stochastic optimization approach of a wind and storage power plant participating in day-ahead and reserve markets.

In this chapter, a decision-making framework under uncertainty for a wind and storage power plant participating in day-ahead and reserve markets is developed. Available wind energy and regulation requirements by the system operator are considered as uncertain parameters. To maximize the net income of this system under uncertainty, a two-stage convex stochastic model is developed. In order to create meaningful scenarios to be used in our proposed stochastic model, at first, a Long Short-Term Memory Recurrent Neural Network is designed to generate forecasts for regulation requirements. Univariate and multivariate clustering based on k-means algorithms are also used to generate influential scenarios from historical data. Several simulation experiments are carried out to evaluate the quality of the proposed stochastic approach using real-world wind farm data. Simulation result shows the validity and usefulness of the proposed data-driven approaches to handle the uncertainty in regulation requirements. The work described in this chapter was published in [53].

5.1 Introduction

Wind farms are exploring the possibility of adding *energy storage systems* (ESS) to boost their options of participating in the power market to increase their revenues [54]. A review of storage technologies and their applications to integrate renewable energy generators into power systems can be found in [55].
Firstly, the problem of optimizing the participation of renewable-based generators in day-ahead energy markets in uncertain environments has been dealt with extensively in the literature considering with or without storage capability. The bidding strategy of a wind and storage power plant in the day-ahead market is studied in [56]. In this work, the uncertainty linked with available wind energy is modeled by using a probability distribution instead of using scenarios which leads to a nonlinear problem formulation. Participation of a wind farm with ESS in DAM and *balance market* (BM) under uncertainty in power prices and available wind energy is considered in [57]. This work proposes a set of linear decision rules to define policies to operate the ESS in real time. In study [58], a model predictive control approach and a dynamic programming approach are used to optimize the dispatch strategy of a wind-storage power plant participating in DAM. Participation of a wind-storage system in DAM and BM is also considered in [59]. It considers two ESSs. One is aimed to optimize the wind-storage production scheduling with day-ahead forecast data, while the another one is used to handle errors in the predictions in real-time operation. A two-stage robust optimization approach is used in [60] to optimize a wind-storage plant which can sell/buy energy in both DAM and real-time market. Uncertainties in both available wind energy and market prices are represented through confidence intervals. A stochastic mixed integer linear framework is proposed in [61] to optimize the operation of a wind-hydro system which can sell energy in DAM and also through bilateral contracts. The developed model includes risk-hedging by considering the conditional value at risk. To schedule a generation portfolio incorporating large shares of intermittent wind generation and ESS, a chance-constrained approach is proposed in [62]. The chance constraint is factorized into a set of linear deterministic inequalities to preserve the mixed-integer linear structure of the problem. Uncertainty in available wind energy is considered in [63] for both the planning and operation of a wind farm with electrochemical storage participating in DAM; a two-stage stochastic problem is proposed in [64] to derive the bidding strategy of a wind-solar-storage power plant in the DAM under uncertainty in renewable generation; the uncertainty affecting a DAM scheduling problem of a wind generator is handled in [65] by using chance constraints; and a two-stage stochastic problem using data-driven scenarios is presented in [66] as a potential

solution to maximize the expected profit of a *virtual power plant* (VPP) participating in day-ahead and balancing markets.

To increase the income of a wind and storage power plant, a more comprehensive participation in the power market may be considered. Thus, for example, a stochastic approach is presented in [67] to optimize the participation of a VPP in energy and spinning reserve markets and Montecarlo simulations are used in [68] to handle the uncertainty in the planning and scheduling problem of energy storage systems and renewable energy generators offering congestion management services. In this framework, special interest has been devoted to the participation in regulation and reserve markets. Wind farms are not usually allowed to participate in this market, but this situation is starting to change. Thus, recently, some papers have dealt with the problem of scheduling of power producers in reserve and regulation markets as well.

Several papers address the above issue of considering DAM and reserve market (RM) simultaneously. Among them, a deterministic mixed integer linear program for the energy and reserve scheduling of pumped storage hydro plant is proposed in [43]. A stochastic programming framework is proposed in [69] to choose optimal energy and reserve bids for a group of storage units. In this work, the actual requirements of regulation by the *system operator* (SO) in the RM is modeled by using a constraint limiting it to a maximum value calculated by solving a standard stochastic unit commitment problem. Study [70] proposes a two-stage robust optimization approach to decide the operation of energy storage units in day ahead and reserve markets; a stochastic framework is proposed in [71] to optimize the joint operation of a wind farm, photovoltaic generation and energy storage devices in energy and reserve markets. In this work, only wind and solar generation and market prices are considered uncertain. A day-ahead scheduling framework is presented in [72] for a VPP including wind generation and electric vehicles participating in a joint energy and regulation reserve markets. Wind energy is considered uncertain and probabilities of regulation up and down are estimated using a point estimate method. On the other hand, two different strategies are compared in [44] to deal with the problem of optimal offering of a wind farm in energy and primary reserve markets under wind uncertainty. A robust optimization approach is proposed in [73] to decide the optimal participation of an integrated community energy system in energy and ancillary service markets. Renewable energy generation and market prices are modeled as uncertain parameters through confidence intervals.

When considering the participation in reserve markets, it is crucial to handle an important source of uncertainty associated with regulation requirements in real-time operation. These regulation requirements are defined by the system operator (SO). A very few research has been done to address this issue. For instance, several deterministic cases were considered in [74] as a mechanism to model such uncertainty; a point estimate based statistical framework is proposed to derive a probabilistic distribution of SO requirements in [72]; a method based on generating a big number of scenarios for regulation requirements followed by an algorithm to select a smaller number of scenarios is proposed in [75] and; a statistical method is proposed in [76] to calculate the regulation requirements for a specific power system.

From the above literature, we have observed that very limited effort has been made to address the uncertainty associated with the regulation requirements. Therefore, in this research, we propose a decisión-making framework to address this uncertainty so that the wind farms can run their operation efficiently. More specifically, a novel 2-stage continuous convex stochastic programming model is developed for a W&SPP participating in DAM and RM. To generate meaningful scenarios to be used in our proposed stochastic model, we have developed several approaches. At first, a *Long Short-Term Memory Recurrent Neural Network* (LSTM-RNN) is designed to generate deterministic forecasts for SO requirements. Univariate and multivariate clustering based *k*-means algorithms are also developed to generate influential scenarios from historical data. The concept of perfect information is introduced and presented as an ideal case to benchmark the proposed scenario generation approaches. Finally, using simulation experiments, the quality of the proposed stochastic approach is evaluated for several test-cases using real-world wind firm data.

The rest of this chapter is organized as follows: Section 5.2 describes the proposed stochastic model; Section 5.3 describes the proposed scenario generation approaches with simulation results; and lastly, Section 5.4 sets the conclusions of this work.

Nomenclature:

The following sets, parameters and decision variables will be used in our model.

Sets and Subindex:

S	Set of Scenarios .
T	Set of time slots.
s	Subindex for scenarios, s = 1, …., Ns.
t	Subindex for time slot, t = 1,….., T.

Parameters

T Number of periods.

l_t Duration of each period.

$\hat{P}_t^{wind}$ Available wind power in time t.

E_0^{ess} Initial energy stored in the ESS.

η_{in} Charging efficiency of the ESS.

η_{out} Discharging efficiency of the ESS.

$\overline{E}^{ess}$ Maximum energy stored in the ESS .

$\overline{P}^{ess}$ Maximum power to/from ESS.

$SOC_t^{\min}$ Minimum state of charge of ESS

β_t^{dam} Energy price in the DAM.

$\hat{\lambda}_t^{bm,up}$ Energy price of deviation up BM

$\hat{\lambda}_t^{bm,dw}$ Energy price of deviation down in BM

κ^{bm} Correction factor of deviation prices in BM

$\lambda_t^{bm,up}$ Corrected energy price of deviation up in BM.

$\lambda_t^{bm,dw}$ Corrected energy price of deviation down in BM

$\varphi_t^{bm}, \gamma_t^{bm}$ Auxiliary parameters.

γ_t^{rm} Price of power reserve.

$\beta_t^{rm,up}$ Energy price under regulation up.

$\beta_t^{rm,dw}$ Energy price under regulation down.

$\beta_{desv,t}^{rm,up}$ Price of energy not supplied for regulation up.

$\beta_{desv,t}^{rm,dw}$ Price of energy not supplied for regulation down.

$\pi_t^{rm,up}$ Ratio of reserves required for regulation up.

$\pi_t^{rm,dw}$ Ratio of reserves required for regulation down .

$R_t^{rm,up}$ Ratio between reserve up and total reserve.

N_s Number of scenarios

ρ_s Probability of occurrence of scenario s.

Decision variables

P_t^{wind} Wind power used in time t.

E_t^{ess} Energy stored in time t.

$P_t^{ess,in}$ Power entering the ESS in time t.

$P_t^{ess,out}$ Power delivered by the ESS in time t

SOC_t State of charge of ESS in time t.

$P_{s,t}$ Power to/from W&SPP in time t and scenario s.

$\hat{P}_t^{dam}$ Power offered in the DAM for every hour of day D.

$P_{s,t}^{dam}$ Power actually delivered/taken in time t in the DAM.

$\Delta_{s,t}^{bm}$ Participation in the BM in every scenario s.

$\Delta_{s,t}^{bm,up}$ Deviation up in BM in every scenario s.

$\Delta_{s,t}^{bm,dw}$ Deviation down in BM in every scenario s.

$\hat{P}_t^{rm}$ Total power committed in the RM.

$\hat{P}_t^{rm,up}$ Power committed for regulation up.

$\hat{P}_t^{rm,dw}$ Power committed for regulation down.

$\hat{E}_{s,t,reg}^{rm,up}$ Energy required by SO for reg. up in every scenario s.

$\hat{E}_{s,t,reg}^{rm,dw}$ Energy required by SO for reg. down in every scenario s.

$E_{s,t}^{rm,up}$ Energy actually offered for reg. up in every scenario s.

$E_{s,t}^{rm,dw}$ Energy actually offered for reg. down in every scenario s.

$D_{s,t}^{rm,up}$ Deviation in regulation up in every scenario s.

$D_{s,t}^{rm,dw}$ Deviation in regulation down in every scenario

5.2 Description of the model.

The proposed optimization problem aims at maximizing the net income of the W&SPP participating in both DAM and RM, as already explained in chapter 4, considering the uncertain environment. Therefore, the mathematical model should be able to handle this uncertainty in the input data. A two-stage stochastic approach is chosen to deal with this situation and a set of scenarios is proposed to handle the uncertainty linked with the available wind energy and the regulation requirements by SO in every hour of day D. These scenarios represent plausible realizations of those uncertain parameters with an associated probability of occurrence. Under this approach, two kinds of variables appear: first stage and second stage variables. First stage variables are associated with the decisions to be made in day D-1 under uncertainty. These decisions are also called here-and-now decisions in the optimization literature [14]. On the other hand, second stage variables are associated with the decisions that are made in day D provided that first stage decisions are already made. These decisions are also known as wait-and-see decisions in the optimization literature. Thus, the two-stage stochastic optimization problem is solved in day D-1 when the first-stage decisions are to be made. The optimization problem finds the best first stage decisions by considering the values of second stage decisions for all scenarios.
Here, we make a price taker assumption, which means the agent is not able to influence the market prices no matter how much power/energy it offers.

In the following subsections 5.2.1 and 5.2.2, the proposed model is described. It uses a convex two-stage stochastic approach to model the participation of a W&SPP in power markets: DAM, RM, and BM.

5.2.1 Objective function

The objective function will maximize the net income of the operation of the system participating in DAM, RM, and BM. Equations (50) and, (51) define the income from the participation in the DAM and the RM respectively from a deterministic point of view. The participation in the DAM implies the participation in the BM to handle the deviations with respect to the commitments acquired in the DAM.

$$IDAM = l_t \cdot (\sum_t \beta_t^{dam} \cdot \hat{P}_t^{dam} + \sum_t \lambda_t^{bm,up} \cdot \Delta_t^{bm,up} - \sum_t \lambda_t^{bm,dw} \cdot \Delta_t^{bm,dw}) \tag{50}$$

$$\begin{aligned} IRM = & \sum_t \gamma_t^{rm} \cdot \hat{P}_t^{rm} + \sum_t \beta_t^{rm,up} \cdot E_t^{rm,up} - \sum_t \beta_t^{rm,dw} \cdot E_t^{rm,dw} \\ & - \sum_t \beta_{desv,t}^{rm,up} \cdot D_t^{rm,up} - \sum_t \beta_{desv,t}^{rm,dw} \cdot D_t^{rm,dw} \end{aligned} \tag{51}$$

Thus, the net income in DAM (IDAM) comes from the energy committed for selling/buying in every hour of day D and the participation in the BM.
It is important to note that in the Iberian market, as exposed in chapter 2, the prices in the BM have to follow equations (52) and, (53). In this case, a situation may arise, where there are no penalties for deviation with respect to the commitments acquired in DAM. From our point of view, this situation should be avoided and agents should be encouraged to bid as accurately as possible in the DAM. To force this behavior, a parameter $\kappa^{bm} \in (0,1]$ is defined to correct the BM prices as to the equations (54) and, (55). This means that deviation up price will be lower than that found in the market data, and the deviation down price will be higher. Thus, an actual penalty will always appear if the power agent does not follow the commitments acquired in the DAM.

$$\hat{\lambda}_t^{bm,up} \leq \beta_t^{dam} \tag{52}$$

$$\hat{\lambda}_t^{bm,dw} \geq \beta_t^{dam} \tag{53}$$

$$\lambda_t^{bm,up} = \hat{\lambda}_t^{bm,up} \cdot \left(1 - \kappa^{bm}\right) < \beta_t^{dam} \tag{54}$$

$$\lambda_t^{bm,dw} = \hat{\lambda}_t^{bm,dw} \cdot \left(1 + \kappa^{bm}\right) > \beta_t^{dam} \tag{55}$$

In this problem, the time step considered is one hour, so the parameter l_t will be omitted in the objective function for the sake of simplicity from now onwards.
As we said, available wind energy and regulation requirements by SO are not known by the W&SPP when the decision-making problem is to be solved. To handle this uncertainty, a two-stage stochastic problem is proposed. The concept of stochastic programming and in particular, a two-stage approach was introduced in section 3.2.2.
Commitments to participate in DAM are modeled as first stage decisions and deviations, i.e., participation in the BM are modeled as second stage decisions. The second-stage decisions depend on the first-stage decisions and the considered scenarios modeling plausible realizations of the uncertain parameters. Also, as described in the equation (51) the net income from RM comes from the regulation band committed in day D-1 (first stage decision) and, the actual energy supply for regulation in day D (second stage decision), which depends on the realization of the uncertain parameters as well.
Thus, the objective function (56) for the two-stage stochastic problem considers the sum of the income related to the first-stage decisions plus the expected value of the net income related to the second-stage decision for all the considered scenarios.

$$\begin{aligned} maximize \quad & \sum_t \beta_t^{dam} \cdot \hat{P}_t^{dam} + \sum_t \gamma_t^{rm} \cdot \hat{P}_t^{rm} + \\ & \sum_{s=1}^{Ns} \rho_s \cdot \Big(\sum_t \lambda_t^{dam,up} \cdot \Delta_{s,t}^{dam,up} - \sum_t \lambda_t^{dam,dw} \cdot \Delta_{s,t}^{dam,dw} + \\ & \qquad \sum_t \beta_t^{rm,up} \cdot E_{s,t}^{rm,up} - \sum_t \beta_t^{rm,dw} \cdot E_{s,t}^{rm,dw} \\ & \qquad - \sum_t \beta_{desv,t}^{rm,up} \cdot D_{s,t}^{rm,up} - \sum_t \beta_{desv,t}^{rm,dw} \cdot D_{s,t}^{rm,dw} \Big) \end{aligned} \tag{56}$$

To avoid the use of binary variables in the model, utilization of convex functions to model the participation in the balancing market is proposed in [37]. Following the same procedure, we can rewrite the objective function (56) as a minimization problem. Thus, the deviation with respect to the commitments acquired in DAM, which is equivalent to the participation in the BM, is defined according to equation (57) and deviations up and down according to equations (58) and, (59).

$$\Delta_{s,t}^{bm} = P_{s,t}^{dam} - \hat{P}_t^{dam} \tag{57}$$

$$\Delta_{s,t}^{bm,dw} = max\left\{-\Delta_{s,t}^{bm}, 0\right\} = [\Delta_t^{bm}]^- \tag{58}$$

$$\Delta_{s,t}^{bm,up} = max\left\{\Delta_{s,t}^{bm}, 0\right\} = [\Delta_t^{bm}]^+ \tag{59}$$

The following equation (60) shows the resulting objective function:

$$\begin{aligned} minimize \quad & -\sum_t \beta_t^{dam} \cdot \hat{P}_t^{dam} - \sum_t \gamma_t^{rm} \cdot \hat{P}_t^{rm} + \\ & \sum_{s=1}^{Ns} \rho_s \cdot (\sum_t \lambda_t^{bm,dw} \cdot [\Delta_t^{bm}]^- - \sum_t \lambda_t^{bm,up} \cdot [\Delta_t^{bm}]^+ - \\ & \qquad \sum_t \beta_t^{rm,up} \cdot E_{s,t}^{rm,up} + \sum_t \beta_t^{rm,dw} \cdot E_{s,t}^{rm,dw} + \\ & \qquad \sum_t \beta_{desv,t}^{rm,up} \cdot D_{s,t}^{rm,up} + \sum_t \beta_{desv,t}^{rm,dw} \cdot D_{s,t}^{rm,dw} \;) \end{aligned} \tag{60}$$

The objective function (60) is a convex function if equation (61) holds.

$$\lambda_t^{bm,dw} \geq \lambda_t^{bm,up} \tag{61}$$

$$\varphi_t^{bm} = \frac{\lambda_t^{bm,dw} - \lambda_t^{bm,up}}{2} \tag{62}$$

$$\gamma_t^{bm} = \frac{\lambda_t^{bm,dw} + \lambda_t^{bm,up}}{2} \tag{63}$$

In this case, by applying transformations (62) and, (63) the objective function can be written as (64), which is more convenient to be handled by convex optimization solvers [37]. This transformation was explained in detail in Chapter 4.

$$\begin{aligned} minimize \quad & -\sum_t \beta_t^{dam} \cdot \hat{P}_t^{dam} - \sum_t \gamma_t^{rm} \cdot \hat{P}_t^{rm} + \\ & \sum_{s=1}^{Ns} \rho_s \cdot (\sum_t \varphi_t \cdot \left|\Delta_{s,t}^{bm}\right| - \sum_t \lambda_t \cdot \Delta_{s,t}^{bm} - \\ & \quad \sum_t \beta_t^{rm,up} \cdot E_{s,t}^{rm,up} + \sum_t \beta_t^{rm,dw} \cdot E_{s,t}^{rm,dw} + \\ & \quad \sum_t \beta_{desv,t}^{rm,up} \cdot D_{s,t}^{rm,up} + \sum_t \beta_{desv,t}^{rm,dw} \cdot D_{s,t}^{rm,dw} \;) \end{aligned} \tag{64}$$

5.2.2 Model constraints

The following set of constraints define the feasible set of the optimization problem. All the equations in this section are defined for all time steps and for all scenarios.

$$\forall t \in T, \forall s \in S$$

Equation (65) sets the amount of energy stored in the ESS in every time step as a function of the initial conditions, the power entering and leaving the ESS and the efficiency of charging and discharging processes

$$E_t^{ess} = E_0^{ess} + l_t \cdot \sum_{\tau=1}^{t} \eta_{in} P_\tau^{ess,in} - l_t \cdot \sum_{\tau=1}^{t} \frac{1}{\eta_{out}} P_\tau^{ess,out} \tag{65}$$

Constraint (66) ensures the maximum allowable limit for wind power. The right-hand side of this constraint is one of the parameters affected by the uncertainty and modeled by scenarios.

$$P_{s,t}^{wind} \le \hat{P}_{s,t}^{wind} \tag{66}$$

Also related with the ESS, constraint (67) requires to have the same energy stored at the beginning and at the end of the period under study (one day in our case); and (68), (69) and, (70) limit the maximum and minimum energy stored in the ESS, while constraints (71) and, (72) limit the maximum power that can be exchanged by the ESS.

$$E_0^{ess} = E_T^{ess} \tag{67}$$

$$E_t^{ess} \leq \overline{E}^{ess} \tag{68}$$

$$SOC_t = E_t^{ess} \ / \ \overline{E}^{ess} \tag{69}$$

$$SOC_t \geq SOC^{\min} \tag{70}$$

$$\hat{P}_t^{ess,out} \leq \overline{P}^{ess} \tag{71}$$

$$\hat{P}_t^{ess,in} \leq \overline{P}^{ess} \tag{72}$$

Constraint (73) defines the power balance in the W&SPP and (74) ensures some bounding constraints.

$$P_{s,t} = P_{s,t}^{wind} + P_t^{ess,out} - P_t^{ess,in} \tag{73}$$

$$P_t^{ess,out} \ ; \ P_t^{ess,in} \ ; \ E_t^{ess} \geq 0 \tag{74}$$

The set of constraints (75) - (86) deal with the participation in the reserve market. Equations (75), (76) and, (77) define the regulation band that can be offered by the W&SPP. In this work, it is supposed that just the ESS may be used for regulation requirements, constraints (76) and (77), although renewable generators, under certain requirements, are starting to be allowed to participate in adjustment markets in some countries.

$$\hat{P}_t^{rm} = \hat{P}_t^{rm,up} + \hat{P}_t^{rm,dw} \tag{75}$$

$$\hat{P}_t^{rm,up} \leq \overline{P}^{ess} \tag{76}$$

$$\hat{P}_t^{rm,dw} \leq \overline{P}^{ess} \tag{77}$$

It is also needed to set the ratio between the regulations up and the total regulation band offered. This ratio must follow the ratio asigned for the entire system defined by equation (78).

$$\frac{\hat{P}_t^{rm,up}}{\hat{P}_t^{rm}} = R_t^{rm,up} \quad (78)$$

Constraints (79) and, (80) set the amount of energy actually required by SO for regulation tasks. Regulation requirements are also parameters affected by the uncertainty and modeled by scenarios.

$$\hat{E}_{s,t,reg}^{rm,up} = l_t \cdot \pi_{s,t}^{rm,up} \cdot \hat{P}_t^{rm,up} \quad (79)$$

$$\hat{E}_{s,t,reg}^{rm,dw} = l_t \cdot \pi_{s,t}^{rm,dw} \cdot \hat{P}_t^{rm,dw} \quad (80)$$

Constraints (81) and, (82) deal with the actual energy supplied by W&SPP for regulation tasks while constraints (83) and, (84) define the deviations in the RM.

$$E_{s,t}^{rm,up} \leq \hat{E}_{s,t,reg}^{rm,up} \quad (81)$$

$$E_{s,t}^{rm,dw} \leq \hat{E}_{s,t,reg}^{rm,dw} \quad (82)$$

$$D_{s,t}^{rm,up} = \hat{E}_{s,t,reg}^{rm,up} - E_{s,t}^{rm,up} \quad (83)$$

$$D_{s,t}^{rm,dw} = \hat{E}_{s,t,reg}^{rm,dw} - E_{s,t}^{rm,dw} \quad (84)$$

Lastly, Constraint (85) ensures the power balance between the system and the power market and constraint (86) establishes some nonnegativity requirements.

$$l_t \cdot P_{s,t} = l_t \cdot P_{s,t}^{dam} + E_{s,t}^{rm,up} - E_{s,t}^{rm,dw} \quad (85)$$

$$\hat{P}_t^{rm,up}; \hat{P}_t^{rm,dw}; E_{s,t}^{rm,up}; E_{s,t}^{rm,dw} \geq 0 \quad (86)$$

5.3 Case study

The goal of this section is to describe and evaluate the proposed stochastic approach. For that purpose, in the first subsection, a set of methods to handle the uncertainty associated with the available wind energy and regulation requirements by SO is presented. These methods are scenario generation procedures, which will generate influential scenarios to be fed into the proposed stochastic optimization framework. In the second subsection, the concept of perfect information is introduced and presented as an ideal case against which the stochastic solution is evaluated. Lastly, the results of several simulations are presented and discussed. A real-world case study is considered for a wind farm located in Northwestern Spain, Sotavento experimental wind park , and for the Iberian electricity market.

5.3.1 Methods to handle uncertainty

The stochastic approach presented in section 5.2 needs the definition of scenarios which represent the uncertainty in some parameters of the model. In particular, available wind energy and regulation requirements by SO are considered uncertain in this model while market prices are considered as known parameters in this work. With this aim, several ways of handling lack of information (i.e., uncertainty) by using data-driven techniques are proposed. In one hand, uncertainty about available wind energy is handled by defining scenarios from the available forecast data. This procedure is explained in subsection 5.3.1.1. On the other hand, uncertainty concerning regulation requirements by SO is handled from the historical data because there is no forecast available. Four approaches are presented to handle the uncertainty about the regulation requirements as follows:

- First, a neural network is used to build a deterministic forecast of the regulation requirements.
- Second, a univariate clustering procedure is applied to classify the historical hourly regulation requirements and two assumptions are made to expand this hourly information to build daily scenarios.
- Third, a multivariate clustering approach is used to build daily scenarios in a more straightforward way.
- Lastly, a look-back procedure is presented to consider as a set of scenarios the most recent events of regulation requirements by SO.

Thus, a set of scenarios associated with the available wind energy and SO regulation requirements will be defined and fed into the stochastic optimization problem.

5.3.1.1 Available wind energy scenarios

Under a stochastic approach, the probabilistic forecast of available wind energy is of paramount importance to handle the uncertainty associated with wind energy production. Several papers have dealt with the problem of forecasting the available wind energy in a wind farm. Just to name a few, the work presented in [77] presents an autoregressive model; an innovative hybrid model based on neural networks is proposed in [78] to establish wind speed interval forecasts; while that recent advances in deep learning techniques are used in [79]. A method to generate statistical scenarios of wind generation based on the statistical analysis of the prediction errors is proposed in [80]; more recently, a combination of machine learning and quantile regression is proposed in [81] to provide a multistep probabilistic forecast of 10-minutes intervals of wind generation; and a deep learning based ensemble approach is proposed in [82].
In this work, this problem is not dealt with and the forecast for available wind energy (AWE) in every hour of day D is provided by the WF operator as a set of time series instead. This data is provided on a percentile basis. Therefore, each of this time series corresponds to a set of hourly values defining an upper bound on the actual available wind energy with a given probability. For example, according to the 75th percentile forecast, the actual wind energy available should be less than the p75 curve with a 75% probability as shown in Figure 31.

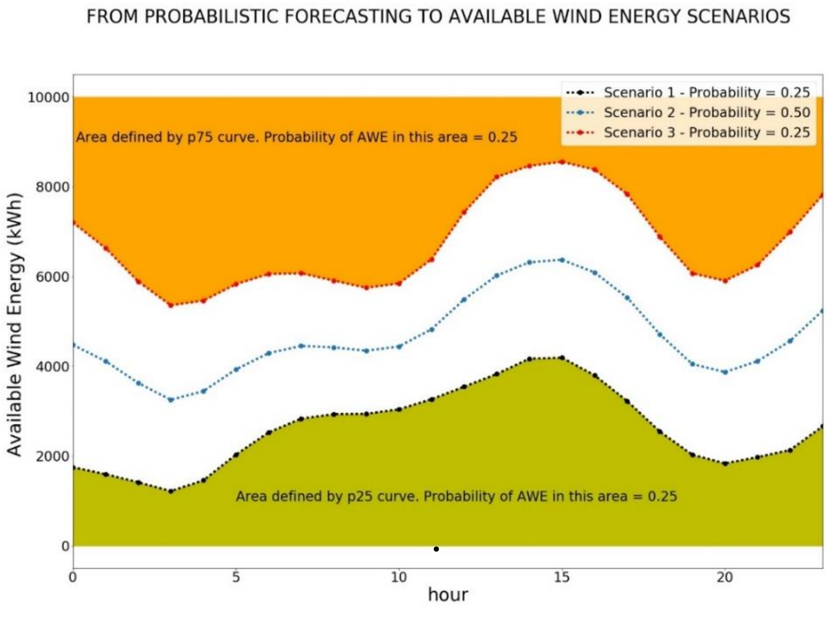


Figure 31.- Definition of scenarios from probabilistic forecast of available wind energy.

If the p75 curve is considered, according to the definition given above, available wind energy will be less than that curve with a probability of 0.75. This is equivalent to say that available wind energy will be more than that curve with a probability of 0.25. Thus, under a conservative approach, this curve can be considered as the right-hand side of the equation (66) for the scenario p75. Analogously, another scenario may be defined as the p50 curve. The last scenario is defined as the p25 curve with a probability of 0.25. In this case, this is an optimistic approach because we are considering the upper values of the complete set as the available wind energy. In Figure 31, this idea to translate a probabilistic forecasting into scenarios is shown.
The available dataset for available wind energy in day D is made up of five curves: p90, p75, p50, p25 and, p10; corresponding to percentiles 90, 75, 50, 25 and 10. From this dataset, three cases are considered as follows:

1. Firstly, six scenarios are generated from the available probabilistic forecasting (AWE_STOCHASTIC_6)
2. Secondly, three scenarios are generated from curves p75, p50 and, p25 (AWE_STOCHASTIC_3).
3. Lastly, the p50 curve is considered as deterministic forecasting (AWE_DETERMINISTIC).

To build the scenarios in the first case, a conservative approach is followed. As an example, let us consider the p90 curve. According to the definition given above, the wind energy available will be less than that curve with a probability of 90%, which is the same as saying that wind energy available will be more than that curve with a 10% probability. Thus, this curve can be considered as the right-hand side of the equation (66) for the scenario p90 under a conservative approach. The same idea is used to define a set of 6 scenarios. In a less conservative approach, 3 scenarios are defined only considering p75, p50 and, p25 curves. The probabilities assigned to those scenarios are shown in the right figure of Figure 32.

SCENARIOS & PROBABILITIES			
SCENARIOS	AWE_STOCHASTIC_6	AWE_STOCHASTIC_3	AWE_DETERMINISTIC
$\hat{P}_t^{wind} = P_t^{90}$	0.1	------	-------
$\hat{P}_t^{wind} = P_t^{75}$	0.15	0.25	-------
$\hat{P}_t^{wind} = P_t^{50}$	0.25	0.50	1
$\hat{P}_t^{wind} = P_t^{25}$	0.25	0.25	-------
$\hat{P}_t^{wind} = P_t^{10}$	0.15	-------	-------
$\hat{P}_t^{wind} = 0$	0.10	-------	-------

Figure 32.- Probabilities of considered scenarios

Lastly, a deterministic case is defined by considered as the only forecast available that corresponding to the curve p50.

5.3.1.2 Handling uncertainty for regulation requirements by SO

In this subsection, several approaches to deal with the uncertainty for regulation requirements by SO are proposed and discussed.

5.3.1.2.1 Deterministic forecast of regulation requirements

The first approach to deal with uncertainty for regulation requirements from SO both upward and downward is to forecast hourly values for day D based on the values taken by these parameters in the previous days. To do this, time series forecasting techniques are used. Recently, among all the techniques available to deal with the time series forecast, recurrent neural networks (RNN) are found to be effective [83]. In particular, a Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) [35] demonstrated its ability to overcome the problem of vanishing gradient during the training process of RNN over long-term sequences [84]. This advantage will allow using longer periods as input data for the forecasting purposes. In particular, for our problem, when decisions are to be made, there is no available forecast about how much of the committed regulation up and down will be required by the SO in real time. To deal with this lack of information, an LSTM-RNN is proposed to generate forecasts for regulation up and another LSTM-RNN is used to forecast regulation requirements downward. These LSTM-RNNs are trained by using hourly data of one year. Once the model

is trained, the forecast for day D is performed by feeding the last data available (defined as look-back data) into the model. The LSTM-RNNs are implemented using the machine learning library Tensorflow [85]. Some of the hyperparameters used for the neural network are summarized in the following Table 3.
One example of forecasting requirements for regulation upward can be seen in the following Figure 33. In this figure, the green dotted line represents the data used to make the prediction, the light blue line represents the actual data for day D and the solid blue line represents the forecasted data by the neural network. Forecasting is performed at 9 a.m. in day D-1 (red dot) for a time span including the rest of day D-1 and day D. The vertical red line shows the beginning of useful forecasting corresponding to day D. As it can be seen, the forecasted time series cannot follow the random extreme values, both when it becomes 0 or 1. This is due to the high randomness of the regulation requirements by SO.

Table 3: Hyperparameters used for training in the LSTM-RNN.

Type	**LSTM – RNN**
Number of layers	3
Internal Size of the LSTM Cell	128
Optimizer	ADAM
Error function	Mean Square Error
Implementation	TensorFlow - Python

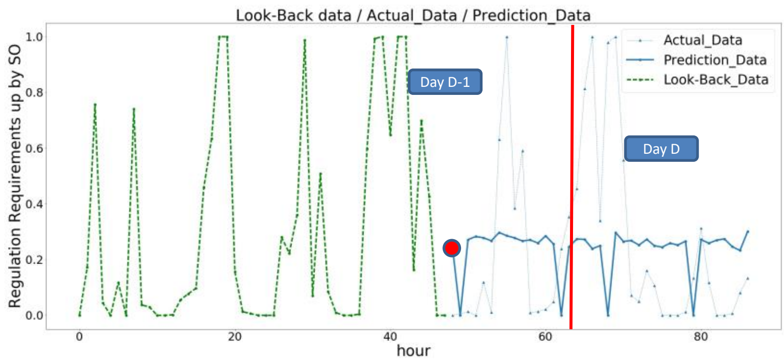
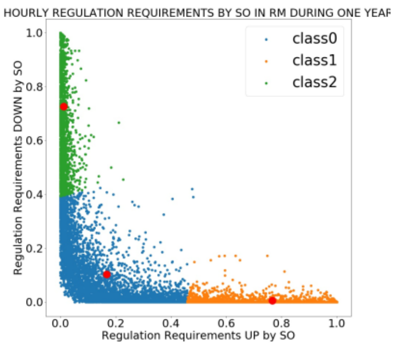


Figure 33.- Forecasting of regulation requirements up by a LSTM-RNN

5.3.1.2.2 Scenarios based on univariate clustering

The second approach to handle the uncertainty associated with the regulation requirements by SO is to find a discrete set of regulation requirements which may be representative of the values taken during one year of historical data. To perform this, a univariate k-means clustering algorithm [86] is proposed. The application of such a procedure is aimed to get several clusters, their respective centroids and their probability of occurrence. The results are shown in Figure 34; it shows that for more than 50% of the hours, the regulation requirements by SO are small both for regulation up and down (class 0). Around 20% of times the SO requires a higher value of regulation down while requirements down are low (class 2). Lastly, around 27% of times SO requires a higher value of regulation up while regulation down is low (class 1). This clustering process provides useful hourly information.



CLASSES & PROBABILITIES			
CLASS	REGULATION REQUIREMENTS UP	REGULATION REQUIREMENTS DOWN	PROBABILITY OF OCURRENCE
0	0.167	0.103	0.516
1	0.766	0.00	0.272
2	0.00	0.725	0.212

Figure 34.- Left: Clustering of hourly regulation requirements data. Right: Centroids and associated probability of considered classes.

However, the objective is to define scenarios for regulation requirements for day D, i.e., 24 hourly values are needed. Two different approaches are proposed to build such scenarios which are discussed below.

The first approach to generate scenarios from this clustering is based on considering three scenarios every day, which are characterized by the values and associated probabilities defined above. This means that in each scenario, the regulation requirements will be the same in the entire 24 hours, corresponding to each of the computed classes. The probability of each of these scenarios will be considered as the probability of occurrence of the class defining each scenario as shown in Figure 35. This approach will be referred to as univariate-A during our simulation.

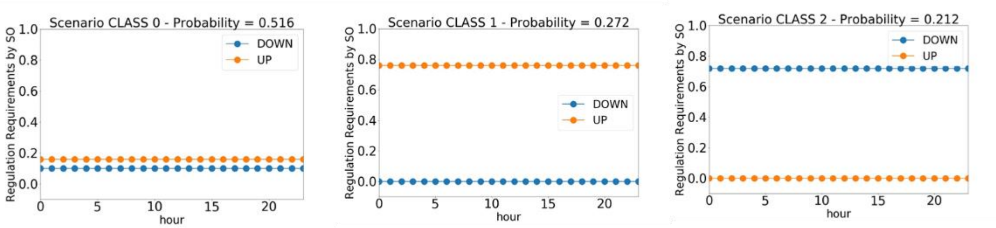


Figure 35.- Scenarios as to Univariate-A case.

The second approach to generate daily scenarios from the univariate clustering is by assuming that the yearly pattern of regulation requirements is replicated in a daily basis. Thus, the procedure starts by generating random combinations of the three computed classes for the 24 hours of a day D. This combination needs to follow the calculated probability of ocurrence of the yearly data. In other words, the probability of ocurrence of every class in the generated scenario must be equal to the probability of ocurrence of the same class in the yearly set of historical data. The main goal of the scenario generation process is to build daily patterns of regulation requirements in which each class has a probability of ocurrence equal to the probability specified by the cluster for one year data. Lastly, a random subset among all the daily scenarios is chosen. All the generated scenarios are considered equiprobable. This approach will be referred to as univariate-B and is shown in the following Figure 36.

Figure 36.- Scenarios as to Univariate-B case.

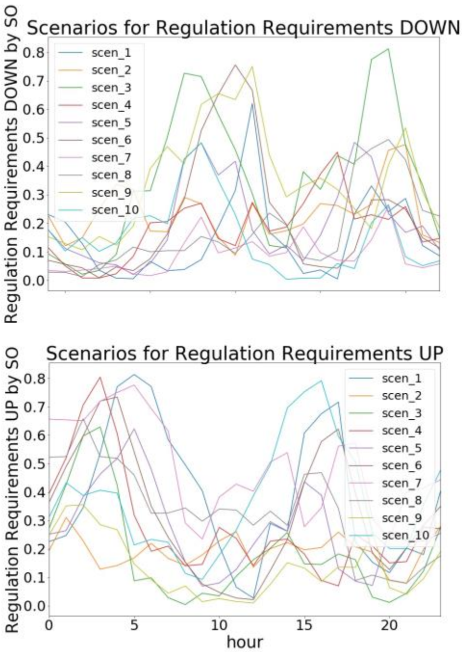
5.3.1.2.3 Scenarios based on multivariate clustering

In this case, the scenarios are generated by following a multivariate approach. The idea is to perform a clustering of n-dimensional data points [87]. In our problem, it means that daily scenarios are generated directly from daily data. A k-means clustering algorithm is also used in this case.

Thus, the way to build scenarios for regulation requirements for the whole day D is to perform a clustering of multidimensional vectors. These vectors represent the hourly values of regulations requirements up and down. The resulting vector belongs to R^{48} after concatenating two vectors of 24 values each. One year of daily vectors is used as the original discrete distribution. The goal of the clustering is to find a set of mass points that minimizes the probabilistic distance to the original distribution. Each of these points in the multidimensional space will be considered as a scenario. The probability of occurrence of that scenario is computed as the ratio between the number of elements in each cluster and the total number of points in the original distribution.
In particular, ten scenarios are generated as shown in the following Figure 37, and the probability of each of them is calculated. The clustering allows us to visualize patterns of the uncertain parameters. It can be observed from the clustering process that during the first hours of the day and the afternoon, the requirements for regulation down are small. By contrast, it is during morning and evening when the requirements for regulation upward are small.

5.3.1.2.4 Scenarios based on look-back procedure

The final approach to build scenarios to handle uncertainty is a look-back procedure. Thus, the daily data for the last N days before D-1 are considered as scenarios to perform the optimization for day D. A look-back period of one week is considered, meaning that seven scenarios which correspond with the actual data for regulation requirements of seven days before D-1 are fed into the stochastic model with an assumption of equiprobability.



SCENARIOS	PROBABILITY OF OCURRENCE
1	0.063
2	0.101
3	0.058
4	0.118
5	0.112
6	0.115
7	0.088
8	0.12
9	0.115
10	0.11

Figure 37.- Multivariate clustering scenario generation for regulation requirements.

5.3.2 Result

A real-world example is used to evaluate the proposed techniques discussed above to handle the lack of information associated with the available wind energy and regulation requirements by SO. To evaluate the quality of the solution of the stochastic problem, two situations will be compared. In one hand, under a perfect information (PI) hypothesis, decisions are made as if the actual values of uncertain parameters for day D were known. On the other hand, the real information (RI) hypothesis will consider the actual data available on day D-1 to solve the problem. This procedure is similar to that used in section 4.5.
The wind farm of Sotavento, located in Northwestern Spain is chosen [2]. The WF operator kindly provided data associated with the available wind energy forecast. This WF does not have storage capability. We have used an ESS of 2 MW / 2 MWh for this study. Data concerning power market prices and parameters were downloaded from the Spanish system operator website [1]. All the cases presented above are implemented with MATLAB and modeled with CVX [50]. Several simulation experiments are carried out for a period of 2 months for several test-cases to estimate the achievable net income.

The details about the considered scenarios are summarized in the following Table 4 and Table 5.

The results of all the performed simulation experiments are summarized in Table 6. Firstly, a simulation experiment is carried out under a perfect information hypothesis for both available wind energy and regulation requirements. Actual data for uncertain parameters are fed into the model and an upper bound on the achievable net income by the W&SPP is calculated.

Table 4: Scenarios considered to model uncertainty in available wind energy.

AVAILABLE WIND ENERGY SCENARIOS	
NOMENCLATURE	DESCRIPTION
PI	Perfect knowledge of available wind energy.
AWE-DETERMINISTIC	One scenario is considered matching the p50 forecast curve as to section 5.3.1.1
AWE-STOCHASTIC-3	Three scenarios are considered matching the p25, p50, and p75 forecast curves as to section 5.3.1.1
AWE-STOCHASTIC-6	Six scenarios are considered matching the p10, p25, p50, p75 and, p90 forecast curves as to section 5.3.1.1

Table 5: Scenarios considered to model uncertainty in regulation requirements.

REGULATION REQUIREMENTS SCENARIOS	
NOMENCLATURE	DESCRIPTION
PI	Perfect knowledge of regulation requirements.
LSTM	Deterministic forecasting of regulation requirements by using LSTM-RNN as to section 5.3.1.2.1
univariate-deterministic-class0	Scenarios generated following the univariate approach explained in section 5.3.1.2.2. Only one scenario corresponding to class0 is chosen for simulation.
univariate-deterministic-class1	Scenarios generated following the univariate approach explained in section 5.3.1.2.2. Only one scenario corresponding to class1 is chosen for simulation.
univariate-deterministic-class2	Scenarios generated following the univariate approach explained in section 5.3.1.2.2. Only one scenario corresponding to class2 is chosen for simulation.
univariate-A-stochastic-3scen	Scenarios generated following the univariate approach explained in section 5.3.1.2.2. Three scenarios corresponding with probabilities of class0,class1 and class2 are chosen for simulation.
univariate-B-deterministic	Scenarios generated following the univariate-B approach explained in section 5.3.1.2.2. Only one scenario is chosen for simulation.
univariate-B-stochastic-9scen	Scenarios generated following the univariate-B approach explained in section 5.3.1.2.2. A set of 9 scenarios is chosen for simulation.
multivariate-10scen	Multidimensional clustering is performed over a set of daily data for regulation requirements as to section 5.3.1.2.3. Ten scenarios are used for simulation.
LOOK-BACK	Regulation requirements of previous days are considered as scenarios with equal probability of ocurrence as to section 5.3.1.2.4
RANDOM	Hourly values of regulation requirements are generated randomly for every day of the simulation.

The first column and the first row of Table 6 show the results when only one of the uncertain parameters is considered as unknown. Thus, the first column considers perfect knowledge of available wind energy and models the uncertainty

linked with the regulation requirements with several sets of scenarios. On the other hand, perfect knowledge of regulation requirements is supposed to be known in the first raw.
The rest of the simulations consider the uncertainty in both available wind energy and regulation requirements. The best results are always achieved when three scenarios are used to model the available wind energy. This is because of the less conservative approach used to generate them. The net income decreases when just one scenario is considered by matching the p50 forecasting curve (as if it was a deterministic case). The simillar phenomenon is observed when six scenarios are used. For example, the net income decreases by 5.3% compared to PI situation when three scenarios are considered.

Table 6: Net Income (€) over the simulation period (2 months) under several combinations of scenarios.

SCENARIOS & NET INCOME				
	PI	**AWE_DETERMINISTIC**	**AWE_STOCHASTIC_3**	**AWE_STOCHASTIC_6**
PI	**430549**	400996	409160	406145
LSTM	414062	394593	404692	402732
univariate-deterministic-class0	414163	394721	404720	402702
univariate-deterministic-class1	400750	384963	393237	385338
univariate-deterministic-class2	397214	384687	396513	403032
univariate-A-stochastic-3scen	418444	404616	407139	403813
univariate-B-deterministic	409746	391111	400396	398471
univariate-B-stochastic-9scen	417127	401019	406110	402126
multivariate-10scen	420227	401776	**407392**	403974
LOOK-BACK	419538	402653	406689	403977
RANDOM	409117	390200	400506	399100

We have also observed from our simulation experiments that stochastic cases to model regulation requirements performed better than the deterministic case. That happens regardless of any approach used to define the scenarios: univariate A, univariate B, multivariate or Look-Back. The difference between them as to the net income achievable is negligible.

Table 6 also provides insights into how to evaluate where the W&SPP should focus to improve its results. If considering the best approaches, it can be seen that there is not too much margin to improve by trying to get a better modeling of the uncertainty for regulation requirements. On the contrary, efforts should be made on improving the forecast of available wind energy. For example, in the multivariate-10scen /AWE-STOCHASTIC-3 simulation, the net income achievable is 407392 €. The net income would rise to 409160 € if we consider perfect knowledge of regulation requirements, whereas the net income would be 420227 € if the operator would know the actual available wind energy. By splitting the total net income in the net income achievable in each market, the strategy of the W&SPP could be better understood. In Table 7, the net income achievable in every market is shown for several sets of scenarios associated with the regulation requirements. As to the available wind energy, all the cases shown consider three scenarios (AWE_STOCHASTIC_3).

The W&SPP always commits a similar amount of power in the reserve market. Similarly, it always provides a similar amount of energy for regulation no matter the scenario set considered for the simulation. This may be different under another prices or regulation of the market. Once these two conditions are fixed, depending on how accurate the W&SPP would model the uncertainty, it would participate more or less in the deviation market.

Table 7: Influence of every market in the net income under several scenarios to model regulation requirements uncertainty.

	DAM		BM		REG. BAND		REG. REQU.		TOTAL
	Net Income	%	Net Income	%	Net Income	%	Net Income	%	NI
Perfect Information	289346	67.2%	0	0.0%	113922	26.5%	27319	6.3%	430549
LOOK-BACK	271745	66.8%	-6359	-1.6%	113943	28.0%	27397	6.7%	406689
UNIVARIATE - A - 3	262473	64.5%	3345	0.8%	113926	28.0%	27432	6.7%	407139
UNIVARIATE - B - 9	257489	63.4%	7258	1.8%	113861	28.0%	27538	6.8%	406110
LSTM	261156	64.5%	1977	0.5%	113943	28.2%	27397	6.8%	404692
MULTIVARIATE	262539	64.4%	3550	0.9%	113943	28.0%	27397	6.7%	407392
RANDOM	271184	67.7%	-13270	-3.3%	113854	28.4%	28795	7.2%	400506

5.4 Conclusions

A two-stage stochastic convex model is developed to evaluate the participation of a W&SPP in both DAM and RM. This model avoids the use of binary variables and it is successfully applied to optimize the operation of such a plant seeking to maximize the net income of the system. Several simulation experiments were

designed and carried out considering different approaches to model the uncertainty in the available wind energy and regulation requirements by SO when the decisions are to be made by the energy planner. A data-driven approach was considered to handle the uncertainty due to lack of information. While raw forecast data for available wind energy was translated into a set of meaningful and useful scenarios, historical data about regulation requirements was used to train an LSTM-RNN and perform a clustering to generate scenarios using both univariate and multivariate analysis. While an LSTM-RNN based forecast of regulation requirements by SO provides satisfactory results, a scenario-based approach outperforms all the considered approaches. Because of the highly random behavior of regulation requirements, the associated uncertainty with this parameter is better handled by a scenario-based approach. With the scenario based approach, the reduction of net income (cost of uncertainty) ranges between 6-8.5% when compared to the net income under the PI hypothesis. From the reduction of net income perspective, the importance of scenario generation technique is clear and the reduction of net income in the worst-case scenario is higher than that of the best-case scenario by a factor of two.
As to the operation of the W&SPP, the participation in the reserve and regulation market is a priority. Therefore, the system will have to deviate in the DAM, i.e., participate in the BM, in an amount depending on how the uncertainty has been modeled. The scenario generation approaches, especially multivariate and LOOK-BACK show an efficient way to model the uncertainty of regulation requirements by SO. The results obtained are very close with respect to the case where there is a perfect information for these requirements. Therefore, in both cases, W&SPP should focus on improving the available wind energy forecast.

CHAPTER 6

6 A novel data-driven scenario generation process. Application to a wind and storage power plant participating in the pool market.

In this chapter, the problem of maximizing the net income of a Wind and Storage Power Plant (W&SPP) participating in the pool market is formulated as a two-stage convex stochastic program. A novel hybrid approach using multivariate clustering techniques and the recurrent neural network is used to derive scenarios to handle the uncertainty associated with the energy price. Lastly, a simulation experiment is carried out to show the effectiveness of the proposed methods using a real-world case study. This chapter is based on [88].

6.1 Introduction:

Generation from variable renewable energy resources has increased their penetration in the power market worldwide. Wind farms and solar photovoltaic plants have reached the status of a mature technology. The main problem of these generators participating in pool markets (PM) is the time gap that exists between the time when the commitments of selling/buying energy in the markets are made and the actual realization of those commitments. This is not a problem for conventional generators, however, it is a real challenge for *variable renewable resources generators* (VRRG), like solar plants and wind farms. To better handle the participation of VRRG in the pool market, *day-ahead market* (DAM), *intraday market* (IDM) and *balancing market* (BM) are considered separately [4]. The first two markets run sequentially. IDM is run after DAM and it is meant to give the VRRG the possibility of updating generator commitments when more accurate information about uncertain parameters is available. The last one, the BM, gives the possibility of buying/selling energy to compensate for the deviations in real time.
The decision-making problem of defining the participation of a VRRG in the pool market can be formulated as an optimization problem under uncertainty, i.e, several parameters of the problem are not known when the decisions are to be made. Among the existing approaches to handle a decision-making problem under uncertainty, the most widely used technique is a stochastic programming approach. When dealing with uncertainty using a stochastic approach, a set of scenarios need to be defined to model the uncertain parameters. Each of these scenarios should correspond to a feasible realization of the uncertain parameters and an associated probability of occurrence.
The stochastic approach has been used to optimize the participation of power generators, both the traditional and renewable resource-based, in the energy pool markets. In particular, several papers are available in the literature considering the participation of power producers in the day-ahead market (DAM) and real-time or balancing market (BM) under uncertainty. For example, a pumped-hydro system is proposed as a storage system to cope with the variability of the generation of a wind farm in [89], where a two-stage stochastic approach is presented to optimize the expected profit of the system participation in the day-ahead and real-time markets. Scenarios for available wind energy are considered as input data and scenarios for day-ahead prices are generated through input/output hidden Markov model and prices in the real-time market are considered as known. On the other hand, a Virtual Power Plant with a Wind farm is considered in [66]. In this case, a two-stage stochastic mixed integer linear

program is proposed to maximize its expected profit when participating in the day-ahead and balancing markets. Available wind energy and market prices are considered uncertain and modeled by scenarios. Twenty-five days of data, both for available wind energy and market price, are chosen to generate equiprobable scenarios. A two-stage stochastic mixed integer linear program is also used to optimize the participation of a hybrid wind-solar plant in DAM under uncertainty in market price, available wind and solar energy [64], where scenarios are defined by selecting a number of daily actual data. To optimize the participation of an *Independent Power Producer* (IPP) in day-ahead and real-time markets, a two-stage stochastic approach is proposed in [90], where it groups a wind farm and traditional generation as thermal and hydro plants. Their objective was to maximize the profit of the IPP while ensuring a participation of the wind farm as high as possible. Uncertainty in wind generation and power prices were modeled by scenarios. A two-stage robust optimization approach is used in [60] to optimize a wind-storage plant which can sell/buy energy in both DAM and real-time market. Uncertainties in both available wind energy and market prices were represented through confidence intervals.

However, a comprehensive participation in the pool market including the IDM has received limited attention in the literature. A model to evaluate the participation of a hydropower plant in DAM, IDM and BM is presented in [91] addressing German market whereas a rolling horizon optimization framework is proposed in [92] to optimize the participation of a wind farm in DAM and IDM. Only available wind energy is considered uncertain and modeled by scenarios while electricity prices are considered as known. A strategy to participate in Elbas intraday market is presented in [93] where the DAM prices are certainly known and just balancing prices are forecast by using a statistical regression-type model.

As already stated, a stochastic approach needs a set of scenarios to be defined. There are several approaches available in the literature to generate scenarios. One approach is to consider a deterministic forecast, also called point forecast of the uncertain parameter as a single scenario. In particular, several techniques were employed to perform a point forecast of market prices. A feedforward neural network is used to predict DAM price in [94] while a deterministic framework to forecast DAM price is proposed in [95] by using clustering techniques over the original dataset and deploying dedicated feedforward neural networks for each cluster. A neural network based forecast of intraday market prices is presented in [96], where the explanatory variables are exposed in detail and a conventional Multi-Layer Perceptron neural network is applied to perform a point forecast of prices in the intraday market. A forecast of the daily average electricity price in the Nord Pool Market is presented in [97], where univariate and

multivariate forecast models are presented and compared. Lastly, a point forecast for day-ahead market prices in several countries is performed in [98], where a lasso estimation technique is proposed to capture the intraday dependency among hourly prices.
Another way to handle the uncertainty is to define a set of feasible scenarios for the uncertain parameters. Several techniques have been used to define scenarios and their associated probability of occurrence. For example, scenarios chosen directly from historical data are used in [64]. More complex scenario generation methods based on *autoregressive moving average* (ARMA) and *autoregressive integrated moving average* (ARIMA) models are used in [99], [75] and [100], whereas scenarios to model uncertainty in solar and wind power generation and power prices are generated by Montecarlo simulation in [101].
A more recent approach that is used to define scenarios is related with multivariate probabilistic forecasting techniques. For example, a feedforward neural network is used in [102] to perform a point forecast of the generation capacity of a photovoltaic solar generator. This forecast is used, along with other variables, to perform a probabilistic forecast by using an analog ensemble procedure. A probabilistic price forecast for the day-ahead and intraday markets is performed in [103]. It uses a set of explanatory variables and statistical learning algorithms. In particular, linear quantile regression and gradient boosting trees algorithms were proposed in their work. The result is a set of quantiles between 5% and 95% with a 5% increment.
A set of explanatory variables and quantile regression are used to perform a probabilistic forecast of wholesale electricity price in the UK electricity market in [104]. A sensitivity analysis of how the fundamental explanatory variables influence the price is also presented. Recently, in [105] a comprehensive review of probabilistic forecasting techniques applied to forecast electricity price is presented.
From the literature review, we see that although the optimization of VRRG participation in DAM has been considered in the literature, a limited attention has been given to consider a comprehensive participation in the energy pool market, i.e., simultaneously consider DAM, IDM, and BM. On the other hand, several techniques for defining scenarios have been presented. Among them, the recent probabilistic forecasting techniques show a promising result to develop data-driven scenarios, however, novel approaches are needed to obtain meaningful scenarios from a stochastic programming point of view.
In this work, a decision-making problem to deal with the problem of a wind farm participating in the pool market is considered. While this wind farm is considered to have an *energy storage system* (ESS), the participation in the IDM is also

explicitly considered with the DAM and BM to allow the operator not only to be able to perform a time-based arbitrage strategy but also a market-based arbitrage between DAM and IDM. The problem is clearly affected by the uncertainty associated with input data: available wind energy and market prices are not known at the time of making a decision. Furthermore, generating influential scenarios to capture the real-world uncertainty associated with the price is also a key challenge, which is not addressed well in the literature as well. Therefore, in this chapter, a new two-stage convex stochastic programming model is proposed to optimize the participation of a W&SPP by simultaneously considering DAM, IDM, and BM in the energy pool market. To generate influential scenarios to be fed into the stochastic problem, we proposed a hybrid novel data-driven scenario generation framework by using supervised and unsupervised machine learning techniques. More specifically, a multivariate clustering technique is proposed to find representative patterns of daily market price and a recurrent neural network is designed to extract information from the temporal sequence of those daily patterns to extract a set of scenarios, which can truly represent the underlying uncertainty.

The rest of this chapter is organized as follows: section 6.2 describes the system and power market under study; section 6.3 describes the proposed stochastic model; section 6.4 describes the proposed methods to generate scenarios to be fed into the stochastic problem; section 6.5 analyzes a real-world application of the developed approach and lastly, section 6.6 includes concluding discussion.

6.2 Description of the problem

A Wind and Storage Power Plant (W&SPP) is also considered in this chapter. This power agent will be allowed to participate in the pool market, i.e., day-ahead market (DAM), intraday market (IDM), also known as adjustment market, and balancing market (BM).

Let us consider that the W&SPP participates in the pool market in a day D. The first step is to participate in the DAM. This market runs under a bidding process through which the power agents commit to sell/buy a certain amount of energy at every hour in the day D. The energy prices are not known at the time of bidding and they are known after the market clearing process is over in the morning in day D-1 when all the bids from all the generators are revealed. The participation in the DAM is challenging for a W&SPP. The W&SPP operator has to submit its bids for participation in the DAM one day in advance with a high degree of uncertainty associated with the important parameters such as available wind energy and market prices for day D.

To better handle this challenge, the market operator (MO) runs several sessions of the IDM. In each session, the agents are allowed to buy/sell energy in order to adjust their acquired commitments in DAM through a bidding process. These IDM sessions are run closer to the time of actual delivery of energy by the agents so a less uncertain information is supposed to be available for the agents. The first session of the IDM for day D ends in late evening of day D-1 with a time span including the entire day D. Although several IDM sessions are run afterward to let even further adjustment, only the first session will be considered in this work. The final commitment of the power agent will be the added commitments in both the DAM and IDM. The existence of DAM and IDM results in the possibility to have two prices for the same amount of energy sold in the same hour. This is the base for the market-based arbitrage strategy that an agent may exploit. Due to the existence of storage capacity in the W&SPP, a time-based arbitrage strategy may also be investigated i.e., to buy/store energy when energy has low price and sell/discharge energy when energy has a high price. Also, both arbitrages may be combined to look for the biggest gap in price for both the DAM and IDM.

Lastly, in every hour of day D, a real-time balancing market is run to handle the deviations between the commitments in DAM and IDM and the actual delivery of energy in real time. This BM will determine the price of the deviation upwards and deviation downwards of the power agent with respect to what it was committed in DAM and IDM. The decision-making process for the participation in the energy pool market is shown in Figure 38. In this figure, it can be seen that the participation of the agent in the DAM is decided in the first place. Later, the agent may participate in the IDM to correct the commitments acquired in the DAM. Lastly, in real time, the agent participates in the BM to buy/sell energy that compensates the deviations with respect to the commitments acquired by the DAM and IDM.

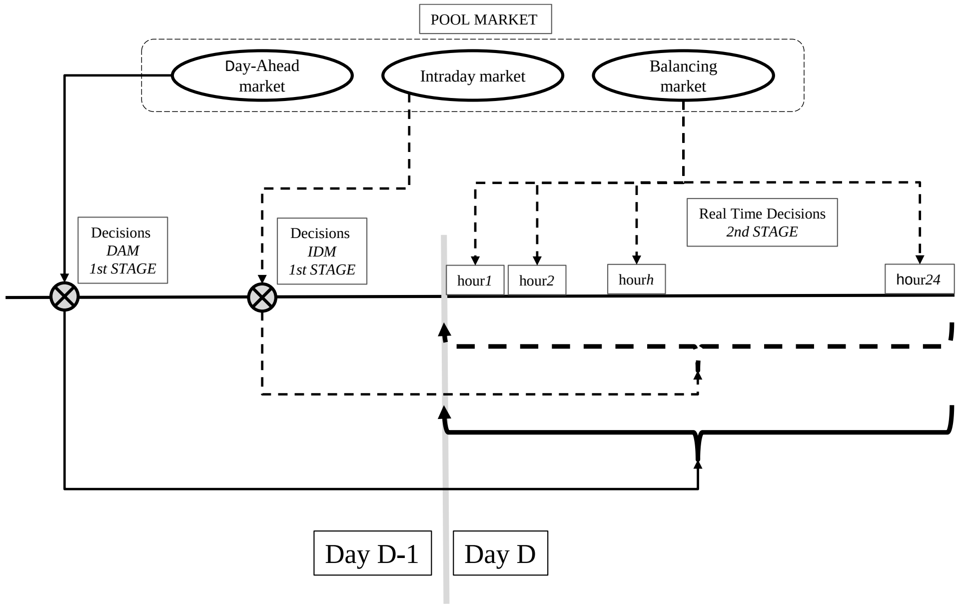


Figure 38. Pool market mechanism

6.3 Model Description

In this section, the proposed mathematical model to optimize the participation of the W&SPP in the pool market is discussed. First, a price-taker assumption is made, meaning that the agent is not able to influence the market price. When decisions to participate in DAM and IDM are to be made, several uncertainties make this decision problem challenging. These uncertainties are modeled as random variables. For instance, pool market price and available wind energy in day D are considered as random variables. To handle this uncertainty, a two-stage stochastic approach is proposed. Under the stochastic approach, uncertainty is modeled by defining scenarios which represent several realizations of the random variables. A two-stage stochastic problem considers two kinds of variables: first stage and second stage variables. First stage variables are associated with decisions to be made before random variables take values and second stage variables are associated with decisions to be made depending on the first stage decisions and realizations of random variables (i.e., depending on the considered scenarios). Thus, the two-stage stochastic problem aims to find an optimal solution which includes the first stage decisions to be made in day D-1 and the second stage decisions to be made after random variables take values in day D.

Decisions associated with the participation of W&SPP in DAM and IDM will be considered as first stage variables in our model as shown in Figure 38. The operation of the ESS is considered as a first stage decision as well. All these decisions are made in day D-1. For all considered scenarios, random variables become input data. Participation of the W&SPP in the BM is modeled as scenario dependent second stage variables.

The following notation will be used to formulate the proposed model:

Nomenclature

Sets and Subindex:

S Set of Scenarios.

T Set of time slots.

s Subindex for scenarios, s = 1, …., Ns.

t Subindex for time slot, t = 1,….., T

Parameters

T Number of periods under consideration .

$\overline{P}^{wind}$ Rated power of the wind farm (MW).

E_0^{ess} Initial energy stored in the ESS (MWh).

η_{in} Charging efficiency of the ESS.

η_{out} Discharging efficiency of the ESS

$\overline{E}^{ess}$ Maximum energy stored in the ESS (MWh).

$\overline{P}^{ess}$ Maximum power to/from ESS (MW).

$SOC_t^{\min}$ Minimum state of charge of ESS.

κ^{bm} Correction factor of deviation prices in BM.

ρ_s Probability of scenario s

Ns Number of scenarios

Random variables

$\beta_t^{dam}, \beta_{s,t}^{dam}$ Energy price in the DAM (€/MWh).

$\beta_t^{idm}, \beta_{s,t}^{idm}$ Energy price in the IDM (€/MWh).

$\hat{\lambda}_t^{bm,up}, \hat{\lambda}_{s,t}^{bm,up}$ Energy price of deviation up (€/MWh).

$\hat{\lambda}_t^{bm,dw}, \hat{\lambda}_{s,t}^{bm,dw}$ Energy price of deviation down (€/MWh).

$\lambda_t^{bm,up}, \lambda_{s,t}^{bm,up}$ Corrected price of deviation up (€/MWh).

$\lambda_t^{bm,dw}, \lambda_{s,t}^{bm,dw}$ Corrected price of deviation down (€/MWh).

$\varphi_t, \varphi_{s,t}, \gamma_t, \gamma_{s,t}$ Auxiliary parameters for the convex model.

$\hat{P}_t^{wind}, \hat{P}_{s,t}^{wind}$ Wind power available (MW).

Decision Variables

$P_{s,t}^{wind}$ Wind power actually used (MW).

E_t^{ess} Energy stored in the ESS (MWh).

$P_t^{ess,in}$ Power entering the ESS (MW).

$P_t^{ess,out}$ Power delivered by the ESS (MW).

SOC_t State of charge of ESS in time t.

$P_{s,t}$ Power to/from W&SPP in time t (MW).

$\hat{P}_t^{dam}$ Power committed in the DAM (MW).

$\hat{P}_t^{idm}$ Power committed in the IDM (MW).

$\hat{P}_t^{pm}$ Power committed in the PM (MW).

$P_{s,t}^{pm}$ Power actually delivered/taken in the PM (MW).

$\Delta_{s,t}^{pm}$ Unbalance in PM (MW)

The following equation (87) states a generic objective function of a two-stage stochastic programming problem:

$$\textit{minimize}\;\; f(X) + \mathrm{E}\big[g(X,Y,\xi)\big] \qquad (87)$$

In the equation (87), X is the set of first stage variables, which are not scenario dependent variables. This means that decision concerning these variables are made before the information about uncertain parameters is revealed. In this problem, commitments in the DAM and IDM, and operating variables of the ESS are considered as first-stage variables. The decision variables showed in the nomenclature with only "*t*" in the subindex belongs to the set of first stage variables. On the other hand, Y is the set of second stage variables, which are scenario dependent variables. These variables take different values depending on the considered scenario. These decisions variables include both "*t*" and "*s*" as subindex in the nomenclature. Lastly, ξ is the set of random variable and the operator E computes the expected value of function *g*.
In the following subsections 6.3.1 and 6.3.2, we will describe our proposed model, which proposes a convex two-stage stochastic model to optimize the participation of a W&SPP in the pool market.

6.3.1 Objective Function

The objective of the decision-making problem is to maximize the net income of the operation of W&SPP participating in DAM, IDM, and BM. The objective function is defined by the equation (88). All markets considered in this paper run on an hourly basis. Therefore, it is equivalent to consider sell/buy energy or power.

$$\textit{maximize} \quad \sum_{t=1}^{T}\left(\beta_t^{dam}\cdot\hat{P}_t^{dam}+\beta_t^{idm}\cdot\hat{P}_t^{idm}\right)+\sum_{t=1}^{T}\lambda_t^{bm,up}\cdot\Delta_t^{up}-\sum_{t=1}^{T}\lambda_t^{bm,dw}\cdot\Delta_t^{dw} \qquad (88)$$

The first term in equation (88) accounts for the net income for participating in DAM and IDM while the second and third terms account for the implications of deviation with respect to the commitments acquired in day D-1. These deviations are handled by buying/selling energy in the BM. All the prices in this equation are not actually known and thus modeled as random variables.

The above objective function can be equivalently reformulated as a minimization problem as follows, as to equation (89), to better implement the solution process:

$$\begin{aligned} \textit{minimize} \quad & -\sum_{t=1}^{T}\left(\beta_t^{dam}\cdot\hat{P}_t^{dam}+\beta_t^{idm}\cdot\hat{P}_t^{idm}\right)- \\ & \sum_{t=1}^{T}\lambda_t^{bm,up}\cdot\Delta_t^{up}+\sum_{t=1}^{T}\lambda_t^{bm,dw}\cdot\Delta_t^{dw} \end{aligned} \tag{89}$$

Some variables are defined using equations (90)-(93) to use a convex function to model the participation in BM [37]. These variables avoid the use of binary variables. Thus, the equation (90) defines the deviation in the energy market with respect to the commitments acquired in day D-1, which are defined in the equation (91). Equations (92) and, (93) define the deviations up and down in the energy market by using convex functions.

$$\Delta_t^{pm}=P_t^{pm}-\hat{P}_t^{pm} \tag{90}$$

$$\hat{P}_t^{pm}=\hat{P}_t^{dam}+\hat{P}_t^{idm} \tag{91}$$

$$\Delta_t^{up}=\left[\Delta_t^{pm}\right]^{+}=\max\left\{\Delta_t^{pm};0\right\} \tag{92}$$

$$\Delta_t^{dw}=\left[\Delta_t^{pm}\right]^{-}=\max\left\{-\Delta_t^{pm};0\right\} \tag{93}$$

As a result, objective function can be written as follows:

$$\begin{aligned} \textit{minimize} \quad & -\sum_{t=1}^{T}\left(\beta_t^{dam}\cdot\hat{P}_t^{dam}+\beta_t^{idm}\cdot\hat{P}_t^{idm}\right)- \\ & \sum_{t=1}^{T}\lambda_t^{bm,up}\cdot\left[\Delta_t^{pm}\right]^{+}+\sum_{t=1}^{T}\lambda_t^{bm,dw}\cdot\left[\Delta_t^{pm}\right]^{-} \end{aligned} \tag{94}$$

Equation (94) may be rewritten as equation (95) to make it more convenient for convex optimization solvers, as explained in chapter 4.

$$minimize \quad -\sum_{t=1}^{T}\left(\beta_t^{dam}\cdot\hat{P}_t^{dam}+\beta_t^{idm}\cdot\hat{P}_t^{idm}\right)+\sum_{t=1}^{T}\varphi_t\cdot\left|\Delta_t^{pm}\right|-\sum_{t=1}^{T}\gamma_t\cdot\Delta_t^{pm} \quad (95)$$

Where,

$$\varphi_t=\frac{\lambda_t^{bm,dw}-\lambda_t^{bm,up}}{2} \quad (96)$$

$$\gamma_t=\frac{\lambda_t^{bm,dw}+\lambda_t^{bm,up}}{2} \quad (97)$$

Just remember that equation (95) will be a convex function as long as condition (98) holds. Interestingly, it is always the case in the spanish market [49].

$$\lambda_t^{bm,dw}\geq\lambda_t^{bm,up} \quad (98)$$

As we mentioned earlier, the energy price for all markets and available wind energy are considered as random variables. To model these random variables, a set of scenarios with an associated probability of occurrence needs to be defined. Thus, customizing equation (87) according to our problem, we obtain the objective function (99) of a two-stage stochastic problem as follows:

$$\begin{aligned} minimize \quad & -\sum_{s=1}^{Ns}\rho_s\cdot(\sum_{t=1}^{T}\left(\beta_{s,t}^{dam}\cdot\hat{P}_t^{dam}+\beta_{s,t}^{idm}\cdot\hat{P}_t^{idm}\right)- \\ & \sum_{t=1}^{T}\varphi_{s,t}\cdot\left|\Delta_{s,t}^{em}\right|+\sum_{t=1}^{T}\gamma_{s,t}\cdot\Delta_{s,t}^{em}\ ) \end{aligned} \quad (99)$$

In the equation (99), random variables become actual parameters for every considered scenario. Likewise, it is straightforward to define equations (100), (101) and (102) from equations (90), (96) and, (97).

$$\Delta_{s,t}^{pm}=P_{s,t}^{pm}-\hat{P}_t^{pm} \quad (100)$$

$$\varphi_{s,t}=\frac{\lambda_{s,t}^{bm,dw}-\lambda_{s,t}^{bm,up}}{2} \quad (101)$$

$$\gamma_{s,t} = \frac{\lambda_{s,t}^{bm,dw} + \lambda_{s,t}^{bm,up}}{2} \tag{102}$$

6.3.2 Constraints

The following set of additional constraints define the feasible set for the proposed stochastic optimization problem. The set of constraints (103)-(112) define the operation of the W&SPP, while the constraints (113)-(115) deal with the participation in the pool market.

Constraint (103) sets the energy stored in the ESS in every time step as a function of the initial condition, the power entering and leaving the ESS and, the efficiency of charging and discharging process.

$$\forall t \in T, \forall s \in S$$

$$E_t^{ess} = E_0^{ess} + \sum_{\tau=1}^{t} \eta_{in} P_\tau^{ess,in} - \sum_{\tau=1}^{t} \frac{1}{\eta_{out}} P_\tau^{ess,out} \tag{103}$$

Constraint (104) limits the wind power to the available capacity in every considered scenario. The right-hand side of this constraint is one of the random variables modeled through scenarios.

$$P_{s,t}^{wind} \leq \hat{P}_{s,t}^{wind} \tag{104}$$

Also related with the ESS, constraint (105) requires to have the same energy stored at the beginning and at the end of the period under study (one day in our case); constraints (106), (107) and (108) limit the maximum and minimum energy stored in the ESS. Constraints (109) and (110) limit the power leaving/entering the ESS in every hour.

$$E_0^{ess} = E_T^{ess} \tag{105}$$

$$E_t^{ess} \leq \bar{E}^{ess} \tag{106}$$

$$SOC_t = E_t^{ess} \ / \ \bar{E}^{ess} \tag{107}$$

$$SOC_t \geq SOC_t^{\min} \tag{108}$$

$$\hat{P}_t^{ess,out} \leq \overline{P}^{ess} \tag{109}$$

$$\hat{P}_t^{ess,in} \leq \overline{P}^{ess} \tag{110}$$

Constraint (111) defines the power balance in the W&SPP and constraint (112) sets some nonnegative restrictions.

$$P_{s,t} = P_{s,t}^{wind} + P_t^{ess,out} - P_t^{ess,in} \tag{111}$$

$$P_t^{ess,out}\, ;\, P_t^{ess,in}\, ;\, E_t^{ess} \geq 0 \tag{112}$$

As to the pool market constraints, constraint (113) limits the maximum power that can be bought/sold in DAM while constraint (114) does the same for IDM. It is to note that limits in the IDM are wider to allow to fully correct previous decisions concerning DAM commitments. Lastly, constraint (115) sets the relationship between the power exchange by the W&SPP and the power market.

$$-\overline{P}^{ess} \leq \hat{P}_t^{dam} \leq \overline{P}^{wind} + \overline{P}^{ess} \tag{113}$$

$$\left|\hat{P}_t^{idm}\right| \leq \overline{P}^{wind} + \overline{P}^{ess} \tag{114}$$

$$P_{s,t} = P_{s,t}^{pm} \tag{115}$$

6.4 Scenario Generation Methods

In this section, the proposed methods used to generate scenarios for both available wind energy and energy price are discussed. Available wind energy and energy price are not known when decisions concerning the participation in the pool market are to be made. Here, a set of wind energy scenarios is derived from the forecast data obtained from [106]. On the other hand, a set of scenarios for market price is derived from historical data by using machine learning techniques. Firstly, a multivariate clustering technique is proposed to find patterns of market price that can be considered as scenarios. Although clustering techniques has been used as a scenario reduction technique in the literature, its pattern identification capability has not been leveraged yet as a scenario generation approach. In this work, at first, a frequentist approach which only considers how often each pattern appears in the dataset is proposed to assign a probability of occurrence to each scenario. Then a novel Bayesian approach is proposed. Using an LSTM Recurrent Neural Network, information is extracted from the sequence of patterns that occurred during the days before day D-1. In other words, the probability of each scenario is calculated depending on the sequence of actual prices in the previous days. This approach is promising in the sense that it gets information not only from the pattern of price themselves but also from the temporal sequence in which they occur.

6.4.1 Wind Energy Scenario

The approach to handle the uncertainty in available wind energy is the same as in chapter 5. Thus, the available wind energy forecast is provided by the WF operator and scenarios are generated from the available data as explained in section 5.3.1.1.

6.4.2 Energy Market Price Scenario

We consider one-year historical data of daily energy price for all the markets to extract information to generate scenarios to be fed into the stochastic optimization model. To generate scenarios for the energy market price, we have proposed the following two approaches:

a. **Static approach:** In this approach, a clustering technique is applied as explained in subsection 6.4.2.1 to define a set of scenarios. Probability of occurrence of each scenario is calculated based on a frequentist reasoning. The probability is calculated from the clustering procedure by taking into account the number of elements in each cluster. We consider this approach as a static scenario generation approach as both clustering/scenario definition and assigned probabilities do not change if the historical dataset remains the same. The frequentist reasoning process is briefly explained in subsection 6.4.2.2.1.

b. **Dynamic approach:** In this approach, scenario set is also defined by the clustering technique explained in subsection 6.4.2.1. However, probability of occurence of each scenario is calculated based on a bayesian reasoning. Information associated with the temporal sequence of events is used to update the probability of each scenario on a daily basis. The detail process of probability calculation is described in subsection 6.4.2.2.2. Unlikewise the frequentist reasoning explained above, this approach can be seen as a dynamic approach as the probability of occurrence of the scenarios are updated every day during the simulation process.

To set a base case, a random approach is also considered to compare the performance of the proposed approaches. A set of data points is randomly chosen from the dataset and defined as scenarios. In order to assign probabilities to these scenarios, an assumption of equiprobability is made. The relationships among approaches to defining scenarios and assignment of probabilities of occurrence to them are shown in the following Figure 39.

.

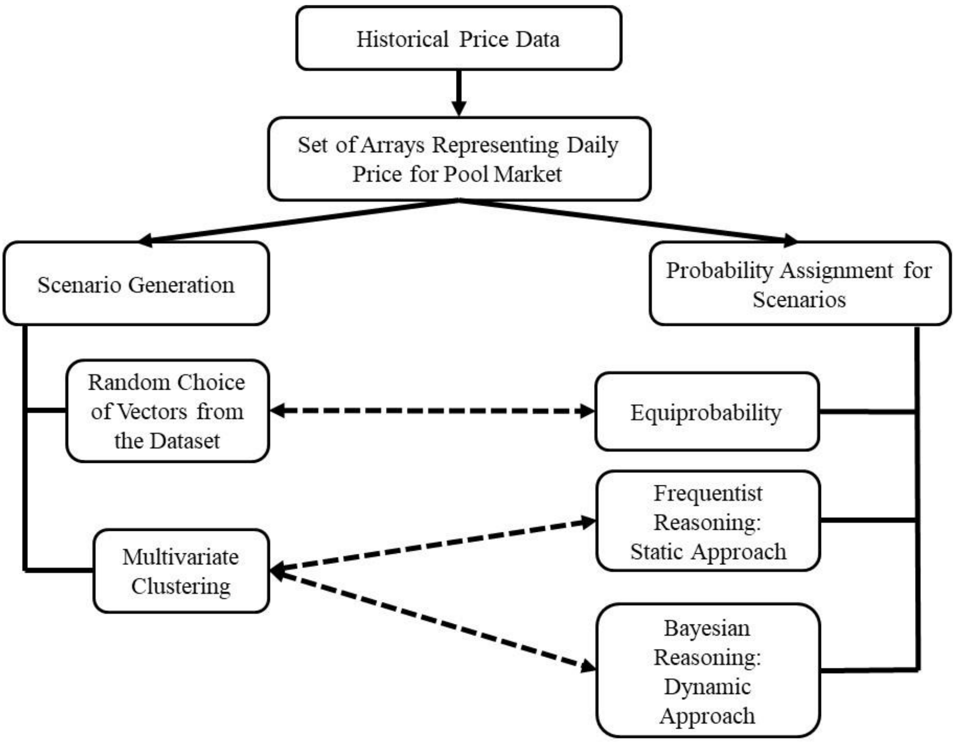


Figure 39.- Scenario generation approaches for energy price

6.4.2.1 Clustering-Based Scenario Generation.

The scenario generation process will follow a multidimensional data-driven approach by using historical data of daily energy price for the considered power markets: DAM, IDM, and BM. Therefore, the data set is made of arrays of 96 elements as shown in Figure 40.

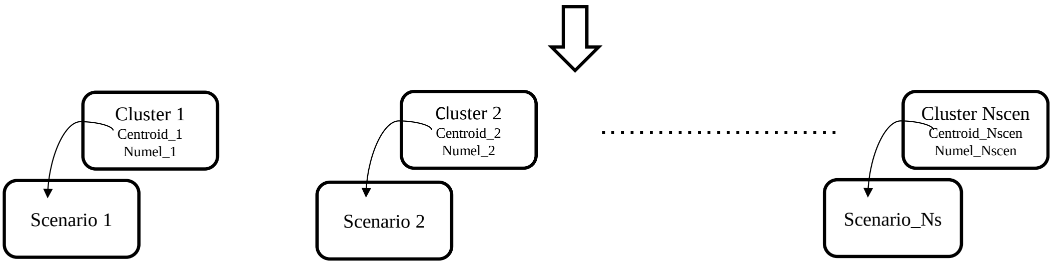
Each array is constructed by concatenating the hourly prices for one day and for each market. Hence, a scenario generation procedure involves finding representative points of the whole dataset. This may be seen as a scenario reduction technique from the original dataset defined by the historical data. One popular approach to performing this scenario reduction is by using clustering techniques [87], which are defined as an unsupervised learning task because no labeled data is available. These clustering techniques aim at finding a discrete distribution with smaller support than the original one minimizing a probabilistic distance between them.

$$\boxed{\text{Day 1}}\ \Omega_1 = \left[\beta_{1,1}^{dam},\dots,\beta_{1,T}^{dam};\beta_{1,1}^{idm},\dots,\beta_{1,T}^{idm};\lambda_{1,1}^{bm,up},\dots,\lambda_{1,T}^{bm,up};\lambda_{1,1}^{bm,dw},\dots,\lambda_{1,T}^{bm,dw}\right]$$

$$\boxed{\text{Day 2}}\ \Omega_2 = \left[\beta_{2,1}^{dam},\dots,\beta_{2,T}^{dam};\beta_{2,1}^{idm},\dots,\beta_{2,T}^{idm};\lambda_{2,1}^{bm,up},\dots,\lambda_{2,T}^{bm,up};\lambda_{2,1}^{bm,dw},\dots,\lambda_{2,T}^{bm,dw}\right]$$

$$\boxed{\text{Day d}}\ \Omega_d = \left[\beta_{d,1}^{dam},\dots,\beta_{d,T}^{dam};\beta_{d,1}^{idm},\dots,\beta_{d,T}^{idm};\lambda_{d,1}^{bm,up},\dots,\lambda_{d,T}^{bm,up};\lambda_{d,1}^{bm,dw},\dots,\lambda_{d,T}^{bm,dw}\right]$$

$$\boxed{\text{Day N}}\ \Omega_N = \left[\beta_{N,1}^{dam},\dots,\beta_{N,T}^{dam};\beta_{N,1}^{idm},\dots,\beta_{N,T}^{idm};\lambda_{N,1}^{bm,up},\dots,\lambda_{N,T}^{bm,up};\lambda_{N,1}^{bm,dw},\dots,\lambda_{N,T}^{bm,dw}\right]$$



* Numel = number of elements in the corresponding cluster.

Figure 40.- Clustering-based scenario generation.

In particular, in this case, a k-means algorithm is proposed to generate scenarios out of the available historical price data.

In our case, the original dataset is made up of one year of daily prices arrays. Each of these arrays is made of 96 elements, corresponding to the hourly prices of energy in DAM, IDM, deviation upwards, and deviation downwards in BM. Using the clustering technique, the whole data set will be divided into a set of clusters. Each of these clusters is defined with a centroid and a set of points assigned for each cluster. These centroids will become the considered scenarios for the stochastic problem.

6.4.2.2 Probability of occurrence

As we mentioned earlier, once the scenario set has been generated, the probability of occurrence for each scenario must be assigned. We will consider two approaches to calculate the probability of occurrence as follows:

6.4.2.2.1 Frequentist Reasoning

The probability of occurrence can be calculated from the clustering procedure itself using a frequentist reasoning. It means that the probability of occurrence of each scenario depends on the number of data points assigned to each cluster/scenario. Thus, by computing the ratio between the number of data points assigned to each cluster and the total amount of points in the dataset, the probability of occurrence can be defined.

6.4.2.2.2 Bayesian Reasoning

One step forward to feed meaningful data to the stochastic problem is to update the probability of occurrence for each scenario when new information is available. Therefore, a Bayesian reasoning-based approach is proposed in this paper to take into account the most recent event.

To implement this idea, a hybrid unsupervised-supervised machine learning framework is proposed. It aims at extracting more information from the dataset. As we said earlier, one year of daily price data is available and a clustering approach is carried out to define scenarios. Once the clustering is performed, a sequence of daily patterns can be drawn. Then it is possible to compute the probability of occurrence of each scenario in the sequence given what happened in the previous days.

At first, it is needed to build a labeled data set from the available data that may be used in the supervised learning step of our framework. As explained in subsection 6.4.2.1, the historical price data available is rearranged as a set of 365 arrays of daily prices. Each of these arrays is assigned to one of the defined clusters. As a result, a sequence of daily price patterns/classes is obtained. This idea is shown in Figure 41. In this figure, K_d denotes the cluster assigned to the daily price array of day D.

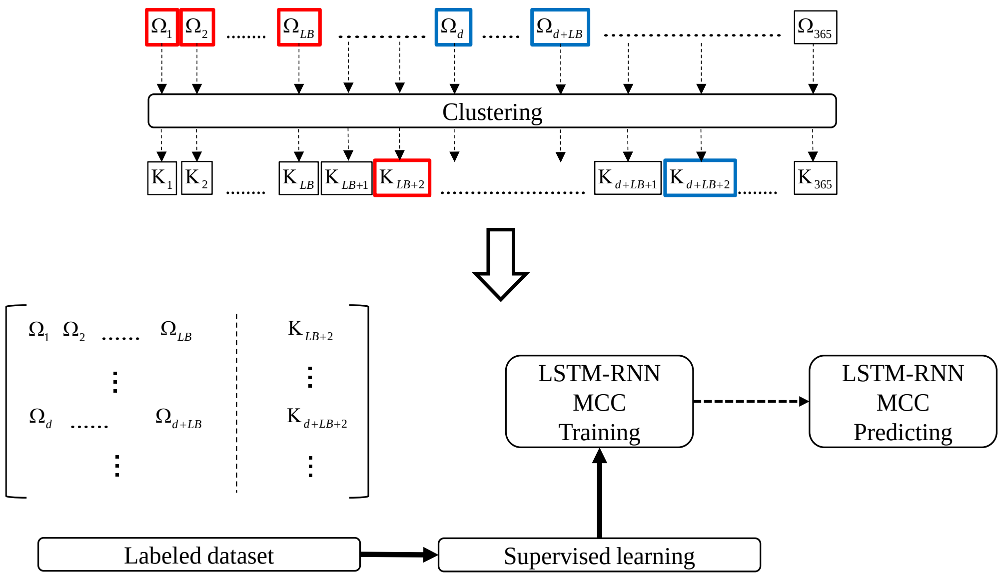


Figure 41.- Definition of labeled dataset to train the LSTM-RNN MCC.

Once the daily price and corresponding daily price patterns are computed, it is possible to generate the labeled dataset. To do that, the actual decision process must be kept in mind. Our goal is to forecast the probability of occurrence of each scenario for day D when decisions are to be made in day D-1. At that time, the decision maker only knows the actual data from day D-2 backward. A look-back (LB) period is defined as the number of days that the decision maker will look backward to forecast the future. With this time framework in mind, the labeled dataset can be generated.
With this new labeled dataset, supervised machine learning techniques can be used. In particular, a recurrent neural network-based multiclass classifier is proposed in this chapter. *Recurrent Neural Networks* (RNNs) are a kind of neural network well suited to perform learning and prediction tasks over sequences of data. This sequence may be a text, a video or a time series of data. This kind of neural network outperforms the traditional feedforward neural network for these

tasks due to its ability to handle the sequence of information in the input data [107]. The main limitation of RNN is the so-called vanishing-exploding gradient problem which makes it difficult the process of training [84]. During the training procedure, the backpropagation algorithm is used to update the weights and bias of the cells. This algorithm set a way to compute the gradient of the error in each cell and update the weight and bias accordingly. When facing long sequences, the gradient tends to become very large, explodes, or very small, vanishes, which is a major drawback for the training of the RNN. To overcome this problem, an evolution of the RNN called *Long Short-Term Memory Recurrent Neural Network* (LSTM-RNN) has been proposed [35]. In this neural networks, the cell becomes more complicated in order to provide the cells with the ability to decide which information from the previous steps in the sequence should be kept or deleted.
Usually, the objective of a neural network is to provide a deterministic forecast of the desired output, given some input data. However, sometimes, a deterministic forecast from a Neural Network is not the most desirable output [108]. Instead, the goal of a neural network is to assign the input sequence to any of the classes defined previously. This kind of neural network is also called multiclass classifiers and the neural network may include an output layer called a softmax layer to assign the probability of belonging to any of the defined classes [109].
In this work, we proposed to tie together the capability of extracting information from a sequence of an LSTM-RNN and the capability of providing a probabilistic classification of the multiclass classifiers. To do so, a set of target classes should be defined in advance. In our case, we obtain these target classes by applying a clustering algorithm to the available dataset. Our proposed LSTM based multiclass classifier (LSTM-MCC) is described in the following Figure 42. Training of the LSTM-MCC is performed by using the labeled dataset built above. Once the training is finished and the parameters of the LSTM-MCC are computed, we can predict the probability of occurrence for each scenario. During D-1, price vectors for the LB period are fed into the LSTM-MCC and the array of probability for every cluster/scenario is updated.

6.5 Simulation and Result

The objective of this simulation is threefold. First, it evaluates several approaches to generate scenarios and handle the uncertainty linked to energy price. Second, it evaluates the impact of adding storage capacity to a wind farm to participate in the pool market and the impact of participating in the IDM. Lastly, it evaluates the quality of the stochastic solutions by comparison with a perfect information hypothesis.

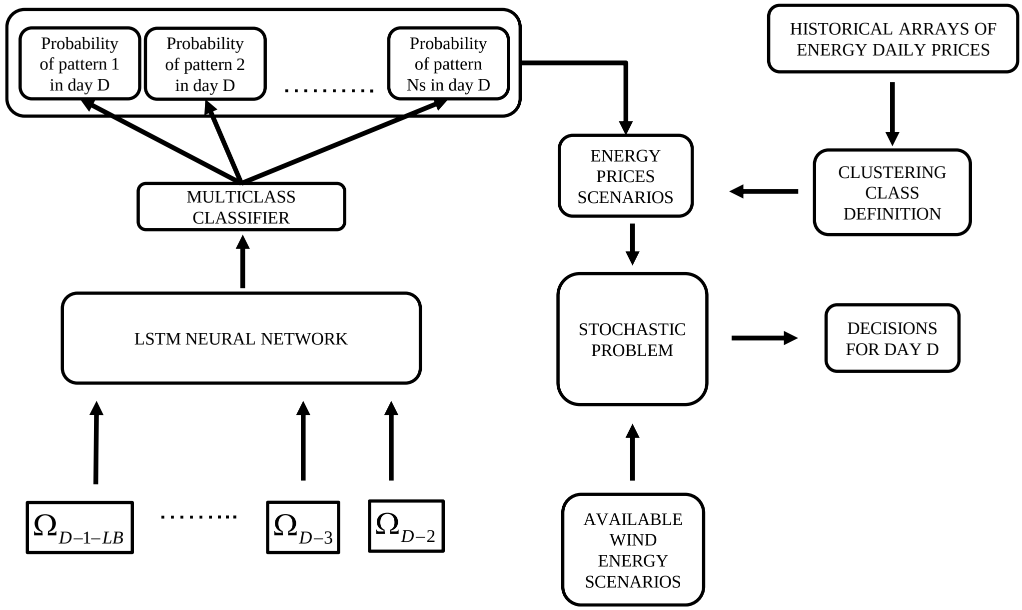


Figure 42.- Dynamic approach to update the probability of occurrence for each scenario.

Data associated with market prices is downloaded from the website of the Spanish system operator where this data is publicly available. The historical dataset is made of 365 daily price vectors corresponding to one year of data. Both clustering and construction of training set for the LSTM-MCC are performed using this historical data set. Several software and libraries are used for the implementation of the proposed methods. All of them are shown in the following
Table 8. This case study focuses on a wind farm located in Northwestern Spain with an installed generation capacity of 15 MW [2]. A sensitivity analysis is made by considering several ESS. Simulations are run over 60 days and the aggregated net income is calculated.
All the simulations are run on a PC with an Intel Core i7-5500U processor at 2.40 GHz and 8 GB of RAM. The time needed for running a 60 days case considering 30 scenarios (3 scenarios for available wind energy and 10 scenarios for the market price) is about 300 seconds.

Table 8. Software and libraries used in this work.

Software / Library	Description	Application
CVX – MATLAB [50]	Convex optimization problem modelling.	Implementation of the stochastic convex problem.
GUROBI	Solver for convex optimization problems.	Solve optimization problem.
SCIKIT-LEARN	Python-based machine learning library.	Clustering. Scenario definition.
KERAS – TENSORFLOW	Python-based library for deep learning.	Implementation, training and prediction of the LSTM-MCC.

6.5.1 Scenario Generation

In section 6.4, two approaches were presented to generate scenarios to be fed into the stochastic model. Both methods rely on a multivariate k-means clustering algorithm to define several clusters from daily price vectors. The centroids of these clusters will be considered as the market price scenarios. One year of daily price for DAM, IDM, and BM in the Spanish pool market are considered in this work. It means that the historical dataset is made up of 365 arrays of 96 elements. It is to note that the Spanish market follows the market structure presented in chapter 2. When analyzing the market prices in all the markets of the pool, it often happens that either $\lambda_t^{bm,dw} = \beta_t^{dam}$ or $\lambda_t^{bm,up} = \beta_t^{dam}$. It means that there is not an actual penalty if the generators deviate from the commitments acquired in the DAM and IDM.

In this work, a parameter $\kappa^{bm} \in (0,1]$ is defined to model a case where there is always a penalty if participating in the BM as stated in equations (116) and (117). Including this modification, the additional energy delivered in real time by the W&SPP are always paid at a lower price compared to the price resulting from the DAM. In fact, this is a penalty for the agent in the sense that if the agent has offered the same energy in advance would have gotten more money. A similar analogy is used for all other deviation cases.

Here, the original data for balancing market prices is modified by considering $\kappa^{bm} = 0.2$.

Of course, different markets would have different behaviour associated with the market price. The decision framework developed in this work would be completely replicable in other markets.

$$\lambda_t^{bm,up} = \hat{\lambda}_t^{bm,up} \cdot \left(1 - \kappa^{bm}\right) < \beta_t^{dam} \quad (116)$$

$$\lambda_t^{bm,dw} = \hat{\lambda}_t^{bm,dw} \cdot \left(1 + \kappa^{bm}\right) > \beta_t^{dam} \quad (117)$$

The number of scenarios to be generated should represent the original dataset while being as small as possible to keep the stochastic problem tractable. To this aim, previous knowledge of which properties of the data should be highlighted by the scenarios are useful. In our case, scenarios are meant to capture two important features in the dataset. In one hand, scenarios should represent different levels of price, i.e., scenarios of high, medium and low prices. On the other hand, the scenarios should also capture different daily profiles of price, i.e, the gap between highest and lowest prices in one day.

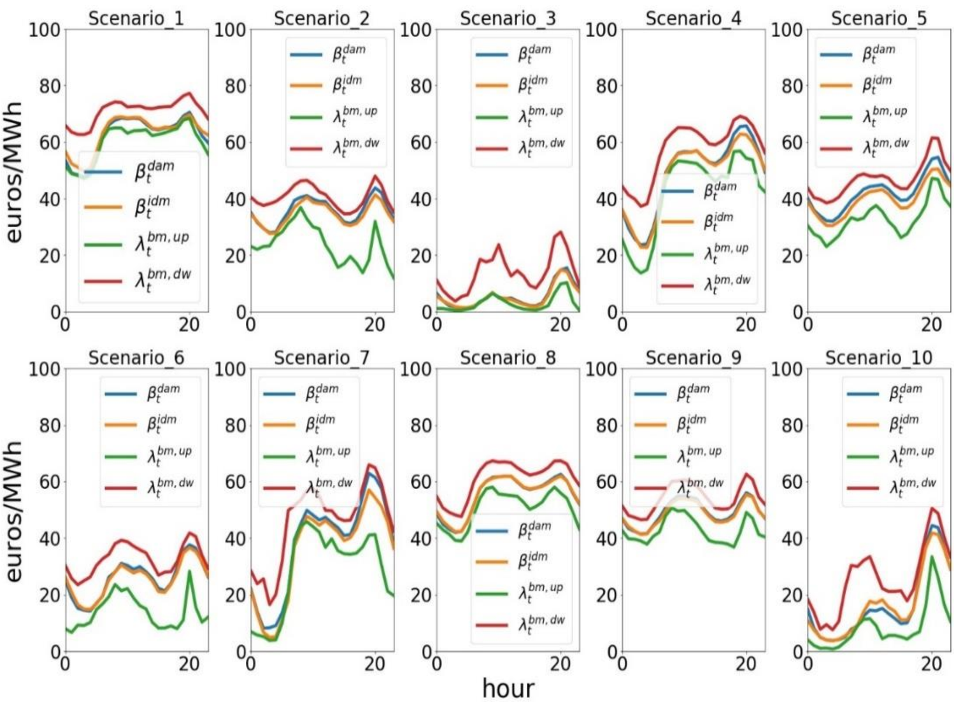


Figure 43.- Scenarios for daily market prices.

With this in mind, ten scenarios are found to provide a good representation of the historical dataset as shown in Figure 43.
Thus, for example, scenario 1 and scenario 5 represent profiles of the small difference between peak and valley prices with scenario 1 accounting for higher prices during the whole day. By contrast, scenario 4 and scenario 10 both have a similar price profile characterized by the high difference between peak and valley prices but scenario 10 shows lower prices during the whole day.
The next step, after the clusters have been identified and the scenarios have been defined, is to assign a probability of occurrence for each of those scenarios. It is in this point where the differences between the static and the dynamic approaches arise. In the static approach, the probability of occurrence of each scenario is calculated while the clustering itself. This calculation is based on the number of elements in each cluster. This probability of occurrence will remain the same every day of the simulation process as it can be seen in Figure 45.
In the dynamic approach, the probability of occurrence of each scenario is updated every day based on recent price events as shown in Figure 45 (upper). This is performed by an LSTM-based MCC which is trained with one-year data.
In Figure 44, the sequence of daily price patterns is represented. This sequence is built by assigning the price array of a given day to its corresponding cluster.

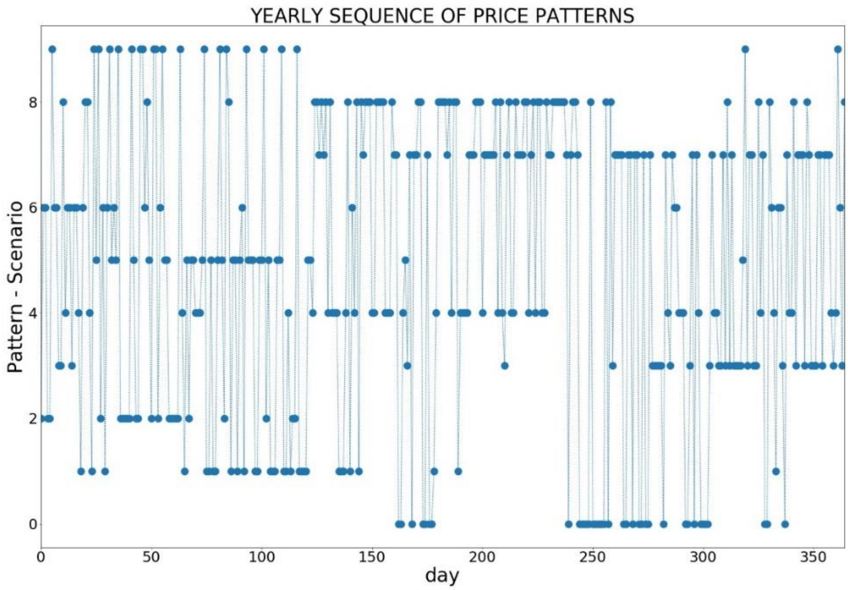


Figure 44.- Sequence of daily price patterns from historical dataset.

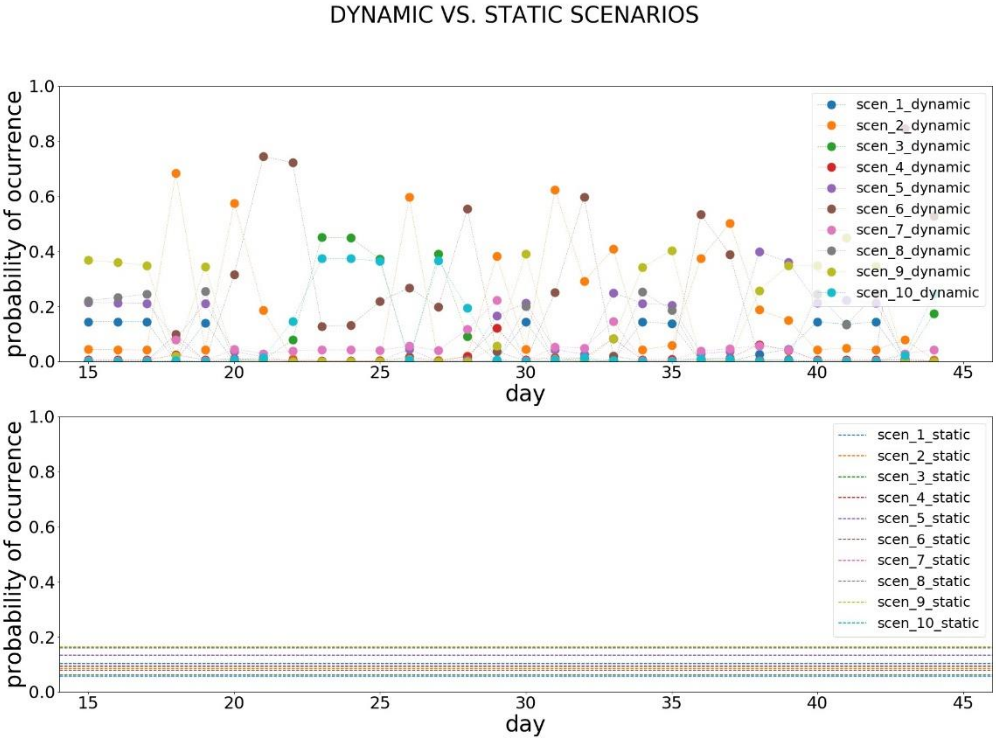


Figure 45.- Probability of ocurrence for scenarios under dynamic (upper) and static (bottom) approaches during 30 consecutive days.

6.5.2 Result

In this subsection, at first, we will evaluate the proposed approaches for scenario generation. Second, we will compare the net achievable income participating in the DAM and IDM with the net income achievable by just participating in the DAM. This is helpful to evaluate the market-based arbitrage strategy. In parallel, we will carry out a sensitivity analysis to evaluate the impact of the size of energy storage systems on the net income of the proposed W&SPP which is helpful to evaluate the time-based arbitrage strategy.

Thus, the net income of the W&SPP is evaluated during a simulation span of two months. On one hand, an upper bound on the achievable net income is calculated under perfect information hypothesis (PI). Under this assumption, energy prices in all considered markets and available wind energy in day D are supposed to be known when the optimization problem is solved in day D-1. On the other hand,

simulation considering perfect information only for market price and only for available wind energy are also performed. This is useful to evaluate the marginal influence of the uncertainty affecting a single parameter.
When considering real information (RI) associated with the energy price, one more approach is evaluated. This approach is a random approach which may be used as a base case. In this case, ten actual price vectors are chosen out of the whole dataset. This set of random vectors is updated every day during the simulation span. Because of the random nature of this problem, this case is run several times to evaluate the range of achievable net income. The achievable net income is shown in Table 9. Net Income (€) participating in DAM, IDM, and BM for a simulation of 2 months. for several sizes of ESS. Furthermore, to show the effectiveness of the proposed two-stage stochastic approach, two deterministic cases are also considered. In both cases, the scenarios resulting from the static approach in section 6.5.1 are averaged, with their corresponding probability of occurrence to get one meaningful scenario to be considered in the deterministic case. As to the available wind energy, an optimistic and a conservative forecast are considered.
The main objective of the simulation experiment is to evaluate the proposed scenario generation approaches. As it can be seen, the dynamic approach outperforms the static and random approaches no matter the size of the ESS considered, including the no-storage case. This is not surprising because more information from the dataset is extracted under Bayesian framework through the utilization of LSTM-RNN and MCC. More specifically, sequence information is also extracted out of the dataset. Although the proposed dynamic approach offers the best performance among all the approaches, there is still room for improvements with respect to the perfect information case.
From Table 9, two more interesting insights may be extracted. In one hand, net income slightly increases as we add ESS. For example, the net income increases 3.2% when adding a 2MW/2MWh ESS under PI hypothesis, whereas the net income increases only 1.7% with the dynamic approach for the case with RI. As it was stated above, the addition of an ESS is justified by a time-based arbitrage strategy that may allow a wind farm to take advantage of the gap between peak and valley market prices.
On the other hand, it also can be observed that the cost of uncertainty in terms of losses of net income with respect to the PI hypothesis is similar when marginal uncertainty in available wind energy or pool market price is considered. As an example, for the no-storage case, the cost of the uncertainty in available wind energy is 7.2 % with respect to the perfect information hypothesis. If just the

uncertainty in market prices is considered, this percentage decreases, thus being a 6.1%.

Table 9. Net Income (€) participating in DAM, IDM, and BM for a simulation of 2 months.

NET INCOME (€) - DayAhead, Intraday & Balancing Markets

Uncertainty Case		ESS			
Available Wind Energy	**Market Prices**	**NO STORAGE**	**1 MW / 1 MWh**	**2 MW / 2 MWh**	**5 MW / 5 MWh**
PI	**PI**	293814	298647	303177	317471
Determ - Optimistic	**Determ - Static Equiv**	222147	224192	226235	231902
Determ - Conservative	**Determ - Static Equiv**	235987	238041	240094	245768
RI	**PI**	272499	277322	282125	296143
PI	**RANDOM**	266980 - 271880	266800 - 275450	268360 - 275390	273850 - 284450
	STATIC	274654	276702	278752	284412
	DYNAMIC	275995	278258	280519	286813
RI	**RANDOM**	233780 - 242670	235010 - 244240	235910 - 243210	242960 - 249320
	STATIC	243540	245584	247236	253301
	DYNAMIC	244174	246429	248225	254962

To evaluate the importance of market-based arbitrage strategy, a simulation is run only considering the DAM and BM. As to the input, only perfect information hypothesis and dynamic approach are considered. These cases are enough to conclude some meaningful insights. The achievable net income is shown in Table 10.

In the following Figure 46, simulation results for a no-storage case and a 2 MW/MWh case are shown.

Table 10.- Net Income (€) participating in DAM and BM for a simulation of 2 months

NET INCOME (€) - DayAhead & Balancing Markets

Uncertainty Case		ESS			
Available Wind Energy	**Market Prices**	**NO STORAGE**	**1 MW / 1 MWh**	**2 MW / 2 MWh**	**5 MW / 5 MWh**
PI	**PI**	262563	263845	265046	268260
RI	**DYNAMIC**	229906	230797	231689	233857

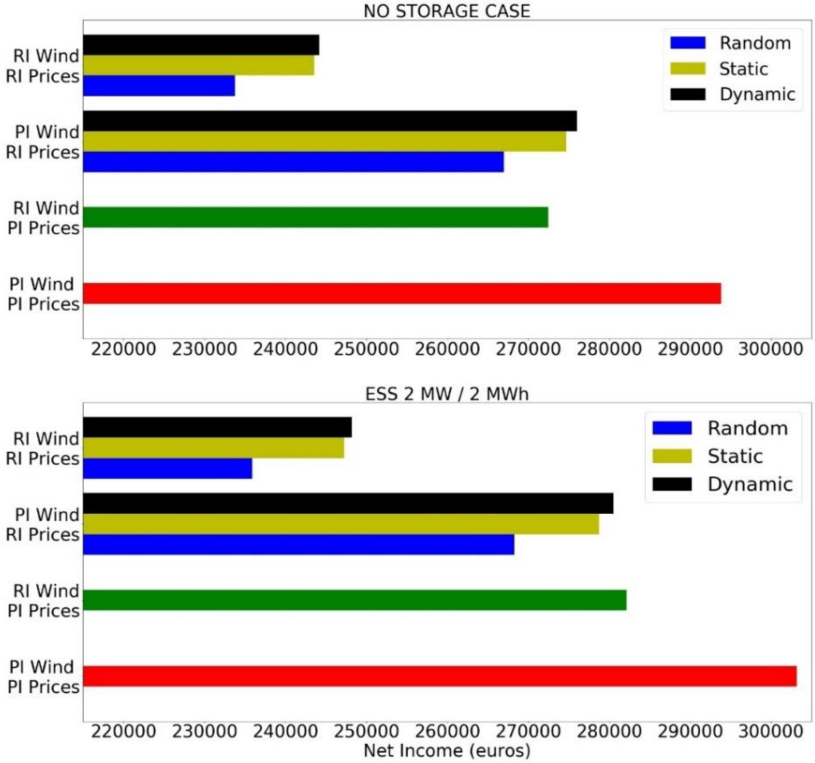


Figure 46.- Influence of uncertainty and ESS capacity in net income.

As we stated earlier, time-based arbitrage relies on the price difference among hours to gain a profit. For a VRRG, the only way of taking advantage of this kind of arbitrage is to have storage capability. Thus, in Table 9 and Table 10, it is possible to evaluate the benefits of time-based arbitrage by looking at each raw. In Table 9, for instance, it is shown that, under PI hypothesis, the fact of adding a 1 MW/1MWh ESS, only increases the net income by 1.6%. If the W&SPP is only allowed to participate in the DAM and BM, this increase is only 0.5%. Thus, although the time-based arbitrage is more profitable if participation in IDM is allowed, it seems that net income increase is not enough to justify the investment in ESS.

Conversely, if a market-based arbitrage is considered, more interesting results are observed. Under PI hypothesis and with no storage, the net income increases by 12%. In a more realistic setting, considering the proposed dynamic approach, the net income increases by 6.2% as shown in Figure 47.

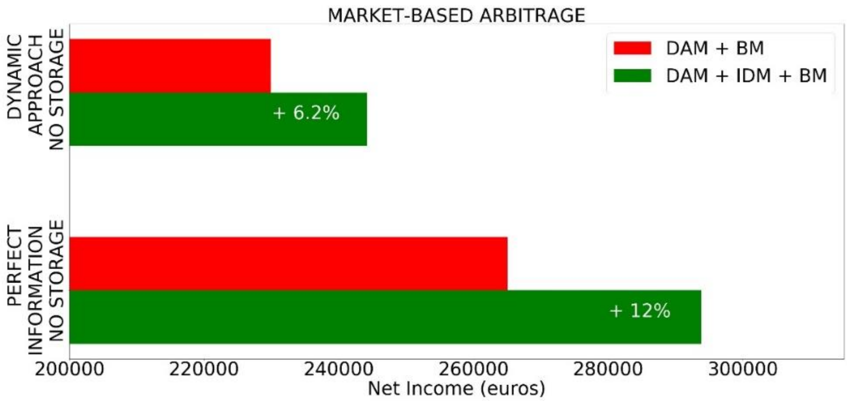


Figure 47.- Impact of participation in IDM. Perfect Information and Dynamic Approach cases.

6.6 Conclusion

A two-stage stochastic convex program is proposed to model the decision-making problem under uncertainty of a W&SPP participating in the pool market. On one hand, several approaches are proposed to generate scenarios to quantify the uncertainty in market price. The dynamic approach based on an LSTM-MCC shows the best performance in terms of achievable net income. This is due to its ability to extract influential scenarios considering both price patterns, through the utilization of multivariate clustering techniques, and the sequence of patterns by using an LSTM recurrent neural network. Uncertainty in available wind energy is also considered. A marginal analysis shows that both uncertainties, available wind energy and market price, have a similar effect on the achievable net income under PI hypothesis.

On another hand, simulation results also have revealed interesting insights about the participation of a W&SPP in the pool market. A time-based arbitrage strategy does not seem feasible from an economic point of view. The increase in the net income with this strategy is small and does not seem enough to justify an investment on the necessary ESS. Conversely, it is interesting to exploit a market-based arbitrage strategy. Under this strategy, the W&SPP operator may decide in which market is more profitable to buy or sell energy. Therefore, the proposed robust decision-making framework could be used by the W&SPP managers to gain competitive advantage from the energy pool market. In the future, we could extend our approach to apply in other decision-making problems which require to quantify uncertainty as well. Furthermore, the power market is a sequential process, which requires to develop dynamic decision tools. We could explore the opportunity to use our proposed scenario generation techniques in a Model Predictive Control framework to develop a dynamic decision-making tool.

CHAPTER 7

7 Summary, conclusions and future work.

7.1 Summary

During this thesis, we have dealt with the decision-making problem of a renewable energy based generator participating in the electricity markets. More specifically, a wind farm with storage capabilities was studied. Firstly, the idea of an optimization problem, from a mathematical point of view, was introduced as a framework to model decision-making problems, and machine learning techniques were also presented as a way to generate meaningful input data to the aforementioned problem. Once the tools to handle the decision-making problem were introduced, several problems were treated more specifically. First, a deterministic model of a wind and storage power plant participating in day-ahead and reserve markets was developed. The deterministic model was used to evaluate how much does it cost to not accurately know the input data of the problem. Secondly, a stochastic approach is proposed to handle the uncertainty in the input data of the same problem. In particular, a two-stage stochastic program is used to model the decision-making problem. Several methods were proposed to define scenarios which can model the uncertainty related to available wind energy and regulation requirements. For example, deterministic forecasting of regulation requirements and multivariate clustering of actual daily data were analyzed. Lastly, the participation of the W&SPP in the pool market is considered. In this case, uncertainty in market prices is also handled and a two-stage stochastic program is proposed. A scenario definition framework, based on supervised and unsupervised learning techniques was proposed and validated.

7.2 Conclusions

At the decision-making framework level, some conclusions are extracted out of this work. Firstly, that a stochastic approach outperforms the deterministic one in an uncertain environment when the decision problem is solved in a repeated way. Secondly, that leveraging machine learning techniques to define the scenarios modeling the uncertain data seems a promising field when dealing with extracting information out of available data.

During this thesis, three sources of uncertainty were considered: available wind energy, regulation requirements, and market prices.

In the first case, it is shown that the influence of uncertainty in available wind energy has an important impact on the achievable net income of the W&SPP when participating in the electricity markets. To model that uncertainty, the hypothesis with different levels of conservatism are made to define scenarios. The results showed that an excess of conservatism penalizes the result but, even in that case, the net income achievable is better than using a deterministic forecast of the available wind energy.

In the second place, the regulation requirements from SO is also considered an uncertain parameter in this work, and several proposals are made and evaluated to model such uncertainty. Both a multivariate clustering and a more simple look-back approach outperform both neural network based forecast and univariate clustering approaches. The simulation showed that the margin for improvement, by comparison with the perfect information hypothesis, is small if the more successful strategies for generating scenarios are used.

Finally, as to the price uncertainty in the pool market, the multiclass classifier based on pattern definition through a multivariate clustering plus an LSTM neural network to extract information out of the temporal sequence of such patterns shows promising results.

As to the optimization problem of a W&SPP participating in the electricity markets, it is shown that the presence of an energy storage system does not add significant value when the W&SPP is only allowed to participate in DAM. On another hand, if the W&SPP is allowed to participate in the RM, the net income increases significantly. Likewise, the participation in the pool market is also an efficient way of increasing the net income of a W&SPP. In this case, the added value comes from the availability to follow a market-based arbitrage strategy, in which, the operator may decide to buy/sell energy not just at the time when it is cheaper but also by participating in the most interesting market.

7.3 Future work

Data-driven decision frameworks have a huge potential for further development thus helping to accomplish the challenges that power systems are facing. From our point of view, further research should be undertaken in the following issues:

Firstly, and given the time structure of the electricity markets, longer periods should be considered for the optimization of the participation in the markets. With this idea, multistage approaches fit the decision-making problem quite well. In this case, how to define scenario trees that can model the growing uncertainty when the time span of the problem increases becomes of paramount importance.

Data-driven approaches, based on machine learning techniques, also showed their potential to generate meaningful input data to decision-making problems. It is also important to explore and compare, for example, different clustering algorithms and more complex neural networks structures that can extract out of the available data as much information as possible.

REFERENCES

[1] “Sistema de Información del Operador del Sistema.” [Online]. Available: www.esios.ree.es.

[2] A. Dorado, J. Alvarez, A. E. Feijoó, C. Carrillo, J. Cidrás, and E. Menéndez, “The Sotavento Experimental Wind Park,” in *Global Windpower*, 2002, p. Poster.

[3] C. de R. del MIBEL, “Descripción de funcionamiento del MIBEL,” 2009.

[4] A. J. Conejo, M. Carrion, and J. M. Morales, *Decision Making Under Uncertainty in Electricity Markets*. Springer, 2010.

[5] EPEX, G.- NordPool, OMIE, OPCOM, OTE, and TGE, “EUPHEMIA Public Description, PCR Market Coupling Algorithm,” 2016.

[6] A. Carbajo, “Los mercados eléctricos y los servicios de ajuste del sistema,” 2006.

[7] R. E. ESPAÑA, “INFORME SERVICIOS AJUSTE DEL SISTEMA. AVANCE 2016.”

[8] B. oficial del Estado, *Royal Decree 413/2014*. 2015.

[9] R. E. ESPAÑA, “P.O 14.4 - Derechos de cobro y obligaciones de pago por los servicios de ajuste del sistema.”

[10] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2004.

[11] J. Nocedal and S. J. Wright, *Numerical Optimization*. Springer Series in Operations Research, 2006.

[12] A. Prékopa, *Stochastic Programming*. 1995.

[13] A. Shapiro, D. Dentcheva, and A. Ruszczynski, *Lectures on Stochastic Programming. Modeling and theory*. SIAM, 2009.

[14] J. R. Birge and F. Louveaux, *Introduction to Stochastic Programming*. New York, NY, USA: Springer, 2011.

[15] A. J. Conejo, E. Castillo, R. Minguez, and R. Garcia-Bertrand, *Decomposition Techniques in Mathematical Programming*. Springer, 2006.

[16] A. Ben-tal, L. El Ghaoui, and A. Nemirovski, *Robust Optimization*. Princeton Unviersity Press, 2009.

[17] Z. Yang, K. Li, Q. Niu, and Y. Xue, “A comprehensive study of economic unit commitment of power systems integrating various renewable generations and plug-in electric vehicles,” *Energy Convers. Manag.*, vol. 132, pp. 460–481, 2017.

[18] M. I. Alizadeh, M. P. Moghaddam, and N. Amjady, "Multistage Multiresolution Robust Unit Commitment With Nondeterministic Flexible Ramp Considering Load and Wind Variabilities," *IEEE Trans. Sustain. Energy*, vol. 9, no. 2, pp. 872–883, 2018.
[19] A. Lorca, A. Sun, E. Litvinov, and T. Zheng, "Multistage Adaptive Robust Optimization for the Unit Commitment Problem," *Oper. Res.*, vol. 64, no. 1, pp. 32–51, 2016.
[20] A. Lorca and X. A. Sun, "Multistage Robust Unit Commitment With Dynamic Uncertainty Sets and Energy Storage," *IEEE Trans. Power Syst.*, vol. 32, no. 3, pp. 1678–1688, 2017.
[21] B. Zhao, A. J. Conejo, and S. Ramteen, "Unit Commitment Under Gas-Supply Uncertainty and Gas-Price Variability," vol. 32, no. 3, pp. 2394–2405, 2017.
[22] Y. Zhang, J. Wang, B. Zeng, and Z. Hu, "Chance-Constrained Two-Stage Unit Commitment Under Uncertain Load and Wind Power Output Using Bilinear Benders Decomposition," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3637–3647, 2017.
[23] S. Abbasi and H. Abdi, "Multiobjective transmission expansion planning problem based on ACOPF considering load and wind power generation uncertainties," *Int. Trans. Electr. Energy Syst.*, no. October 2016, pp. 1–15, 2017.
[24] P. V. Gomes and J. T. Saraiva, "Electrical Power and Energy Systems A novel e ffi cient method for multiyear multiobjective dynamic transmission system planning," *Electr. Power Energy Syst.*, vol. 100, no. February, pp. 10–18, 2018.
[25] M. Jadidoleslam, A. Ebrahimi, and M. A. Latify, "Probabilistic transmission expansion planning to maximize the integration of wind power," *Renew. Energy*, vol. 114, pp. 866–878, 2017.
[26] M. Bucciarelli, S. Paoletti, and A. Vicino, "Optimal sizing of energy storage systems under uncertain demand and generation," *Appl. Energy*, vol. 225, no. November 2017, pp. 611–621, 2018.
[27] S. Xie, Z. Hu, D. Zhou, Y. Li, S. Kong, W. Lin, Y. Zheng, and Γ. L. Γ. D. Γ. Tr, "Multi-objective active distribution networks expansion planning by scenario-based stochastic programming considering uncertain and random weight of network," *Appl. Energy*, vol. 219, no. February, pp. 207–225, 2018.

[28] I. Kinias, I. Tsakalos, and N. Konstantopoulos, "' Investment evaluation in renewable projects under uncertainty , using real options analysis : the case of wind power industry ' Investment evaluation in renewable projects under uncertainty , using real options analysis : the case of wind power industry," *Invest. Manag. Financ. Innov.*, vol. 14, no. 1, 2018.

[29] R. Laia, H. M. I. Pousinho, R. Melíco, and V. M. F. Mendes, "Self-scheduling and bidding strategies of thermal units with stochastic emission constraints," *Energy Convers. Manag.*, vol. 89, pp. 975–984, 2015.

[30] K. Pan, "Data-Driven Risk-Averse Stochastic Self-Scheduling for Combined-Cycle Units," *IEEE Trans. Ind. Informatics*, vol. 13, no. 6, pp. 3058–3069, 2017.

[31] K.-L. Du and M. N. S. Swamy, *Neural Networks and Statistical Learning*. Springer, 2014.

[32] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning representations by back-propagating errors," *Nature*, vol. 323, pp. 533–536, 1986.

[33] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016.

[34] M. A. Nielsen, *Neural Networks and Deep Learning*. Determination Press, 2015.

[35] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Comput.*, vol. 9, no. 8, pp. 1–32, 1997.

[36] C. Colah, "http://colah.github.io/posts/2015-08-Understanding-LSTMs/," 2018. .

[37] J. L. Crespo-Vazquez, C. Carrillo, and E. Diaz-Dorado, "Evaluation of the Uncertainty in the Scheduling of a Wind and Storage Power Plant Participating in Day-Ahead and Reserve Markets," *Energy Procedia*, vol. 136, pp. 79–84, 2017.

[38] P. Denholm, E. Ela, B. Kirby, and M. Milligan, "The Role of Energy Storage with Renewable Electricity Generation," *NREL/TP-6A2-47187*, pp. 1–53, 2010.

[39] D. Connolly, H. Lund, P. Finn, B. V. Mathiesen, and M. Leahy, "Practical operation strategies for pumped hydroelectric energy storage (PHES) utilising electricity price arbitrage," *Energy Policy*, vol. 39, no. 7, pp. 4189–4196, 2011.

[40] G. Ardizzon, G. Cavazzini, and G. Pavesi, "A new generation of small hydro and pumped-hydro power plants: Advances and future challenges," *Renew. Sustain. Energy Rev.*, vol. 31, pp. 746–761, 2014.

[41] A. A. S. De La Nieta, J. Contreras, and J. I. Muñoz, "Optimal coordinated wind-hydro bidding strategies in day-ahead markets," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 798–809, 2013.

[42] J. I. Pérez-Díaz, M. Chazarra, J. García-González, G. Cavazzini, and A. Stoppato, “Trends and challenges in the operation of pumped-storage hydropower plants,” *Renew. Sustain. Energy Rev.*, vol. 44, pp. 767–784, 2015.

[43] M. Chazarra, J. Perez-Diaz, and J. Garcia-Gonzalez, “Optimal Energy and Reserve Scheduling of Pumped-Storage Power Plants Considering Hydraulic Short-Circuit Operation,” *IEEE Trans. Power Syst.*, vol. 8950, no. c, pp. 1–1, 2016.

[44] T. Soares, P. Pinson, T. V. Jensen, and H. Morais, “Optimal offering strategies for wind power in energy and primary reserve markets,” *IEEE Trans. Sustain. Energy*, vol. 7, no. 3, pp. 1036–1045, 2016.

[45] M. Doostizadeh, F. Aminifar, H. Ghasemi, and H. Lesani, “Energy and Reserve Scheduling under Wind Power Uncertainty: An Adjustable Interval Approach,” *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2943–2952, 2016.

[46] R. Hemmati, H. Saboori, and S. Saboori, “Assessing wind uncertainty impact on short term operation scheduling of coordinated energy storage systems and thermal units,” *Renew. Energy*, vol. 95, pp. 74–84, 2016.

[47] Z. Tan, L. Ju, H. Li, J. Li, and H. Zhang, “A two-stage scheduling optimization model and solution algorithm for wind power and energy storage system considering uncertainty and demand response,” *Int. J. Electr. Power Energy Syst.*, vol. 63, pp. 1057–1069, 2014.

[48] J. Matevosyan and L. Söder, “Minimization of imbalance cost trading wind power on the short-term power market,” *IEEE Trans. Power Syst.*, vol. 21, no. 3, pp. 1396–1404, 2006.

[49] J. M. Morales, A. J. Conejo, and J. Pérez-Ruiz, “Short-term trading for a wind power producer,” *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 554–564, 2010.

[50] Michael Grant and Stephen Boyd, “CVX: Matlab software for disciplined convex programming.” http://cvxr.com/cvx, 2013.

[51] Y. Zhang, N. Gatsis, and G. B. Giannakis, “Robust energy management for microgrids with high-penetration renewables,” *IEEE Trans. Sustain. Energy*, vol. 4, no. 4, pp. 944–953, 2013.

[52] E. Saiz-Marin, J. Garcia-Gonzalez, J. Barquin, and E. Lobato, “Economic assessment of the participation of wind generation in the secondary regulation market,” *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 866–874, 2012.

[53] J. L. Crespo-Vazquez, C. Carrillo, E. Diaz-Dorado, J. A. Martinez-Lorenzo, and M. Noor-E-Alam, "Evaluation of a data driven stochastic approach to optimize the participation of a wind and storage power plant in day-ahead and reserve markets," *Energy*, vol. 156, pp. 278–291, 2018.

[54] T. R. Ayodele and A. S. O. Ogunjuyigbe, "Mitigation of wind power intermittency : Storage technology approach," *Renew. Sustain. Energy Rev.*, vol. 44, pp. 447–456, 2015.

[55] M. Yekini, M. Wazir, and N. Bashir, "Energy storage systems for renewable energy power sector integration and mitigation of intermittency," *Renew. Sustain. Energy Rev.*, vol. 35, pp. 499–514, 2014.

[56] H. Ding, P. Pinson, and Z. Hu, "Integrated Bidding and Operating Strategies for Wind-Storage Systems," *IEEE Trans. Sustain. Energy*, vol. 7, no. 1, pp. 163–172, 2016.

[57] H. Ding, P. Pinson, Z. Hu, and Y. Song, "Optimal Offering and Operating Strategies for Wind-Storage Systems With Linear Decision Rules," *IEEE Trans. Power Syst.*, vol. 31, no. 6, pp. 4755–4764, 2016.

[58] M. Khalid, R. P. Aguilera, A. V Savkin, and V. G. Agelidis, "On maximizing profit of wind-battery supported power station based on wind power and energy price forecasting," *Appl. Energy*, vol. 211, no. March 2017, pp. 764–773, 2018.

[59] M. Liu, F. L. Quilumba, and W. Lee, "Dispatch Scheduling for a Wind Farm With Hybrid Energy Storage Based on Wind and LMP Forecasting," *IEEE Trans. Ind. Appl.*, vol. 51, no. 3, pp. 1970–1977, 2015.

[60] M. Rahimiyan and L. Baringo, "Strategic Bidding for a Virtual Power Plant in the Day-Ahead and Real-Time Markets: A Price-Taker Robust Optimization Approach," *IEEE Trans. Power Syst.*, vol. 31, no. 4, pp. 2676–2687, 2016.

[61] A. A. Sanchez de la Nieta, J. Contreras, and J. P. S. Catalao, "Optimal Single Wind Hydro-Pump Storage Bidding in Day-Ahead Markets including Bilateral Contracts," *IEEE Trans. Sustain. Energy*, vol. 3029, no. c, pp. 1–1, 2016.

[62] W. Tan and M. Shaaban, "Chance-constrained programming for day-ahead scheduling of variable wind power amongst conventional generation mix and energy storage," *IET Renew. Power Gener.*, vol. 11, pp. 1785–1793, 2017.

[63] M. Dicorato, G. Forte, M. Pisani, and M. Trovato, "Planning and Operating Combined Wind-Storage System in Electricity Market," *IEEE Trans. Sustain. Energy*, vol. 3, no. 2, pp. 209–217, 2012.

[64] I. L. R. Gomes, H. M. I. Pousinho, R. Melício, and V. M. F. Mendes, "Stochastic coordination of joint wind and photovoltaic systems with energy storage in day-ahead market," *Energy*, vol. 124, pp. 310–320, 2017.

[65] F. Liu, Z. Bie, S. Liu, and T. Ding, "Day-ahead optimal dispatch for wind integrated power system considering zonal reserve requirements," *Appl. Energy*, vol. 188, pp. 399–408, 2017.

[66] H. Pandzic, J. M. Morales, A. J. Conejo, and I. Kuzle, "Offering model for a virtual power plant based on stochastic programming," *Appl. Energy*, vol. 105, pp. 282–292, 2013.

[67] A. Ghahgharaee, A. Zakariazadeh, S. Jadid, and A. Kazemi, "Stochastic operational scheduling of distributed energy resources in a large scale virtual power plant," *Int. J. Electr. Power Energy Syst.*, vol. 82, pp. 608–620, 2016.

[68] R. Hemmati, H. Saboori, and M. A. Jirdehi, "Stochastic planning and scheduling of energy storage systems for congestion management in electric power systems including renewable energy resources," *Energy*, vol. 133, pp. 380–387, 2017.

[69] H. Akhavan-hejazi and H. Mohsenian-rad, "Optimal Operation of Independent Storage Systems in Energy and Reserve Markets With High Wind Penetration," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 1088–1097, 2014.

[70] N. G. Cobos, J. M. Arroyo, N. Alguacil, and J. Wang, "Robust Energy and Reserve Scheduling Considering Bulk Energy Storage Units and Wind Uncertainty," *IEEE Trans. Power Syst.*, vol. 8950, no. c, pp. 1–11, 2018.

[71] M. Parastegari, R. Hooshmand, A. Khodabakhshian, and A. Zare, "Electrical Power and Energy Systems Joint operation of wind farm , photovoltaic , pump-storage and energy storage devices in energy and reserve markets," *Int. J. Electr. Power Energy Syst.*, vol. 64, pp. 275–284, 2015.

[72] A. Shayegan-rad, A. Badri, and A. Zangeneh, "Day-ahead scheduling of virtual power plant in joint energy and regulation reserve markets under uncertainties," *Energy*, vol. 121, pp. 114–125, 2017.

[73] Y. Zhou, Z. Wei, G. Sun, K. W. Cheung, H. Zang, and S. Chen, "A robust optimization approach for integrated community energy system in energy and ancillary service markets," *Energy*, vol. 148, pp. 1–15, 2018.

[74] M. Chazarra, J. I. Pérez-Díaz, J. García-González, and A. Helseth, "Modeling the Real-Time use of Reserves in the Joint Energy and Reserve Hourly Scheduling of a Pumped Storage Plant," *Energy Procedia*, vol. 87, pp. 53–60, 2016.

[75] M. S. Al-swaiti, A. T. Al-awami, and M. W. Khalid, “Co-optimized trading of wind-thermal-pumped storage system in energy and regulation markets,” *Energy*, vol. 138, pp. 991–1005, 2017.
[76] A. Goudarzi, Z. N. C. Viray, P. Siano, A. G. Swanson, J. V Coller, and M. Kazemi, “A probabilistic determination of required reserve levels in an energy and reserve co-optimized electricity market with variable generation,” *Energy*, vol. 130, pp. 258–275, 2017.
[77] P. Chen, T. Pedersen, and B. Bak-jensen, “ARIMA-Based Time Series Model of Stochastic Wind Power Generation,” vol. 25, no. 2, pp. 667–676, 2010.
[78] S. Qin, F. Liu, J. Wang, and Y. Song, “Interval forecasts of a novelty hybrid model for wind speeds,” *Energy Reports*, vol. 1, pp. 8–16, 2015.
[79] M. Khodayar and O. Kaynak, “Rough Deep Neural Architecture for Short-term Wind Speed Forecasting,” *IEEE Trans. Ind. Informatics*, vol. 3203, no. c, pp. 1–10, 2017.
[80] P. Pinson, H. Madsen, and G. Papaefthymiou, “From Probabilistic Forecasts to Wind Power Production,” *Wind Energy*, vol. 12, pp. 51–62, 2009.
[81] C. Wan, J. Lin, and J. Wang, “Direct Quantile Regression for Nonparametric Probabilistic Forecasting of Wind Power Generation,” *IEEE Trans. Power Syst.*, vol. 32, no. 4, pp. 2767–2778, 2017.
[82] H. Wang, G. Li, G. Wang, J. Peng, H. Jiang, and Y. Liu, “Deep learning based ensemble approach for probabilistic wind power forecasting,” *Appl. Energy*, vol. 188, pp. 56–70, 2017.
[83] Z. C. Lipton, J. Berkowitz, and C. Elkan, “A Critical Review of Recurrent Neural Networks for Sequence Learning,” *arXiv:1506.00019v4 [cs.LG]*, 2015.
[84] Y. Bengio, P. Simard, and P. Frasconi, “Learning Long-Term Dependencies with Gradient Descent is Difficult,” *IEEE Trans. Neural Networks*, vol. 5, no. 2, pp. 157–166, 1994.
[85] A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin, S. Ghemawat, I. Goodfellow, A. Harp, G. Irving, M. Isard, Y. Jia, R. Jozefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Man, R. Monga, S. Moore, D. Murray, C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke, V. Vasudevan, F. Vi, O. Vinyals, P. Warden, M. Wattenberg, M. Wicke, Y. Yu, and X. Zheng, “TensorFlow : Large-Scale Machine Learning on Heterogeneous Distributed Systems,” 2015.
[86] D. Arthur and S. Vassilvitskii, “k-means ++ : The Advantages of Careful Seeding,” in *Proceedings of the eighteenth annual ACM-SIAM symposium on Discrete algorithms*, 2007, vol. 8, pp. 1–11.

[87] N. Löhndorf, “An empirical analysis of scenario generation methods for stochastic optimization,” *Eur. J. Oper. Res.*, vol. 255, no. 1, pp. 121–132, 2016.

[88] J. L. Crespo-Vazquez, C. J. Carrillo, E. Diaz-Dorado, J. A. Martinez-Lorenzo, and M. Noor-E-Alam, “A Machine Learning Based Stochastic Optimization Framework for a Wind and Storage Power Plant Participating in Energy Pool Market,” *Appl. Energy, Accept. Publ.*

[89] J. García-González, R. M. R. de la Muela, L. M. Santos, and A. M. Gonzalez, “Stochastic joint optimization of wind generation and pumped-storage units in an electricity market,” *IEEE Trans. Power Syst.*, vol. 23, no. 2, pp. 460–468, 2008.

[90] Q. Wang, J. Wang, and Y. Guan, “Price-based unit commitment with wind power utilization constraints,” *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2718–2726, 2013.

[91] S. Braun, “Hydropower Storage Optimization Considering Spot and Intraday Auction Market,” *Energy Procedia*, vol. 87, pp. 36–44, 2016.

[92] H. Ding, Z. Hu, and Y. Song, “Rolling Optimization of Wind Farm and Energy Storage System in Electricity Markets,” *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2676–2684, 2015.

[93] A. Skajaa, K. Edlund, and J. M. Morales, “Intraday Trading of Wind Energy,” *IEEE Trans. Power Syst.*, vol. 30, no. 6, pp. 3181–3189, 2015.

[94] D. Keles, J. Scelle, F. Paraschiv, and W. Fichtner, “Extended forecast methods for day-ahead electricity spot prices applying artificial neural networks,” *Appl. Energy*, vol. 162, pp. 218–230, 2016.

[95] I. P. Panapakidis and A. S. Dagoumas, “Day-ahead electricity price forecasting via the application of artificial neural network based models,” *Appl. Energy*, vol. 172, pp. 132–151, 2016.

[96] C. Monteiro, I. J. Ramirez-Rosado, L. A. Fernandez-Jimenez, and P. Conde, “Short-term price forecasting models based on artificial neural networks for intraday sessions in the Iberian electricity market,” *Energies*, vol. 9, no. 9, 2016.

[97] E. Raviv, K. E. Bouwman, and D. van Dijk, “Forecasting day-ahead electricity prices: Utilizing hourly prices,” *Energy Econ.*, vol. 50, pp. 227–239, 2015.

[98] F. Ziel, “Forecasting Electricity Spot Prices Using Lasso: On Capturing the Autoregressive Intraday Structure,” *IEEE Trans. Power Syst.*, vol. 31, no. 6, pp. 4977–4987, 2016.

[99] A. Mohamed, S. Kazim, and L. Alvarado, “Optimal sizing for a hybrid power system with wind / energy storage based in stochastic environment,” *Renew. Sustain. Energy Rev.*, vol. 59, pp. 1149–1158, 2016.

[100] A. J. Conejo, M. A. Plazas, R. Espínola, and A. B. Molina, “Day-Ahead Electricity Price Forecasting Using the Wavelet Transform and ARIMA Models,” *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 1035–1042, 2005.

[101] M. Amin, A. Rahimi-kian, and A. Soroudi, “Risk averse optimal operation of a virtual power plant using two stage stochastic programming,” *Energy*, vol. 73, pp. 958–967, 2014.

[102] G. Cervone, L. Clemente-harding, S. Alessandrini, and L. Delle, “Short-term photovoltaic power forecasting using Artificial Neural Networks and an Analog Ensemble,” *Renew. Energy*, vol. 108, pp. 274–286, 2017.

[103] J. R. Andrade, J. Filipe, M. Reis, and R. J. Bessa, “Probabilistic price forecasting for day-ahead and intraday markets: Beyond the statistical model,” *Sustain.*, vol. 9, no. 11, 2017.

[104] L. I. Hagfors, D. Bunn, E. Kristoffersen, T. T. Staver, and S. Westgaard, “Modeling the UK electricity price distributions using quantile regression,” *Energy*, vol. 102, pp. 231–243, 2016.

[105] J. Nowotarski and R. Weron, “Recent advances in electricity price forecasting : A review of probabilistic forecasting,” *Renew. Sustain. Energy Rev.*, vol. 81, pp. 1548–1568, 2018.

[106] “http://www.sotaventogalicia.com/es/datos-tiempo-real/prediccion-meteologica,” *Date accesed: 2017-12-01*. .

[107] Y. Bengio, “Artificial Neural Networks and Their Application to Sequence Recognition,” Ph.D Thesis, McGill University, Montreal, Quebec, Canada, 1991.

[108] G. Ou, Y. L. Murphey, and A. Feldkamp, “Multiclass Pattern Classification Using Neural Networks,” in *International Conference on Pattern Recognition*, 2004, pp. 585–588.

[109] J. S. Denker and Y. LeCun, “Transforming Neural-Net Output Levels to Probability Distributions,” *AT&T Bell Labs*, 1990.