

**Co-optimized Trading of Wind, Thermal & Pumped
Hydro Storage System in Electricity Markets Using
Fuzzy Programming**

BY

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A Thesis Presented to the
DEANSHIP OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

Electrical Engineering

October 2019

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN- 31261, SAUDI ARABIA
DEANSHIP OF GRADUATE STUDIES

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2019

Dedicated to

My Beloved Wife, Farah

My Adorable Parents, Najat & Abdul-Aziz

And

My Family and to the Soul of my Uncle, Salim

ACKNOWLEDGEMENT

“Sow a thought, and you reap an act;
Sow an act, and you reap a habit;
Sow a habit, and you reap a character;
Sow a character, and you reap a destiny.”

... Samuel Smiles

To my soulmate, my life partner, Farah: because I owe it all to you. No words can explain how grateful I'm.

After this, I would like to express my sincere gratitude to my parents who have helped me growing up with ambitious and provided me with moral and emotional support along the way. I'm also grateful to my brother Yazeed, my six adorable sisters, Taghreed, Nada, Alaa, Nouf, Fay and my little angle Rana for their endless gorgeous compassion. Many Thanks!

My eternal cheerleader, Abdulaziz Alraddadi: I miss our discussion about science, politics and philosophy which helped me grasped the nature of science and research.

Acknowledgment goes out all down to King Fahd University of Petroleum & Minerals, the home that I spent my entire academic life in, which granted me the opportunity to peruse the master's degree in electrical engineering and also for the exceptional support and resources provided to complete this research.

A very special gratitude to my thesis advisor Dr. Ali Al-Awami for his unfailing guidance and supervision from the very beginning of this research.

Although our long-lasting discussions contributed substantially to the quality of this work, it has significantly empowered my academic skills and research abilities. My appreciation is also extended to my thesis committee members: Dr. Ibrahim El-Amin

and Dr. Fahad Al-Ismail for their feedbacks, valuable discussions and for their time spent in reviewing this research.

TABLE OF CONTENTS

ACKNOWLEDGEMENT	v
LIST OF TABLES	ix
LIST OF FIGURES	x
ACRONYMS	xi
THESIS ABSTRACT (ENGLISH)	xvii
THESIS ABSTRACT (ARABIC)	xix
CHAPTER I INTRODUCTION	1
1.1. BACKGROUND	1
1.2. MOTIVATION PROBLEM DISCRIPTION	5
1.2.1. Market Framework- TSO Point of View	6
1.2.2. Market Framework- Producer Point of View	9
1.3. THESIS OBJECTIVE	12
1.4. THESIS ORGANIZATION	14
CHAPTER II RELATED WORK	15
2.1. WIND IN ELECTRICIY MARKETS	15
2.2. STORAGE SYSTEMS & DEMAND RESPONSE PROGRAMS	16
2.3. ENERGY COORDINATION	18
2.4. FUZZY OPTUMIZATION	19
CHAPTER III COORDINATED BIDDING STRATEGY IN DAY AHEAD ENERGY MARKET	22
3.1. COORDINATED BIDDING STRATEGY – DETERMINISTIC MODEL	22
3.1.1. Objective Function	22
3.1.2. System Constraints	24
3.2. COORDINATED BIDDING STRATEGY – MIXED INTEGER LINEAR FUZZY MODEL (MILFO)	28
3.2.1. Fuzzy Model of Thermal Profit	30
3.2.2. Fuzzy Model of Wind profit	31
3.2.3. Fuzzy Model of PHS profit	32
3.2.4. Fuzzy Model of Imbalance Profit	32
3.2.5. Fuzzy Model of Wind Power	33
3.2.6. Fuzzy Model of DA Energy Market Prices	33
3.2.7. Fuzzy Model of Real-Time Imbalance Prices	34
3.2.8. The Complete fuzzy model	35
3.3. TEST SYSTEM	36
3.4. RESULTS & ANALYSIS	36

3.4.1.	Deterministic MILP Bidding Strategy	37
3.4.2.	Proposed MILFO Bidding Strategy	39
3.4.3.	Fuzzy and Deterministic Comparison	43
3.5.	CONCLUSION	45
CHAPTER IV	CO-OPTIMIZED BIDDING STRATEGY IN DAY AHEAD ENERGY & REGULATION MARKETS	46
4.1.	CO-OPTIMIZATION BIDDING STRATEGY – DETERMINISTIC MODEL	46
4.1.1.	Objective Function	47
4.1.2.	Regulation Market Constraints	48
4.2.	CO-OPTIMIZATION BIDDING STRATEGY – MIXED INTEGER LINEAR FUZZY MODEL (MILFO)	49
4.2.1.	Fuzzy Model of Regulation Profit	50
4.2.2.	Fuzzy Model of Regulation Signals	51
4.2.3.	Fuzzy Model of The Energy Regulation Price	52
4.2.4.	The Complete Fuzzy Model	52
4.3.	TEST SYSTEM	54
4.4.	RESULTS & ANALYSIS	54
4.4.1.	Deterministic MILP Bidding Strategy	55
4.4.2.	Fuzzy Based Bidding Strategy	59
4.4.3.	Deterministic & Fuzzy Comparison	63
4.5.	CONCLUSION	69
CHAPTER V	CONCLUSION AND FUTURE WORK	70
5.1.	CONCLUSION	70
5.2.	FUTURE WORK	71
APPENDIX – I		72
References		73
Vitae		77

LIST OF TABLES

Table 1- 1: Renewable energy status in GCC.....	2
Table 3 - 1: HYDRO UNITS FOR DETERMINISTIC & FUZZY BIDS.....	41
Table 3 - 2: PHS Energy Reservoir	42
Table 4 - 1: Expected Energy Imbalance	60
Table 4 - 2: Validation Process	65
Table 4 - 3: Hourly transferred energy from Wind to PHS (Fuzzy).....	67

LIST OF FIGURES

Figure 1 - 1: Global power generation of renewable energy resources [1]	1
Figure 1 - 2: Number of Countries with Renewable Energy Regulatory Policies 2004-2017 [2].....	3
Figure 1 - 3: ISO Standpoint in DA energy and DA regulation Markets	8
Figure 1 - 4: Single line Diagram for energy resources. PHS: Pumped Hydro Storage, Th: thermal W: Wind.....	9
Figure 1 - 5: Producer process to participate in DA energy and regulation Markets	10
Figure 1 - 6: Energy market schematic diagram	11
Figure 1 - 7: Milestones of the proposed thesis	13
Figure 3 - 1: Example of a membership function	30
Figure 3 - 2: Market bid vs. forecast for wind using the deterministic strategy.....	37
Figure 3 - 3: System energy (deterministic)	38
Figure 3 - 4: Coordinated Bidding (deterministic).....	38
Figure 3 - 5: Market bid vs. forecast for wind using proposed MILFO strategy	39
Figure 3 - 6: System Energy (fuzzy)	39
Figure 3 - 7: Imbalance penalty (reward) factor	40
Figure 3 - 8: Fuzzy Bidding in DA energy market	41
Figure 3 - 9: DA energy bidding from thermal (Fuzzy vs. Deterministic)	44
Figure 4 - 1: Wind bidding vs. forecasts	55
Figure 4 - 2: Co-optimized DA energy market bidding (Deterministic).....	56
Figure 4 - 3: Co-optimized Bidding in Regulation market (Deterministic)	57
Figure 4 - 4: Regulation Signals Probabilities (Forecast)	58
Figure 4 - 5: Wind forecast vs. Wind bidding (Co-optimized Fuzzy)	59
Figure 4 - 6: DA energy Imbalance Coefficients	60
Figure 4 - 7: Co-optimized bidding in regulation market	62
Figure 4 - 8: Validation Process.....	64
Figure 4 - 9: Co-optimized Thermal bids in DA energy market.....	66
Figure 4 -10: Co-optimized regulation bids from thermal vs. regulation signal	66
Figure 4 -11: Co-optimized PHS bidding	67

ACRONYMS

ABBREVIATION

DA	Day- Ahead
FO	Fuzzy Optimization
GCC	Gulf Cooperation Countries
RES	Renewable Energy Resources
PHS	Pumped Storage Systems
FIT	Feed-in-tariff
DR	Demand Response
BESS	Battery Energy Storage Systems
REPDO	Renewable Energy Project Development Office
USD	United State Dollar
MILP	Mixed-integer Linear Program
MILFO	Mixed-integer linear Fuzzy Program
GRE	Generate Reduce Eliminate
GENCO	Generation Company that participates in DA markets
PV	Photovoltaic
PPA	Power Purchase Agreement
TSO	Transmission System Operator
VPP	Virtual Power Plant

CVaR	Conditional Value at Risk
RT	Real time
MIBEL	Iberian Market operates in Spain & Portugal

NOMENCLATURE

INDICES, SUBSCRIPTS, AND SUPERSSCRIPTS

t	Time in hours over 24 hours of the day
g	Thermal Unit index
n	PHS unit index
d	Wind Plant
e	Segment

DECISION VARIABLES

P_t, P_w, P_h	Optimal bid of thermal/wind/PHS unit
P	Total actual thermal power output
p^{acm}	Actual thermal power output to the market
p^{acp}	Actual thermal power output to PHS
Pg^{reg}, Pp^{reg}	PHS regulation capacity in generation and pumping modes
Pt^{reg}	Thermal regulation capacity
W^{acm}	Actual wind power output to the market
W^{acp}	Actual wind power output to PHS
W^{ac}	Total actual power output from wind

H^{ac}	Actual power output from PHS unit
M	Optimal offer from PHS to the market
$Pump$	Total pumped energy through PHS
V	Energy level in the upper reservoir
U	Thermal unit state; 1 means ON; 0 means OFF
Pu	PHS unit state; 1 means the unit in pumping mode; 0 means Not
G	PHS unit state; 1 means the unit in generation mode; 0 means Not
δ	Thermal power output corresponding to a segment of piecewise linear heat rate curve

PARAMETERS

PF	Total expected profits
PFT	Thermal profits
PFW	Wind profits
PFH	PHS profits
$PFIM$	Imbalances profit
$PFREG$	Regulation profit
$ImUp$	Imbalance-up, or total over-generated energy in excess of combined schedule
$ImDn$	Imbalance-down, or total under-generated energy in deficit of combined schedule

π	Hourly DA energy market price
π_u, π_o	Under, over generation penalties coefficients (multiplier of energy price)
π^R	Hourly regulation market price
αRu	Probability to do regulation up
αRd	Probability to do regulation down
Auxiliary & Constraints Variable	
OC	Operation cost for PHS unit
$V^{initial}$	Initial energy level in upper reservoir
V^{final}	Final energy level in upper reservoir
$\varepsilon_p, \varepsilon_G$	Pumping, generation efficiency
$\underline{V}, \bar{V}$	Min, Max. Energy level in the upper reservoir
$\bar{H}$	Rated PHS unit power output
$StUp$	Start-up cost of a thermal unit
$MinUp$	Minimum Up time of a thermal unit
$MinDn$	Minimum Down time of a thermal unit
$InitUp$	Initial minimum-Up time of a thermal unit
$InitDn$	Initial minimum-Down time of a thermal unit
RU, RD	Thermal ramp-up/down rate (MW/h)

FC	Fuel cost of a thermal unit
a, b, c, d	Thermal heat curve coefficients
AA	Offset of a piecewise thermal heat curve
$S, BrktPt$	Slope, break point of a segment piecewise linear thermal heat curve
uic	Initial state of a thermal unit
$\underline{P_g}, \overline{P_g}$	Minimum, maximum power output of a thermal unit
$\overline{W_d}$	Rated wind power output
$V^{initial}, V^{final}$	Initial, final energy level in upper reservoir
μ_p, μ_g	Pumping, generation efficiency
$\bar{H}$	Rated PHS power output
N_T	Number of periods
N_G, N_D, N_U	Number of thermal, wind PHS units
N_E	Number of segments
αR_d	Probability of regulation down
αR_u	Probability of regulation up

THESIS ABSTRACT (ENGLISH)

Full Name : Naif Abdulaziz Mohammed Makki
Thesis Title : Co-optimized trading of wind, thermal and Pumped Storage System in Electricity Market Using Fuzzy Programming
Degree : Master of science
Major Field : Electrical Engineering
Date of Degree : October 2019

Recently, the integration of renewable energy sources (RES) in liberalized electricity markets has increased substantially. As a result, several approaches have been proposed to accommodate the uncertain nature of these resources such as wind and solar in the day-ahead (DA) markets from the producer's standpoint. This thesis suggests a comprehensive strategy by coordinating the trading of wind, thermal and pumped storage system and by co-optimizing trading in DA energy and regulation markets based on fuzzy optimization. The objective is to devise a bidding strategy that maximizes the profit of a producer that participates in DA energy and regulation markets while considering the uncertainties of wind generation and markets variables.

Initially, the coordination of wind, thermal and pumped hydro storage system (PHS) in day-ahead energy (DA) market is proposed based on fuzzy theory. Next, the proposed strategy is extended to co-optimize the coordinated trading in DA energy and regulation markets. The proposed model is formulated as mixed integer linear fuzzy optimization (MILFO) to incorporate the uncertainty of wind, DA energy and regulation prices, and regulation

deployment signals. Alongside the proposed model, a comparable deterministic model based on mixed integer linear programming (MILP) is also discussed to demonstrate the effectiveness of the proposed algorithm. Simulation results show that the proposed approach excel the deterministic analogue in terms of producer's profit and risk accountability.

THESIS ABSTRACT (ARABIC)

الاسم الكامل: نايف بن عبدالعزيز بن محمد مكي
عنوان الرسالة: التحسين المشترك لطاقة الرياح والطاقة الحرارية وطاقة المضخات المائية في أسواق الكهرباء باستخدام برمجيات الفزي
التخصص: الهندسة الكهربائية
تاريخ الدرجة العلمية: تشرين الأول 2019

نظرا لتزايد تداخل مصادر الطاقة المتجددة في أسواق الكهرباء مؤخرا، قامت الأبحاث بعدة مقترحات لاستيعاب فوضوية هذه المصادر المتغيرة. خاصة فيما يتعلق بدور طاقة الرياح والطاقة الشمسية في أسواق الكهرباء من منظور منتج الطاقة. هذه الرسالة تقترح استراتيجية المتاجرة (المضاربة) المنسقة بين طاقة الرياح والطاقة الحرارية وطاقة مضخات التخزين المائية، إضافة إلى التحسين المشترك في سوق الطاقة اليومي وسوق التنظيم الكهربائي. الهدف من ذلك هو زيادة ربحية شركة توليد تمتلك مولد رياح ومولدات حرارية ومولدات مضخات التخزين الرياحية وتضارب في سوق الطاقة اليومي وسوق التنظيم الكهربائي مع الأخذ في الاعتبار فوضوية طاقة الرياح ومتغيرات السوق.

في هذا العمل تم تمثيل استراتيجية المتاجرة بواسطة برمجة الفزي للأعداد الصحيحة الخطية المختلطة إضافة إلى تطوير طريقة مبتكرة لتحسين المتاجرة (المضاربة) المشتركة في كل من سوق الطاقة اليومي وكذلك سوق التنظيم الكهربائي. إضافة إلى الاستراتيجية المقترحة وطريقة تحسين المتاجرة المشتركة، ولأجل المقارنة، تم مناقشة استراتيجية مماثلة تتخذ من النموذج الحتمي أساسا لها وتمثل بواسطة برمجة الأعداد الصحيحة الخطية المختلطة. وأخيرا، فإن نتائج المحاكات تشيل إلى جدوى الاستراتيجية المقترحة في زيادة ربحية المنتج وتقلل من تعرضه لإخطار المتغيرات.

CHAPTER I INTRODUCTION

1.1. BACKGROUND

The growing appeals to address the underlying risks of climate change increases substantially. As the global carbon emissions projected to increase by 16% in 2024 [1], considerable efforts are applied to shift the current energy resources from fossil fuel toward renewables of which expected to play a vital role in future power systems. In fact, renewable energy resources are projected to make up 73% of global generation by 2050 [1]. Therefore, a significant amount of RES is expected to be installed in the upcoming years as shown in Figure 1-1.

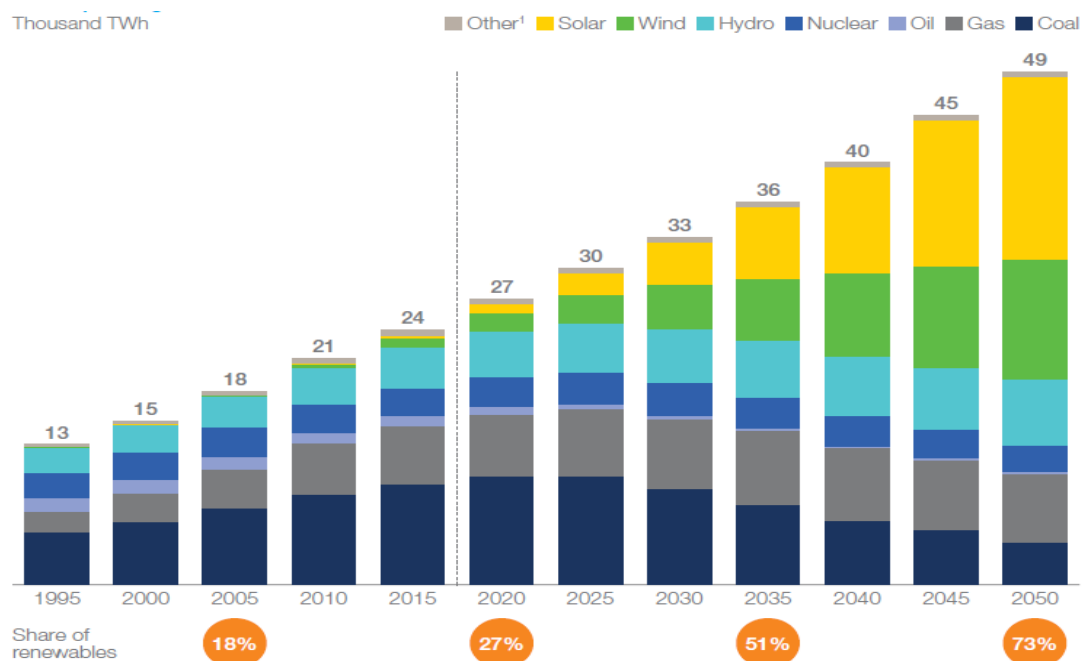


Figure 1 - 1: Global power generation of renewable energy resources [1]

Recently, 60% of the installed capacities between 2015 and 2017. Knowing that wind and solar are expected to share almost half of the global total capacity by 2035 [1]. Due to the undergoing development in non-OECD countries such as India and

China, the demand on electricity is forecasted to be doubled by 2035. Accordingly, due to its economic feasibility and the growing environmental concerns, additional generation capacities from renewable energy resources are being installed to equalize the growing demand. In fact, the Global Energy Prospective (2019) report shows that 75% of the total global generation capacity by 2050 are projected to be from renewable energy resources. For instance, France has announced its plan to tender 3 GW of wind generation, annually. Additionally, a total of 2.45 GW solar PV tenders will be released on annual basis. In Spain, renewable mix (wind and solar PV) projects of 8 GW has been awarded, and 1.7 GW of wind generation has been tendered in Russia [2].

While developed countries accounts for nearly 70% of the current global investment in renewable

power, the undergoing investment in developing countries is also significant [2]. For example, in Saudi Arabia,

Table 1- 1: Renewable energy status in GCC

Country	Installed Capacity MW	Projects in Pipelines		Projected Capacity	
		MW	Target	MW	Target
Saudi Arabia	142	700	2020	30	2030
UAE	589	3140	2022	15	2050
Qatar	43	350	2020	20	2030
Kuwait	79	1200	2022	15	2030
Oman	8	2300	2023	10	2040
Bahrain	6	100	2019	10	2035

a plan to add 9.5 GW of renewable power generation by 2023 has been announced. Similarly, in 2030, 15% of the electricity generated in Kuwait will be from renewables and 2% of greenhouse emission will be eliminated in Oman by 2030. Note that, renewables will make up 10% of Oman total generation [3].

The decline in wind prices (offshore and onshore) and market incentives have made wind the least-cost energy resource option of which are renewables [2]. Hence, wind projects increased rapidly to take the advantage of incentive schemes offered by today's markets. Nowadays, wind power covers around 6% of the global electricity demand. According to Wind World Energy Association, the total installed capacity

from wind is 600 Gigawatts. Knowing that around 200 Gigawatts of wind are currently installed in the Chinese market, and 7.6 Gigawatts of wind power are being traded in united states [48]. Almost 52 GW of wind power was in 2017, followed by 53.9 GW in 2018 where 48% of which at Asia. In 2017, breaking record power purchase agreements were awarded in several deregulated markets. In countries such as Morocco, India, Mexico and Canada the prices were almost around 30 USD per MWh [2]. In Saudi Arabia, a 500 MW onshore wind farm project Dumat Al Jandal was awarded at 21.3 USD per MWh [45].

Besides incentives offered by deregulated and regulated markets, several policies were developed to accelerate the integration of renewable energy resources in many countries. For instance, in Germany, Renewable Energy Act becomes effective in 2017. Moreover, Feed-in tariff (FIT) mechanisms were established by two countries in 2017 and others revised it existing FIT to advance the RES penetration level by incentivize small scale producers [2].

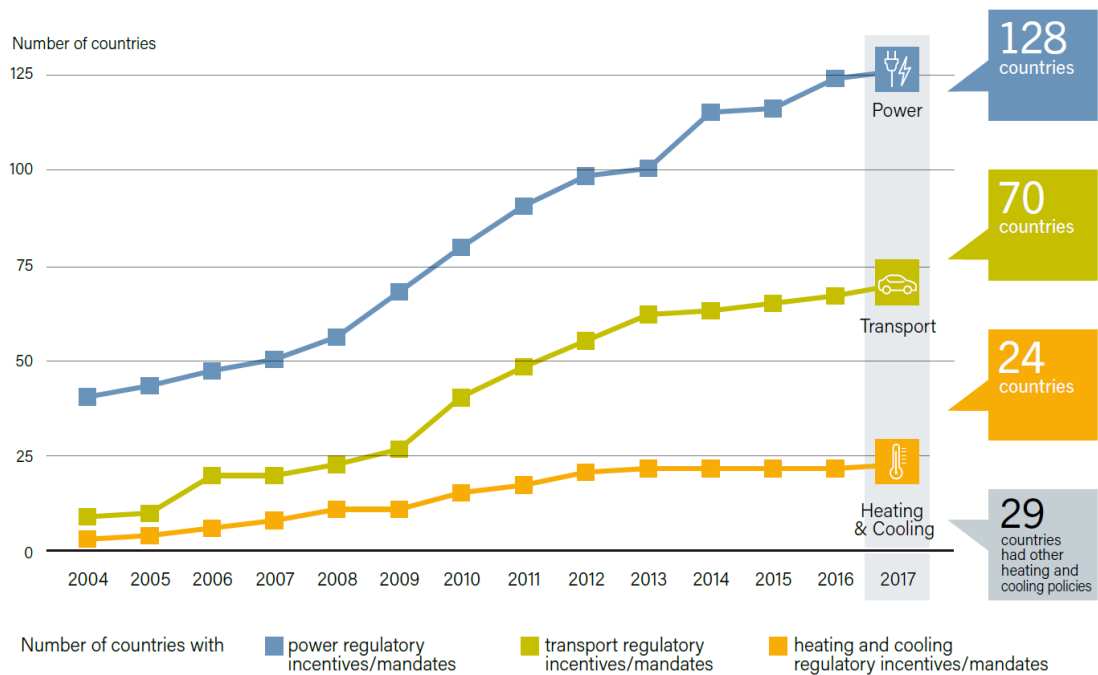


Figure 1 - 2: Number of Countries with Renewable Energy Regulatory Policies 2004-2017 [2]

However, unless the uncertainty associated with RES addressed, substantial growth in balancing needs are expected in today's electricity markets [1]. In addition to its impacts on power system operation, uncertainty pertaining to wind and solar forecasts makes it difficult to dispatch. Recently, several policies were developed to promote the deployment of RES. For instance, in Czech Republic, coupling between each solar PV kW with at least 5 kW of storage capacity is required. Small scale combined RES with storage systems projects are subsidized in Germany [2]. Furthermore, to address the system reliability, RES integration policies are under development. For instance, the Australian Energy Market Operator published a guide to address fast frequency response and, a total of six states in India published forecasting and scheduling regulations of wind and solar power generators in 2017 [2].

Furthermore, the ever-falling prices of wind turbines derive the innovation global manufacturer to increase its efficiency while maintaining operational costs. However, the considerable prosperity in wind energy poses several challenges. One primary problem is the vulnerability of wind generation. Hence, to overcome this problem, developers and manufacturers are exploring the potential innovations to enhance the capacity factor of wind turbines. For example, in 2017, Siemens proposed wind-heat turbines to be installed in Germany. Moreover, Max Bogl has delivered four wind turbines integrated with pumped storage systems and GE studying the potential of integrating Microsoft batteries with wind turbines [2].

Broadly speaking, wind producers are interested in mitigating the trading risk associated with wind generation in day-ahead electricity markets. correspondingly, the integration of wind with storage systems and other flexible energy resources has been found to cope with the uncertainty problem more efficiently. Hence, this thesis documents several key contributions made on this field by coordinating the energy

trading of wind, thermal and pumped storage systems and co-optimizing the trading strategy for an energy producer in DA energy and regulation markets. The aim is to develop a trading strategy that maximize producer's profit in both markets by modelling the uncertainty of wind generation, DA energy, regulation and imbalance prices using fuzzy membership theory. Therefore, the optimal bidding strategy is formulated as a mixed-integer linear fuzzy optimization (MILFO). Data from Iberian market are used to examine the effectiveness of the proposed approach. Simulation results demonstrate a significant advantage of MILFO over the classical optimization approach in terms of profitability and model complexity.

1.2. MOTIVATION PROBLEM DISCERPTION

This work suggests a comprehensive trading strategy by coordinating the producer's energy resources such as wind, pumped-hydro storage and thermal units and by co-optimizing the producer trading strategy in DA energy and regulation markets. Since the trading in such markets are subject to several uncertainties, the fuzzy theory is employed to model the vulnerability of wind generation and different market variables. In addition, the framework of Iberian market (MIBEL) is considered in this work. The total power in MIBEL (Spanish side) is 78.2 GW, 19.09 GW of which are renewables. Therefore, this study assumes that the producer is a price taker. Hence, the next two subsections are devoted to the market framework from the Transmission system operator (TSO) and the producer point of view, respectively.

1.2.1. Market Framework- TSO Point of View

In DA energy market, participants can submit hourly biddings and offers up to the 12th to the market operator. All biddings from MIBEL and other European markets are collected by the European market solver (EUPHEMIA). EUPHEMIA aggregates all bids submitted to sell energy in ascending order and offers to purchase energy in descending order to clear the market. Thus, at the 13th hour, the hourly energy volumes (MWh) and prices in (€/MWh) are cleared based on the intersection between bids and offers such that the social welfare is maximized. Next, bilateral contracts are added to the DA market schedules. Before the 16th hour, congestion management process is activated by the transmission system operator (TSO) and revised DA energy schedule are published. As a result, market based on technical constraints are established [50].

After clearing the market, each supplier is committed to generate its cleared volume of energy in real time. The market operator (MO) settles the financial transaction. In real time, all deviations are settled at imbalances prices. In Spain, the positive and negative imbalance prices are derived by a formula described in [51]. If the supply is more than the demand, the market is said to be long. Hence, the system operator compensates producers willing to reduce their energy output at negative imbalance prices (tends to be less than DA energy prices). On the other hand, if the market short (supply is less than demand), the system operator rewards producers willing to increase their energy output at positive imbalance price (tends to be equal or greater than the DA

energy prices). Otherwise, if the generation is equal to the actual demand, no imbalance mechanism is applied.

In addition to the DA energy market price, some producers prefer to participate in DA regulation market. Primary, secondary and tertiary are the three type of frequency regulation reserves available in the Iberian market. The first one is mandatory. Thus, all producers must provide a primary reserve and no trading aspects are involved. However, the secondary regulation reserve is established as the well-known ancillary services market platform. Hence, producers that are willing to participate shall submit their hourly bids to the system operator. In Spain, the secondary regulation is paid based on availability (power band) and use (energy). That is, bidders must quantify the amount of energy that the producer would accept to add or subtract from its energy schedule if called by the system operator to do so. The submission period of regulation bands is between 19:00 to 19:45 the day before delivery. Next, the hourly DA regulation market are cleared based on the intersection of aggregated regulation bids and the forecasted -by TSO- regulation requirements. In the operation day, the TSO dispatch the band (regulated energy) via AGC signals. Hence, the regulated energy is valued at the tertiary regulation prices (€/MW) of MIBEL.

Following the DA regulation market clearing process, all winning participants receive their assigned capacity volume. Moreover, each participant is paid the DA regulation MCP times the cleared regulation capacity volume for each hour. Consequently, there is an enormous desirability by producers to participate in DA regulation market because once the market is cleared, each producer will be compensated for providing the capability to move above or

below their scheduled energy regardless of if they are called by the TSO to deploy that energy or not in real time. Moreover, there are three states of regulation at the end of each period; regulation up, regulation down or none. The third state occurs when there is no need to deploy any regulation capacity.

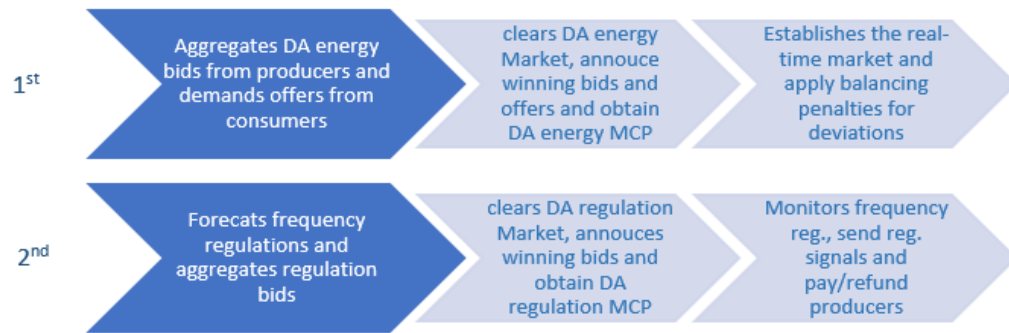


Figure 1 - 3: TSO Standpoint in DA energy and DA regulation Markets

However, if producers are called to deploy regulated energy, each producer receives additional compensation equal to the hourly energy price when the regulation energy is up. Similarly, when the regulation energy is down, each producer receives a refund based on the hourly energy price [32]. Eventually, the process flow of TSO in DA energy and regulation markets can be summarized in Figure 1-3.

1.2.2. Market Framework- Producer Point of View

This work considers a producer that owns thermal, wind and pumped-hydro storage system as depicted by Figure 1-4. Also, this study assumes that the producers is a price taker. The

producer aims to maximize its profit from DA energy & regulation market by co-optimizing its bidding strategy. This can be done coordinating these three resources and submit

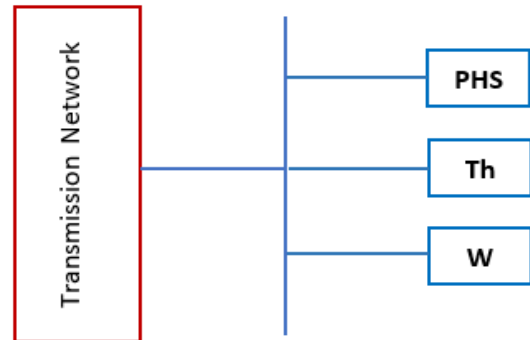


Figure 1 - 4: Single line Diagram for energy resources. PHS: Pumped Hydro Storage, Th: thermal W: Wind

the optimal hourly bids to the DA energy

and regulation markets. Note that, the PHS operates either in pumping or generation mode. When it operates in pumping mode, it consumes energy generated by the thermal or wind resources or purchased from the market. In contrast, when it is in generation mode, the PHS sells energy to the DA or secondary regulation market.

The uncertainty of wind generation imposes a significant risk for the producer. When the producer deviates from the cleared energy volume in DA energy market, it is penalized by the TSO. For example, in the Iberian market, the imbalance charges are subject to the overall system imbalance as well as the supply imbalance. In other words, when the producer is under-generating and the system is short, it will be penalized. In contrast, if the system is long, no penalty charges will be applied for this producer. Similarly, the producer is rewarded only if it is over-generating when the system is short. The under-

generating penalty is greater than or equal to the DA energy price, and it is uncertain. The over-generating penalty (reward) is normally less than or equal to the DA energy price [32]. As a result, whether a producer participates in real-time market or not, it is exposed to real-time prices. Therefore, in this model, wind deficit can be compensated by the thermal and/or PHS resources. On the other hand, wind surplus can be stored in PHS or sold to the TSO at the over-generating price.

In addition to the DA energy market, the producer can also participate in regulation market. Hence, the producer submits an hourly schedule to the market operator. The schedule shows the hourly regulation capacity that the producer can deploy (consume) based on the received regulation signals. Therefore, the producer is remunerated based on the band offered and its regulated energy deployment as described in 1.2.2. Figure 1-5 shows the producers participation process in both DA markets.

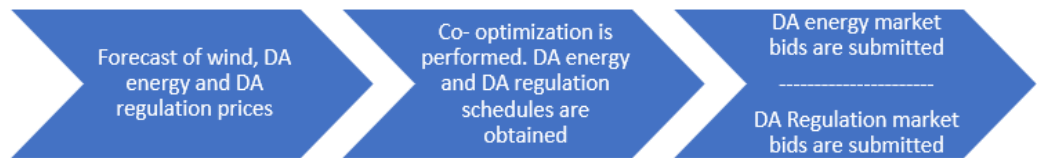


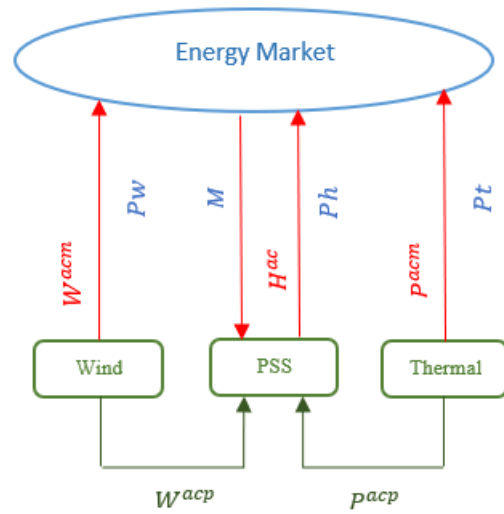
Figure 1 - 5: Producer process to participate in DA energy and regulation Markets

Finally, the role of PHS can be summarized as the following:

1. It consumes the excess power generated from wind.
2. It participates by selling (purchasing) energy from the DA energy market or by utilizing the thermal & wind generations whichever profitable.

3. It can participate in the secondary regulation markets by providing regulation up (down) capacities.

Thus, Figure 1-6 shows the energy exchange for the producer considered in this proposed research.



Furthermore, the producer submits *Figure 1 - 6: Energy market schematic diagram*

a non-priced DA energy & regulation bids to the DA markets, sequentially. Hence, the producer submits the DA energy bids at the 12th hour, and the regulation bids between 19:00 and 19:45. Also note that, DA energy bids are remunerated at the market prices of DA energy (Cap prices) whereas regulation bands are remunerated at the market prices of the secondary reserve. Furthermore, the energy deployed from the regulation bands are compensated at the tertiary reserve prices [50].

1.3. THESIS OBJECTIVE

In this thesis, a comprehensive trading strategy by the coordination of wind, pumped-hydro storage and thermal units and co-optimizing the producer trading. The objective is to devise a coordinated bidding strategy and co-optimized trading to maximize the profits for a producer that participates in the day-ahead energy and regulation markets. The proposed model incorporates the uncertainties associated with wind generation, DA energy market prices, imbalance penalties, regulation signals and prices using fuzzy membership functions. The main contributions of this work can be summaries as follows:

- 1) The optimal trading strategy in day-ahead energy and regulation markets are formulated. Thus, the producer's total profit is maximized respecting the size of the model and its traceability.
- 2) Stochastic parameters such as wind power outputs, DA energy prices, regulation prices and signals are represented using the fuzzy membership functions.
- 3) Using Monte Carlo simulation, the effectiveness of the proposed model is validated to ensure superiority over the deterministic approach.

Yet, to the best of the author knowledge, this has not been presented in literature. Furthermore, the main milestones of the proposed work can be summarized as follows:

- 1) The coordinated trading strategy in DA energy market is formulated as mixed integer linear program (MILP).

- 2) Fuzzy set theory is employed to capture the uncertainties first in DA energy market. Hence, the mixed integer linear fuzzy optimization problem is developed.
- 3) Simulate and validate the proposed trading strategy in DA energy market to realize the producer's profit and risk exposure.
- 4) Extend the deterministic model to include the DA regulation market. Therefore, the co-optimized model is formulated as mixed integer linear program (MILP).
- 5) Apply fuzzy theory to model the DA energy and DA regulation markets uncertainties. Therefore, the co-optimized trading strategy is formulated as mixed integer linear fuzzy optimization (MILFO) problem.
- 6) Simulation of both co-optimization models and validation processes are executed to obtain the producer's realized profit and risk accountability.

The comprehensive milestones of this work are shown in Figure 1-7.

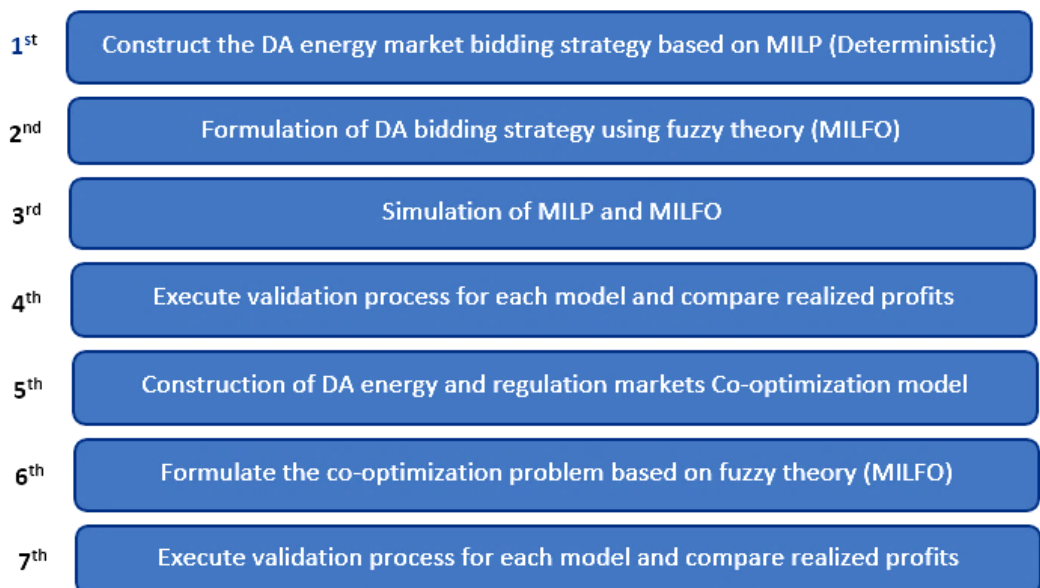


Figure 1 - 7: Milestones of the proposed thesis

1.4. THESIS ORGANIZATION

The rest of this thesis is organized as follows:

Chapter 2 composed of a comprehensive literature survey on the trading of wind energy in electricity market, cutting-edge storage systems and demand response programs, coordination of energy resources and the application fuzzy optimization in modern power system.

In Chapter 3, the mixed integer linear programming model of the coordinated bidding in DA energy market is presented. Then, the coordinated bidding in DA energy market is formulated as mixed integer linear fuzzy program. Results from each approach is investigated and finally, a comparison between the two approaches is drawn.

In Chapter 4, the mixed integer linear programming model is expanded to co-optimize trading in DA energy and regulation market. Next, the deterministic model is transformed to a mixed integer linear fuzzy optimization model. Outcomes from the both approaches are examined and compared.

In Chapter 5, this thesis is concluded, and a list of future works is suggested.

CHAPTER II RELATED WORK

2.1. WIND IN ELECTRICITY MARKETS

Considerable studies investigate the trading of wind in electricity markets. For example, research [4]-[8] suggest several stochastic methodologies to model the uncertainty of wind generation. In [4] the optimal bidding strategy for a wind producer in energy and regulation markets is presented. Probabilistic forecasting technique is used to model the wind vulnerability. In addition, the sensitivity of wind production to regulation cost is also considered. A flexible wind dispatch margin and reserve scheduling policy is proposed in [7]. Authors suggest under-scheduling of wind. Therefore, the excessive wind power can be used to balance deviations in real-time market. The conditional probability distribution of the wind generation is calculated based on a spatial-temporal finite-state Markov chain. In [8] wavelet transform combined with linear neural network are used to forecast the wind power output. Moreover, historical data from Ontario Electricity market is used to validate the proposed technique. Note that, seasonal aspects are also considered. However, stochastic models are computationally expensive.

Furthermore, stochastic optimization approaches are also considered in [9]-[13] to account for wind and electricity market prices. Optimal offering strategies based on two-stage stochastic model is developed in [9]. The uncertainty is presented via scenarios that generated using a combination of wavelet transform, particle swarm optimization and adaptive network based fuzzy interface system. Also, the producer's trading risk is evaluated using the conditional value-at-risk (*CVaR*). In [10], stochastic optimization model is suggested to maximize the total

profit of wind producers. Hence, a new type of bilateral reserve market between wind and conventional power producers is created and the game theory is employed to clear the reserve prices. The objective is to diversify the reserve options for wind producers. Thus, real-time penalties can be avoided. A bilevel stochastic optimization model is formulated in [11]. The upper level problem is to maximize the wind producer profit. Whereas the lower level models the market aspects of DA energy and real-time markets. Moreover, a scenario-based bidding strategy is considered to accommodate the variabilities such as energy demand, wind production and market prices. Furthermore, using Karush-Khun-Tucker condition and duality theory, the bilevel model is transformed to mixed-integer linear program. However, stochastic models are computationally expensive.

2.2. STORAGE SYSTEMS & DEMAND RESPONSE PROGRAMS

Alternatively, there exist a considerable body on literature on the integration of wind power with storage systems [14]-[18]. Researches [14]-[18] suggest storage systems to mitigate the forecasting error of wind generation. For instance, in [14] coordination of wind generation and pumped storage system (PHS) in DA markets is presented. A stochastic price-based model is formulated, and the unit commitment problem of wind and PHS units is solved. Forecasting errors of wind production and market price are addressed to maximize producer's profit. In [16] the optimal bidding of wind-storage pair is presented. The trading strategy is then formulated as a mixed-integer nonlinear program considering the wind forecast error. The modified gradient descent algorithm is employed to derive the optimal bidding in DA energy market. However, energy market prices and imbalance

penalties are not addressed. In [18], coordination of wind and battery energy storage system (BESS) is suggested to mitigate the deviation of wind power production. Authors consider BESS to participate in DA and RT markets. Hence, a strategy based on receding horizon control (RHC) scheme is suggested to control the operation of BESS considering its operational cost and constraints.

On the other hand, several demand response (DR) schemes to smooth wind power vulnerability are introduced [19]-[23]. A two-stage plan where the producer addresses the uncertainty of wind production and market variables using demand response program is presented in [19]. In the first stage, the wind producer determines the DA market offers and DR contracts with DR aggregators. Consequently, the balancing market offers are determined in the second stage beside the necessary DR agreements. This plan is formulated using stochastic programming and data from Nordic market are used to validate the effectiveness. Moreover, a stochastic decision-making strategy for wind-DR pair in DA market are introduced in [20]. Authors suggest a bilateral contract mechanism between wind producer and DR aggregator to account for variation in wind power output and market price. A two-stage stochastic model to schedule DR option in DA and real-time markets is employed in [23]. The optimal DR options schedule for DR aggregator is obtained to balance wind power deviation in real-time market. Furthermore, A bi-level optimization model is developed in [24] to minimize DA market operational cost. Thus, scenarios are used to model the variation in wind power output. Despite its effectiveness in addressing uncertainties, demand response policies usually are subject to the local requirements and regulatory constraints.

Subsequently, other researchers have suggested coordinated trading strategies using robust optimization (RO) [24]-[27]. In [24], distributionally robust optimization model is used to determine the optimal reserve schedule considering wind uncertainty. In [25], robust optimization model is suggested to optimize the joint scheduling in energy and ancillary service markets. Wind vulnerability is addressed, and a participation factor is established to ensure the energy balance. Moreover, in [26], wind uncertainty is modelled using an ambiguity set and the bidding strategy is formulated as distributionally robust optimization. However, RO tends to produce conservative results, which might not be desirable if this coordination is to be applied in a market environment. In addition, the RO version for a linear deterministic optimization model is usually nonlinear.

2.3. ENERGY COORDINATION

Over time, the coordination of wind generation with conventional energy resources for trading in electricity markets has been suggested in literature. Due to its controllability and ramping capability, conventional resources can effectively mitigate RES variability. References [28]-[33] consider stochastic optimization models to coordinate wind generation with conventional energy resources. For instance, a two-stage stochastic program is considered in [29]. The forecast error in wind, water-flow, electric load and power system outages are addressed via scenarios and Monte Carlo (MC) simulation is executed. Furthermore, the optimal bidding strategy of coordinated wind-thermal energy is presented in [30]. The problem is formulated using mixed-integer linear stochastic optimization. Also, the trading risk is controlled via the conditional value at risk in the objective function

as a weighting term. A further study in [32] suggests a coordinated trading of wind, thermal and pumped storage system. The trading strategy in DA energy and regulation markets is formulated as a mixed-integer linear stochastic program. In [33], cascaded hydro or gas turbine units are introduced to incorporate the fluctuation in wind power outputs. Thus, a bi-level stochastic optimization model is developed, and risk aversion is also considered. However, scalability presents a major challenge for stochastic programming (SP). That is, as the number of stochastic parameters increases, the SP computational burden grows substantially.

Subsequently, other researchers have suggested coordinated trading using robust optimization (RO) [34]-[36]. RO is applied for the centralized unit commitment of wind, thermal, and PHS in [34]. A modified distributionally robust optimization based on semi-definite programming is considered in [35] to obtain the joint dispatch of hydro-thermal-wind units. However, RO tends to produce conservative results, which might not be desirable if this coordination is to be applied in a market environment. In addition, the RO version for a linear deterministic optimization model is usually nonlinear.

2.4. FUZZY OPTUMIZATION

Following its introduction in 1965, fuzzy set theory has been widely employed to handle uncertainties [37]. In addition to its effectiveness in modelling increased number of imprecise or conflicting decisions, the problem size under fuzzy optimization (FO) remains reasonable. Also, if the underlying deterministic model is linear, its FO counterpart, if carefully formulated, can be maintained linear.

Therefore, several optimization models based on the fuzzy set theory are developed in [38]-[44].

The unit commitment problem is formulated using FO in [38]. The objective was to reduce the operational cost of thermal units in the presence of wind and solar energy resources. FO is introduced to incorporate load, water flow, wind speed, and solar radiation forecast errors. However, market aspects are not considered. In [39], a bidding strategy of electric vehicles aggregator participating in ancillary services markets is formulated using FO, considering the uncertainties of the regulation and reserve prices and deployment signals. However, coordination with other resources is not addressed. In [42], FO is used to optimize the demand response bidding strategy of a virtual power plant (VPP). Furthermore, the optimal sizing of battery energy storage system (BESS) is formulated using FO in [43]. The proposed model aims to obtain the optimal BESS power and energy capacities to guarantee sustainable profitability in the ancillary services market. Recently, a multi-objective FO model is introduced for asset planning of distribution system [44]. The goal has been to minimize the annual investment cost and system average interruption duration index (SAIDI) considering high penetration level of renewables and BESS. Market aspects have not been considered here, though.

In this thesis, the co-optimization of wind, thermal and pumped hydro storage (PHS) units using mixed-integer linear fuzzy optimization (MILFO) is proposed. The objective is to devise a co-optimized bidding strategy that maximizes the profits for a producer that participates in the day-ahead energy and regulation markets. The proposed model incorporates the uncertainties associated with wind generation, energy market prices, imbalance penalties, regulation market prices and regulation signals using fuzzy membership functions. To the best of the authors'

knowledge, this is the first fuzzy optimization model available in the literature for a market-based coordinated bidding strategy of generation resources and storage media.

CHAPTER III COORDINATED BIDDING STRATEGY

IN DAY AHEAD ENERGY MARKET

In this chapter, coordinated bidding strategies in DA energy market based on deterministic and fuzzy approaches are presented. In the first section, the objective function and constraints of deterministic model are developed. Hence, the coordinated bidding strategy in DA energy market is formulated as a mixed integer linear program. Next, using fuzzy theory, the developed model is expanded, and the coordinated bidding strategy is then formulated using mixed integer linear fuzzy optimization (MILFO) to address the uncertainty of wind generation, DA energy market and imbalance prices.

3.1. COORDINATED BIDDING STRATEGY – DETERMINISTIC MODEL

In this section, the deterministic trading strategy of wind, thermal, and PHS resources is introduced. The objective is to maximize the producer's profit in DA energy market. Note that, this model neglects the uncertainties associated with forecasting wind power, DA energy and imbalance prices.

3.1.1. Objective Function

$$\text{Maximize } PF \quad (3.1)$$

Where

$$PF = PFT + PFW + PFH + PFIM \quad (3.2)$$

$$PFW = \sum_{t=1}^{N_T} \sum_{d=1}^{N_D} \pi_t * Pw_{dt} \quad (3.3)$$

$$PFH = \sum_{t=1}^{N_T} \sum_1^{N_U} \pi_t * Ph_{tn} - \pi_t * M_t - OC * (\sum_n^{N_u} H_{tn}^{ac} + M_t + W_t^{acp} + \sum_{g=1}^{N_g} P_{tg}^{acp}) \quad (3.4)$$

$$PFT = \sum_{t=1}^{N_T} \sum_{g=1}^{N_G} \pi_t * Pt_t - C_g(P_{tg}^{total}) - \max(StUp_{tg} \cdot (U_{tg} - U_{t-1g}), 0) \quad (3.5)$$

$$PFIM = \sum_1^{N_T} \pi_t^u \pi_t * ImUP_t - \pi_t^d \pi_t * ImDN_t \quad (3.6)$$

As shown in (3.1), the objective of the producer is to maximize the total profit from DA energy market. The profit consists of four components as described by (3.2). The wind profit for the 24 hours is given in (3.3). Equation (3.4) describes the profit (cost) of PHS scheduled generation (pumping) to (from) the market. Note that the hourly generation (pumping) cost is included in the third term of (3.4). The thermal profit is given in (3.5).

Equation (3.6) describes the imbalance profit (cost). Note that imbalances occur whenever there is a mismatch between the hourly scheduled and actual power output from wind, thermal and PHS. Hence, if the producer is over-generating (under-generating), the imbalance is positive (negative). Also note that if the total generating is equal to the scheduled power output, the imbalance is zero.

3.1.2. System Constraints

a. Wind Constraints

Actual wind power output is forecasted for each hour of the day.

Some of this power can be stored via the PHS units and the remaining is supplied to the market, as given in (3.7). Constraint (3.8) ensures that the hourly bid from the wind is within the plant capacity.

$$W_{td}^{ac} = W_{td}^{acm} + W_{td}^{acp} \quad (3.7)$$

$$0 \leq Pw_{td} \leq \overline{W_d} \quad (3.8)$$

b. Thermal Units Constraints

Similarly, the actual power generated by the thermal unit is divided into two parts. The first part represents the hourly energy sold to the market, and the second part models the energy stored into PHS units, as shown in (3.9). The thermal power output is constrained by ramping up/down limits, as in (3.10).

Thermal hourly bid and actual power output of each unit is constrained by its capacity as shown in (3.11) and (3.12), respectively. Relations (3.13) - (3.15) are used to impose the minimum-up time limits. Similar constraints are used for the minimum-down time. The total output thermal power is given in (3.16). The nonlinear thermal cost function is given in (3.17). The piece-wise linearization of (3.17) is expressed in (3.18) - (3.21).

$$P_{tg}^{ac} = P_{tg}^{acm} + P_{tg}^{acp} \quad (3.9)$$

$$-RD_g \leq P_{tg}^{ac} - P_{t-1,g}^{ac} \leq RU_g \quad (3.10)$$

$$U_{tg} * \underline{P_g} \leq Pt_{tg} \leq U_{tg} * \overline{P_g} \quad (3.11)$$

$$U_{tg} * \underline{P_g} \leq P_{tg} \leq U_{tg} * \overline{P_g} \quad (3.12)$$

$$\sum_{t=1}^{initUp_g} (1 - u_{tg}) = 0 \quad (3.13)$$

$$\begin{aligned} \sum_{n=t}^{t+initUp_g-1} u_{ng} &\geq MinUp_g (u_{tg} - \\ u_{t-1,g}) \quad \forall t &= initUp_g + 1 \dots Nt - \\ MinUp_g + 1 \end{aligned} \quad (3.14)$$

$$\begin{aligned} \sum_{n=t}^{N_T} u_{ng} - (u_{tg} - u_{t-1,g}) &\geq 0 \quad \forall g, \\ \forall t &= Nt - MinUp_g + 2 \dots Nt \end{aligned} \quad (3.15)$$

$$P_{tg}^{total} = P_{tg}^{ac} + (Ru_t - Rd_t) * \sum_{g=1}^{N_G} P_{tg}^{reg} \quad (3.16)$$

$$\begin{aligned} C_g(P_{tg}^{total}) &= FC_g \cdot (a + bP_{tg}^{total} \\ &\quad + c(P_{tg}^{total})^2) \end{aligned} \quad (3.17)$$

$$\begin{aligned} C_g(P_{tg}^{total}) &= FC_g \cdot \left(u_{tg} * AA_g \right. \\ &\quad \left. + \sum_{e=1}^{N_E} S_{etg} \cdot \delta_{etg} \right) \end{aligned} \quad (3.18)$$

$$P_{tg}^{total} = \underline{P_g} * u_{tg} + \sum_{e=1}^{N_E} \delta_{etg} \quad (3.19)$$

$$0 \leq \delta_{etg} \leq BrkPt_{eg} - BrkPt_{e-1,g} \quad (3.20)$$

$$AA_g = a + b\underline{P_g^{ac}} + c \left(\underline{P_g^{ac}} \right)^2 \quad (3.21)$$

c. PHS units Constraints

The hourly bid and actual power output of each PHS unit operating in generation mode are constrained by (3.22) and (3.23), respectively. Similarly, relation (3.24) is employed to ensure the power pumped to PHS units is within the desirable limits. The energy level in each PHS reservoir is represented by relation (3.25). Therefore, the pumped energy is added to the available energy in the reservoir in an hourly basis. Relation (3.26) ensures that the energy level in all hours are within the upper and lower limits. Relations (3.27) and (3.28) specify the initial and final energy levels.

The total pumped energy to the PHS upper reservoir is given in (3.29), and it is a combination of wind, thermal and purchased energy from the market. Relation (3.30) limits the operational mode of PHS units. Thus, the unit works as either a pump or a generator. Constraint (3.31) and (3.32) are to ensure that a PHS unit stay offline for 1 hour to switch from pumping to generating modes, or vice versa. Finally, equation (3.33) is to set initially all PHS units to offline, which is an assumption that can be changed according to the real initial conditions.

$$0 \leq Ph_{tn} \leq G_{tn} * \overline{H_n} \quad (3.22)$$

$$0 \leq H_{tn}^{ac} \leq G_{tn} * \overline{H_n} \quad (2.23)$$

$$0 \leq \sum_{n=1}^{N_U} Pump_{tn} \leq \sum_{n=11}^{N_U} Pu_{tn} * \bar{H}_n \quad (3.24)$$

$$V_t = V_{t-1} + \left\{ \mu_p * \left(\sum_{n=1}^{N_U} Pump_{tn} \right) - \frac{1}{\mu_G} \left(\sum_{n=1}^{N_U} H_{tn}^{ac} + (\alpha_U - \alpha_D) * \sum_{n=1}^{N_u} Pg_{tn}^{reg} \right) \right\} \quad (3.25)$$

$$\underline{V} \leq V_t \leq \bar{V} \quad (3.26)$$

$$V_t = V^{initial}, t = 0 \quad (3.27)$$

$$V_t = V^{final}, t = 24 \quad (3.28)$$

$$\sum_{n=1}^{N_U} Pump_{tn} = M_t + W_t^{acp} + \sum_{g=1}^{N_G} P_{tg}^{ac} + (\alpha_U - \alpha_D) * \sum_{n=1}^{N_u} Pg_{tn}^{reg} \quad (3.29)$$

$$Pu_{tn} + G_{tn} \leq 1 \quad (3.30)$$

$$Pu_{t-1,n} + G_{tn} \leq 1 \quad (3.31)$$

$$Pu_{tn} + G_{t-1,n} \leq 1 \quad (3.32)$$

$$G_{0n} = 0, Pu_{0n} = 0 \quad (3.33)$$

d. Imbalance Constraints

The imbalance profit (loss) is given by (3.34). As described earlier, the overall imbalance modelled as the difference between the imbalance up and imbalance down. In other words, it is the mismatch between the schedule bid and the actual power output of wind, thermal

and PHS in the DA energy market. Relations (3.35) and (3.36) set the limits for up and down imbalance.

$$\begin{aligned}
ImbUP_t - ImbDN_t = & \sum_{n=1}^{N_U} Ph_t + \\
& \sum_{g=1}^{N_G} Pt_t + \sum_{d=1}^{N_D} Pw_t - \sum_{d=1}^{N_D} W_{td}^{acm} - \\
& \sum_{g=1}^{N_G} P_{tg}^{acm} - \sum_{n=1}^{N_U} H_{tn}^{ac}
\end{aligned} \tag{3.34}$$

$$0 \leq ImbUP_t \leq \sum_{d=1}^{N_D} W_{td}^{ac} + \sum_{g=1}^{N_G} P_{tg}^{acm} + \sum_{n=1}^{N_U} H_{tn}^{ac} \tag{3.35}$$

$$\begin{aligned}
0 \leq ImbDN_t \leq & \sum_{d=1}^{N_D} \overline{W}_d \\
& + \sum_{g=1}^{N_G} U_{tg} * P_{tg}^{max} + \sum_{n=1}^{N_U} G_{tn} * \overline{H}_n
\end{aligned} \tag{3.36}$$

3.2. COORDINATED BIDDING STRATEGY – MIXED INTEGER LINEAR Fuzzy MODEL (MILFO)

The above deterministic model can be expressed as follows:

$$\begin{aligned}
& \text{Maximize } f(x, \zeta, \xi) \\
& \text{Subject to } g_j(x, \zeta, \xi) \leq 0, \quad j = 1, \dots, k \\
& \quad \quad \quad g_j(x, \zeta) \leq 0, \quad j = k + 1, \dots, K
\end{aligned} \tag{3.37}$$

where x , ζ , and ξ are vectors of decision variable, certain (or crisp) parameters, and uncertain parameters, respectively.

In classical (deterministic) optimization approaches, the uncertain parameters ξ are forecasted or estimated, and the estimated values are used to determine the optimal solution. In contrast, in fuzzy optimization (FO) models, the objective function and constraints that are functions of the uncertain parameters ξ are represented by membership functions. The membership function can be used to observe how close each objective function or constraint from the optimal solution. Therefore, the above optimization problem can be formulated using FO as follows:

$$\begin{aligned} & \text{Maximize } \lambda = \min \{\mu_f, \mu_{g1}, \dots, \mu_{gk}\} \\ & \text{subject to } g_j(x, \zeta) \leq 0, j = k + 1, \dots, K \end{aligned} \quad (3.38)$$

where μ_f refers to the membership function of the objective function, and μ_{gj} represents the membership function of the j -th fuzzy constraint. The values of the defined membership function range between 0 and 1. Figure 3-1 shows an example of fuzzy membership function, where $\overline{PFT}$ and $\underline{PFT}$ are parameters to be determined by the decision maker. Note that, constraints of the deterministic (MILP) optimization model are also included in the MILFO model. Hence, by maximizing the smallest membership function, optimality can be achieved while the problem size remains tractable.

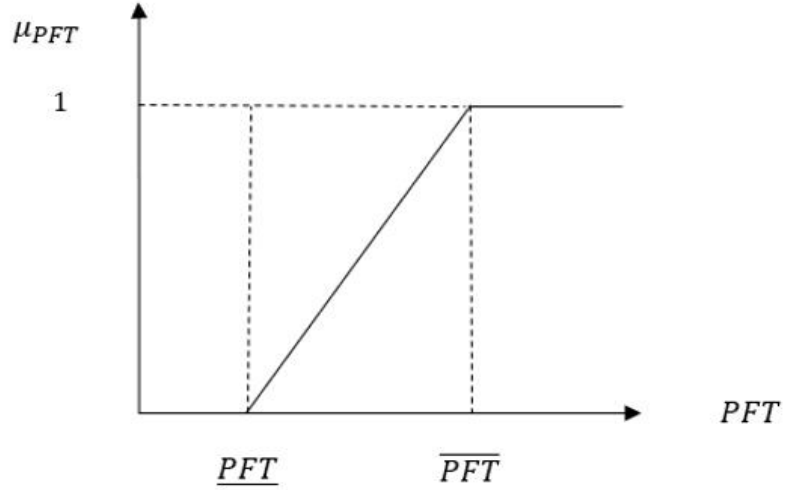


Figure 3 - 1: Example of a membership function

3.2.1. Fuzzy Model of Thermal Profit

For the coordination optimization problem, the fuzzy set of the thermal profit, given in (3.5), is shown in (3.39a). The membership function of the thermal profit is defined in (3.39b), where $\overline{PFT}$ is a parameter defined by the decision maker. It is a common practice to set $\overline{PFT}$ to equal the expected profits obtained by the deterministic optimization model. Note that (3.39b) is the mathematical representation of the function shown in Figure 3-1 after setting $\underline{PFT}$ to 0, which is done for simplicity. Relation (3.39b) is converted to a fuzzy constraint as shown in (3.39c). Consequently, the objective function is translated into the inequality constraint given in (3.39d), where γ and PFT are new decision variables.

$$\widetilde{PFT} = [PFT, \mu_{PFT}], \quad 0 \leq PFT \leq \overline{PFT} \quad (3.39a)$$

$$\mu_{PFT} = \begin{cases} 0, & PFT \leq 0 \\ \frac{PFT}{\overline{PFT}}, & 0 \leq PFT \leq \overline{PFT} \\ 1, & PFT \geq \overline{PFT} \end{cases} \quad (3.39b)$$

$$\gamma \leq \mu_{PFT} = \frac{PFT}{\overline{PFT}} \quad (3.39c)$$

$$\overline{PFT} * \gamma \leq PFT \quad (3.39d)$$

3.2.2. Fuzzy Model of Wind profit

Similarly, the wind profit, the fuzzy set is shown in (3.40a). The membership function of the wind profit is defined in (3.40b). Relation (3.40b) is converted to a fuzzy constrain as shown in (3.40c). As a result, the objective function is translated into the inequality constraint given in (3.40d).

$$\widetilde{PFW} = [PFW, \mu_{PFW}], \quad 0 \leq PFW \leq \overline{PFW} \quad (3.40a)$$

$$\mu_{PFW} = \begin{cases} 0, & PFW \leq 0 \\ \frac{PFW}{\overline{PFW}}, & 0 \leq PFW \leq \overline{PFW} \\ 1, & PFW \geq \overline{PFW} \end{cases} \quad (3.40b)$$

$$\gamma \leq \mu_{PFW} = \frac{PFW}{\overline{PFW}} \quad (3.40c)$$

$$\overline{PFW} * \gamma \leq PFW \quad (3.40d)$$

3.2.3. Fuzzy Model of PHS profit

Similarly, the membership function of PHS profit is converted to a fuzzy constraint as shown in (3.41c). Consequently, the objective function is translated into the inequality constraint given in (3.41d).

$$\widetilde{PFH} = [PFH, \mu_{PFH}], \quad 0 \leq PFH \leq \overline{PFH} \quad (3.41a)$$

$$\mu_{PFH} = \begin{cases} 0, & PFH \leq 0 \\ \frac{PFH}{\overline{PFH}}, & 0 \leq PFH \leq \overline{PFH} \\ 1, & PFH \geq \overline{PFH} \end{cases} \quad (3.41b)$$

$$\gamma \leq \mu_{PFH} = \frac{PFH}{\overline{PFH}} \quad (3.41c)$$

$$\overline{PFH} * \gamma \leq PFH \quad (3.41d)$$

3.2.4. Fuzzy Model of Imbalance Profit

Likewise, the membership function of imbalance profit is converted to a fuzzy constraint as shown in (3.42c). Due to the absence of imbalance profit in the deterministic model, the maximum expected profit from imbalances is set to 10% of the total profit. Consequently, the objective function is translated into the inequality constraint given in (3.42d).

$$\widetilde{PFIM} = [PFIM, \mu_{PFIM}], \quad 0 \leq PFIM \leq \overline{PFIM} \quad (3.42a)$$

$$\mu_{PFIM} = \begin{cases} 0, & PFIM \leq 0 \\ \frac{PFIM}{\overline{PFIM}}, & 0 \leq PFIM \leq \overline{PFIM} \\ 1, & PFIM \geq \overline{PFIM} \end{cases} \quad (3.42b)$$

$$\gamma \leq \mu_{PFH} = \frac{PFIM}{\overline{PFIM}} \quad (3.42c)$$

$$\overline{PFIM} * \gamma \leq PFIM \quad (3.42d)$$

3.2.5. Fuzzy Model of Wind Power

Equation (3.43a) defines the fuzzy model of wind power and the membership is defined in (3.43b). Relation (3.43c) converts the fuzzy membership function into fuzzy constraint. Based on gaussian distribution of wind power outputs given in [49]. In this model. That is, if the forecasted wind is $\widetilde{W}^{ac}$ and the standard deviation is e_w , then $\overline{W}^{ac}$ and $\underline{W}^{ac}$ are defined by (3.43d).

$$\widetilde{W}^{ac} = [W^{ac}, \mu_{P_{W_d}}], \quad \underline{W}^{ac} \leq W^{ac} \leq \overline{W}^{ac} \quad (3.43a)$$

$$\mu_W = \begin{cases} 0, & W^{ac} \leq 0 \\ \frac{W^{ac} - \underline{W}^{ac}}{\overline{W}^{ac} - \underline{W}^{ac}}, & \underline{W}^{ac} \leq W^{ac} \leq \overline{W}^{ac} \\ 1, & W^{ac} \geq \overline{W}^{ac} \end{cases} \quad (3.43b)$$

$$(\overline{W}^{ac} - \underline{W}^{ac}) * \gamma \leq (W^{ac} - \underline{W}^{ac}) \quad (3.43c)$$

$$\overline{W}^{ac} = \widetilde{W}^{ac}(1 + e_w), \quad \underline{W}^{ac} = \widetilde{W}^{ac}(1 - e_w) \quad (3.43d)$$

3.2.6. Fuzzy Model of DA Energy Market Prices

Relations (3.44a) to (3.44d) are employed to model the hourly DA energy market prices. Hence, the fuzzy membership function is given is (3.44b). equation (3.44c) converts the membership function into fuzzy constraint. Like wind boundaries, based on MAPE, the lower ($\underline{\pi}$) and upper ($\bar{\pi}$) bounds of DA energy prices are calculated as shown in (3.44d)

$$\tilde{\pi} = [\pi, \mu_{\pi}], \quad \underline{\pi} \leq \pi \leq \bar{\pi} \quad (3.44a)$$

$$\mu_{\pi} = \begin{cases} 0, & \pi \leq \underline{\pi} \\ \frac{\pi - \underline{\pi}}{\bar{\pi} - \underline{\pi}}, & \underline{\pi} \leq \pi \leq \bar{\pi} \\ 1, & \pi \geq \bar{\pi} \end{cases} \quad (3.44b)$$

$$(\bar{\pi} - \underline{\pi}) * \gamma \leq (\pi - \underline{\pi}) \quad (3.44c)$$

$$\bar{\pi} = \tilde{\pi}(1 + e_{\pi}), \quad \underline{\pi} = \tilde{\pi}(1 - e_{\pi}) \quad (3.44d)$$

3.2.7. Fuzzy Model of Real-Time Imbalance Prices

The fuzzy model of imbalance up coefficient is defined in equation (3.45a), and the fuzzy membership function is defined in (3.45b). This converted to a fuzzy constraint in (3.45c). $\overline{\pi^u}$ and $\underline{\pi^u}$ are to be defined by the producer. In this study, historical data from [46] is used to calculate the mean absolute percentage error (MAPE) between the forecasted π^u and actual π^u . Hence, $\overline{\pi^u}$ and $\underline{\pi^u}$ are given in (3.45d). in addition, relations (3.46a) to (3.46d) are employed to model the imbalance up coefficient is similar fashion.

$$\widetilde{\pi^u} = [\pi^u, \mu_{\pi^u}], \quad \underline{\pi^u} \leq \pi^u \leq \overline{\pi^u} \quad (3.45a)$$

$$\mu_{\pi^u} = \begin{cases} 0, & \pi^u \leq \underline{\pi^u} \\ \frac{\pi^u - \underline{\pi^u}}{\overline{\pi^u} - \underline{\pi^u}}, & \underline{\pi^u} \leq \pi^u \leq \overline{\pi^u} \\ 1, & \pi^u \geq \overline{\pi^u} \end{cases} \quad (3.45b)$$

$$(\overline{\pi^u} - \underline{\pi^u}) * \gamma \leq (\pi^u - \underline{\pi^u}) \quad (3.45c)$$

$$\overline{\pi^u} = \pi^u(1 + e_{\pi^u}), \quad \underline{\pi^u} = \pi^u(1 - e_{\pi^u}) \quad (3.45d)$$

$$\widetilde{\pi^d} = [\pi^d, \mu_{\pi^d}], \quad \underline{\pi^d} \leq \pi^d \leq \overline{\pi^d} \quad (3.46a)$$

$$\mu_{\pi^d} = \begin{cases} 0, & \pi^d \leq 0 \\ \frac{\pi^d - \underline{\pi^d}}{\overline{\pi^d} - \underline{\pi^d}}, & \underline{\pi^d} \leq \pi^d \leq \overline{\pi^d} \\ 1, & \pi^d \geq \overline{\pi^d} \end{cases} \quad (3.46b)$$

$$(\overline{\pi^d} - \underline{\pi^d}) * \gamma \leq (\pi^d - \underline{\pi^d}) \quad (3.46c)$$

$$\overline{\pi^d} = \pi^d(1 + e_{\pi^d}), \quad \underline{\pi^d} = \pi^d(1 - e_{\pi^d}) \quad (3.46d)$$

3.2.8. The Complete fuzzy model

In the FO version, the objective is to maximize the minimum membership function subject to the system physical and economical constraints. Therefore, the complete fuzzy model is as follows:

Maximize γ

Subject to (3.2) – (3.36), (3.39c), (3.40c), (3.41c), (3.42c),

(3.43c), (3.44c), (3.45c) and (3.46c)

Therefore, in this optimization, the decision variables Pw_{td} , Pt_{tn} and Ph_{th} , P , P^{acm} , P^{acp} , W^{acm} , W^{acp} , H^{ac} , M , $Pump$, V , U , Pu , G and δ . The parameters are PF , PFT , PFW , PFH , $PFIM$, $ImUp$, $ImDn$. Auxiliary variables are μ_{PFT} , μ_{PFW} , μ_{PFH} , μ_W , μ_π , μ_{π^u} , and μ_{π^d} . Note that, forecasts of wind power output W^{ac} are obtained from [30], forecasts of DA energy π , and imbalance coefficients π^u and π^d are developed using ARIMA model described in [47], and data of thermal and PHS units from [32] are used as an input for the optimization problem.

3.3. TEST SYSTEM

The test system consists of one wind power plant with a capacity of 200 MW, five thermal units with a total capacity of 340 MW, and four PHS units with a capacity of 30 MW each. The details of the thermal and PHS units used in this work are from [32] and presented in Appendix-I. DA energy, imbalance up and imbalance down prices are imported from the Spanish side of the Iberian Market [46] for May to August 2018. Using ARIMA model, DA energy and imbalance prices are forecasted. To avoid outliers, national vacation days and weekends are excluded. Using CPLEX 12.7.1, which is called from the IBM ILOG package, the mixed integer linear programming (MILP) problem is solved using HP ENVY Core i7.

3.4. RESULTS & ANALYSIS

In this section, the results of the DA bidding strategies of the classical deterministic (MILP) and the proposed fuzzy (MILFO) approaches are presented and discussed. Note that, in the MILP approach, a perfect forecast for the DA energy and imbalance prices and wind power outputs are assumed. Whereas, in the proposed approach, the optimal bidding strategy is formulated as a mixed-integer linear fuzzy optimization (MILFO) to address uncertainties. Finally, a comparison between both approaches is drawn.

3.4.1. Deterministic MILP Bidding Strategy

Since uncertainties are neglected, perfect forecasts of wind energy, DA energy price and imbalance prices are assumed. Hence, the optimal DA energy bids for a sample day (September 2nd, 2018) for wind are identical to wind forecast, as depicted in Figure 3-2.

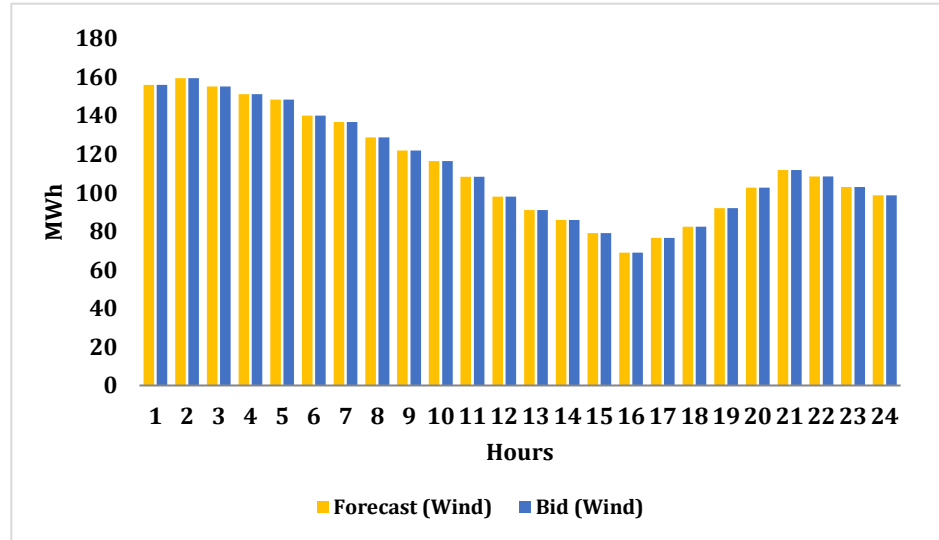


Figure 3 - 2: Market bid vs. forecast for wind using the deterministic strategy

Furthermore, the total actual energy generated by the system is presented in Figure 3-3. Note that since the price difference is insignificant over the 24 hours, no contribution from PHS units and only wind and thermal biddings are observed. Moreover, the optimal coordinated bidding in DA energy market is shown in Figure 3-4. Note that the coordinated bidding increases significantly during the peak hours (i. e. at hours 8 and 21) due to the increase in DA energy hourly price. Also, no offers are submitted by PHS units to purchase energy. Hence, the total bidding is identical to the total generation from wind and thermal units. This is because the difference in the hourly DA energy

pricing is small. Moreover, due to the efficiency constraints, no bids are scheduled out of PHS units.

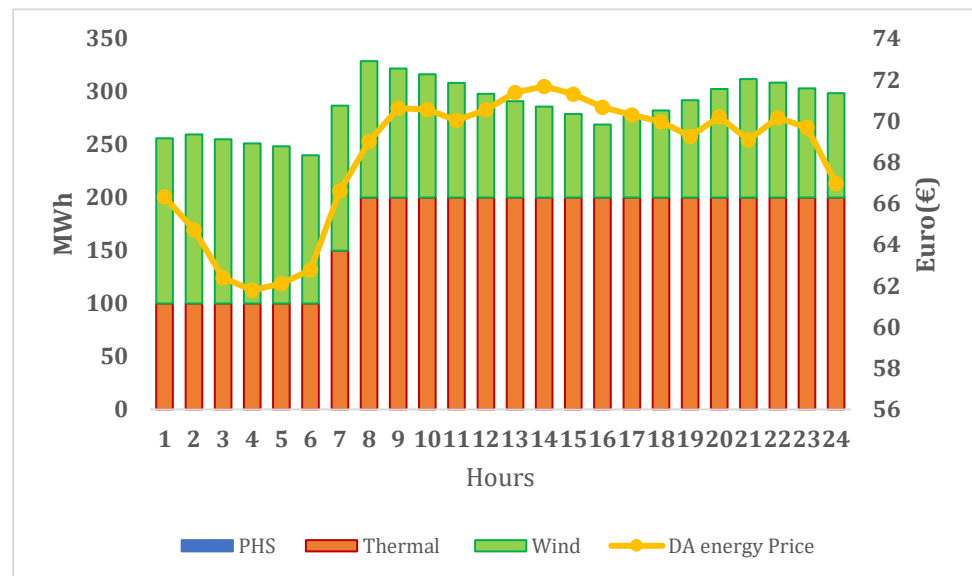


Figure 3 - 3: Coordinated Bidding (deterministic)

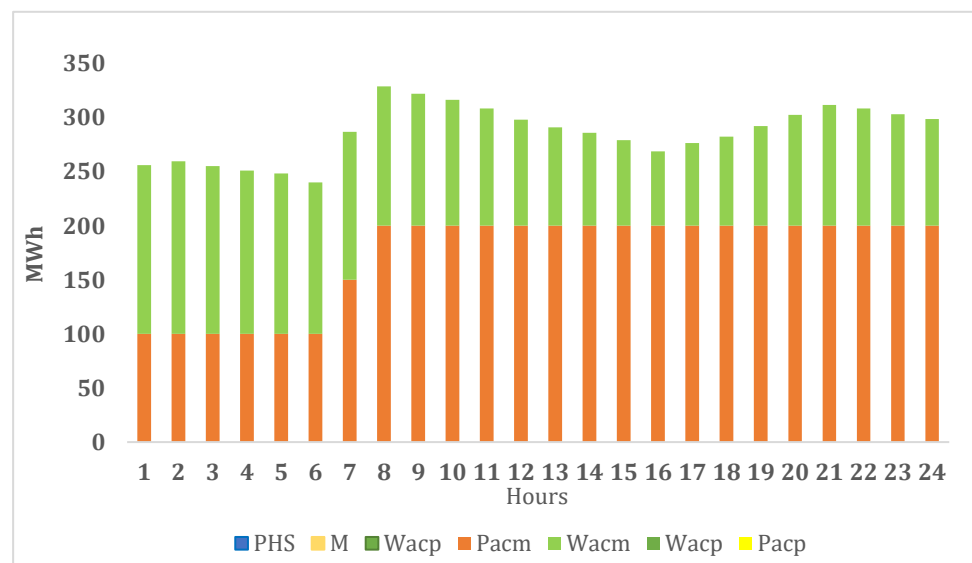


Figure 3 - 4: System energy (deterministic)

3.4.2. Proposed MILFO Bidding Strategy

In this section, the simulations of the proposed fuzzy optimization are presented. Figure 3-5 shows the hourly bidding of wind in DA energy market vs. the wind forecasts. To account for uncertainty, optimal bids deviates from the wind forecast i.e. hour 3 and 6, the bids are 125.2 and 80.1 MWh, while the forecasts are 155.2 and 140.1 MWh, respectively. As a result, the remaining power output from wind is used to charge PHS units as shown in Figure 3-6.

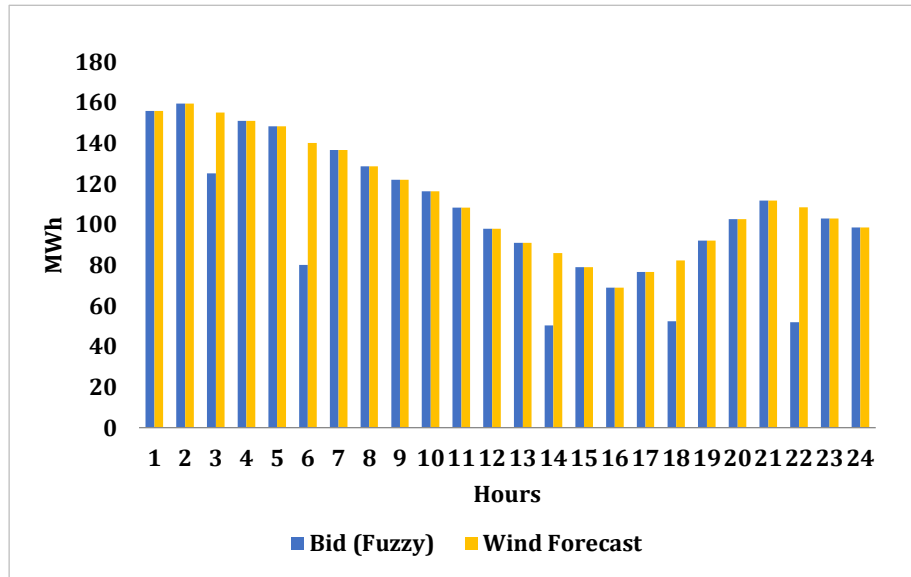


Figure 3 - 5: Market bid vs. forecast for wind using proposed MILFO strategy

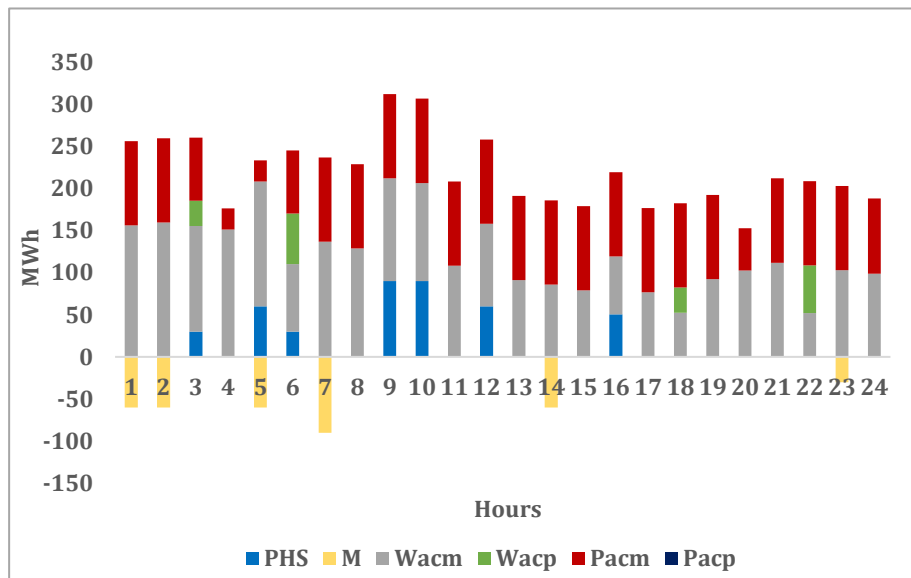


Figure 3 - 6: System Energy (fuzzy)

Also, as the imbalance up coefficient is among the highest at hour 14 (Figure 3-7), the bid from wind is 50.3 MWh while the wind forecast is 85.9 MWh. Hence, the remaining amount of wind is expected to be used as an imbalance up capacity. Moreover, to ensure restoring the energy to its initial level at the reservoir by the end of the 24 hours period, PHS units pump energy from wind at hours 18 and 22 as shown in Figure 13 to avoid purchasing energy since the market prices among the highest.

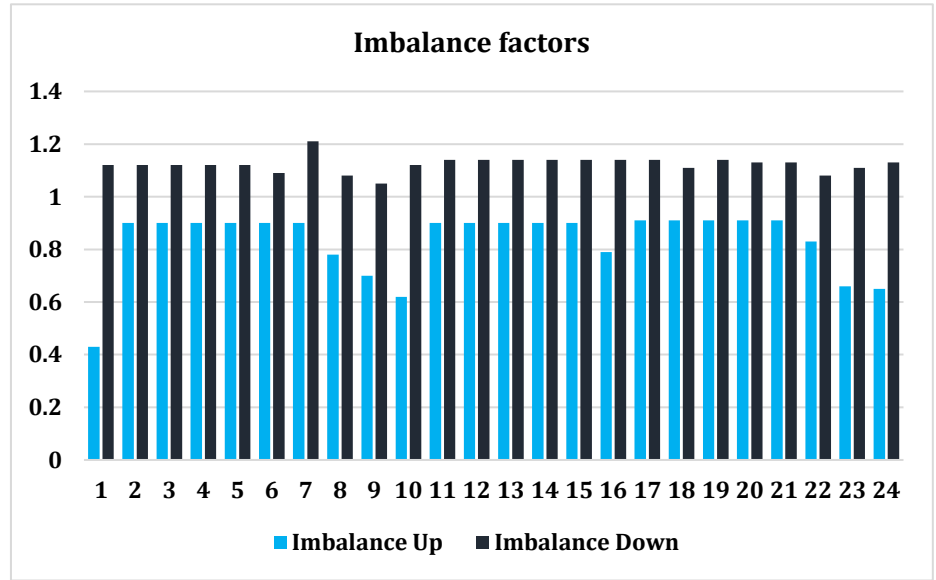


Figure 3 - 5: Imbalance penalty (reward) factor

As Table 2 and Table 3 indicate, PHS units pump energy from the market at off-peak hours to generate energy at peak hours to maximize its profit by reselling that energy during the peak hours. For instance, PHS units offer to purchase energy from DA market at hours 1, 2, and 7. On the other hand, PHS purchases from the market at hour 23 to ensure that energy level in the reservoir is exactly equals to V^{final} as given by (3.28). Furthermore, PHS units participate by generating energy to the DA energy market during the peak hours to maximize

profit as presented in hours 9, 10, 12, and 16. Note that the DA energy price forecasts are 70.63, 70.56, 71.69, 70.68 respectively.

Similarly, Figure 3-8 shows the contribution of thermal units in DA energy market increases at peak hours when the prices are at the highest. For example, at hours 15, and 17 the thermal bid is 200 MWh. In contrast, lower bids out of thermal units occur during the off-peak hours, e.g. at hours 4 and 5, the thermal bids are only about 25 MWh each.

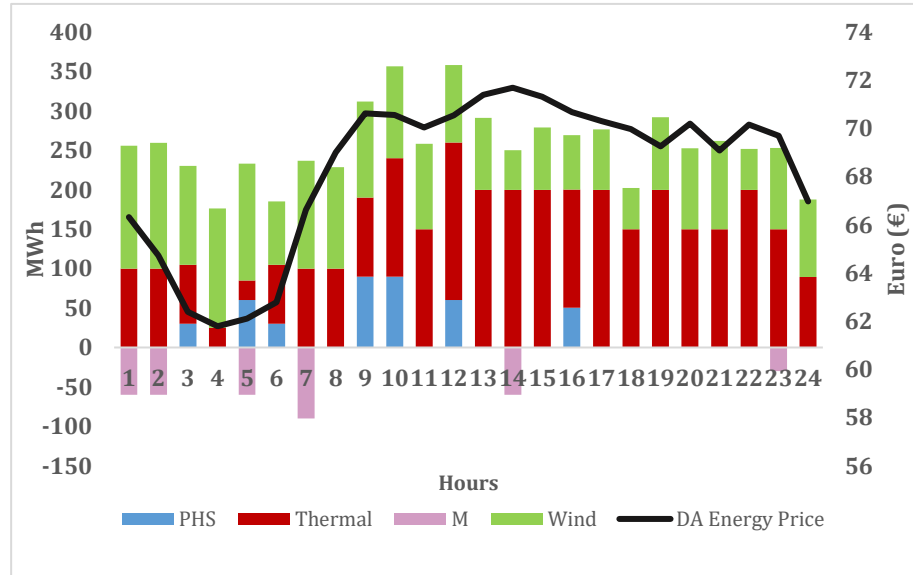


Figure 3 - 6: Fuzzy Bidding in DA energy market

Table 3 - 1: HYDRO UNITS FOR DETERMINISTIC & FUZZY BIDS

Unit no.	1234 <i>P Dr</i>	1234 <i>G Dr</i>	1234 <i>P Fuzzy</i>	1234 <i>G Fuzzy</i>
Hours				
1	0000	0000	1100	0000
2	0000	0000	1001	0000
3	0000	0000	1011	0100
4	0000	0000	0000	0000
5	0000	0000	1001	0110
6	0000	0000	1001	0100
7	0000	0000	1011	0000
8	0000	0000	0000	0000
9	0000	0000	0000	0111
10	0000	0000	0000	0111

11	0000	0000	0000	0000
12	0000	0000	0000	1100
13	0000	0000	0000	1000
14	0000	0000	0110	1001
15	0000	0000	0000	0000
16	0000	0000	0000	0111
17	0000	0000	0000	0000
18	0000	0000	0010	0000
19	0000	0000	0000	0000
20	0000	0000	0000	0000
21	0000	0000	0000	0000
22	0000	0000	1100	0000
23	0000	0000	0010	0000
24	0000	0000	0000	0000

Table 3 - 2: PHS Energy Reservoir

Hours	PHS Reservoir Level (MWh)
Energy from Previous day	120
00:00	171
01:00	222
02:00	214.1667
03:00	214.1667
04:00	198.5
05:00	216.1667
06:00	292.6667
07:00	292.6667
08:00	192.6667
09:00	92.66667
10:00	92.66667
11:00	26
12:00	26
13:00	77
14:00	77
15:00	20.95873
16:00	20.95873
17:00	46.45873
18:00	46.45873
19:00	46.45873
20:00	46.45873
21:00	94.5
22:00	120
23:00	120
24:00	120

3.4.3. Fuzzy and Deterministic Comparison

To validate the optimization performances of the deterministic and fuzzy models, Monte Carlo simulations are carried out. Using the wind forecast and ramping rate, a set of 4000 wind profile scenarios are generated. The wind forecast data is obtained from [49]. The wind power ramping rate is assumed to follow a Gaussian distribution with a zero mean and 25 MW standard deviation [13].

To account for coupling of consecutive hours, the Generate-Rearrange-Eliminate (GRE) method, proposed in [30], is applied. For the DA energy and imbalance prices, ARIMA model are used to generate a set of 4000 scenarios for each price type, and then matched one-on-one to produce 4000 price profile pairs. As a result, a scenarios tree of 16,000,000 scenarios is considered to simulate possible realizations of the DA energy market. Then, DA energy market bids obtained from each of the optimization models are used to calculate the realized profit for each scenario. This process is repeated over all scenarios, and the average realized profit is reported.

Furthermore, to quantify the risk associated with each bidding strategy, the widely used metric of conditional value at risk (CVaR) is applied. The CVaR is used to quantify the risk exposure of a given portfolio. That is, for a certain number of scenarios with the confidence interval α , CVaR represents the average profit for the least $(1 - \alpha) \times 100$ profitable scenarios. In this paper, The CVaR with a confidence level of 0.95 is used. Roughly speaking, this represents the average realized

profits for the 5 % least profitable scenarios. Therefore, higher CVaR indicates lower risk of loss or higher profitability.

Table II compares the realized profits of deterministic and fuzzy optimization. Due its ability to account for wind and price uncertainties, the fuzzy realized profits are more than 5.34% higher than the deterministic profits. Furthermore, thermal bids of both strategies are presented in Figure 3-9. Using the proposed algorithm, the operation of thermal units is optimized which results a significant reduction on the daily operational cost. Note that, MILFO results in an 18.9% reduction in CVaR, which is a significant risk reduction.

Table 1: Comparison

	MILP	Fuzzy
Realized Profit (€)	30,307.30	31,926.53
<i>CVaR</i> (€)	-64,613	-54,358.83
Simulation time (sec)	17.01	18.02

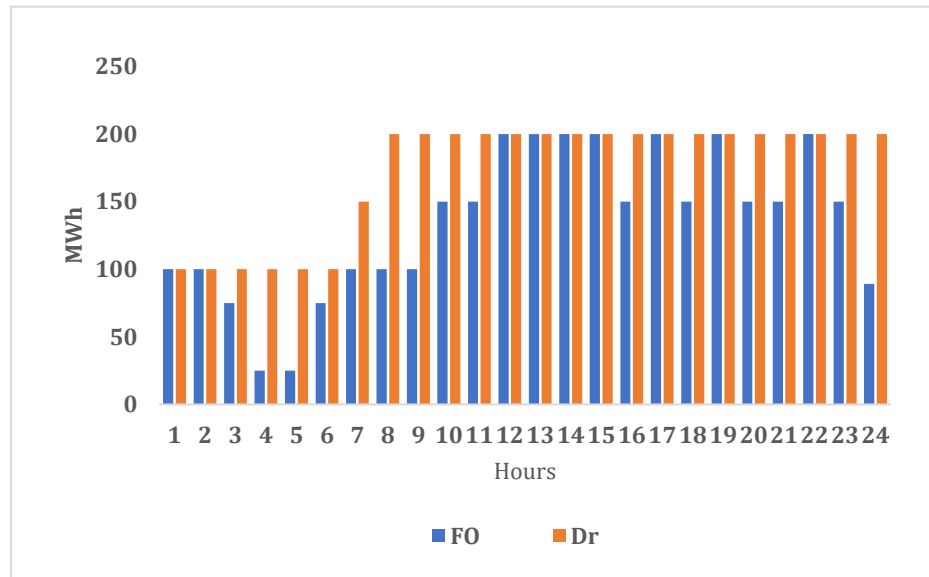


Figure 3 - 7: DA energy bidding from thermal (Fuzzy vs. Deterministic)

3.5. CONCLUSION

In this chapter, a coordinated bidding strategy of wind, pumped-hydro storage system and thermal units for a producer that participates in DA energy market is suggested using the mixed integer fuzzy optimization. First, the coordinated bidding strategy is formulated as a mixed integer linear program (MILP). Next, the fuzzy based model is developed. Therefore, the uncertain nature of DA energy price, imbalance prices and wind power output are modelled using fuzzy membership concept. Simulation results shows that the MILFO enhance the producer's profit in DA energy market by its accountability to uncertainties. Due to the proposed approach ability to incorporate wind and market variables uncertainties, and to minimize the overall operational cost of thermal and PHS system, the realized profit improved by 5.34 % compare to the deterministic approach. Also, the producer's exposure to risk is minimized.

CHAPTER IV CO-OPTIMIZED BIDDING STRATEGY IN DAY AHEAD ENERGY & REGULATION MARKETS

In this chapter, the producer participates in DA energy and regulation market simultaneously. Hence, the optimal DA energy and regulation market bids are obtained to maximize the producer's profit. Note that, this work assumes that the producer participates in the secondary regulation reserve market only.

In addition to the DA energy market described in previous section, the regulation market is modelled in this part and the objective function of the co-optimization problem is also derived. Therefore, the rest of this chapter is divided as follows: section one describes the deterministic co-optimization bidding strategy and section two explains the proposed fuzzy based co-optimization bidding strategy.

4.1. CO-OPTIMIZATION BIDDING STRATEGY –

DETERMINISTIC MODEL

In this section, the deterministic model of the co-optimization problem is presented. Hence, the producer bidding strategy is formulated as mixed integer linear programming (MILP) problem. The co-optimization here refers to the process of maximizing the profit from participating in DA ahead energy and regulation markets. Note that, in this optimization, uncertainties are

neglected. Therefore, forecasts of inputs data are directly used. Firstly, the objective function is derived, this includes the model of the regulation profit. Secondly, part two presents the constraints imposed to the regulation market.

4.1.1. Objective Function

Maximize CPF

Where,

$$CPF = PFW + PFH + PFT + PFIM + PFREG \quad (4.1)$$

And,

$$\begin{aligned} PFREG = & \sum_{t=1}^{N_T} \pi_t^R * (\sum_{n=1}^{N_U} (Pg_{tn}^{reg} + Pp_{tn}^{reg}) + \\ & \sum_{g=1}^{N_G} Pt_{tg}^{reg}) + \pi_t * (\alpha Ru_t - \alpha Rd_t) * (\sum_{n=1}^{N_U} (Pg_{tn}^{reg} + \\ & Pp_{tn}^{reg}) + \sum_{g=1}^{N_G} Pt_{tg}^{reg}) \end{aligned} \quad (4.2)$$

Equation (4.1) determines the producer profit from the co-optimization bidding strategy. Relation (4.2) models profit from the regulation market. The first part refers to the expected revenue obtained only from participating in regulation market with a predetermined capacity. Whereas, the second part models the expected revenue from regulated energy which the producer is called to deploy (reduce) during the real-time. Note that, PHS units participate in regulation market in both generation and pumping modes.

4.1.2. Regulation Market Constraints

Like most of liberalized markets, the Iberian markets requires the hourly regulation up and regulation down capacities to be equal. In other words, a qualified energy regulation resource must submit a single bid to the regulation market and be able to perform regulation up or down whenever needed. Hence, the regulation bid must be constrained by the least available regulation up and available regulation down capacities.

Equation (4.3) and (4.4) constrains the bidding capacity from PHS units when it operates as a generator in the secondary regulation market. To ensure the regulation up capacity from each PHS does not exceed the unit capacity, constraint (4.3) is employed. Moreover, while PHS also participates in DA energy market, the maximum regulation up capacity must be equal $\bar{H} - H_{tn}^{ac}$ as constraints by (4.4). Therefore, PHS regulation capacity in generation mode is limited by the minimum between H_{tn}^{ac} and $\bar{H} - H_{tn}^{ac}$. Due to the symmetrical property, this yields to that the maximum capacity that each PHS unit can provide in regulation market is 50% of its full capacity.

Also, this study also assumes that PHS units participate in regulation market in pumping mode. Hence, equation (4.5) is employed to limit the bidding capacity of each PHS to its pumped energy. Equation (4.6) constrains the total pumped power from each PHS and the regulation market bidding capacity to the unit rated power. Like

generation mode, the maximum capacity PHS units can participate with in the pumping mode is 50% of its full capacity.

Thermal units also can participate in the secondary regulation reserve market. Therefore, relations (4.7) and (4.8) ensure that the regulation bid of thermal units is within the unit's ramping capability. Constraints (4.9) and (4.10) ensure the regulation bid for each thermal unit is within the rated power.

$$Pg_{tn}^{reg} \leq H_{tn}^{ac} \quad (4.3)$$

$$Pg_{tn}^{reg} + H_{tn}^{ac} \leq G_{tn} * \bar{H}_n \quad (4.4)$$

$$\sum_{n=1}^{N_U} Pp_{tn}^{reg} \leq M_t \quad (4.5)$$

$$Pp_{tn}^{reg} + Pump_{tn} \leq \bar{H}_n * Pu_{tn} \quad (4.6)$$

$$Pt_{tn}^{reg} \leq RU_g * U_{tg} \quad (4.7)$$

$$Pt_{tn}^{reg} \leq RD_g * U_{tg} \quad (4.8)$$

$$Pt_{tn}^{reg} + P_{tn}^{ac} \leq \bar{P}_g * U_{tg} \quad (4.9)$$

$$Pt_{tn}^{reg} + P_{tn}^{ac} \leq \underline{P}_g * U_{tg} \quad (4.10)$$

4.2. CO-OPTIMIZATION BIDDING STRATEGY – MIEXD

INTEGER LINEAR FUZZY MODEL (MILFO)

In this section, the fuzzy set theory introduced in [37] is employed to model the uncertainties for the energy producer while it participates in DA energy and regulation. The producer aims to maximize the total profit by co-optimizing the DA energy and regulation market bids. However, in addition to

the uncertainties discussed in DA energy market, the producer is exposed to other uncertainties associated with regulation market. such as the hourly regulation price, and regulation deployment signals. Therefore, the fuzzy membership function for each uncertainty is developed. Finally, producer bidding strategy is formulated as a mixed integer linear fuzzy optimization (MILFO) problem.

4.2.1. Fuzzy Model of Regulation Profit

For the co-optimization problem, the fuzzy set of the regulation profit, given in (4.1) is shown in (4.11a). The membership function is defined in (4.11b), where $\overline{PFREG}$ is a parameter defined by the decision maker. For this study, regulation's profit obtained from the deterministic approach is used. Relation (4.11b) is converted to a fuzzy constraint as shown in (4.11c), where γ and $PFREG$ are new decision variables.

$$\widetilde{PFREG} = [PFREG, \mu_{PFREG}], \quad 0 \leq PFREG \leq \overline{PFREG} \quad (4.11a)$$

$$\mu_{PFREG} = \begin{cases} 0, & PFREG \leq 0 \\ \frac{PFREG}{\overline{PFREG}}, & 0 \leq PFREG \leq \overline{PFREG} \\ 1, & PFREG \geq \overline{PFREG} \end{cases} \quad (4.11b)$$

$$\gamma \leq \mu_{PFREG} = \frac{PFREG}{\overline{PFREG}} \quad (4.11c)$$

$$\overline{PFREG} * \gamma = PFREG \quad (4.11d)$$

4.2.2. Fuzzy Model of Regulation Signals

Since the expected amount of energy to be deployed in real time is depends on probability of receiving regulation up (αRu) and regulation down (αRd) signals. Thus, the producer's profit is highly affected by the forecast of both signals. Therefore, to account for the forecasting error, both signals are fuzzified. Relation (4.12a) to (4.12d) are used to model the probability of regulation down and relations (4.13a) to (4.13d) model the probability of regulation up. Note that, using the mean absolute percentage error (MAPE) which can be obtained from the error between actual and forecasted historical data from [46], the upper and lower limits are calculated as shown in (4.12d) and (4.13d).

$$\widetilde{\alpha Rd} = [\alpha Rd, \mu_{\alpha Rd}], \quad \underline{\alpha Rd} \leq \alpha Rd \leq \overline{\alpha Rd} \quad (4.12a)$$

$$\mu_{\alpha Rd} = \begin{cases} 0, & \alpha Rd \leq 0 \\ \frac{\alpha Rd - \underline{\alpha Rd}}{\overline{\alpha Rd} - \underline{\alpha Rd}}, & \underline{\alpha Rd} \leq \alpha Rd \leq \overline{\alpha Rd} \\ 1, & \alpha Rd \geq \overline{\alpha Rd} \end{cases} \quad (4.12b)$$

$$(\overline{\alpha Rd} - \underline{\alpha Rd}) * \gamma \leq (\alpha Rd - \underline{\alpha Rd}) \quad (4.12c)$$

$$\overline{\alpha Rd} = \widetilde{\alpha Rd}(1 + e_{\alpha Rd}), \quad \underline{\alpha Rd} = \widetilde{\alpha Rd}(1 - e_{\alpha Rd}) \quad (4.12d)$$

$$\widetilde{\alpha Ru} = [\alpha Ru, \mu_{\alpha Ru}], \quad \underline{\alpha Ru} \leq \alpha Ru \leq \overline{\alpha Ru} \quad (4.13a)$$

$$\mu_{\alpha Ru} = \begin{cases} 0, & \alpha Ru \leq 0 \\ \frac{\alpha Ru - \underline{\alpha Ru}}{\overline{\alpha Ru} - \underline{\alpha Ru}}, & \underline{\alpha Ru} \leq \alpha Ru \leq \overline{\alpha Ru} \\ 1, & \alpha Ru \geq \overline{\alpha Ru} \end{cases} \quad (4.13b)$$

$$(\overline{\alpha Ru} - \underline{\alpha Ru}) * \gamma \leq (\alpha Ru - \underline{\alpha Ru}) \quad (4.13c)$$

$$\overline{\alpha Ru} = \widetilde{\alpha Ru}(1 + e_{\alpha Ru}), \quad \underline{\alpha Ru} = \widetilde{\alpha Ru}(1 - e_{\alpha Ru}) \quad (4.13d)$$

4.2.3. Fuzzy Model of The Energy Regulation Price

For the DA energy market prices, relations (4.14a) to (4.14d) describe the fuzzy model of the hourly energy regulation market prices. Equation (4.14a) defines the fuzzy model of DA regulation prices. To model the fuzzy membership function relation (4.14b) is employed. Relation (4.14c) converts the membership function into fuzzy constrains. Like regulation signals, using the mean absolute percentage error (MAPE) between the actual and forecasts of DA regulation prices, the upper and lower boundaries are calculated as shown (4.14d).

$$\widetilde{\pi^R} = [\pi^R, \mu_{\pi^R}], \quad \underline{\pi} \leq \pi \leq \bar{\pi} \quad (4.14a)$$

$$\mu_{\pi^R} = \begin{cases} 0, & \pi \leq 0 \\ \frac{\pi^R - \underline{\pi}}{\pi^R - \underline{\pi}}, & \underline{\pi} \leq \pi \leq \bar{\pi} \\ 1, & \pi \geq \bar{\pi} \end{cases} \quad (4.14b)$$

$$(\bar{\pi^R} - \underline{\pi^R}) * \gamma \leq (\pi^R - \underline{\pi^R}) \quad (4.14c)$$

$$\bar{\pi^R} = \widetilde{\pi^R}(1 + e_{\pi}), \quad \underline{\pi^R} = \widetilde{\pi^R}(1 - e_{\pi}) \quad (4.14d)$$

4.2.4. The Complete Fuzzy Model

Like the fuzzy model constructed in 3.2.8, to maximize the minimum membership function subject to the system constraints. Thus, the complete fuzzy based co-optimization model can be stated as follows:

Maximize γ

Subject to (3.2) – (3.36), (3.39c), (3.40c), (3.41c), (3.42c),

$$(3.43c), (3.44c), (3.45c), (3.46c), (4.1)$$

$$- (4.10), (4.11c), (4.12c), (4.13c), (4.14c)$$

In this co-optimization, the decision variables are the hourly DA energy bids from wind (Pw_{td}), thermal (Pt_{tn}), PHS (Ph_{th}). Moreover, the hourly DA regulation capacity from PHS in generation mode (Pg_{tn}^{reg}), the hourly regulation capacity from PHS in pumping mode (Pp_{tn}^{reg}), and the hourly regulation capacity from thermal (Pt_{tg}^{reg}). Also, the actual thermal generation P^{ac} , actual thermal generation to the market P^{acm} , actual thermal generation to PHS P^{acp} , actual wind generation to the market W^{acm} , actual wind generation to PHS W^{acp} , actual wind generation W^{ac} , actual PHS generation H^{ac} , the hourly energy purchase offer M_t , and the actual PHS pumped energy $Pump_{tn}$.

The auxiliary decision variables PF , PFT , PFW , PFH , $PFIM$, $PFREG$, $ImUp$, $ImDn$, π , π_u and π_o . Finally, the fuzzy-based auxiliary variables are μ_{PFT} , μ_{PFW} , μ_{PFH} , μ_W , μ_π , μ_{π^u} , μ_{π^d} , μ_{π^R} , $\mu_{\alpha Ru}$, $\mu_{\alpha Rd}$, and μ_{PFREG} .

Note that, forecasts of wind power output, DA energy, regulation and imbalance price, regulation signals, and data of thermal and PHS units are used as an input for the co-optimization problem.

4.3. TEST SYSTEM

The test system described in section 3.3 is used for the in this co-optimization problem. However, forecast of DA energy (π) prices, regulation prices (π^R) and regulation signals (αRu) and αRd are developed using the ARIMA model suggested in [47] are added to the test system to include the secondary regulation reserve market aspects. Note that, historical data are imported from the Iberian market [46], Spanish side (node 3) for July to September 2018. Using CPLEX 12.7.1, which is called from the IBM ILOG package, the mixed integer linear programming (MILP) and the mixed integer linear fuzzy optimization problems are solved using HP ENVY Core i7.

4.4. RESULTS & ANALYSIS

In this section, a case study is presented to test the proposed co-optimization bidding strategies. Firstly, the optimal bidding in a sample day (November 1st, 2018) from the deterministic co-optimization model is discussed. Next, the outcomes of the proposed fuzzy based co-optimization model are presented. Finally, a comparison between the deterministic (MILP) approach and fuzzy based (MILFO) approach is drawn.

4.4.1. Deterministic MILP Bidding Strategy

As shown in Figure 4-1, the hourly bids from wind are equal to the forecast. This is because of the deterministic approach assumes an accurate forecast and does not consider the uncertainty of wind power outputs. Note that, because of the negligible operational cost, the optimizer tends to bid all the forecasted wind and no energy is used for charging PHS units. Also note that, this study assumes no contribution from wind in the secondary reserve regulation market.

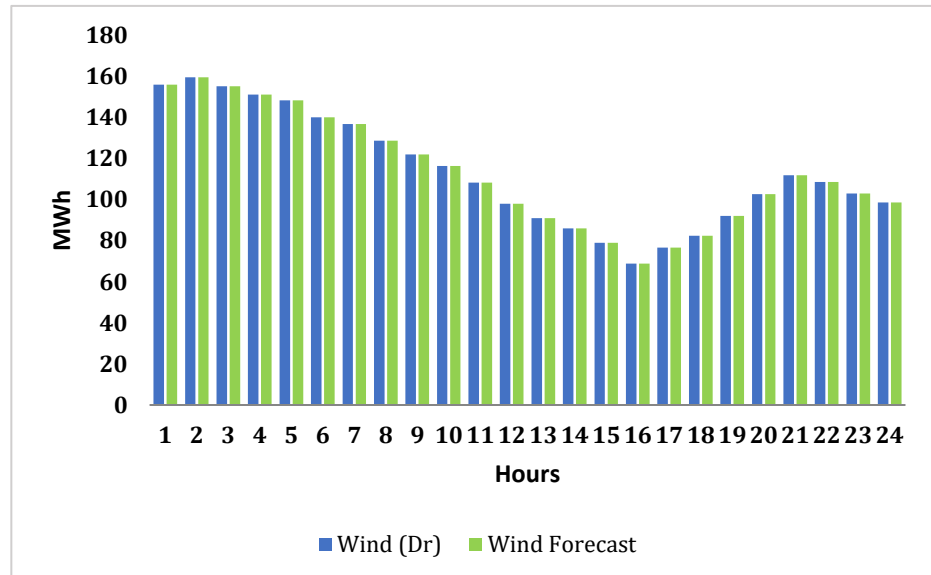


Figure 4 - 1: Wind bidding vs. forecasts

The producer hourly bids (offers) are shown in Figure 4-2. As it can be seen, PHS units offer to purchase energy from DA energy market during the off-peak hours. For example, during the period from 1 to 6, PHS offers range between 53.57 MWh to 60 MWh. However, at hour 7 when the DA energy price increases steadily, PHS offer drops to 24.48 MWh. Note that, no offers are submitted for the rest of the day. However, during the peak hours, PHS submit bids to produce energy in DA energy market. For instance, at hours 8, 9, 20, 21 and 22, where the

DA energy prices are among the highest, PHS bids are 30, 60, 60, and 58.35, respectively. In addition, to restore the reservoir to its initial energy level, PHS submit a bid to generate energy at hour 24.

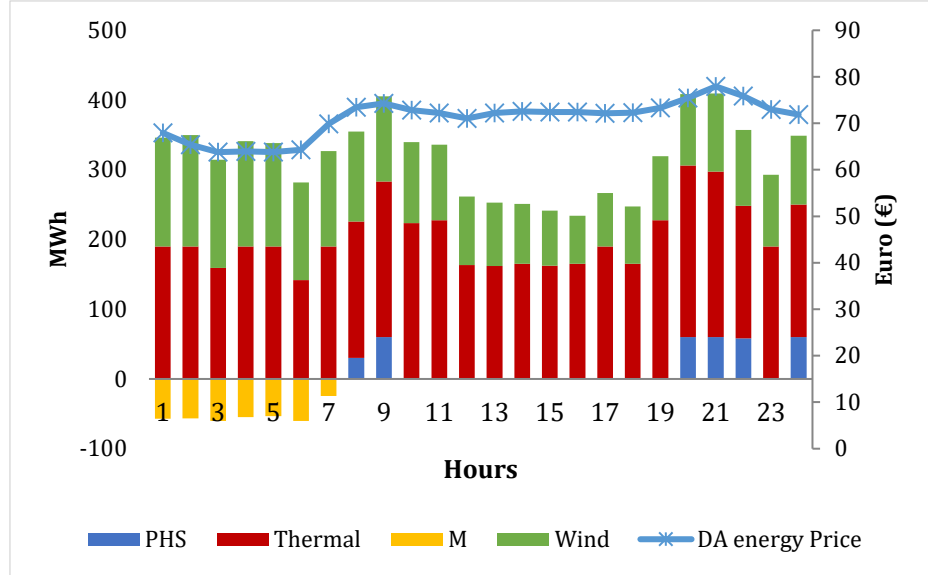


Figure 4 - 2: Co-optimized DA energy market bidding (Deterministic)

Beside the DA energy market, PHS units participate also in regulation market in both pumping and generation modes. Therefore, PHS provide regulation bids during the off-peak hours (from 1 to 7) as shown in Figure 4-3. Notably, regulation bids are influenced by three different factors, the DA energy price, regulation price and regulation signals as depicted by equation (4.1). Hence, participation of PHS units in regulation market is desirable at low DA energy prices periods especially when the regulation up signal is apparently plausible (i.e. hours 3 and 6). Note that, PHS regulation bids are identical to its purchase offers in DA energy market. This implies that if the producer is called to deploy a regulation up (down), PHS units can spill (pump) energy equal to its DA energy bids (offers). That is, based on the hourly

mode of the regulation market, PHS units participate by charging or discharging whichever is required.

Similarly, due to competitive DA energy prices, PHS also submit regulation bids during the peak hours. For instance, at hours 8, 9, 20, 21, 22, and 24, where the DA energy prices are 73.45, 74.24, 75.45, 77.92, 75.83, and 71.88 euros, respectively.

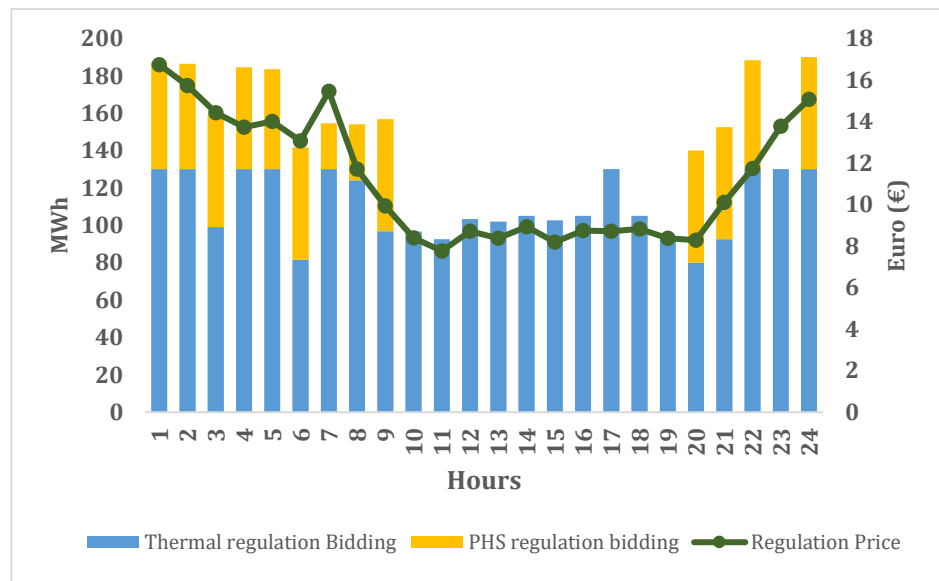


Figure 4 - 3: Co-optimized Bidding in Regulation market (Deterministic)

Moreover, the DA energy market bids from thermal and DA energy prices are positively proportional. This, however, constrained by the regulation prices and regulation signals. In general, at low DA energy prices periods, thermal bids are at its minimal. For example, at hours 3 and 6, the total bids are 141.6 MWh and 159.02 MWh, respectively. Furthermore, regulation bids at hours 3 and 6 are 99.09 MWh and 81.67 MWh, respectively. However, if regulation prices are among the highest, DA energy bids increase to 190 MWh as it can be observed at hours 1, 2, 4, 5 and 7. This is because the market is expected to be long, hence, producers are more likely to be called to regulate energy down as figure 4-4 indicates.

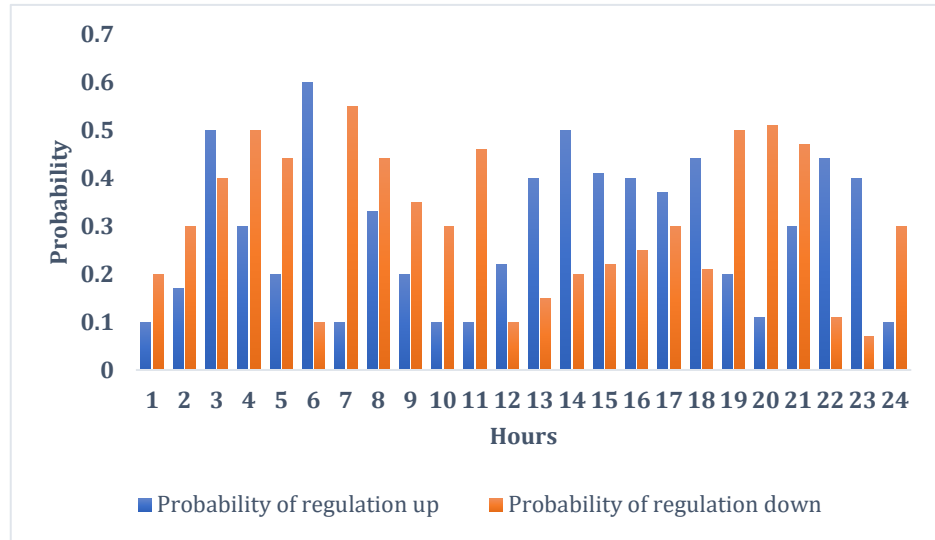


Figure 4 - 4: Regulation Signals Probabilities (Forecast)

In addition, due to significance of regulation up probability at hours 12-16, total DA energy bids from thermal are at its lowest and varies between 162 to 165 MWh. Similarly, regulation bids submitted at this period range between 102 to 105 MWh. In contrast, when high DA energy prices are expected, thermal bids increase significantly. Being at hours 9, 19, 20, and 21, thermal bids are 223.5, 227.5, 246, and 237.6 MWh, respectively. Nonetheless, if regulation prices are also among the highest (i.e. hours 22, 23, and 24) thermal bids drop to 190 MWh and the regulation capacities increase to 130 MWh.

4.4.2. Fuzzy Based Bidding Strategy

Figure 4-5 shows the hourly forecast vs. wind bidding in DA energy market. Clearly, bids are responsive to DA energy prices. Notably, at low prices periods, DA energy bids from wind are less than the forecast. Hence, the remaining energy is used to charge PHS units i.e. at hours 1-8. In contrast, wind schedules surpass the forecasts during the peak hours because of noticeable increase in DA energy prices recognizing that the absence of imbalance down penalties (Figure 4-6). For instance, at hours 9, 20, 21 and 22, bids are 175.98, 200, 200, and 200 MWh, respectively. Note that, DA energy price is more than 74 € for all the above-mentioned hours and the imbalance down coefficients are at 1.0. Note also that, this study assumes that wind does not participate in regulation market. Table 4-1 shows the expected amount of energy imbalance during the 24 hours.

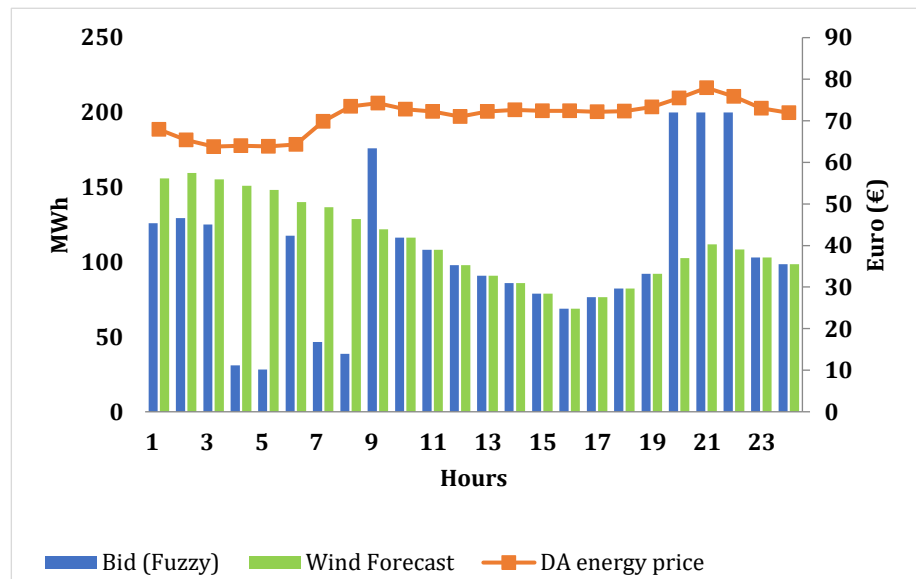


Figure 4 - 5: Wind forecast vs. Wind bidding (Co-optimized Fuzzy)

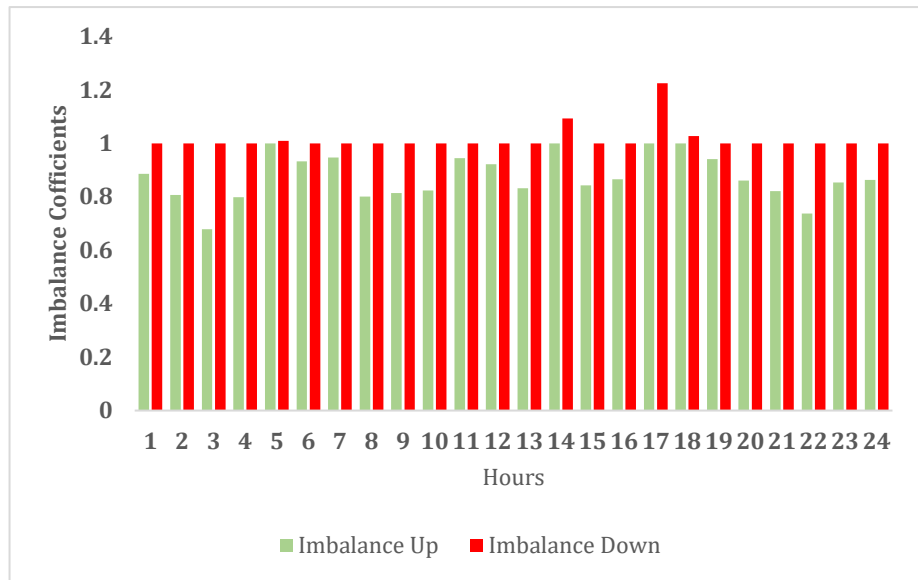


Figure 4 - 6: DA energy Imbalance Coefficients

Table 4 - 1: Expected Energy Imbalance

Hours	Imbalance Down	Imbalance Up
00:00	0	0
01:00	0	0
02:00	0	0
03:00	0	0
04:00	0	0
05:00	0	0
06:00	0	0
07:00	0	0
08:00	0	0
09:00	83.98	0
10:00	0	0
11:00	0	0
12:00	0	0
13:00	0	0
14:00	0	0
15:00	0	0
16:00	0	0
17:00	0	0
18:00	0	0
19:00	0	0
20:00	97.4	0
21:00	88.2	0
22:00	91.5	0
23:00	0	0
24:00	0	0

Alongside wind and thermal bidding, PHS bidding in DA energy market is presented in Figure 4-7. Due to the capacity constraints

imposed by relation (4.3), hourly bids from PHS to DA energy and regulation markets are symmetrical. That is, if the hourly DA energy bid (offer) from PHS is non-zero, PHS can regulate energy up (down) by increasing its energy output (input) an amount that less than of equals to its DA energy bid (offer). Note that, PHS units do not contribute in regulation market if its DA energy bid is equal to zero. In general, PHS bidding strategy is responsive to DA energy, regulation price, imbalance and DA regulation prices. At low prices periods, PHS units offer to purchase energy from DA energy market, i.e. at hour 6. Note that, an identical regulation bid is also submitted. Moreover, caused by a remarkable increase in DA energy price, bids from PHS occur at hour 8, 22 and 23. Furthermore, due to the significance of regulation up probabilities at hours 12 and 15, bids from PHS are also submitted. Hence, PHS can maximize its profit by exporting energy if need arises while operating in generation mode. Also, to avoid the vulnerability of

In addition, thermal bids in DA energy market are also susceptible to DA energy prices. For example, at low DA energy price periods, the hourly bid is 110 MWh (i.e. at hours 3 and 6). However, at hours 9, 21, 22 and 23, when the DA energy prices are among the highest, thermal bids are 223, 237.6, 235, and 220 MWh, respectively. For all other periods, based on the hourly DA energy price, the hourly bid ranges between 190 to 215 MWh. On the other hand, regulation bids from thermal are sensitive to the hourly DA energy and regulation prices. This, however, is conditional to the probability of regulation signals. For instance, at hour 1 and 2, when low DA energy prices are expected,

given that regulation prices are among the highest and regulation down probabilities are slightly greater than regulation up, thermal regulation bids are 101.1 and 95.7 MWh, respectively as Figure 4-8 indicates.

In addition, despite the drop-in regulation prices, regulation bids reach 130 MWh when the chances of regulation down increase significantly i.e. at hours 4, 5 and 7. Moreover, regulation bids from

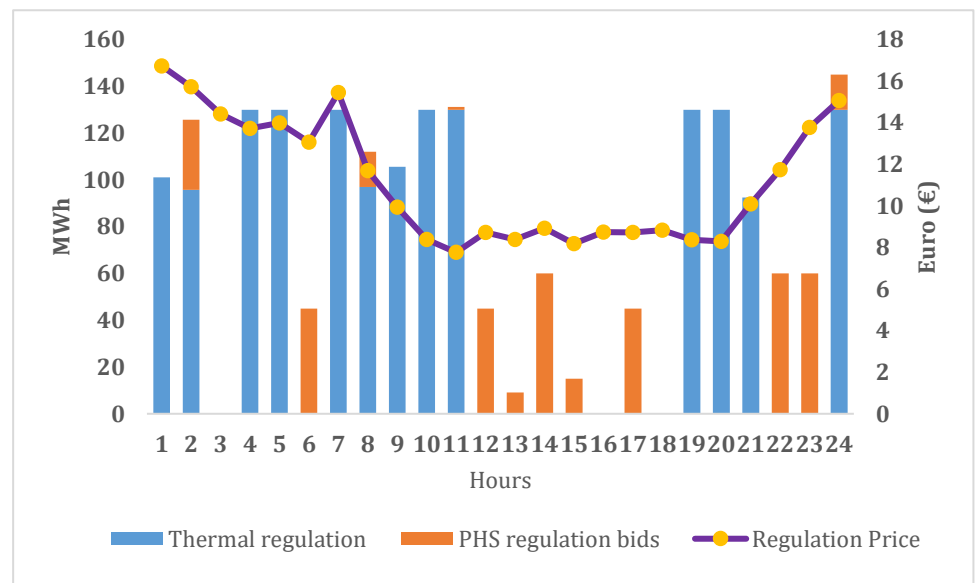


Figure 4 - 7: Co-optimized bidding in regulation market

thermal are also at 130 MWh during the peak hours caused by the rising of DA energy prices as it can be seen at hours 19, 20 and 24. Conversely, if regulation up probabilities are among the highest, no regulation bids are submitted from thermal units to avoid incurring extra operational cost seen at hours 3, 6, 12-18, 22 and 23.

4.4.3. Deterministic & Fuzzy Comparison

To examine the performance of both approaches in real-time, Monte-Carlo simulation is used. Hence, the following steps are executed:

- 1) Using the gaussian distribution of wind forecast presented in [49], 1000 scenarios of wind energy outputs are generated. Also, using the hourly forecasted values as means, and standard deviations equal to 7% of the means, for each of DA energy, regulation prices and imbalance prices, 1000 scenarios are generated using a normal distribution function generator.
- 2) GRE methodology introduced in [30] is used to rearrange scenarios to ensure that generated scenarios reflect the statistical properties of forecasted variables. Note that, the ramping rate of wind plant is assumed to follow normal distribution with zero mean and standard deviation equals to 25 MW. Hence, a total of 1,600,000,000 scenarios are created.
- 3) Real-time Monte–Carlo simulation process is established. The DA energy and regulation schedules are examined against each scenario obtained from step 2. Hence, if there is an energy deficit or surplus between the scheduled capacity and the selected scenario at any specific hour, balancing mechanisms of Iberian market are imposed. Next, the

realized profit from each scenario minus the cost of the mismatch is obtained.

- 4) Expected realized profit from each of two DA schedules and conditional value at risk with a confidence interval of 95% are calculated.

Figure 25 summarizes the steps executed through the validation process.

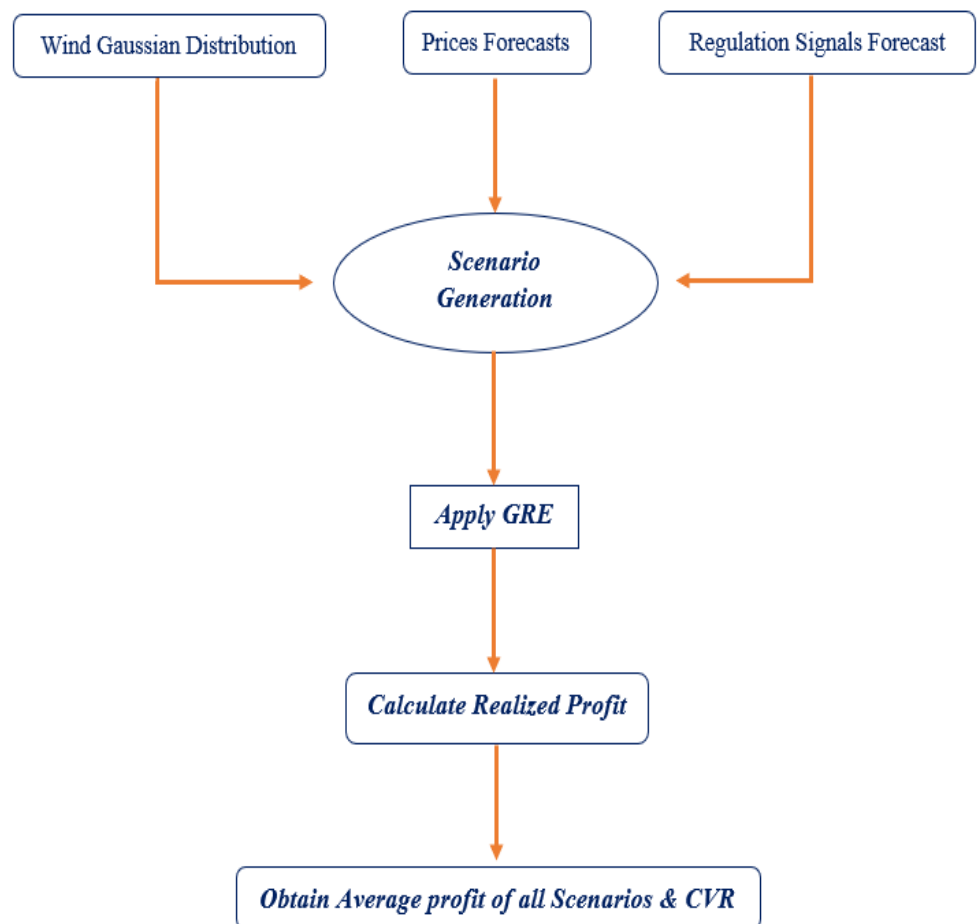


Figure 4 - 8: Validation Process

Table 4-2 shows the validation process outcomes. Essentially, the DA schedule obtained from the mixed integer linear fuzzy optimization (MILFO) improves the realized profit by 11.7%. Furthermore, the conditional value at risk indicates that proposed

algorithm reduces the producer's exposure to markets vulnerability, significantly. This demonstrates the advantage of the proposed algorithm over the deterministic approach. This is accomplished by the optimal allocation of wind, thermal and PHS energy outputs while considering wind generation and markets uncertainties.

Table 4 - 2: Validation Process

	MILP	MILFO
Realized Profit (€)	282,372	135,620
CVR (€)	130,451	158,152
Simulation time (sec)	14.3	16.7

Moreover, Figure 4-10 shows the difference in DA energy schedule from each method. Notably, in DA energy market, thermal bidding obtained by the proposed algorithm are much susceptible to DA energy, imbalance, regulation prices and regulation signals. That is, low DA energy bids are submitted during the off-peak hours. However, as the hourly DA energy prices increase, thermal biddings increase proportionally to reach its maximum at 237.6 MWh at hour 21. Therefore, to avoid wind and market variability and imbalance penalties,

flexibility of thermal units is utilized to avert deficits in DA energy bidding that might arise especially at high pricing periods.

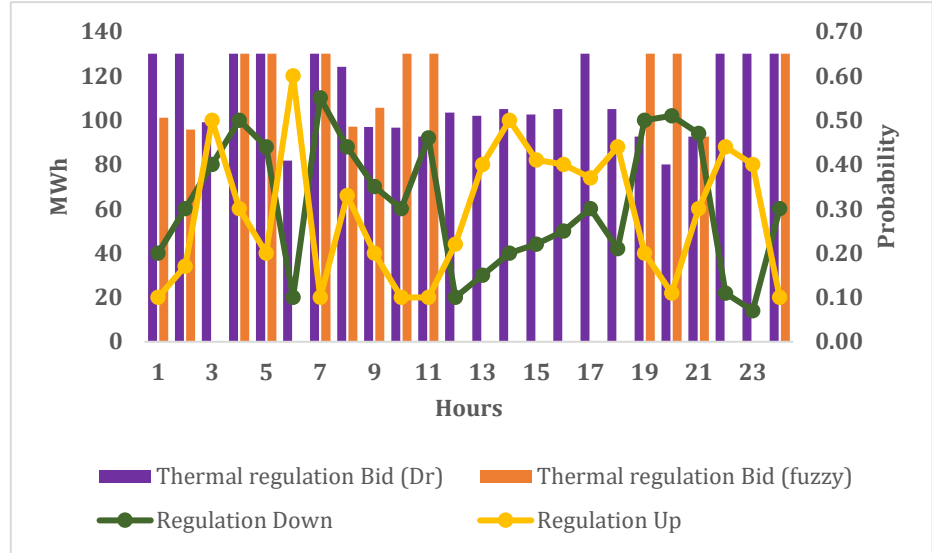


Figure 4 - 10: Co-optimized regulation bids from thermal vs. regulation signal

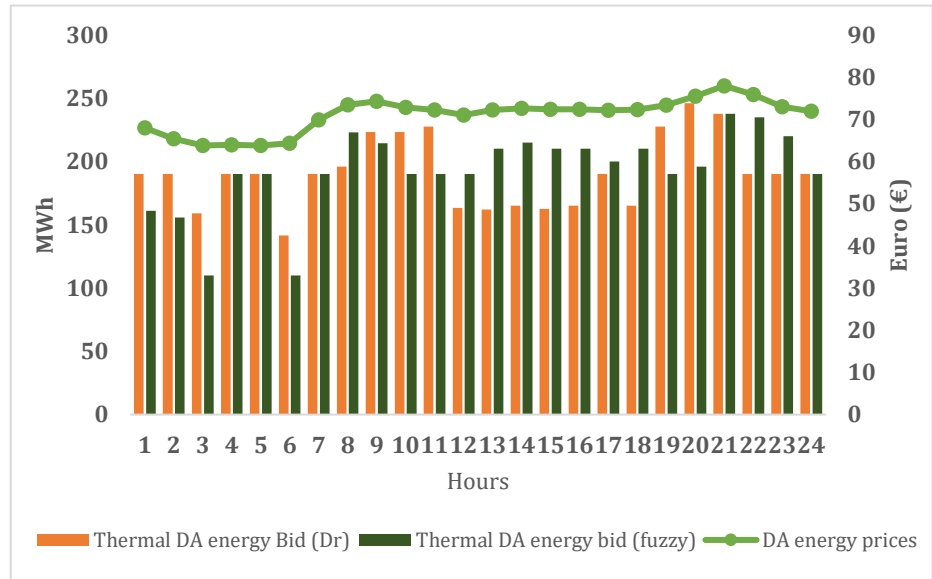


Figure 4 - 9: Co-optimized Thermal bids in DA energy market

Also, to avoid additional operational cost, regulation bids from thermal obtained by the proposed algorithm are extremely responsive to regulation signals. Therefore, if the regulation up probability is higher

than the regulation down probability, no regulation bids are submitted as Figure 4-11 indicates.

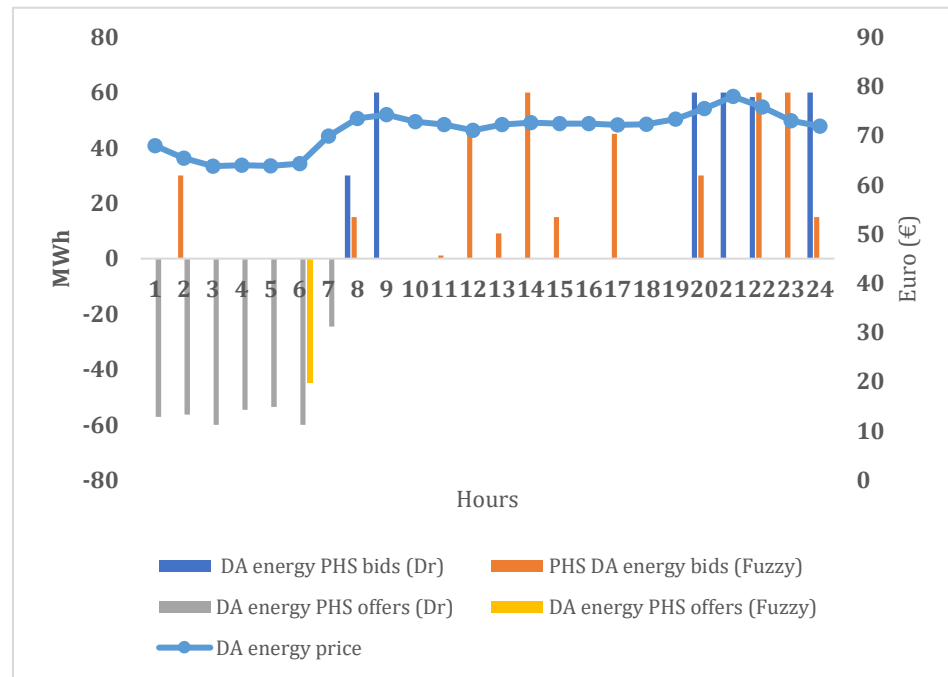


Figure 4 - 11: Co-optimized PHS bidding

Figure 4-12 presents the discrepancy between deterministic and fuzzy bids (offer) submitted by PHS units to DA energy market. Instead of pumping from DA energy market, the fuzzy approach suggests pumping part of wind energy to PHS energy reservoir when DA energy prices are among the lowest. As a result, a viable coordination between wind and PHS units lead to reducing costs incurred by PHS units substantially. Table 7 shows the hourly wind energy pumped by PHS.

Table 4 - 3: Hourly transferred energy from Wind to PHS (Fuzzy)

Hours	Wind to PHS (Dr)	Wind to PHS (Fuzzy)
01:00	0	30
02:00	0	30
03:00	0	30
04:00	0	120
05:00	0	120
06:00	0	22.5
07:00	0	90
08:00	0	90

09:00	0	0
10:00	0	0
11:00	0	0
12:00	0	0
13:00	0	0
14:00	0	0
15:00	0	0
16:00	0	0
17:00	0	0
18:00	0	0
19:00	0	0
20:00	0	0
21:00	0	0
22:00	0	0
23:00	0	0
24:00	0	0

4.5. CONCLUSION

In this chapter, an optimal bidding strategy in DA energy and regulation markets for a generation company that own wind plant, pumped-hydro storage system and thermal units is presented. The trading strategy is formulated as a mixed integer linear fuzzy optimization problem. The stochasticity of DA energy prices, imbalance prices, regulation prices, regulation signals and wind power outputs are incorporated using the fuzzy theory. Hence, each uncertainty is modelled via a membership function. A case study shows the proposed algorithm outperforms the deterministic approach in terms of profitability. Compare to the realized profit obtained from the deterministic approach, profit increased by 11.7 %. Also, a significant decrease in the producer risk has been reported. Unlike the deterministic algorithm, suggested DA energy and regulation schedules by the proposed algorithm are much susceptible to market variables. Therefore, markets uncertainties are realized. Furthermore, by the optimal coordination of wind, PHS and thermal units, the overall operational costs and energy imbalances are significantly minimized.

CHAPTER V CONCLUSION AND FUTURE WORK

5.1. CONCLUSION

In this thesis, energy trading of wind, pumped-hydro storage system and thermal units and co-optimized trading in DA energy and regulation markets using mixed integer linear fuzzy optimization is proposed. Firstly, the developed algorithm is applied to energy trading DA energy market. The objective is to maximize the producer's profit in DA energy market. Hence, the optimal bidding strategy in DA energy market is formulated as mixed integer linear fuzzy program. The uncertainty of DA energy prices and the hourly wind energy are modelled using fuzzy membership functions. Then, the proposed approach is compared with the state of art deterministic approach which formulated as a mixed integer linear program. Although the expected profits from both approaches are approximately equal, Monte-Carlo simulation shows that the proposed approach increases the trading profit significantly.

Secondly, the mixed integer linear fuzzy optimization model is expanded to co-optimize the trading in DA energy and regulation markets. The objective is to maximize the producer's total profit from DA energy and regulation markets. Hence, in addition to the uncertainty of DA energy prices, imbalance prices and wind power outputs, the vulnerability of regulation prices, regulation deployment signals are also considered. Hence, the fuzzy theory is applied to obtain the optimal DA energy and regulation schedules. Compare to the deterministic

approach, simulation results show the effectiveness of the proposed algorithm in maximizing the producer's realized profit from both markets. Also, using the conditional value at risk, the proposed approach succeeds in minimizing the overall exposure to the trading risk. Therefore, by the optimal coordination between all energy resources, and its accountability to the forecasting errors, the fuzzy based algorithm surpasses deterministic. Eventually, results demonstrate that the performance of the proposed algorithm in the co-optimized trading improved substantially rationalizes the use of this algorithm as the number of uncertainties increases.

5.2. FUTURE WORK

The following topics are suggested to be included in future work:

- a. The developed co-optimization model can be expanded to include different energy resources such as Electric Vehicles (EV), Biomass energy or Battery storage systems (BESS).
- b. Further comparison between the proposed algorithm and other novel optimization algorithm such as robust optimization and stochastic optimization.
- c. The proposed mixed integer fuzzy optimization can be expanded to include additional type of frequency regulation reserve market such as the tertiary regulation reserve.

APPENDIX – I

Data of thermal units (adopted from [32])

UNITS	P_{min} (MW)	P_{max} (MW)	$MinUp$ (hr.)	$MinDn$ (hr.)	RU (MW/hr.)	RD (MW/hr.)	Uic (hr.)	$StUp$ (€)	a (Mbtu/h)	b (Mbtu/h)	c (Mbtu/h)
1	0.01	50	1	1	50	50	0	0	0	80	0
2	5	45	1	1	15	15	0	88	85.51	70.86	0.188
3	5	45	1	1	15	15	0	88	82.34	68.23	0.181
4	25	100	5	5	50	50	0	110	32.99	64.42	0.042
5	25	100	5	5	50	50	0	110	32.99	57.92	0.042

Data of PHS units (adopted from [32])

UNITS	P_{min} (MW)	P_{max} (MW)	$MinUp$ (hr.)	$MinDn$ (hr.)	RU (MW/hr.)	RD (MW/hr.)	$StUp$ (€)	OC (€/MWh)	Generation efficiency	Pumping efficiency
All	0	30	0	0	30	30	0	3	0.90	0.85

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