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Optimal Operation and Bidding of Renewable-based VPP under Uncertainty in the Electricity Markets

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Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

Hadi Nemati
Madrid, October 2025

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Abstract

This thesis proposes a novel Virtual Power Plant (VPP) operation model, that is composed, exclusively, of Renewable Energy Sources (RES); including hydro, Wind Farm (WF), solar Photo-Voltaic (PV), Concentrated Solar Power Plant (CSP) and biomass; and/or Flexible Demands (FDs). The main objective that is pursued in this thesis is to investigate how to optimally operate and configure a RES-only Virtual Power Plant (RVPP) for maximum profitability in the energy and Ancillary Service Market (ASM). To this aim, the RVPP optimization model includes features to account for the various characteristics of the RVPP itself, the electrical network to which it is connected, and the market mechanisms that can help the RVPP become economically efficient. Such characteristics include: (i) the RVPP components, such as generating units, demands, and RES-based storage units (pumped hydro, CSP); (ii) the electrical network in terms of, for example, nodal power balances and line active power flow limits; (iii) the markets in which the RVPP may participate, such as energy markets and ASM; and (iv) the uncertainties that characterize several parameters of the model, such as stochastic energy sources (wind and solar), market prices, and demand pattern. Different business models for the RVPP have been identified in the form of the electric energy and power markets that can be suitable for its participation. Among all the market schemes currently implemented in Europe, the most relevant from the RVPP perspective are the Day-Ahead Market (DAM) and Intra-Day Market (IDM) (energy); and the Secondary Reserve Market (SRM) (power). With this in mind, the RVPP operator could select the appropriate objective functions within the proposed model presented so that the RVPP can follow the desired business model.

Resumen

Esta tesis propone un nuevo modelo de operación de VPP, compuesto exclusivamente por RES; incluyendo hidráulica, eólica, solar PV, CSP y biomasa; y/o demandas flexibles. El objetivo principal que se persigue en esta tesis es investigar cómo operar y configurar de manera óptima un RVPP para lograr la máxima rentabilidad en los mercados de energía y ASM. Con este fin, el modelo de optimización del RVPP incorpora características que permiten considerar los distintos aspectos tanto del propio RVPP, como de la red eléctrica a la que está conectado, así como de los mecanismos de mercado que pueden contribuir a que el RVPP sea económicamente eficiente. Dichas características incluyen: (i) los componentes del RVPP, tales como unidades de generación, demandas y unidades de almacenamiento basadas en RES (bombeo hidroeléctrico, CSP); (ii) la red eléctrica, en términos de, por ejemplo, balances nodales de potencia y límites de flujo de potencia activa en las líneas; (iii) los mercados en los que el RVPP puede participar, tales como los mercados de energía y ASM; y (iv) las incertidumbres que caracterizan varios parámetros del modelo, como las fuentes estocásticas de energía (eólica y solar), los precios de mercado y el perfil de la demanda. Se han identificado distintos modelos de negocio para el RVPP en forma de mercados eléctricos de energía y potencia que pueden resultar adecuados para su participación. Entre todos los esquemas de mercado actualmente implementados en Europa, los más relevantes desde la perspectiva del RVPP son el DAM y el IDM (energía); y el SRM (potencia). Con esto en mente, el operador del RVPP podría seleccionar las funciones objetivo apropiadas dentro del modelo propuesto, de modo que el RVPP pueda seguir el modelo de negocio deseado.

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Acronyms

aFRR	Automatic Frequency Restoration Reserve
AGC	Automatic Generation Control
AMI	Advanced Metering Infrastructure
ARO	Adaptive Robust Optimization
ASM	Ancillary Service Market
BAM	Balancing Market
BESS	Battery Energy Storage System
BRP	Balance Responsible Partie
C&CG	Column & Constraint Generation
CG	Conventional Generator
CSP	Concentrated Solar Power Plant
CTM	Carbon Trading Market
CVaR	Conditional Value-at-Risk
D-RES	Dispatchable Renewable Energy Sources
DAM	Day-Ahead Market
DER	Distributed Energy Resources

DRO	Distributionally Robust Optimization
DSO	Distribution System Operator
ESS	Energy Storage System
ETS	Emissions Trading System
EV	Electric Vehicle
FCR	Frequency Containment Reserve
FD	Flexible Demand
FSP	Flexibility Service Provider
GAMS	General Algebraic Modeling System
HPA	Heat Purchase Agreement
HPP	Hydroelectric Power Plant
IDM	Intra-Day Market
IGDT	Information Gap Decision Theory
ISO	Independent System Operator
LMP	Locational Marginal Price
MEVPP	Multi-Energy VPP
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
MO	Market Operator
ND-RES	Non-Dispatchable Renewable Energy Sources
NGM	Natural Gas Market
OMIE	Operador del Mercado Ibérico de Energía
PB	Power Block
PDF	Probability Density Function
PR	Primary Reserve
PRM	Primary Reserve Market
PTC	Parabolic Trough Collector
PV	Photo-Voltaic
REE	Red Eléctrica de España
RES	Renewable Energy Sources
RO	Robust Optimization
RTM	Real-Time Market
RTO	Regional Transmission Organization
RVPP	RES-only Virtual Power Plant
SARO	Stochastic Adaptive Robust Optimization
SF	Solar Field
SIDC	Single Intra-Day Coupling
SoC	State of Charge
SOS-2	Special Ordered Set of Type 2
SP	Stochastic Programming
SR	Secondary Reserve
SRM	Secondary Reserve Market
TEM	Transactive Energy Management
TR	Tertiary Reserve
TRM	Tertiary Reserve Market
TS	Thermal Storage
TSO	Transmission System Operator
VPP	Virtual Power Plant
WF	Wind Farm

Nomenclature

The Nomenclature section is divided into subsections to make it easier to use. Variables, functions, indices, and sets are mentioned in the definition of each symbol.

Index:

$c \in \mathscr{C}$	Set of D-RESs
$d \in \mathscr{D}$	Set of demands
$k \in \mathscr{K}$	Set of IDM sessions
$m \in \mathscr{M}$	Set of daily load profiles
$n \in \mathscr{N}$	Set of segments of piecewise efficiency function of PB of CSPs
$p \in \mathscr{P}$	Set of daily load profiles
$r \in \mathscr{R}$	Set of ND-RESs
$t \in \mathscr{T}$	Set of time periods
$t \in \mathscr{T}_k$	Set of IDM# k time periods
$\theta \in \Theta$	Set of CSPs
Ξ	Set of decision variables

Parameters:

C	Operation and maintenance costs of units [€/MWh]
C^I	Installation costs of units [€]
$C^{SU/SD}$	Start-up/shut-down costs of units [€]
E	Electricity energy capacity of units [MWh]
E^{TS}	Thermal energy capacity of TS of CSPs [MWh]
M	Big positive value [-] or [MW]
$N^{OF/ON}$	Initial periods units must be offline/online [hour]
P	Electricity power capacity or forecast of units [MW]
$P^{SF/PB/TS}$	Thermal power capacity or forecast of SF/PB/TS of CSPs [MW]
R^{SR}	Electricity reserve ramp rate of units [MW]
RR	Ramp rate of units [MW/hour]
T^{SR}	Required time for SR action [hour]
UT/DT	Minimum up/down time of units [hour]
β	Percentage of flexibility of demands [%]
η^{PB}	Thermal to electrical output efficiency of PB of CSPs [%]

η^{TS}	Thermal power efficiency of TS of CSPs [%]
Γ	Uncertainty budget [-]
Δt	Duration of periods [hour]
ε	Small positive value [MW]
κ	The limit of reserve as a percentage of total power capacity of RVPP [%]
λ	Electricity market price prediction [€/MWh] or [€/MW]

Superscript and subscript:

$\hat{\tilde{A}}$, $\check{\tilde{A}}$	Upper/lower bound in the forecast distribution of uncertain parameter
$\hat{A}$, $\check{A}$	Positive/negative deviation of uncertain parameter
$\tilde{A}$	Median value of uncertain parameter
A^{SR}	SRM
$\bar{A}$, $\underline{A}$	Maximum/Minimum value
A^{+}, A^{-}	Charging/discharging state of storage
$A^{\uparrow}$, $A^{\downarrow}$	Upward/downward SR
A^{DA}	DAM
A^{ID}	IDM
A^{PB}	PB of CSPs
A^{SF}	SF of CSPs
A^{TS}	Thermal storage
A^{*}	Optimal value of variable
A^{SU}, A^{SD}	Start-up/shut-down status of units

Variable:

e	Electricity energy of units [MWh]
e^{TS}	Thermal energy of TS of CSPs [MWh]
p	Electricity power of units or RVPP [MW]
$p^{SF/PB/TS}$	Thermal power of SF/PB/TS of CSPs [MW]
r	Electricity reserve of units or RVPP [MW]
r^{TS}	Thermal reserve of TS of CSPs [MW]
y	Positive auxiliary variable related to uncertainty modeling [MW] or [MWh] or [€]
z	Positive auxiliary variable related to uncertainty modeling [-]
ϕ	Dual variable to model uncertainty [MW] or [€]
σ^{TS}	Share of thermal energy capacity of TS of CSPs allocated to provide reserve [%]
ζ	Dual variable to model uncertainty [MW] or [€]

Binary variable:

u	Binary variable related to status of units

u^{TS}	Binary variable related to status of TS of CSPs
$v^{SU/SD}$	Binary variable related to start-up/shut-down status of units
χ	Binary variable related to uncertainty
ς	Binary variable related to piecewise function of CSPs

Vectors:

$\boldsymbol{r}$	Vector for possible reserve activation scenarios of units [MW]
$\boldsymbol{r}^{SR}$	Vector for possible reserve activation scenarios of RVPP [MW]
$\boldsymbol{r}^{TS}$	Vector for possible reserve activation scenarios of TS of CSP [MW]
$\boldsymbol{x}$	Vector related to piecewise function of PB of CSPs for possible reserve activation scenarios [-]
$\boldsymbol{\varsigma}$	Vector related to piecewise function of PB of CSPs for possible reserve activation scenarios [-]

1 Introduction

In the transition toward a sustainable power system, RES-only Virtual Power Plants (RVPPs) have emerged as a promising solution to the challenges of integrating Renewable Energy Sources (RES) into electricity markets. By aggregating geographically dispersed RES, RVPPs can reduce variability through the portfolio effect, offering a smoother production profile and greater competitiveness. Their viability, however, depends on effective market participation strategies and the ability to manage uncertainties in generation and market conditions. This chapter introduces the context and motivation of the thesis, presents the general approach for modeling and optimizing RVPP under uncertainty, and highlights the main contributions and related publications.

1.1 Motivation

The urgent need to combat climate change in search of a greener, more sustainable environment, is compelling countries around the world to embrace RES. However, as the penetration of RES in the grid increases, the system operators and the renewable units face significant challenges in terms of operation and market participation [1]. This is mainly due to the unpredictability of Non-Dispatchable Renewable Energy Sources (ND-RES) production, resulting in volatile energy output of these units. To increase the low competitiveness of ND-RES compared to large, dispatchable Conventional Generators (CGs) such as hydro and thermal power plants is clearly essential for the eventual mass integration of RES. To cope with the volatility of ND-RES production and to avoid penalties in the electricity markets, operating several ND-RES in different geographical locations as RVPP is an effective way by taking advantage of the portfolio effect. The RVPP can offer a smoother profile of production than each individual ND-RES, leading to more income and less penalties [2].

The competitiveness of the RVPP depends on its viability, which in turn is related to costs and benefits. The benefits arise from the participation in the electricity markets. Thus, in order to operate the RVPP in an economically viable way, the RVPP should participate in different electricity markets to cover its costs and to make profit. Short-term electricity trading usually spans a time window of up to 24 hours, and different pools take place prior to the power delivery. According to the quantity traded, short-term electricity markets can also be categorized into energy markets, in which the Market Operator (MO) gives/receives payments according to the amount of energy supplied to/consumed from the network, and Ancillary Service Market (ASM), related to the reliability and security of the grid [3]. The main income of RVPP comes from participation in the energy market due to its high liquidity [4]. To cope with the increasing number and volume of uncertainties specially for the RES in the Day-Ahead Market (DAM) both in offers and bids, the operators have designed different market mechanisms that allow units to (i) "update" their submitted energy volumes after the DAM has been cleared, and (ii) to compensate any unpredicted imbalance. This set of solutions comprises additional market windows complementary to the DAM. The most common one of these is the Intra-Day Market (IDM), which allows the bid/offer of blocks to be updated with more accurate weather/demand forecasts, and is cleared after the DAM, up to several minutes before the start of the first delivery period of the time horizon [5]. Apart from DAM and IDM, ASM exist, efficiently assigning resources to guarantee a reliable power system operation. Most of such markets are based on the availability of certain levels of power reserves (capacities) that were adequately scheduled in advance. Whereas the DAM settles the energy interchange, the clearing of the reserve provision can be carried out in different markets such as Primary Reserve Market (PRM), Secondary Reserve Market (SRM), and Tertiary Reserve Market (TRM). The existence of these markets is very country specific [6]. In addition, the scheduled energy and reserve of RVPP is never guaranteed, as various events can lead to mismatches between scheduled and finally traded energy/reserve. Such events may be directly related to the RVPP (e.g., technical malfunction of units, unexpected low wind and cloudy days) or external to the RVPP (e.g. the loss of a line which may require redispatch of assets to avoid line congestion/overload, or changes in the Secondary Reserve (SR) set points from the Transmission System Operator (TSO)) [7]. The Balancing Market (BAM) is designed to compensate the energy imbalance that may happen after the gate-closure of an energy market until the beginning of the delivery horizon of the subsequent session. This market is called by TSO if the expected hourly deviation reaches a determined value [8]. Therefore, deciding the participation of RVPP in different energy and ASM is essential and needs to be carefully evaluated by researchers and engineers.

The operation and planning of power systems, in general, and market participation in particular, are subject to multiple sources of uncertainties [9, 10]. Copping with the wide set of uncertainties that characterize the behavior of the RVPP units is essential to increase its competitiveness. These include the ND-RES production (from wind speed and solar irradiation), as well as demand consumption patterns [11]. Such uncertainties can significantly affect the DAM and/or ASM participation of the RVPP and, thus, their expected benefits. The RVPP operator thus needs to capture different uncertainties with appropriate techniques. Moreover, the forecasted market prices, used to plan the participation of the RVPP in different markets, are also subject to uncertainties that depend, e.g., on the markets' time scale and forecast horizon [12]. Therefore, the development of bidding approaches for RVPP participation in different markets, taking into account the characteristics of RVPP units, market rules, and internal and external uncertainties, has at most importance for RVPP operators and researchers. In this context, this thesis also contributes by proposing Robust Optimization (RO) approaches that explicitly address the main sources of uncertainty—renewable production, demand profiles, and electricity prices—thus providing the RVPP operator with more reliable and competitive bidding strategies.

An alternative to the classical Virtual Power Plant (VPP) concept that is rapidly gaining interest to increment ND-RES penetration levels and mitigate the aforementioned issues is the installation of Battery Energy Storage System (BESS), due to their capability to provide both active and reactive power regulation with very short time responses (down to several tens of milliseconds) [13]. Moreover, the advances in the BESS technology and their modularity imply a remarkable flexibility that allows the installation of BESS of up to 400 MW and over 1600 MWh, such as the Moss Landing BESS installed in California, USA, by Vistra Energy Corporation in 2021. The potential of BESSs to provide a large number of ancillary services and to mitigate the effects of the stochastic nature of ND-RES, together with the gradual decrease in the price per MW and MWh, justify their current popularity as a solution to increase the competitiveness of ND-RES. However, the main limitations of BESS that prevent their massive integration in the power grids are their still high installation (capital) cost, their relatively short life span depending on the application (up to 7 years, or a few thousand cycles), their intrinsic self-discharge (up to two percentual digits per day of their State of Charge (SoC)), the limited availability of the materials required for their construction, and their negative environmental impact at the time of their disposal. The RVPP framework proposed in this thesis offers a promising alternative to address the limitations commonly associated with BESS solutions and presents a competitive strategy to enhance the viability of ND-RES. Importantly, the primary cost associated with establishing an RVPP—built upon already installed RES and flexible loads—is limited to implementing the communication infrastructure needed to effectively coordinate these assets. By enabling optimal operation of all interconnected resources, the RVPP can potentially provide a level of competitiveness for ND-RES that may even exceed the benefits delivered by standalone BESS solutions.

1.2 Overview

In line with the interest of the European countries to increase the penetration of RES and to reduce greenhouse gases, this thesis focuses on the operation and bidding of RVPP composed exclusively of RES of different nature (both dispatchable and non-dispatchable), as well as Flexible Demands (FDs). They are selected with the aim of ensuring a safe and reliable operation by offering their combined flexibility (e.g., fast ramp-up/down capability for frequency control), the possibility to internally balance the stochastic RES fluctuations, and to sell their aggregate generation output in the wholesale market [14]. The RVPP proposed in this work thus appears as a competitive solution to increase the viability of ND-RES. Considering the characteristics of RVPP, such as the integration of multiple units, effective uncertainty management, dispatchability, and flexibility, the RVPP is capable of participating in several markets and has the ability to offer various products in electricity markets. However, since it is not feasible to cover all of electricity markets, this thesis focuses on a selection of the most promising electricity markets from the perspective of RVPP benefits.

1.2.1 On the electricity markets

Medium/long-term and short-term electricity trading markets are distinguished by the time horizon of each market. Medium/long-term electricity trading time horizons typically range from weeks to years for large-scale planning and investment decisions. The main participants in the long-term electricity markets are large electricity producers, TSO, Distribution System Operators (DSOs), regulators, and investors. Long-term electricity trading is mostly based on electricity purchase agreements, capacity contracts, and bilateral contracts [15, 16]. Short-term electricity trading time horizons typically range from hours to days to ensure real-time operation and balance of supply and demand. The main groups of participants are present in the short-term markets, namely generation (both large and small scale producers, including both Dispatchable Renewable Energy Sources (D-RES) and ND-RES), demand (retailers and large consumers, and demand response providers), DSO, and Balance Responsible Parties (BRPs). Short-term trading is generally based on competitive auctions or different various pre-delivery pools for trading electricity, capacity and ancillary services [3, 17]. Since this thesis considers an RVPP composed mainly of a few RES units, its overall scale is relatively small compared to the network. Consequently, the analysis focuses on short-term electricity markets within a 24-hour horizon.

The first pool that is cleared in the electric energy trading covers the entire 24-hour window of the corresponding day, evenly divided into 24 one-hour periods. This pool is commonly referred to as DAM, although other terms such as spot market (Europe) and forward market (USA) can be found. In this market, which is usually cleared 12 hours prior to the energy delivery period of the covered market window, generation and demand participants submit selling offers and purchasing bids, respectively, for each and every period of such a window. Such offers/bids consist of individual blocks characterized by an amount of energy that generators/demands are willing to sell/buy (an amount of power during a market-dependent period) and the corresponding price. The market is then cleared by the MO by constructing the so-called sale/purchase curves by sorting the offering/bidding blocks according to their corresponding prices, from lower to higher, and whose intersection determines the electricity price and the total energy traded. This wholesale price is then used to remunerate/charge all generation/demand units whose offers/bids prices were lower/higher than or equal to the cleared one, i.e., the generating/demand units with the highest/lowest prices are excluded from the trading [11, 18].

RVPP bids in the electricity markets can thus be classified into price-quantity bids, specifying a quantity and a price, and self-scheduled bids, specifying only a quantity by setting the bid price to the minimum or maximum price value according to whether the quantity is consumed or sold. Furthermore, bids can be either single price-quantity bids or multiple price-quantity bids [11, 18, 19]. Regarding the bidding structure that is used in this thesis, it is assumed that RVPP bids at zero or low prices such that the bid is always cleared. This assumption is relevant since the size of RVPP is relatively small in the context of the overall system, and it mainly includes ND-RES with low operation costs. Accordingly, the RVPP is considered to be in a price-taker position, meaning its bids do not influence the market-clearing price. The proposed bidding strategy for RVPP in this thesis does not use the supply-demand balancing constraints to determine the electricity price. Indeed, it is assumed that the unknown electricity prices are input forecast parameters in the proposed model. This assumption is valid since knowing the full network configuration is not reasonable for any RVPP operator. As the size of the RVPP becomes larger, bidding in both quantity and price clearly becomes relevant and needed. The price-maker approach would imply predicting the strategies of other participants in a multi-level algorithm, which further complicates the problem (knowing what others will do is quite challenging, to say the least). Also, although no precise regulation is available in this regard at a general level in Europe, discussions with the Spanish system regulators indicate that they would tend to minimize the risk of having an oligopoly in this regard, by limiting the maximum capacity of the so-called "portfolio bidding".

In the DAM, offers are submitted several hours before the delivery period based on predictions of available energy. Uncertainties in such predictions are not negligible and cumulate over the delivery period. Risks and penalties associated to such uncertainties are thus the main aspects that limit the competitiveness of ND-RES in the energy market. Minimizing the uncertainties at the time of placing the offers is crucial for ND-RES. This can be achieved by having a DAM clearing time closer to the actual delivery period, thus reducing the forecast horizon. However, this cannot be implemented in practice, as dispatchable generation units need to know the result of the schedule well in advance given their relatively low flexibility against changes in their generation. As an intermediate solution, IDM, also referred to as adjustment markets, have been developed and implemented. IDM are trading pools (usually more than one) that close between the DAM clearing time and the start of the delivery period (the last IDM usually clears 30 minutes or 1 hour before the delivery period). IDM thus allow ND-RES and other market participants to "adjust" their offer/bid blocks according to updates on their predictions in weather/load profiles, which are characterized by higher certainty, and which usually imply higher profits with lower volatility [5, 11, 20, 21].

IDM can be applied in a discrete (auction-based), continuous, or hybrid form. In the discrete IDM, such as those of the Spanish and Italian electricity markets up until mid-2024, participants received a market-clearing price in each auction session with a 60-minute resolution [22]. In the continuous IDM, such as the German electricity market, participants can continuously submit or withdraw bids during the trading period. This type of IDM is implemented similarly to a stock market with a pay-as-bid structure [23]. IDM are therefore essential for ND-RES, and thus for RVPP, to increase their competitiveness and viability. In this thesis, the Spanish discrete IDM structure, in place up until mid-2024 with its seven auction sessions, is used as the basis for modeling RVPP market participation—a choice aligned with the market conditions at the time the research began. It is worth noting that nowadays, the Spanish IDM operates under a hybrid model with three IDM sessions at 15-minute resolution, as part of the Single Intra-Day Coupling (SIDC), which creates a single European cross-zonal IDM [24].

The DAM and IDM participation assumes that, once the last market of each delivery period is cleared, the RVPP will be able to generate/consume the energy/power that was scheduled at each period. However, this is never guaranteed, as various events can lead to mismatches between scheduled and finally traded energy/power. Such events may be directly related to the RVPP (e.g., technical malfunction of units, unexpected low wind and cloudy days) or external to the RVPP (e.g. the loss of a line which may require redispatch of assets to avoid line congestion/overload, or changes in the SR set points from the TSO). The BAM is designed to compensate the energy imbalance that may happen after the gate-closure of an energy market until the beginning of the delivery horizon of the subsequent session. This market is called by TSO if the expected hourly deviation reaches a determined value [7, 25, 26]. In this thesis, the RVPP operation is designed to minimize potential penalty costs in the BAM by accounting for various actual energy and reserve activation scenarios in real-time. However, real-time bidding and clearing for the RVPP in the BAM are not considered, as their timescale is shorter and differs from that of the primary problem [27].

The reserve is a margin of power that the power plants should include in their generation program to cope with unexpected load changes or generation losses. The TSO is responsible for maintaining the reliability of the power system [8, 28]. Hence, unlike the energy markets (DAM and IDM), which are supervised by the MO, the reserve markets are settled by the TSO.The term 'reserve' has different definitions in different countries; therefore, some works do not distinguish it with specific type of reserve and model the participation of VPP in the reserve market as a general term [21, 29, 30, 31]. However, the reserve term can be distinguished mainly by Primary Reserve (PR), SR, and Tertiary Reserve (TR). In case of power imbalances, e.g. due to equipment failures or sudden load increases, the PR is the first one to act, and is responsible for bringing the frequency back to acceptable values. The PR service is usually not market-based, being mandatory in these cases for security reasons. However, some works in [6, 32, 33, 34] include the participation of VPP in the PRM. After a few tens of seconds, SR or Automatic Frequency Restoration Reserve (aFRR), also known as Automatic Generation Control (AGC), comes into play with the aim of bringing the frequency and the area power interchange back to their reference values. The unit that wants to provide aFRR in the market needs to be qualified by TSO. Examples of requirements involved in the SR provision include providing reserve for 15 min uninterruptedly in the resolution time of 1 hour and with a response time of 100 s [8]. In order to avoid undesirable interactions between control loops, aFRR time response is considerably slower than PR (usually from 30 seconds to 15 minutes) [35, 36]. Considering the suitability of the SR service from the point of view of security and timing for market provisioning, the participation of VPP in the SRM is widely studied in [6, 32, 33, 34, 37, 38, 39]. Finally, the goal of the TR is to replace SR if aFRR cannot completely bring back frequency to its schedule value [35, 36]. TR is activated manually when requested by the system. Since power imbalances can be negative or positive, the TR is determined and activated for both the upward and downward regulation. Generally, TR is slow, with small ramp-up rates and long start-up times. Thus, TR is usually provided by thermal power plants, which are notified in advance when they need to change their power output. Some few works [6, 33] consider the VPP participation in the TRM.

In this thesis the RVPP participation in the SRM is considered as the most relevant and well-established electricity market for reserve. The control underlying, for example, the Spanish aFRR, (the AGC), is a hierarchical control, consisting of a central controller sending reference signals to zonal controllers. A zone comprises all qualified generating units of a generation company, which can be distributed across the overall system, and should not be understood as a specific geographic area. In real time, TSO assigns the aFRR requirement for each zone of the Spanish system according to the cleared relative regulation band, and each zone sends commands to its units for providing reserve. Each zone has thus the responsibility for providing its determined reserve [28]. The participants in the aFRR market receive the marginal price of the market (€/MW) and energy price (€/MWh) if TSO activates aFRR in real time [3]. The RVPP needs to provide the SR according to the accepted bid in the market. Therefore, the possible scenarios for the provision of up/down promised reserve are considered in the RVPP model in such a way as to ensure the feasible operation of the RVPP in real time. Although the prices of the ancillary services in general and of the secondary reserve, in particular, are considered for the bidding in the market, the income from the actual delivery of the SR has however not been considered in this thesis. The reason is that the considered timeframe is on an hourly basis, whereas the activation of SR takes place in real time and is highly uncertain. Since such activations cannot be reliably predicted or incorporated a day ahead when the bidding takes place, they are excluded from the scope of this work. The sequential handling of bidding and real-time cost quantification proposed in this thesis is also partially due to the current remuneration mechanism of SR services. In Spain, the remuneration is separated into two phases: first, the reserve power bids are cleared in the day-ahead SRM, providing a remuneration according to the offered power, and second, the activated reserve energy is basically remunerated according to the price of the TRM. Although the actual reserve delivery can modify the overall remuneration, the remuneration of the day-ahead SRM is guaranteed.

With the current schemes of electricity markets, DAM, IDM and SRM are particularly well suited for this thesis. The reasons are that a significant part of the RVPP benefit comes from these markets and the time scale of different markets are considered for this selection. Also, in some parts of the thesis the BAM is taken into account to evaluate the imbalances that may occur after the gate closure of an energy market until the beginning of the delivery horizon. This thesis considers the Iberian electricity market system with a sequential clearing mechanism, which serves as a unified test-bed for all simulations used to validate the proposed solutions. The choice to focus on sequential markets in this thesis is primarily driven by the market structure prevalent in Europe. Whereas joint clearing is a predominant structure in markets such as the USA [18], the European energy markets, which are the primary context of this research, often operate with a sequential clearing mechanism for energy and reserve markets. Participants can submit bids at any time prior to the clearing time of each market gate [40]. This leads to the possibility explored in this thesis, where sequential optimization problems are solved, also based on the fact that more accurate forecasts of uncertain parameters could be available as time is closer to the power delivery period. In a sequential market clearing structure, the decision making for determining optimal bids can be made jointly (i.e., bids for different markets can be prepared simultaneously, although they are cleared sequentially). The bids for the different markets can then be submitted jointly or sequentially according to the market gate closing times. The methodology used in the thesis is thus specifically tailored to address the intricacies and challenges posed by sequential markets, which offer more flexibility to certain market participants, mainly ND-RES, which are the primary focus of this work. However, the proposed approach could readily be adapted to joint clearing markets, by taking advantage of the fact that, although market clearing is sequential, the determination of the optimal bids in the proposed approach for different markets is made jointly (i.e., different markets are considered simultaneously, such as DAM and SRM, although they are cleared sequentially).

1.2.2 On the uncertainties in the model

Uncertainty modeling is one of the most challenging parts of different power system problems such as unit commitment, economic dispatch, active/reactive power coordination, resilient dispatch, and expansion planning problem [9, 10]. Different uncertainties can be categorized into two main groups: (i) decision-independent uncertainties or exogenous uncertainties, such as market clearing prices and available wind generation; and (ii) decision-dependent uncertainties or endogenous uncertainties, such as real-time reserve deployment requests [41]. The uncertainties which are considered in VPP studies mainly include electricity prices in different electricity markets, the ND-RES output power uncertainties, and demand profiles. Two main mathematical optimization approaches can be generally followed to model market price and stochastic energy production/consumption in optimization problems, namely Stochastic Programming (SP) and RO [18]. Both approaches deal with the problem of uncertain model parameters taking random values that typically affect the decision, i.e., the optimal value of the decision variables. In the SP, scenarios are constructed based on the probability distribution of the uncertain parameters. The scenarios are then used to configure the optimization problem, in which the final results are assigned according to the probability of the scenarios [18]. However, constructing a comprehensive and representative set of scenarios is not always simple or even accurate enough. Moreover, as the number of scenarios increases, the number of constraints and variables in the optimization problem grows, resulting in an exponential increase in computational complexity.

The RO method, on the other hand, is an effective approach to deal with different uncertainties, since it covers the wide range of uncertain parameter deviations, provides feasible results, and is efficient in terms of computational time. The goal of RO is to find the worst case of the optimization problem to minimize the negative impact of uncertainties on the solution [11]. However, the main drawback of RO is that the results obtained tend to be overly conservative. In this regard, Bertsimas [42] proposed a flexible RO method that allows the user to adjust its level of conservatism towards uncertain parameters by defining a new control parameter, called *uncertainty budget*, in the problem. This parameter represents the number of periods that the uncertain parameter deviates from its predicted value to its worst condition. This idea was then further developed to implement flexible RO for different VPP bidding problems in different markets [29, 43, 44]. The flexible RO has also been used in [45, 46, 47, 48, 49] to account for demands uncertainty, ND-RES production uncertainty, and/or electricity market price uncertainty in the VPP bidding optimization models.

The definition of the worst case in the RO can vary depending on how the optimization is implemented, whether it determines the *worst case of energy* or the *worst case of profit*, and can lead to different solutions in each approach. The authors in [43, 45, 46, 47, 48, 49, 50] develop a single-level optimization problem for the VPP market bidding problem to find the *worst case of energy* of ND-RES. The main advantages of the single-level RO programming mentioned in the above papers are the possibility to consider multiple uncertainties, simplicity of implementation, global optimality, and computational efficiency. However, a simplified definition of the worst case of energy for the severe scenarios is implemented. In fact, the worst case of energy defined for ND-RES in the above papers does not lead to the worst condition of profit, considering the possibility of different values of electricity prices. For instance, in a case where the electricity price is low in a certain period, even though the energy of a ND-RES can deviate significantly in this period, the resulting loss for RVPP might not be significant compared to a period with much higher electricity price and average or low energy deviation. To overcome the challenges and difficulties of implementing a multi-level optimization model, and to minimize the computational burden of the problem for real-world practical applications, this thesis proposes a flexible worst-case profit of RVPP against uncertainties by means of a novel single-level Mixed Integer Linear Programming (MILP) problem. The uncertainties that characterize the problem include energy and ASM prices, ND-RES generation, and FD contribution. To account for the impact of such uncertainties in the problem (and in particular, their *couplings*), the proposed methodology builds on the works in [42, 43, 51], and by developing on the idea from the Big-M method [52]. In this process, defining the relationships and couplings between uncertain parameters leads necessarily to non-linear constraints, which are thoroughly linearized by using well-established methods. The proposed implementation of robust constraints allows capturing the relationship between different uncertain parameters in the objective function and constraints of the optimization problem, finding the *exact* worst case profit of RVPP.

Another issue in the existing literature is that the VPP operator needs a monetary interpretation of the *value* of the uncertainty budget to solve the optimization problem. Furthermore, multiple uncertainties must be considered in the optimization problem, and determining the uncertainty budget for each of these uncertainties is not an easy task. The results obtained in [29, 43, 44, 45, 46, 47, 48, 49] show that, expectedly, by increasing the uncertainty budgets, the VPP adopts more conservative strategies in the market, which results in lower bidding profit. However, the VPP operator still does not easily know how to assign specific values to the uncertainty budgets, and what such values imply. In fact, the results provided can be misleading, since they do not show the consequences of each decision when the uncertainties become known, and only consider the expected profit of VPP in the market, which is obviously at its highest value for null uncertainty budget (deterministic case without uncertainty).

Alternatively to the criterion of minimizing the maximum robust cost (*worst case of energy* or the *worst case of profit*) used in [29, 43, 44, 45, 46, 47, 48, 49, 51, 53], the problem can be set to minimize the *maximum regret cost* [54, 55, 56, 57]. In this context, regret is defined as *the loss felt by the decision maker with respect to the use of alternative decisions when uncertainties unfold*. Maximum regret minimization is thus a method for decision makers who do not have the probability of events or are not interested in this information. However, the decisions made in a min-max regret problem tend to also be conservative, as they aim to prevent any single scenario from causing significant regret. A solution to alleviate the potentially unsatisfactory results of the min-max regret problem can be obtained by minimizing the *expected regret* [58, 59, 60, 61]. The expected regret can be defined as the *sum of lost costs by considering the probability of alternative decisions*. Hence, minimizing the expected regret avoids selecting overly conservative solutions. The papers [58, 59, 60, 61] minimize the maximum expected regret for multiple scenarios in the SP, which usually implies high computational time, especially for a large number of scenarios. To address this issue, the use of scenario reduction methods to keep the problem tractable is widely used in the SP. However, these methods may lead to less accurate regret computation, since the expected regret in their model is for reduced scenarios, and the regretful scenarios are good targets for removal in the scenario reduction process. Considering the aforementioned gaps and the advantages of the RO approach, this thesis develops a novel modeling approach to account for the expected regret in the RO for RVPP bidding problem. The profit-minimizing nature of uncertainties is modeled by the flexible RO approach, and the expected regret associated with each uncertain parameter is modeled in the constraints of the optimization problem. In this way, while the expected regret of RVPP operator decisions is controlled in the RO, the problem remains highly tractable, unlike the SP. Moreover, the conservatism level of the problem is controlled by the monetized user-defined parameters, which represent a per-unit value of the maximum regret cost instead of the uncertainty budget used in the literature. This is beneficial because it allows the user to determine the parameter based on a monetized value rather than based on several characteristics related to uncertain parameters, such as the type of uncertainty, deviations of uncertain parameters, type of markets, type of units, and so on.

1.2.3 Thesis organization

The remainder of this thesis is organized as follows.

In Chapter 2 **(RVPP in Electricity Markets)**, different characteristics of RVPP participation in European energy market and ASM are compared with those of other prominent countries. These include (i) the RVPP definition, (ii) suitable electricity markets for RVPP participation, (iii) different types of electricity market clearing, and (iv) different business cases for RVPP.

In Chapter 3 **(RVPP Objective Functions and Components)**, a tractable single-level deterministic model for RVPP operation and bidding in different markets is provided. This model gives the RVPP operator the basic information on how to dispatch its units and how to bid/offer in the different sequences of the electricity markets to maximize its profit, knowing the exact value of uncertain parameters. This model is a base case for comparison with other mature cases in the following chapters. The deterministic model of the RVPP has been formulated with an MILP, and implemented for different case studies. The test case is an RVPP in a region of southern Spain that participates in the Spanish DAM, IDM, and SRM. The Spanish market has been considered due to the fact that it is particularly tailored to allow RES to adjust, several times during the day, their energy volumes to be traded. Moreover, a deep knowledge of its market characteristics and its historical data is readily available to feed the RVPP model.

In Chapter 4 **(Advanced Robust Optimal Bidding of RVPP under Uncertainties)**, different uncertainties arising from demand consumption, ND-RES profiles, and electricity prices are described. Such uncertainties have been considered by developing the so-called RO to find the flexible worst case of energy, which is the key to account for the stochastic nature of wind speed, solar irradiation, Concentrated Solar Power Plant (CSP) thermal production, market prices and demand profiles. Different characteristics of uncertain parameters such as flexibility, non-linear effects, asymmetry, and correlation are discussed. Then, two RO models for RVPP operation and bidding as a single-level problem, named *profit robustness model* and *energy robustness model*, are developed and compared. The uncertain parameters and their effects on the behavior of RVPP are taken into account in the optimization problems. First, the constraints related to the uncertainty in the objective function of the optimization problem corresponding to different electricity prices are defined. Also, the constraints related to the uncertainty in the constraints of the optimization problem corresponding to ND-RES and demands are presented. All uncertainties are formulated in such a way that the flexible worst cases of energy and profit are calculated. Then, an exact solution is proposed to deal with non-linear terms in the defined constraints. Finally, both problems are formulated as a single-level MILP problem and implemented in General Algebraic Modeling System (GAMS) software.

In Chapter 5 **(Regret-based Robust Optimal Bidding of RVPP in Electricity Markets)**, the concept of expected regret cost is implemented in the RO of RVPP bidding in the electricity markets by a set of mixed-integer constraints. The expected regret for a decision of RVPP is defined as the weighted sum of the loss differences between the corresponding solution and other potential solutions associated with the Probability Density Function (PDF) of the uncertain parameter. The RVPP operator controls its desired expected regret cost with respect to uncertain parameters associated with DAM and SRM electricity price and the total output energy of RVPP. In this way, a new control parameter, more tangible in terms of economic factors, is used to determine the level of conservatism of RVPP instead of the using the uncertainty budget. The RO problem then assigns the corresponding flexible worst case of the uncertain parameters based on the level of conservatism determined by the RVPP operator. The robust counterparts of the uncertain terms in the objective function and constraints of the optimization problem are obtained by developing the idea proposed in Chapter 4.

1.3 Contributions

Although the literature on VPP modeling in the electricity markets is rich and mature, there are still many aspects that are neglected or simplified. This justifies the outstanding interest in the study of VPP that currently exists, as can be observed from the many references that have been published in recent years. The main common issue observed from the works done in the literature is that the size of the problem can rapidly escalate; therefore, in most of the papers in the literature the impact of neglecting or simplifying vital parts for VPP viability problem has not been fully quantified. As a result, some critical aspects, such as sequential markets, reserve provisioning strategies, uncertainty modeling, and multi-level features, have not been fully addressed. Moreover, some recent works focus on developing overly complex algorithms that may be mathematically interesting but have limited practical applicability. In contrast, this thesis aims to make the work of RVPP operators easier, without sacrificing rigor or accuracy. In this regard, the detailed contributions of the thesis are proposed and discussed below:

1. **VPP components:** This thesis proposes a novel RVPP operation model, that is composed, exclusively, of RES (including hydro, Wind Farm (WF), solar Photo-Voltaic (PV), CSP, and biomass) and FDs. Literature takes advantage of the benefits of conventional fossil fuel generators and BESS to coordinate with ND-RES, thus increasing VPP competitiveness. This thesis highlights near future scenarios where fossil fuel units are replaced by D-RES and ND-RES. Furthermore, the BESSs are not considered in the RVPP portfolio due to their disadvantages, such as their high investment cost, their negative environmental impact, and their relatively short life span. The main contribution is that the most known clean RES technologies are considered in the thesis by accurate, easily implementable, and practical mathematical models. The proposed general model can be used for any RVPP with *any* number of units and different structure [1]. Although in the literature most of the above aspects are modeled separately, the literature lacks a complete VPP model with all of the above RES-based units, since considering them together to model the participation of VPP (i.e., couplings between VPP units) in multiple markets is neither mathematically nor computationally an easy task. This contribution is mainly presented in Section 3.2 of Chapter 3.

2. **Interaction between different markets:** By including energy (DAM and IDM) and reserve markets, different sequences of markets are studied in the thesis. Most papers optimize energy and reserve markets simultaneously. However, in some European electricity markets, such as the Spanish electricity market, these two markets are usually run separately. Moreover, the forecast data can be updated in each market and the VPP has to use the results of the energy market in the reserve market. Consequently, the literature does only consider the first sequence (DAM offer + reserve estimations) of a multi-market offering sequence of a VPP. Therefore, a complete model is needed to consider these kinds of interactions, which are not properly addressed in the literature due to complex models that cannot handle most of the important markets together. This contribution is mainly presented in Section 3.2 of Chapter 3 and in Section 4.3 of Chapter 4.

3. **Energy balance and reserve provision:** Most papers model the energy balance equations without considering the possible activation scenarios of the reserve in the real time, due to the complexity of the problem. In this respect, they overestimate the available reserve as the capacity minus the power of the VPP units. This overestimation may be reasonable for power systems with sufficiently strong networks and in the case of reserve provisioning of limited duration and limited overload, but it may fail in the case of network flows close to the limits as in weaker networks, and for enduring reserve provisioning. This simplification may lead to market penalties or even exclusion from reserve provisioning. This contribution is mainly presented in Section 3.2 of Chapter 3 and in Section 4.3 of Chapter 4.

4. **Reserve provision by all VPP units:** Many papers do not consider that all VPP units can provide reserve. For instance, in energy-limited devices, the real-time use of reserve energy affects the reserve capacity offering. Therefore, a simple assumption of a fraction of energy may not be sufficient. In this thesis, the reserve supply by CSP storage is considered in such a way that the possible real-time operation is taken into account. This contribution is mainly presented in Section 3.2 of Chapter 3.

5. **New RO modeling techniques:** These are well known in power system problems. However, for VPP applications, the uncertainty modeling needs to be carefully selected for different internal or external uncertainties associated with VPP. This is due to the fact that not all of uncertain parameter statistical distributions are readily available. On the other hand, inappropriate uncertainty modeling can easily lead to high computational burden or even infeasibility and penalty issues in the electricity markets. The literature proposes very complex to update and fit methods for considering VPP uncertain parameters, which are not practical when multiple components and markets are considered. In the thesis, among the available methods, RO approach is selected to capture the stochasticity of ND-RES, demands, and electricity market prices considering its compatibility with large problems. However, there are still some improvements to be made. In this regard, two new single-level RO models for energy robustness and profit robustness are proposed, which are computationally efficient, straightforwardly usable for practical RVPP applications, and also model the uncertain parameters with readily available information. Besides, the newly proposed RO models handle the asymmetric behavior of uncertain parameters, which is neglected in the literature (the uncertainty bounds of stochastic parameters show asymmetric behavior in the real world). With this aim, the modeling of the asymmetry bounds for uncertainty parameters is considered in this thesis as it has a direct impact on the RVPP profit in the electricity market. Furthermore, most of the papers in the literature provide solutions that are quite challenging to implement by actual VPP operators due to their complexity. When using RO, it is not clear which uncertainty budget needs to be considered, and operators generally want methods that are direct and easy to implement and execute. In this regard, this thesis proposes the regret-based flexible RO of RVPP, which to the best of the candidate's knowledge has not yet been addressed in the literature, to help the RVPP operator to decide the best uncertainty budget based on its needs. Moreover, the proposed frameworks are a general contribution to RO that can be applied beyond RVPP, offering a practical approach to selecting and tuning uncertainty budgets in other operations research problems. This contribution is mainly presented in Section 4.3 of Chapter 4 and in Section 5.3 of Chapter 5.

1.4 List of publications

This section provides the list of publications derived from this thesis.

1.4.1 Journal publications

- [51]. H. Nemati, P. Sánchez-Martín, Á. Ortega, L. Sigrist, E. Lobato, and L. Rouco. “Flexible robust optimal bidding of renewable virtual power plants in sequential markets under asymmetric uncertainties”. Sustainable Energy, Grids and Networks, 2025, p. 101801.
- [53]. H. Nemati, P. Sánchez-Martín, A. Baringo, and Á. Ortega. “Single-level flexible robust optimal bidding of renewable-only virtual power plant in energy and secondary reserve markets”. Energy, 2025, p. 136421.
- [62]. H. Nemati, P. Sánchez-Martín, L. Sigrist, L. Rouco, and Á. Ortega. “Flexible robust optimization for renewable-only VPP bidding on electricity markets with economic risk analysis”. International Journal of Electrical Power & Energy Systems 167, 2025, p. 110594.
- [63]. H. Nemati, Á. Ortega, and P. Sánchez-Martín. “Two-stage robust optimization strategy for VPP participation in the energy and reserve markets considering intertemporal carbon trading”. International Journal of Electrical Power & Energy Systems 172, 2025, p. 111093.

1.4.2 Conference publications

- [64]. H. Nemati, L. Sigrist, L. R. Rodríguez, P. Sánchez-Martín, and Á. Ortega. “Addressing unfeasibilities of energy storage systems participating in energy and reserve markets”. In: 2022 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe). IEEE. 2022, pp. 1–5.
- [65]. H. Nemati, P. Sánchez-Martín, L. Sigrist, and Á. Ortega. “Impact of uncertain data in robust optimal bidding of RVPP in energy and reserve markets”. In: IEEE PES International Conference on Innovative Smart Grid Technologies Europe - ISGT Europe 2024, Dubrovnik (Croacia). IEEE. 2024, pp. 1–5.
- [66]. H. Nemati, P. Sánchez-Martín, L. Sigrist, L. Rouco, and Á. Ortega. “Sizing of battery storage systems to mimic the operation of Res-based VPPs in electricity markets”. In: 2025 21st International Conference on the European Energy Market (EEM). IEEE. 2025, pp. 1–6.
- [67]. L. J. Fernández, H. Nemati, L. Sigrist, and Á. Ortega. “Robust optimal portfolio configuration of renewable-based virtual power plants for long-term planning”. In: 2024 IEEE Power & Energy Society General Meeting (PESGM). IEEE. 2024, pp. 1–5.
- [68]. H. Nemati, P. Sánchez-Martín, L. Sigrist, L. Rouco, and Á. Ortega. “Optimizing RVPP bidding strategies in energy and reserve markets under different regulations”. In: IEEE PES Innovative Smart Grid Technologies - ISGT Middle East 2025, Dubai (UAE). IEEE. 2025.

1.4.3 Technical reports

- [1]. Á. Ortega, O. Oladimeji, H. Nemati, L. Sigrist, P. Sánchez-Martín, L. Rouco, E. Lobato, M. Biencinto, and I. López. Modeling of VPPs for their optimal operation and configuration. Technical report. POSYTYF Consortium, Tech. Rep., deliverable 5.1., 2021.
- [69]. H. Nemati, Á. Ortega, P. Sánchez-Martín, L. Sigrist, and L. Rouco. Tool for the optimal operation of DVPPs under uncertainty of non-dispatchable RES. Technical report. POSYTYF Consortium, Tech. Rep., deliverable 5.2., 2022. 2024, pp. 1–5.

- [70]. Á. Ortega, L. Sigrist, H. Nemati, P. Sánchez-Martín, and L. Rouco. Definition of case studies.Technical report. POSYTYF Consortium, Tech. Rep., deliverable 5.4., 2023.

- [71]. H. Nemati, L. J. Fernández, Á. Ortega, P. Sánchez-Martín, and L. Sigrist. Viability of DVPPs. Technical report. POSYTYF Consortium, Tech. Rep., deliverable 5.5., 2023.

1.4.4 Publications arising

- [72]. H. Nemati, P. Sánchez-Martín, Á. Ortega, L. Sigrist, and L. Rouco. "Integration of concentrated solar power plants in renewable-only VPP with electrical and thermal demands: A two-stage robust bidding approach". arXiv preprint arXiv:2509.18769, 2025.

- [73]. H. Nemati, I. Egido, P. Sánchez-Martín, and Á. Ortega. "Assessing value of renewable-based VPP versus electrical storage: Multi-market participation under different scheduling regimes and uncertainties". arXiv preprint arXiv:2507.22496, 2025.

- [74]. H. Nemati, Á. Ortega, P. Sánchez-Martín, L Sigrist, L. Rouco, and I. Egido. "Enhancing robust multi-market participation of renewable-based VPPs through flexible resources", Electric Power Systems Research, Under Review.

2 RVPP in Electricity Markets

In this chapter, different types of markets for RVPP participation are reviewed and the characteristics of these markets are described. Different types of market clearing in the joint and sequential markets as well as the RVPP studied in the multi-energy markets are studied. The market power of RVPP and regulatory aspects of different markets are pointed out. The business cases and the difference between electricity markets in different countries are outlined.

2.1 RVPP definition

Traditionally, a VPP aggregates heterogeneous Distributed Energy Resources (DER)—typically a mix of controllable generators, storage, and flexible loads—so they can be operated and traded as a single unit [75]. The RVPP developed in this thesis builds on that idea but is composed mainly of RESs (including both D-RESs and ND-RESs), whose weather-driven variability, forecast errors, and limited dispatchability introduce greater stochasticity than in traditional VPP portfolios. Consequently, an RVPP must emphasize probabilistic techniques and risk-aware coordination (e.g., stochastic/robust scheduling, reserve co-optimization, and strategic use of assets) to deliver flexibility and ancillary services while remaining competitive in electricity markets [76].

The initial concept of the RVPP emerged from the need to address the relatively low competitiveness of the then-emerging ND-RESs, such as wind and solar generation, compared to large, dispatchable CGs like hydro and thermal power plants. Enhancing this competitiveness is crucial for the large-scale integration of such RESs [1]. Over the past two decades, the RVPP concept has attracted significant interest, leading to the exploration, testing, and, to some extent, implementation of numerous assets, applications, scenarios, and business models. Nonetheless, the core idea behind the RVPP remains unchanged: to combine and coordinate the operation of multiple independent assets to deliver a flexible and economically viable solution for utilities—achieving capabilities that would otherwise not be possible. This coordination helps mitigate some of the key challenges of ND-RESs, such as their inherent variability and non-firm nature [77].

The RVPP proposed in this thesis comprises ND-RESs, including WF and solar PV; D-RESs, such as hydro and biomass plants; CSP units, which are dispatchable but subject to thermal input uncertainty; and FDs. The main objective of this thesis is to investigate how to optimally operate the proposed RVPP in a viable and effective manner.

2.2 Business cases

2.2.1 Alternative objective functions

The literature identifies several objective functions that can be used to model the operation of VPPs. The most common include profit maximization, cost minimization, self-supply cost minimization, and demand-side utility maximization [78, 79]. Profit maximization typically reflects the behavior of VPPs participating in wholesale energy and ASMs. Cost minimization often arises in formulations that focus on operational efficiency and unit commitment. Self-supply cost minimization appears in contexts where the VPP manages both demand and distributed generation, aiming to reduce overall expenditure. Finally, demand-side utility maximization emphasizes consumer satisfaction and flexibility, often in demand response or community energy settings. These formulations represent distinct ways of expressing the objectives of a VPP within different market and operational environments.

2.2.2 Different applications

Each of the identified objective functions corresponds to a particular business case or application of VPPs. Profit maximization is most relevant for market-oriented aggregators that seek to optimize revenues from energy sales, ancillary services, and demand response programs [80]. Cost minimization is widely applied in unit commitment and dispatch studies, where the aim is to schedule DER as efficiently as possible [81]. Self-supply cost minimization is particularly suited to microgrid-based VPPs or local energy communities, where both generation and demand are integrated within the same portfolio. Demand-side utility maximization, in contrast, applies primarily to consumer-centric VPPs, where enhancing the value of participation for end-users is a priority [82]. These applications demonstrate how the choice of objective function reflects the strategic role and business environment of the VPP under consideration.

2.3 Electricity markets suitable for RVPP

To ensure the economic viability of the RVPP, active participation in various electricity markets is essential for covering operational costs and securing revenue. The primary income stream originates from the DAM, where energy transactions—based on injections or withdrawals from the grid—are financially settled by the MO [2, 11]. IDMs offer mechanisms for adjusting previously committed volumes and addressing imbalances arising from forecast deviations [22]. Unlike energy markets, which are managed by the MO, ASMs are coordinated by the TSO. These markets ensure system reliability through pre-allocated reserve margins that can respond to contingencies such as generation outages or load spikes. PR serves as the first response mechanism to stabilize frequency deviations, but it is typically excluded from market-based procurement due to its critical role in system reliability. It is followed by SR, which are suitable for market-based activation given their longer response times and operational flexibility [28]. As such, a comprehensive evaluation of RVPP participation across both energy markets and ASMs is essential. This section reviews the time span characteristics and operational relevance of markets accessible to RVPPs, focusing specifically on the DAM, IDMs, and ASM, including BAM, SRM, TRM, and the reactive market. Figure 2.1 shows market landscape for RVPP participation across different time scales considered in this section.

2.3.1 Medium/long term vs. short term markets

Electricity trading markets are typically categorized based on the time frame they cover. Medium- and long-term markets operate over extended periods—ranging from several weeks to multiple years—and primarily support strategic planning, infrastructure development, and investment decisions. In contrast, short-term markets focus on operational timelines spanning from a few hours to several days, aiming to maintain real-time grid stability and balance supply with demand. In long-term markets, key stakeholders include large-scale electricity producers, TSO, DSO, regulators, and financial investors. Meanwhile, short-term markets involve a broader set of active participants such as centralized and decentralized generators (including both D-RES and ND-RES), retailers, major energy consumers, demand response providers, DSO, and BRP. Trading mechanisms also differ: long-term contracts typically revolve around purchase agreements, capacity deals, and tailored bilateral contracts, whereas short-term markets are driven by competitive bidding processes and a variety of pre-delivery trading platforms for electricity, capacity, and ancillary services [3, 15, 17].

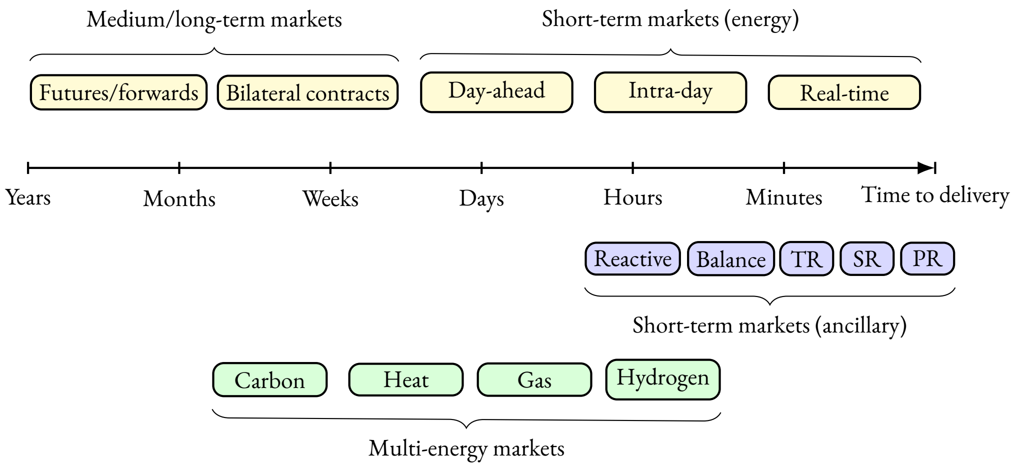


Figure 2.1: Market landscape for RVPP participation across different time scales.

Short-term electricity markets can also be classified based on the nature of the commodity traded. In energy markets, transactions are settled based on the volume of energy injected into or withdrawn from the grid, with financial exchanges reflecting these quantities. In contrast, ASM primarily involve trading power—mostly active power, though markets for reactive power are increasingly emerging in importance. Energy and power markets form the backbone of electricity trading, with energy markets alone accounting for over 75% of the total traded volume. Ancillary services are essential operational tools that help maintain grid stability and secure the real-time balance between generation and demand. Their role has become even more critical with the growing integration of ND-RES, which introduce greater variability into the system. Reserve markets, which procure upward and downward flexibility to maintain system balance, are commonly considered a key subset of ASM. Depending on the jurisdiction, some ancillary services are procured through competitive mechanisms within ASM, while others are non-negotiable requirements enforced and overseen by the system operator [83, 84]. A detailed discussion of short-term energy markets and ASM is provided in Sections 2.3.3 and 2.3.4, respectively.

2.3.2 Future/forward markets and bilateral contracts

In the future/forward electricity markets, participants can trade standardized contracts for the future delivery of a specified amount of electricity within a pre-defined time period. These markets are typically organized and provide transparent pricing, centralized clearing, reduced counterparty risk, and access to a broader pool of participants, which enhances liquidity, market efficiency, and price discovery [16, 33, 85, 86]. In contrast, bilateral contracts are customized agreements between two parties, negotiated privately outside of a central market or organized exchange. They provide greater flexibility in terms of contract structure, volume, pricing, and duration, allowing the terms to be tailored to the specific needs of the parties involved [87, 88, 89]. Both instruments allow electricity producers and consumers to hedge against price volatility, secure revenue streams, and ensure supply-demand balance over longer planning horizons [15, 17, 90].

2.3.3 Energy markets

Day-ahead market

The first pool in the electricity trading process involves clearing a market that spans the full 24-hour period of the delivery day, segmented into hourly intervals. This market is typically known as the DAM, though it may also be referred to as the spot market in Europe or forward market in the USA. Participants—both producers and consumers—submit offers and bids for each hourly segment, generally around 12 hours prior to the start of electricity delivery. These submissions consist of discrete blocks, each defined by a specific quantity of electricity and an associated price the party is willing to accept or pay [29, 91]. To determine the market outcome, the operator compiles aggregated supply and demand curves by sorting these blocks in ascending order of price. The point at which these curves intersect establishes the market-clearing price and traded volume. Only offers and bids priced more competitively than or equal to this clearing point are accepted; those with less favorable prices are excluded. This price serves as the benchmark for compensating generators and billing consumers [92, 93].

To manage discrepancies between forecasted and actual energy production, MOs impose various penalty mechanisms on ND-RES when their submitted forecasts deviate from real output. Additionally, many of the financial incentives that once supported ND-RES deployment have been phased out. As a result, ND-RES must now compete in the DAM under the same regulatory and operational frameworks as dispatchable units. This exposes them to potential penalties for forecast inaccuracies, putting them at a structural disadvantage compared to more controllable generation sources [41, 94]. Given the inherent variability of ND-RES, participating in the DAM can expose operators to financial risks from forecast errors. Aggregating multiple, geographically distributed ND-RES into a VPP can mitigate this risk through diversification, thereby smoothing the overall generation profile. This aggregation reduces the likelihood of deviations and associated penalties while enhancing profitability [22, 30, 95].

Intra-day market

In the DAM, market participants must submit their offers several hours ahead of the actual delivery period, relying on forecasts of energy availability. These forecasts are inherently uncertain, and this uncertainty tends to increase as the forecast horizon extends. As a result, the associated risks and financial penalties significantly compromise the competitiveness of ND-RES in energy markets [6]. Reducing these forecast errors at the time of offer submission is therefore vital for ND-RES. One potential solution is to shorten the interval between the DAM clearing and the delivery period, which would improve forecast accuracy. However, this approach is not feasible in practice, as dispatchable generators require sufficient lead time to adjust their schedules due to their operational constraints. To address this, IDM, also known as adjustment markets, have been introduced. These markets serve as intermediate trading platforms that operate between the DAM and the delivery period, with the final IDM session typically closing 30 minutes to 1 hour before delivery [11, 20]. IDM provide an opportunity for ND-RES and other stakeholders to revise their offers and bids based on updated weather and demand forecasts, which are typically more reliable closer to real-time. This reduces forecast error, increases revenue stability, and lowers market exposure [5, 21]. IDM mechanisms vary in design. In discrete IDM, such as in the Spanish market up until mid-2024, participants engage in auction-based trading and receive a uniform clearing price [22]. Conversely, in continuous IDM systems like the German market, participants can submit and update bids in real time, following a pay-as-bid format similar to stock market trading [23]. These markets play a crucial role in enhancing the flexibility and market integration of ND-RES, and by extension, of the VPP, thereby boosting their competitiveness and viability.

2.3.4 Ancillary service markets

Balancing market

Participation in the DAM and IDM operates under the assumption that the VPP can deliver or consume the exact quantities of energy or power committed in each cleared market interval. However, this assumption does not always hold true, as unforeseen factors often lead to deviations between the scheduled and actual performance [25, 44]. These discrepancies may stem from internal issues within the VPP, such as the unexpected failure of a generation unit, or from external grid-related factors—for instance, transmission line outages necessitating redispatch, or updated SR instructions issued by the TSO [27, 30]. To address such imbalances occurring between the closure of the final IDM session and the start of the next delivery period, the BAM is activated [43]. This market, initiated by the TSO, is designed to correct energy deviations that exceed predefined thresholds. The settlement interval for balancing actions can range from one hour to several hours, depending on the system's operational needs and the severity of the imbalance [31]. Various approaches have been developed for determining optimal bidding strategies for VPP participation in the DAM, especially by accounting for potential real-time deviations and the financial implications in the BAM. These strategies typically aim to improve profitability while mitigating risks linked to forecast uncertainties [44, 96, 97]. However, most of these methods do not directly address bidding in the BAM, as its gate-closure occurs after the final IDM session, making it inaccessible for optimization during DAM bidding. To overcome this limitation, some approaches treat the BAM as a distinct market stage, introducing a second bidding step once the DAM outcomes are known, thereby enabling more adaptive and responsive trading behavior [31, 43, 98, 99].

Reserve market

Reserve refers to additional power capacity that generators must maintain in their schedules to respond to sudden fluctuations in demand or unexpected outages in generation. While DAM and IDM are managed by the MO, reserve markets fall under the supervision of the TSO, who is tasked with maintaining system reliability [8, 28]. The definition and categorization of reserves vary by country, leading many studies to address reserve provision without strict classification. However, research has extensively explored how VPP can participate in reserve markets, particularly to leverage their flexibility and portfolio composition [29, 81, 99, 100]. Some works distinguish reserves into specific types: PR, SR, and TR. PR is the initial response mechanism during frequency deviations caused by incidents such as equipment failures or rapid load increases. Shortly after, SR takes over to restore system frequency and inter-area power exchange to reference values. Participation in SR requires TSO qualification, with technical criteria such as the ability to sustain reserve delivery for 15 minutes within an hourly resolution, and a response time within 100 seconds [8]. Unlike PR, SR is intentionally slower to prevent instability due to overlapping control actions, which means the system frequency may temporarily deviate from nominal values [36].

In some countries, such as Spain, the control framework for SR involves a hierarchical system. A central controller dispatches signals to multiple zones, which coordinate reserve provision using their distributed generation assets. Each zone is accountable for meeting its reserve obligations based on cleared regulation bands. If activated in real time, participating units are compensated through both capacity and energy payments [28]. A comparable example can be found in Germany, where VPPs have already demonstrated participation in SRMs through platforms such as Next Kraftwerke, which aggregates thousands of distributed units to provide secondary control reserves [101]. This highlights that while design details differ across jurisdictions, the principle of enabling VPPs to provide reserve capacity is broadly applicable across regions.

To meet stringent reserve performance requirements, VPP configurations often combine variable ND-RES with more controllable resources like hydro plants or storage systems (e.g., pumped hydro or short-term storage units). Such aggregation enables VPP to offer consistent and reliable reserve services. Studies have analyzed VPP participation across several types of reserve markets, including PRM [33, 34] and

SRM [33, 34, 38], highlighting their potential for increased flexibility and system support. If the SR is insufficient, TR is activated [36]. This service, typically provided by large generators connected to the transmission network, addresses sustained power imbalances and is available for both upward and downward adjustments. TR involves slower ramp rates and longer start-up times, making it suitable for thermal power plants with predictable activation schedules. It is designed to support or replace SR if frequency targets are not met [35]. Although participation in TR is optional, units that opt in are required to submit bids. No obligation to be qualified to providing this service, but once scheduling, the bidding is mandatory. Research on VPP involvement in TRM is less common, though some studies highlight its potential benefits for grid reliability and operational efficiency [6, 33].

Reactive power market

Voltage in the transmission grid is mainly regulated through the deployment of reactive power resources. Reactive power and voltage control services can be either mandatory or supplementary. For mandatory services, service providers are required to meet specific connection criteria based on the voltage level at their connection point and their available capacity [102]. Supplementary services, on the other hand, refer to optional, additional provisions of reactive power or voltage control. Most EU countries adopt a mandatory framework for reactive power and voltage control. In some regions, this service is compensated, while in others it is not. Certain DER, depending on their capacity, are also required to support voltage control. The aggregation of multiple DER in the form of a VPP has been explored as a means of providing voltage regulation [103, 104]. As shown in [39], VPP units can often deliver local grid support services—such as voltage and reactive power regulation—without significantly impacting their active power schedules, resulting in additional economic benefit. Several studies [34, 105, 106, 107] consider the reactive power market as a viable opportunity for VPP participation.

2.4 Multi-energy and carbon markets

2.4.1 Multi-energy markets

Multi-Energy VPP (MEVPP) represents an advanced form of VPP that integrates multiple types of energy sources—such as electricity, hydrogen, natural gas, and thermal energy—to enhance flexibility, efficiency, and coordination across different energy networks. By leveraging sector coupling and diverse load engagement, MEVPPs can effectively participate in various power markets, ASMs, and demand response programs, offering superior energy management capabilities [108].

In many studies, MEVPPs have been designed to incorporate electrical, thermal (heating and cooling), and even water-based systems to provide enhanced grid-supporting services such as peak shaving, frequency regulation, and voltage control [95, 109, 110, 111, 112]. Integrating thermal markets with electricity markets enables smoother transitions between energy types and supports operational and economic optimization [113, 114, 115]. Thermal energy trading can be realized through centralized thermal markets [113, 114], localized exchanges [115], or bilateral contracts [116] such as Heat Purchase Agreement (HPA) [117, 118], which offer price stability and support in meeting thermal demand, especially when internal generation is limited.

Moreover, coupling the electricity and natural gas networks improves the economic, environmental, and operational performance of MEVPPs. The high transport and storage capacity of gas infrastructure can mitigate the variability of renewable generation, allowing more reliable and flexible energy balancing. Participation in both electricity and Natural Gas Markets (NGMs) enables MEVPPs to optimize resource allocation and enhance grid resilience [47, 48, 113, 114].

Hydrogen markets are emerging as an additional avenue for MEVPP participation [119]. As hydrogen becomes increasingly relevant in the decarbonization of the energy sector, MEVPPs can engage in hydrogen trading by incorporating electrolyzers and storage systems. This allows them to convert excess renewable electricity into hydrogen, which can later be used as a fuel or traded, adding a further layer of flexibility and revenue potential [120]. Hydrogen thus represents a novel energy vector that can serve as a long-term storage medium for power in the coming decades, further enhancing system flexibility.

2.4.2 Carbon trading market

The VPP can participate in the Carbon Trading Market (CTM) by trading carbon credit allowances, where each credit corresponds to offsetting 1 tCO_2 of emissions from polluting units [121]. Under the EU Emissions Trading System (ETS), carbon allowances are allocated annually to emitting units based on predefined criteria. Each unit must surrender sufficient credits to match its verified yearly emissions [122]. Although the CTM is traded daily—often at a fixed price—it is more effective for VPP operators to schedule fossil-based units on an annual basis due to seasonal variations in RES output and demand, which leads to different level of pollution [123]. Meanwhile, the CTM—as part of the EU ETS—regulates emissions through a cap-and-trade mechanism. Allowances are distributed based on historical activity and performance benchmarks, with participants required to cover annual emissions by holding or trading sufficient credits [122]. The joint consideration of environmental factors and economic objectives in VPP operation—particularly through coordinated participation in electricity markets and the CTM—has been explored in the literature [50, 124]. VPP incorporating fossil-fueled units or industrial demand can participate in carbon trading, adding both environmental value and an additional revenue stream to their operations.

2.5 Joint vs. sequential markets

2.5.1 Sequential markets

In sequential markets, different markets—such as the DAM, SRM, and Real-Time Market (RTM)—are cleared one after another, independently. Bids submitted to each market are treated separately, and participants may not always have full knowledge of the outcomes from earlier markets when placing bids in later ones. For example, in some reserve markets, bids must be placed before the DAM results are published, so participants commit capacity without knowing their exact cleared energy positions. This differs from the European DAM–IDM sequence, where IDM participants can adjust their positions after DAM results are known [125]. While this approach offers benefits such as a simpler market structure and lower computational requirements, clearing markets independently can still prevent the achievement of a globally optimal solution. Coordination between energy and reserve procurement is limited, as these services are cleared separately. Consequently, participants make decisions with incomplete information about other market results. Moreover, this lack of coordination can lead to inefficiencies, such as unintentionally committing the same capacity in both energy and reserve markets [18]. It is worth noting that in most European countries, the sequential market clearing approach still dominates electricity markets. However, efforts toward implementing joint markets and improving overall market efficiency are currently underway [102, 125, 126].

Although energy and reserve clearing are handled separately in sequential markets, the RVPP can optimize its energy and reserve decisions simultaneously before each market session to achieve better coordination and higher efficiency. In Spain, for instance, the DAM clears only energy, while reserve requirements are procured later through specific ASM. In this approach, the RVPP first optimizes both products internally and submits its energy bid to the DAM. It can then re-optimize based on DAM results (once available) and updated forecasts to submit the corresponding reserve bids. In this regard, Chapter 3 presents a comprehensive bidding strategy for RVPP participation in Spain's sequential electricity markets, considering coordinated optimization of energy and reserve.

2.5.2 Joint markets

In joint markets, a centralized clearing mechanism simultaneously evaluates bids for energy, reserves, and other potential services. The market optimization problem aims to maximize overall social welfare by balancing supply, demand, and ancillary service requirements while maintaining operational limits such as generator capacity and ramping constraints. These constraints are enforced across all products to guarantee feasibility. Joint markets feature a unified optimization process that determines all market outcomes—such as prices and dispatch schedules simultaneously [127]. This integrated approach offers benefits like enhancing social welfare or reducing total system costs across services, which results in more efficient resource utilization. It also improves price signals by capturing the opportunity costs across different services. However, joint market designs demand sophisticated optimization techniques and higher computational resources. Moreover, moving from sequential to joint markets often requires modifications in regulatory policies and system operator practices [18].

In the USA, joint electricity markets are commonly implemented by various Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs) such as PJM, MISO, CAISO, NYISO, and ISO-NE. Unlike sequential markets, these joint markets use co-optimization to clear multiple products—mainly energy and ancillary services like reserves—in a single market process. This co-optimization yields Locational Marginal Prices (LMPs) for energy and shadow prices (dual values) for reserves and other ancillary services, reflecting overall system value and congestion costs [128].

2.6 Market power

2.6.1 Price-taker RVPP

The VPP model for participation in electricity markets can be established based on the size of the VPP. If the VPP is small compared to other units in the network, it does not have enough influence to affect the market electricity price and can only bid or offer energy and reserve according to predicted market prices. In other words, the VPP model takes market prices as given inputs, i.e., it acts as a price taker. The price-taker approach is appropriate for analyzing the behavior of a small VPP aiming to maximize its profit in the market under fixed price scenarios. Many studies have adopted this approach to model VPP participation [20, 22, 29, 30, 33, 37, 41, 43, 44, 45, 46, 89, 91, 93, 97, 113, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142].

2.6.2 Price-maker RVPP

The price-taker approach does not capture the strategic influence that a larger VPP might exert in the market. When the VPP's size increases—either individually or through the aggregation of multiple VPPs—its impact on market prices can no longer be neglected. In such cases, the price-taker assumption becomes unrealistic, and a price-maker framework is needed to model market power effects. In the price-maker approach, the VPP's size and strategic position enable it to influence market-clearing prices. Therefore, the optimization model must consider the VPP's ability to affect prices through its bidding strategy, aiming to maximize profit by leveraging its market power. This results in more complex bi-level or multi-level optimization problems. At the first level, the VPP optimizes its profit, while at the second level, the market-clearing mechanism determines prices based on all submitted bids, including those from the VPP. The price-maker approach is studied, for instance, in [32, 92, 143, 144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155, 156, 157, 158, 159, 160]. A key assumption in this approach is that the VPP has some knowledge of other participants' strategies—an assumption that greatly increases modeling complexity. In reality, this information is often incomplete or uncertain, requiring robust or stochastic methods to better represent strategic behavior under imperfect information. While price-maker models provide a more realistic framework for large VPPs, they pose significant challenges in computation and data acquisition.

2.7 Regulatory barriers for RVPP

While the European energy market is gradually opening up to new entrants, there are significant barriers that prevent RVPPs from participating on an equal footing with traditional power plants. There is a quite significant number of barriers that are related to the regulatory framework. Regulation might bear disincentives to RVPP participation in markets. This section analyzes the major regulatory barriers in place today in the European context, as well as how to overcome them in the future. These barriers are gathered in two groups: (i) barriers associated to the product definition in markets and to the bidding formats (Section 2.7.1); and (ii) barriers introduced by missing markets and imperfect price signals (Section 2.7.2). The aforementioned groups of barriers are discussed in detailed in the remainder of this section.

2.7.1 The product definition in markets and the bidding formats

This section identifies the main barriers that RVPP need to facerelated to the products that are currently available for these agents to participate.

Facilitating conditions to participate in the market

First and foremost, it is worth mentioning that some of the resources that can potentially form a RVPP often face barriers to (individually) entry in electricity markets due to restrictive pre-qualification requirements, minimum size, strict technical specifications or cumbersome registration processes. Sometimes these demanding conditions apply only to some of the markets.

The main issue is when these requirements are unjustified from a cost benefit standpoint, since they exclude some valuable resources from market participation. The requirements will clearly depend on the particular type of market. In this line, for instance, it is proposed the following minimum size in the context of the project OneNet [161]:

"The minimum quantity or bid size will be set at 10 kW for DSO products or 1 MW for TSO products (in case of active power). These values trade-off the technical requirements for the system operators to have quantities that are meaningful for their needs with the capacity of individual Flexibility Service Providers (FSPs) to deliver the product which could facilitate liquidity in the market."

Facilitating as much as possible market access is thus a fundamental prerequisite to increase RVPP participation in markets.

The need to rethink ancillary services and other related products

Some ancillary services that might have value in the future are not procured and remunerated based on market mechanisms. This is for example the case with Frequency Containment Reserve (FCR) in many systems. Solar PV inverters could be used to provide FCR, but they will do so only to the extent that this service is appropriately priced and rewarded (and, clearly, available). Therefore, all participants in general, and RVPPs in particular, will have to be paid for all products they provide. To this aim, disaggregating these products as much as possible is required (i.e. there will be an availability price and an energy use price if the product includes capacity and energy).

Moreover, in order to define products that can particularly engage FDs to participate, a learning process is required where consumers would play a central role analyzing and disclosing the value they associate with their consumption, and how much they are willing to ask for different types of interruptions involving different amounts of energy, as well as their duration.

The need to rethink bidding formats

The goal of a market exchange is to facilitate trading to help participants manage their risks and efficiently match available supply with demand. In this respect, a key element for electricity markets is the design of bidding formats that allow market agents to include information about their costs and operating constraints. For instance, significant limitations to optimally bid with an Energy Storage System (ESS) exist in some European markets. In some cases, bidding formats require the participant to anticipate specifically in which periods the ESS should be producing electricity and in which periods it should be consuming electricity, and to place separate bids. In some other cases, it is not properly accounted for the energy limitations when providing some ancillary services.

Allowing portfolio bidding

Portfolio bidding allows several resources (within the same pricing zone) to submit a joint bid in the market as if the portfolio was a single plant. It is then possible to internally decide the operation of each resource to reach the required production. For an effective integration of RVPPs, portfolio bidding will need to be allowed to all relevant type of configurations of RVPPs.

RVPPs face technical and regulatory barriers that constrain their full integration and participation in electricity markets [162]. Market rules for portfolio bidding vary across countries and often restrict aggregation to specific configurations, such as generation-only portfolios [163]. For instance, DAMs in Italy, Spain, and Portugal exclude certain generation types from portfolio bidding. While reserve markets more commonly permit portfolio bidding, it is typically limited to portfolios managed by a single agent [164]. These restrictions, particularly on configurations combining generation and demand-side resources, limit RVPP profitability. Addressing these barriers is thus essential to unlocking their full potential in modern electricity markets.

In the context of RVPP energy market and ASMs participation across different European countries, two key factors are typically considered in relation to unit aggregation. The first is *Aggregation Allowance*, which determines whether it is permissible to combine multiple assets into a single offering or bidding unit within the market. The second is *Heterogeneity Allowance*, which assesses whether aggregators can include DERs and RESs from different technologies (both dispatchable and stochastic), or not [14].

Defining the perimeter of RVPP

As introduced in [14], the RVPP is a new concept which brings together generation and grid aspects, where resources can be connected to both transmission and distribution grids, and thus the RVPP perimeter may contain both types of grids.

However, the maximum geographic scope that would be reasonable for an RVPP aiming at bidding all resources within the portfolio as a single plant will depend on the particular type of market in which they are selling services. In general, physical products will involve some restricted perimeters. The constraints over the proximity of resources will depend on the type of services the RVPP is aimed at (e.g., some local services can only be provided by resources that are electrically close).

2.7.2 Inefficient price signals and missing markets

Simulation results from Chapter 4 as well as from [71, 165] demonstrate that, as variability increases, the need for reliable market price signals increases. In general, price signals are robust in the DAM time frame, for markets in this time frame are liquid enough (see Section 4 of [71]). However, this is unfortunately not the case neither in the very long (see Section 3 of [71]) nor in the shorter term (see Sections 3 through 5 of [165]). Note that there are also missing price signals at the distribution level, since the markets are still in an early stage of development.

The lack of efficient long-term signals

One of the relevant problems related to electricity markets in general is the lack of liquid signals in the very long-term. This situation creates a double (and specular) source of uncertainty that does not allow to take advantage of all potential benefits from RVPPs (or any other resources) in the long term. On the one hand, the system operators (both TSOs and DSOs) cannot predict accurately the potential response of RVPPs in the long-term and, therefore, cannot include their role in the long-term when planning. On the other hand, RVPPs cannot shield against the risks associated to any investment decision to be carried out.

Selling services in the long term can provide stable signals for the potential investors and, if there is a reliable commitment from RVPPs with system operators, the latter can better plan in the long-term the different requirements for the system counting with the RVPP response.

These long-term signals can come from selling capacity in capacity markets, energy in long-term energy markets or ancillary services with longer term contracts.

However, these long-term signals often do not currently exist for one of the following two reasons: (i) either its participation is not allowed in some of these markets (either directly, or indirectly because of the existence of significant barriers) or (ii) these markets simply do not exist in the long-term (for example, not all countries have implemented the provision of ancillary services in the long-term).

The lack of efficient shorter-term signals

The expression shorter-term refers to the time interval between the DAM and the real-time dispatch. During this period, market participants may, in some cases, adjust their positions (bids) in the market, and the system operator must carry out all the necessary actions to ensure supply in real time, managing the resources under its control according to the information available at any given moment. Generally speaking, it can be said that RES penetration has increased the importance of very short-term markets and mechanisms in electrical systems, because it is within this time horizon that the relevant information for the dispatch of these technologies is generated.

The IDM allows participants to adjust their offers from the DAM before real time, based on the information that is updated. This operation reduces the difference between market schedules and the actual operation of the system, and with it the deviations, minimizing (in principle) also the need for reserves. Being a market for adjustments of the position matched in the DAM, the product is the same as in this market, i.e., energy.

Current debates point to the creation of more liquid IDMs, and to reform their design to improve efficiency in a context of high RES penetration. Introducing auctions to complement the continuous market, increasing the time resolution of the product, increasing the frequency of these auctions, and bringing them closer to real time are elements that move in this direction.

2.8 Conclusions and thesis scope

This thesis considers an RVPP composed mainly of renewable and flexible distributed units, with emphasis on their variability and limited dispatchability compared to CGs. The profit maximization perspective is adopted because the RVPP is modeled as a market participant that strategically coordinates different RES to optimize its economic return. The analysis focuses on short-term electricity markets—specifically the DAM, IDM, and SRM—and models the RVPP as a small-scale, price-taking entity with exogenous electricity prices. Medium- and long-term contracting, bilateral agreements, and participation in multi-energy (gas, heat, hydrogen) markets or CTM are acknowledged as relevant but remain outside the scope. Furthermore, while price-maker behavior and strategic bidding of large RVPPs are recognized as important, they are left for future research. Finally, although regulatory barriers and imperfect price signals currently restrict RVPP participation in European markets, this thesis assumes idealized market access conditions to focus on the methodological development of bidding strategies under uncertainty.

3 RVPP Objective Functions and Components – Description, Characterization and Modeling

To effectively manage the participation of the RVPP in both electricity and reserve markets, a comprehensive mathematical formulation is required. The optimization framework must account for the technical characteristics of the units, market mechanisms, and forecast data. In this chapter, a deterministic formulation is presented for the operation and bidding of the RVPP in the *sequential electricity markets*, assuming the *exact* value of uncertain parameters.

3.1 Framework

In order to operate the RVPP in an economically viable manner, it is necessary for the RVPP to participate in different electricity markets to cover its costs and generate profit. It has already been mentioned that the primary source of income for the RVPP comes from its participation in the DAM, in which the MO provides or receives payments based on the amount of energy supplied to or consumed from the network [2, 11]. Additionally, operators have designed distinct IDMs mechanisms that allow units to (i) "update" their submitted energy volumes after the DAM has been cleared and (ii) compensate for any unexpected imbalance [22]. In the literature, there is a vast body of papers that model the behavior of VPP in the energy markets, which mainly includes DAM and IDM [5, 22, 113, 166]. In [22], a multi-stage programming model is proposed for a VPP, including WFs, for participation in the DAM and the sequential Spanish IDM. A Conditional Value-at-Risk (CVaR) approach and sensitivity analysis are performed to evaluate the effects of risk and parameter variations on the optimization problem. In [5], a coordination strategy for different power producers, including CSP, ESS, WFs, and demand response providers, is proposed for DAM and IDM participation using a three-stage decision-making framework. In [113], to achieve the lowest operating cost under the worst-case scheduling scenario, the participation of a MEVPP in the DAM, considering deviation balancing in the IDM, is taken into account. In [166], a rolling horizon optimization approach is proposed for the integration of distributed generation in the form of a VPP for DAM and IDM participation. The interactions between MOs, aggregators, and customers are taken into account in the models.

In addition to energy markets, several reserve markets are run to guarantee the security of the system. Most of such markets are based on the availability of certain levels of power reserves (capacities) that were adequately scheduled in advance. The papers [29, 33, 41, 46, 131, 138] study the VPP participation in multi-markets, including energy and reserve markets. In contrast to the energy markets, such as the DAM and IDM, which are overseen by the MO, the reserve markets are settled by the TSO. The reserve is a margin of power that the power plants are required to include in their generation programs to address unexpected load changes or generation failures. In [33], a co-optimization method is proposed to model an urban VPP participating in energy market and ASMs considering BAM. In [131], a deterministic price-taker model is proposed for the participation of a VPP in energy, reserve, and reactive power markets. The VPP in this paper includes CG, ESS, and interruptible loads. A nonlinear deterministic model is proposed for the participation of a price-taker VPP in the energy and spinning reserve markets in [138]. Paper [46] proposes a multi-objective RO problem to maximize the operational benefit of a VPP while minimizing operational risk and carbon emissions. The authors use weight coefficients and a payoff table to transform the multi-objective problem into a single-objective one and apply fuzzy logic to solve the resulting MILP problem. In [29, 41], VPP participation in the DAM for trading both energy and reserves is modeled using a Stochastic Adaptive Robust Optimization (SARO) problem. However, the complete formulation for the reserve provision of each VPP unit and the associated constraints is simplified.

Overall, these studies share a common focus on developing optimization-based strategies that capture the interplay between different markets. Building on these common lines, this chapter formulates a deterministic framework for the RVPP objective function and its components in order to analyze its participation in different electricity markets. Within the context of this thesis, the purpose of the chapter is to provide the "skeleton" of the model that will serve as the foundation for the subsequent chapters. Most elements presented here are drawn from existing works in the literature, while certain aspects—such as adjustments in reserve modeling, market interactions, and the representation of specific components like CSP—constitute original contributions of this thesis.

3.2 Methodology

While many system operators opt for joint market clearing, especially in day-ahead and intra-day trading, there exist notable instances and specific segments where a sequential market clearing approach is observed. This is particularly evident in the balancing and reserve markets, where individual countries often manage these aspects separately from the main energy market [18, 167]. This distinction is crucial as the dynamics, rules, and challenges of sequential markets differ from those of joint clearing markets. Further, it is important to distinguish between joint market clearing, joint decision-making for determining optimal bids, and joint bidding. In a sequential market clearing structure, decision-making for determining optimal bids can be made jointly (i.e., different markets can be considered simultaneously at the time of making the optimal decision for the market participant, although such markets are cleared sequentially by the operator). The bids for the different markets can then be submitted jointly or sequentially according to market gate closing times. Hence, the choice is to consider sequentially cleared markets for the formulation of the bidding model in this thesis. In this section, the concept of sequential electricity markets is first introduced, using the Spanish electricity market as a representative example of a typical market sequence in European countries. Accordingly, the bidding strategy of the RVPP used in this thesis for participation in sequential markets is presented. Subsequently, different optimization problems for RVPP participation in these sequential markets are formulated.

3.2.1 RVPP bidding in sequential markets

Figure 3.1 depicts the Spanish electricity market structure until mid-2024 as an example of a typical market sequence in European countries [22]. The Spanish energy markets included the DAM and seven IDMs. The generation units and demands send DAM offers for an upcoming day, including both electricity price and energy, to the Operador del Mercado Ibérico de Energía (OMIE). The OMIE is responsible for clearing the DAM based on the offers and bids submitted by the RVPP and other participants in the electricity markets [18]. The TSO of Spanish network (Red Eléctrica de España (REE)) assigns the required SR according to security economic dispatch to maintain network security. Additionally, the REE and OMIE determine the final accepted reserve offers in the SRM to ensure sufficient reserves are available to manage real-time imbalances [8]. Units have opportunities to adjust their DAM energy offers by participating in IDMs. The sequential optimization problems are solved in this thesis based on the fact that more accurate forecasts of uncertain parameters could be available as time approaches the power delivery period. It is worth noting

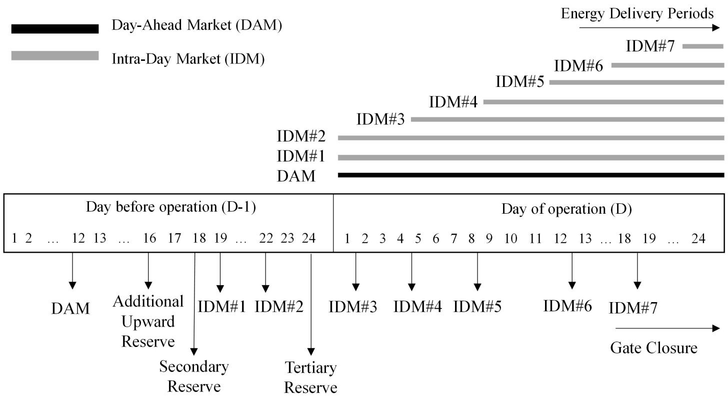


Figure 3.1: Spanish electricity markets structure until mid-2024 [8].

that from mid-2024 onward, the Spanish market design was updated and now includes only three IDMs, which is the current structure. However, in this thesis the previous structure of the Spanish market is used.

Figure 3.2 illustrates the bidding strategy of the RVPP in sequential electricity markets, including the DAM, SRM, and IDMs. It also depicts the information flow between these markets and the required input data for solving the corresponding optimization problems. The RVPP is assumed to be a price taker, offering electricity at zero price in the energy and reserve markets, and bidding at a high price for electricity purchases. This strategy increases the likelihood of the RVPP's offers and bids being accepted. Given that all RVPP units are renewable and have low operational costs, and considering the relatively small size of the RVPP compared to the overall system, this assumption is both reasonable and consistent with renewable energy integration practices. Since market prices are unknown prior to market clearing, the RVPP optimization model uses electricity price forecasts as inputs, derived from large sets of historical data. It is important to note that the problem is formulated from the perspective of the RVPP operator as a bidding entity, without access to the bids of other market participants—unlike a system operator. Furthermore, the proposed bidding strategy can be adapted for joint-clearing market structures; for instance, if the DAM and SRM are cleared simultaneously, the RVPP can apply the top pane of Figure 3.2 to submit offers to both markets concurrently.

According to Figure 3.2, the step-by-step solution methodology of the optimization problems for different market sessions in the Spanish electricity market is summarized below:

1. The RVPP receives the input data of its units in addition to the forecast of uncertain parameters before the gate closure of each electricity market selected for participation.

2. The RVPP maximizes its benefits by solving different optimization problems defined in Sections 3.2.2–3.2.4 related to each market session.

3. The results of solving the optimization problems are used to bid energy or reserve in the corresponding electricity market and to determine the dispatch of RVPP units.

4. The bids submitted by RVPP to the markets are cleared based on the priorities of OMIE and REE, and then the results are sent to the RVPP operator. The energy and reserve bids may or may not be accepted according to the decision of the MO. Note that the RVPP finds the optimal bids according to the forecast data and whether they are feasible or not will be determined by the system operator.

5. The RVPP uses its accepted bids from previous market sessions as well as the updated input data and forecast of uncertain parameters to solve the optimization problem for the upcoming market session.

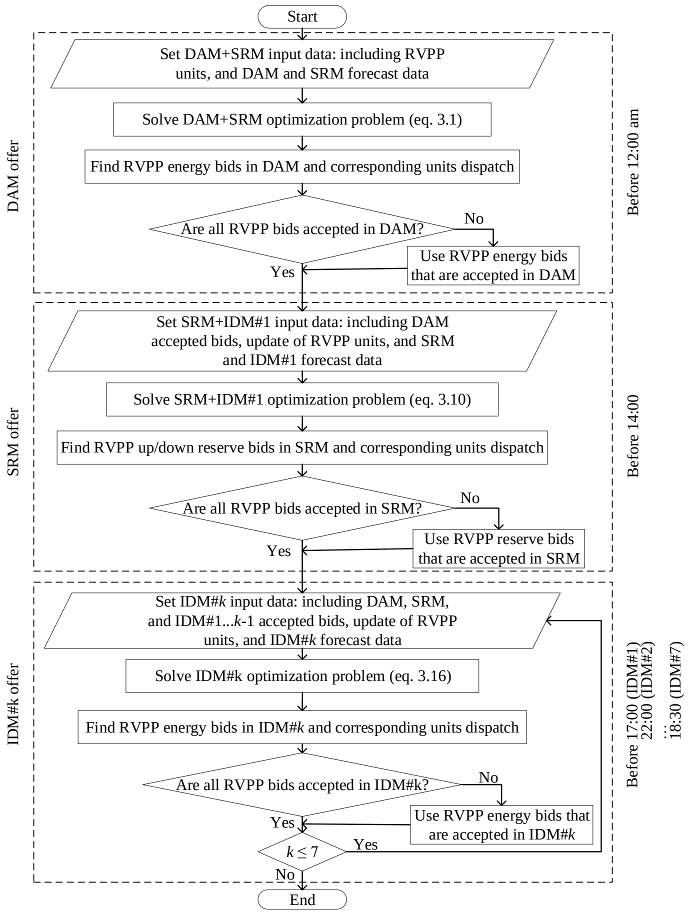


Figure 3.2: Bidding strategy of RVPP in the sequential electricity markets.

In the proposed RVPP bidding scheme, the interconnection between the markets is appropriately addressed. For example, in the case of the DAM objective function, the possibility of providing reserve in the SRM needs to be considered. Therefore, the optimization problem for both DAM and SRM is performed (see upper pane of Figure 3.2). The RVPP offers energy to the DAM before the DAM gate closure. However, the up/down reserve *is not offered* and can be reoptimized before the SRM gate closure. In addition, the first IDM (IDM#1) effect in the SRM objective function is considered, but the IDM#1 bid results *are not offered* in the SRM (see middle pane of Figure 3.2). Finally, the objective function for each IDM is optimized by considering the bidding results of DAM, SRM, and previous IDMs (see bottom pane of Figure 3.2). The proposed bidding approach allows the RVPP to omit some of the above electricity markets if so deemed. For instance, the SRM or a number of IDMs can be ignored, and RVPP can go for the subsequent market, in which the input data is based on previously implemented markets. It is worth noting that IDMs are not included in the co-optimization problem of the DAM snapshot. The reason is that the co-optimization of DAM and IDMs can lead to a speculation effect. For instance, a net seller RVPP might attempt to benefit by, e.g., buying a large amount of energy in the DAM to sell it later at a higher price in the IDMs or vice versa. However, this co-optimization is not implemented because usually, the regulator of the system does not allow this kind of participation in the market. Besides, IDMs tend to have much less liquidity than DAM and are mainly used for minor energy adjustments (however, there are some IDMs with relatively high traded energy such as IDM#1 in the Spanish system). Therefore, with low market liquidity, there is a high risk of not being called in the IDM, thus potentially incurring notable economic losses for the RVPP.

The optimization problems involved in the different electricity markets shown in Figure 3.2, namely (i) DAM+SRM; (ii) SRM+IDM#1; and (iii) IDM#k, will be developed in Sections 3.2.2–3.2.4 of this chapter.

3.2.2 Deterministic DAM+SRM formulation

The deterministic formulation accounts for the operation and bidding of the RVPP in the electrical energy and reserve markets, assuming the *exact* value of uncertain parameters. This section presents the deterministic objective function and constraints of the optimization problem.

The main sets used in this section are as follows: $d \in \mathscr{D}$ denotes the set of demands, $c \in \mathscr{C}$ the set of D-RESs, $r \in \mathscr{R}$ the set of ND-RESs, $\theta \in \Theta$ the set of CSPs, $t \in \mathscr{T}$ the set of time periods, $t \in \mathscr{T}_k$ the set of IDM#k time periods, $p \in \mathscr{P}$ the set of daily load profiles, $k \in \mathscr{K}$ the set of IDM sessions, $n \in \mathscr{N}$ the set of segments of the piecewise efficiency function of Power Block (PB) of CSPs, $m \in \mathscr{M}$ the set of daily load profiles, and Ξ the set of decision variables. In addition, p denotes power, λ represents market prices, C indicates costs, and r refers to reserves. A complete list of notation is provided in the preamble of this document.

Objective function

The deterministic objective function, outlined in (3.1), aims to maximize the RVPP's benefits in the electrical DAM and SRM, while accounting for operational costs of units. The first term of (3.1) represents the expected revenues from the RVPP's bids in the DAM, as well as upward (↑) and downward (↓) SRM. The second and third terms calculate the operational costs associated with ND-RES and CSP. The fourth term calculates the operational costs of D-RES, including their start-up and shut-down costs.

$$
\begin{aligned}
&\max_{\Xi^{DA+SR}} \sum_{t\in\mathscr{T}} \left[\lambda_t^{DA} p_t^{DA} \Delta t + \lambda_t^{SR,\uparrow} r_t^{SR,\uparrow} + \lambda_t^{SR,\downarrow} r_t^{SR,\downarrow}\right] \\
&- \sum_{t\in\mathscr{T}} \sum_{r\in\mathscr{R}} C_r p_{r,t} \Delta t - \sum_{t\in\mathscr{T}} \sum_{\theta\in\Theta} C_\theta p_{\theta,t} \Delta t \\
&- \sum_{t\in\mathscr{T}} \sum_{c\in\mathscr{C}} \left[C_c p_{c,t} \Delta t + C_c^{SU} v_{c,t}^{SU} + C_c^{SD} v_{c,t}^{SD}\right]
\end{aligned}
\tag{3.1}
$$

Supply & demand traded constraints

The equality constraint governing the supply-demand balance of electrical energy and reserve for RVPP units is defined in (3.2a). This accounts for all possible reserve activation scenarios in real-time, including upward reserve activation, downward reserve activation, and no reserve activation. To model these scenarios, vectors $\boldsymbol{r}_t^{SR} = \{r_t^{SR,\uparrow}, -r_t^{SR,\downarrow}, 0\}$; $\boldsymbol{r}_{r,t} = \{r_{r,t}^{\uparrow}, -r_{r,t}^{\downarrow}, 0\}$; $\boldsymbol{r}_{\theta,t} = \{r_{\theta,t}^{\uparrow}, -r_{\theta,t}^{\downarrow}, 0\}$; $\boldsymbol{r}_{c,t} = \{r_{c,t}^{\uparrow}, -r_{c,t}^{\downarrow}, 0\}$; and $\boldsymbol{r}_{d,t} = \{r_{d,t}^{\uparrow}, -r_{d,t}^{\downarrow}, 0\}$ are defined for the VPP, ND-RES, CSP, D-RES, and FD, respectively. Hence, (3.2a) conforms a set of three equations. The upper and lower bounds for the total electrical energy and reserve traded by the RVPP are governed by equations (3.2b) and (3.2c), respectively. The traded up and down reserve of the RVPP is limited to a proportion of its maximum electrical production minus its FD capacity, as outlined in constraints (3.2d) and (3.2e) [51].

$$\sum_{r\in\mathscr{R}}[p_{r,t}+\boldsymbol{r}_{r,t}]+\sum_{\theta\in\Theta}[p_{\theta,t}+\boldsymbol{r}_{\theta,t}]+\sum_{c\in\mathscr{C}}[p_{c,t}+\boldsymbol{r}_{c,t}]$$
$$-\sum_{d\in\mathscr{D}}[p_{d,t}-\boldsymbol{r}_{d,t}]=p_t^{DA}+\boldsymbol{r}_t^{SR}\,; \qquad \forall t \tag{3.2a}$$

$$p_t^{DA}+r_t^{SR,\uparrow}\leq\sum_{r\in\mathscr{R}}\bar{P}_r+\sum_{\theta\in\Theta}\bar{P}_\theta+\sum_{c\in\mathscr{C}}\bar{P}_c\,; \qquad \forall t \tag{3.2b}$$

$$-\sum_{d\in\mathscr{D}}\bar{P}_d\leq p_t^{DA}-r_t^{SR,\downarrow}\,; \qquad \forall t \tag{3.2c}$$

$$r_t^{SR,\uparrow}\leq\kappa\left(\sum_{r\in\mathscr{R}}\bar{P}_r+\sum_{\theta\in\Theta}\bar{P}_\theta+\sum_{c\in\mathscr{C}}\bar{P}_c-\sum_{d\in\mathscr{D}}\bar{P}_d\right); \qquad \forall t \tag{3.2d}$$

$$r_t^{SR,\downarrow}\leq\kappa\left(\sum_{r\in\mathscr{R}}\bar{P}_r+\sum_{\theta\in\Theta}\bar{P}_\theta+\sum_{c\in\mathscr{C}}\bar{P}_c-\sum_{d\in\mathscr{D}}\bar{P}_d\right); \qquad \forall t \tag{3.2e}$$

Concentrated solar power plant

CSP are synchronous power plants that harness sunlight to produce thermal energy, which can be utilized for electricity generation, residential heating, or industrial applications. Parabolic Trough Collector (PTC) consist of long, curved mirrors that concentrate sunlight onto a tube containing a heat-transfer fluid, which absorbs the heat and facilitates energy transfer in the Solar Field (SF). The conversion of thermal energy into electrical power occurs in the PB of the CSP, where steam generated by the heated fluid drives a turbine. Additionally, molten salt Thermal Storage (TS) enable CSP to store heat for several hours, allowing for electricity production or heat supply even after sunset [168]. As a note, the TS can only be charged if energy is available at the SF, i.e., it cannot be charged by consuming (*purchasing*) energy from the grid. Figure 3.3 illustrates the CSP configuration proposed in this thesis, which can deliver both energy and reserve in the market. It is apparent that solar resource variability affects thermal energy production within the SF. Furthermore, the conversion process from thermal to electrical energy requires explicit modeling while considering reserve provision. Additionally, the presence of TS requires to account for different states of charging and discharging. The model must ensure that reserve provision does not compromise the availability of stored energy in the TS for later use. These interdependencies make the modeling of CSP significantly more intricate than that of ND-RES assets.

A. CSP power block constraints

The formulation for converting thermal energy into electrical energy in the PB of the CSP, considering reserve provision, is provided in (3.3) [1]. Constraint (3.3a) defines the limits for the thermal power output of the SF, taking into account a fixed value for the uncertain parameter of solar irradiation energy. The thermal power delivered to the PB for electricity generation via the steam turbine, as defined in (3.3b), is determined by several components as Figure 3.3 shows. These include the thermal power supplied by the SF, the discharging/charging power of the TS, and the last term accounting for turbine startup losses. The thermal power and reserve supplied to the PB of the CSP are constrained by the PB's capacity and the turbine's commitment status, represented by the binary variable $u_{\theta,t}$, as outlined in (3.3c)–(3.3d). The turbine's commitment status and its related constraints, such as minimum up/down time requirements, outlined in Section 3.2.2. The thermal power and reserve supplied to the PB are converted into electrical power and reserve according to the piecewise linear efficiency relationship described in (3.3e). It is worth noting that

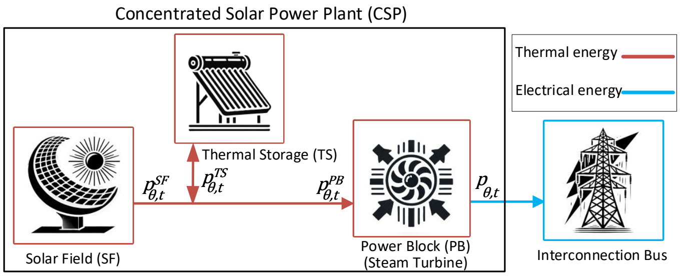


Figure 3.3: Scheme of the CSP providing energy and reserve.

real plants exhibit non-linear efficiency, which in this work is approximated by a piecewise linear function. If the thermal energy injected into the PB falls below a specified threshold, the turbine cannot turn on, resulting in zero output, as defined by the first term on the right-hand side of (3.3e). Once the injected thermal energy exceeds this threshold, the turbine begins generating electricity, according to the piecewise linear segments represented by the second term on the right-hand side of (3.3e). The efficiency $\eta_{\theta,n}$ of each segment in the piecewise linear function varies based on the thermal power and reserve injected into the PB. The real-time reserve activation scenarios for the TS, encompassing upward reserve activation, downward reserve activation, and no reserve activation, are represented by the vector $\boldsymbol{r}^{TS}_{\theta,t} = \{r^{TS,\uparrow}_{\theta,t}, -r^{TS,\downarrow}_{\theta,t}, 0\}$. The vector $\boldsymbol{r}_{\theta,t} = \{r^{\uparrow}_{\theta,t}, -r^{\downarrow}_{\theta,t}, 0\}$ represents the different states of reserve activation for the final reserve supplied by the CSP (see (3.2a)). The final up/down reserve is limited by reserve provision capability of CSP in (3.3f)–(3.3g). Finally, the nature of the binary variables is determined according to (3.3h).

$$0 \le p^{SF}_{\theta,t} \le P^{SF}_{\theta,t}\,; \qquad \forall \theta, t \qquad (3.3a)$$

$$p^{PB}_{\theta,t} = p^{SF}_{\theta,t} + p^{TS,-}_{\theta,t} - p^{TS,+}_{\theta,t} - K^{PB}_{\theta} v^{SU}_{\theta,t} \bar{P}^{PB}_{\theta}\,; \qquad \forall \theta, t \qquad (3.3b)$$

$$p^{PB}_{\theta,t} + r^{TS,\uparrow}_{\theta,t} \le \bar{P}^{PB}_{\theta} u_{\theta,t}\,; \qquad \forall \theta, t \qquad (3.3c)$$

$$\underline{P}^{PB}_{\theta} u_{\theta,t} \le p^{PB}_{\theta,t} - r^{TS,\downarrow}_{\theta,t}\,; \qquad \forall \theta, t \qquad (3.3d)$$

$$p_{\theta,t} + \boldsymbol{r}_{\theta,t} = \begin{cases} 0, & \text{if} \quad 0 \le p^{PB}_{\theta,t} + \boldsymbol{r}^{TS}_{\theta,t} \le P^{PB}_{\theta,n=1}\,; \quad \forall \theta, t \\ \eta_{\theta,n}(p^{PB}_{\theta,t} + \boldsymbol{r}^{TS}_{\theta,t}), & \text{if } P^{PB}_{\theta,n-1} \le p^{PB}_{\theta,t} + \boldsymbol{r}^{TS}_{\theta,t} \le P^{PB}_{\theta,n}\,; \ \forall \theta, t, n \backslash \{0,1\} \end{cases} \qquad (3.3e)$$

$$r^{\uparrow}_{\theta,t} \le T^{SR} \underline{R}^{SR}_{\theta}\,; \qquad \forall \theta, t \qquad (3.3f)$$

$$r^{\downarrow}_{\theta,t} \le T^{SR} \bar{R}^{SR}_{\theta}\,; \qquad \forall \theta, t \qquad (3.3g)$$

$$u_{\theta,t}, v^{SU}_{\theta,t} \in \{0,1\}\,; \qquad \forall \theta, t \qquad (3.3h)$$

The conditional piecewise function (3.3e) must be expressed as mathematical constraints to be compatible with the MILP framework. To achieve this, Special Ordered Set of Type 2 (SOS-2) constraints (3.4) are introduced. Constraint (3.4a) ensures that the input variables related to the thermal energy and reserve lie within the breakpoints of each piecewise segment of PB. Constraint (3.4b) defines the output variables related to the electrical energy and reserve of CSP. Constraints (3.4c)–(3.4f) enforce the SOS-2 property by ensuring the solution falls between two consecutive breakpoints. The vectors $\boldsymbol{x}_{\theta,t,n} =$

$\{x^{\uparrow}_{\theta,t,n}, -x^{\downarrow}_{\theta,t,n}, 0\}$ and $\varsigma_{\theta,t,n} = \{\varsigma^{\uparrow}_{\theta,t,n}, -\varsigma^{\downarrow}_{\theta,t,n}, 0\}$ are defined for the different reserve activation scenarios. Constraints (3.4g)–(3.4h) specify the nature of the positive and binary variables, respectively.

$$p^{PB}_{\theta,t} + \boldsymbol{r}^{TS}_{\theta,t} = \sum_{n \in \mathscr{N}} P^{PB}_{\theta,n} \boldsymbol{x}_{\theta,t,n}\,; \qquad \forall \theta, t \tag{3.4a}$$

$$p_{\theta,t} + \boldsymbol{r}_{\theta,t} = \sum_{n \in \mathscr{N}} \eta_{\theta,n} P^{PB}_{\theta,n} \boldsymbol{x}_{\theta,t,n}\,; \qquad \forall \theta, t \tag{3.4b}$$

$$\sum_{n \in \mathscr{N}} \boldsymbol{x}_{\theta,t,n} = 1\,; \qquad \forall \theta, t \tag{3.4c}$$

$$\sum_{n \in \mathscr{N}} \boldsymbol{\varsigma}_{\theta,t,n} \leq 2\,; \qquad \forall \theta, t \tag{3.4d}$$

$$\boldsymbol{x}_{\theta,t,n} \leq \boldsymbol{\varsigma}_{\theta,t,n}\,; \qquad \forall \theta, t, n \tag{3.4e}$$

$$\boldsymbol{\varsigma}_{\theta,t,n} + \boldsymbol{\varsigma}_{\theta,t,n'} \leq 1\,; \qquad \forall \theta, t, n \leq |\mathscr{N}| - 3, n' \geq n+2 \tag{3.4f}$$

$$\boldsymbol{x}_{\theta,t,n} \geq 0\,; \qquad \forall \theta, t, n \tag{3.4g}$$

$$\boldsymbol{\varsigma}_{\theta,t,n} \in \{0,1\}\,; \qquad \forall \theta, t, n \tag{3.4h}$$

B. CSP thermal storage constraints

A detailed formulation for the TS of the CSP is provided in (3.5), designed to incorporate both the thermal energy and reserve provision capabilities of the TS. Additionally, to mitigate potential infeasibility issues in the operation of the TS, the model, inspired by the approach in [1], allocates a specific portion of the TS energy capacity exclusively for the provision of upward (↑) and downward (↓) reserves. Constraints (3.5a)–(3.5d) limit the charging (+) and discharging (−) thermal power of the TS, accounting for the provision of upward and downward reserves. Notably, according to these constraints, the TS can provide upward or downward reserve in both charging and discharging states. The binary variable $u^{TS}_{\theta,t}$ defines the state of the TS, taking a value of 1 or 0 for charging or discharging, respectively. The final value of the upward or downward reserve provided by the TS is determined based on its reserve contributions during either the charging or discharging state, as described by equations (3.5e)–(3.5f). The relationship between thermal energy and power of the TS, considering its charging and discharging efficiency, is determined by (3.5g). To complement (3.5g), equation (3.5h) ensures that the SoC is equal in the initial and final periods. This constraint is relevant for DAM operation and scheduling of representative periods, as it maintains the TS energy level at the same state at the start of each cycle. It is worth noting that the initial TS energy level can be set according to the operator's perspective. A percentage of the TS's energy during the operational period is allocated for the provision of upward and downward reserves, as defined by the variables $\sigma^{\uparrow}_{\theta}$ and $\sigma^{\downarrow}_{\theta}$ in (3.5i)–(3.5j). Based on the energy allocated for reserve provision, the operational energy limits of the TS are established in (3.5k). The nature of the binary variable $u^{TS}_{\theta,t}$ is specified in (3.5l).

$$\underline{P}^{TS,+}_{\theta} u^{TS}_{\theta,t} \leq p^{TS,+}_{\theta,t} - r^{TS,+,\uparrow}_{\theta,t}\,; \qquad \forall \theta, t \tag{3.5a}$$

$$p^{TS,+}_{\theta,t} + r^{TS,+,\downarrow}_{\theta,t} \leq \bar{P}^{TS,+}_{\theta} u^{TS}_{\theta,t}\,; \qquad \forall \theta, t \tag{3.5b}$$

$$p^{TS,-}_{\theta,t} + r^{TS,-,\uparrow}_{\theta,t} \leq \bar{P}^{TS,-}_{\theta} (1 - u^{TS}_{\theta,t})\,; \qquad \forall \theta, t \tag{3.5c}$$

$$\underline{P}^{TS,-}_{\theta} (1 - u^{TS}_{\theta,t}) \leq p^{TS,-}_{\theta,t} - r^{TS,-,\downarrow}_{\theta,t}\,; \qquad \forall \theta, t \tag{3.5d}$$

$$r^{TS,\uparrow}_{\theta,t} = r^{TS,+,\uparrow}_{\theta,t} + r^{TS,-,\uparrow}_{\theta,t}\,; \qquad \forall \theta, t \tag{3.5e}$$

$$r^{TS,\downarrow}_{\theta,t} = r^{TS,+,\downarrow}_{\theta,t} + r^{TS,-,\downarrow}_{\theta,t} \,; \qquad \forall \theta, t \qquad (3.5f)$$

$$e^{TS}_{\theta,t} = e^{TS}_{\theta,t-1} + p^{TS,+}_{\theta,t} \eta^{TS,+}_{\theta} \Delta t - \frac{p^{TS,-}_{\theta,t} \Delta t}{\eta^{TS,-}_{\theta}} \,; \qquad \forall \theta, t \backslash \{1\} \qquad (3.5g)$$

$$e^{TS}_{\theta,1} = e^{TS}_{\theta,t=T} \,; \qquad \forall \theta \qquad (3.5h)$$

$$\sum_{t \in \mathscr{T}} \frac{r^{TS,\uparrow}_{\theta,t} \Delta t}{\eta^{TS,-}_{\theta}} \leq \sigma^{TS,\uparrow}_{\theta} \left(\bar{E}^{TS}_{\theta} - \underline{E}^{TS}_{\theta} \right) \,; \qquad \forall \theta \qquad (3.5i)$$

$$\sum_{t \in \mathscr{T}} r^{TS,\downarrow}_{\theta,t} \eta^{TS,+}_{\theta} \Delta t \leq \sigma^{TS,\downarrow}_{\theta} \left(\bar{E}^{TS}_{\theta} - \underline{E}^{TS}_{\theta} \right) \,; \qquad \forall \theta \qquad (3.5j)$$

$$\underline{E}^{TS}_{\theta} + \sigma^{TS,\downarrow}_{\theta} \left(\bar{E}^{TS}_{\theta} - \underline{E}^{TS}_{\theta} \right) \leq e^{TS}_{\theta,t} \leq \bar{E}^{TS}_{\theta} - \sigma^{TS,\downarrow}_{\theta} \left(\bar{E}^{TS}_{\theta} - \underline{E}^{TS}_{\theta} \right) \,; \qquad \forall \theta, t \qquad (3.5k)$$

$$u^{TS}_{\theta,t} \in \{0, 1\} \,; \qquad \forall \theta, t \qquad (3.5l)$$

C. CSP turn on/Off constraints

The minimum up and down time constraints for the turbine of CSP are formulated in (3.6) and are adopted from [169]. Constraints (3.6a) and (3.6b) define the commitment status of the turbine. The parameters N^{ON}_{θ} and N^{OFF}_{θ} are the number of initial periods during which turbine must be online/offline, respectively. Equation (3.6c) defines the initial status of turbine as defined by N^{ON}_{θ}. Constraint (3.6d) restricts the minimum up time during all combination of the subsequent periods UT_{θ}. Constraint (3.6e) defines the minimum up time for the final periods $UT_{\theta} - 1$. Constraints (3.6f)–(3.6h) are the minimum down time version of (3.6c)–(3.6e). Finally, the nature of binary variables is shown in (3.6i).

$$u_{\theta,t} - u_{\theta,t-1} = v^{SU}_{\theta,t} - v^{SD}_{\theta,t} \,; \qquad \forall \theta, t \qquad (3.6a)$$

$$v^{SU}_{\theta,t} + v^{SD}_{\theta,t} \leq 1 \,; \qquad \forall \theta, t \qquad (3.6b)$$

$$\sum_{t=1}^{N^{ON}_{\theta}} [1 - u_{\theta,t}] = 0 \,; \qquad \forall \theta \qquad (3.6c)$$

$$UT_{\theta}(u_{\theta,t} - u_{\theta,t-1}) \leq \sum_{t'=t}^{t+UT_{\theta}-1} u_{\theta,t'} \,; \qquad \forall \theta, t = N^{ON}_{\theta} + 1, ..., T - UT_{\theta} + 1 \qquad (3.6d)$$

$$0 \leq \sum_{t'=t}^{T} [u_{\theta,t'} - (u_{\theta,t} - u_{\theta,t-1})] \,; \qquad \forall \theta, t = T - UT_{\theta} + 2, .., T \qquad (3.6e)$$

$$\sum_{t=1}^{N^{OFF}_{\theta}} u_{\theta,t} = 0 \,; \qquad \forall \theta \qquad (3.6f)$$

$$DT_{\theta}(u_{\theta,t-1} - u_{\theta,t}) \leq \sum_{t'=t}^{t+DT_{\theta}-1} [1 - u_{\theta,t'}] \,; \qquad \forall \theta, t = N^{OFF}_{\theta} + 1, .., T - DT_{\theta} + 1 \qquad (3.6g)$$

$$0 \leq \sum_{t'=t}^{T} [1 - u_{\theta,t'} - (u_{\theta,t-1} - u_{\theta,t})] \,; \qquad \forall \theta, t = T - DT_{\theta} + 2, ..., T \qquad (3.6h)$$

$$u_{\theta,t}, v^{SU}_{\theta,t}, v^{SD}_{\theta,t} \in \{0, 1\} \,; \qquad \forall \theta, t \qquad (3.6i)$$

ND-RES constraints

ND-RES, such as WFs and solar PVs, are characterized in this thesis by their uncertain and variable output, low marginal operating costs, and limited controllability. Nevertheless, they can still contribute to system flexibility by providing reserve in the SRM, subject to their technical capabilities [170, 171]. Upward reserve can be supplied when ND-RES are operated at a curtailed level and then increase their generation during reserve activation. In contrast, downward reserve is provided by reducing their output power from the existing operational level. The constraints related to ND-RES are formulated in (3.7). The upper and lower bounds for the output energy and reserve of ND-RES, using the precise value for the uncertain parameter $P_{r,t}$, are defined in constraints (3.7a) and (3.7b), respectively. The up and down reserve provision capabilities by ND-RES are constrained by equations (3.7c) and (3.7d), respectively.

$$p_{r,t} + r^{\uparrow}_{r,t} \leq P_{r,t}\,; \qquad \forall r, t \tag{3.7a}$$

$$\underline{P}_r \leq p_{r,t} - r^{\downarrow}_{r,t}\,; \qquad \forall r, t \tag{3.7b}$$

$$r^{\uparrow}_{r,t} \leq T^{SR} \bar{R}^{SR}_r\,; \qquad \forall r, t \tag{3.7c}$$

$$r^{\downarrow}_{r,t} \leq T^{SR} \underline{R}^{SR}_r\,; \qquad \forall r, t \tag{3.7d}$$

Demand constraints

In this thesis, FD is modeled using two levels of flexibility: (i) FD profiles, which represent alternative consumption patterns that the RVPP operator can choose from, and (ii) bounds, which define the allowable deviations around each selected profile. This representation enables the RVPP to adapt its FD behavior by either switching among profiles or adjusting within the limits associated with the chosen profile. It should be noted that this is only one of several possible approaches to capture FD flexibility; for instance, shiftable-load or load-scheduling formulations are also commonly used in the literature [172]. Within the proposed framework, FD flexibility is modeled differently across markets: in the DAM, only profile selection is considered, whereas in the IDMs the additional flexibility captured by the bounds is applied.

The constraints for FD are outlined in (3.8), following the approach in [173]. Constraint (3.8a) establishes the minimum limit for FD in each time period, based on predefined demand profiles and fixed values for the uncertainties within each profile. Constraint (3.8b) ensures that only one demand profile is selected by the algorithm from multiple available profiles. The allowable range for FD, including reserve provision, is defined by the lower and upper bounds in (3.8c) and (3.8d), respectively. FD are permitted a specific percentage of flexibility relative to their predefined profiles, which is allocated for upward and downward reserve provision as defined in (3.8e) and (3.8f), respectively. The upward and downward reserves provided by FD are further limited by the demand's reserve provision capability, as detailed in (3.8g) and (3.8h). Additionally, the minimum energy consumption over the time horizon for FD is assigned by (3.8i). The nature of binary variables is indicated in (3.8j).

$$p_{d,t} \geq \sum_{m \in \mathscr{M}} \left[P_{d,m,t} u_{d,m} \right]; \qquad \forall d, t \tag{3.8a}$$

$$\sum_{m \in \mathscr{M}} u_{d,m} = 1\,; \qquad \forall d \tag{3.8b}$$

$$\underline{P}_d \leq p_{d,t} - r^{\uparrow}_{d,t}\,; \qquad \forall d, t \tag{3.8c}$$

$$p_{d,t} + r^{\downarrow}_{d,t} \leq \bar{P}_d\,; \qquad \forall d, t \tag{3.8d}$$

$$r^{\uparrow}_{d,t} \leq \underline{\beta}_{d,t} p_{d,t} \; ; \qquad \forall d,t \tag{3.8e}$$

$$r^{\downarrow}_{d,t} \leq \bar{\beta}_{d,t} p_{d,t} \; ; \qquad \forall d,t \tag{3.8f}$$

$$r^{\uparrow}_{d,t} \leq T^{SR} \underline{R}^{SR}_{d} \; ; \qquad \forall d,t \tag{3.8g}$$

$$r^{\downarrow}_{d,t} \leq T^{SR} \bar{R}^{SR}_{d} \; ; \qquad \forall d,t \tag{3.8h}$$

$$\underline{E}_d \leq \sum_{t \in \mathscr{T}} \left[p_{d,t} \Delta t - r^{\uparrow}_{d,t} \right] ; \qquad \forall d \tag{3.8i}$$

$$u_{d,m} \in \{0,1\} \; ; \qquad \forall d,m \tag{3.8j}$$

D-RES constraints

D-RESs in this thesis refer to renewable-based units that can be operated in a controllable manner, similar to conventional thermal units. A typical example is a hydro power plant, which can schedule its output and provide reserves according to system requirements. The modeling approach applied to D-RESs is therefore the same as that used for conventional thermal units and does not involve any uncertainty.

Constraints (3.9a)–(3.9b) define the upper and lower bounds for the production of each D-RES, taking into account the provision of SR. Constraints (3.9c)–(3.9d) regulate the upward and downward reserves of D-RES based on the activation time of the SR and the SR ramp rate capabilities of D-RES. The binary nature of the status of D-RES is indicated in (3.9e). The minimum up and down time requirements for D-RES are modeled similarly to the CSP constraints in (3.6). The only difference is that the index $\theta \in \Theta$ for CSP must be replaced with the index $c \in \mathscr{C}$.

$$p_{c,t} + r^{\uparrow}_{c,t} \leq \bar{P}_c u_{c,t} \; ; \qquad \forall c,t \tag{3.9a}$$

$$\underline{P}_c u_{c,t} \leq p_{c,t} - r^{\downarrow}_{c,t} \; ; \qquad \forall c,t \tag{3.9b}$$

$$r^{\uparrow}_{c,t} \leq T^{SR} \bar{R}^{SR}_{c} \; ; \qquad \forall c,t \tag{3.9c}$$

$$r^{\downarrow}_{c,t} \leq T^{SR} \underline{R}^{SR}_{c} \; ; \qquad \forall c,t \tag{3.9d}$$

$$u_{c,t} \in \{0,1\} \; ; \qquad \forall c,t \tag{3.9e}$$

3.2.3 Deterministic SRM+IDM#1 formulation

In the DAM+SRM problem discussed in Section 3.2.2, the viability of participating in the SRM is also considered. However, when the offer/bid is submitted to the MO, only the energy to be traded in the DAM is submitted (see Section 3.2.1 for more details on the market structure). In the SRM+IDM#1 session, the clearance results from the DAM are available, and forecasts of uncertain parameters are updated. Based on this new information, the RVPP can re-optimize both its IDM#1 energy and SRM reserve to achieve improved economic results while maintaining feasibility for subsequent market sessions.

Objective function

Assuming, without loss of generality, that the RVPP is a net energy seller, then the energy that the RVPP had available (at least from the forecast) and was not offered in the DAM, is considered as *reserved* for the SRM. In Spain, the SRM closure time before mid-2024 was almost simultaneous with the first IDM. Since this time was also closer to the first power delivery period, it is expected that the forecasts of the uncertain data, if updated with respect to those available when the DAM problem was solved, are more accurate. This is formulated in (3.10). The first term of (3.10) represents the expected revenues from the RVPP's bids in the upward (↑) and downward (↓) SRM, as well as IDM#1. The second and third terms calculate the rescheduled operational costs associated with ND-RES and CSP. The fourth term calculates the rescheduled operational costs of D-RES, including start-up and shut-down costs. The result of this deterministic optimization problem will then be submitted for participating in both the SRM and IDM#1.

$$\begin{aligned}\max_{\Xi^{SR+ID1}} & \sum_{t\in\mathscr{T}} \left[\lambda_t^{SR,\uparrow} r_t^{SR,\uparrow} + \lambda_t^{SR,\downarrow} r_t^{SR,\downarrow} + \lambda_{(k=1),t}^{ID} p_{(k=1),t}^{ID} \Delta t\right] \\ & - \sum_{t\in\mathscr{T}} \sum_{r\in\mathscr{R}} C_r p_{(k=1),r,t}^{ID} \Delta t - \sum_{t\in\mathscr{T}} \sum_{\theta\in\Theta} C_\theta p_{(k=1),\theta,t}^{ID} \Delta t \\ & - \sum_{t\in\mathscr{T}} \sum_{c\in\mathscr{C}} \left[C_c p_{(k=1),c,t}^{ID} \Delta t + C_c^{SU} v_{c,t}^{SU} + C_c^{SD} v_{c,t}^{SD}\right]\end{aligned} \tag{3.10}$$

Supply & demand traded constraints

The supply-demand balancing constraint in the SRM+IDM#1 is fairly similar to DAM+SRM problem previously solved. If SRM+IDM#1 is solved, the power related to units in the DAM $\left(p_{r,t}^{DA^*}, p_{\theta,t}^{DA^*}, p_{c,t}^{DA^*}\right.$, and $\left.p_{d,t}^{DA^*}\right)$ and the total power traded in the DAM $\left(p_t^{DA^*}\right)$ now become known parameters, and the variable related to the IDM#1 units power $\left(p_{(k=1),r,t}^{ID}, p_{(k=1),\theta,t}^{ID}, p_{(k=1),c,t}^{ID}\right.$, and $\left.p_{(k=1),d,t}^{ID}\right)$ and total power traded in IDM#1 $\left(p_{(k=1),r,t}^{ID}\right)$ are added to (3.11a). The power traded constraints in the SRM+IDM#1 are written in (3.11b)–(3.11c). The power that had already been traded in the DAM is fixed, and the IDM#1 power is added to these constraints. Constraints (3.11d) are equivalent to the DAM+SRM problem.

$$\begin{aligned}& \sum_{r\in\mathscr{R}} \left[p_{r,t}^{DA^*} + p_{(k=1),r,t}^{ID} + \boldsymbol{r}_{r,t}\right] + \sum_{\theta\in\Theta} \left[p_{\theta,t}^{DA^*} + p_{(k=1),\theta,t}^{ID} + \boldsymbol{r}_{\theta,t}\right] \\ & + \sum_{c\in\mathscr{C}} \left[p_{c,t}^{DA^*} + p_{(k=1),c,t}^{ID} + \boldsymbol{r}_{c,t}\right] - \sum_{d\in\mathscr{D}} \left[p_{d,t}^{DA^*} + p_{(k=1),d,t}^{ID} - \boldsymbol{r}_{d,t}\right] \\ & = p_t^{DA^*} + p_{(k=1),t}^{ID} + \boldsymbol{r}_t^{SR}\,; \qquad \forall t\end{aligned} \tag{3.11a}$$

$$p_t^{DA^*} + p_{(k=1),t}^{ID} + r_t^{SR,\uparrow} \leq \sum_{r\in\mathscr{R}} \bar{P}_r + \sum_{\theta\in\Theta} \bar{P}_\theta + \sum_{c\in\mathscr{C}} \bar{P}_c\,; \qquad \forall t \tag{3.11b}$$

$$-\sum_{d\in\mathscr{D}} \bar{P}_d \leq p_t^{DA^*} + p_{(k=1),t}^{ID} - r_t^{SR,\downarrow}\,; \qquad \forall t \tag{3.11c}$$

$$\text{(3.2d)–(3.2e)}\,; \tag{3.11d}$$

CSP constraints

The electrical output power of CSP in the SRM+IDM#1 is updated by considering the CSP power change in the IDM#1 according to (3.12a) and (3.12b). Equations (3.12b) represents other constraints that are equivalent to the DAM+SRM problem.

$$\begin{aligned}& p_{\theta,t}^{DA^*} + p_{(k=1),\theta,t}^{ID} + \boldsymbol{r}_{\theta,t} = \\ & \begin{cases} 0, & if \quad 0 \leq p_{\theta,t}^{PB} + \boldsymbol{r}_{\theta,t}^{TS} \leq P_{\theta,n=1}^{PB}\,; \quad \forall\theta,t \\ \eta_{\theta,n}(p_{\theta,t}^{PB} + \boldsymbol{r}_{\theta,t}^{TS}), & if \ P_{\theta,n-1}^{PB} \leq p_{\theta,t}^{PB} + \boldsymbol{r}_{\theta,t}^{TS} \leq P_{\theta,n}^{PB}\,; \ \forall\theta,t,n\backslash\{0,1\} \end{cases}\end{aligned} \tag{3.12a}$$

$$p_{\theta,t}^{DA^*} + p_{(k=1),\theta,t}^{ID} + \boldsymbol{r}_{\theta,t} = \sum_{n\in\mathscr{N}} \eta_{\theta,n} P_{\theta,n}^{PB} \boldsymbol{x}_{\theta,t,n}\,; \qquad \forall\theta,t \tag{3.12b}$$

$$\text{(3.3a)–(3.3d), (3.3f)–(3.3h), (3.4a), (3.4c)–(3.4h), (3.5), (3.6)}\,; \tag{3.12c}$$

ND-RES constraints

The way ND-RES is formulated in the SRM+IDM#1 problem is quite similar to the DAM+SRM. If SRM+IDM#1 is solved, the power traded in the DAM $\left(p_{r,t}^{DA^*}\right)$ becomes a parameter, and the variable related to the IDM#1 power $\left(p_{(k=1),r,t}^{ID}\right)$ is added to (3.13a) and (3.13b). The forecast data of ND-RES r production in the SRM+IDM#1 $(P_{r,t})$ can be updated. Constraints (3.13c) are equivalent to the DAM+SRM problem.

$$p_{r,t}^{DA^*} + p_{(k=1),r,t}^{ID} + r_{r,t}^{\uparrow} \leq P_{r,t}\,; \qquad \forall r, t \tag{3.13a}$$

$$\underline{P}_r \leq p_{r,t}^{DA^*} + p_{(k=1),r,t}^{ID} - r_{r,t}^{\downarrow}\,; \qquad \forall r, t \tag{3.13b}$$

$$(3.7c)\text{–}(3.7d)\,; \tag{3.13c}$$

Demand constraints

The constraints of demand in the SRM+IDM#1 are similar to the corresponding DAM+SRM constraints but with some differences. The DAM power of demand is fixed at its optimal solution, and IDM#1 power of demand is added to the equations (3.14a)–(3.14f) to ensure the arbitrage strategy for RVPP. Similar constraints to DAM+SRM problem are represented in (3.14g).

$$p_{d,t}^{DA^*} + p_{(k=1),d,t}^{ID} \geq \sum_{m \in \mathscr{M}} \left[P_{d,m,t} u_{d,m}^{*}\right]; \qquad \forall d, t \tag{3.14a}$$

$$\underline{P}_d \leq p_{d,t}^{DA^*} + p_{(k=1),d,t}^{ID} - r_{d,t}^{\uparrow}\,; \qquad \forall d, t \tag{3.14b}$$

$$p_{d,t}^{DA^*} + p_{(k=1),d,t}^{ID} + r_{d,t}^{\downarrow} \leq \bar{P}_d\,; \qquad \forall d, t \tag{3.14c}$$

$$r_{d,t}^{\uparrow} \leq \underline{\beta}_{d,t} p_{d,t}^{DA^*}\,; \qquad \forall d, t \tag{3.14d}$$

$$r_{d,t}^{\downarrow} \leq \bar{\beta}_{d,t} p_{d,t}^{DA^*}\,; \qquad \forall d, t \tag{3.14e}$$

$$\underline{E}_d \leq \sum_{t \in \mathscr{T}} \left[p_{d,t}^{DA^*} \Delta t + p_{(k=1),d,t}^{ID} \Delta t - r_{d,t}^{\uparrow}\right]; \qquad \forall d \tag{3.14f}$$

$$(3.8b), (3.8g), (3.8h), (3.8j)\,; \tag{3.14g}$$

D-RES constraints

The SRM+IDM#1 constraints of D-RES are shown in equations (3.15a)–(3.15b). These constraints are similar to the DAM+SRM version in (3.9), but the power of DAM is fixed. Also, the power related to the IDM#1 is added to the D-RES constraints when necessary. The constraints that remain similar to DAM+SRM problem are represented as (3.15c).

$$p_{c,t}^{DA^*} + p_{(k=1),c,t}^{ID} + r_{c,t}^{\uparrow} \leq \bar{P}_c u_{c,t}\,; \qquad \forall c, t \tag{3.15a}$$

$$\underline{P}_c u_{c,t} \leq p_{c,t}^{DA^*} + p_{(k=1),c,t}^{ID} - r_{c,t}^{\downarrow}\,; \qquad \forall c, t \tag{3.15b}$$

$$(3.9c)\text{–}(3.9e)\,; \tag{3.15c}$$

3.2.4 Deterministic IDM#k formulation

In this section, the deterministic formulation of the IDM#k problem is introduced. In contrast to the joint DAM+SRM problem, the focus here is on the individual IDM#k session. The time horizon considered in each IDM#k problem may be shorter than 24 hours, depending on the specific session, and corresponds to the trading interval.

Objective function

The objective function of IDM#k participation is provided in (3.16), where the first term calculates the bidding income in each IDM. The second and third terms compute the rescheduled deterministic operation costs of ND-RES and CSP in each IDM. The fourth term calculates the rescheduled operation costs of D-RES. It is worth noting that the index τ represents the time periods associated with each IDM.

$$\max_{\Xi_k^{ID}} \sum_{t\geq\tau} \lambda_{k,t}^{ID}\, p_{(k=1),t}^{ID} \Delta t - \sum_{t\geq\tau}\sum_{r\in\mathscr{R}} C_r p_{k,r,t}^{ID} \Delta t - \sum_{t\geq\tau}\sum_{\theta\in\Theta} C_\theta p_{k,\theta,t}^{ID} \Delta t$$
$$- \sum_{t\geq\tau}\sum_{c\in\mathscr{C}} C_c p_{k,c,t}^{ID} \Delta t \tag{3.16}$$

Supply & demand traded constraints

In IDM#k, in addition to power related to units in the DAM and the total power traded in the DAM, the reserve provided in the SRM+IDM#1 $\left(\boldsymbol{r}_t^{SR^*}\right)$, the power related to units in the previous IDMs $\left(p_{k,r,t}^{ID^*},\right.$ $p_{k,\theta,t}^{ID^*}, p_{k,c,t}^{ID^*}$, and $\left.p_{k,d,t}^{ID^*}\right)$, and the power traded in the previous IDMs $\left(p_{k,t}^{ID^*}\right)$ become parameters. Besides, the time periods for each session of the IDM#k are updated in (3.17). It is worth noting that in (3.17), while the traded reserve $\left(\boldsymbol{r}_t^{SR^*}\right)$ is known, the reserves provided by units ($\boldsymbol{r}_{r,t}$, $\boldsymbol{r}_{\theta,t}$, $\boldsymbol{r}_{c,t}$, and $\boldsymbol{r}_{d,t}$) are not.

$$\sum_{r\in\mathscr{R}}\left[p_{r,t}^{DA^*} + \sum_{k=1}^{\mathscr{K}-1} p_{k,r,t}^{ID^*} + p_{k,r,t}^{ID} + \boldsymbol{r}_{r,t}\right] + \sum_{\theta\in\Theta}\left[p_{\theta,t}^{DA^*} + \sum_{k=1}^{\mathscr{K}-1} p_{k,\theta,t}^{ID^*} + p_{k,\theta,t}^{ID} + \boldsymbol{r}_{\theta,t}\right]$$
$$+ \sum_{c\in\mathscr{C}}\left[p_{c,t}^{DA^*} + \sum_{k=1}^{\mathscr{K}-1} p_{k,c,t}^{ID^*} + p_{k,c,t}^{ID} + \boldsymbol{r}_{c,t}\right] - \sum_{d\in\mathscr{D}}\left[p_{d,t}^{DA^*} + \sum_{k=1}^{\mathscr{K}-1} p_{k,d,t}^{ID^*} + p_{k,d,t}^{ID} - \boldsymbol{r}_{d,t}\right]$$
$$= p_t^{DA^*} + \sum_{k=1}^{\mathscr{K}-1} p_{k,t}^{ID^*} + p_{k,t}^{ID} + \boldsymbol{r}_t^{SR^*}; \qquad \forall t \geq \tau \tag{3.17a}$$

$$p_t^{DA^*} + \sum_{k=1}^{\mathscr{K}-1} p_{k,t}^{ID^*} + p_{k,t}^{ID} + r_t^{SR^*,\uparrow} \leq \sum_{r\in\mathscr{R}} \bar{P}_r + \sum_{\theta\in\Theta} \bar{P}_\theta + \sum_{c\in\mathscr{C}} \bar{P}_c; \qquad \forall t \geq \tau \tag{3.17b}$$

$$-\sum_{d\in\mathscr{D}} \bar{P}_d \leq p_t^{DA^*} + \sum_{k=1}^{\mathscr{K}-1} p_{k,t}^{ID^*} + p_{k,t}^{ID} - r_t^{SR^*,\downarrow}; \qquad \forall t \geq \tau \tag{3.17c}$$

CSP constraints

The CSP constraints in IDM#k are defined in (3.18). The forecast data of CSP θ thermal production in the IDM ($P^{SF}_{\theta,t}$) can be updated. The commitment status of CSP is considered the same as in the previous market session SRM+IDM#1. The time span for each session of CSP is considered in the formulation. Besides, the output power of CSP is updated based on the DAM output power of CSP, and the power change in the previous IDM sessions.

$$p^{DA^*}_{\theta,t} + \sum_{k=1}^{\mathscr{K}-1} p^{ID^*}_{k,\theta,t} + p^{ID}_{k,\theta,t} + \boldsymbol{r}_{\theta,t} = \begin{cases} 0, & if\ 0 \le p^{PB}_{\theta,t} + \boldsymbol{r}^{TS}_{\theta,t} \le P^{PB}_{\theta,n=1}\,; \quad \forall \theta, t \ge \tau \\ \eta_{\theta,n}(p^{PB}_{\theta,t} + \boldsymbol{r}^{TS}_{\theta,t}), & if\ P^{PB}_{\theta,n-1} \le p^{PB}_{\theta,t} + \boldsymbol{r}^{TS}_{\theta,t} \le P^{PB}_{\theta,n}\,; \ \forall \theta, t \ge \tau, n \backslash \{0,1\} \end{cases} \tag{3.18a}$$

$$p^{DA^*}_{\theta,t} + \sum_{k=1}^{\mathscr{K}-1} p^{ID^*}_{k,\theta,t} + p^{ID}_{k,\theta,t} + \boldsymbol{r}_{\theta,t} = \sum_{n \in \mathscr{N}} \eta_{\theta,n} P^{PB}_{\theta,n} \boldsymbol{x}_{\theta,t,n}\,; \qquad \forall \theta, t \ge \tau \tag{3.18b}$$

(3.3a)–(3.3d), (3.3f)–(3.3h), (3.4a), (3.4c)–(3.4h), (3.5); (3.18c)

ND-RES constraints

In IDM#k, in addition to the power traded in the DAM, the power in the previous IDMs $(p^{ID^*}_{k,r,t})$ becomes a parameter. The forecast data of ND-RES r production in the IDM ($P_{r,t}$) can be updated. Besides, the time periods for each session of the IDM#k are updated in (3.19).

$$p^{DA^*}_{r,t} + \sum_{k=1}^{\mathscr{K}-1} p^{ID^*}_{k,r,t} + p^{ID}_{k,r,t} + r^{\uparrow}_{r,t} \le P_{r,t}\,; \qquad \forall r, t \ge \tau \tag{3.19a}$$

$$\underline{P}_r \le p^{DA^*}_{r,t} + \sum_{k=1}^{\mathscr{K}-1} p^{ID^*}_{k,r,t} + p^{ID}_{k,r,t} - r^{\downarrow}_{r,t}\,; \qquad \forall r, t \ge \tau \tag{3.19b}$$

Demand constraints

The constraints of the demand in IDM#k are shown in (3.20). The DAM power of demand, and the power of demand in the previous IDMs are fixed at their optimal values.

$$p^{DA^*}_{d,t} + \sum_{k=1}^{\mathscr{K}-1} p^{ID^*}_{k,d,t} + p^{ID}_{k,d,t} \ge \sum_{m \in \mathscr{M}} \left[P_{d,m,t} u^*_{d,m}\right]; \qquad \forall d, t \ge \tau \tag{3.20a}$$

$$\underline{P}_d \le p^{DA^*}_{d,t} + \sum_{k=1}^{\mathscr{K}-1} p^{ID^*}_{k,d,t} + p^{ID}_{k,d,t} - r^{\uparrow}_{d,t}\,; \qquad \forall d, t \ge \tau \tag{3.20b}$$

$$p^{DA^*}_{d,t} + \sum_{k=1}^{\mathscr{K}-1} p^{ID^*}_{k,d,t} + p^{ID}_{k,d,t} + r^{\downarrow}_{d,t} \le \bar{P}_d\,; \qquad \forall d, t \ge \tau \tag{3.20c}$$

$$\underline{E}_d \leq \sum_{t=1}^{\tau-1}\left[p_{d,t}^{DA^*}\Delta t + \sum_{k=1}^{\mathscr{K}-1} p_{k,d,t}^{ID^*}\Delta t - r_{d,t}^{\uparrow}\right] + \sum_{t=\tau}^{\mathscr{T}}\left[p_{d,t}^{DA^*}\Delta t + \sum_{k=1}^{\mathscr{K}-1} p_{k,d,t}^{ID^*}\Delta t + p_{k,d,t}^{ID}\Delta t - r_{d,t}^{\uparrow}\right]; \quad \forall d \tag{3.20d}$$

(3.8b), (3.8g), (3.8h), (3.8j), (3.14d), (3.14e); (3.20e)

D-RES CONSTRAINTS

The constraints of D-RES in IDM#k are depicted in (3.21). The DAM power, and the power related to previous IDMs, which had already been assigned in the previous markets, are fixed in these equations. The commitment status of D-RES is considered the same as in the previous market session SRM+IDM#1.

$$p_{c,t}^{DA^*} + \sum_{k=1}^{\mathscr{K}-1} p_{k,c,t}^{ID^*} + p_{k,c,t}^{ID} + r_{c,t}^{\uparrow} \leq \bar{P}_c u_{c,t}; \quad \forall c,t \tag{3.21a}$$

$$\underline{P}_c u_{c,t} \leq p_{c,t}^{DA^*} + \sum_{k=1}^{\mathscr{K}-1} p_{k,c,t}^{ID^*} + p_{k,c,t}^{ID} - r_{c,t}^{\downarrow}; \quad \forall c,t \tag{3.21b}$$

(3.9c)–(3.9d) ; (3.21c)

3.3 Case studies

This section presents the simulation results based on the proposed deterministic framework for evaluating RVPP participation in the DAM, SRM, and IDMs. Simulations are performed on a Dell XPS with an i7-1165G7 2.8 GHz processor and 16 GB of RAM using the CPLEX solver in GAMS 39.1.1.

3.3.1 Data

The simulations consider an RVPP in Southern Spain consisting of a hydro plant, a biomass unit, a WF, a solar PV plant, a CSP equipped with TS, and a FD. The energy forecast for the ND-RES units—including the electrical outputs of the WF and solar PV, and the thermal output of the CSP—are illustrated in Figure 3.4. These energy forecasts are derived from historical data from March 2021: solar PV and CSP from CIEMAT Spain [174], and the WF from Iberdrola Spain [175]. The technical specifications of WF, solar PV, and CSP are provided in Tables 3.1 and 3.2. The efficiency of thermal-to-electrical energy conversion in the turbine varies depending on the thermal power of the PB, following the piecewise linear relationship depicted in Figure 3.5. Operating costs for all units have been levelized based on estimated operational expenses of different generation technologies in [176]. Information related to the D-RES, including the hydro and biomass plants, is drawn from [1, 126] and consolidated in Table 3.3. The energy forecasts for the FD are shown in Figure 3.6, using three representative demand profiles taken from [1]. Each base demand profile includes a 10% flexibility margin, meaning that the actual demand is allowed to deviate by up to 10% above or below the given profile. This margin reflects the level of adjustment that consumers can provide around their nominal demand. The main technical data related to the demands are provided in Table 3.4. Additionally, the forecasts for electricity prices in the DAM, SRM, and IDMs are based on historical data from [126] and visualized in Figure 3.7.

Table 3.1: ND-RES data.

Parameter	PV	WF
Maximum/minimum power output [MW]	50/0	50/0
SR ramp up rate [MW/min]	0.3	0.2
SR ramp down rate [MW/min]	0.5	0.5
SR relative to power capacity [%]	10	10

Table 3.2: CSP data.

SF	
SF maximum thermal power output [MW]	300
PB/Turbine	
PB maximum thermal power input [MW]	140
Turbine maximum electrical power output [MW]	55
Turbine minimum electrical power output [MW]	5
Turbine minimum up/down time [hour]	6
CSP output thermal power efficiency [%]	90
CSP SR ramp rate [MW/min]	2
CSP SR relative to power capacity [%]	50
CSP operation cost [€/MWh]	25
TS	
Maximum thermal energy [MWh]	1100
Minimum thermal energy [MWh]	110
Discharging thermal power [MW]	115
Charging thermal power [MW]	140
Dis/charging efficiency [%]	95

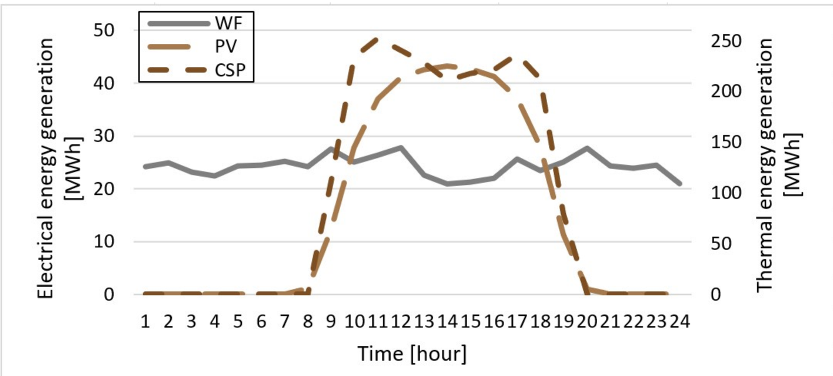


Figure 3.4: The energy forecast of WF, solar PV, and CSP.

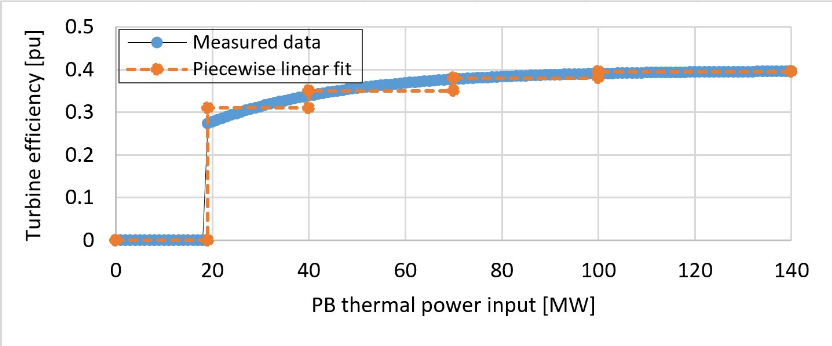


Figure 3.5: Thermal to electrical conversion efficiency of PB.

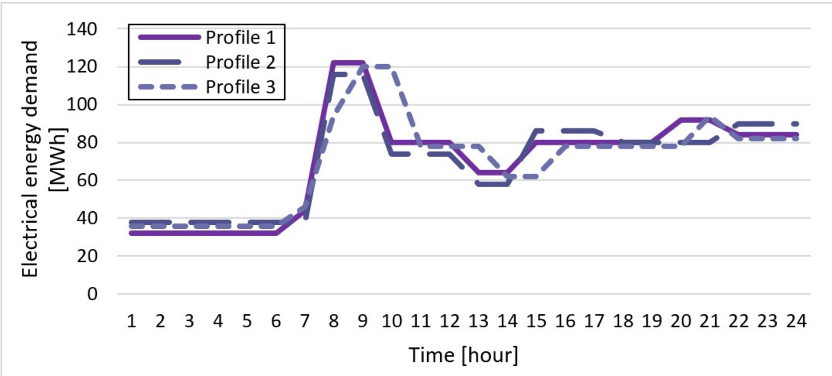


Figure 3.6: The energy forecast of FD.

Table 3.3: D-RES data.

Parameter	Hydro	Biomass
Maximum/minimum power output [MW]	50/10	10/2
Startup/shutdown cost [€]	100/50	300/150
Operation cost [€/MWh]	12.5	60
Minimum up/down time [hour]	1/0	3/3
SR ramp rate [MW/min]	3	0.1
Energy limit [MWh]	996	-

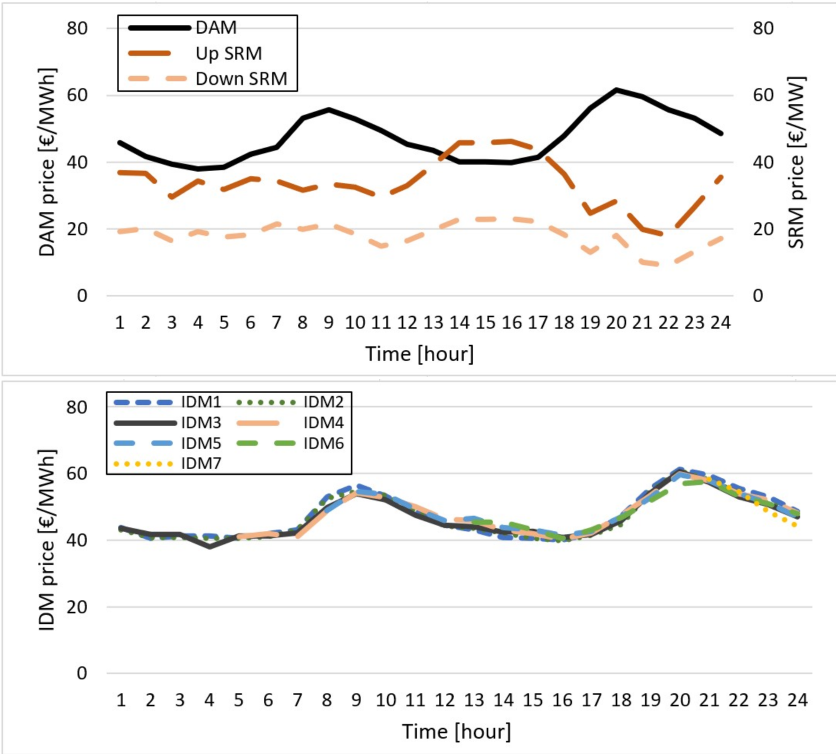


Figure 3.7: The DAM, SRM, and IDMs price forecast data.

Table 3.4: FD data.

Parameter	Value
Minimum daily energy consumption [MWh]	1684
Minimum power input [MW]	0
Maximum power input [MW]	180
Initial power input [MW]	84
SR ramp rate [MW/min]	3
SR relative to the power capacity [%]	10

3.3.2 Results

The results in this section include the bidding strategy of the RVPP in sequential markets, taking into account the updated forecast data at each electricity market session.

Figure 3.8 shows the cumulative traded energy and reserve of the RVPP up to each electricity market session. In the DAM, the RVPP acts as an energy seller during most hours, except in the early morning at hour 8. During this hour, solar PV and CSP have zero production, and the other RVPP units can only partially supply the demand. At hour 9, the CSP becomes operational, and solar PV begins generating electricity, allowing the RVPP to fully supply its demand. Between hours 10 and 12, the RVPP achieves its highest energy sales due to high availability from solar PV and CSP, and higher electricity prices (see Figure 3.7). Between hours 15 and 17, the RVPP sells less energy in the DAM due to lower electricity prices. In the subsequent hours (18–21), energy sales increase to take advantage of the second peak in electricity prices. After hour 22 until hour 7 of the morning, energy sales decrease due to reduced or zero production from CSP and solar PV.

The SRM results show that the RVPP provides both upward and downward reserves during most hours. However, the provided reserve decreases at hour 8 because most of the available RVPP units operate at their maximum capacity to supply internal demand. Additionally, between hours 19 and 23, reserve provision is reduced due to lower SRM prices, making it less profitable for the RVPP to participate in the reserve market.

In each session of the IDM, electricity price data are updated, and the RVPP accordingly adjusts its previous bids submitted in the DAM. Specifically, the RVPP purchases energy in IDM#1 during hours 2, 6, 7, 13, and 16, which results in a reduction in the total energy sold until IDM#1 (as shown in Figure 3.8). Additionally, it sells energy in hours 14, 15, and 17 to maximize profit. In the subsequent IDM sessions, the RVPP further adjusts its traded energy based on the updated data in each session to optimize its profit.

Figure 3.9 presents the scheduling of different RVPP units in the DAM+SRM session, providing a more in-depth analysis of the contribution of each technology to the traded energy of the RVPP. The results show that the output of the dispatchable hydro plant is reduced during hours 3–5 and 14–17, when the DAM electricity price is low. Additionally, the results indicate that the CSP unit is activated at hour 9 and continues to produce energy until hour 24. Thanks to its TS, it can continue generating electricity even after sunset.

Figure 3.10 shows the contribution of each technology in providing upward and downward reserves in the SRM. The figure illustrates that the hydro plant supplies the majority of the upward reserve between hours 1–7, as it operates below its maximum generation capacity during these hours. Between hours 9–18, most of the upward reserve is provided by the CSP unit, thanks to the flexibility of its TS. The FD and biomass plants also contribute to upward reserve in most hours due to their flexibility and consistent availability. During the night hours 1–7, the WF contributes a small portion of the upward reserve as well. Downward reserve is primarily provided by the hydro plant throughout most hours, as it is consistently generating energy and can effectively reduce its output when needed. Other RVPP units also participate in providing downward reserve, depending on their availability.

Table 3.5 shows different economic results including profit, revenue, and operation costs of RVPP until each session of electricity market. The results show that until last session of market the proposed RVPP configuration obtains 24 k€. Additionally there are changes in economic results in some session of market. Since the deterministic results (accurate forecast for generation of ND-RES units and electricity price) are provided, these economic results are not substantially changed in different sessions of markets.

Table 3.6 compares the economic results of units when they participate individually in the DAM+SRM and when they operate as an integrated RVPP. The results show that the total profit of units under individual participation in the market is only 13.67 k€. In contrast, when a coordinated strategy is adopted, their profit increases by 76.1%.

The computation time of proposed approach for all session of markets is below 1 second, shows the effectiveness of proposed approach for running multiple simulation in different market.

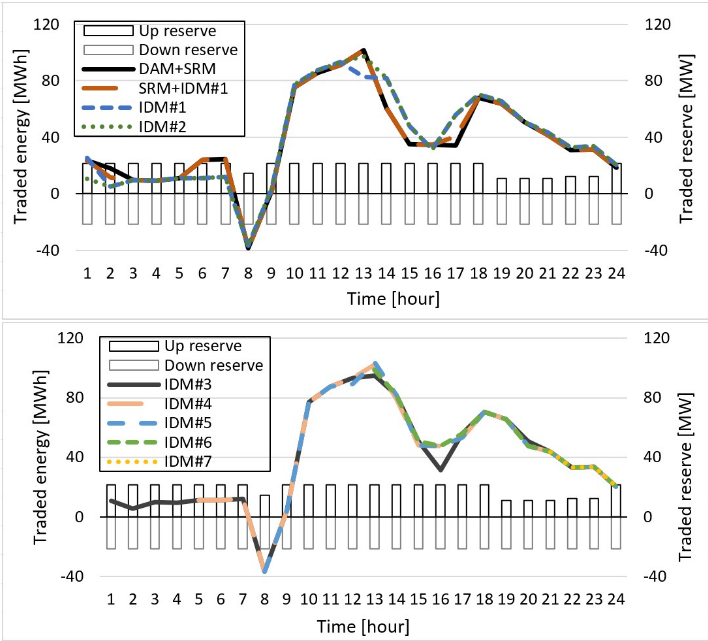


Figure 3.8: Total traded energy of RVPP until different sessions of electricity markets and traded reserve of RVPP.

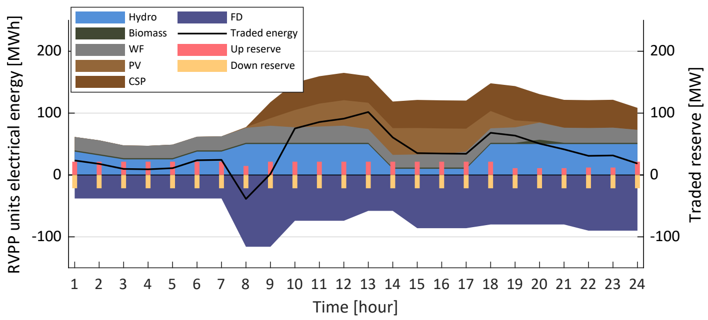


Figure 3.9: Electrical energy generation by RVPP units and traded energy and reserve by the RVPP in the DAM+SRM.

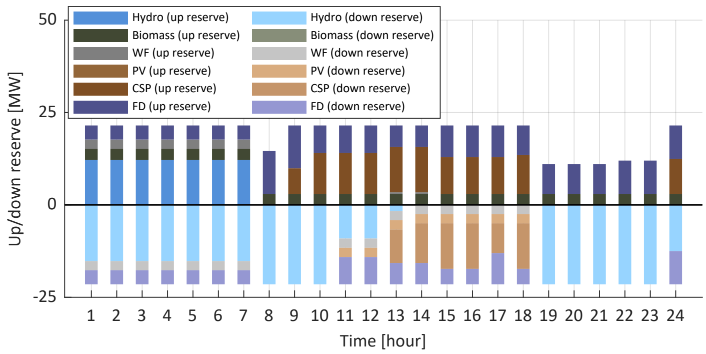


Figure 3.10: Up and down reserve provided by RVPP units in the DAM+SRM.

Table 3.5: RVPP economic results until different sessions of electricity markets (deterministic).

Market	Profit [k€]	Revenue [k€]	Cost* [k€]	Computational time [s]
DAM+SRM	24.07	68.56	44.49	0.26
SRM+IDM#1	24.08	68.57	44.49	0.20
IDM#1	23.73	69.55	45.81	0.14
IDM#2	23.74	69.56	45.81	0.23
IDM#3	23.74	69.55	45.81	0.18
IDM#4	24.00	70.04	46.04	0.14
IDM#5	24.00	70.04	46.04	0.11
IDM#6	24.00	70.03	46.03	0.09
IDM#7	24.00	70.03	46.03	0.09

**Cost includes operation cost of RVPP units.*

Table 3.6: Units economic results for individual and coordinated participation strategies in the DAM+SRM (deterministic).

Unit	Profit [k€]	Revenue [k€]	Cost [k€]
Hydro	38.84	50.58	11.74
Biomass	0.06	4.14	4.08
WF	20.39	28.55	8.16
PV	13.50	17.04	3.54
CSP	21.89	40.58	18.69
FD	-81.01	-81.01	0
Total	13.67	59.88	46.21
RVPP	24.07	68.56	44.49

3.4 Remarks

In this chapter, the main markets for RVPP participation and its viability are first reviewed. A deterministic formulation is proposed for the sequential market participation of the RVPP in both energy and reserve markets. The proposed algorithm accounts for the technical constraints of the RVPP, as well as the various market interactions that can influence its viability. Simulations are conducted for an RVPP located in Southern Spain, considering its participation across different Spanish electricity market sessions. The results highlight the contribution of the sequential market framework, showing how the RVPP updates its bidding strategy at each stage (DAM, SRM, IDM) according to forecast revisions and market prices. The results show that the proposed RVPP configuration achieves 24 k€ by the final session, with only minor changes across sessions due to the deterministic assumption (perfect forecasts for ND-RES generation and prices). The results also demonstrate that the RVPP primarily participates in the DAM as its main source of income and adjusts its scheduling in each IDM session based on updated forecast data. The findings also show that, using the proposed approach, the RVPP efficiently schedules its units and capitalizes on hours with higher electricity prices to maximize profitability. The RVPP acts as an energy seller during most hours, primarily due to the availability of its solar-dependent units during the day and hydro plant production during the night. However, the RVPP becomes an energy buyer in some early morning hours when its internal demand is high and its solar-dependent units are not generating electricity. Moreover, the algorithm enables coordinated energy and reserve provision, enhancing overall revenue by considering multi-market participation of RVPP. Reserve provision in the SRM is mainly supported by the flexibility of the hydro plant and the CSP, and partially by other units—such as FD, WF, solar PV, and the biomass plant—depending on their availability.

The proposed deterministic formulation will serve as a foundation for the following chapters, where various uncertainties related to RVPP unit production and market conditions will be incorporated.

4 Advanced Robust Optimal Bidding of RVPPs under Uncertainties

The previous chapter presented a deterministic optimization problem for RVPP participation in sequential markets. However, various uncertainties can significantly impact the operation and bidding strategies of the RVPP, and thus must be taken into account. In this regard, this chapter models multiple uncertainties using a two-stage RO framework, which allows flexibility in defining the level of conservatism by the RVPP operator and also captures the asymmetric nature of the uncertain parameters. First, an *energy robustness approach* is developed, where different uncertain parameters are modeled separately. The model is then extended to a more advanced framework, referred to as the *profit robustness approach*, which explicitly considers the interactions among uncertain parameters and identifies the worst-case scenario in terms of profit rather than energy.

The penetration of ND-RES has experienced a remarkable growth in the last decades. However, the stochastic nature of these sources implies that ND-RES are less reliable when it comes to predictable and controllable power injection over a given period of time [177]. This makes ND-RES participation in the energy and reserve difficult, as failure to meet with the contracted energy and reserve in the market will lead to penalties if not suspension from future market activities. In addition to the internal uncertainties of RVPP units in their production and demand, there are various external uncertainties in the markets, such as the energy and reserve electricity price uncertainties, and also the combination of these uncertainties may affect the final profit of RVPP [41]. Therefore, the development of bidding approaches for RVPP participation in different markets, taking into account the characteristics of RVPP units, market rules, and internal and external uncertainties, remains a critical area of focus for both RVPP operators and researchers [12].

4.1 Framework

Many papers in the literature use mathematical optimization models to capture different uncertainties associated with VPP due to ease of implementation, convergence to the global optimum, and computational efficiency of these models [178]. Two main approaches can be generally followed to model market price and stochastic energy production/consumption in optimization problems, namely SP and RO [18]. In the SP, scenarios are constructed based on the probability distribution of uncertain parameters. The scenarios are then used to configure the optimization problem, in which the final results are assigned according to the probability of the scenarios [18]. By contrast, RO establishes a formulation that allows obtaining the values of the decision variables based on adverse realizations of the model parameters. RO has the advantage that the mathematical formulation does not grow in the number of variables and constraints as much as it occurs with SP. RO programming is an efficient way to deal with different sets of uncertainties that vary in their possible values. The goal of RO is to find the worst case of the optimization problem to minimize the negative impact of uncertainties on the solution [11]. However, the definition of the worst case can vary depending on how the optimization is implemented, whether it is single-level or multi-level, and can lead to different solutions in each approach.

The authors in [43, 45, 46, 47, 48, 51, 76, 179, 180, 181] develop a single-level optimization problem for the VPP market bidding problem to find the worst case of energy of ND-RES. The literature addresses VPP scheduling and bidding problems by considering different uncertainty characterizations in demand [45, 46, 47, 51, 179, 181], ND-RES production [43, 45, 46, 47, 48, 51, 76, 179, 180, 181], and electricity price [43, 47, 48, 51, 76, 180, 181], focusing on multi-market [43, 45, 47, 48, 51, 181], multi-objective [46, 76, 181], and multi-energy models [47, 48, 180, 181]. The study [45] employs a MILP RO method to model VPP participation in energy and reserve markets. Uncertainties in demand and ND-RES are represented via bounded intervals, with uncertainty budgets adjusting the conservatism of the optimization model. The paper [46] formulates a multi-objective optimization model for VPP, aiming to maximize operational revenue while minimizing carbon emissions and risk. The risk-averse strategy based on CVaR leverages RO to address uncertainties in demand, wind generation, and solar PV output. A payoff table is generated to compare trade-offs between objectives, and a fuzzy linearization technique is applied to solve the resulting MILP problem. In [43], a single-level model is used to formulate the DAM participation of a VPP, which includes a WF, demand, and ESS. The model accounts for symmetric uncertainties in electricity prices and wind production using confidence bounds. The authors of [48] investigate a MEVPP for energy and reserve scheduling, incorporating the capacity market, DAM, ASM, and NGM. Uncertainties in PV unit production are addressed through an RO model, while market price uncertainties are represented using PDF. In [47], a two-stage SP-RO problem is introduced to handle multiple uncertainties, including DAM electricity prices, ND-RES production, and demand within a virtual energy hub comprising industrial energy hubs and customers. The participation in DAM, local energy markets, RTM, and NGM is modeled to minimize operating costs and enhance customer welfare through Transactive Energy Management (TEM) ancillary service. The study in [179] proposes a single-level model for a VPP that includes ND-RES, ESS, and demand. A light RO approach is used to reduce the conservatism of RO and account for the uncertainties of ND-RES and load. The paper [51] presents a single-level RO model for RVPP participation in sequential energy and reserve markets, addressing the asymmetry of energy and reserve prices and defining the uncertainty budget over global scheduling horizons rather than individual time periods. The study in [180] introduces an RO model for a VPP incorporating power-to-hydrogen facilities to participate in both the DAM and RTM. Uncertainties in market electricity prices and wind power are addressed using an MILP framework. In [76], the optimal bidding strategy for electricity market participation of an RVPP, which includes ND-RES and dispatchable loads, is examined using a Mixed Integer Non-Linear Programming (MINLP) approach based on Information Gap Decision Theory (IGDT). Market price uncertainties are modeled through three strategies—risk-neutral, risk-averse, and risk-seeking—to reflect varying levels of robustness, and ND-RES uncertainties are modeled by PDF. The work in [181] proposes a multi-objective optimization approach for a virtual energy hub that includes a data center and Electric Vehicles (EVs). A SP-RO approach is utilized to model uncertainties in ND-RES, electricity demand, and electricity prices.

The main advantages of the mentioned single-level RO programming in [43, 45, 46, 47, 48, 51, 76, 179, 180, 181] are the possibility to consider multiple uncertainties, simplicity of implementation, global optimality, and calculation efficiency. However, a simplified definition of the worst case of energy for the severe scenarios is implemented. In fact, the worst case of energy defined for ND-RES in the above papers does not lead to the worst condition of profit, considering the possibility of different values of electricity prices. For instance, in a case where the electricity price is low in a certain period, even though the energy of a ND-RES can deviate significantly in this period, the resulting loss for RVPP might not be significant compared to a period with much higher electricity price and average or low energy deviation.

Some works in the literature consider the asymmetric nature of uncertain parameters in the RO problem in power system applications. In [182], an uncertainty set, called forward and backward deviations, is introduced to capture the asymmetric distribution of random variables. The authors subsequently refine the proposed method to identify a tractable solution for stochastic linear optimization problems. In [183], an asymmetric uncertainty set is proposed by considering a limited distributional information. In [184], the asymmetric RO model proposed in [183] is developed for reserve scheduling of a wind unit. The authors utilize dual theory to identify the robust counterpart of the proposed bi-level asymmetric RO model. A linear RO is proposed in [185] by considering asymmetric uncertainty bounds for optimal control of systems. The bounds on uncertain parameters are built for cases when full distributional information is available and the case that only limited distributional information is available. Another method for addressing asymmetric uncertainty is multi-band RO uncertainty modeling, which was first introduced in [186] for wireless network design. The objective of this method is to reduce the conservatism level of RO problem against uncertainty. The main idea of this method is to divide the bound of uncertain parameters to several intervals by considering the probability of each interval according to PDF of uncertain parameters. In this context, a multi-band uncertainty modeling approach is proposed in [187] for unit commitment problems. This method addresses the limitations of the RO approach regarding the selection of intervals with low probability. The application of multi-band uncertainty modeling in security-constrained unit commitment problem is developed in [188, 189] by considering nodal load uncertainty. The authors of [190] employ multi-band uncertainty modeling for transmission expansion problem, considering renewable sources and demand uncertainties. However, defining multiple new uncertainty budgets into the optimization problem increases problem complexity and limits the applicability of the proposed method. Furthermore, adding more binary variables to the optimization problem and the need for having knowledge on the distribution of uncertain parameters are other disadvantages of this method.

Multi-level RO models provide more flexibility to find the actual worst-case of the VPP bidding problem compared to single-level models. This is due to the definition of a new level for the optimization problem that models the behavior of uncertain parameters (both electricity price and energy uncertainties). Therefore, the objective function of this level can be defined to find the worst case of energy or profit of VPP. In addition, another level for the problem can be included to define the corrective or remedial actions after the occurrence of uncertainties. The literature on multi-level models proposes mathematical techniques, including RO [191, 192, 193], Adaptive Robust Optimization (ARO) [194], SP-RO [113], SARO [29, 41], Distributionally Robust Optimization (DRO) [195, 196, 197], and data-driven methods [198, 199] to account for various uncertainties in ND-RES production [29, 41, 113, 191, 192, 193, 194, 195, 196, 197, 198, 199], demand [113, 192, 194, 198, 199], electricity prices [29, 41, 198], and reserve deployment or dispatch order of TSO [29, 41, 191]. These models are implemented for the multi-market participation of VPP [29, 41, 194, 196] and for a MEVPP [113, 196]. Different techniques, including Benders and other decomposition techniques [41, 194], the Column & Constraint Generation (C&CG) algorithm [29, 192, 193, 196], and improved versions of these algorithms [113, 191, 195, 198], are proposed to accelerate the solution time of the optimization problem.

In [191], an RO approach is introduced to aggregate distribution systems as a VPP in the DAM, considering uncertainties in ND-RES and the dispatch order of the TSO. An enhanced C&CG algorithm, incorporating period decomposition and a connection method, is proposed to reduce the computational time of the RO problem. The work in [192] presents a bidding strategy for a VPP that integrates responsive-based EVs to balance economic and environmental goals. A two-stage RO approach is employed to account for uncertainties in wind power, solar PV power, and load. In [193], the optimal scheduling of a VPP is investigated by considering the controllability of EVs. A two-stage max-min-max RO approach is introduced to account for uncertainties in ND-RES and EVs, with the C&CG algorithm used to solve the optimization problem. The study in [194] focuses on the participation of an aggregator, incorporating flexible resources and demands, across various energy and flexibility markets. The worst-case scenario for the aggregator's profit, influenced by uncertainties in ND-RES and demand, is modeled using an ARO approach. A decomposed bi-level technique is employed to iteratively transfer cutting planes representing the worst-case realization to the upper-level problem, facilitating the solution of the optimization problem.

In [113], a three-level model is used to capture source-side and load-side uncertainties of a MEVPP through adjustable RO and clustering algorithms, respectively. Based on this model, a two-stage SP-RO problem is formulated and subsequently solved using a C&CG algorithm. The participation of a VPP in the DAM for both energy and reserve trading is modeled using a SARO problem in [41]. A modified Benders decomposition approach is developed to solve the proposed multi-level SARO model. Similarly, a SARO problem is presented in [29]. The first level of the optimization problem maximizes the worst-case expected profit of the VPP, while the second level minimizes the expected profit to model the worst-case uncertainties in wind generation and reserve deployment requests. The third level implements operational decisions following the first-level market participation and second-level uncertainty realizations to maximize the VPP's expected profit. The C&CG algorithm is utilized to solve this three-level model, with the worst-case objective function of the second level approximated iteratively until a predefined threshold is reached. In [195], a two-stage DRO framework is proposed for DAM and RTM scheduling of a VPP that includes ESS and EVs. A tri-level optimization approach is employed to model uncertainties in ND-RES, and an enhanced nested C&CG algorithm is developed to solve the optimization problem. The paper [196] presents a two-stage RO approach based on data-driven methods for a rural VPP, incorporating carbon-green certificates. Uncertainties in wind and solar PV production are managed using the strong duality theorem and the C&CG algorithm. The study in [197] introduces a bi-level model for a price-maker VPP, where the first level focuses on minimizing the VPP cost, and the second level aims to minimize the social cost of market. Uncertainties in wind unit production are addressed using a DRO approach. The paper in [198] proposes a data-driven interval approach for a VPP participating in the DAM and RTM. A two-stage interval RO model, leveraging an improved C&CG algorithm, is adopted to handle uncertainties in ND-RES production, demand consumption, and electricity prices. The paper in [199] formulates the bidding problem of a VPP in the energy market using a two-stage stochastic MILP approach, with uncertainties in ND-RES and demand response addressed through a data-driven RO (sample RO) method.

4.2 Gaps and contributions

The main limitations of the multi-level approaches in general, and in the above works in particular, are the complexity of programming and the fact that the size of the problem grows with the number of iterations in the solving procedure. In addition, they usually imply long computational times, which can compromise applications such as sensitivity analysis. In contrast, a two-stage RO approach is used in this thesis, which is ultimately reformulated as a single-level MILP, simplifying the optimization process by eliminating the need for iterative master-slave problem solving. The first stage aims to maximize the benefits of the RVPP, while the second stage considers the flexible worst cases of uncertain parameters. Here, "level" refers to the mathematical structure of the optimization problem (single-level vs. multi-level), while "stage" refers to the temporal sequence of decisions in the RO framework. The single-level structure also ensures that the problem size does not increase significantly, leading to more efficient solving procedures and shorter solution times compared to multi-level models. This reduction in complexity allows for faster computation and more straightforward implementation, making it easier to scale and apply to various real-world scenarios.

A common feature among the aforementioned RO-based single-level studies on VPP market participation is the assumption of symmetric distributions for the uncertain profiles. This assumption, which simplifies the problem implementation and input data generation, does not accurately represent the reality of, e.g., solar irradiation or wind speed profiles, nor the different market prices. In particular, the modeling of asymmetric uncertainty on electricity prices allows RO to identify scenarios where buying or selling energy worsens the RVPP objective function.

The uncertainties that characterize the problem include energy and reserve market prices, ND-RES generation, and demand consumption. To account for the impact of these uncertainties—particularly their *couplings*—the relationships between different uncertain parameters in the objective function and constraints of the optimization problem are established. This enables the identification of the *exact* worst-case profit of the RVPP. In this process, defining the interdependencies among uncertain parameters naturally leads to non-linear constraints, which are thoroughly linearized by building upon the Big-M method [52]. Table 4.1 compares different aspects of the reviewed literature with the proposed approach presented in this chapter. The contributions of this chapter are outlined below:

- *Flexible Worst-Case Profit Robustness Modeling in a Single-Level MINLP Framework:* While single-level classical RO models exist in the literature [43, 47, 48, 76, 180, 181], the proposed model in this chapter introduces a new approach to handle multiple uncertainties and their interactions. In most existing single-level models, uncertainties related to electricity prices and energy (including ND-RES production and demand) are modeled separately, without explicitly considering their interactions. This separate treatment often results in the selection of worst-case energy scenarios that do not actually correspond to the worst-case overall profit scenarios for the RVPP. As a result, using these classical single-level methods prevents the RVPP operator from providing optimal and reliable bidding strategies across different markets. To address this shortcoming, the proposed model adopts a flexible RO approach based on the worst-case selection of the RVPP's profit, rather than focusing only on energy robustness. This profit-oriented robustness framework allows the RVPP to participate simultaneously in the energy and reserve markets, while effectively capturing the impact of uncertainties in prices, energy production, and demand consumption, as well as their interactions. Beyond the RVPP bidding context, this profit-driven robustness concept can be applied to other multi-market or multi-product decision-making problems where interacting uncertainties affect financial outcomes.

Table 4.1: Comparison of proposed approach in this chapter and literature.

	Uncertainty			Uncertainty couplings	Profit robustness	Asymmetric uncertainty	Computational efficiency[1]	Method
Ref.	**Price**	**ND-RES**	**Load**					
[45]	×	✓	✓	×	×		High	Single-level, RO, MILP
[46]	×	✓	✓	×	×		High	Single-level, SP-RO, MILP
[43]	✓	✓	×	×	×		High	Single-level, RO, MILP
[48]	✓	✓	×	×	×		High	Single-level, RO, PDF, MILP
[47]	✓	✓	✓	×	×		High	Single-level, SP-RO, MILP
[179]	×	✓	✓	×	×		Medium	Single-level, Light RO, Non-liner
[51]	✓	✓	✓	×	×		High	Single-level, RO, MILP
[180]	✓	✓	×	×	×		High	Single-level, RO, MILP
[76]	✓	✓	×	×	×		High	Single-level, IGDT, Non-linear
[181]	✓	✓	✓	×	×		Medium-High	Single-level, SP-RO, MILP
[191]	×	✓	×	×	✓		High	Multi-level, RO, MILP
[192]	×	✓	✓	×	✓		Low-Medium	Multi-level, RO, MILP
[193]	×	✓	×	×	✓		Low-Medium	Multi-level, RO, MILP
[194]	×	✓	✓	×	✓		Low-Medium	Multi-level, ARO, MILP
[113]	×	✓	✓	×	✓		Low-Medium	Multi-level, SP-RO, MILP
[41]	✓	✓	×	✓	✓		Low-Medium	Multi-level, SARO, MILP
[29]	✓	✓	×	✓	✓		Low-Medium	Multi-level, SARO, MILP
[195]	×	✓	×	×	✓		High	Multi-level, DRO, MILP
[196]	×	✓	×	×	✓		Medium-High	Multi-level, DRO, MILP
[197]	×	✓	×	×	×		High	Bi-level, DRO, MILP
[198]	✓	✓	✓	×	✓		Medium	Multi-level, RO, Non-linear
[199]	×	✓	✓	×	×		Medium	Bi-level, SP-RO, MILP
This thesis	✓	✓	✓	✓	✓	✓	High	Single-level, RO, MILP

1: High: under 60 seconds; Medium-High: between 1 and 10 minutes; Medium: between 10 and 30 minutes; Low-Medium: between 30 and 90 minutes; Low: over 90 minutes.

- *Asymmetric uncertainty on RO:* Existing single-level models for VPP market participation assume symmetric uncertainties, which may not accurately represent the real-world scenarios RVPP face. The proposed RO model handles the asymmetric behavior of uncertain parameters, providing a more realistic representation. The proposed model is also agnostic with respect to the methodology used to generate the forecasts of the probability distributions of the uncertainties. This flexibility ensures that the proposed model remains relevant and adaptable to a wide range of forecasting methodologies, enhancing its practical applicability. This contribution is not limited to energy systems; asymmetric uncertainty modeling is also valuable in logistics, manufacturing, and financial planning, where risks are rarely symmetric.

- *Uncertainty budget on global scheduling horizons:* Traditional single-level RO models often require defining uncertainty budgets on an hourly basis for each uncertain parameter in the constraints. This process can be cumbersome and less intuitive for RVPP operators, specially as the size of the RVPP increases. The proposed approach simplifies this by allowing operators to define a single uncertainty budget for each parameter across the entire scheduling horizon (e.g., 24 hours). This innovation reduces the complexity of parameterization and enhances the model's practicality, particularly for real-world applications where operators must frequently update their models to align with market windows. The global-budget perspective is general and can be applied in other scheduling and planning contexts, such as supply chains or transportation networks, where long-horizon planning under uncertainty is required.

- *Handling the Non-linear Couplings Between Different Uncertainties:* The proposed approach addresses how different types of uncertainties in the objective function and constraints interact with each other within the optimization framework. Modeling these interactions leads to non-linear constraints, particularly when capturing the joint impact of price and energy uncertainties on the RVPP's profit in a single-level model. In the existing literature, these types of interactions are typically handled by multi-level models [29, 41, 198], which are often complex, computationally demanding, and difficult to implement. In contrast, the proposed model captures these interactions between uncertain parameters through an exact linearization of the initial MINLP problem, ensuring a mathematically equivalent MILP formulation. By addressing the interactions between uncertainties within a single-level MILP model, the proposed approach represents a novel contribution that provide an effective and practical solution for RVPP bidding strategies across different markets in the presence of several uncertainties. More generally, this methodology enables tractable single-level formulations in other application domains where interacting uncertainties arise, such as portfolio optimization, infrastructure planning, and operational scheduling.

4.3 Methodology

The deterministic formulation presented in Chapter 3 neglects the variation of uncertain parameters. However, we have discussed how uncertainty in electricity energy and reserve market prices can negatively (or positively) affect the RVPP profit. Additionally, uncertainties in the production and demand of RVPP units can lead to reduced production or increased demand, thus impacting RVPP market profits. Therefore, the RVPP operator must account for the effect of various uncertainties in its decision-making process. In the following section, the optimization problem of the RVPP is extended to incorporate these variations. The RO presented in this chapter corresponds to the DAM+SRM problem discussed in Chapter 3. The RO problems related to SRM+IDM#1 and IDMs can be developed in a similar manner and are omitted for brevity.

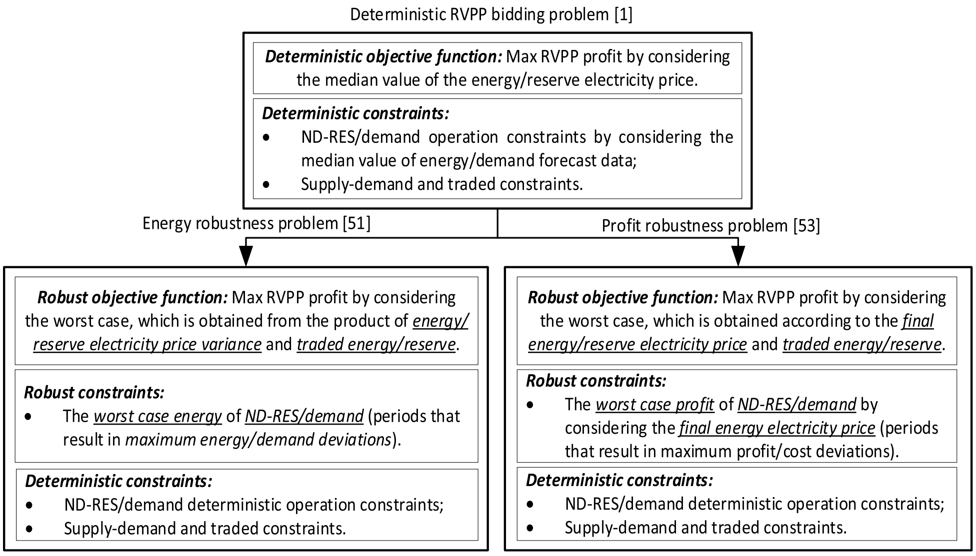


Figure 4.1: A comparison between the energy and profit robustness approaches.

4.3.1 Comparing energy and profit robustness

Figure 4.1 shows the structure of a deterministic RVPP bidding problem and a comparison between the energy and the profit robustness approaches. The top pane of this figure shows the deterministic RVPP problem (see Chapter 3). The left lower pane of this figure represents the energy robustness problem presented in [51]. The right lower pane of this figure shows the profit robustness problem presented in this chapter. In the deterministic approach, a single value (usually the median, average or upper bound) of the forecast data is considered to solve the optimization problem. The deterministic constraints are related mainly to the operation of the RVPP units, and supply-demand balance [1]. When considering the uncertainties, depending on whether the uncertainties affect the objective function or the constraints of the optimization problem, different sets of constraints need to be defined in each of the RO approaches. The uncertainties related to the energy/reserve electricity price affect the objective function of the optimization problem, whereas the uncertainties associated with the ND-RES generation and demand consumption affect the constraints.

In the energy robustness approach, those periods that result in more deviation of the energy/reserve electricity price variance multiplied by the total traded energy/reserve of RVPP are selected as the worst-case scenarios of the electricity price [51]. In the energy robustness constraints, the periods that have higher deviation of energy are selected as the worst case of ND-RES production or demand regardless of the electricity price.

In the profit robustness approach proposed in this chapter and for the uncertain parameters in the objective function of the optimization problem (energy/reserve electricity price), the worst case is defined according to the final value of the energy/reserve electricity price by means of binary variables. The final value of the energy electricity price is also used to calculate the worst case of profit/cost of each unit (uncertainty of ND-RES and demand in the constraints of the optimization problem). For this purpose, the final energy electricity price is multiplied by the energy variable of ND-RES/demand and is limited by the profit reduction effect due to ND-RES/demand uncertainty.

In the reminder of this section, the proposed energy and profit robustness approaches are formulated as single-level optimization problems. The RO formulation builds on the principle introduced by Bertsimas and Sim in [42], which is summarized in Appendix A for interested readers. In Section 4.4, these two approaches are compared using an illustrative example.

4.3.2 Energy robustness formulation

Two-stage robust model

A two-stage RO problem is formulated in (4.1) as a max-min problem to account for various uncertain parameters in the objective function and constraints of the optimization problem. In the first stage, the RVPP operator maximizes its objective function (4.1a), which is analogous to deterministic objective function Chapter 3. The Λ^O refers to the terms in the objective function of the deterministic DAM+SRM problem that are not affected by uncertainty. [1] The set of first-stage decision variables, Ξ^{DA+SR}, is also similar to those in the deterministic model. In the second stage, uncertainty adversely impacts the electricity energy and reserve prices in the objective function (4.1a). This is modeled through the minimization in the inner problem, which is defined for the objective function's uncertainty set $\Xi^O = \{\lambda_t^{DA}, \lambda_t^{SR,\downarrow}, \lambda_t^{SR,\uparrow}\}$. Additionally, uncertainty is modeled to potentially decrease the thermal production of the SF of CSP and the electrical production of ND-RES, while increasing the consumption of demand, as reflected in constraints (4.1b)-(4.1d). The decision variables associated with uncertainty in these constraints are defined by the set $\Xi^C = \{P_{r,t}, P_{\theta,t}^{SF}, P_{d,t}\}$. It is important to note that, unlike the deterministic problem, the new sets Ξ^O and Ξ^C include second-stage decision variables, which were parameters in the deterministic problem. The constraints of the deterministic problem that are unaffected by uncertainty are defined by Λ^C in (4.1e).[2]

$$\max_{\Xi^{DA+SR}} \left\{ \min_{\Xi^O} \left\{ \sum_{t\in\mathscr{T}} \left[\lambda_t^{DA} p_t^{DA} \Delta t + \lambda_t^{SR,\uparrow} r_t^{SR,\uparrow} + \lambda_t^{SR,\downarrow} r_t^{SR,\downarrow}\right] - \Lambda^O \right\} \right\} \tag{4.1a}$$

st.

$$p_{r,t} + r_{r,t}^{\uparrow} \le \min_{P_{r,t}}\{P_{r,t}\}\,; \qquad \forall r,t \tag{4.1b}$$

$$p_{\theta,t}^{SF} \le \min_{P_{\theta,t}^{SF}}\{P_{\theta,t}^{SF}\}\,; \qquad \forall \theta,t \tag{4.1c}$$

$$p_{d,t} \ge -\min_{P_{d,t}}\{-P_{d,t}\}\,; \qquad \forall d,t \tag{4.1d}$$

$$\Lambda^C \le 0\,; \tag{4.1e}$$

In this section, a flexible risk-averse strategy is developed by extending the theory of RO presented in [42] and the forward-backward asymmetric RO approach in [182] to model the behavior of the RVPP operator under uncertain parameters. Flexibility in addressing uncertainty is achieved through the *uncertainty budget* parameter, applied to different uncertain parameters in the objective function (i.e., Γ^{DA}, $\Gamma^{SR,\uparrow}$, and $\Gamma^{SR,\downarrow}$) and constraints (Γ_r, Γ_θ, and Γ_d) of the optimization problem. The uncertainty budget represents the maximum number of time periods within the horizon during which uncertain parameters simultaneously take their worst-case values. Each uncertainty budget is defined as an integer parameter over the operation horizon (e.g., between 0 and 24 in the case of a 24-hour DAM or SRM) and determines the conservatism level of the RVPP operator. By adjusting these parameters, the RVPP operator can modify the level of conservatism to avoid results that are too pessimistic (assuming many worst-case deviations) or too optimistic (assuming very few deviations). Electricity (energy) market price uncertain parameters are defined by asymmetric uncertainty bound $\lambda_t^{DA} \in \left[\tilde{\lambda}_t^{DA} - \check{\lambda}_t^{DA}, \tilde{\lambda}_t^{DA} + \hat{\lambda}_t^{DA}\right]$, where, generally, $\check{\lambda}_t^{DA} \ne \hat{\lambda}_t^{DA}$. In the defined bound, the worst-case electricity prices are determined based on the direction of the RVPP's traded energy in a given period; i.e., the minimum price represents the worst

[1] These include the second through fourth terms in the objective function (3.1).
[2] Deterministic constraints include: (3.2), (3.3b)-(3.3h), (3.4), (3.5), (3.6), (3.7b)-(3.7d), (3.8b)-(3.8j), (3.9).

case when the RVPP is selling energy, and the maximum price represents the worst case when the RVPP is buying energy. For the uncertainty of up/down reserve prices $\left(\lambda_t^{SR,\uparrow}\in\left[\hat{\tilde{\lambda}}_t^{SR,\uparrow}-\check{\lambda}_t^{SR,\uparrow},\hat{\tilde{\lambda}}_t^{SR,\uparrow}\right]\right.$ and $\left.\lambda_t^{SR,\downarrow}\in\left[\hat{\tilde{\lambda}}_t^{SR,\downarrow}-\check{\lambda}_t^{SR,\downarrow},\hat{\tilde{\lambda}}_t^{SR,\downarrow}\right]\right)$, thermal production of SF of CSP $\left(P_{\theta,t}^{SF}\in\left[\hat{\tilde{P}}_{\theta,t}^{SF}-\check{P}_{\theta,t}^{SF},\hat{\tilde{P}}_{\theta,t}^{SF}\right]\right)$, and electrical production of ND-RES $\left(P_{r,t}\in\left[\hat{\tilde{P}}_{r,t}-\check{P}_{r,t},\hat{\tilde{P}}_{r,t}\right]\right)$, only negative deviations are considered, while for demand $\left(P_{d,t}\in\left[\tilde{\tilde{P}}_{d,t},\tilde{\tilde{P}}_{d,t}+\hat{P}_{d,t}\right]\right)$, only positive deviations are taken into account. This ensures that the worst-case scenario, according to the strategy or level of conservatism chosen by the RVPP operator through the uncertainty budgets, is appropriately represented in the optimization problem, as deviations in opposite directions would result in higher profits for the RVPP.

The objective function (4.2a) is formulated by considering the defined bounds for different uncertain parameters in the objective function of the problem. The inner maximization problem in (4.2a) identifies the worst-case scenario for RVPP profit across different market participation. This is achieved by introducing new time period sets $\mathscr{T}^{DA}$, $\mathscr{T}^{SR,\uparrow}$, and $\mathscr{T}^{SR,\downarrow}$, which represent the periods where price deviations from the median value or upper bound have the greatest negative impact on the RVPP's profit.[3] Since the RVPP's profit for the median values of the DAM price and the upper bound of the SRM price, as well as the term Λ^O related to the deterministic part of the objective function, are not influenced by these uncertainties, the corresponding terms can be moved to the outer-layer problem. Additionally, a new positive auxiliary variable ${y_t}^{DA}$ is introduced to represent the traded electrical energy in (4.2a). This variable is bounded by constraint (4.2b), effectively modeling the asymmetric behavior of electricity price uncertainties based on the direction of traded energy in the market.

Equations (4.2c)-(4.2e) address the uncertainty in the electrical production of ND-RES, thermal production of SF of CSP, and demand consumption, respectively. These constraints are developed by incorporating the described uncertainty bounds and the newly defined worst-case sets $\mathscr{T}_r$, $\mathscr{T}_\theta$, and $\mathscr{T}_d$ for each time period. For example, in constraint (4.2c), the worst-case deviation of electrical power of ND-RES due to uncertainty, $\check{P}_{r,t'}$, is reduced from the upper bound of forecast value $\hat{\tilde{P}}_{r,t}$ only when t' corresponds to period t and belongs to the set $\mathscr{T}_r$ (i.e., $t'\in\mathscr{T}_r, t'=t$). The positive nature of the auxiliary variables is established in (4.2f), while constraint (4.2g) is identical to (4.1e).

$$\max_{\Xi^{DA+SR}}\left\{\sum_{t\in\mathscr{T}}\left[\tilde{\lambda}_t^{DA}p_t^{DA}\Delta t+\hat{\tilde{\lambda}}_t^{SR,\uparrow}r_t^{SR,\uparrow}+\hat{\tilde{\lambda}}_t^{SR,\downarrow}r_t^{SR,\downarrow}\right]-\Lambda^O\right.$$
$$-\max_{\left\{\begin{array}{l}\mathscr{T}^{DA},\\ \mathscr{T}^{SR,\uparrow},\\ \mathscr{T}^{SR,\downarrow}\end{array}\middle|\begin{array}{l}\left|\mathscr{T}^{DA}\right|=\Gamma^{DA},\\ \left|\mathscr{T}^{SR,\uparrow}\right|=\Gamma^{SR,\uparrow},\\ \left|\mathscr{T}^{SR,\downarrow}\right|=\Gamma^{SR,\downarrow}\end{array}\right\}}\left\{\sum_{t\in\mathscr{T}^{DA}}\check{\lambda}_t^{DA}{y_t}^{DA}\right.$$
$$\left.\left.+\sum_{t\in\mathscr{T}^{SR,\uparrow}}\check{\lambda}_t^{SR,\uparrow}r_t^{SR,\uparrow}+\sum_{t\in\mathscr{T}^{SR,\downarrow}}\check{\lambda}_t^{SR,\downarrow}r_t^{SR,\downarrow}\right\}\right\} \tag{4.2a}$$

st.

$$-\frac{\check{\lambda}_t^{DA}}{\tilde{\lambda}_t^{DA}}{y_t}^{DA}\leq {p_t}^{DA}\Delta t\leq {y_t}^{DA}\,; \qquad \forall t\in\mathscr{T}^{DA} \tag{4.2b}$$

[3]When not explicitly indicated in (4.2), the time set considered for t is $\mathscr{T}$.

$$p_{r,t} + r^{\uparrow}_{r,t} \leq \hat{\tilde{P}}_{r,t} - \max_{\{\mathcal{T}_r| \ |\mathcal{T}_r|=\Gamma_r\}} \left\{ \sum_{t' \in \mathcal{T}_r, t'=t} \check{P}_{r,t'} \right\}; \qquad \forall r, t \qquad (4.2c)$$

$$p^{SF}_{\theta,t} \leq \hat{\tilde{P}}^{SF}_{\theta,t} - \max_{\{\mathcal{T}_\theta| \ |\mathcal{T}_\theta|=\Gamma_\theta\}} \left\{ \sum_{t' \in \mathcal{T}_\theta, t'=t} \check{P}^{SF}_{\theta,t'} \right\}; \qquad \forall \theta, t \qquad (4.2d)$$

$$p_{d,t} \geq \check{\tilde{P}}_{d,t} + \max_{\{\mathcal{T}_d| \ |\mathcal{T}_d|=\Gamma_d\}} \left\{ \sum_{t' \in \mathcal{T}_d, t'=t} \hat{P}_{d,t'} \right\}; \qquad \forall d, t \qquad (4.2e)$$

$$y_t{}^{DA} \geq 0; \qquad \forall t \qquad (4.2f)$$

$$\Lambda^C \leq 0; \qquad (4.2g)$$

Inner problems reformulation

Although the maximization term in the last part of the objective function (4.2a) (the protection function) captures the worst-case scenario for the uncertain parameters, the process of selecting values based on the defined sets can be expressed in a linear manner. To achieve this, assuming the optimal values (indicated with superscript *) of the upper-level variables $y_t{}^{DA^*}$, $r_t^{SR,\uparrow^*}$, and $r_t^{SR,\downarrow^*}$ and using Proposition 1 from [42], linear problem (4.3) is equivalent to the protection function in (4.2a). Constraints (4.3b)-(4.3d) limit the summation of the new auxiliary variables $z_t{}^{DA}$, $z_t{}^{SR,\uparrow}$, and $z_t{}^{SR,\downarrow}$ for each uncertain parameter in the objective function of the problem to the corresponding uncertainty budgets Γ^{DA}, $\Gamma^{SR,\uparrow}$, and $\Gamma^{SR,\downarrow}$, respectively. These constraints ensure that the positive auxiliary variables $z_t{}^{DA}$, $z_t{}^{SR,\uparrow}$, and $z_t{}^{SR,\downarrow}$ are less or equal than 1, thereby achieving the same optimal value for the objective function in (4.3a) and the protection function in (4.2a). The dual variables of each constraint are defined in these equations, which are then used in next section to derive the final MILP formulation. In the linear equivalent problem (4.3), ϕ is the dual variable associated with the uncertainty-budget constraints (4.3b)–(4.3d), while ζ_t is the dual variable corresponding to the individual deviations in each period in constraints (4.3e)–(4.3g).

$$\max \left\{ \sum_{t \in \mathcal{T}^{DA}} \check{\lambda}^{DA}_t y_t{}^{DA^*} z_t{}^{DA} + \sum_{t \in \mathcal{T}^{SR,\uparrow}} \check{\lambda}^{SR,\uparrow}_t r_t^{SR,\uparrow^*} z_t{}^{SR,\uparrow} + \sum_{t \in \mathcal{T}^{SR,\downarrow}} \check{\lambda}^{SR,\downarrow}_t r_t^{SR,\downarrow^*} z_t{}^{SR,\downarrow} \right\} \qquad (4.3a)$$

st.

$$\sum_{t \in \mathcal{T}^{DA}} z_t{}^{DA} \leq \Gamma^{DA} : \phi^{DA}; \qquad (4.3b)$$

$$\sum_{t \in \mathcal{T}^{SR,\uparrow}} z_t{}^{SR,\uparrow} \leq \Gamma^{SR,\uparrow} : \phi^{SR,\uparrow}; \qquad (4.3c)$$

$$\sum_{t \in \mathcal{T}^{SR,\downarrow}} z_t{}^{SR,\downarrow} \leq \Gamma^{SR,\downarrow} : \phi^{SR,\downarrow}; \qquad (4.3d)$$

$$0 \leq z_t{}^{DA} \leq 1 : \zeta^{DA}_t; \qquad \forall t \in \mathcal{T}^{DA} \qquad (4.3e)$$

$$0 \leq z_t{}^{SR,\uparrow} \leq 1 : \zeta^{SR,\uparrow}_t; \qquad \forall t \in \mathcal{T}^{SR,\uparrow} \qquad (4.3f)$$

$$0 \leq z_t{}^{SR,\downarrow} \leq 1 : \zeta^{SR,\downarrow}_t; \qquad \forall t \in \mathcal{T}^{SR,\downarrow} \qquad (4.3g)$$

The equivalent linear formulation for selecting the worst-case scenarios of production uncertainty of ND-RES in constraint (4.2c) is presented as linear formulation (4.4). The objective function (4.4a) maximizes the production deviation caused by uncertainty in the corresponding period t ($t' \in \mathscr{T}_r, t' = t$). The summation of the auxiliary positive variables $z_{r,t'}$ for the corresponding period t and other worst-case periods, which are fixed at their optimal values, is constrained to be less than the uncertainty budget Γ_r. The bound for the auxiliary variable $z_{r,t'}$ is defined in (4.4c). Worth noting that the linear formulation (4.4) considers the temporal constraints of the uncertainty parameter over the entire operation period, rather than defining the worst case of the uncertain parameter in a single period. This feature allows the RVPP to adjust a single uncertain parameter for the entire period instead of multiple parameters for each time period and uncertain parameter.

The equivalent linear formulations for worst-case selection in constraints (4.2d)-(4.2e), addressing CSP thermal production, and demand uncertainty, respectively, can be derived similarly to (4.4). These are omitted here for brevity.

$$\max \sum_{t' \in \mathscr{T}_r, t'=t} \check{P}_{r,t'} z_{r,t'} \; ; \qquad \forall r, t \tag{4.4a}$$

st.

$$\sum_{t' \in \mathscr{T}_r, t'=t} z_{r,t'} + \sum_{t' \in \mathscr{T}_r, t' \neq t} z^*_{r,t'} \leq \Gamma_r : \phi_r \; ; \tag{4.4b}$$

$$0 \leq z_{r,t'} \leq 1 : \zeta_{r,t'} \; ; \qquad \forall t' \in \mathscr{T}_r, t' = t \tag{4.4c}$$

MILP formulation for energy robustness

By applying strong duality [52] to the linear formulations in (4.3) and (4.4) (and similarly for equivalent linear formulations related to other uncertain constraints), and replacing their dual problems instead of the protection function in the objective function (4.2a) and the protection functions in the constraints (4.2c)-(4.2e), respectively, the final MILP is formulated as (4.5). The first line of the objective function (4.5a) is identical to the first line of (4.2a). The second line captures the negative effects of uncertainties in electricity (energy and reserve) prices. Constraint (4.5b) is equivalent to (4.2b). Constraints (4.5c)-(4.5e) are the dual constraints of the linear problem related to electricity prices uncertainties in (4.3). Constraint (4.5f) represents the upper limit of electrical production of ND-RES while accounting for uncertainty. Since the term $\Gamma_r - \sum_{t' \in \mathscr{T}_r, t' \neq t} z^*_{r,t'}$ in (4.4b) can only take a value of zero or one, depending on the number of worst-case periods in its defined set, a new binary variable $\chi_{r,t}$ is introduced to represent these conditions. Additionally, a new positive auxiliary variable $y_{r,t}$ is defined in (4.5f) and constrained in (4.5g) using the Big-M method [52] to represent the dual term $\chi_{r,t}\phi_r + \zeta_{r,t}$. Constraint (4.5h) is the dual constraint of the linear problem associated with ND-RES production uncertainty in (4.4). Constraint (4.5i) assigns the uncertainty budget for production of ND-RES. Constraints (4.5j)-(4.5m) represent the CSP thermal production uncertain constraints, constraints (4.5n)-(4.5q) represent the demand uncertain constraints. These constraints are defined similarly to the electrical production uncertainty of ND-RES constraints (4.5f)-(4.5i). The main difference is that, for demand, the worst-case uncertainty results in an increase in these parameters, whereas, for ND-RES electrical production and thermal production of SF of CSP, it results in a decrease. The nature of the positive and binary variables is defined in (4.5r)-(4.5t). Finally, the deterministic constraints that remain unaffected by uncertainty are outlined in (4.5u).

$$\max_{\Xi^{DA+SR}} \left\{ \sum_{t\in\mathscr{T}} \left[\tilde{\lambda}_t^{DA} p_t^{DA} \Delta t + \hat{\tilde{\lambda}}_t^{SR,\uparrow} r_t^{SR,\uparrow} + \hat{\tilde{\lambda}}_t^{SR,\downarrow} r_t^{SR,\downarrow}\right] - \Lambda^O \right.$$

$$\left. - \Gamma^{DA}\phi^{DA} - \Gamma^{SR,\uparrow}\phi^{SR,\uparrow} - \Gamma^{SR,\downarrow}\phi^{SR,\downarrow} - \sum_{t\in\mathscr{T}}\left[\zeta_t^{DA} + \zeta_t^{SR,\uparrow} + \zeta_t^{SR,\downarrow}\right]\right\} \tag{4.5a}$$

st.

$$-\frac{\check{\lambda}_t^{DA}}{\hat{\lambda}_t^{DA}} {y_t}^{DA} \le {p_t}^{DA}\Delta t \le {y_t}^{DA}\,; \qquad \forall t \quad (4.5b)$$

$$\phi^{DA} + \zeta_t^{DA} \ge \check{\lambda}_t^{DA} y_t^{DA}\,; \qquad \forall t \quad (4.5c)$$

$$\phi^{SR,\uparrow} + \zeta_t^{SR,\uparrow} \ge \check{\lambda}_t^{SR,\uparrow} r_t^{SR,\uparrow}\,; \qquad \forall t \quad (4.5d)$$

$$\phi^{SR,\downarrow} + \zeta_t^{SR,\downarrow} \ge \check{\lambda}_t^{SR,\downarrow} r_t^{SR,\downarrow}\,; \qquad \forall t \quad (4.5e)$$

$$p_{r,t} + r_{r,t}^{\uparrow} \le \hat{\tilde{P}}_{r,t} - \chi_{r,t}\,\phi_r - \zeta_{r,t} = \hat{\tilde{P}}_{r,t} - y_{r,t}\,; \qquad \forall r,t \quad (4.5f)$$

$$\phi_r + \zeta_{r,t} - M(1-\chi_{r,t}) \le y_{r,t} \le M\chi_{r,t}\,; \qquad \forall r,t \quad (4.5g)$$

$$\phi_r + \zeta_{r,t} \ge \check{P}_{r,t}\,; \qquad \forall r,t \quad (4.5h)$$

$$\sum_t \chi_{r,t} = \Gamma_r\,; \qquad \forall r \quad (4.5i)$$

$$p_{\theta,t}^{SF} \le \hat{\tilde{P}}_{\theta,t}^{SF} - \chi_{\theta,t}\,\phi_\theta - \zeta_{\theta,t} = \hat{\tilde{P}}_{\theta,t}^{SF} - y_{\theta,t}\,; \qquad \forall \theta,t \quad (4.5j)$$

$$\phi_\theta + \zeta_{\theta,t} - M(1-\chi_{\theta,t}) \le y_{\theta,t} \le M\chi_{\theta,t}\,; \qquad \forall \theta,t \quad (4.5k)$$

$$\phi_\theta + \zeta_{\theta,t} \ge \check{P}_{\theta,t}\,; \qquad \forall \theta,t \quad (4.5l)$$

$$\sum_t \chi_{\theta,t} = \Gamma_\theta\,; \qquad \forall \theta \quad (4.5m)$$

$$p_{d,t} \ge \tilde{\tilde{P}}_{d,t} + \chi_{d,t}\,\phi_d + \zeta_{d,t} = \tilde{\tilde{P}}_{d,t} + y_{d,t}\,; \qquad \forall d,t \quad (4.5n)$$

$$\phi_d + \zeta_{d,t} - M(1-\chi_{d,t}) \le y_{d,t} \le M\chi_{d,t}\,; \qquad \forall d,t \quad (4.5o)$$

$$\phi_d + \zeta_{d,t} \ge \hat{P}_{d,t}\,; \qquad \forall d,t \quad (4.5p)$$

$$\sum_t \chi_{d,t} = \Gamma_d\,; \qquad \forall d \quad (4.5q)$$

$$\phi^{DA}, \phi^{SR,\uparrow}, \phi^{SR,\downarrow}, \zeta_t^{DA}, \zeta_t^{SR,\uparrow}, \zeta_t^{SR,\downarrow}, y_t^{DA} \ge 0\,; \qquad \forall t \quad (4.5r)$$

$$\phi_\theta, \phi_r, \phi_d, \zeta_{\theta,t}, \zeta_{r,t}, \zeta_{d,t}, y_{\theta,t}, y_{r,t}, y_{d,t} \ge 0\,; \qquad \forall \theta,r,d,t \quad (4.5s)$$

$$\chi_{\theta,t}, \chi_{r,t}, \chi_{d,t} \in \{0,1\}\,; \qquad \forall \theta,r,d,t \quad (4.5t)$$

$$\Lambda^C \le 0\,; \qquad (4.5u)$$

4.3.3 Profit robustness formulation

The main advantages of the energy robustness formulation proposed in Section 4.3.2 are the possibility to consider multiple uncertainties, simplicity of implementation, global optimality, and calculation efficiency. However, a simplified definition of the worst case of energy for the severe scenarios is implemented. In fact, the worst case of energy defined for ND-RESs does not lead to the worst condition of profit, considering the possibility of different values of electricity prices. For instance, in a case where the electricity price is low in a certain period, even though the energy of a ND-RES can deviate significantly in this period, the resulting loss for RVPP might not be significant compared to a period with much higher electricity price and average or low energy deviation. In this section, the energy robustness formulation presented in Section 4.3.2 is extended to a profit robustness formulation. To this end, the additional constraints and modifications related to uncertainty in the objective function and constraints of the optimization problem are presented in the following sections.

Objective function uncertainties in profit robustness

To account for the effect of uncertainties related to price and energy on each other and to obtain a profit robustness approach, it is necessary to explicitly define different conditions for electricity price and accordingly modify the energy robustness formulation. To this end, the set of additional constraints for profit robustness related to uncertainties in the DAM electricity price are provided in (4.6). Constraint (4.6a) determines the DAM electricity price in each time period according to the condition of binary variables χ_t^{DA} and $\chi_t'^{DA}$, which are related to the negative and positive price volatility, respectively. Depending on whether RVPP sells or buys electricity on the market, the worst DAM price conditions occur at the price values $\tilde{\lambda}_t^{DA} - \check{\lambda}_t^{DA}$ and $\tilde{\lambda}_t^{DA} + \hat{\lambda}_t^{DA}$, respectively. Constraints (4.6b) and (4.6c) define the lower and upper bounds for the possible profit reductions (due to the negative price deviation $\check{\lambda}_t^{DA} p_t^{DA} \Delta t$ and the positive price deviation $-\hat{\lambda}_t^{DA} p_t^{DA} \Delta t$). According to these constraints, the possible profit reductions must be greater than or equal to the dual variables $\phi^{DA} + \zeta_t^{DA}$ for those periods that the electricity price fluctuates to its worst case. Constraints (4.6b) and (4.6c) are thus essential to avoid selecting incorrect periods for the worst case of profit deviations, especially when other uncertain parameters such as ND-RES production and demand (see equations (4.8), (4.9), and (4.10)) affect the total power traded by the RVPP (p_t^{DA}). As previously introduced, the uncertainty budget Γ^{DA} in (4.6d) specifies the number of periods in which the electricity price can deviate to its worst condition. In this formulation, Γ^{DA} plays a key role in achieving flexible robustness: the larger the value of Γ^{DA}, the more adverse the bidding scenario becomes. Constraint (4.6e) prevents positive and negative electricity price deviations in the same period. Constraint (4.6f) defines the nature of binary variables.

$$\lambda_t^{DA} = \tilde{\lambda}_t^{DA} - \check{\lambda}_t^{DA} \chi_t^{DA} + \hat{\lambda}_t^{DA} \chi_t'^{DA} \,; \qquad \forall t \tag{4.6a}$$

$$\phi^{DA} + \zeta_t^{DA} - M(1 - \chi_t^{DA}) \leq \check{\lambda}_t^{DA} p_t^{DA} \Delta t \leq M(\chi_t^{DA}) \,; \qquad \forall t \tag{4.6b}$$

$$\phi^{DA} + \zeta_t^{DA} - M(1 - \chi_t'^{DA}) \leq -\hat{\lambda}_t^{DA} p_t^{DA} \Delta t \leq M(\chi_t'^{DA}) \,; \qquad \forall t \tag{4.6c}$$

$$\sum_{t \in \mathscr{T}} (\chi_t^{DA} + \chi_t'^{DA}) = \Gamma^{DA} \,; \tag{4.6d}$$

$$\chi_t^{DA} + \chi_t'^{DA} \leq 1 \,; \qquad \forall t \tag{4.6e}$$

$$\chi_t^{DA}, \chi_t'^{DA} \in \{0, 1\} \,; \qquad \forall t \tag{4.6f}$$

The set of additional constraints for profit robustness, related to the uncertainty in the up and down SRM prices, is defined in constraints (4.7), similarly to (4.6). The main difference is that for both up and down SRM price, only the negative SRM price deviations due to uncertainty are evaluated in (4.7a) and (4.7b), respectively. This is due to the fact that the positive SRM price deviations usually result in more benefit for RVPP. Constraints (4.7c) and (4.7d) set the bounds for the possible profit reductions due to up and down SRM price deviations, respectively. The uncertainty budgets $\Gamma^{SR,\uparrow}$ and $\Gamma^{SR,\downarrow}$ for up and down SRM price uncertainty are assigned in (4.7e) and (4.7f), respectively. Finally, the nature of the binary variables is determined by (4.7g).

$$\lambda_t^{SR,\uparrow} = \hat{\hat{\lambda}}_t^{SR,\uparrow} - \check{\lambda}_t^{SR,\uparrow}\chi_t^{SR,\uparrow}\,; \qquad \forall t \qquad (4.7a)$$

$$\lambda_t^{SR,\downarrow} = \hat{\hat{\lambda}}_t^{SR,\downarrow} - \check{\lambda}_t^{SR,\downarrow}\chi_t^{SR,\downarrow}\,; \qquad \forall t \qquad (4.7b)$$

$$\phi^{SR,\uparrow} + \zeta_t^{SR,\uparrow} - M(1-\chi_t^{SR,\uparrow}) \leq \check{\lambda}_t^{SR,\uparrow} r_t^{SR,\uparrow} \leq M(\chi_t^{SR,\uparrow})\,; \qquad \forall t \qquad (4.7c)$$

$$\phi^{SR,\downarrow} + \zeta_t^{SR,\downarrow} - M(1-\chi_t^{SR,\downarrow}) \leq \check{\lambda}_t^{SR,\downarrow} r_t^{SR,\downarrow} \leq M(\chi_t^{SR,\downarrow})\,; \qquad \forall t \qquad (4.7d)$$

$$\sum_{t\in\mathcal{T}} \chi_t^{SR,\uparrow} = \Gamma^{SR,\uparrow}\,; \qquad (4.7e)$$

$$\sum_{t\in\mathcal{T}} \chi_t^{SR,\downarrow} = \Gamma^{SR,\downarrow}\,; \qquad (4.7f)$$

$$\chi_t^{SR,\uparrow}, \chi_t^{SR,\downarrow} \in \{0,1\}\,; \qquad \forall t \qquad (4.7g)$$

ND-RES and demand uncertainties in profit robustness

The uncertain constraints of ND-RES and demand, defined in (4.1b) and (4.1d), need to be reformulated as (4.8a) and (4.8b) to account for profit robustness. Constraint (4.8a) limits the profit of the ND-RES for each time period by considering profit robustness against the uncertainty in ND-RES production. The upper bound of this constraint is computed as the maximum profit minus the profit reduction due to the worst-case negative deviation in ND-RES production. The maximum profit is calculated by multiplying the electricity price λ_t^{DA} with the maximum production of ND-RES minus the provided up reserve, both multiplied by the time period duration: $(\hat{\hat{P}}_{r,t} - r_{r,t}^{SR,\uparrow})\Delta t$. Constraint (4.8b) sets a lower bound on the cost of purchasing electricity from the DAM to supply demand. This value equals the cost of purchasing electricity for the minimum demand forecast, $\lambda_t^{DA}\check{\check{P}}_{d,t}\Delta t$, plus the additional cost resulting from the worst-case positive deviation in demand. The uncertain constraint of CSP in (4.1c) remains unchanged, as the uncertainty affects the thermal power of the SF and does not directly impact the final profit, which depends on the electrical output of the CSP. Given that the conversion of thermal to electrical power in the CSP is handled by a piecewise linear function, and considering the temporal constraints of the TS that influence the final electrical output, there is no direct link between the uncertainty in the SF thermal power and the electrical power output in each time period. Therefore, the energy robustness formulation for the CSP is also applicable to the profit robustness formulation.

$$\lambda_t^{DA} p_{r,t}\Delta t \leq \lambda_t^{DA}\left(\hat{\hat{P}}_{r,t} - r_{r,t}^{\uparrow}\right)\Delta t - \max_{\{\mathcal{T}_r|\ \ |\mathcal{T}_r|=\Gamma_r\}} \left\{ \sum_{t'\in\mathcal{T}_r, t'=t} \lambda_t^{DA}\check{P}_{r,t'}\Delta t \right\}; \qquad \forall r,t \qquad (4.8a)$$

$$\lambda_t^{DA} p_{d,t}\Delta t \geq \lambda_t^{DA}\check{\check{P}}_{d,t}\Delta t + \max_{\{\mathcal{T}_d|\ \ |\mathcal{T}_d|=\Gamma_d\}} \left\{ \sum_{t'\in\mathcal{T}_d, t'=t} \lambda_t^{DA}\hat{P}_{d,t'}\Delta t \right\}; \qquad \forall d,t \qquad (4.8b)$$

The profit robustness formulation of ND-RES is given in (4.9). This formulation is derived from (4.8a) using the same procedure as the energy robustness approach, as explained in Section 4.3.2. Constraint (4.9a) defines the ND-RES output based on the maximum forecast generation $\hat{\hat{P}}_{r,t}$ and a possible negative power deviation $\chi_{r,t}\check{P}_{r,t}$ (active when $\chi_{r,t} = 1$). Constraint (4.9b) represents the upper limit on the profit of ND-RES for each time period, considering the uncertainty in ND-RES production. In contrast to constraint (4.5f) for energy robustness, constraint (4.9b) is a nonlinear expression (due to terms $\lambda_t^{DA} p_{r,t}$ and $\lambda_t^{DA} r_{r,t}^{\uparrow}$) and must be linearized to achieve an MILP formulation, as shown in equation (4.11). Constraint (4.9c) sets the bounds for the dual variable $y_{r,t}$. Constraint (4.9d) imposes a lower bound on the sum of the dual variables ϕ_r and $\zeta_{r,t}$, corresponding to the maximum profit reduction for each ND-RES in each time period. Constraint (4.9e) defines the profit robustness budget for each ND-RES. To implement the profit robustness formulation for ND-RES, the formulation (4.9) must be used in place of constraints (4.5f)-(4.5i).

$$p_{r,t} + r_{r,t}^{\uparrow} \leq \hat{\tilde{P}}_{r,t} - \chi_{r,t}\check{P}_{r,t}\,; \qquad \forall r,t \tag{4.9a}$$

$$\lambda_t^{DA} p_{r,t}\Delta t \leq \lambda_t^{DA}\left(\hat{\tilde{P}}_{r,t} - r_{r,t}^{\uparrow}\right)\Delta t - y_{r,t}\,; \qquad \forall r,t \tag{4.9b}$$

$$\phi_r + \zeta_{r,t} - M(1-\chi_{r,t}) \leq y_{r,t} \leq M\chi_{r,t}\,; \qquad \forall r,t \tag{4.9c}$$

$$\phi_r + \zeta_{r,t} \geq \lambda_t^{DA}\check{P}_{r,t}\Delta t\,; \qquad \forall r,t \tag{4.9d}$$

$$\sum_t \chi_{r,t} = \Gamma_r\,; \qquad \forall r \tag{4.9e}$$

The demand cost robustness formulation is presented in (4.10), which is derived from (4.8b). When the binary variable $\chi_{d,t}$ in (4.10a) is equal to 1 for a given period, the possible positive deviation in demand becomes active. Constraint (4.10b) sets the lower bound on the cost of purchasing electricity from the DAM to meet the demand. This constraint is also a nonlinear expression (due to term $\lambda_t^{DA} p_{d,t}$) and must be linearized. The bounds of the dual variable $y_{d,t}$ are specified in Constraint (4.10c). The dual variables ϕ_d and $\zeta_{d,t}$ are logically constrained in (4.10d) to identify the periods in which positive demand deviations result in worst-case cost robustness scenarios. Constraint (4.10e) assigns the user-defined uncertainty budget parameter Γ_d, which limits the number of periods allowed to exhibit positive demand deviations due to cost robustness. To implement the cost robustness formulation for demand, formulation (4.10) must be used instead of constraints (4.5n)–(4.5q).

$$p_{d,t} \geq \tilde{\tilde{P}}_{d,t} + \chi_{d,t}\hat{P}_{d,t}\,; \qquad \forall d,t \tag{4.10a}$$

$$\lambda_t^{DA} p_{d,t}\Delta t \geq \lambda_t^{DA}\tilde{\tilde{P}}_{d,t}\Delta t + y_{d,t}\,; \qquad \forall d,t \tag{4.10b}$$

$$\phi_d + \zeta_{d,t} - M(1-\chi_{d,t}) \leq y_{d,t} \leq M\chi_{d,t}\,; \qquad \forall d,t \tag{4.10c}$$

$$\phi_d + \zeta_{d,t} \geq \lambda_t^{DA}\hat{P}_{d,t}\Delta t\,; \qquad \forall d,t \tag{4.10d}$$

$$\sum_t \chi_{d,t} = \Gamma_d\,; \qquad \forall d \tag{4.10e}$$

Coping with non-linear constraints

This section discusses the transformation from the non-linear terms in sets of equations (4.9b) and (4.10b) to obtain a single-level MILP formulation with an exact solution (i.e. it is *not* a linear approximation).

The electricity price variable λ_t^{DA} is modeled by equation (4.6a), which assigns different possible values for the electricity price depending on the status of the binary variables χ_t^{DA} and $\chi_t^{\prime DA}$. These binary variables are determined based on the worst-case scenario of the uncertain parameter for electricity price in the objective function of the optimization problem. Therefore, there are three possible combinations for the value of the electricity price. If $\chi_t^{DA} = \chi_t^{\prime DA} = 0$ for a specific period, that period is not the worst case, and $\lambda_t^{DA} = \tilde{\lambda}_t^{DA}$. If the RVPP operator acts as an energy seller during a specific period and that

Product of binary and continuous variables ($x \cdot y$):

$$
\begin{gathered}
y^Q = x \cdot y \\
y^Q = y - y^A \\
\varepsilon \cdot x \leq y^Q \leq M \cdot x \\
\varepsilon \cdot (1 - x) \leq y^A \leq M \cdot (1 - x)
\end{gathered}
$$

Product of binary and binary variables ($x \cdot u$):

$$
\begin{gathered}
z = x \cdot u \\
z \leq x \\
z \leq u \\
z + 1 \geq x + u
\end{gathered}
$$

Figure 4.2: Big-M method [52] to linearize multiplication of binary and continuous variables and binary and binary variables.

period represents the worst case, we have $\chi_t^{DA} = 1$ and $\chi_t^{\prime DA} = 0$. In this scenario, the lower bound of the electricity price is given by $\lambda_t^{DA} = \tilde{\lambda}_t^{DA} - \check{\lambda}_t^{DA}$. Lastly, if the RVPP operator acts as an energy buyer in a specific period and that period is the worst case, we have $\chi_t^{DA} = 0$ and $\chi_t^{\prime DA} = 1$. In this case, the price is obtained as the upper bound value $\lambda_t^{DA} = \tilde{\lambda}_t^{DA} + \hat{\lambda}_t^{DA}$. The electricity price variable λ_t^{DA} is used in equations (4.9b) and (4.10b), which are related to the uncertain constraints of ND-RES and demand, to model the profit robustness formulation. By substituting the electricity price from the equation (4.6a) into the constraints (4.9b) and (4.10b), nonlinear terms appear in the form of the multiplication of binary and continuous variables, as well as the product of two binary variables. These nonlinear terms need to be replaced with their exact equivalent linear constraints.

The equation (4.9b) contains two non-linear terms on the left and right hand sides due to the multiplication of the electricity price variable λ_t^{DA} and the continuous variables $p_{r,t}$ and $r_{r,t}^{\uparrow}$. By substituting the electricity price from constraint (4.6a) into the non-linear terms, the profit robustness constraint (4.9b) can be rewritten as (4.11a). In equation (4.11a), the non-linear terms $\check{\lambda}_t^{DA} \chi_t^{DA} (p_{r,t}^{DA} + r_{r,t}^{SR,\uparrow}) \Delta t$ and $\hat{\lambda}_t^{DA} \chi_t^{\prime DA} (p_{r,t}^{DA} + r_{r,t}^{SR,\uparrow}) \Delta t$ are multiplications of binary and continuous variables. Note that assigning discrete rather than continuous values for the electricity price in (4.6a) is relevant to the robustness concept, since the flexible worst-case scenarios always occur in the boundary values of the electricity price. Finally, the non-linear equation (4.11a) can be replaced by the set of linear constraints (4.11b)-(4.11h) using the Big-M method in [52].

In this regard, Figure 4.2 represents the general formulation presented in [52] for converting nonlinear equations arising from the multiplication of two variables (at least one of them being of binary nature) into a linear format. For the multiplication of a binary variable and a continuous variable, $x \cdot y$, two new positive variables, y^Q and y^A, need to be introduced to represent the final result of $x \cdot y$. These two new positive variables must be constrained by the values of ε and M, depending on the status of the binary variable x. For the multiplication of two binary variables, $x \cdot u$, a new binary variable, z, must be introduced. The value of z should be less than or equal to each of the binary variables x and u, and additionally, $z + 1$ must be greater than or equal to the sum of $x + u$.

The auxiliary variables $p_{r,t}^{Q}$ and $p_{r,t}^{A}$ with the same possible lower and upper bounds as the term $p_{r,t} + r_{r,t}^{\uparrow}$ are defined to determine the final result of the non-linear term $\check{\lambda}_t^{DA} \chi_t^{DA} (p_{r,t} + r_{r,t}^{\uparrow}) \Delta t$. When the binary variable χ_t^{DA} related to the negative electricity price deviation is 1, equations (4.11c)-(4.11e) set $p_{r,t}^{Q} = p_{r,t} + r_{r,t}^{\uparrow}$ and $p_{r,t}^{A} = 0$. On the other hand, for $\chi_t^{DA} = 0$, equations (4.11c)-(4.11e) lead to $p_{r,t}^{Q} = 0$ and $p_{r,t}^{A} = p_{r,t} + r_{r,t}^{\uparrow}$. Similarly, the auxiliary variables $p_{r,t}^{\prime Q}$ and $p_{r,t}^{\prime A}$ in equations (4.11f)-(4.11h) can define the final result of the non-linear term $\hat{\lambda}_t^{DA}\chi_t'^{DA}(p_{r,t}+r_{r,t}^{\uparrow})\Delta t$ in (4.11a). Therefore, the linear equations (4.11b)-(4.11h) can replace the non-linear constraint (4.11a). Note that since auxiliary variables $p_{r,t}^{Q}$ and $p_{r,t}^{A}$ represent the final results of the variable $p_{r,t}+r_{r,t}^{\uparrow}$ and the binary variable χ_t^{DA}, they have the same bounds as $p_{r,t}+r_{r,t}^{\uparrow}$. Therefore, the value of M in the Big-M method in equation (4.11) is exact and equal to the upper bound of $p_{r,t}+r_{r,t}^{\uparrow}$ ($\hat{\bar{P}}_{r,t}$). Note that the non-linear term $\lambda_t^{DA}p_{d,t}\Delta t$ in (4.10b) can be linearized in the same way as in (4.11) by introducing auxiliary variables. This linearization is omitted here for brevity.

$$
\begin{aligned}
&\tilde{\lambda}_t^{DA}(p_{r,t}+r_{r,t}^{\uparrow})\Delta t-\check{\lambda}_t^{DA}\chi_t^{DA}(p_{r,t}+r_{r,t}^{\uparrow})\Delta t+\hat{\lambda}_t^{DA}\chi_t'^{DA}(p_{r,t}+r_{r,t}^{\uparrow})\Delta t\\
&\le \lambda_t^{DA}\hat{\bar{P}}_{r,t}\Delta t-y_{r,t}\,; && \forall r,t \quad (4.11a)\\
&\tilde{\lambda}_t^{DA}(p_{r,t}+r_{r,t}^{\uparrow})\Delta t-\check{\lambda}_t^{DA}p_{r,t}^{Q}\Delta t+\hat{\lambda}_t^{DA}p_{r,t}'^{Q}\Delta t\le \lambda_t^{DA}\hat{\bar{P}}_{r,t}\Delta t-y_{r,t}\,; && \forall r,t \quad (4.11b)\\
&p_{r,t}^{Q}=p_{r,t}+r_{r,t}^{\uparrow}-p_{r,t}^{A}\,; && \forall r,t \quad (4.11c)\\
&\underline{P}_r\chi_t^{DA}\le p_{r,t}^{Q}\le \hat{\bar{P}}_{r,t}\chi_t^{DA}\,; && \forall r,t \quad (4.11d)\\
&\underline{P}_r(1-\chi_t^{DA})\le p_{r,t}^{A}\le \hat{\bar{P}}_{r,t}(1-\chi_t^{DA})\,; && \forall r,t \quad (4.11e)\\
&p_{r,t}'^{Q}=p_{r,t}^{DA}+r_{r,t}^{\uparrow}-p_{r,t}'^{A}\,; && \forall r,t \quad (4.11f)\\
&\underline{P}_r\chi_t'^{DA}\le p_{r,t}'^{Q}\le \hat{\bar{P}}_{r,t}\chi_t'^{DA}\,; && \forall r,t \quad (4.11g)\\
&\underline{P}_r(1-\chi_t'^{DA})\le p_{r,t}'^{A}\le \hat{\bar{P}}_{r,t}(1-\chi_t'^{DA})\,; && \forall r,t \quad (4.11h)
\end{aligned}
$$

MILP formulation for profit robustness

Finally, by substituting the linear equivalent of the non-linear constraints, the profit robustness problem can be formulated as an MILP problem (4.12) solvable with available MILP solvers such as CPLEX.

$$
\begin{aligned}
&(4.5a) && (4.12a)\\
&\text{st.}\\
&(4.5b)\text{–}(4.5e) && (4.12b)\\
&(4.6),\ (4.7) && (4.12c)\\
&(4.9a),\ (4.11b)\text{–}(4.11h),\ (4.9c)\text{–}(4.9e) && (4.12d)\\
&(4.5j)\text{–}(4.5m) && (4.12e)\\
&(4.10) && (4.12f)\\
&(4.5r)\text{–}(4.5u) && (4.12g)
\end{aligned}
$$

It is worth noting that the novel MILP formulation (4.12) proposed in this section is developed to flexibly consider both source- and load-side uncertainty by adjusting the uncertainty budget defined for temporal constraints. The flexibility to address different levels of uncertainty and the computational efficiency of the proposed approach are extensively studied through various case studies in the next sections.

4.4 Illustrative example

This section presents a simple illustrative example to show the performance of the proposed profit RO formulation in finding the worst-case profit robustness scenarios by considering the asymmetry of the DAM electricity price. The example provides a detailed description of how the worst cases of the electricity price deviations affect the worst cases of energy deviations. This illustrative example is particularly relevant as it highlights how the proposed profit robustness approach fundamentally differs from traditional energy robustness approaches, which typically focus only on energy worst-case selection.

4.4.1 Description

An RVPP with two ND-RES and one demand in a sample period of 5 hours is considered. The forecast bounds of production and demand of the RVPP units and the DAM electricity price are given in Table 4.2. Five cases are defined below to compare different conditions for the values of energy and price uncertainty budgets and to compare the results of the models formulated in Sections 4.3.2 and 4.3.3:

Case 1: Deterministic case with no deviations on electricity price, ND-RES production, and demand (i.e., $\Gamma^{DA} = \Gamma_r = \Gamma_d = 0$). This case serves as the deterministic benchmark, allowing us to evaluate the model's performance without any uncertainty;

Case 2: Only the DAM electricity price uncertainty is considered in the profit robustness model. It is assumed that the values of the DAM electricity price can deviate from the median to the worst case values in three periods (i.e., $\Gamma^{DA} = 3$ and $\Gamma_r = \Gamma_d = 0$). This case isolates the effect of price uncertainty, which is important since market prices are highly volatile and have a direct impact on the profitability of the RVPP;

Case 3: Only the uncertainty of ND-RES units energy and demand is considered in the profit robustness model. It is assumed that the production values of ND-RES 1 and ND-RES 2 and the demand can deviate from the upper or lower bound to the worst case values in three, one, and two periods, respectively (i.e., $\Gamma^{DA} = 0$ and $\Gamma_{r1} = 3$, $\Gamma_{r2} = 1$, and $\Gamma_d = 2$). This cases isolates the effect of energy uncertainty, which tests the capability of the model in handling these deviations;

Case 4: Both price and energy uncertainties are considered. The electricity price, the production of ND-RES 1 and ND-RES 2, and the demand values can deviate from the median, lower bound or upper bound to the worst case values ($\Gamma^{DA} = 3$ and $\Gamma_{r1} = 3$, $\Gamma_{r2} = 1$, and $\Gamma_d = 2$). This case combines both price and energy uncertainties, representing the most realistic operating environment. This case allows us to assess the joint impact of uncertainties in the profit robustness model.

Case 5: The energy robustness problem presented in Section 4.3.2 is solved for the same uncertainty budgets as in Case 4. This case highlights the practical differences between profit robustness and energy robustness models, particularly in terms of profit protection.

4.4.2 Results from Example

Figure 4.3 shows the final results of DAM electricity price, ND-RES energy, and demand for different cases proposed in this example. The final values of the above variables, corresponding to the whole period in each hour, are shown by different bars in this figure. If the value of a variable is equal to the median of the DAM price forecast (solid black line in the figure), the corresponding period is not considered as a worst case. For ND-RES and demand, if the variable is equal to the upper bound and lower bound of the forecast, respectively, the corresponding period is also not considered as a worst case. Figure 4.4 shows the values

Table 4.2: RVPP units and DAM electricity price forecast data.

	ND-RES1		**ND-RES2**		**Demand**		**DAM price**		
Time	$\tilde{\hat{P}}_{r,t}$ **[MW]**	$\check{P}_{r,t}$ **[MW]**	$\tilde{\hat{P}}_{r,t}$ **[MW]**	$\check{P}_{r,t}$ **[MW]**	$\tilde{\check{P}}_{d,t}$ **[MW]**	$\hat{P}_{d,t}$ **[MW]**	$\tilde{\lambda}_t^{DA}$ **[€/MWh]**	$\hat{\lambda}_t^{DA}$ **[€/MWh]**	$\check{\lambda}_t^{DA}$ **[€/MWh]**
1	5	2	0	0	5	2	4	1	1
2	5	3	4	2	15	5	8	2	3
3	10	5	15	5	12	4	6	3	4
4	10	4	12	4	20	3	10	5	2
5	15	6	6	3	20	6	6	3	1

of the auxiliary variables y_t^{DA} and $y_{r(d),t}$ related to the profit/cost affected by different uncertainties for defined cases. Note that, in the energy robustness model from Section 4.3.2, the variable $y_{r(d),t}$ is defined with units of [MW], whereas in the profit robustness model the unit is [€]. Therefore, the comparison of this variable is only provided for the first four cases related to profit robustness.

Case 1:

The RVPP obtains a profit of €56 by bidding its maximum values of ND-RES production according to Figure 4.3. The final values for the DAM electricity price are also obtained as the median values as the length of all bars is equal to the median. As shown in Figure 4.4, due to not considering the robustness, all auxiliary variables y_t^{DA} and $y_{r(d),t}$ are equal to zero, since the problem is a deterministic optimization one.

Case 2:

In Case 2, the RVPP profit in the DAM is −€12, where the negative value indicates that the cost of buying electricity to supply demand is higher than the profit obtained by selling electricity on the market. The algorithm chooses periods 3 and 4 for the negative price fluctuation and period 2 for the positive price fluctuation. Therefore, the final electricity prices in periods 3 and 4 (2) are decreased (increased) to their minimum (maximum) values compared to Case 1. As shown in Figure 4.4, the selected periods lead to auxiliary variables y_t^{DA}, representing profit reductions of €52 and €4 for negative price deviations in periods 3 and 4, respectively, and €12 for a positive price deviation in period 2.

Note that the maximum possible profit reduction in each period can be calculated by finding the maximum value of $\check{\lambda}_t^{DA} p_t^{DA} \Delta t$ for the negative price deviation and $-\hat{\lambda}_t^{DA} p_t^{DA} \Delta t$ for the positive price deviation. Therefore, the algorithm correctly identifies the periods that lead to the worst cases of profit reduction due to price uncertainty.

Case 3:

In Case 3, the RVPP profit in the DAM is −€166. The maximum possible profit reduction for each period can be calculated by $\lambda_t^{DA} \check{P}_{r,t} \Delta t$ for ND-RES and the maximum possible cost increase for demand can be calculated by $\lambda_t^{DA} \hat{P}_{d,t} \Delta t$. The worst cases of profit reductions for ND-RES 1 occur in periods 3, 4, and 5, whereas for ND-RES 2 this occurs in period 4. The worst cases of demand cost occur in periods 2 and 5, resulting in maximum demand in these periods. It can be easily verified that the algorithm correctly selects the worst periods in terms of profit reduction for ND-RES or cost increase for demand. For example, using Figure 4.4, the auxiliary variable $y_{d,t}$ takes nonzero values only in the worst-case periods, which are periods 2 and 5, with values of €40 and €36, respectively. These are obtained by multiplying the electricity prices λ_t^{DA} by the maximum possible demand deviations $\hat{P}_{d,t}$ in those periods. From Table 4.2,

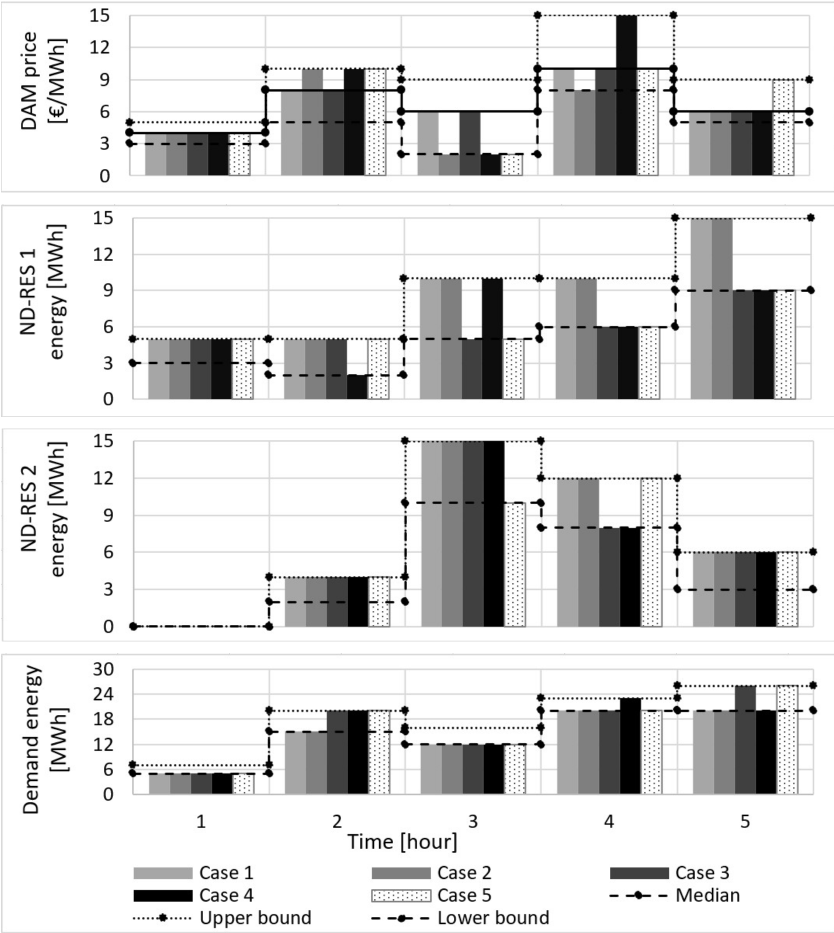


Figure 4.3: Final values of DAM electricity price and RVPP unit output energy in different case studies.

the corresponding values for periods 1–5 are €8, €40, €24, €30, and €36. Thus, the algorithm correctly identifies periods 2 and 5 as those with the worst impact on profit reductions.

Case 4:

The RVPP profit in the DAM is −€279. This case shows one of the significant differences between the models in Sections 4.3.2 and 4.3.3 (by comparing the black (Case 4) and white (Case 5) bars), where instead of selecting the periods with higher energy reductions, the profit robustness algorithm selects the periods that result in higher profit reductions. For instance, the worst case of ND-RES 2 production occurs in period 4 with profit reduction of €60 and energy reduction of 4 MW. However, the period 3 with the highest amount of energy deviation (5 MW) in Case 5 is selected as the worst case. It is worth noting that in Case 4, the DAM price deviation is positive in periods 2 and 4 and negative in period 3.

Case 5:

In Case 5, those periods that result in more deviations of ND-RES production and demand are selected as the worst cases. Moreover, the worst cases of electricity price deviations are determined according to the

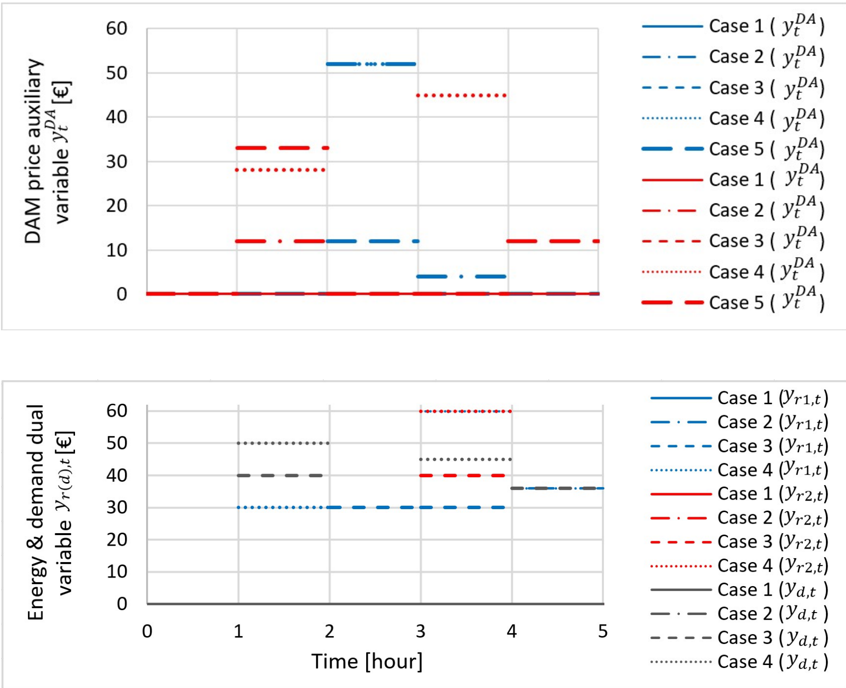


Figure 4.4: The profit/cost auxiliary variables affected by different uncertainties in various case studies.

final values of ND-RES production and demand. For example, for ND-RES 1 in Figure 4.3, periods 3, 4, and 5 exhibit the highest energy deviation and are selected as the worst-case scenarios. For demand, hours 2 and 5 are chosen as the worst-case scenarios with the highest positive deviation in energy. For the DAM electricity price, deviations to higher values occur in periods 2 and 5, while a deviation to a lower value occurs in period 3, which are the worst-case scenarios. Considering the different selection of worst-case periods for Cases 4 and 5, the RVPP obtains a profit of −€279 in the former, which is lower than the profit of −€223 obtained in Case 5. Note that the profit obtained is for bidding in the market and is different from the actual profit after clearing the market. Suppose the RVPP uses the profit robustness bidding strategy proposed in Section 4.3.3, even though its profit is lower. In this condition, it reduces the risk of significant losses and penalties (e.g., due to buying energy in real time or penalties for the energy it promised to provide but cannot) for not considering the actual worst cases. Moreover, the results indicate that the energy robustness approach from Section 4.3.2 cannot fully cope with the actual worst cases for both energy (ND-RES production and demand) and price uncertainty. On the contrary, the profit robustness approach proposed in this thesis considers the worst cases of profit/cost deviations for ND-RES/demand instead of the maximum energy deviation. As a final remark, illustrative results indicate that the profit robustness model accurately selects the worst-case profit for different uncertainty budgets, and shows better performance in finding the worst-case scenarios compared to the energy robustness model.

The illustrative example presented in this section has clarified the application of the proposed models in a simplified setting; in the following section, the analysis is extended to a full simulation study to evaluate their performance under realistic conditions.

4.5 Case studies

This section presents the simulation results based on the proposed energy and profit robustness frameworks to evaluate the impact of various uncertain parameters on the scheduling and profitability of the RVPP across different electricity markets.

4.5.1 Data

The same RVPP described in Chapter 3 (see Section 3.3.1) is used for the simulations in this section. However, unlike the previous deterministic setup, the forecast data for the RVPP units and the various market parameters are now modeled using forecast bounds derived from historical data from March 2021. To avoid overly conservative solutions, these bounds are defined between the 20th and 80th percentiles of the historical data. The forecast bounds for the energy production of the RVPP units—including the WF, solar PV, CSP, and FD—are shown in Figures 4.5 and 4.6. Additionally, the forecast bounds for electricity prices in the DAM, SRM, and IDMs are presented in Figure 4.7. Table 4.3 presents the predefined uncertainty budgets associated with different uncertain parameters used throughout the case studies. Since the solar PV and the thermal output of the CSP are zero during nighttime, these uncertainty budgets are assigned smaller numbers. Additionally, the uncertainty budgets for the IDM sessions, which cover fewer than 24 hours, are proportionally reduced. This allocation strategy maintains a consistent proportion of uncertain hours across the simulation horizon for all parameters.

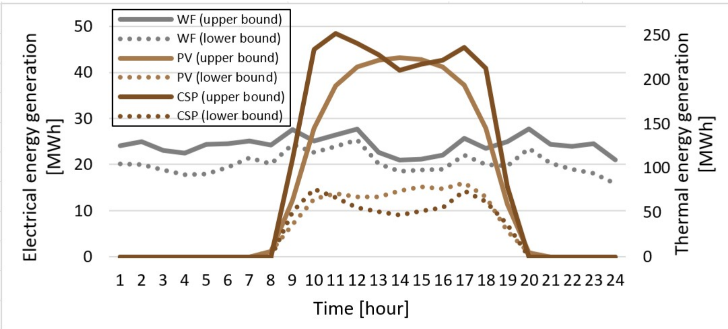


Figure 4.5: The forecast bounds of WF, solar PV, and CSP.

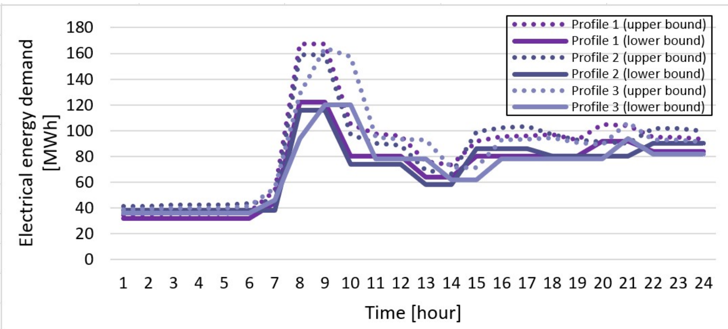


Figure 4.6: The forecast bounds of FD.

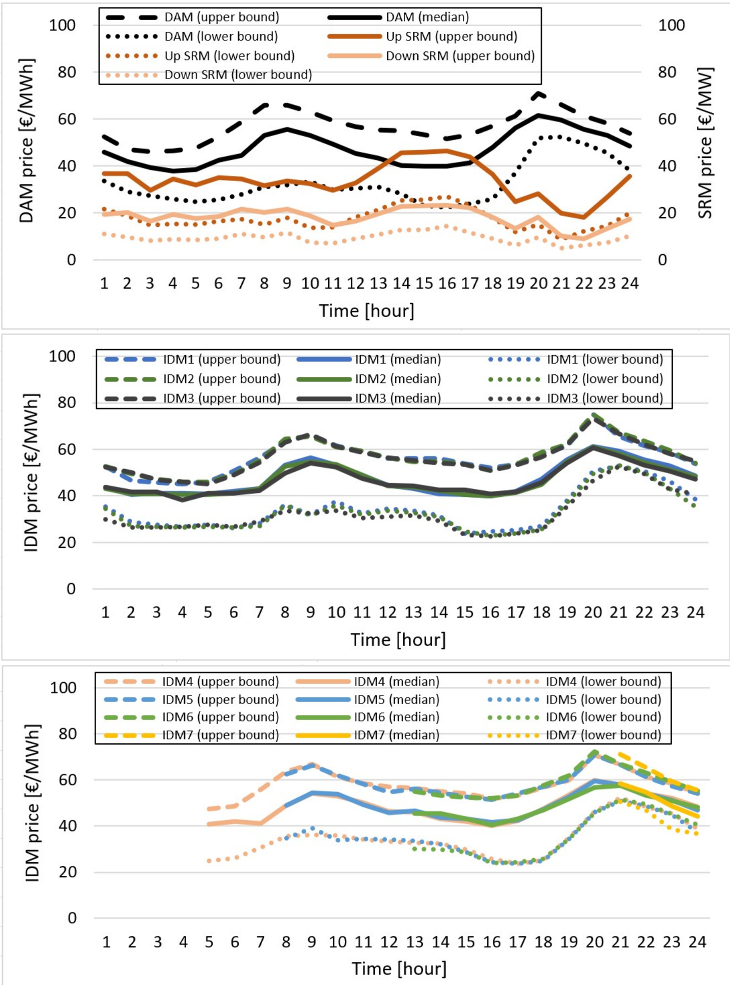


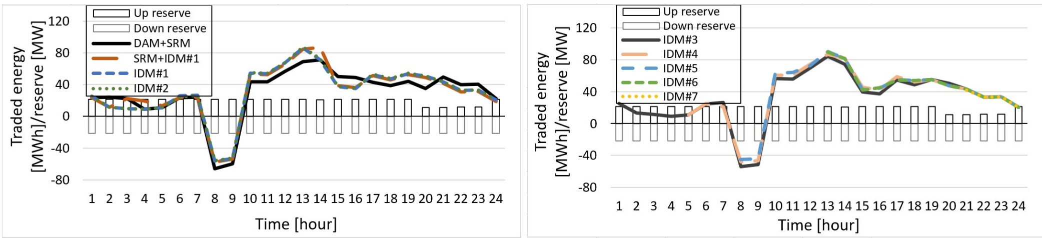
Figure 4.7: The forecast bounds of DAM, SRM, and IDMs price.

Table 4.3: Uncertainty budgets of the RVPP operator's strategic approaches: optimistic, balanced, and pessimistic.

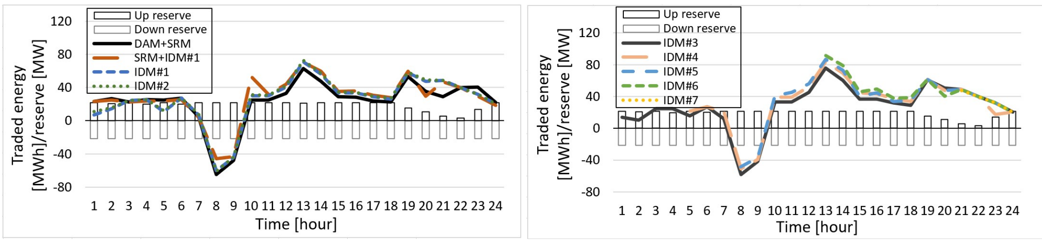
Uncertainty type	Parameter	Optimistic	Balanced	Pessimistic
Market price	DAM/SRM	4	8	12
	IDM#1–IDM#3	4	8	12
	IDM#4	3	6	10
	IDM#5	3	6	9
	IDM#6	2	4	6
	IDM#7	1	1	2
Renewable production	WF	4	8	12
	PV	2	4	6
	CSP thermal	2	4	6
Load consumption	FD	4	8	12

4.5.2 Results

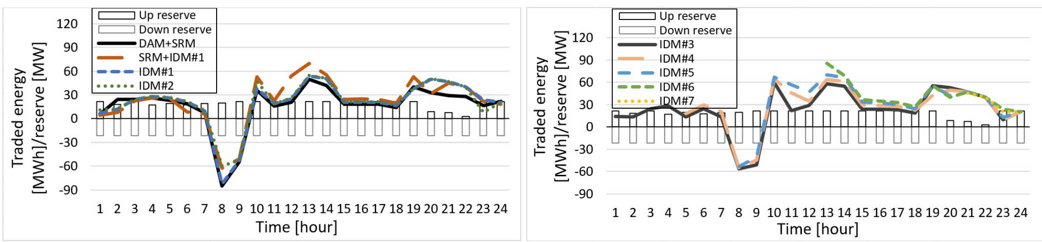
Figure 4.8 shows the traded energy and reserve of the RVPP across different electricity market sessions under various strategic approaches taken by the RVPP operator. The RVPP is primarily an energy seller in the optimistic, balanced, and pessimistic cases, except during hours 8–9. In the optimistic case, where uncertain parameters are allowed to deviate to their worst-case values in only a limited number of hours, changes in total traded energy are observed up to IDM#5, with the most significant changes occurring in IDM#1. In IDM#1, the RVPP acts as an energy seller during hours 8–13 and 17–20, and as an energy buyer during hours 2–3, 15–16, and 21–24. This leads to an increase in total energy sold during hours 10–13 and 17–20, and a decrease in both the energy sold during hours 2–3, 15–16, and 21–24, and the energy bought during hours 8–9, compared to the DAM+SRM session. In the balanced case, uncertain parameters are allowed to deviate in a greater number of hours. As a result, the energy sold by the RVPP in the DAM decreases compared to the optimistic case, particularly in hours 7, 10–18, and 21. Additionally, the up reserve provided by the RVPP is reduced in hours 19–22 compared to the optimistic case. Moreover, changes in the traded energy of the RVPP are observed in more IDM sessions (even up to IDM#7), and these changes are of higher magnitude than in the optimistic case. This is because, with increased uncertainty, greater fluctuations in the production of ND-RESs are considered, making the role of the IDM in adjusting the RVPP's energy more critical. In the pessimistic case, higher uncertainty budgets are applied compared to



(a) Optimistic case.



(b) Balanced case.

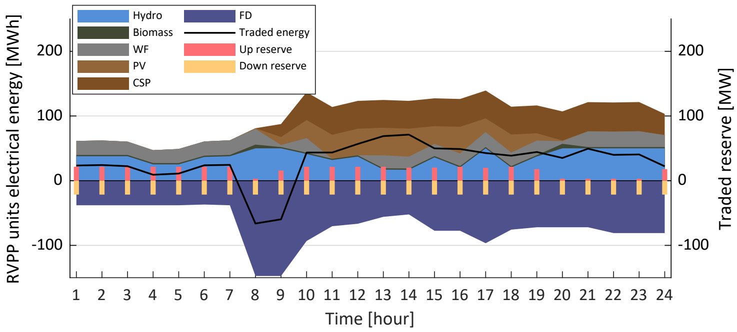


(c) Pessimistic case.

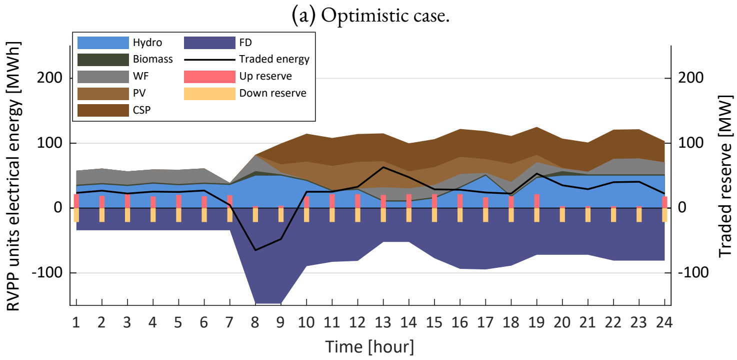
Figure 4.8: Total traded energy and reserve of RVPP until different sessions of electricity markets under the energy robustness approach for different RVPP operator's strategies: optimistic, balanced, and pessimistic.

the previous optimistic and balanced scenarios. This leads to further reductions in the energy sold and reserves provided across more hours, along with an increase in energy purchased during hours 8–9 to supply internal demand. Additionally, more substantial changes in the traded energy of the RVPP are observed across the IDM sessions compared to the earlier strategies.

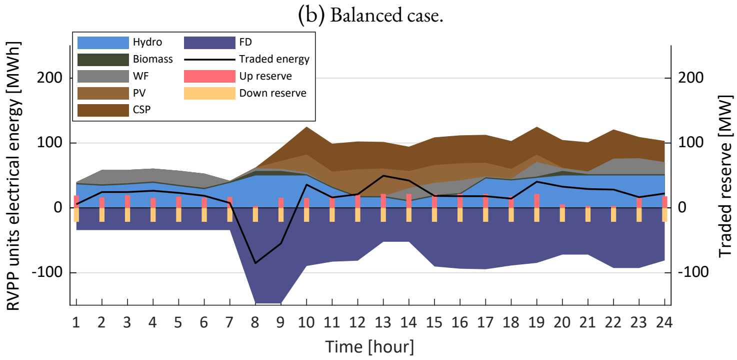
Figure 4.9 illustrates the electrical energy generation by RVPP units in the DAM+SRM for different strategic approaches of the RVPP operator. The figure shows that under more conservative strategies, fluctuations in the output of solar PV, WF, and demand increase. For example, energy fluctuations of the WF occur in hours 9, 11, 12, and 20 in the optimistic case. In the balanced and pessimistic cases, these fluctuations occur in hours 7, 9–12, 17, 20, and 21, and in hours 1, 7–13, 17, 18, 20, and 21, respectively. It is worth noting that although uncertainty in the thermal input energy of the CSP is considered, the CSP



(a) Optimistic case.



(b) Balanced case.

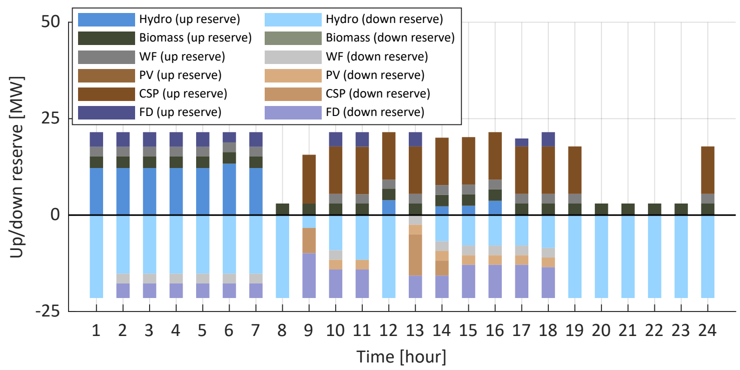


(c) Pessimistic case.

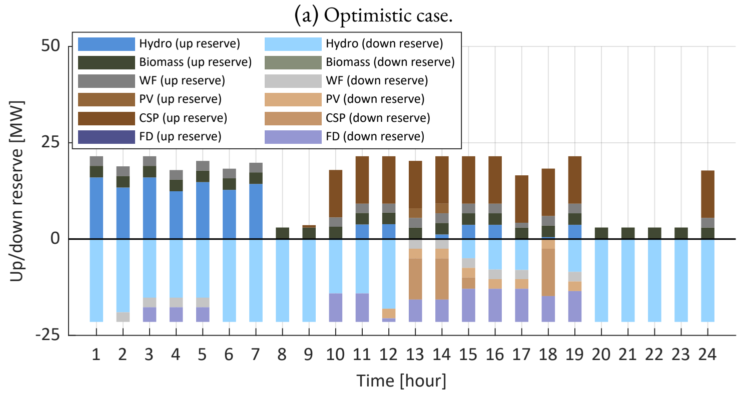
Figure 4.9: Electrical energy generation by RVPP units and traded energy and reserve by the RVPP in the DAM+SRM under the energy robustness approach for different RVPP operator's strategic approaches.

can effectively mitigate these energy fluctuations with the support of its TS. As a result, its final electrical energy output is only marginally affected. Additionally, the hydro plant plays a key role in compensating for energy shortages from the ND-RESs. For example, in hour 18, the WF produces energy in the optimistic and balanced cases, but not in the pessimistic case. This shortage of energy in the pessimistic case is compensated by higher energy generation from the hydro plant at that hour.

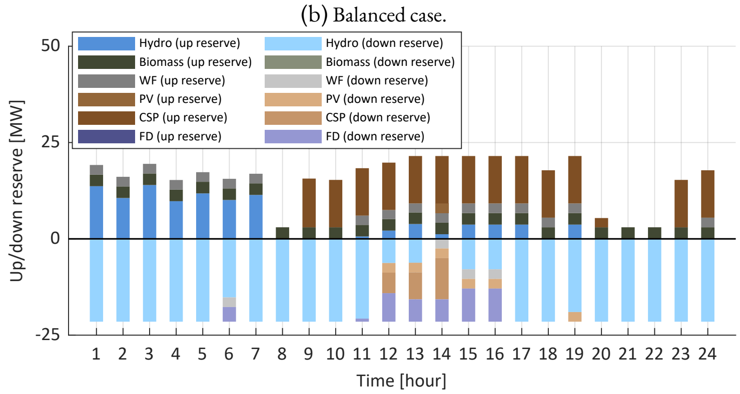
Figure 4.10 shows the reserve provided by RVPP units in the DAM+SRM for different RVPP operator strategic approaches. The results indicate that adopting more conservative strategies leads to a reduction in



(a) Optimistic case.



(b) Balanced case.



(c) Pessimistic case.

Figure 4.10: Up and down reserve provided by RVPP units in the DAM+SRM under the energy robustness approach for different RVPP operator's strategic approaches.

the total up reserve provided by RVPP units. For example, in the pessimistic case, there are reductions in up reserve provision during hours 1–7, 10–12, and 18 compared to the optimistic case. These reductions are due to the fact that increased uncertainty negatively affects the production of ND-RES and the consumption of demand, requiring D-RES units to compensate for energy shortages. As a result, the availability of these units for reserve provision decreases. In all cases, the hydro plant and CSP provide the highest amount of up reserve due to their inherent flexibility. Specifically, the hydro plant contributes significantly in hours 1–7, while the CSP efficiently provides up reserve during hours 9–19 when it is available. It is also worth noting that although the FD provides up reserve in the optimistic case, it does not do so in the balanced and pessimistic cases, as its flexibility is primarily utilized for energy reduction in those scenarios.

Table 4.4 presents the economic results across different sessions of the electricity market under various uncertainty strategies. The values in this table are cumulative, as they include the results from all previous market stages. The main income of the RVPP comes from energy and reserve provision in the DAM and

Table 4.4: RVPP economic results until different sessions of electricity markets under the energy robustness approach for different uncertainty strategies.

Strategy	**Market**	Profit [k€]	Revenue [k€]	Cost* [k€]	Computational time [s]
Optimistic	DAM+SRM	8.75	56.28	47.53	0.62
	SRM+IDM#1	12.16	61.18	49.02	0.23
	IDM#1	11.10	60.70	49.60	0.51
	IDM#2	11.30	61.08	49.78	0.55
	IDM#3	11.69	61.88	50.19	0.65
	IDM#4	12.84	63.94	51.10	0.19
	IDM#5	13.09	64.48	51.39	0.19
	IDM#6	13.08	64.42	51.34	0.18
	IDM#7	12.88	64.35	51.47	0.08
Balanced	DAM+SRM	-1.67	48.36	50.03	0.51
	SRM+IDM#1	3.53	56.40	52.87	0.33
	IDM#1	2.38	53.66	51.28	1.03
	IDM#2	2.74	54.54	51.80	0.98
	IDM#3	3.36	56.18	52.82	1.21
	IDM#4	4.60	59.14	54.54	0.39
	IDM#5	5.30	60.79	55.49	0.46
	IDM#6	5.26	61.65	56.40	0.19
	IDM#7	5.05	61.57	56.52	0.08
Pessimistic	DAM+SRM	-10.66	40.54	51.20	0.67
	SRM+IDM#1	-4.01	50.44	54.45	0.44
	IDM#1	-4.92	47.29	52.21	1.43
	IDM#2	-4.73	48.72	53.45	0.81
	IDM#3	-4.00	51.42	55.42	1.52
	IDM#4	-2.97	54.73	57.70	0.42
	IDM#5	-2.22	57.65	59.87	0.32
	IDM#6	-1.63	59.41	61.04	0.29
	IDM#7	-1.99	59.16	61.15	0.11

**Cost includes operation cost of RVPP units and robust cost due to price uncertainty.*

SRM, while the IDMs are primarily used for energy adjustments. By adopting more conservative strategies (i.e., the balanced and pessimistic cases), greater changes in RVPP profit are observed in the IDM sessions compared to the optimistic case. For example, the profit change from IDM#1 to IDM#7 is 16.0%, 112.2%, and 59.5% for the optimistic, balanced, and pessimistic cases, respectively. Furthermore, the total profit across all market sessions is lower in the more conservative cases compared to the optimistic case. This is because, under conservative strategies, the RVPP submits lower bids in energy and reserve markets, leading to reduced total revenue. Additionally, the cost associated with electricity price uncertainty is higher in the conservative cases. For instance, in the DAM+SRM session, the profit of the RVPP in the balanced and pessimistic cases is reduced by 119.1% and 221.8%, respectively, compared to the optimistic case. Corresponding reductions in revenue are 14.1% and 27.0%, while cost increases in the same comparisons are 5.2% and 7.7%.

Table 4.5 compares the economic results of units when they participate individually in the DAM+SRM and when they operate as an integrated RVPP under different uncertainty strategies. The results show that the total profit of units under individual participation in the market for the optimistic, balanced, and pessimistic strategies is -11.97 k€, -30.89 k€, and -46.27 k€, respectively. In contrast, when a coordi-

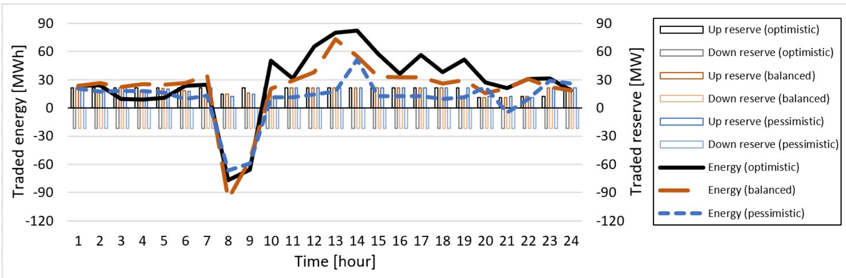
Table 4.5: Units economic results for individual and coordinated participation strategies in the DAM+SRM under the energy robustness approach for different uncertainty strategies.

Strategy	**Unit**	Profit [k€]	Revenue [k€]	Cost [k€]
Optimistic	Hydro	34.32	49.40	15.08
	Biomass	0	0	0
	WF	14.50	23.25	8.75
	PV	9.71	15.65	5.94
	CSP	17.19	40.08	22.89
	FD	-87.69	-82.11	5.58
	Total	-11.97	46.27	58.24
	RVPP	8.75	56.28	47.53
Balanced	Hydro	31.38	48.35	16.97
	Biomass	0	0	0
	WF	10.05	19.03	8.98
	PV	7.06	14.57	7.51
	CSP	13.33	37.92	24.59
	FD	-92.71	-83.38	9.33
	Total	-30.89	36.49	67.38
	RVPP	-1.67	48.36	50.03
Pessimistic	Hydro	28.75	48.50	19.75
	Biomass	0	0	0
	WF	6.96	15.44	8.48
	PV	5.66	13.27	7.61
	CSP	10.62	35.59	24.97
	FD	-98.26	-85.89	12.37
	Total	-46.27	26.91	73.18
	RVPP	-10.66	40.54	51.20

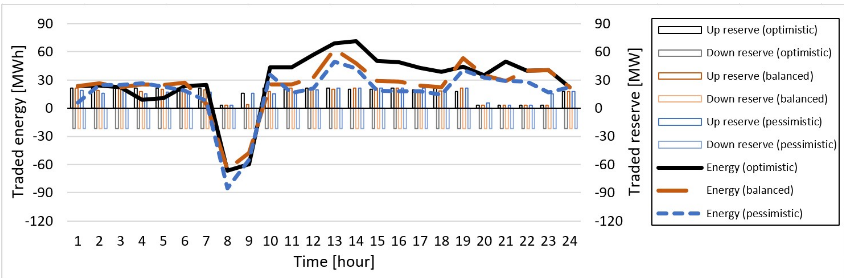
nated strategy is adopted, their profit increases by 173.1%, 94.6%, and 77.0% for these strategies, respectively. These results highlight the importance of aggregation for enhancing RVPP profitability in the market.

Figure 4.11 compares the total traded energy and reserve of the RVPP under the profit robustness and energy robustness models in the DAM+SRM session for different uncertainty handling strategies. The results indicate that the profit robustness approach adopts a different bidding strategy than the energy robustness approach, as it considers the interaction between electricity prices and energy. For example, during hours 20–22—when the DAM electricity price is high (see Figure 4.7)—the traded energy of the RVPP in the profit robustness model is lower than in the energy robustness model across all optimistic, balanced, and pessimistic cases. Instead, the RVPP allocates more capacity to provide up reserve in these hours under the profit robustness model. It is important to note that providing less energy during high-price hours should not be misinterpreted. In the profit robustness model, the bidding strategy is designed to be more robust in hours that, in reality, may have a greater impact on profit fluctuations. As a result, the RVPP avoids submitting high energy bids in these hours to reduce potential financial risks.

Table 4.6 compares the economic results of the RVPP in the DAM+SRM session under the profit robustness and energy robustness models for different uncertainty-handling strategies. In the profit robustness approach, a lower profit is obtained compared to the energy robustness model across all optimistic, balanced, and pessimistic cases. As discussed earlier, this is because the RVPP prefers not to submit very high bids during hours that have a highly volatile effect on its final profit in the profit robustness model. Although this strategy results in lower market revenues, the submitted bids are more robust in terms of the actual provision of promised energy, thereby reducing the likelihood of penalties. Regarding computational time, the profit robustness approach is more demanding for all uncertainty-handling strategies. This is due to the inclusion of interactions between price and energy uncertainties, making the approach more complex than the energy robustness model. Nevertheless, the computational time for the profit robustness model remains very efficient and is under five minutes in all cases.



(a) Profit robustness model.



(b) Energy robustness model.

Figure 4.11: Total traded energy and reserve of RVPP in the DAM+SRM session for different uncertainty handling strategies.

Table 4.6: RVPP economic results in the DAM+SRM session for different uncertainty handling strategies.

Model	**Strategy**	Profit [k€]	Revenue [k€]	Cost [k€]	Computational time [s]
Profit robustness	Optimistic	5.70	55.18	49.48	1.81
	Balanced	-5.88	46.56	52.44	51.01
	Pessimistic	-14.81	34.41	49.22	224.05
Energy robustness	Optimistic	8.75	56.28	47.53	0.62
	Balanced	-1.67	48.36	50.03	0.51
	Pessimistic	-10.66	40.54	51.20	0.67

4.6 Conclusions

The uncertain parameters related to electricity prices in different energy and reserve markets, as well as the energy production of ND-RES and CSP units and the consumption of FD, can significantly affect the scheduling and bidding strategy of the RVPP across various electricity markets. In this regard, this chapter extends the deterministic formulation proposed in the previous chapter to incorporate these uncertainties. First, a two-stage energy robustness model is proposed to address these uncertain parameters with their asymmetric nature. In the first stage, the RVPP maximizes its profit in the electricity market; in the second stage, the adverse effects of uncertainty on the optimization problem are considered. Recognizing that uncertainty impacts the entire scheduling horizon rather than just individual periods, the proposed two-stage RO model is transformed into a single-level MILP optimization problem. The energy robustness approach is then further developed into a profit robustness approach to capture the interactions between different price and energy uncertainties and their combined effect on the RVPP's final profit. Simulation results illustrate how the RVPP operator decides on unit scheduling as well as final energy and reserve bids in the electricity markets under different strategies, ranging from optimistic to conservative. The results show that adopting more conservative strategies decreases sold energy and increases bought energy, providing a more robust solution against worst-case scenarios. Furthermore, in the balanced and pessimistic cases, changes in the traded energy of the RVPP across various IDMs sessions are greater than in the optimistic case, indicating a greater need for adjustments in the IDMs and enhancing their importance. The results also indicate that, under more conservative strategies, profit reductions are more pronounced than the corresponding changes in the revenue and costs of the RVPP. Additionally, the hydro plant and CSP compensate for energy shortages of ND-RES units under more conservative strategies, which in turn affects their reserve provision. Finally, the profit robustness approach yields more robust energy and reserve bids, especially during hours with the highest profit volatility, compared to the energy robustness approach.

In this chapter, only profit related to bidding in the electricity market is considered, and possible penalties for failing to fulfill market commitments are not addressed. The next chapter will incorporate the concept of regret to account for the potential penalization effects on the RVPP's bidding strategy. The RVPP will then be capable of adjusting its level of conservatism against uncertainty using more tangible input parameters based on economic factors, instead of the uncertainty budget used in this chapter, which determines the number of worst-case hours within the scheduling horizon.

5 Regret-based Robust Optimal Bidding of RVPP in Electricity Markets

In the previous chapter, the proposed RO relies on the well-known parameter called the *uncertainty budget* to define the level of conservatism. However, this parameter was not defined based on economic factors but rather on the nature of each uncertainty. The VPP operator needs a monetary interpretation of *value* of the uncertainty budget to solve the optimization problem. This chapter introduces a regret-based flexible RO problem to address this gap, accounting for various sources of uncertainties. The concept of expected regret is developed and implemented through a set of mixed-integer linear constraints to help the RVPP operator gain relevant economic insights regarding this budget parameter.

5.1 Framework

We have discussed how uncertainty characterization is one of the challenging aspects of RVPP market participation. The RVPP operator must consider various uncertainties using appropriate optimization techniques. These techniques need to be computationally efficient so that the RVPP can determine its optimal bids and offers before the energy and reserve markets' gate closure or adjust the scheduling of its units accordingly [9, 10, 200]. Furthermore, the RVPP operator must decide on the level of conservatism to apply to different uncertainties and conduct sensitivity analyses, as varying strategies for handling uncertainties can significantly affect profitability.

A significant issue identified from the RO models presented in the previous chapter is that the RVPP operator needs a monetary interpretation of *value* of the uncertainty budget to solve the optimization problem. Furthermore, multiple uncertainties must be considered in the optimization problem, and determining the uncertainty budget for each of these uncertainties is not an easy task. The results presented and discussed in Chapter 4 show that, expectedly, by increasing the uncertainty budgets, the RVPP adopts more conservative strategies in the market, which results in lower bidding profit. However, the RVPP operator still does not easily know how to assign specific values to uncertainty budgets, and what such values imply. In fact, the provided results can be misleading, since they do not show the consequences of each decision when the uncertainties become known, and only consider the expected profit of RVPP in the market, which is obviously at its highest value for null uncertainty budget (deterministic case without uncertainty).

Alternatively to the criterion of minimizing the maximum robust cost used in Chapter 4, as well as in other works such as [29, 43, 44, 45, 46, 47, 48, 49, 110, 201], the problem can be set to minimize the *maximum regret cost* [54, 55, 56, 57]. In this context, regret is defined as *the loss felt by the decision maker with respect to the use of alternative decisions when uncertainties unfold*. Maximum regret minimization is thus a method for decision makers who do not have the probability of events or are not interested in this information. In [54], a min-max regret problem is solved by a relaxation process for the linear programming problems. The paper in [55] develops a mixed-integer min-max regret formulation to account for the uncertain coefficients in the objective function of the problem. The paper in [56] develops an iterative solution to account for the uncertainties of investment cost and fuel cost in the objective function by using min-max regret criteria in the strategic energy planning problem. In [57], a two-stage min-max regret-based model is proposed to model the VPP scheduling in the DAM by considering the power deviations in the BAM. The RO is used to capture the uncertainties in the electricity price and wind unit production for some specific uncertainty budgets.

However, the decisions made in a min-max regret problem tend to be overly conservative, as they aim to prevent any single scenario from causing significant regret. A solution to alleviate the potentially unsatisfactory results of the min-max regret problem can be obtained by minimizing the *expected regret* [58, 59, 60, 61]. The expected regret can be defined as the *sum of lost costs by considering the probability of alternative decisions*. In [58], a cooperative framework between VPP and EV charging stations is proposed to maximize the benefits of the multi-stakeholder system. The expected maximum regret of the EV charging demands and its associated electricity price in the charging station problem, as well as the expected maximum regret of the renewable production of VPP are minimized by two stochastic min-max regret problems. In [59], a hierarchical stochastic min-max regret algorithm is proposed to account for the uncertainties of electricity price, wind production production, and reserve deployment. The worst case of expected regret with respect to wind production in different scenarios is minimized in the optimization problem. However, identifying the expected regret in multiple scenarios and in the hierarchical structure of the min-max problem proposed in [58, 59] is challenging in both modeling and computation. In [60], a multi-objective model considering both economic and risk measures is proposed for scheduling and bidding strategy of VPP in the energy market. A stochastic p-robust optimization model is used to capture the uncertainties of ND-RES production, load, and electricity price. In this algorithm, the maximum value of the relative regret in all scenarios is confined in each iteration until the optimization problem becomes infeasible. In [61], the stochastic p-robust optimization method is used to consider different uncertainties related to electricity price and ND-RES production of a generation company participating in the energy and reserve markets. However, the methodologies suggested in [60, 61] require iterative solutions to SP, which limits their practical application due to high computational burden especially for a high or even a moderate number of scenarios. Additionally, although the p-parameter plays a critical role in the optimization outcomes, defining its value and the step reduction in each iteration is quite difficult.

5.2 Gaps and contributions

The papers described above minimize the maximum expected regret for multiple scenarios in the SP, which usually implies high computational time, especially for a large number of scenarios. To address this issue, the use of scenario reduction methods to keep the problem tractable is widely used in the SP. However, these methods may lead to less accurate regret computation, since the expected regret in their model is for reduced scenarios, and the regretful scenarios are good targets for removal in the scenario reduction process. Considering the aforementioned gaps and the advantages of the RO approach, this chapter develops a novel modeling approach to account for the expected regret in the RO for RVPP bidding problem. The profit-minimizing nature of uncertainties is modeled by the flexible RO approach, and the expected regret associated with each uncertain parameter is modeled in the constraints of the optimization problem. In this way, while the expected regret of RVPP operator decisions is controlled in the RO, the problem remains highly tractable, unlike the SP. Moreover, the conservatism level of the problem is controlled by the monetized user-defined parameters, which represent a per-unit value of the maximum regret cost instead of the uncertainty budget used in Chapter 4. This is beneficial because it allows the user to determine the parameter based on a monetized value rather than based on several characteristics related to uncertain parameters, such as the type of uncertainty, deviations of uncertain parameters, type of markets, type of units, and so on. Although the focus here is on the RVPP bidding problem, the proposed framework is generic and can be applied to other decision-making contexts with uncertainty, such as microgrid operation, generation and demand scheduling, or portfolio management, where control of expected regret is desirable.

In this chapter, the concept of expected regret cost is implemented in the RO of RVPP bidding in the electricity markets by a set of mixed-integer constraints. The expected regret for a decision of RVPP is defined as the weighted sum of the loss differences between the corresponding solution and other potential solutions associated with the PDF of the uncertain parameter. The RVPP operator controls its desired expected regret cost with respect to uncertain parameters associated with DAM and SRM electricity price and the total output energy of RVPP. In this way, a new control parameter, more tangible in terms of economic factors, is used to determine the level of conservatism of RVPP instead of the uncertainty budget. The RO problem then assigns the corresponding flexible worst case of the uncertain parameters based on the level of conservatism determined by the RVPP operator. The profit robustness approach proposed in Chapter 4 has been thus updated to incorporate additional constraints related to expected regret.

The contributions of this chapter are outlined below:

- *Expected-regret-based RO framework:* The expected regret associated with different decisions regarding the electricity and reserve prices, as well as the bidding energy and reserve of the RVPP operator in electricity markets, is modeled by a set of mixed-integer constraints in the RO problem. The proposed framework ensures the tractability of the MILP problem solutions while enhancing the computational efficiency.

- *Economic evaluation of conservatism levels for RVPP operation:* The proposed uncertainty modeling assists the RVPP operator to evaluate its level of conservatism based on economic factors (different regret costs) in the optimization problem. This is an improvement over most papers in the literature that use RO methods, where the VPP operator usually defines the RO parameter, called the uncertainty budget, based on the number of hours that uncertain parameters deviate from the median to the worst case.

- *Simplified and monetized selection of a level of conservatism:* The proposed regret-based approach simplifies the determination of input parameters for RO problems. Rather than requiring the operator to determine different uncertainty budgets for each RVPP unit and electricity price while accounting for the operator's level of conservatism and various technical characteristics (e.g., production availability hours and fluctuation levels), the framework greatly simplifies this process by allowing the operator to specify a desired level of conservatism directly in terms of costs. The optimization problem then accounts for the characteristics of individual units, allowing for a more structured solution.

5.3 Methodology

In this section, the regret-based flexible RO formulation for the RVPP bidding problem in DAM+SRM participation, considering the penalty costs of BAM, is presented. The proposed formulation is an extension of the profit robustness approach introduced in Chapter 4. To achieve this, constraints related to expected regret are formulated as a MILP problem, aiding the RVPP operator in determining an appropriate level of conservatism in decision-making.

5.3.1 Regret-based flexible robust approach

The *profit robustness* approach presented in Chapter 4 identifies the worst-case scenario of the optimization problem when various uncertainties in both the objective function and constraints interact. In this context, uncertainty budgets are used to represent the number of hours or periods during which uncertain parameters deviate from their median values toward their worst-case realizations. However, it is often challenging for the RVPP operator to predefine these values—especially when multiple uncertain parameters are involved in the optimization problem. In this section, the concept of expected regret is introduced for various decision alternatives of the RVPP. The objective is to allow the RVPP operator to assign a desired level of regret to each parameter, instead of defining uncertainty budgets to represent the chosen level of conservatism. By using expected regret, a more intuitive and interpretable metric—expressed in cost terms—is provided. Normal distributions are assumed to compute the expected regret for different uncertain parameters; however, the proposed approach is general and can be applied to any probability distribution. In cases where the PDF of uncertain parameters is unavailable, expected regret can still be estimated using assumed or approximated distributions such as normal, triangular, or uniform. Therefore, the proposed probabilistic approach is well-suited for RO problems, where incomplete information about uncertain parameters is a common challenge. The remainder of this section formulates the regret-based flexible RO framework proposed in this thesis as an MILP, which automatically determines uncertainty budgets based on the level of conservatism specified by the user. This is achieved by constraining the estimated expected regret associated with penalty costs from RVPP's uncertain energy deviations in the BAM, as well as regret costs arising from DAM and SRM price fluctuations.

5.3.2 Expected regret definition

We recall that, in the context of the work presented in this thesis, *expected regret* can be defined as the weighted sum of the loss felt by the decision maker (RVPP operator) with respect to the use of alternative decisions when uncertainties related to RVPP output energy and DAM and SRM electricity prices unfold. The additional costs in the BAM due to not providing promised energy of the DAM and potential profit decrease due to electricity price fluctuation in the DAM and SRM clearing are considered as the loss felt by RVPP. Note that the profits from bidding in the DAM and SRM in different decisions are neglected in the calculation of the expected regret to easily control the regret level in the constraints of the optimization problem. In this way, the expected regret of more conservative strategies will be lower than optimistic decisions resulting in a better control of the expected regret. This estimated expected regret can help the RVPP operator to assign its level of conservatism. A simple example is presented in this section to help understand the definition of expected regret.

Suppose the RVPP operator can make 4 different decisions with equal probability regarding its output energy as $D = \{d0, d1, d2, d3\}$. The corresponding RVPP output energy and electricity price for each of these decisions are {9,7,5,3} MWh, and {7,6,5,4} €/MWh, respectively. The penalty for not providing promised energy is assumed to be 10 €/MWh. Table 5.1 provides information about the energy and price regret of decision $d0$ corresponding to alternative decisions $D = \{d0, d1, d2, d3\}$. The expected energy and price regret for decision $d0$ is calculated as the average of the last two columns as €30 and €13.5, respectively. By using similar tables to calculate the expected energy and price regret for other decisions, the results for decisions $D = \{d0, d1, d2, d3\}$ can be calculated as €$\{30, 15, 5, 0\}$ and €$\{13.5, 5.25, 1.25, 0\}$, respectively. It can be seen how choosing more conservative strategies reduces the expected regret of RVPP.

5.3.3 Expected regret of RVPP's uncertain output energy

Equation (5.1) calculates the expected regret related to the uncertainty of the total output energy of RVPP. The expected regret associated with the output energy of RVPP in (5.1a) is calculated by multiplying the probability factor $J_{z,t}$ associated with each segment of PDF of RVPP's uncertain output energy, the penalty cost of not providing bid energy in the BAM Z_t, and the auxiliary variable $\rho_{z,t}^{DA,Q}$, which represents the deviation of the RVPP's output energy forecast from the submitted energy and reserve bids. Segments of the PDF represent different decisions for RVPP's uncertain output energy as the uncertainties unfold. The auxiliary variable $\rho_{z,t}^{DA,Q}$ is calculated according to (5.1b). The auxiliary variable $\rho_{z,t}^{DA,Q}$ is the difference

Table 5.1: Example for regret calculation.

Decision made/ Actual realization	Energy shortage [MWh]	Price deviation [€/MWh]	Regret energy cost [€]	Regret price cost [€]
$d0/d0$	0	0	0	0
$d0/d1$	2	1	20	9
$d0/d2$	4	2	40	18
$d0/d3$	6	3	60	27

between the total energy and reserve comes from units with uncertain production (ρ_t^{DA}) minus the energy forecast value in each segment (alternative decisions) of the RVPP output energy PDF ($P_{z,t}^F$). The auxiliary variable $\rho_{z,t}^{DA,A}$ thus has value when the above difference is negative and avoids calculating regret for decisions with null regret. The variable ρ_t^{DA} is calculated based on equation (5.1c) to obtain the output energy and reserve of RVPP units with uncertain production or consumption. It is worth noting that, since the uncertainty in the electrical output energy of CSP units is extensively mitigated by their TS, the output of the CSP is not considered in this formulation.

The expected regret in (5.1a) is limited by a user-defined coefficient Υ, which represents a per-unit fraction of the maximum possible regret of the uncertain output energy of RVPP. By selecting the coefficient Υ, the user has the flexibility to adjust the level of conservatism of the optimization problem against uncertainty by knowing the maximum possible regret Reg^{Max}. The maximum possible regret is computed by summing all regrets in all segments z if none of the uncertain parameters deviate from their deterministic value in all time periods $\left(Reg^{Max} = \sum_{t\in\mathscr{T}}\sum_{z\in\mathscr{Z}} J_{z,t}Z_t\Big[\sum_{r\in\mathscr{R}}\hat{\tilde{P}}_{r,t} - \sum_{d\in\mathscr{D}}\tilde{\tilde{P}}_{d,t} - P_{z,t}^F\Big]\Delta t\right)$.

For instance, with Z_t set to 100 €/MWh and other parameters as defined in Figure 5.1, the maximum regret of the RVPP's uncertain output energy is calculated Reg^{Max} = €68.7.[1] This value is used as an input parameter in constraint (5.1a), allowing the RVPP operator to adjust the desired regret limit related to the uncertain output energy of the RVPP through the per-unit parameter Υ. Based on (5.1b)-(5.1f), the auxiliary variable $\rho_{z,t}^{DA,Q}$ is not null only if the sum of the energy and reserve bid of RVPP is greater than $P_{z,t}^F$. This condition ensures that the regret associated with each segment of PDF is calculated only for those segments that are active, i.e., have values less than the sum of the energy and reserve bid of RVPP. The binary variable $\iota_{z,t}$ in (5.1d)-(5.1e) enforces this condition. Both $\rho_{z,t}^{DA,Q}$ and $\rho_{z,t}^{DA,A}$ are mutually exclusive in (5.1d)-(5.1e).

$$\sum_{t\in\mathscr{T}}\sum_{z\in\mathscr{Z}}\Big[J_{z,t}Z_t\rho_{z,t}^{DA,Q}\Delta t\Big] \leq \Upsilon Reg^{Max}\,; \tag{5.1a}$$

$$\rho_{z,t}^{DA,Q} = \rho_t^{DA} - P_{z,t}^F + \rho_{z,t}^{DA,A}\,; \qquad \forall z,t \tag{5.1b}$$

$$\rho_t^{DA} = \sum_{r\in\mathscr{R}}\Big[p_{r,t} + r_{r,t}^{\uparrow}\Big] - \sum_{d\in\mathscr{D}} p_{d,t}\,; \qquad \forall t \tag{5.1c}$$

$$\rho_{z,t}^{DA,Q} \leq \bar{P}_t\iota_{z,t}\,; \qquad \forall z,t \tag{5.1d}$$

$$\rho_{z,t}^{DA,A} \leq \bar{P}_t(1-\iota_{z,t})\,; \qquad \forall z,t \tag{5.1e}$$

$$\rho_{z,t}^{DA,Q}, \rho_{z,t}^{DA,A} \geq 0\,; \qquad \forall z,t \tag{5.1f}$$

[1] The maximum regret of the RVPP output energy can be calculated as: Reg^{Max} = 100 €/MWh × (0.34 × 1 MWh + 0.135 × 2 MWh + 0.023 × 3 MWh + 0.002 × 4 MWh) = €68.7.

Figure 5.1 shows the calculation of the expected regret according to the PDF of the total uncertain output energy of RVPP to further illustrate the formulation in (5.1). For this purpose, the value of different parameters and variables ($J_{z,t}, \rho_{z,t}^{DA,Q}, P_{z,t}^{F}, \iota_{z,t}$) in (5.1a) is provided by assuming ρ_t^{DA} at the instant t is equal to -1.2 MW. According to Section 5.3.2, the regret for each decision can be calculated by the weighted sum of the loss felt by the RVPP operator corresponding to alternative decisions. Assuming that the DAM and SRM bidding profit does not affect the loss felt in different decisions, the loss felt for the decision $\rho_t^{DA} = -1.2$ MW corresponding to alternative decisions can be calculated by the use of PDF of uncertainty. The value of energy regret (loss felt) of the above decision compared to alternative decisions is determined based on the probability of each segment ($J_{z,t}$), the penalty cost in the BAM (Z_t), and the difference between the energy value of each segment and the uncertain output of RVPP ($\rho_{z,t}$). The expected regret is calculated based on the sum of the regrets for each segment of PDF of the total uncertain output energy. Assuming Z_t= 100 €/MWh, the regret of the proposed decision compared to the alternative decisions $z = 2, 3, 4$ according to the PDF of the RVPP's uncertain output energy is €80, €180, and €280. Considering the cumulative probability of the alternative decisions $z = 2, 3, 4$ as 13.5%, 2.3%, and 0.2%, the expected regret for this decision at the sample hour is €15.5.[2] Note that the number of segments can be chosen to maintain the accuracy of the regret calculation without compromising the computational efficiency of the optimization problem.

5.3.4 Expected regret of DAM electricity price

Formulations (5.2) calculate the expected regret related to the uncertainty of the DAM electricity price. Since equation (4.6a) in Chapter 4 enforces to have three final values for DAM electricity price (lower bound, median, and upper bound of the uncertainty bound), the expected regret calculation is formulated for these three conditions in (5.2). Note that in the calculation of the expected regret related to the DAM electricity price in (5.2), different type of parameters and variables are used compared to the constraints of the expected regret related to the RVPP output energy in (5.1). The expected regret associated with the uncertainty of the DAM electricity price for the cases where RVPP is an energy seller and an energy buyer is calculated in (5.2a) and (5.2b), respectively.

The expected regret related to the DAM electricity price when the RVPP is an energy seller is calculated in (5.2a) by multiplying the probability of each segment of the PDF of the DAM electricity price ($J_{z,t}^{DA}$), by the negative deviation of the DAM electricity price from the median in each segment of the PDF of the DAM electricity price ($K_{z,t}^{DA}$), and the auxiliary $p_t^{DA,Q}$, which represents the total energy traded by the RVPP for the condition that the electricity price is at its median (χ_t^{DA}=0) and the RVPP is an energy seller ($\iota_t^{DA} = 1$). A similar approach with a different direction of the DAM electricity price deviation is used in (5.2b) to calculate the expected regret in the case where RVPP is an energy buyer in the market ($\iota_t^{DA} = 0$). The maximum regret parameters for the DAM price, when the RVPP is an energy seller and an energy buyer, are calculated using $Reg^{Max,DA} = \sum_{t\in\mathcal{T}} \sum_{z\in\mathcal{Z}} J_{z,t}^{DA} K_{z,t}^{DA} \bar{P}_t \Delta t$ and $Reg'^{Max,DA} = \sum_{t\in\mathcal{T}} \sum_{z\in\mathcal{Z}} J_{z,t}'^{DA} K_{z,t}'^{DA} \bar{P}_t' \Delta t$, respectively. The expected regret associated with DAM in (5.2a) and (5.2b) is controlled by the user-defined per-unit coefficients Υ^{DA} and Υ'^{DA} for the hours when RVPP is an energy seller and buyer, respectively. In accordance with the conditions specified in (5.2c)-(5.2l), the auxiliary variable $p_t^{DA,Q}$ is not null only when the electricity price is at its median value and RVPP is an energy seller. These conditions are determined based on the binary variables χ_t^{DA} and ι_t^{DA}, respectively. For the hours when RVPP is an energy buyer, the auxiliary variable $p_t^{DA,A}$ is not null only when the electricity price is at its median and RVPP is an energy buyer. These conditions are determined based on the binary

[2] The expected regret can be calculated as: $\sum_{t\in\mathcal{T}} \sum_{z\in\mathcal{Z}} \left[J_{z,t} Z_t \rho_{z,t}^{DA,Q} \Delta t\right]$ = 100 €/MWh × (0.135 × 0.8 MWh + 0.023 × 1.8 MWh + 0.002 × 2.8 MWh) = €15.5.

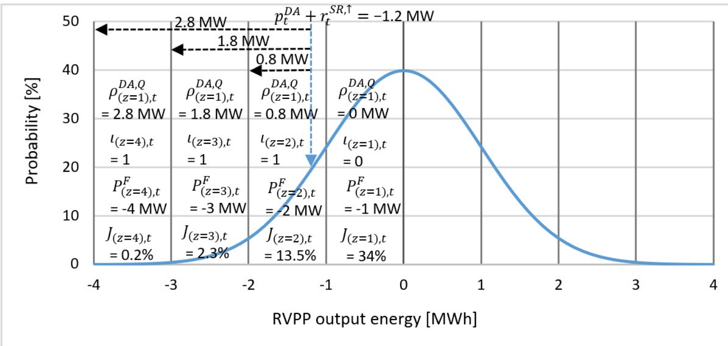


Figure 5.1: Expected regret calculation according to the PDF of total output energy of RVPP in a sample hour.

variables $\chi_t'^{DA}$ and ι_t^{DA}, respectively. The logic of different binary and auxiliary variables in equations (5.2) is represented in Table 5.2.

$$\sum_{t\in\mathcal{T}}\sum_{z\in\mathcal{Z}}\left[J_{z,t}^{DA}K_{z,t}^{DA}p_t^{DA,Q}\Delta t\right] \le \Upsilon^{DA}Reg^{Max,DA}\,; \tag{5.2a}$$

$$\sum_{t\in\mathcal{T}}\sum_{z\in\mathcal{Z}}\left[J_{z,t}'^{DA}K_{z,t}'^{DA}p_t^{DA,A}\Delta t\right] \le \Upsilon'^{DA}Reg'^{Max,DA}\,; \tag{5.2b}$$

$$p_t^{DA,Q}+p_t^{DA,Q'} = p_t^{DA}+p_t^{DA,A}+p_t^{DA,A'}\,; \qquad \forall t \tag{5.2c}$$

$$p_t^{DA,Q} \le \bar{P}_t\iota_t^{DA}\,; \qquad \forall t \tag{5.2d}$$

$$p_t^{DA,Q} \le \bar{P}_t(1-\chi_t^{DA})\,; \qquad \forall t \tag{5.2e}$$

$$p_t^{DA,Q'} \le \bar{P}_t\iota_t^{DA}\,; \qquad \forall t \tag{5.2f}$$

$$p_t^{DA,Q'} \le \bar{P}_t\chi_t^{DA}\,; \qquad \forall t \tag{5.2g}$$

$$p_t^{DA,A} \le \bar{P}_t'(1-\iota_t^{DA})\,; \qquad \forall t \tag{5.2h}$$

$$p_t^{DA,A} \le \bar{P}_t'(1-\chi_t'^{DA})\,; \qquad \forall t \tag{5.2i}$$

$$p_t^{DA,A'} \le \bar{P}_t'(1-\iota_t^{DA})\,; \qquad \forall t \tag{5.2j}$$

$$p_t^{DA,A'} \le \bar{P}_t'\chi_t'^{DA}\,; \qquad \forall t \tag{5.2k}$$

$$p_t^{DA,Q}, p_t^{DA,Q'}, p_t^{DA,A}, p_t^{DA,A'} \ge 0\,; \qquad \forall t \tag{5.2l}$$

Figure 5.2 shows the calculation of the expected regret for DAM electricity price when RVPP is an energy buyer ($\iota_t^{DA}=0$) in the market. If the optimization problem chooses the median value for the electricity price ($\chi_t'^{DA}$=0), it can lead to regret for RVPP, because when the market clears, the deviation of the electricity price from the median value to a larger value results in additional costs or profit reduction for RVPP. The calculation of regret for each segment of DAM electricity price is based on the probability of each segment ($J_{z,t}'^{DA}$), the difference between the predicted price and the median price ($K_{z,t}'^{DA}$), and the final output energy of RVPP ($p_t^{DA,A}\Delta t$).

Table 5.2: Logic of different binary and auxiliary variables in equations (5.2).

ι_t^{DA}	χ_t^{DA}	$\chi_t^{\prime DA}$	$p_t^{DA,Q}$	$p_t^{DA,Q'}$	$p_t^{DA,A}$	$p_t^{DA,A'}$
1	1	-	0	p_t^{DA}	0	0
1	0	-	p_t^{DA}	0	0	0
0	-	1	0	0	0	$-p_t^{DA}$
0	-	0	0	0	$-p_t^{DA}$	0

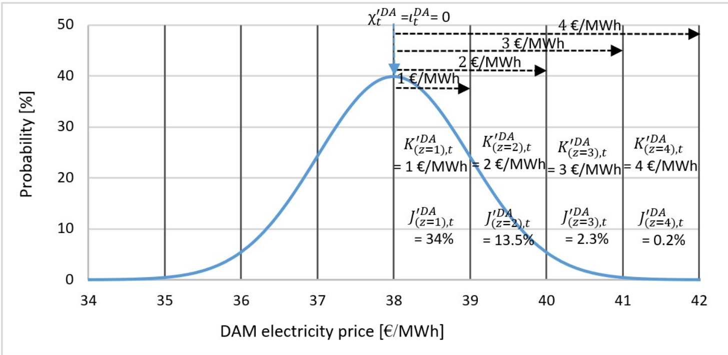


Figure 5.2: Expected regret calculation according to the PDF of DAM price when RVPP is energy buyer.

5.3.5 Expected regret of SRM electricity price

Equations (5.3) limit the expected regret related to the uncertainty of the up and down SRM price. According to constraints (4.7a) and (4.7b) in Chapter 4, the SRM price takes two conditions (upper and lower bounds of the SRM price). The loss felt associated with the condition that the upper value is chosen in the optimization problem compared to decisions with the lower SRM clearance price is calculated in (5.3). The regret associated with the up and down SRM price uncertainty can be interpreted as the loss of profit due to considering a higher SRM prediction than the actual SRM price clearance.

The expected regret in (5.3a) and (5.3b) is calculated by multiplying the probability of each segment of the PDF of the SRM electricity price ($J_{z,t}^{SR,\uparrow}/J_{z,t}^{SR,\downarrow}$), by the negative deviation of the SRM electricity price compared to the deterministic value in each segment of the PDF of the SRM electricity price ($K_{z,t}^{SR,\uparrow}/K_{z,t}^{SR,\downarrow}$), and the total reserve traded by RVPP when the SRM price is at its deterministic value, represented by the auxiliary variable $r_t^{SR,Q,\uparrow}/r_t^{SR,Q,\downarrow}$. The expected regret related to SRM price in (5.3a) and (5.3b) is controlled by the user-defined coefficient $\Upsilon^{SR,\uparrow}/\Upsilon^{SR,\downarrow}$. The maximum regret parameter for the SRM price is calculated using $Reg^{Max,SR,\uparrow(\downarrow)}$[3]. The state of the auxiliary variable $r_t^{SR,Q,\uparrow}/r_t^{SR,Q,\downarrow}$ is controlled by (5.3c)-(5.3i) to set the regret value to zero when the SRM price deviates from its upper bound to its worst case.

$$\sum_{t\in\mathcal{T}}\sum_{z\in\mathcal{Z}}\left[J_{z,t}^{SR,\uparrow}K_{z,t}^{SR,\uparrow}r_t^{SR,Q,\uparrow}\right] \leq \Upsilon^{SR,\uparrow}Reg^{Max,SR,\uparrow}\;; \tag{5.3a}$$

$$\sum_{t\in\mathcal{T}}\sum_{z\in\mathcal{Z}}\left[J_{z,t}^{SR,\downarrow}K_{z,t}^{SR,\downarrow}r_t^{SR,Q,\downarrow}\right] \leq \Upsilon^{SR,\downarrow}Reg^{Max,SR,\downarrow}\;; \tag{5.3b}$$

[3] $Reg^{Max,SR,\uparrow(\downarrow)} = \sum_{t\in\mathcal{T}}\sum_{z\in\mathcal{Z}} J_{z,t}^{SR,\uparrow(\downarrow)}K_{z,t}^{SR,\uparrow(\downarrow)}\bar{R}_t^{SR,\uparrow(\downarrow)}$

$$r_t^{SR,Q,\uparrow} = r_t^{SR,\uparrow} - r_t^{SR,A,\uparrow}\,; \qquad \forall t \qquad (5.3c)$$

$$r_t^{SR,Q,\downarrow} = r_t^{SR,\downarrow} - r_t^{SR,A,\downarrow}\,; \qquad \forall t \qquad (5.3d)$$

$$r_t^{SR,Q,\uparrow} \leq \bar{R}_t^{SR,\uparrow}(1 - \chi_t^{SR,\uparrow})\,; \qquad \forall t \qquad (5.3e)$$

$$r_t^{SR,Q,\downarrow} \leq \bar{R}_t^{SR,\downarrow}(1 - \chi_t^{SR,\downarrow})\,; \qquad \forall t \qquad (5.3f)$$

$$r_t^{SR,A,\uparrow} \leq \bar{R}_t^{SR,\uparrow}\chi_t^{SR,\uparrow}\,; \qquad \forall t \qquad (5.3g)$$

$$r_t^{SR,A,\downarrow} \leq \bar{R}_t^{SR,\downarrow}\chi_t^{SR,\downarrow}\,; \qquad \forall t \qquad (5.3h)$$

$$r_t^{SR,Q,\uparrow}, r_t^{SR,A,\uparrow} \geq 0\,; \qquad \forall t \qquad (5.3i)$$

$$r_t^{SR,Q,\downarrow}, r_t^{SR,A,\downarrow} \geq 0\,; \qquad \forall t \qquad (5.3j)$$

5.4 Case studies

This section presents the simulation results based on the proposed regret-based RO framework to assign the optimal solution for different penalization cost for RVPP participation in the DAM+SRM session.

5.4.1 Data

The same RVPP described in Chapter 4 is used for the simulations in this section. The deviations and probabilities of DAM and SRM prices across different segments of their PDFs are presented in Figure 5.3. The RVPP output energy and its associated probabilities across different segments of its PDF are shown in Figure 5.4. The PDFs of the various uncertain parameters are extracted from the same historical dataset used in the previous chapter, corresponding to March 2021.

5.4.2 Results

Figure 5.5 presents the RVPP's economic results in the DAM+SRM session under the regret-based model for different regret limits. The results indicate that with a high regret limit (i.e., when the RVPP is nearly indifferent to penalization), the RVPP submits an optimistic bid in both the DAM and SRM, resulting in a high volume of energy sold in most hours—for example, more than 82 MW in hour 14. With a lower regret limit of 0.6 p.u., the RVPP adopts a more cautious strategy, offering less energy to the market to reduce the risk of penalties. In this case, the maximum energy sold is about 64 MW in hour 14. Finally, at a regret limit of 0.4 p.u., the RVPP adopts a very conservative approach, selling significantly less energy in most hours. For instance, the energy sold is below 20 MW in the majority of hours, with a maximum of around 34 MW occurring in hour 22.

Table 5.3 presents the RVPP's economic results in the DAM+SRM session under the regret-based model for various regret limits and penalty costs. For each penalty cost, the row corresponding to the highest expected profit is highlighted, representing the optimal strategy the RVPP operator can adopt based on the assumed level of penalization cost. For a low penalty cost (1 × DAM price), the best strategy is a very optimistic one with the highest regret limit of 1 p.u. When the penalty cost increases to 1.5 × DAM price, the optimal strategy becomes slightly less optimistic, corresponding to a regret limit of 0.8 p.u. Finally, under a higher penalty cost assumption (2 × DAM price), the most profitable decision is a pessimistic strategy with a regret limit of 0.2 p.u. It is worth noting that this table allows the RVPP operator to select a market strategy based on monetary considerations, as the regret limit has a direct financial interpretation. This contrasts with the uncertainty budget used in the previous chapter, which only indicated the number of

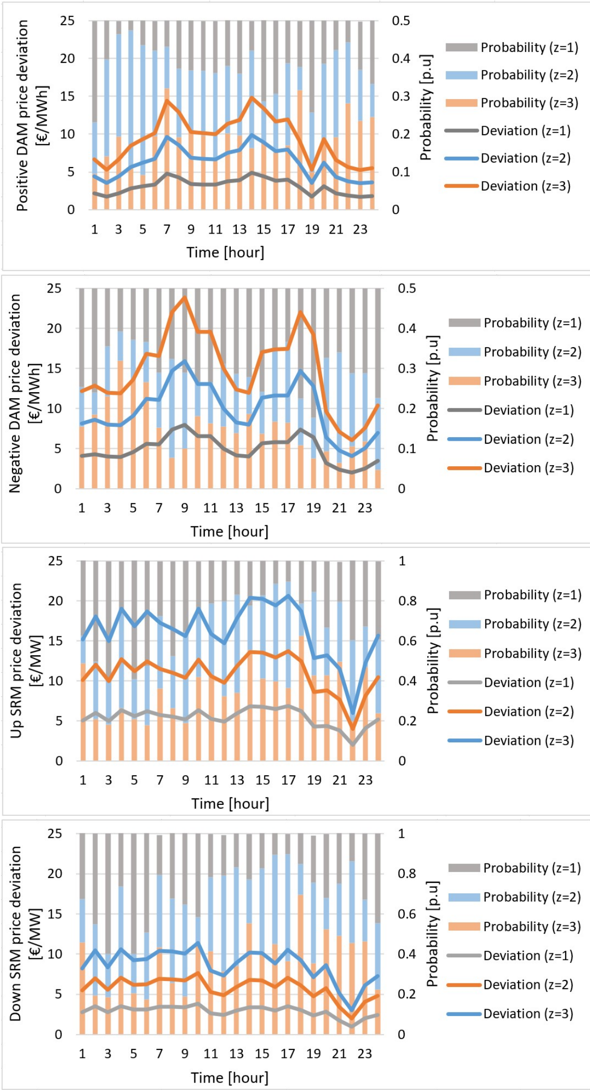


Figure 5.3: The deviation and probability of DAM and SRM prices across different segments of their PDF.

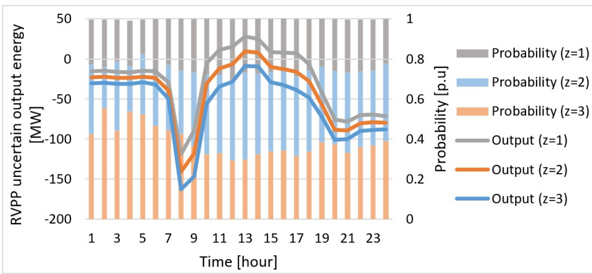


Figure 5.4: The RVPP output energy and its probability across different segments of its PDF.

hours during which worst-case uncertainty scenarios could occur. It is worth noting that the highest computational time in the regret-based model reaches up to 15 minutes in some cases. However, this approach requires the RVPP operator to perform fewer sensitivity analyses compared to the profit robustness approach presented in Chapter 4, as there is no need to assign multiple uncertainty budgets. As a result, the computational time of the regret-based approach is acceptable for real-world applications.

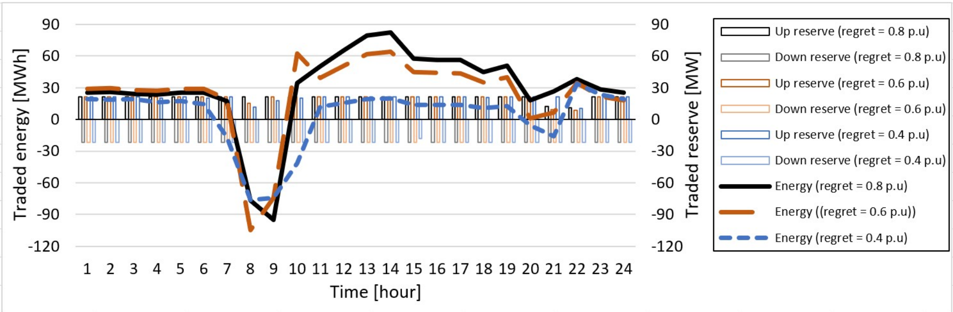


Figure 5.5: Total traded energy and reserve of RVPP in the DAM+SRM session in the regret-based model for different regret limits (penalty cost = 1.5 × DAM price).

Table 5.3: RVPP economic results in the DAM+SRM session in the regret-based model for different regret limits.

Penalty cost [€/MWh]	**Regret limit [p.u]**	Expected profit* [k€]	Profit [k€]	Revenue [k€]	Cost** [k€]	Regret cost [k€]	Computational time [s]
1 × DAM price	**1.0**	**-15.52**	**24.06**	**68.59**	**44.53**	**39.58**	**0.38**
	0.8	-19.25	11.59	52.92	41.33	30.84	2.80
	0.6	-23.04	0.68	46.96	46.28	23.72	76.56
	0.4	-25.12	-9.66	25.22	34.88	15.46	233.09
	0.2	-31.51	-23.82	12.05	35.87	7.69	665.78
1.5 × DAM price	1.0	-32.53	24.06	68.59	44.53	56.59	0.38
	0.8	**-31.73**	**11.66**	**57.37**	**45.71**	**43.39**	**3.99**
	0.6	-33.30	0.69	45.58	44.89	33.99	87.81
	0.4	-31.93	-9.65	25.23	34.88	22.28	370.32
	0.2	-34.92	-23.81	12.05	35.86	11.11	768.88
2 × DAM price	1.0	-49.49	24.06	68.59	44.53	73.55	0.60
	0.8	-44.79	11.66	57.37	45.71	56.45	3.51
	0.6	-43.42	0.68	46.94	46.26	44.10	121.46
	0.4	-38.74	-9.69	25.18	34.87	29.05	334.54
	0.2	**-38.31**	**-23.82**	**12.03**	**35.85**	**14.49**	**853**

**Expected profit equals profit minus regret cost.*
***Cost includes operation cost of RVPP units and robust cost due to price uncertainty.*

5.5 Conclusions

In Chapter 4, multiple uncertainties were considered, requiring the RVPP operator to select an appropriate level of conservatism against these uncertain parameters using several uncertainty budget values associated with each one. However, a limitation of this approach is that the RVPP operator lacks a clear monetary interpretation of the uncertainty budget's value and must also consider the potential penalties that each decision may incur. In this chapter, the concept of expected regret is introduced to help the RVPP operator visualize and control the appropriate degree of conservatism regarding multiple uncertain parameters, including DAM and SRM electricity prices and the RVPP's output energy. The expected regret for a decision of RVPP is defined as the weighted sum of the loss differences between the corresponding solution and other potential solutions associated with the PDF of the uncertain parameter. The RVPP operator can control its desired expected regret cost with respect to the uncertain parameters. The profit robustness approach proposed in the previous chapter is extended by adding constraints related to expected regret. This regret-based flexible RO model offers a more intuitive way to determine the conservatism level, using a monetary regret limit instead of the uncertainty budget used previously. Simulation results show that lowering the regret limit leads the RVPP operator to adopt more conservative strategies to avoid penalties in the BAM—specifically, lower regret limits result in reduced energy sold by the RVPP. Furthermore, the results demonstrate that depending on the desired regret limit and expected penalty costs in the BAM, the optimal strategy for the RVPP may be optimistic, balanced, or conservative. Although the regret-based model may require up to 15 minutes of computation, its reduced need for sensitivity analyses makes it computationally acceptable for real-world applications.

6 Summary, Conclusions, and Future Studies

This chapter outlines the key challenges tackled in this thesis and the approaches developed to address them. It also presents the key contributions and outlines potential directions for future research.

6.1 Problem statement

The RVPPs face several challenges in operation, market participation, and uncertainty management compared to classical VPPs. The characteristics of RVPPs and these challenges are discussed in Chapters 1 and 2. These challenges are summarized below:

- **Renewable-based units:** Compared to classical VPPs that include fossil fuel generators and ESS, RVPPs rely solely on RES. This poses challenges, as their market participation and, consequently, economic profitability are highly affected by resource intermittency.
- **Different market participation:** The RVPP needs to take advantage of electricity markets beyond the DAM, particularly those with gate closures closer to real-time, where improved forecasts can help adjust DAM bids and consequently avoid penalties or imbalances. This is challenging because it requires accounting for market interactions, forecast updates, and advanced optimization techniques to effectively manage these issues.
- **Energy and reserve coordination:** Compared to classical VPPs, where reserve is primarily provided by fossil fuel generators, reserve provision by RVPPs is more limited. Therefore, it is essential to leverage all available resources to provide reserves and maximize potential benefits. This is challenging, as it requires incorporating the technical constraints of RVPP units while accounting for the impact of reserve provision on energy bidding. Reserve allocation becomes particularly complex for energy-limited and storage-based units such as CSP, since providing reserve in one period can affect their energy availability in subsequent periods.
- **Stochasticity:** Since a significant share of RVPP production comes from ND-RES units such as WF and solar PV, whose outputs cannot be precisely forecasted, a deterministic approach is not viable for RVPP. In addition, uncertainties related to demand consumption and electricity market prices further complicate the problem. These challenges are more pronounced compared to classical VPPs, which typically have a lower share of stochastic generation. The situation becomes even more complex when stochastic data are unavailable—a common occurrence in practice.
- **Interactions of uncertain parameters:** The RVPP must account for multiple sources of uncertainty and remain robust against their worst-case realizations. However, it is essential to prioritize robustness where uncertainties have the greatest impact on profitability. For instance, an hour with high production fluctuations during a period of low electricity prices has a much smaller effect on

profitability than an hour with moderate fluctuations but significantly higher prices. Considering these interactions between uncertain parameters is challenging and requires more sophisticated modeling approaches.

- **Non-monetized uncertain parameters:** Assigning specific values to uncertain input parameters is a challenging task. On one hand, each market bidding decision requires the definition of a set of uncertainty parameters for each RVPP unit and electricity prices. On the other hand, the appropriate value of each uncertainty parameter depends not only on the viewpoint of RVPP operator (level of conservatism) but also on different characteristics of units, such as production availability hours, production fluctuation level, and operational constraints.

- **Computational burden:** The RVPP problem becomes computationally challenging due to several factors, including the need to consider participation in multiple markets, the technical characteristics of diverse units, the presence of multiple sources of uncertainty, and time-dependent operational constraints. Therefore, a holistic approach is required—one that can efficiently incorporate all these aspects and remain solvable within a reasonable time frame. This computational efficiency is especially important, as the RVPP operator must often perform multiple sensitivity analyses and prepare various market bids within short time intervals.

In this thesis, the above challenges are addressed through the approaches proposed in Chapters 3, 4, and 5. The summary and main conclusions drawn from each chapter are discussed in the following sections.

6.2 Conclusions

6.2.1 RVPP objective functions and components – description, characterization and modeling

The main objective of chapter 3 is to develop a deterministic model for RVPP participation in sequential energy and reserve markets to enhance its viability. The objective functions for participation in each market, along with the associated technical constraints of the units and market constraints, are thoroughly detailed. Simulations are carried out for an RVPP located in Southern Spain, considering its participation across various sessions of the Spanish electricity market. Several optimization models—namely DAM+SRM, SRM+IDM#1, and IDMs—are formulated for different bidding sessions. The key characteristics and contributions of this chapter are summarized below:

- The deterministic model in this chapter considers the interactions and sequences of different energy and reserve markets, thus being specifically tailored to address the intricacies and challenges posed by sequential markets in the European context.

- The reserve provision by each of RVPP units are explicitly molded in technical constraints of units by considering all possible reserve activation scenario in real time (up reserve activation, down reserve activation, no reserve activation).

- The mathematical model in this chapter considers an adjustable share of energy from the energy-limited device TS for the provision of up and down reserve. This share of energy is assigned by the optimization problem to maximize RVPP profitability.

- The conversion of thermal to electrical energy in CSP is modeled by considering the reserve provision.

- Different profiles of FD are considered. RVPP selects best profile based its available energy of its different technology and also based on uncertainty considered the selected profile can change.

- The simulations are conducted on an RVPP that includes D-RES of hydro plant and biomass plant, ND-RES of WF and solar PV, CSP with TS, and FD with different profiles. The historical data of units as well market prices are adopted from realistic historical data in March 2021 from Spanish electrcity market.

The key findings from chapter 3 are summarized below. The results of chapter 3 have also been published in [51].

- The RVPP efficiently schedules its units and capitalizes on hours with higher electricity prices to maximize profitability. The RVPP acts as an energy seller during most hours, primarily due to the availability of its solar-dependent units during the day and hydro plant production during the night. However, the RVPP becomes an energy buyer in some early morning hours when its internal demand is high and its solar-dependent units are not generating electricity.
- The RVPP primarily participates in the DAM as its main source of income and adjusts its scheduling in each IDM session based on updated forecast data.
- In the deterministic approach, energy adjustments in the IDMs are minimal and occur only in a few hours, as exact forecast values are assumed. However, the RVPP still takes advantage of price differences between the DAM and IDMs, and performs some energy adjustments based on updated forecasts of unit outputs.
- Coordinating energy and reserve provision enhances overall revenue. Reserve provision in the SRM is mainly supported by the flexibility of the hydro plant and the CSP, and partially by other units—such as FD, WF, solar PV, and the biomass plant—depending on their availability.
- Reserve provision by the RVPP can be affected by the availability of its units and SRM prices. In particular, during hours when RVPP units operate at their maximum capacity due to high DAM prices or elevated internal demand, the up reserve provision may be reduced.
- Given that RVPP problem is developed as a single-level MILP optimization, it is highly effective for running multiple simulations across different market sessions. The computation time for all market sessions is under one second.

6.2.2 Advanced robust optimal bidding of RVPPs under uncertainties

The main objective of Chapter chapter 4 is to analyze the impact of various uncertainties on the operation and bidding strategies of the RVPP, and consequently, on its profitability in different energy and reserve markets. To achieve this objective, a two-stage RO framework is first developed and reformulated as a single-level optimization problem. This model is referred to as the *energy robustness approach*, as it treats each uncertain parameter independently. The model is then extended to a more advanced framework, termed the *profit robustness approach*, which explicitly captures the interactions among uncertain parameters and identifies the worst-case scenario in terms of profit rather than energy. The simulations are conducted on the same RVPP structure described in chapter 3, located in Southern Spain. However, instead of using exact values as in the deterministic model, forecast bounds derived from historical data are employed for the uncertain parameters. The simulations consider a range of strategic approaches by the RVPP operator, from optimistic to pessimistic perspectives. The key characteristics and contributions of this chapter are summarized below:

- The proposed RO model addresses the asymmetric behavior of uncertain parameters, providing a more realistic representation. The protection function originally proposed by Bertsimas [42], which is defined for symmetric uncertainty, is extended, and the corresponding dual constraints are reformulated to account for asymmetric deviations in the uncertain parameters.

- The uncertain parameters are defined over global scheduling horizons rather than on an hourly basis, reducing the complexity of parameterization and enhancing the model's practicality. This approach is particularly beneficial for real-world applications, where operators must frequently update their models to align with market windows. A refined MILP formulation is presented, incorporating temporal considerations to capture the worst-case uncertainties on both the source and load sides.

- The proposed approach addresses how different types of uncertainties in the objective function and constraints interact within the optimization framework. Modeling these interactions results in non-linear constraints, particularly when capturing the joint impact of price and energy uncertainties on the RVPP's profit in a single-level model. These interactions are accurately represented through an exact linearization of the original MINLP problem, yielding a mathematically equivalent MILP formulation.

- Historical data are used to determine the upper and lower bounds of the asymmetric uncertain parameters. The dataset of past observations is analyzed to capture the behavior of these uncertainties. Based on the histograms of the historical data, the median, 20th percentile, and 80th percentile are extracted and used as bounds in the RO simulations to avoid overly conservative results.

The key conclusions from Chapter 4 are provided below. Chapter 4 has been published in [53].

- The uncertain parameters related to electricity prices in different energy and reserve markets, as well as the energy production of ND-RES and CSP units and the consumption of FD, can significantly affect the scheduling and bidding strategy of the RVPP across various electricity markets.

- The RVPP operator determines unit scheduling as well as final energy and reserve bids in the electricity markets based on different uncertainty-handling strategies, ranging from optimistic to conservative. Adopting more conservative strategies decreases sold energy and increases bought energy, providing a more robust solution against worst-case scenarios.

- In the balanced and pessimistic cases, changes in the traded energy of the RVPP across various IDMs sessions are more significant than in the optimistic case, indicating a greater need for adjustments through IDMs and highlighting their increased importance.

- The hydro plant and CSP compensate for energy shortages from ND-RES units under more conservative strategies, which in turn impacts their ability to provide reserves.

- The profit robustness approach yields more robust energy and reserve bids, particularly during hours of high profit volatility, compared to the energy robustness approach.

- The computational burden in the energy robustness approach is under 2 seconds. The high computational efficiency of the proposed model enables parametric sensitivity analysis to evaluate the impact of different uncertainty budgets for the model's uncertain parameters, providing the RVPP operator with suitable solutions for varying market conditions.

- The profit robustness approach is more computationally demanding than the energy robustness approach across all uncertainty-handling strategies. This increased complexity arises from the inclusion of interactions between price and energy uncertainties. Nevertheless, the computational time for the profit robustness model remains highly efficient, staying under five minutes in all cases.

6.2.3 Regret-based robust optimal bidding of RVPP in electricity markets

Finally, the main objective of chapter 5 is to assist the RVPP operator in assigning input values for uncertain parameters based on economic considerations rather than the intrinsic nature of each uncertainty. To this end, a regret-based flexible RO problem is developed by incorporating additional mixed-integer linear constraints into the profit robustness approach introduced in chapter 4. These added constraints enable the RVPP operator to limit the average regret—defined as the weighted sum of the loss felt by the decision maker with respect to the use of alternative decisions when uncertainties unfold—thereby providing economically meaningful insights into uncertainty parameterization. The simulations are conducted on the same RVPP system as in Chapters 3 and 4. However, the RVPP operator must perform precalculation of deviations and corresponding probabilities for different uncertain parameters, based on the PDF of uncertain parameters. The main features and contributions of this chapter are outlined below:

- The average regret associated with different decisions regarding the electricity and reserve prices, as well as the bidding energy and reserve of the RVPP operator in electricity markets, is modeled through a set of mixed-integer constraints within the RO framework.

- The proposed regret-based approach simplifies the determination of input parameters for RO problems. The framework allows the operator to specify a desired level of conservatism directly in terms of costs, rather than requiring the operator to determine different uncertainty budgets.

- The calculation of average regret based on the proposed mixed-integer constraints is illustrated through an example. Historical dataset are used to estimate the deviations and associated probabilities of different segments of the uncertain parameters.

The main conclusions of Chapter 5 are mentioned below. The contents of Chapter 5 have been published in [62].

- With a high regret limit (i.e., when the RVPP is nearly indifferent to penalization), the RVPP submits optimistic bids in both the DAM and SRM, resulting in a high volume of energy and reserve sold during most hours.

- Lowering the regret limit leads the RVPP operator to adopt more conservative strategies to avoid penalties in the BAM—specifically, lower regret limits lead to a reduction in the amount of energy sold by the RVPP.

- Depending on the desired regret limit and the expected penalty costs in the BAM, the optimal strategy for the RVPP may be optimistic, balanced, or pessimistic. When penalty costs are low, an optimistic strategy with a high regret limit is most effective. As penalty costs increase, the optimal strategy shifts toward a more pessimistic stance.

- Regret-based economic analysis enables the RVPP operator to select a market strategy based on monetary considerations, as the regret limit has a direct financial interpretation.

- Compared to the profit robustness approach, the regret-based approach is more computationally demanding, with computational times reaching up to 15 minutes in some cases. However, since there is no need to assign multiple uncertainty budgets, the RVPP operator needs to perform fewer sensitivity analyses. This makes the regret-based approach practical for real-world applications.

6.3 Future studies

- **Price-maker RVPP:** In this thesis, given the small size of the RVPP in the market, a price-taker approach is adopted for RVPP bidding across different electricity markets. However, if the RVPP expands its resources, it may gain the ability to influence market prices and thus become a price-maker. This scenario requires more sophisticated multi-level mathematical models that account for strategic interactions between the RVPP and other market participants. In such a framework, regulatory aspects of the system and the estimated strategies of competing market players must also be incorporated into the developed model.
- **Long-term and real-time markets:** The models presented in this thesis focus primarily on short-term market participation, particularly in the DAM, SRM, and IDMs, and do not account for long-term planning or RTM dynamics. By considering long-term bilateral contracts with short-term market participation, the RVPP can hedge against price uncertainty more effectively than by relying solely on short-term electricity markets. In this context, developing fair pricing mechanisms that balance the interests of both the RVPP and consumers is a relevant area of research. Additionally, since the RVPP is subject to a greater number of uncertainties compared to a conventional VPP, participation in the RTM and enhancing the adaptability of the RVPP to dynamic market conditions remain challenging and present valuable directions for future work. In addition, while the current formulation is based on the discrete IDM (as applied in Spain), the market is progressively transitioning toward a continuous IDM. Extending the proposed model to accommodate this continuous setting is an important direction for future research work.
- **Multi-energy markets:** The RVPP developed in this thesis is designed for participation in electricity markets. However, incorporating other energy carriers such as natural gas, thermal energy, and hydrogen—and enabling coordinated participation across relevant markets—can significantly enhance the profitability of the RVPP. Integrating resources beyond electricity can improve flexibility, efficiency, and coordination across different energy sectors. This can be achieved through sector coupling and diverse load engagement, allowing the RVPP to participate more effectively in power markets, ASMs, and demand response programs. Such integration offers superior energy management capabilities, supports smoother transitions between energy types, and enables both operational and economic optimization. For example, the high transport and storage capacity of gas infrastructure can help mitigate the variability of renewable generation, providing more reliable and flexible energy balancing. Additionally, as hydrogen becomes increasingly important in the decarbonization of the energy sector, RVPPs can engage in hydrogen trading by incorporating electrolyzers and storage systems. This enables them to convert excess renewable electricity into hydrogen, which can later be used as fuel or sold, adding further flexibility and revenue potential. Therefore, extending the current framework to include additional energy carriers and their interactions with electricity markets represents a valuable direction for future research.
- **Hybrid optimization techniques:** Another potential area for further investigation is the integration of hybrid models that combine RO with other uncertainty modeling techniques, such as SP, to better capture complex risk profiles and system behaviors under extreme conditions. Additionally, modeling and analyzing the potential spatiotemporal correlations among uncertain parameters—and understanding how these correlations influence RVPP performance—represent promising directions for future work.

A Bertsimas and Sim Robust Approach

The robust approach of Bertsimas and Sim [42] is summarized in this appendix, which initially considers the linear optimization problem (A.1).

$$\max\ \boldsymbol{c}^\top \boldsymbol{x}\,, \tag{A.1a}$$

st.

$$\boldsymbol{A}\boldsymbol{x} \le \boldsymbol{b}\,, \tag{A.1b}$$

$$\boldsymbol{l} \le \boldsymbol{x} \le \boldsymbol{u}\,, \tag{A.1c}$$

In (A.1a), $\boldsymbol{x}$ is the vector of free decision variables; $\boldsymbol{c}^\top$ is the transposed vector of fixed parameters of the objective function; $\boldsymbol{A}$ is the matrix of uncertain parameters; a_{ij} are the elements of the matrix $\boldsymbol{A}$; and it is assumed that J_i is the set of elements in row i of the matrix $\boldsymbol{A}$ that are subject to uncertainty. Each entry of $a_{ij},\ j \in J_i$ is a symmetric bounded random parameter $\tilde{a}_{ij}$ (i.e., $a_{ij} \in [\tilde{a}_{ij} - \check{a}_{ij}, \tilde{a}_{ij} + \hat{a}_{ij}]$, $\check{a}_{ij} = \hat{a}_{ij}$; $\boldsymbol{b}$ is the vector of upper bounds of the uncertain constraint (A.1b); $\boldsymbol{l}$ and $\boldsymbol{u}$ are the vectors of lower and upper bounds of the inequality constraint (A.1c), respectively.

In (A.1), it is assumed that uncertainty only affects matrix $\boldsymbol{A}$ in (A.1b) since if the uncertainty of objective function $\boldsymbol{c}$ needs to be modeled, it can be done by including the constraint $z - \boldsymbol{c}^\top \boldsymbol{x} \le 0$ into constraint (A.1b) and maximize the auxiliary objective function z.

Then, the non-linear formulation (A.2) is proposed as the RO of the problem (A.1).

$$\max \boldsymbol{c}^\top \boldsymbol{x}\,, \tag{A.2a}$$

st.

$$\sum_j \tilde{a}_{ij} x_j + \max_{\{S_i \cup \{h_i\} | S_i \subseteq J_i,\, |S_i| = \lfloor \Gamma_i \rfloor, h_i \in J_i \setminus S_i\}} \left\{ \sum_{j \in S_i} \check{a}_{ij} y_j + (\Gamma_i - \lfloor \Gamma_i \rfloor) \check{a}_{ih_i} y_h \right\} \le b_i\,, \quad \forall i \tag{A.2b}$$

$$-y_j \le x_j \le y_j\,, \quad \forall j \tag{A.2c}$$

$$\boldsymbol{l} \le \boldsymbol{x} \le \boldsymbol{u}\,, \tag{A.2d}$$

$$\boldsymbol{y} \ge 0\,, \tag{A.2e}$$

where set S_i includes the optimization variables in problem (A.2b)-(A.2e) that correspond to the integer part of the uncertainty budget Γ_i ($\lfloor \Gamma_i \rfloor$) and is defined by a subset of the uncertainty set J_i; index h_i contains one optimization variable in problem (A.2b)-(A.2e) that corresponds to the non-integer remaining part of the uncertainty budget $(\Gamma_i - \lfloor\Gamma_i\rfloor)$ and belongs to the uncertainty set J_i, while it is not contained in the set S_i; parameter Γ_i takes value in the interval $[0, |J_i|]$ and adjusts the level of robustness that the user chooses for the uncertainty.

Given the vector of optimal values $\boldsymbol{x}^*$, it is proved that the objective function of the linear problem (A.3) is equivalent to selecting the subset $\{S_i \cup \{h_i\} | S_i \subseteq J_i, |S_i| = \lfloor\Gamma_i\rfloor, h_i \in J_i \backslash S_i\}$ within the protection function of ith constraint (A.2b) (second term on the left-hand side of (A.2b)).

$$\beta_i(\boldsymbol{x}^*, \Gamma_i) = max \sum_{j \in J_i} \check{a}_{ij} |x_j^*| z_{ij} \,, \tag{A.3a}$$

st.

$$\sum_{j \in J_i} z_{ij} \leq \Gamma_i \,, \tag{A.3b}$$

$$0 \leq z_{ij} \leq 1 \,, \qquad \forall j \in J_i \tag{A.3c}$$

where x_j^* is the optimal value of the ith constraint; and z_{ij} is a positive variable less than 1.

Finally, by applying the strong duality theorem to (A.3) and substituting the result to the problem (A.2b)-(A.2e), the equivalent linear robust formulation is obtained as (A.4):

$$\max \boldsymbol{c}^\top \boldsymbol{x} \,, \tag{A.4a}$$

st.

$$\sum_j \tilde{a}_{ij} x_j + z_i \Gamma_i + \sum_{j \in J_i} p_{ij} \leq b_i \,, \qquad \forall i \tag{A.4b}$$

$$z_i + p_{ij} \geq \check{a}_{ij} y_j \,, \qquad \forall i, j \in J_i \tag{A.4c}$$

$$-y_j \leq x_j \leq y_j \,, \qquad \forall j \tag{A.4d}$$

$$l_j \leq x_j \leq u_j \,, \qquad \forall j \tag{A.4e}$$

$$p_{ij} \geq 0 \,, \qquad \forall i, j \in J_i \tag{A.4f}$$

$$y_j \geq 0 \,, \qquad \forall j \tag{A.4g}$$

$$z_i \geq 0 \,, \qquad \forall i \tag{A.4h}$$

where z_i and p_{ij} are dual variables of constraints (A.3b) and (A.3c), respectively; y_j is the auxiliary variable that calculates the x_j absolute value function; l_j and u_j are the elements of vectors $\boldsymbol{l}$ and $\boldsymbol{u}$, respectively.

The proposed model by Bertsimas and Sim in (A.4) is a linear optimization problem; however, it is shown in [42] that the proposed approach is also valid when the original problem is an MILP (i.e., when some of the variables in the vector $\boldsymbol{x}$ are integer), such as the problem proposed in this paper.

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