This article is a accepted version. Please cite the published version:
https://doi.org/10.1016/j.segan.2026.102281

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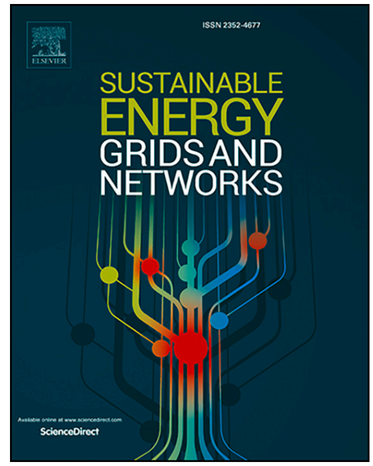

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PII: S2352-4677(26)00163-3
DOI: https://doi.org/10.1016/j.segan.2026.102281
Reference: SEGAN 102281

To appear in: *Sustainable Energy, Grids and Networks*

Received Date: 15 November 2025
Revised Date: 24 March 2026
Accepted Date: 25 April 2026

Please cite this article as: Nemati H, Egido I, Sánchez-Martín P, Ortega ´, Assessing Value of Renewable-based VPP Versus Electrochemical Storage: Multi-market Participation Under Different Scheduling Regimes and Uncertainties, *Sustainable Energy, Grids and Networks* (2026), doi: https://doi.org/10.1016/j.segan.2026.102281.

Assessing Value of Renewable-based VPP Versus Electrochemical Storage: Multi-market Participation Under Different Scheduling Regimes and Uncertainties

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Abstract

To explore clean and cost-effective alternatives to Electrochemical Storage Systems (ESSs), this study focuses on Renewable-based Virtual Power Plants (RVPPs) that employ Dispatchable Renewable Energy Sources (D-RES), Concentrated Solar Power Plant (CSP), and demand flexibility as primary sources of flexibility. In this context, the paper compares the participation of RVPPs and grid-scale ESSs in energy and reserve markets, evaluating their technical performance, market strategies, and economic outcomes. To ensure a fair comparison, scheduling is analyzed over representative sample days that capture seasonal operating regimes, and the associated uncertainties are explicitly modeled. An uncertainty-aware scheduling and bidding framework is developed, explicitly capturing price, generation, and demand uncertainties. It also incorporates a tailored algorithm for sizing the ESS so that its market performance aligns with that of the RVPP. Simulations cover both *favorable* and *unfavorable* scenarios, reflecting seasonal energy limits for dispatchable resources, varying forecast errors for nondispatchable resources, and alternative uncertainty-management strategies. The results provide operators with quantitative guidance on the relative value of each approach.

Keywords

Renewable-based virtual power plant, electrochemical storage system, energy market, reserve market, uncertainty.

Nomenclature

General Notation Concepts

$\bar{A}$, $\underline{A}$ Upper/lower bounds

$\hat{\bar{A}}$, $\tilde{\bar{A}}$ Upper/lower bounds of forecast

$\hat{A}$, $\check{A}$ Positive/negative deviation from forecast

$\tilde{A}$ Median of a forecast distribution

A^{+}, A^{-} Charging/discharging state for storage

$A^{\uparrow}$, $A^{\downarrow}$ Up/down regulation direction

Indexes and Sets

$c \in \mathcal{C}$ Set of D-RES

$d \in \mathcal{D}$ Set of FDs

$m \in \mathcal{M}$ Set of daily load profiles

$r \in \mathcal{R}$ Set of ND-RES

$s \in \mathcal{S}$ Set of ESSs

$t \in \mathcal{T}$ Set of time periods in each sample day

$u \in \mathcal{U}$ Set of units

$\theta \in \Theta$ Set of CSPs

$\Xi^{\mathrm{R/S}}$ Set of decision variables of RVPP/ESS operator

Parameters

C_u Operation costs of unit u	[€/MWh]
$C_u^{SU/SD}$ Start-up/shut-down costs of unit u	[€]
E_u Electrical energy capacity of unit u	[MWh]
K_θ Start up output multiplier of turbine of CSP θ	[p.u.]
M Big positive value	[-]
$P_{\theta,t}^{SF}$ Thermal power of SF of CSP θ during period t	[MW]
$P_{d,m,t}$ FD d of profile m consumption during period t	[MW]
$P_{r,t}$ ND-RES r production during period t	[MW]
P_u Electrical power capacity of unit u	[MW]
$\Gamma^{DA/SR}$ Uncertainty budget of DAM/SRM price	[-]
Γ_u Uncertainty budget of unit u's power output	[-]
Δt Duration of periods	[hour]
η_θ Thermal to electrical output efficiency of CSP θ	[%]
η_s Electrical power efficiency of ESS s	[%]
λ_t^{DA} DAM price during period t	[€/MWh]
$\lambda_t^{SR,\uparrow(\downarrow)}$ Up (down) SRM price during period t	[€/MW]

Variables

$e_{s,t}$	Electrical energy of ESS s during period t	[MWh]
p_t^{DA}	Electrical power traded by RVPP during period t	[MW]
$p_{\theta,t}^{SF/TS}$	Thermal power of SF/TS of CSP θ during period t	[MW]
$p_{u,t}$	Electrical power of unit u during period t	[MW]
r_t^{SR}	Reserve traded by RVPP during period t	[MW]
$r_{u,t}$	Reserve provided by unit u during period t	[MW]
x_t^{DA}	Auxiliary variable of traded electrical energy	[MWh]
$x_{u,t}$	Auxiliary variable of unit u's power uncertainty	[MW]
σ_s	Share of ESS s capacity allocated for reserve	[%]
$\mu^{DA/SR}$	Dual variable of DAM/SRM price uncertainty	[€]
μ_u	Dual variable of unit u's power uncertainty	[MW]
$\xi_t^{DA/SR}$	Dual variable of DAM/SRM price uncertainty	[€]
$\xi_{u,t}$	Dual variable of unit u's power uncertainty	[MW]
$q_{u,t}$	Binary variable of unit u's power uncertainty	[-]
$u_{d,m}$	Binary variable of selection of profile m of FD d	[-]
$u_{s,t}$	Binary variable of charging/discharging state of ESS s	[-]
$u_{u,t}$	Binary variable of on/off status of unit u's turbine	[-]
$v_{u,t}^{SU}$	Binary variable of start-up status of unit u's turbine	[-]

1. Introduction

The transition toward high shares of renewable generation demands new paradigms for system flexibility that ensure operational reliability while minimizing environmental impact and long-term costs. Within this context, the European *Powering System Flexibility in the Future* (POSYTYF) project [1] advocates Renewable-based Virtual Power Plant (RVPP) architectures designed to deliver flexibility without dependence on Electrochemical Storage Systems (ESSs). The project promotes clean and enduring flexibility solutions as sustainable alternatives to ESSs, which face challenges related to cost, lifetime, and material sustainability. The RVPP functions as a unified operational entity that consolidates Dispatchable Renewable Energy Sources (D-RES), Concentrated Solar Power Plant (CSP), Non-dispatchable Renewable Energy Sources (ND-RES), and Flexible Demand (FD) through digitalized infrastructure enabled by advanced forecasting, real-time monitoring, and decentralized energy management systems. By combining dispatchable assets such as hydro and biomass plants with variable resources like Wind Farm (WF), solar Photovoltaic (PV), and CSP, alongside FD, an RVPP can offer enhanced operational flexibility and reliability. This enables participation in both Day Ahead Market (DAM) and Secondary Reserve Market (SRM), where it can provide energy, up/down reserves, and demand-side response services through unified bidding strategies [2, 3]. The ability to coordinate diverse units allows the RVPP to smooth out renewable generation variability, optimize resource utilization, and manage power imbalances. Additionally, this aggregation framework enables inclusion of smaller or distributed energy resources that typically lack capacity to participate independently, thus promoting the integration of variable Renewable Energy Sources (RES) into wholesale electricity markets and contributing to grid reliability and economic performance [4].

On the other hand, grid-scale ESSs are increasingly recognized as critical enablers of high RES penetration, offering fast response for both active and reactive power support to mitigate RES variability [5]. Recent advances in lithium-ion technology have enhanced efficiency and scalability, while declining costs have accelerated deployment—evidenced by the Edwards & Sanborn ESS in California, which now operates at 3,287 MWh capacity [6]. Nonetheless, technical and environmental limitations remain. Lithium-ion ESSs generally maintain performance for approximately 2,000 to 5,000 charge-discharge cycles before experiencing significant degradation. Additionally, raw material extraction (e.g., lithium, cobalt) poses sustainability concerns, and recycling inefficiencies at end-of-life stages exacerbate environmental risks [7]. Overcoming these challenges is essential to ensure the long-term viability and environmental compatibility of ESSs in renewable-based power systems.

While both RVPP and grid-scale ESS possess the flexibility to participate in energy trading, arbitrage, and ancillary services such as reserve support [5, 8], their operational characteristics and energy availability differ significantly across scheduling regimes. For instance, ESSs are constrained by storage capacity and State of Charge (SoC) for energy and reserve provision, whereas RVPPs are limited by seasonal and weather-dependent resource availability across aggregated assets. These differences become especially pronounced under high uncertainty from market price volatility, renewable output fluctuations, and unpredictable load profiles [9]. As a result, the technical and economic performance of each solution varies depending on the market context and operational constraints. To accurately quantify and compare the value of RVPP and ESS participation, it is essential to develop advanced optimization frameworks that reflect these operational nuances. Such models must consider multiple scheduling regimes, technology-specific constraints, and stochastic representations of uncertainty. By integrating these aspects, a more realistic and comprehensive evaluation can be achieved, enabling stakeholders and decision makers to identify optimal strategies for resource coordination and market participation.

The participation of RVPPs in energy and reserve markets under multiple uncertainties to maximize profitability has been widely studied [2, 3, 8, 10–20]. Table 1 categorizes existing works based on considered components, market structures, uncertainties, and scheduling horizons. The fundamental concept behind an RVPP lies in coordinating controllable and dispatchable units to mitigate the stochastic nature of ND-RES generation, thereby ensuring operational viability and enabling the provision of multiple services across electricity markets. In this context, the integrating flexible resources such as hydro plant [2, 19], ESS [2, 3, 12, 14, 17, 18], FD [3, 10–15, 20], and Electric Vehicle (EV) [8, 16] is crucial for improving the controllability of intermittent RES. To

Table 1: Comparison of RVPP approach in this paper and literature.

	Components								Market		Uncertainty			Multiple scheduling	RVPP versus
Ref.	**PV**	**WF**	**Hydro**	**Biomass**	**CSP**	**ESS**	**EV**	**FD**	**Energy**	**Reserve**	**Price**	**RES**	**Demand**	**horizons**	**ESS sizing**
[2]	•	•	•			•			•	•		•			
[3]	•	•						•	•		•	•			
[11, 15]	•	•						•	•	•	•	•	•		
[8]	•					•	•		•			•	•	•	
[12]	•	•				•		•	•	•	•	•	•		
[14]	•	•				•		•	•	•		•			
[16]		•					•		•		•	•			
[19]	•	•	•			•			•						
[17]		•				•		•	•		•	•			
[18]		•			•				•			•			
This paper	•	•	•	•	•	•		•	•	•	•	•	•	•	•

address the complexities arising from multi-market participation and uncertainty, various optimization techniques have been employed, including Mixed Integer Linear Programming (MILP) [19], Stochastic Optimization (SO) [2, 8, 12, 16], Robust Optimization (RO) [11, 13–15, 17, 18], and Information Gap Decision Theory (IGDT) approaches [3]. These methods are favored due to their ability to capture various technical constraints and efficiently handle multiple sources of uncertainty across scheduling horizons.

Recent studies have further extended uncertainty-aware scheduling and market participation through both two-stage and multi-stage formulations. Among two-stage models, [21] proposes an RO-based framework with a refined demand response strategy that accounts for the regulatory characteristics of flexible loads and the satisfaction level of residents, solved through a decomposed master-subproblem structure using the Column & Constraint Generation (C&CG) algorithm. The papers [22–24] develop two-stage distributionally RO formulations to address uncertainties in renewable generation, charging demand, electricity prices, and carbon-market participation. In parallel, multi-stage formulations have been introduced to better capture the sequential revelation of uncertainty. For example, [25] presents a three-stage SO bi-level model for the joint energy and reserve scheduling of a VPP with internal load aggregators participating in a local intraday demand response exchange. Multi-stage RO approaches have also been reported for ESS scheduling under distributed RES uncertainty [26], virtual energy storage dispatch with time-coupled operational constraints [27], day-ahead scheduling of hybrid thermal-hydro-wind-solar systems [28], and reserve provision by microgrids with ESS under decision-dependent uncertainty [29]. These studies show that, although multi-stage frameworks can better preserve non-anticipativity and reduce infeasibility risk under sequential uncertainty realization, they generally require tractability-enhancing reformulations, tailored feasible regions, or decomposition-based solution methods.

Although the above studies demonstrate the growing use of both two-stage and multi-stage uncertainty-aware formulations for RVPP scheduling and market participation, important challenges remain. In particular, while multi-stage approaches can better capture the sequential revelation of uncertainty and reduce infeasibility risk, they often entail significantly higher computational complexity when multiple uncertainty sources, coupled market decisions, and detailed unit-level operational constraints are considered. Moreover, most existing studies either focus on a specific technology or market setting, or emphasize methodological developments in uncertainty handling rather than a holistic and methodologically consistent comparison between diverse RVPP configurations and ESS participation across energy and reserve markets. Additionally, the literature offers limited insight into comparative profitability analyses of RVPP and ESS across energy and reserve markets. To address these gaps, this paper conducts a comprehensive technical and economic comparison of RVPP and ESS, considering multiple sources of uncertainty, seasonal variability in renewable output, and different scheduling regimes. Accordingly, the objective of this work is not to establish the universal superiority of RVPPs over grid-scale ESSs, but to provide a fair and uncertainty-aware comparative assessment of their relative technical and economic performance under the considered market settings and portfolio assumptions. An uncertainty-aware scheduling framework is developed using a flexible two-stage RO optimization formulation [11, 14, 15, 21], which is adapted and extended to enable a consistent comparison between ESS-free renewable aggregation and ESS. The flexible two-stage structure is particularly suitable for this study, as it allows a comprehensive comparison across a wide range of characteristics, including different configurations, uncertainty-management strategies, and scheduling regimes for both RVPP and ESS optimization problems. This approach captures distinct uncertainty sources—price, generation, and demand—and supports multi-market participation across scheduling horizons, providing a transparent basis for risk-informed evaluation. In addition, the analysis explores how individual technologies contribute to economic performance, providing a more comprehensive insight into the role of different configurations under practical market conditions. The comparative assessment against different ESS-based configurations presented in this study thus offers valuable information for system operators and decision-makers involved in deploying flexible, renewable-based assets.

The contributions of this work are thus twofold:

- To evaluate the robustness and adaptability of ESS-free RVPP-based renewable aggregation frameworks that leverage clean and sustainable flexibility resources under generation and demand uncertainty.
- To compare and evaluate the technical and economic performance of RVPP and ESS using an efficient solution algorithm, and to conduct a comparative analysis under different uncertainty-handling strategies and scheduling regimes.

The remainder of this paper is structured as follows: Section 2 outlines the problem scope. Section 3 formulates the proposed algorithm for comparing the RVPP and ESS in DAM and SRM participation. Section 4 presents and discusses the case studies considered. Finally, Section 5 outlines concluding remarks and future work directions.

2. Problem Description

Figure 1 illustrates the schematic of the RVPP and the ESS participating in energy and reserve markets. By aggregating multiple RES, the RVPP can coordinate internal dispatch and optimize market participation more effectively than individual units operating independently. The RVPP operator uses forecasts of its ND-RES generation units and market prices, along with information on the availability of its dispatchable units and FD, to determine an optimal bidding and scheduling strategy aimed at profit maximization. In this study, the RVPP is modeled as a price-taker, submitting zero-price bids to reflect its relatively small scale compared to the overall electric grid. After receiving market-clearing results, the RVPP operator communicates the dispatch decisions to its internal units. The ESS problem is developed to determine the minimum required storage capacity needed to achieve economic performance equivalent to that of the RVPP. The same market data is used for both problems to ensure a fair and comprehensive comparison between the two approaches. The comparison is further focused on participation in the DAM and SRM under unit-level technical constraints. Therefore, the present framework does not explicitly account for network operational limits, grid-code compliance requirements, or additional stability-oriented ancillary services such as fast frequency response, synthetic inertia, black-start capability, and voltage support. It should be noted that the comparison is made against standalone grid-scale ESSs. Although the considered RVPP includes embedded flexibility resources with storage-like behavior, particularly the CSP equipped with Thermal Storage (TS) and the hydro reservoir, these are treated as intrinsic components of the renewable aggregation rather than as separate storage assets. While standalone ESS is modeled, it is also analyzed in joint configurations with ND-RES such as WF and solar PV to better reflect realistic market participation. It should be noted that this study focuses exclusively on electricity-market participation. Although the CSP includes TS, the stored thermal energy is modeled only as an internal state supporting electricity generation, rather than as participation in a separate heat market [30].

To further understand the impact of different technologies, multiple RVPP configurations are evaluated by excluding key units (e.g., FD, CSP, hydro) from RVPP, enabling a detailed sensitivity analysis of their contributions. Accordingly, the corresponding ESS setups for each configuration are analyzed. Given the seasonal variability of renewable energy availability and its effect on RVPP profitability and scheduling, representative days for each season are modeled. These representative days are used to capture season-dependent operating conditions in a tractable manner; therefore, the resulting schedules should be interpreted as representative seasonal outcomes rather than as a formal guarantee for all chronological days within a season or for prolonged effects such as multi-season resource droughts and inter-seasonal carryover risk. Additionally, various uncertainty-handling strategies are considered to capture the impact of forecast variations in generation, consumption, and market prices. These factors enable a robust evaluation of both RVPP and ESS across diverse operational and market conditions. Flexible two-stage optimization technique [11, 14, 15, 21] is employed in the next section to address the market participation problems of RVPP and ESS, as it is well-suited for incorporating multiple uncertainties across different scheduling horizons.

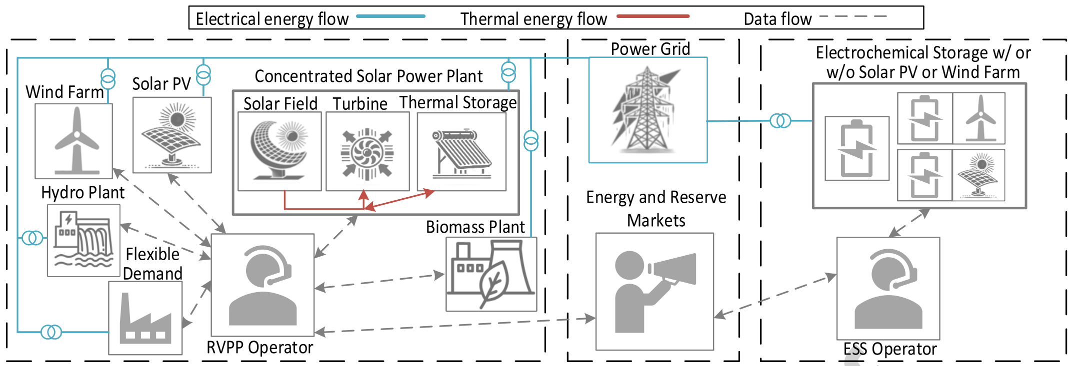

Figure 1: The scheme of considered RVPP and ESS.

3. Formulation

In this section, the deterministic models for RVPP and ESS participation in the electricity energy and reserve markets are first developed. Then, recognizing that price volatility, as well as generation and demand uncertainties, impact market outcomes, both models are extended to account for the corresponding uncertainties specific to each problem. In line with established formulations in the literature [11, 14, 15, 21], the two-stage framework is adopted here; however, the comparative analysis developed for evaluating RVPP and ESS performance under different uncertainty and scheduling regimes constitutes a new contribution of this work.

3.1. Deterministic RVPP Problem

This section presents the deterministic RVPP problem for joint participation in DAM and SRM. The objective is to maximize the RVPP profit, subject to unit technical and trading constraints.

3.1.1. Objective Function

The RVPP objective function (1) maximizes profit across the DAM and SRM, incorporating the operational expenses of its units. The terms represent, respectively: expected revenues from DAM bids; revenues from upward and downward SRM participation; operating costs of ND-RES and CSPs; and operating, start-up, and shut-down costs of D-RES.

$$
\begin{aligned}
\max_{\Xi^{\mathrm{R}}} & \sum_{t\in\mathcal{T}} \lambda_t^{DA} p_t^{DA} \Delta t + \sum_{t\in\mathcal{T}} \left[\lambda_t^{SR,\uparrow} r_t^{SR,\uparrow} + \lambda_t^{SR,\downarrow} r_t^{SR,\downarrow}\right] \\
& - \sum_{t\in\mathcal{T}} \sum_{r\in\mathcal{R}} C_r p_{r,t} \Delta t - \sum_{t\in\mathcal{T}} \sum_{\theta\in\Theta} C_\theta p_{\theta,t} \Delta t \\
& - \sum_{t\in\mathcal{T}} \sum_{c\in\mathcal{C}} \left[C_c p_{c,t} \Delta t + C_c^{SU} v_{c,t}^{SU} + C_c^{SD} v_{c,t}^{SD}\right]
\end{aligned}
\tag{1}
$$

3.1.2. Electrical Supply & Demand Traded Constraints

The equality constraint for supply-demand balance among RVPP units is formulated in (2). It accounts for all real-time reserve activation scenarios, including upward activation, downward activation, and no activation. To model these conditions, 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 introduced for the RVPP, ND-RES, CSP, D-RES, and FD, capturing the respective reserve states. Consequently, (2) yields three distinct equations. Reserve capacity is co-optimized with energy and is always bounded by the feasible operating capability of each unit. For uncertain ND-RES, the same available uncertain production constrains both scheduled energy and reserve. For D-RES, reserve provision is restricted by the technical operating limits and the corresponding headroom/footroom. For the CSP, reserve provision is limited by the turbine operating constraints together with the available thermal energy represented through the Solar Field (SF) and TS constraints, while for FD it is bounded by the admissible demand flexibility range. Therefore, (2) ensures feasible co-optimization of energy and reserve capacity under the three modeled operating states and mitigates the risk of reserve unavailability within the proposed two-stage RO framework and the adopted uncertainty set. The formulation does not, however, explicitly represent the real-time delivery of reserve energy, since actual reserve activation is itself highly uncertain in terms of occurrence, direction, timing, duration, and the amount requested by the system operator.

$$\begin{aligned}&\sum_{r\in\mathcal{R}}[p_{r,t}+\boldsymbol{r}_{r,t}]+\sum_{\theta\in\Theta}[p_{\theta,t}+\boldsymbol{r}_{\theta,t}]+\sum_{c\in\mathcal{C}}[p_{c,t}+\boldsymbol{r}_{c,t}]\\&-\sum_{d\in\mathcal{D}}[p_{d,t}-\boldsymbol{r}_{d,t}]=p_t^{DA}+\boldsymbol{r}_t^{SR}\ ; \qquad \forall t \qquad (2)\end{aligned}$$

3.1.3. Dispatchable Unit Constraints

Constraints (3a)-(3b) bound D-RES production considering reserve provision. Minimum up/down time constraints, following the formulation in [31], are omitted here for brevity. Daily energy limits due to seasonal regulations are addressed in (3c).

$$p_{c,t}+r_{c,t}^{\uparrow}\le \bar{P}_c u_{c,t}\ ; \qquad \forall c,t \qquad (3a)$$

$$\underline{P}_c u_{c,t}\le p_{c,t}-r_{c,t}^{\downarrow}\ ; \qquad \forall c,t \qquad (3b)$$

$$\sum_{t\in\mathcal{T}}\left[p_{c,t}\Delta t+r_{c,t}^{\uparrow}\right]\le \bar{E}_c\ ; \qquad \forall c \qquad (3c)$$

3.1.4. Non-dispatchable Unit Constraints

The constraints for ND-RES are defined in (4). Equations (4a) and (4b) specify the bounds on energy and reserve outputs based on the available uncertain production [32], so that the same uncertainty realization directly limits both scheduled energy and reserve provision.

$$p_{r,t} + r^{\uparrow}_{r,t} \leq P_{r,t} \; ; \qquad \forall r, t \qquad (4a)$$

$$\underline{P}_r \leq p_{r,t} - r^{\downarrow}_{r,t} \; ; \qquad \forall r, t \qquad (4b)$$

3.1.5. Concentrated Solar Power Plant Constraints

The transformation of thermal to electrical energy in the CSP turbine is represented by (5) [33]. Constraint (5a) defines the allowable range of thermal output from the SF, given a fixed solar irradiation parameter. Equation (5b) integrates the thermal power dispatched to the turbine from the SF, the charging and discharging of TS, and turbine startup losses. The conversion efficiency of the turbine is represented by the efficiency parameter η_θ. Constraints (5c)-(5d) bound the CSP's electrical output and reserve according to maximum/minimum limits and the turbine's binary commitment status $u_{\theta,t}$. Commitment status and minimum up/down time constraints are based on [31]. The TS constraints follow the formulation for ESSs described in Section 3.2.1 and are omitted here for brevity.

$$0 \leq p^{SF}_{\theta,t} \leq P^{SF}_{\theta,t} \; ; \qquad \forall \theta, t \qquad (5a)$$

$$\frac{p_{\theta,t}}{\eta_\theta} = p^{SF}_{\theta,t} + p^{TS,-}_{\theta,t} - p^{TS,+}_{\theta,t} - K_\theta v^{SU}_{\theta,t} \bar{P}_\theta \; ; \qquad \forall \theta, t \qquad (5b)$$

$$p_{\theta,t} + r^{\uparrow}_{\theta,t} \leq \bar{P}_\theta u_{\theta,t} \; ; \qquad \forall \theta, t \qquad (5c)$$

$$\underline{P}_\theta u_{\theta,t} \leq p_{\theta,t} - r^{\downarrow}_{\theta,t} \; ; \qquad \forall \theta, t \qquad (5d)$$

3.1.6. Flexible Demand Constraints

The deterministic constraints governing the FDs are formulated in (6) [33]. Constraint (6a) defines the minimum consumption level for FDs during each time period, considering the possibility of selecting different demand profiles. Constraint (6b) enforces the selection of exactly one demand profile among multiple candidates. The permissible operating range for FDs, encompassing both energy consumption and reserve provision, is bounded by (6c) and (6d).

$$p_{d,t} \geq \sum_{m \in \mathcal{M}} \left[P_{d,m,t} u_{d,m} \right] \; ; \qquad \forall d, t \qquad (6a)$$

$$\sum_{m \in \mathcal{M}} u_{d,m} = 1 \; ; \qquad \forall d \qquad (6b)$$

$$\underline{P}_d \leq p_{d,t} - r^{\uparrow}_{d,t} \; ; \qquad \forall d, t \qquad (6c)$$

$$p_{d,t} + r^{\downarrow}_{d,t} \leq \bar{P}_d \; ; \qquad \forall d, t \qquad (6d)$$

3.2. Electrochemical Storage System Problem

This section focuses on identifying the ESS capacity required to match the operational and market performance of an RVPP across energy and reserve markets. First, the operational modeling of ESS participation in the DAM and SRM is detailed. Then, an algorithm for sizing the ESS to achieve comparable economic profitability to the RVPP is introduced.

3.2.1. ESS Operation Constraints

The ESS formulation in (7) integrates energy trading and reserve provision. The objective (7a) maximizes DAM and SRM profits minus operation and degradation costs. Constraints (7b)–(7e) manage ESS charging (+) and discharging (−), considering upward and downward reserves in both states, with the binary variable $u_{s,t}$ indicating the ESS state. Output power and reserve are determined in (7f)–(7h), based on contributions from the charging and discharging states. The SoC of the ESS is modeled in (7i), while (7j) ensures daily energy balance by maintaining consistent initial and final SoC. Variables $\sigma_s^{\uparrow}$ and $\sigma_s^{\downarrow}$ in (7k)–(7m) represent the shares of ESS capacity allocated for upward and downward regulation, respectively [33].

$$\max_{\Xi^{\mathcal{S}}} \sum_{t\in\mathcal{T}} \sum_{s\in\mathcal{S}} \left[\lambda_t^{DA} p_{s,t}\Delta t + \lambda_t^{SR,\uparrow} r_{s,t}^{\uparrow} + \lambda_t^{SR,\downarrow} r_{s,t}^{\downarrow} - C_s p_{s,t}^{-}\right] \tag{7a}$$

st.

$$\underline{P}_s^{+} u_{s,t} \le p_{s,t}^{+} - r_{s,t}^{+,\uparrow} \; ; \qquad \forall s,t \tag{7b}$$

$$p_{s,t}^{+} + r_{s,t}^{+,\downarrow} \le \bar{P}_s^{+} u_{s,t} \; ; \qquad \forall s,t \tag{7c}$$

$$p_{s,t}^{-} + r_{s,t}^{-,\uparrow} \le \bar{P}_s^{-} \left(1 - u_{s,t}\right) \; ; \qquad \forall s,t \tag{7d}$$

$$\underline{P}_s^{-} \left(1 - u_{s,t}\right) \le p_{s,t}^{-} - r_{s,t}^{-,\downarrow} \; ; \qquad \forall s,t \tag{7e}$$

$$p_{s,t} = p_{s,t}^{-} - p_{s,t}^{+} \; ; \qquad \forall s,t \tag{7f}$$

$$r_{s,t}^{\uparrow} = r_{s,t}^{+,\uparrow} + r_{s,t}^{-,\uparrow} \; ; \qquad \forall s,t \tag{7g}$$

$$r_{s,t}^{\downarrow} = r_{s,t}^{+,\downarrow} + r_{s,t}^{-,\downarrow} \; ; \qquad \forall s,t \tag{7h}$$

$$e_{s,t} = e_{s,t-1} + p_{s,t}^{+}\eta_s^{+}\Delta t - \frac{p_{s,t}^{-}\Delta t}{\eta_s^{-}} \; ; \qquad \forall s, t\backslash\{1\} \tag{7i}$$

$$e_{s,1} = e_{s,t=T} \; ; \qquad \forall s \tag{7j}$$

$$\sum_{t\in\mathcal{T}} \frac{r_{s,t}^{\uparrow}\Delta t}{\eta_s^{-}} \le \sigma_s^{\uparrow}\left(\bar{E}_s - \underline{E}_s\right) \; ; \qquad \forall s \tag{7k}$$

$$\sum_{t\in\mathcal{T}} r_{s,t}^{\downarrow}\eta_s^{+}\Delta t \le \sigma_s^{\downarrow}\left(\bar{E}_s - \underline{E}_s\right) \; ; \qquad \forall s \tag{7l}$$

$$\underline{E}_s + \sigma_s^{\downarrow}\left(\bar{E}_s - \underline{E}_s\right) \le e_{s,t} \le \bar{E}_s - \sigma_s^{\downarrow}\left(\bar{E}_s - \underline{E}_s\right); \qquad \forall s,t \tag{7m}$$

3.2.2. ESS Sizing

To determine the ESS capacity required to match the economic performance as the RVPP, both the RVPP optimization model (1)–(6) and the ESS operation model (7) are employed. First, the profitability of the RVPP in the DAM and SRM is compared with the aggregated operation profit of the individual units under the assumption that each participates independently in the markets. This difference is then used as the Lower Bound (LB) in the ESS optimization model (7). The parameters of the ESS are iteratively updated by incrementally adding modules of the ESS until the operation profit of the ESS reaches or exceeds the profitability level of the RVPP. The steps for determining appropriate ESS capacity are illustrated in Algorithm 1. It should be noted that the proposed sizing method is intended to identify the minimum modular ESS capacity required to match the operational market performance of the RVPP under the assumed market conditions, rather than to provide either a globally optimal joint power-energy capacity design or a full techno-economic investment evaluation. Accordingly, the procedure is implemented over identical ESS modules with fixed technical characteristics, so that the comparison remains transparent and methodologically consistent with the comparative objective of this work. Capital expenditure, discount rates, and long-term lifecycle cash-flow assumptions are therefore outside the scope of the present sizing problem.

3.3. Robust RVPP Problem

The robust RVPP problem considers uncertainties in DAM and SRM prices, ND-RES and CSPs generation, and FDs consumption. A flexible two-stage RO model [11, 14, 15, 21] is developed and reformulated as a single-level MILP to handle uncertainties.

3.3.1. Two-stage Problem

In the first stage of model (8), the RVPP operator maximizes its objective function (8a), which mirrors the deterministic objective function (1). O^{R} refers to the terms in the objective function of the deterministic RVPP problem that are not affected by uncertainty. In the second stage, uncertainties negatively impact the electricity prices in the DAM and SRM, as represented by the

Algorithm 1 Size of ESS to match RVPP economic performance.

Input: Technical parameters and forecast data for RVPP and ESS.
Solve the RVPP optimization problem (1)-(6).
Compare RVPP profitability with individual unit participation and set this value as the LB of the ESS problem (7).
repeat
    Solve the ESS optimization problem (7).
    if problem (7) is not feasible **then**
        Update ESS input parameters $\underline{P}_s^{+}$, $\bar{P}_s^{+}$, $\underline{P}_s^{-}$, $\bar{P}_s^{-}$, $\underline{E}_s$, $\bar{E}_s$ by adding one module.
    end if
until problem (7) becomes feasible
Output: Final ESS capacity and its optimal scheduling and operation.

minimization part in the objective function. Uncertainties are also modeled to potentially reduce the electrical output of ND-RES and the thermal output of CSPs, while increasing the consumption of FDs, as expressed in constraints (8b)-(8d). Notably, unlike the deterministic formulation, the uncertainty sets $\{\lambda_t^{DA}, \lambda_t^{SR,\uparrow}, \lambda_t^{SR,\downarrow}\}$ and $\{P_{r,t}, P_{\theta,t}^{SF}, P_{d,t}\}$ (index m in $P_{d,m,t}$ from (6a) is omitted for simplicity) now include second-stage decision variables, which were treated as fixed parameters in the deterministic model. Constraints from Section 3.1 unaffected by uncertainty are defined by C^{R} in (8e)[1].

$$\max_{\Xi^{\mathrm{R}}} \left\{ \min_{\{\lambda_t^{DA}, \lambda_t^{SR,\uparrow}, \lambda_t^{SR,\downarrow}\}} \left\{ \sum_{t\in\mathcal{T}} \lambda_t^{DA} p_t^{DA} \Delta t + \sum_{t\in\mathcal{T}} \left[\lambda_t^{SR,\uparrow} r_t^{SR,\uparrow} + \lambda_t^{SR,\downarrow} r_t^{SR,\downarrow} \right] - O^{\mathrm{R}} \right\} \right\} \tag{8a}$$

st.

$$p_{r,t} + r_{r,t}^{\uparrow} \leq \min_{P_{r,t}} \{P_{r,t}\} \;; \qquad \forall r, t \tag{8b}$$

$$p_{\theta,t}^{SF} \leq \min_{P_{\theta,t}^{SF}} \left\{P_{\theta,t}^{SF}\right\} \;; \qquad \forall \theta, t \tag{8c}$$

$$p_{d,t} \geq -\min_{P_{d,t}} \{-P_{d,t}\} \;; \qquad \forall d, t \tag{8d}$$

$$C^{\mathrm{R}} \leq 0; \tag{8e}$$

3.3.2. Single-level Reformulation

The single-level MILP formulation (9) is derived by applying the strong duality principle to the original RO problem (8) [11]. The uncertainty bounds in the optimization problem (9) are governed by *uncertainty budget* parameters. Each budget is an integer from 0 to 24 for each hour of the sample day, allowing the conservatism level to vary from optimistic to pessimistic. The uncertainty-budget parameters determine how many periods within the 24-hour sample day may simultaneously attain adverse realizations, thereby controlling the conservatism of the robust counterpart. Accordingly, they should be interpreted as tuning parameters for uncertainty handling rather than as direct statistical confidence levels. This approach provides a balanced treatment of uncertainty, as the RVPP operator can adjust the budget to select the desired level of conservatism and thereby avoid overly conservative solutions. The objective function (9a) captures the worst-case impact of uncertainties in DAM and SRM prices. Asymmetric price deviations in the DAM are modeled via constraint (9b). Dual representations of the DAM and SRM price uncertainties are formulated in constraints (9c)–(9e). Uncertainty associated with the electrical production of ND-RESs is addressed through constraints (9f)–(9i). Similarly, uncertainties in CSPs thermal production and FDs consumption are handled by analogous constraints, which are omitted for brevity. The remaining deterministic constraints are included in (9j).

[1]Deterministic constraints include: (2), (3), (4b) , (5b)-(5d), (6b)-(6d).

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

$$- \Gamma^{DA} \mu^{DA} - \sum_{t \in \mathfrak{T}} \xi_t^{DA} - \Gamma^{SR,\uparrow} \mu^{SR,\uparrow} - \Gamma^{SR,\downarrow} \mu^{SR,\downarrow}$$

$$- \sum_{t \in \mathfrak{T}} \left[\xi_t^{SR,\uparrow} + \xi_t^{SR,\downarrow} \right] \Bigg\} \tag{9a}$$

st.

$$- \frac{\check{\lambda}_t^{DA}}{\hat{\lambda}_t^{DA}} x_t{}^{DA} \leq p_t{}^{DA} \Delta t \leq x_t{}^{DA} \; ; \qquad \forall t \tag{9b}$$

$$\mu^{DA} + \xi_t^{DA} \geq \check{\lambda}_t^{DA} x_t^{DA} \; ; \qquad \forall t \tag{9c}$$

$$\mu^{SR,\uparrow} + \xi_t^{SR,\uparrow} \geq \check{\lambda}_t^{SR,\uparrow} r_t^{SR,\uparrow} \; ; \qquad \forall t \tag{9d}$$

$$\mu^{SR,\downarrow} + \xi_t^{SR,\downarrow} \geq \check{\lambda}_t^{SR,\downarrow} r_t^{SR,\downarrow} \; ; \qquad \forall t \tag{9e}$$

$$p_{r,t} + r_{r,t}^{\uparrow} \leq \hat{\tilde{P}}_{r,t} - x_{r,t} \; ; \qquad \forall r, t \tag{9f}$$

$$\mu_r + \xi_{r,t} - M(1 - q_{r,t}) \leq x_{r,t} \leq M q_{r,t}; \qquad \forall r, t \tag{9g}$$

$$\mu_r + \xi_{r,t} \geq \check{P}_{r,t} \; ; \qquad \forall r, t \tag{9h}$$

$$\sum_t q_{r,t} = \Gamma_r \; ; \qquad \forall r \tag{9i}$$

$$C^{\mathrm{R}} \leq 0; \tag{9j}$$

3.4. Robust ESS Problem

The two-stage RO model for ESS addresses price uncertainty in the DAM and SRM. Adopting the methodology outlined in Section 3.3, the ESS problem is recast as the single-level MILP given in (10). Using the same two-stage RO framework for both RVPP and ESS ensures methodological consistency, allowing a fair comparison between the two technologies under identical sources of uncertainty. The symbols O^{S} in (10a) denotes the objective terms in the deterministic ESS model (7) that remain unaffected by uncertainty. In the objective function (10a), the first line captures all deterministic components, whereas the second line introduces dual variables that penalize the worst-case realizations of DAM and SRM price uncertainty. The corresponding dual feasibility conditions, which distinguish between the charging and discharging modes of the ESS, are specified in (10b)–(10d). The remaining operational constraints unaffected by uncertainty are consolidated in (10e).

$$\max_{\Xi^{S}} \Bigg\{ \sum_{t\in\mathcal{T}} \sum_{s\in\mathcal{S}} \Big[\tilde{\lambda}_t^{DA} p_{s,t} \Delta t + \hat{\tilde{\lambda}}_t^{SR,\uparrow} r_{s,t}^{\uparrow} + \hat{\tilde{\lambda}}_t^{SR,\downarrow} r_{s,t}^{\downarrow} \Big] - O^{S}$$

$$- \Gamma^{DA}\mu^{DA} - \sum_{t\in\mathcal{T}} \xi_t^{DA} - \Gamma^{SR,\uparrow}\mu^{SR,\uparrow} - \Gamma^{SR,\downarrow}\mu^{SR,\downarrow}$$

$$- \sum_{t\in\mathcal{T}} \Big[\xi_t^{SR,\uparrow} + \xi_t^{SR,\downarrow} \Big] \Bigg\} \tag{10a}$$

st.

$$\mu^{DA} + \xi_t^{DA} \geq \check{\lambda}_t^{DA} \Delta t \sum_{s\in\mathcal{S}} p_{s,t}^{-} + \hat{\lambda}_t^{DA} \Delta t \sum_{s\in\mathcal{S}} p_{s,t}^{+} \,; \qquad \forall t \tag{10b}$$

$$\mu^{SR,\uparrow} + \xi_t^{SR,\uparrow} \geq \check{\lambda}_t^{SR,\uparrow} \sum_{s\in\mathcal{S}} r_{s,t}^{\uparrow} \,; \qquad \forall t \tag{10c}$$

$$\mu^{SR,\downarrow} + \xi_t^{SR,\downarrow} \geq \check{\lambda}_t^{SR,\downarrow} \sum_{s\in\mathcal{S}} r_{s,t}^{\downarrow} \,; \qquad \forall t \tag{10d}$$

$$C^{S} \leq 0; \tag{10e}$$

4. Case Studies

This section presents the simulation results based on the proposed RO framework for evaluating RVPP participation in the DAM and SRM. Additional simulations assess the sizing and operation of an individual ESS, as well as its integration with ND-RES, to replicate RVPP performance under similar market conditions. The simulations consider an RVPP comprising a hydro plant, a biomass unit, a WF, a solar PV plant, a CSP equipped with TS, and a FD. It should be noted that the considered case studies are intended to reflect the performance of the proposed multi-resource RVPP under season-dependent availability conditions. Therefore, the numerical results should be interpreted as representative of the studied portfolio and its alternative configurations, rather than as universally transferable to all RVPPs with different regional resource compositions. For the electricity market simulations involving the ESS, multiple 1 MWh Li-ion ESSs are aggregated to provide the necessary capacity, with their characteristics provided in Table 2 based on [33]. Forecast bounds for the ND-RES units—including electrical outputs of the WF and solar PV, and thermal output of the CSP—are shown in Figure 2 across four representative days. Accordingly, the seasonal analysis is intended to reflect representative operating regimes under season-specific data and uncertainty bounds, rather than to provide a full chronological feasibility assessment over an entire season. These bounds are derived from historical data: solar PV and CSP from CIEMAT Spain [34], and the WF from Iberdrola Spain [35]. Figure 2 includes the Upper Bound (UB) representing the deterministic forecast, and two LB scenarios: *favorable* (FAV), indicating moderate uncertainty, and *unfavorable* (UNF), representing greater forecast variability. Both the WF and solar PV plants are modeled with nominal capacities of 50 MW, with operating costs of 15 €/MWh and 10 €/MWh, respectively. The technical specifications of CSP are provided in Table 3. Operating costs for all units have been levelized based on estimated operational expenses of different generation technologies in [36]. Information related to the D-RES, including the hydro and biomass plants, is drawn from [33] and consolidated in Table 4. The seasonal energy limits of the hydro plant are based on the historical scheduling of units with water reservoir constraints and are set at 1164, 972, 528, and 708 MWh for favorable representative days in winter, spring, summer, and autumn, respectively, according to [37]. Accordingly, under unfavorable condition, these values are reduced to 804, 624, 420, and 612 MWh, respectively. The forecast boundaries for the FD are shown in Figure 3, using three representative demand profiles from [33]. Each base demand profile includes a 10% flexibility margin, and the UB is specified for both favorable and unfavorable scenarios. Additionally, the forecast bounds for electricity prices in the DAM and SRM are based on historical data from [37] and visualized in Figure 4. Table 5 presents the uncertainty budgets associated with various uncertain parameters. These budget values are selected to represent optimistic, balanced, and pessimistic uncertainty-handling strategies. The associated uncertainty bounds are derived from historical data using the 10th and 90th percentiles of deviations, so as to avoid overly conservative uncertainty sets. Since the solar PV production, thermal output of the SF are zero at night, and demand fluctuations are minimal, these uncertainty budgets are assigned smaller numbers. This allocation strategy maintains a consistent proportion of uncertain hours across the simulation horizon for all parameters. Accordingly, the uncertainty calibration adopted in this study should be interpreted as conditional on the historical data, representative seasonal operating conditions, and assumed market design, rather than as explicitly accounting for abrupt policy-driven changes or strongly non-stationary forecasting-error patterns. The simulation analysis comprises four case studies to assess the performance of the proposed models for both the RVPP and the ESS as follows:

- Case 1: Examine the optimal operation of RVPP units, and the RVPP's trading strategy in the DAM and SRM under an optimistic strategy over different sample days.
- Case 2: Evaluate the optimal trading strategy of the RVPP under different scheduling regimes: *favorable* (moderate energy limits for the hydro plant and moderate forecast variation in solar PV, CSP, WF production, and demand consumption), and *unfavorable* (strict energy limits and high forecast variation), across three uncertainty-handling strategies: optimistic, balanced, and pessimistic.
- Case 3: Assess the value of different RVPP configurations compared to the individual participation of units in the market. Additionally, evaluate the ESS required to match the RVPP's performance under different uncertainty-handling and ESS integration strategies.
- Case 4: Evaluate the trading strategy of the ESS required to match the performance of the RVPP under different uncertainty-handling strategies.

The simulations are executed on a Dell XPS with an i7-1165G7 2.8 GHz processor and 16 GB RAM, using the CPLEX solver in GAMS 49. In all simulations, solution time stays under five minutes, highlighting the proposed model's efficiency in solving multi-market scheduling problems.

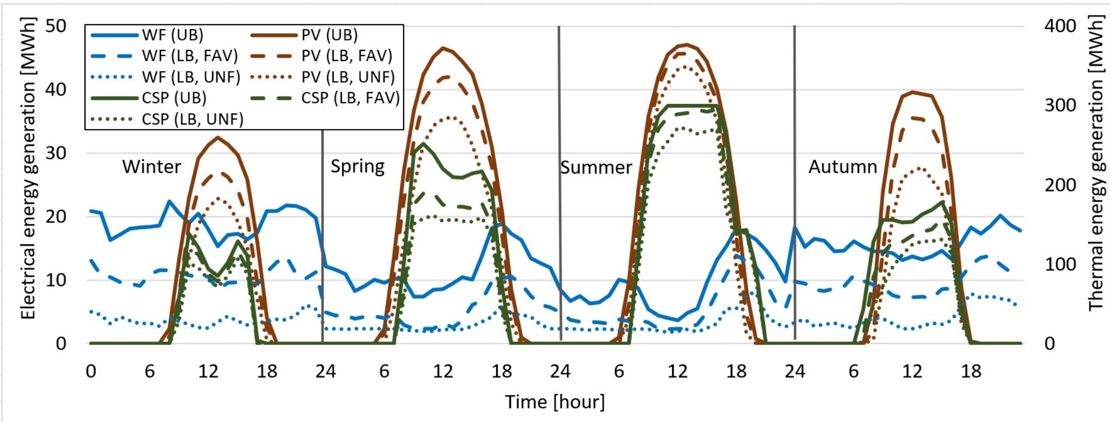

Figure 2: The forecast bounds of WF, solar PV, and CSP.

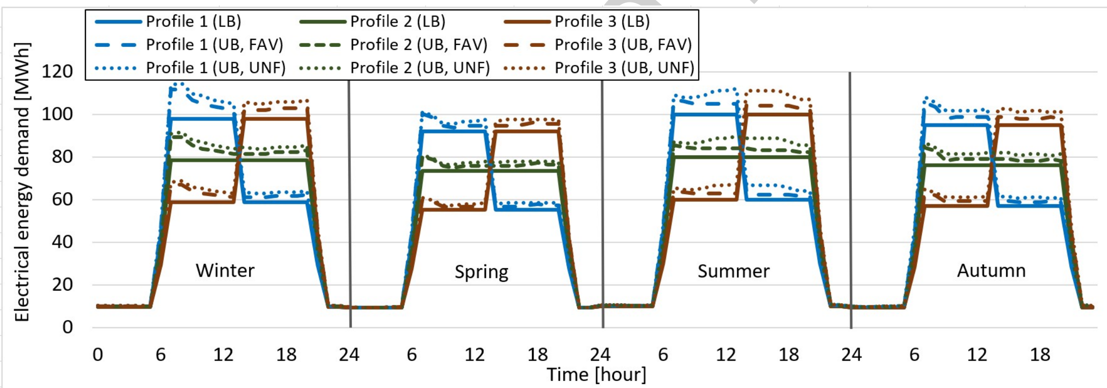

Figure 3: The forecast bounds of different profiles of FD.

Table 2: Li-ion ESS data.

Parameter	ESS
Charging/discharging power [MW]	0.5/0.5
Maximum/minimum energy [MWh]	1/0.1
Degradation and operational costs [€/MWh]	30
Charging/discharging efficiency [%]	95

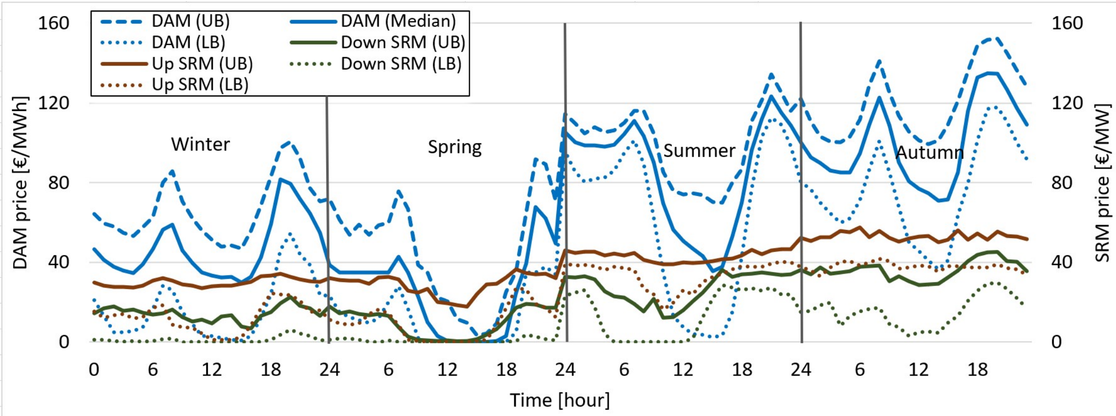

Figure 4: The forecast bounds of DAM and SRM price.

Table 3: CSP data.

Parameter	Value
SF maximum thermal power output [MW]	300
Turbine maximum thermal power input [MW]	140
Turbine maximum electrical power output [MW]	55
Turbine minimum up/down time [hour]	3/2
TS maximum/minimum thermal energy [MWh]	1100/110
TS charging/discharging thermal power [MW]	140/115
TS charging/discharging efficiency [%]	95
CSP operation cost [€/MWh]	25

Table 4: 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

Table 5: Uncertainty budgets for the RVPP operator's strategies.

Strategy	DAM/SRM price	WF production	PV production	SF thermal production	FD consumption
Optimistic	3	3	2	2	2
Balanced	6	6	4	4	4
Pessimistic	9	9	6	6	6

4.1. Case 1

Figure 5 illustrates the energy scheduling of the RVPP units, and the energy and reserve traded by the RVPP in the electricity markets under favorable condition and the optimistic strategy. The results indicate that the RVPP effectively schedules its units based on the availability of their production across seasons. In winter, the highest share of the RVPP's energy comes from the hydro plant, while solar PV and CSP generation is lower due to limited solar availability. In contrast, during the summer, most of the RVPP's energy is provided by solar PV and CSP, and hydro generation is mostly limited to the morning and night hours. In spring, due to low electricity prices during hours 12–18, a significant portion of the RVPP's production is curtailed, and the RVPP primarily supplies its demand by purchasing energy from the market. During these hours, the RVPP has limited capacity to provide down reserve due to reduced production, while its capacity to provide up reserve is increased. In autumn, although the available energy from solar PV and CSP is lower compared to summer, this shortfall is compensated by other RVPP units such as the WF and the hydro plant. Different profiles of FD are selected across the seasons (profile 1 in winter and autumn, and profile 3 in spring and summer) to maximize the profitability of the RVPP. In winter and autumn, due to higher energy demand during the morning hours, the RVPP acts as an energy buyer during hours 8–10 and hour 8, respectively. The selection of profile 1, which features lower demand during the late hours, allows the RVPP to exploit higher electricity prices in the afternoon and evening by selling excess energy to the market. In contrast, profile 3, with higher late-hour demand, is optimal in spring and summer due to low afternoon prices (hours 12–18 in Figure 4), enabling the RVPP to sell energy in the morning and increase profitability. Furthermore, the biomass plant primarily generates electricity during the evening and/or morning hours—periods when either electricity prices are higher or the RVPP lacks sufficient production from other units. This operational strategy is consistent across most seasons, as the biomass plant has a higher production cost compared to other generating units.

Figure 6 shows each RVPP unit's contribution to up and down reserve across seasons. The results indicate that the RVPP units are effectively scheduled to provide reserves, enhancing the overall profitability of the RVPP. Specifically, both the CSP—owing to the flexibility from its TS—and the FD contribute significantly to up and down reserve provision in most seasons. The hydro plant is mainly used for energy generation but also offers capacity for up reserve in certain seasons, particularly spring and partially in winter. Moreover, it plays a substantial role in providing down reserve, especially in winter when its production is at its peak. Other units, including the WF, solar PV, and biomass plant, contribute marginally to reserve provision due to limited flexibility, lower reserve capability, or lower energy production capacity.

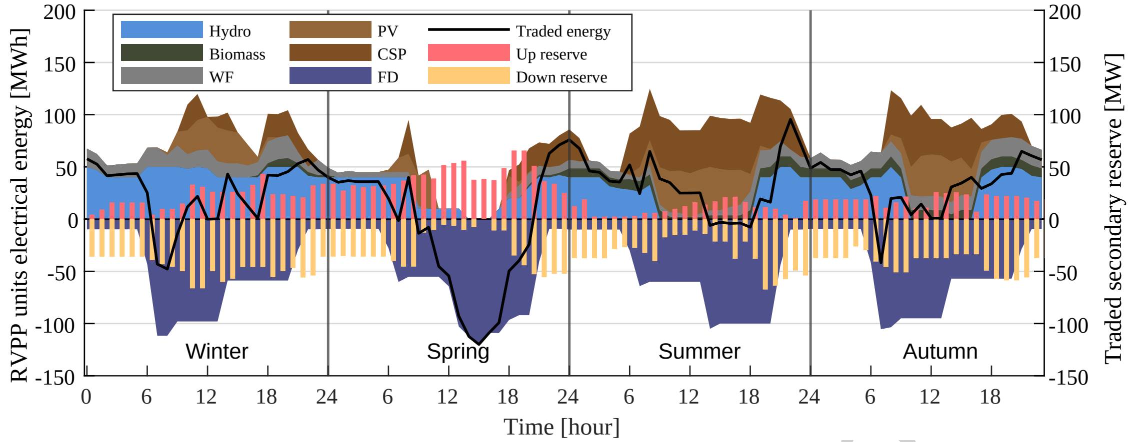

Figure 5: Electrical energy generation by RVPP units and traded energy and reserve by the RVPP (Case 1).

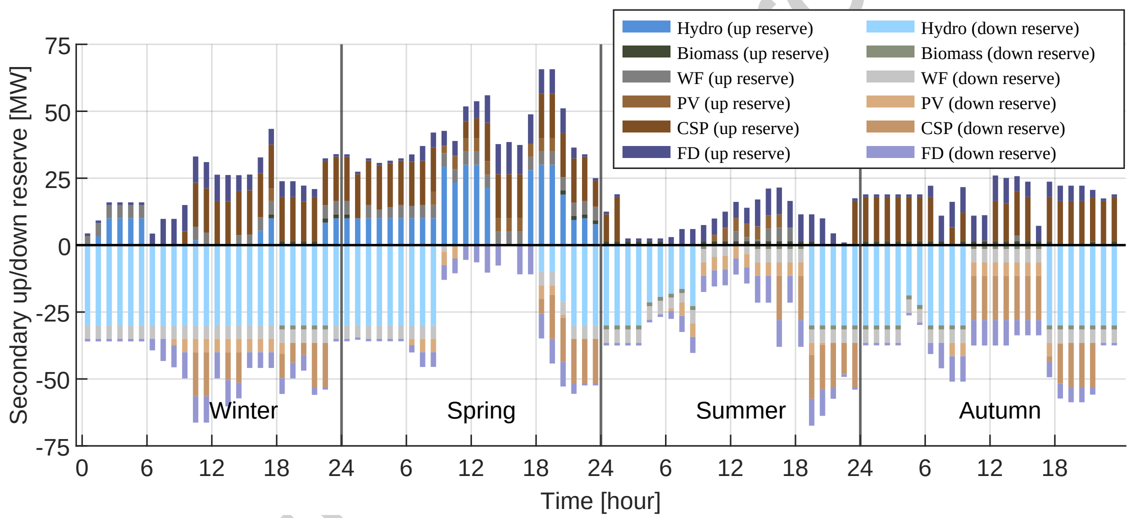

Figure 6: Up and down reserve provided by RVPP units (Case 1).

4.2. Case 2

Figure 7 presents the electrical energy traded by the RVPP under different scheduling regimes (favorable and unfavorable) and uncertainty-handling strategies (optimistic, balanced, and pessimistic). The results show that, under favorable condition, the RVPP tends to reduce energy sales in most hours and seasons as more conservative strategies (i.e., balanced and pessimistic) are adopted to manage uncertainty. However, this trend is not uniform across all hours, due to the RVPP's flexibility in selecting different FD profiles. For instance, in summer, the balanced and pessimistic strategies result in the selection of profile 2 of FD, whereas the optimistic strategy selects profile 3, which has higher demand during late hours. Consequently, the RVPP trades more

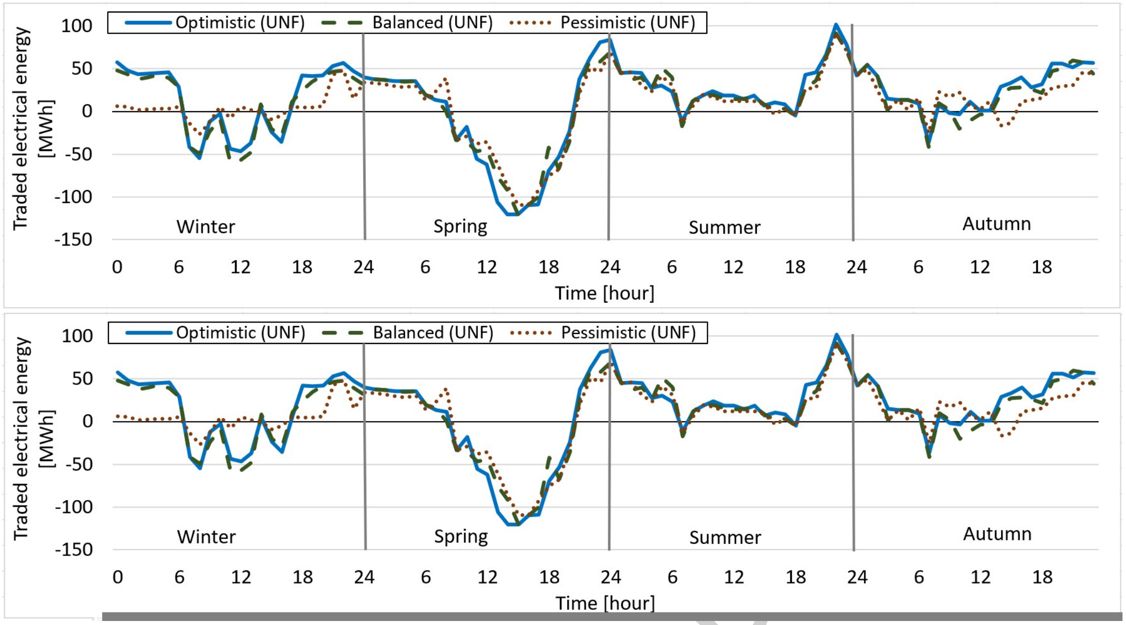

Figure 7: Electrical energy traded by the RVPP (Case 2).

energy between hours 15–21 under the balanced and pessimistic strategies than in the optimistic case. Under unfavorable condition, the RVPP's energy trading is constrained in more hours, particularly when employing the pessimistic strategy. For example, during winter under the unfavorable-pessimistic scenario, the energy sold by the RVPP is nearly zero throughout most hours, except for a limited period between hours 22–24. In autumn, high variability in generation—especially from solar-dependent units—leads to significant changes in the RVPP's trading behavior. By contrast, in summer, solar generation is less affected under unfavorable condition during daylight hours, allowing for more stable trading patterns. However, in hour 8, the RVPP acts as an energy buyer across all uncertainty-handling strategies under unfavorable condition, whereas it operates as an energy seller in the favorable case.

Figure 8 illustrates the up and down reserves traded by the RVPP in the SRM under different scheduling regimes and uncertainty-handling strategies. The reserve capacity provided by the RVPP is influenced by both its traded energy and the level of uncertainty. Under favorable condition, particularly during winter in hours 1–6, up reserve provision increases in the balanced and pessimistic strategies compared to the optimistic one. This is primarily because the RVPP schedules less energy for market sale during these hours (see Figure 7), thereby retaining more capacity to offer up reserves. However, this pattern is not consistent across all hours. For example, in hour 20 of winter, both traded energy and up reserve are reduced in the balanced and pessimistic strategies compared to the optimistic strategy. Similar trends are observed for down reserve provision, where the reserve levels vary depending on the chosen uncertainty-handling strategy. In the unfa-

Figure 8: Up and down reserves traded by the RVPP (Case 2).

vorable scenario, the RVPP's ability to provide down reserves is more significantly impacted than up reserves—both in comparison to the favorable condition and across strategies. This is mainly due to the reduced generation availability from RVPP units. For instance, during winter in hours 1–5, the down reserve provided under the pessimistic strategy is substantially lower than under the optimistic and balanced strategies, primarily due to minimal or zero output from the hydro plant. Conversely, during hours 12–17, the hydro plant is dispatched under the pessimistic strategy (but not under the optimistic and balanced ones), enabling greater down reserve provision in the pessimistic case for those hours.

Table 6: Individual versus aggregated Profit of RVPP Units under FAV (green) and UNF (orange) scheduling regimes (Case 3).

	Profit (cost) [k€]		
Unit	**Optimistic**	**Balanced**	**Pessimistic**
Hydro	208.87/172.81	191.69/156.69	176.49/142.85
Biomass	17.35/17.35	15.89/15.89	14.65/14.65
WF	68.59/65.91	58.73/52.16	51.89/40.28
PV	39.51/38.07	27.83/25.91	22.11/19.43
CSP	117.13/114.34	101.53/99.27	92.80/90.02
FD	-301.38/-301.87	-329.40/-332.16	-352.41/-357.08
Total	150.07/106.61	66.27/17.76	5.53/-49.85
RVPP	215.41/170.92	178.68/128.34	150.02/94.35

4.3. Case 3

Table 6 presents a comparison of the profit generated by each RVPP unit when participating individually in the DAM and SRM, along with the total profit from individual participation of all units and the profit achieved by the RVPP under different scheduling regimes and uncertainty-handling strategies. The results indicate that as more conservative strategies are adopted (i.e., balanced and pessimistic), the individual profits of units generally decrease—or their costs increase—under both favorable and unfavorable conditions. For instance, under favorable condition and individual participation, the profit reduction (or cost increase) in the pessimistic strategy compared to the optimistic one is observed to be 15.5%, 15.5%, 24.3%, 44.0%, 20.8%, and 16.9% for the hydro, biomass, WF, solar PV, CSP, and FD units, respectively. These reductions are more pronounced under unfavorable condition, reaching 17.3%, 15.5%, 38.9%, 48.9%, 21.3%, and 18.3%. When the units participate collectively as an RVPP, the resulting profits exceed the sum of individual profits by 65.34/64.31 k€, 112.41/110.58 k€, and 144.49/144.20 k€ under optimistic, balanced, and pessimistic strategies in favorable/unfavorable condition, respectively. These values serve as the LB for the ESS sizing problem, which aims to achieve equivalent economic performance to that of the RVPP problem. For example, the required energy storage capacities to match the RVPP profit under favorable condition are 63, 124, and 177 MWh for the optimistic, balanced, and pessimistic strategies, respectively. Since the RVPP becomes more beneficial as uncertainty increases, the required capacity of ESS must also increase to achieve a similar performance as the RVPP.

To examine the effect of the ESS power-to-energy ratio, an additional sensitivity analysis is carried out by considering different ratios instead of the baseline value of 0.5 adopted in Table 2. For each ratio, the minimum ESS energy required to match the RVPP profit is re-evaluated under each uncertainty-handling strategy, as shown in Table 7. This analysis is intended to assess how allowing different combinations of power capacity and energy duration affects the market partic-

Table 7: Minimum ESS energy required to match RVPP profit under different ESS power-to-energy ratios (Case 3).

Power/Energy ratio	**ESS energy [MWh]**		
[MW/MWh]	**Optimistic**	**Balanced**	**Pessimistic**
0.25	87	166	230
0.33	73	141	201
0.5	63	124	177
1.0	62	121	166
1.5	61	119	163

ipation of the ESS. The results show that increasing the ESS power-to-energy ratio improves the competitiveness of the ESS, since a lower energy capacity is required to reach the same profit target. This effect is more pronounced under the balanced and pessimistic strategies, where reserve provision becomes more valuable. The results also indicate diminishing returns beyond a certain ratio, as further increases in power capacity lead to only limited reductions in the minimum required ESS size. For example, under the optimistic strategy, increasing the power-to-energy ratio beyond the baseline value of 0.5 leads to only a marginal reduction in the required ESS size, from 63 MWh to 62 MWh and 61 MWh for ratios of 1.0 and 1.5, respectively. Under the balanced and pessimistic strategies, a similar trend is observed; however, the reduction in the required ESS size remains more noticeable at higher power-to-energy ratios, indicating that the benefit of additional power capacity persists over a wider range of values under more conservative uncertainty-handling strategies.

Table 8 presents the additional profit of various RVPP configurations compared to individual participation, under different scheduling regimes and uncertainty-handling strategies. It also presents the required ESS size to match the RVPP's performance for each configuration. In each configuration, one unit technology is excluded from the RVPP to better assess the contribution of each technology. The results reveal that the value of each unit within the RVPP depends on several factors, such as its capacity, available production, and dispatchability. In the configurations without the biomass plant and WF, the additional profit under optimistic and favorable conditions is reduced by only 1% and 4.9%, respectively, compared to the full RVPP. This is because these units either have a low capacity (biomass plant) or limited available production (WF) compared to other RVPP units. Conversely, excluding the FD from the RVPP results in a significant 78.5% reduction in additional profit. The reason is that a considerable share of the energy produced by the RVPP is consumed by its internal demand. Including the FD in the RVPP significantly increases profitability due to its flexibility and its role in reducing energy spillage from ND-RES. The CSP and hydro plants provide considerable value within the RVPP and are crucial for its profitability. When excluded, the additional RVPP profit decreases by 20.2% and 23.4%, respectively. For example, under the optimistic strategy and favorable condition, the additional profit drops from 65.34 k€ in the full RVPP to 52.14 k€ without CSP and 50.03 k€ without hydro. These results indicate

Table 8: Additional profit of different RVPP configurations and corresponding ESS size to match RVPP performance (Case 3).

	RVPP additional profit [k€]			ESS maximum energy [MWh]		
Configuration	Optimistic	Balanced	Pessimistic	Optimistic	Balanced	Pessimistic
RVPP	65.34/64.31	112.41/110.58	144.49/144.20	63/62	124/121	177/176
RVPP w/o Hydro	50.03/49.62	89.37/86.74	115.56/110.33	48/48	98/95	141/136
RVPP w/o Biomass	64.65/63.55	111.44/109.37	143.37/142.31	62/61	122/120	175/174
RVPP w/o WF	62.13/61.52	107.25/105.53	137.84/135.67	60/59	117/115	170/166
RVPP w/o PV	52.41/50.42	89.76/87.56	116.99/115.34	51/49	98/96	143/141
RVPP w/o CSP	52.14/50.80	88.84/86.21	115.99/114.05	50/49	97/95	142/140
RVPP w/o FD	14.05/14.63	21.50/23.49	22.19/25.98	14/14	24/26	28/32

that both units materially strengthen the performance of the studied RVPP. At the same time, they show that the coordination benefit of the aggregation is not driven by either unit alone, since the configurations without CSP or hydro still preserve a substantial improvement over individual market participation. This is because the CSP, supported by its TS, mitigates input thermal energy uncertainty and offers dispatchable energy, while the hydro plant contributes inherent dispatchability and substantial operational flexibility.

Table 9 shows the additional profit of the RVPP compared to individual participation, assuming different percentages of FD capacity relative to the values in Figure 3. The results indicate that increasing the capacity of the FD leads to higher additional profit for the RVPP. However, the percentage increase in profit is more substantial at lower FD capacities. For instance, when the FD capacity is 50%, the additional profit—under optimistic and favorable conditions—is 203.2% higher compared to the RVPP configuration without FD. Increasing the capacity from 50% to 100% results in a 53.4% profit increase, while a further increase from 100% to 150% yields an additional 20.8% profit increase. The primary reason for this trend is that the initial increase in FD capacity significantly reduces energy curtailment from ND-RES. At higher capacities, the additional profit mainly comes from the FD's ability to provide more efficient trading strategies through coordination with the RVPP units.

Table 10 shows the required size of the ESS when it is coordinated with ND-RES, such as WF and solar PV, to match the performance of the RVPP. The results indicate that, in order to achieve the same percentage increase in profit as the RVPP, larger ESS capacities are generally needed, especially under more conservative strategies and unfavorable condition. For example, in the balanced and pessimistic cases compared to the optimistic case, achieving the same percentage profit increase as the RVPP requires a 100% and 200% increase in the size of the ESS integrated with the WF, and a 66.6% and 141.7% increase in the size of the ESS integrated with the PV, respectively. The findings also reveal that solar PV is more economically viable than WF, primarily due to its lower energy variability, as a smaller increase in ESS size is sufficient when coordinated with solar PV compared to WF.

Table 9: RVPP additional profit compared to individual profits for different capacity of FD (Case 3).

	Additional profit [k€]		
FD capacity	**Optimistic**	**Balanced**	**Pessimistic**
0%	14.05/14.63	21.50/23.49	22.19/25.98
50%	42.60/41.58	72.39/72.22	91.52/91.61
100%	65.34/64.31	112.41/110.58	144.49/144.20
150%	78.92/76.40	135.88/131.95	176.23/168.39

Table 10: Size of ESS to match the RVPP's performance (Case 3).

	Maximum energy [MWh]		
Unit	**Optimistic**	**Balanced**	**Pessimistic**
ESS+WF	19/23	37/46	57/69
ESS+PV	10/12	15/20	20/29

4.4. Case 4

Figure 9 illustrates the energy traded by the ESS in the DAM to achieve the same economic performance as the aggregated RVPP under different uncertainty-handling strategies in the unfavorable condition. The figure also depicts the corresponding SoC profile of the ESS. In all strategies, the ESS maximizes market profitability by charging during low-price periods and discharging during high-price periods in the DAM. Notably, in the pessimistic case, larger fluctuations in both traded energy and the SoC of the ESS are observed, reflecting the need to manage higher uncertainty more effectively.

Figure 10 presents the up and down reserves traded by the ESS in the SRM. The results indicate that, particularly under the pessimistic strategy—where larger storage capacity is utilized—the provision of both up and down reserves is significantly increased across most hours. Additionally, greater variability in the traded reserve is observed in the pessimistic and balanced strategies compared to the optimistic strategy, reflecting the need to hedge against higher levels of uncertainty. Moreover, the ESS tends to allocate more capacity to reserve provision during hours with higher SRM prices (compare Figure 10 with Figure 4), adapting its scheduling across seasons and uncertainty-handling strategies. For instance, in winter under the balanced and pessimistic strategies, a larger share of up reserve is provided during hours 7, 8, and 19–22, corresponding to periods of higher reserve prices.

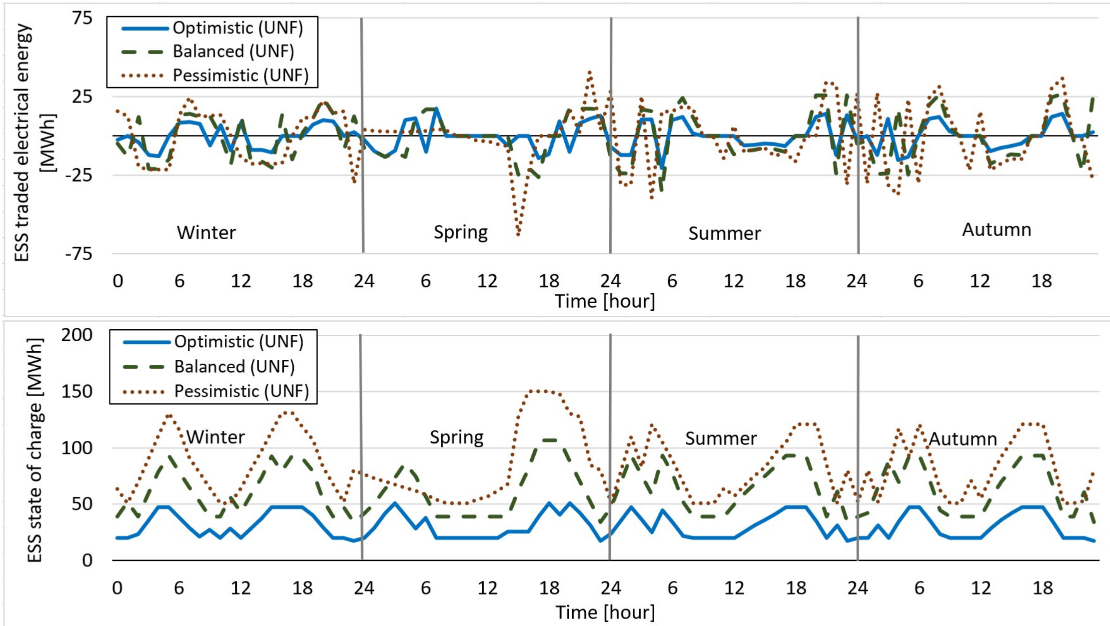

Figure 9: Electrical energy traded by the ESS and its SoC (Case 4).

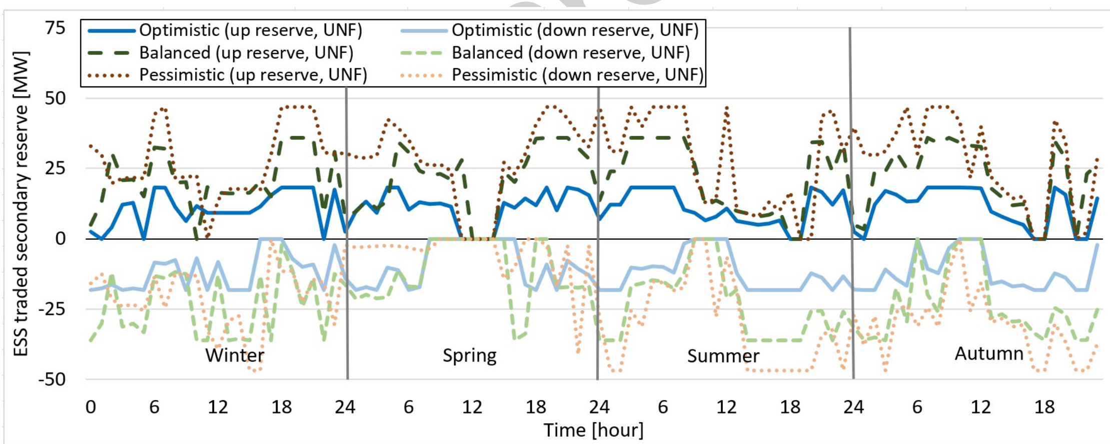

Figure 10: Up and down reserves traded by the ESS (Case 4).

5. Concluding Remarks

This paper compares ESS-free RVPPs and grid-scale ESSs for participation in energy and reserve markets using a two-stage RO optimization framework grounded in previous literature [11, 14, 15, 21]. The RVPP is considered ESS-free in line with emerging concepts that promote renewable-based flexibility without relying on ESS. Building on this established modeling foundation, the contribution of the paper lies in conducting a systematic and fair case-study-based comparison of RVPP and ESS performance under different scheduling regimes, uncertainty sources, and operating conditions. Four representative case studies—covering favorable and unfavorable seasons and three uncertainty stances (optimistic, balanced, and pessimistic)—enable the extraction of practical insights for operators and planners. The key findings are summarized and interpreted below:

- *Seasonal operational patterns and flexibility*: In winter, the hydro unit delivers most RVPP energy due to high inflows, whereas summer operation relies primarily on solar PV and the dispatchable CSP. These seasonal shifts highlight the importance of resource complementarity: when hydro output decreases, the portfolio increasingly depends on solar-based units to sustain energy revenues. The hydro unit consistently dominates down-reserve provision, while CSP and FD contribute the majority of up reserves. The RVPP's reserve provision depends heavily on the seasonal availability of its main reserve-providing units, directly influencing reserve revenues and highlighting the value of exploiting seasonal complementarities to maintain stable earnings.

- *Impact of uncertainty handling and scheduling adaptation*: More conservative strategies reduce the RVPP's hourly energy sales because more cautious scheduling is adopted. However, the portfolio's flexibility—particularly from dispatchable units—helps offset these reductions by reallocating energy and reserve participation, thereby limiting the overall loss in profit. Under unfavorable resource conditions, winter and autumn energy outputs decline sharply, while summer remains comparatively stable due to the availability and predictability of solar resources. These findings indicate that flexible scheduling is especially valuable in seasons with high uncertainty or low resource availability, as it allows operators to reduce revenue losses and maintain more stable market participation.

- *Economic comparison between RVPP and ESS*: The RVPP outperforms individual unit participation, with its profit advantage increasing under higher uncertainty. Specifically, it achieves 72% and 121.1% higher profit under balanced and pessimistic strategies, respectively, compared to the optimistic case. This increasing advantage is driven by the RVPP's ability to reallocate energy and reserve among heterogeneous units, enabling it to hedge against uncertainty more effectively than single-technology participation. While an ESS benefits from energy arbitrage and reserve provision, achieving comparable profitability requires a capacity increase of 96.8% and 180.9% under balanced and pessimistic strategies, respectively. Moreover, integrating ESS with solar PV is more economically viable than WF, mainly due to its lower energy variability. The higher predictability of solar PV enables more reliable charging cycles for ESS and reduces energy-delivery risk. This suggests that operators planning storage investments should prioritize renewable resources with stable and predictable generation profiles, rather than those that merely produce higher annual energy.

- *Contribution of individual units to RVPP performance*: The units that contribute most to RVPP profitability are those that combine steady energy availability with a high degree of controllability. The FD adds significant value by reducing energy spillage from the ND-RES, effectively converting otherwise wasted energy into marketable output. Meanwhile, the CSP and hydro units enhance overall performance by providing both dispatchable energy and reliable reserve capacity, improving the RVPP's ability to react to market fluctuations. A particularly important insight is that controllability often matters more than raw energy production: units with modest energy output but high flexibility can improve revenues more than units with larger but highly variable output. For operators, this means that RVPP design should prioritize a mix of technologies that complement each other not only in energy generation but also in their ability to shift, store, or modulate output across markets.

Future work may extend this study in several directions. A natural next step is to incorporate real-time market participation and intra-day rescheduling, allowing a more detailed assessment of balancing costs, deviations, and the operational value of fast-responding technologies within both RVPP and ESS settings. From a methodological perspective, this could be further supported by extending the present framework toward multi-stage robust scheduling with sequential recourse, which would better represent dynamic decision updates under uncertainty. A further extension would be to incorporate adaptive or rolling recalibration of representative days and uncertainty sets, so that structural changes in market conditions and non-stationary forecasting behavior can be captured more explicitly. Such an extension could also explicitly capture reserve-availability risk and non-delivery events during actual operation, particularly for resources affected by forecast errors or activation uncertainty. In addition, it would enable a more detailed representation of actual reserve activation and delivery, including activation direction, timing, duration, and the amount requested by the system operator, which are more appropriately handled through intraday or real-time recourse than within the day-ahead framework considered in this study. Another important extension would be to incorporate network-constrained dispatch, grid-code compliance requirements, and additional ancillary services such as fast frequency response, voltage support, synthetic inertia, and black-start capability, in order to enable a broader system-level comparison between RVPP and ESS. Another promising direction is to complement the operational analysis with long-term investment evaluation. From a techno-economic perspective, this could be further extended by integrating capital expenditure, discount rates, replacement planning, and lifecycle cash-flow analysis for both ESS and the compared RVPP configurations. Considering metrics such as the Levelized Cost of Storage (LCOS) and capital cost trajectories would provide deeper insight into the long-term viability of these flexibility solutions under varying uncertainty and price scenarios. If the problem is extended toward general storage planning rather than comparative equivalence sizing, another relevant direction would be to adopt a joint power-energy capacity-operation optimization framework that captures nonlinear scaling effects and allows independent design of storage ratings across multiple markets. A further extension would be to move from representative-day analysis to chronological multi-day or full-season simulations, which would provide a stronger assessment of seasonal operability under prolonged uncertainty, including persistent low-resource periods and potential multi-season drought effects.

Acknowledgments

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 883985.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: