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Flexible robust optimization for Renewable-only VPP bidding on electricity markets with economic risk analysis

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ABSTRACT

This paper investigates the joint participation of Renewable-only Virtual Power Plants (RVPPs) in the energy and reserve markets while considering the imbalance costs in the balancing market. Existing research on robust optimization typically relies on the well-known parameter called the *uncertainty budget* to define the level of conservatism. However, this parameter is not defined based on economic factors but rather on the nature of each uncertainty. This work introduces a regret-based flexible robust optimization problem to address this gap, accounting for various sources of uncertainty in energy and reserve prices, as well as the production of non-dispatchable renewable energy sources and demand consumption. The concept of average regret is developed and implemented through a set of mixed-integer linear constraints to help the RVPP operator gain relevant economic insights regarding this parameter. Simulation results demonstrate the applicability of the regret-based robust optimization formulation in determining an interpretable level of conservatism against different uncertainties.

1. Introduction

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 Renewable Energy Sources (RESs). However, as the penetration of RESs 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 Sourcess (ND-RESs) production, resulting in volatile energy output of these units. To cope with the volatility of ND-RESs production and to avoid penalties in the electricity markets, operating several ND-RESs in different geographical locations as Renewable-only Virtual Power Plant (RVPP) is an effective way by taking advantage of the portfolio effect. The RVPP can bid a smoother profile of production than each individual ND-RES, leading to more income and less penalties [2].

The main income of RVPP comes from participation in the energy market due to its high liquidity [3]. The RVPP would also allow stochastic ND-RESs to compensate for their inherent power output variations, which could ease the participation in reserve markets and the subsequent provision of reserves [4]. However, 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 set points from the Transmission System Operator (TSO)) [5]. 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. Therefore, deciding the participation of RVPP in different energy and reserve markets, taking into account the imbalance effects in the BAM, is essential and needs to be carefully evaluated by researchers and engineers.

1.2. Literature review

Dealing with several sources of uncertainty in the optimization problem of RVPP bidding on electricity markets is thus necessary. This is because the deviation of uncertain parameters from their predicted values can lead to significant consequences, such as penalties, loss of profit, and exclusion from the market due to failure to deliver the promised bids to the market. In this regard, the Robust Optimization (RO) method is an effective approach to deal with different

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Nomenclature

General Notation Concepts

- An uncertain parameter with a tilde symbol denotes the median value in the forecast distribution, representing a point where half of the observations are lower ($\tilde{A}$);
- The hat/inverse hat symbol on uncertain parameters signifies the positive/negative permitted deviation from the forecast's median ($\hat{A}$, $\check{A}$);
- Parameters with an upper/lower bar represent their upper/lower bounds ($\bar{A}$, $\underline{A}$);
- Upward/downward arrows indicate up/down direction of regulation in variables and parameters ($a^{\uparrow}$, $A^{\uparrow}/a^{\downarrow}$, $A^{\downarrow}$).

Indexes and Sets

$d \in \mathcal{D}$	Set of demands
$p \in \mathcal{P}$	Set of daily load profiles
$r \in \mathcal{R}$	Set of Non-dispatchable Renewable Energy Sourcess (ND-RESs)
$t \in \mathcal{T}$	Set of time periods
$z \in \mathcal{Z}$	Set of segments of PDF of uncertain parameters
Ξ^{DA+SR}	Set of decision variables of DAM and SRM

Parameters

C_r	Operation and maintenance costs of ND-RES r [€/MWh]
$C_{d,p}$	Cost of load profile p of demand d [€]
E_d	Energy consumption of demand d throughout the planning horizon [MWh]
$J_{z,t}$	Probability of segment z of PDF of RVPP output energy considering the negative deviation during time period t
$J_{z,t}^{(\prime)DA}$	Probability of segment z of PDF of DAM price considering the negative (positive) deviation during time period t [%]
$J_{z,t}^{SR}$	Probability of segment z of PDF of SRM price considering the negative deviation during time period t [%]
$K_{z,t}^{(\prime)DA}$	The difference between the value of each segment of PDF of DAM electricity price considering the negative (positive) deviation from the median value during time period t [€/MWh]
$K_{z,t}^{SR}$	The difference between the value of each segment of PDF of SRM electricity price considering the negative deviation from the median value during time period t [€/MW]
M	Big positive value [€]
P_d	Power consumption of demand d [MW]
P_r	Power production of ND-RES r [MW]
$P_{d,p,t}$	Profile p of demand d value during period t [MW]
$P_{r,t}$	ND-RES r production forecast during period t [MW]
$P_t^{(\prime)}$	Net power traded by RVPP when RVPP is energy seller (buyer) during time period t [MW]
$P_{z,t}^{F}$	The value of segment z of PDF of RVPP output energy during time period t [MW]
$R_{r(d)}^{SR}$	Secondary reserve ramp rate of ND-RES r (demand d) [MW/min]
R_t^{SR}	Secondary reserve provided by RVPP during time period t [MW]
$Reg^{(\prime)Max,DA}$	Maximum regret related to DAM electricity price when RVPP is energy seller (buyer) [€]
$Reg^{Max,SR}$	Maximum regret related to SRM price [€]
Reg^{Max}	Maximum regret related to output energy of RVPP [€]
T^{SR}	Required time for secondary reserve action [min]
Z_t	Penalty cost of not providing energy during time period t [€/MWh]
$\beta_{d,t}$	Percentage of flexibility of demand d during period t [%]
Γ	User-defined per unit value of maximum possible RVPP output energy regret (assigned by the user) [p.u]
$\Gamma^{(\prime)DA}$	User-defined per unit value of maximum possible DAM regret when RVPP is energy seller (buyer) in the market (assigned by the user) [p.u]
Γ^{SR}	User-defined per unit value of maximum possible SRM regret (assigned by the user) [p.u]
Δt	Duration of periods [hour]
ϵ	Small positive value [€]
κ	User-defined parameter to set the limit of up reserve traded in the SRM as a percentage of total power capacity of RVPP [%]
$\lambda_t^{DA/SR}$	DAM/SRM price forecast during period t [€/MWh]/[€/MW]
ϱ_t	Coefficient to calculate the ratio of down-to-up reserve requested by the Transmission System Operator (TSO) during period t [%]

Continuous Variables

p_t^{DA}	Total power traded (positive for selling and negative for buying) by RVPP in the DAM during period t [MW]
$p_{r(d),t}$	Production of ND-RES r (consumption of demand d) during period t [MW]
$p_{r(d),t}^{(\prime)Q(A)}$	Auxiliary variable to linearize the multiplication of binary and continuous variables [MW]
$p_t^{DA,Q(A)}$	Auxiliary variable to calculate the net traded energy for a net seller (buyer) RVPP when the DAM price is at its median [MW]
r_t^{SR}	Total secondary reserve traded by RVPP for different TSO calls on conditions during period t [MW]
$r_{r(d),t}^{SR}$	Secondary reserve provided by ND-RES r (demand d) for different TSO calls on conditions during period t [MW]
$r_t^{SR,Q(A)}$	Auxiliary variable to calculate the traded reserve of RVPP when the SRM price is at its median/worst case [MW]
$y_t^{(\prime)DA}$	RVPP profit affected by DAM negative (positive) price uncertainty during period t [€]
y_t^{SR}	RVPP profit affected by SRM price uncertainty during period t [€]
$y_{r(d),t}$	RVPP profit (cost) affected by ND-RES r production (demand d) uncertainty during period t [€]
$\eta_t^{(\prime)DA}$	Dual variable to model the negative (positive) price uncertainty of DAM during period t [€]

η_t^{SR}	Dual variable to model the price uncertainty of SRM during period t [€]
$\eta_{r(d),t}$	Dual variable to model the ND-RES r production (demand d) uncertainty during period t [€]
$\nu^{DA/SR}$	Dual variable to model the price uncertainty of DAM/SRM [€]
$\nu_{r(d)}$	Dual variable to model the ND-RES r production (demand d) uncertainty during period t [€]
$\rho_{z,t}^{DA,Q(A)}$	Auxiliary variable to calculate the positive (negative) difference between the total RVPP energy and reserve bid in the market minus the value obtained from the segment z of PDF of RVPP output energy [MW]

Binary Variables

$u_{d,p}$	Indicator of selection of profile p of demand d [-]
ι_t^{DA}	Binary variable that is 1 if RVPP is energy seller in the market, and 0 otherwise [-]
$\iota_{z,t}$	Binary variable that is 1 if total energy plus up reserve bid of RVPP is higher than the value of segment z of PDF of RVPP output energy during time period t, and 0 otherwise [-]
$\chi_t^{(\prime)DA}$	Binary variable that is 1 if DAM negative (positive) price robustness constraints are active during period t, and 0 otherwise [-]
χ_t^{SR}	Binary variable that is 1 if SRM price robustness constraints are active during period t, and 0 otherwise [-]
$\chi_{r(d),t}$	Binary variable that is 1 if ND-RES r (demand d) robust constraints are active during period t, and 0 otherwise [-]

uncertainties, since it covers the wide range of uncertain parameter deviations, provides feasible results, and is extremely efficient in terms of computational time [6]. However, the main drawback of RO is that the results obtained tend to be overly conservative. In this regard, Bertsimas [7] 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 hours 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 Virtual Power Plant (VPP) bidding problems in different markets [8–11]. The flexible RO has also been used in [6,12–18] to account for demands uncertainty, ND-RESs production uncertainty, and/or electricity market price uncertainty in the VPP bidding optimization models.

In [8], the Day Ahead Market (DAM) participation of a VPP, including wind farm, demand, and Energy Storage System (ESS), is formulated using a single-level model that incorporates confidence bounds for symmetric uncertainties. A stochastic RO approach is presented in [9] to model VPP participation in the DAM and real-time markets, allowing for corrective actions after uncertainties occur, thus providing increased flexibility. Similarly, the participation of RVPP in energy and reserve markets is studied in [10] using the same methodology. The work in [11] introduces a robust Stackelberg game approach for VPP energy management in both the DAM and real-time market, accounting for uncertainties in electricity prices and RES production. In [12], a Mixed Integer Linear Programming (MILP) RO approach is used to model the bidding problem for a VPP consisting of hydro pumped storage and RES units in energy and reserve markets. A multi-objective model that accounts for profitability, risk, and carbon emissions for VPP participation in energy markets is proposed in [13]. The single-level robust optimization framework in [14] models RVPP participation in sequential energy and reserve markets, considering asymmetric uncertainties. Further, a two-stage stochastic RO framework is proposed in [15] for virtual energy hubs participating in DAM, local energy, real-time, and natural gas markets. In [16], a multi-energy VPP is studied for energy and reserve scheduling in the capacity and natural gas markets, incorporating uncertainties in electricity prices and Photovoltaic (PV) unit capacity. The paper [17] proposes a single-period light RO model for optimizing DAM participation under wind generation uncertainty and varying reserve regimes. The study in [18] employs a RO framework to investigate a multi-energy VPP that integrates electrical and thermal (heating and cooling) devices, along with water resources, to deliver balancing and grid support services.

A significant issue in the existing literature is that the VPP 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 obtained in [6,8–18] 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 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 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 used in [6,8–18], the problem can be set to minimize the *maximum regret cost* [19–22]. 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 [19], a min–max regret problem is solved by a relaxation process for the linear programming problems. The paper in [20] develops a mixed-integer min–max regret formulation to account for the uncertain coefficients in the objective function of the problem. The paper in [21] 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 [22], 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 also 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 *average regret* [23–26]. The average regret can be defined as the *sum of lost costs by considering the probability of alternative decisions*. Hence, minimizing the average regret avoids selecting overly conservative solutions. In [23], a cooperative framework between VPPs and Electric Vehicle (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 [24], a hierarchical stochastic min–max regret algorithm is proposed to account for the uncertainties of electricity price, wind 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 [23,24] is challenging in both modeling and computation. In [25], 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-RESs 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 [26], the stochastic p-robust optimization method is used to consider different uncertainties related to electricity price and ND-RESs production of a generation company participating in the energy and reserve markets. However, the methodologies suggested in [25,26] require iterative solutions to stochastic programming, 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.

The papers described above minimize the maximum expected regret for multiple scenarios in the stochastic programming, 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 stochastic programming. 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 paper develops a novel modeling approach to account for the average regret in the RO for RVPP bidding problem. The profit-minimizing nature of uncertainties is modeled by the flexible RO approach, and the average regret associated with each uncertain parameter is modeled in the constraints of the optimization problem. In this way, while the average regret of RVPP operator decisions is controlled in the RO, the problem remains highly tractable, unlike the stochastic programming. 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.

1.3. Paper contributions

In this paper, the concept of average regret cost is implemented in the RO of RVPP bidding in the electricity markets by a set of mixed-integer constraints. The average 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 average regret cost with respect to uncertain parameters associated with DAM and Secondary Reserve Market (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 recently proposed by the authors in [6].

The contributions of this paper are outlined below:

- *Average-regret-based robust optimization framework:* 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 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 compared to average regret stochastic programming in the literature.
- *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.

1.4. Paper organization

The remainder of this paper is organized as follows. The proposed regret-based flexible RO model for RVPP bidding on electricity markets is described and formulated in Section 2. In this section, the deterministic formulation for RVPP market participation is developed, then the RO and the regret-based constrained are implemented. The simulation results are presented and discussed in Section 3. The simulations are performed to find the necessary level of conservatism of RVPP against different uncertain parameters. Finally, main conclusions and future work directions are drawn in Section 4.

2. Regret-based flexible robust formulation

In this section, the regret-based flexible RO formulation proposed in this paper for the RVPP bidding problem in the DAM and SRM by considering the BAM is presented. In Section 2.1, the RVPP problem structure is described. In Section 2.2, the deterministic problem is formulated by considering only a single value for uncertain parameters. Section 2.3 then presents the robust formulation for the uncertain parameters in the objective function of the optimization problem. In Section 2.4, the robust counterpart for the uncertain parameters related to ND-RESs and demands in the constraints of the optimization problem is presented. Finally, the main contribution of the paper, the *average-regret-based RO framework*, is proposed and formulated in Sections 2.5 and 2.6, where the constraints related to average regret are defined as an MILP problem to assist the RVPP operator in determining the appropriate level of conservatism in decision making.

2.1. Problem description

Fig. 1 illustrates the proposed RVPP bidding framework. The RVPP operator is tasked with optimizing both the energy and reserve dispatch of RVPP units and their market participation. The objective function of RVPP operator is to maximize the RVPP benefits in the DAM and SRM, while accounting for the operational costs of the RVPP units [27]. In the deterministic optimization problem (i.e., all parameters and input data are fixed and known), the RVPP operator considers the technical constraints of its units to ensure feasible energy and reserve provisions in the market. For simplicity and without loss of generality, all RVPP units are assumed to be connected to a single bus. Therefore, the traded energy and reserve of RVPP must be constrained by the capacity of the

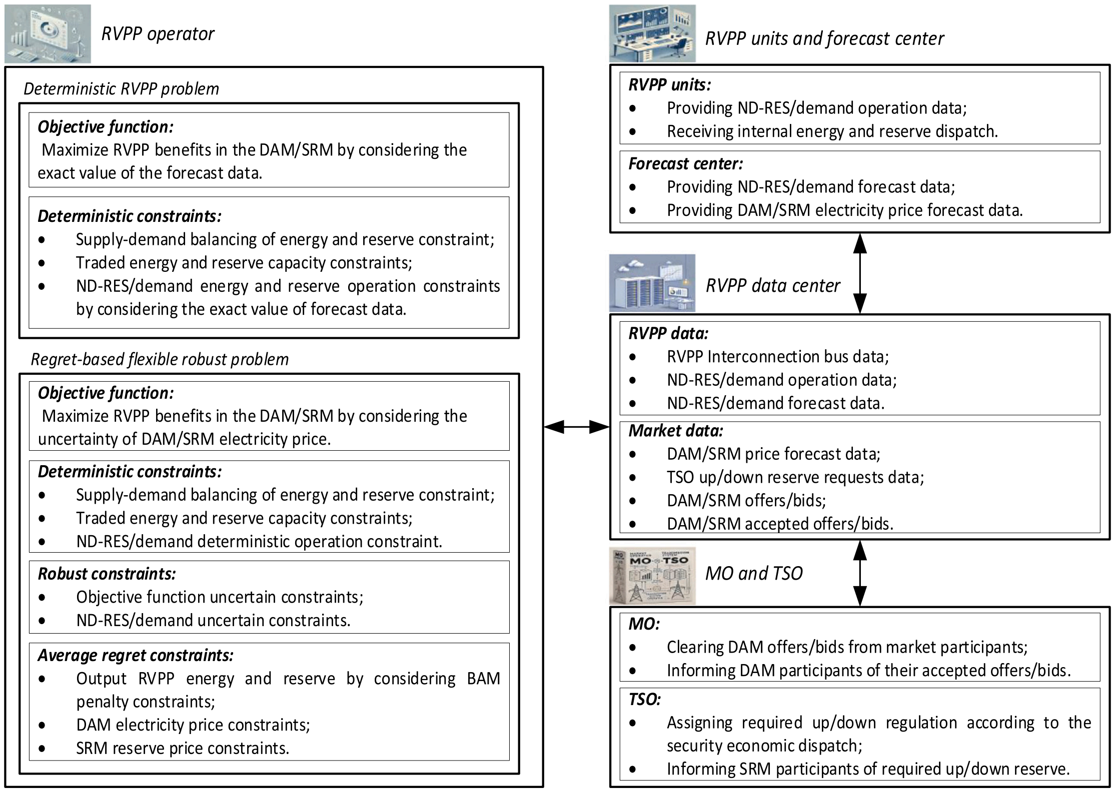

Fig. 1. The schematic of the proposed regret-based flexible robust approach.

point of common coupling with the main network. This approximation is reasonable as the focus is on optimizing the bidding strategy of the RVPP in the electricity and reserve markets, rather than modeling the internal network dynamics. Since the operational characteristics of the RVPP units are considered at the aggregate level for market participation, the interactions between units within the internal network are less relevant for the bidding optimization process. This assumption is safe to apply in the context of market bidding, where the main objective is to determine optimal bidding strategies, and the internal network structure has minimal impact on these decisions. However, in real-time market operations, considering the network becomes more relevant, as internal network dynamics can significantly affect the operation of units and guaranteeing the provision of offered energy and reserve. If uncertainties related to DAM and SRM electricity prices, ND-RES production, and demand are considered, the impact of variations in these parameters on the objective function and constraints of the optimization problem must be addressed.

Coping with a wide range of exogenous and endogenous uncertainties [28] is essential to enhance the RVPP's competitiveness in electricity markets. Such uncertainties can significantly impact the DAM and SRM participation of the RVPP, thereby influencing its expected benefits. The RO approach is well-suited for addressing multiple uncertainties simultaneously in electricity market problems, as it considers the bounds of uncertain parameters rather than relying on their exact PDF [12,13,15]. In this paper, the uncertain parameters affect both the objective function and the constraints of the optimization problem. Therefore, additional constraints should be incorporated into the optimization model, depending on whether the uncertainty influences the objective function or the constraints. The RVPP operator can control its level of conservatism against these uncertainties if a *flexible* RO problem is implemented [7]. This control comes in the form of the so-called *uncertainty budgets*. These parameters represent the number of hours during which the uncertain parameter deviates from its predicted value to its worst-case condition and must be defined for each uncertain parameter. The flexible RO approach, by considering the *worst case of energy*, demonstrates a high capability to address different uncertainties in the RVPP bidding optimization models [14,16,17]. The *worst-case profit* approach identifies the worst case of the optimization problem when various uncertainties in the objective function and constraints interact with each other [6,29,30]. However, in both the *worst-case energy* and *worst-case profit* approaches, the RVPP operator must define multiple uncertainty budgets as input parameters for each solution, considering the different characteristics of uncertainties, units, and electricity markets. The remainder of this section formulates the regret-based flexible RO framework proposed in this paper to automatically define the uncertainty budgets in the problem according to the level of conservatism sought by the user. This is achieved by limiting the estimated average regret associated with the penalty costs of RVPP energy deviations in the BAM, as well as the regret costs arising from DAM and SRM price fluctuations.

The necessary information for solving the proposed optimization problem includes the technical features and forecast data of RVPP units, data related to capacity of interconnection bus between the RVPP and the network, and market data such as electricity price forecasts and reserve requirements provided by the TSO. Once the optimization problem is solved, the RVPP submits offers/bids of energy and reserve before DAM and SRM gate closure. To maximize RVPP market participation, this paper assumes zero-price bids, leveraging the fact that RVPP units rely on renewable resources, have near-zero marginal costs, and their production volume is small compared to the energy volume cleared in those markets. The Market Operator (MO) is responsible for clearing the DAM based on energy offers/bids from various participants. The TSO assigns the required reserve for each SRM participant, including the RVPP. This paper assumes all possible scenarios for up reserve activation, down reserve activation, and no reserve activation in the power dispatch of RVPP units. Consequently, the optimization problem yields a feasible solution for any reserve activation scenario in real-time, as requested by the TSO. Once the energy and reserve offers/bids of RVPP are accepted, the results are communicated to the RVPP, which then coordinates the internal dispatch of its units accordingly.

2.2. Deterministic formulation

This section presents the deterministic formulation of RVPP for the simultaneous DAM and SRM participation. The deterministic formulation assumes that forecasts of electricity and reserve prices, and stochastic energy sources such as wind production and solar irradiation, are *exact* [14]. The idea is to develop the base formulation here and then in the following sections to add the uncertainties of different parameters to the model.

2.2.1. Deterministic objective function

The deterministic objective function, as defined in (1), seeks to maximize the benefits of RVPP in the DAM and SRM.

$$\max_{\Xi^{DA+SR}} \sum_{t\in\mathcal{T}} \left[\tilde{\lambda}_t^{DA} p_t^{DA} \Delta t + \tilde{\lambda}_t^{SR,\uparrow} r_t^{SR,\uparrow} + \tilde{\lambda}_t^{SR,\downarrow} r_t^{SR,\downarrow}\right] - \sum_{t\in\mathcal{T}}\sum_{r\in\mathcal{R}} C_r p_{r,t}\Delta t - \sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} C_{d,p} u_{d,p} \tag{1}$$

The first term of (1) determines the expected RVPP incomes from bidding in the DAM, up SRM, and down SRM. The second and third terms in (1) calculate the operational costs of ND-RESs, and the costs associated with the selection of load profiles, respectively.

2.2.2. Supply–demand balance constraint

The equality constraint related to the supply–demand balancing of energy and reserve for RVPP units is described in (2).

$$\sum_{r\in\mathcal{R}} (p_{r,t} + \boldsymbol{r}_{r,t}^{SR}) - \sum_{d\in\mathcal{D}} (p_{d,t} - \boldsymbol{r}_{d,t}^{SR}) = p_t^{DA} + \boldsymbol{r}_t^{SR}, \qquad \forall t \tag{2}$$

The reserve activation scenarios are considered for all possible up reserve activation, down reserve activation, and no reserve activation in real-time by use of defining general variables $\boldsymbol{r}_t^{SR} = \{r_t^{SR,\uparrow}, -r_t^{SR,\downarrow}, 0\}$, $\boldsymbol{r}_{r,t}^{SR} = \{r_{r,t}^{SR,\uparrow}, -r_{r,t}^{SR,\downarrow}, 0\}$, and $\boldsymbol{r}_{d,t}^{SR} = \{r_{d,t}^{SR,\uparrow}, -r_{d,t}^{SR,\downarrow}, 0\}$.

2.2.3. Trade constraints

The traded energy and reserve of RVPP need to be constrained according to the capacity of the interconnection bus and the TSO request for reserve according to (3).

$$p_t^{DA} + r_t^{SR,\uparrow} \le \sum_{r\in\mathcal{R}} \bar{P}_r, \qquad \forall t \tag{3a}$$

$$-\sum_{d\in\mathcal{D}} \bar{P}_d \le p_t^{DA} - r_t^{SR,\downarrow}, \qquad \forall t \tag{3b}$$

$$r_t^{SR,\uparrow} = \varrho_t r_t^{SR,\downarrow}, \qquad \forall t \tag{3c}$$

$$r_t^{SR,\uparrow} \le \kappa \sum_{r\in\mathcal{R}} \bar{P}_r, \qquad \forall t \tag{3d}$$

The upper and lower limits of total traded energy plus reserve by RVPP is constrained by Eqs. (3a) and (3b), respectively. The requested down-to-up reserve by TSO is limited by constraint (3c). The traded up reserve of RVPP is confined to a ratio of the maximum production capacity of RVPP by constraint (3d).

2.2.4. ND-RESs constraints

ND-RESs, such as PV and wind units, can provide both upward and downward reserves in electricity markets, depending on their technical capabilities and regulatory conditions [31,32]. Upward reserve can be provided when ND-RESs operate at a curtailed level under normal conditions and then increase their generation during reserve activation. On the other hand, downward reserve can be offered by reducing their output power from the current operational level. The ND-RESs constraints by considering the reserve provision are formulated in (4).

$$\underline{P}_r \le p_{r,t} - r_{r,t}^{SR,\downarrow}, \qquad \forall r,t \tag{4a}$$

$$p_{r,t} + r_{r,t}^{SR,\uparrow} = \tilde{P}_{r,t}, \qquad \forall r,t \tag{4b}$$

$$r_{r,t}^{SR,\uparrow} \le T^{SR} \bar{R}_r^{SR}, \qquad \forall r,t \tag{4c}$$

$$r_{r,t}^{SR,\downarrow} \le T^{SR} \underline{R}_r^{SR}, \qquad \forall r,t \tag{4d}$$

The lower and upper bounds for the output energy and reserve of ND-RESs, using the minimum and median production, are defined in constraints (4a) and (4b), respectively. The up and down reserve provided by ND-RESs are constrained in Eqs. (4c) and (4d), respectively.

2.2.5. Demands constraints

The constraints (5) are flexible demands constraints by taking the idea from the deterministic approach proposed in [33].

$$p_{d,t} = \sum_{p\in\mathcal{P}} (\tilde{P}_{d,p,t} u_{d,p}), \qquad \forall d,t \tag{5a}$$

$$\sum_{p\in\mathcal{P}} u_{d,p} = 1, \qquad \forall d \tag{5b}$$

$$r_{d,t}^{SR,\uparrow} \le \underline{\beta}_{d,t} p_{d,t}, \qquad \forall d,t \tag{5c}$$

$$r_{d,t}^{SR,\uparrow} \le p_{d,t} - \underline{P}_d, \qquad \forall d,t \tag{5d}$$

$$r_{d,t}^{SR,\uparrow} \le T^{SR} \underline{R}_d^{SR}, \qquad \forall d,t \tag{5e}$$

$$r_{d,t}^{SR,\downarrow} \le \bar{\beta}_{d,t} p_{d,t}, \qquad \forall d,t \tag{5f}$$

$$r_{d,t}^{SR,\downarrow} \le \bar{P}_d - p_{d,t}, \qquad \forall d,t \tag{5g}$$

$$r_{d,t}^{SR,\downarrow} \le T^{SR} \bar{R}_d^{SR}, \qquad \forall d,t \tag{5h}$$

$$\underline{E}_d \le \sum_{t\in\mathcal{T}} (p_{d,t}\Delta t - r_{d,t}^{SR,\uparrow}), \qquad \forall d \tag{5i}$$

$$u_{d,p} \in \{0,1\}, \qquad \forall d,p \tag{5j}$$

The RVPP is allowed to choose one demand profile among several defined profiles according to the constraints (5a) and (5b). The up reserve provided by demands is confined by the downward flexibility of demand, the minimum possible demand, and the capability of demand to provide reserve in constraints (5c)–(5e), respectively. The constraints (5f)–(5h) are defined for the down reserve provided by demands. The minimum energy along the time horizon that each demand is allowed to consume is constrained by Eq. (5i). Finally, the nature of binary variables is described by constraint (5j).

The deterministic formulation proposed in (1)–(5) assumes an exact single forecast value for each uncertain parameter. However, the variations of the uncertain parameters in the optimization problem need to be considered as they affect the optimal RVPP decision and its profit in different electricity markets. This is discussed in the following Section.

2.3. Robust optimization in the objective function

In the objective function (1) there are three parameters related to DAM, up and down SRM electricity prices that are uncertain. In order to find the robust counterpart of the objective function, the range of these uncertain parameters must first be defined. The uncertainty bounds for these parameters in each period can be defined as $[\tilde{\lambda}_t^{DA} - \check{\lambda}_t^{DA}, \tilde{\lambda}_t^{DA}, \tilde{\lambda}_t^{DA} +$

$\hat{\lambda}_t^{DA}$], $[\tilde{\lambda}_t^{SR,\uparrow} - \check{\lambda}_t^{SR,\uparrow}, \tilde{\lambda}_t^{SR,\uparrow}]$, and $[\tilde{\lambda}_t^{SR,\downarrow} - \check{\lambda}_t^{SR,\downarrow}, \tilde{\lambda}_t^{SR,\downarrow}]$, respectively. Note that, for the hourly DAM price, depending on whether the RVPP is an energy seller or buyer in the market, the worst case condition occurs at the minimum or maximum of the corresponding hourly DAM electricity price bound, respectively. For the SRM price, RVPP is always seller, and thus, only negative deviation of the price leads to the worst case, hence the upper bounds of the SRM uncertain parameters are defined as median values. Authors in [8] defined the robust counterpart of DAM electricity price uncertainty term in a way that results in finding the hours that lead to the most electricity price variance multiplied by the traded energy of RVPP. However, this approach has some limitations in finding the actual worst case of the optimization problem, especially when the uncertainties related to ND-RESs and demands (see Section 2.4) are also considered. The authors in [6] have recently developed a counterpart for the uncertain terms in the objective function based on binary variables that considers the final electricity price and also the effect of uncertainties related to ND-RESs and demands (uncertainties in the constraints of the optimization problem) on the final value of the traded energy of RVPP. To achieve this, the electricity price (DAM, and up and down SRM) in each time period is assigned in (6). Depending on the direction of the electricity price variation, which is modeled by the binary variable $\chi_t^{DA}, \chi_t'^{DA}, \chi_t^{SR,\uparrow}, \chi_t^{SR,\downarrow}$, the electricity price in each time period can take the minimum, median, or maximum value from its corresponding bound.

$$\lambda_t^{DA} = \tilde{\lambda}_t^{DA} - \check{\lambda}_t^{DA}\chi_t^{DA} + \hat{\lambda}_t^{DA}\chi_t'^{DA} \ , \qquad \forall t \qquad (6a)$$

$$\lambda_t^{SR,\uparrow} = \tilde{\lambda}_t^{SR,\uparrow} - \check{\lambda}_t^{SR,\uparrow}\chi_t^{SR,\uparrow} \ , \qquad \forall t \qquad (6b)$$

$$\lambda_t^{SR,\downarrow} = \tilde{\lambda}_t^{SR,\downarrow} - \check{\lambda}_t^{SR,\downarrow}\chi_t^{SR,\downarrow} \ , \qquad \forall t \qquad (6c)$$

$$\chi_t^{DA} + \chi_t'^{DA} \leq 1 \ , \qquad \forall t \qquad (6d)$$

$$\chi_t^{DA}, \chi_t'^{DA}, \chi_t^{SR,\uparrow}, \chi_t^{SR,\downarrow} \in \{0,1\} \ , \qquad \forall t \qquad (6e)$$

Considering the approach proposed in [6], the robust counterpart of the deterministic objective function (1) can be written as:

$$\max_{\Xi^{DA+SR}} \sum_{t\in\mathcal{T}} \left[\tilde{\lambda}_t^{DA} p_t^{DA}\Delta t + \tilde{\lambda}_t^{SR,\uparrow} r_t^{SR,\uparrow} + \tilde{\lambda}_t^{SR,\downarrow} r_t^{SR,\downarrow}\right] - \sum_{t\in\mathcal{T}}\sum_{r\in\mathcal{R}} C_r p_{r,t}\Delta t - \sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} C_{d,p}u_{d,p} - \sum\sum_{t\in\mathcal{T}} \boldsymbol{y}_t^{EM} \qquad (7a)$$

s.t.

$$\boldsymbol{v}^{EM} + \boldsymbol{\eta}_t^{EM} \geq \hat{\check{\boldsymbol{\lambda}}}_t^{EM} \odot \boldsymbol{p}_t^{EM} \ , \qquad \forall t \qquad (7b)$$

$$\boldsymbol{y}_t^{EM} \geq \boldsymbol{v}^{EM} + \boldsymbol{\eta}_t^{EM} - M(1-\boldsymbol{\chi}_t^{EM}) \ , \qquad \forall t \qquad (7c)$$

$$\varepsilon(\boldsymbol{\chi}_t^{EM}) \leq \boldsymbol{\eta}_t^{EM} \leq M(\boldsymbol{\chi}_t^{EM}) \ , \qquad \forall t \qquad (7d)$$

$$-M(1-\boldsymbol{\chi}_t^{EM}) \leq \hat{\check{\boldsymbol{\lambda}}}_t^{EM} \odot \boldsymbol{p}_t^{EM} - \boldsymbol{v}^{EM} \leq M(\boldsymbol{\chi}_t^{EM}) \ , \qquad \forall t \qquad (7e)$$

$$\boldsymbol{v}^{EM}, \boldsymbol{\eta}_t^{EM}, \boldsymbol{y}_t^{EM} \geq 0 \ , \qquad \forall t \qquad (7f)$$

$$\boldsymbol{\chi}_t^{EM} \in \{0,1\} \ , \qquad \forall t \qquad (7g)$$

where $\odot$ represents the Hadamard product, which results in a vector of the same dimension, with elements given by the product of the corresponding elements of the original two vectors.

Vectors of parameters and variables defined in (7) include: the uncertain parameter related to the variation of the negative and positive DAM and up and down SRM prices $\hat{\check{\boldsymbol{\lambda}}}_t^{EM} = \{\check{\lambda}_t^{DA}, -\hat{\lambda}_t^{DA}, \check{\lambda}_t^{SR,\uparrow}, \check{\lambda}_t^{SR,\downarrow}\}$; the binary variable related to the electricity price variation $\boldsymbol{\chi}_t^{EM} = \{\chi_t^{DA}, \chi_t'^{DA}, \chi_t^{SR,\uparrow}, \chi_t^{SR,\downarrow}\}$; the auxiliary dual variables $\boldsymbol{v}^{EM} = \{v^{DA}, v^{DA}, v^{SR,\uparrow}, v^{SR,\downarrow}\}$, and $\boldsymbol{\eta}_t^{EM} = \{\eta_t^{DA}, \eta_t'^{DA}, \eta_t^{SR,\uparrow}, \eta_t^{SR,\downarrow}\}$; the variables related to traded energy and up and down reserve $\boldsymbol{p}_t^{EM} = \{p_t^{DA}\Delta t, p_t^{DA}\Delta t, r_t^{SR,\uparrow}, r_t^{SR,\downarrow}\}$; and the profit reduction due to price uncertainty represented by the auxiliary variable $\boldsymbol{y}_t^{EM} = \{y_t^{DA}, y_t'^{DA}, y_t^{SR,\uparrow}, y_t^{SR,\downarrow}\}$.

The first three terms in the robust objective function (7a) are similar to the deterministic objective function (1). The last term in (7a) is the profit reduction due to DAM negative and positive price uncertainty and up and down SRM reserve price uncertainty. Constraint (7b) assigns the lower bounds of the dual variables $\boldsymbol{v}^{EM}$ and $\boldsymbol{\eta}_t^{EM}$ to the absolute value of the profit reduction due to the price volatility. The lower bound of the profit reduction $\boldsymbol{y}_t^{EM}$, which is reduced in the objective function (7a), is assigned based on the constraint (7c). The variable $\boldsymbol{y}_t^{EM}$ gets positive values only when the binary variable χ_t^{EM} is 1, i.e. when the optimization problem chooses the worst condition of the electricity price in a given time period. The dual variable $\boldsymbol{\eta}_t^{EM}$ is bounded in the constraint (7d) based on the condition of the binary variable χ_t^{EM}. The difference between the possible profit reduction and the dual variable $\boldsymbol{v}^{EM}$ is bounded by the binary variable χ_t^{EM} in the constraint (7e). Eq. (7e) has the purpose of setting a lower bound $\boldsymbol{v}^{EM} \geq \hat{\check{\boldsymbol{\lambda}}}_t^{EM} \odot \boldsymbol{p}_t^{EM}$ when χ_t^{EM} is zero and setting an upper bound $\boldsymbol{v}^{EM} \leq \hat{\check{\boldsymbol{\lambda}}}_t^{EM} \odot \boldsymbol{p}_t^{EM}$ when χ_t^{EM} is 1. This constraint is essential for the case that uncertain parameters related to ND-RESs production and demands (see Section 2.4) affect the energy/reserve traded by RVPP ($\boldsymbol{p}_t^{EM}$), and it avoids choosing wrong periods for the worst-case electricity price. Finally, the nature of positive dual variables and binary variables is represented by the constraints (7f) and (7g), respectively.

2.4. Robust optimization in the ND-RESs and demands constraints

In constraints (4b) and (5a) of problem (1)–(5), there are two parameters related to ND-RESs production and demands consumption, respectively, that are actually uncertain, namely $P_{r,t}$ and $P_{d,p,t}$ (index p is neglected here for the sake of simplicity). The range of these uncertain parameters to find the robust counterpart of these constraints are defined as $[\tilde{P}_{r,t} - \check{P}_{r,t}, \tilde{P}_{r,t}]$ and $[\tilde{P}_{d,t}, \tilde{P}_{d,t} + \hat{P}_{d,t}]$, respectively. Note that only the negative deviation of ND-RESs and the positive deviation of demands are considered to find the robust counterparts of these constraints, since the deviation in the opposite direction usually leads to more profit for RVPP [34].

Elaborating from [6], the flexible robust counterpart of the constraints (4b) and (5a) can be written in the general form (8).

$$\boldsymbol{p}_{u,t} = \tilde{\boldsymbol{P}}_{u,t} \mp \chi_{u,t}\hat{\check{\boldsymbol{P}}}_{u,t} \ , \qquad \forall \boldsymbol{u}, t \qquad (8a)$$

$$\lambda_t^{DA}\boldsymbol{p}_{u,t}\Delta t \leq \lambda_t^{DA}\tilde{\boldsymbol{P}}_{u,t}\Delta t \mp \boldsymbol{y}_{u,t} \ , \qquad \forall \boldsymbol{u}, t \qquad (8b)$$

$$\boldsymbol{y}_{u,t} \leq \lambda_t^{DA}\hat{\check{\boldsymbol{P}}}_{u,t}\Delta t \ , \qquad \forall \boldsymbol{u}, t \qquad (8c)$$

$$\boldsymbol{y}_{u,t} \geq \boldsymbol{v}_u + \boldsymbol{\eta}_{u,t} - M(1-\chi_{u,t}) \ , \qquad \forall \boldsymbol{u}, t \qquad (8d)$$

$$\boldsymbol{v}_u + \boldsymbol{\eta}_{u,t} \geq \lambda_t^{DA}\hat{\check{\boldsymbol{P}}}_{u,t}\Delta t \ , \qquad \forall \boldsymbol{u}, t \qquad (8e)$$

$$\varepsilon\chi_{u,t} \leq \boldsymbol{\eta}_{u,t} \leq M\chi_{u,t} \ , \qquad \forall \boldsymbol{u}, t \qquad (8f)$$

$$\boldsymbol{v}_u, \boldsymbol{\eta}_{u,t}, \boldsymbol{y}_{u,t} \geq 0 \ , \qquad \forall \boldsymbol{u}, t \qquad (8g)$$

$$\chi_{u,t} \in \{0,1\} \ , \qquad \forall \boldsymbol{u}, t \qquad (8h)$$

Vectors of indices, parameters and variables defined in (8) include: the general index for ND-RESs and demands $\boldsymbol{u} = \{r, d\}$; the variable related to traded energy of ND-RESs and demands $\boldsymbol{p}_{u,t} = \{p_{r,t}, p_{d,t}\}$; the parameters related to the general form of median and deviation of uncertain parameters $\tilde{\boldsymbol{P}}_{u,t} = \{\tilde{P}_{r,t}, \tilde{P}_{d,t}\}$ and $\hat{\check{\boldsymbol{P}}}_{u,t} = \{\check{P}_{r,t}, \hat{P}_{d,t}\}$; the binary variable of ND-RESs and demands robust constraints $\chi_{u,t} = \{\chi_{r,t}, \chi_{d,t}\}$; the auxiliary variable related to the profit reduction (cost increase) due to the units' output deviation due to uncertainty $\boldsymbol{y}_{u,t} = \{y_{r,t}, y_{d,t}\}$; and the auxiliary dual variables $\boldsymbol{v}_u = \{v_r, v_d\}$, and $\boldsymbol{\eta}_{u,t} = \{\eta_{r,t}, \eta_{d,t}\}$.

Constraint (8a) sets the output energy of uncertain units (ND-RESs or demands) by considering the possible deviation from the median value of the forecast (active when $\chi_{u,t} = 1$). In the constraint (8a), only the negative deviation for ND-RESs and the positive deviation for demands are assumed. The worst condition of unit profit deviations is given by the constraints (8b)–(8h) based on the condition of the binary variable $\chi_{u,t}$. The profit of each unit for each time period is constrained in Eq. (8b) to the median profit minus (plus) the profit reduction (cost increase) due to the units' output deviation due to uncertainty, $y_{u,t}$. The dual variable $y_{u,t}$ is confined to the maximum possible profit reduction of each unit in each time period in (8c). The lower bound of the dual variable $y_{u,t}$ is limited to the sum of the dual variables v_u and $\eta_{u,t}$ and the uncertainty activation binary variable $\chi_{u,t}$ in (8d). For those periods where $\chi_{u,t} = 1$, the dual variable $y_{u,t}$ has a positive value, resulting in the profit reduction in the constraint (8b). The sum of the dual variables v_u and $\eta_{u,t}$ is set higher than the maximum profit reduction for each unit in each time period in the constraint (8e). Constraint (8f) bounds the dual variable $\eta_{u,t}$ based on the condition of the binary variable $\chi_{u,t}$. Finally, the nature of positive dual variables and binary variables is specified in the constraint (8g) and (8h), respectively.

Note that, the term $\lambda_t^{DA} p_{u,t}$ on the left side of the constraint (8b) is a nonlinear expression. By substituting the electricity price from Eq. (6a) into (8b), the resulting nonlinear term involves the multiplication of binary and continuous variables $\chi_t^{(\prime)DA} p_{u,t}$. This nonlinear term can be formulated linearly (see (9) below) by the method proposed in [35] using equivalent linear constraints.

$$p_{u,t}^{(\prime)Q} = p_{u,t} - p_{u,t}^{(\prime)A} , \quad \forall u, t \tag{9a}$$

$$\underline{P}_u \chi_t^{(\prime)DA} \le p_{u,t}^{(\prime)Q} \le \bar{P}_u \chi_t^{(\prime)DA} , \quad \forall u, t \tag{9b}$$

$$\underline{P}_u (1 - \chi_t^{(\prime)DA}) \le p_{u,t}^{(\prime)A} \le \bar{P}_u (1 - \chi_t^{(\prime)DA}) , \quad \forall u, t \tag{9c}$$

The vectors of auxiliary variables $p_{u,t}^{(\prime)Q}$ and $p_{u,t}^{(\prime)A}$ are defined to determine the final result of the nonlinear term $\chi_t^{(\prime)DA} p_{u,t}$ when the RVPP is a net energy seller (buyer). When the binary variable $\chi_t^{(\prime)DA}$ related to the electricity price deviation is 1, the Eqs. (9) set $p_{u,t}^{(\prime)Q} = p_{u,t}$ and $p_{u,t}^{(\prime)A} = 0$. On the other hand, for $\chi_t^{(\prime)DA} = 0$, the Eqs. (9) lead to $p_{u,t}^{(\prime)Q} = 0$ and $p_{u,t}^{(\prime)A} = p_{u,t}$.

2.5. Average regret constraints

In this section, the average regret for different decision alternatives of the RVPP, which constitutes the main contribution of the paper, is formulated. The objective is that the RVPP operator could assign the desired amount of regret for each parameter, instead of assigning the uncertainty budget parameters, which are usually used in the literature to define the chosen level of conservatism. These uncertainty budgets are defined as the number of hours/periods that uncertain parameters deviate from their median value to their worst case. Usually, it is difficult for RVPP operator to predefine their values, especially when several uncertain parameters are considered in the optimization problem. By using the concept of average regret in this paper, the RVPP operator obtains a more expedient interpretation since the average regret is represented in terms of cost. In this section, normal distributions are used to compute the average regret for different uncertain parameters. However, the proposed approach is general and can be used for any type of distribution. Furthermore, in the case of unavailability of PDF of uncertain parameters, it is still possible to compute the average regret in the proposed model by assuming known, approximated distributions, such as normal, triangular, or uniform distributions for uncertain parameters. Therefore, the proposed probabilistic approach is suitable in the RO problems, where usually the unavailability of complete information about uncertain parameters is a common issue.

2.5.1. Average regret definition

In the context of the work presented in this paper, *average 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 average regret to easily control the regret level in the constraints of the optimization problem. In this way, the average regret of more conservative strategies will be lower than optimistic decisions resulting in a better control of the average regret. This estimated average regret can help the RVPP operator to assign its level of conservatism. A simple example is used in this section to help understand the definition of average regret in this paper.

Table 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

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} MW, and {7,6,5,4} €/MWh, respectively. The penalty for not providing promised energy is assumed to be 10 €/MWh. Table 1 provides information about the energy and price regret of decision $d0$ corresponding to alternative decisions $D = \{d0, d1, d2, d3\}$. The average 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 average 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 average regret of RVPP.

2.5.2. Average regret of RVPP output energy

Eq. (10) calculates the average regret related to the uncertainty of the total output energy of RVPP.

$$\sum_{t \in \mathcal{T}} \sum_{z \in \mathcal{Z}} \left[J_{z,t} Z_t \rho_{z,t}^{DA,Q} \Delta t \right] \le \Gamma Reg^{Max}, \tag{10a}$$

$$\rho_{z,t}^{DA,Q} = p_t^{DA} + r_t^{SR,\uparrow} - P_{z,t}^F + \rho_{z,t}^{DA,A} , \quad \forall z, t \tag{10b}$$

$$\rho_{z,t}^{DA,Q} \le \bar{P}_t \iota_{z,t} , \quad \forall z, t \tag{10c}$$

$$\rho_{z,t}^{DA,A} \le \bar{P}_t (1 - \iota_{z,t}) , \quad \forall z, t \tag{10d}$$

$$\rho_{z,t}^{DA,Q}, \rho_{z,t}^{DA,A} \ge 0 , \quad \forall z, t \tag{10e}$$

The average regret associated with the output energy of RVPP in (10a) is calculated by multiplying the probability factor $J_{z,t}$ associated with each segment of RVPP output energy PDF, the penalty cost of not providing bid energy in the BAM Z_t, and the auxiliary variable $\rho_{z,t}^{DA,Q}$. Segments of the PDF represent different decisions for RVPP output energy as the uncertainties unfold. The auxiliary variable $\rho_{z,t}^{DA,Q}$ is the difference between the total energy and reserve bid of the RVPP 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 lower regret. Both $\rho_{z,t}^{DA,Q}$ and $\rho_{z,t}^{DA,A}$ are mutually exclusive in (10c)–(10d). The average regret in (10a) is limited by a user-defined coefficient Γ, which represents a per-unit fraction of the maximum possible regret of the output energy of RVPP. By selecting the coefficient Γ, 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 median in all time periods

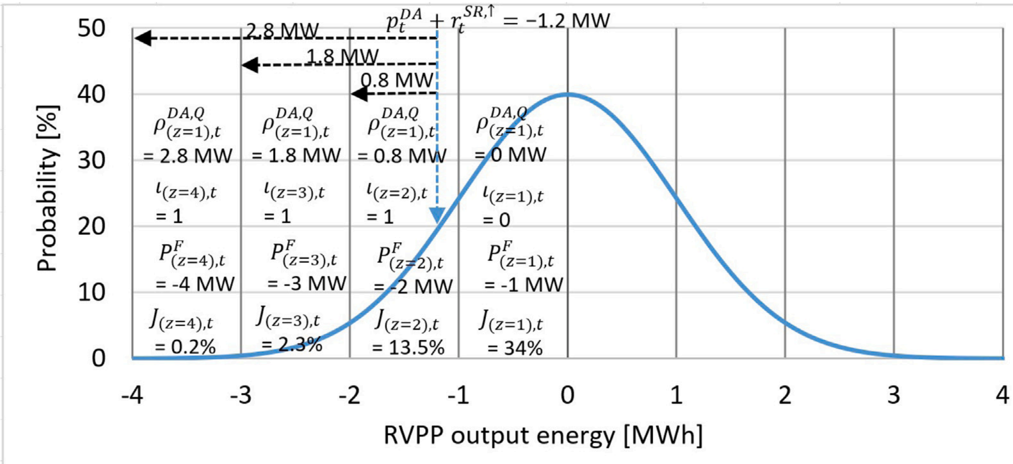

Fig. 2. Calculation of average regret according to the PDF of total output energy of RVPP in a sample hour.

$\left(Reg^{Max} = \sum_{t\in\mathcal{T}}\sum_{z\in\mathcal{Z}} J_{z,t} Z_t \left[\sum_{r\in\mathcal{R}} \tilde{P}_{r,t} - \sum_{d\in\mathcal{D}} \tilde{P}_{d,t} - P^F_{z,t}\right]\Delta t\right)$. With Z_t set to 114 €/MWh and other parameters as defined in Fig. 2, the maximum regret of the RVPP output energy is calculated Reg^{Max} = 78.32 €. This value is used as an input parameter in constraint (10a), allowing the RVPP operator to adjust the desired regret limit related to the output energy of the RVPP through the per-unit parameter Γ. Based on (10b)–(10e), the auxiliary variable $\rho^{DA,Q}_{z,t}$ has value only if the sum of the energy and reserve bid of RVPP is greater than $P^F_{z,t}$. 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 (10c)–(10d) enforces this condition.

Fig. 2 shows the calculation of the average regret according to the PDF of the total output energy of RVPP to further illustrate the formulation in (10). For this purpose, the value of different parameters and variables ($J_{z,t}, \rho^{DA,Q}_{z,t}, P^F_{z,t}, \iota_{z,t}$) in (10a) is provided by assuming the total energy and reserve bid of the RVPP (decision of RVPP operator) at the instant t ($p^{DA}_t + r^{SR,\uparrow}_t$) is equal to −1.2 MW. According to Section 2.5.1, 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 $p^{DA}_t + r^{SR,\uparrow}_t = -1.2$ 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 final energy plus the reserve bid of RVPP ($\rho^{DA,Q}_{z,t}\Delta t$). The average regret is calculated based on the sum of the regrets for each segment of PDF of the total output energy. Assuming $Z_t = 114$ €/MWh, the regret of the proposed decision compared to the alternative decisions $z = 2, 3, 4$ according to the PDF of the RVPP output energy is 91.2 €, 205.2 €, and 319.2 €. Considering the probability of the alternative decisions $z = 2, 3, 4$ as 13.5%, 2.3%, and 0.2%, the average regret for this decision at the sample hour is 17.67 €. 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.

2.5.3. Average regret of DAM electricity price

Formulations (11) calculate the average regret related to the uncertainty of the DAM electricity price.

$$\sum_{t\in\mathcal{T}}\sum_{z\in\mathcal{Z}} \left[J^{DA}_{z,t} K^{DA}_{z,t} p^{DA,Q}_t \Delta t\right] \leq \Gamma^{DA} Reg^{Max,DA}, \tag{11a}$$

$$\sum_{t\in\mathcal{T}}\sum_{z\in\mathcal{Z}} \left[J'^{DA}_{z,t} K'^{DA}_{z,t} p^{DA,A}_t \Delta t\right] \leq \Gamma'^{DA} Reg'^{Max,DA}, \tag{11b}$$

$$p^{DA,Q}_t + p^{DA,Q'}_t = p^{DA}_t + p^{DA,A}_t + p^{DA,A'}_t, \quad \forall t \tag{11c}$$

$$p^{DA,Q}_t \leq \bar{P}_t \iota^{DA}_t, \quad \forall t \tag{11d}$$

$$p^{DA,Q}_t \leq \bar{P}_t (1-\chi^{DA}_t), \quad \forall t \tag{11e}$$

$$p^{DA,Q'}_t \leq \bar{P}_t \iota^{DA}_t, \quad \forall t \tag{11f}$$

$$p^{DA,Q'}_t \leq \bar{P}_t \chi^{DA}_t, \quad \forall t \tag{11g}$$

$$p^{DA,A}_t \leq \bar{P}'_t (1-\iota^{DA}_t), \quad \forall t \tag{11h}$$

$$p^{DA,A}_t \leq \bar{P}'_t (1-\chi'^{DA}_t), \quad \forall t \tag{11i}$$

$$p^{DA,A'}_t \leq \bar{P}'_t (1-\iota^{DA}_t), \quad \forall t \tag{11j}$$

$$p^{DA,A'}_t \leq \bar{P}'_t \chi'^{DA}_t, \quad \forall t \tag{11k}$$

$$p^{DA,Q}_t, p^{DA,Q'}_t, p^{DA,A}_t, p^{DA,A'}_t \geq 0, \quad \forall t \tag{11l}$$

Since Eq. (6a) enforces to have three final values for DAM electricity price (lower bound, median, and upper bound of the uncertainty bound), the average regret calculation is formulated for these three conditions in (11). Note that in the calculation of the average regret related to the DAM electricity price in (11), different type of parameters and variables are used compared to the constraints of the average regret related to the RVPP output energy in (10). The average 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 (11a) and (11b), respectively.

The average regret related to the DAM electricity price when the RVPP is an energy seller is calculated in (11a) by multiplying the probability of each segment of the PDF of the DAM electricity price ($J^{DA}_{z,t}$), by the negative deviation of the DAM electricity price from the median in each segment of the PDF of the DAM electricity price ($K^{DA}_{z,t}$), and by the total energy traded by the RVPP ($p^{DA,Q}_t$) for the condition that the electricity price is at its median ($\chi^{DA}_t = 0$) and the RVPP is an energy seller ($\iota^{DA}_t = 1$). A similar approach with a different direction of the DAM electricity price deviation is used in (11b) to calculate the average regret in the case where RVPP is an energy buyer in the market. The maximum regret parameters for the DAM price, when the RVPP is an energy seller and an energy buyer, are calculated using $Reg^{Max,DA} = \sum_{t\in\mathcal{T}}\sum_{z\in\mathcal{Z}} J^{DA}_{z,t} K^{DA}_{z,t} \bar{P}_t \Delta t$ and $Reg'^{Max,DA} = \sum_{t\in\mathcal{T}}\sum_{z\in\mathcal{Z}} J'^{DA}_{z,t} K'^{DA}_{z,t} \bar{P}'_t \Delta t$, respectively. The average regret associated with DAM in (11a) and (11b) is controlled by the user-defined per-unit coefficients Γ^{DA} and Γ'^{DA} for the hours when RVPP is an energy seller and buyer, respectively. In accordance with the conditions specified in (11c)–(11l), the auxiliary variable $p^{DA,Q}_t$ has value only when the electricity price is at its median value and RVPP is an energy seller. These conditions are

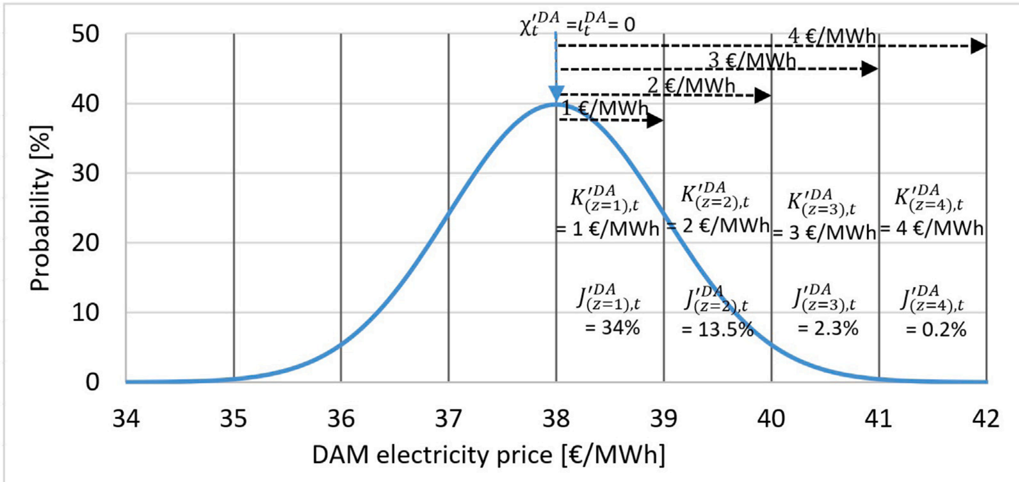

Fig. 3. Calculation of average regret according to the PDF of DAM price in a sample hour that RVPP is energy buyer.

Table 2
Logic of different binary and auxiliary variables in Eqs. (11).

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

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 $p_t^{DA,A}$ has value only when the electricity price is at its median and RVPP is an energy buyer. These conditions are determined based on the binary variables $\chi_t^{\prime DA}$ and ι_t^{DA}, respectively. The logic of different binary and auxiliary variables in Eqs. (11) is represented in Table 2.

Fig. 3 shows the calculation of the average 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 ($\chi_t^{\prime DA} = 0$), 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 ($J^{\prime DA}_{z,t}$), the difference between the predicted price and the median price ($K^{\prime DA}_{z,t}$), and the final output energy of RVPP ($p_t^{DA,A}\Delta t$).

2.5.4. Average regret of SRM electricity price

Formulations (12) limit the average regret related to the uncertainty of the up and down SRM price.

$$\sum_{t\in\mathcal{T}}\sum_{z\in\mathcal{Z}}\left[J_{z,t}^{SR,\uparrow(\downarrow)}K_{z,t}^{SR,\uparrow(\downarrow)}r_t^{SR,Q,\uparrow(\downarrow)}\right] \leq \Gamma^{SR,\uparrow(\downarrow)}Reg^{Max,SR,\uparrow(\downarrow)}, \tag{12a}$$

$$r_t^{SR,Q,\uparrow(\downarrow)} = r_t^{SR,\uparrow(\downarrow)} - r_t^{SR,A,\uparrow(\downarrow)}\,, \quad \forall t \tag{12b}$$

$$r_t^{SR,Q,\uparrow(\downarrow)} \leq \bar{R}_t^{SR,\uparrow(\downarrow)}(1-\chi_t^{SR,\uparrow(\downarrow)})\,, \quad \forall t \tag{12c}$$

$$r_t^{SR,A,\uparrow(\downarrow)} \leq \bar{R}_t^{SR,\uparrow(\downarrow)}\chi_t^{SR,\uparrow(\downarrow)}\,, \quad \forall t \tag{12d}$$

$$r_t^{SR,Q,\uparrow(\downarrow)}, r_t^{SR,A,\uparrow(\downarrow)} \geq 0\,, \quad \forall t \tag{12e}$$

According to constraints (6b) and (6c), the SRM price takes two conditions (median and lower bound of the SRM price). The loss felt associated with the condition that the median value is chosen in the optimization problem compared to decisions with the lower SRM clearance price is calculated in (12). 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 average regret in (12a) is calculated by multiplying the probability of each segment of the PDF of the SRM electricity price ($J_{z,t}^{SR,\uparrow(\downarrow)}$), by the negative deviation of the SRM electricity price compared to the median value in each segment of the PDF of the SRM electricity price ($K_{z,t}^{SR,\uparrow(\downarrow)}$), and the total reserve traded by RVPP when the SRM price is at its median value, represented by the auxiliary variable $r_t^{SR,Q,\uparrow(\downarrow)}$. The average regret related to SRM price in (12a) is controlled by the user-defined coefficient $\Gamma^{SR,\uparrow(\downarrow)}$. The maximum regret parameter for the SRM price is calculated using $Reg^{Max,SR,\uparrow(\downarrow)} = \sum_{t\in\mathcal{T}}\sum_{z\in\mathcal{Z}} J_{z,t}^{SR,\uparrow(\downarrow)}K_{z,t}^{SR,\uparrow(\downarrow)}\bar{R}_t^{SR,\uparrow(\downarrow)}$. The state of the auxiliary variable $r_t^{SR,Q,\uparrow(\downarrow)}$ is controlled by (12b)–(12e) to set the regret value to zero when the SRM price deviates from its median to its worst case.

Fig. 4 shows the calculation of the average regret for the SRM electricity price. The regret must be considered for the time periods when the optimization problem chooses the median value for the SRM electricity price ($\chi_t^{SR,\uparrow(\downarrow)} = 0$). The regret for each segment of the PDF of the SRM electricity price is calculated based on the probability of each segment ($J_{z,t}^{SR,\uparrow(\downarrow)}$), the differences between the median electricity price and the predicted price ($K_{z,t}^{SR,\uparrow(\downarrow)}$), and the reserve bid of the RVPP in the SRM when the reserve price does not deviate ($r_t^{SR,Q,\uparrow(\downarrow)}$).

2.6. MILP formulation

The set of equations that formulates, as an MILP, the regret-based flexible RO problem of RVPP proposed in this paper is thus as follows: (2); (3); (4a); (4c)–(4d); (5b)–(5j); (6); (7); (8a); (8c)–(8h); (9); (10); (11); and (12). Note that (7a) is the objective function of the MILP problem. In addition to the input parameters related to the characteristics of the RVPP units, the forecast data of the units and the forecast data of the electricity prices, the RVPP operator needs to assign its per unit regret limit by having the estimation of the maximum possible regret to solve the optimization problem. The optimization results include the economic and technical outputs of the RVPP and its units.

3. Simulation results

The simulation results of the proposed regret-based flexible RO model for RVPP are presented in this section. Without loss of generality, an RVPP in southern Spain with one wind farm, two solar PV plants, and a flexible demand is first used in the simulations. The computational efficiency of the proposed model is then assessed using a larger RVPP comprising 21 units. This RVPP includes 10 PV plants, 7 wind farms, one ESS (LI-ION battery), and 3 demands. The data for these

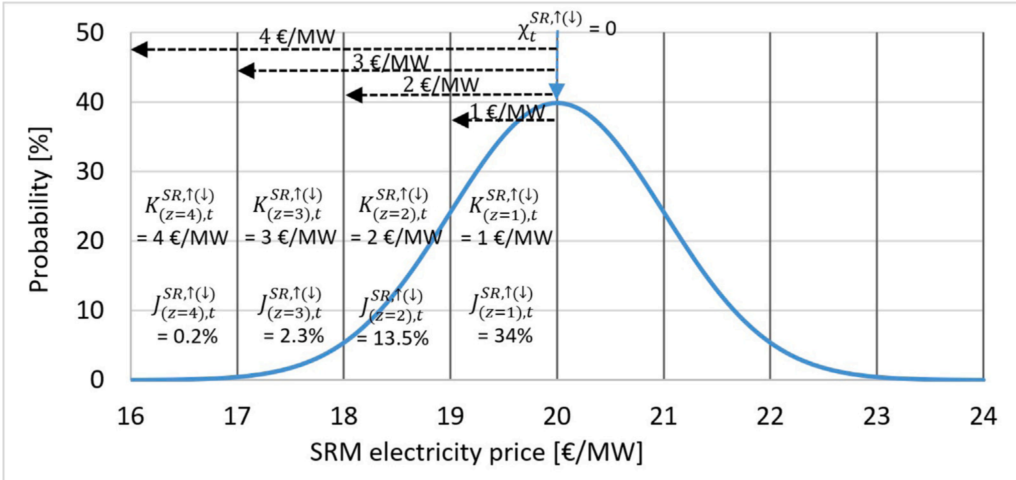

Fig. 4. Calculation of average regret according to the PDF of SRM price in a sample hour.

units are generated by applying specific modifications to the units in the *original* RVPP described above. The ESS model and its associated data are sourced from [36]. The energy forecast bounds for different units of RVPP for a sample day of the spring season in southern Spain are presented in Fig. 5 [37,38]. The nominal capacity of the wind farm and the solar PV plants is 50 MW, and their operation costs are 10 €/MWh and 5 €/MWh, respectively. A flexible demand with 10% tolerance for additional demand flexibility is considered according to [33]. The forecast bounds of DAM and SRM electricity prices, which are taken from [39], are shown in Fig. 6.

Three case studies are conducted to analyze the performance of the proposed model, as follows.

- Case 1: Determine the optimal scheduling and bidding of RVPP by considering different percentage of regret limit of RVPP output energy, and DAM and SRM electricity price. $\Gamma = \Gamma^{DA} = \Gamma^{SR} = 1.0 - 0$ for imbalance penalty cost $Z_t = 3$ times the DAM price.
- Case 2: Determine the necessary level of conservatism of RVPP against different uncertainties to obtain the maximum expected profit by considering different levels of forecast data accuracy and penalty costs in the BAM. $\Gamma = \Gamma^{DA} = \Gamma^{SR} = 1.0 - 0$; forecast deviations: 0%, 50%, and 100%; imbalance penalty costs $Z_t = 3$, 6 and 9 times the DAM price.
- Case 3: Evaluate the solution results and computational performance of the proposed model for an RVPP with 21 units, compared to the stochastic model presented in [27], using out-of-sample assessment. In the proposed model, $\Gamma = \Gamma^{DA} = \Gamma^{SR} = 1.0 - 0$, while the number of scenarios in the stochastic model [27] ranges from 10 to 50. The imbalance penalty cost, Z_t, is set to 9 times the DAM price.

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. The computation time of the different simulations of Case 1 and Case 2 ranges between 1 and 60 s, which is highly suitable for market optimization problems. Additionally, the computation time in Case 3 for different input parameters is less than 722 s, as detailed in Table 4.

3.1. Case 1

Fig. 6 shows the total traded energy and reserve of RVPP for different regret limits. Note that the input parameters Γ, Γ^{DA}, and Γ^{SR} are per-unit economic values, which user can quickly compute these values from reasonable monetary numbers. The results show that depending on the value of total production and demand, RVPP can be a seller or buyer of energy in the market. A similar trend regarding the trading energy direction of RVPP is kept for almost all regret limits except for hour 13. Between hours 1–7, although the demand is low, since the RVPP has no wind nor PV production in these hours, the RVPP is an energy buyer in the market. Between hours 8–9, the RVPP buys a significant amount of energy to supply its early morning demand. Between hours 14–19, due to the higher available energy of the ND-RESs of the RVPP and the reduction in demand, the RVPP behaves as an energy seller on the market.

For a per unit regret limit of 1.0, the uncertainty is not taken into account and the final values of DAM and SRM are equal to their median values. In this case, the RVPP usually sells more energy when it is an energy seller in the market and buys less energy when it is an energy buyer in the market compared to the lower per unit regret limits of 0.6 and 0.2. However, in some hours, for example hours 10, 14, 23, this is not the case because RVPP prefers to provide more reserve compared to the lower regret limits. For a per unit regret limit of 0.6, the DAM electricity price variables deviate from the median to their worst case in hours 9, 11, 16, and 17. When the RVPP is the energy seller, the worst condition for the electricity price is when the price takes its minimum value, and for an energy buyer RVPP it occurs in the maximum bound of the electricity price forecast. The worst hours for the SRM prices are hours 17 and 18. For a regret limit of 0.2 per unit, the DAM and SRM electricity price deviations from the median to the worst case occur more often than for the regret limits of 1.0 and 0.6 per unit. The worst cases of positive deviations of DAM electricity price occur in hours 8, 9, 10, 11, 13, and 21, while the worst cases of negative DAM electricity price deviations occur in hours 16, 17, 18, and 20. In most of these hours, the traded energy of RVPP is high, which results in the highest negative impact on the objective function.

Fig. 7 shows different financial metrics of RVPP for different per unit regret limits. The negative value for incomes means that the RVPP incomes from selling electricity are less than the RVPP costs of buying electricity from the market. The incomes come from bidding for the energy and/or reserve in the DAM and SRM (first term in the objective function (7a)). The operation costs are the second and third terms of (7a). The profit is the incomes from bidding on the market minus operation costs. The expected profit is the profit minus the robust cost (fourth term of (7a)) minus any regret cost (Eqs. (10a), (11a), (11b), and (12a)), which can be declared as the final profit of RVPP by taking into account the bidding and the clearing of the BAM. By considering a per unit regret limit of 1.0, the RVPP obtains the highest profit. However, this approach can result in a significant amount of regret. By lowering the regret limit, both the profit and the regret of RVPP decrease. The operation cost of RVPP for lower values of the regret limits is reduced because RVPP produces less energy in the

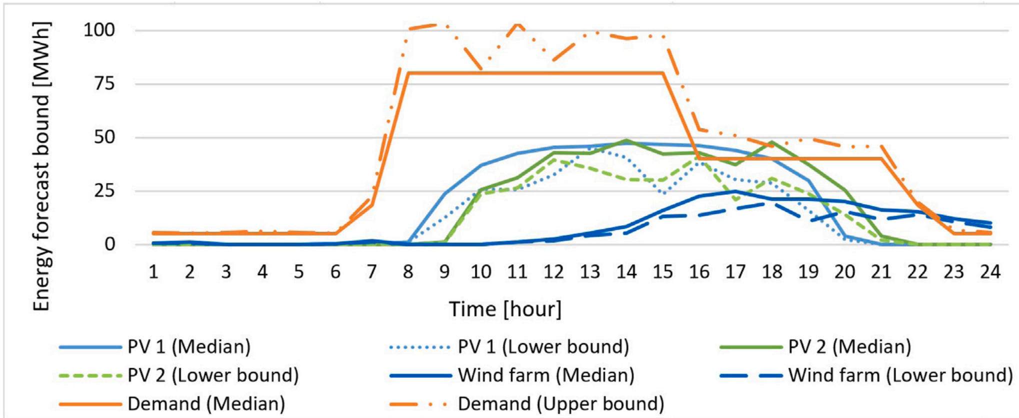

Fig. 5. The energy forecast data.

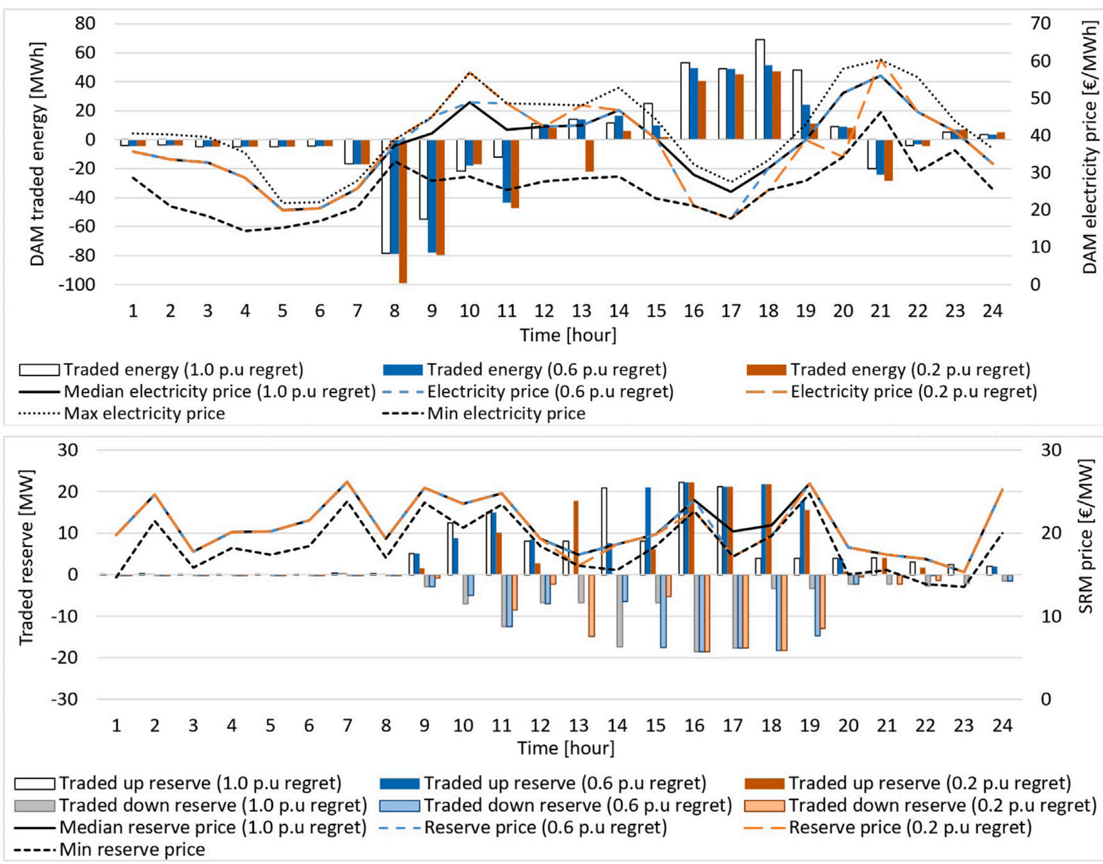

Fig. 6. RVPP traded energy and reserve versus electricity price for different regret limits $\Gamma = \Gamma^{DA} = \Gamma^{SR} = 1.0, 0.6, 0.2$ per unit.

market and buys more energy. In Fig. 7, the RVPP decision areas are categorized as optimistic, balanced, and pessimistic as an example. In this case, the RVPP with an optimistic decision (for regret limit per unit between 1.0–0.7) can achieve a higher expected profit compared to more conservative strategies. The maximum expected profit of −9.56 k€ on the market is obtained by considering a regret limit per unit of 0.9. Note that in the Case 2, it is shown that the best decision of RVPP to achieve the highest expected profit varies depending on the forecast accuracy and BAM penalty cost.

Table 3 shows the information about the number of hours the uncertain parameters deviate from the median value to the worst case (uncertainty budget in the literature). The table shows that to achieve a per unit regret limit of 0.7, the worst case hours for all uncertain parameters are equal to or less than 2. To achieve lower regret limits, deviations of more uncertain parameters are needed. To achieve a low per unit regret limit of 0.2, the maximum number of hours chosen for the uncertain parameters deviations related to SRM price and ND-RESs/demand energy is 4.

3.2. Case 2

Fig. 8 shows the expected profit of RVPP for different forecast deviations and different penalty costs Z_t. For all penalty costs, a similar trend can be seen in the figure. By decreasing the regret limit, the expected profit first increases, since the decrement of the regret costs reduction is usually greater than the decrement of the profit reduction for higher values of the regret limit. This is due to the fact that a few

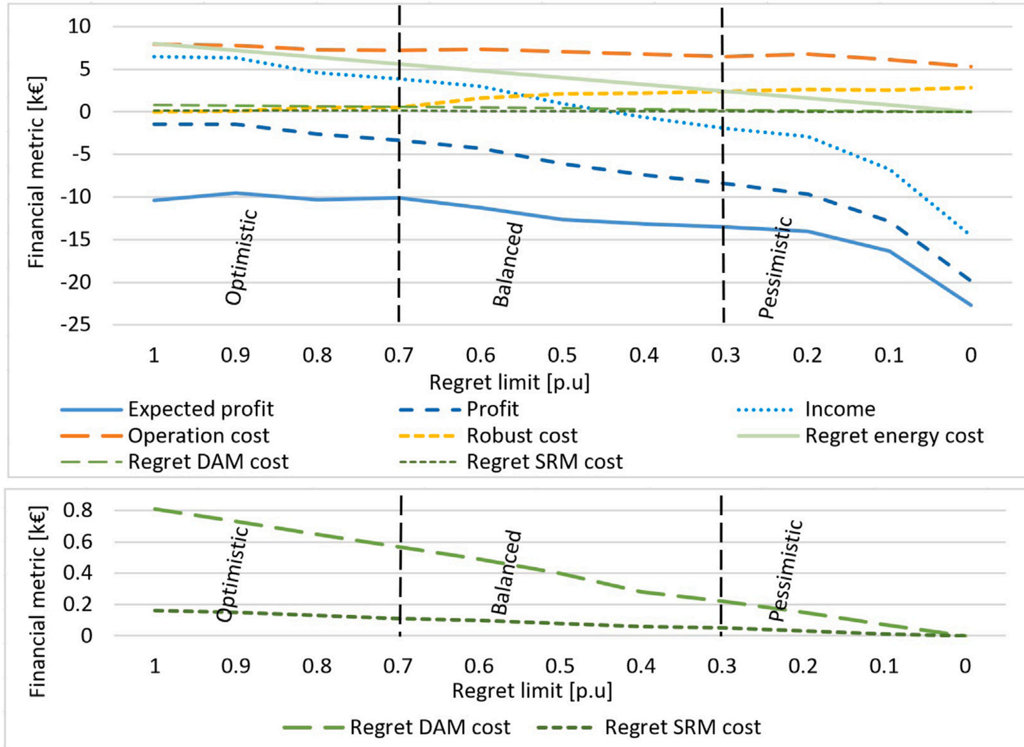

Fig. 7. Financial metrics of RVPP by considering different regret limits $\Gamma = \Gamma^{DA} = \Gamma^{SR} = 1.0 - 0$ per unit.

Table 3
Number of parameters' deviations from the median value to the worst case versus regret limits Γ, Γ^{DA}, and Γ^{SR}.

$\Gamma, \Gamma^{DA}, \Gamma^{SR}$ [p.u]	DAM price [–]	Up/down SRM price [–]	Wind/PV1/PV2/demand [–]
1.0	0	0	0,0,0,0
0.9	0	0,1	0,0,0,0
0.8	1	2,2	2,0,0,1
0.7	1	2,2	2,0,1,1
0.6	4	2,2	2,0,0,2
0.5	5	4,4	1,3,1,2
0.4	7	3,3	2,1,3,2
0.3	9	4,4	4,2,4,3
0.2	10	4,4	3,2,2,4
0.1	14	5,5	6,5,6,4
0	24	11,11	22,22,22,24

hours for the high regret limits are chosen as the worst case in the optimization problem (see Table 3), and these hours are the hours that have the greatest impact on regret reduction. By decreasing the regret limit after reaching the maximum expected profit, the expected profit has a slow decreasing trend up to a certain regret limit. For the low values of the regret limits, the expected profit decreases significantly due to the fact that the profit of RVPP suddenly decreases, while reducing the regret cost becomes more difficult and requires selecting more number of hours as the worst-case hours. For the higher values of the penalty cost, the RVPP must adopt more conservative strategies to achieve the maximum expected profit. The figure also shows that the expected profit of RVPP decreases as the percentage of forecast deviation increases. For the high regret limits, the expected profit reduction is less than for the lower value of the regret limits. This is due to the fact that a higher number of hours is selected as the worst case for the lower regret limits. The RVPP operator can use this figure to decide its appropriate level of conservatism against different uncertainties. The results of this figure will guide the RVPP operator when bidding in the market. For example, for the $Z_t = 3, 6, 9$ times the DAM price, the optimistic, balanced, and pessimistic decisions against different uncertainties would each be appropriate approaches for the RVPP in each case.

3.3. Case 3

Fig. 9 shows the traded energy of the RVPP with 21 units, along with the output energy of its different production technologies and demands. The results indicate that the RVPP acts as an energy buyer in the market between hours 1–10 and as an energy seller between hours 11–24. The output energy from the RVPP units demonstrates that a significant portion of the RVPP energy comes from solar PVs production. The figure also shows that the ESS mainly discharges between hours 7–9 and 20–22, to meet early morning and late-day demands, as solar PV production is zero or small at these hours. The ESS charges mainly between hours 16–19 when solar PV production is high and demand is lower.

The performance of the proposed model is compared against the stochastic model [27] using an out-of-sample assessment presented in [10]. To ensure a fair comparison, scenarios for different uncertain parameters in the stochastic programming model [27] are generated using Monte Carlo sampling based on the same historical dataset used to determine the bounds of the uncertain parameters in the proposed model. Additionally, distinct sets of data are utilized for the models and the out-of-sample assessment. It is worth noting that, for a fair comparison between the proposed model and the model in [27], the same set of scenarios is used for the out-of-sample assessment, ensuring that the same randomness (or uncertainty) is introduced in both methods. The basic idea is to compare both methods under similar experimental conditions to ensure that any observed differences in performance are attributable to differences in the methodologies rather than to fluctuations in the experimental conditions.

Table 4 presents the out-of-sample assessment results for the proposed model under different per-unit regret limits. The table represents

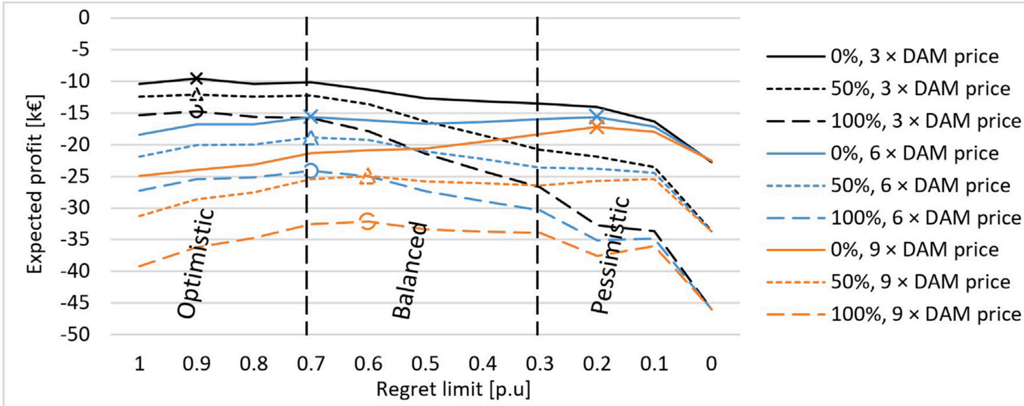

Fig. 8. Expected profit of RVPP for different forecast deviations 0%, 50%, and 100%, for different penalty costs $Z_t = 3, 6, 9 \times$ DAM price for $\Gamma = \Gamma^{DA} = \Gamma^{SR} = 1.0 - 0$ per unit.

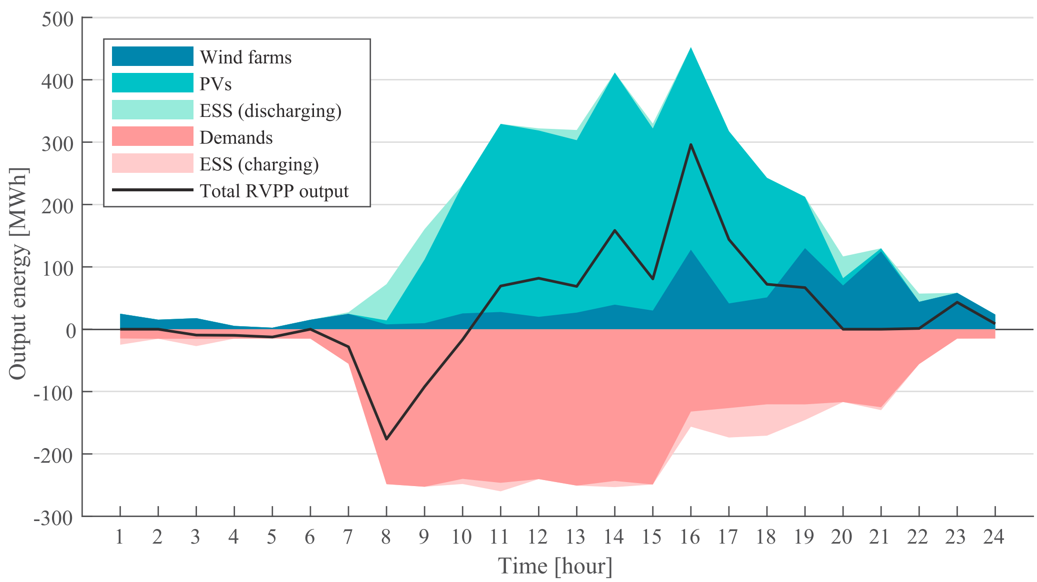

Fig. 9. Traded energy of RVPP with 21 units and the output energy of its different units ($\Gamma = \Gamma^{DA} = \Gamma^{SR} = 0.2$ per unit).

the average sampled profit (excluding the penalization cost in each sample), the average sampled penalization cost, and the average sampled net profit (calculated as the average sampled profit minus the penalization cost). These metrics are defined in [10]; for more information, refer to the paper. The simulation results show that decreasing the per-unit regret limit (by adopting more robust strategies) significantly reduces the penalization cost of the RVPP, leading to a higher net profit for the RVPP. The RVPP achieves its highest net profit by adopting a per-unit regret limit of 0.2. For this regret limit, the penalization cost is reduced by 70.7% compared to the penalization cost at the maximum per-unit regret limit of 1. Table 5 provides the results for the stochastic programming model presented in [27], considering different numbers of scenarios. As the number of scenarios increases, the net profit of the RVPP also improves, underscoring the importance of selecting an appropriate number of scenarios in the stochastic optimization problem. The maximum net profit of the RVPP is achieved with 50 scenarios. However, the computational burden for 50 scenarios increases significantly, reaching 12,474 s.

To further illustrate the effectiveness of the proposed method, Figs. 10, 11, and 12 illustrate the distribution of different out-of-sample financial metrics across samples for the proposed model in comparison to the stochastic programming model [27]. The per-unit regret limit of 0.2 in the proposed model and 50 scenarios in the model presented by [27] are selected for comparison, as these values result in the highest net profit for each model. The results demonstrate that the proposed model effectively maximizes the RVPP's net profit across samples. Samples with higher profit occur more frequently in the model presented by [27] compared to the proposed model, as shown in Fig. 10. However, Fig. 11 demonstrates that the proposed model performs better in reducing penalization costs, with high penalization costs occurring less frequently. The proposed approach handles worse-case condition better than stochastic programming in most samples. In contrast, the stochastic programming model provides a less resilient solution that offers less protection against penalization compared to the

Table 4
The out-of-sample assessment for the proposed model (21-unit RVPP) for $\Gamma = \Gamma^{DA} = \Gamma^{SR} = 1.0 - 0$ per unit.

$\Gamma, \Gamma^{DA}, \Gamma^{SR}$ [p.u]	Average sampled profit [k€]	Average sampled penalization cost [k€]	Average sampled net profit [k€]	Computational time [s]
1	45.24	63.62	−18.38	9
0.8	42.39	56.52	−14.13	73
0.6	37.62	54.79	−17.17	217
0.4	32.25	39.65	−7.40	404
0.2	23.34	18.60	4.74	722
0	11.61	7.33	4.28	114

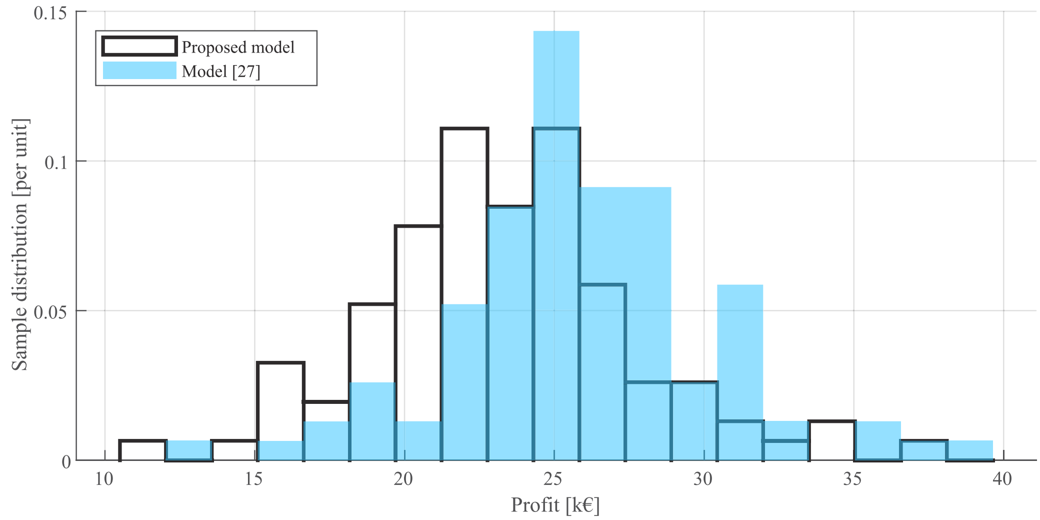

Fig. 10. Sample distribution of profit for the proposed model and the model in [27] ($\Gamma = \Gamma^{DA} = \Gamma^{SR} = 0.2$ per unit or 50 scenarios).

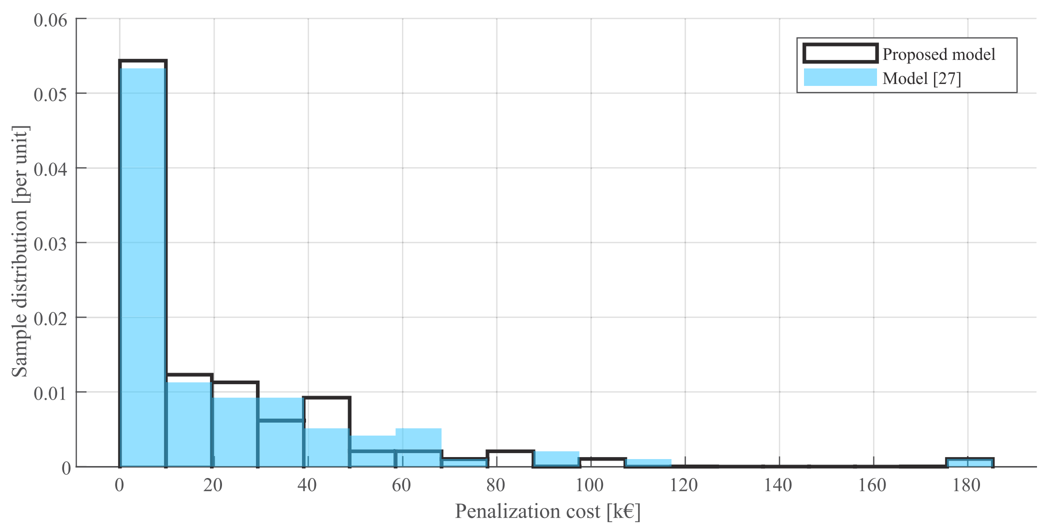

Fig. 11. Sample distribution of penalization cost for the proposed model and the model in [27] ($\Gamma = \Gamma^{DA} = \Gamma^{SR} = 0.2$ per unit or 50 scenarios).

Table 5
The out-of-sample assessment for the stochastic programming model [27] (21-unit RVPP) for the number of scenarios ranges from 10 to 50.

Number of scenarios [–]	Average sampled profit [k€]	Average sampled penalization cost [k€]	Average sampled net profit [k€]	Computational time [s]
10	40.65	44.08	−3.43	57
20	36.08	34.99	1.09	851
30	35.69	34.67	1.01	784
40	27.73	26.31	1.42	1574
50	25.94	21.03	4.91	12 474

proposed regret-based model. Finally, the results in Fig. 12 for the net profit of the RVPP demonstrate the strong performance of the proposed model across different samples.

4. Conclusion

This paper studies the simultaneous participation of RVPP in the day ahead and secondary reserve markets by considering the imbalance penalty cost in the balancing market. The concept of average regret is used to assist the RVPP operator in visualizing the appropriate degree of conservatism against multiple uncertain parameters in the day ahead and secondary reserve market electricity prices, as well as the output energy of the RVPP. The proposed regret-based flexible robust optimization model provides a more convenient way to determine the level of conservatism of the RVPP operator by determining the monetary parameter of the regret limit instead of the uncertainty budget used in the literature. The simulation results show that the hours with the highest traded energy are usually selected as the worst cases of the electricity price. By decreasing the regret limit, the sold and bought energy of RVPP is decreased and increased, respectively. Furthermore, the simulation results illustrate that depending on the desired regret limit of the RVPP, the penalty cost in the balancing market, and different forecast deviations, the best decision for RVPP can be an optimistic, balanced, or conservative strategy. Finally, the simulation results for a larger RVPP demonstrate the computational efficiency of the proposed method. In the future work, the proposed average regret concept will be developed in the adaptive robust optimization of RVPP.

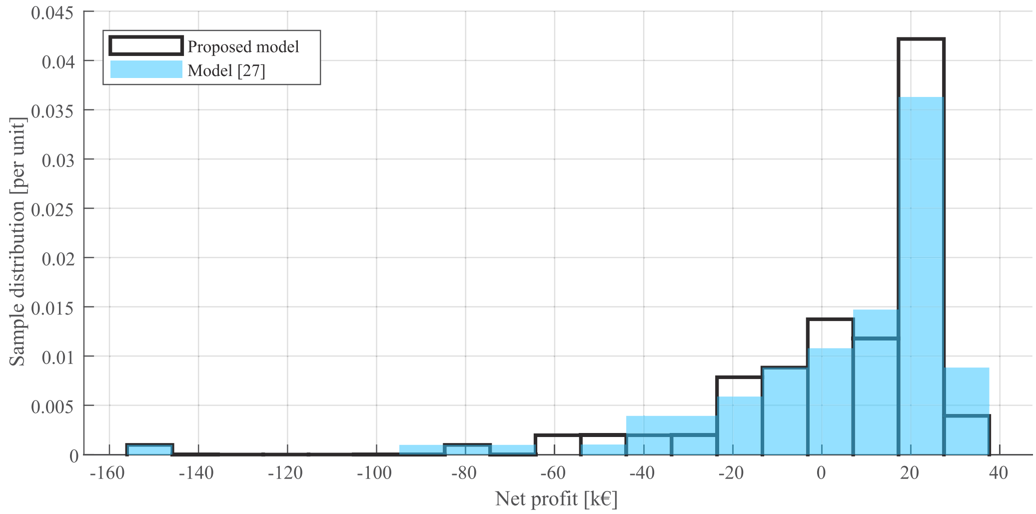

Fig. 12. Sample distribution of net profit for the proposed model and the model in [27] ($\Gamma = \Gamma^{DA} = \Gamma^{SR} = 0.2$ per unit or 50 scenarios).

CRediT authorship contribution statement

Hadi Nemati: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Pedro Sánchez-Martín:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Investigation, Conceptualization. **Lukas Sigrist:** Writing – review & editing, Project administration, Funding acquisition. **Luis Rouco:** Writing – review & editing, Project administration, Funding acquisition. **Álvaro Ortega:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Investigation, Conceptualization.

Declaration of competing interest

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.

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Data availability

Data will be made available on request.

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