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Risk-Constrained Self-Scheduling of a Hybrid Power Plant Considering Interval-Based Intraday Demand Response Exchange Market Prices

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Abstract

Hybrid power plants (HPPs) integrating dispatchable and non-dispatchable generation are gaining attention by generation companies due to their increased flexibility in the operation of the power system. In this paper, an offering and bidding framework for an HPP consisting wind, photovoltaic (PV), compressed air energy storage (CAES), battery energy storage (BES), and thermal units in day-ahead (DA) and intraday markets is presented. Moreover, the interaction between the HPP and demand response providers (DRPs) through the intraday demand response exchange (IDREX) market is incorporated into the proposed model. The existing uncertainties such as DA, intraday, imbalance prices, along with renewable energy and IDREX market, are tackled via a hybrid stochastic-interval approach. The suggested structure is not only capable of handling both stochastic and interval uncertainties but also can manage the risk associated with both uncertainty characterization methods. To this end, the proposed risk-constrained offering and bidding model turns into a tri-objective optimization problem in which the normal boundary intersection (NBI) procedure is applied for its solution. The numerical results demonstrate that the proposed framework

is well capable of simultaneously reaching risk-taker and risk-averse strategies.
Keywords: Electricity markets, Hybrid Power Plant (HPP), Hybrid stochastic-interval model, Multi-objective approach, Offering and bidding strategies.

1. Introduction

The decarbonized electricity industry with increased infiltration of renewable energy sources faces numerous challenges. The intermittent nature of renewable production, especially coming from wind, has increased the necessity of using energy storage systems and demand-side flexibility [1]. According to [2], supplying notable levels of electricity demand would not be possible without the utilization of energy storage systems. Batteries, pumped hydro storage plants, and compressed air energy storage (CAES) technologies are among the most prominent and the most widely-used energy storage technologies in electric power industries. The investigations show that increasing the usage level of large-scale energy storage systems reduces pollution and curtailed energy in a power system with high infiltration of renewable sources [3].

Significant interest in the offering strategy of energy storage technologies, such as CAES and battery energy storage (BES) systems in electricity markets has been shown in the last years [4]-[10]. Risk-based participation of a large-scale CAES in the day-ahead (DA) market is presented in [4], while the DA price is considered as the uncertain parameter. The authors have benefited from the information gap decision theory to derive risk aversion and risk-seeking strategies. In [5], the impact of thermodynamic specifications of a CAES system on the self-scheduling problem is analyzed. The self-scheduling of a price-maker CAES system in the electricity market for a five-year scheduling horizon is studied in [6]. In [7], a look-ahead approach for optimal participation of a CAES facility in the DA, ancillary service, and real-time markets has been presented. From another viewpoint, the optimal operation of a BES system in various electricity markets, by incorporating the battery cycle life in the bidding mechanism, has been assessed in [8]. In [9], a bidding framework for optimal involvement of a price-maker energy storage facility in DA and balancing markets was developed. In [10], the authors have presented a new pattern for optimal involvement of a BES unit in energy and reserve markets considering battery degradation.

At the same time, the design of appropriate decision-making tools for the participation of intermittent energy resources in diverse electricity markets has also been extensively studied. The comprehensive problem formulation for the strategic operation of a wind turbines is presented in [11]. A CVaR-constrained architecture for a price-maker wind plant is discussed in [12]. Another approach based on the joint offering of a set of wind power plants in the DA market has been suggested in [13]. In [14], an offering model for a photovoltaic (PV) system in DA and intraday markets was suggested. It is worth mentioning that in works [11]-[14], multi-stage stochastic programming has been employed to tackle the present uncertainties efficiently.

In many cases studied so far, the offering model is based on the coordinated operation of several production units, in order to increase their profitability. In this regard, the final profit is considered as the main parameter for evaluating the effectiveness of the offering mechanism. A combined offering structure for both demand response resources and wind farms by means of stochastic programming has been addressed in [15]. A different structure for the joint offering of wind farms and demand response resources using a three-stage stochastic model has been provided in [16]. In [17], the optimal behavior of electric vehicle aggregators in DA and intraday markets has been investigated, while the interaction between electric vehicle aggregators and demand response resources has been established through intraday demand response exchange (IDREX) market. An offering strategy for a wind power installation paired with an electric vehicle aggregator has been proposed in [18]. It has to be noted that all papers, [15], [16], and [17], have suggested different participation types of demand response resources in their offering framework, while all of them are profitable. Moreover, a bidding approach for a virtual power plant in the attendance of the IDREX market has been developed in [19]. Another methodology for offering and bidding strategies of a pumped hydro storage plant in the DA market based on the downside risk optimization model has been suggested in [20]. It is noteworthy to say that since hydro units are capable to provide regulation reserve services [21], an efficient offering and bidding strategy in the ancillary service markets, comprising regulation and spinning reserve markets, can further enhance the profitability of hydro power producer units [22]. These are not considered in this paper.

The variety of self-scheduling or offering/bidding strategy problems in the literature is enormous. So here, it has been attempted to review the most pertinent works to this study. In addition to the previously reviewed works [4]-[20], a distributionally robust optimization-based methodology has been applied for the bidding behavior of a wind-hydro power system in [23]. In [24], an economic-environmental offering strategy for a wind-thermal-PV producer on the basis of emission trading pattern has been introduced. A risk-based decision-making tool for participation of a wind-storage generation company with linear decision rules has been proposed in [25]. In [26], a robust chance-constrained framework has been established for the self-scheduling of a price-maker wind-storage system in the DA market. In [27], a distributionally robust model has been established for the bidding strategy of a wind-BES producer in the DA and balancing markets. A risk-based offering pattern for the joint operation of a solar plant, a BES system, and thermal units has been studied in [28], employing a three-stage stochastic framework to tackle related uncertainties. The same uncertainty modeling technique for the self-scheduling of a wind-CAES system has been applied in [29]. A robust-based model for a participation of a thermal-BES system in the DA market by taking into account the physical connection between thermal units and the BES system has been suggested in [30]. Finally, a risk-involved offering approach for a wind-CAES plant on the basis of three-stage stochastic programming was suggested in [31].

This paper focuses on the coordinated self-scheduling of a price-taker hybrid power plant (HPP) in DA and intraday markets under a uniform pricing plan. The proposed HPP possesses wind and PV units as renewable energy sources, BES and CAES as storage facilities, and thermal units as the conventional generation units. Besides, the energy procurement mechanism from demand response providers (DRPs) through the IDREX market is embedded in the proposed structure to decrease the HPP's imbalance cost. The uncertainty associated with the IDREX market is taken into account via interval numbers, while uncertainty and volatility originating from pool prices along with renewable power generation are modeled via a three-stage scenario-based method. The intended problem is then transformed into a hybrid stochastic-interval optimization problem. In order to facilitate the adoption of risk-based strategies for optimal self-scheduling of the HPP, a multi-objective optimization framework is proposed to manage risk associated with both interval and stochastic parameters. In summary, the contributions of this work in comparison to previous studies in the relevant context which have been analyzed in Table 1 can be outlined as follows:

1. We present a coordinated operation strategy for optimal participation of an HPP containing wind, PV, BES, CAES, and thermal units in DA and intraday markets. To the authors' knowledge, no study in the literature tackles the self-scheduling problem of an HPP with all these mentioned elements. Referring to Table 1, this study is one of the most comprehensive studies in the literature that provides a coordinated self-scheduling architecture from the viewpoint of a hybrid power plant that holds the most prominent electricity suppliers in electricity markets worldwide.
2. For the first time in the literature, we address the uncertainty concerns in the IDREX market price using the interval arithmetic, which has not been covered in [17] and [19]. Embedding the energy procurement capability from the IDREX market aids the HPP to further mitigate its power deviations in the balancing market resulting from the electricity production of intermittent power units, namely, wind and PV units. In this regard, according to reviewed works [4]-[31], a very limited number of papers has

included the IDREX market into their methodology [17] and [19], whereas none of these works copes with the uncertainty stemming from the IDREX market price.

3. We propose a framework for simultaneous managing the risk associated with both interval and stochastic parameters. In this regard, to the best of the authors' knowledge, for the first time in the literature, two risk measuring indices corresponding to stochastic and interval parameters, namely, conditional value-at-risk (CVaR) and deviation of the objective function, are simultaneously controlled. The proposed problem is transformed into a tri-objective optimization problem to facilitate the adoption of risk-based strategies. The proposed stochastic-interval model can provide a new direction for researchers in the context of power system and operations research to simultaneously capturing the risk and uncertainty of interval and stochastic parameters.

4. We employ the normal boundary intersection (NBI) method to solve the developed multicriteria optimization model in 3., while the proficiency of the suggested method in terms of covering the whole Pareto frontier is analyzed. Most of the bi-objective stochastic programming models for the self-scheduling problem in the existing literature have employed the weighted sum technique [12], [14]-[16], and [31], while in this paper, the NBI procedure is applied to resolve the weakness of the weighted sum approach in covering the entire Pareto frontier. It is worth mentioning that the efficiency of the NBI technique compared to the weighted sum method is investigated in a bi-objective optimization study, whereas no tri-objective optimization architecture exists in the literature.

Section 2 provides the stochastic coordinated operation model. Section 3 presents the proposed hybrid stochastic-interval approach. Section 4 gives the numerical results, and lastly, Section 5 presents the conclusions.

Table 1: Comparison between different aspects of this work and the reviewed papers.

Ref.	System	Considered markets			Modeling approach	Risk parameter	DR	Offering curve	Bidding curve
		DA	Intraday	Balancing					
[4]	CAES	Yes	-	-	IGDT-based MINLP	IGDT	-	Yes	Yes
[5]	CAES	Yes	-	-	Deterministic MILP	-	-	-	-
[6]	CAES	Yes	-	-	Deterministic MILP	-	-	Yes	Yes
[7]	CAES	Yes	-	Yes	Deterministic MILP	-	-	-	-
[8]	BES	Yes	-	Yes	Stochastic NLP	-	-	-	-
[9]	BES	Yes	-	Yes	Stochastic MILP	-	-	-	-
[10]	BES	Yes	-	-	Deterministic MILP	-	-	-	-
[11]	Wind	Yes	-	Yes	Two-stage stochastic MILP	-	-	-	-
[12]	Wind	Yes	-	Yes	Two-stage stochastic MILP	Stochastic	-	Yes	Yes
[13]	Wind	Yes	Yes	Yes	Three-stage stochastic MILP	Stochastic	-	-	-
[14]	PV	Yes	Yes	Yes	Two-stage stochastic MILP	Stochastic	-	-	-
[15]	Wind	Yes	-	Yes	Stochastic MILP	Stochastic	Yes	-	-
[16]	Wind	Yes	Yes	Yes	Three-stage stochastic MILP	Stochastic	Yes	Yes	-
[17]	EVA	Yes	Yes	Yes	Three-stage stochastic MILP	-	Yes	-	-
[18]	Wind+EVA	Yes	-	Yes	Stochastic MILP	Stochastic	-	Yes	Yes
[19]	VPP	Yes	Yes	Yes	Three-stage stochastic MILP	-	Yes	-	-
[20]	Pumped hydro	Yes	-	-	Downside risk MILP	Stochastic	-	Yes	Yes
[23]	Wind+ hydro	Yes	-	-	Distributionally robust MILP	robust	-	-	-
[24]	Wind+PV+ Thermal units	Yes	-	Yes	Stochastic MILP	-	-	Yes	-
[25]	Wind+BES	Yes	-	Yes	Two-stage stochastic MILP	Stochastic	-	-	-
[26]	Wind+BES	Yes	-	-	Robust chance-constrained MILP	Robust	-	-	-
[27]	Wind+BES	Yes	-	Yes	Distributionally robust MILP	Robust	-	-	-
[28]	PV+BES+ Thermal units	Yes	-	Yes	Two-stage stochastic MILP	Stochastic	-	Yes	-
[29]	Wind+CAES	Yes	-	Yes	Adaptive robust MILP	Robust	-	-	-
[30]	BES+Thermal units	Yes	-	-	Robust MILP	Robust	-	-	-
[31]	Wind+CAES	Yes	Yes	Yes	Three-stage stochastic MILP	Stochastic	-	Yes	Yes
This work	CAES+BES+ Wind+PV+ Thermal units	Yes	Yes	Yes	Three-stage hybrid stochastic-inteval MILP	Stochastic+ interval	Yes	Yes	Yes

Note: DR-Demand Response; MINLP-Mixed Integer Nonlinear Programming; IGDT-Information Gap Decision Theory; MILP-Mixed Integer Linear Programming; NLP-Nonlinear Programming; EVA-Electric Vehicle Aggregator; VPP-Virtual Power Plant; DRO-Distributionally Robust Optimization

2. Stochastic Coordinated Operation Model

Here, the stochastic formulation of the self-scheduling problem for the intended HPP in DA and intraday markets is presented, while CVaR is incorporated as the risk assessment method. The proposed self-scheduling model is expressed as a three-stage bi-objective mixed-integer linear programming (MILP) problem, while the volatility and the uncertainty arising from output power of renewable sources and electricity market prices are managed with stochastic scenarios, and the HPP's expected profit and CVaR are two objective functions of the self-scheduling problem. It is worthwhile to note that the considered market framework in this work follows the structure proposed in [16]. The sequence of decisions made at each stage of the developed three-stage architecture (Table 2) are as follows:

1. The first series of the first-stage decisions, i.e., *here-and-now* decisions, includes the operation modes of conventional power units and storage facilities. The second series named *special here-and-now* decisions involves participation packages of all units in the DA market. Ref. [32] has called the second series *special here-and-now* decisions since they are dependent on DA price scenarios.
2. The second-stage decisions, i.e., 1^{st} *wait-and-see* decisions, are related to the energy transaction of the HPP in the intraday market as well as energy procurements in the IDREX market.
3. Finally, the last-stage decisions, i.e., 2^{nd} *wait-and-see* decisions, cope with the HPP's energy deviation in the balancing market.

Accordingly, as we express in the subsequent section, the final structure of the self-scheduling problem would be a tri-objective hybrid stochastic-interval optimization model by incorporating the uncertainty of the IDREX market into the scenario-based bi-objective model proposed in this section. In the following, first, the nomenclature list is given, and then, the mathematical formulation of the stochastic model is presented.

Table 2: The sequence of decisions at the elaborated three-stage stochastic programming model.

<table>
<tr><th colspan="4">Decisions made at each stage</th></tr>
<tr><th colspan="2">First-stage</th><th>Second-stage</th><th>Third-stage</th></tr>
<tr><th>Here-and-now</th><th>Special here-and-now</th><th>1^{st} Wait-and-see</th><th>2^{nd} Wait-and-see</th></tr>
<tr><td>$v_t^{ch/dis}$, $u_t^{ch/dis/s}$
$x_{g,t}$, $y_{g,t}$, $z_{g,t}$</td><td>$\chi_{t,\theta}^{D,RE}$, $\chi_{t,\theta}^{D,Th}$
$\chi_{t,\theta}^{D,B,dis}$, $\sigma_{t,\theta}^{D,B}$
$\chi_{t,\theta}^{D,C,dis/s}$, $\sigma_{t,\theta}^{D,C}$</td><td>$\chi_{t,\theta}^{I,RE}$, $\sigma_{t,\theta}^{I,RE}$, $\chi_{t,\theta}^{I,Th}$
$\chi_{t,\theta}^{I,B,dis}$, $\sigma_{t,\theta}^{I,B}$, $\sigma_{t,\theta}^{I,C}$
$\chi_{t,\theta}^{I,C,dis/s}$, $\nu_{f,t,\theta}$</td><td>$\delta_{t,\theta}^{+}$, $\delta_{t,\theta}^{-}$, $\delta_{t,\theta}$</td></tr>
</table>

Nomenclature

Indices

f	Index concerning blocks of the DRP's offer (1 to N_F).
g	Index of thermal (conventional) units (1 to N_G).
m	Index of blocks in the linearized cost curve (1 to N_M).
q	Index of objective functions (1 to N_Q).
t	Index of time periods (1 to N_T).
θ	Index of scenarios (1 to N_θ).

Superscripts

B (C)	An index reflecting BES (CAES) variables.
$ch/$ $dis/$ s	Indices reflecting charging/discharging/simple-cycle mode of storage facilities.
$D/$ $I/$ IX	Indices of DA/ intraday/ IDREX market variables.
HPP	An index reflecting HPP variables.
RE (Th)	An index reflecting renewable energy sources (thermal units) variables.
Sch	An index reflecting the total scheduled power.

Parameters

$CapDR$	Maximum offering capacity of DRPs, MW.
$Cap^{I,HPP,se(bu)}$	Maximum permissible selling (buying) energy of the HPP in the intraday market, MW.

Cap^{RE}	Rated capacity of renewable energy resources, MW.
CF	Blocks' slope in the linearised cost curve of thermal units (€/MWh).
$ELMax$	Maximum permitted stored energy in storage facilities, MWh.
Htr/ER	CAES heat rate (MBtu/MWh)/ energy ratio.
$Max^{ch(dis)}$	Maximum charging (discharging) limit of the BES, MW.
$Max^{co(exp)}$	Maximum compression (expansion) limit of the CAES, MW.
$Max^{Th}(Min^{Th})$	Maximum (minimum) allowed power of thermal units, MW.
NGP	Price of natural gas, €/MBtu.
$OM^{co(exp)}$	CAES maintenance and operation costs during compressing (expanding) mode, €/MWh.
$RU(RD)$	Upward (Downward) ramping rate of conventional units.
$SRD(SRU)$	Shut-down (Start-up) ramp limit of conventional units.
SUC (SDC)	Cost of conventional units' start-up (shut-down), €.
α	Parameter indicating the confidence level.
$\kappa^{up(down)}$	Minimum up (down) time of conventional units.
λ	A factor for restricting the participation level of the system in the intraday market.
ν^{Max}	Maximum procured energy in each block of the DRP's offering curve, MW.
π_{θ}	Probability of stochastic scenarios.
Υ	BES efficiency.
$\underline{\varphi^{IX}}$ $(\overline{\varphi^{IX}})$	Lower (upper) bound of IDREX market price, €/MWh.
Variables	
DR	Total procured energy from DRPs, MW.
EL	Stored energy in storage facilities, MWh.
$P^{Sch,HPP}$	Final scheduled power of the HPP, MW.
RP	Actualized production power, MW.
SU (SD)	A variable indicating cost of conventional units' start-up (shut-down), €.
$v/\ u$	Binary variables reflecting the status of the BES/ CAES system.
$x/\ y/\ z$	Binary variables reflecting the start-up/ shut-down/ online status of conventional units.
γ	Value-at-risk, €.
$\delta_{t,\theta}^{-(+)}$	Upward (downward) imbalance in the balancing market, MWh.

$\delta_{t,\theta}$	HPP's total energy deviations, MWh.
η_θ	Ancillary variable used for CVaR computation.
ν	Procured energy in each block of the DRP's offering curve, MW.
$\rho_{t,\theta}^{-(+)}$	Upward (downward) imbalance ratio.
σ	Bidding (purchasing) quantity, MW.
φ	Energy price of electricity markets, €/MWh.
χ	Offering (selling) quantity, MW.

Abbreviations

BES	Battery energy storage.
CAES	Compressed air energy storage.
CVaR	Conditional value-at-risk.
DA	Day-ahead.
DR	Demand response.
DRP	Demand response provider.
HPP	Hybrid power plant.
IDREX	Intraday demand response exchange.
MILP	Mixed-integer linear programming.
NBI	Normal boundary intersection.
PV	Photovoltaic.

2.1. Objective functions

2.1.1. First objective function: Maximizing HPP's expected profit

The first objective function aims at maximizing the expected profit of the HPP through involving in multiple markets throughout the trading horizon. This objective function can be written as:

$$\text{Max } H1(x) = \sum_{\Theta=1}^{N_\theta} \pi_\theta \times [\text{Profit}_\theta] \tag{1}$$

$$
\begin{aligned}
\text{Profit}_\theta = \sum_{t=1}^{N_T} \Bigg[& \varphi^D_{t,\theta}\chi^{D,RE}_{t,\theta} + \left(\sum_{g=1}^{N_G} \varphi^D_{t,\theta}\chi^{D,Th}_{g,t,\theta}\right) + \varphi^D_{t,\theta}\chi^{D,B,dis}_{t,\theta} + \varphi^D_{t,\theta}\chi^{D,C,dis}_{t,\theta} + \varphi^D_{t,\theta}\chi^{D,C,s}_{t,\theta} \\
& + \varphi^I_{t,\theta}\chi^{I,RE}_{t,\theta} + \left(\sum_{g=1}^{N_G} \varphi^I_{t,\theta}\chi^{I,Th}_{g,t,\theta}\right) + \varphi^I_{t,\theta}\chi^{I,B,dis}_{t,\theta} + \varphi^I_{t,\theta}\chi^{I,C,dis}_{t,\theta} + \varphi^I_{t,\theta}\chi^{I,C,s}_{t,\theta} \\
& - \varphi^D_{t,\theta}\sigma^{D,B}_{t,\theta} - \varphi^D_{t,\theta}\sigma^{D,C}_{t,\theta} - \varphi^I_{t,\theta}\sigma^{I,RE} - \varphi^I_{t,\theta}\sigma^{I,B}_{t,\theta} - \varphi^I_{t,\theta}\sigma^{I,C}_{t,\theta} \\
& - \left(\sum_{f=1}^{N_F} (\varphi^{IX}_{f,t})(\nu_{f,t,\theta})\right) - CF^C_{t,\theta} - \left(\sum_{g=1}^{N_G}\sum_{m=1}^{N_M} CF^{Th}_{g,m} \times \left(\chi^{D,Th}_{g,m,t,\theta} + \chi^{I,Th}_{g,m,t,\theta}\right)\right) \\
& - \left(\sum_{g=1}^{N_G} SU_{g,t} + SD_{g,t}\right) - \left(\varphi^D_{t,\theta}\rho^-_{t,\theta}\delta^-_{t,\theta}\right) + \left(\varphi^D_{t,\theta}\rho^+_{t,\theta}\delta^+_{t,\theta}\right) \Bigg] \qquad (2)
\end{aligned}
$$

The total expected profit of the HPP is computed by (1), while its profit per scenario is calculated by (2). The first five terms of (2) represent the HPP's revenue through selling production offers in the DA market, while the next five terms denote the obtained income by submitting energy offers in the intraday market. The five terms of the third row illustrate the incurred costs of the HPP for procuring energy from DA and intraday markets. It is worthwhile to note that offering (χ) and bidding (φ) quantities correspond to selling and purchasing values, respectively. The first term of the fourth row indicates the costs of procuring energy from DRPs in the IDREX market. The last two terms in the fourth row are the operation costs of CAES and thermal units. For the benefit of clarification, similar to [33], a linearized model is adopted to cover the cost function of thermal units. Note that idling cost associated with thermal units has been overlooked in this study. The first expression of the last row represents the shut-down and start-up costs of conventional power units, while the next two terms stand for HPP's expenses and revenues in the balancing market.

2.1.2. Second objective function: Maximizing CVaR

The risk-measuring index CVaR is taken into account to control the risk of stochastic parameters. The CVaR for a particular confidence level α is calculated as:

$$\text{Max } H2(x) = \gamma - \frac{1}{1-\alpha}\sum_{\Theta=1}^{N_\theta} \pi_\theta \eta_\theta, \quad \forall \gamma \in \mathbb{R} \tag{3}$$

where γ, π_θ, and η_θ are value-at-risk, probability of each scenario, and an auxiliary variable employed for CVaR computation, respectively. The optimal value of γ states the highest profit in such a way that the probability of experiencing a profit lower than γ is lower than or equal to $(1-\alpha)$.

2.2. Constraints

Constraints (4) and (5) are employed to compute the CVaR.

$$-\text{Profit}_\theta + \gamma - \eta_\theta \leq 0, \quad \forall \theta, \quad \forall \gamma \in \mathbb{R} \tag{4}$$

$$\eta_\theta \geq 0, \quad \forall \theta \tag{5}$$

The total scheduled power of energy storage facilities in different operating modes is calculated through equations (6)-(8).

$$\chi_{t,\theta}^{Sch,\Gamma,dis} = \chi_{t,\theta}^{D,\Gamma,dis} + \chi_{t,\theta}^{I,\Gamma,dis}, \quad \forall t, \forall \theta, \;\; \Gamma = \Big[B, C\Big] \tag{6}$$

$$\chi_{t,\theta}^{Sch,C,s} = \chi_{t,\theta}^{D,C,s} + \chi_{t,\theta}^{I,C,s}, \quad \forall t, \forall \theta \tag{7}$$

$$\sigma_{t,\theta}^{Sch,\Gamma} = \sigma_{t,\theta}^{D,\Gamma} + \sigma_{t,\theta}^{I,\Gamma}, \quad \forall t, \forall \theta, \;\; \Gamma = \Big[B, C\Big] \tag{8}$$

Constraints (9) and (10) impose lower and upper limits of the total scheduled power of the BES system in discharging and charging modes, respectively, while corresponding limitations for the CAES system are expressed by (11) and (12).

$$0 \leq \chi_{t,\theta}^{Sch,B,dis} \leq Max^{dis} v_t^{dis}, \quad \forall t, \forall \theta, \quad \forall v_t^{dis} \in \{0,1\} \tag{9}$$

$$0 \leq \sigma_{t,\theta}^{Sch,B,ch} \leq Max^{ch} v_t^{ch}, \quad \forall t, \forall \theta, \quad \forall v_t^{ch} \in \{0,1\} \tag{10}$$

$$0 \leq \chi_{t,\theta}^{Sch,C,\Gamma} \leq Max^{exp} u_t^{\Gamma}, \quad \forall t, \forall \theta, \;\; \Gamma = \Big[dis, s\Big], \quad \forall u_t^{\Gamma} \in \{0,1\} \tag{11}$$

$$0 \leq \sigma_{t,\theta}^{Sch,C} \leq Max^{co} u_t^{ch}, \quad \forall t, \forall \theta, \quad \forall u_t^{ch} \in \{0,1\} \tag{12}$$

To ensure that energy storage facilities operate at one specific mode, restrictions (13) and (14) are employed.

$$v_t^{dis} + v_t^{ch} \leq 1, \quad \forall t, \quad \forall (v_t^{dis}, v_t^{ch}) \in \{0,1\} \tag{13}$$

$$u_t^{dis} + u_t^{s} + u_t^{ch} \leq 1, \quad \forall t, \quad \forall (u_t^{dis}, u_t^{s}, u_t^{ch}) \in \{0,1\} \tag{14}$$

The amount of the stored energy in BES and CAES systems is calculated using equations (15) and (16), respectively, while constraint (17) enforces maximum and minimum limits to the calculated values in (15) and (16). Note that the external rated power limits have been exploited in these equations, while the interested readers are referred to [34] for the internal one. Lastly, equation (18) calculates the operational costs imposed to the system from the CAES unit.

$$\begin{aligned} EL_{t,\theta}^{B} = EL_{t-1,\theta}^{B} - \left(\frac{1}{\Upsilon^{B,dis}}\right)\left(\chi_{t,\theta}^{Sch,B,dis}\right) + \\ \Upsilon^{B,ch}\left(\sigma_{t,\theta}^{Sch,B}\right), \quad \forall t, \forall \theta \end{aligned} \tag{15}$$

$$EL_{t,\theta}^{C} = EL_{t-1,\theta}^{C} + ER\left(\chi_{t,\theta}^{Sch,C,dis} - \sigma_{t,\theta}^{Sch,C}\right), \forall t, \forall \theta \tag{16}$$

$$0 \leq EL_{t,\theta}^{\Gamma} \leq ELMax^{\Gamma}, \quad \forall t, \forall \theta, \;\; \Gamma = \Big[B, C\Big] \tag{17}$$

$$\begin{aligned} CF_{t,\theta}^{C} = {} & \chi_{t,\theta}^{Sch,C,dis}\left(Htr^{dis} NGP + OM^{exp}\right) \\ & + \chi_{t,\theta}^{Sch,C,s}\left(Htr^{s} NGP + OM^{exp} + OM^{co}\right) \\ & + \sigma_{t,\theta}^{Sch,C,ch}\left(OM^{co}\right), \quad \forall t, \forall \theta \end{aligned} \tag{18}$$

Constraints (19)-(21) ensure that the production offer of thermal units does not exceed the limit of each block in the linearized cost curve. Equations (22) and (23) calculate the production offer of each thermal unit in the DA and intraday markets, respectively. Equation (24) states the scheduled power of each thermal unit, while constraint (25) defines that the this variable should be retained within the permissible range. Constraint (26) describes the shut-down and start-up costs of conventional power units. Furthermore, other well-known and frequently used restrictions of thermal units like minimum up and down times, and upward and downward ramping rates during both normal and start-up and shut-down circumstances are entered the optimization problem through in (27)-(31).

$$0 \leq \chi^{D,Th}_{g,m,t,\theta} \leq Max^{Th}_{g,m}, \quad \forall g, \forall m, \forall t, \forall \theta \tag{19}$$

$$0 \leq \chi^{I,Th}_{g,m,t,\theta} \leq Max^{Th}_{g,m}, \quad \forall g, \forall m, \forall t, \forall \theta \tag{20}$$

$$0 \leq \chi^{D,Th}_{g,m,t,\theta} + \chi^{I,Th}_{g,m,t,\theta} \leq Max^{Th}_{g,m}, \quad \forall g, \forall m, \forall t, \forall \theta \tag{21}$$

$$\chi^{D,Th}_{g,t,\theta} = \sum_{m=1}^{N_M} \chi^{D,Th}_{g,m,t,\theta}, \quad \forall g, \forall t, \forall \theta \tag{22}$$

$$\chi^{I,Th}_{g,t,\theta} = \sum_{m=1}^{N_M} \chi^{I,Th}_{g,m,t,\theta}, \quad \forall g, \forall t, \forall \theta \tag{23}$$

$$\chi^{Sch,Th}_{g,t,\theta} = \chi^{D,Th}_{g,t,\theta} + \chi^{I,Th}_{g,t,\theta}, \quad \forall g, \forall t, \forall \theta \tag{24}$$

$$Min^{Th}_{g} z_{g,t} \leq \chi^{Sch,Th}_{g,t,\theta} \leq Max^{Th}_{g} z_{g,t}, \quad \forall g, \forall t, \forall \theta, \quad \forall z_{g,t} \in \{0,1\} \tag{25}$$

$$\begin{bmatrix} 0 \\ 0 \end{bmatrix} \leq \begin{bmatrix} SU_{g,t} \\ SD_{g,t} \end{bmatrix} \geq \begin{bmatrix} SUC_g x_{g,t} \\ SDC_g y_{g,t} \end{bmatrix}, \quad \forall g, \forall t, \quad \forall (x_{g,t}, y_{g,t}) \in \{0,1\} \tag{26}$$

$$\sum_{n=t-\kappa^{up}_g+1}^{t} x_{g,t} \leq z_{g,t}, \quad \forall g, \forall t, \quad \forall (x_{g,t}, z_{g,t}) \in \{0,1\} \tag{27}$$

$$\left(\sum_{n=t-\kappa^{down}+1}^{t} y_{g,t} \right) + z_{g,t} \leq 1, \quad \forall g, \forall t, \quad \forall (y_{g,t}, z_{g,t}) \in \{0,1\} \tag{28}$$

$$y_{g,t-1} - z_{g,t} + x_{g,t} - y_{g,t} = 0, \quad \forall g, \forall t, \quad \forall (x_{g,t}, y_{g,t}, z_{g,t}) \in \{0,1\} \tag{29}$$

$$\begin{aligned} \chi_{g,t,\theta}^{Sch,Th} \leq \chi_{g,t-1,\theta}^{Sch,Th} + RU_g z_{g,t-1} + SRU_g x_{g,t}, \quad \forall g, \forall t, \forall \theta, \\ \forall (x_{g,t}, z_{g,t}) \in \{0,1\} \end{aligned} \tag{30}$$

$$\begin{aligned} \chi_{g,t-1,\theta}^{Sch,Th} \leq \chi_{g,t,\theta}^{Sch,Th} + RD_g z_{g,t} + SRD_g y_{g,t}, \quad \forall g, \forall t, \forall \theta, \\ \forall (y_{g,t}, z_{g,t}) \in \{0,1\} \end{aligned} \tag{31}$$

DRPs' involvement in the IDREX market contains a price-quantity offer, which will be illustrated later in this paper (Fig. 1). Constraint (32) denotes that the procured power in each block of the DRPs' offer in the IDREX market does not exceed its maximum value.

$$\nu_{f,t,\theta} \leq \nu_{f,t}^{Max}, \quad \forall f, \forall t, \forall \theta \tag{32}$$

The total procured energy from the IDREX market is computed by (33), while its maximum limit is enforced through constraint (34).

$$DR_{t,\theta} = \sum_{f=1}^{N_F} \nu_{f,t,\theta}, \quad \forall t, \forall \theta \tag{33}$$

$$DR_{t,\theta} \leq CapDR, \quad \forall t, \forall \theta \tag{34}$$

The HPP's total imbalance in every trading period is expressed by equation (35), which is equal to the difference of positive and negative imbalances, while maximum limits of negative and positive imbalances are fulfilled by (36) and (37), respectively.

$$\begin{aligned} \delta_{t,\theta} =& \delta_{t,\theta}^{+} - \delta_{t,\theta}^{-} = RP_{t,\theta}^{RE} + \left(\sum_{g=1}^{N_G} \chi_{t,\theta}^{Sch,Th} \right) + \chi_{t,\theta}^{Sch,B,dis} \\ &+ \chi_{t,\theta}^{Sch,C,dis} + \chi_{t,\theta}^{Sch,C,s} - P_{t,\theta}^{Sch,HPP}, \quad \forall t, \forall \theta \end{aligned} \tag{35}$$

$$\begin{aligned} \delta_{t,\theta}^{-} \leq& Cap^{RE} + \left(\sum_{g=1}^{N_G} (Max_g^{Th}) z_{g,t} \right) + \left(Max^{dis} v_t^{dis} \right) \\ &+ \left(Max^{exp} u_t^{dis} \right) + \left(Max^{exp} u_t^{s} \right), \quad \forall t, \forall \theta, \\ &\forall (u_t^{dis}, u_t^{s}, v_t^{dis}, z_{g,t}) \in \{0,1\} \end{aligned} \tag{36}$$

$$
\begin{aligned}
\delta^{+}_{t,\theta} \leq & RP^{RE}_{t,\theta} + \left(\sum_{g=1}^{N_G} \chi^{Sch,Th}_{t,\theta}\right) + \chi^{Sch,B,dis}_{t,\theta} + \chi^{Sch,C,dis}_{t,\theta} \\
& + \chi^{Sch,C,s}_{t,\theta}, \quad \forall t, \forall \theta
\end{aligned} \tag{37}
$$

The offering and bidding values of comprising facilities of the HPP in the DA market are constrained between a minimum and maximum value, which are denoted by (38) and (39), respectively.

$$
\begin{bmatrix} 0 \\ Min^{Th}_{g} z_{g,t} \\ 0 \\ 0 \\ 0 \end{bmatrix} \leq \begin{bmatrix} \chi^{D,RE}_{t,\theta} \\ \chi^{D,Th}_{g,t,\theta} \\ \chi^{D,B,dis}_{t,\theta} \\ \chi^{D,C,dis}_{t,\theta} \\ \chi^{D,C,s}_{t,\theta} \end{bmatrix} \leq \begin{bmatrix} Cap^{RE} \\ Max^{Th}_{g} z_{g,t} \\ Max^{dis} \\ Max^{exp} \\ Max^{exp} \end{bmatrix} \quad \forall g, \forall t, \forall \theta \tag{38}
$$

$$
\begin{bmatrix} 0 \\ 0 \end{bmatrix} \leq \begin{bmatrix} \sigma^{D,B}_{t,\theta} \\ \sigma^{D,C}_{t,\theta} \end{bmatrix} \leq \begin{bmatrix} Max^{ch} \\ Max^{co} \end{bmatrix} \quad \forall t, \forall \theta \tag{39}
$$

The HPP's offering and bidding quotas in the intraday market are calculated using (40) and (41), respectively, although corresponding limitations concerning these quotas are imposed through constraints (42) and (43).

$$
Cap^{I,HPP,se} = \lambda \left(Cap^{RE} + \sum_{g=1}^{N_G} Cap^{Th}_{g} + Max^{dis} + Max^{exp} \right) \tag{40}
$$

$$
Cap^{I,HPP,bu} = \lambda \left(Cap^{RE} + Max^{ch} + Max^{co} \right) \tag{41}
$$

$$
\begin{aligned}
& 0 \leq \chi^{I,RE}_{t,\theta} + \sum_{g=1}^{N_G} \chi^{I,Th}_{g,t,\theta} + \chi^{I,B,dis}_{t,\theta} + \chi^{I,C,dis}_{t,\theta} + \chi^{I,C,s}_{t,\theta} \leq Cap^{I,HPP,se}, \\
& \forall t, \forall \theta
\end{aligned} \tag{42}
$$

$$
0 \leq \sigma^{I,RE}_{t,\theta} + \sigma^{I,B}_{t,\theta} + \sigma^{I,C}_{t,\theta} \leq Cap^{I,HPP,bu}, \quad \forall t, \forall \theta \tag{43}
$$

Equation (44) and constraint (45) computes and restricts the total scheduled power of the HPP, respectively.

$$
\begin{aligned}
P_{t,\theta}^{Sch,HPP} =& \chi_{t,\theta}^{D,RE} + \chi_{t,\theta}^{I,RE} - \sigma_{t,\theta}^{I,RE} + \left(\sum_{g=1}^{N_G} \chi_{t,\theta}^{Sch,Th}\right) - DR_{t,\theta} \\
&+ \chi_{t,\theta}^{Sch,B,dis} + \chi_{t,\theta}^{Sch,C,dis} + \chi_{t,\theta}^{Sch,C,s}, \quad \forall t, \forall \theta
\end{aligned} \tag{44}
$$

$$
\begin{aligned}
0 \leq P_{t,\theta}^{Sch,HPP} \leq& Cap^{RE} + \left(\sum_{g=1}^{N_G} (Max_g^{Th}) z_{g,t}\right) + \left(Max^{dis} v_t^{dis}\right) \\
&+ \left(Max^{exp} u_t^{dis}\right) + \left(Max^{exp} u_t^{s}\right), \quad \forall t, \forall \theta, \\
&\forall (u_t^{dis}, u_t^{s}, v_t^{dis}, z_{g,t}) \in \{0,1\}
\end{aligned} \tag{45}
$$

The decreasing and non-decreasing requirements of the bidding curves along with offering ones in the DA market are enforced by (46) and (47). Restriction (46) states that for two different scenarios θ and $\widetilde{\theta}$, if the DA market price in scenario θ is greater than in scenario $\widetilde{\theta}$, then the bidding quantity of the decision-maker for scenario θ should be less than or equal to the bidding quantity for scenario $\widetilde{\theta}$. In (48) and (49), the non-anticipativity necessity of the DA bidding and offering curves are imposed. Correspondingly, non-anticipativity restrictions for the bidding and offering curves in the intraday market are represented by (50) and (51), respectively.

$$
\sigma_{t,\theta}^{D,\Gamma} \leq \sigma_{t,\widetilde{\theta}}^{D,\Gamma}, \quad \forall \theta, \widetilde{\theta} : [\varphi_{t,\theta}^{D} \geq \varphi_{t,\widetilde{\theta}}^{D}], \quad \forall t \quad \& \ \Gamma = [B, C] \tag{46}
$$

$$
\begin{aligned}
\chi_{t,\theta}^{D,\Gamma} \leq \chi_{t,\widetilde{\theta}}^{D,\Gamma}, \quad \forall \theta, \widetilde{\theta} : [\varphi_{t,\theta}^{D} \leq \varphi_{t,\widetilde{\theta}}^{D}], \quad \forall t \quad \& \\
\Gamma = \Big[RE, Th, (B, dis), (C, dis), (C, s)\Big]
\end{aligned} \tag{47}
$$

$$
\sigma_{t,\theta}^{D,\Gamma} = \sigma_{t,\widetilde{\theta}}^{D,\Gamma}, \quad \forall \theta, \widetilde{\theta} : [\varphi_{t,\theta}^{D} = \varphi_{t,\widetilde{\theta}}^{D}], \quad \forall t \quad \& \ \Gamma = [B, C] \tag{48}
$$

$$
\begin{aligned}
\chi_{t,\theta}^{D,\Gamma} = \chi_{t,\widetilde{\theta}}^{D,\Gamma}, \quad \forall \theta, \widetilde{\theta} : [\varphi_{t,\theta}^{D} = \varphi_{t,\widetilde{\theta}}^{D}], \quad \forall t \quad \& \\
\Gamma = \Big[RE, Th, (B, dis), (C, dis), (C, s)\Big]
\end{aligned} \tag{49}
$$

$$\sigma^{I,\Gamma}_{t,\theta} = \sigma^{I,\Gamma}_{t,\widetilde{\theta}}, \quad \forall\theta,\widetilde{\theta} : [\varphi^{D}_{t,\theta} = \varphi^{D}_{t,\widetilde{\theta}}], \;\; \forall t \;\; \& \;\; \Gamma = \Big[RE, B, C\Big] \tag{50}$$

$$\begin{aligned} \chi^{I,\Gamma}_{t,\theta} = \chi^{I,\Gamma}_{t,\widetilde{\theta}}, \quad \forall\theta,\widetilde{\theta} : [\varphi^{D}_{t,\theta} = \varphi^{D}_{t,\widetilde{\theta}}], \quad \forall t \quad \& \\ \Gamma = \Big[RE, Th, (B, dis), (C, dis), (C, s)\Big] \end{aligned} \tag{51}$$

3. Hybrid Stochastic-Interval Optimization Model

As already stated in the previous section, stochastic scenarios are utilized to tackle the uncertainties associated with renewable sources and DA, intraday, and imbalance prices. Another uncertain parameter is the IDREX market price, which is handled via interval numbers. Most of the time, appropriate stochastic modeling of parameters necessitates encompassing a large historical data set, which is not practical for the decision-makers. In such circumstances, interval arithmetic, which solely requires the upper and lower bounds of the uncertain parameter, is a very effective uncertainty handling manner for both nonlinear [35] and linear [36] programming problems. Fig. 1 illustrates a price-quantity curve of the DRPs in the IDREX market with their predicted intervals. In this regard, the optimization problem possessing an interval number which aims at maximizing the value of objective function $H(x, j)$, e.g., the HPP's expected profit, can be written in the following general form:

$$\begin{aligned} &\text{Max} \;\; H(x, j) \\ &s.t. \quad R(x, j) = 0 \\ &\qquad Q(x, j) \leq 0 \\ &\qquad j \in [\underline{j}, \overline{j}]. \end{aligned} \tag{52}$$

where x and j are the vectors of decision variables and the interval parameter, respectively. In the presence of an interval number $j \in [\underline{j}, \overline{j}]$, the lower and upper values of the objective function, i.e., $\underline{H}(x)$ and $\overline{H}(x)$, with both equality $R(x, j)$ and inequality $Q(x, j)$ constraints can be obtained as follows:

$$\begin{aligned} \underline{H}(x) = \underset{j}{\text{Min}} \;\; H(x, j) \\ \overline{H}(x) = \underset{j}{\text{Max}} \;\; H(x, j) \end{aligned} \tag{53}$$

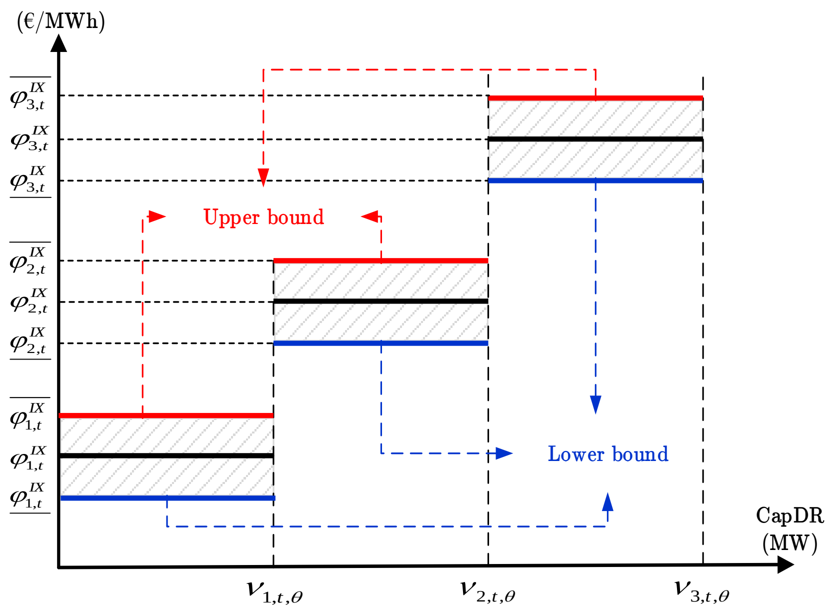


Figure 1: DRPs' price-quantity offer with the predicted intervals.

It must be stressed that for our problem, the upper ($\overline{H1}(x)$) and lower ($\underline{H1}(x)$) values of the HPP's profit are obtained at the lower ($\underline{j}$) and upper ($\overline{j}$) bounds of the IDREX market price, respectively. The reason for this lies in the fact that the lower the price of procuring energy from the IDREX market is, the higher the HPP's profit would be and vice versa. Correspondingly, to seek the best deterministic solution, the interval optimization transmutes into a bi-objective optimization problem by employing (54), whose first objective function aims at maximizing the mid-point values of the objective function $H^m(x)$, and the second one intends to minimize the deviation of the objective function $H^w(x)$.

$$
\begin{aligned}
H^m(x) &= \frac{\overline{H}(x) + \underline{H}(x)}{2} \rightarrow \text{should be maximized} \\
H^w(x) &= \frac{\overline{H}(x) - \underline{H}(x)}{2} \rightarrow \text{should be minimized}
\end{aligned}
\tag{54}
$$

For the sake of clarity, $H^m(x)$ and $H^w(x)$ reflect the best optimal quantity and the uncertainty degree of objective function $H(x, j)$, respectively. Without loss of generality, the proposed hybrid stochastic-interval self-scheduling problem with the idea of maximizing both expected mid-point of the HPP's profit ($H1^m(x)$) and CVaR ($H2$(x)), as well as minimizing the expected deviation of the HPP's profit ($H1^w(x)$), is a tri-objective optimization problem which can be posed as follows:

$$
\begin{aligned}
&\text{Objective function 1}: \ f_1(x) = H1^m(x) \rightarrow \text{should be maximized}\\
&\text{Objective function 2}: \ f_2(x) = H2(x) \rightarrow \text{should be maximized}\\
&\text{Objective function 3}: \ f_3(x) = H1^w(x) \rightarrow \text{should be minimized}\\
&Subject\ to:\\
&\text{Amended version of constraints} \quad (6)-(51) \text{ in the form of interval numbers}\\
&\qquad -\text{Profit}_\theta^m + \gamma - \eta_\theta \leq 0, \quad \forall\theta\\
&\qquad \eta_\theta \geq 0, \quad \forall\theta\\
&\qquad \varphi_{f,t}^{IX} \in [\underline{\varphi_{f,t}^{IX}}, \overline{\varphi_{f,t}^{IX}}].
\end{aligned}
\tag{55}
$$

It should be noted that in order to efficiently tackle the risk of stochastic parameters in the presence of interval numbers, constraints (4) and (6)-(51) need updating. Constraint (4) is related to CVaR computation, and thus it has been changed to $-\text{Profit}_\theta^m + \gamma - \eta_\theta \leq 0$, as expressed in (55). In addition, Constraints (6)-(51) require amendments in the form of interval numbers. The model presented in (55) is a multicriteria optimization problem that demands a proper solving tool, such as NBI method [37], ϵ-constraint technique [38], and non-dominated sorting genetic algorithm-II (NSGA-II) [39]. In this paper, the Pareto solution set of tri-objective optimization problem (55) is achieved via the hybrid implementation of lexicographic optimization [33] and the NBI method [37]. Other well-known multi-objective optimization methods such as the NSGA-II can be also employed to find the Pareto solutions, especially, if the problem is expressed as a nonlinear programming problem [39]. However, since the suggested optimization problem is linear, the NBI method is more efficient than NSGA-II. Based on the foregoing, the flowchart of the proposed risk-constrained hybrid stochastic-interval model is portrayed in Fig. 2.

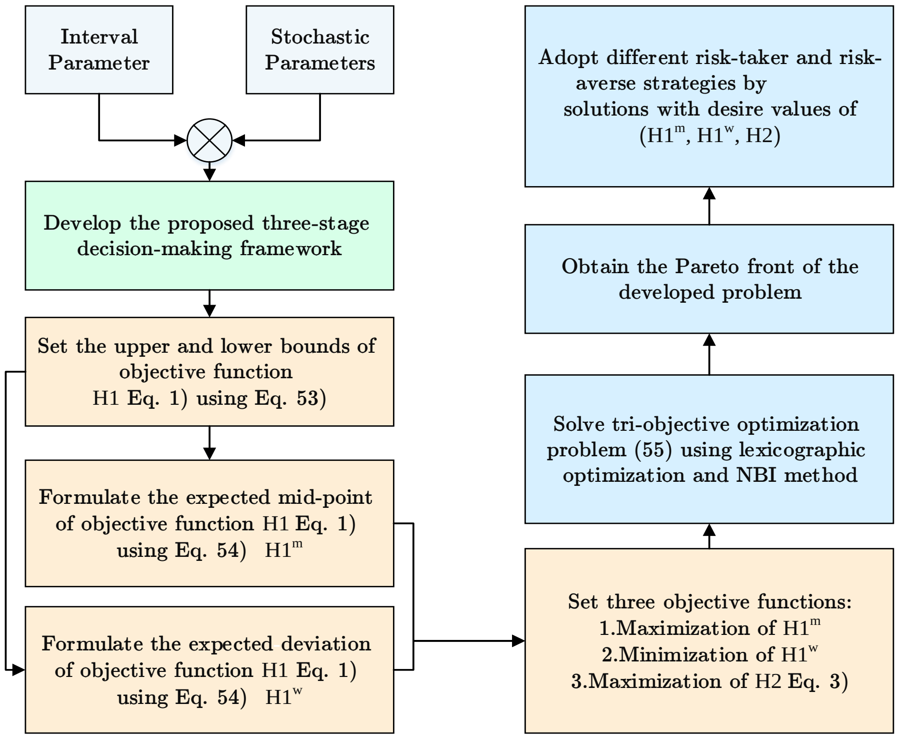


Figure 2: Flowchart of the proposed risk-constrained hybrid stochastic-interval model.

4. Numerical Case Studies

An HPP comprising a 60-MW PV plant, a 60-MW wind farm, two similar 25-MW thermal units, a CAES unit, and a BES system with data presented in Table 3 is considered to verify the performance of the suggested structure. A maximum of 10 MW involvement in the IDREX market is considered for the DRPs. Figures 3-5 provide the information of the DRPs' offer in the IDREX market with the predicted intervals for three different periods, i.e., valley, off-peak, and peak. As shown in these figures, the upper bound of the interval parameter is assumed to be the *expected value* +15%, and the lower bound is the *expected value* -15%. In other words, a ±15% forecast error is taken into account as the width of the interval parameter. The cost parameters of the thermal units, as well as their technical characteristics, have been shown in Tables 4-5. The values of NGP and λ are 3.5 €/MBtu and 0.3, respectively. The confidence level α for CVaR computation is set to 0.95 [40]. The actual data for DA, intraday, and balancing markets [41], as well as wind speed and solar irradiance [42] for six months period, have been collected for the scenario generation procedure employing the roulette wheel mechanism [28]. It has to be noted that normal, Rayleigh, and beta distributions are utilized for electricity market prices, wind speed, and solar irradiance in the scenario generation phase, respectively [43]. Afterwards, a GAMS-based software tool, namely, SCENRED2 [44], is applied to decrease the initially generated scenarios to six distinct ones for each stochastic uncertain source. The proposed self-scheduling problem is a multi-objective MILP problem for which CPLEX solver within GAMS is employed. CPLEX is a very powerful solver for linear, MILP, and quadratically constrained programming problems. In MILP problems, CPLEX benefits from the branch and cut algorithm, which is capable of finding the global optimum solution by correctly setting the gap parameters. In order to enhance performance, the CPLEX solver in GAMS software provides extensive solving options to customize the optimization process for the operator. It is worth mentioning that by converting the multi-objective optimization problem into a single objective optimization problem through the NBI method, CPLEX can be easily employed to find the global optimum solution. For instance, in many studies, the decision-maker may require to limit the number of iterations [45], an ability available in CPLEX options. Detailed information about CPLEX solver can be found in [46].

Two different analyses are conducted to investigate various aspects of the suggested architecture as follows:

1. **First Analysis**: The first analysis deals purely with the stochastic operation of the HPP in the target markets, while the IDREX market uncertainty is ignored.
2. **Second Analysis**: The second analysis concerns the proposed hybrid stochastic-interval architecture in which the interval IDREX market price

Table 3: Technical data on energy storage facilities.

Parameter	Value	Unit	Parameter	Value	Unit
Max^{exp}	100	MW	Htr^{s}	8.37	MBtu/MWh
Max^{co}	60	MW	ER	0.95	scalar
$ELMax^{C}$	20 $\times$ 100	MWh	OM^{exp}	0.87	€/MWh
Htr^{dis}	4.185	MBtu/MWh	OM^{co}	0.87	€/MWh
$\Upsilon^{B,ch}$	80	%	$Max^{ch(dis)}$	40	MW
$\Upsilon^{B,dis}$	95	%	$ELMax^{B}$	5×40	MWh

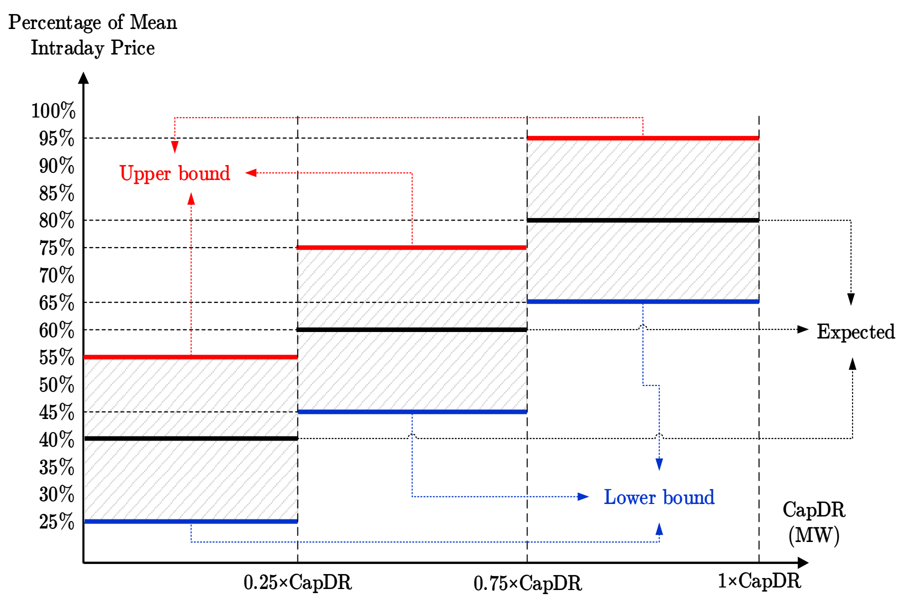


Figure 3: Information of DRPs' offer with the predicted intervals in the valley period (1-9 a.m.).

is also incorporated into the previous analysis. In order to validate the second and third proposed contributions of this paper, the intentions of the second analysis are the risk-constrained investigation of simultaneous stochastic and interval parameters, and the adoption of various risk-involved strategies for the HPP's decision-making.

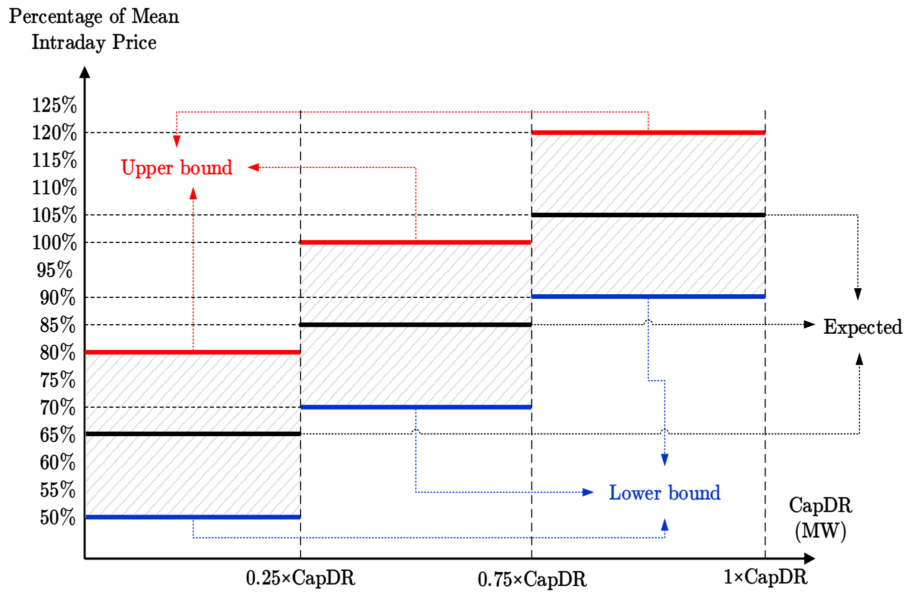


Figure 4: Information of DRPs' offer with the predicted intervals in the off-peak period (10 a.m.-7 p.m.).

Table 6 shows the optimization model of each above-mentioned analysis.

4.1. First Analysis: Stochastic self-scheduling model without IDREX uncertainty consideration

In this subsection, three different operational strategies are used to examine the profitability of the proposed self-scheduling structure. The first operational strategy addresses the uncoordinated self-scheduling of all available resources, and the second operational strategy deals with the coordinated self-scheduling, whereas, in the third one, the interaction between the HPP and DRPs is further considered in the self-scheduling architecture. It has to be mentioned that the first operational strategy contains four distinct optimization processes for CAES, BES, thermal, and wind+PV units. To avoid repetition, the mathematical formulation of uncoordinated resources has not been presented here since previous studies have described it superbly [16], [31], [32]. For the second operational strategy, the first term of the fourth row in objective function (2)

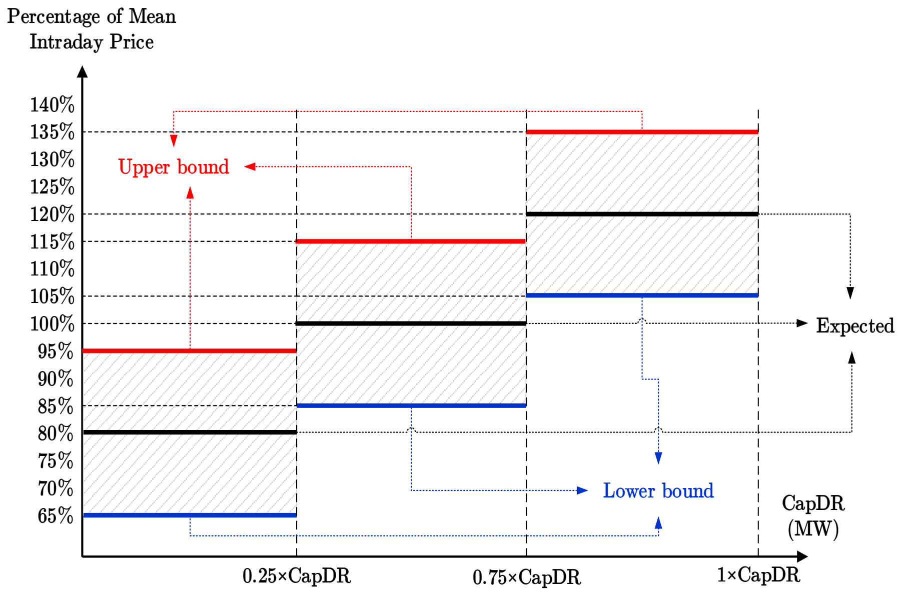


Figure 5: Information of DRPs' offer with the predicted intervals in the peak period (8-12 p.m.).

should be omitted, while constraints (32)-(34) have to be neglected. Furthermore, variable $DR_{t,\theta}$ must be eliminated from equation (44). Lastly, the third operational strategy concerns the mathematical formulation provided in this paper (equations (1)-(51)).

Fig. 6 illustrates the expected profit versus CVaR for diverse operational strategies. As seen, the first operational strategy provides the lowest expected profit and CVaR for the corresponding Pareto solutions, while the third operational strategy achieves the highest values. Furthermore, the second operational strategy, which is related to the coordinated self-scheduling of the HPP, leads to considerable CVaR and profit gains compared to the first operational strategy. This is better shown in Table 7, where the second operational strategy in the risk-neutral condition provides gains of 2.68% and 3.79% in the expected profit and CVaR, respectively. Similarly, gain values close to the risk-neutral state are obtained for the most conservative scenario. Another important point of attention is that adding DRPs' interaction in the form of the third operational

Table 4: The cost parameters of thermal units.

Unit	***Piece wise linearization parameters*** ($Max^{Th}_{g,m}$) (MW)				***Cost related to each block*** ($CF^{Th}_{g,m}$) (€/MWh)			
	$Max^{Th}_{g,1}$	$Max^{Th}_{g,2}$	$Max^{Th}_{g,3}$	$Max^{Th}_{g,4}$	$CF^{Th}_{g,1}$	$CF^{Th}_{g,2}$	$CF^{Th}_{g,3}$	$CF^{Th}_{g,4}$
G1 / G2	5.3	7.2	7.2	5.3	48.41	48.78	51.84	55.4

Table 5: Technical characteristics of thermal units.

Unit	Min^{Th}_g	Max^{Th}_g	RU_g / RD_g SRU_g / SRD_g	SUC_g	SDC_g	κ^{up}_g	κ^{down}_g
G1 / G2	10 (MW)	25 (MW)	20 (MW/hr)	87.4 (€)	8.74 (€)	4 (hr)	2 (hr)

Table 6: The optimization model of the designed analyses.

	Objective Functions	**Constraints**
First Analysis	$H1(x) \rightarrow$ should be maximized $H2(x) \rightarrow$ should be maximized	(4)-(51)
Second Analysis	$H1^m(x) \rightarrow$ should be maximized $H2(x) \rightarrow$ should be maximized $H1^w(x) \rightarrow$ should be minimized	[Amended version of constraints (6)-(51) in the form of interval numbers] $-\text{Profit}^m_\theta + \gamma - \eta_\theta \leq 0, \quad \forall\theta$ $\eta_\theta \geq 0, \quad \forall\theta$ $\varphi^{IX}_{f,t} \in [\underline{\varphi^{IX}_{f,t}}, \overline{\varphi^{IX}_{f,t}}]$

strategy gives rise to approximately double expected profit and CVaR gains in comparison with the second operational strategy.

In order to assess the proficiency of the NBI technique versus the classical method (weighted sum) of CVaR-based offering and bidding [12], [14]-[16], and [31], Fig. 7 shows the obtained efficient solutions for the second operational strategy. As seen, the proposed method, in contrast to the classical approach, is capable of covering the whole Pareto front. It is worth mentioning that evenly

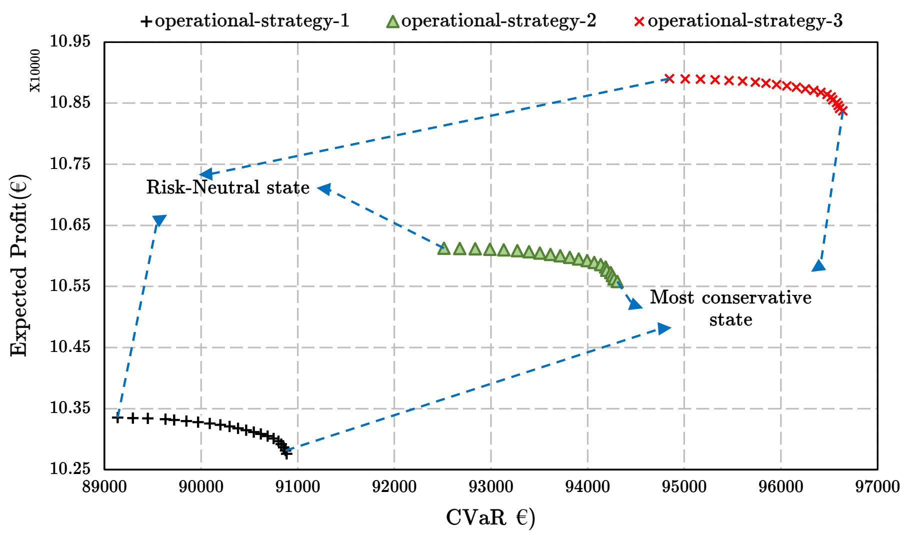


Figure 6: Expected profit versus CVaR in various operational policies.

Table 7: Profit and CVaR gains in two distinct states compared to the first operational strategy.

	Gain (%)			
	Risk-neutral state		**Most conservative state**	
	Expected profit	CVaR	Expected profit	CVaR
Operational strategy 2	2.68	3.79	2.74	3.76
Operational strategy 3	5.37	6.40	5.46	6.33

separated values are applied for both NBI and the weighted sum methods to achieve the Pareto solution sets. However, as can be seen in Fig. 7, the classical method is unable to discover ranges of € 119.618 and € 231.261 for CVaR and the expected profit, respectively. Moreover, in the risk-neutral state, the proposed approach achieves a higher value of CVaR compared to the classical method, while the quantities of expected profit for both approaches are the

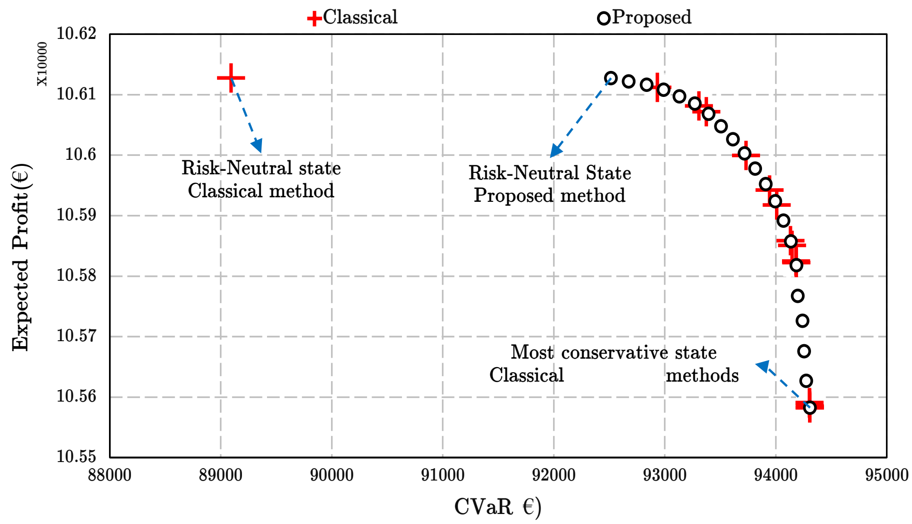


Figure 7: Comparison of the proposed method and the classical method in terms of obtaining Pareto solutions in the second operational strategy.

same, which reveals a more desirable solution. It is worth highlighting that the greater the CVaR, the smaller the risk.

4.2. Second Analysis: Hybrid stochastic-interval self-scheduling model with IDREX uncertainty consideration

This analysis is performed to appraise the risk associated with the interval number (IDREX market price). All case studies in this subsection belong to the third operational strategy, meanwhile, the risk arising from the IDREX market price is added to the foregoing studies, and accordingly, the developed problem in (55) is solved with the NBI method. The obtained efficient solutions of the NBI technique for the second analysis are shown in Fig. 8. In this figure, the x-axis, y-axis, and z-axis indicate CVaR, expected mid-point of the profit, and expected deviation of the profit, respectively. As observed, the implemented NBI method can obtain uniformly distributed Pareto solutions in the tri-objective optimization state. The average computational time of the optimization algorithm on an Asus laptop with Intel Core i5 2.30 GHz CPU and 4GB RAM for each efficient solution is two minutes and two seconds.

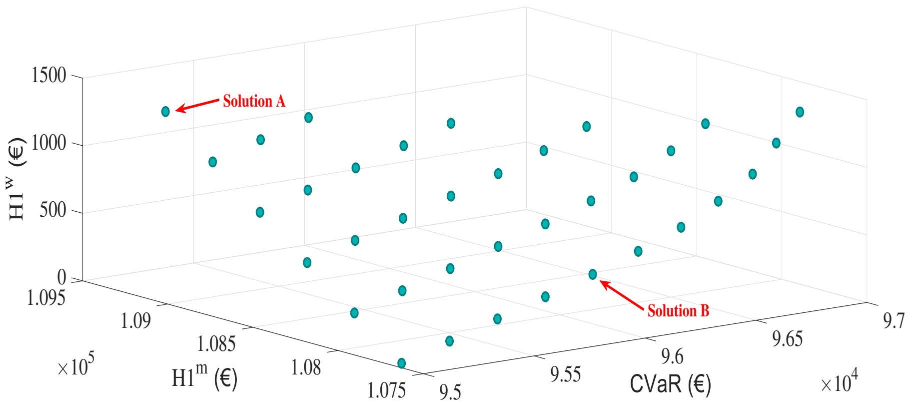


Figure 8: Pareto solution set in the second analysis.

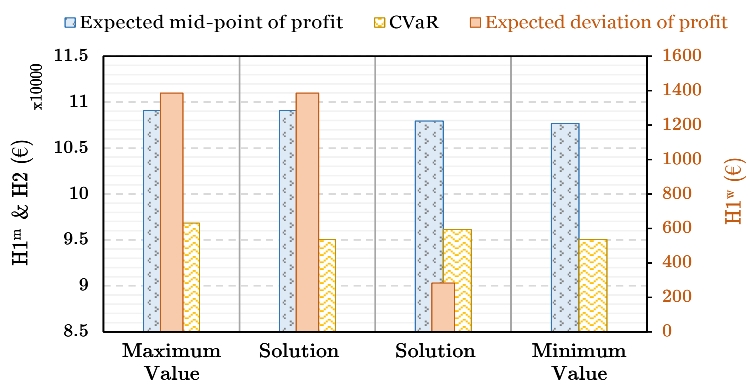


Figure 9: Comparison of the selected solutions in terms of objective functions' values.

To assess the effectiveness of the proposed risk-based architecture, two solutions, namely, Solution A and Solution B, are chosen by the HPP's decision-making unit. The values of all objective functions alongside with their maximum and minimum values for the selected solutions are exhibited in Fig. 9. Solution A represents a risk-taker strategy as it contains the highest value of the expected deviation of the profit and the lowest CVaR. By contrast, Solution B is picked as an arbitrary risk-averse strategy by the HPP, since both expected deviation and expected mid-point are lower compared to Solution A, and CVaR is greater than Solution A.

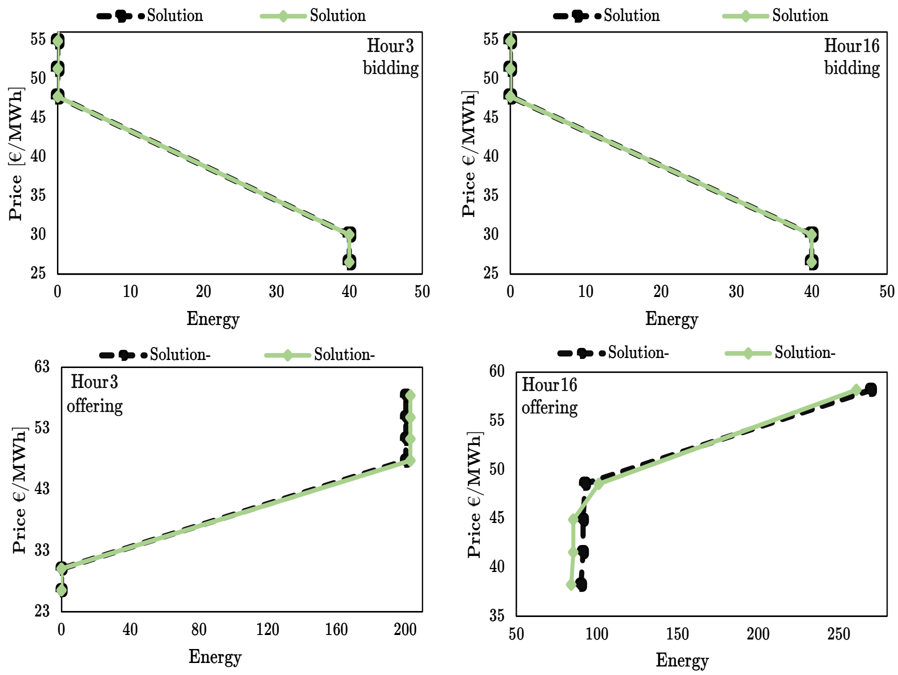


Figure 10: HPP's bidding and offering curves at two specific hours.

Fig. 10 portrays the DA bidding (buying) and offering (selling) curves of the HPP for both risk-taker and risk-averse strategies at two separate hours. It would be beneficial to note that all presented results in Figures 10-12 are the expected mid-point of output variables. According to Fig. 10, it can be observed that neither risk-taker (Solution A) nor risk-averse (Solution B) approaches can suffer changes in the DA bidding curves. On the other hand, a comparison between the risk-averse and risk-taker offering curves at 4 p.m. allows concluding that as the HPP's attitude becomes more conservative, the HPP's production offers are reduced for most price realizations. To be more precise, moving from the risk-taker strategy to the risk-averse one leads to a reduction in the offering values of the HPP at hour 16, while the HPP's production offers at hour 3 are approximately the same.

Fig. 11 depicts the expected mid-point of the hourly contracted DR by the HPP in two risk-taker and risk-averse situations. A comparison between

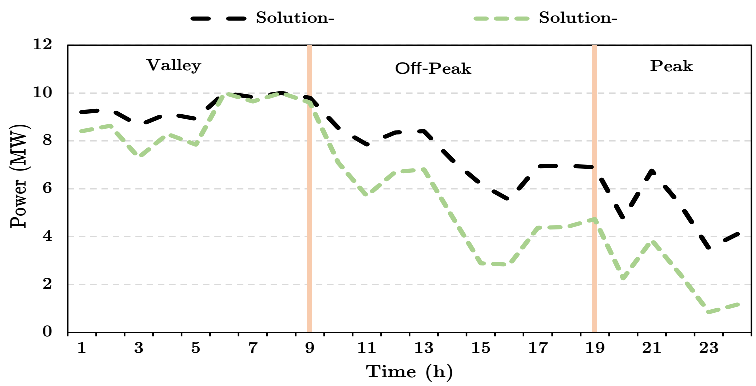


Figure 11: Hourly contracted DR in the IDREX market for two selected solutions.

the traded DR in both situations shows that the more risk-taker the HPP is, the more DR is contracted by the HPP. Similarly, a risk-hedging strategy for reducing the risk associated with the interval IDREX price results in a considerable reduction in the procured energy by the DRPs. Furthermore, not only the risk-controlling level results in a change in the traded DR, but the scheduling period (valley, off-peak, peak) also affects the participation level of the HPP in the IDREX market. The largest share of DR contracts is devoted to valley, off-peak, and peak periods, respectively.

Some other significant output variables regarding these two decision-making strategies (Solutions A and B) for the whole scheduling horizon are shown in Fig. 12. All output variables shown in this figure are the total scheduled values; for instance, blue bars represent the total selling offers minus the total purchasing bids of the HPP in the DA market for the whole trading period. According to the presented results, the total scheduled power in the DA market is almost equal for both strategies. On the other hand, by shifting from a risk-seeking strategy (Solution A) to a risk-averse one (Solution B), the total scheduled intraday energy is reduced. Similarly, by becoming a risk-averse producer (Solution B), both positive and negative imbalances are increased.

Finally, to further test the performance of the proposed model, a sensitivity analysis related to the forecast error of the interval parameter, i.e., IDREX

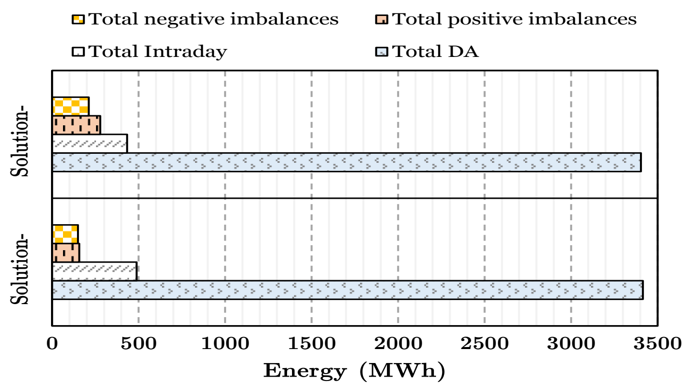
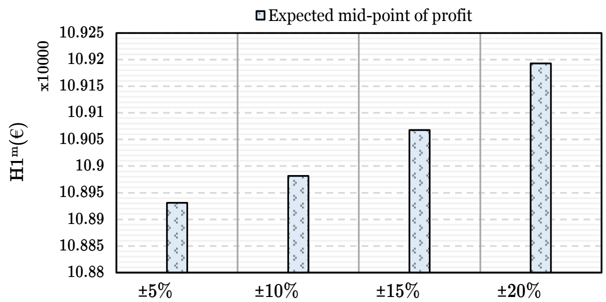


Figure 12: Some important output variables in two different solutions.

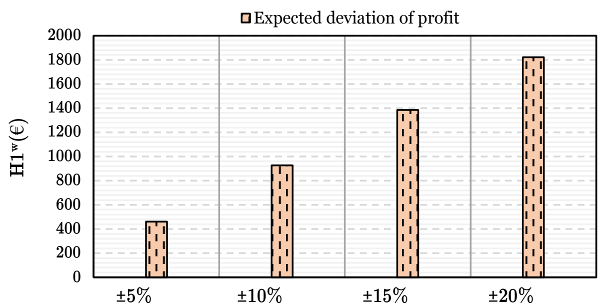
market price, is carried out. To this end, in addition to the forecast error of $\pm 15\%$, the optimization algorithm is executed for three more forecast errors, namely, $\pm 5\%$, $\pm 10\%$, and $\pm 20\%$. The expected mid-point and deviation of profit for Solution A are presented in Fig. 13. The results indicate that the greater the forecast error, the higher the expected mid-point of profit. The same goes for the expected deviation of profit. This implies that by enlarging the forecast error, a higher profit under a higher risk is achievable by the decision-maker in the suggested risk-based architecture.

5. Conclusions and future works

In this paper, a novel hybrid stochastic-interval architecture for the self-scheduling problem of an HPP comprising thermal, wind, PV, BES, and CAES units is proposed. A mathematical formulation for the coordinated running of these facilities in the consecutive markets is first developed. The energy procurement mechanism from DRPs in terms of the IDREX market is also included in the formulation. The proposed self-scheduling is exposed to two kinds of uncertainties, i.e., stochastic and interval parameters. In order to hedge the decision-making against the financial risks associated with both stochastic and interval uncertainties, an innovative multi-objective architecture is proposed. Two different case studies are used to assess the efficacy of the proposed struc-



(a) Expected mid-point of profit



(b) Expected deviation of profit

Figure 13: Expected mid-point and deviation of profit in Solution A for different forecast errors.

ture. The primary findings are:

1. The integrated operation of all resources in the electricity markets, including DRPs, leads to profits.
2. The implemented NBI technique is fully capable of generating uniformly distributed Pareto solutions in both bi-objective and tri-objective analyses, in contrast to previous methods used for CVaR-constrained bidding problems.
3. The proposed hybrid stochastic-interval architecture is able to provide different risk options by obtaining numerous Pareto solutions with specific values of the expected mid-point and expected deviation of the profit, and CVaR.
4. Optimal traded DR in the risk-seeking strategy is considerably higher than in the risk-averse approach. This is explained by the fact that the

risk-taker HPP is more willing to take advantage of DRPs to substantially reduce the incurred imbalance costs.

The developed framework could help real-world generation companies hedge against various risk sources in different electricity markets running worldwide. Besides, the suggested approach would be beneficial in terms of providing a better decision-making process and offsetting the imbalances arising from intermittent energy resources using demand-side resources. For future work, the proposed framework is extended to the participation of the suggested HPP in the balancing market under a pay-as-bid pricing scheme as a practical investigation on the Italian electricity market. Furthermore, the considered framework might be expanded to evaluate the effect of considering the prohibited operating zones of conventional power units in the process of the self-scheduling problem. Also, it would be interesting and challenging to analyze the impact of moving the operation modes of storage facilities from the *here-and-now* stage to 1^{st} and 2^{nd} *wait-and-see* decisions on the expected profit of the producer.

References

[1] Liu, Y., Du, J., 2020. A multi criteria decision support framework for renewable energy storage technology selection. J. Clean. Prod. 122183.

[2] Moser, M., Gils, H.-C., Pivaro, G., 2020. A sensitivity analysis on large-scale electrical energy storage requirements in Europe under consideration of innovative storage technologies. J. Clean. Prod. 122261.

[3] Pupo-Roncallo, O., Ingham, D., Pourkashanian, M., 2020. Techno-economic benefits of grid-scale energy storage in future energy systems. Energy Reports 6, 242–248.

[4] Shafiee, S., Zareipour, H., Knight, A.M., Amjady, N., Mohammadi-Ivatloo, B., 2017. Risk-Constrained Bidding and Offering Strategy for a Merchant Compressed Air Energy Storage Plant. IEEE Trans. Power Syst. 32, 946–957. https://doi.org/10.1109/TPWRS.2016.2565467

[5] Shafiee, S., Zareipour, H., Knight, A., 2016. Considering Thermodynamic Characteristics of a CAES Facility in Self-scheduling in Energy and Reserve Markets. IEEE Trans. Smart Grid 3053, 1–1. https://doi.org/10.1109/TSG.2016.2633280

[6] Shafiee, S., Zamani-Dehkordi, P., Zareipour, H., Knight, A.M., 2016. Economic assessment of a price-maker energy storage facility in the Alberta electricity market. Energy 111, 537–547. https://doi.org/10.1016/j.energy.2016.05.086

[7] Khatami, R., Oikonomou, K., Parvania, M., 2019. Look-Ahead Optimal Participation of Compressed Air Energy Storage in Day-ahead and Real-time Markets. IEEE Trans. Sustain. Energy.

[8] He, G., Chen, Q., Kang, C., Pinson, P., Xia, Q., 2016. Optimal bidding strategy of battery storage in power markets considering performance-based regulation and battery cycle life. IEEE Trans. Smart Grid 7, 2359–2367.

[9] Nasrolahpour, E., Kazempour, J., Zareipour, H., Rosehart, W.D., 2018. A Bilevel Model for Participation of a Storage System in Energy and Reserve Markets. IEEE Trans. Sustain. Energy. https://doi.org/10.1109/TSTE.2017.2749434

[10] Padmanabhan, N., Ahmed, M., Bhattacharya, K., 2019. Battery Energy Storage Systems in Energy and Reserve Markets. IEEE Trans. Power Syst.

[11] Baringo, L., Conejo, A.J., 2013. Strategic offering for a wind power producer. IEEE Trans. Power Syst. https://doi.org/10.1109/TPWRS.2013.2273276

[12] Baringo, L., Conejo, A.J., 2016. Offering Strategy of Wind-Power Producer: A Multi-Stage Risk-Constrained Approach. IEEE Trans. Power Syst. https://doi.org/10.1109/TPWRS.2015.2411332

[13] Nguyen, H.T., Le, L.B., 2018. Sharing Profit from Joint Offering of a Group of Wind Power Producers in Day Ahead Markets. IEEE Trans. Sustain. Energy. https://doi.org/10.1109/TSTE.2018.2819137

[14] de la Nieta, A.A.S., Paterakis, N.G., Gibescu, M., 2020. Participation of photovoltaic power producers in short-term electricity markets based on rescheduling and risk-hedging mapping. Appl. Energy 266, 114741.

[15] Asensio, M., Contreras, J., 2017. Risk-Constrained Optimal Bidding Strategy for Pairing of Wind and Demand Response Resources. IEEE Trans. Smart Grid 8, 200–208. https://doi.org/10.1109/TSG.2015.2425044

[16] Aghaei, J., Barani, M., Shafie-Khah, M., Sanchez De La Nieta, A.A., Catalao, J.P.S., 2016. Risk-Constrained Offering Strategy for Aggregated Hybrid Power Plant Including Wind Power Producer and Demand Response Provider. IEEE Trans. Sustain. Energy 7, 513–525. https://doi.org/10.1109/TSTE.2015.2500539

[17] Shafie-khah, M., Heydarian-Forushani, E., Golshan, M.E.H., Siano, P., Moghaddam, M.P., Sheikh-El-Eslami, M.K., Catalão, J.P.S., 2016. Optimal trading of plug-in electric vehicle aggregation agents in a market environment for sustainability. Appl. Energy. https://doi.org/10.1016/j.apenergy.2015.10.134

[18] Gao, X., Chan, K.W., Xia, S., Zhou, B., Lu, X., Xu, D., 2019. Risk-constrained offering strategy for a hybrid power plant consisting of wind power producer and electric vehicle aggregator. Energy. https://doi.org/10.1016/j.energy.2019.04.048

[19] Nguyen, H.T., Le, L.B., Wang, Z., 2018. A Bidding Strategy for Virtual Power Plants with the Intraday Demand Response Exchange Market Using the Stochastic Programming. IEEE Trans. Ind. Appl. https://doi.org/10.1109/TIA.2018.2828379

[20] Tian, M.-W., Yan, S.-R., Tian, X.-X., Nojavan, S., Jermsittiparsert, K., 2020. Risk and profit-based bidding and offering strategies for pumped hydro storage in the energy market. J. Clean. Prod. 256, 120715.

[21] Feng, Z., Niu, W., Wang, W., Zhou, J., Cheng, C., 2019. A mixed integer linear programming model for unit commitment of thermal plants with peak shaving operation aspect in regional power grid lack of flexible hydropower energy. Energy 175, 618–629.

[22] Feng, Z., Niu, W., Cheng, X., Wang, J., Wang, S., Song, Z., 2020. An effective three-stage hybrid optimization method for source-network-load power generation of cascade hydropower reservoirs serving multiple interconnected power grids. J. Clean. Prod. 246, 119035.

[23] Liu, Y., Shen, Z., Tang, X., Lian, H., Li, J., Gong, J., 2019. Worst-case conditional value-at-risk based bidding strategy for wind-hydro hybrid systems under probability distribution uncertainties. Appl. Energy. https://doi.org/10.1016/j.apenergy.2019.113918

[24] Khaloie, H., Abdollahi, A., Shafie-Khah, M., Siano, P., Nojavan, S., Anvari-Moghaddam, A., Catalão, J.P.S., 2020. Co-optimized bidding strategy of an integrated wind-thermal-photovoltaic system in deregulated electricity market under uncertainties. J. Clean. Prod. 242, 118434. https://doi.org/10.1016/j.jclepro.2019.118434

[25] Ding, H., Pinson, P., Hu, Z., Song, Y., 2016. Optimal offering and operating strategies for wind-storage systems with linear decision rules. IEEE Trans. Power Syst. 31, 4755–4764.

[26] Mohamed, M.A., Jin, T., Su, W., 2020. An effective stochastic framework for smart coordinated operation of wind park and energy storage unit. Appl. Energy 272, 115228.

[27] Han, X., Hug, G., 2020. A distributionally robust bidding strategy for a wind-storage aggregator. Electr. Power Syst. Res. 189, 106745.

[28] Khaloie, H., Abdollahi, A., Nojavan, S., Shafie-Khah, M., Anvari-Moghaddam, A., Siano, P., Catalão, J.P.S., 2020. Offering Strategy of Thermal-Photovoltaic-Storage Based Generation Company in Day-Ahead Market, in: Electricity Markets. Springer, pp. 113–133.

[29] Attarha, A., Amjady, N., Dehghan, S., Vatani, B., 2018. Adaptive Robust Self-scheduling for a Wind Producer with Compressed Air Energy Storage. IEEE Trans. Sustain. Energy 3029. https://doi.org/10.1109/TSTE.2018.2806444

[30] Khaloie, H., Anvari-Moghaddam, A., 2020. Robust Optimization Approach for Generation Scheduling of a Hybrid Thermal-Energy Storage System, in: 2020 IEEE 29th International Symposium on Industrial Electronics (ISIE). IEEE, pp. 971–976.

[31] Ghavidel, S., Ghadi, M.J., Azizivahed, A., Aghaei, J., Li, L., Zhang, J., 2020. Risk-Constrained Bidding Strategy for a Joint Operation of Wind Power and CAES Aggregators. IEEE Trans. Sustain. Energy. https://doi.org/10.1109/TSTE.2019.2895332

[32] Garcés, L.P., Conejo, A.J., 2010. Weekly self-scheduling, forward contracting, and offering strategy for a producer. IEEE Trans. Power Syst. 25, 657–666. https://doi.org/10.1109/TPWRS.2009.2032658

[33] Khaloie, H., Abdollahi, A., Shafie-khah, M., Anvari-Moghaddam, A., Nojavan, S., Siano, P., Catalão, J.P.S., 2020. Coordinated wind-thermal-energy storage offering strategy in energy and spinning reserve markets using a multi-stage model. Appl. Energy 259, 114168. https://doi.org/10.1016/j.apenergy.2019.114168

[34] Sarker, M.R., Dvorkin, Y., Ortega-Vazquez, M.A., 2015. Optimal participation of an electric vehicle aggregator in day-ahead energy and reserve markets. IEEE Trans. Power Syst. 31, 3506–3515.

[35] Bai, L., Li, F., Cui, H., Jiang, T., Sun, H., Zhu, J., 2016. Interval optimization based operating strategy for gas-electricity integrated energy systems considering demand response and wind uncertainty. Appl. Energy 167, 270–279

[36] Jiang, Y., Wan, C., Chen, C., Shahidehpour, M., Song, Y., 2019. A hybrid stochastic-interval operation strategy for multi-energy microgrids. IEEE Trans. Smart Grid 11, 440–456

[37] Bagheri, A., Vahidinasab, V., Mehran, K., 2018. A novel multiobjective generation and transmission investment framework for implementing 100% renewable energy sources. IET Gener. Transm. Distrib. 12, 455–465. https://doi.org/10.1049/iet-gtd.2017.0976

[38] Mollaei, A., Mohammadi, M., Naderi, B., 2019. A bi-objective MILP model for blocking hybrid flexible flow shop scheduling problem: robust possibilistic programming approach. Int. J. Manag. Sci. Eng. Manag. 14, 137–146.

[39] Feng, Z., Niu, W., Cheng, C., 2018. Optimization of hydropower reservoirs operation balancing generation benefit and ecological requirement with parallel multi-objective genetic algorithm. Energy 153, 706–718

[40] Khaloie, H., Abdollahi, A., Rashidinejad, M., Siano, P., 2019. Risk-based probabilistic-possibilistic self-scheduling considering high-impact low-probability events uncertainty. Int. J. Electr. Power Energy Syst. 110, 598–612. https://doi.org/10.1016/j.ijepes.2019.03.021.

[41] Bienvenido — ESIOS electricidad · datos · transparencia [WWW Document], n.d. URL https://www.esios.ree.es/es (accessed 3.14.19).

[42] Weather history+ - meteoblue [WWW Document], n.d. URL https://www.meteoblue.com/en/historyplus (accessed 4.22.19).

[43] Khaloie, H., Mollahassani-pour, M., Anvari-Moghaddam, A., 2020. Optimal Behavior of a Hybrid Power Producer in Day-Ahead and Intraday Mar-

kets: A Bi-Objective CVaR-Based Approach. IEEE Trans. Sustain. Energy. https://doi.org/10.1109/TSTE.2020.3026066

[44] SCENRED2 [WWW Document], n.d. URL https://www.gams.com/24.8/docs/tools/scenred2/index.html (accessed 9.5.19).

[45] Vahdani, H., Shams, A., 2020. Multi-mode capital-constrained project payment scheduling model considering bonus-penalty structure. Int. J. Manag. Sci. Eng. Manag. 15, 17–25.

[46] CPLEX 12 [WWW Document], n.d. URL https://www.gams.com/latest/docs/S_CPLEX.html (accessed 8.27.20).