Coordinated Wind-Thermal-Energy Storage Offering Strategy in Energy and Spinning Reserve Markets Using a Multi-Stage Model

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Abstract

Renewable energy resources such as wind, either individually or integrated with other resources, are widely considered in different power system studies, especially self-scheduling and offering strategy problems. In the current paper, a three-stage stochastic multi-objective offering framework based on mixed-integer programming formulation for a wind-thermal-energy storage generation company in the energy and spinning reserve markets is proposed. The commitment decisions of dispatchable energy sources, the offering curves of the generation company in the energy and spinning reserve markets, and dealing with energy deviations in the balancing market are the decisions of the proposed three-stage offering strategy problem, respectively. In the suggested methodology, the participation model of the energy storage system in the spinning reserve market extends to both charging and discharging modes. The proposed framework concurrently maximizes generation company's expected profit and minimizes the expected emission of thermal units applying lexicographic optimization and hybrid augmented-weighted ϵ-constraint method. In this regard, the uncertainties associated with imbalance prices and wind power output as well as day-ahead energy and spinning reserve market prices are modeled via a set of scenarios. Eventually, two different strategies, i.e., a preference-based approach and emission trading pattern, are utilized to select the most favored solution among Pareto optimal solutions. Numerical results reveal that taking advantage of spinning reserve market alongside with energy market will substantially increase the profitability of the generation company. Also, the results disclose that spinning reserve market is more lucrative than the energy market for the energy storage system in the offering strategy structure.

Keywords: offering strategy, electricity markets, environmental-economic, energy storage system, multi-stage stochastic programming, ϵ-constraint method

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Nomenclature	
Indices	
t	Period index.
g	Index for thermal units.
ω	Scenario index.
q	Index for emission group.
Constants	
π_ω	Probability of occurrence of scenario ω.
$P^{W,Max}$	Rated wind power output, MW.
$STUC_g/STDC_g$	Cost pertaining to start-up/shut-down of every thermal unit, €.
MDT_g/MUT_g	Minimum down/up times of every thermal unit, hr.
RUR_g/RDR_g	Ramp up/down rate of every thermal unit, MW/hr.
E^{Qo}	Emission quota of system, lbs.

$P_g^{th,Max}/P_g^{th,Min}$	Maximum/minimum allowable production power for every thermal unit, MW.
$P^{dis,Max}/P^{ch,Max}$	Maximum allowed charging/discharging power for ESS, MW.
$PS_g^{th,S,Max}$	Maximum allowable power of every thermal unit for taking part in spinning reserve market, MW.
$E_{q,g}$	Rate of emission pertaining to every emission group and thermal unit, lbs/MWhr.
EMG	Emission group including NO_X and SO_2.
$STURL_g/STDRL_g$	Start-up/shut-down ramp bound of every thermal unit, MW/hr.
$C^{(L)}$	Cost pertaining to block of L in linearized cost curve of every thermal unit, €/MWh, where L=1,...,4 .
λ^{EE}	Price of emission market, €/lbs.
$Prob^{cal}$	Probability of being invited by the system operator to deliver the spinning reserve offer in the balancing market.
$Z^{S,dis}/Z^{S,ch}$	Discharging/charging efficiency of ESS.
$EB^{S,Max}$	Maximum quantity of stored energy in the ESS, MWh.
Variables	
$M_{t,\omega}^E/M_{t,\omega}^S/M_{t,\omega}^{bal}$	Price pertaining to energy/spinning reserve/balancing markets , €/MW.
$B_{t,\omega}^{E,th}/B_{t,\omega}^{S,th}$	offering curve of thermal units in the energy/spinning reserve markets, MW.
$B_{t,\omega}^{E,W}$	offering curve of wind units in the energy market, MW.
$B_{t,\omega}^{E,S,dis}/B_{t,\omega}^{S,S,dis}$	offering curve of ESS in the energy/spinning reserve markets during the discharging mode, MW.
$B_t^{E,S,ch}$	Optimal purchasing power by the ESS from the energy market, MW.
$B_{t,\omega}^{S,S,ch}$	offering curve of ESS in the spinning reserve market during charging mode, MW.
$P_{t,\omega}^W$	Realized output power of wind units, MW.
$EG_{t,\omega}^{EXP,th}$	Scheduled generated power of every thermal unit, MW.
$\Delta_{t,\omega}^+/\Delta_{t,\omega}^-$	Imbalance-up/down, MW.
$U_{g,t}/D_{g,t}$	Cost pertaining to start-up/shut-down of every thermal unit throughout the scheduling horizon, €.

$C_{g,t,\omega}()$	Cost function of every thermal unit.
$EG^{E,th}_{g,t,\omega}/EG^{S,th}_{g,t,\omega}$	offering curve of every thermal unit in the energy/spinning reserve markets, MW.
$EGCH_{g,t}/PCH^{th}_{t}/PCH^{W}_{t}$	Provided charging power for the ESS by every thermal unit/all thermal units/wind units, MW.
v^{dis}_{t}/v^{ch}_{t}	0 or 1 variable that represents ESS is working in the discharging/charging mode.
$u_{g,t}/x_{g,t}/y_{g,t}$	0 or 1 variable that represents every thermal unit is online/ in the start-up situation/ in the shut-down situation.
$EB^{S}_{t,\omega}$	Quantity of stored energy in the ESS, MWh.
$r^{+}_{t,\omega}/r^{-}_{t,\omega}$	Imbalance ratio for over-generation/under-generation as a multiplier of energy price.

1. Introduction

1.1. Motivation and Aim

Nowadays, the utilization of renewable energy resources has become an inseparable part of power systems. In fact, the availability of different renewable energy resources such as wind and solar as well as considering the policy of diminishing greenhouse gas emissions and demand growth are among crucial factors for communities to focus on these resources [1]. Renewable energy resources are divided into five general groups: wind power, solar power, hydropower, biomass, and geothermal [1]. Since early 2000, wind power has a significant share in the supply of electricity needed by customers [2]. In 2000, 17 gigawatts of worldwide customers were provided by wind turbines, while in 2014, it was increased to 361 gigawatts [2]. This reflects the interest of various communities in increasing the use of wind energy. The most significant advantages of wind energy are summarized to diminishing greenhouse gas emissions as well as lessening electricity costs [1]. Despite the benefits of wind power, there are many challenges for the owners of these resources to participate in the deregulated electricity markets. The wind power intermittency is known as the greatest challenge of wind power producers (WPPs) in the literature [3]. To this end, generation companies (GenCos) mainly design an integrated strategy for the offering strategy of stochastic renewable-based energy systems alongside dispatchable energy resources like thermal units and energy storage systems to cope with the intermittent nature of their output power.

1.2. Literature Review

The optimal participation problem of wind power resources in the electricity markets has been taken into consideration by various perspectives. Reference [4] has presented an integrated operation of a group of wind farms for participating in the day-ahead (DA) electricity market. The uncertain nature of wind power and electricity prices are modeled via multiple stochastic scenarios. Authors in [5] focused on the optimal offering strategy for a typical WPP in a pay-as-bids market. Authors addressed the optimal offering strategy of WPPs through a bi-level stochastic optimization problem. The optimal scheduling of a WPP using information gap decision theory to deal with the wind power and market price uncertainties has been discussed in [6]. The scheduling of a renewable-based microgrid in the attendance of demand response programs has been investigated in [7]. A multi-stage bidding framework for home microgrids has been proposed in [8]. In [9], a self-scheduling (SS) model for micro grid based on a hybrid price-based demand response program has been developed while two-point estimate method has been used to handle the existing uncertainties.

The offering strategy problem is not limited to wind power plants. Thermal units as the vital part of supplying customer's electricity have been widely studied in the literature of SS problem. According to the provided reports in [1], more than 80 % of the US electricity is supplied by energy sources such as petroleum, natural gas, and coal that can be implemented by thermal units. The impact of possibilistic reserve deployment and forced outages of thermal units on the SS problem have been studied in [10] while the same problem of a thermal GenCo has been addressed in [11] based on the information gap decision theory.

The authors formulated the SS problem as mixed-integer nonlinear programming model while the uncertain parameters (market prices) have been modeled via information gap decision theory approach. A new framework for optimal SS of thermal units in the presence of upcoming high-impact low-probability events is suggested in [12].

From another standpoint, integrated operation of various energy sources like wind and thermal power plants have been studied in the context of offering strategy [13]. The authors in [13] have benefited from stochastic programming to address the offering strategy of a wind-thermal power producer. In the aforementioned research works, the uncertain nature of wind power production and market prices have been considered through a set of realizations. In [14], the stochastic optimization has been utilized to deal with the uncertainties related to prices, load, and production power of wind farm and photovoltaic system. The coordinated wind-thermal-pumped storage offering strategy in energy and regulation reserve markets has been proposed in [15]. In [15], The authors modeled the inherent risk of uncertain parameters via conditional value-at-risk in the suggested strategy. It should be noted that in the uncoordinated operation, a single optimization problem runs for every distinct generation facility, while in the coordinated one, the decision-making unit runs one unique optimization problem on behalf of all generation facilities. Accordingly, in the coordinated operation, the constraints and specifications of each generation unit can influence the decision of other units, and as a result, the decision-making unit optimizes the problem by considering the limitations on all generation units which ultimately leads to the profitability of all units. The bidding and offering strategies of a wind-hydro-pumped storage system in energy and ancillary service markets can also be found in [16]. The previously introduced conditional value-at-risk tool has also been utilized in [16] while the authors have been benefited from a novel improved clonal selection algorithm in order to acquire the optimal solution. Furthermore, appropriate economic models for supplying the electricity needed for a water treatment plant and an irrigation network in the presence of an integrated wind-hydro system are presented in [17] and [18], respectively.

Due to the dramatic increase in the utilization of energy storage systems (ESSs) in all sectors of the power system, the optimal offering strategy problem of ESSs individually and alongside other resources have been attracted the attention of many researchers worldwide. The impact of the battery life cycle on the offering strategy of an ESS in the energy, spinning reserve, and regulation markets has been investigated in [19]. An optimization approach for robust SS of a compressed air energy storage has been discussed in [20]. Reference [21] focused on the offering strategy of an integrated wind-storage system on the basis of linear decision rules. Authors in [22] have developed a two-stage approach for optimal operation of wind and photovoltaic units in the presence of an ESS with a focus on on the participation of all available units in the DA energy market. A bi-level model for optimal involvement of an electric vehicle aggregator in sequential electricity markets is proposed in [23] while the associated risk is modeled via conditional value-at-risk.

The optimal scheduling of renewable energy-driven systems has received considerable attention from researchers in the literature and is not limited to the aforementioned references. A risk-constrained mechanism for optimal bidding of a price-taker wind-hydro system in the DA market has been proposed in [24] while wind power, electricity prices, and natural water flows are taken into account as the uncertain sources. In [25], the problem proposed in [24] has been extended to the bidding strategy of a wind hydro-pump storage system in the presence of bilateral contracts. In [26], two-point estimate method has been applied to deal with the uncertainties of renewable power productions and load demand in the optimal scheduling problem of a system consisting of thermal, solar, wind, and batteries. A risk-based scheduling methodology for a wind-hydro-thermal generation system with the aim of minimizing total cost has been presented in [27]. Lastly, in [28], an appropriate offering model for a price-maker hybrid wind system and electric vehicle aggregators in the DA market has been introduced.

A risk-based offering strategy for a wind-hydro power producer using worst-case conditional value-at-risk has been proposed in [29]. Another offering approach for a WPP paired with electric vehicles in DA and intraday markets has been presented in [30]. Moreover, authors in [31] have introduced a novel SS model for plug-in electric vehicles in the presence of intraday demand response exchange market. In the context of the virtual power plant's offering strategy, the application of robust optimization and bi-level scheduling have been analyzed in [32] and [33], respectively. A dynamic programming-based offering strategy for a wind-battery system has been provided in [34], while the investigation of bid structures on the offering strategy of large-scale energy storage systems has been conducted in [35]. In [36] and [37] two different SS structures for an electricity retailer and aggregators of prosumers have been developed, respectively, while the proposed model in [37] can dramatically decrease the costs of both prosumers and aggregators in comparison with routinely introduced frameworks by retailers. The considered model in [36] benefits from demand response programs to effectively increase the profitability of the retailer while the uncertainty associated with load demand is modeled using stochastic scenarios. Another useful approach for handling the risk arising from demand response providers based on the information gap decision theory has been presented in [38]. Finally, a bi-level strategic offering mechanism for a wind-thermal power producer in energy and balancing markets has been proposed in [39].

All papers presented above are single objective and aimed at profit maximization. The multi-objective model for optimal SS of hydrothermal power producers has been addressed in [40], respectively. The previously mentioned papers considered the profit maximization and emission minimization as the conflicting objectives in the optimization process and the ϵ-constraint method has been applied to solve the multi-objective optimization problem. In [41], the bi-objective SS of a hydrothermal system in the presence of market price uncertainty and forced outages of generation facilities has been proposed as an extension of the presented model in [40]. A bi-level multi-objective bidding strategy for a virtual power plant in the energy and regulation markets has been developed in [42] while the augmented ϵ-constraint method has been employed to find the Pareto solution set. Performance of the lexicographic optimization

(LO) and hybrid augmented-weighted ϵ-constraint (HAW-Eps) method for the bi-objective SS of a microgrid has been assessed in [43]. Among the recently introduced research works on SS and as a traditional approach in power system problems, a great significant has been given to the multi-objective scheduling of various generation units regarding cost and emission minimization. The study presented in [44] solve the cost and emission optimization problem by applying the ϵ-constraint method. Also, investigation of the effects of pumped-storage units on the multi-objective scheduling of hydrothermal units has been analyzed in [44]. Sun et al. [45] proposed the optimal scheduling of wind and thermal units in the form of a unit commitment problem. Alternatively, the problem of hydro-wind-thermal scheduling with the goal of minimizing total operative costs in an economic dispatch problem has been investigated in [46] and [47]. An extended non-dominated sorting genetic algorithm, the third version and bee colony optimization algorithm as optimization techniques have been applied for solving the hydro-wind-thermal scheduling problem in references [46] and [47], respectively.

1.3. Novelty of this contribution

This paper presents a novel three-stage multi-objective framework for determining the optimal participation of a wind-thermal-energy storage (WTES) system in the electricity markets. In the proposed multi-objective framework, the WTES system tries to maximize its profit as the first objective while at the same time, the emission minimization is taken into account as the second objective. To the best of authors' knowledge and concerning the previous works in this topic, no relevant research work in the literature proposes a multi-objective model for the WTES offering strategy problem. In the presented framework, the WTES system participates in the DA energy and spinning reserve markets. On the other hand, the uncertainty associated with many of the parameters in the optimization process is one of the challenges faced by GenCos. To this end, the uncertain nature of various market prices and output power of the wind farm in the optimization problem is modeled by a set of realizations. Accordingly, the main contributions of this paper in comparison with other research works in this area are as follows:

- Proposing a three-stage stochastic multi-objective model for the offering strategy problem of a WTES system on the basis of a mixed-integer programming (MIP) formulation. In the suggested model, simultaneously profit maximization and emission minimization are considered as conflicting objectives in the optimization problem while the uncertain parameters including energy, spinning reserve and imbalance prices, as well as wind power production, are modeled via stochastic scenarios.

- Providing a participation model for the ESS in the spinning reserve market in both charging and discharging modes, and subsequently, deriving appropriate offering curves in this market.

- Presenting the physical connection between the ESS system and both thermal and wind units for charging the ESS system in the mathematical formulation of the proposed problem.

- Implementing the LO and HAW-Eps procedures to solve the multi-objective WTES offering strategy problem. The LO helps the ϵ-constraint method to more effectively specify objective functions' range in comparison with the traditional ϵ-constraint technique, while the HAW-Eps merely obtains efficient Pareto solutions. Indeed, applying these two methods jointly guarantees to reach the optimal Pareto solution set while the traditional ϵ-constraint procedure cannot ascertain the effectiveness of the obtained solutions. Also, a practical approach, i.e., a preference-based method, is utilized to choose the best possible solution.

- Designing a new pattern based on the emission trading for the WTES system to adopt the most suitable strategy while the emission quota is taken into consideration.

1.4. Paper Organization

The rest of the paper is categorized as follows: The problem description is presented in the second section. The problem formulation for the WTES system based on the three-stage stochastic optimization framework is presented in Section 3. The suggested approach for solving the multi-objective optimization model is proposed in section 4. The emission trading approach is presented in section 5. Section 6 describes the solution procedure of the suggested the multi-objective optimization problem. Section 7 is dedicated to the numerical results, and finally, the related conclusions are drawn in section 8.

2. Problem Description

In the deregulated electricity markets, GenCos or power producers are in charge of maximizing their profits in the form of an offering strategy problem. The considered GenCo in this paper consists of thermal, wind, and energy storage units. The GenCo faces various challenges that are not limited to addressing uncertainties, but optimization of the offering strategy with conflicting objectives. In this context, GenCo should not only maximize its profits but must simultaneously minimize the emission arising from thermal units. Hence, the survey of coordinated trading of wind and thermal units with ESS in the presence of an additional objective function (OF), i.e., emission minimization of thermal units, seems necessary and challenging. In addition, the participation of thermal units and ESS in the spinning reserve market can be named as another profitable source for GenCos which in this study, contrary to the reviewed works, the effects of this partnership on both OFs of the GenCo, i.e., profit maximization and emission minimization, will be thoroughly investigated.

Dealing with energy deviations in the balancing market is the main concern of GenCos with intermittent energy resources. A power producer chooses its target markets depending on a variety of factors, including experience, insight, technical specifications of units, and its investment programs [48]. Consider a WPP who is going to participate in the energy market of day k. For this purpose, the WPP should submit its production offer to the DA energy market in day *k-1*. After the market closures, the independent system operator clears the DA market. Assuming the acceptance of the WPP's offer in the DA market, the WPP must deliver the same amount of offered energy on day *k*. The mismatch between the offered energy and the delivered energy is known as the biggest challenge of WPPs. Accordingly, if the WPP experiences negative energy deviation in the balancing market, i.e., the delivered energy is lower than the offered energy in the DA market, the WPP is penalized based on the negative imbalance ratio ($r^{-}_{t,\omega}$). Otherwise, the WPP experiences positive energy deviation, i.e., the delivered energy is greater than the offered energy in the DA market, and as a result, the surplus energy is purchased at a different price in the balancing market based on the positive imbalance ratio ($r^{+}_{t,\omega}$). To grasp the reason for such a mechanism, we should point out that multiplying these imbalance ratios by the DA market prices ($(r^{-/+}_{t,\omega}) \times M^{E}_{t,\omega}$) determines the corresponding prices for penalizing and purchasing the negative and positive energy deviations, respectively. It is worth mentioning that the negative imbalance ratios are values greater or equal to 1 ($r^{-}_{t,\omega} \geq 1$), while the positive imbalance ratios are values lower or equal to 1 ($r^{+}_{t,\omega} \leq 1$) [49].

2.1. Decision Making Framework

The offering strategy problem of a WTES system in the DA energy and spinning reserve markets is formulated as a three-stage stochastic programming problem. The utilization of stochastic programming to cope with uncertainties is extremely prevalent in power system problems. In this model, all uncertain parameters are characterized by a set of scenarios. The order of the decision-making process of the WTES system in the proposed three-stage stochastic programming is as follows:

1. **Stage 1**: In the first stage, GenCo's decisions are split into two groups. The first group includes the GenCo's decision regarding the operation scheduling of thermal units and ESS. In particular, the on or off status of thermal units and the charging and discharging modes of ESS for the

whole scheduling horizon will be determined in this stage. In the second group, the decisions regarding the charging power for the ESS from three different sources, namely, thermal and wind units as well as the DA energy market will be made. The first stage decisions are made prior to the ization of stochastic variables, which are known as *here-and-now* decisions.

2. **Stage 2**: The second stage decisions are pertained to designing the offering curves that should be submitted by the system in the DA energy and spinning reserve markets. Decisions of the second stage are contingent on the decisions of the first stage. These decisions are entitled as *special here-and-now* decisions.

3. **Stage 3**: The third stage decisions of stochastic programming appertains to the balancing market and the energy deviations of the system in this market. At this stage, the imbalance costs caused by deviation of wind turbines and the revenue arising from reserve deployment will be calculated. It should be noted that the third stage decisions will be made after the realization of all stochastic variables (DA energy market, spinning reserve market, balancing market, and wind power). These decisions are denominated as *wait-and-see* decisions.

The classification of the decision variables in the proposed three-stage stochastic programming has been listed in Table 1.

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3. Problem Formulation

The multi-objective offering strategy problem of a WTES system has two separate OFs. The first OF is intended to maximize the system's expected profit from participation in the energy and spinning reserve markets. The second OF is aimed at minimizing the expected emission of thermal units. In the following subsections, each of the mentioned OFs will be introduced.

3.1. First Objective Function: Maximizing the Expected Profit of WTES System

As stated above, the first OF is the maximization of the system's expected profit in the desired time horizon (DA scheduling horizon). In this regard, the system's optimal participation in each of the selected markets, that are the outputs of the offering strategy problem, will be obtained. The considered system in this paper consists of several thermal units, a wind farm, and an ESS. Due to the intermittent nature of wind power, the system only takes advantage of the wind farm to offer in the energy market [49]. Thermal units and ESS are also able to participate in the energy and spinning reserve markets. The considered ESS in this paper can be used in either charging or discharging mode to participate in the energy and spinning reserve markets. The ESS can be treated as a producer (discharging mode) or a consumer (charging mode) in the energy market. In addition to participating in spinning reserve market during discharging mode, the ESS can also act as a responsive load in the discharging mode for participating in the spinning reserve market [50]. The first OF, maximizing the expected profit of the WTES system, based on the three-stage stochastic programming is formulated as follows:

$$\begin{aligned}
\text{Max } F_1^{WTES} = &\sum_{\omega=1}^{N_\Omega} \pi_\omega \times [\sum_{t=1}^{N_T} \{ \left(M_{t,\omega}^E B_{t,\omega}^{E,th} \right) + \left(M_{t,\omega}^E B_{t,\omega}^{E,W} \right) + \left(M_{t,\omega}^E B_{t,\omega}^{E,S,dis} \right) \\
&- \left(M_{t,\omega}^E B_t^{E,S,ch} \right) + \left(M_{t,\omega}^S B_{t,\omega}^{S,th} \right) + \left(M_{t,\omega}^S B_{t,\omega}^{S,S,dis} \right) + \left(M_{t,\omega}^S B_{t,\omega}^{S,S,ch} \right) \\
&+ Prob^{cal} \times \left(B_{t,\omega}^{S,th} + B_{t,\omega}^{S,S,dis} + B_{t,\omega}^{S,S,ch} \right) \times M_{t,\omega}^{bal} \\
&+ \left(M_{t,\omega}^E r_{t,\omega}^{+} \Delta_{t,\omega}^{+} \right) - \left(M_{t,\omega}^E r_{t,\omega}^{-} \Delta_{t,\omega}^{-} \right) \\
&- \sum_{g=1}^{N_G} C_{g,t,\omega} \left(EG_{g,t,\omega}^{E,th} + EGCH_{g,t} + Prob^{cal} \times (EG_{g,t,\omega}^{S,th}) \right) \}] \\
&- \sum_{t=1}^{T} \sum_{g=1}^{N_G} (U_{g,t} + D_{g,t})
\end{aligned} \tag{1}$$

where the first line of F_1^{WTES} represents the income of WTES system from participating in the energy market. The first, second, and third parentheses of this line relate to the involvement of thermal units, wind farm, and ESS in the energy market, respectively. The first parenthesis in the second line of (1) indicates the cost incurred by the WTES system for purchasing the charging energy for the ESS from the energy market while the next three parentheses express the earned income by WTES system from participating in the spinning reserve market. The third line models the expected income of the WTES system due to spinning reserve deployment in the balancing market. The fourth line of (1) shows the system's revenue/cost arising from the energy deviations in the balancing market. The first parenthesis in this line represents the system's income due to the over-generation between the real and scheduled generation while the second parenthesis relates to the under-generation between the actual and scheduled production, which is a cost term. Finally, the fifth and sixth lines denote the generation costs, start-up, and shut-down costs incurred by each thermal unit, respectively. It must be stressed that a series of piecewise linearized blocks are utilized to approximate the quadratic cost function of thermal units, which would be helpful to benefit from the advantages of linear programming [51].

3.2. Second Objective Function: Minimizing the Expected Emission of WTES System

The second OF is to minimize the pollution produced by thermal units during the scheduling horizon, which is expressed according to the following equation:

$$\text{Min } \; F_2^{WTES} = \sum_{\omega=1}^{N_\Omega} \pi_\omega \times [\sum_{q=1}^{EMG} \sum_{g=1}^{N_G} E_{q,g} \times \left(EG_{g,t,\omega}^{E,th} + EGCH_{g,t} + Prob^{cal} EG_{g,t,\omega}^{S,th} \right)] \tag{2}$$

where the produced pollution arises from there sources. The first source is the generated emission by thermal units while contributing to the energy market, i.e., $EG_{t,\omega}^{E,th}$. The produced emission arising from providing the charging power for ESS ($EGCH_{g,t}$) and spinning reserve deployment in the balancing market ($Prob^{cal} EG_{g,t,\omega}^{S,th}$) are the second and third sources of emission, respectively. In this paper, the SO_2 and NO_X are considered as the source of pollutions due to their great importance in the environment [52]. It is worthwhile to note that the emission function of thermal units is approximated with a piecewise linearized segment [52].

3.3. Constraints

The constraints of the proposed WTES offering strategy are classified into the following categories.

3.3.1. Modeling Imbalances

In order to model the imbalances in the suggested offering strategy problem, constraints (3)-(5) are used. As stated above, imbalances arise when there is a difference between actual production and the submitted bid to the energy market. Constraints (3) calculates the whole energy deviations of WTES system in the balancing market. The first parenthesis expresses the total available and actual generated power by the WTES system, while the second parenthesis indicates the offered energy by the WTES system in the energy market. Equation (4) restricts the upper bound of the positive deviation, which is equivalent to the total available and actual generated power by the WTES system in each scenario. Similarly, constraint (5) restricts the maximum value of the negative deviation.

$$\begin{aligned}\Delta^{+}_{t,\omega} - \Delta^{-}_{t,\omega} = &\left(B^{E,th}_{t,\omega} + B^{E,S,dis}_{t,\omega} + P^{W}_{t,\omega} - PCH^{W}_{t}\right) \\ &- \left(B^{E,W}_{t,\omega} + B^{E,th}_{t,\omega} + B^{E,S,dis}\right), \quad \forall t, \forall \omega \end{aligned} \tag{3}$$

$$0 \leq \Delta^{+}_{t,\omega} \leq B^{E,th}_{t,\omega} + B^{E,S,dis}_{t,\omega} + P^{W}_{t,\omega} - PCH^{W}_{t}, \quad \forall t, \forall \omega \tag{4}$$

$$0 \leq \Delta^{-}_{t,\omega} \leq P^{W,Max} + \sum_{g=1}^{N_G} P^{th,Max}_{g}.u_{g,t} + P^{dis,Max}.v^{dis}_{t}, \quad \forall t, \forall \omega \tag{5}$$

3.3.2. Modeling Operational Constraints of Wind Farm

In this subsection, the operation constraints pertaining to the wind farm will be introduced. Constraints (6)-(9) model the maximum and minimum value of the offered energy by the wind farm in the energy market, provided charging energy for the ESS, and the total scheduled energy by the wind farm, respectively.

$$0 \leq B_{t,\omega}^{E,W} \leq P^{W,Max}, \quad \forall t, \forall \omega \tag{6}$$

$$0 \leq PCH_t^W \leq P^{W,Max}, \quad \forall t \tag{7}$$

$$0 \leq PCH_t^W \leq P^{ch,Max}, \quad \forall t \tag{8}$$

$$0 \leq PCH_t^W + B_{t,\omega}^{E,W} \leq P^{W,Max}, \quad \forall t, \forall \omega \tag{9}$$

3.3.3. Modeling Operational Constraints of Thermal Units

Equalities (10) and (11) calculate the total energy and spinning reserve offers by thermal units. Constraints (12)-(14) are employed to model the limitations related to the maximum and minimum value of produced and offered energies by thermal units. It is worth to note that the maximum capacity of units offer in the spinning reserve market would be defined based on their ramp-up rate, which is equivalent to $RUR_g \times \frac{1}{6}$. This issue comes from the fact that the spinning reserve should be ready to deliver in ten minutes [53]. The upper bound of the provided charging power for ESS by thermal units is limited using (15). The start-up and shut-down costs incurred by each thermal units are modeled by equations (16) and (17), respectively. The restrictions associated with the minimum up and down times of thermal units are enforced by (18) and (19), respectively. Furthermore, the logical relationship between the status of thermal units and start-up and shut-down variables are modeled via constraint (20). Equality (21) calculates the total expected production power by thermal units. Finally, the constraints associated with the unit's ramp-up and ramp-down limits are modeled by restrictions (22) and (23). It should be noted that the technical limitations pertaining to the start-up and shut-down ramps are considered in these constraints. It has to be noted that the prohibited operating zones of thermal units are not considered in the proposed model, whereas it can be easily adapted from the suggested model in [54]. It should be noted that the forced outage of thermal units is not considered in this paper, while appropriate modeling of them can be found in [55].

$$\sum_{g=1}^{N_G} EG_{g,t,\omega}^{E,th} = B_{t,\omega}^{E,th}, \quad \forall t, \forall \omega \tag{10}$$

$$\sum_{g=1}^{N_G} EG_{g,t,\omega}^{S,th} = B_{t,\omega}^{S,th}, \quad \forall t, \forall \omega \tag{11}$$

$$P_g^{th,Min}.u_{g,t} \leq EG_{g,t,\omega}^{E,th} + EGCH_{g,t} \leq P_g^{th,Max}.u_{g,t}, \quad \forall g, \forall t, \forall \omega \tag{12}$$

$$0 \leq EG_{g,t,\omega}^{S,th} \leq P_g^{th,S,Max}.u_{g,t}, \quad \forall g, \forall t, \forall \omega \tag{13}$$

$$P_g^{th,Min}.u_{g,t} \leq EG_{g,t,\omega}^{E,th} + EG_{g,t,\omega}^{S,th} + EGCH_{g,t} \leq P_g^{th,Max}.u_{g,t}, \quad \forall g, \forall t, \forall \omega \tag{14}$$

$$0 \leq EGCH_{g,t} \leq P^{ch,Max}.u_{g,t}, \quad \forall g, \forall t \tag{15}$$

$$0 \leq U_{g,t} \geq STUC_g.x_{g,t}, \quad \forall g, \forall t \tag{16}$$

$$0 \leq D_{g,t} \geq STDC_g.y_{g,t}, \quad \forall g, \forall t \tag{17}$$

$$\sum_{n=t-MUT_g+1}^{t} x_{g,t} \leq u_{g,t}, \quad \forall g, \forall t \tag{18}$$

$$\left(\sum_{n=t-MDT_g+1}^{t} y_{g,t}\right) + u_{g,t} \leq 1, \quad \forall g, \forall t \tag{19}$$

$$y_{g,t-1} - u_{g,t} + x_{g,t} - y_{g,t} = 0, \quad \forall g, \forall t \tag{20}$$

$$EG_{t,\omega}^{E,th} + EGCH_{g,t} + Prob^{cal} EG_{g,t,\omega}^{S,th} = EG_{g,t,\omega}^{EXP,th}, \quad \forall g, \forall t, \forall \omega \tag{21}$$

$$EG_{g,t,\omega}^{EXP,th} \leq EG_{g,t-1,\omega}^{EXP,th} + RUR_g.u_{g,t-1} + STURL_g.x_{g,t}, \quad \forall g, \forall t, \forall \omega \tag{22}$$

$$EG_{g,t-1,\omega}^{EXP,th} \leq EG_{g,t,\omega}^{EXP,th} + RDR_g.u_{g,t} + STDRL_g.y_{g,t}, \quad \forall g, \forall t, \forall \omega \tag{23}$$

3.3.4. Modeling Operational Constraints of ESS

Equations (24)-(32) are utilized to model the operational constraints of the ESS during the scheduling horizon. Equality (24) computes the total provided charging energy for ESS by the thermal units. Constraints (25) and (26) restrict the energy and spinning reserve offers of ESS during the discharging mode within its maximum discharging power. The total energy and spinning reserve offers of ESS also should not be higher than the maximum discharging power of ESS, which is modeled via (27). Equation (28) ensures that the total charging power of ESS does not exceed the maximum charging power of ESS in every time interval and scenario. Constraint (29) limits the spinning reserve offer of ESS during the charging mode. Restriction (30) models the operation mode of ESS at each time step. Eventually, the state of charge of ESS is calculated applying equation (31) while its maximum and minimum limitations are imposed by equation (32).

$$\sum_{g=1}^{N_G} EGCH_{g,t} = PCH_t^{th}, \quad \forall t \tag{24}$$

$$0 \leq B_{t,\omega}^{E,S,dis} \leq P^{dis,Max}.v_t^{dis}, \quad \forall t, \forall \omega \tag{25}$$

$$0 \leq B^{S,S,dis}_{t,\omega} \leq P^{dis,Max}.v^{dis}_t, \quad \forall t, \forall \omega \tag{26}$$

$$0 \leq B^{E,S,dis}_{t,\omega} + B^{S,S,dis}_{t,\omega} \leq P^{dis,Max}.v^{dis}_t, \quad \forall t, \forall \omega \tag{27}$$

$$0 \leq B^{E,S,ch}_{t,\omega} + PCH^{th}_t + PCH^{W}_t \leq P^{ch,Max}.v^{ch}_t, \quad \forall t, \forall \omega \tag{28}$$

$$0 \leq B^{S,S,ch}_{t,\omega} \leq B^{E,S,ch}_t, \quad \forall t, \forall \omega \tag{29}$$

$$v^{dis}_t + v^{ch}_t \leq 1, \quad \forall t \tag{30}$$

$$\begin{aligned} EB^{S}_{t,\omega} = EB^{S}_{t-1,\omega} + & \\ & Z^{S,ch}\left(B^{E,S,ch}_t + PCH^{th} + PCH^{W} - B^{S,S,Ch}_{t,\omega} \times Prob^{cal}\right) - \\ & \left(\frac{1}{Z^{S,dis}}\right)\left(B^{E,S,dis}_{t,\omega} + B^{S,S,dis}_{t,\omega} \times Prob^{cal}\right), \quad \forall t, \forall \omega \end{aligned} \tag{31}$$

$$0 \leq EB^{S}_{t,\omega} \leq EB^{S,Max}, \quad \forall t, \forall \omega \tag{32}$$

3.3.5. Modeling offering Curves

In order to extract the offering curves of the WTES system in the energy and spinning reserve markets, two conditions must always be met: the non-decreasing and the non-anticipativity constraints. Restrictions (33)-(35) and (36)-(38) provide the non-decreasing condition for submitting offering curves in the energy and spinning reserve market, respectively. Analogously, the non-anticipativity constraint of the energy and spinning reserve curves is ensured by equations (39)-(41) and (42)-(44), respectively.

$$B^{E,th}_{t,\omega} \leq B^{E,th}_{t,\widetilde{\omega}}, \quad \forall \omega, \widetilde{\omega} : [M^{E}_{t,\omega} \leq M^{E}_{t,\widetilde{\omega}}], \quad \forall t \tag{33}$$

$$B^{E,W}_{t,\omega} \leq B^{E,W}_{t,\widetilde{\omega}}, \quad \forall \omega, \widetilde{\omega} : [M^{E}_{t,\omega} \leq M^{E}_{t,\widetilde{\omega}}], \quad \forall t \tag{34}$$

$$B^{E,S,dis}_{t,\omega} \leq B^{E,S,dis}_{t,\widetilde{\omega}}, \quad \forall \omega, \widetilde{\omega} : [M^{E}_{t,\omega} \leq M^{E}_{t,\widetilde{\omega}}], \quad \forall t \tag{35}$$

$$B_{t,\omega}^{S,th} \leq B_{t,\widetilde{\omega}}^{S,th}, \quad \forall \omega, \widetilde{\omega} : [M_{t,\omega}^{S} \leq M_{t,\widetilde{\omega}}^{S}], \quad \forall t \tag{36}$$

$$B_{t,\omega}^{S,S,dis} \leq B_{t,\widetilde{\omega}}^{S,S,dis}, \quad \forall \omega, \widetilde{\omega} : [M_{t,\omega}^{S} \leq M_{t,\widetilde{\omega}}^{S}], \quad \forall t \tag{37}$$

$$B_{t,\omega}^{S,S,ch} \leq B_{t,\widetilde{\omega}}^{S,S,ch}, \quad \forall \omega, \widetilde{\omega} : [M_{t,\omega}^{S} \leq M_{t,\widetilde{\omega}}^{S}], \quad \forall t \tag{38}$$

$$B_{t,\omega}^{E,th} = B_{t,\widetilde{\omega}}^{E,th}, \quad \forall \omega, \widetilde{\omega} : [M_{t,\omega}^{E} = M_{t,\widetilde{\omega}}^{E}], \quad \forall t \tag{39}$$

$$B_{t,\omega}^{E,W} = B_{t,\widetilde{\omega}}^{E,W}, \quad \forall \omega, \widetilde{\omega} : [M_{t,\omega}^{E} = M_{t,\widetilde{\omega}}^{E}], \quad \forall t \tag{40}$$

$$B_{t,\omega}^{E,S,dis} = B_{t,\widetilde{\omega}}^{E,S,dis}, \quad \forall \omega, \widetilde{\omega} : [M_{t,\omega}^{E} = M_{t,\widetilde{\omega}}^{E}], \quad \forall t \tag{41}$$

$$B_{t,\omega}^{S,th} = B_{t,\widetilde{\omega}}^{S,th}, \quad \forall \omega, \widetilde{\omega} : [M_{t,\omega}^{S} = M_{t,\widetilde{\omega}}^{S}], \quad \forall t \tag{42}$$

$$B_{t,\omega}^{S,S,dis} = B_{t,\widetilde{\omega}}^{S,S,dis}, \quad \forall \omega, \widetilde{\omega} : [M_{t,\omega}^{S} = M_{t,\widetilde{\omega}}^{S}], \quad \forall t \tag{43}$$

$$B_{t,\omega}^{S,S,ch} = B_{t,\widetilde{\omega}}^{S,S,ch}, \quad \forall \omega, \widetilde{\omega} : [M_{t,\omega}^{S} = M_{t,\widetilde{\omega}}^{S}], \quad \forall t \tag{44}$$

Fig. 1 illustrates the schematic of the proposed WTES system participating in the energy and spinning reserve market using three-stage stochastic programming.

Fig. 1 is placed here

4. Multi-objective solution method

4.1. Modified ϵ-constraint method

In real engineering problems, the decision makers often confront further than one OF that has to be optimized. The ϵ-constraint [40] and weighted sum [56] methods are among common approaches to solve the multi-objective problems in the context of the power system. In the weighted sum technique, the OFs are merged while in the ϵ-constraint approach, one OF is considered as the principal OF and other OFs appear as the constraints in the problem formulation. Researchers have noted many advantages of the ϵ-constraint method versus the weighted sum approach in the literature of multi-objective optimization problems [57]. The main advantages of epsilon constraint are as follows:

1. Unlike the weighted sum method which is only capable of producing efficient extreme solutions, the ϵ-constraint method also has the ability to create non-extreme efficient solutions in linear problems [57].
2. Contrary to the weighted sum technique, the scaling of OFs in the ϵ-constraint method is not a problem [57].
3. It is possible to control the number of solutions obtained from ϵ-constraint technique only by changing the grid points associated with each of the OFs [57].

In accordance with the outlined advantages, the ϵ-constraint method has been implemented in some power system problems including self-scheduling problems [40] and [41] which indicate the performance of the suggested approach. On the other hand, researchers have consistently taken two points into account to improve the performance of the traditional ϵ-constraint. The researchers' first concern is that the range of OFs is not optimal over the efficient set, and secondly, the productivity of the attained results by the ϵ-constraint technique cannot be ensured. In order to prevail over these shortcomings, the LO and HAW-Eps methods are suggested in this paper. Hence, the proposed method for solving multi-objective optimization problem is contained the joint LO and HAW-Eps technique. It's worth mentioning that the effectiveness of the joint LO and HAW-Eps technique for obtaining the optimal Pareto solutions in multi-objective programming problems has been proved in [58].

Consider a multi-objective optimization problem with n OFs. The generic form of HAW-Eps technique would be formulated as follows:

$$Min/Max \;\; f_1(x) + \left(\frac{dir_1}{w_1}\right)\sum_{i=2}^{n} w_i \left(\frac{r_1 s_i^k}{r_i}\right) \tag{45}$$

subject to.

$$\begin{aligned} & e_i^k = f_i(x) - dir_i s_i^k \\ & s_i \in R^+ \end{aligned} \tag{46}$$

$$\begin{aligned} & e_i^k = f_i^{max} - \left(\frac{f_i^{max} - f_i^{min}}{q_i}\right) \times k \\ & k = 0, 1, ..., q_i \qquad i = 2, 3, ..., n \end{aligned} \tag{47}$$

where in (28), $f_1(x)$ is the selected principal OF among n OFs of the multi-objective optimization problem. It is worth noting that in the proposed multi-objective solution method, namely, HAW-Eps, there is no difference between the various objective functions in terms of being selected as the principal objective function. In order to determine the direction of each OF (minimization or maximization), dir_i is considered in the problem formulation. This parameter can be assigned values of $+1$ or -1. $dir_i = +1$ is related to the functions aimed at maximizing and $dir_i = -1$ is dedicated to the functions aimed at minimizing. S_i denotes the extra variables used for the constraint of the multi-objective optimization problem. The term w_i refers to the weights of each OF in the optimization process. In fact, this parameter reflects the comparative significance of OFs for the decision maker. Also, the range of every OF is represented by r_i which is calculated from the payoff table. As stated above, the productivity of the attained solutions through the ϵ-constraint technique is the first drawback of this approach, which the LO is introduced as the remedy to this matter [57]. In fact, the LO is applied to calculate the payoff table (matrix). The way to create this table by providing an example would be as follows.

Consider a multi-objective optimization problem with three OFs $Maxf_1(x)$, $Maxf_2(x)$ and $Maxf_3(x)$. The payoff table for this problem consists of 3 rows and columns. In general, the payoff table pertaining to a multi-objective optimization problem with n OFs would be a n*n matrix. Therefore, the payoff table of the aforementioned example would be as follows:

$$\Phi = \begin{bmatrix} f_1^*(x_1^*) & f_2^*(x_1^*) & f_3^*(x_1^*) \\ f_1^*(x_2^*) & f_2^*(x_2^*) & f_3^*(x_2^*) \\ f_1^*(x_3^*) & f_2^*(x_3^*) & f_3^*(x_3^*) \end{bmatrix} \quad (48)$$

where $f_1^*(x_1^*)$, $f_2^*(x_2^*)$ and $f_3^*(x_3^*)$ are the optimal values of OFs $f_1(x)$, $f_2(x)$ and $f_3(x)$ from a single objective optimization process, respectively. Hence, the single-objective optimization results of each of the OFs constitute the main diagonal of the payoff matrix. The fundamental difference in the calculation of the payoff matrix in the conventional approach and the LO relates to the calculation of non-main diagonal elements of this matrix. According to this matrix, there is a main OF in each row. The first row is related to the first OF ($f_1(x)$), the second row corresponds to the second OF ($f_2(x)$) and so forth. Based on the LO, the optimal values of OFs (e.g., $f_2(x)$ and $f_3(x)$) in rows with a different main OF ($f_1(x)$) would be calculated as follows:

$$\begin{aligned} f_2^*(x_1^*) &= Max f_2(x) \;\; s.t. \;\; Max f_1(x) = f_1^*(x_1^*) \\ f_3^*(x_1^*) &= Max f_3(x) \;\; s.t. \;\; Max f_1(x) = f_1^*(x_1^*) \end{aligned} \quad (49)$$

Finally, by constructing the payoff matrix, the upper and lower bounds of the ith OFs ($f_i(x)$) will be obtained from the ith column of the payoff matrix. Consequently, the range of$i$th OF r_i would be calculated as follows:

$$r_i = f_i^{max} - f_i^{min} \quad (50)$$

It should be noted that in order to prevent any scaling difficulty, $\frac{r_1 s_i}{r_i}$ is considered in the latter term of (45). Eventually, in the ultimate step, the decision maker should divide the range of $n-1$ OFs to the identical intervals

(q_i). By iteratively varying parameter e_i, the Pareto optimal solutions will be obtained. In other words, by selecting the appropriate number of grid points q_i for each OF $f_i(x)$, the optimization problem will be solved for $q_i + 1$ times, and thus, $q_i + 1$ efficient solutions will be obtained for each $f_i(x)$. In this regard, the multi-objective optimization problem will be divided into $\prod_{i=2}^{n}(q_i + 1)$ sub-problems, and as a result, $\prod_{i=2}^{n}(q_i + 1)$ efficient solutions as the Pareto optimal solutions will be acquired.

4.2. Decision maker's attitude to pick the most favored solution

After achieving the final result set, one of the most common questions that may arise for the decision-maker is: which of the obtained solutions is the most favored solution among the Pareto optimal solutions? A variety of approaches, such as the fuzzy technique [40], VIKOR [59], and a preference-based approach [60] have been used by researchers to pick the most favored solution among all set of solutions. In the fuzzy technique, a linear membership function is assigned to all OFs for measuring the optimal degree of each Pareto optimal solution. Whatever the obtained values from these membership functions are greater, the optimal degree of those specific solutions will also be greater. By contrast, the VIKOR technique specifies the most favored solution by ranking all obtained Pareto solutions in terms of being the closest to the ideal. In the current paper, the authors have benefitted from a preference-based approach according to the presented mechanism in [60]. Based on this approach, the ultimate decision maker's strategy will be implemented based on priority, preferences, and preconditions. To this end, the power producer (decision-maker), based on the prospect, past experiences, different operating conditions, market rules, and so on, selects boundaries for the OFs. In this regard, lower bounds are devoted to the maximizing OFs and upper bounds are assigned to the minimizing OFs by the decision-maker, and ultimately, the most favored solution is selected on the basis of these boundaries. For better clarification, the following example would be of interest.

Assume that the presented Pareto set in Fig. 2 concerns with a bi-objective optimization problem with OFs $G1$ and $G2$. The decision-maker aims at minimizing both OFs while the relevant upper bounds for $G1$ and $G2$ in the preference-based technique are considered equal to €7 and €6, respectively. According to these restrictions, Pareto solution 3 is selected as the most favored solution as it overcomes both limitations imposed by the decision-maker.

Fig. 2 is placed here

5. Emission trading

In many countries, the emission quotas pertaining to each GenCo are limited. For example, in the US, the environmental protection agency is in charge of the legislation in the area of greenhouse gas emission. According to the presented reports in [61], the emission quotas of power plants are determined by various factors such as the type of fuel consumption, the location of the power plants and long-term clean power plans by the environmental protection agency. In many cases, achieving maximum profit through the offering strategy problem leads to the procurement of extra emission quotas by the GenCo. This occurs when the emission quota is lower than the produced emission by the GenCo ($E^{Qo} < EG$). From a different point of view, depending on the market conditions, participation in the energy market may not be as profitable as selling a portion of the emission quota. In this case, the generated emission is lower than the assigned emission quota to the GenCo ($E^{Qo} > EG$). Consequently, after solving the multi-objective WTES offering strategy problem and achieving to the Pareto optimal solution set, the GenCo will face two situations in any of Pareto optimal solution: generation over emission quota and generation under emission quota. As stated above, the total expected GenCo's income in each Pareto optimal solution will be calculated as follows:

$$TPF = PF + \left[\lambda^{EE} \times \left(E^{Qo} - EG\right)\right] \tag{51}$$

Where TPF is the GenCo's total expected profit ($), PF indicates the system's profit in any of Pareto optimal solutions ($), E^{Qo} refers to the emission quota of the GenCo (lbs) and in the end, EG is the produced emission by the system in any of Pareto optimal solutions (lbs). Eventually, the Pareto optimal solution with the greatest quantity of TPF is selected as the final optimal solution among the total Pareto optimal solutions.

6. Solution procedure

In this section, the solution procedure of multi-objective WTES offering strategy with the implementation of LO and HAW-Eps method following the presented flowchart in Fig. 3 will be as the following steps:

1. The first step is related to dealing with the uncertain parameters in the WTES offering strategy problem. In the current paper, authors benefit from a scenario-based approach to address the uncertain nature of parameters in the multi-stage WTES offering strategy problem. The uncertain parameters consist of energy, spinning reserve, up and down imbalance ratios (balancing market) and finally, wind power. For this purpose, the roulette wheel process [62] is employed to generate an arbitrary level of stochastic scenarios for each uncertain parameter. It is worth to note that the normal [63] and Rayleigh [64] distributions are assigned as suitable probability density functions for extracting the behavior of electricity prices and wind speed, respectively. In this regard, a large number of scenarios are generated based on the statistical characteristic of each parameter (scenario generation stage). Constructing the scenario tree based on a large number of scenarios will cause the problem to become intractable. To this end, the initial scenarios pertaining to each uncertain parameter are reduced to five representing scenarios using SCENRED tool [65] in GAMS (scenario reduction stage). This tool allows stochastic programming researchers to reduce their initial scenario set to a smaller scenario subset to avoid the computational explosion. SCENRED consists of two

scenario reduction algorithms, namely, forward and backward algorithms. The initial scenario set is reduced to the desired number using each of these algorithms, and subsequently, the final preserved scenarios and their updated probabilities are the outputs of the aforementioned algorithms. It has to be noted that the forward algorithm due to the lower computation time has been employed in this paper.

2. In the second step, the LO is applied to calculate the payoff matrix for the multi-objective WTES offering problem.

3. In the third step, equation (50) based on the payoff matrix is utilized to calculate the range of each OF $f_i(x)$ (i=2, 3,..., n).

4. In the next step, equation (47) is employed to divide the range of n-1 OFs to q_i identical intervals.

5. The fifth step is concerned with obtaining the Pareto optimal solutions by solving $\prod_{i=2}^{n}(q_i+1)$ optimization sub-problems. It must be stressed that applying the HAW-Eps method in this stage will ensure the efficiency of the obtained solutions.

6. finally, the last step is to pick the most favored Pareto optimal solution among the all Pareto optimal solutions by applying the suggested approach in subsection 4.2.

Fig. 3 is placed here

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7. Numerical results

In this section, the system under study is initially introduced. Then, the input data and case studies intended to assess the effectiveness and applicability of the suggested model will be presented in detail.

The system under study contains a wind farm, fourteen thermal units, and an ESS. The capacity of the wind farm and ESS is 360 MW and 50 MWh, respectively, whereas the total installed capacity of the thermal units is equal to 794 MW. The cost and emission information of thermal units with their permissible output power are presented in Table 2. It is worthwhile to note that this information has been extracted from [52]. According to previously published work in this area, the SO_2 and NO_X are considered as the primary sources of emission in this study [52]. The technical specification of thermal units including ramp up/down limits, minimum up/down times, shut-down ramp limit, start-up ramp limit as well as their start-up and shut-down costs are shown in Table 3. It can be noticed that the units' shut-down cost ($STDC(g)$) are equal to $0.1 \times STUC(g)$. As stated in subsection 3.3.3, the maximum unit's offer in the spinning reserve market is determined as $RUR_g \times \frac{1}{6}$ [12]. Also, the value of $Prob^{cal}$ is assumed to be 0.05 [19]. The characteristics of the ESS and wind turbines have been exhibited in Table 4. The efficiency data of ESS in either charging or discharging mode is used from [22] while the maximum energy volume of ESS has been adopted from [19].

Table 2, Table 3 and Table 4 are placed here

As already mentioned in the solution procedure section, there are four sources of uncertainty in the suggested problem. First, abundant scenarios for each parameter is generated. Afterward, in order to avoid any computational burden, the generated scenarios pertaining to each parameter are reduced to five scenarios using SCENRED. The data for the first six months of 2018 is considered for the statistical analysis in the scenario generation process. The data on the electricity market and wind speed can be found in [66] and [67], respectively. For instance, the data on energy and spinning reserve prices have been shown in Fig. 4 [66]. Lastly, the probability of reduced scenarios for each uncertain parameter is listed in Table 5.

Fig. 4 is placed here

The proposed bi-objective WTES offering strategy problem is formulated as a MIP problem and solved with GAMS software using CPLEX12. It is worthwhile to mention that the authors are currently working on a book in the context of offering strategy in which the integration of various energy sources and application of diverse uncertainty modeling techniques will be investigated while all GAMS codes pertaining to this paper and other analyses will be available for readers [68].

This problem will be analyzed under three different case studies each includes two different decision-making schemes:

1. First scheme: In the first scheme, the comparative significance of both OFs is equivalent (w_1, w_2= 1). Thus, in the proposed multi-objective optimization framework, the WTES system makes no distinction between the goals of profit maximization and emission minimization.
2. Second scheme: Since system's primary goal is to attain the maximum profit by participating in the electricity markets, the significance of maximizing profits in the second scheme is considered three times higher than the emission minimization, thus, w_1=3 and w_2=1.

It has to be noted that the different aspects of each case study are characterized in Table 6. The first case study addresses the bi-objective offering strategy of a wind-thermal system in the energy market. In the latter case study, the multi-objective offering strategy problem is developed for a WTES system, in which only thermal units participate in the spinning reserve market. Finally, the third case study examines the previous case by taking into account the involvement of the ESS in the spinning reserve market. Finally, as expressed in subsection 4.2, the decision maker should determine the limitations of each OF in every decision-making scheme to choose the final decision in the bi-objective optimization problem. The maximum prearranged limits for the emission of the WTES system in the first and the second decision-making schemes are 55×10^3 lbs and 215×10^3 lbs, respectively, while the minimum restrictions for the system's profit are selected € 240×10^3 and € 345×10^3 for the first and the second decision-making schemes, respectively.

Table 6 is placed here

Tables 7, 8, and 9 show a set of optimal Pareto solutions for case studies one, two, and three correspondings to the first decision-making scheme, respectively. The first three columns present the number, expected profit and expected emission of each Pareto optimal solution. The next two columns indicate the total submitted offers from the system to energy and spinning reserve markets through the 24-hour scheduling horizon. According to the reported solutions in these tables, decreasing the system's expected profit will lead to a lower level of participation in the energy market. The first row with highlighted cells represents the final decision of the system for whole case studies based on the prearranged values. The expected profits of the system in the first to third case studies are € 243637.717, € 249915.654, and € 262167.583, respectively, indicating the performance of the third case study in comparison with other cases. The offering strategy in the third case study of first decision-making scheme results in an increase of € 18529.866 and € 12251.929 compared to the first and second cases, respectively. From a different point of view, the second and third case studies will also result in a lower level of pollution compared to the first case. The reason behind the variation of the system's emission in the first case study in contrast to the second and third cases is the participation of thermal units in the spinning reserve market.

Table 7, Table 8 and Table 9 are placed here

The results of the second decision-making scheme are listed in Tables 10, 11, and 12. Analogous to the first case study, the highlighted rows of the tables demonstrate the picked solution for all case studies. It is worth to note that the increment in the system's expected profit will raise the generated pollution by the system. Another point of attention is that the amount of total submitted offers by the system under study in both the energy and spinning reserve markets will increase in the second decision-making scheme compared to the first one.

Table 10, Table 11 and Table 12 are placed here

The status of thermal units within the scheduling horizon for the selected solutions of the whole case studies are shown in Table 13 and Table 14. According to Table 13, in the first decision-making scheme, units $G6 - G9$ and $G14$ are off for the entire scheduling period. This issue stems from the fact of having high production cost for units $G6 - G9$ and exorbitant start-up and shut-down costs for unit $G19$. By changing the producer's decision-making approach from the first scheme to the second one, unit $G14$ starts to produce electricity at the first hour and remains online for the rest of the scheduling period. Also, by altering the offering strategy of the system from the first case study to the second/third case study, units G1-G5 generate power during hours 1-5 in contrast with the first case study. It should be noted that the variation in the commitment program of units in each case study is distinguished by highlighted cells.

Table 13 and Table 14 are placed here

The expected energy offers in the spinning reserve market for the selected solutions have been shown in Fig. 5. From Fig. 5 (a), two things can be concluded: first, by increasing the significance of the profit function for the decision maker, the participation of thermal units in the spinning reserve market will dramatically grow and second, at hour 20, the system's involvement in the spinning reserve market will diminish due to its lowest spinning reserve price. Fig. 5 (b) and Fig. 5 (c) provide the expected involvement of WTES system in the spinning reserve market for two different decision-making schemes of the third case study. As can be seen from these figures, changing the decision-making scheme does not have an effect on the amount of submitted energy offers by the ESS in the spinning reserve market, and the attitude of thermal units in this market only suffers changes.

Fig. 5 are placed here

The optimal involvement of ESS in the energy market and its state of charge for the second and the third case studies have been depicted in Fig. 6. As can be seen in Fig. 6 (a), the ESS system purchase energy at hours 1 and 3 as a result of experiencing the lowest energy prices at these hours. The ESS system sells the stored energy during hours 8, 14, 19 and 20 due to the facts that the peak of energy market prices occur during these hours (hours 19 and 20) or ESS experiences extremely high energy price in a specific scenario (hours 8 and 14). In the second decision-making scheme (Fig. 6 (b)), the ESS would supply most of its charging power at hour 3 through the thermal units instead of buying it from the energy market. In other words, providing the charging energy at this hour through the thermal units is more profitable than purchasing it from the energy market. Fig. 6 (c) illustrates the optimal operation of ESS in the third case study. Fig. 6 (c) and Fig. 5 (b/c) permit concluding that the mere participation of ESS in the spinning reserve market is more profitable than offering in the energy market.

Fig. 6 is placed here

The offering curves of the WTES system in the energy and spinning reserve markets for two distinct hours are presented in Fig. 7 and Fig. 8, respectively. It must be stressed that these curves are related to the first decision-making scheme. In fact, thermal units will diminish their participation in the energy market whenever the option of spinning reserve market is available. Another important point that can be deduced from Fig. 7 (a) is that the ESS offers in the energy market at hour 8 due to the fact of experiencing an extremely high energy price (67.21 €/MWh) in a scenario. Fig. 9 presents the variation of the system's expected profit for different values of ESS production capacity in the third case study of the first scheme. As can be observed from this curve, the suggested offering strategy in the third case study can significantly raise the expected profit of the system by increasing the production capacity of ESS. Specifically, in the suggested approach, every five megawatts increment in the production capacity of ESS will lead to a € 1299 increase in the total expected profit of the system while in the proposed method of [22], each extra 5 MW production capacity will result in a € 14 increase in the expected profit.

Fig. 7, Fig. 8, and Fig. 9 are placed here

One of the most critical issues encountered by the researchers in the multi-objective stochastic programming problems is the number of scenarios arising from the uncertain parameters. To this end, a further study based on the larger number of reduced scenarios, i.e., ten scenarios, has been accomplished, and subsequently, the results are compared with the previous studies. It has to be noted that this additional study is carried out on the third case study of the second decision-making scheme. The suggested model is solved with CPLEX12 under GAMS environment in an ASUS K series laptop computer powered by a core i5 processor and 4 GB of RAM. Table 15 reports the results of the third case study for the second decision-making scheme under two different analyses, namely, five and ten representative scenarios for each uncertain source. The reported results demonstrate that increasing the number of scenarios will result in a 1.26% gain and a 0.87% decrease in the expected profit and emission, respectively, while the solution time for the payoff table and each sub-problem significantly raises. Another point of attention is that altering the number of scenarios from five to ten considerably augment the number of variables and equations as well as CPLEX iterations to reach the optimal solution. Another key point is that since a multi-objective optimization problem consists of many sub-problems to obtain the Pareto solution set, decision-makers may ignore slight changes in the output variables due to substantial computational time.

Table 15 is placed here

As already mentioned in the second decision-making scheme, the primary purpose of GenCos from participating in the multi-auction electricity markets is to attain their expected profit to its maximum possible value through the offering process. Due to the importance of maximizing profit versus minimizing emissions for a power producer, emission trading as a new pattern can also be used to acquire the most-favored solution in the multi-objective offering strategy problem when this option is available for the WTES system. The results of applying this technique in terms of various emission prices (λ^{EE}) are exhibited in Table 16. It has to be noted that the emission quota of the WTES system is assumed to be E^{Qo}= 215×10^3 lbs. The highlighted cells in each column illustrate the optimal solutions of the multi-objective WTES offering strategy problem through emission trading paradigm for that special emission price.

Table 16 is placed here

8. Conclusion

In this paper, a stochastic three-stage bi-objective offering framework for a wind-thermal-energy storage system based on mixed-integer programming formulation was proposed. In the proposed framework, the uncertain nature of various parameters was modeled via a scenario-based approach. A powerful and effective method based on the joint utilization of lexicographic optimization and hybrid augmented-weighted ϵ-constraint was applied to solve the bi-objective wind-thermal-energy storage offering problem. In this regard, the hybrid augmented-weighted ϵ-constraint method aids the decision-makers to import the comparative importance degree of objective functions in the optimization process. By achieving the Pareto optimal solution set, two suggested strategies were used to select the final solution. Three different case studies which each of them represents diverse offering frameworks under two distinct decision-making schemes were carried out to examine all aspects of the designed offering structure. After achieving the results, it can be concluded that:

1. Utilizing the third offering structure (case study 3) not only leads to a significant increase in the expected profits of the system in both decision-making schemes.
2. The first stage decisions of the proposed offering problem, especially the status of thermal units, will be influenced by the system's decision-making attitude.
3. The mere participation of energy storage system in the spinning reserve is considerably more profitable than participating in the energy market.
4. The emission trading pattern will allow us to determine the most favored solution after attaining the Pareto solution set regarding various emission quotas. This approach is economically beneficial for those societies with this capability.

For future research, the authors would expand the proposed offering strategy for a price-maker wind-thermal-energy storage producer, which will augment challenges to the problem.

References

[1] Philibert C. Renewable Energy for Industry: Offshore Wind in Northern Europe. Int Energy Agency 2018.

[2] Taylor M, Ralon P, Ilas A. The power to change: solar and wind cost reduction potential to 2025. Int Renew Energy Agency 2016.

[3] Ren G, Liu J, Wan J, Guo Y, Yu D. Overview of wind power intermittency: Impacts, measurements, and mitigation solutions. Appl Energy 2017;204:47–65. doi:10.1016/j.apenergy.2017.06.098.

[4] Guerrero-Mestre V, Sanchez De La Nieta AA, Contreras J, Catalao JPS. Optimal Bidding of a Group of Wind Farms in Day-Ahead Markets Through an External Agent. IEEE Trans Power Syst 2016;31:2688–700. doi:10.1109/TPWRS.2015.2477466.

[5] Afshar K, Ghiasvand FS, Bigdeli N. Optimal Bidding Strategy of Wind Power Producers in Pay-as-Bid Power Markets. Renew Energy 2018;127:575–86. doi:10.1016/j.renene.2018.05.015.

[6] Moradi-Dalvand M, Mohammadi-Ivatloo B, Amjady N, Zareipour H, Mazhab-Jafari A. Self-scheduling of a wind producer based on Information Gap Decision Theory. Energy 2015;81:588–600. doi:10.1016/j.energy.2015.01.002.

[7] Vahedipour-Dahraie M, Anvari-Moghaddam A, Guerrero JM. Evaluation of reliability in risk-constrained scheduling of autonomous microgrids with demand response and renewable resources. IET Renew Power Gener 2018. doi:10.1049/iet-rpg.2017.0720.

[8] Marzband M, Azarinejadian F, Savaghebi M, Pouresmaeil E, Guerrero JM, Lightbody G. Smart transactive energy framework in grid-connected multiple home microgrids under independent and coalition operations. Renew Energy 2018. doi:10.1016/j.renene.2018.03.021.

[9] Monfared HJ, Ghasemi A, Loni A, Marzband M. A hybrid price-based demand response program for the residential micro-grid. Energy 2019;185:274–85.

[10] Khaloie H, Abdollahi A, Rashidineiad M. Risk-Constrained Self-Scheduling and Forward Contracting Under Probabilistic-Possibilistic Uncertainties. Electr. Eng. (ICEE), Iran. Conf., IEEE; 2018, p. 1138–43. doi:10.1109/ICEE.2018.8472668.

[11] Nojavan S, Zare K, Ashpazi MA. A hybrid approach based on IGDT-MPSO method for optimal bidding strategy of price-taker generation sta-

tion in day-ahead electricity market. Int J Electr Power Energy Syst 2015. doi:10.1016/j.ijepes.2015.01.006.

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

[13] Laia R, Pousinho HMI, Melíco R, Mendes VMF. Bidding strategy of wind-thermal energy producers. Renew Energy 2016;99:673–81. doi:10.1016/j.renene.2016.07.049.

[14] Ghalelou AN, Fakhri AP, Nojavan S, Majidi M, Hatami H. A stochastic self-scheduling program for compressed air energy storage (CAES) of renewable energy sources (RESs) based on a demand response mechanism. Energy Convers Manag 2016;120:388–96. doi:10.1016/j.enconman.2016.04.082.

[15] Al-Swaiti MS, Al-Awami AT, Khalid MW. Co-optimized trading of wind-thermal-pumped storage system in energy and regulation markets. Energy 2017;138:991–1005. doi:10.1016/j.energy.2017.07.101.

[16] Afshari Igder M, Niknam T, Khooban M-H. Bidding strategies of the joint wind, hydro, and pumped-storage in generation company using novel improved clonal selection optimisation algorithm. IET Sci Meas Technol 2017;11:991–1001. doi:10.1049/iet-smt.2017.0014.

[17] Kose F, Kaya MN. Analysis on meeting the electric energy demand of an active plant with a wind-hydro hybrid power station in Konya, Turkey: Konya water treatment plant. Renew Energy 2013;55:196–201.

[18] Kose F, Kaya MN. Wind-Hydro Pumped Storage Power Stations to Meet the Energy Demands of Irrigation: Feasibility, Optimal Design and Simulation of a System. 中械工程刊 2018;39:223–32.

[19] He G, Chen Q, Kang C, Pinson P, Xia Q. Optimal bidding strategy of battery storage in power markets considering performance-based regulation and battery cycle life. IEEE Trans Smart Grid 2016;7:2359–67.

[20] Nojavan S, Najafi-Ghalelou A, Majidi M, Zare K. Optimal bidding and offering strategies of merchant compressed air energy storage in deregulated electricity market using robust optimization approach. Energy 2018;142:250–7. doi:10.1016/j.energy.2017.10.028.

[21] Ding H, Pinson P, Hu Z, Song Y. Optimal offering and operating strategies for wind-storage systems with linear decision rules. IEEE Trans Power Syst 2016;31:4755–64.

[22] Gomes ILR, Pousinho HMI, Melicio R, Mendes VMF. Stochastic coordination of joint wind and photovoltaic systems with energy storage in day-ahead market. Energy 2017;124:310–20.

[23] Rashidizadeh-Kermani H, Najafi HR, Anvari-Moghaddam A, Guerrero JM. Optimal decision-making strategy of an electric vehicle aggregator in short-term electricity markets. Energies 2018. doi:10.3390/en11092413.

[24] De La Nieta AAS, Contreras J, Munoz JI. Optimal coordinated wind-hydro bidding strategies in day-ahead markets. IEEE Trans Power Syst 2013;28:798–809. doi:10.1109/TPWRS.2012.2225852.

[25] De La Nieta AAS, Contreras J, Catalão JPS. Optimal Single Wind Hydro-Pump Storage Bidding in Day-Ahead Markets Including Bilateral Contracts. IEEE Trans Sustain Energy 2016. doi:10.1109/TSTE.2016.2544704.

[26] Reddy SS. Optimal scheduling of thermal-wind-solar power system with storage. Renew Energy 2017. doi:10.1016/j.renene.2016.10.022.

[27] Chen JJ, Zhuang YB, Li YZ, Wang P, Zhao YL, Zhang CS. Risk-aware short term hydro-wind-thermal scheduling using a probability interval optimization model. Appl Energy 2017. doi:10.1016/j.apenergy.2016.12.031.

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

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

[30] Abbasi MH, Taki M, Rajabi A, Li L, Zhang J. Coordinated operation of electric vehicle charging and wind power generation as a virtual power plant: A multi-stage risk constrained approach. Appl Energy 2019. doi:10.1016/j.apenergy.2019.01.238.

[31] Shafie-khah M, Heydarian-Forushani E, Golshan MEH, Siano P, Moghaddam MP, Sheikh-El-Eslami MK, Catalão JPS. Optimal trading of plug-in electric vehicle aggregation agents in a market environment for sustainability. Appl Energy 2016. doi:10.1016/j.apenergy.2015.10.134.

[32] Shabanzadeh M, Sheikh-El-Eslami MK, Haghifam MR. The design of a risk-hedging tool for virtual power plants via robust optimization approach. Appl Energy 2015. doi:10.1016/j.apenergy.2015.06.059.

[33] Kong X, Xiao J, Wang C, Cui K, Jin Q, Kong D. Bi-level multi-time scale scheduling method based on bidding for multi-operator virtual power plant. Appl Energy 2019. doi:10.1016/j.apenergy.2019.04.130.

[34] Khalid M, Aguilera RP, Savkin A V., Agelidis VG. On maximizing profit of wind-battery supported power station based on wind power and energy price forecasting. Appl Energy 2018. doi:10.1016/j.apenergy.2017.11.061.

[35] De Vivero-Serrano G, Bruninx K, Delarue E. Implications of bid structures on the offering strategies of merchant energy storage systems. Appl Energy 2019. doi:10.1016/j.apenergy.2019.113375.

[36] Nojavan S, Zare K, Mohammadi-Ivatloo B. Optimal stochastic energy management of retailer based on selling price determination under smart grid environment in the presence of demand response program. Appl Energy 2017. doi:10.1016/j.apenergy.2016.11.024.

[37] Iria J, Soares F, Matos M. Optimal bidding strategy for an aggregator of prosumers in energy and secondary reserve markets. Appl Energy 2019. doi:10.1016/j.apenergy.2019.01.191.

[38] Ghahary K, Abdollahi A, Rashidinejad M, Alizadeh MI. Optimal reserve market clearing considering uncertain demand response using information gap decision theory. Int J Electr Power Energy Syst 2018;101:213–22.

[39] Tsimopoulos EG, Georgiadis MC. Optimal strategic offerings for a conventional producer in jointly cleared energy and balancing markets under high penetration of wind power production. Appl Energy 2019. doi:10.1016/j.apenergy.2019.03.161.

[40] Ahmadi A, Aghaei J, Shayanfar HA, Rabiee A. Mixed integer programming of multi-objective hydro-thermal self scheduling. Appl Soft Comput J 2012;12:2137–46. doi:10.1016/j.asoc.2012.03.020.

[41] Aghaei J, Ahmadi A, Rabiee A, Agelidis VG, Muttaqi KM, Shayanfar HA. Uncertainty management in multiobjective hydro-thermal self-scheduling under emission considerations. Appl Soft Comput J 2015;37:737–50. doi:10.1016/j.asoc.2015.08.046.

[42] Shafiekhani M, Badri A, Shafie-khah M, Catalão JPS. Strategic bidding of virtual power plant in energy markets: A bi-level multi-objective approach. Int J Electr Power Energy Syst 2019. doi:10.1016/j.ijepes.2019.05.023.

[43] Aghaei J, Alizadeh MI. Multi-objective self-scheduling of CHP (combined heat and power)-based microgrids considering demand response programs and ESSs (energy storage systems). Energy 2013;55:1044–54. doi:10.1016/j.energy.2013.04.048.

[44] Nezhad AE, Javadi MS, Rahimi E. Applying augmented ϵ-constraint approach and lexicographic optimization to solve multi-objective hydrothermal generation scheduling considering the impacts of pumped-storage units. Int J Electr Power Energy Syst 2014;55:195–204. doi:10.1016/j.ijepes.2013.09.006.

[45] Sun Y, Dong J, Ding L. Optimal day-ahead wind-thermal unit commitment considering statistical and predicted features of wind speeds. Energy Convers Manag 2017;142:347–56. doi:10.1016/j.enconman.2017.03.025.

[46] Yuan X, Tian H, Yuan Y, Huang Y, Ikram RM. An extended NSGA-III for solution multi-objective hydro-thermal-wind scheduling considering wind power cost. Energy Convers Manag 2015;96:568–78. doi:10.1016/j.enconman.2015.03.009.

[47] Zhou J, Lu P, Li Y, Wang C, Yuan L, Mo L. Short-term hydro-thermal-wind complementary scheduling considering uncertainty of wind power using an enhanced multi-objective bee colony optimization algorithm. Energy Convers Manag 2016;123:116–29. doi:10.1016/j.enconman.2016.05.073.

[48] Valinejad J, Barforoshi T, Marzband M, Pouresmaeil E, Godina R, PS Catalão J. Investment incentives in competitive electricity markets. Appl Sci 2018;8:1978.

[49] Khaloie H, Abdollahi A, Shafie-Khah M, Siano P, Nojavan S, Anvari-Moghaddam A, Catalão JPS. Co-optimized Bidding Strategy of an Integrated Wind-Thermal-Photovoltaic System in Deregulated Electricity Market Under Uncertainties. J Clean Prod 2019:118434. doi:10.1016/j.jclepro.2019.118434.

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

[51] Naderi E, Pourakbari-Kasmaei M, Abdi H. An efficient particle swarm optimization algorithm to solve optimal power flow problem integrated with FACTS devices. Appl Soft Comput 2019;80:243–62.

[52] Khaloie H, Abdollahi A, Nojavan S, Shafie-Khah M, Anvari-Moghaddam A, Siano P, Catalão JPS. Offering strategy of thermal-photovoltaic-storage based generation company in day-ahead market. Electricity Markets: New Players and Pricing Uncertainties., Springer International Publishing; (in press).

[53] Elmitwally A, Eladl A. Planning of multi-type FACTS devices in restructured power systems with wind generation. Int J Electr Power Energy Syst 2016;77:33–42.

[54] Pourakbari-Kasmaei M, Lehtonen M, Fotuhi-Firuzabad M, Marzband M, Mantovani JRS. Optimal power flow problem considering multiple-fuel options and disjoint operating zones: A solver-friendly MINLP model. Int J Electr Power Energy Syst 2019. doi:10.1016/j.ijepes.2019.05.020.

[55] Tabandeh A, Abdollahi A, Rashidinejad M. Reliability constrained congestion management with uncertain negawatt demand response firms considering repairable advanced metering infrastructures. Energy 2016. doi:10.1016/j.energy.2016.03.118.

[56] Somma M Di, Yan B, Bianco N, Graditi G, Luh PB, Mongibello L, Naso V. Multi-objective design optimization of distributed energy systems through cost and exergy assessments. Appl Energy 2017. doi:10.1016/j.apenergy.2017.03.105.

[57] Mavrotas G. Generation of efficient solutions in Multiobjective Mathematical Programming problems using GAMS. Effective implementation of the ϵ-constraint method. Lect Lab Ind Energy Econ Sch Chem Eng Natl Tech Univ Athens 2007.

[58] Mavrotas G. Effective implementation of the ϵ-constraint method in Multi-Objective Mathematical Programming problems. Appl Math Comput 2009;213:455–65. doi:10.1016/j.amc.2009.03.037.

[59] Ahmadi A, Nezhad AE, Siano P, Hredzak B, Saha S. Information-Gap Decision Theory for Robust Security-Constrained Unit Commitment of Joint Renewable Energy and Gridable Vehicles. IEEE Trans Ind Informatics 2019.

[60] Zakariazadeh A, Jadid S, Siano P. Stochastic multi-objective operational planning of smart distribution systems considering demand response programs. Electr Power Syst Res 2014;111:156–68.

[61] Regulating Power Sector Carbon Emissions — Center for Climate and Energy Solutions n.d. https://www.c2es.org/content/regulating-power-sector-carbon-emissions/ (accessed May 7, 2019).

[62] Heydarian-Forushani E, Moghaddam MP, Sheikh-El-Eslami MK, Shafie-Khah M, Catalão JPS. Risk-constrained offering strategy of wind power producers considering intraday demand response exchange. IEEE Trans Sustain Energy 2014. doi:10.1109/TSTE.2014.2324035.

[63] Mirzaei MA, Yazdankhah AS, Mohammadi-Ivatloo B, Marzband M, Shafie-khah M, Catalão JPS. Stochastic network-constrained co-optimization of energy and reserve products in renewable energy integrated power and gas networks with energy storage systems. J Clean Prod 2019;223:748–58.

[64] Mazidi M, Zakariazadeh A, Jadid S, Siano P. Integrated scheduling of renewable generation and demand response programs in a microgrid. Energy Convers Manag 2014. doi:10.1016/j.enconman.2014.06.078.

[65] SCENRED2 n.d. https://www.gams.com/24.8/docs/tools/scenred2/index.html (accessed September 5, 2019).

[66] Bienvenido — ESIOS electricidad · datos · transparencia n.d. https://www.esios.ree.es/es (accessed March 14, 2019).

[67] Weather history+ - meteoblue n.d. https://www.meteoblue.com/en/historyplus (accessed April 22, 2019).

[68] Khaloie H, Abdollahi A, Shafie-Khah M, Anvari-Moghaddam A, Nojavan S, Siano P, Catalão JPS. Optimal operation of hybrid power plants in electricity markets. Book in preparation.

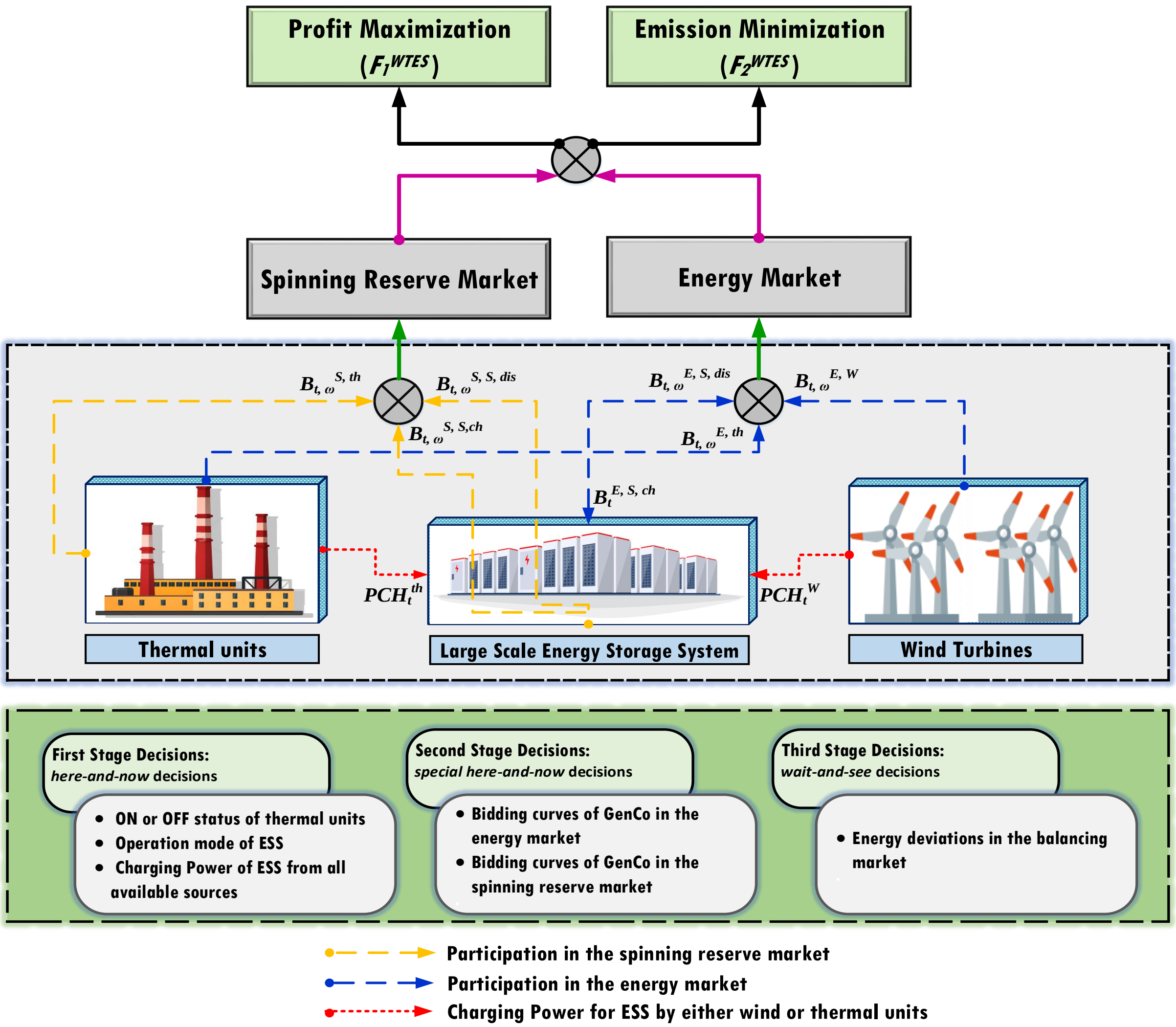


Figure 1: Schematic of the proposed three-stage offering strategy for the WTES system

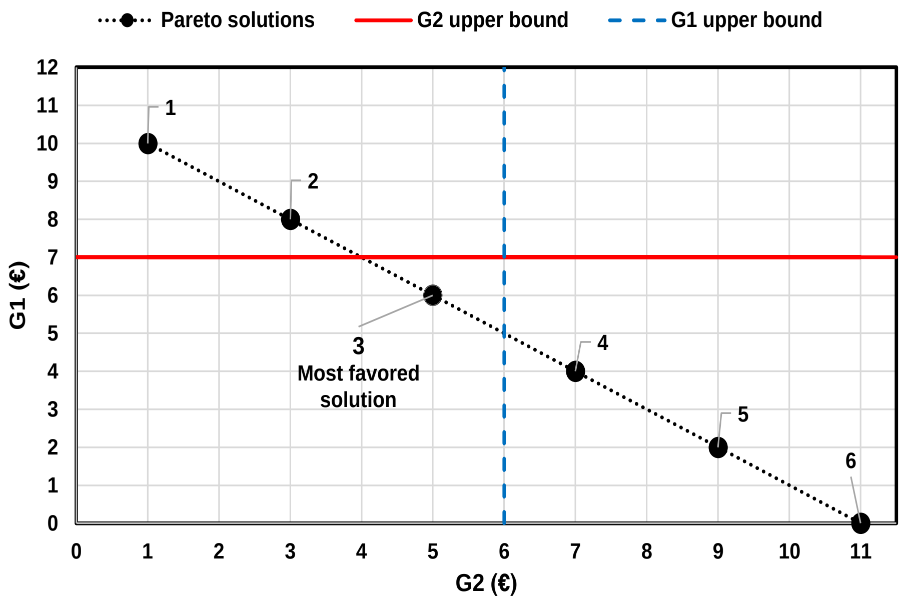


Figure 2: Sample of a Pareto solution set for demonstrating the performance of the preference-based technique

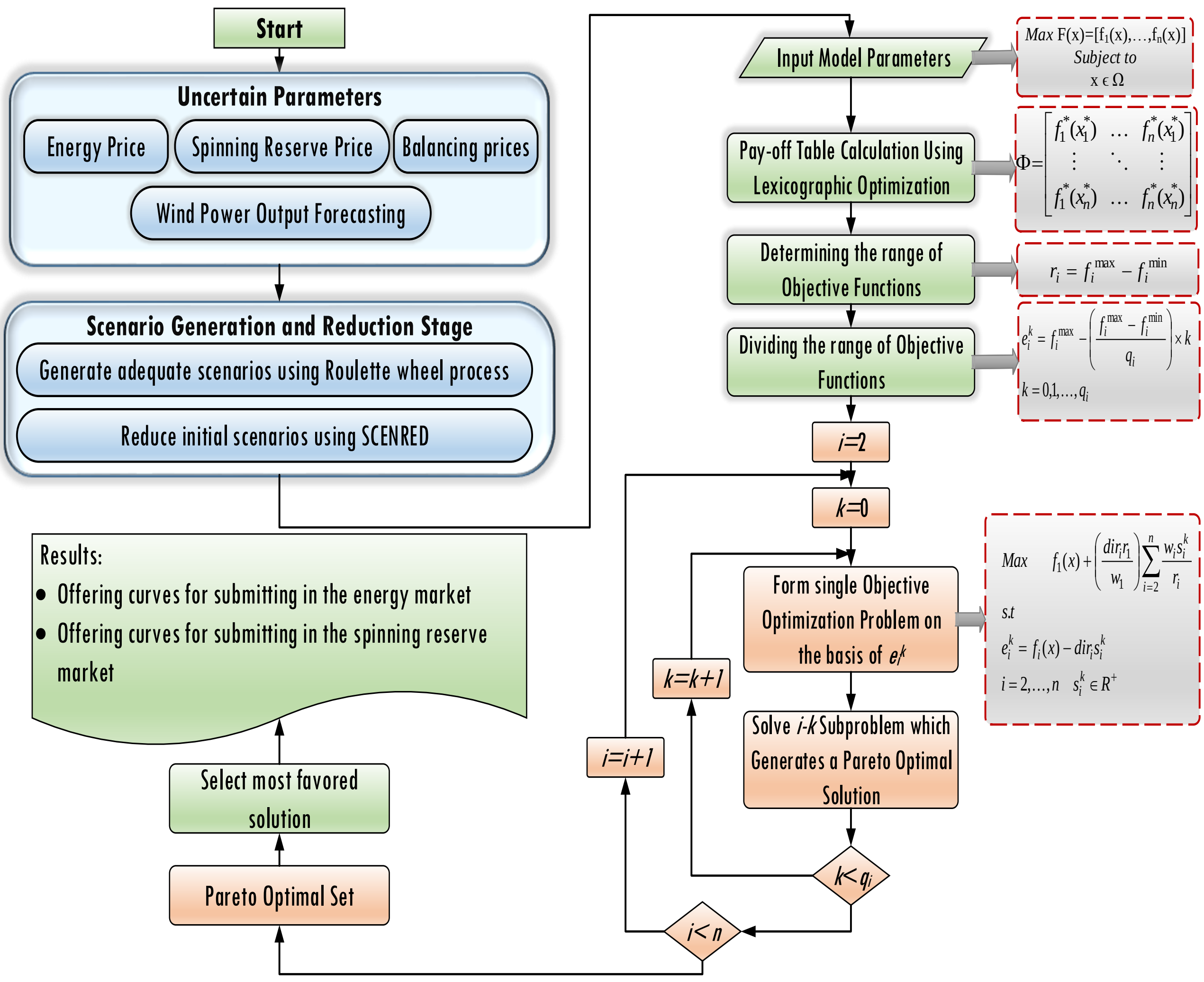


Figure 3: Schematic of the proposed solution procedure for the multi-objective offering strategy problem

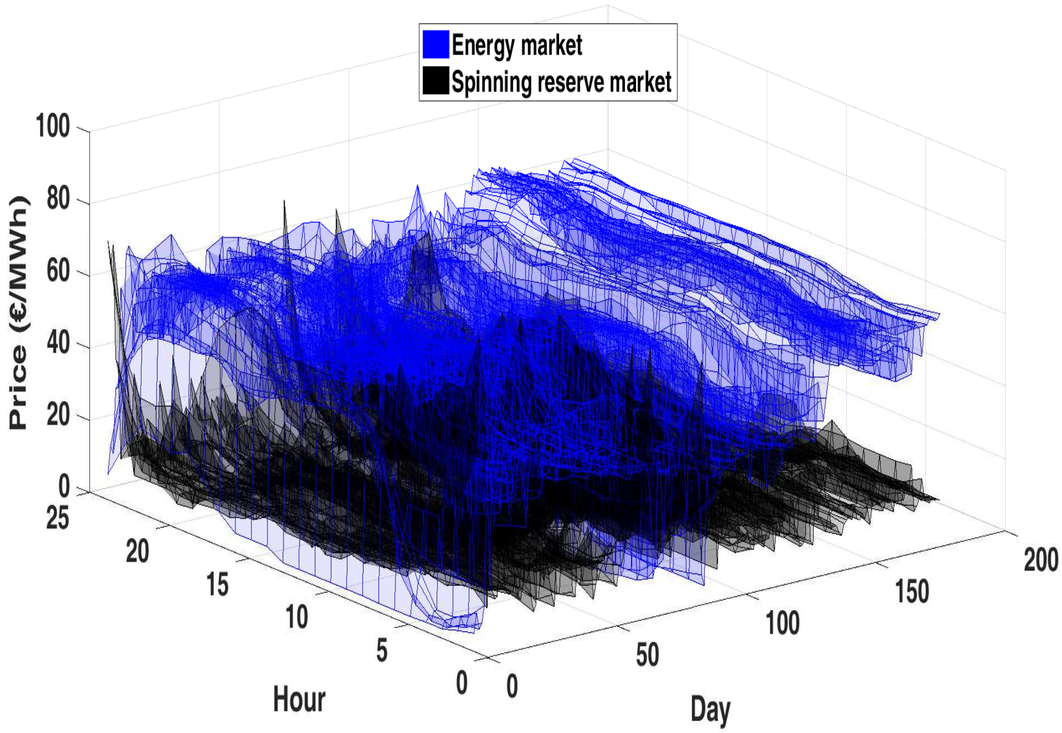
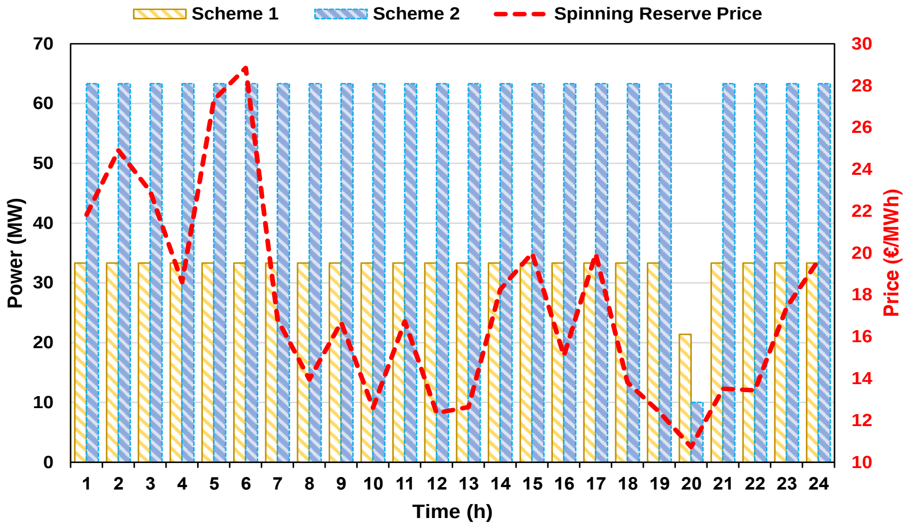
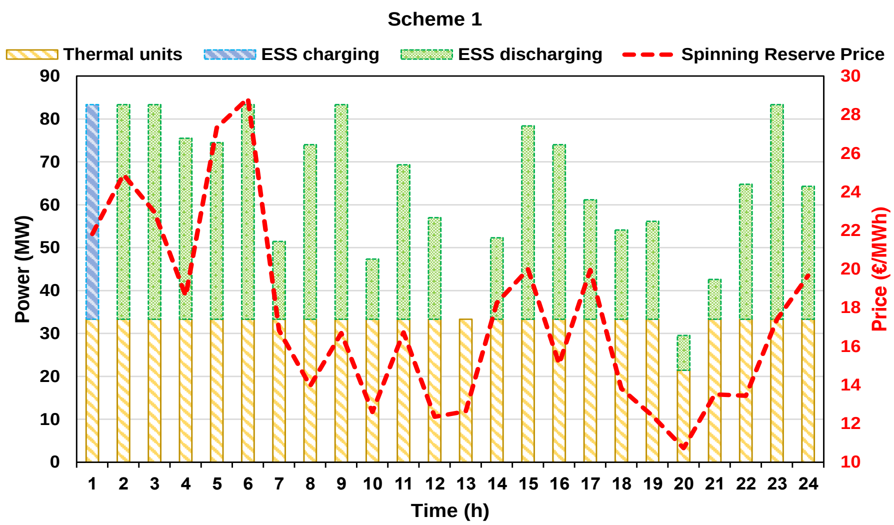


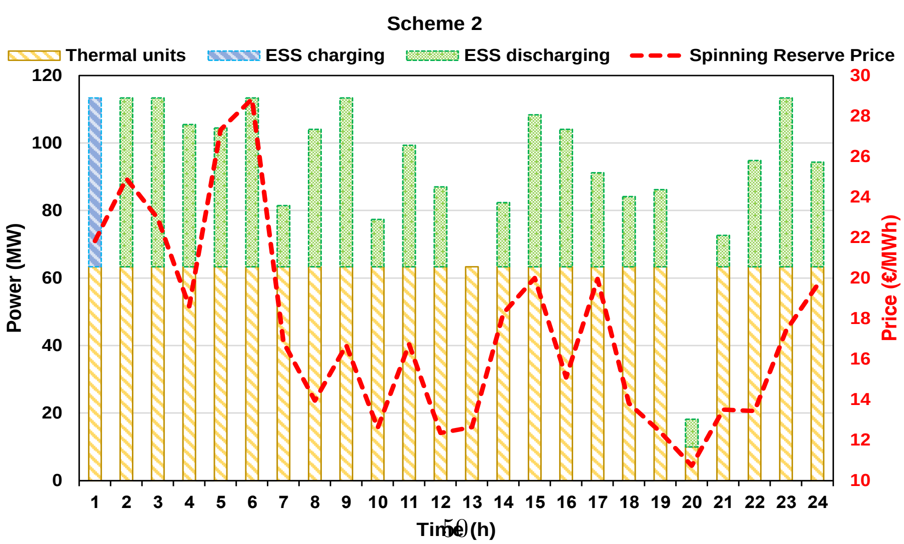
Figure 4: Historical data of energy and spinning reserve market prices



(a) Case study 2

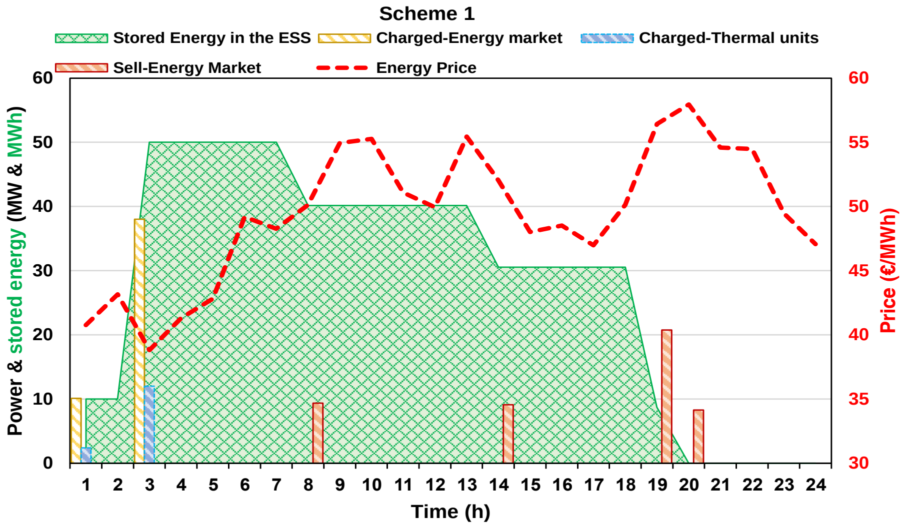


(b) Case study 3 (First decision-making scheme)

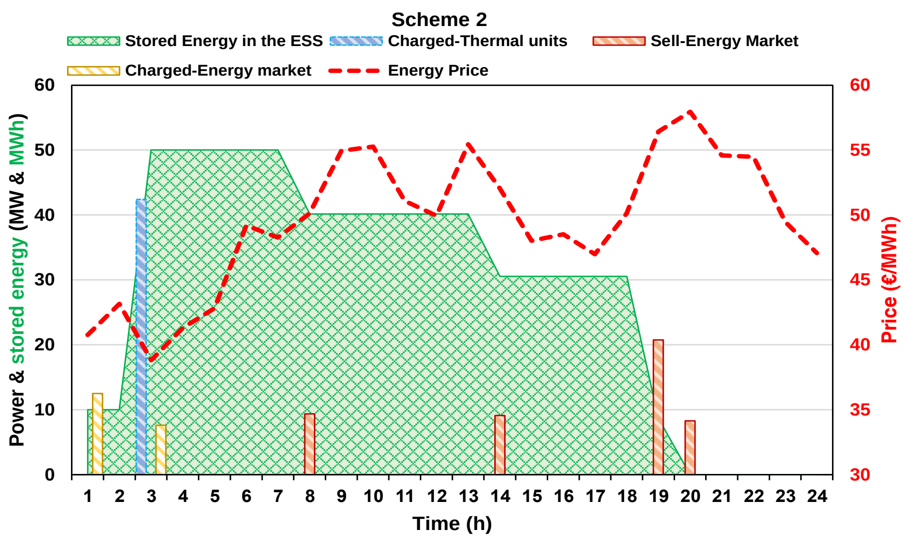


(c) Case study 3 (Second decision-making scheme)

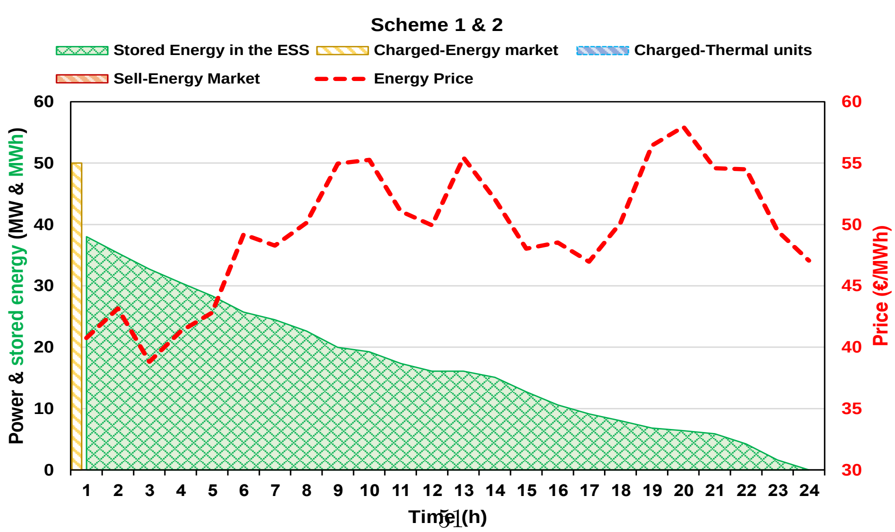
Figure 5: Expected participation of system in the spinning reserve market



(a) Case study 2 (First decision-making scheme)

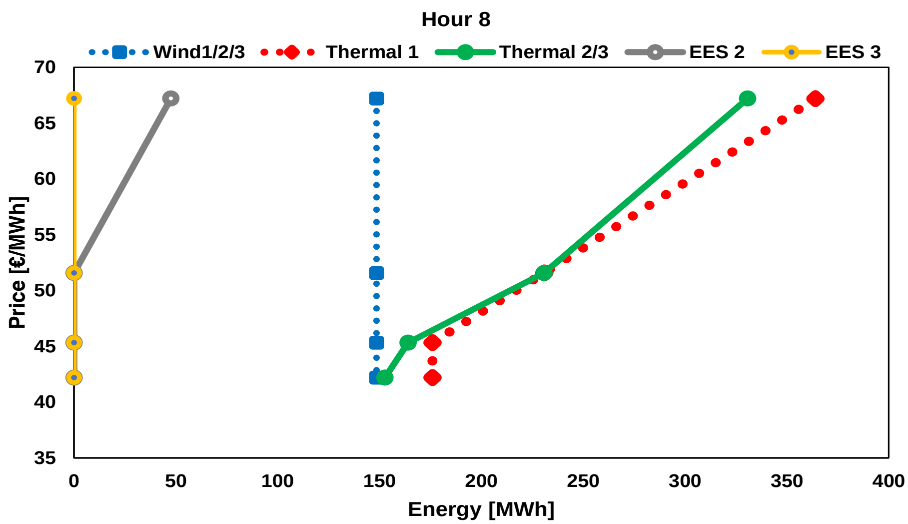


(b) Case study 2 (Second decision-making scheme)

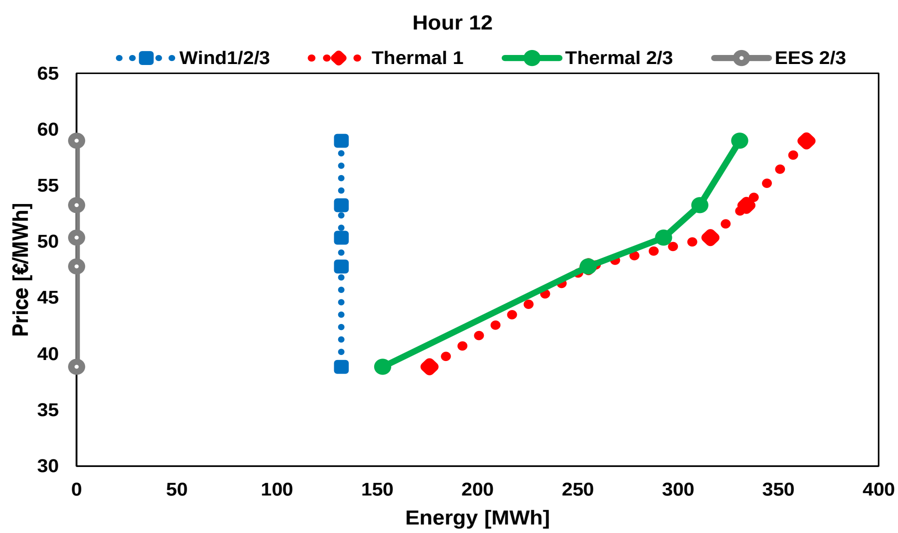


(c) Case study 3

Figure 6: Operational situation of ESS in various case studies and decision-making schemes



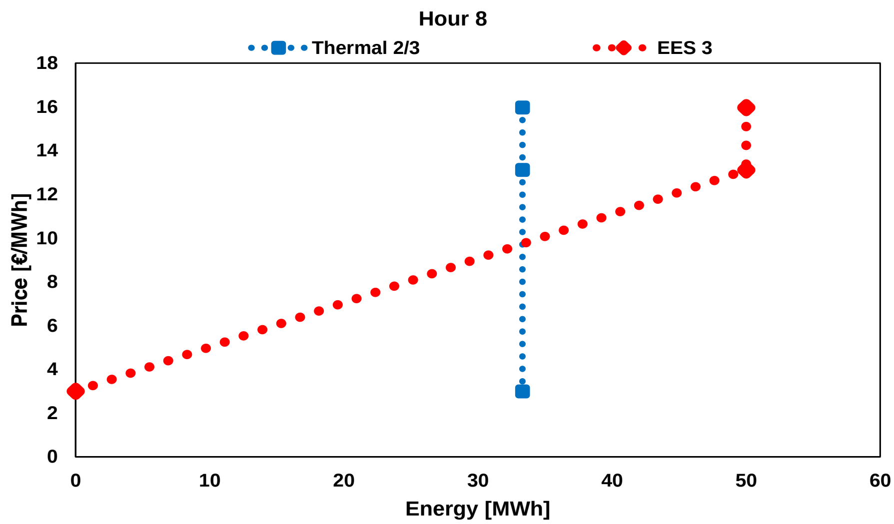
(a) Hour 8



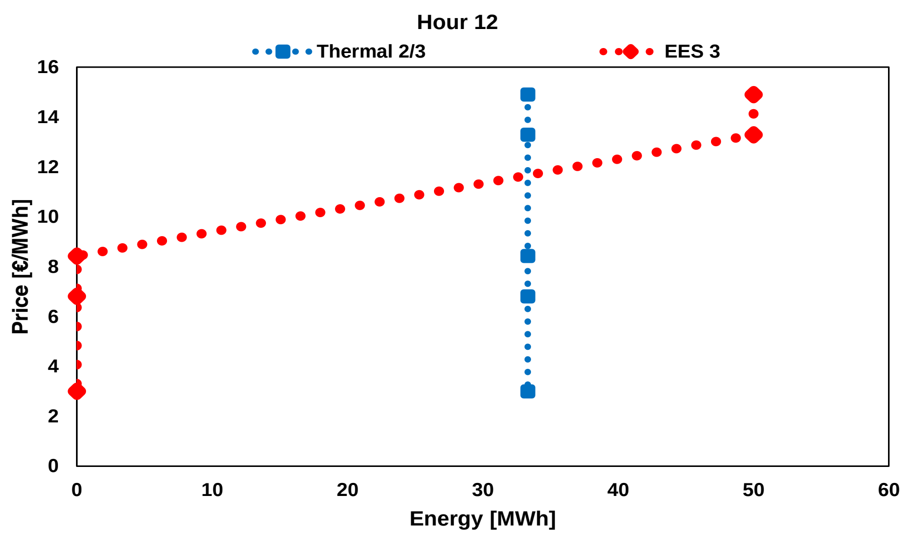
(b) Hour 12

Figure 7: Offering curves of the system in the energy market at two sample hours

$Note$: thermal 2/3 refers to the offering energy of thermal units in case study two/three and so on for other parameters.



(a) Hour 8



(b) Hour 12

Figure 8: Offering curves of the system in the spinning reserve market at two sample hours

$Note$: thermal 2/3 refers to the offering energy of thermal units in case study two/three and so on for other parameters.

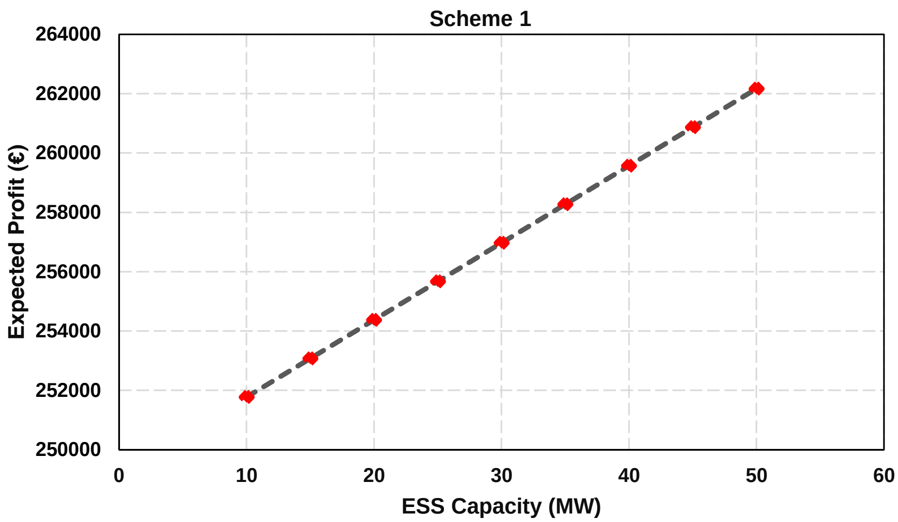


Figure 9: Expected profit of WTES system versus production capacity of ESS in the third case study

Table 1: Classification of decision variables in the proposed three-stage stochastic programming

Fist stage decisions (*here-and-now* decisions)	Second stage decisions (*special here-and-now* decisions)	Third stage decisions (*wait-and-see* decisions)
$B_t^{E,S,ch}$, PCH_t^{th}, PCH_t^{W}	$B_{t,\omega}^{E,th}$, $B_{t,\omega}^{E,W}$, $B_{t,\omega}^{E,S,dis}$	$\Delta_{t,\omega}^{+}$, $\Delta_{t,\omega}^{-}$
$u_{g,t}$, $x_{g,t}$, $y_{g,t}$, v_t^{dis}, v_t^{ch}	$B_{t,\omega}^{S,th}$, $B_{t,\omega}^{S,S,dis}$, $B_{t,\omega}^{S,S,ch}$	

Table 2: Information on emission and cost curve of thermal units

Units	Piece wise linearization parameters (MW)				Cost pertaining to each block (€/MW)				Emission ratios (lbs/MWh)	
	P^{min}	$P^{(1)}$	$P^{(2)}$	P^{max}	$C^{(1)}$	$C^{(2)}$	$C^{(3)}$	$C^{(4)}$	$E_{NOX,g}$	$E_{SO_2,g}$
G1-G5	2.4	6	9.6	12	48.41	48.78	51.84	55.4	2.513	1.005
G6-G9	15.8	16	19.8	20	54.58	55.42	67.82	68.28	1.834	0.734
G10-G13	15.2	38	60.8	76	36.46	36.96	38.89	40.97	6.889	2.755
G14	140	227.5	280	350	35.08	35.66	36.09	36.72	18.371	7.348

Table 3: Technical specifications of thermal units

Unit	RUR_g & RDR_g $STURL_g$ & $STDRL_g$ (MW/hr)	$STUC_g$ (€)	$STDC_g$ (€)	MUT_g (hr)	MDT_g (hr)
G1-G5	12	87.4	8.74	4	2
G6-G9	20	15	1.5	1	1
G10-G13	35	715.2	71.52	8	4
G14	180	2298	229.8	4	4

Table 4: Information on wind turbines and ESS

Parameter	Value	unit	Parameter	Value	unit
v_{ci}	3	m/s	$Z^{S,dis}$	0.95	%
v_r	15	m/s	$P^{dis,Max}$	50	MW
v_{co}	25	m/s	$P^{ch,Max}$	50	MW
$Z^{S,ch}$	80	%	$EB^{S,Max}$	50	MWh

Table 5: Probability of reduced scenarios in the proposed offering problem

Uncertain parameter	No. of scenarios				
	S1	S2	S3	S4	S5
Energy market	0.250	0.192	0.187	0.174	0.197
Spinning reserve market	0.177	0.186	0.163	0.280	0.194
Wind Power	0.257	0.188	0.178	0.218	0.159
Imbalance ratios	0.136	0.204	0.345	0.175	0.140

Table 6: Features of each case study

Case studies	Generation units			Target Markets			OFs		Uncertainty Sources			
	WT	TU	ESS	WT	TU	ESS	Prof	EMS	ENM	SPRM	WP	BM
Case 1	√	√	×	ENM	ENM	×	√	√	√	×	√	√
Case 2	√	√	√	ENM	ENM+SPRM	ENM	√	√	√	√	√	√
Case 3	√	√	√	ENM	ENM+SPRM	ENM+SPRM	√	√	√	√	√	√

Note : OFs-Objective Functions; WT-Wind Turbines; TU-Thermal Units; ESS-Energy Storage System; Prof- Profit; EMS-Emission; ENM-Energy Market; SPRM-Spinning Reserve Market; WP-Wind Production; BM=Balancing Market; Res Dep-Reserve Deployment

Table 7: Pareto solutions of case study 1 for the first decision-making scheme

No. of Pareto	F1 (€)	F2 (lbs)	Total PE (MWh)	Total PS (MWh)
1	**243637.717**	**53709.581**	**9626.620**	**0**
2	241055.662	50562.623	9274.909	0
3	237169.819	45966.021	8776.962	0
4	232428.017	41369.419	8294.880	0
5	226974.682	36772.817	7812.735	0
6	220749.192	32176.215	7302.057	0
7	213432.952	27579.613	6547.369	0
8	205811.414	22983.010	6070.741	0
9	197689.200	18386.408	5662.513	0
10	188732.879	13789.806	5117.485	0

Table 8: Pareto solutions of case study 2 for the first decision-making scheme

No. of Pareto	F1 (€)	F2 (lbs)	Total PE (MWh)	Total PS (MWh)
1	**249915.654**	**50216.421**	**9275.983**	**787.764**
2	248769.569	48809.869	9109.785	799.680
3	244415.141	44372.608	8638.483	799.680
4	239274.283	39935.347	8147.810	799.680
5	233643.939	35498.087	7722.287	706.400
6	227353.701	31060.826	7309.770	706.400
7	220358.157	26623.565	6769.568	673.080
8	212463.541	22186.304	6360.549	673.080
9	203236.793	17749.043	5886.178	673.080
10	192143.822	13311.782	5369.203	643.080

Table 9: Pareto solutions of case study 3 for the first decision-making scheme

No. of Pareto	F1 (€)	F2 (lbs)	Total PE (MWh)	Total PS (MWh)
1	**262167.583**	**50216.421**	**9242.883**	**1559.764**
2	261021.498	48809.869	9083.885	1571.680
3	256667.070	44372.608	8614.983	1571.680
4	251526.213	39935.347	8154.710	1571.680
5	245895.868	35498.087	7691.587	1478.400
6	239605.631	31060.826	7210.670	1478.400
7	232610.086	26623.565	6734.068	1445.080
8	224715.470	22186.304	6254.249	1445.080
9	215488.723	17749.043	5784.579	1445.080
10	206121.241	13311.782	5323.637	1193.540

Table 10: Pareto solutions of case study 1 for the second decision-making scheme

No. of Pareto	F1 (€)	F2 (lbs)	Total PE (MWh)	Total PS (MWh)
1	358933.622	248723.438	17866.110	0
2	358809.176	248216.513	17846.400	0
3	357551.834	243619.911	17607.335	0
4	356150.944	239023.309	17384.925	0
5	354629.384	234426.707	17160.105	0
6	352943.769	229830.105	16970.151	0
7	351335.332	225233.503	16961.793	0
8	350068.601	220636.900	16695.302	0
9	347630.871	216040.298	16590.437	0
10	**347040.454**	**211443.696**	**16255.550**	**0**

Table 11: Pareto solutions of case study 2 for the second decision-making scheme

No. of Pareto	F1 (€)	F2 (lbs)	Total PE (MWh)	Total PS (MWh)
1	367905.042	233349.286	17380.685	1404.404
2	367186.420	230737.563	17242.639	1445.808
3	365854.369	226300.302	16996.484	1482.770
4	364408.279	221863.041	16801.980	1522.960
5	362807.703	217425.781	16577.312	1522.960
6	**361099.986**	**212988.520**	**15995.154**	**1466.360**
7	359174.153	208551.259	15783.163	1496.360
8	357108.009	204113.998	15555.498	1496.360
9	355055.080	199676.737	15561.055	1323.040
10	353429.820	195239.476	15360.131	1323.040

Table 12: Pareto solutions of case study 3 for the second decision-making scheme

No. of Pareto	F1 (€)	F2 (lbs)	Total PE (MWh)	Total PS (MWh)
1	380156.971	233349.286	17357.185	2176.404
2	379438.349	230737.563	17222.339	2217.808
3	378106.298	226300.302	16996.184	2254.770
4	376660.208	221863.041	16766.480	2294.960
5	375059.632	217425.781	16579.812	2294.960
6	**373351.916**	**212988.520**	**15997.654**	**2238.360**
7	371426.083	208551.259	15785.663	2268.360
8	369359.938	204113.998	15557.998	2268.360
9	367307.010	199676.737	15550.355	2095.040
10	365681.749	195239.476	15374.631	2095.040

Table 13: Status of thermal units within the scheduling horizon- Case study 1

Hour		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
First Scheme	G1-G5	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	G6-G9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	G10-G13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	G14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Second Scheme	G1-G5	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	G6-G9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	G10-G13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	G14	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 14: Status of thermal units within the scheduling horizon- Case study 2 and 3

Hour		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
	G1-G5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
First	G6-G9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Scheme	G10-G13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	G14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	G1-G5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Second	G6-G9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Scheme	G10-G13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	G14	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 15: Impact of a larger scenario set on the computational statistics as well as the expected profit and emission

	Number of reduced scenarios	
	5 scenarios	10 scenarios
F1 (€)	373351.916	378082.910
F2 (lbs)	212988.520	211116.566
# Single equations	96578	360939
# Single variables	32897	143267
# Discrete variables	1056	1056
# Iterations	8404	49586
Payoff table calculation time (s)	28	1141
Sub-problem solution time (s)	10	595

Table 16: Results of emission quota arbitraging for Pareto optimal solutions of case study 3

Total Emission (lbs)	Profit without emission trade (€)	Emission trades (lbs)	Net profits (€)									
			λ^{EE}=0.1	λ^{EE}=0.2	λ^{EE}=0.3	λ^{EE}=0.4	λ^{EE}=0.5	λ^{EE}=0.6	λ^{EE}=0.7	λ^{EE}=0.8	λ^{EE}=0.9	λ^{EE}=1
233349.2	380156.9	-18349.2	378322.0	376487.1	374652.1	372817.2	370982.3	369147.3	367312.4	365477.5	363642.6	361807.6
230737.5	379438.3	-15737.5	377864.5	376290.8	374717.0	373143.3	371569.5	369995.8	368422.0	366848.2	365274.5	363700.7
226300.3	378106.2	-11300.3	376976.2	375846.2	374716.2	373586.1	372456.1	371326.1	370196.0	369066.0	367936.0	366805.9
221863.0	376660.2	-6863.0	375973.9	375287.6	374601.2	373914.9	373229.6	372542.3	371856.0	371169.7	370483.4	369797.1
217425.7	375059.6	-2425.7	374817.0	374574.4	374331.8	374089.3	373846.7	373604.1	373361.5	373119.007	372876.4	372633.8
212988.5	373351.9	+2011.4	373553.0	373754.2	373955.3	374156.5	374357.6	374558.8	374759.9	374961.1	375162.2	375363.3
208551.2	371426.0	+6448.7	372070.9	372715.8	373360.7	374005.5	374650.4	375295.3	375940.2	376585.0	377229.9	377874.8
204113.9	369359.9	+10886.0	370448.5	371537.1	372625.7	373714.3	374802.9	375891.5	376980.1	378068.7	379157.3	380245.9
199676.7	367307.0	+15323.2	368839.3	370371.6	371903.8	373436.3	374968.6	376500.9	378033.2	379565.6	381097.9	382630.2
195239.4	365681.7	+19760.5	367765.8	369633.8	371609.9	373585.9	375562.0	377538.0	379514.1	381490.1	383466.2	385442.2