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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

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, <i>lbs</i> /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 $L=1,\dots,4$.
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.
$EG_{g,t,\omega}^{E,th}/EG_{g,t,\omega}^{S,th}$	offering curve of every thermal unit in the energy/spinning reserve markets, MW.
$EGCH_{g,t}/PCH_t^{th}/PCH_t^W$	Provided charging power for the ESS by every thermal unit/all thermal units/wind units, MW.
v_t^{dis}/v_t^{ch}	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.
$EB_{t,\omega}^S$	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

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9 deregulated electricity markets. The wind power intermittency is known as the
10 greatest challenge of wind power producers (WPPs) in the literature [3]. To
11 this end, generation companies (GenCos) mainly design an integrated strategy
12 for the offering strategy of stochastic renewable-based energy systems alongside
13 dispatchable energy resources like thermal units and energy storage systems to
14 cope with the intermittent nature of their output power.
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19 *1.2. Literature Review*

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21 The optimal participation problem of wind power resources in the electricity
22 markets has been taken into consideration by various perspectives. Reference [4]
23 has presented an integrated operation of a group of wind farms for participating
24 in the day-ahead (DA) electricity market. The uncertain nature of wind power
25 and electricity prices are modeled via multiple stochastic scenarios. Authors in
26 [5] focused on the optimal offering strategy for a typical WPP in a pay-as-bids
27 market. Authors addressed the optimal offering strategy of WPPs through a bi-
28 level stochastic optimization problem. The optimal scheduling of a WPP using
29 information gap decision theory to deal with the wind power and market price
30 uncertainties has been discussed in [6]. The scheduling of a renewable-based
31 microgrid in the attendance of demand response programs has been investigated
32 in [7]. A multi-stage bidding framework for home microgrids has been proposed
33 in [8]. In [9], a self-scheduling (SS) model for micro grid based on a hybrid price-
34 based demand response program has been developed while two-point estimate
35 method has been used to handle the existing uncertainties.
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45 The offering strategy problem is not limited to wind power plants. Ther-
46 mal units as the vital part of supplying customer's electricity have been widely
47 studied in the literature of SS problem. According to the provided reports in
48 [1], more than 80 % of the US electricity is supplied by energy sources such as
49 petroleum, natural gas, and coal that can be implemented by thermal units. The
50 impact of possibilistic reserve deployment and forced outages of thermal units
51 on the SS problem have been studied in [10] while the same problem of a thermal
52 GenCo has been addressed in [11] based on the information gap decision theory.
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9 The authors formulated the SS problem as mixed-integer nonlinear program-
10 ming model while the uncertain parameters (market prices) have been modeled
11 via information gap decision theory approach. A new framework for optimal SS
12 of thermal units in the presence of upcoming high-impact low-probability events
13 is suggested in [12].
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16 From another standpoint, integrated operation of various energy sources like
17 wind and thermal power plants have been studied in the context of offering s-
18 trategy [13]. The authors in [13] have benefited from stochastic programming
19 to address the offering strategy of a wind-thermal power producer. In the afore-
20 mentioned research works, the uncertain nature of wind power production and
21 market prices have been considered through a set of realizations. In [14], the
22 stochastic optimization has been utilized to deal with the uncertainties related
23 to prices, load, and production power of wind farm and photovoltaic system.
24 The coordinated wind-thermal-pumped storage offering strategy in energy and
25 regulation reserve markets has been proposed in [15]. In [15], The authors mod-
26 eled the inherent risk of uncertain parameters via conditional value-at-risk in
27 the suggested strategy. It should be noted that in the uncoordinated operation,
28 a single optimization problem runs for every distinct generation facility, while
29 in the coordinated one, the decision-making unit runs one unique optimization
30 problem on behalf of all generation facilities. Accordingly, in the coordinated op-
31 eration, the constraints and specifications of each generation unit can influence
32 the decision of other units, and as a result, the decision-making unit optimizes
33 the problem by considering the limitations on all generation units which ulti-
34 mately leads to the profitability of all units. The bidding and offering strategies
35 of a wind-hydro-pumped storage system in energy and ancillary service markets
36 can also be found in [16]. The previously introduced conditional value-at-risk
37 tool has also been utilized in [16] while the authors have been benefited from
38 a novel improved clonal selection algorithm in order to acquire the optimal so-
39 lution. Furthermore, appropriate economic models for supplying the electricity
40 needed for a water treatment plant and an irrigation network in the presence of
41 an integrated wind-hydro system are presented in [17] and [18], respectively.
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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 ap-

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proach 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 an-
alyzed in [32] and [33], respectively. A dynamic programming-based offering
strategy for a wind-battery system has been provided in [34], while the inves-
tigation 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, re-
spectively, 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 re-
sponse 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].

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All papers presented above are single objective and aimed at profit max-
imization. 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 s-
trategy 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

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9 (LO) and hybrid augmented-weighted ϵ -constraint (HAW-Eps) method for the
10 bi-objective SS of a microgrid has been assessed in [43]. Among the recently
11 introduced research works on SS and as a traditional approach in power system
12 problems, a great significant has been given to the multi-objective scheduling of
13 various generation units regarding cost and emission minimization. The study
14 presented in [44] solve the cost and emission optimization problem by applying
15 the ϵ -constraint method. Also, investigation of the effects of pumped-storage
16 units on the multi-objective scheduling of hydrothermal units has been analyzed
17 in [44]. Sun et al. [45] proposed the optimal scheduling of wind and thermal
18 units in the form of a unit commitment problem. Alternatively, the problem
19 of hydro-wind-thermal scheduling with the goal of minimizing total operative
20 costs in an economic dispatch problem has been investigated in [46] and [47]. An
21 extended non-dominated sorting genetic algorithm, the third version and bee
22 colony optimization algorithm as optimization techniques have been applied for
23 solving the hydro-wind-thermal scheduling problem in references [46] and [47],
24 respectively.
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34 *1.3. Novelty of this contribution*

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37 This paper presents a novel three-stage multi-objective framework for de-
38 termining the optimal participation of a wind-thermal-energy storage (WTES)
39 system in the electricity markets. In the proposed multi-objective framework,
40 the WTES system tries to maximize its profit as the first objective while at the
41 same time, the emission minimization is taken into account as the second ob-
42 jective. To the best of authors' knowledge and concerning the previous works in
43 this topic, no relevant research work in the literature proposes a multi-objective
44 model for the WTES offering strategy problem. In the presented framework, the
45 WTES system participates in the DA energy and spinning reserve markets. On
46 the other hand, the uncertainty associated with many of the parameters in the
47 optimization process is one of the challenges faced by GenCos. To this end, the
48 uncertain nature of various market prices and output power of the wind farm
49 in the optimization problem is modeled by a set of realizations. Accordingly,
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9 the main contributions of this paper in comparison with other research works
10 in this area are as follows:
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13 • Proposing a three-stage stochastic multi-objective model for the offering
14 strategy problem of a WTES system on the basis of a mixed-integer pro-
15 gramming (MIP) formulation. In the suggested model, simultaneously
16 profit maximization and emission minimization are considered as conflict-
17 ing objectives in the optimization problem while the uncertain parameters
18 including energy, spinning reserve and imbalance prices, as well as wind
19 power production, are modeled via stochastic scenarios.
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- 22 • Providing a participation model for the ESS in the spinning reserve mar-
23 ket in both charging and discharging modes, and subsequently, deriving
24 appropriate offering curves in this market.
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- 27 • Presenting the physical connection between the ESS system and both
28 thermal and wind units for charging the ESS system in the mathematical
29 formulation of the proposed problem.
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- 32 • Implementing the LO and HAW-Eps procedures to solve the multi-objective
33 WTES offering strategy problem. The LO helps the ϵ -constraint method
34 to more effectively specify objective functions' range in comparison with
35 the traditional ϵ -constraint technique, while the HAW-Eps merely obtain-
36 s efficient Pareto solutions. Indeed, applying these two methods jointly
37 guarantees to reach the optimal Pareto solution set while the traditional
38 ϵ -constraint procedure cannot ascertain the effectiveness of the obtained
39 solutions. Also, a practical approach, i.e., a preference-based method, is
40 utilized to choose the best possible solution.
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- 43 • Designing a new pattern based on the emission trading for the WTES
44 system to adopt the most suitable strategy while the emission quota is
45 taken into consideration.
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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 pur-

pose, 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 ($(r_{t,\omega}^{-/+}) \times M_{t,\omega}^E$) 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

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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 realization 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.

Table 1 is placed here

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.

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9 *3.1. First Objective Function: Maximizing the Expected Profit of WTES System*

10 As stated above, the first OF is the maximization of the system's expected
11 profit in the desired time horizon (DA scheduling horizon). In this regard,
12 the system's optimal participation in each of the selected markets, that are
13 the outputs of the offering strategy problem, will be obtained. The considered
14 system in this paper consists of several thermal units, a wind farm, and an ESS.
15 Due to the intermittent nature of wind power, the system only takes advantage
16 of the wind farm to offer in the energy market [49]. Thermal units and ESS
17 are also able to participate in the energy and spinning reserve markets. The
18 considered ESS in this paper can be used in either charging or discharging
19 mode to participate in the energy and spinning reserve markets. The ESS can
20 be treated as a producer (discharging mode) or a consumer (charging mode)
21 in the energy market. In addition to participating in spinning reserve market
22 during discharging mode, the ESS can also act as a responsive load in the
23 discharging mode for participating in the spinning reserve market [50]. The
24 first OF, maximizing the expected profit of the WTES system, based on the
25 three-stage stochastic programming is formulated as follows:
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$$\begin{aligned}
\text{Max } F_1^{WTES} = & \sum_{\omega=1}^{N_{\Omega}} \pi_{\omega} \times \left[\sum_{t=1}^{N_T} \left\{ \left(M_{t,\omega}^E B_{t,\omega}^{E,th} \right) + \left(M_{t,\omega}^E B_{t,\omega}^{E,W} \right) + \left(M_{t,\omega}^E B_{t,\omega}^{E,S,dis} \right) \right. \right. \\
& - \left(M_{t,\omega}^E B_{t,\omega}^{E,S,ch} \right) + \left(M_{t,\omega}^S B_{t,\omega}^{S,th} \right) + \left(M_{t,\omega}^S B_{t,\omega}^{S,S,dis} \right) + \left(M_{t,\omega}^S B_{t,\omega}^{S,S,ch} \right) \\
& + Prob^{cal} \times \left(B_{t,\omega}^{S,th} + B_{t,\omega}^{S,S,dis} + B_{t,\omega}^{S,S,ch} \right) \times M_{t,\omega}^{bal} \\
& + \left(M_{t,\omega}^E r_{t,\omega}^+ \Delta_{t,\omega}^+ \right) - \left(M_{t,\omega}^E r_{t,\omega}^- \Delta_{t,\omega}^- \right) \\
& - \sum_{g=1}^{N_G} C_{g,t,\omega} \left(EG_{g,t,\omega}^{E,th} + EGCH_{g,t} + Prob^{cal} \times \left(EG_{g,t,\omega}^{S,th} \right) \right) \left. \right\} \\
& - \sum_{t=1}^T \sum_{g=1}^{N_G} (U_{g,t} + D_{g,t}) \tag{1}
\end{aligned}$$

38 where the first line of F_1^{WTES} represents the income of WTES system from
39 participating in the energy market. The first, second, and third parentheses
40 of this line relate to the involvement of thermal units, wind farm, and ESS in
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9 the energy market, respectively. The first parenthesis in the second line of (1)
10 indicates the cost incurred by the WTES system for purchasing the charging
11 energy for the ESS from the energy market while the next three parentheses
12 express the earned income by WTES system from participating in the spinning
13 reserve market. The third line models the expected income of the WTES system
14 due to spinning reserve deployment in the balancing market. The fourth line
15 of (1) shows the system's revenue/cost arising from the energy deviations in
16 the balancing market. The first parenthesis in this line represents the system's
17 income due to the over-generation between the real and scheduled generation
18 while the second parenthesis relates to the under-generation between the ac-
19 tual and scheduled production, which is a cost term. Finally, the fifth and
20 sixth lines denote the generation costs, start-up, and shut-down costs incurred
21 by each thermal unit, respectively. It must be stressed that a series of piece-
22 wise linearized blocks are utilized to approximate the quadratic cost function of
23 thermal units, which would be helpful to benefit from the advantages of linear
24 programming [51].
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3.2. Second Objective Function: Minimizing the Expected Emission of WTES System

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

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

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., $EG_{g,t,\omega}^{E,th}$. 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

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9 this paper, the SO_2 and NO_X are considered as the source of pollutions due to
10 their great importance in the environment [52]. It is worthwhile to note that the
11 emission function of thermal units is approximated with a piecewise linearized
12 segment [52].
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15 16 3.3. Constraints

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18 The constraints of the proposed WTES offering strategy are classified into
19 the following categories.
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22 3.3.1. Modeling Imbalances

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24 In order to model the imbalances in the suggested offering strategy problem,
25 constraints (3)-(5) are used. As stated above, imbalances arise when there is a
26 difference between actual production and the submitted bid to the energy mar-
27 ket. Constraints (3) calculates the whole energy deviations of WTES system
28 in the balancing market. The first parenthesis expresses the total available and
29 actual generated power by the WTES system, while the second parenthesis in-
30 dicates the offered energy by the WTES system in the energy market. Equation
31 (4) restricts the upper bound of the positive deviation, which is equivalent to
32 the total available and actual generated power by the WTES system in each
33 scenario. Similarly, constraint (5) restricts the maximum value of the negative
34 deviation.
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$$44 \Delta_{t,\omega}^+ - \Delta_{t,\omega}^- = \left(B_{t,\omega}^{E,th} + B_{t,\omega}^{E,S,dis} + P_{t,\omega}^W - PCH_t^W \right) \\ 45 - \left(B_{t,\omega}^{E,W} + B_{t,\omega}^{E,th} + B_{t,\omega}^{E,S,dis} \right), \quad \forall t, \forall \omega \quad (3)$$

$$46 0 \leq \Delta_{t,\omega}^+ \leq B_{t,\omega}^{E,th} + B_{t,\omega}^{E,S,dis} + P_{t,\omega}^W - PCH_t^W, \quad \forall t, \forall \omega \quad (4)$$

$$47 \\ 48 \\ 49 \\ 50 0 \leq \Delta_{t,\omega}^- \leq P^{W,Max} + \sum_{g=1}^{N_G} P_g^{th,Max} \cdot u_{g,t} + P^{dis,Max} \cdot v_t^{dis}, \quad \forall t, \forall \omega \quad (5)$$

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9 *3.3.2. Modeling Operational Constraints of Wind Farm*

10 In this subsection, the operation constraints pertaining to the wind farm
11 will be introduced. Constraints (6)-(9) model the maximum and minimum
12 value of the offered energy by the wind farm in the energy market, provided
13 charging energy for the ESS, and the total scheduled energy by the wind farm,
14 respectively.
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$$0 \leq B_{t,\omega}^{E,W} \leq P^{W,Max}, \quad \forall t, \forall \omega \quad (6)$$

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

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

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

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33 *3.3.3. Modeling Operational Constraints of Thermal Units*

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35 Equalities (10) and (11) calculate the total energy and spinning reserve offers
36 by thermal units. Constraints (12)-(14) are employed to model the limitations
37 related to the maximum and minimum value of produced and offered energies
38 by thermal units. It is worth to note that the maximum capacity of units offer
39 in the spinning reserve market would be defined based on their ramp-up rate,
40 which is equivalent to $RUR_g \times \frac{1}{6}$. This issue comes from the fact that the
41 spinning reserve should be ready to deliver in ten minutes [53]. The upper
42 bound of the provided charging power for ESS by thermal units is limited using
43 (15). The start-up and shut-down costs incurred by each thermal units are
44 modeled by equations (16) and (17), respectively. The restrictions associated
45 with the minimum up and down times of thermal units are enforced by (18) and
46 (19), respectively. Furthermore, the logical relationship between the status of
47 thermal units and start-up and shut-down variables are modeled via constraint
48 (20). Equality (21) calculates the total expected production power by thermal
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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].

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

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

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

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

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

$$0 \leq EGCH_{g,t} \leq P^{ch,Max} \cdot u_{g,t}, \quad \forall g, \forall t \quad (15)$$

$$0 \leq U_{g,t} \geq STUC_g \cdot x_{g,t}, \quad \forall g, \forall t \quad (16)$$

$$0 \leq D_{g,t} \geq STDC_g \cdot y_{g,t}, \quad \forall g, \forall t \quad (17)$$

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

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

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

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

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

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

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).

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

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

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$$0 \leq B_{t,\omega}^{S,S,dis} \leq P^{dis,Max} \cdot v_t^{dis}, \quad \forall t, \forall \omega \quad (26)$$

$$0 \leq B_{t,\omega}^{E,S,dis} + B_{t,\omega}^{S,S,dis} \leq P^{dis,Max} \cdot v_t^{dis}, \quad \forall t, \forall \omega \quad (27)$$

$$0 \leq B_{t,\omega}^{E,S,ch} + PCH_t^{th} + PCH_t^W \leq P^{ch,Max} \cdot v_t^{ch}, \quad \forall t, \forall \omega \quad (28)$$

$$0 \leq B_{t,\omega}^{S,S,ch} \leq B_t^{E,S,ch}, \quad \forall t, \forall \omega \quad (29)$$

$$v_t^{dis} + v_t^{ch} \leq 1, \quad \forall t \quad (30)$$

$$\begin{aligned} EB_{t,\omega}^S &= EB_{t-1,\omega}^S + \\ &Z^{S,ch} \left(B_t^{E,S,ch} + PCH_t^{th} + PCH_t^W - B_{t,\omega}^{S,S,Ch} \times Prob^{cal} \right) - \\ &\left(\frac{1}{Z^{S,dis}} \right) \left(B_{t,\omega}^{E,S,dis} + B_{t,\omega}^{S,S,dis} \times Prob^{cal} \right), \quad \forall t, \forall \omega \end{aligned} \quad (31)$$

$$0 \leq EB_{t,\omega}^S \leq EB^{S,Max}, \quad \forall t, \forall \omega \quad (32)$$

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.

$$B_{t,\omega}^{E,th} \leq B_{t,\tilde{\omega}}^{E,th}, \quad \forall \omega, \tilde{\omega} : [M_{t,\omega}^E \leq M_{t,\tilde{\omega}}^E], \quad \forall t \quad (33)$$

$$B_{t,\omega}^{E,W} \leq B_{t,\tilde{\omega}}^{E,W}, \quad \forall \omega, \tilde{\omega} : [M_{t,\omega}^E \leq M_{t,\tilde{\omega}}^E], \quad \forall t \quad (34)$$

$$B_{t,\omega}^{E,S,dis} \leq B_{t,\tilde{\omega}}^{E,S,dis}, \quad \forall \omega, \tilde{\omega} : [M_{t,\omega}^E \leq M_{t,\tilde{\omega}}^E], \quad \forall t \quad (35)$$

$$B_{t,\omega}^{S,th} \leq B_{t,\tilde{\omega}}^{S,th}, \quad \forall \omega, \tilde{\omega} : [M_{t,\omega}^S \leq M_{t,\tilde{\omega}}^S], \quad \forall t \quad (36)$$

$$B_{t,\omega}^{S,S,dis} \leq B_{t,\tilde{\omega}}^{S,S,dis}, \quad \forall \omega, \tilde{\omega} : [M_{t,\omega}^S \leq M_{t,\tilde{\omega}}^S], \quad \forall t \quad (37)$$

$$B_{t,\omega}^{S,S,ch} \leq B_{t,\tilde{\omega}}^{S,S,ch}, \quad \forall \omega, \tilde{\omega} : [M_{t,\omega}^S \leq M_{t,\tilde{\omega}}^S], \quad \forall t \quad (38)$$

$$B_{t,\omega}^{E,th} = B_{t,\tilde{\omega}}^{E,th}, \quad \forall \omega, \tilde{\omega} : [M_{t,\omega}^E = M_{t,\tilde{\omega}}^E], \quad \forall t \quad (39)$$

$$B_{t,\omega}^{E,W} = B_{t,\tilde{\omega}}^{E,W}, \quad \forall \omega, \tilde{\omega} : [M_{t,\omega}^E = M_{t,\tilde{\omega}}^E], \quad \forall t \quad (40)$$

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

$$B_{t,\omega}^{S,th} = B_{t,\tilde{\omega}}^{S,th}, \quad \forall \omega, \tilde{\omega} : [M_{t,\omega}^S = M_{t,\tilde{\omega}}^S], \quad \forall t \quad (42)$$

$$B_{t,\omega}^{S,S,dis} = B_{t,\tilde{\omega}}^{S,S,dis}, \quad \forall \omega, \tilde{\omega} : [M_{t,\omega}^S = M_{t,\tilde{\omega}}^S], \quad \forall t \quad (43)$$

$$B_{t,\omega}^{S,S,ch} = B_{t,\tilde{\omega}}^{S,S,ch}, \quad \forall \omega, \tilde{\omega} : [M_{t,\omega}^S = M_{t,\tilde{\omega}}^S], \quad \forall t \quad (44)$$

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

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9 in the context of the power system. In the weighted sum technique, the OFs are
10 merged while in the ϵ -constraint approach, one OF is considered as the princi-
11 pal OF and other OFs appear as the constraints in the problem formulation.
12 Researchers have noted many advantages of the ϵ -constraint method versus the
13 weighted sum approach in the literature of multi-objective optimization prob-
14 lems [57]. The main advantages of epsilon constraint are as follows:
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- 18 1. Unlike the weighted sum method which is only capable of producing ef-
19 ficient extreme solutions, the ϵ -constraint method also has the ability to
20 create non-extreme efficient solutions in linear problems [57].
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- 22 2. Contrary to the weighted sum technique, the scaling of OFs in the ϵ -
23 constraint method is not a problem [57].
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- 25 3. It is possible to control the number of solutions obtained from ϵ -constraint
26 technique only by changing the grid points associated with each of the OFs
27 [57].
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32 In accordance with the outlined advantages, the ϵ -constraint method has
33 been implemented in some power system problems including self-scheduling
34 problems [40] and [41] which indicate the performance of the suggested ap-
35 proach. On the other hand, researchers have consistently taken two points into
36 account to improve the performance of the traditional ϵ -constraint. The re-
37 searchers' first concern is that the range of OFs is not optimal over the efficient
38 set, and secondly, the productivity of the attained results by the ϵ -constraint
39 technique cannot be ensured. In order to prevail over these shortcomings, the
40 LO and HAW-Eps methods are suggested in this paper. Hence, the proposed
41 method for solving multi-objective optimization problem is contained the joint
42 LO and HAW-Eps technique. It's worth mentioning that the effectiveness of the
43 joint LO and HAW-Eps technique for obtaining the optimal Pareto solutions in
44 multi-objective programming problems has been proved in [58].
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53 Consider a multi-objective optimization problem with n OFs. The generic
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form of HAW-Eps technique would be formulated as follows:

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

subject to.

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

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

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:

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

Finally, by constructing the payoff matrix, the upper and lower bounds of the i th OFs ($f_i(x)$) will be obtained from the i th 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

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(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

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9 optimization problem with OFs $G1$ and $G2$. The decision-maker aims at mini-
10 mizing both OFs while the relevant upper bounds for $G1$ and $G2$ in the preference-
11 based technique are considered equal to €7 and €6, respectively. According to
12 these restrictions, Pareto solution 3 is selected as the most favored solution as
13 it overcomes both limitations imposed by the decision-maker.
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18 Fig. 2 is placed here
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23 5. Emission trading

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25 In many countries, the emission quotas pertaining to each GenCo are limited.
26 For example, in the US, the environmental protection agency is in charge of the
27 legislation in the area of greenhouse gas emission. According to the presented
28 reports in [61], the emission quotas of power plants are determined by various
29 factors such as the type of fuel consumption, the location of the power plants and
30 long-term clean power plans by the environmental protection agency. In many
31 cases, achieving maximum profit through the offering strategy problem leads
32 to the procurement of extra emission quotas by the GenCo. This occurs when
33 the emission quota is lower than the produced emission by the GenCo ($E^{Qo} <$
34 EG). From a different point of view, depending on the market conditions,
35 participation in the energy market may not be as profitable as selling a portion
36 of the emission quota. In this case, the generated emission is lower than the
37 assigned emission quota to the GenCo ($E^{Qo} > EG$). Consequently, after solving
38 the multi-objective WTES offering strategy problem and achieving to the Pareto
39 optimal solution set, the GenCo will face two situations in any of Pareto optimal
40 solution: generation over emission quota and generation under emission quota.
41 As stated above, the total expected GenCo's income in each Pareto optimal
42 solution will be calculated as follows:
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$$54 \quad TPF = PF + [\lambda^{EE} \times (E^{Qo} - EG)] \quad (51)$$

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

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22 In this section, the solution procedure of multi-objective WTES offering
23 strategy with the implementation of LO and HAW-Eps method following the
24 presented flowchart in Fig. 3 will be as the following steps:
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- 27 1. The first step is related to dealing with the uncertain parameters in the
28 WTES offering strategy problem. In the current paper, authors benefit
29 from a scenario-based approach to address the uncertain nature of param-
30 eters in the multi-stage WTES offering strategy problem. The uncertain
31 parameters consist of energy, spinning reserve, up and down imbalance
32 ratios (balancing market) and finally, wind power. For this purpose, the
33 roulette wheel process [62] is employed to generate an arbitrary level of
34 stochastic scenarios for each uncertain parameter. It is worth to note
35 that the normal [63] and Rayleigh [64] distributions are assigned as suit-
36 able probability density functions for extracting the behavior of electricity
37 prices and wind speed, respectively. In this regard, a large number of sce-
38 narios are generated based on the statistical characteristic of each param-
39 eter (scenario generation stage). Constructing the scenario tree based on
40 a large number of scenarios will cause the problem to become intractable.
41 To this end, the initial scenarios pertaining to each uncertain parameter
42 are reduced to five representing scenarios using SCENRED tool [65] in
43 GAMS (scenario reduction stage). This tool allows stochastic program-
44 ming researchers to reduce their initial scenario set to a smaller scenario
45 subset to avoid the computational explosion. SCENRED consists of two
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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 $f_i(x)$ ($i=2, 3, \dots, n$).
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

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,

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9 respectively, whereas the total installed capacity of the thermal units is equal to
10 794 MW. The cost and emission information of thermal units with their permis-
11 sible output power are presented in Table 2. It is worthwhile to note that this
12 information has been extracted from [52]. According to previously published
13 work in this area, the SO_2 and NO_X are considered as the primary sources
14 of emission in this study [52]. The technical specification of thermal units in-
15 cluding ramp up/down limits, minimum up/down times, shut-down ramp limit,
16 start-up ramp limit as well as their start-up and shut-down costs are shown in
17 Table 3. It can be noticed that the units' shut-down cost ($STDC(g)$) are equal
18 to $0.1 \times STUC(g)$. As stated in subsection 3.3.3, the maximum unit's offer in
19 the spinning reserve market is determined as $RUR_g \times \frac{1}{6}$ [12]. Also, the val-
20 ue of $Prob^{cal}$ is assumed to be 0.05 [19]. The characteristics of the ESS and
21 wind turbines have been exhibited in Table 4. The efficiency data of ESS in ei-
22 ther charging or discharging mode is used from [22] while the maximum energy
23 volume of ESS has been adopted from [19].
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33 Table 2, Table 3 and Table 4 are placed here
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37 As already mentioned in the solution procedure section, there are four sources
38 of uncertainty in the suggested problem. First, abundant scenarios for each pa-
39 rameter is generated. Afterward, in order to avoid any computational burden,
40 the generated scenarios pertaining to each parameter are reduced to five sce-
41 narios using SCENRED. The data for the first six months of 2018 is considered
42 for the statistical analysis in the scenario generation process. The data on the
43 electricity market and wind speed can be found in [66] and [67], respectively.
44 For instance, the data on energy and spinning reserve prices have been shown
45 in Fig. 4 [66]. Lastly, the probability of reduced scenarios for each uncertain
46 parameter is listed in Table 5.
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53 Fig. 4 is placed here
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9 The proposed bi-objective WTES offering strategy problem is formulated
10 as a MIP problem and solved with GAMS software using CPLEX12. It is
11 worthwhile to mention that the authors are currently working on a book in the
12 context of offering strategy in which the integration of various energy sources and
13 application of diverse uncertainty modeling techniques will be investigated while
14 all GAMS codes pertaining to this paper and other analyses will be available
15 for readers [68].
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20 This problem will be analyzed under three different case studies each includes
21 two different decision-making schemes:
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- 24 1. First scheme: In the first scheme, the comparative significance of both
25 OFs is equivalent ($w_1, w_2=1$). Thus, in the proposed multi-objective
26 optimization framework, the WTES system makes no distinction between
27 the goals of profit maximization and emission minimization.
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- 30 2. Second scheme: Since system's primary goal is to attain the maximum
31 profit by participating in the electricity markets, the significance of maxi-
32 mizing profits in the second scheme is considered three times higher than
33 the emission minimization, thus, $w_1=3$ and $w_2=1$.
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37 It has to be noted that the different aspects of each case study are characterized
38 in Table 6. The first case study addresses the bi-objective offering strategy
39 of a wind-thermal system in the energy market. In the latter case study, the
40 multi-objective offering strategy problem is developed for a WTES system, in
41 which only thermal units participate in the spinning reserve market. Finally,
42 the third case study examines the previous case by taking into account the
43 involvement of the ESS in the spinning reserve market. Finally, as expressed in
44 subsection 4.2, the decision maker should determine the limitations of each OF
45 in every decision-making scheme to choose the final decision in the bi-objective
46 optimization problem. The maximum prearranged limits for the emission of
47 the WTES system in the first and the second decision-making schemes are
48 55×10^3 lbs and 215×10^3 lbs, respectively, while the minimum restrictions for
49 the system's profit are selected $\text{€ } 240 \times 10^3$ and $\text{€ } 345 \times 10^3$ for the first and the
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9 second decision-making schemes, respectively.

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11 Table 6 is placed here
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15 Tables 7, 8, and 9 show a set of optimal Pareto solutions for case studies one,
16 two, and three correspondings to the first decision-making scheme, respective-
17 ly. The first three columns present the number, expected profit and expected
18 emission of each Pareto optimal solution. The next two columns indicate the
19 total submitted offers from the system to energy and spinning reserve markets
20 through the 24-hour scheduling horizon. According to the reported solutions
21 in these tables, decreasing the system's expected profit will lead to a lower lev-
22 el of participation in the energy market. The first row with highlighted cells
23 represents the final decision of the system for whole case studies based on the
24 prearranged values. The expected profits of the system in the first to third case
25 studies are € 243637.717, € 249915.654, and € 262167.583, respectively, indi-
26 cating the performance of the third case study in comparison with other cases.
27 The offering strategy in the third case study of first decision-making scheme
28 results in an increase of € 18529.866 and € 12251.929 compared to the first and
29 second cases, respectively. From a different point of view, the second and third
30 case studies will also result in a lower level of pollution compared to the first
31 case. The reason behind the variation of the system's emission in the first case
32 study in contrast to the second and third cases is the participation of thermal
33 units in the spinning reserve market.
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46 Table 7, Table 8 and Table 9 are placed here
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50 The results of the second decision-making scheme are listed in Tables 10, 11,
51 and 12. Analogous to the first case study, the highlighted rows of the tables
52 demonstrate the picked solution for all case studies. It is worth to note that the
53 increment in the system's expected profit will raise the generated pollution by
54 the system. Another point of attention is that the amount of total submitted
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9 offers by the system under study in both the energy and spinning reserve markets
10 will increase in the second decision-making scheme compared to the first one.
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13 Table 10, Table 11 and Table 12 are placed here
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17 The status of thermal units within the scheduling horizon for the selected
18 solutions of the whole case studies are shown in Table 13 and Table 14. Accord-
19 ing to Table 13, in the first decision-making scheme, units $G6 - G9$ and $G14$
20 are off for the entire scheduling period. This issue stems from the fact of having
21 high production cost for units $G6 - G9$ and exorbitant start-up and shut-down
22 costs for unit $G19$. By changing the producer's decision-making approach from
23 the first scheme to the second one, unit $G14$ starts to produce electricity at
24 the first hour and remains online for the rest of the scheduling period. Also,
25 by altering the offering strategy of the system from the first case study to the
26 second/third case study, units $G1-G5$ generate power during hours 1-5 in con-
27 trast with the first case study. It should be noted that the variation in the
28 commitment program of units in each case study is distinguished by highlighted
29 cells.
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39 Table 13 and Table 14 are placed here
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42 The expected energy offers in the spinning reserve market for the selected so-
43 lutions have been shown in Fig. 5. From Fig. 5 (a), two things can be concluded:
44 first, by increasing the significance of the profit function for the decision maker,
45 the participation of thermal units in the spinning reserve market will dramati-
46 cally grow and second, at hour 20, the system's involvement in the spinning
47 reserve market will diminish due to its lowest spinning reserve price. Fig. 5 (b)
48 and Fig. 5 (c) provide the expected involvement of WTES system in the spin-
49 ning reserve market for two different decision-making schemes of the third case
50 study. As can be seen from these figures, changing the decision-making scheme
51 does not have an effect on the amount of submitted energy offers by the ESS in
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9 the spinning reserve market, and the attitude of thermal units in this market
10 only suffers changes.
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12 Fig. 5 are placed here
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16 The optimal involvement of ESS in the energy market and its state of charge
17 for the second and the third case studies have been depicted in Fig. 6. As can
18 be seen in Fig. 6 (a), the ESS system purchase energy at hours 1 and 3 as a
19 result of experiencing the lowest energy prices at these hours. The ESS system
20 sells the stored energy during hours 8, 14, 19 and 20 due to the facts that the
21 peak of energy market prices occur during these hours (hours 19 and 20) or ESS
22 experiences extremely high energy price in a specific scenario (hours 8 and 14).
23 In the second decision-making scheme (Fig. 6 (b)), the ESS would supply most of
24 its charging power at hour 3 through the thermal units instead of buying it from
25 the energy market. In other words, providing the charging energy at this hour
26 through the thermal units is more profitable than purchasing it from the energy
27 market. Fig. 6 (c) illustrates the optimal operation of ESS in the third case
28 study. Fig. 6 (c) and Fig. 5 (b/c) permit concluding that the mere participation
29 of ESS in the spinning reserve market is more profitable than offering in the
30 energy market.
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41 Fig. 6 is placed here
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45 The offering curves of the WTES system in the energy and spinning reserve
46 markets for two distinct hours are presented in Fig. 7 and Fig. 8, respectively.
47 It must be stressed that these curves are related to the first decision-making
48 scheme. In fact, thermal units will diminish their participation in the energy
49 market whenever the option of spinning reserve market is available. Another
50 important point that can be deduced from Fig. 7 (a) is that the ESS offers in
51 the energy market at hour 8 due to the fact of experiencing an extremely high
52 energy price (67.21 €/MWh) in a scenario. Fig. 9 presents the variation of
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9 the system's expected profit for different values of ESS production capacity in
10 the third case study of the first scheme. As can be observed from this curve,
11 the suggested offering strategy in the third case study can significantly raise
12 the expected profit of the system by increasing the production capacity of ESS.
13 Specifically, in the suggested approach, every five megawatts increment in the
14 production capacity of ESS will lead to a € 1299 increase in the total expected
15 profit of the system while in the proposed method of [22], each extra 5 MW
16 production capacity will result in a € 14 increase in the expected profit.
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23 Fig. 7, Fig. 8, and Fig. 9 are placed here
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26 One of the most critical issues encountered by the researchers in the multi-
27 objective stochastic programming problems is the number of scenarios arising
28 from the uncertain parameters. To this end, a further study based on the larger
29 number of reduced scenarios, i.e., ten scenarios, has been accomplished, and
30 subsequently, the results are compared with the previous studies. It has to be
31 noted that this additional study is carried out on the third case study of the
32 second decision-making scheme. The suggested model is solved with CPLEX12
33 under GAMS environment in an ASUS K series laptop computer powered by a
34 core i5 processor and 4 GB of RAM. Table 15 reports the results of the third
35 case study for the second decision-making scheme under two different analyses,
36 namely, five and ten representative scenarios for each uncertain source. The
37 reported results demonstrate that increasing the number of scenarios will result
38 in a 1.26% gain and a 0.87% decrease in the expected profit and emission,
39 respectively, while the solution time for the payoff table and each sub-problem
40 significantly raises. Another point of attention is that altering the number of
41 scenarios from five to ten considerably augment the number of variables and
42 equations as well as CPLEX iterations to reach the optimal solution. Another
43 key point is that since a multi-objective optimization problem consists of many
44 sub-problems to obtain the Pareto solution set, decision-makers may ignore
45 slight changes in the output variables due to substantial computational time.
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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 $E^{Qo} = 215 \times 10^3$ 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

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9 strategies were used to select the final solution. Three different case studies
10 which each of them represents diverse offering frameworks under two distinct
11 decision-making schemes were carried out to examine all aspects of the designed
12 offering structure. After achieving the results, it can be concluded that:
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- 15 1. Utilizing the third offering structure (case study 3) not only leads to a
16 significant increase in the expected profits of the system in both decision-
17 making schemes.
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- 19 2. The first stage decisions of the proposed offering problem, especially the
20 status of thermal units, will be influenced by the system's decision-making
21 attitude.
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- 23 3. The mere participation of energy storage system in the spinning reserve
24 is considerably more profitable than participating in the energy market.
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- 26 4. The emission trading pattern will allow us to determine the most favored
27 solution after attaining the Pareto solution set regarding various emission
28 quotas. This approach is economically beneficial for those societies with
29 this capability.
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35 For future research, the authors would expand the proposed offering strategy
36 for a price-maker wind-thermal-energy storage producer, which will augment
37 challenges to the problem.
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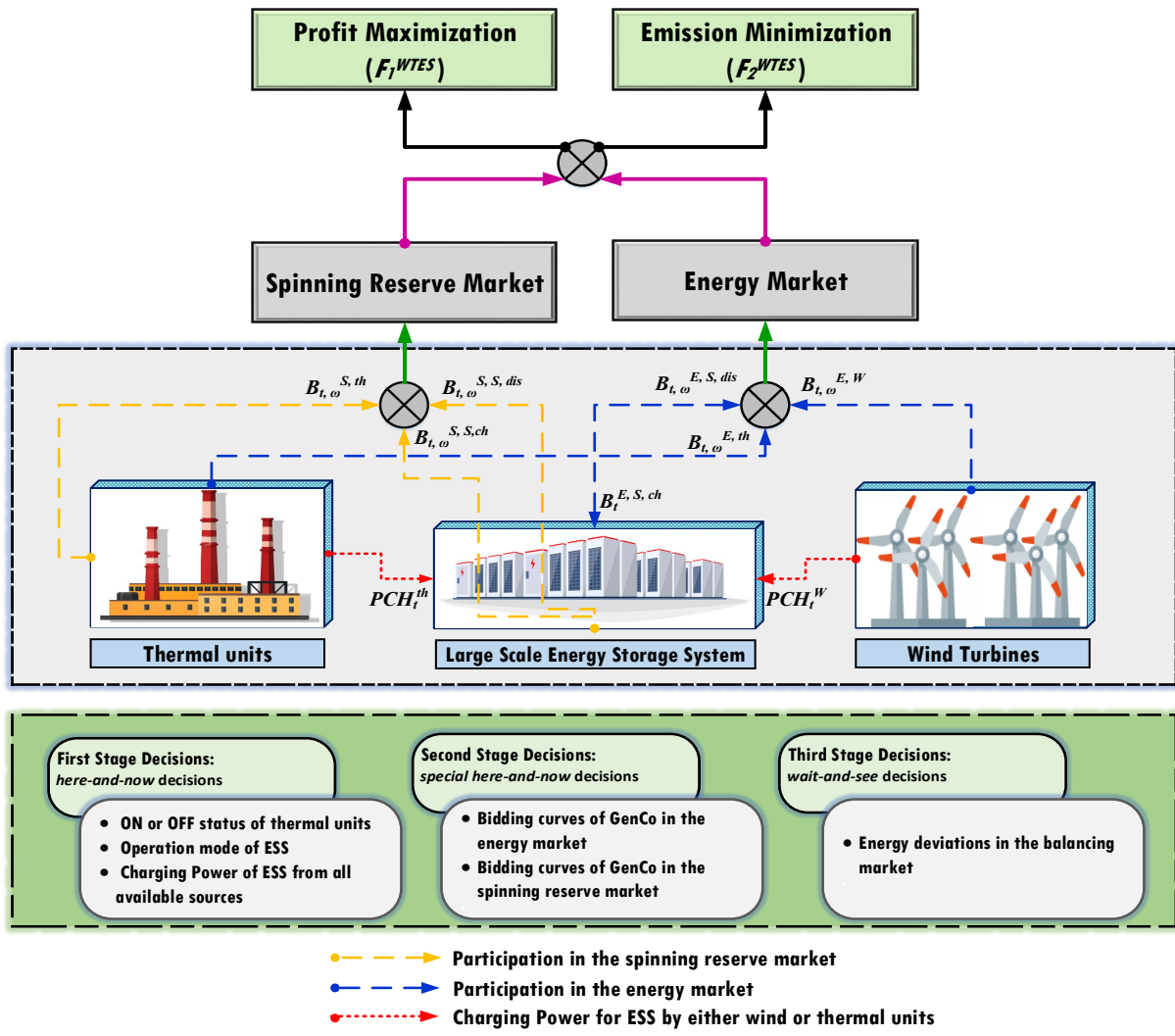


Figure 1: Schematic of the proposed three-stage offering strategy for the WTES system

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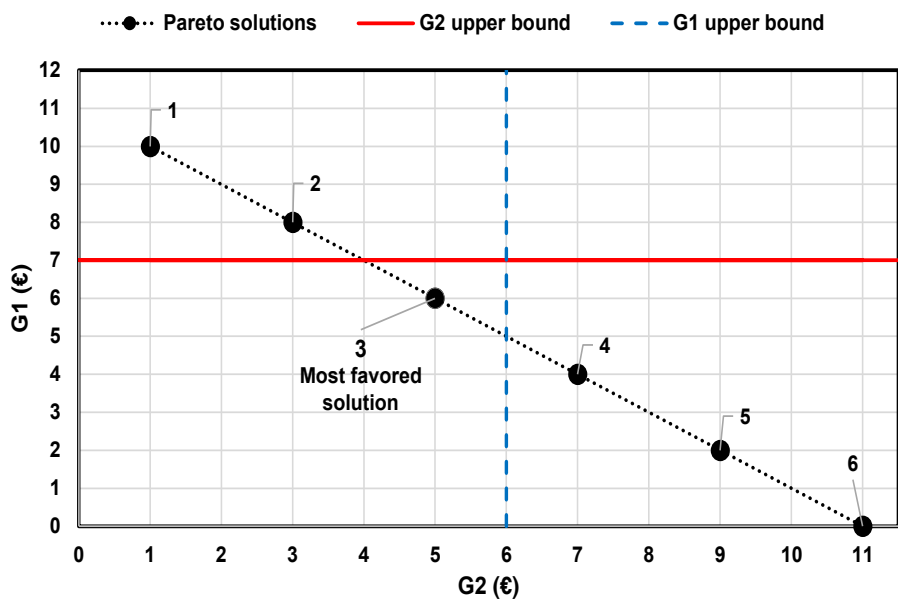


Figure 2: Sample of a Pareto solution set for demonstrating the performance of the preference-based technique

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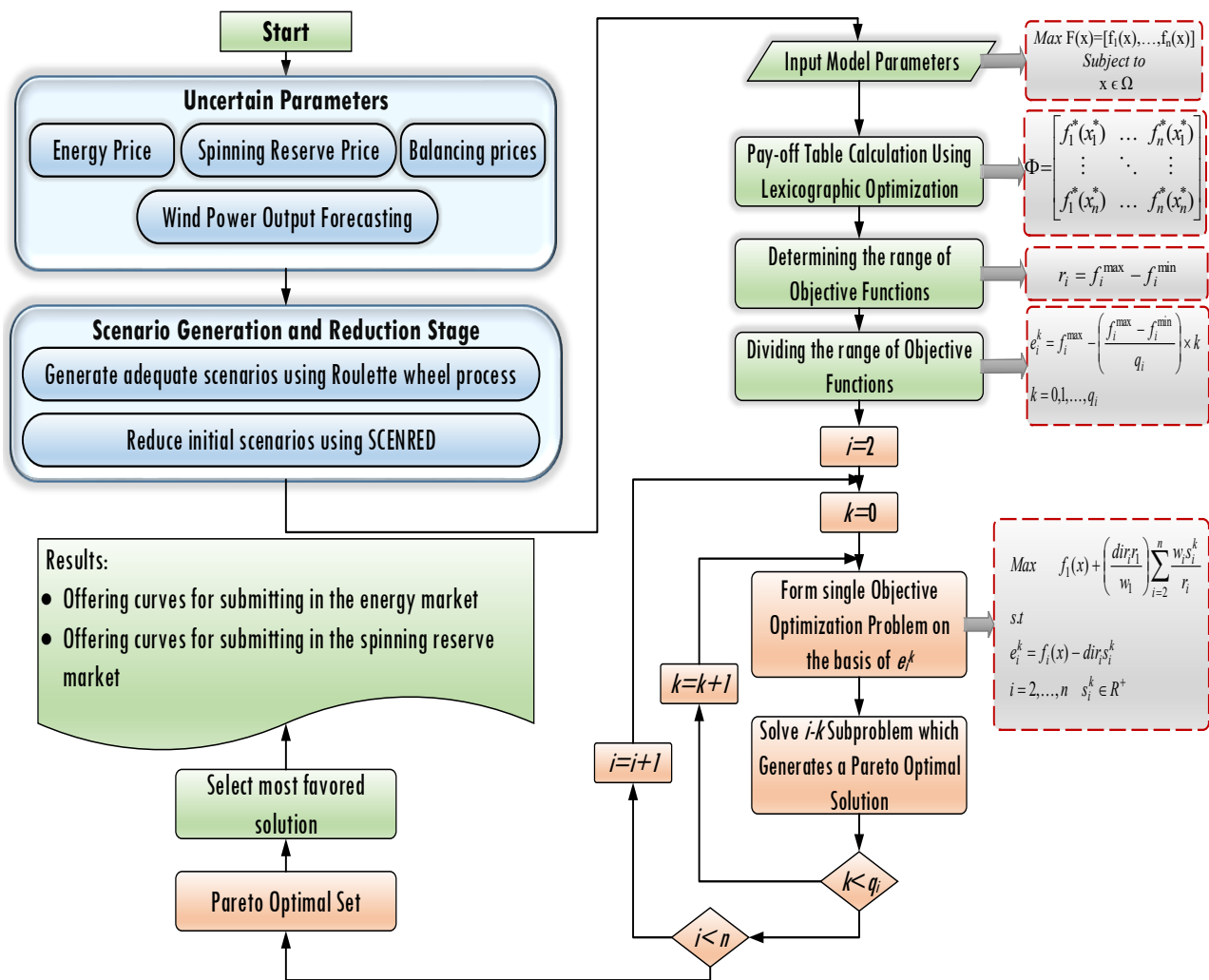


Figure 3: Schematic of the proposed solution procedure for the multi-objective offering strategy problem

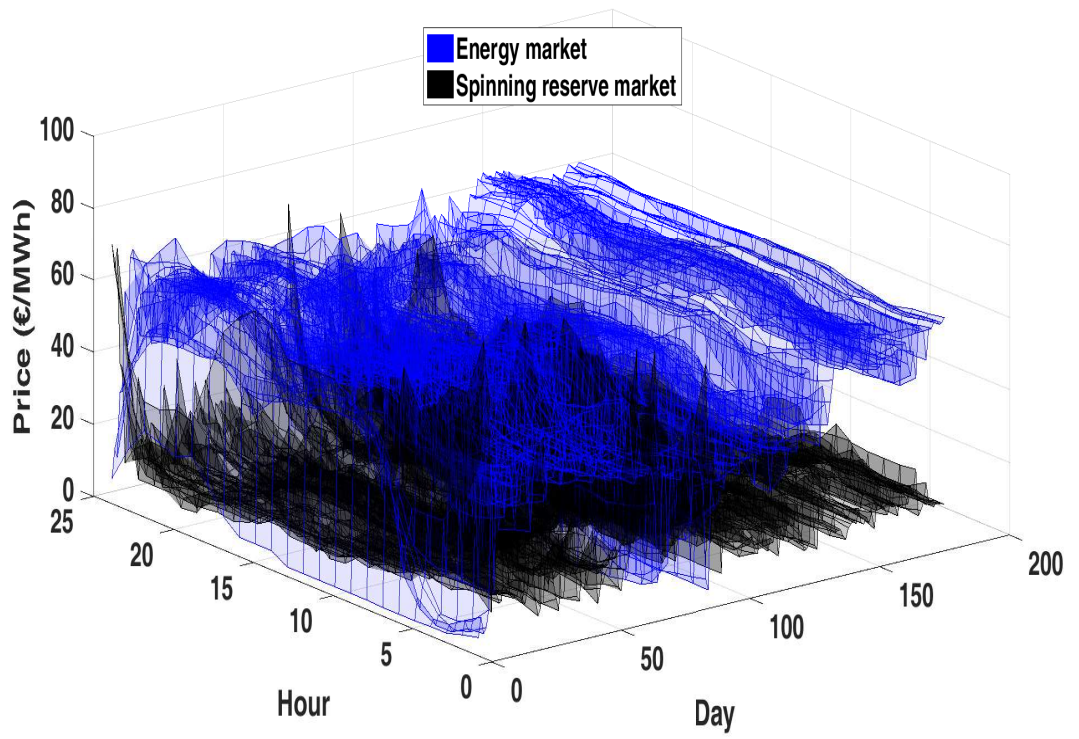
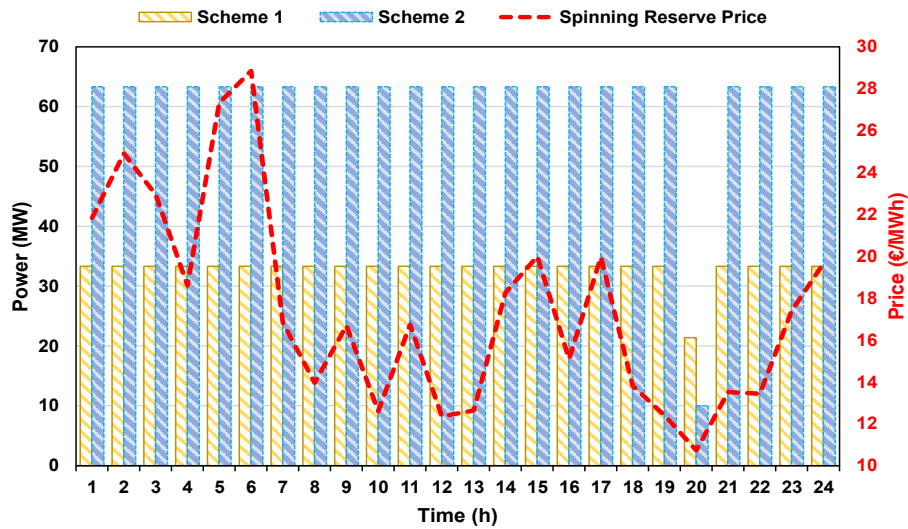
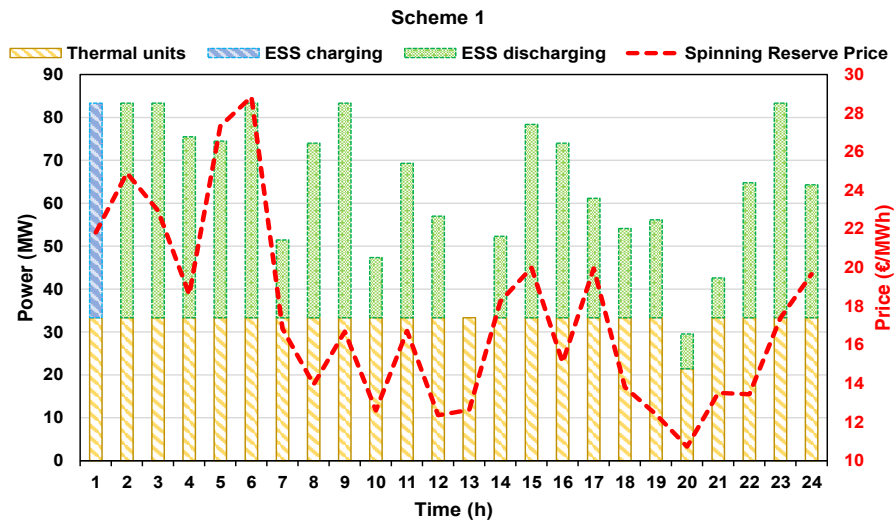


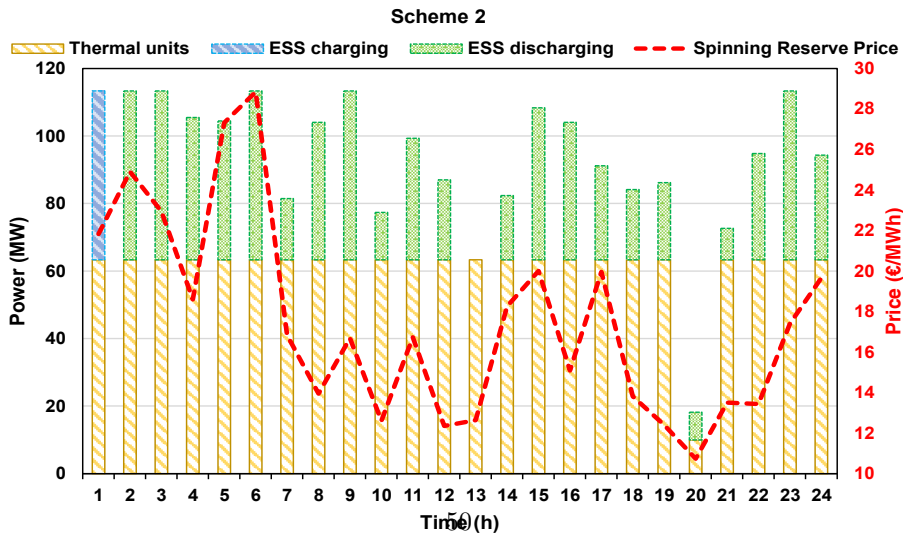
Figure 4: Historical data of energy and spinning reserve market prices



(a) Case study 2

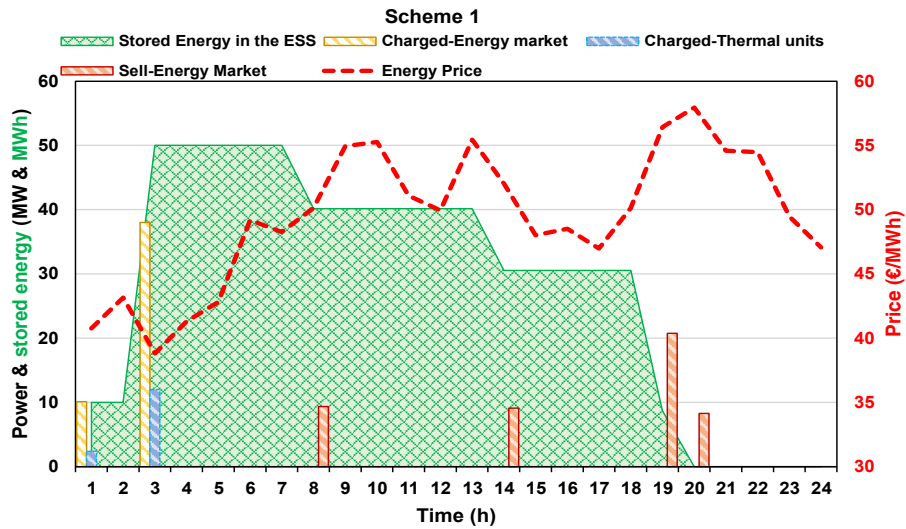


(b) Case study 3 (First decision-making scheme)

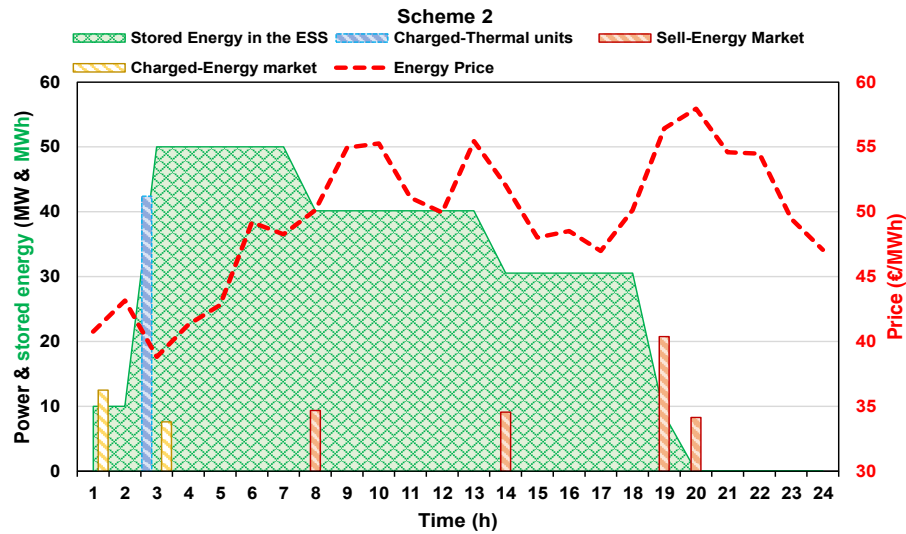


(c) Case study 3 (Second decision-making scheme)

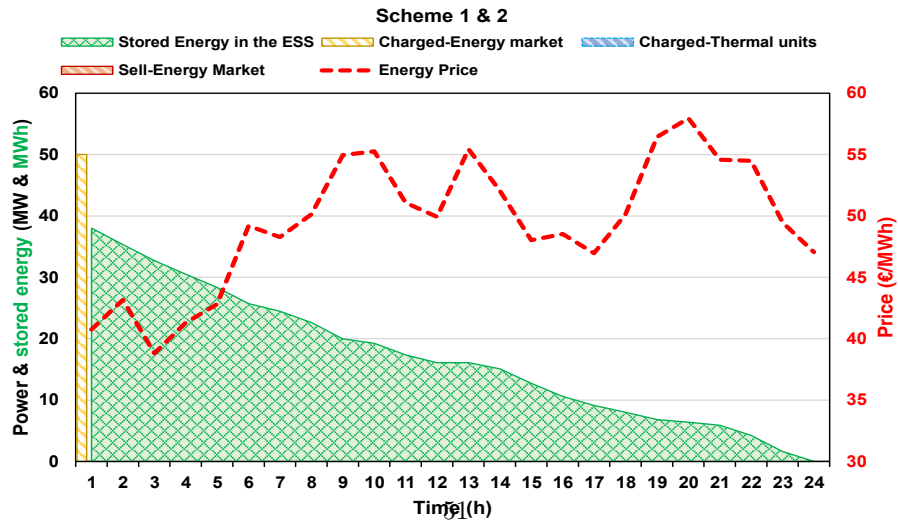
Figure 5: Expected participation of system in the spinning reserve market



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

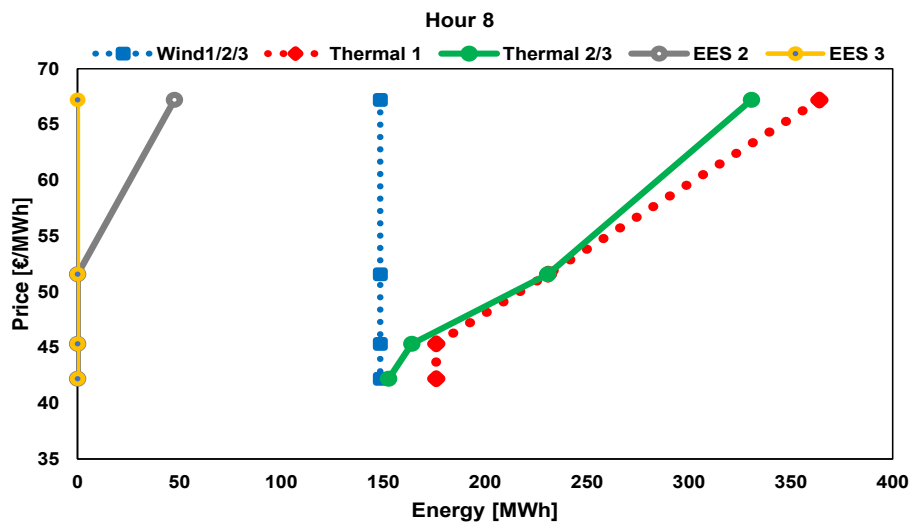


(b) Case study 2 (Second decision-making scheme)

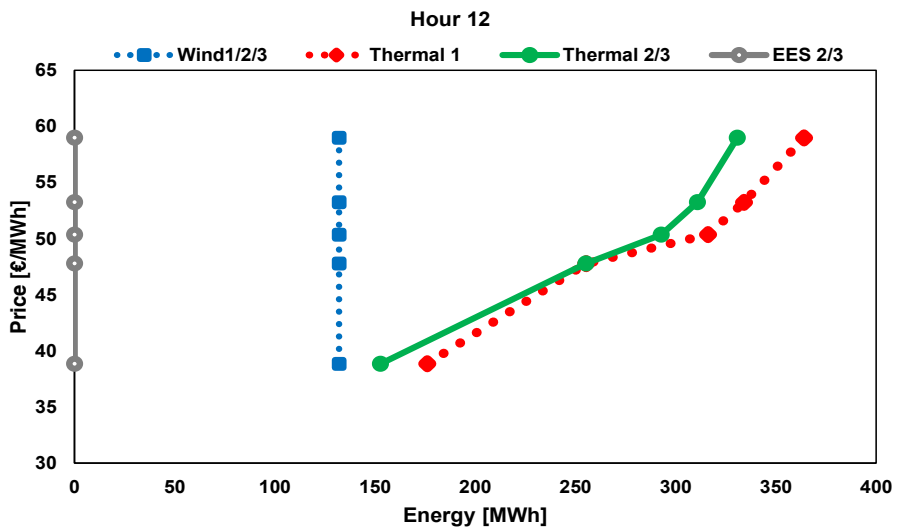


(c) Case study 3

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.

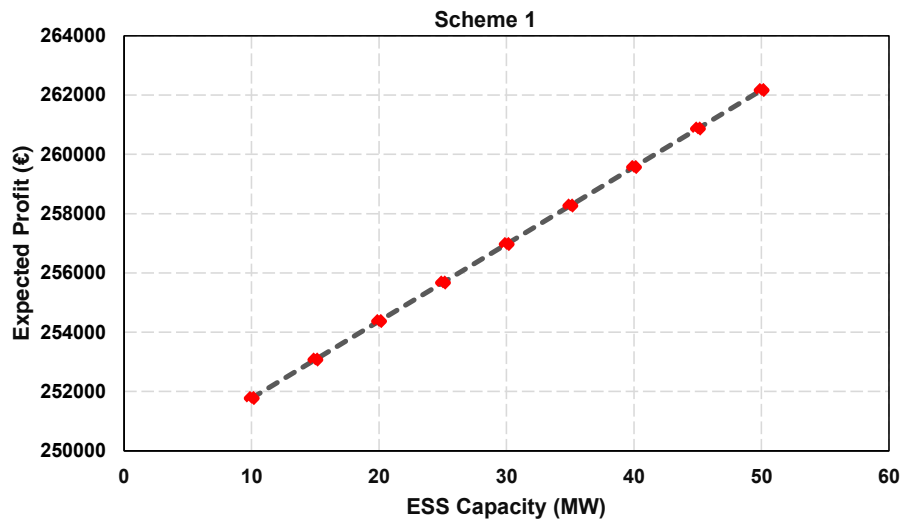


Figure 9: Expected profit of WTES system versus production capacity of ESS in the third case study

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

Fist stage decisions (<i>here-and-now</i> decisions)	Second stage decisions (<i>special here-and-now</i> decisions)	Third stage decisions (<i>wait-and-see</i> 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

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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

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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

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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

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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

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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

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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

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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
First Scheme	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
	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
	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
	G14	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	1	1	1	1	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
	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
	G14	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

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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 (€)									
			$\lambda^{EE}=0.1$	$\lambda^{EE}=0.2$	$\lambda^{EE}=0.3$	$\lambda^{EE}=0.4$	$\lambda^{EE}=0.5$	$\lambda^{EE}=0.6$	$\lambda^{EE}=0.7$	$\lambda^{EE}=0.8$	$\lambda^{EE}=0.9$	$\lambda^{EE}=1$
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