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1 Co-optimized Bidding Strategy of an Integrated
2 Wind-Thermal-Photovoltaic System in Deregulated
3 Electricity Market Under Uncertainties

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15 **Abstract**

16 Clean Energy sources, such as wind and solar, have become an inseparable
17 part of today's power grids. However, the intermittent nature of these sources
18 has become the greatest challenge for their owners, which makes the bidding
19 in the restructured electricity market more challenging. Hence, the main goal
20 of this paper is to propose a novel multi-objective bidding strategy framework
21 for a wind-thermal-photovoltaic system in the deregulated electricity market for
22 the first time. Contrary to the existing bidding models, in the proposed mod-
23 el, two objective functions are taken into account that the first one copes with
24 profit maximization while the second objective function concerns with emis-
25 sion minimization of thermal units. The proposed multi-objective optimization
26 problem is solved using the weighted sum approach. The uncertainties associ-
27 ated with electricity market prices and the output power of renewable energy
28 sources are characterized by a set of scenarios. Ultimately, in order to select
29 the best-compromised solution among the obtained Pareto optimal solutions,

30 two diverse approaches are applied. The proposed bidding strategy problem is
 31 being formulated and examined in various modes of joint and disjoint opera-
 32 tion of dispatchable and non-dispatchable energy sources. Simulation results
 33 illustrate that not only the integrated participation of these resources increases
 34 the producer's expected profit, but also decreases the amount of the produced
 35 pollution by the thermal units.

36 *Keywords:* Integrated operation, bidding strategy, Multi-objective
 37 optimization, Wind-thermal-Photovoltaic system, weighted-sum technique,
 38 Emission trading

Nomenclature

Indices

t	time index.
g	Index for thermal units.
ω	Scenario index.
b	Index for blocks of the generation cost curve and emission curve of thermal units.

Constants

π_ω	Probability of occurrence of scenario ω
$P^{W,Max}$	Rated wind power output, MW.
$P^{PV,Max}$	Rated PV power output, MW.
$STUC(g)$	Start-up cost of every thermal unit, €/each start-up.
$MDT(g)$	Minimum down-time of every thermal unit, hr.
$MUT(g)$	Minimum up-time of every thermal unit, hr.
$RUR(g)$	Ramp-up rate of every thermal unit, MW/hr.
$RDR(g)$	Ramp-down rate of every thermal unit, MW/hr.
E^{EQ}	Emission quota of power producer, lbs.

$P^{Maxb}(b, g)$	Maximum power output of every thermal unit in b th block of the piecewise linear cost function, MW.
$P^{Max}(g)$	Maximum power output of every thermal unit, MW.
$P^{Min}(g)$	Minimum power output of every thermal unit, MW.
$PS^{Max}(g)$	Maximum capacity of every thermal unit for participating in the spinning reserve market, MW.
$NC(g)$	No-load generating cost of every thermal unit, €/hr.
$IC(b, g)$	Incremental generating cost of b th block of unit g , €/MWhr.
$E(q, b, g)$	Slope of block b in emission group q of every thermal unit, lbs/MWhr.
EMG	Emission group including NO_X and SO_2 .
$STURL(g)$	Start-up ramp bound of every thermal unit, MW/hr.
$STDRL(g)$	Shut-down ramp bound of every thermal unit g , MW/hr.
a_g, b_g, c_g	Coefficients of thermal generation cost function.
$\alpha_g, \beta_g, \gamma_g$	Emission coefficients of thermal unit g .
N_T	Number of periods.
N_G	Number of thermal units.
N_Ω	Number of scenarios.
N_b	Number of segments of the production cost and emission curve.
λ^{EM}	Emission market price, €/lbs.
Variables	
$\lambda^E(t, \omega)$	Price of day-ahead energy market, €/MW.
$\lambda^S(t, \omega)$	Price of spinning reserve market, €/MW.
$P^{th,S}(t, \omega)$	Optimal bid of thermal units in the spinning reserve market, MW.
$P^{th,E}(t, \omega)$	Optimal bid of thermal units in the day-ahead energy market, MW.
$P^W(t, \omega)$	Optimal bid of wind power plant in the day-ahead energy market, MW.
$P^{PV}(t, \omega)$	Optimal bid of PV system in the day-ahead energy market, MW.
$P^{th,Ac}(t, \omega)$	Actual power output of thermal units, MW.
$P^{W,F}(t, \omega)$	Realized power output of wind power plant, MW.
$P^{PV,F}(t, \omega)$	Realized power output of PV system, MW.
$P^C(t, \omega)$	Joint energy offer of the all energy resources in the day-ahead energy market, MW.

$\Delta^+(t, \omega)$	Imbalance-up, MW.
$\Delta^-(t, \omega)$	Imbalance-down, MW.
$STU(g, t, \omega)$	Start-up cost of every thermal unit, €.
$C(g, t, \omega)$	Generation cost of every thermal unit, €.
$EG(b, g, t, \omega)$	Produced power of thermal units through the b th block of the piecewise linear cost function for participating in the day-ahead energy market, MW.
$ES(g, t, \omega)$	Power offer of every thermal unit in the spinning reserve market, MW.
$ET(g, t, \omega)$	Total power offer by every thermal unit in all selected markets, MW.
$u(g, t, \omega)$	Binary variable which indicates acceptance situation of every thermal unit in the day-ahead energy market.
$x(g, t, \omega)$	Binary variable which indicates start-up situation of thermal units in the day-ahead energy market.
$y(g, t, \omega)$	Binary variable which indicates shut-down situation of thermal units in the day-ahead energy market.
$r^+(t, \omega)$	Imbalance penalty for over-generation as multiplier of energy price
$r^-(t, \omega)$	Imbalance penalty for under-generation as multiplier of energy price

39 1. Introduction

40 1.1. Motivation and Aim

41 Nowadays, a wide range of power system issues is affected by the presence of
42 renewable energy resources. With the growth of industries and communities, the
43 request for supplying customers demand is rising day-to-day [1]. In this regard,
44 conventional energy sources such as coal, gas and nuclear, as well as renewable
45 energy sources, e.g., hydro, wind and solar, are the two main options for gov-
46 ernments to supply the required electricity of communities [2]. Generally, the
47 rising cost of fossil fuels and attention to environmental concerns can be men-
48 tioned as the main reasons for the desire of diverse communities to augment the
49 penetration of renewable energy sources [3]. Briefly, sustainability, environmen-
50 tally friendly, reducing fossil fuel consumption, and low maintenance costs are

51 among the reasons for increasing the interest of various communities in renew-
52 able energy sources [4]. Despite many subsidies that governments have devoted
53 to renewable energy developers, we will witness a significant increase in invest-
54 ments in this sector [5]-[6]. On the other hand, the existence of subsidies will not
55 guarantee the profits of investors. Hence, the deregulated electricity market lay
56 the groundwork for both producers and consumers to devise the best possible
57 strategy for themselves. Consequently, renewable energy sources owned by gen-
58 eration companies (GenCos)/large consumers must design the most profitable
59 bidding strategy by participating in various electricity markets.

60 1.2. Literature Review

61 The problem of optimal bidding strategy/self-scheduling has attracted the
62 attention of many researchers so far [7]-[22]. A bidding structure based on the
63 joint implementation of stochastic and robust uncertainty modeling approach-
64 es for an industrial consumer has been addressed in [7]. Likewise, in [8], the
65 authors conducted a stochastic-robust optimization-based framework for a bid-
66 ding strategy of a large consumer in a deregulated electricity market. In both
67 papers [7] and [8], the uncertainty of load is addressed by the specified range,
68 and the uncertainty related to renewable productions and market prices are
69 modeled via independent scenarios. A self-scheduling model for the participa-
70 tion of a sample microgrid containing plug-in electric vehicles, wind turbines,
71 and fuel cell units has been developed in [9]. In [10], authors have proposed
72 a coordinated self-production and load-scheduling framework for an industrial
73 plant in joint electricity and carbon emission markets. A hybrid probabilistic-
74 possibilistic technique has been employed in [11] to cope with the uncertainties
75 in the self-scheduling of thermal units. In [12], authors have focused on pre-
76 senting a bi-objective self-scheduling structure for a typical factory as a large
77 consumer. In [13], a risk-constrained self-scheduling model for a real virtual
78 power plant in Iran has been suggested.

79 Integrated energy resources scheduling is one of the most challenging prob-
80 lems in the electrical power system which has attracted much attention. Wind

81 power generation as one of the most favorite organ of integrated energy re-
82 sources has been widely considered alongside other production resources such
83 as thermal, hydro, solar, and pumped storage power plants. In [14], the authors
84 present an integrated self-scheduling model for a wind-pumped-storage system
85 while the uncertainty of wind power generation is modeled by a neural network
86 based technique. Authors illustrated that presenting a coordinated bidding s-
87 trategy of both resources can remarkably raise their profitability. A critical
88 shortage of this work is that the authors have not modeled the uncertainty
89 associated with electricity market prices. Authors in [15], presented a linear
90 programming framework for self-scheduling of a hydro-thermal system, whereas
91 the electricity market prices and forced outages of generating units have been
92 considered as uncertain sources. Likewise, the investigation of integrated wind
93 and thermal energy sources in the context of the bidding strategy problem have
94 been accomplished in [16]-[18]. The ultimate goal of all these three works is
95 to prove the profitability of integrated scheduling compared to non-integrated
96 one. In [19], a risk-based bidding framework for a wind-thermal-pumped storage
97 system is presented.

98 Contrary to the mentioned studies, the bi-objective scheduling of integrated
99 energy systems with the aim of minimizing pollution emission has also been con-
100 sidered by researchers [20]-[21]. In [20], a bi-objective microgrid self-scheduling
101 model is presented in which the microgrid cost and emission minimizations are
102 taking into account. A multi-objective self-scheduling model for a hydro-thermal
103 system considering joint energy and ancillary services markets is proposed in
104 [21]. In [22], a multi-objective economic dispatch model for pumped-hydro-
105 thermal systems is presented in which the normal boundary intersection is uti-
106 lized to achieve the Pareto optimal solutions. The taxonomy of reviewed papers
107 [7]-[22] based on different aspects of their works has been listed in Table 1.

108

109

Table 1 is placed here

110

111 *1.3. Contributions*

112 According to the reviewed papers in subsection 1.2 and the specified char-
113 acteristics for each paper in Table 1, this paper focuses on presenting a novel
114 bi-objective bidding strategy of a wind-thermal-photovoltaic system in the en-
115 ergy and spinning reserve markets. To the best of authors' knowledge, this work
116 proposes the most comprehensive study in the context of multi-objective and
117 single-objective coordinated bidding strategy of wind, thermal and photovoltaic
118 units in the literature, so the major contributions of this paper are:

- 119 • A comprehensive coordinated mathematical formulation is presented for
120 the multi-objective bidding strategy of all existing sources.
- 121 • A novel bi-objective bidding strategy is proposed for a wind-thermal-
122 photovoltaic (WTPV) system participating in the energy and spinning
123 reserve markets. The process of profit maximization and emission mini-
124 mization are concurrently accomplished while the uncertainty arising from
125 day-ahead energy, spinning reserve, and imbalance prices along with the
126 output power of renewable energy resources are addressed in the proposed
127 framework.
- 128 • An efficient solution method, namely, the hybrid weighted sum method
129 and fuzzy satisfying approach, is introduced as the solution methodology
130 of the bi-objective bidding strategy problem
- 131 • A decision-making scheme based on the preferences of decision-maker is
132 suggested in the bidding strategy problem to select the most favored so-
133 lution.
- 134 • An additional pattern based on the emission trading concept is proposed
135 for an emission-constrained WTPV power producer to select the best pos-
136 sible strategy.

137 **2. Problem formulation**

138 The multi-objective bidding strategy problem of a WTPV system is formu-
 139 lated as a stochastic mixed integer programming (MIP) which maximizing the
 140 expected profit of WTPV system and minimizing the expected emission aris-
 141 ing from thermal units are considered as two distinct objective functions of the
 142 decision-maker. In the following subsections, separate objective functions of the
 143 bi-objective bidding strategy problem will be thoroughly explained.

144 *2.1. First objective function: Maximizing expected profit*

145 The primary purpose of the WTPV system is to maximize its profits through
 146 participation in diverse electricity markets in the 24-hour scheduled horizon. In
 147 the coordinated bidding structure, a single offering package will be offered to
 148 the energy market from all existing energy resources while the offering package
 149 of power producer in the spinning reserve market exclusively contains the par-
 150 ticipation of thermal units in this market. The first objective function of the
 151 power producer for the coordinated operation of all resources is formulated as
 152 follows:

$$\begin{aligned}
 \text{Max } F_1^C = & \sum_{\omega=1}^{N_\Omega} \pi_\omega \times \left[\sum_{t=1}^T (\lambda^E(t, \omega) P^{th,E}(t, \omega) + \lambda^E(t, \omega) P^W(t, \omega) \right. \\
 & + \lambda^E(t, \omega) P^{PV}(t, \omega) + \lambda^S(t, \omega) P^{th,S}(t, \omega) \\
 & + \lambda^E(t, \omega) r^+(t, \omega) \Delta^+(t, \omega) - \lambda^E(t, \omega) r^-(t, \omega) \Delta^-(t, \omega) \left. \right] \\
 & - \sum_{\omega=1}^{N_\Omega} \pi_\omega \times \left[\sum_{t=1}^T \sum_{g=1}^{N_G} C(g, t, \omega) - \sum_{t=1}^T \sum_{g=1}^{N_G} (STU(g, t, \omega)) \right] \quad (1)
 \end{aligned}$$

153 where the first two lines of (1) represent the expected income of power pro-
 154 ducer from participating in the day-ahead energy and spinning reserve markets
 155 while the third line relates to the imbalances of power producer in the balancing
 156 market, finally, the last line refers to the costs of operating and start-up costs
 157 of the thermal units. The constraints of the objective function (1) would be
 158 presented as follows:

$$0 \leq EG(b, g, t, \omega) \leq P^{Maxb}(b, g), \quad \forall b, \forall g, \forall t, \forall \omega \quad (2)$$

$$P^{Min}(g)u(g, t, \omega) \leq \sum_{b=1}^{N_b} EG(b, g, t, \omega) \leq P^{Max}(g)u(g, t, \omega), \quad \forall g, \forall t, \forall \omega \quad (3)$$

$$0 \leq ES(g, t, \omega) \leq PS^{Max}(g)u(g, t, \omega), \quad \forall g, \forall t, \forall \omega \quad (4)$$

$$P^{Min}(g)u(g, t, \omega) \leq ET(g, t, \omega) \leq P^{Max}(g)u(g, t, \omega), \quad \forall g, \forall t, \forall \omega \quad (5)$$

$$0 \leq P^W(t, \omega) \leq P^{W,Max}, \quad \forall t, \forall \omega \quad (6)$$

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

$$0 \leq STU(g, t, \omega) \geq STUC(g)x(g, t, \omega), \quad \forall g, \forall t, \forall \omega \quad (8)$$

$$\sum_{n=t-MUT(g)+1}^t x(g, t, \omega) \leq u(g, t, \omega), \quad \forall g, \forall t, \forall \omega \quad (9)$$

$$u(g, t, \omega) + \sum_{n=t-MDT(g)+1}^t y(g, t, \omega) \leq 1, \quad \forall g, \forall t, \forall \omega \quad (10)$$

$$\begin{aligned} \sum_{b=1}^{N_b} EG(b, g, t, \omega) &\leq \sum_{b=1}^{N_b} EG(b, g, t-1, \omega) + RUR(g)u(g, t-1, \omega) \\ &+ STURL(g)x(g, t, \omega), \quad \forall g, \forall t > 1, \forall \omega \end{aligned} \quad (11)$$

$$\begin{aligned} \sum_{b=1}^{N_b} EG(b, g, t-1, \omega) &\leq \sum_{b=1}^{N_b} EG(b, g, t, \omega) + RDR(g)u(g, t, \omega) \\ &+ STDRL(g)y(g, t, \omega), \quad \forall g, \forall t > 1, \forall \omega \end{aligned} \quad (12)$$

$$0 \leq \Delta^+(t, \omega) \leq P^{PV,F}(t, \omega) + P^{W,F}(t, \omega) + P^{th,Ac}(t, \omega), \quad \forall t, \forall \omega \quad (13)$$

$$0 \leq \Delta^-(t, \omega) \leq P^{PV,Max} + P^{W,Max} + \sum_{g=1}^{N_G} P^{Max}(g)u(g, t, \omega), \quad \forall t, \forall \omega \quad (14)$$

$$P^C(t, \omega) \leq P^C(t, \tilde{\omega}), \quad \forall \omega, \tilde{\omega} : [\lambda^E(t, \omega) \leq \lambda^E(t, \tilde{\omega})], \quad \forall t \quad (15)$$

$$P^{th,S}(t, \omega) \leq P^{th,S}(t, \tilde{\omega}), \quad \forall \omega, \tilde{\omega} : [\lambda^S(t, \omega) \leq \lambda^S(t, \tilde{\omega})], \quad \forall t \quad (16)$$

$$P^C(t, \omega) = P^C(t, \tilde{\omega}), \quad \forall \omega, \tilde{\omega} : [\lambda^E(t, \omega) = \lambda^E(t, \tilde{\omega})], \quad \forall t \quad (17)$$

$$P^{th,S}(t, \omega) = P^{th,S}(t, \tilde{\omega}), \quad \forall \omega, \tilde{\omega} : [\lambda^S(t, \omega) = \lambda^S(t, \tilde{\omega})], \quad \forall t \quad (18)$$

$$C(g, t, \omega) = NC(g)u(g, t, \omega) + \sum_{b=1}^{N_b} IC(b, g)EG(b, g, t, \omega), \quad \forall t, \forall \omega \quad (19)$$

$$\sum_{g=1}^{N_G} \sum_{b=1}^{N_b} EG(b, g, t, \omega) = P^{th,E}(t, \omega), \quad \forall t, \forall \omega \quad (20)$$

$$\sum_{g=1}^{N_G} ES(g, t, \omega) = P^{th,S}(t, \omega), \quad \forall t, \forall \omega \quad (21)$$

$$ET(g, t, \omega) = \sum_{b=1}^{N_b} EG(b, g, t, \omega) + ES(g, t, \omega), \quad \forall g, \forall t, \forall \omega \quad (22)$$

$$P^C(t, \omega) = P^{th,E}(t, \omega) + P^W(t, \omega) + P^{PV}(t, \omega) \quad \forall t, \forall \omega \quad (23)$$

$$\Delta(t, \omega) = P^{PV,F}(t, \omega) + P^{W,F}(t, \omega) + P^{th,Ac}(t, \omega) - P^C(t, \omega), \quad \forall t, \forall \omega \quad (24)$$

$$\Delta(t, \omega) = \Delta^+(t, \omega) - \Delta^-(t, \omega), \quad \forall t, \forall \omega \quad (25)$$

$$u(g, t - 1, \omega) - u(g, t, \omega) + x(g, t, \omega) - y(g, t, \omega) = 0, \quad \forall g, \forall t, \forall \omega \quad (26)$$

159 Inequalities (2) and (3) restrict the generated power of thermal units within
 160 their minimum and maximum bounds while constraint (4) is implemented to
 161 limit the spinning reserve offer of generation facility within their maximum capa-
 162 bility in providing upward spinning reserve. Constraint (5) is fulfilled to restrict
 163 the total bids of thermal units in the day-ahead energy and spinning reserve
 164 market within their limited operating areas. Constraints (6) and (7) represent
 165 the upper and lower bounds of the scheduled power of renewable energy sources.
 166 Constraints (8) is fulfilled to calculate the start-up costs incurred by thermal
 167 units during the scheduling horizon. Other technical restrictions of thermal u-
 168 nits, as well as the minimum up/down time are enforced by constraints (9)-(10).
 169 The ramp-up and ramp-down limitations, considering the shut-down and start-
 170 up ramps of thermal units are modeled by constraints (11)-(12). Restriction (13)
 171 limits the positive energy deviations of power producer within the total actual
 172 power output of all three sources while constraint (14) ensures that the negative
 173 energy deviations should not exceed the maximum capacity of renewable ener-
 174 gy sources plus the maximum available capacity of thermal units. Constraints
 175 (15)-(16) and (17)-(18) are the non-decreasing and non-anticipativity settings
 176 for the offering packages in the energy and spinning reserve markets, respec-
 177 tively. The generation cost of thermal units for energy delivery is computed
 178 through constraint (19). The quadratic cost curve of thermal units makes the
 179 problem nonlinear. In order to overcome this issue, many researchers have been
 180 approximated this cost curve using various piecewise blocks [20]. In the current
 181 paper, these piecewise linearized segments are indexed by letter b . Constraint
 182 (20) represents the total bid of thermal units in the energy market. Equation
 183 (21) calculates total bid of thermal units in the spinning reserve market while
 184 equation (22) computes the total bid of thermal units in energy and spinning
 185 reserve markets. Coordinated operation constraints: Constraint (23) calculates
 186 the final bid of power producer that should be offered to the energy market.
 187 Constraints (24) and (25) model the imbalances of the power producer in the

188 balancing market. Finally, the logical relationship between the various status
 189 of thermal units is enforced by equality (26).

190 *2.2. Second objective function: Minimizing expected emission*

191 The second objective function of the power producer in the proposed struc-
 192 ture is emission minimization. In fact, due to the worldwide rising concerns
 193 about environmental issues, minimizing the produced pollution by thermal u-
 194 nits is consistently considered as one of the objective functions of the power
 195 producers in the optimization process. The linear form of this objective func-
 196 tion would be as follows:

$$\text{Min } F_2^{th} = \sum_{\omega=1}^{N_{\Omega}} \pi_{\omega} \times \left[\sum_{q=1}^{EMG} \sum_{g=1}^{N_G} \sum_{b=1}^{N_b} E(q, b, g) EG(b, g, t, \omega) \right] \quad (27)$$

197 It is worth to note that in order to take advantage of linear programming in
 198 the proposed structure, the emission functions of thermal units, which generally
 199 have a quadratic form, are approximated by some piecewise linearized blocks.
 200 In the current paper, the SO_2 and NO_X are taken into consideration as the
 201 primary sources of emission [21].

202 In this paper, three different bidding strategies, including the coordinated
 203 and uncoordinated operation of various energy sources, are considered to thor-
 204 oughly examine the productivity of the proposed structure. Fig. 1 shows these
 205 three different bidding strategies with their determinant constraints. These
 206 three trading strategies are designed to exhaustively assess the multi-objective
 207 bidding strategy problem based on the following modes of operation:

- 208 1. Uncoordinated operation of all three available energy resources.
- 209 2. Coordinated operation of two energy resources + Uncoordinated operation
 210 of the last energy resources.
- 211 3. Coordinated operation of all three available energy resources.

212 Note that the authors have passed up to present the formulation of the first
 213 and second trading strategies to avoid tautology in writing. It is notable that
 214 the superscript numbers in the constraints of the second strategy point out two
 215 distinct trading strategy in this case study.

216

Fig. 1 is placed here

217

218

219 2.3. Solution method of the multi-objective optimization problem

220 Most practical engineering issues are faced with more than one objective
 221 function, which in many cases, these objective functions conflict with each other.
 222 Multifarious techniques and methods have been employed in the literature
 223 to solve multi-objective problems, which ϵ -constraint technique [20] and the
 224 weighted sum (WS) approach [24] are among these methods. In the present
 225 paper, the weighted sum technique has been used to solve the multi-objective
 226 bidding strategy of wind-thermal-photovoltaic energy resources. In the weight-
 227 ed sum method, all objective functions with different weighting factors that
 228 represent the relative significance of each objective function are put together in
 229 a separate objective function according to the following equation:

$$\text{Min } [OF] = w_1 F_1' + w_2 F_2 \quad (28)$$

230 subject to

$$\begin{cases} w_1 + w_2 = 1 \\ F_1' = -F_1 \\ \text{All restrictions of the proposed problem} \end{cases} \quad (29)$$

231 where F_1 and F_2 stand for the two conflicting objective functions of the
 232 proposed problem, i.e., profit maximization and emission minimization. One
 233 of the difficulties faced by decision-makers in the weighted sum method is the
 234 different scale of objective functions in (28). To this end, a fuzzy satisfying

235 approach is proposed to overcome this issue in the literature of multi-objective
 236 programming problems [21]. Based on this approach, the objective functions in
 237 (28) are normalized as follows:

$$F_{1,pu} = \frac{F_1 - F_1^{max}}{F_1^{max} - F_1^{min}} \quad (30)$$

$$F_{2,pu} = \frac{F_2^{max} - F_2}{F_2^{max} - F_2^{min}} \quad (31)$$

238 where $F_{1,pu}$ and $F_{2,pu}$ are the per unit values of objective functions F_1 and
 239 F_2 , respectively. In fact, the equations (30) and (31) map the objective functions
 240 F_1 and F_2 in the range 0 and 1. (F_1^{max}, F_2^{max}) and (F_1^{min}, F_2^{min}) represent the
 241 obtained maximum and minimum values of each objective function through the
 242 single objective optimization process, respectively. After normalizing each ob-
 243 jective function, the objective function of the weighted sum method is rewritten
 244 as follows:

$$\text{Min } [OF] = w_1 F'_{1,pu} + w_2 F_{2,pu} \quad (32)$$

245 2.4. Decision-maker's approach to select the best compromise solution

246 After obtaining the Pareto solutions via the WS method, the most favored
 247 solution among all set of solutions should be picked up. In the present paper,
 248 the final selection of the best compromise solution is accomplished based on the
 249 mindset, inclination, and preferences of decision-makers [25]. Indeed, decision-
 250 makers ascertain the minimum and maximum permissible values for the objec-
 251 tive functions based on insight, the experience of previous years, short-term and
 252 long-term plans, and restrictions imposed by system operators. In this regard,
 253 for the objective function of maximizing profit, the minimum acceptable profit
 254 and for the objective function of minimizing emission, the maximum allowable
 255 emission is determined by the decision-maker, and finally, the most favored
 256 solution is selected based on these preconditions.

257 *2.5. Uncertainty characterization*

258 The uncertain sources in the optimal bidding strategy of a GenCo are gener-
 259 ally divided into two groups: the price of various target markets and generation
 260 power of renewable energy sources. The methodology for modeling the uncer-
 261 tainties arising from electricity market prices and output power of renewable
 262 energy sources will be explained in the following subsections.

263 *2.5.1. Market Prices uncertainty model*

264 In the proposed framework, the normal probability density function (PDF)
 265 is utilized to model the three uncertain market prices: the day-ahead energy and
 266 spinning reserve market prices along with the real-time market price. The PDF
 267 of an electricity market price λ_{price} with mean μ_{price} and standard deviation
 268 σ_{price} would be formulated as follows:

$$f_{price}(\lambda_{price}, \mu_{price}, \sigma_{price}) = \frac{1}{\sigma_{price}\sqrt{2\pi}} \exp \left[-\frac{(\lambda_{price} - \mu_{price})^2}{2\sigma_{price}^2} \right] \quad (33)$$

269 *2.5.2. Wind power uncertainty model*

270 As it is evident, the production power of a wind turbine is not constant and
 271 changes as a function of wind speed. In the current paper, the Weibull PDF
 272 has been considered for modeling wind speed. The Weibull PDF of wind speed
 273 V with scale and shape factors c and k is defined as follows:

$$f_{wind}(V, c, k) = \frac{k}{c} \left(\frac{V}{c} \right)^{k-1} \exp \left[-\left(\frac{V}{c} \right)^k \right] \quad (34)$$

274 The generated power of a wind turbine in specified wind speed V has fully
 275 corresponded to its technical specifications, namely, cut-out speed v_{co} , cut-in
 276 speed v_{ci} , and rated speed v_r , which is calculated using the following equation:

277

$$P_{wind} = \begin{cases} 0, & 0 \leq V \leq v_{ci} \\ P_{rated} \times \left(\frac{V-v_{ci}}{v_r-v_{ci}} \right), & v_{ci} \leq V \leq v_r \\ P_{rated}, & v_r \leq V \leq v_{co} \end{cases} \quad (35)$$

278 *2.5.3. Solar power uncertainty model*

279 Solar irradiance is the most significant factor in determining the output
 280 power of photovoltaic units, which is always confronted with uncertainties. In
 281 this paper, the Beta PDF is utilized as an appropriate expression pattern of
 282 solar irradiance. The Beta PDF of solar irradiance Si is expressed as follows:

$$f_{irr}(Si, \alpha, \beta) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \times (Si)^{\alpha-1} \times (1-Si)^{\beta-1}, & 0 \leq Si \leq 1, \alpha \geq 0, \beta \geq 0 \\ 0, & otherwise \end{cases} \quad (36)$$

283 Given the solar irradiance Si of photovoltaic units, their efficiency η^{PV} and
 284 total area S^{PV} , the output power of PV units P_{PV} are calculated as follows
 285 [23]:

$$P_{PV} = \eta^{PV} \times S^{PV} \times Si \quad (37)$$

286 Finally, By assigning appropriate probability density functions to each un-
 287 certain parameter, scenarios associated with these parameters are constructed
 288 by the roulette wheel mechanism [23].

289 **3. Emission trading**

290 In this paper, a solution fits the purchasing or selling emission quotas is pre-
 291 sented for those occasions that taking advantage of emission trading is accessible
 292 for GenCos/industrial consumers. In this regard, [26] and [27] have focused on
 293 the detailed investigation of emission trading pattern in China's container ter-
 294 minal and building materials industry, respectively. Based on this approach,
 295 after solving the multi-objective bidding strategy problem, a specific strategy
 296 for each Pareto optimal solution will be adopted. If the emission of thermal
 297 units per Pareto exceeds the emission quota, the GenCo will have to purchase
 298 additional emission quotas. However, if the emission of a GenCo in each Pareto
 299 is less than the assigned emission quota, the Genco can sell its surplus emission
 300 quota. As mentioned above, the total expected earnings of GenCo in every
 301 Pareto optimal solution will be calculated as follows:

$$TPF = EPP + [\lambda^{EM} \times (E^{EQ} - EEG)] \quad (38)$$

302 where the TPF is net expected profit, EPP is the expected profit of Gen-
 303 Co per Pareto, E^{EQ} is the assigned emission quota to GenCo, λ^{EM} refers to
 304 emission price, and the EEG stands for the expected emission of GenCo per
 305 Pareto. Ultimately, for each emission price, a Pareto with the maximum val-
 306 ue of TEP is selected as the optimal Pareto solution of the proposed bidding
 307 strategy problem.

308 4. Results and discussion

309 4.1. Input data

310 The proposed system under study comprises five thermal units, a wind farm,
 311 and a PV site with the maximum capacity of 340 MW, 250 MW, and 150
 312 MW for each, respectively. The economic and technical information on thermal
 313 units is provided in Table 2 and Table 3. These data have been extracted with
 314 some adjustments from [16]. Also, the data related to the emission curve of
 315 thermal units are given in Table 4. It is worthwhile to mention again that
 316 the quadratic cost and emission curves of thermal units are approximated by
 317 three piecewise blocks. This action, along with the proper formulation of the
 318 problem, leads to the absence of any nonlinear term in the proposed issue. On
 319 the basis of previously published papers, the SO_2 and NO_x are considered as the
 320 fundamental origins of emission [21]. The expected values of forecasted wind
 321 speed and solar irradiance [28] are portrayed in Fig. 2 while information on wind
 322 turbines and PV site are provided in Table 5.

323

Tables 2, 3, 4, and 5 are placed here

324

325

326

Figure 2 is placed here

327

329 In the proposed model, GenCo only allows the thermal units to participate
330 in the spinning reserve market, and since the offer of each unit in this market
331 has to be ready to deliver in ten minutes, the maximum offer for each unit in
332 this market is calculated using $PS^{\text{Max}}(g) = \frac{1}{6} \times \text{RUR}(g)$ [29]. As outlined in
333 subsection 2.5, five uncertainty sources exist in the proposed structure (day-
334 ahead market, spinning reserve market, and imbalance prices as well as wind
335 and PV generation). Based on the suggested model, for each parameter, the
336 adequate number of scenarios based on the statistical analysis of [28] and [30] is
337 constructed using roulette wheel mechanism, and with a common approach, i.e.,
338 fast forward reduction technique [16] and [19], the initially generated scenarios
339 for each parameter are reduced to three representative scenarios. Consequently,
340 the final scenario set will contain $3^5 = 243$ scenarios. The proposed structure
341 is formulated based on the MIP and has been implemented in GAMS (general
342 algebraic modeling system), with CPLEX as the solver.

343 4.2. Results

344 In order to assess the performance of the proposed structure, two different
345 case studies are considered in this paper. In the first case study, we examine the
346 single objective framework for the bidding strategy of the system under consid-
347 eration, and in the second case study, the multi-objective bidding strategy of
348 the wind-thermal-PV system is discussed. It is worth to note that in all case
349 studies, the three trading strategies shown in Fig. 1 is fully explored. The first
350 trading strategy appertained to the disjoint operation of all three energy sources
351 in the electricity markets. The second trading strategy refers to the coordinated
352 operation of wind and thermal units, while the PV system individually and in-
353 dependently participates in the electricity market. Eventually, the third trading
354 strategy relates to the coordinated operation of all available energy sources.

355 *4.2.1. Case study 1*

356 As already mentioned, this case study focuses on the single objective bidding
357 strategy of the system under study. In other words, this case study focuses solely
358 on maximizing producer's profit without having a program or goal to minimize
359 emissions. The results of this case study have been exhibited in Table 6. It
360 is necessary to mention that this table will allow us to compare the economic
361 and environmental aspects of different trading strategies. According to the ob-
362 tained results, trading strategy 1 has the lowest expected profit (€302434.636)
363 and the highest imbalance cost (€25369.536) among all three trading strategies.
364 In contrast, coordinated operations of all three resources (trading strategy 3)
365 have resulted in the highest profitability and the lowest imbalance cost, which
366 the obtained results are €304509.778 and €15278.357, respectively. Similar-
367 ly, in the second trading strategy that includes the coordinated operation of
368 wind and thermal resources, more profit (€303221.192) and fewer imbalance
369 cost (€23037.277) are obtained compared to the first strategy. From a differ-
370 ent point of view, coordinated operation of energy resources in the proposed
371 bidding strategy not only increase the profitability of the power producer but
372 also reduces the emission of thermal units. It has to be noted that the numeric
373 percent for comparing the decreasing or increasing values related to expected
374 profit, expected emission, and expected imbalance cost of trading strategies two
375 and three will be presented later to check out the effectiveness of the proposed
376 bidding strategy.

377

Table 6 is placed here

378

379

380 Fig. 3 shows the expected participation of WTPV system in the energy
381 and spinning reserve markets for all trading strategies. According to Fig. 3a,
382 it is observed that at almost most of the hours, trading strategy 1 has more
383 participation in the energy market. This issue has led the trading strategy 1 to
384 have the highest imbalance cost, which ultimately leads to more reduction in the

385 expected profit of WTPV system. Besides, it can be viewed that the difference
386 in the participation of various trading strategies in the day-ahead energy market
387 reflects more during high market prices. On the other hand, as shown in Fig. 3b,
388 the participation of WTPV system in the spinning reserve market for trading
389 strategies 2 and 3 are similar at most hours. Also, the high day-ahead market
390 prices during hours 11-14 have led to a reduction in producer's participation
391 in the spinning reserve market for the specified time interval. In other words,
392 the producer will have a greater willingness to participate in the energy market
393 instead of participating in the spinning reserve market to gain more profit in the
394 aforementioned time interval. Finally, Fig. 4 presents the comparison between
395 the share of thermal units from the entire participation of WTPV system in the
396 energy market for all trading strategies. The share of thermal units in trading
397 strategies 1 and 2 are lower than the first trading strategy, which leads to lower
398 emission of power producer, as reported in Table 6. It is worth mentioning
399 that Fig. 3 and Fig. 4 are demonstrated to unfold how the coordinated trading
400 strategy of various available sources will alter the expected participation of the
401 whole system and thermal units in the energy and spinning reserve markets,
402 respectively.

403
404 Figures 3 and 4 are placed here
405

406 4.2.2. Case study 2

407 This case study is designed to address the multi-objective bidding strategy
408 of the wind-thermal-PV system. Contrary to the first case study, in this case
409 study, minimizing the emission of thermal units is also added to one of the
410 decision-maker's goals in the optimization process. As discussed in the previous
411 sections, the weighted sum method is used to solve the multi-objective optimiza-
412 tion problem. In this method, different weighting factors for objective functions
413 (here, w_1 and w_2) are chosen subject to $w_1 + w_2 = 1$, and finally, the Pareto
414 solutions of the proposed problem will be obtained. The results of Pareto for

415 trading Strategies 1, 2, and 3 are shown in Fig. 5, Fig. 6, and Fig. 7, respective-
416 ly. Also, the normalized values of objective functions $F1$ and $F2$ in equations
417 (30) and (31), i.e., $F_{1,pu}$ and $F_{2,pu}$, are reported in the aforementioned figures.
418 These normalized values let us observe that the proposed bi-objective model can
419 efficiently obtain various results in the range of 0 and 1 that do not agglutinate
420 in a specific space and it is capable of covering almost any range of $F_{1,pu}$ and
421 $F_{2,pu}$. After obtaining Pareto results, the proposed approach in subsection 2.4
422 is implemented to select the most favored solution among all Pareto solutions.
423 The minimum and maximum predetermined limits for the profit and emission
424 are assumed to be 20×10^3 lbs and $\text{€ } 250 \times 10^3$, respectively. It has to be not-
425 ed that these limits are determined by the decision-maker (GenCo) to merely
426 compare the results of different trading strategies under similar conditions and
427 consequently, every other restriction can be imposed by the decision-maker. Ac-
428 cordingly, the presented Pareto solutions in Fig. 5, Fig. 6, and Fig. 7 will let us
429 pick the most favored solution under different predetermined restrictions. The
430 summary results of different trading strategies in terms of the environmental
431 and economic evaluation of the multi-objective bidding strategy have been pro-
432 vided in Table 7. It is worth noting that the results of Table 7 correspond to the
433 red box of Fig. 5, Fig. 6 and Fig. 7 ($P14$) that obtained through the suggested
434 approach in subsection 2.4.

435
436 Table 7 is placed here

437
438
439 Figures 5, 6 and 7 are placed here

441 According to the provided results in Table 7, trading strategies 2 and 3 have
442 also led to an increase in the producer's expected profit in the multi-objective
443 bidding strategy. The expected profit for trading strategies one, two, and three
444 is $\text{€}253638.926$, $\text{€}255566.283$, and $\text{€}256978.704$, respectively. In this regard, the
445 most expected profit is achieved via the third trading strategy ($\text{€}256978.704$)

446 Which is consistent with the results of the previous case study. Similar to the
447 first case study, in the second case study, the trading strategies 2 and 3 also
448 diminish the imbalance costs and emissions in comparison with the first trading
449 strategy.

450 Similar to Fig. 3, Fig. 8 illustrates the expected bids of power producer
451 that are going to be submitted in the energy and spinning reserve markets for
452 all three trading strategies. The expected production bids in the energy market
453 (Fig. 8a) follow the explanation given about Fig. 3a, with the difference that the
454 rates of production bids are significantly reduced. Fig. 8b allows us to conclude
455 that the power producer's bidding approach in the spinning reserve market for
456 all trading strategies will not affect the producer's strategy in this market. This
457 issue stems from the fact that the producer tends to utilize the maximum level
458 of participation in the spinning reserve market to gain its expected profit in
459 whole trading strategies while the pollution constraints restrict its production
460 in the energy market. At the remaining hours, the rising level of GenCo's
461 participation in the energy market, the GenCo's involvement in the spinning
462 reserve also increases. Analogous to Fig. 4, the comparison between the portion
463 of thermal units from the total participation of the WTPV system in the energy
464 market for all trading strategies in the multi-objective optimization approach is
465 captured in Fig. 9. In fact, this figure exposes how the emission of both trading
466 strategies 2 and 3 will be reduced in comparison with the first trading strategy.
467 In comparison with the first case study, a large portion of the thermal units'
468 production bids has been reduced, which is more evident in time intervals with
469 lower energy prices.

470

471 Figures 8 and 9 are placed here

472

473 In order to participate in diverse electricity markets, the producers should
474 submit their bidding packages to each specific market. The bidding curves of the
475 power producer in the energy market for hours 8 and 22 for both single-objective
476 and bi-objective bidding approaches are captured in Fig. 10 and Fig. 11. It can

477 be noticed that in the coordinated operation of energy resources, for example,
478 trading strategy 3, a bidding curve from all three energy resources is submit-
479 ted to the day-ahead energy market. As can be seen from these curves, the
480 coordinated operation of two or all units (strategy 2 or 3) leads to a change in
481 the producer's bidding curve compared to the uncoordinated one (strategy 1).
482 This is evident for both single objective and bi-objective bidding approaches.
483 Moreover, the drop in bid volumes of bi-objective bidding approach compared
484 to the single objective one is noticeable as can be seen from these figures.

485
486 Figures 10 and 11 are placed here

487
488 In this paper, along with the proposed approach in subsection 2.4, emission
489 trading is also taken into consideration as a new scheme in the decision-making
490 process of the power producer. Following the explanations given in section 3,
491 after solving the multi-objective bidding strategy problem and obtaining corre-
492 sponding Pareto solutions, this approach is implemented to select the optimal
493 solution among all Pareto solutions. The maximum TPF obtained by equation
494 (38) will be the optimal solution corresponding to each emission price. One of
495 the superiorities and advantages of this method versus other techniques is that
496 the emission quota of the power producer is implicitly included in the bidding
497 process. In the current paper, in order to avoid tautology in the demonstration
498 of results, only the results of emission quota arbitraging for trading strategy 3
499 have been reported in Table 8. The emission quota of the power producer is
500 considered 20×10^3 lbs. The bold numbers in each column pertaining to emission
501 prices indicate the optimal Pareto solution for that particular emission price.
502 As can be seen from this table, the increase in the price of emission leads to a
503 reduction in the expected net profit of the power producer.

504
505 Table 8 is placed here

506
507 The final investigation of this paper is dedicated to examining the effect of

508 the number of scenarios on the principal output variables of the problem, i.e.,
509 expected profit and emission, and their standard deviation. To this end, dif-
510 ferent analyses under the different number of scenarios of operating variables,
511 namely, renewable power productions and electricity market prices, are carried
512 out, and results will be compared. It has to be noted that these analyses are
513 conducted on the third trading strategy because of two reasons: first, the coordi-
514 nated operation of wind, thermal, and PV units is selected as the final preferred
515 bidding strategy and second, the third trading strategy involves one optimiza-
516 tion problem where all existing uncertainty sources are present and, as a result,
517 all uncertainties affect the outputs of the problem. The considered analyses are
518 as follows:

- 519 1. Analysis 1: two representative scenarios for each uncertain parameter is
520 considered in the scenario reduction stage. Consequently, the total number
521 of scenarios in this analysis would be $2^5=32$.
- 522 2. Analysis 2: three scenarios for each uncertain parameter is taken into
523 account. The total number of scenarios is $3^5=243$. In fact, this analysis
524 is the same as the one proposed in this paper.
- 525 3. Analysis 3: the reduced number of scenarios for each uncertain parameter
526 is equal to four, so the entire scenario set includes $4^5=1024$ scenarios.

527 It is worth mentioning that the reduced scenarios are obtained according to
528 provided descriptions in subsection 4.1. Fig. 12 and Fig. 13 demonstrate the
529 attained expected profit and emission versus their standard deviations in var-
530 ious analyses. According to Fig. 12, raising the total number of scenarios will
531 result in an increment in both expected profit and its standard deviation. On
532 the contrary, based on Fig. 13, it can be observed that the expected emission
533 of the system and its standard deviation will be reduced by moving toward
534 larger scenario sets. In summary, enlarging scenario numbers will modify both
535 expected profit and emission of the power producer, but it may seriously lead
536 to a computational explosion. The results of the computation time for diverse

537 analyses have been depicted in Fig. 14. It can be seen from this figure that
538 increasing the number of scenarios will considerably raise the solution time, e-
539 specially in the bi-objective bidding approach. In this regard, by changing the
540 attitude of the WTPV system from the second analysis to the third one in the
541 case study 2, a 1% increase in the expected profit results in a 462% increment
542 in the solution time. It has to be noticed that the scale of the vertical axis in
543 Fig. 14 is logarithmic.

544

545 Figures 12, 13 and 14 are placed here

546

547

547 *4.3. Discussion*

548 In the current paper, a comprehensive bidding model for the participation
549 of wind, thermal, and photovoltaic units has been proposed. In summary, by
550 examining the presented results in two case studies using the suggested approach
551 in subsection 2.4, we can conclude that the proposed trading strategies will
552 increase the expected profit and reduce the expected emission of the power
553 producer. In order to assess the effectiveness of the second and third trading
554 strategies in comparison with the first trading strategy, Fig. 15 and Fig. 16 are
555 provided. According to these figures, it can be concluded that:

- 556 1. In both case studies, the third trading strategy has the highest profit
557 increment, which these values are 1.36% and 0.68% for the first and second
558 case studies, respectively.
- 559 2. In both case studies of the second and third trading strategies, the emission
560 of thermal units decreases compared to the first trading strategy, which is
561 more striking in the first case study.
- 562 3. Trading strategy 3 has the highest imbalance reduction, especially in the
563 bi-objective bidding approach.

- 564 4. Reducing the expected production bids in the energy market has led to a
565 decrease in the cost of imbalances and, consequently, an increase in the
566 producer's profit.
- 567 5. In the bi-objective bidding approach, the trading strategy of power pro-
568 ducer will not affect the participation level of thermal units in the spinning
569 reserve market.

570
571 Figures 15 and 16 are placed here
572

573 Nevertheless, the following directions are suggested for further research:

- 574 1. Considering a risk measuring index in the bi-objective bidding strategy of
575 WTPV system as an additional parameter.
- 576 2. Proposing a bi-level bidding model for the WTPV system while it behaves
577 as a price-maker producer in one of the target electricity markets.

578 5. Conclusion

579 In this paper, a new framework for multi-objective bidding strategy of an
580 integrated wind-thermal-photovoltaic system alongside two different decision-
581 making schemes was proposed to attain the introduced contributions. In order
582 to assess the effectiveness of the suggested bidding structure, three different trad-
583 ing strategies, including coordinated and uncoordinated operation of generation
584 units, along with their relevant formulation were comprehensively presented,
585 and subsequently, an efficient technique was applied to solve the bi-objective
586 problem.

587 The key findings of the suggested model are listed as follows:

- 588 1. The coordinated operation of all energy resources was led to the high-
589 est expected profit in both single-objective and multi-objective bidding
590 strategies. In fact, in the bi-objective model, the aim was to evaluate the

591 profitability of the coordinated bidding strategy of all available sources in
592 the presence of an additional objective function, which in this occasion,
593 the proposed bidding strategy was also able to gain the total expected
594 profit of the system.

595 2. The reduction in the output power of thermal units in the bi-objective
596 approach will lead to considerable imbalance reduction in comparison with
597 the single-objective one. This imbalance reduction was accompanied by a
598 decrease in the participation of the system in the energy market.

599 3. The variation in the trading approach of the system in the bi-objective
600 model did not affect the bidding decisions in the spinning reserve market.

601 4. The emission trading mechanism can be used as a beneficial pattern by
602 the power producers to increase their profitability as the presented model
603 in this paper results in higher values of expected profit for all emission
604 prices lower than 1 €/lbs.

605 5. The greater scenario sets result in higher values of expected profit and its
606 standard deviation while the expected emission and its standard deviation
607 are reduced. In this regard, a slight variation in the fundamental output
608 variables of the problem, i.e., expected profit and expected emission, by
609 increasing the total number of scenarios will lead to a computational ex-
610 plosion.

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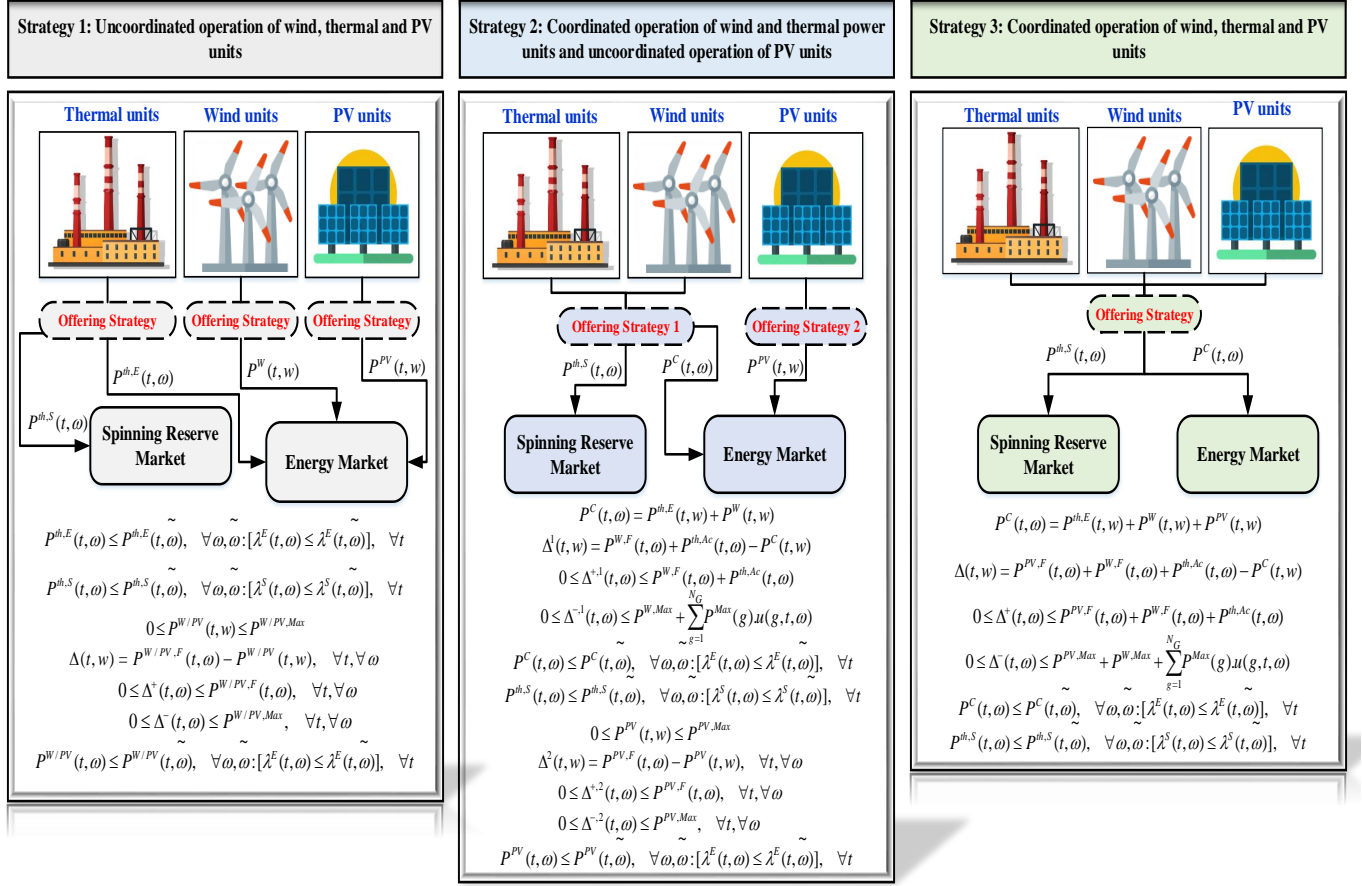


Figure 1: Schematic of different bidding strategies

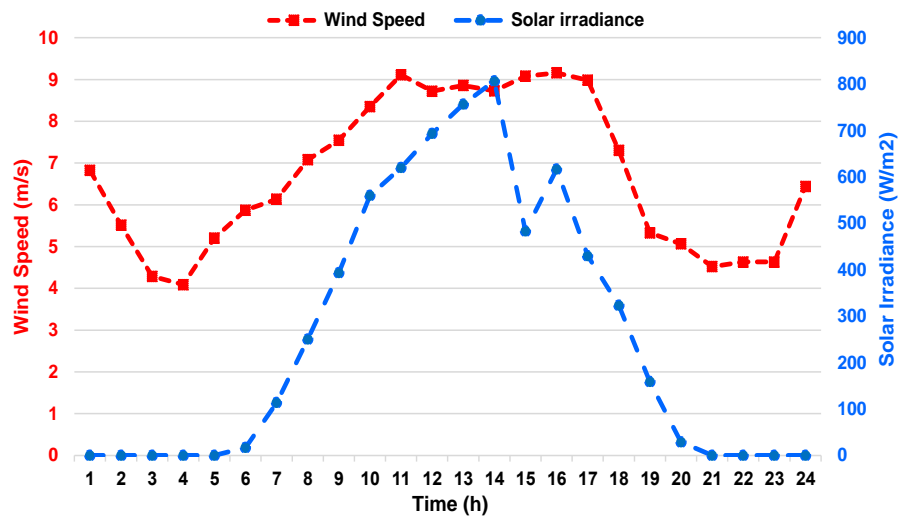
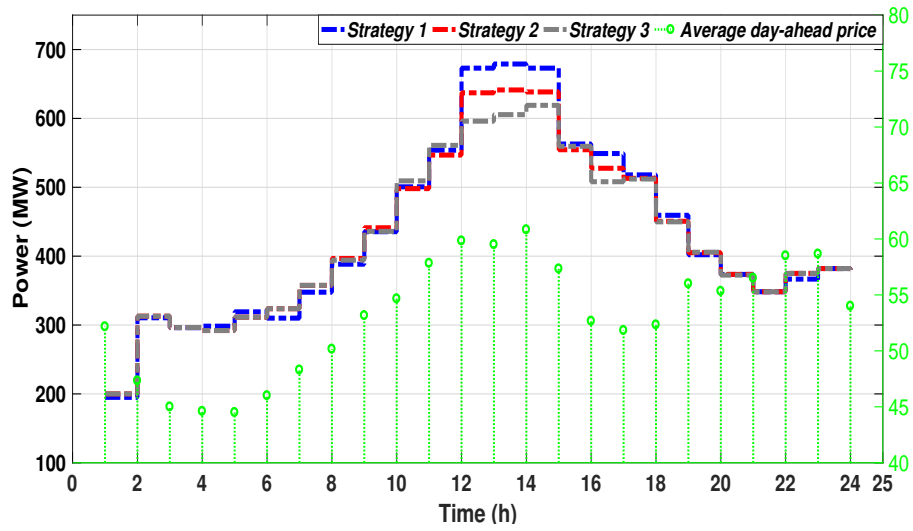
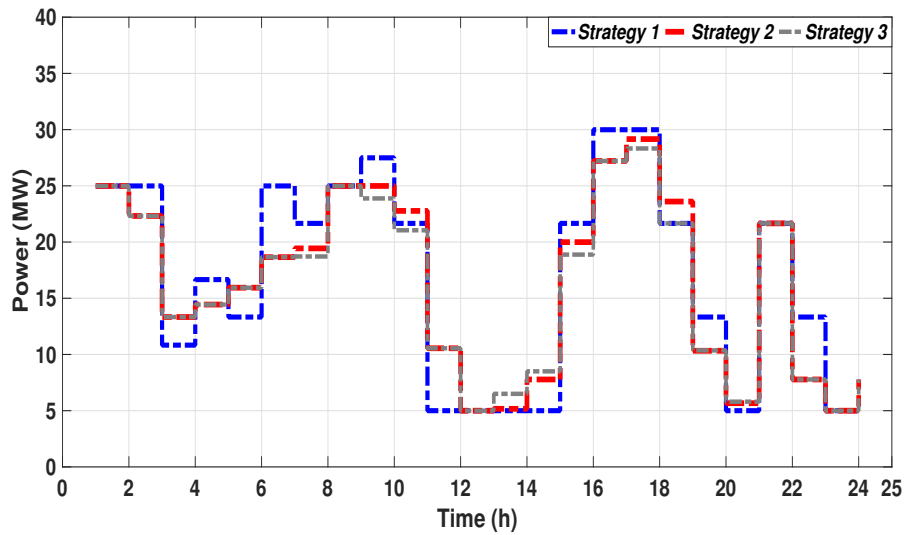


Figure 2: Expected values for hourly wind speed and solar irradiance



(a) Expected participation in the day-ahead energy market in different trading strategies



(b) Expected participation in the spinning reserve market in different trading strategies

Figure 3: Single objective bidding approach

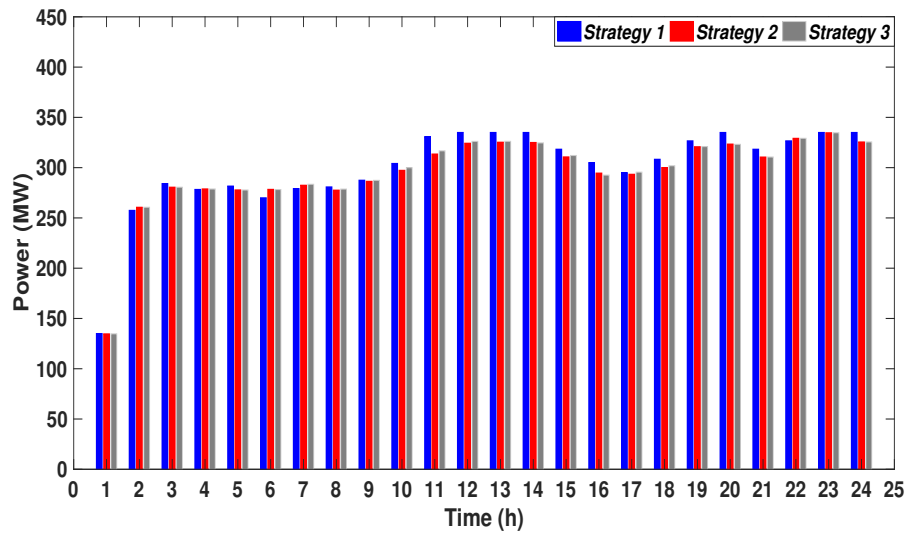
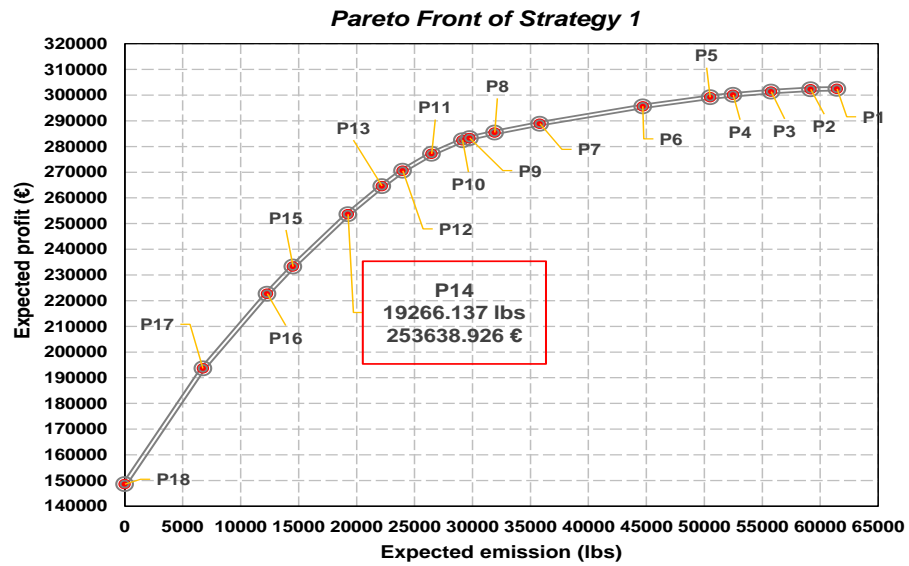
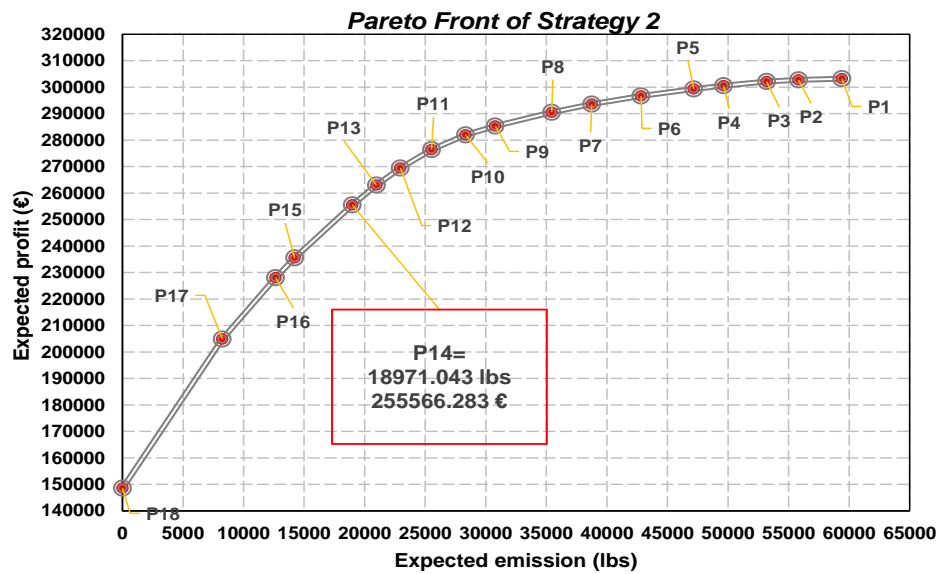


Figure 4: Comparison of expected amount of production bids of thermal units in the day-ahead energy market for all trading strategies (case study 1)



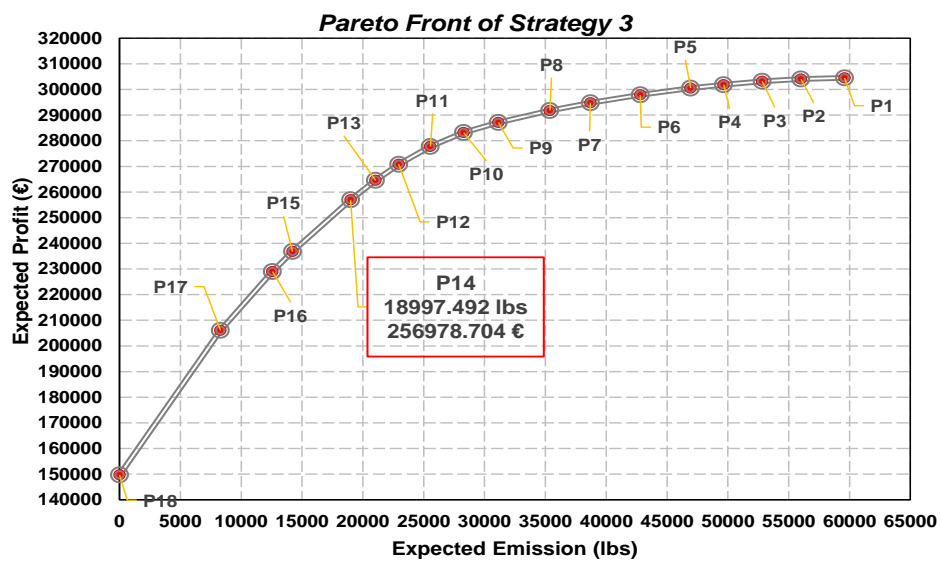
	P1	P2	P3	P4	P5	P6	P7	P8	P9
$F_{1,pu}$	1	0.9990	0.9929	0.9847	0.9787	0.9556	0.9117	0.8896	0.8754
$F_{2,pu}$	0	0.0370	0.0925	0.1459	0.1780	0.2726	0.4173	0.4805	0.5158
	P10	P11	P12	P13	P14	P15	P16	P17	P18
$F_{1,pu}$	0.8700	0.8356	0.7927	0.7541	0.6827	0.5503	0.4818	0.2927	0
$F_{2,pu}$	0.5257	0.5691	0.6097	0.6388	0.6865	0.7638	0.8001	0.8902	1

Figure 5: Pareto front for trading strategy 1



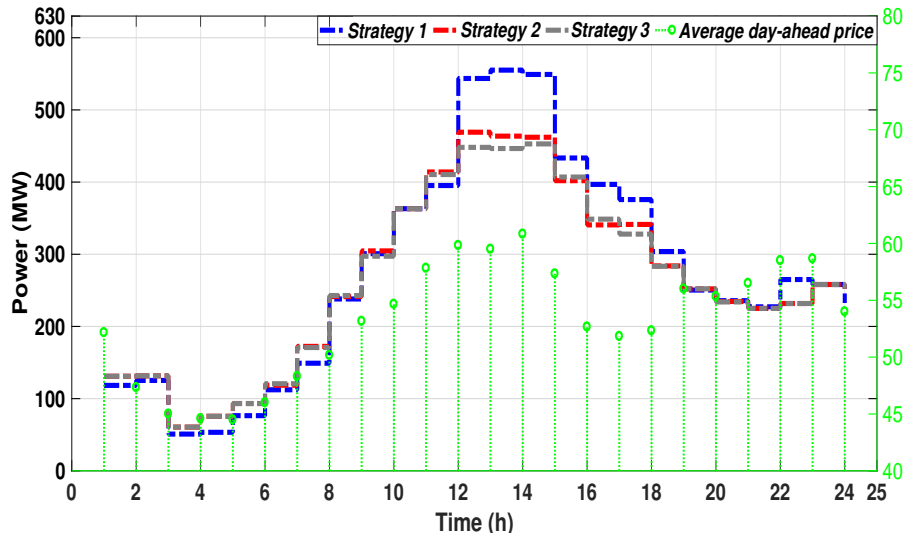
	P1	P2	P3	P4	P5	P6	P7	P8	P9
F _{1,pu}	1	0.9968	0.9928	0.9831	0.9750	0.9575	0.9375	0.9180	0.8843
F _{2,pu}	0	0.0603	0.1045	0.1645	0.2059	0.2791	0.3478	0.4034	0.4819
	P10	P11	P12	P13	P14	P15	P16	P17	P18
F _{1,pu}	0.8626	0.8268	0.7817	0.7397	0.6917	0.5622	0.5139	0.3640	0
F _{2,pu}	0.5231	0.5703	0.6138	0.6469	0.6806	0.7606	0.7872	0.8610	1

Figure 6: Pareto for trading strategy 2

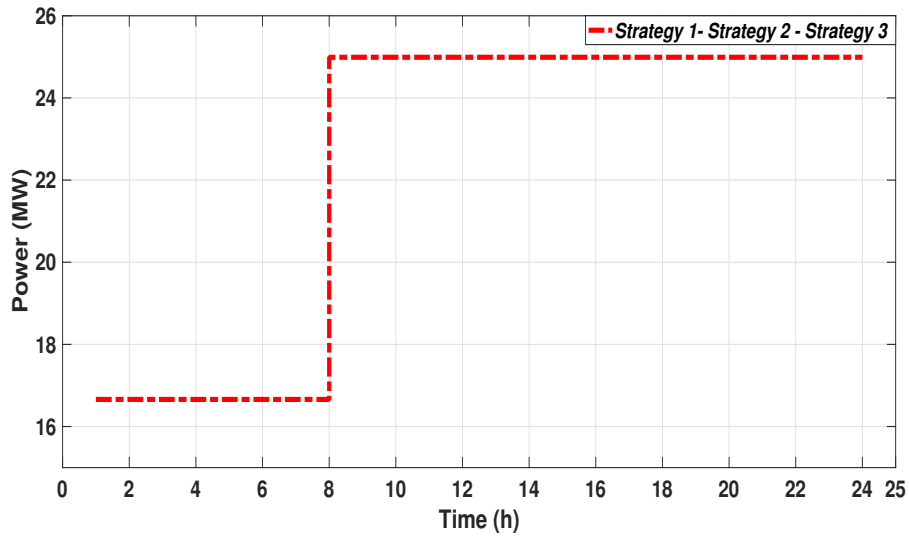


	P1	P2	P3	P4	P5	P6	P7	P8	P9
F_{1,pu}	1	0.9970	0.9914	0.9828	0.9742	0.9572	0.9372	0.9177	0.8874
F_{2,pu}	0	0.0600	0.1136	0.1667	0.2122	0.2816	0.3505	0.4063	0.4773
	P10	P11	P12	P13	P14	P15	P16	P17	P18
F_{1,pu}	0.8621	0.8272	0.7824	0.7418	0.6929	0.5627	0.5121	0.3637	0
F_{2,pu}	0.5253	0.5713	0.6148	0.6468	0.6811	0.7613	0.7891	0.8606	1

Figure 7: Pareto front for trading strategy 3



(a) Expected participation in the day-ahead energy market in different trading strategies



(b) Expected participation in the spinning reserve market in different trading strategies

Figure 8: Multi-objective bidding approach

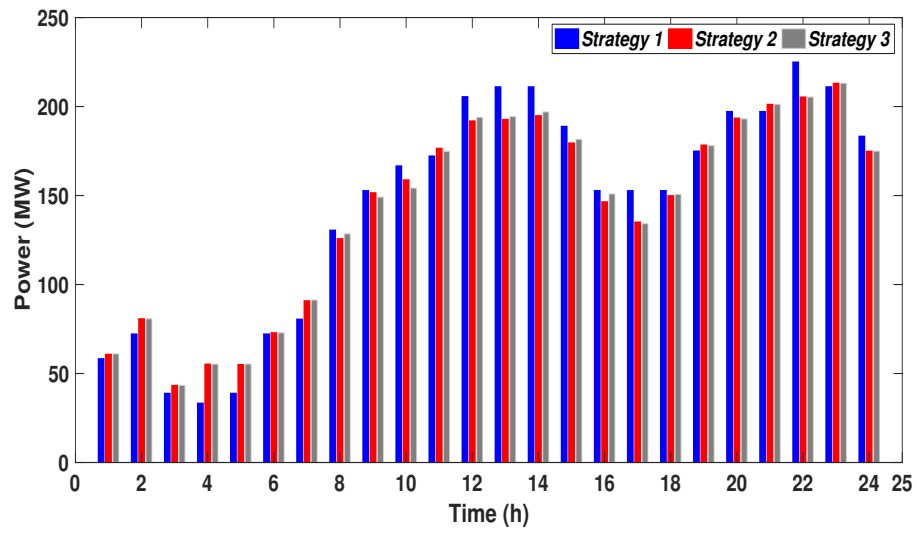
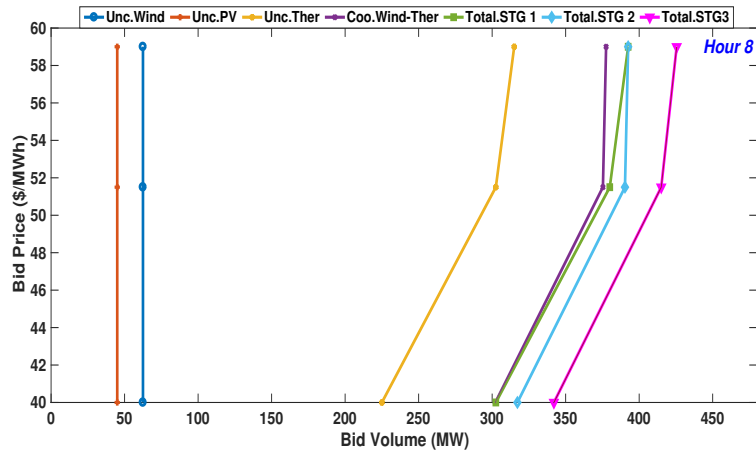
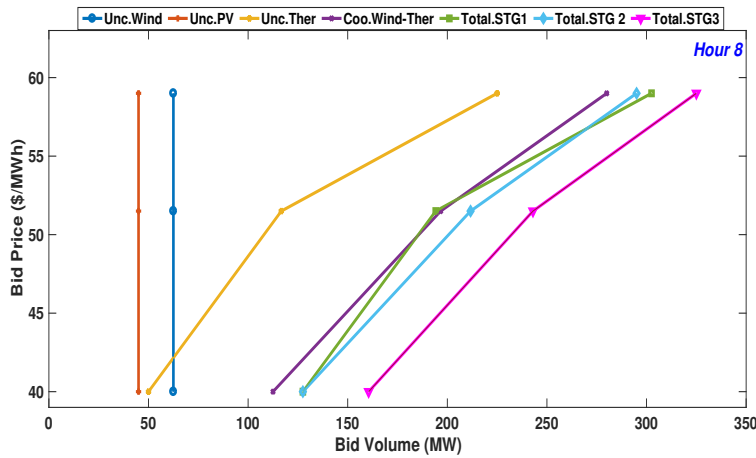


Figure 9: Comparison of expected amount of production bids of thermal units in the day-ahead energy market for all trading strategies (case study 2)

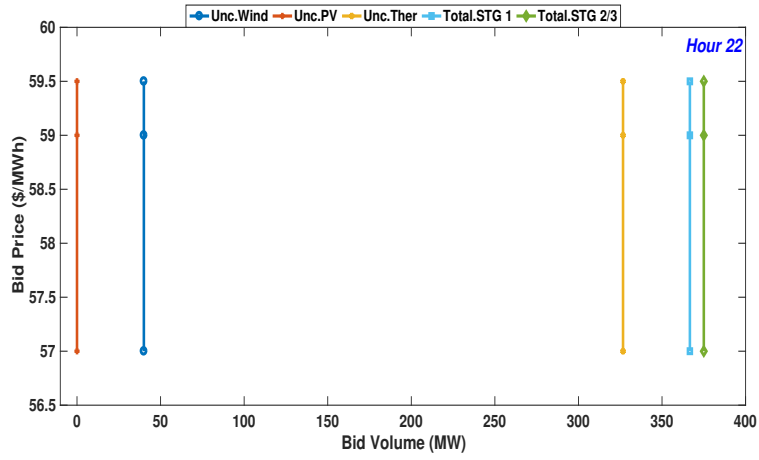


(a) Single objective bidding approach

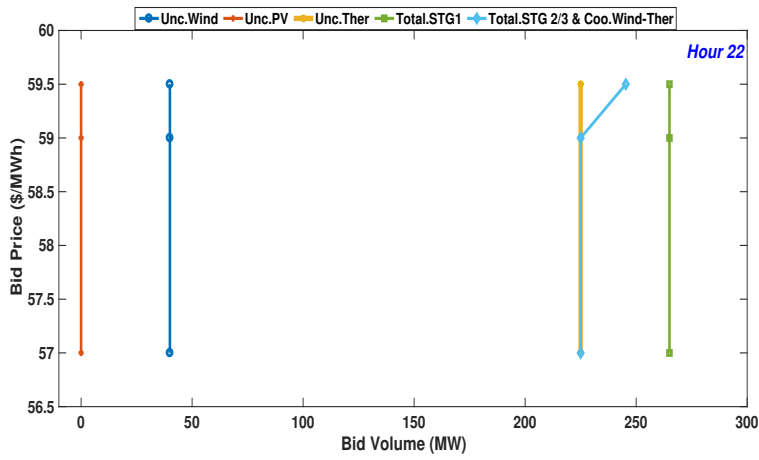


(b) Multi-objective bidding approach

Figure 10: Day-ahead energy market bidding for hour 8



(a) Single objective bidding approach



(b) Multi-objective bidding approach

Figure 11: Day-ahead energy market bidding for hour 22

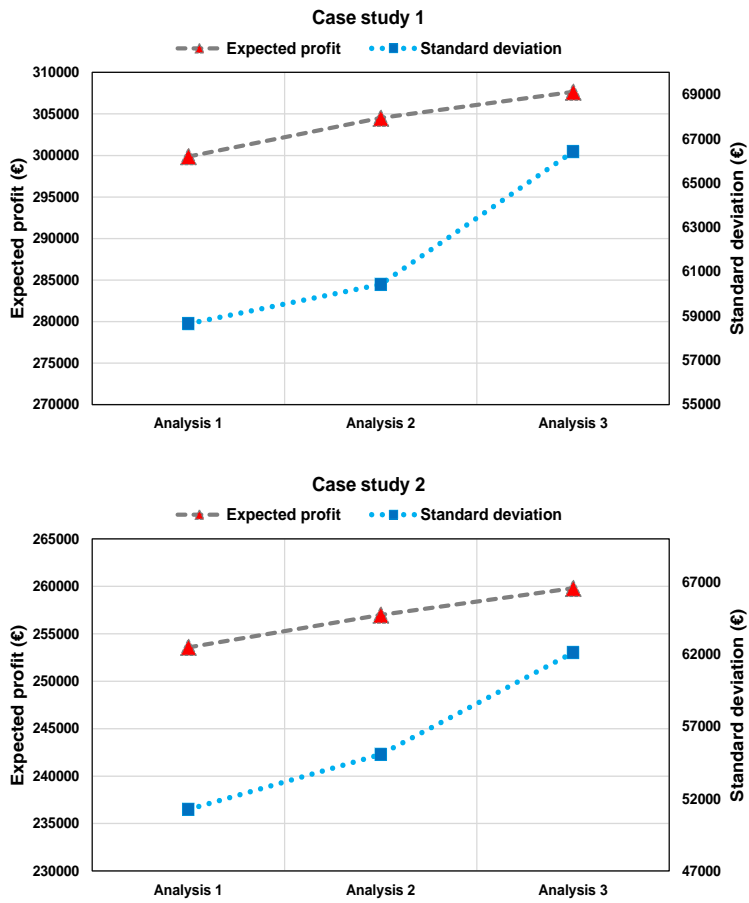


Figure 12: Comparison of expected profit and its standard deviation in various analyses

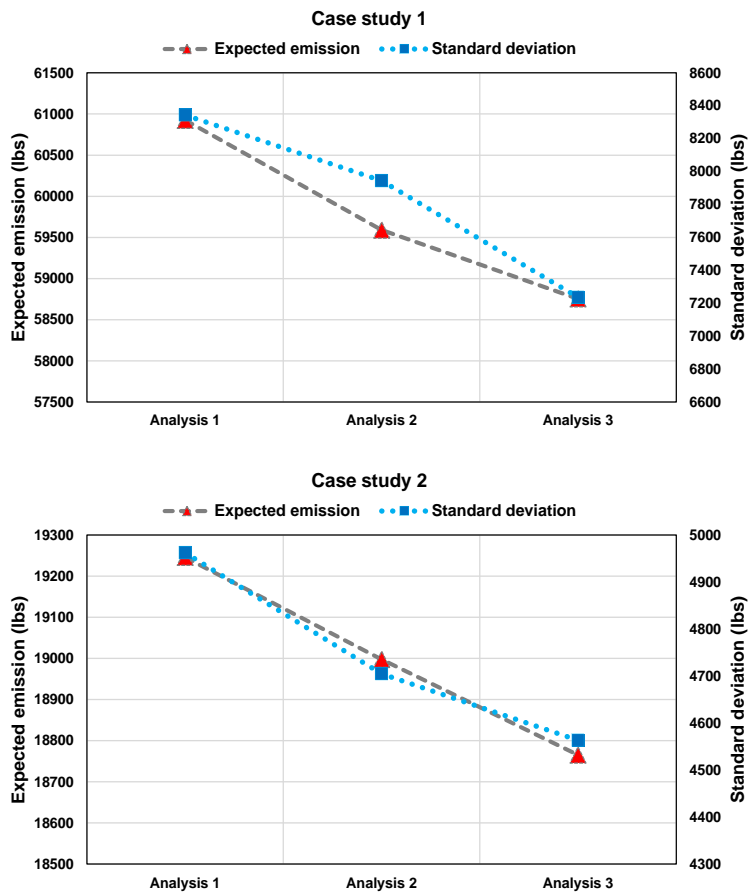


Figure 13: Comparison of expected emission and its standard deviation in various analyses

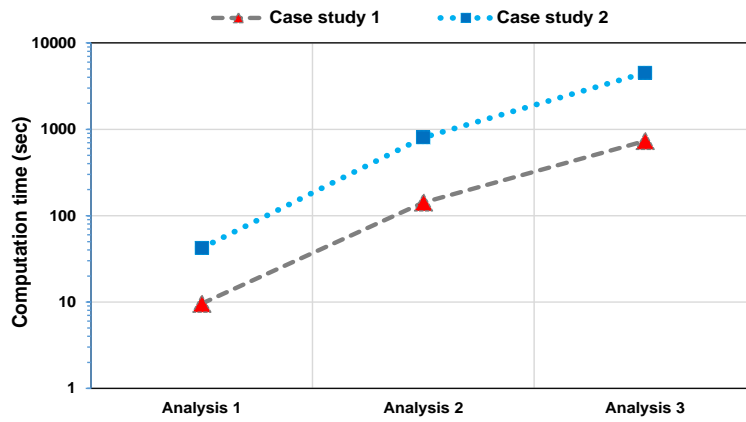
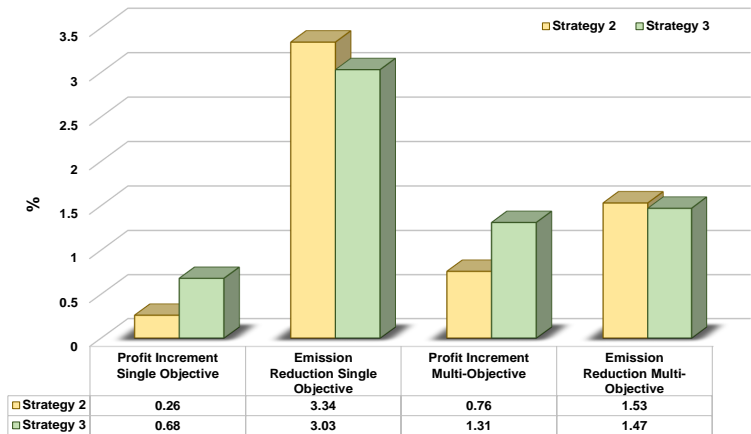
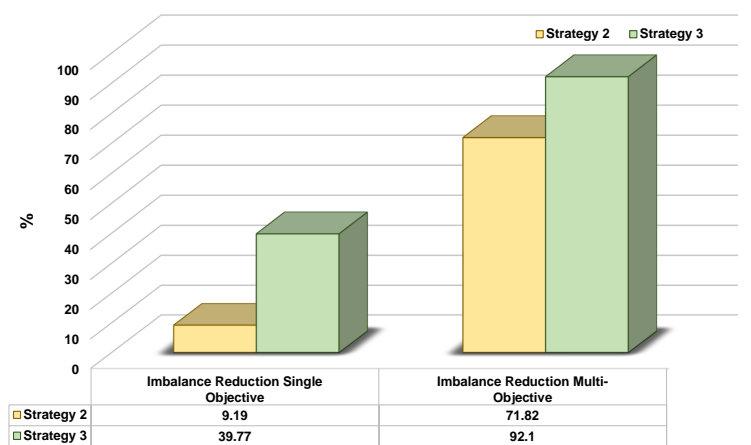


Figure 14: Comparison of computation time in various analyses

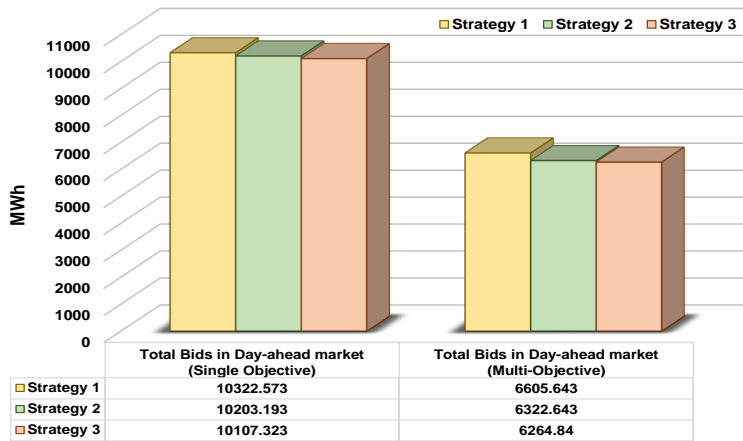


(a) Profit increment and emission reduction in both case studies

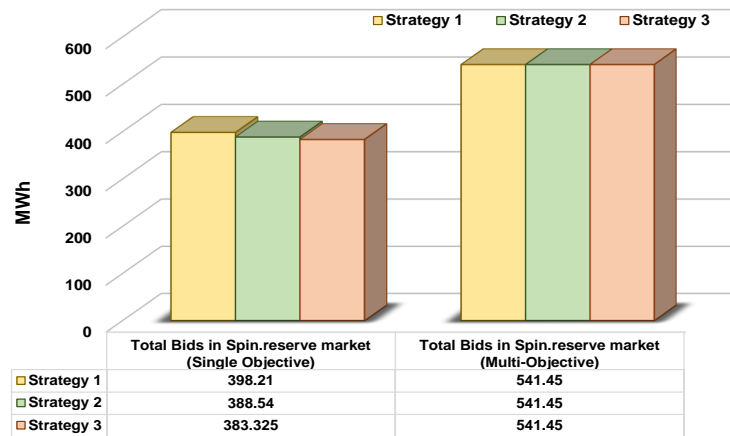


(b) Imbalance reduction in both case studies

Figure 15: Comparison of profit increment, emission and imbalance reductions in the second and third trading strategies



(a) Expected total bids in the day-ahead energy market for both case studies



(b) Expected total bids in the spinning reserve market for both case studies

Figure 16: Comparison of expected total day-ahead energy and spinning reserve bids in different trading strategies

Table 1: Taxonomy of the reviewed papers

Ref.	Combination of Various Energy Sources	Problem Type	Uncertain Parameters					Uncertainty Modeling	Objective Functions	Solution Methodology of MOP	
			EM	SPRM	BM	REP	OS				
[7]	Large consumer	BS	✓	—	—	✓	—	✓	—	CSM	—
[8]	Large consumer	BS	✓	—	—	✓	—	✓	—	CSM	—
[9]	Microgrid	SS	✓	✓	—	✓	—	SP	—	CSM	—
[10]	Industrial Plant	SS	—	—	—	—	—	—	—	CSM	—
[11]	Thermal	SS	✓	✓	—	✓	—	PP	—	PFM	—
[12]	Large consumer	SS	—	—	—	—	—	—	—	CSM+ICM	WSM
[13]	VPP	SS	✓	✓	—	✓	—	SP	—	PFM	—
[14]	Wind-PSP	SS	—	—	—	✓	—	SP	—	PFM	—
[15]	Hydro-thermal	SS	✓	✓	—	—	—	SP	—	PFM	—
[16]	Wind-thermal	BS	✓	—	—	✓	—	SP	—	PFM	—
[17]	Wind-thermal	SS	—	—	✓	—	—	—	—	PFM	—
[18]	Wind-thermal	BS	✓	—	—	✓	—	SP	—	PFM	—
[19]	Wind-thermal-PSP	BS	✓	—	✓	✓	—	SP	—	PFM	—
[20]	Microgrid	SS	—	—	✓	—	—	—	—	CSM+EMM	EPM
[21]	Hydro-thermal	SS	—	—	—	—	—	—	—	PFM+EMM	EPM
[22]	Hydro-thermal-PSP	EED	—	—	—	—	—	SP	—	CSM+EM	NBIM
This paper	Wind-thermal-PV	BS	✓	✓	✓	✓	—	SP	—	PFM+EMM	WSM+FSA

Note : EM-Energy market; SPRM-Spinning reserve market; BM-Balancing market; REP-Renewable production; OS-Other sources;

MOP-Multi-objective programming; PSP-Pumped storage Plant; VPP-Virtual Power Plant;

MG-Microgrid; PV-Photovoltaic; BS-Bidding strategy; SS-Self-Scheduling; EED-Economic emission dispatch; SP-Stochastic programming;

RO-Robust optimization; PP-Probabilistic possibilistic; PFM-Profit maximization; CSM-Cost minimization;

EMM-Emission minimization; ICM-Investment cost minimization; WSM-Weighted sum method;

WSM+FSA-Weighted sum method+Fuzzy satisfying approach; EPM-Epsilon Constraint method; NBIM-Normal boundary intersection method

Table 2: Thermal units information

Thermal Units	Cost coefficients of generator			P_{min} (MW)	P_{max} (MW)
	$a_g(\text{€}/\text{MW}^2\text{h})$	$b_g(\text{€}/\text{MWh})$	$c_g(\text{€}/\text{h})$		
G1	0.0144	31.400	40.260	0	50
G2	0.0339	43.022	85.509	5	45
G3	0.0339	42.022	82.342	5	45
G4	0.0330	28.090	42.760	25	100
G5	0.0248	26.504	49.140	25	100

Table 3: Technical specification of thermal units

Thermal units	RDR(g) (MW/hr)	RUR(g) (MW/hr)	STDRL(g) (MW/hr)	STURL(g) (MW/hr)	STUC(g) (€)
G1	50	50	30	20	0
G2	15	15	20	15	88
G3	15	15	20	15	88
G4	50	50	60	50	110
G5	50	50	60	50	110

Table 4: Emission coefficients of thermal units

Thermal units	Coefficient of SO ₂ emission function			Coefficient of NO _x emission function		
	α_g (lbs/MW ²)	β_g (lbs/MW)	γ_g (lbs)	α_g (lbs/MW ²)	β_g (lbs/MW)	γ_g (lbs)
G1	0.0249	3.554	1.866	0.0087	1.345	3.716
G2	0.0167	12.259	4.470	0.0073	5.945	5.298
G3	0.0167	11.259	4.470	0.0073	5.945	5.298
G4	0.0157	2.762	2.262	0.0095	0.820	4.653
G5	0.0157	2.762	2.262	0.0095	0.820	4.653

Table 5: Information on wind turbines and PV site

Parameter	Value	unit	Parameter	Value	unit
v_{ci}	3	m/s	η^{PV}	15	%
v_r	15	m/s	S^{PV}	10^6	m^2
v_{co}	25	m/s	P_{rated}^{PV}	150	MW
P_{rated}^W	250	MW	-	-	-

Table 6: Results of single objective bidding strategy in various trading strategies

Trading strategy	Expected profit (€)	Expected emission (lbs)	Imbalance cost (€)
Wind uncoordinated	94868.919	—	16995.914
PV uncoordinated	53734.278	—	8373.622
Thermal uncoordinated	153831.439	61455.848	—
Sum uncoordinated wind and thermal	248700.358	61455.848	16955.914
Coordinated wind and thermal	249486.914	59401.666	14663.655
Sum uncoordinated wind, PV and thermal (Strategy 1)	302434.636	61455.848	25369.536
Sum uncoordinated PV and coordinated wind-thermal (Strategy 2)	303221.192	59401.666	23037.277
Coordinated wind, PV and Thermal (Strategy 3)	304509.778	59590.001	15278.357

Table 7: Results of Multi-objective bidding strategy in various trading strategies

Trading strategy	Expected profit (€)	Expected emission (lbs)	Imbalance cost (€)
Wind uncoordinated	94868.919	—	16995.914
PV uncoordinated	53734.278	—	8373.622
Thermal uncoordinated	105035.729	19266.137	—
Sum uncoordinated wind and thermal	199904.648	19266.137	16955.914
Coordinated wind and thermal	201832.005	18971.043	-1225.947
Sum uncoordinated wind, PV and thermal (Strategy 1)	253638.926	19266.137	25369.536
Sum uncoordinated PV and coordinated wind-thermal (Strategy 2)	255566.283	18971.043	7147.675
Coordinated wind, PV and Thermal (Strategy 3)	256978.704	18997.492	2003.541

Table 8: Results of emission quota arbitraging for Pareto optimal solutions of strategy 3

Total Emission (lbs)	Profit without emission trade (€)	Emission trades (lbs)	Net profits (€)			
			$\lambda^{EM}=0.1$ (€/lbs)	$\lambda^{EM}=0.3$ (€/lbs)	$\lambda^{EM}=0.5$ (€/lbs)	$\lambda^{EM}=1$ (€/lbs)
59590.001	304509.778	-39590.001	300550.778	292632.778	284714.778	264919.777
56009.132	304058.522	-36009.132	300457.608	293255.782	286053.956	268049.390
52814.999	303192.137	-32814.990	299910.637	293347.637	286784.638	270377.147
49652.657	301854.928	-29652.657	298889.662	292959.131	287028.600	272202.271
46939.804	300526.825	-26939.804	297832.845	292444.884	287056.923	273587.021
42807.933	297896.198	-22807.933	295615.405	291053.818	286492.232	275088.265
38700.833	294798.142	-18700.833	292928.059	289187.892	285447.726	276097.309
35374.524	291777.572	-15374.524	290240.120	287165.215	284090.310	276403.048
31145.031	287088.975	-11145.031	285974.472	283745.466	281516.460	275943.944
28286.335	283176.988	-8286.335	282348.355	280691.088	279033.821	274890.653
25544.215	277774.429	-5544.215	277220.008	276111.165	275002.322	272230.214
22952.056	270843.444	-2952.056	270548.238	269957.827	269367.416	267891.388
21044.007	264561.387	-1044.007	264456.986	264248.185	264039.384	263517.380
18997.492	256978.704	1002.508	257078.955	257279.456	257479.958	257981.212
14221.486	236828.236	5778.514	237406.087	238561.790	239717.493	242757.218
12567.015	229008.445	7432.985	229751.744	231238.341	232724.938	236441.430
8303.996	206041.240	11696.004	207210.840	209550.041	211889.242	217737.244
0	149735.991	20000.000	151735.991	155735.991	159735.991	169735.991