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Optimal modeling of power market tariff and wind speed based on optimization algorithm

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Abstract
Employing of wind turbine (WT) similar to most green power sources is grew recently because of its eco-friendly property. This work suggested a novel organization for integrated system with energy storage system (ESS) and WTs, in which, charging of battery can be done via wind turbine or supplied electricity from upper grid. Moreover, we can sell the saved energy of battery to power market in peak and high tariff times whereas regarding to electricity market tariffs, outlet power of wind turbine can straightly be inserted to upstream grid also it can be utilized for ESS charging. Also, this paper suggested a case-based stochastic frame for modeling of power market tariff and wind speed as uncertain parameters. Production of power yield price scenarios is made by standard distribution function whereas wind speed ones are produced by Weibull function. For achieving to optimum offering and bidding trends at all times, a mixed-integer linear programming (MILP) approach is employed for bidding and offering power respectively in order to purchase and sell energy from and to upper grid. Eventually, achieved results are provided and analyzed.

Keywords: Wind turbine; Battery storage system; Renewable energy; stochastic framework; Optimal bidding and offering curves;

Nomenclature

Indices	
s	Index of scenario
t	Index of time
Parameters	
P_r	The rated power of the wind turbine [MW]
$P_{\min}^{ch}$	Minimum amount of charging power of the BSS [MW]
$P_{\max}^{ch}$	Maximum amount of charging power of the BSS [MW]
$P_{\min}^{disc}$	Minimum amount of discharging power of the BSS [MW]
$P_{\max}^{disc}$	Maximum amount of discharging power of the BSS [MW]
$P_{\max}^{proc}$	Maximum amount of procured power from the grid [MW]
$P_{\max}^{sell}$	Maximum amount of sold power to the grid [MW]
$SOC_{\max}^{B} / SOC_{\min}^{B}$	Maximum and minimum amount of the battery's state of charge [MWh]
V_r	The rated speed of the wind turbine [m/s]
$V_{cut-out}$	The cut-out speed of the wind turbine k [m/s]
V_{cut-in}	The cut-in speed of the wind turbine [m/s]
η_{disc}	Discharging efficiency of the BSS
η_{ch}	Charging efficiency of the BSS
ρ_s	Probability of the scenario s
$\lambda_{t,s}$	Power price at each time t and scenario s
$V_{t,s}$	The predicated wind speed at time t and scenario s [m/s]

Variables	
$P_{t,s}^{sell}$	Sold power to the market at time t and scenario s [MW]
$P_{t,s}^{pro}$	Procured power from the market at time t and scenario s [MW]
$P_{t,s}^{WT}$	Total produced power by the wind turbine at time t and scenario s[MW]
$P_{t,s}^{WT-G}$	Injected power from wind turbine to the grid at time t and scenario s [MW]
$P_{t,s}^{WT-B}$	Injected power from wind turbine to the battery at time t and scenario s [MW]
$P_{t,s}^{B-G}$	Injected power from the battery to the grid at time t and scenario s [MW]
$P_{t,s}^{purchase}$	Purchased power from the upstream grid at time t and scenario s [MW]
$P_{t,s}^{G-B}$	Procured power by the battery from the upstream grid at time t and scenario s [MW]
$SOC_{t,s}^{B}$	State of charge of the battery at time t and scenario s [MWh]
$U_{t,s}^{ch}$	Binary variable of the charging state of the BSS at time t and scenario s
$U_{t,s}^{disc}$	Binary variable of the discharging state of the BSS at time t and scenario s

1. Introduction

With growth of power usage and reduction of conventional fuels [1] that are utilized for electricity production, employing of alternative power resources became a necessary issue [2]. Regarding environmental problems including pollutions and climate alteration, enforces more and more requirement for this alternative [3]. Respect to wide accessibility [4] as well as developed technology [5], wind power is taken into account as an important green power sources [6]. Since exist various uncertainty in programing and working of wind energy plants [8], wind energy isn't dispatchable power dissimilar to conventional energy sources [7]. In order to deal with sporadic behavior as well as uncertainties of this energy, [9-10] offered integrated system with including WTs and power storage units. In restructured electricity market that gives a competitive situation [11], there is great power tariff oscillations [12]. Thus, obtaining optimum offering/bidding methods has high importance [13]. Aiming this regard, various approaches are studied in many papers. For example, [14] suggested a bi-level stochastic method for reaching to optimum bidding method in case of wind energy in short-term power market, and [15] represented an optimum day-ahead bidding method for wind energy subject to both wind energy and market tariff uncertainties. Authors in [16] have suggested a new bidding method around large scale storage devices in order to augment total revenue. Also, [17] presented 2 phase stochastic model for reaching to optimum bidding method of green power based Microgrids (MGs). Equal work is provided by [18] with synthetic robust-stochastic method. Moreover, [19] studied equal problem through gam-theory method for electric vehicle (EV) collectors in day-ahead power and auxiliary service markets with variant wind power. In [20], a robust bidding model is proposed for arbitrage, with regarding some uncertain parameters such as power price prediction and wind energy prediction. Furthermore, [21] proposed information gap decision theory (IGDT) to get optimum bidding methods in case of day-ahead market. An inclusive stochastic decision making method is presented in [22] with regarding uncertainties for wind generators, and by considering partaking of demand response (DR) collectors. Also, [23] suggested a novel method to specify day-ahead market bidding methods in presence of DRP for obtain optimum offering method in case of large-scale synthetic power electrical power company. As well, [24] discussed around hourly offering/bidding trends for buying/selling power for a price-maker commercial power storage facility by means of maximum-minimum MILP method. Authors in [25], suggested a bidding and offering approach in case of a synthetic energy station generator with risk-limited 2 stage stochastic, bi-level formulization for modeling of problem. In addition, a new strategy is proposed in [26] to make offers for a virtual energy system sharing which contains conventional energy system, a wind generator, an energy storage device and flexible loads. Bidding approach is formulized by a robust-stochastic strategy, with considering day-ahead market tariffs as uncertain parameter in [27]. For profit maximization of integrated system including WT and ESS, MILP approach is employed to get optimum offering/bidding trends with considering uncertainty of wind speed and prices of power market.

1.2. Novelty and contribution

Primarily, this work represented a novel organization for integrated WT with ESS where ESS is able to get energy from both wind turbines and upper grid and it can give energy to power market. Besides, optimum bidding/offering methods are proposed in this paper in presence of uncertainty in energy tariff. It's remarkable, a collection of scenarios are considered for modeling of power price uncertainties.

1.3. Paper organization

Remainder of article is constructed in following scheme: part two of paper suggested formulation of considered model. Part 3 represented needed data in addition to results analysis. Eventually, conclusion of whole paper is given in part 4.

2. Problem formulation

This part of paper presented a novel form of integrated wind turbine and ESS. As can be seen from Fig. 1, respect to prices of yield, produced electricity can be perfused into main grid or it can be save in storage system. Besides, charging of battery can be done from wind turbine or purchased energy from main grid in off-peak and low tariff times. We can sell this saved energy in high consumption times. Below sub-section formulized offered structure.

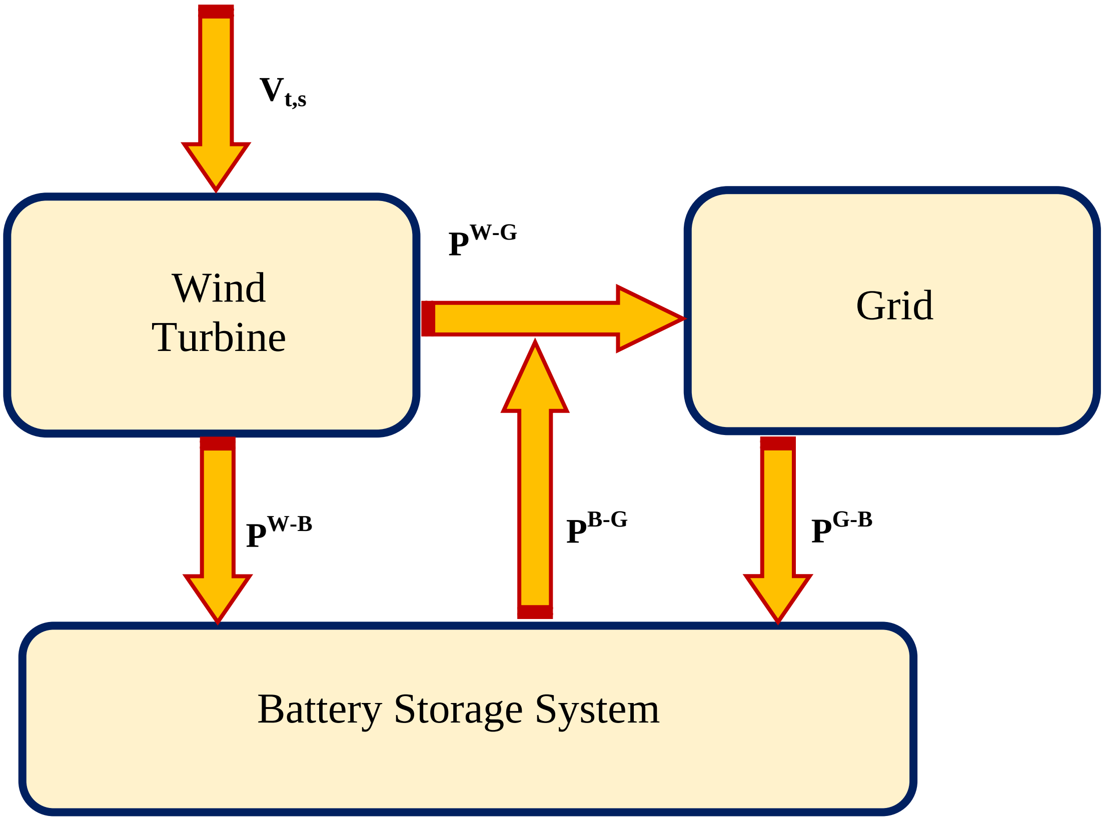

Fig. 1. Configuration of proposed model

2.1. Objective function

For achieving to max revenue in suggested scheme of prior part, cost function is provided as:

$$\max\ profit = \sum_{s=1}^{N_s} \rho_s \sum_{t=1}^{N_t} \lambda_{t,s} [P_{t,s}^{sell} - P_{t,s}^{pro}] \tag{1}$$

2.2. Modeling of wind turbine

Modeling of this unit is presented in equations (2)-(5). It's worthy to note, operational expense of wind energy is assumed to be too low and mostly ignored in related works [28]. Entire produced energy of a WT that is reliant on wind speed can be formulized by [29]:

$$P_{t,s}^{WT}=\begin{cases}0 & ,V_{t,s}\le V_{cut-in}\\ P_r[\frac{V_{t,s}-V_{cut-in}}{V_r-V_{cut-in}}]^3 & ,V_{cut-in}\le V_{t,s}\le V_{rated}\\ P_r & ,V_{rated}\le V_{t,s}\le V_{cut-out}\\ 0 & ,V_{t,s}>V_{cut-out}\end{cases} \tag{2}$$

Produced energy of wind turbine can be perfused to main grid or saved in battery, which is represented in following equation:

$$P_{t,s}^{WT}=P_{t,s}^{WT-G}+P_{t,s}^{WT-B} \tag{3}$$

Moreover, below formula expresses, the sold energy to upstream grid is equal to total generated energy of wind turbine and procured energy by storage system.

$$P_{t,s}^{sell}=P_{t,s}^{WT-G}+P_{t,s}^{B-G} \tag{4}$$

The provided electrical energy from main grid, in suggested configuration, is straightly saved in storage battery that is formulized as follows:

$$P_{t,s}^{purchase}=P_{t,s}^{G-B} \tag{5}$$

2.3. Modeling of storage battery

Equations (6)-(10) provided mathematical model of ESS. As mentioned, it's considered, charging of this unit can be through wind turbine or procured energy from main grid in off-peak times and it can give purchased energy to main grid in peak time intervals. Equation (6) presented state of charge (SOC) for battery. Also, state of charge of battery is bounded by (7). Moreover, charged and discharged energy of battery are respectively bounded with equations (8) and (9). Finally, equation (10) ensures that charging and discharging of this unit are not in a same time.

$$SOC_{t,s}^{B}=SOC_{t-1,s}^{B}+\eta_{ch}(P_{t,s}^{G-B}+P_{t,s}^{W-B})-\frac{P_{t,s}^{B-G}}{\eta_{disc}} \tag{6}$$

$$SOC_{\min}^{B}\le SOC_{t,s}^{B}\le SOC_{\max}^{B} \tag{7}$$

$$P_{\min}^{ch}.U_{t,s}^{ch}\le P_{t,s}^{WT-B}+P_{t,s}^{G-B}\le P_{\max}^{ch}.U_{t,s}^{ch} \tag{8}$$

$$P_{\min}^{disc}.U_{t,s}^{disc}\le P_{t,s}^{B-G}\le P_{\max}^{disc}.U_{t,s}^{disc} \tag{9}$$

$$U_{t,s}^{ch}+U_{t,s}^{disc}\le 1 \tag{10}$$

For achieving to optimum offering/bidding profiles, MILP approach is used. Also, equations (11) and (12) are respectively implemented in order to guarantee, offering and bidding trends are incessantly increasing and reducing that is usual demand in power market limitations. Furthermore, equations (13) and (14) are respectively presented to limit the sold and purchased electricity to and from upstream grid. Relation (15) expresses that selling and procuring of energy can't be coincide.

$$P_{t,s}^{sell}\ge P_{t,s'}^{sell}\mid\lambda_{t,s}\ge\lambda_{t,s'} \tag{11}$$

$$P_{t,s}^{\mathrm{Pro}}\ge P_{t,s'}^{sell}\mid\lambda_{t,s}\ge\lambda_{t,s'} \tag{12}$$

$$P_{t,s}^{sell}\le P_{\max}^{sell}.U_{t,s}^{sell} \tag{13}$$

$$P_{t,s}^{pro}\le P_{\max}^{proc}.U_{t,s}^{pro} \tag{14}$$

$$U_{t,s}^{pro}+U_{t,s}^{sell}\le 1 \tag{15}$$

3. Proposed Approach

Particle swarm optimization (PSO) is an evolutionary population base optimization algorithm that motivated by social behavior of bird flocking or fish schooling and introduced by Dr. Eberhart and Dr. Kennedy for the first time in 1995 [30-33]. In general, position vector *x* of a particle *i* at the $(k+1)^{th}$ iteration step can be presented as:

$$x_{k+1}^{i} = x_{k}^{i} + v_{k+1}^{i}\Delta t \tag{16}$$

In this equation, v_{k+1}^{i} defines the velocity vector update in i[th] particle for k[th] step, the time step is presented by Δt, and the velocity vector for each particle can be defines as:

$$v_{k+1}^{i} = wv_{k}^{i} + c_1 r_1 \frac{(p_{k}^{i} - x_{k}^{i})}{\Delta t} + c2r2\frac{(p_{k}^{g} - x_{k}^{i})}{\Delta t} \tag{17}$$

In this equation, the $\mathbf{v}^{i}_{k}$ is the velocity vector for the k^{th} iteration step, the random vectors with magnitudes presented by **r**1 and **r**2 which is generated in the range of 0 and 1. The best position is defined by $\mathbf{p}^{i}_{k}$ and global best position is defined by $\mathbf{p}^{g}_{k}$ up to the k^{th} iteration step. In this algorithm, *c*1 and *c*2 are based on optimization problem which named 'trust' parameters. The *w* introduce the inertia weight, which affects to the control in exploration ability in PSO algorithm.

3.1. Improved version of PSO

In this sub-section, the improvements of proposed algorithm is presented. For the first step, the chaotic operator is considered to improve the abilities of PSO algorithm which used previously in different works [34-37]. This operator is based on ergodicity, randomness, and regularity characteristics. This model is sensitive for initial condition as well as the parameters value. The chaotic operator is very strong to jump out a local optimal solution in comparison with random search model. Accordingly, it can solve the premature convergence which can happen in all stochastic search algorithms [38]. For this purpose, in this paper we used the Logistic mapping function to generate the chaotic variables as formulated in the following:

$$\begin{cases} y_{k+1} = 4y(1-y_k),\, y_k \in (0,1) \\ y_0 = rand(.),\, y_0 \notin \{0.25, 0.5, 0.75\} \end{cases} \tag{18}$$

where, the chaotic variables are presented by y_k in the k^{th} iteration and the initial values are defined by y_0.

For the second step of improvements, due to discrete space of proposed optimization problem, the binary operator is added to the classic PSO to tackle the deficiency problems. In this model, the particles velocity will change by probability of change of particles location, not the rate of change of particle location. In this model, the velocity of particles will define the locations by 0 and 1 based on confident probability. Accordingly, the velocity equation for update in next iterations can be defines as follows:

$$\begin{gathered} v_{k+1}^{i,d} = v_{k}^{i,d} + c_1 r_1 \frac{(p_{k}^{i,d} - x_{k}^{i,d})}{\Delta t} + c_2 r_2 \frac{(p_{k}^{g,d} - x_{k}^{i,d})}{\Delta t} \\ x_{k}^{i,d} = \begin{cases} 1 & \mathrm{r}_3 < \mathrm{sigmond}(\mathrm{v}_{k}^{i,d}) \\ 0 & \mathrm{other} \end{cases} \end{gathered} \tag{19}$$

In this relationship, the best position of the i^{th} particle is defined by $p_{k}^{i,d}$; the best position of entire particle swarm is shown by $p_{k}^{g,d}$, and the velocity and location of i^{th} particle in k^{th} iteration is presented with $v_{k}^{i,d}$ and $x_{k}^{i,d}$, respectively. The learning factor of algorithm are defined by c_1 and c_2 and the free parameters which generated randomly between 0 and 1, are resented with r_1, r_2 and r_3. The sigmoid function of algorithm is presented in the following to transfer the velocity of particles to probability domains between [0,1]:

$$sigmoid(v_{k}^{i,d}) = \begin{cases} \dfrac{2}{1+e^{-v_{k}^{i,d}}} - 1 & v_{k}^{i,d} \geq 0 \\ 1 - \dfrac{2}{1+e^{-v_{k}^{i,d}}} & v_{k}^{i,d} < 0 \end{cases} \tag{20}$$

For the next improvement, we added a sensitivity for initial values and ergodicity of chaos in proposed algorithm. This improvement helps the algorithm in global search diversity. In this model, once a particle is near to the fixed particles, it can search just a limit area. So, we will evaluate the distance of arbitrary particles and the best one to choose the best searching process. This evaluation can be modeled as:

$$D_i = (X_i - X_{best})^2 \tag{21}$$

where, the proposed distance is presented by D_i; the location of i^{th} particle as well as the best one can be presented by Xi and X_{best}, respectively. In this model, the particles which are overlapped will divided by chaos search algorithm. In this model, the best particles will remain and other ones mapped to the chaotic space through (17). So, the new generated particles can replaced with previous particles.
For the last improvement, an additional operator is added to the proposed algorithm to tackle the fast convergence based on false Pareto front. In this work, a new operator of mutation is utilized to improve the algorithm exploration abilities. This operator is based on nonlinear function which enhanced the control of each particles probability and range of mutation. The proposed function is updated in each iteration based on the following formula:

$$P_m = 0.5 * e^{(-10*t/T)} + 0.01 \quad (22)$$

where, the maximum iteration is shown by T. By this equation, the exponential rate will be decrease through iteration growth. So, if: $P > rand$ (generated between 0 and 1), then the mutation operator will be run for the first pick randomly K elements from this particle, so we can initialize again in search space. The
K elements can be calculated as:

$$K = \max\{1, \lceil D * P_m \rceil\} \quad (23)$$

This operator can improve the exploration behavior and the probability range of proposed operator will decrease by improving the iteration. The pseudo-code of this operator is presented in Fig. 2.

```
Input: the swarms
Output: the swarm after mutation
For i=1 to Ns
    If Pm> r1    %r1 generated between 0 and 1 by chaotic model%
        Evaluate the K by (22)
        S={I1,I2,…,Ik}    % randomly generate the K between [1,D] and save in set of S%
        For k=1:K
            Pi,Ik = initialize (Pi,Ik)   % reinitialize the Ik-th element of the particle %
        End For
    End If
End For
```

Figure 2. The pseudo-code of the mutation operator

4. Numerical simulation

This part of paper applied the suggested method on a test system and achieved results are shown in this section.

4.1. Data

Uncertainties of electricity market tariffs are modeled through a collection of 10 cases that are get with standard distribution function. Table 1 listed the data of these ten cases. Also, modeling of wind speed uncertainty is made via a collection of scenarios that are get by Weibull distribution function. Information of wind speed scenarios are also provided in Table 2. In addition, Tables 3 and 4 are represented respectively the needed data for wind turbine and battery storage device. Also, the graphical representation of these tables are presented in Fig. 3 and 4, respectively.

Table 1: Information of market price scenarios

	Scenarios									
Time	1	2	3	4	5	6	7	8	9	10
1	31.15	32.41	25.04	32.55	29.47	24.57	26.7	28.81	33.63	33.89
2	22.75	30.47	30.01	25.27	27.65	22.48	24.16	28.41	26.89	29.4
3	23.42	18.04	24.85	25.98	23.48	24.05	23.26	21.03	22.65	19.41
4	21.65	16.29	19.07	16.67	17.51	22.41	20.81	18.64	23.31	15.69
5	23.07	22.71	25.27	25.52	21.24	23.4	22.35	23.63	24.07	24.41
6	24.79	27.77	27.58	23.71	23.16	26.45	30.58	24.54	26.29	23.56
7	30.5	26.48	28.5	30.03	32.15	33.69	28.05	24.43	24.57	25.74
8	27.05	22.74	26.78	22.65	28.28	23.46	21.47	21.95	24.46	23.52
9	19.62	22.57	20.93	20.73	23.51	19.22	21.22	21.2	19.02	20.07

10	31.87	31.19	37.76	40.46	43.33	33.07	38.14	37.16	28.64	35.82
11	34.19	41.42	36.16	38.42	34.24	39.16	35.59	39.72	40.1	40.8
12	42.57	36.92	39.79	49.26	38.51	47.35	43.56	55.12	36.75	42.48
13	41.91	57	35.12	51.91	52.66	53.73	41.25	46.86	44.91	52.34
14	37.44	43.51	34.5	35.6	33.91	33.74	42.62	38.93	38.63	33.9
15	33.49	31.12	28.91	30.24	29.33	25.55	27.87	26.42	27.25	27.87
16	17.71	14.83	20.72	21.32	18.08	18.08	17.29	20.69	17.46	15.69
17	28.69	25.75	24.57	25.85	22.88	23.4	30.93	31.24	26.99	22.1
18	43.06	44.72	50.95	36.16	38.29	41.93	48.37	49.43	48.28	45.87
19	54.18	50.59	57.15	48.68	56.21	48.57	51.68	55.22	57.71	45.77
20	77.68	72.76	67.3	66.42	66.61	64.04	67.68	67.65	73.71	73.14
21	57.57	53.7	60.5	55.35	52.69	63.69	61.46	55.6	56.66	56.13
22	46.23	47.75	50.08	46.05	55.14	45.41	45.97	44.93	46	49.04
23	38.39	46.46	39.72	36.11	45.38	48.48	39.23	34.75	37.15	38.91
24	34.3	31.23	34.37	34.83	30.2	28.72	31.01	31.23	32.21	32.95

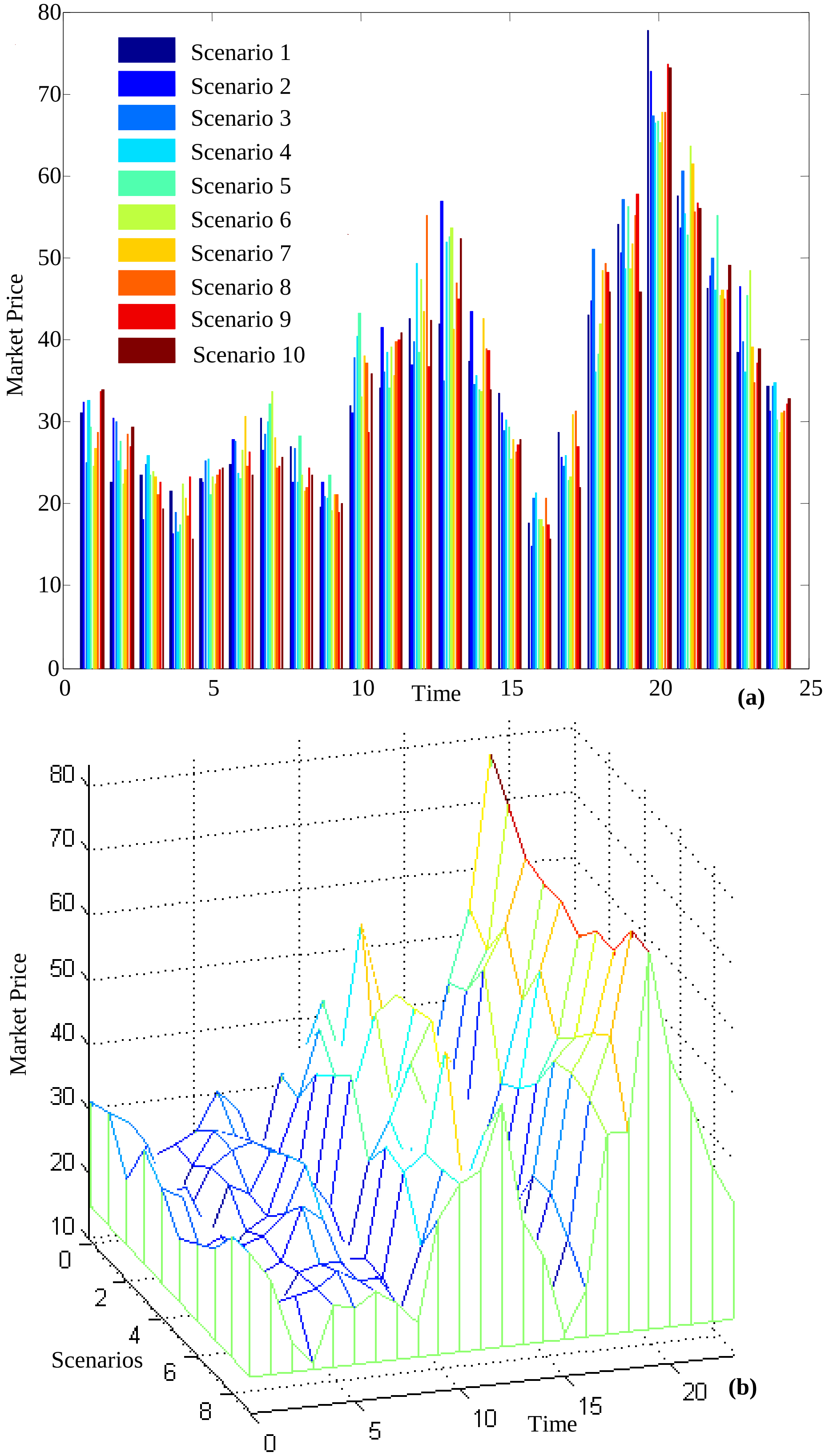

Fig. 3. Graphical representation of Table 1: (a) bar chart, (b) mesh plot

Table 2: Information of market price scenarios

Time	Scenarios

	1	2	3	4	5	6	7	8	9	10
1	3.64	3.83	2.67	3.86	3.37	2.59	2.93	3.27	4.03	4.07
2	2.87	4.2	4.11	3.25	3.68	2.74	2.49	3.26	2.99	3.44
3	7.82	5.75	8.3	8.73	7.79	8	7.28	6.44	7.05	5.84
4	11.32	8.31	9.85	8.52	8.99	11.7	10.51	9.31	11.9	7.67
5	11.46	11.26	12.62	12.75	10.49	11.63	10.71	11.39	11.62	11.8
6	7.4	8.4	8.34	7.03	6.84	7.96	8.85	6.8	7.39	6.47
7	10.21	8.74	9.48	10.03	10.81	11.38	8.82	7.49	7.55	7.97
8	9.46	7.8	9.35	7.76	9.93	8.07	6.84	7.02	7.99	7.62
9	8.08	9.42	8.68	8.58	9.85	7.89	8.39	8.38	7.39	7.86
10	11.48	11.22	13.78	14.83	15.95	11.95	13.92	13.54	10.22	13.02
11	11.11	13.71	11.82	12.63	11.13	12.9	11.62	13.1	13.24	13.49
12	14.67	12.57	13.64	17.16	13.16	16.45	15.04	19.34	12.51	14.64
13	13.89	19.32	11.45	17.49	17.76	18.15	13.65	15.67	14.97	17.65
14	18.18	21.27	16.68	17.24	16.38	16.29	20.82	18.94	18.79	16.37
15	25.2	23.39	21.69	22.71	22.02	19.12	20.9	19.79	20.42	20.9
16	23.78	20.01	27.73	28.51	24.27	24.26	23.23	27.69	23.46	21.13
17	28.05	25.16	24.01	25.26	22.36	22.87	30.24	30.54	26.38	21.59
18	15.92	16.57	19	13.23	14.06	15.48	18	18.37	17.92	16.98
19	13.71	12.73	14.52	12.21	14.26	12.18	13.03	13.94	14.62	11.36
20	14.02	13.05	11.99	11.81	11.85	11.35	12.06	12	13.18	13.07
21	8.42	7.76	8.91	7.56	7.11	8.96	8.59	7.6	7.78	7.69
22	3.97	4.15	4.42	3.44	4.49	3.36	3.43	3.31	3.43	3.78
23	2.64	3.49	2.78	1.89	2.86	3.18	2.21	1.74	1.99	2.18
24	2.15	1.83	2.15	1.68	1.2	1.05	1.29	1.31	1.41	1.49

Table 3: Coefficients of the WT

V_{cut-in}	V_{rated}	$V_{cut-out}$	P_{rated}
5	14	25	2.05

Table 4: Coefficients of the BSS

$SOC^{B}_{\min}$	$SOC^{B}_{\max}$	$P^{ch}_{\min}$	$P^{ch}_{\max}$	$P^{disc}_{\min}$	$P^{disc}_{\min}$
2	10	1	5	1	5

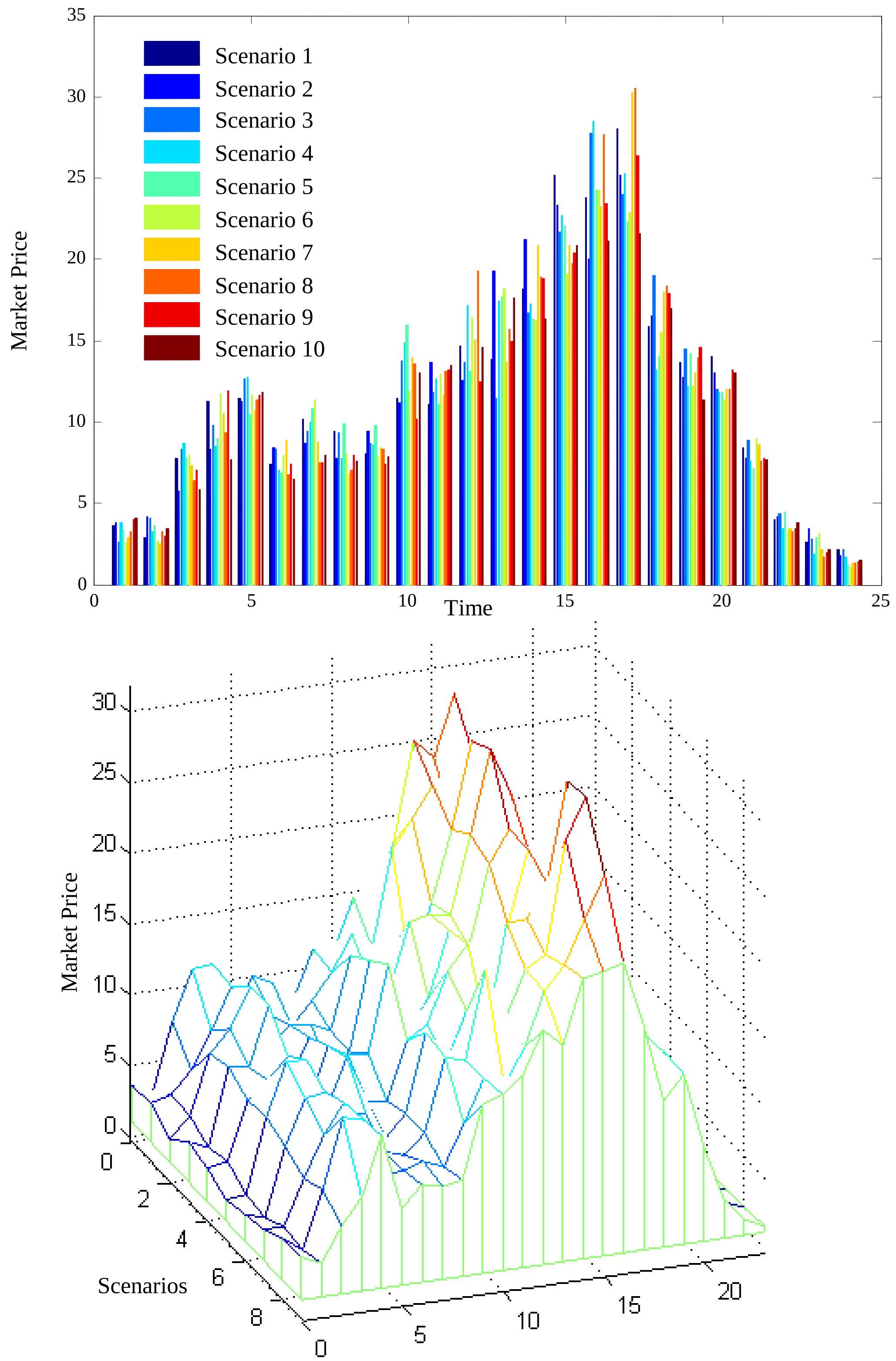

Fig. 4. Graphical representation of Table 2: (a) bar chart, (b) mesh plot

4.2. Results

For reaching to optimum offering/bidding trends represented problem by (1)-(15), solving of this problem is made by means of CPLEX solver [39] with GAMS software [40]. As discussed, for modeling of market tariff uncertainty, various cased are regarded. The obtained results depict, applying of suggested method leaded to $1,23 for entire revenue. Fig. 5 illustrated charging/discharging battery at all times in case of 3 various methods. It's remarkable, positive and minor number are respectively signify to charged and discharged electricity. As shown in this figure, clearly, the discharged electrical energy of case six is a little more compared to other 2 cases. Besides, in 9-th case, battery storage system is charged higher than remain cases.

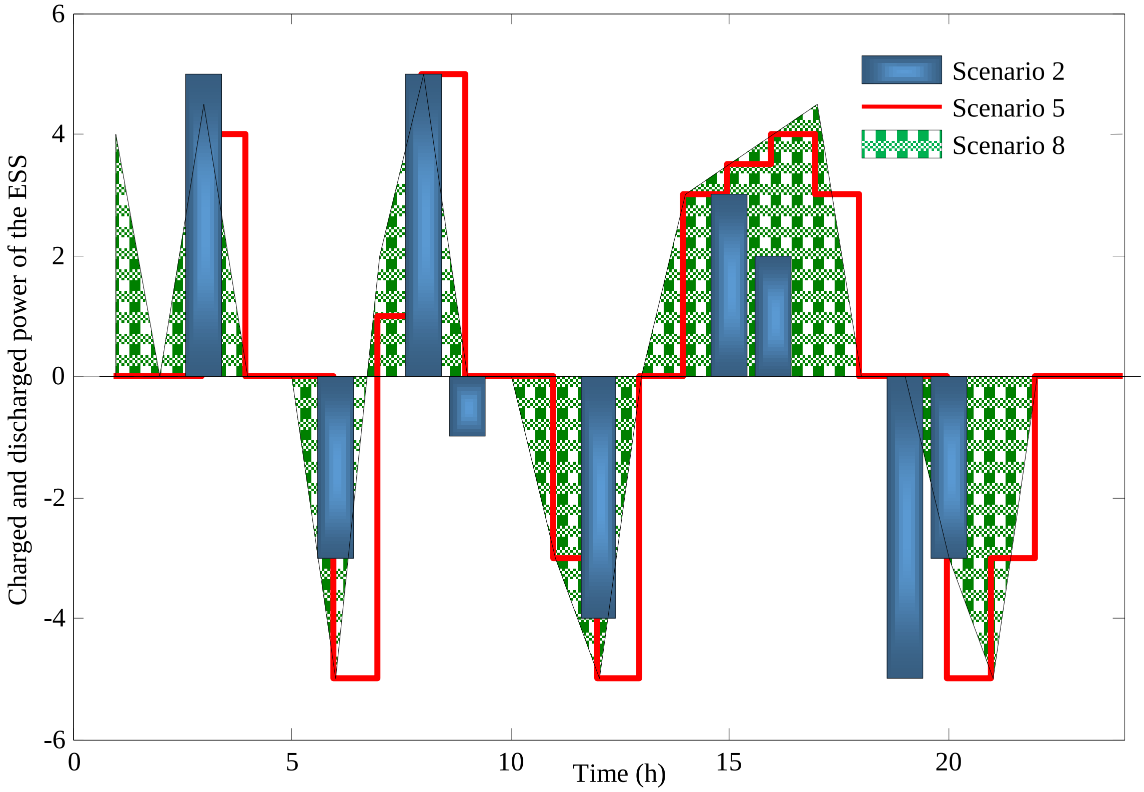

Fig. 5. Charged and discharged power of the BSS for different scenarios

Swapped electricity with main grid at different time intervals for various cases is depicted in Fig. 6. Provided/given electricity from/to main grid is expressed by positive/negative numbers. It's worthy to note, given energy to upstream grid is sum of wind turbine outlet power and discharged energy of battery. According to this figure, given energy to upstream grin in case five is higher compared to 2 other cases whereas provided electricity from upstream grid of case two is more than other scenarios.

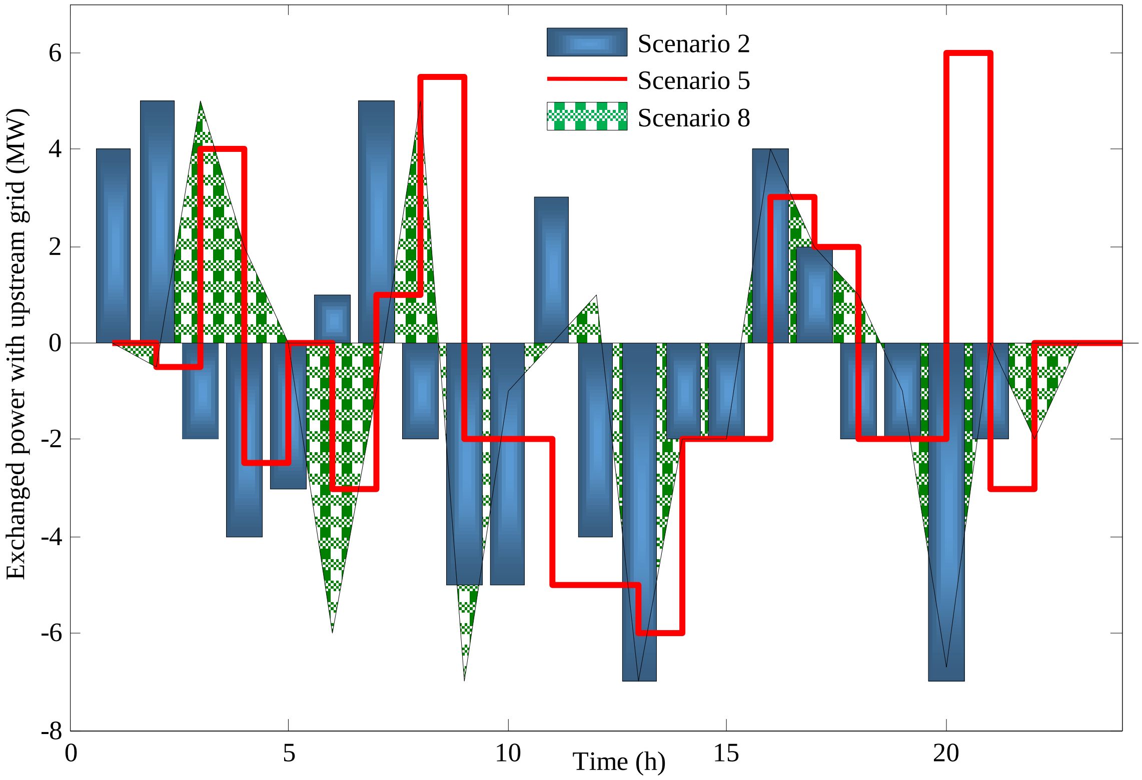

Fig. 6. Exchanged power with the upstream for different scenarios

This paper is aimed to get optimum offering/bidding trends. Fig. 7 to Fig. 9 show optimized bidding profiles for 3 and 7-8 time steps. Growth of electricity market tariff results in mitigation of bidding energy to power market. Fig. 4 depicts optimum bidding curves at 3-th time step in which max bidding energy is 4.66MW once price is 17.63$/MW. Fig. 8 shows optimum bidding profile at hour seven. In this time, once market price is more the 25.12$/MW, bidding energy to yield is 0.

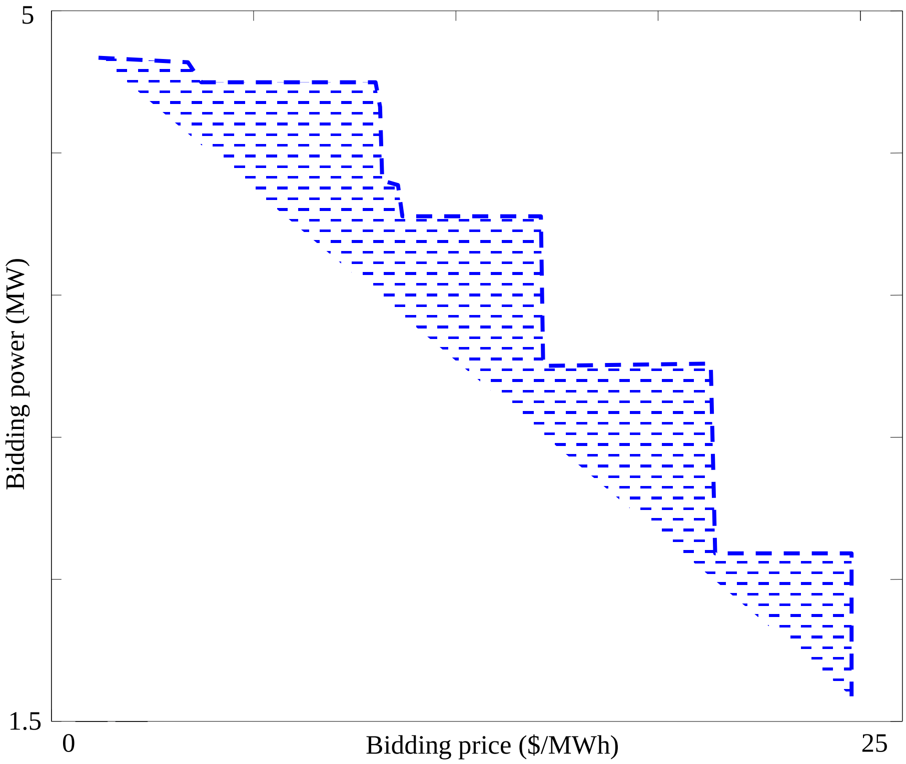

Fig. 7. The optimal bidding curve for 3-th hour

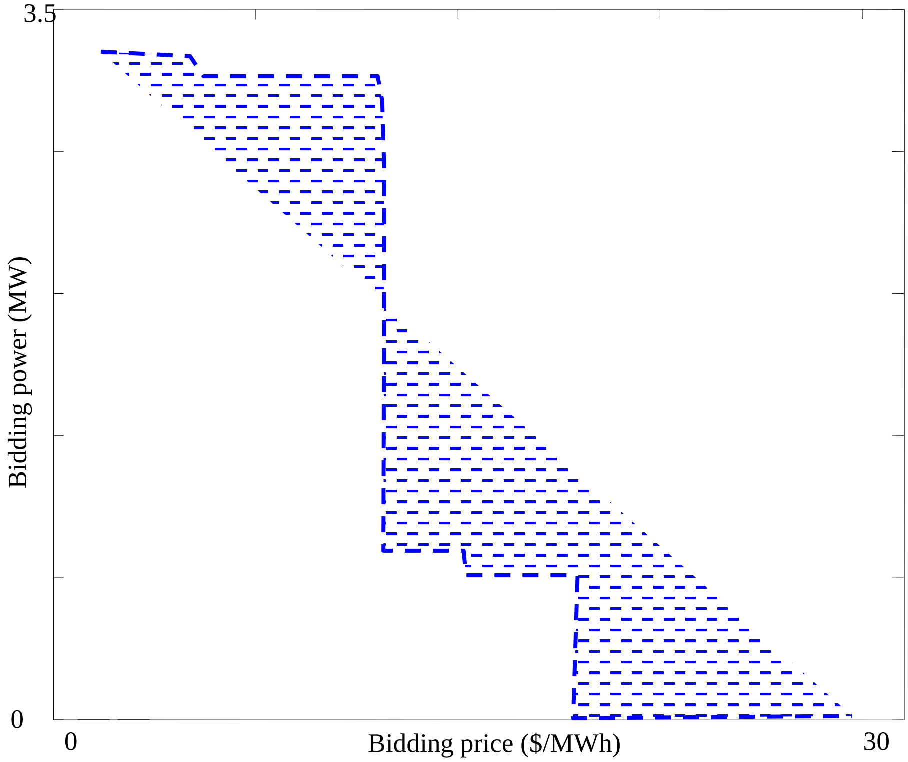

Fig. 8. The optimal bidding curve for 7-th hour

Also, optimum bidding curve at 8-th time step is illustrated by Fig. 9. The max bidding electricity is occurred once market tariff is 20.68$/MW whereas min bidding energy is happened once price is 25.04$/MW. Max and min bidding electricity are respectively 4.76MW and 4.27MW.

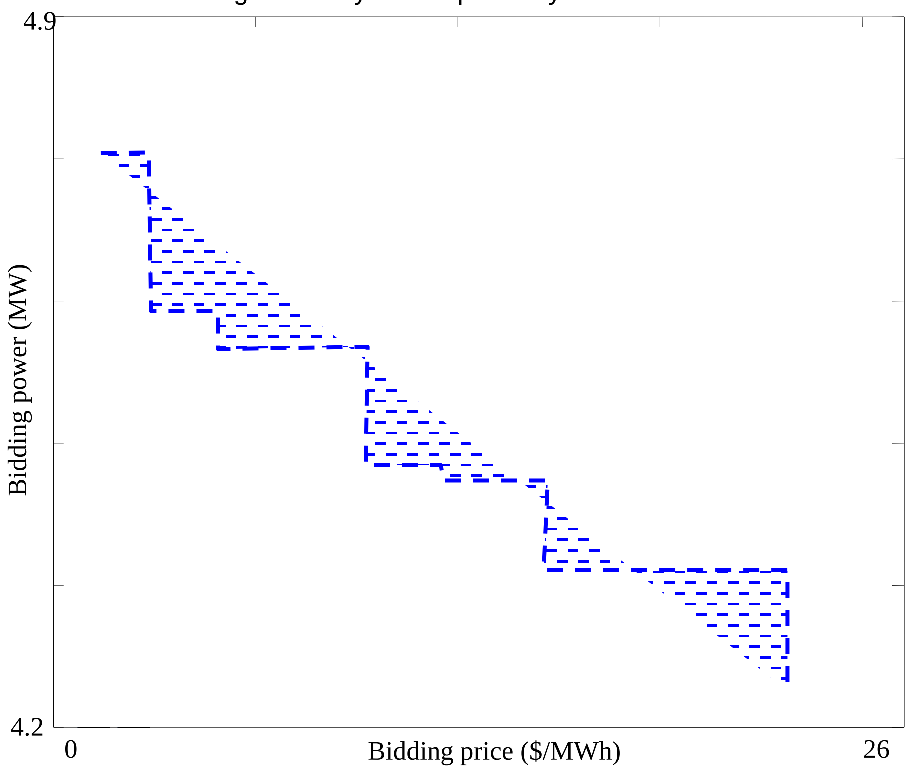

Fig. 9. The optimal bidding curve for 8-th hour

Besides, optimized offering curves are presented by Fig. 10 to Fig. 12 for 2, 10 and 18 time intervals. As estimated, offering trends are ascending that is requirement of market. Fig. 10 depicts offering trends at hour 2, in which offering electricity to market is 0 once market tariff is lower that 23.28$/MW. Furthermore, offering profile at 10-th time step is illustrated in Fig. 11. According to this figure, max and min offering energies that are respectively 4.65MW and 1.43MW, are occurred once market tariffs are 43.14 and 36.01$/MW. Finally, optimum offering trend is shown in Fig. 12 at 18-th hour. Respect to this figure, max and min offering energies are respectively 2.05MW and 1.39MW that are recorded when electricity market tariffs are equal to 59.14 and 47.25$ per MW.

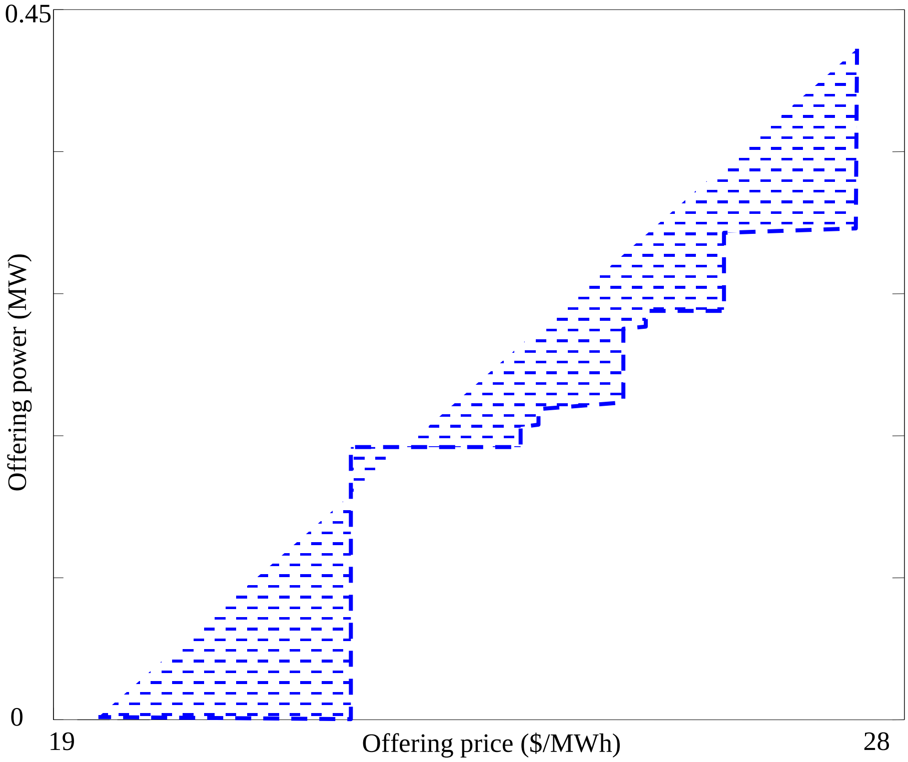

Fig. 10. The optimal offering curve for 2-th hour

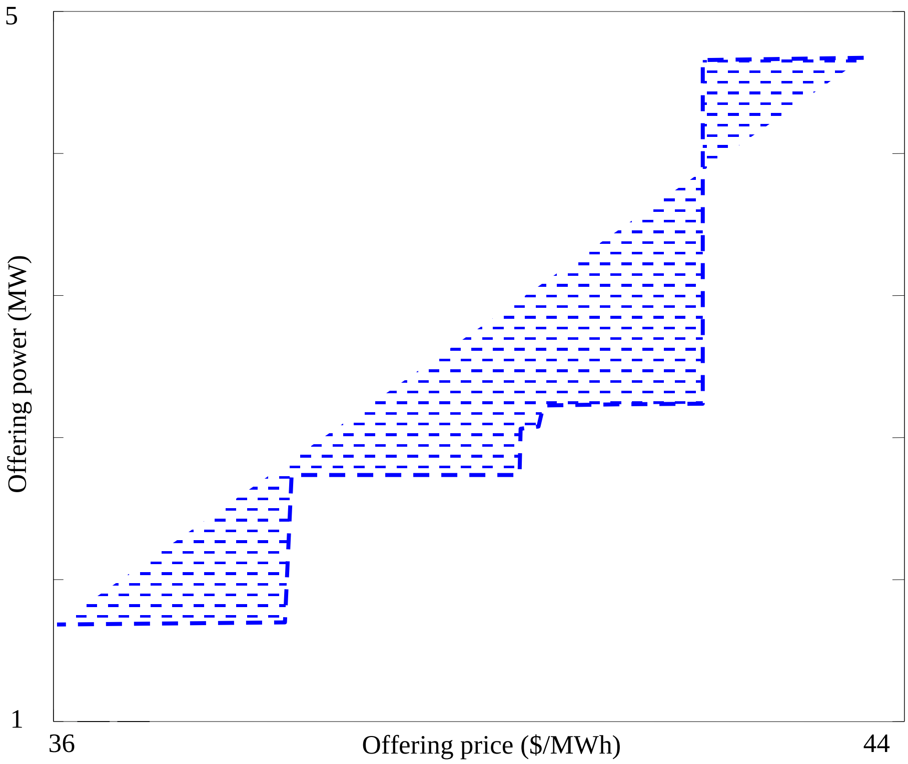

Fig. 11. The optimal offering curve for 10-th hour

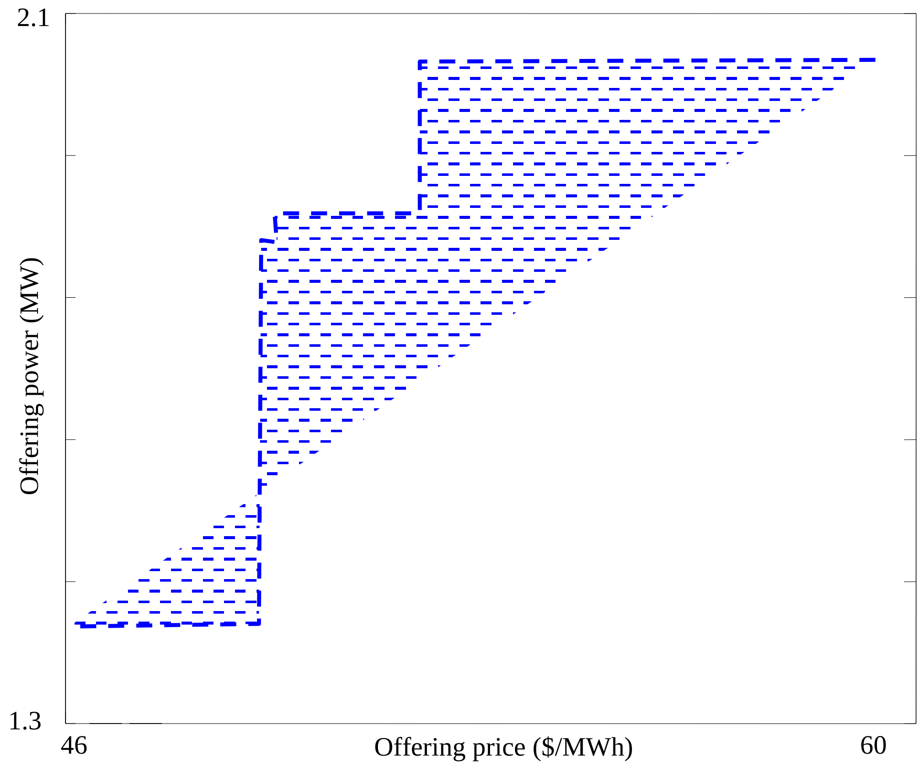

Fig. 12. The optimal offering curve for 18-th hour

5. Conclusion

This study suggested a novel strategy for integration of wind turbine with battery storage facility in grid-connected operation, in which, ESS is able to charge with both wind turbine and supplied energy from market in off-peak times. Through giving the saved energy of battery in expensive time intervals, integrated plant can get revenue. Besides, regarding to electricity market tariffs, outlet power of wind turbine can be straightly perfused to upstream grid or it can be stored in battery. Moreover, a collection of 10 scenarios are considered for modeling of power market price uncertainty using stochastic approach, while Weibull distribution function is employed in order to model wind speed as uncertain parameter. Achieved results confirmed, entire revenue of suggested method is $1,23. At last, through mixed-integer linear programing strategy, optimum offering/bidding curves are achieved at all times.

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