Supplier's Strategic Bidding for Profit Maximization with Solar Power in a Day-Ahead Market

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1 Introduction

Deregulation in the electrical energy market has been begun since the 1980s to make competition at all stages, from production to the purchaser. This procedure has developed for improving the operational efficiencies and planning of the electrical power system. In this type of markets, different problems have been introduced for example oligopolistic behavior of the market, abuses of the market power, price-demand elasticity, strategic bidding behavior of power producers, etc. [1]. Theoretically, power suppliers maximize their profit by utilizing bid at, or very near to, their marginal production cost in a perfectly competitive power market. Additionally, suppliers, who are little enough to influence market costs with their offers, are price players, and their optimum strategy is to offer at the marginal production cost. However, in practice, the power markets are oligopolistic, and power providers may try to build their benefit by providing a price higher than the marginal cost of production. The power suppliers faces the problem when they try to develop the best optimum bid, due to the knowledge of their expenses, technical restrictions, market behavior and their expectation of rival. This is known as a strategic bidding problem.

The extensive studies on strategic bidding have been attempted by many researchers to how power producers dispatch their every unit's generation output for the market operator and how they maximize their profit by utilizing predicted market-clearing price. The literature survey on strategic bidding on competitive power markets for power producers has been introduced [2]. In [3–5], authors show that due to the uncertain bidding behavior of rival producers is mostly effect to the

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process of strategic bidding decision model. Taking this reason as point of concern, the vast majority of the researchers have utilized a linear bid function and uniform market-clearing price model to construct the strategic bidding problem for profit maximization of the competitive power producers. In this type of strategic bidding, authors have modeled the rival's behavior using normal probability function and then solve the maximization of profit for competitive power producers utilizing heuristic algorithms [3–5]. However, these strategies only have been employed for traditional generators. Renewable energy in recent years is rapidly growing and further clean power productions with low carbon emission are incorporated into the electrical power system. Electrical power productions and percent of installed capacities of solar power plants go higher and will turn into the significant power generators soon. In this manner, considering the new round power foundation change and the expanding renewable power source in entire world, it is of incredible significance for the renewable power organizations to study the optimal bidding strategy of solar-based units taking an interest in the power market.

There have been several studies on the development of the joint strategic bid of renewable energy source (RES) with conventional generators. In this context, an optimal strategic bidding with solar photovoltaic (SPV) has also been considered in bidding strategy [6–10] that the uncertain output of solar power increases power imbalances and costs and also reduces solar power revenues. This mismatch between actual and forecasted power has been addressed by introducing a penalty. However, these works have not considered uncertainty associated with SPV. Thus, a method is required to model solar prediction in convincing way. In this work, a coordinated strategic bidding with the objectives of profit maximization is formulated with the amalgamation of traditional power suppliers and substantial solar power generation. This problem has been solved using novel heuristic technique [11], gravitational search algorithm (GSA), which is based on the law of gravity and interactions of masses with its application on power system problem is well established in [11–14]. Further, solar is used as a probabilistic manner to model the uncertainty and their prediction error is considered in cost function using underestimation and overestimation.

2 Modeling of Solar Power

It is necessary to handle the uncertainty associated with solar irradiation in order to deal with strategic bidding in the presence of solar power. Conversion of the solar irradiations is usually dependent upon the solar cell temperature, insolation of solar and technical properties of different PV modules. The output of solar power can be calculated by using solar irradiance and temperature. To model the solar power, a temperature and solar irradiance-based equations have been used and then a probabilistic beta distribution is utilized to model the uncertainty of solar power. For more detail, reader may refer [15].

2.1 Solar Power Scenarios Reduction

One thousand (1000) scenarios of solar power are generated. However, the probability of few scenarios might be very small and is some cases probabilities may be same. Subsequently, it is important to scrutinize the scenarios to obtain significant fewer scenarios while remaining lower and equal probability scenarios. The reduction should be such that the stochastic properties do not change. The amount of scenarios decreased depends on the type and nature of the problem to be optimized and must be reduced to or less than one-fourth of generated scenarios. In this, a scenario reduction technique known as Kantorovich distance matrix (KDM) has been employed [12]. It is based on the Euclidian distance between scenarios and their corresponding probabilities. This reduced the scenarios with closest and low probabilities.

2.2 Assessment of Scheduled Solar Power Amount for Bidding

The planned wind (W_g) and solar (S_g) power are obtained using KDM and the appropriate probabilities are calculated as follows

$$S_g = \sum_{i=1}^{\upsilon_i} S_{ai} \times \text{prob}_i \tag{1}$$

Here, prob_i is the probability of reduced ith generated scenario.

2.3 Solar Power Cost Evaluation

The imbalance cost of solar measure difference in forecasted and actual power which is the summation of underestimation and underestimation cost. It can be expressed as

$$\text{IMC}(Sg_n) = O_c(S_g) + U_c(S_g) \tag{2}$$

where $O_c(S_g)$ represents the overestimation cost, $U_c(S_g)$ represents the cost of underestimation for available solar energy. The underestimation and overestimation of the available solar energy is assessed as

$$U_c(S_g) = K_u * \int_{S_g}^{S_{\max}} (S_a - S_g) * f_{S_a}(S_a) * \mathrm{d}S_a \tag{3}$$

$$O_c(S_g) = K_o * \int_{0}^{S_g} (S_g - S_a) * f_{S_a}(S_a) * \mathrm{d}S_a \tag{4}$$

where K_u is the penalty for situational loss of profit per $/kWh due to power underestimation. K_o is the penalty coefficient for overestimating power.

3 Problem Formulation

It is assumed that each power supplier (PS) has one generator to formulate the proposed strategic bidding problem. In addition, each generator bus has only one power supplier (PS). Any cost function of the power supplier can be formulated as follows

$$\mathrm{PC}_m(Pg_m) = a_m Pg_m + b_m Pg_m^2 \tag{5}$$

where the mth power supplier's cost parameters are a_m and b_m, and active power generation is Pg_m. It is known that all PS submit their bid to independent system operator (ISO) using linear supply function [3–5]. The function of the linear supply model is as follows:

$$CP_m(Pg_m) = \pi_m + \phi_m Pg_m \quad m = 1, 2, \ldots, \mathrm{CPS} \tag{6}$$

where π_m and ϕ_m are coefficients of bidding that must be non-negative. After receiving the offers from the PS, the ISO matches the output of power with the system's total demand and then minimizes the purchase costs. It is to be noted that Eqs. (6)–(9) should be satisfied when considering the constraints of power balance (8) and the constraints of power inequality (9).

$$\pi_m + \phi_m Pg_m = R \tag{7}$$

$$\sum_{m=1}^{\mathrm{CPS}} Pg_m + \sum_{n=1}^{sg} sg_n = Q(R) \tag{8}$$

$$Pg_{\min,m} \leq Pg_m \leq Pg_{\max,m} \tag{9}$$

where the market-clearing price is R, the market operator's forecast load is $Q(R)$. Let us suppose that

$$Q(R) = L_c - k * R \tag{10}$$

where L_c is constant and $k = 0$ is non-negative load price elasticity. Solution for Eqs. (7) and (8) when ignoring (9)

$$\left(R = \frac{L_c - \sum_{n=1}^{sg} Sg_n + \sum_{m=1}^{cps} \frac{\pi_m}{\phi_m}}{k + \sum_{m=1}^{\text{CPS}} \frac{1}{\phi_m}} \right) \tag{11}$$

$$Pg_m = \frac{R - \pi_m}{\phi_m} \tag{12}$$

If in Eq. (12), the solution of Pg_m exceeds its maximum limits, it will be set in accordance with (9).

It is possible to express the optimal strategic bid by conventional power suppliers (CPS) with renewable sources to maximize profit.

Maximize

$$F(\pi_m, \phi_m) = R \times Pg_m - \mathrm{PC}_m(Pg_m) + R \times Sg_n - \mathrm{IMC}(Sg_n) \tag{13}$$

Subject to: Eqs. (1), (2), (5), (11) and (12).

Information about the next bidding period is hidden in a competitive energy market with a sealed bid. Members do not have information about the bid data of other members in this way. Be that as it might be, information of previous bidding data is available; the estimation of market-clearing price (MCP) is possible in the light of this information. Each member is endeavoring to evaluate various members that bid coefficients, but this is troublesome. Therefore, the coefficient of bidding follows a normal joint distribution with the following probability density function (pdf)

$$\mathrm{pdf}(\pi_m, \phi_m) = \frac{1}{2\pi\sigma_m^{(\pi)}\sigma_m^{(\phi)}\sqrt{1-\rho_m^2}} \times \exp\left\{ -\frac{1}{2\left(1-\rho_m^2\right)} \left[\left(\frac{\pi_m - \mu_m^{(\pi)}}{\sigma_m^{(\pi)}} \right)^2 + \left(\frac{\phi_m - \mu_m^{(\phi)}}{\sigma_m^{(\phi)}} \right) - \frac{2\rho_m \left(\pi_m - \mu_m^{(\pi)}\right)\left(\phi_m - \mu_m^{(\phi)}\right)}{\sigma_m^{(\pi)}\sigma_m^{(\phi)}} \right] \right\} \tag{14}$$

where the combined distribution parameters are $\mu_m^{(\pi)}$, $\mu_m^{(\phi)}$, $\sigma_m^{(\pi)}$ and $\sigma_m^{(\phi)}$, the coefficient of correlation between π_m and ϕ_m is ρ_n. Considering the mean values $\mu_m^{(\pi)}$ and $\mu_m^{(\phi)}$, and standard deviations values $\sigma_m^{(\pi)}$ and $\sigma_m^{(\phi)}$ of π_m and ϕ_m, marginal distribution for both is normal. Build on the last hour bidding; these can be calculated [3]. Joint distribution of π_m and ϕ_m is characterized by the function of distribution of probabilities with the objective function (13) subject to Eqs. (1), (2), (5), (11) and (12) is a stochastic optimization problem.

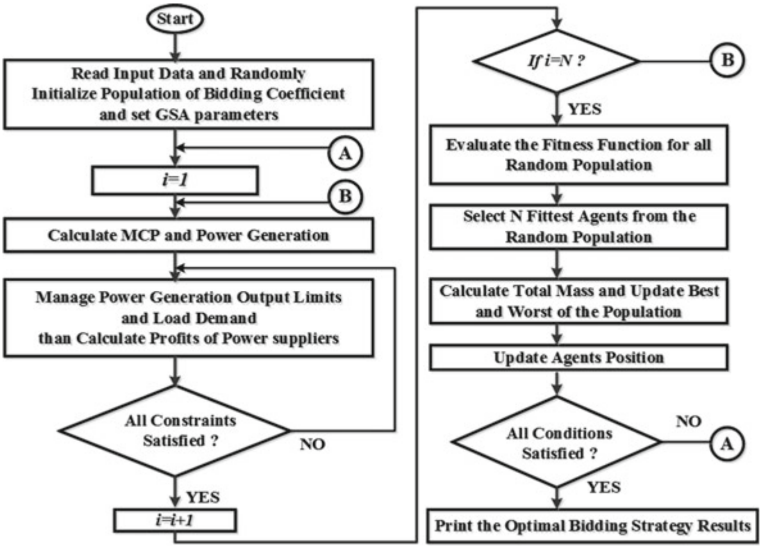

Fig. 1 Solution approach as a flowchart

4 Gravitational Search Algorithm

In [11], authors proposed a GSA to solve the problems of non-differentiable and nonlinear optimization. The flowchart solution procedure is given in Fig. 1.

5 Result and Discussion

In this segment, optimal strategic bidding model is considered for IEEE 30-bus system. The considered framework is utilized to obtain the maximum profit for power suppliers. The system data are taken from [12]. First, the test is conducted and analyzed on this system. Further, the considered model is modified to accommodate one solar power supplier to extent the influence of solar source. One solar supplier of 200 MW rated capacity is assumed in this work. The suggested formulation is solved on a 3.20 GHz, i5 processor, 4 GB RAM PC using the gravitational search algorithm (GSA) in MATLAB R2014a. For the solar power estimation, single hour wind speed data from January 1 to December 31, 2013 of Barnstable city, Massachusetts, USA is taken as study [16]. Solar irradiation is converted into solar power by using PV module specifications are taken from [15]. The solar irradiation data is fitted into various probability distributions are shown in Fig. 2. The log-likelihood, mean and variance values are calculated using various distributions and are presented in Table 1. It should be noted that the log-likelihood value of beta distribution is better than others, indicating the best fitting of the data in the distribution.

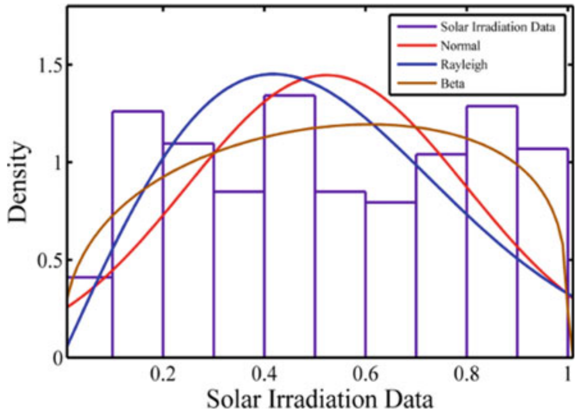

Fig. 2 Historical solar irradiation data for different distribution

Table 1 Mean, log-likelihood and variance values for historical solar irradiation data distribution

	Normal fit	Rayleigh fit	Beta fit
Log-likelihood value	−47.2392	−34.9839	10.1446
Mean	0.52266	0.523565	0.526305
Variance	0.0760555	0.0749005	0.06844

The values of beta distribution parameters are 1.3909 and 1.2518, respectively, for historical solar irradiation data. Then, a thousand solar irradiation scenarios are generated and convert into power scenarios using PV module specifications. The each generated scenario assigned a probability of normalization obtained using beta distribution to make their summation equal to unity. The beta and normalize the density function of probabilities shown in Fig. 3 for generated power scenarios. Since, the large number of scenarios predicts the uncertainty of solar power. However, there are few scenarios exhibit the same assessment. Therefore, KDM [12] method is employed to eliminate such scenario for better modeling of solar power. Here, 10 reduced scenarios are generated using 1000 scenarios for solar. Based on the final obtained value of solar power outputs and their corresponding probabilities, the expected values of solar power is 73.29 MW. Thereafter, the proposed optimal bidding strategies are investigated without solar and with solar using GSA. In this bidding process, the interdependency of bidding coefficients is contemplated by fixing one value and value of other coefficient is determined using an optimization method [3]. Therefore, the value of coefficient π_m is fixed in this work and the GSA is used to determine the optimum value of coefficient ϕ_m from the interval of $[b_m\ M * b_m]$. The value of M is set to be 10. The value of joint parameters of normal distribution in Eq. (14) is taken from [3]. The optimum value for coefficients of bidding of different CPS with and without solar and wind power using GSA is given in Table 2. The suggested optimal strategic bidding to clear the market-clearing price (MCP) for

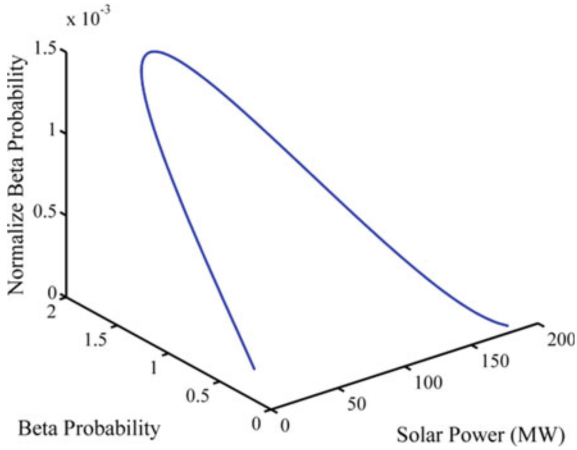

Fig. 3 Beta and normalize the density of beta distribution for generated solar power scenarios

Table 2 Optimum bidding results for standard IEEE 30-bus system with and without solar

PSs	π_m	Standard IEEE 30-bus system without solar			Standard IEEE 30-bus system with solar		
		ϕ_m	Pg (MW)	Profit ($)	ϕ_m	Pg (MW)	Profit ($)
1	2.0	0.049231	160	1815.32	0.049575	160	1495.4
2	1.75	0.224134	77.45	839.65	0.215113	55.53	512.23
3	1.0	0.722945	40.95	425.33	0.453362	32.27	288.17
4	3.25	0.097653	100	986.18	0.104385	91.44	725.46
5	3.0	0.289934	60.80	573.06	0.251243	43.74	343.46
6	3.0	0.289934	60.80	573.06	0.251243	43.74	343.46
MCP		13.9458			11.95		
Total profit for TPS ($)		5212.6			3708.22		
Total generation for TPS (MW)		500			426.71		
Sg (MW)		00			73.2897		
$O_c(S_g)$($)		00			114.7551		
$U_c(S_g)$($)		00			248.4213		
IMC(Sg_n)($)		00			363.1764		
Profit for SPS ($)		00			512.6355		

the standard IEEE 30-bus system is evaluated with the help of bidding coefficients predicated by the GSA and their corresponding profits and individual dispatch of generators are measured.

Effects of renewable power sources are successively considered on IEEE 30-bus system. For bidding strategy of renewable power, the system operator is allowed to modifying the existing demand, which means actual demand excluding renewable power generation, and then updates the bidding coefficients in accordance with the changing demand [12]. Based on this approach, solar power is considered to determine the new MCP. First, the solar power generator is considered and new value of MCP is calculated by updating the bidding coefficients at modified demand. In this analysis, the consideration of operating cost for solar power source has not been taken into account. However, due to the associated intermittency of these renewable sources it is acceptable to consider their imbalance cost. This cost is determined in terms of overestimation and underestimation of generation from solar. And the effect of this cost is reflected on total profit obtained by renewable suppliers in terms of revenue minus the imbalance cost. Also, the penalty coefficient and reserve coefficient linked with underestimation and overestimation separately are considered as 50% of MCP and equivalent to MCP, respectively [12].

The results of the proposed bidding strategy on considered system, considered system with solar by using GSA are presented in Table 2. From Table 2, it is observed that the market is cleared at MCP value of 13.94 $/MW, total generation of CPS is 500 MW and net profit is $5212.6 with standard CPS. In the second case, i.e., only solar power with CPS, the net profit value, overestimation and underestimation cost is 512.6355, $114.7551, and $248.4213, respectively. For this case, the MCP value is 11.95 $/MW with total generation of CPS 426.71 MW which is lower than conventional due to significant power generation from the solar. From Tables 2, it can be observed that all the purchase bids would satisfy by the lower MCP value. Due to the presence of solar supplier in the process of dispatch, there will be fewer CPS requirements in power system operation. Further, the overestimation estimate is very small compared to the underestimation of solar power uncertainties. Therefore, applying KDM in reduction of scenarios is better in modeling uncertainty. This will encourage to the solar power suppliers for bidding the extra power into the real-time market if the underestimation is positive.

6 Conclusion

This paper investigates optimal bidding strategies to maximize the profit of power producers with the amalgamation of renewable energy sources. Integration of solar is considered in the probabilistic approach using beta distribution and transform into power variable. Further, this power incorporated in cost model as overestimation and underestimation terms in order to consider the variability of power output. The proposed method considers the rival's behavior using normal probability distribution function to minimize the dynamics of competitor in the power market. Incorporation of solar power affects the bidding such as it reduces the CPS generation and provides lowered value of MCP which would deliver sufficient electricity from accepted sales bids to satisfy all the accepted purchase bids. Therefore, the proposed method is capable of satisfactory results with the consideration of uncertainty model of renewable sources.

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