Optimal Block Bidding Analysis for Electricity Market with Carbon Emission using MRPSO

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Abstract

Oligopolistic electricity market exhibits recent bidding strategies for maximization of profit for generators. Suitable bidding model with appropriate consideration of power operating constraints and price uncertainty within the market is the urgent requisite in electricity trading with utmost profit.

In this paper, a new Moderate-Random-Search Particle Swarm Optimization Strategy (MRPSO) is proposed for an optimal block bidding strategy of a thermal generator considering block bidding curve model with a precise model of nonlinear operating cost function and emission as constraints. Bidding strategy of a generator is solved by MRPSO, where mean best position (mbest) boost up the diversity and the exploration ability of particle. The MRPSO adopts an attractor pd as the main moving direction of particles, which replaces the velocity update procedure in the particle swarm optimization. The effectiveness of the proposed approach is tested with block bidding model and the results are compared with the solutions obtained using classical PSO under the rules of a competitive power market considering carbon emission.

In this paper the potential impacts of emissions on power industries and electricity markets are elaborated. Increasing environmental issues and regulations have forced, Generation companies (GENCOs) to consider the emission used for long term planning. Constraints on CO2 emission have restricted the GENCOs to adopt the green technologies.

Keywords: Block Bid model, Bid Price, Market Clearing Price, Carbon Emission, MRPSO.

Introduction

In this emerging electricity market each power supplier can increase its own profit through strategic bidding. The imperfect knowledge of rival suppliers extensively affects the profit of each supplier[1]. In the day-ahead electricity market bids have been submitted to the market operator, who matches generation level of each participant for hourly aggregate supply and decides market clearing prices (MCP). The generators have desired to participate through this market, have submitted their bidding power in the form of blocks along with prices for 24-hours. The framing of a best optimal bid for supplier with their own costs, technical constraints and behavior of rival's and market is known as strategic bidding problem. There are lots of work have been done on strategic bidding in competitive electricity market. There are some approaches to frame the SBP on the basis of their MCP and rival's bidding behavior[2]. A basic model of optimal bidding has been framed firstly, solved by using dynamic programming based technique[3]. A strategic bidding problem has been solved by Lagrange relaxation-based approach in[4] and same has been suggested by Zhang et al for daily bidding and self-scheduling decision[5]. In[6] SBP in oligopolistic dynamic electricity double-sided auctions is solved by using Nash-Cournot strategies for the market participants. The Reanalysis has been done for Nash Equilibrium Bidding Strategies in a Bilateral Electricity Market in[7].

Ugedo et al[8] have proposed a stochastic optimization model for submitting the block bids to obtain the distribution of the electricity resources of a generation firm among the different sequential markets within a wholesale electricity market. In[9] a genetic algorithm evolves a framework in which bidding strategies may be tested and modified. In[10] authors have extended same approach price based UC formulation for competitive market. In[11] author has been proposed two different bidding schemes by using Genetic Algorithm. The same approach for spinning reserve market coordinated with energy market has been suggested by David and Wen[12]. The heuristics approaches such as Evolutionary Algorithm-Based Hybrid Approach[13], fuzzy mixed integer Linear Programming[14], simulated annealing[15] and combination of these[16]. These heuristics approaches are commonly restricted by their receptivity to the choice of parameters, such as the crossover and mutation probabilities, in GA, temperature in SA, scaling factor in EP and inertia weight and learning factors in PSO. In[17] a moderate random- search (MRS) strategy is introduced into the new PSO algorithm with a view to enhance its global search ability and improves the convergence rate for the particle. In the unit commitment and monetary evaluation of power plants, the price of emissions is one of the decisive factors. Authors investigate an influence of emission constraints on generation scheduling and solving the new profit-based UC problem with carbon trading[16,18-20]. Hence it is essential to investigate the resulting market price for emissions[23].The lots of work has been done with PSO in strategic bidding for competitive electricity market[22,24] but the growing issue of emissions from generation of electricity, which affects environmentally, socially and economically to all mankind, is not being discussed yet. In this paper it is proposed to control CO_2 emissions by providing economic penalty for achieving reductions in the CO_2 emissions with MRPSO.

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(i) Block bidding problem is solved by MRPSO for single generator.

(ii) Penalty for emission is incorporated in the objective function.

(iii) The output of the problem is the quantity-price offers.

(iv)The output of the problem is compared between MRPSO and various parameters of PSO with both emission and non-emission condition.

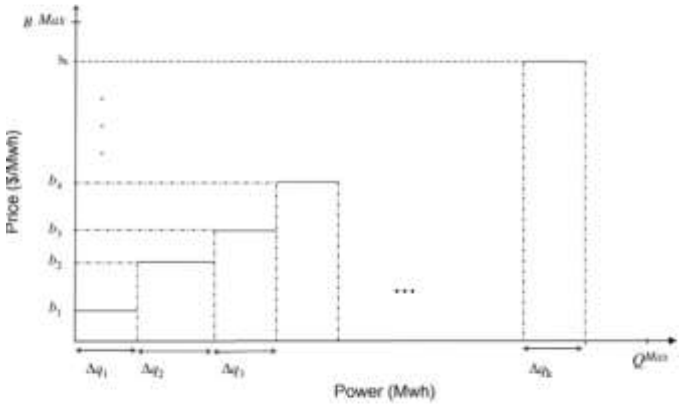
Problem Formulation

In the present work a block bid model is considered. In the block bid model the blocks considered for the auction are standard megawatts (MW). Some of the assumptions are taken as: (a) the previous power blocks are cheaper than the latter blocks of the same generator (b) One-part price-bid format is used in which the bidders for formation of their bids, total costs of productions acquired by generating plants and physical constraints have internalized (c) System demand considered in a trading period is assumed to be insensitive to change in price. It is assumed that the bidders are having the information about system demand (d) sealed bid, pay-as-bid auction mechanism is considered.

Let in an electricity market having n independent generators selling their power outputs and optimal strategic bidding generator of generator G is to be developed and all remaining (n-1) independent generators combined together into a single entity

Block Bid Model: There are (n-1) rivals in the market and generator 'G' with set of generating units which offers a block bid curve for each hour in 24-h horizon to compete in a day-ahead market for its each unit with uniform market clearing price (MCP) system. There are maximum 'n' blocks of output for which Generator-G and rival generator submit their bid for each trading period.

Individual generators have 'k' pairs of bid price 'bi' and bid quantity 'qi' where i=1,2,…,k for an optimal offer curve, 'q_i' is that much amount of energy for achieving the bid for releasing the energy at any time of next day. The whole energy blocks, offered at the lower and equal price from market clearing price at hour 't', which is equal to or higher than the offered price 'b_i' are accepted by the market operator.



Block Bid Model

The generator energy production costs depend on the amount of fuel consumed and is defined by a non-differentiable, non-convex, quadratic production cost function C (q).[18]

$$c(q) = a_0 + a_1 q + a_2 q^2 \quad (1)$$

where 'q' is quantity of generated energy, a0, a1, a2 are no-load, linear, and quadratic cost coefficients of the generator's cost function respectively. The objective function for optimal bidding strategy of generator-G for maximization of benefit can be, in terms of dispatched power output and market clearing price, expressed as:

$$\max_{\Delta q, b} f\{q_{it}, b_i\} = \sum_{t=1}^{T} \sum_{i=1}^{k} \begin{bmatrix} \underbrace{\Delta q_{it} * b_i}_{Revenue} - \underbrace{c_{it}(q_{it})}_{Generationcost} \pm \underbrace{Emiss_{it}(q_{it})}_{Emissioncost} \end{bmatrix} \quad (2)$$

Subject to

$$\sum_{i=1}^{k} \Delta q_i \le Q^{max} \quad (3)$$

$$0 \le b_i \le B^{max} \quad \text{for i=1,...,k} \quad (4)$$

$$0 \le \Delta q_i \le Q^{max} \quad \text{for i=1,...,k} \quad (5)$$

$$\left.\begin{array}{l} q_{it}^{sold} - q_{it}^{bou} + \in_{it}^{CO_2} * (q_{it}) = A_{it}^{CO_2} \\ q_{it}^{sold} \ge 0 \\ q_{it}^{bou} \ge 0 \end{array}\right\} \quad (6)$$

'-' is used when the preferred technologies in generation have high emissions; '+' is used when the preferred technologies in generation have low emissions.

c(q) : Generation cost ($/MWh), M_t : market clearing price at hour t ($/MWh), Q^{max}: Maximum generation capacity of the generator (MWh), B^{max}: Maximum acceptable bid price in the market, b_i : Bid price of block i ($/MWh), Δq_i : Bid energy amount increases of block i (MWh), $A_{it}^{CO_2}$ Yearly CO_2 allowance.

$Emiss_{it}(q_{it})$ is the emission cost function, expressed as:

$$Emiss_{it}(q_{it}) = \in_{it}^{CO_2} * q_{it} \tag{7}$$

$\in_{it}^{CO_2}$, is defined as emission coefficient and formulated as:

$$\in_{it}^{CO_2} = \frac{860 * c_{fuel}}{\eta_T * LHV_{fuel}} * q_{it} \tag{8}$$

c_{fuel} : Fuel unit price; η_T : Thermodynamic efficiency of the plant; LHV_{fuel} : Fuel lower heating value [Mcal/kg].

Moderate-Random-Search Particle Swarm Optimization Strategy (MRPSO)

MRS Strategy: The MRS strategy has been used with PSO algorithm for improving the global search ability of the PSO without slowing down its convergence rate. In this strategy only position update equation is used. The position of the r^{th} particle at the (k+1)th iteration can be calculated by using the formula:

$$X_r^{k+1} = P_d + \left[\alpha^k * \gamma\left(m_{best_r} - X_r^k\right)\right]$$

In the MRPSO, an attractor Pd is used as the main moving direction of particles due to the system converges to its one and only local attractor of points. It is described as:

$$P_d = rand_0 * P_{best} + (1 - rand_0) G_{best}$$

where $rand_0$ is a uniformly distributed random variable varies within [0, 1]. Attractor "Pd" varies within the range [1, 2] during iterations. The m_{best} term used in (11) is called the mean best position [17] which provides the step size for the particle movement and makes the participation of all P_{best} to the evolution of particles. Then, it improves the multiplicity and the searching ability of particle. The term is calculated using the following equation:

$$m_{best} = \sum_{i=1}^{S} \frac{P_{best_i}}{S}$$

where S denotes the population size in the MRPSO and γ used in (11) represents the random property of the MRPSO. The value of γ is calculated from

$$\gamma = (rand_1 - rand_2)/rand_3$$

$rand_1$ and $rand_2$ are two random variables within [0, 1], $rand_3$ is a random variable within [-1, 1]. The convergence rate of the MRPSO can be controlled during iterations by $\propto^k$, which works similarly as inertia weight used in the PSO. For better searching ability of particles, 'α' is tuned for higher value & lower value gives more precise searching ability. The following LD formula is suggested for the correct selection of 'α' are as:

$$\alpha^k = \alpha_{max} - \frac{\alpha_{max} - \alpha_{min}}{k_{max}} * k \tag{15}$$

where the values are set in the range $0.35 \le \alpha \le 0.45$.

MRPSO Algorithm for bidding problem: For the bidding problem position of each particle 'r' of generator 'G' is represented by the slope of the supply curve $X_r = m_G^r$. The fitness function for each particle is the benefit of generator 'G' in eqn (6). The MRPSO algorithm, for the bidding-search process, is as follows:

Step 1: Define input parameters with all constraints for the swarm.

Step 2: Initialize the position (m_G) for all particles randomly with satisfying all the constraints.

Step 3: Find supply quantity of Generator 'G' for randomly generated position (m_G) using eqn. (4).

Step 4: Calculate the fitness value (benefit) of each particle in the swarm using fitness function (6).

Step 5: Compare the fitness value of each particle found in step 4 with P_{best} of each particle. Update P_{best} of a particle if its fitness is greater than its P_{best}.

Step 6: Update G_{best} if any particle has greater fitness than fitness of current G_{best}.

Step 7: Update the attractor 'P_d' by using eqn. (12).

Step 8: Calculate the value of 'm_{best}' from (13), 'γ' from (14) & 'α' from (15).

Step 9: Modify the position of each particle by using eq. 11 with the updated value of attractor in step 7.

Step 10: Check iteration counter, if it reaches its maximum then go to step 11, else go to step 3.

Step 11: The swarm that generates the latest G_{best} in step 6 is the optimal value.

Result and Analysis

To validate the results, data has been referred from the example given in[22]. The optimal bid price calculated in[22] for block 1 is \$70 and for block 2 is \$73.4, corresponding to profit of \$ 21156. The value of optimal bid prices with consideration of carbon emission due to used generation technologies for block 1 and block 2 are \$69.4 and \$75 respectively, giving profit of \$ 20743, which is almost similar as shown by P. Bajpai et al. The effect of emissions is demonstrated on numerical examples.

Let generator 'G' has two blocks of power to bid as (a) G_1 = 350 MW; c_1 = \$45 (b) G_2 = 300; c_2 = \$60. Table 1 shows the five opponents' power blocks with capacity and bid price ranges.

Table 1
Opponents' bidding Data

Opponent Blocks (j)	1	2	3	4	5
MW block capacity	350	250	200	150	200
bid price (ρ_i)	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5
min. bid price ($\rho_{i_{min}}$)	35	35	60	60	75
max. bid price ($\rho_{i_{max}}$)	65	65	80	80	90

Lossless 3 Bus Test System: A simple lossless 3-bus system as illustrated in figure 3is used to explain the basic concept of approach. This system has two generators of equal generation capacity of 500MW, one is coal based and another is gas based. Generators are located at bus number 1 and 2. At bus no 2 there is a load of 100 MW with generator and another load of 900 MW capacities is on the bus no. 3.

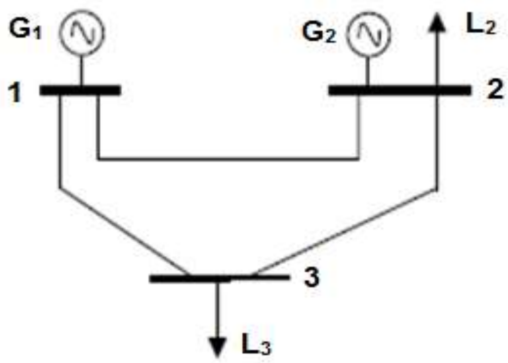


Fig. 3: Lossless 3Bus Test System

For this bus test system the benefit for the generator are same when the emission effect is not considered. As the emission effect comes into the leading role it proposes a penalty of an amount which is calculated on the basis of their carbon emission during generation and at the same time it also proposes a reward scheme to those generators who are trying to cut down their emissions by using low emissive generation technologies or shifting their generation towards green technologies. Table 2 shows the comparison for benefit of generator 'G' with & without consideration of emission coefficient. Table 3 gives the computation time for both techniques.

Parameters are tested for 50 particles with 100 no of iterations with MRS-strategy compared with classical-PSO.[22,24]

Table 2
Comparison of profit (\$) in Block bid model (50 particles 100 iterations)

Demand (in MW)	Without Emission		With Emission	
	Classical PSO	MRPSO	Classical PSO	MRPSO
200	263.37	269.22	255.93	259.33
400	807.16	825.09	784.36	794.78
600	1716.60	1754.73	1668.11	1690.27
800	3770.51	3854.27	3664.00	3712.68
1000	5959.16	6091.54	5790.82	5867.76

Table 3
Comparison of Computation times (50 particles 100 iterations)

	Without Emission		With Emission	
	Classical PSO	MRPSO	Classical PSO	MRPSO
Computation Time (in sec)	0.069734	0.051435	0.072556	0.054651

Conclusion

In this paper, the electricity market model has been proposed with considering generators carbon emissions and put a penalty scheme on the high carbon emitters and the amount is collected by imposing such penalty, is distributed among those generators in ratio of slashing down the emissions by taking green initiatives or using other lower emission technologies for generation. MRPSO method is used to optimize the strategic bidding of generators. The block bidding or discrete bidding model is used. The MRPSO executes in well manner and gives the global optimum solution in both emissive and non-emissive environment.

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