

Bidding strategy for generators considering ramp rates in a day-ahead electricity market

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Abstract: In a day-ahead electricity market, competitive bidding strategy plays a vital role for power suppliers to maximize their profit. In this type of market, each power supplier submits a set of hourly production prices and offers capacity for the next period. The market operator, after receiving this data along with forecasted hourly load from the demand side, allocates production output to each unit. Power suppliers face the problem in trading their offers in the market, due to the uncertain behavior of competitive power suppliers and power demand. Therefore, the power supplier requires a suitable bidding strategy for handling uncertainty in the market to maximize their profits. Moreover, the considerations of ramp rates are necessary for the precise representation of practical power system. Thus, in the present work, a modified gravitational search algorithm based on oppositional learning concept is used to solve strategic bidding problem for power suppliers considering six generators with ramp rates, 24-h load data and rivals behavior. The total hourly profits of generators with and without considering ramp rates have been compared.

Key words: Bidding strategies, electricity market, gravitation search algorithm, market clearing price, ramp rates

1. Introduction

Global electricity markets are continuously being restructured, which introduces fair competition among participants for the trading of their product and maximizing economic productivity. In restructured electricity markets, generation companies (GENCOs) own generation facilities and participate in the market with the sole objective of profit maximization, overlooking system concerns like security and reliability unless there is an incentive. In microeconomics theory, GENCOs take benefits of market uncertainty to raise their profits through bidding [1]. Theoretically, they raise their profit through bidding a price equal to their marginal production cost, whereas in practice they have higher prices of bidding over the marginal cost. However, power suppliers face a problem when they try to develop the best optimum bid based on the knowledge of their expenses, technical restrictions, market behavior, and their expectation of rivalry. This is known as a strategic bidding problem [2, 3].

In a day-ahead electricity market, strategic bidding mechanism is a very vital research area. In the last few decades, many researchers have carried out their research over strategic bidding problem. A conceptual optimal bidding strategy problem was solved firstly by dynamic programming (DP)-based method [4]. The authors in this work show that there are several factors which may affect the bidding strategies. The uncertain demand, supplier's production cost, operating constraints, and bidding behavior of other competitors are few of them. Among these, the most uncertain is the bidding behavior of rival generators that can intensify the

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difficulties in strategic bidding decision process [5] due to the natural behavior of participants who aim for profit maximization. The effectiveness of dynamic programming is investigated in [6] to find the optimal strategies for single power plants or groups of power plants under various electricity prices and fuel cost forecasts. In [7–20], the problem of optimal bidding strategies has been studied to maximize the profits of GENCOs while considering rival behavior. In this process, GENCOs first recognize their rival's behavior and then solve the profit maximization problem using different optimization methods such as particle swarm optimization (PSO) [7], fuzzy adaptive PSO [8], decomposition-based PSO [9], PSO combined with simulated annealing (SA) [10], self-organizing hierarchical PSO [11], genetic algorithm [12, 13], bat-inspired algorithm [14], gravitational search algorithm (GSA) [15], fuzzy adaptive GSA [16], shuffled frog leaping algorithm [17], temporal difference learning method [18], hybrid SAGA [19], and differential evolution [20]. The normal probability distribution functions are used to model the competitive behavior of rivals. The generation limit constraints have also been considered in strategic bidding problem. This consideration is not pragmatic as real-time generation is limited by ramp rates; this would affect the operation of generating units [21, 22].

In the literature, strategic bidding problem with ramp rates constraints has been given less attention, which is critical to ensure practical optimal results. Therefore, without ramp rates, dispatch of generation is optimal but it does not represent the practical situation of generation unit. Thus, to obtain the practical optimal solution, in this paper, the generators with ramp rates have been considered. However, if ramp rates are considered a constraint, the number of decision variables involved in the problem will increase, and hence increases the complexity of the problem which requires an effective solution process. Classical and heuristic methodologies have been implemented to solve strategic bidding problems. As the size of the system increases with the number of decision variables, the classical approaches face problems in finding the global optimal solution. On the other hand, the heuristic approaches take lower computation time [12] and find the global optimal solution.

In this regard, a heuristic technique, namely the GSA is used. This technique is based on the law of gravity and interactions of masses. GSA implementation for optimization problem provides high-quality results [14, 23–26]. As this algorithm has the best tunable parameters, its most important feature is adjustment of gravitational constant for improvement of the search accuracy. It provides fast solution with high-quality results [27]. The initialization of population parameter is configured randomly in the GSA, and the activity approach of reinforcement agents is at first dependent on randomness [28]. If the random guess is not far away from the optimal result, it can be solved in a quick convergence. Notwithstanding, it is normal to express that on the off chance that we start with a random guess, which is exceptionally far from the existing result, let us say in the most pessimistic scenario, it is in the opposite area. At that point, the guess, search, or enhancement will take impressively additional time, or in the most pessimistic scenario, it ends up immovable. Obviously, in nonappearance of any from the earlier information, it is not conceivable that we can make the best introductory guess. Coherently, we ought to be looking every way all the while, or more solidly, the opposite way. In this context, this paper has the following contributions:

1. In the modified gravitational search algorithm (MGSA), the oppositional-based learning concept is incorporated to generate the population opposite to the initial population. This feature will further exploit the search space more appropriately, which will lead to optimal solution in lesser number of iterations.
2. The optimal bidding strategy with the aim of profit maximization of power suppliers considering ramp rates is formulated, and solved by using a MGSA.

The rest of this paper is organized as follows: Section 2 describes a strategic bidding problem formulation considering ramp rates. Section 3 discusses modified gravitational search algorithm. Section 4 demonstrates simulation results and discussion. In Section 5, conclusion is given.

2. Problem formulation

In a pool-based day-ahead electricity market, sealed bid and uniform market clearing price (MCP) are considered. It is assumed that the individual power supplier submits a bid to the market operator (MO) as a linear supply bid function in a pool-based electricity market. The linear supply bid of n^{th} supplier can be expressed as:

$$B_{nt}(G_{nt}) = X_{nt} + Y_{nt}G_{nt} \quad n = 1, 2, \dots, S, \quad (1)$$

where $t \in T$ is the interval of time, T is the number of time intervals, S is number of power suppliers, G_{nt} is the active power generation at t^{th} hour, X_{nt} and Y_{nt} are bidding coefficients which must be nonnegative. After receiving bid from the power suppliers, MO sets generation output of active power that meets the total demand of the system. It ensures that (2) to (5) must satisfy the dispatch of the generation when the load flow balance (3), generation limits (4), and ramp rates constraints (5) are considered.

$$X_{nt} + Y_{nt}G_{nt} = R_t \quad n = 1, 2, \dots, s \quad (2)$$

$$\sum_{n=1, t=1}^{s, T} G_{nt} = Q(R_t) \quad (3)$$

$$G_{\min, n} \leq G_{nt} \leq G_{\max, n} \quad n = 1, 2, \dots, s \quad (4)$$

$$-RD_n \leq G_{nt} - G_{n, t-1} \leq RU_n, \quad (5)$$

where $G_{\min, n}$ and $G_{\max, n}$ are lower and upper limits of the active power output of n^{th} supplier respectively. R_t is the MCP, RD_n and RU_n is the ramp down and ramp up limits of generators. $Q(R_t)$ is the forecasted load by the MO at hour t .

The solution of equality constraints (2) and (3) when inequality constraints (4) and (5) is ignored, are:

$$R_t = \frac{Q(R_t) + \sum_{n=1, t=1}^{s, T} \frac{X_{nt}}{Y_{nt}}}{\sum_{n=1, t=1}^{s, T} \frac{1}{Y_{nt}}} \quad (6)$$

$$G_{nt} = \frac{R_t - X_{nt}}{Y_{nt}} \quad n = 1, 2, \dots, s. \quad (7)$$

If the solution of G_{nt} in (6) exceeds the maximum limits, G_{nt} is set to $G_{\max, nt}$. If $G_{nt} < G_{\min, nt}$, G_{nt} is set to zero.

The production cost function of the n^{th} supplier is

$$C_n(G_{nt}) = x_n G_{nt} + y_n G_{nt}^2, \quad (8)$$

where x_n and y_n are cost coefficients of the n^{th} supplier.

For the n^{th} power supplier, the objective function for profit maximization can be defined as:

$$\text{Maximize : } F(X_{nt}, Y_{nt}) = R_t G_{nt} - C_n(G_{nt}) \tag{9}$$

Subject to: (6) and (7).

The overall objective of the supplier is to determine X_{nt} and Y_{nt} so as to maximize $F(X_{nt}, Y_{nt})$ subject to (6) and (7).

In a day-ahead electricity market bidding data of next duration is confidential because sealed bid is submitted by the suppliers to the pool. Therefore, rival bidding behavior information is hidden from the suppliers. However, the last bidding information is available, based on this information calculation of MCP is possible. Thus, the estimation of bidding coefficients of rivals is difficult for individual supplier.

Let X_{nt} and Y_{nt} follow the joint normal distribution with following probability density function (pdf)

$$\text{pdf}_{nt}(X_{nt}, Y_{nt}) = \frac{1}{2\pi\sigma_{nt}^{(X)}\sigma_{nt}^{(Y)}\sqrt{1-\rho_{nt}^2}} \exp \left\{ -\frac{1}{2(1-\rho_{nt}^2)} \left[\left(\frac{X_{nt}-\mu_{nt}^{(X)}}{\sigma_{nt}^{(X)}} \right)^2 + \left(\frac{Y_{nt}-\mu_{nt}^{(Y)}}{\sigma_{nt}^{(Y)}} \right)^2 - \frac{2\rho_{nt}(X_{nt}-\mu_{nt}^{(X)})(Y_{nt}-\mu_{nt}^{(Y)})}{\sigma_{nt}^{(X)}\sigma_{nt}^{(Y)}} \right] \right\} \tag{10}$$

This approximation can be indicated in the form of

$$(X_{nt}, Y_{nt}) \sim N \left\{ \begin{bmatrix} \mu_{nt}^{(X)} \\ \mu_{nt}^{(Y)} \end{bmatrix}, \begin{bmatrix} (\sigma_{nt}^{(X)})^2 & \rho_{nt}\sigma_{nt}^{(X)}\sigma_{nt}^{(Y)} \\ \rho_{nt}\sigma_{nt}^{(X)}\sigma_{nt}^{(Y)} & (\sigma_{nt}^{(Y)})^2 \end{bmatrix} \right\} \tag{11}$$

where ρ_{nt} is correlation coefficient between X_{nt} and Y_{nt} at hour t , parameters of the joint distribution is $\mu_{nt}^{(X)}$, $\mu_{nt}^{(Y)}$, $\sigma_{nt}^{(X)}$, and $\sigma_{nt}^{(Y)}$. The marginal distributions of X_{nt} and Y_{nt} are both normal with mean values of $\mu_{nt}^{(X)}$ and $\mu_{nt}^{(Y)}$, and standard deviations $\sigma_{nt}^{(X)}$ and $\sigma_{nt}^{(Y)}$ respectively.

Based on the data from the last bidding, these distributions can be determined [5]. Probability distribution function which represents the combined distribution of X_{nt} and Y_{nt} along with the objective function (9), equality constraint (6), and inequality constraints (7) forms a stochastic optimization problem.

In the next section, a modified gravitational search algorithm is presented, which is used to solve the above stochastic optimization problem.

3. Modified gravitational search algorithm

Solution of the nondifferentiable and nonlinear optimization problems by GSA has been proposed in [29]. In GSA, individual agents provide a better solution to the problem. The solution procedure of MGSA in the form of flowchart is given in Figure 1.

3.1. Population initialization

Consider that a system has N agents (masses), the position of i^{th} agent is denoted by:

$$\lambda_i = (\lambda_i^1, \dots, \lambda_i^B, \dots, \lambda_i^A) \quad \text{for} \quad i = 1, 2, \dots, N, \tag{12}$$

where $\lambda_i^B \in [L_i^B, U_i^B]$, $B = 1, 2, \dots, A$ is the i^{th} agent position in the B^{th} dimension and A is search space dimension, U_i^A and L_i^B are upper bound and lower bound limits of i^{th} agents in B^{th} dimension.

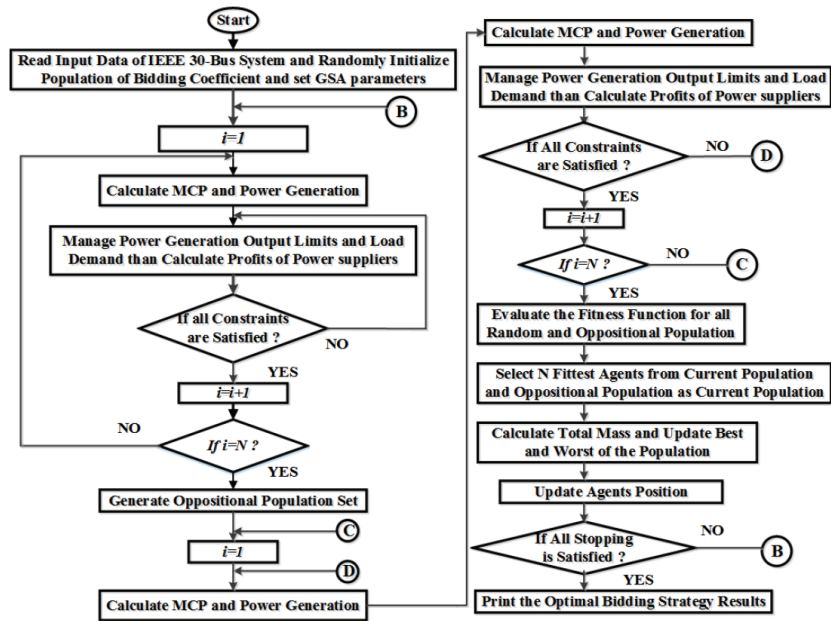


Figure 1. Solution procedure of MGSA.

3.2. Opposition phenomenon in GSA

Oppositional-based learning approach has been presented in [30]. In this work, opposite and current agents are considered in order to get a better approximation of current agent solution. It is established that an opposite agent provides improved optimal results compared to that of random agent result. The opposite agent’s position ($O\lambda_i$) is completely denoted by components of λ_i .

$$O\lambda_i = [O\lambda_i^1, \dots, O\lambda_i^B, \dots, O\lambda_i^A], \tag{13}$$

where $O\lambda_i^B = L_i^B + U_i^B - \lambda_i^B$ with $O\lambda_i^B \in [L_i^B, U_i^B]$ is the position of i^{th} opposite agent $O\lambda_i$ in the B^{th} dimension of oppositional population.

3.3. Fitness evaluation

Here the total profit of suppliers is designed as the fitness function fit_i . At the modified gravitational search algorithm for starting an iterative method, a combined population of $\{\lambda, O\lambda\}$ is created with all the constraints satisfied. Selection approach is used to select the N number of suitable agents from the combined population set of $\{\lambda, O\lambda\}$ to create current population λ .

$$\lambda_i(j) = \begin{cases} O\lambda_i(j) & \text{if } fit(O\lambda_i(j)) > fit(\lambda_i(j)) \\ \lambda_i(j) & \text{otherwise} \end{cases} \tag{14}$$

The algorithm simultaneously evaluates the fitness of an agent and its opposite agent. The agent with better fitness value is used in further computation and the other agent is discarded.

3.4. Acceleration of agents

The fitness of an individual agent is used to estimate its mass. The estimation of individual agent mass is as follows:

$$\begin{cases} M_i(j) = \frac{m_i(j)}{\sum_{i=1}^N m_i(j)} \\ m_i(j) = \frac{fit_i(j) - worst(j)}{best(j) - worst(j)} \end{cases} \quad (15)$$

where $M_i(j)$ is the normalized mass of i^{th} agent at j^{th} iteration, and $best(j)$ and $worst(j)$ are the best and worst fitness of all agents at j^{th} iteration.

The acceleration $a_i^B(j)$ acting on i^{th} agent at iteration j is evaluated as follows:

$$a_i^B(j) = \sum_{l \in Gbest, l \neq i} rand_l \cdot G(j) \frac{M_i(j)}{R_{il}(j) + E} (\lambda_l^B(j) - \lambda_i^B(j)) \quad (16)$$

where set of first 2% agents is $Gbest$ with best value of fitness and greatest mass $rand_l$ is the uniform random number within the interval $[0,1]$, $R_{il}(j)$ is the Eculidean distance between two agents i^{th} and l^{th} at j^{th} iteration and E is a small positive constant. The gravitational function $G(j)$ in (15) is represented by:

$$\begin{cases} G(j) = G \times \left(1 - \frac{iteration}{Total \ iteration} \right) \\ G = c \max_{B \in \{1,2,\dots,A\}} (\lambda_U^B - \lambda_L^B) \end{cases} \quad (17)$$

where c is search space.

3.5. Update the position and velocity of agents

In next $(j + 1)^{th}$ iteration, the position and agents velocity are calculated as follows:

$$\begin{cases} v_i^B(j + 1) = rand_i \times v_i^B(j) + a_i^B(j) \\ \lambda_i^B(j + 1) = \lambda_i^B(j) + v_i^B(j + 1) \end{cases} \quad (18)$$

where $rand_i$ is a random number within the interval $[0,1]$, $v_i^B(j)$ is the velocity of i^{th} agent at B^{th} dimension during j^{th} iteration, and $\lambda_i^B(j)$ is the position of i^{th} agent at B^{th} dimension during j^{th} iteration.

3.6. The solution procedure of MGSA for bidding strategy problem

The main steps of the MGSA for bidding strategy problem are explained in detail as follows:

- Step 1. Set input data of considered test system for bidding strategy and parameters of the proposed MGSA.
- Step 2. Randomly generate initial population (λ) for Y_{nt} in the interval between y_n and $M \times y_n$ and M is set to be 10.
- Step 3. Determine the market clearing price and dispatch of each generator.
- Step 4. Set power generation limits and system load balance, and then calculate profit of each generator.

Table 1. Six generators data with ramp rates.

Generator	x	y	G_{min} (MW)	G_{max} (MW)	RD (MW)	RU (MW)
1	4.10	0.00028	50	680	80	85
2	4.50	0.00312	30	150	45	60
3	4.10	0.00048	50	360	60	65
4	3.74	0.00324	60	240	45	80
5	3.82	0.00056	60	300	70	80
6	3.78	0.00334	40	160	35	40

Table 2. Load data for 24 h.

Time	1	2	3	4	5	6	7	8	9	10	11	12
Load	1033	1000	1013	1027	1066	1120	1186	1253	1300	1340	1313	1313
Time	13	14	15	16	17	18	19	20	21	22	23	24
Load	1273	1322	1233	1253	1280	1433	1273	1580	1520	1420	1300	1193

Step 5. Generate oppositional population ($O\lambda$), and then determine the market clearing price and dispatch of each generator.

Step 6. Set power generation limits and system load balance, and then calculate profit of each generator.

Step 7. Evaluate the fitness function for all random and oppositional population.

Step 8. Select N fittest agents from current and oppositional population as current population.

Step 9. Determine the mass of every agent and gravitational constant respectively.

Step 10. Calculate all agents' acceleration.

Step 11. Update the velocity and the position of the agent, respectively.

Step 12. If the maximum number of iterations is not exceeded go to Step 3, otherwise the procedure will be stopped and the optimum bidding strategy will be printed.

4. Simulation results & discussion

In this section, the proposed algorithm, the MGSA, is tested on a system of six generators having a load demand of 1033 MW for a single-hour trading period of power suppliers' profit maximization as a base study. Furthermore, it is analyzed with other well-known established methods such as GA [12], PSO [7], and GSA [29] using the statistical results. Then, a proposed bidding strategy for profit maximization of power supplier of six generators with the consideration of ramp rate for 24-h trading period is investigated using the MGSA. The results are presented without and with ramp rates using the MGSA. The generator data for six generators with ramp rates are given in Table 1 and load data for 24 h is given in Table 2. The simulations are carried out using MATLAB R2014a with a 3.20 GHz, i5 processor, 4GB RAM PC. The schematic diagram of the considered test system is given in Figure 2 and the best tuned parameters for the proposed MGSA, GSA [29], PSO [7], and GA [12] are given in Table 3.

The bidding coefficients X_{nt} and Y_{nt} cannot be considered separately in order to maximize the profit of generators. As the coefficients X_{nt} and Y_{nt} are interdependent parameters [31], where one coefficient has been

Table 3. Best tuned parameters.

Parameters	GSA [29] and MGSA	PSO	GA
Size of population	50	50	50
Iterations	1000	1000	1000
Gravitational constant (G)	100		
Learning factors (c1 = c2)		2.0	
inertia constant (w)		0.9 to 0.4	
Length of chromosome			12
Elitism probability (Pe)			0.15
Crossover probability (Pc)			0.85
Mutation probability (Pm)			0.005

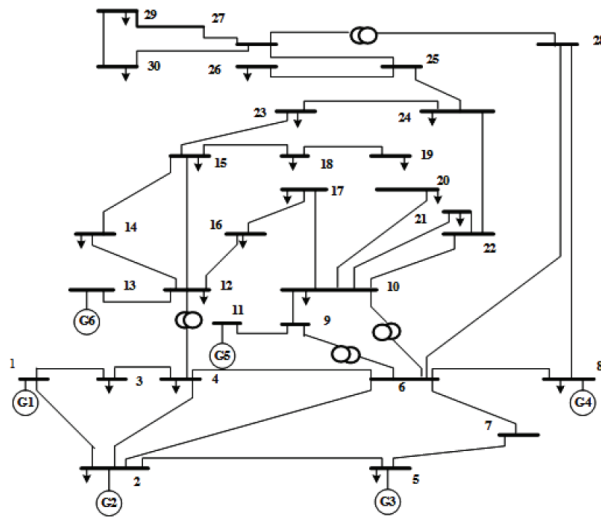


Figure 2. Schematic diagram of the six-generator system.

known as a priori, and the other is determined using an optimization approach. These parameters are used to maximize the GENCO’s profit. Therefore, in this work, the considered value of coefficient X_{nt} is kept fixed. The optimal values of bidding coefficients Y_{nt} is searched from the interval between y_n and $M \times y_n$, and M is set to be 10. This assumption is kept unchanged for single and 24 h.

Table 4. Optimal bidding coefficients for single-hour trading period

Generators	X_{nt}	Y_{nt}			
		GA [12]	PSO [7]	GSA [29]	MGSA
1	4.10	0.003359	0.003409	0.003440	0.003539
2	4.50	0.034909	0.018594	0.021818	0.035696
3	4.10	0.005428	0.005616	0.005368	0.005467
4	3.74	0.028061	0.038421	0.038694	0.035635
5	3.82	0.005037	0.006140	0.006722	0.006149
6	3.78	0.035641	0.030983	0.032325	0.040405

Here first, the optimal bidding strategy for a system of six generators with load demand of 1033 MW is investigated using the proposed MGSA, standard GSA [29], PSO [7], and GA [12] in single-hour trading period

for power suppliers' profit maximization. The MCP and net profits evaluated at corresponding optimal bidding coefficients as given in Table 4 obtained using GA [12], PSO [7], GSA [29], and MGSA are 5.35 \$/MW, 5.43 \$/MW, 5.46 \$/MW, 5.48 \$/MW, and \$ 1265.21, \$ 1328.61, \$ 1362.6, and \$ 1394.67, respectively. The optimal coefficient values and net profit using the proposed MGSA and other methods for comparison are presented in Tables 4 and 5, respectively. It can be observed from Table 5 that MGSA is getting higher MCP and highest profit amongst all the methods, showing the effectiveness of the MGSA.

Table 5. Optimal bidding results for single-hour trading period.

Generators	GA [12]		PSO [7]		GSA [29]		MGSA	
	G_{nt} (MW)	Profit (\$)	G_{nt} (MW)	Profit (\$)	G_{nt} (MW)	Profit (\$)	G_{nt} (MW)	Profit (\$)
1	371.48	426.25	385.58	469.4	392.2	490.3	387.1	493.5
2	30	22.74	46.54	36.31	40.88	34.03	30	26.69
3	229.53	261.96	232.78	282.5	250.2	310.2	249.2	315.0
4	60	85.02	60	89.46	60	91.53	60	92.94
5	298.95	407.79	258.22	377.2	240.8	362.5	266.7	403.7
6	43.04	61.45	49.88	73.76	48.86	74.1	40	62.79
MCP (\$/MW)	5.35		5.43		5.46		5.48	
Total Profit (\$)	1265.21		1328.61		1362.6		1394.67	
Total Generation (MW)	1033		1033		1033		1033	

Table 6. Performance comparison of the considered algorithms for the six-supplier system.

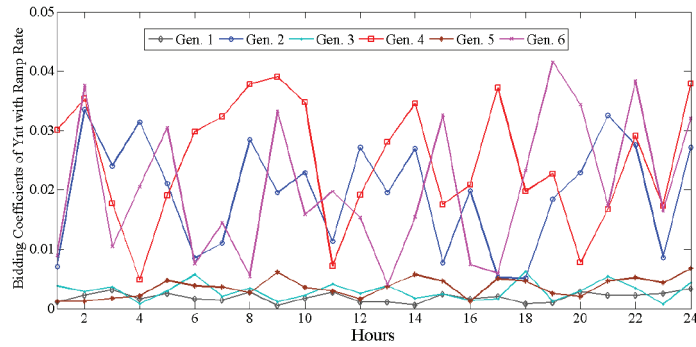
Total Profits (\$)	GA [12]	PSO [7]	GSA [29]	MGSA
Best (\$)	1265.21	1328.61	1362.60	1394.66
Worst (\$)	1117.81	1200.75	1268.19	1287.44
Mean	1166.54	1234.83	1297.44	1313.86
SD	31.85	29.60	28.15	24.40

Furthermore, to compare the algorithms' robustness, quality solutions of 100 trials for all the considered algorithms are obtained and presented in Table 6. It can be observed from Table 6 that the proposed MGSA is getting better results in terms of mean and standard deviation showing its strength.

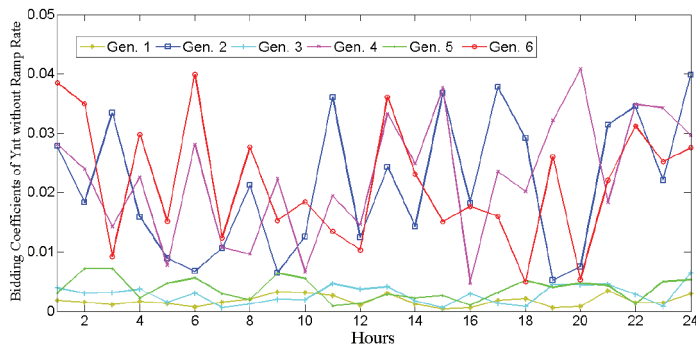
On the basis of this, the proposed bidding strategy for profit maximization of power suppliers with and without ramp rate is evaluated using the MGSA for a trading period of 24 h. The values of bidding coefficient X_{nt} given in Table 4 are kept constant for 24 h and optimal values of bidding coefficient Y_{nt} are obtained using the MGSA. Finally, using these coefficients X_{nt} and Y_{nt} , MCPs are calculated for every hour. These procedures are systematically estimated for both with and without ramp rates and bidding coefficients for all six generators are plotted for with and without ramp rates shown in Figure 3.

Similarly, MCPs with and without ramp rates are shown in Figure 4 for each hour. From figure 4, it can be assessed that in case of ramp rates, MCP values vary dynamically for each hour in contrast to without ramp rates which exhibit sudden variation while operating at the same levels for many hours, showing the inadequacy of the method to apprehend the realistic state of generators operation. Thus, ramp rate is essential to measure the dynamics of generator operation which is here correlated with obtained MCPs.

Based on the obtained bidding coefficients and MCP values, generator dispatch and their corresponding profit are evaluated. The individual generator power dispatch and their profits are shown in Figures 5 and 6



(a) Values of Y_{nt} for different generators with ramp rates



(b) Values of Y_{nt} for different generators without ramp rates

Figure 3. Values of Y_{nt} for different generators with and without ramp rates

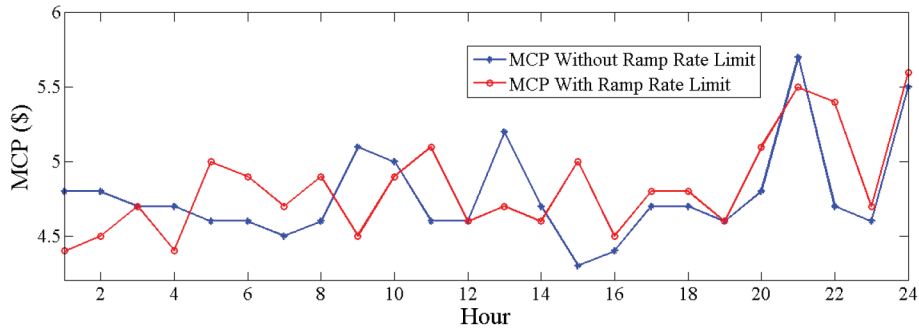


Figure 4. MCP with and without ramp rates.

and Table 7, respectively. Graphical representation of Table 7 is shown in Figure 7.

From Figure 3, it can be observed that with ramp rates, lower values of the bidding coefficients are obtained than without ramp rates in the majority of hours contemplating the higher values of MCPs. Thus, results in increased profit of generators by \$ 1612 in comparison to without ramp rates. This is shown in Figure 8. This profit may be further increased for a larger system and for longer bidding duration.

The convergence characteristics of the MGSA are shown in Figure 9. It is deduced that the MGSA provides fast convergence characteristics at initial stage and reaches to the better optimum solution with the

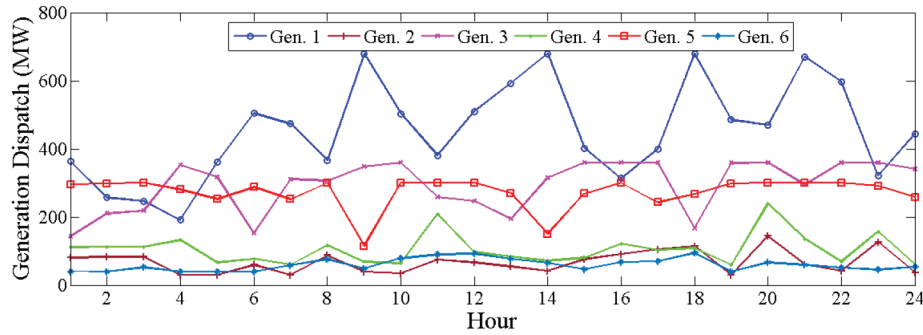


Figure 5. Generation dispatch with ramp rates.

Table 7. Profit of individual generators with and without ramp rates.

Hours	Profit of generators without ramp rates						Profit of generators with ramp rates					
	1	2	3	4	5	6	1	2	3	4	5	6
1	543.56	27.92	251.19	95.39	459.53	64.42	497.32	66.42	201.07	163.46	469.96	66.41
2	641.52	27.92	313.2	95.39	214.07	64.42	359.77	67.47	288.72	165.51	472.59	66.41
3	668.3	27.92	250.3	98.7	189.34	134.95	346.68	67.55	298.16	165.68	475.78	85.45
4	508.81	36.9	236.69	110.61	460.85	80.55	271.69	29.41	460.06	185.93	448.32	66.41
5	495.28	27.92	424.24	157.24	263.16	80.62	494.67	29.41	418.85	107.31	407.3	66.41
6	838.03	27.92	229.24	95.39	227.75	64.42	672.01	52.71	212.82	121.41	458.7	66.41
7	386.43	55.35	450.49	153.98	416.61	135.48	635.82	29.41	412.05	98.37	406.74	93.72
8	413.1	56.69	450.49	180.19	460.85	118.74	502.57	69.89	406.59	170.37	475.78	116.78
9	469.65	80.86	450.49	139.48	374.1	162.02	872.8	37.19	455	111.2	193.71	79.98
10	445.74	57.64	450.49	237.52	391.51	137.92	670.46	33.02	468.41	104.29	475.78	120.62
11	420.06	82.31	299.19	210.04	460.85	193.56	520.93	62.86	349.1	241.5	475.78	134.56
12	659.32	61.98	240.54	157.09	460.85	168.54	678.46	57.89	334.31	147.31	475.78	137.82
13	545.86	55.28	396.59	143.86	460.85	115.86	774.29	49.23	268.61	131.78	433.14	118.78
14	652.72	37.3	436.93	111.3	460.85	81.28	872.8	39	416.03	114.24	250.13	102.81
15	735.55	27.92	429.85	95.39	286.48	64.42	547.71	63.64	468.41	126.18	430.22	75.69
16	634.73	55.86	184.16	213.5	460.85	117.03	434.08	72.01	468.41	174.72	475.78	105.73
17	506	49.09	450.49	132.26	460.85	128.89	543.15	78.3	468.41	154.42	393.47	109.62
18	497.71	78.75	450.49	197.09	404.69	193.56	872.8	82.21	233.01	161.08	429.72	139.41
19	838.96	50.62	197.18	135.07	355.9	106.51	649.52	29.41	467.03	98.37	474.05	66.41
20	838.96	74.28	302.11	170.03	432.25	193.56	631.01	89.92	468.41	253.52	475.78	103.99
21	657.61	59.85	450.49	190.73	460.85	165.96	861.59	53.27	393.17	189.03	475.78	94.91
22	640.15	71.35	361.92	177.5	460.85	151.78	780.44	39.82	468.41	110.87	475.78	83.73
23	574.27	62.46	450.49	158.08	341.32	131.01	443.27	85.9	468.41	207.57	463.62	74.75
24	644.34	30.8	298.32	100.73	460.85	101.69	598.96	35.68	446.03	98.37	414.95	86.88

lapse of time, thereby not trapped in local minima. The reason for obtaining better results using the MGSA is that the gravitational constant maintains search accuracy in the GSA [29], which drops with time resulting in a rapid convergence rate. In addition, in the standard GSA [29], the opposition operator provides the search space beyond the reach of agents and thus enhances the GSA's [29] exploration capacity.

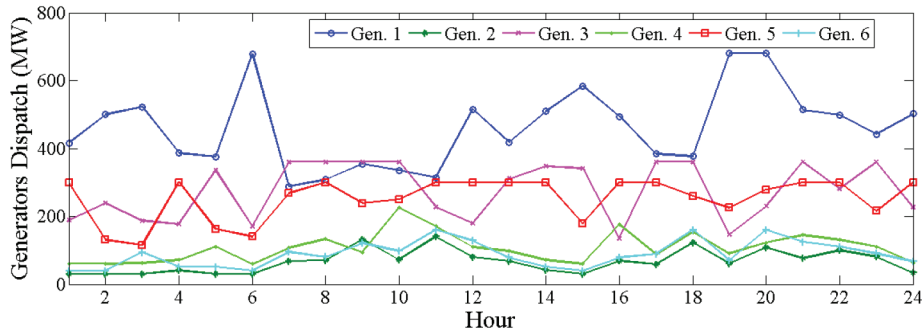
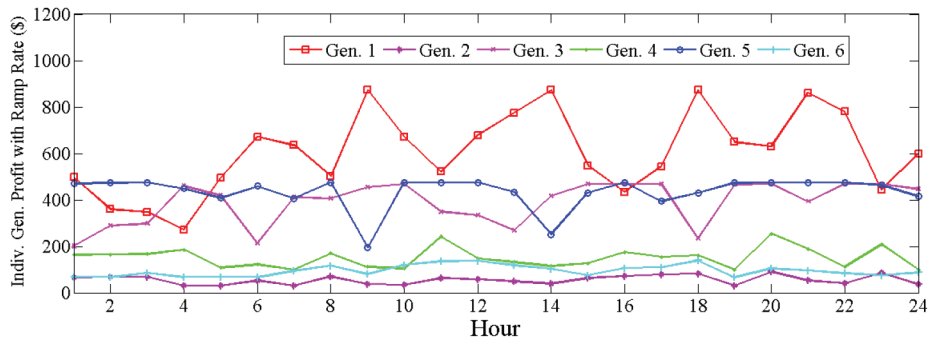


Figure 6. Generation dispatch without ramp rates.



(a) Profit of individual generators for each hour with ramp rates

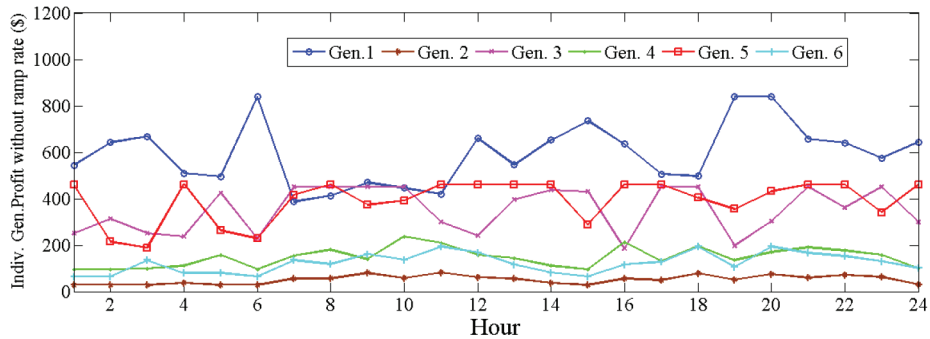


Figure 7. Profit of individual generators for each hour with and without ramp rates.

5. Conclusions

In this paper, the bidding strategy problem for profit maximization of power generators in a day-ahead electricity market is formulated considering ramp rate constraints and solved by using the MGSA. The profit obtained by a supplier in this formulation is not only related to its price-energy curve but also to its ramp rate. This work investigates the ramp rate effect on the profit of the power supplier. A standard is established for the estimation of the outcome of the competition between suppliers for commitment. Moreover, the process for optimizing the profit of an individual power supplier while ensuring its success in competition with its rivals are proposed by fine-tuning the ramp rate and bidding coefficients. The results obtained indicate that the participation of generators in a day-ahead electricity market bidding process without considering ramp rate

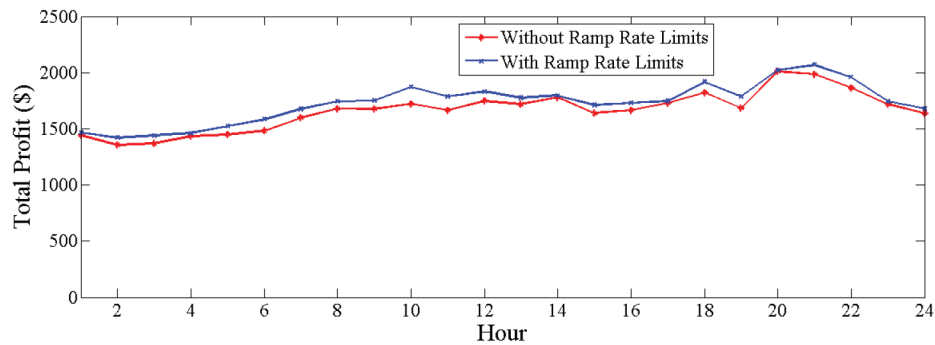


Figure 8. Comparative total profit assessment of generators with and without ramp rates.

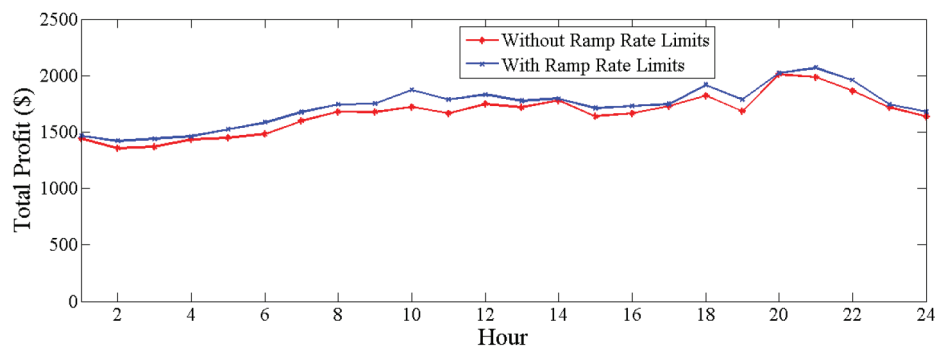


Figure 9. Convergence characteristics for the MGSA.

limits will cause economic loss to the generators as this extra cost is beared by generators. Consideration of hourly ramp rates provides practically feasible values of generation dispatch for each unit. The net profit of generators is also increased by incorporation of hourly ramp rate limits because the market clearing price for each hour is changed. The possible advantages cannot be ignored, and that bidding strategy can provide an opportunity for an individual power supplier to enhance their profit by adjusting their bid to the ramp rates and bidding coefficients. Therefore, the proposed bidding strategy considering ramp rate constraints is valuable for the market operator to recognize the effect of ramp rate constraints on the market outcomes and for the power supplier to develop bidding strategy in the light of operational results.

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