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A Novel Zero-Sum Polymatrix Game Theory Bidding Strategy for Power Supply Market

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Abstract*: *The competitive power system market involves very high financial risk due to the essential requirements of real-time bidding decision making. Decisions once taken cannot be altered easily because multiple generators participate in bidding process while simultaneously dispatching to meet the load demand most economically. In order to avoid such risks it becomes pertinent to re-structure the bidding strategies from time to time to meet upcoming techno-economical challenges. In this paper, three generating units are studied using Matrix Laboratory software with a novel approach for deciding the best strategy from the most economical strategy viewpoint. A scenario of different formulations is created for muti-player game, which then is solved with the help of zero-sum polymatrix game theory. A systematic tabular layout of revenues pertaining to each formulation in terms of mixed strategies is developed. The minimax and maximin revenues, identified using Game theoretic approach, gave the most economical strategy. Thus exact and self-enforcing generalized method for best bidding strategies of all three generators are logically derived for the most optimal solution.

Index Terms*: *Game Theory, Bidding Strategy,

I. INTRODUCTION

The global energy development in the electricity supply industry has created the deregulation and restructuring of power system bringing in competition among GENCOs (Generation Companies) [1], [2], [3]. The major task is planning and optimal operations of power systems competitive market for selling power at a lower price resulting in maximization of GENCOs profits [4], [5], [6]. New market mechanisms have changed the economics of power generation but maximization of GENCOs profits has appeared as an unwanted situation as it causes higher market prices than estimated [7], [8], [9]. Many mechanisms have already been reported to solve this complex problem to find the solutions under different situations such as the exhaustive search approach, the co-evolutionary programming approach, the payoff matrix approach, and the mathematical programming approach.

Exhaustive search is also known as the brute-force approach to solve combinatorial problems. According to that, all the generating elements of the problem domain, that satisfy all the constraints, are selected and then the desired element is found. Although the idea of this approach is quite easy, its execution requires a complex algorithm and not suitable for hierarchical arrangement and involves logical operations [10], [11]. A co-evolutionary programming algorithm is a collection of evolutionary algorithms in order to solve the large problems. The co-evolutionary programming and exhaustive search approaches require neither differentiability nor concavity of the payoffs. Therefore, they are not able to design to find mixed equilibria [12], [13]. The payoff matrix approach, in case of two players, can find a global solution for the given payoff matrix and can represent strategy results. This approach gives a linear complementarity pivot based on Lemke's algorithm. However, the optimality conditions are nonlinear in a case of the multiplayer game. So, this approach has been limited only to bimatrix player conditions [14] [15]. The mathematical programming approach is one of the techniques that uses a numerical framework for quantitative decision making. This approach can be used to solve a multi-player game that has differentiable and concave payoffs by the linear complementarity or conventional optimization technique. But for non-differentiable and non-convex payoffs, the optimality conditions are achieved only by taking a number of assumptions [16], [17], [18].

In all above approaches, it is difficult is to deal with a multi-player game where three or more players participate in an electricity market. Such a problem can be analyzed with zero-sum polymatrix game theory. In this paper a new approach is reported to obtain solutions of muti-player games with the help of zero-sum polymatrix game theory using various bidding formulations. In this approach, it is impossible for payoffs to flow out of the system estimation because all common situations interrelate pairwise and create decision in a closed matrix form, for betterment by redefining the generation scheduling problem to share the prevailing demand satisfactorily by developing an advanced technique and strategies for overcoming the different techniques as well as electricity management challenges.

II. PROPOSED RESEARCH METHODOLOGIES

A. *Economic Load Dispatch*

The second-order polynomial represented the fuel cost function of a generator, mostly used in power system and control problems operation, $\zeta_i(\rho_i)$ is the fuel cost of ith unit in $\Re$ where ρ_i is the power output of ith generating unit in MW [19].

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$$\zeta_i(\rho_i) = \lambda_i + \varpi_i(\rho_i) + \varsigma_i(\rho_i)^2 \quad (1)$$

The system total fuel cost function for n number of generating units is defined as

$$\zeta_T = \sum_{i=1}^{n} \zeta_i(\rho_i) = \sum_{i=1}^{n} \{\lambda_i + \varpi_i(\rho_i) + \varsigma_i(\rho_i)^2\} \quad (2)$$

Where λ, ϖ and ς are non-negative cost coefficient constants of the i[th] generator in $\Re$, $\Re$/MW, $\Re$/MW^2 respectively.

For the power balance constraints, ρ_i is the generation in MW of i[th] unit and ℓ_∂ is the load demand [20]. Then,

$$\sum_{i=1}^{n} \rho_i = \ell_\partial \quad (3)$$

For inequality constraints of generation limit, the maximum generation amount of the generator is predefined and the output power of any generator should not exceed its operating range of rating. If ρ_i (min) is the minimum and ρ_i (max) is the maximum generation in MW of i[th] unit then,

$$\rho_{i(\min)} \le \rho_i \le \rho_{i(\max)} \quad (4)$$

From solving equation (2) with constraints considered here by equation (3) and (4), the real power generation is easily obtained for each GENCO.

B. *Pricing*

It is envisaged that the GENCOs can set their bidding marginal costs slightly lower or higher than their respective marginal costs [21], [22], [23]. The prime objective of GENCOs under economic load dispatch is to maximize the profit while satisfying the load demand by selecting an optimal bidding strategy [21], [22], [24]. In this paper, it is assumed that the market clearing price of the generating system is the marginal costs of scheduled at lowest strategies of all generators for meeting the next hour MW of generation individually. Thus, $M\zeta_i(\rho_i)$ is the marginal cost of i[th] unit in $\Re$/MW with power output (ρ_i) in MW. The marginal cost expression is given by equation (5) [23], [25].

$$M\zeta_i(\rho_i) = \varpi_i + 2\varsigma_i(\rho_i) \quad (5)$$

Thus, bidding strategies combinations of all generators get created reflecting their incremental costs for further interpretation and analysis. It is essential to estimate the marginal cost for each participating generator and for their all bidding strategies accurately in order to evaluate efficient optimal bidding strategies of GENCOs.

C. *Bidding Strategy*

The bidding for the next MW of generation by a unit should be such that its marginal cost equals the market clearing cost [21], [25], [26]. The lowest case of all three generators for each set is considered to be the market clearing price for all set of strategy. The underlying reason for the above is that if the cost of generation of one additional MW of a generator is higher than the overall lowest marginal cost, then that generator will be selling the power at profit only in all the cases. This exercise created a combination of strategies revealing the contributions of all the three generators in terms of revenue for all the possible sets of bidding strategies. The generator wise marginal costs are evaluated separately for all the strategies. The bidding strategies applied in this paper is shown in Table 1.

Table 1 – Bidding Strategies.

Bidding Strategy	Cost
Low (Ꝋ)	80% of the $M\zeta$ of unit
Base (ɸ)	$M\zeta$ of unit
High (l)	120% of the $M\zeta$ of unit

D. *Polymatrix game theory for zero-sum*

In zero-sum polymatrix games, equilibrium can be found by the following properties [27]. (i) For the value of game, each player should have a unique payoff value in equilibria. (ii) For worst-case payoff, equilibrium strategies should be maximin or minimax strategies with respect to opponents. (iii) For exchangeable equilibrium strategies, the set of each player strategies is convex and the set is the corresponding product set. (iv) For the marginal sets that do not constitute equilibrium with respect to the players, there are no correlated equilibria. A game includes three key elements: players, actions, and payoffs. The functions of these three elements and their description are explained as follows [28]. (i) A set of players is a finite set of $G = \{1, 2, 3, ..., n\}$ indexed by *i*. (ii) A set of strategy actions $A = \{A_1, A_2, A_3, ..., A_n\} \in A$ available to each player to determine their possible strategies. (iii) A revenue function $R = \{R_1, R_2, R_3, ..., R_n\}$ represents preferences of each player on the basis of the payoff received by a player at the end of the game.

A case of generation by three players $\dot{G}_1$ (Generator1), $\dot{G}_2$ (Generator2), and $\dot{G}_3$ (Generator3) are considered. If player $\dot{G}_1$ has a single strategy Ꝋ (Low), then players $\dot{G}_2$ and $\dot{G}_3$ can chose to operate at any of the three strategies Ꝋ (Low), ɸ (Base) or l (High). For different operational equilibria, the different strategies give different payoffs to the players in zero-sum polymatrix games.

Such games revenue features can be represented by

$$R_1(G_1, G_2, G_3) + R_2(G_1, G_2, G_3) + R_3(G_1, G_2, G_3) = 0 \forall (G_1, G_2, G_3) \in A \quad (6)$$

$$R_1(G_1, G_2, G_3) = -\{R_2(G_1, G_2, G_3) + R_3(G_1, G_2, G_3)\} \quad (7)$$

$$R_2(G_1, G_2, G_3) = -\{R_1(G_1, G_2, G_3) + R_3(G_1, G_2, G_3)\} \quad (8)$$

$$R_3(G_1, G_2, G_3) = -\{R_1(G_1, G_2, G_3) + R_2(G_1, G_2, G_3)\} \quad (9)$$

The above order relations clearly represent the condition of a zero-sum game as it gets satisfied for all $(G_1, G_2, G_3) \in A$

If $R_1(G_1, G_2, G_3) + R_2(G_1, G_2, G_3) + R_3(G_1, G_2, G_3) = C$, (a non-zero constant) for all $(G_1, G_2, G_3) \in A$, then, an appropriate normalization can be used to convert it into a zero-sum game. The Maximin strategy, in game theory, is used in zero-sum games to denote maximum of the opponents' minimum payoff. In non-zero-sum games Maximin describes the strategy which minimizes overall maximum payoff. Minimax strategy is distinct from maximin. In zero sum game it is used to denote minimum of the opponents' maximum payoff. In a non-zero-sum game, this is identical to maximize overall minimum payoff [29].

III. SIMULATION RESULTS AND ANALYSIS

The simulation of economic load dispatch by three generators for three different constant loads was carried out separately on the Matrix Laboratory software. The data of three generators are given in Table 2 [19], [20].

Table 2 – Data of Generators

Generator	$\rho_{(max)}$	$\rho_{i(min)}$	ς	ϖ	ƛ
$\dot{G}_1$	600	150	0.00156	7.92	561
$\dot{G}_2$	400	100	0.00194	7.85	310
$\dot{G}_3$	200	50	0.00482	7.97	78

The bidding strategies Ό, ф and l were applied on all the three generators individually to evolve 3^3 =27 sets of the combinations for each load. ρ_1, ρ_2 and ρ_3 are power generated through economic load dispatch, based on particle swarm optimization technique. Then the revenues for G_1, G_2 and G_3 were obtained as represented by R_1, R_2 and R_3. These revenues for the three loads of 485MW, 585MW, and 685MW are given in Table 3, Table 4 and Table 5 respectively

Table 3 – Simulation result with scheduled load of 485 MW

S.No	Strategies			Power Generation (MW)			Revenue (Marginal Cost - Market Clearing Price) (ℜ /MW)		
	$\dot{G}_1$	$\dot{G}_2$	$\dot{G}_3$	ρ_1	ρ_2	ρ_3	R_1	R_2	R_3
1	Ό	Ό	Ό	151	247	87	0.0	0.0	0.0
2	Ό	Ό	ф	151	284	*50*	0.0	0.0	1.6
3	Ό	Ό	l	151	284	50	0.0	0.0	3.2
4	Ό	ф	Ό	189	*100*	196	0.2	1.3	0.1
5	Ό	ф	ф	265	*170*	*50*	0.3	1.3	1.6
6	Ό	ф	l	265	*170*	50	0.3	1.3	3.2
7	Ό	l	Ό	189	100	196	0.2	3.0	0.1
8	Ό	l	ф	300	100	*85*	0.3	3.0	1.6
9	Ό	l	l	335	100	50	0.3	3.0	3.2
10	ф	Ό	Ό	*151*	247	87	1.5	0.1	0.1
11	ф	Ό	ф	*151*	284	*50*	1.5	0.3	1.5
12	ф	Ό	l	*151*	284	50	1.2	0.3	3.2
13	ф	ф	Ό	*151*	*134*	200	1.5	1.5	1.0
14	ф	ф	ф	*223*	*196*	*66*	1.7	1.7	1.7
15	ф	ф	l	*232*	*203*	50	1.7	1.7	3.2
16	ф	l	Ό	*185*	100	200	1.6	3.0	1.0
17	ф	l	ф	*296*	100	*89*	2.0	3.0	1.9
18	ф	l	l	*335*	100	50	2.1	3.0	3.2
19	l	Ό	Ό	151	247	87	3.2	0.1	0.1
20	l	Ό	ф	151	284	*50*	3.2	0.3	1.5
21	l	Ό	l	151	284	50	3.2	0.3	3.2
22	l	ф	Ό	151	*134*	200	3.2	1.5	1.0
23	l	ф	ф	151	*247*	*87*	3.2	1.9	1.9
24	l	ф	l	151	*284*	50	3.2	2.1	3.2
25	l	l	Ό	151	134	200	3.2	3.1	1.1
26	l	l	ф	151	134	*200*	3.2	3.1	3.0
27	l	l	l	223	196	66	3.4	3.4	3.4

Table 4 – Simulation result with scheduled load of 585 MW

S.No	Strategies			Power Generation (MW)			Revenue Marginal Cost - Market Clearing Price (ℜ /MW)		
	$\dot{G}_1$	$\dot{G}_2$	$\dot{G}_3$	ρ_1	ρ_2	ρ_3	R_1	R_2	R_3
1	Ό	Ό	Ό	151	318	116	0	0	0
2	Ό	Ό	ф	151	384	50	0	0	1.5
3	Ό	Ό	l	151	384	50	0	0	3.1
4	Ό	ф	Ό	249	136	200	0.3	1.2	0.3
5	Ό	ф	ф	288	221	76	0.4	1.2	1.5
6	Ό	ф	l	297	238	50	0.4	1.2	3.1
7	Ό	l	Ό	285	100	200	0.3	2.9	0.3
8	Ό	l	ф	354	100	131	0.4	2.9	1.5
9	Ό	l	l	433	102	50	0.4	2.9	3.1
10	ф	Ό	Ό	151	319	115	1.4	0.3	0.3
11	ф	Ό	ф	151	384	50	1.4	0.5	1.5
12	ф	Ό	l	151	384	50	1.4	0.5	3.1
13	ф	ф	Ό	204	181	200	1.6	1.6	0.9
14	ф	ф	ф	270	234	81	1.8	1.8	1.8
15	ф	ф	l	270	249	50	1.8	1.8	3.1
16	ф	l	Ό	285	100	200	1.8	2.9	0.9
17	ф	l	ф	371	100	114	2.1	2.9	2.1
18	ф	l	l	435	100	50	2.3	2.9	3.1
19	l	Ό	Ό	151	319	115	3.1	0.3	0.3
20	l	Ό	ф	151	384	50	3.1	0.5	1.5
21	l	Ό	l	151	384	50	3.1	0.5	3.1
22	l	ф	Ό	151	234	200	3.1	1.8	0.9
23	l	ф	ф	151	318	116	3.1	2.1	2.1
24	l	ф	l	151	384	50	3.1	2.3	3.2
25	l	l	Ό	204	181	200	3.3	3.3	0.9
26	l	l	ф	204	181	200	3.3	3.3	2.9
27	l	l	l	270	234	81	3.5	3.5	3.5

Table 5 – Simulation result with scheduled load of 685 MW

S.No	Strategies			Power Generation (MW)			Revenue Marginal Cost - Market Clearing Price (ℜ /MW)		
	$\dot{G}_1$	$\dot{G}_2$	$\dot{G}_3$	ρ_1	ρ_2	ρ_3	R_1	R_2	R_3
1	Ό	Ό	Ό	151	400	134	0	0	0
2	Ό	Ό	ф	235	400	50	0.1	0.1	1.4
3	Ό	Ό	l	235	400	50	0.1	0.1	3
4	Ό	ф	Ό	281	204	200	0.3	1.1	0.3
5	Ό	ф	ф	313	275	97	0.6	1.1	1.4
6	Ό	ф	l	329	308	50	0.6	1.1	3
7	Ό	l	Ό	385	100	200	0.3	2.8	0.3
8	Ό	l	ф	407	100	178	0.6	2.8	1.4
9	Ό	l	l	467	165	53	0.6	2.8	3
10	ф	Ό	Ό	151	400	134	1.3	0.4	0.3
11	ф	Ό	ф	220	400	65	1.5	0.4	1.5
12	ф	Ό	l	235	400	50	1.6	0.4	3

13	ф	ф	Ό	260	225	200	1.6	1.6	0.8
14	ф	ф	ф	317	272	96	1.8	1.8	1.8
15	ф	ф	l	343	292	50	1.9	1.9	3
16	ф	l	Ό	385	100	200	2	2.8	0.8
17	ф	l	ф	447	100	138	2.2	2.8	2.2
18	ф	l	l	535	100	50	2.5	2.8	3
19	l	Ό	Ό	151	400	134	3	0.4	0.3
20	l	Ό	ф	151	400	134	3	0.4	2.2
21	l	Ό	l	220	400	65	3.2	0.4	3.2
22	l	ф	Ό	151	334	200	3	2	0.8
23	l	ф	ф	151	390	144	3	2.3	2.3
24	l	ф	l	220	400	65	3.2	2.3	3.2
25	l	l	Ό	260	225	200	3.4	3.4	0.8
26	l	l	ф	260	225	200	3.4	3.4	2.8
27	l	l	l	317	272	96	3.6	3.6	3.6

The zero values in the above tables indicate that the corresponding generator would run on no profit, no loss basis. The others, however, would run with a profit range.

The output data, in terms of revenues given in Table 3, Table 4 and Table 5 and are plotted as Figure 1, Figure 2 and Figure 3 respectively. From these figures, it is observed that the revenue trends are identical corresponding to the different sets of bidding strategies, applied on particular generators (G1, G2 or G3) with the three different loads (485 MW, 585 MW and 685 MW).

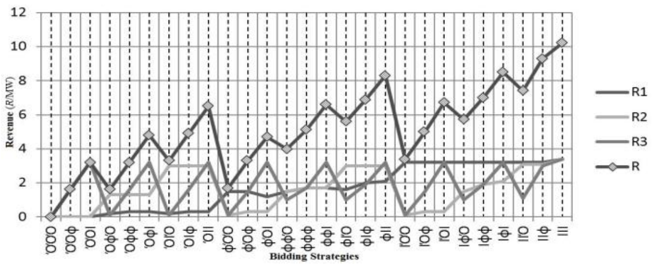

Figure 1– Revenue graph for scheduled load of 485 MW

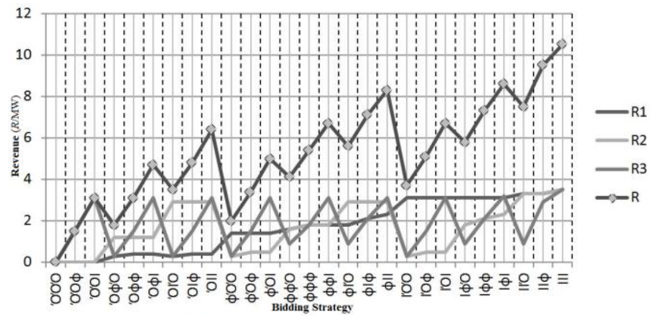

Figure 2– Revenue graph for scheduled load of 585 MW

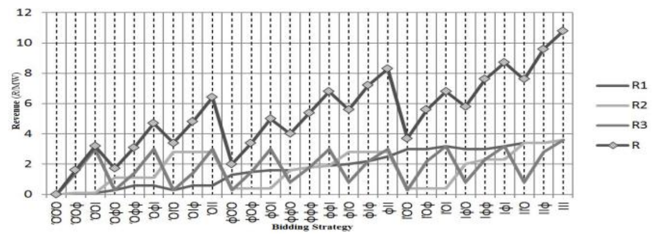

Figure 3– Revenue graph for scheduled load of 685 MW

It is interesting to note that the four types of lines in all the above figures indicate the revenue in terms of profit. This can be observed that the 27 strategies give maximum, moderate or low profit for individual generators. Based on the results obtained, a matrix is formulated to facilitate application of game theory. Here, the symbols '√' are and 'X' are assigned to the conditions of 'optimal solution' and of 'non-optimal solution' respectively as concluded from Figure 1, Figure 2 and Figure 3. An exercise was carried out to identified the strategies giving minimum profit by running a particular generator at low, base or high throughout, in combination with all other possibilities for the rest the generators. The matrix, shown in Table 6 is so developed that all possible combinations appear together for each of the three generators under consideration, catering to the three constant loads separately.

Table 6 – Game theory strategic matrix for all scheduled load

Matrix for three Generator		Ġ3: Ό			Ġ3: ф			Ġ3: l		
	Ġ2 →	Ό	ф	l	Ό	ф	l	Ό	ф	l
Ġ1 (485MW)	Ό	X	√	√	√	X	X	√	X	X
	ф	√	X	X	X	X	X	X	X	X
	l	√	X	X	X	X	X	X	X	X
Ġ1 (585MW)	Ό	X	√	√	√	X	X	√	X	X
	ф	√	X	X	X	X	X	X	X	X
	l	√	X	X	X	X	X	X	X	X
Ġ1 (685MW)	Ό	X	√	√	√	X	X	√	X	X
	ф	√	X	X	X	X	X	X	X	X
	l	√	X	X	X	X	X	X	X	X

It is observed from Table 6 that out of twenty seven strategies, only six identical strategies, represented by '√', give optimal solutions for the three different loading conditions. It is interesting to note that in all such six strategies, two out of the three generators operate at Ό strategy.

Further in this study, the zero-sum matrix game theory was applied on the above data to find the maximum profit giving combination. Table 7, developed using the data from Table 6, contains the strategies giving maximum profits for the three loading conditions.

Table 7– Optimal simulation result for all scheduled load

S.No	Strategies			Marginal Cost - Market Clearing Price (ℜ /MW)									For 485 MW Maximum (ℜ /MW)	For 585 MW Maximum (ℜ /MW)	For 685 MW Maximum (ℜ /MW)
				485 MW			585 MW			685 MW					
	Ġ1	**Ġ2**	**Ġ3**	**R_1**	**R_2**	**R_3**	**R_1**	**R_2**	**R_3**	**R_1**	**R_2**	**R_3**			
1	Ό	Ό	ϕ	0	0	1.6	0	0	1.5	0	0	1.4	1.6	1.5	**1.4**
2	Ό	Ό	ι	0	0	3.2	0	0	3.1	0	0	3	3.2	3.1	**3**
3	Ό	ϕ	Ό	0	1.3	0	0.	1.2	0	0	1.1	0	1.3	1.2	**1.1**
4	Ό	ι	Ό	0	3	0	0	2.9	0	0	2.8	0	3	2.9	**2.8**
5	ϕ	Ό	Ό	1.5	0	0	1.4	0	0	1.3	0	0	1.5	1.4	**1.3**
6	ι	Ό	Ό	3.2	0	0	3.1	0	0	3	0	0	3.2	3.1	**3**
Minimum (ℜ /MW)				**1.5**	**1.3**	**1.6**	**1.4**	**1.2**	**1.5**	**1.3**	**1.1**	**1.4**			

Next, in the same Table, the maximin and minimax game theory is applied to find out the maximum and the minimum values of R_1, R_2 and R_3. For simplicity, the revenues less than 0.5 are represented as zeros in this Table. From the last three columns and the last row of Table 7, the maximin and minimax values respectively were obtained for the three different loading conditions. It is seen from the Table that these maximin and the minimax values are found to be identical and to be equal to 1.3 ℜ /MW, 1.2 ℜ /MW, and 1.1 ℜ /MW for the loads of 485 MW, 585MW and 685 MW respectively. It was revealed that all these values belonged to the ΌϕΌ combinatorial strategy identically for all the three loading conditions. This inference does not change even if the values smaller than 0.5 were not considered to be zero. It is further observed from the Table 3, 4 and 5, that the differences of revenues among the three generators is minimum for the strategies so chosen.

IV. CONCLUSION

In an electricity trading process, contemporary upcoming global fossil fuel crisis and social welfare challenges create competition in power supply market. This necessitates modification of bidding strategy from time to time to meet the optimal techno- economical solution. Bidding is done on a real-time basis and imperfect information in conventional bidding strategies may cause serve loss to generating companies. In this paper, behavior and performance of three GENCOs, supplying to three different constant loads, are considered. Their bidding strategies are analyzed in an electricity power market with the zero-sum game theory principle. Firstly, the economic load dispatch was obtained using Matrix Laboratory software for various bidding strategy scenarios. Thereafter, the performances of all possible combinations of the bidding strategies for the three generating units are obtained and analyzed. Next, the exact revenue strategies for making a profit are identified for all possible bidding combinations. The optimal best for results were then investigated by zero-sum matrix game theory to find out the maximum profit giving combination. The proposed approach is based on the techno-economical solution in the term of revenue, to obtain the profitable strategies. Thus, by this multi-players Game Theoretic based approach, one can predetermine the revenue values and avert loss making bad bidding strategy decisions in real-time bidding market.

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