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Risk-constrained Optimal Bidding Strategies for Generation Companies using Differential Evolution

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Abstract— The emerging electricity market behaves more like an oligopoly than a perfectly competitive market. The profit of each supplier is influenced to varying extents by differences in the degree of imperfection of knowledge of their rivals. This paper discusses the optimal bidding strategies of Generating companies (Gencos) solved using Differential Evolution (DE) algorithm for the first time. It is assumed that each Genco bids a linear supply function, and chooses the coefficient in the linear supply function to maximize their benefits, subject to expectations about how the rivals will bid. A normal probability distribution function (pdf) is used to describe the bidding behaviors of rivals and the problem of building optimal bidding strategies for Gencos is formulated as stochastic optimization problem. The proposed algorithm is tested for six generating companies with different risk coefficients and load price elasticity factor. The obtained results are compared with those obtained by Reference [14].

Keywords – Electricity market, Gencos (Generating Companies), Bidding Strategy, Stochastic Optimization, Monte Carlo Method, Differential Evolution.

I. INTRODUCTION

In the past several years, the power industry, in many countries around the globe, has been undergoing massive changes to introduce competition. Accordingly, a variety of restructuring models have been proposed, considered and experimented with in different countries. Among these models, the power pool (Pool co-type) market structure is the most popular.

The power pool acts, effectively, like a broker for managing energy suppliers, bidders and large customers, and establishes a market clearing price (MCP). MCP is the bid price of the most expensive supplier that is needed to completely meet the demand and is used as the basis for the settlement of market commitments. Regardless of the bidding prices from suppliers, all selected bidders are paid the MCP. This approach is adopted to encourage suppliers in a competitive market to price energy close to their marginal costs. The sealed bid auction is widely used in the pool-co type electricity market. Each supplier submits a sealed bid to the pool to compete for the supply of the forecast load that is broadcast by the pool. Theoretically, in a perfectly competitive market, suppliers should bid at, or very close to their marginal production costs to maximize returns. However, the electricity market is not perfectly competitive due to special features, such as large investment size (barrier to entry) and economy of scale in the generation sector, and therefore more akin to oligopoly.

In oligopolistic electricity markets, Gencos could exercise strategic bidding to maximize their own profits. The problem of how to develop optimal bidding strategies for competitive Gencos in the electricity market environment was addressed for the first time in [1]. A comprehensive review of optimal bidding strategies in Electricity market has been reported in [2].The main factors which affect the bidding behavior are the demand variation, generator production cost, operating (or) some regulatory constraints and other competitors bidding behavior etc. Among them, the most uncertain factor is rivals bidding behavior that compounds the difficulties in bidding strategy decision process due to special nature of electricity compared to the other commodities where each player tries to play game to maximize their own profit.

At present most of the research work is based on the estimation of rival's bidding behaviors by employing available information such as historical bidding data. Bidding decision based on incomplete information will surely incur certain risks to the Gencos concerned. For example, if the estimations of a Genco about rival are higher than their actual bidding prices and this will lead to the risk of not being dispatched or the dispatched generation level significantly lower than expected.

David and Wen [3]-[5], have modeled the strategic bidding as a stochastic optimization problem for single period auction where competitor's bidding behavior is estimated through stochastic Monte Carlo simulation. Monte Carlo simulation [6] is a technique which provides probabilistically approximate solutions to mathematical, physical and engineering problems by performing stochastic simulation using random numbers. It can be directly applied

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to problems with inherent probabilistic structures and requires the physical or mathematical system to be described by probability density functions.

Markov decision process was applied in [7] to solve multi-stage probabilistic bidding decision problem. Richter and Sheble have applied genetic algorithm GA [8]-[9] to Genco strategies and schedules in which an intelligent bidding strategy was developed using GP-Automata algorithm for the bidding strategy. Although GA has an advantage of searching the solution space more thoroughly, they are sensitive to the choice of parameter such as the cross-over parameter and mutation probabilities. The other frequently applied AI techniques [10]-[12] such as Simulated Annealing (SA), Evolutionary Programming (EP) and Particle Swarm Optimization (PSO) also suffer from proper selection of parameter such as temperature in SA, scaling factor in EP, and inertia weight and learning factors in PSO. Bajpai et al., [13] have studied the bidding strategy in uniform price spot market using Fuzzy Adaptive Particle swarm Optimization. Ma et al., [14] have developed the risk constrained optimal bidding strategies for single sided auction using an optimization based method.

Although the importance of risk management in bidding decision-making is widely recognized [14], very limited research work has been done in this field up to now and the research outputs achieved so far are very preliminary.

This paper suggests an alternative framework of developing optimal bidding strategies for Gencos in a deregulated market with associated risks taken into account. A normal probability distribution function (pdf) is used to describe the bidding behaviors of rivals. The problem is stochastic in nature which is solved by Monte-Carlo method and the optimal solution is obtained by Differential Evolution method [16] for the first time. Differential evolution method, a modified GA, which is an efficient and robust method, is used that can generate better optimal solution in less calculation time with stable convergence characteristics compared to other population based methods. The technique presented in this paper can be adapted to the more complex situation, and this will be accounted for in later studies.

This paper is organized as follows. Section II explains the formulation of the problem for the single sided auction. Section III describes the proposed solution algorithm using Monte Carlo and Differential evolution methods. Section IV illustrates conceptual analysis for a test system. The results and discussions are presented in the Section V. Conclusive remarks are given in section VI.

II. PROBLEM FORMULATION

Consider there are n independent Gencos participating in a pool based single-buyer electricity market in which the sealed auction with a uniform MCP is employed. Assume that each Genco is required to submit a linear supply function to the pool together with the generation output limits and the j^{th} Genco's supply function is $B_j(P_j) = \alpha_j + \beta_j P_j$, where P_j is the generation output and α_j and β_j are the bidding coefficients. In a well competitive situation, the bidding coefficients will be equal to the production cost coefficients. Generation output limits $P_{j\max}$ and $P_{j\min}$ are also specified by the bidder. Upon receiving bids from Gencos, the pool determines a set of generation outputs that meets the load demand and minimizes the total purchasing cost. It is clear that dispatch of the generated power should satisfy the following Eqn. (1)-(3).

$$\alpha_j + \beta_j P_j = R \qquad (j = 1, 2, ..., n) \tag{1}$$

$$\sum_{j=1}^{n} P_j = Q(R) \tag{2}$$

$$P_{j\min} \le P_j \le P_{j\max} \tag{3}$$

where, R is the market clearing price, and $Q(R)$ is the total demand given by

$$Q(R) = Q_0 - KR \tag{4}$$

K is a nonnegative constant used to represent the load – price elasticity. When the inequality constraints (3) are ignored, the solutions to (1) and (2) are,

$$R = \frac{Q_0 + \sum_{j=1}^{n} (\alpha_j / \beta_j)}{K + \sum_{j=1}^{n} (1/\beta_j)} \tag{5}$$

$$P_j = \frac{(R - \alpha_j)}{\beta_j} \tag{6}$$

The calculated values of P_j should be checked for violation of limits as follows

if $P_j < P_{j\min}$

set $P_j = 0$

and the Genco j should be removed from the competition since the dispatch is less than the minimum output of the supplier and

if $P_j > P_{j\max}$

set $P_j = P_{j\max}$

and fix the dispatched level of this generator since it is no longer a marginal unit. Repeat this procedure until the dispatched levels of all generators are fixed and no constraints are violated. In this case we have not considered the transmission losses into account.

The profit of Genco i $(i = 1, 2, ...n)$ in a unit time can be described as

$$\pi_i = RP_i - C_i(P_i) \tag{7}$$

If P_i does not violate the constraints (3), the eqn. (7) can be rewritten as

$$\pi_i = \frac{R(R-\alpha_i)}{\beta_i} - C_i\left(\frac{R-\alpha_i}{\beta_i}\right) \quad (8)$$

where $, C_i(P_i)$ is the production cost function of the i^{th} Genco.

Since the i^{th} Genco does not know the rivals bidding price before the auction, the optimization problem of maximizing the profit of Genco is not possible. But the rival's bidding behavior can however be estimated using the historical data, load forecast and any other available information.

We assumed that the rival's bidding coefficients α_j and β_j $(j \neq i)$ as estimated by i^{th} Genco, obey a jointly normal distribution as follows,

$$(\alpha_j, \beta_j) \sim N\left\{\begin{bmatrix}\mu_j^{(\alpha)} \\ \mu_j^{(\beta)}\end{bmatrix}, \begin{bmatrix}(\sigma_j^{(\alpha)})^2 & \rho_j\sigma_j^{(\alpha)}\sigma_j^{(\beta)} \\ \rho_j\sigma_j^{(\alpha)}\sigma_j^{(\beta)} & (\sigma_j^{(\beta)})^2\end{bmatrix}\right\} \quad (9)$$

where, ρ_j is the correlation coefficient between α_j and β_j. The marginal distributions of α_j and β_j are both normal with mean values $\mu_j^{(\alpha)}$, $\mu_j^{(\beta)}$, and $\sigma_j^{(\alpha)}$, $\sigma_j^{(\beta)}$, respectively.

From the well developed investment theory, it is known that the variance of the potential profit could be used to evaluate the risk of an investment. Following this concept, the problem of building an optimal bidding strategy for the i^{th} Genco with associated risks taken into account could be formulated as the following stochastic optimization problem.
Maximize

$$\Psi(\alpha_i, \beta_i) = (1-\lambda)E(\pi_i) - \lambda D(\pi_i) \quad (10)$$

Subject to

$$P_{i,\min} \le \frac{E(R)-\alpha_i}{\beta_i} \le P_{i\max} \quad (11)$$

where $E(\pi_i)$ and $D(\pi_i) = \sqrt{\{\mathrm{var}(\pi_i)\}}$ are the expected value and standard deviation of the profit π_i and $E(R)$ is the expected value of MCP. Risk coefficient λ ($0 \le \lambda \ge 1$) is used to represent the degree of risk averseness of Genco i. The value $\lambda = 0$ denotes the situation that the only objective is to maximize profit without consideration of risks, and $\lambda = 1$ represents the other extreme where risk minimization is the unique objective. Henceforth Genco should balance these conflicting objectives (i.e.,), profit maximization and risk minimization. Hence the problem of building an optimal bidding strategy for the i^{th} Genco with risk management can be described as: for a given risk coefficient λ, determine bidding coefficients α_i and β_i so as to maximize $\Psi(\alpha_i, \beta_i)$ subject to (11).

While maximizing $\Psi(\alpha_i, \beta_i)$, with the constraint (11), since two bidding coefficients cannot be optimized at the same time, one of the coefficients is fixed and the other can be searched using any optimization procedure. In this work, we fixed α_i and the values of β_i are searched through Differential Evolution technique [16].

III. PROPOSED ALGORITHM

The stochastic optimization problem formulated in the previous section has been solved using Monte-Carlo simulation, a technique which obtains a probabilistic approximation of a mathematical problem by using statistical sampling technique. It performs stochastic simulation using random numbers and repeatedly calculates the equations to arrive at a solution. A recent population based heuristic algorithm, Differential Evolution has been used for the first time in this paper to obtain the optimal bidding strategy of a Generating Company.

A. A Brief Introduction to the Monte Carlo method

The Monte Carlo method provides approximate solutions to a variety of mathematical problems by performing statistical sampling experiments on a computer. This method can be directly applied to problems with inherent probabilistic structures. It requires that the physical or mathematical system be described by probability density functions (pdf's). Simulation can be done by random sampling from these pdf's and necessitates a fast and effective way to generate random numbers uniformly distributed in the interval [0, 1]. The outcomes of these trials are accumulated or tallied. Many simulations are performed and the desired result is taken as an average or expectation over all the trials.

B. Differential Evolution

Differential Evolution (DE) is an optimization algorithm developed by Storn and Price, which solves real-valued problems based on the principles of natural evolution [16]. DE uses a population P of size N_p, composed of floating point encoded individuals that evolve over G generations to reach an optimal solution. Each individual X_i is a vector that contains as many parameters as the problem decision variables D. The population size N_p is an algorithm control parameter selected by the user which remains constant throughout the optimization process.

$$X_i^{(G)} = [X_{1,i}^{(G)}, ..., X_{D,i}^{(G)}]^T, \quad i = 1,...,N_p \quad (12)$$

The optimization process in differential evolution is carried out with three basic operations viz, mutation, crossover and selection. This algorithm starts by creating an initial population of N_p vectors. Random values are assigned to each decision parameter in every vector according to

$$X_{j,i}^{(0)} = X_j^{\min} + \eta_j(X_j^{\max} - X_j^{\min}) \quad (13)$$

where $i = 1,...,N_p$ and $j = 1,....D$; $X_j^{\min}$ and $X_j^{\max}$ are the lower and upper bounds of the j^{th} decision parameter; and η_j is an uniformly distributed random number within [0,1] generated a new for each value of j. $X_{j,i}^{(0)}$ is the j^{th} parameter of the i^{th} individual of the initial population.

The mutation operator creates mutant vectors $(X_i^{'})$ by perturbing a randomly selected vector (X_a) with the difference of two other randomly selected vectors $(X_b$ and $X_c)$.

$$X_i^{'(G)} = X_a^{(G)} + F(X_b^{(G)} - X_c^{(G)}) \quad i = 1,...,N_p \tag{14}$$

where X_a, X_b and X_c, are randomly chosen vectors $\in \{1,...,N_p\}$ and $a \neq b \neq c \neq i$. X_a, X_b and X_c are selected newly for each parent vector. The scaling constant (F) is an algorithm control parameter used to control the perturbation size in the mutation operator and improve algorithm convergence.

The crossover operation generates trial vectors $(X_i^{''})$ by mixing the parameters of the mutant vectors with the target vectors (X_i), according to a selected probability distribution,

$$X_{j,i}^{''(G)} = \begin{cases} X_{j,i}^{'(G)} & \text{if } \eta_j^{'} \leq C_R \text{ or } j = q, \\ X_{j,i}^{(G)} & \text{otherwise} \end{cases} \tag{15}$$

where $i = 1,...,N_p$ and $j = 1,....D$; q is a randomly chosen index $\in \{1,...,N_p\}$ which guarantees that the trial vector gets at least one parameter from the mutant vector; $\eta_j^{'}$ is a uniformly distributed random number within [0,1] generated newly for each value of j. Crossover constant C_R is an algorithm parameter that controls the diversity of the population and aids the algorithm to escape from local optima. $X_{j,i}^{(G)}$, $X_{j,i}^{'(G)}$ and $X_{j,i}^{''(G)}$ are the j^{th} parameter of the i^{th} target vector, mutant vector, and trial vector at generation G, respectively.

Finally, the selection operator determines the population by choosing, among the trial vectors and their predecessors (target vectors), those individuals which present a better fitness or are more optimal according to

$$X_i^{(G+1)} = \begin{cases} X_i^{''(G)} & \text{if } f(X_i^{''(G)}) \leq f(X_i^{(G)}), \; i = 1,.....,N_p, \\ X_i^{(G)} & \text{otherwise} \end{cases} \tag{16}$$

The optimization process is repeated for several generations, allowing individuals to improve their fitness as they explore the solution space in the search for optimal values.

DE has three essential control parameters: scaling factor (F), crossover constant (C_R) and population size (N_p). The scaling factor is a value in the range (0, 2) that controls the amount of perturbation in the mutation process. The crossover constant is a value in the range (0, 1) that controls the diversity of the population. The population size determines the number of individuals in the population and provides the algorithm enough diversity to search the solution space [20]. DE offers several variants or strategies for optimization. These can be denoted by DE/x/y/z, where x refers to the vector used to generate mutant vectors, y the number of difference vectors used in the mutations process and z the crossover scheme used in the crossover operation. Totally ten different working strategies have been proposed by Price & Storn [16].

The algorithm used in this paper is the seventh strategy of DE (i.e.,) DE/rand/1/bin in which 'DE' represents differential evolution, 'rand' is any randomly chosen vector for perturbations, '1' represents the number of difference vectors to be perturbed and 'bin' is the binomial type of crossover used. Price and Storn [16], [20]-[21] have given some simple rules for choosing the parameter of DE for any given application. According to them, the following ranges are the good initial estimates while using the strategy DE/rand/1/bin: F = [0.5, 0.6], C_R = [0.75, 0.9], and N_p = [3*D, 8*D]. Values of scaling factor lower than 0.5 may result in premature convergence, while greater than 1 tend to slow down convergence speed. To avoid local optima, cross over constant should be reduced to provide more diversity of parameters. Large populations help to maintain diverse individuals but slow down convergence speed. Therefore in order to avoid premature convergence, either F or N_p should be increased or C_R should be decreased. Larger values of F result in larger perturbations and better probabilities to escape from local optima, while lower C_R preserves more diversity in the population, thus avoiding local optima.

The solution algorithm used in the present study for solving the optimal bidding problem for Genco i is as follows

1) Specify α_i for the i^{th} Genco, Q_0, K, $P_{j\min}$, $P_{j\max}$ ($j = 1,2..n$) and the parameters of pdf's of the rivals bidding strategies as (18).
2) Create the Differential evolution algorithm whose population members represent β_i for the i^{th} Genco in the interval of $(0.5\beta_i,\ 5\beta_i)$.
3) Initialize DE population and the maximum generation number T_{gen}.
4) Set the iteration counter $t_{gen} = 0$.
5) Execute a Monte-Carlo simulation for every member of the population to calculate the expected profit and standard deviation as follows:
   a. Specify the maximum number of Monte-Carlo simulation, *MC*.
   b. Set the Monte-Carlo simulation counter *mc=0*.
   c. Generate random samples for α_j, β_j, $(j = 1,2,....n)$ $(j \neq i)$, based on their pdf's, as given in (9).
   d. Determine the market clearing price *R*, using (5) and calculate π using (7).
   e. Increment the Monte-Carlo simulation counter *mc*=*mc*+1.
   f. If *mc* <*MC*, go to c: else go to g.
   g. Calculate the expectation value $E(\pi)$ and the standard deviation $D(\pi)$ and then calculate $\psi(\alpha_i, \beta_i)$ using (10).

6) Use $\psi(\alpha_i, \beta_i)$ as the fitness function for the population members.

7) Increment $t_{gen} = t_{gen} + 1$.

8) Perform mutation, crossover and selection operation.

9) If $t_{gen} < T_{gen}$, go to 5c. Else go to 10.

10) Obtain the fittest member of the Differential Evolution as the optimal bidding strategy, and print the results.

IV. NUMERICAL EXAMPLE

Consider six independent Genco's participating in an electricity market, and the production cost function of the j^{th} ($j = 1,2...n$) Genco is given by,

$$C_j(P_j) = b_j P_j + \frac{1}{2} c_j P^2{}_j \tag{17}$$

The production cost function coefficients and output limits of all six genco's are given in Appendix I. Suppose that the second Genco is our subject of research, and its estimation of the rivals bidding parameters i.e. the expected values and the standard deviations are specified as follows:

$$\left.\begin{aligned} &\mu_j^{(\alpha)} = 1.2 b_j, \mu_j^{(\beta)} = 1.2 c_j \\ &3\sigma_j^{(\alpha)} = 0.15 b_j, 3\sigma_j^{(\beta)} = 0.15 c_j \\ &\rho_j = -0.1 \\ &j = 1,3,4,5,6 \end{aligned}\right\} \tag{18}$$

The specifications of these parameters are the same as in [3]. From (18) it is known that the expected values of α_j and β_j are specified 20% above b_j and c_j respectively and the standard deviations of α_j and β_j are specified to make them fall in the domains

$[1.05b_j,\ 1.35b_j] = [\mu_j^{(\alpha)} - 3\sigma_j^{(\alpha)}, \mu_j^{(\alpha)} + 3\sigma_j^{(\alpha)}]$ and

$[1.05c_j,\ 1.35c_j] = [\mu_j^{(\beta)} - 3\sigma_j^{(\beta)}, \mu_j^{(\beta)} + 3\sigma_j^{(\beta)}]$

respectively. Here ρ_j is specified to be negative because when a Genco decides to increase one of its bidding coefficients, it is more likely that in a mature electricity market it will decrease rather than increasing the other one. Certainly, it is also possible that ρ_j takes a positive value for some Gencos who want to change the bidding patterns significantly.

Now for Genco 2 fix $\alpha_2 = 1.75$ and determine β_2 by solving the optimization problem as described by using Differential Evolution method [16]. Obviously, β_2 should not be less than $0.5\,c_2$, otherwise it will be a loss. The search domain for β_2 is specified to be $[m_1 c_2,\ m_2 c_2]$, and $m_1 = 0.5$, $m_2 = 5$, since this range is wide enough. The simulation parameters are listed in Appendix II.

V. RESULTS AND DISCUSSION

A. Case 1

In this case, we compare the results of dispatched power of all six gencos. The figure (1) shows the values of dispatched powers obtained by the proposed method against those given in Reference [14]. It is seen from the graph that the dispatched power of genco 2 for a given risk coefficient $\lambda = 0.5$ and $K = 20$ is more than the other method proving the effectiveness of the differential evolution method. More the power dispatched, more the profit is and hence the benefit to the consumers is also more.

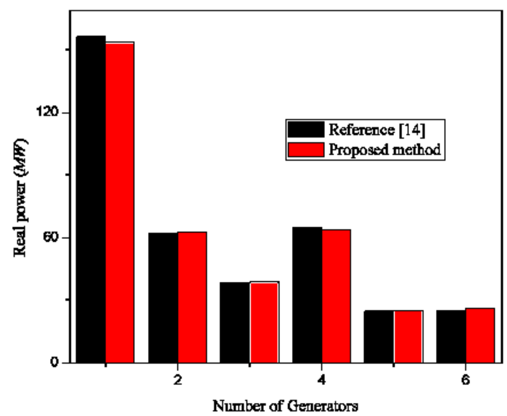

Fig. 1. Optimal Dispatched powers of Generators

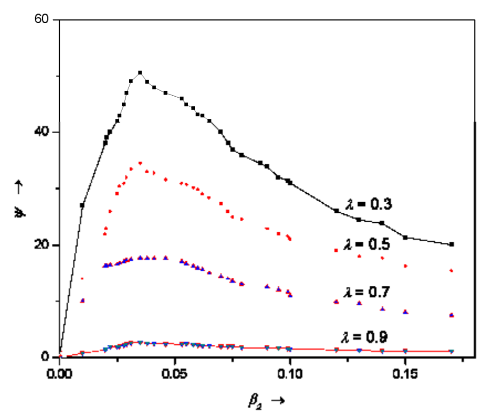

Fig. 2. Variation of profit ψ with respect to bidding coefficient β_2 for different λ

B. Case 2

Table I shows the comparative simulation results for proposed method and the optimization based method [14] for various parameters, and it is found that for a given λ DE gives lesser values of the bidding coefficient β_2 than the other method, thereby increasing the dispatched power, market clearing price, expected profit and the actual profit. This shows the robustness and effectiveness of the differential evolution method. From Figure 2 it can be clearly seen that when the risk coefficient λ increases the profit decreases and when it is very high, say $\lambda = 0.9$ the profit is very less. When λ varies from 0.9 to 0.915 there is a considerable change in the variance of the expected profit which implies that the expected dispatched generation level of a rival is beyond its lower limit and hence the rival quits from the competition. Therefore risk factor should be considered in such a way, that the genco's should survive in the market and also get the maximum benefit compared to their rivals.

C. *Case 3*

This case demonstrates the effect of load price elasticity factor, with increase of λ, on different bidding parameters. When the load price elasticity factor K varies from 15 to 20 and from 20 to 25, with the increase in λ, it can be noted from Tables II-IV, that the expected dispatched power of the genco 2 is increasing, but with a little decrease in the optimal bidding coefficient β_2, expected market clearing price R, as well as the expected value and variance of the profit.

From Figure 3 it can be noticed that the expected dispatch power level of genco 2 is increasing with increasing K, whereas for the rivals, the output decreases as K increases.

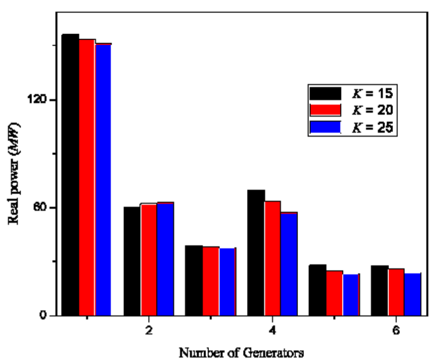

Fig. 3. Dispatched power of six genco's for increased load price elasticity factor

D. *Case 4*

In this case the load is varied with 20% increase from the base case and the results are listed in Table V. From the Table V, it can be clearly seen that when the load is 20% more than the base case the expected market clearing price R is higher than the base case for the constant risk coefficient $\lambda = 0.5$ and $K = 20$. This means that the suppliers have still succeeded in exercising market power. The degree to which the market price of electricity is above the competitive level is 4.14% higher than the base case. But for higher values of K, when load increases, the bidding coefficient β_2, expected dispatched level P_2, expected market clearing price R as well as the expected value and variance of the profit of the genco 2 decrease, thereby facing a more competitive situation to dispatch its power to the consumers.

VI. CONCLUSIONS

Differential evolution method is proposed, for the first time, to solve the bidding strategies for generation companies participating in pool-based single buyer electricity markets with risk factor. An example with six suppliers has been used to demonstrate the method, and it has been revealed that the power suppliers can increase their profits by bidding strategically. The results obtained, using Differential evolution, are more optimal compared to those obtained in Reference [14]. The market power of the suppliers is analyzed for different load price elasticity factors. To show the effectiveness of the proposed method, the bidding strategies of the suppliers is also discussed under the increased load condition. The simulation studies were carried out in Matlab environment and executed in Pentium IV processor.

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VIII. BIOGRAPHIES

R. Rajathy She obtained her B.E in Electrical and Electronics Engineering and M. E in power system with Distinction from Thiagarajar College of Engineering, Madurai and now with the Department of Electrical and Electronics Engineering, Pondicherry Engineering College, Pondicherry, India and currently pursuing for Ph. D. Her special fields of interest are Power System Optimization and Power System Restructuring.

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TABLE II: BIDDING STRATEGIES AND ASSOCIATED VARIABLES FOR LOAD PRICE ELASTICITY FACTOR $K = 15$

λ	β_2	P_2	R	$E(\pi_2)$	$Var(\pi_2)$	ψ
0.000	0.03940	59.300	4.0855	78.112	33.4420	78.1120
0.300	0.03938	59.303	4.0851	78.039	32.5421	52.2164
0.500	0.03881	60.288	4.0850	77.556	28.1490	36.1256
0.700	0.03788	61.596	4.0830	77.429	30.6800	19.3800
0.900	0.03668	63.949	4.0730	77.113	26.4800	3.0799
0.915	0.02329	94.991	4.0120	57.052	19.1650	0.8437

TABLE III: BIDDING STRATEGIES AND ASSOCIATED VARIABLES FOR LOAD PRICE ELASTICITY FACTOR $K = 20$

λ	β_2	P_2	R	$E(\pi_2)$	$Var(\pi_2)$	ψ
0.000	0.03732	61.8000	4.0441	74.9700	28.010	74.9700
0.300	0.03724	61.8300	4.0440	74.9342	27.670	50.8542
0.500	0.03714	62.1800	4.0423	74.9338	26.444	34.8832
0.700	0.03610	63.4297	4.0399	74.9329	26.293	18.8904
0.900	0.03546	64.3349	4.0315	74.4361	25.999	2.8584
0.915	0.02327	95.1914	3.9689	52.7274	17.515	0.8338

TABLE IV: BIDDING STRATEGIES AND ASSOCIATED VARIABLES FOR LOAD PRICE ELASTICITY FACTOR $K = 25$

λ	β_2	P_2	R	$E(\pi_2)$	$Var(\pi_2)$	ψ
0.000	0.03731	61.980	4.0300	72.4456	26.8968	72.4456
0.300	0.03722	62.046	4.0029	72.3373	26.8947	49.0803
0.500	0.03615	62.396	4.0027	72.2507	25.5420	33.7334
0.700	0.03528	63.566	3.9930	71.9531	24.0485	18.1531
0.900	0.03470	64.281	3.9929	71.9530	24.0271	2.7335
0.915	0.022643	95.949	3.9278	47.9198	16.6358	0.3411

TABLE V: OPTIMAL RESULTS OF BIDDING PARAMETERS FOR INCREASE IN LOAD

Load	Parameters	$K = 15$	$K = 20$	$K = 25$
540	β_2	0.3708	0.3698	0.03636
	P_2	67.59	66.68	66.464
	R	4.25	4.21	4.17
	$E(\pi_2)$	89.61	86.50	83.41
	$Var(\pi_2)$	30.49	30.46	30.42
	ψ	42.9	40.49	38.86

TABLE I: COMPARATIVE RESULTS OF BIDDING STRATEGIES AND ASSOCIATED VARIABLES FOR $K = 20$

λ	β_2		P_2		R		$E(\pi_2)$		$Var(\pi_2)$		ψ	
	Proposed method	Reference [14]	Proposed method	Reference [14]	Proposed method	Reference [14]	Proposed method	Reference [14]	Proposed method	Reference [14]	Proposed method	Reference [14]
0.000	0.037032	0.037042	61.8000	61.78	4.0444	4.0386	74.9700	74.698	28.010	28.309	74.970	74.698
0.500	0.037000	0.037041	62.1800	61.79	4.0423	4.0386	74.9338	74.698	26.444	28.309	34.8832	34.829
0.900	0.035463	0.037030	64.3349	61.80	4.0315	4.0386	74.4361	74.698	25.999	28.303	2.8584	2.6817
0.915	0.023277	--	95.1914	--	3.9689	3.9594	52.7274	45.198	17.515	--	0.8338	--

APPENDIX I

PRODUCTION COST COEFFICIENTS AND GENERATOR OUTPUT LIMITS OF GENCOS

Gencos No	b_j (\$/hr)	c_j (\$/MWhr)	$P_{j\min}(MW)$	$P_{j\max}(MW)$
1	2.0	0.00875	50	160
2	1.75	0.035	20	100
3	1.0	0.0625	30	80
4	3.15	0.00334	30	80
5	3.0	0.015	10	60
6	3.0	0.015	10	60

APPENDIX II

SIMULATION PARAMETERS

C_R	F	N_p	MC	T_{gen}	$Q_0(MW)$
0.7	0.55	50	10000	100	450