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Hybrid Differential Evolution with BBO for Genco's multi-hourly strategic bidding

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Abstract—In Day-Ahead (DA) electricity markets, Generating Companies (Gencos) aim to maximize their profit by bidding optimally, under incomplete information of the competitors. This paper develops an optimal bidding strategy for 24 hourly markets over a day, for a multi-unit thermal Genco. Different fuel type units are considered and the problem has been developed for maximization of cumulative profit. Uncertain rivals' bidding behavior is modeled using normal distribution function, and the bidding strategy is formulated as a stochastic optimization problem. Monte Carlo method with a novel hybrid of Differential Evolution (DE) and Biogeography Based Optimization (BBO) (DE/BBO) is proposed as solution approach. The simulation results present the effect of operating constraints and fuel price on the bidding nature of different fuel units. The performance analysis of DE/BBO with GA and its constituents, DE and BBO, proves it to be an efficient tool for this complex problem.

Index Terms—Bidding Strategy; BBO; DE; Electricity Markets; Monte Carlo Simulation.

I. INTRODUCTION

Evolving Electricity Markets (EMs) are oligopolistic owing to few suppliers, expensive energy storage, demand generation imbalance, *etc.* Gencos bid in such markets with an aim to maximize profit. Market settlement between supplier and consumer bids determine Market Clearing Price (MCP). Optimal bidding strategy of a Genco for Pay-as-MCP (PAMCP) pricing is based on the accurate prediction of MCP which cannot be considered deterministic in an oligopolistic market. It is affected by suppliers' bidding behavior, so other competitors' bidding nature becomes a major source of uncertainty being faced by a strategically bidding Genco [1].

World over, thermal generating units are dominant energy suppliers and are categorized on the basis of fuel type and capacity. Consequently their production cost, operating constraints, and operating cost components differ. Marginal cost of a unit depends mainly on its production cost, which varies with its efficiency and fuel price. Optimal bidding strategy of a unit is, thus, governed by the price being paid for

its stored fuel [2, 3]. Also, operating constraints and operating cost components affect profit and thus, bidding strategy of a unit, when developed over multiple hours [4]. Quantum of literature is available on optimal bidding strategy of a Genco under oligopolistic market but lacks analysis for realistic varied fuel generating units with practical fuel prices [5-11].

Extensive research on optimal bidding strategy formulation for Gencos broadly classifies three solution approaches. Conventional optimization techniques like Lagrange Relaxation, Dynamic Programming, *etc.* fall in first set [1]. These techniques fail for realistic non-differentiable, multi-constraint and multi-objective problems and require nonlinear simplification, if adopted. Another approach is based on game theory which assumes that rival Gencos' cost functions and complete bid information are public. This is practically not true. Also, multiple Nash equilibriums exist for large number of players [5, 6]. The third set of approach, Artificial Intelligence (AI) based heuristic algorithms have the potential to solve such complex problems in their original form, thus giving accurate results. These methods look into wide search space and often achieve a fast and near global optimal solution. Literature shows the application of tools like Genetic Algorithm (GA) [7], Evolutionary Programming [8], Particle Swarm Optimization (PSO), and their variants [9-11], *etc.* These suggest that with increasing complexity and constraints of EMs, these can be looked up as reliable solution tools.

This paper takes up the problem of optimal bidding strategy of a multi-unit thermal Genco for multiple hourly Day-Ahead (DA) EMs over 24 hour horizon of the next day. The realistic units of different fuel types are considered. The problem has been developed as maximization of cumulative profit of the Genco with dynamic demand. It has a nonlinear, non-differentiable, constrained, mixed integer form with multiple binary and real variables. Also, market uncertainty due to rival bids make the problem stochastic. Owing to a large size of solution vector with mixed variables, under dynamically changing environment and multiple market clearings, an extensive exploration of the search space is required.

Recently, a novel algorithm, Biogeography Based Optimization (BBO) based on study of geographical

distribution of biological organisms, has been proposed [12]. It works with the population of habitats under migration and mutation operations. Owing to migration, BBO has good exploitation ability and has outperformed other techniques for different power system problems [13-16]. However, it is seen that it has limited exploration capability for large variable complex problems [17, 18]. To overcome this, various improved versions of BBO have been suggested.

Differential Evolution (DE) is a simple and robust tool with mutation, crossover, and selection operators [19]. It is good at exploring search space due to its unique mutation operation. However, initially its solutions move fast towards the optimal point but fail to perform satisfactorily at later stages of fine-tuning, thus having poor exploitation. A new hybrid of DE with BBO (DE/BBO) has recently been proposed which combines exploration of DE and exploitation of BBO and is used for few applications but has not been used for bidding strategies [20]. DE/BBO makes use of hybrid migration operator which is based on BBO's migration and DE's crossover and mutation.

This paper proposes the use of DE/BBO for the optimal bidding strategy problem and compares it with GA as well as its own constituents, DE and BBO, to identify its advantages over them. Nonlinear sinusoidal migration model has been proposed in contrast with the original linear model as it replicates the natural process of migration more closely [21].

II. PROBLEM DESCRIPTION

Consider a pool DA spot EM, with G multi-unit independent Gencos bidding under stepwise bidding protocol. An inelastic and deterministic hourly demand is considered with sealed bid auction and PAMCP pricing. Optimal bidding strategy is to be developed for Genco X , with $G-1$ rivals, over 24 hour horizon of the next day. It is assumed that all Gencos bid in single segment for their each generating unit. Genco X predicts rival bids to formulate its optimal bidding strategy. The size of rival bids is assumed to be known from the historical data available in public domain and their bidding prices are estimated through statistical analysis of historical bidding data. Normal probability distribution function (pdf) is used to model the distribution of rival bid prices and is represented as,

$$pdf(\tilde{P}_{r,i}) = \frac{1}{\sigma_{r,i}\sqrt{2\pi}} \exp\left(-\frac{(\tilde{P}_{r,i} - \rho_{r,i})^2}{2(\sigma_{r,i})^2}\right) \quad (1)$$

where, $\tilde{P}_{r,i}$ is the price bid for i^{th} unit by r^{th} rival (\$/MWh), $\rho_{r,i}$ is the mean of normally distributed $\tilde{P}_{r,i}$ (\$/MWh) and $\sigma_{r,i}$ is its standard deviation (\$/MWh).

Optimal bidding strategy is a profit maximization problem. For Genco X bidding in PAMCP market with generating unit i , profit at any trading interval t is a function of its dispatched power output $Q_{i(t)}$ (MW) and MCP $M_{(t)}$ (\$/MWh). Considering to develop bidding strategy of a N unit Genco over T trading intervals, the objective function is maximization of cumulative profit π (\$) as represented in (2).

$$\text{Maximize } \pi = \sum_{t=1}^T \sum_{i=1}^N h(M_{(t)}Q_{i(t)} - C_{i(t)}) \quad (2)$$

Here, $C_{i(t)}$ is the cost of generating $Q_{i(t)}$ from i^{th} unit in \$/h. h

is the duration of each trading interval in hours.

Various constraints are:

- 1) Generation limits

$$Q_i^{\min} u_{i(t)} \leq Q_{i(t)} \leq Q_i^{\max} u_{i(t)} \quad \forall t \in T \quad (3)$$

- 2) Minimum up time

$$(1 - u_{i(t+1)})MUT_i \leq H_{i(t)}^{on} \quad \text{if } u_{i(t)} = 1 \quad (4)$$

- 3) Minimum down time

$$u_{i(t+1)}MDT_i \leq H_{i(t)}^{off} \quad \text{if } u_{i(t)} = 0 \quad (5)$$

- 4) Limitations on bid price

$$P_{i,\min} \leq P_{i(t)} \leq \text{price cap} \quad \forall t \in T \quad (6)$$

Here, Q_i^{\min} (MW) and Q_i^{\max} (MW) are the minimum and maximum generation limits of i^{th} unit respectively; $u_{i(t)}$ is binary variable and is equal to one for i^{th} unit committed at trading interval t , otherwise equal to 0; MUT_i and MDT_i are the minimum up time and the minimum down time of i^{th} unit in hours respectively; $H_{i(t)}^{on}$ is the number of hour i^{th} unit has been continuously ON at the end of trading hour t ; $H_{i(t)}^{off}$ is the number of hour i^{th} unit has been continuously OFF at the end of hour t ; $P_{i(t)}$ (\$/MWh) is the price bid for total capacity of unit i at a trading interval t , $P_{i,\min}$ (\$/MWh) is the minimum limit on bid price of unit i .

Price cap (\$/MWh) is the maximum limit on bid price for unit i . Generation cost $C_{i(t)}$ (\$/h) is considered to be composed of convex production cost $C_{i(t)}^{pr}$, exponential start-up cost C_i^{su} and constant shut-down cost C_i^{sd} . Hence,

$$C_{i(t)} = C_{i(t)}^{pr} + C_i^{su} \{u_{i(t)}(1 - u_{i(t-1)})\} + C_i^{sd} \{((1 - u_{i(t)})u_{i(t-1)})\} \quad (7)$$

such that,

$$C_{i(t)}^{pr} = a_i + b_i Q_{i(t)} + c_i Q_{i(t)}^2 \quad (8)$$

$$C_i^{su} = \zeta_i + \delta_i \left(1 - \exp\left(-\frac{T_{off_i}}{\tau_i}\right)\right) \quad (9)$$

where, a_i (\$/h), b_i (\$/MWh) and c_i (\$/MW²h) are no load production cost coefficient, linear production cost coefficient and quadratic production cost coefficient, respectively of i^{th} unit; ζ_i (\$) is hot start-up cost considered when i^{th} unit has been shut down for a short time; δ_i (\$) is cold start-up cost considered when i^{th} unit has been shut down for a long time; T_{off_i} is number of hours i^{th} unit has been OFF at the time of start-up, τ_i is cooling time constant of i^{th} unit in hours.

The heat rate characteristic of a fossil fuel unit relates the hourly heat energy requirement (Btu/h or MBtu/h) with the corresponding power output. It can be converted into its production cost curve (\$/h) by multiplying it with the fuel price. Total fuel cost of a unit for any power output is its production cost $C_{i(t)}^{pr}$. This work adopts its quadratic function

representation as in (8). Let ϕ be the fuel price in \$/MBtu. Then,

$$C_{i(t)}^{pp} = \phi(k_{0i} + k_{1i}Q_{i(t)} + k_{2i}Q_{i(t)}^2) \quad (10)$$

Here, k_{0i} , k_{1i} and k_{2i} are heat rate coefficients for unit i in MBtu/h, MBtu/MWh and MBtu/MW²h, respectively. Comparing (10) with (8), the production cost coefficients a_i , b_i and c_i can be expressed in terms of heat rate coefficients and fuel cost as $a_i = \phi k_{0i}$, $b_i = \phi k_{1i}$, and $c_i = \phi k_{2i}$.

The optimization problem defined in (2)-(6) can be solved to obtain the optimal bid price $P_{i(t)}$ for each i^{th} unit of Genco X at trading interval t . In (2), $P_{i(t)}$ and $G-1$ rival bid price $\tilde{P}_{r,i}$ do not appear explicitly but are implicitly included in the process of determining MCP $M_{(t)}$. Using the normal pdf to represent the distribution of rival price, the strategic bidding problem of Genco X becomes a stochastic optimization problem. This is transformed into an equivalent deterministic formulation using Monte Carlo simulations.

III. PROPOSED SOLUTION ALGORITHM

Monte Carlo simulations obtain probabilistic approximation of a mathematical problem by using statistical sampling technique. Expectation of the objective function over whole solution domain gives the required result. In the proposed strategic bidding problem, Monte Carlo simulations of uncertain rival behavior are incorporated with an optimization algorithm to develop optimal bids.

A. Monte Carlo Approach

Corresponding to the proposed problem, main solution steps of Monte Carlo approach proceeds as follows:

- Generate large number of random samples for bid price of rival Gencos' units, considering their pdfs.
- Obtain large trial outcomes of bid price of the units of Genco X for each hour, by solving the optimization problem with sample values of rival bids.
- Calculate expected bid price value by taking expectation over all trial outcomes.

Detailed algorithm:

- 1) Specify number of Monte Carlo simulations, MC .
- 2) Initialize simulation counter $mc = 1$.
- 3) Generate random sample values of bid prices $P_{r,i}$ for each i^{th} unit of $G-1$ rival Gencos; ($r = 1, 2, \dots, G-1$).
- 4) Use DE/BBO to search optimal bid price for each i^{th} unit of Genco X . (This step is detailed in Sec. V).
- 5) Store the optimal prices of each unit and for each trading interval as $P_{i(t)}^{mc}$.
- 6) Update $mc = mc + 1$.
- 7) If $mc < MC$, go to (3); else go to (8).
- 8) Calculate the expected value of optimal bid prices, i.e., mean of $P_{i(t)}^{mc}$ ($mc = 1, 2, \dots, MC$). This is the optimal bid price $P_{i(t)}$ of each i^{th} unit of Genco X for bidding in t^{th} trading period over 24 hour horizon.

IV. HYBRID DE/BBO

Recently, a novel hybrid of DE with BBO, referred as DE/BBO, has been proposed for combining the goodness of both the techniques [20]. In the following sub sections, a brief description of DE, BBO, DE/BBO is given.

A. Differential Evolution (DE)

DE is a population based stochastic parallel search algorithm and creates a new candidate solution set iteratively, by operators: mutation, crossover, and selection [19]. These are briefly described below.

1) *Mutation*: Mutation creates mutant vectors $X_i^{/k}$ by perturbing a randomly selected vector X_{r1}^k with the difference of two other randomly selected vectors, X_{r2}^k and X_{r3}^k , at the k^{th} iteration, as per (11)

$$X_i^{/k} = X_{r1}^k + F \times (X_{r2}^k - X_{r3}^k); \quad i = 1, 2, \dots, N_p \quad (11)$$

X_{r1}^k , X_{r2}^k and $X_{r3}^k \in [i = 1, 2, 3, \dots, N_p]$ and $r1 \neq r2 \neq r3 \neq i$

N_p is the size of parent population. X_{r1}^k , X_{r2}^k and X_{r3}^k are selected afresh for each parent vector. $F \in [0, 2]$ is "scaling factor" and controls the perturbation in the mutation process and helps to improve convergence [19].

2) *Crossover*: Under crossover operation, the parent vector is mixed with the mutant vector to yield an offspring as per (12).

$$X_{ij}^{//k} = \begin{cases} X_{ij}^{/k}, & \text{if } rand_j < CR \text{ or } j = q \\ X_{ij}^k, & \text{otherwise} \end{cases} \quad (12)$$

Here, $j = 1, 2, \dots, D$; D is the number of decision variables; X_{ij}^k is the j^{th} decision variable of i^{th} target vector at k^{th} iteration; $X_{ij}^{/k}$ is the j^{th} decision variable of i^{th} mutant vector at k^{th} iteration; $X_{ij}^{//k}$ is the j^{th} decision variable of i^{th} offspring vector at k^{th} iteration and q is a randomly chosen index $\in [j = 1, 2, 3, \dots, D]$. $CR \in (0, 1)$ is the "Crossover constant" that controls the exploration and diversity of population [19].

3) *Selection*: Selection among the set of offspring and parent vectors is carried out on the basis of respective objective function values. Equation (13) models the process [19].

$$X_i^{k+1} = \begin{cases} X_i^{//k}, & \text{if } f(X_i^{//k}) \leq f(X_i^k); \\ X_i^k, & \text{otherwise} \end{cases} \quad i = 1, 2, \dots, N_p \quad (13)$$

B. Biogeography Based Optimization (BBO)

BBO is a new population based biogeography inspired global optimization algorithm. It describes how species migrate from one island to another, how new species arise and how species become extinct. Migration and mutation are its operators as described below [12-16].

1) *Migration*: It is a probabilistic operation and shares information among habitats. Poor solutions tend to accept more useful information from good solutions. This makes BBO good at exploiting the information of current population. Objective function value for each habitat decides species

count of a habitat, which governs migration rates of a habitat based on migration model. Emigration rate μ and immigration rate λ decides migration between habitats. Elitism is incorporated to prevent the best solutions from being corrupted by immigration.

2) *Mutation*: Catastrophic events are modelled as mutation, where the mutation rates are determined using species count probabilities. BBO uses a unique mutation scheme which avoids medium species count solutions [13].

$$\text{mutation_rate}_i = P_{\text{mutate}}(1 - \text{Prob}_{ik} / \text{Prob}_{\text{max}}) \quad (14)$$

Here, P_{mutate} is mutation probability. Prob_{ik} is the species count probability of habitat i such that it contains exactly k species. Prob_{max} is the maximum of species count probabilities of all habitats. The detailed description of mutation operation in BBO can be referred from [13].

C. DE/BBO with Hybrid Migration Operator

DE has good exploration ability of the search space due to its unique mutation and stochastic crossover. It has been found that, in DE, initially the solutions move very fast towards the optimal point but fail to perform at later stages during fine tuning. In BBO, solutions get fine-tuned gradually during progression of the migration operation. Thus, DE has good exploration ability to find the region of global optima, while BBO has good exploitation ability for global optimization. Hybrid migration operator is the most important step in DE/BBO algorithm [20].

1) *Hybrid Migration Operator*: It is the main operator of DE/BBO to combine DE's crossover and mutation with migration operation of BBO, and is described in Algorithm 1. In this operator, an offspring U_i incorporates new features from population members. Hybrid migration operator can balance exploration and exploitation effectively.

Algorithm 1: Hybrid Migration Operator [20]

```

for  $i = 1$  to  $N_p$  do
  Select uniform randomly  $r_1 \neq r_2 \neq r_3 \neq i$ 
   $j_{\text{rand}} = \text{randint}(1, D)$ 
  for  $j = 1$  to  $D$  do
    if  $\text{randreal}(0,1) < \lambda_i$  do
      if  $\text{randreal}_j(0,1) > CR$  or  $j = j_{\text{rand}}$  do
         $U_i(j) = X_{r_1}(j) + F \times (X_{r_2}(j) - X_{r_3}(j))$ 
      else
        Select another habitat  $X_k$  with probability
        proportional to  $\mu_k$ 
         $U_i(j) = X_k(j)$ 
      end if
    else
       $U_i(j) = X_i(j)$ 
    end if
  end for
end for

```

Here, $\text{randint}(1, D)$ is a uniformly distributed random integer number between 1 and D . $\text{randreal}_j(0,1)$ is a random real

number between 0 and 1. $X_i(j)$ is the j^{th} variable of individual X_i .

2) *Main Procedure of DE/BBO*: Its basic steps are shown in Algorithm 2.

Algorithm 2: DE/BBO Algorithm [20]

```

Generate initial population  $Pop$ 
Evaluate fitness for each individual in  $Pop$ 
while Termination criteria is not satisfied do
  For each individual, map fitness to the number of species
  Calculate immigration rate  $\lambda_i$  and emigration rate  $\mu_i$  for
  each individual
  Modify the population with hybrid migration operation of
  Algorithm 1
  for  $i = 1$  to  $N_p$  do
    Evaluate offspring  $U_i$ 
    if  $U_i$  is better than  $Pop_i$  then
       $Pop_i = U_i$ 
    end if
  end for
end while

```

V. DE/BBO FOR OPTIMAL BIDDING STRATEGY FORMULATION

Multi hour strategic bidding problem of a Genco, facing rivals of uncertain bidding nature, is being proposed to be solved by Monte Carlo method. The corresponding algorithm is detailed in Sec. III. DE/BBO can be used to optimize the profit function for given simulation of rival bids. Step ‘d’ of Sec. III, is detailed below:

- 1) Initialize parent population Pop with number of habitats/individual equal to N_p , BBO parameters like maximum immigration rate I , maximum emigration rate E , habitat modification probability P_{mod} , lower bound λ_{lower} and upper bound λ_{upper} for immigration probability per habitat, maximum number of iterations, and DE parameters like CR and F .
- 2) Initialize all habitats/individuals representing a possible bidding strategy of Genco X .
- 3) For every habitat, MCP is identified for each hour by arranging the bids of competing Gencos in increasing stepwise curve. Finally, cumulative profit of Genco X , i.e., fitness for each habitat/individual is calculated. Then, sort the habitats in descending order.
- 4) Set DE/BBO iteration counter = 1.
- 5) Probabilistically perform hybrid migration operation as per Algorithm 1. Then, calculate cumulative profit/fitness for every habitat and sort the habitats.
- 6) Perform selection operation between initial population and the newly generated population obtained from Step ‘5’.
- 7) Go to Step (5) for next iteration, till all specified iterations are completed.

VI. NUMERICAL RESULTS AND DISCUSSIONS

A practical case study of a thermal Genco X owning three units, including one coal-fired unit, one gas-fired unit and one oil-fired unit, has been considered for trading over 24 hours

horizon in a DA EM. A typical daily load curve is shown in Fig. 1. The unit details are provided in Table 1 [21]. The fuel prices are based on practical market data of year 2013 [2, 22]. Accordingly, the production cost coefficients in \$/h for different units are calculated.

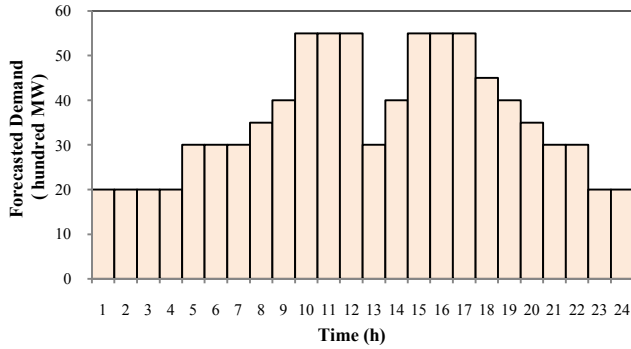


Figure 1. Typical daily load curve

There are four rival Gencos, each having similar three units as Genco X , however, with different capacity. Rivals bidding parameters are given in Table 2. Normal probability distribution parameter $\rho_{r,i}$ of the rival Genco units has been assumed on the basis of their marginal cost. Cumulative profit maximization, given by Eq. (2), is the objective function.

Simulation parameters are: $MC = 10000$, $N_p = 80$, $P_{mod} = 1$, $I = 1$, $\lambda_{lower} = 0$, $\lambda_{upper} = 1$, $P_{mutate} = 0.1$ and $p = 4$, $CR = 0.1$ and $F = 0.7$. Minimum bid price of each unit is set at the marginal cost, without the start-up and shut-down cost. Therefore, minimum bid prices for units 1, 2 and 3 are 82.55 \$/MWh, 109.28 \$/MWh and 21.37 \$/MWh, respectively. Price cap is 120 \$/MWh. Initial state of all three units are kept as ON with their $H_{i(t)}^{on}$ equal to their MUT .

Optimal bid prices of units 1-3, hence obtained, and the expected MCPs for each trading hour are shown in Fig. 2. Table 3 gives the expected hourly power dispatch of the units. ND stands for no dispatch of that unit. Fig. 3 shows the expected hourly profit of Genco X . The optimal cumulative profit is equal to \$913090.

The results clearly reflect that the coal, oil, and gas differ in

their bidding strategy over 24 hours bidding horizon, due to variation in fuel prices and inter-temporal constraints. Coal unit has the least cost of generation but is constrained by large up and down times. Also, start up and shut down costs of coal unit are more than other units. Hence, it may cause negative profit for Genco during low demand periods. Also, due to high shut down time, they may be restrained from giving profit for a longer period. Costly oil unit is suitable only for peak periods. Gas unit can be dispatched during most hours of the day and assist the coal unit to attain high profit by affecting MCP. Also, once shut down, it can be dispatched earlier profitably due its characteristic low down time with low start-up cost. Hence, coal has a tendency to bid low and dispatch for all the hours, while costly gas and oil units become marginal units and affect MCP.

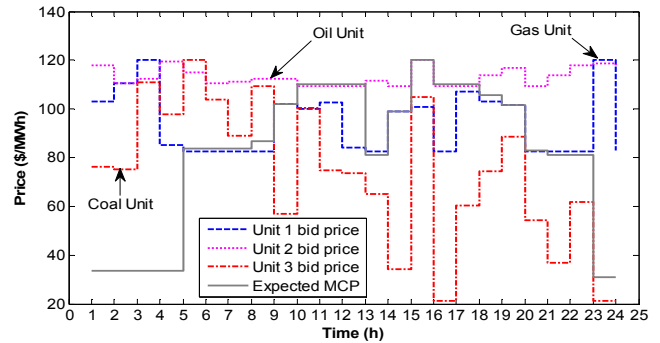


Figure 2. Bid prices and expected hourly MCP

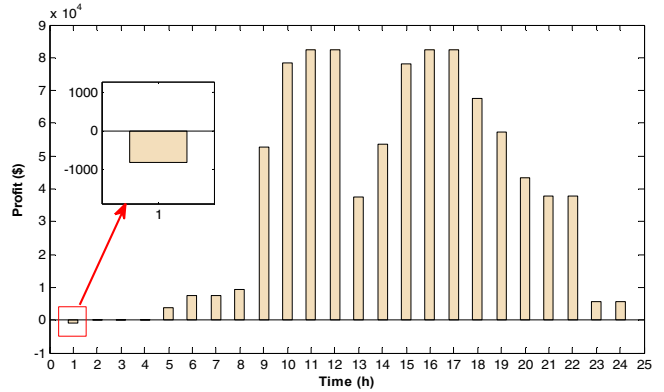


Figure 3. Expected hourly profit curve of Genco X

TABLE I. DATA OF GENCO X

Unit	Fuel Price (\$/MBtu)	k_0 (MBtu/h)	k_1 (MBtu/MWh)	k_2 (MBtu/MW ² h)	a (\$/h)	b (\$/MWh)	c (\$/MW ² h)	Q^{\max} (MW)	Q^{\min} (MW)	MUT (h)	MDT (h)	ζ (\$)	δ (\$)	τ (h)	C^{sd} (\$)
1(Gas)	4.7	67.05	8.71	0.0111	315.14	40.94	0.0520149	400	100	2	1	1500	2500	1	200
2(Oil)	6.5	64.16	8.34	0.0106	417.04	54.21	0.068835	400	100	2	1	1500	2500	1	200
3(Coal)	2.4	510	7.2	0.0014	1224	17.28	0.00341	600	150	8	8	2000	4000	8	400

TABLE II. RIVAL'S BIDDING PARAMETERS

Bid parameters	Unit \rightarrow	Rival 1			Rival 2			Rival 3			Rival 4		
		1(Gas)	2(Oil)	3(Coal)	1(Gas)	2(Oil)	3(Coal)	1(Gas)	2(Oil)	3(Coal)	1(Gas)	2(Oil)	3(Coal)
$\tilde{Q}_{r,i}$ (MW)		200	300	500	300	300	500	300	350	500	400	300	500
$\rho_{r,i}$ (\$/MWh)		82	107	30	84	108	30	84	110	30	83	110	30
$\sigma_{r,i}$ (\$/MWh)		3	3	3	3	3	3	4	4	4	3	3	2

TABLE III. EXPECTED POWER DISPATCH (MW) OF GENCO X

Hour	Expected Power Dispatch			Hour	Expected Power Dispatch		
	Unit 1	Unit 2	Unit 3		Unit 1	Unit 2	Unit 3
1	ND	ND	ND	13	ND	ND	600
2	ND	ND	ND	14	ND	ND	600
3	ND	ND	ND	15	400.0	100.25	600
4	ND	ND	ND	16	400.0	369	600
5	331	ND	ND	17	400.0	369	600
6	331	ND	ND	18	400.0	ND	600
7	331	ND	ND	19	400.0	ND	600
8	397	ND	ND	20	294.0	ND	600
9	188	ND	600.0	21	180.0	ND	600
10	400	369	600.0	22	ND	ND	600
11	400	369	600.0	23	ND	ND	600
12	400	369	600.0	24	ND	ND	600

TABLE IV. CONSISTENCY OVER 20 RUNS OF MONTE CARLO APPROACH

Heuristic Algorithm	Profit (\$)				Simulation time per run(s)
	Minimum	Maximum	Average	Standard Deviation	
GA	912387	930579	920397	8552.8	7.96
BBO	912452.8	930708	920448	8567.5	7.80
DE	912495.6	930984	920466	8469.2	7.16
DE/BBO	912505.6	930984	920467.1	8466.1	7.66

Table IV gives the consistency evaluation of DE/BBO. Algorithm for the proposed solution approach of Sec. III is run 20 times with one Monte Carlo simulation and with different heuristic algorithms. Minimum, maximum, average and standard deviation over the trials is tabulated. It can be seen that performance of DE/BBO is more consistent than others.

VII. CONCLUSION

This paper presents strategic bidding problem of a thermal multi-unit Genco for hourly DA spot EM over a 24 hour horizon. A novel approach based on Hybrid Differential Evolution with Biogeography Based Optimization (DE/BBO) is proposed as the solution tool. 24 hourly trading periods for multi-unit Gencos present a multi-variable and highly nonlinear complex problem due to generator cost functions, inter temporal constraints and dynamic demand. The performance analysis proves that DE/BBO gives competitive performance with DE with better robustness due to enhanced exploitation quality. Also, DE/BBO gives better quality solution, with consistent performance as compared to GA and BBO. The simulations and comparative results prove feasibility and efficiency of DE/BBO algorithm to formulate bidding strategy for Gencos in competitive energy markets, under constrained environment.

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