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Intelligent Optimization of Strategic Bidding in Deregulated Electricity Markets Using An Efficient and Robust Grey Wolf Algorithm

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ABSTRACT

The rapid transition in energy sector is encouraging competition across various segments of the industry by dismantling monopolies. To maximize profits of GENCOs in such a dynamic environment necessitates an advanced model of competitor behavior and market uncertainty. This paper introduces a bidding approach for GENCOs which consists of their bids structured into three price-quantity blocks. Stochastic probability functions are utilized to model the Market Clearing Price (MCP) under uniform market clearing price mechanism. Using this mathematical framework, an objective function is established for each GENCO, aiming to maximize profits in relation to its competitors. To solve this optimization problem, a highly efficient and robust Grey Wolf Optimizer (ERGW) is applied. The findings are derived from 10,000 simulations. To highlight the computational efficiency of ERGW, its outcomes are contrasted with those generated by other meta-heuristic optimization techniques, including the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA) and Grey Wolf Optimization (GWO) algorithm. ERGW algorithm exhibits superior performance as the profit calculated through the dispatch estimation is more than any other algorithm.

Keywords: Electricity markets, Strategic Bidding, Profit maximization

1. INTRODUCTION

Over the last decade, the restructuring of the power system has led many electric utilities to change the way they conduct business. Previously, they operated as vertically integrated entities, but now they have transitioned to open market systems. In pool electricity markets, two primary entities exist: GENCOs and customers. GENCOs participate in the bidding process and determine their bids, while large customers can also be involved in the process. The primary objective of GENCOs is profit maximization when constructing their bidding curves. They base their bid decisions on the observed bidding behavior of competitors, often using historical data. This behavior can be predicted through probability distribution functions (PDFs). GENCOs submit their bids in sealed envelopes to the market operator, who then determines the winning bids. The goal of strategic bidding is to identify an optimal approach for GENCOs to construct their bidding curves, allowing them to maximize profits while considering social welfare.

In recent years, various approaches have been employed to maximize GENCOs' profits through strategic bidding. Some of these include the Dynamic Programming Approach [2]-[3], Stochastic Optimization [4]-[13], and Game Theory Approaches [14]-[16] and deep learning concepts [17-20]. Multi-agent systems are attracting significant attention these days due to their advanced methods of information exchange and collaborative decision-making [22]-[30]. Authors have also modeled bidding strategy under conditions of generation uncertainty [32-33].

In [1], a critical survey of various techniques used for strategic bidding in electricity market is presented. In [2], the dynamic programming approach was employed to maximize the profits of GENCOs. In [3], a precise model was developed by the author, which incorporated a nonlinear operating cost function along with the minimum up/down constraints of unit commitment. M. Kohansal et al. [4] evaluated the effect of convergence bidding on price gaps in nodal electricity markets. Tao jiang et al. [5] formulated a bi-level optimization problem in which upper level problem is to maximize the profit gas-fired unit and lower level problem is to model the market-clearing of electricity and natural gas markets. A selective learning

model was used in [6] to predict the market clearing price. Hussein mehdipourpicha et al. [7] simulated day ahead market clearing process and procured profit from both physical generations and virtual transactions. Mahdi Ghamkhari et al. [8] focused on solving strategic bidding problem with the help of schmudgen'spositivstellensatz theorem and mixed integer linear programming to produce results closer to optimum bidding solutions with less computational time. Jian sun et al. [9] proposed extended locational marginal price to model generator costs and used this function to assess market power in the whole system. Sijiechen et al. [10] proposed distributed strategy update algorithm to accommodate uncertainty in behavior of market participants and formed strategic bids based on the information available from distributed power dispatch algorithms. Hanning mi et al. [11] proposed feature extraction technique to predict locational marginal price which is crucial for forming optimal bidding strategies. In [12], authors discussed the challenges and opportunities of employing AC-optimal power flow (OPF) dispatch to manage electricity market settlement and produced more profit for generation company in contrast to DC-OPF model. A bidding strategy considering demand response is presented in [13].

The concept of Game Theory has been implemented constantly by researchers from 20th century. It has remained relevant in the field of electricity markets due to its ability to analyze market dynamics. Yan Du et al. [14] formulated strategic bidding problem as a markov game model and applied multi-agent deep deterministic policy gradient to counter uncertainty concerning imprecise knowledge regarding bidder's behavior. ImanTaheriEmami et al. [15] applied pareto-dominant nash equilibrium theory to form bidding strategy in an oligopoly and oligopsony market. In [16], authors discussed the effectiveness of virtual bidding to contain operational risks and also price volatility between uncertainty of strategic bidding by implementing nash equilibrium and joint-tax subsidy mechanism.

Deep learning and neural network based approaches have recently garnered widespread acclaim for their resilience and dependability [17]-[20].Yujian et al. [17] applied deep reinforcement learning technique to produce higher profits for Gencos and exhibited better computational performance than other alternative benchmark methods.Feihu et al. [18] focused on determining bidding behaviors of market participants by combining K-mediods clustering with deep learning model. Mihalydolanyi et al. [19] developed a neural network optimization model to map market participants' behavior with market outcomes. Yufeng et al. [20] formulated adversarial multi armed bandit model to estimate power generation companies' bids by observing outcome of the market auction and updating fitness of bids for each interval.

Multi-agent systems (MAS) are increasingly utilized in electricity markets to facilitate strategic bidding. These systems consist of autonomous agents representing market participants such as generators, retailers, and consumers. D. EsmaeiliAliabadi et al. [22] developed an agent based simulation model to study the behavior of market participants under different market clearing mechanism. Hybrid agent [23] and reinforcement learning model [24, 25] analyze market operations and ensures realistic bidding behavior over time. Bilateral negotiations are examined by adaptive agent tracking strategies [26]. Multi agent transfer learning technique assesses varying market conditions and promotes higher bidding efficiency in uncertain market conditions [27]. Multi agent deep learning are particularly effective in Risk management [28], VPP's coordination [29] and modeling of double sided auction [30] in electricity markets. Generation uncertainties are major concern of renewable energy resources; however low carbon emission and depletion of conventional fuel resources necessitates proper utilization of the green energy. Strategic bidding under these conditions is addressed in [32]-[33].

This paper introduces a novel methodology for devising a bidding strategy for a specific GENCO in an electricity market with N competitors, utilizing ERGWO to enhance its profitability.

2. Problem Description

Consider a system with N+1 GENCOs in which GENCO A has N competitors. All GENCOs submit their bids in confidence. Inter-temporal operational limitations have been disregarded because the bidding is conducted for a single hour of trade time, and each GENCO has a single registered unit. Bidding process is complex and to ensure reliability of the process, block-wise bidding is promoted where GENCOs bids in three blocks with their corresponding block capacity $\tilde{P}_i^n$ and block price $\tilde{C}_i^n$ ($i = 3$). This research has established an optimal bidding method to maximize GENCO A's profits. The objective function has been formulated as:

$$\text{Maximize } Y(\mathcal{R}, p) = \mathcal{R} * p * t - F(p, t) \quad (1)$$

Subject to:

$$0 \leq p \leq P \quad (2)$$

$$C_{min} \leq C \leq C_{max} \quad (3)$$

To determine block price C, the objective function given in (1) must be solved with the constraints specified in (2) and (3). Market Clearing Price (MCP) is denoted by R in the equation (1). p denotes dispatched quantity of GENCO A. There is upper limit constraint on dispatched quantity designated by P .

Market regulations such as constraints on price cap (110 \$/MWh) and block bid ($P_i^{min} = 0$ MW and $P_i^{max} = 200$ MW) have been taken into account. Trading period is one hour which is denoted by t . Generation cost function is represented by $F(p, t)$. C_{min} is lower limit price constraint and C_{max} is upper limit price constraint.

The generation cost function of GENCO is given as:

$$F(p, t) = \alpha + \beta p + \gamma p^2 \quad (4)$$

α , β and γ are generator cost coefficients.

Historical data may be used to predict rival's behavior. Normal probability function is used considering rival's bidding prices $\tilde{C}_i^n$.

$$PDF(\tilde{C}_i^n) = \frac{1}{\sqrt{2\pi}\sigma_i^n} \exp\left(-\frac{(\tilde{C}_i^n - \mu_i^n)^2}{2(\sigma_i^n)^2}\right) \quad (5)$$

Price distribution of rival companies may be represented in PDF by two parameters namely mean μ_i and standard deviation σ_i . After predicting rival's behavior, the objective function given in (1) may be solved by using Minitab and ERGWO. In this article, an optimal bidding strategy has been prepared to maximize profit of GENCO A

3. Proposed Solution Algorithm

The objective function given in (i) is multi objective. The block bid prices of GENCO A are estimated knowing behavior of rival companies from historical data with the help of Minitab software. Minitab is a statistical software package that can be used for a variety of purposes, including data analysis, visualization and predictive analytics. The optimal dispatch quantity is obtained by the application of ERGWO. The procedure is given in following steps:

- (i) First random samples of bid prices of rival generation companies are obtained by analyzing historical data. Thereafter, Mean and standard deviation of block bid prices of rival companies are calculated.
- (ii) On the basis of this knowledge, block bid prices of GENCO A are estimated.
- (iii) After estimating block bid prices of GENCO A, optimal dispatch quantity is secured using ERGWO.

3.1 Efficient and Robust Grey Wolf Optimizer

Mirjalili et.al. [21] proposed GWO, a nature inspired meta heuristic algorithm, based on the behavior of grey wolves. In their study, social behavior and leadership hierarchy of grey wolves were used to develop mathematical modeling to solve complex optimization problems. The most optimal solution to the problem was referred to as α while β and δ were ranked second and third in the hierarchy, respectively. The remaining solutions were designated as ω , representing the least optimal solutions.

The mathematical equations describing the encirclement of prey are given in (6).

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}(\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)) \quad (6)$$

Here, coefficient vectors are, $\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a}$ and $\vec{C} = 2 \cdot \vec{r}_2$ in which $\vec{r}_1$ and $\vec{r}_2$ are random vectors and $\vec{a}$ decreases linearly from 2 to 0. $\vec{X}_p$ and $\vec{X}$ indicate the position vector of the prey and grey wolf respectively. Positions of the search agents are improved by using the model equations given below:

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1(\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}) \quad (7)$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2(\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}) \quad (8)$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3(\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}) \quad (9)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (10)$$

The problem with conventional GWO is that it can be trapped in local minima and accuracy of the results are compromised. Hence a modification was suggested by Wen Long et al. in [31] in which parameter $\vec{a}$ is updating non-linearly to incorporate actual search process. In their research, an improved version of GWO, named ERGWO, with better exploration and exploitation was proposed. The value of adaptive parameter $\vec{a}$ dynamically varies as shown in (11).

$$\vec{a} = a_{initial} - (a_{initial} - a_{final}) \times \rho^{-t} \quad (11)$$

$a_{initial}$ and a_{final} are initial and final values of adaptive parameter $\vec{a}$ and non-linear modulation index is given by ρ .

In realistic problems such as strategic bidding in electricity markets, conventional GWO may give significant errors in results due to individuals in the solution space increasingly converge around the most optimal candidates, their ability to explore new regions diminishes, which can result in becoming stuck in local optima. To address this challenge, the enhanced global search mechanism in ERGWO

introduces a revised position-updating strategy that leverages proportional weights which are given as:

$$\omega_1 = \frac{|\vec{x}_1|}{|\vec{x}_1|+|\vec{x}_2|+|\vec{x}_3|} \quad (12)$$

$$\omega_2 = \frac{|\vec{x}_2|}{|\vec{x}_1|+|\vec{x}_2|+|\vec{x}_3|} \quad (13)$$

$$\omega_3 = \frac{|\vec{x}_3|}{|\vec{x}_1|+|\vec{x}_2|+|\vec{x}_3|} \quad (14)$$

ω_1, ω_2 and ω_3 are learning rates of ω wolves from α, β and δ wolves respectively.

A modified position-updating equation is proposed as follows:

$$\vec{X}(t+1) = \frac{1}{\omega_1+\omega_2+\omega_3} \times \frac{\omega_1\vec{x}_1+\omega_2\vec{x}_2+\omega_3\vec{x}_3}{3} \quad (15)$$

4. Simulation Results

This section showcases the simulation outcomes of an optimal bidding strategy designed for GENCO A, which competes against N rivals. By analyzing the historical behavior of competitors through their probability density functions (PDFs), an efficient strategy has been formulated for GENCO A, leading to maximized profitability. The predictive analysis functionality of Minitab software is combined with the advanced exploration and exploitation strengths of ERGWO, offering a highly efficient solution to the bidding problem that significantly boosts GENCO's profitability. To extend the analysis towards more realistic power system, Deviation and mean of the energy price of GENCOs are taken different. The case is simulated with Demand (P_D) = 1500 MW.

Table 1 shows the details of various parameters of energy price. Block capacity, standard deviation and mean of the energy price have been exhibited. Rival companies are denoted by R1, R2 and R3.

Table 1 : Parameters of GENCO A and its Rivals

Block (s)		GENCO A	R1	R2	R3
1	Q_i^n (MW)	200	200	200	150
	Mean	10	10	5	5
	Deviation	3	3	2	2
2	Q_i^n (MW)	200	200	200	150
	Mean	30	30	15	15
	Deviation	3	3	2	2
3	Q_i^n (MW)	200	200	200	150
	Mean	50	50	25	25
	Deviation	3	3	2	2

GEN COs	Block	Genetic Algorithm		Particle Swam Optimization		Gravitational Search Algorithm		Grey Wolf Optimization (GWO)		Efficient and Robust GWO	
		Quantity Dispatched (MW)	Profit (\$)	Quantity Dispatched (MW)	Quantity Dispatched (MW)	Quantity Dispatched (MW)	Profit (\$)	Quantity Dispatched (MW)	Profit (\$)	Quantity Dispatched (MW)	Profit (\$)
GEN CO A	1	115.8906	10326.85	94.0055	11889.25	71.74701	11639.62	50.84733	12783.62	36.83105	13127.18
	2	134.6478		156.1378		158.379		180.1219		195.1848	
	3	155.6669		186.5392		177.0104		195.2287		196.5472	
R1	1	114.3701	10009.24	93.96751	11621.1	119.5045	11537.35	76.74595	10219.85	151.9718	12059.72
	2	133.0438		149.9842		140.8614		83.83877		171.3448	

	3	149.29 56		182.53 15		184.72 2		178.17 79		187.02 42	
R2	1	99.539 49	3462. 764	88.721 92	3644.6 06	54.820 75	4664. 045	30.255 09	1246 7.5	44.492 86	4785. 264
	2	123.74 31		115.34 85		149.63 74		166.30 12		154.04 24	
	3	129.98 55		142.73 93		185.37 74		193.01 43		188.40 58	
R3	1	103.93 39	3279. 676	83.088 18	3055.0 67	26.556 73	3542. 609	50.196 05	1069 9.07	27.692 88	2574. 249
	2	117.88 89		96.497 95		111.01 97		126.60 48		53.620 79	
	3	120.99 47		110.43 85		120.36 35		168.66 78		92.841 25	

Table 2 : Results obtained from various algorithms for $P_D=1500$ MW

Parameters employed for competing algorithms are given in Table 3. For fair comparison, no. of iterations and population size are considered same.

Table 3: Parameters employed for competing algorithms

Algorithms	Parameters	Value
GA	Crossover, Mutation Probability	$8e-1, 1e-3$
PSO	Inertia, $C1, C2$	0.4, 0.2, 0.2
GSA	α, G_0	20, 100
GWO	a	[0, 2]
ERGWO	α, μ	[0, 2], [1.0001, 1005]

Discussion

Optimization performance is computed keeping no. of iteration and population size same. Tolerance of $1e-3$ is set for solution to be converged and considered as the stopping criterion of optimization process. Fig. 10 depicts the convergence behavior of profit values derived from the optimization techniques employed by GA, PSO, GSA and GWO for 1500 MW demand level. It is apparent from the results that profit obtained by GA, PSO, GSA and GWO are less than ERGWO. Convergence characteristics also exhibit the superior computational behavior of ERGWO. Profit obtained by ERGWO is more than GA, PSO, GSA and GWO by 21 %, 9.43 %, 11.33 % and 2.62 % respectively, when the demand level is 1500 MW. Moreover, due to high computational cost, GA and GSA exhibited the highest execution time. Optimization routine with PSO displayed faster convergence but got trapped in local minima, consistent with the fact that proposed methodology is optimally suited to strategic bidding problem in comparison to its counterparts.

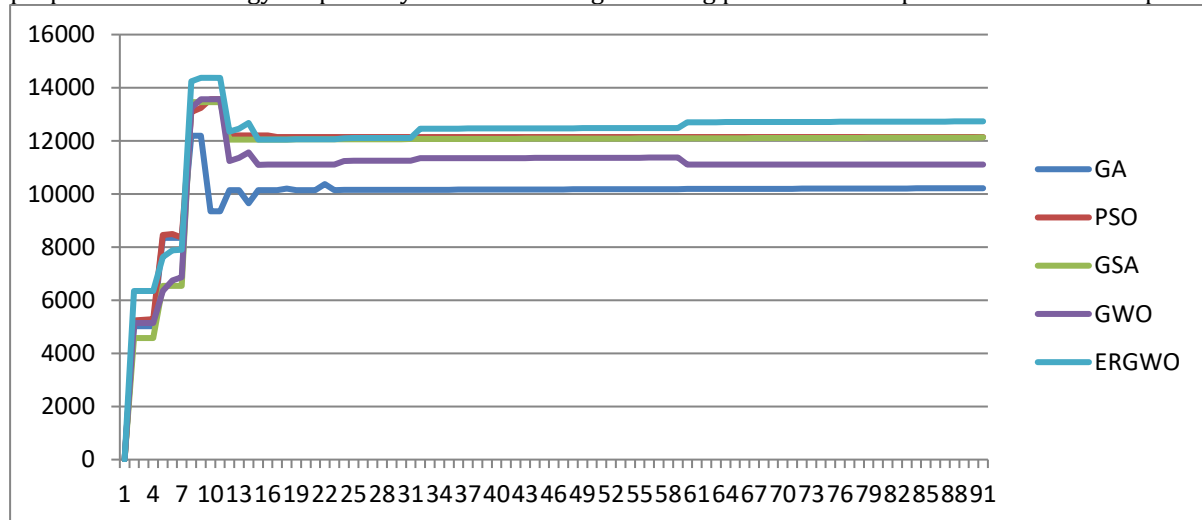


Fig. 10. Convergence curve for $P_D=1500$ MW

4.2 Computational Complexity Analysis

The proposed Efficient and Robust Grey Wolf Optimizer (ERGWO) improves upon the standard Grey Wolf Optimizer (GWO) while maintaining a competitive computational cost compared to other metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Gravitational Search Algorithm (GSA).

4.2.1. Computational Trade-Offs and Practical Implications

- A. ERGWO has a similar computational complexity as GA, PSO and GWO, but it achieves better convergence efficiency by dynamically adjusting the exploration-exploitation process.
- B. Unlike GSA ($O(T \cdot N^2)$), which requires complex force-based calculations, ERGWO maintains a linear relationship with the number of search agents, making it computationally more scalable.
- C. The adaptive mechanisms in ERGWO slightly increase computational cost but the faster convergence compensates for this overhead by reducing the number of required iterations.

5. Conclusion

In this article, an effective bidding strategy has been prepared for GENCO which will lead to profit maximization in the competitive environment of electricity markets. Simulation results are obtained with the application of Minitab and ERGWO algorithm. Mean and standard deviation of price distribution have been adjusted to model variability more effectively, ensuring it accurately represents the dynamics of the real electricity market. Comparison with other classical stochastic algorithm (GA, PSO, GSA, GWO) has been made and following major findings are discovered.

- A. ERGWO performs fairly better than other algorithms (GA, PSO, GSA, GWO). The profit of GENCO A is also improved for all the considered cases.
- B. Convergence characteristics show that GA and PSO got trapped in local minima. The results obtained with the application of GSA are also good as compared to GA and PSO but less profit is obtained when compared with ERGWO.

Despite its strong performance, this study has certain limitations. ERGWO's scalability to large-scale power systems and its ability to handle market uncertainties such as price volatility and renewable energy fluctuations require further investigation.

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