Optimum Bidding Method using MOGWO in Open Energy Market for Customers

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Abstract- **- The deregulation of the electricity sector has dramatically modified the current electricity system. Generators (suppliers) and large consumers (buyers) in an open, competitive energy market need an appropriate bidding method to increase their earnings. Because of this, every generator and large consumer will strategically bid for the choice of bidding factors to assess the opposition's bidding schemes. Power utilities use bidding methods to maximize revenue and minimize risk. In this article, we have demonstrated the essential components of the technique with the help of six power suppliers and two big buyers. We have used a Multi-Objective Grey Wolf Optimizer (MOGWO) to solve the bidding strategy problem as an optimization problem. Under this work, a methodology for electric utilities to bid effectively for expansion in their profits is developed. The competitor's behaviour is ascertained using the probability density function. The MOGWO is employed in an optimization procedure to determine the best conclusion to the bidding problem. The method is verified using a test setup with six generators and two large consumers. The outcomes of using the Monte Carlo (MC), Gravitational Search Algorithm (GSA), Whale Optimization Algorithm (WOA) and Invasive Weed Optimization Algorithm (IWOA) techniques are also compared. Comparing the outcomes demonstrates that MOGWO is a successful solution.**

Keywords– Strategic Bidding, Market Clearing Price (MCP), Monte Carlo Simulation, Multi-Objective Grey Wolf Optimizer (MOGWO).

1. INTRODUCTION

The conventional monopolistic system has been significantly transformed since the 1980s with the objectives of promoting fair competition and enhancing economic efficiency. The primary factor of this transformation is the development of systems that allow electricity to be openly traded between power producers and occasionally large users. In an ideal electrical market, the market structure, management procedures, and rules would be sufficiently well thought out, and participant rivalry would be sufficiently fierce, to steer the market's performance in the direction of maximizing social welfare. In other words, a well-designed power market does not allow for gaming that could disrupt operations or cause pricing distortions. However, rather than having ideal competition in the market, the structure of the emerging power market is more comparable to oligopoly. This is because the energy supply system has unique characteristics, like a high entry barrier, a small number of generators, transmission restrictions that segregate buyers from the practical reach of many generating units, and distribution losses that prevent buyers from buying electricity from far-off providers. Due to all of these factors, only a minority of generating firms (GENCOs) are able to effectively serve a specific geographic area. Every supplier may maximize revenue through competitive bidding in this situation. Detecting potential exploitation of market power through inadequacies in the market structure and management regulations is one of the key goals of researching strategic bidding because the outcomes have significant procedure inferences.

In recent years, some study has been conducted on developing the best bidding tactics for rival suppliers and/or on examining the linked market powers in energy market of the poolco-type, where the uniform pricing rule and sealed bid auction are frequently used. A theoretical optimal auction framework and active programming-based technique were established for energy market of the England-Wales type, in which every generator is needed to tender a fixed tariff for each frame of generation, in [1], which also addressed the strategic bidding issue for the open market energy providers. The model took system demand changes and unit commitment costs into consideration. An analytical design for creating the best bidding scheme in energy markets similar to those in England-Wales was created in [2] under the presumption that the market clearing price (MCP) is self-regulating of the bid of any provider. This presumption looks illogical given that the power market is less like a totally competitive market and more like an oligopoly. A straight forward suboptimal bidding technique was brought in [3] for the scenario in which two buyers (utilities) are seeking for a single power supply block, but it is not able to apply with several generators.

A radial basis function neural-network-based asynchronous or "sequence" bidding technique was proposed in [4], once more allowing the providers to modify their bids. This issue was presented as a two-level improved process in [5].Each supplier uses an implanted variable bidding factor and parametric active software design to determine a profitable bid at the lower level. A centralized economic dispatch is utilized to decide the MCP, the generation and requirement levels of all suppliers and buyers. In order for a centralized economic dispatch to be utilized to create the bidding strategy, an implicit assumption is that each supplier has comprehensive knowledge of competitors. This assumption is undoubtedly unreasonable. In 1999, various new studies were published. A strategic bidding dynamic model of was brought in [6] using historical and present market clearing prices for the scenario involving three power suppliers. This technique is experiential in principle, and not be used with more than 3 provider.To examine planned bidding conduct and to highlight some of the methods market power can be utilized, the researchers in [7] provide a linear supply function model. With the aim of maximizing social welfare, an alike linear demand /supply function method has been utilized by researchers [8] to develop the best bid strategies for rival suppliers. Additionally, the popular uniform pricing rule is contrasted with a pricing system called the "multiple-commodity second price auction," and simulation findings demonstrate that the former rule gives suppliers a greater incentive to bid at minimal prices compared to the latter. A 2-level optimization process to develop bidding strategies was presented in [9], in which market contestants attempt to maximize their revenue while being constrained by the fact that an self-governing method operator sets their communications and market tariff using a transparent optimal power flow (OPF) application with the goal for making highest level of public welfare.

It is assumed that each participant knows the approximate value of each other participant's bid. A bidding plan for providers in the even tariff clearing sale is propose in [10] by evaluating the chance of getting below and on the margin, and a basic bidding scheme is then obtained under a few basic norms. The outcome suggests that sellers have a tendency to score bids over their prices. In [11], an approach for bidding based on optimization and self-planning decisions is provided from the perspective of a utility that, like in New England, can self-schedule some of its energy and bid some of it to the market. The inputs in competing bids are supposed to be obtainable as distinct dispersals, and bids are expressed as quadratic functions of power supply levels. In [12], adaptive and evolutionary bidding strategies are developed using smart trading agents such inherent algorithms, software system, and fixed state simulators. Only a little quantity of research has been done on the demand side of strategic bidding up to this point [13].Some electrical markets also allow demand-side bidding, including those in California and New Zealand, for large customers to respond to energy tariff. The purpose of this research is to propose a outline in which a Monte Carlo technique can be used to generate bidding plans for large customers and suppliers [14]. The market is thought to be cleared at a consistent price because producers and large customers are free to set prices above or below their marginal costs of production or marginal gains.

By merging the Karush-Kuhn-Tucker conditions of all the nonlinear complementarity problems. A mixed nonlinear complementarity problem was implemented by researchers in [15] integrating the Karush-Kuhn-Tucker situations of all strategic producing units. The findings of this study demonstrated that producing firms might use overproduction in congested areas to perform their power in the market. [16] Suggested a binary expansion strategy to tackle the optimal bidding problem. The author found a solution to the issue of unpredictable short-term energy market systems and strategic bidding. Researchers in [17], developed an approach to ascertain the best retailer bidding planning in the short-term power markets. The parameters determining the optimum purchase strategy were optimized using GA. An integrated planning and attempting procedure for building the bidding curve of an energy utility that joined in the day-ahead power bazaars was presented by Mostafa Kazemi et al. [18]. A mathematical model was proposed by article [19] for large consumers to modify pool prices in order to improve the benefits of determining bidding tactics. A stochastic complementarity model served as the uncertainty model. In this work, risk management modeling was not performed. For generation firms competing in a pool-based power industry, a risk-constrained bidding model has been proposed in [20]. The strategic bidding issue was solved using the dynamic programming technique. The system demand uncertainty was taken into account in the bidding model.

The MOGWO [21] is employed to achieve the goal of obtaining a bidding strategy for maximizing Genco's profit. A new Meta heuristic algorithm called MOGWO was motivated by researcher. It imitates the management ladder structure & method of hunting used by authors in nature. When compared to other well-known Meta heuristics methods, the algorithm offers results that are highly competitive. In this study, a comparison between MOGWO and other Meta heuristic algorithms (WOA, and IWOA) has also been performed. The remaining part of the paper is organized as follows; sections 2 and 3 offer a description of the problem and a suggested algorithm for solving it. The simulation findings are reported in section 4, and the conclusion described in section

2. PROBLEM FORMULATION

Consider a network with m large customers who contribute in demand-side bidding, n different energy providers, an interlinked system administered by a self-governing system operator.

A function of linear non-increasing supply/demand, such as the supplier's marginal supply price, $G_j(P_j) = \alpha_j + \beta_j P_j$ for the j^{th} provider and the marginal demand price $L_l(W_l) = \emptyset_l - \varphi_l W_l$ for the l^{th} large customer is assumed to be the one that any provider or large client must bid to PX. P_j stands for active power output, and $\alpha_j \& \beta_j$ are the bidding factors for the j^{th} supplier's. W_l stands for active power load, and $\emptyset_l \& \varphi_l$ are the bidding coefficients for the l^{th} large consumer's. The non-negative terms are α_j, β_j, $\emptyset_l$ and φ_l.

Therefore, PX determines a set of generation outputs $P = (P_1, P_2, \dots P_n)^T$ and a set of large consumers' demands $W = (W_1, W_2, \dots W_n)^T$ by solving problems (1) to (5) when only the load flow constraints, generation output limit, and consumer demand limit constraints are taken into account. In practice, further constraints such transmission capacity constraints must be properly considered. The steps of the method described below can be modified for use in situations that are more complicated, and this will be taken into consideration in further analyses.

$$\boldsymbol{\alpha_j + \beta_j P_j = R} \qquad j = 1 ,2, ..., n \qquad (1.1)$$

$$\boldsymbol{z - \varphi_l W_l = R} \qquad l = 1 , 2, ..., m \qquad (1.2)$$

$$\boldsymbol{\sum_{j=1}^{n} P_j = Q(R) + \sum_{l=1}^{m} W_l} \qquad (1.3)$$

Operating constraints:-

Generation output limits :

$$\boldsymbol{P_{j_{min}} \leq P_j \leq P_{j_{max}}} \qquad j= 1, 2,..., n \qquad (1.4)$$

Demand limits:

$$\boldsymbol{W_{l_{min}} \leq W_l \leq W_{l_{max}}} \qquad l = 1, 2, ..., m \qquad (1.5)$$

R stands for the predicted uniform MCP of electricity. All participants are informed of Q(R), which is total pool load forecast by PX and is predicated on electricity cost.1, 2 and 3 equations can be explained directly if expression for Q(R) is known. Assume that the linear form of the total pool load Q(R) is as follows:

$$\boldsymbol{Q(R) = Q_0 - KR} \qquad (1.6)$$

Where K is a factor indicating the cost elasticity of total demand and Q0 is a constant quantity. K = 0 if pool demand is generally inelastic: The answers to Equations (1)–(3) are as follows when the inequality restrictions (4) and (5) are completely ignored:

$$\boldsymbol{R = \frac{Q_0 + \sum_{j=1}^{n} \alpha_j/\beta_j + \sum_{l=1}^{m} \emptyset_l/\varphi_l}{\sum_{j=1}^{n} 1/\beta_j + \sum_{l=1}^{m} 1/\varphi_l + K}} \qquad (1.7)$$

$$\boldsymbol{P_j = (R - \alpha_j)/\beta_j} \qquad (1.8)$$

$$\boldsymbol{W_l = (\emptyset_l - R)/\varphi_l} \qquad (1.9)$$

The solution set (8)/(9) must be adjusted when it opposes the production output/consumer demand limits (4)/(5). Pj should be set to zero rather than $\boldsymbol{P_{j_{min}}}$ when Pj is less than its lower limit $\boldsymbol{P_{j_{min}}}$ because at that point the supplier is no longer competitive and should be removed from the problem. Since it is no longer a minimal producer when it exceeds the upper edge, its value is set to $\boldsymbol{P_{j_{max}}}$ and Eq. (1) is ignored for this producer. For supplier jth in these two scenarios, Eq. (1) is no longer valid. Wl will receive a comparable response. The profit boosting goal for developing a bidding planning for the jth supplier is as follows:

Maximize: $\boldsymbol{F(\alpha_j, \beta_j) = RP_j - C_j(P_j)}$ (1.10)

Subject to: Eqs. (1) – (5)

This will define $\alpha_j \& \beta_j$ in order to maximize $F(\alpha_j, \beta_j)$ within the limitations of (1) - (5). The jth supplier's production cost function is Cj(Pj). Similarly, the profit boosting goal for developing a bidding strategy for the lth large consumer is as follows:

Maximize: $\boldsymbol{H(\emptyset_l, \varphi_l) = B_l(W_l) - RW_l}$ (1.11)

Subject to: Eqs. (1) – (5)

This will determine $\emptyset_l$ and φ_l in order to maximize $H(\emptyset_l, \varphi_l)$ within the limitations of (1)- (5). The lth large consumer demand function is $\boldsymbol{B_l(W_l)}$. Assume that from the perspective of the pth (p = 1, 2,..., n + m) contestant, the bidding factors of the jth (j = 1, 2,..., n, and j≠ p) provider, α_j and β_j, conform to a joint regular dispersal with the probability density function (pdf) as follows:

$$\mathbf{pdf(\alpha_j, \beta_j) = \frac{1}{2\pi\sigma_j^{(\alpha)}\sigma_j^{(\beta)}\sqrt{1-\rho_j^2}} \times \exp\left\{-\frac{1}{2(1-\rho_j^2)}\left[\left(\frac{\alpha_j - \mu_j^{(\alpha)}}{\sigma_j^{(\alpha)}}\right)^2 + \frac{2\rho_j(\alpha_j-\mu_j^{(\alpha)})(\beta_j-\mu_j^{(\beta)})}{\sigma_j^{(\alpha)}\sigma_j^{(\beta)}} + \left(\frac{\beta_j-\mu_j^{(\beta)}}{\sigma_j^{(\beta)}}\right)^2\right]\right\}} \qquad (1.12)$$

3. PROPOSED ALGORITHM
MOGWO ALGORITHM

The GWO algorithm was published in 2014 by researchers in [21] and was motivated by the community leadership &hunting strategies of grey wolves. The hunting behavior of grey wolves is statistically demonstrated, and the results gained by Alpha (α) wolf are thought to be the best results, while those acquired by the Delta (δ) and Beta ($\boldsymbol{\beta}$) wolves are seen to be the second and third best results, respectively. The remaining answers are viewed as the worst ones that the Omega ($\boldsymbol{\omega}$) wolves could have come up with. The α, $\boldsymbol{\beta}$ and δ wolves are employed to control the hunts, & the $\boldsymbol{\omega}$ wolves follow the α, $\boldsymbol{\beta}$ and δ wolves to find a solution on a worldwide scale.

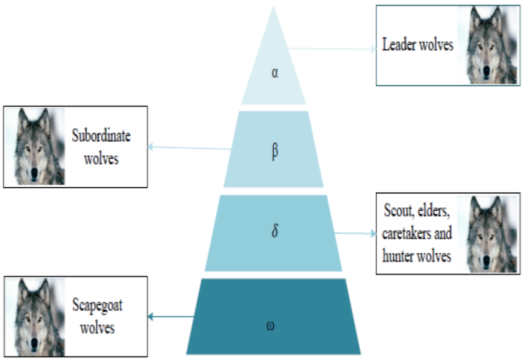

Fig.3.1: Hierarchy of Grey Wolf

The following mathematical model represents how grey wolves hunt.

$$\vec{D} = \left|\vec{c}\,.\overrightarrow{X_p}(t) - \vec{X}(t)\right| \tag{3.1}$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}\vec{D} \tag{3.2}$$

Where t denotes the current iteration,$\vec{A}$ and $\vec{C}$ denotes coefficient vectors, $\overrightarrow{X_p}$ denotes the prey's position vector, and $\vec{X}$ is a grey wolf's position vector. These are the calculations for the vectors $\vec{A}$ and$\vec{C}$:-

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a} \tag{3.3}$$

$$\vec{c} = 2.\vec{r_2} \tag{3.4}$$

Where$\vec{r_1}$, $\vec{r_2}$ are random vectors in [0, 1] and elements of a linearly decline from 2 to 0 during the duration of iterations.

To solve optimization problems, the GWO algorithm makes use of the simulated social leadership and surrounding process. This algorithm compels other hunt agents with the omegas, to change their locations in relation to top three best solutions found thus far. In order to simulate hunting and identify suitable search space regions, the following formulas are continuously executed for each search agent:

$$\overrightarrow{D_\alpha} = \left|\vec{c_1}\,.\overrightarrow{X_\alpha} - \vec{X}\right| \tag{3.5}$$

$$\overrightarrow{D_\beta} = \left|\vec{c_2}\,.\overrightarrow{X_\beta} - \vec{X}\right| \tag{3.6}$$

$$\overrightarrow{D_\delta} = \left|\vec{c_3}\,.\overrightarrow{X_\delta} - \vec{X}\right| \tag{3.7}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}.\overrightarrow{D_\alpha} \tag{3.8}$$

$$\overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}.\overrightarrow{D_\beta} \tag{3.9}$$

$$\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}.\overrightarrow{D_\delta} \tag{3.10}$$

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1}+\overrightarrow{X_2}+\overrightarrow{X_3}}{3} \tag{3.11}$$

For multi-objective optimization, GWO has been merged with two fresh modules. First is an archive, which is in liable of keeping the Pareto front of wolves that are not dominant. The most common method for storing and retrieving Pareto optimum answers is an archive.

The second part of multi-objective optimization is the leader selection strategy of wolves. To meet the user's needs, the three best solutions are employed. Alpha is first utilized to meet user requirements. Beta and delta are then employed. There is an archive controller to regulate the archive if a new wolf position (solution) wishes to enter the archive or the archive is filled. The cases listed below are taken into consideration for an archive:

- The new value need to have a more efficient solution than those found in archive. A fresh value cannot be included to the archive in any other case.
- If the new wolf is more valuable, the existing solutions must be removed from the archive to make room for the new one.
- The fresh solution may be moved into the archive in case the values of the two solutions are equal.
- In case the archive is not empty, the grid tool locates the area that is the most congested and omits its solutions there. The least packed segment should then receive the new solutions.

The second part of MOGWO is the leader selection mechanism. Alpha, beta, and delta are the first three top solutions identified. The leaders are followed by other wolves. There could be some special circumstances.

The least packed segment should produce the top three leaders. The third solution should be chosen from the second least crowded hypercube if there are only two in the least congested hypercube. Additionally, a delta wolf may be chosen from the third least populated segment. There is no prospect of choosing the same wolf to be alpha and beta through this structure. The MOGWO flow chart is provided in fig 3.2.

4. SIMULATION AND RESULTS

In this article, we have used an IEEE 30bus System with 6 generating units & various loading customers, the effectiveness of various optimization strategies to solve the bidding planning issue in an open energy market is calculated. The simulations are performed using MATLAB version 15. The numerical values of various control parameters used during the execution of the suggested procedures are Pop size=200, Mutation Probability = 0.02, Crossover Probability = 0.7, and Iterations = 1000.

The approach is illustrated with the help of a case study with 6 generators and 2 important users. The generation cost function($C_jP_j = b_jP_j + c_jP_j^2$) & production output ranges for the 6 generators are shown in Table 1. Demand functions($B_lW_l = e_lW_l + f_lW_l^2$) and demand constraints for the two largest buyers are presented in Table 2.

Additionally, there is an total load of =300MW that is elastic to the cost of power when K=5 in equation.

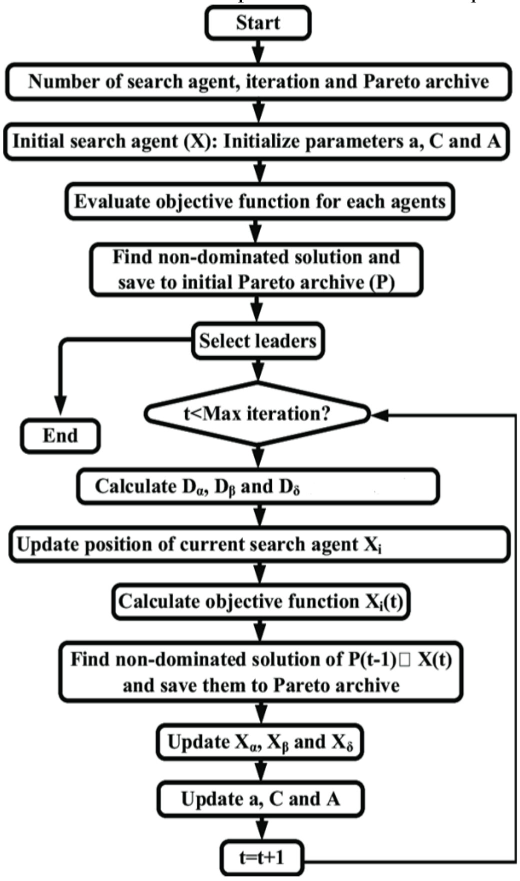

Fig.3.2: Flow chart of MOGWO Algorithm

Obviously, β_j/φ_lmust not be lower than c_j/f_l since the providers/large customers may suffer financial damage. Because this range is sufficiently large, the optimum value of β_j/φ_l is discovered in the interval in $c_j/f_l \& M \times C_j/\mathrm{M} \times f_l$ & M is fixed to 10 in all runs. The proposed multi-objective optimization framework for an optimum double-side bidding method was developed utilizing the same bus structure due to the extensive appropriateness of the IEEE-30 bus system. The system that has been taken into deliberation consists of generators=6, loads=6, and transmission lines=41. The cost coefficient data of suppliers and main customers were modified using reference [1], and the constant value Q0 and the elasticity factor K of the total load were set to 300 and 5, respectively. The MOGWO, which is discussed in this section, is an optimization method based on meta-heuristics that was initially introduced in 2014 by Seyedali Mirjalili, Seyed Mohammad Mirjalili, and Andrew Lewis. MOGWO algorithms are tested and simulated 20 times to find the best solutions to the optimal bidding issue.

Table 1: System Generation data

Generator No.	b	c	P_{min} (MW)	P_{max} (MW)
1	6.0	0.01125	40	160
2	5.25	0.0525	30	130
3	3.0	0.1375	20	90
4	9.75	0.02532	20	120
5	9.0	0.075	20	100
6	9.0	0.075	20	100

Table 2: Large consumer data

Consumer No.	e	f	W_{min} (MW)	W_{max} (MW)
1	30	0.04	0	200
2	25	0.03	0	150

5. CONCLUSIONS

A method for creating strategic bids for energy providers and customers in a poolco-type energy market is described. Electric utilities and large consumers are expected to bid according to a linear function, with grid dispatch levels chosen by an energy exchange that maximizes social benefits and the market settled at a reasonable rate. A stochastic multi-objective optimization model is constructed for characterizing and resolving this issue and an MC-based simulation methodology is applied. Using a case study including six providers and two large consumers, the technique was illustrated. A multi-objective optimal double side bidding approach is created to maximize the overall profit.

The MOGWO evolutionary algorithms are used to solve the proposed model using the IEEE 30 bus system. The findings of a comparison analysis of the gathered results are displayed in Table 4. An overview of the many market power projects that have been completed is provided by this report. Additionally, thorough analyses of recent papers as well as a look at the bid strategy used in the deregulated power market were undertaken.

Table 3: Simulation results by MOGWO Algorithm:

ID	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	Optimal Bid
α_1	**6.0000**	7.1455	7.1663	7.1926	7.2166	7.1958	7.2123	7.2158	**6.0000**
α_2	6.4972	**5.2500**	6.3353	6.4582	6.3397	6.5813	6.3333	7.0875	**5.2500**
α_3	3.6045	3.6374	**3.0000**	3.5339	3.4544	3.7177	3.6786	3.6162	**3.0000**
α_4	11.9650	11.4452	11.7571	**9.7500**	11.4878	11.7813	12.0450	13.1625	**9.7500**
α_5	12.1500	12.1500	10.8611	11.5298	**9.0000**	11.0491	10.4933	11.7682	**9.0000**
α_6	11.7689	10.6546	11.8454	12.1500	12.1500	**9.0000**	11.4366	12.0536	**9.0000**
φ_1	29.2864	27.5368	28.8877	29.2333	30.0000	30.0000	**30.0000**	29.3810	**30.0000**
φ_2	25.0000	25.0000	25.0000	25.0000	25.0000	25.0000	23.4106	**25.0000**	**25.0000**

ID	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	Optimal Bid
β_1	**0.0650**	0.0268	0.0270	0.0270	0.0271	0.0269	0.0271	0.0270	**0.0650**
β_2	0.1266	**0.1910**	0.1257	0.1261	0.1255	0.1181	0.1281	0.1293	**0.1910**
β_3	0.3302	0.3309	**0.4700**	0.3317	0.3506	0.3489	0.3318	0.3286	**0.4700**
β_4	0.0604	0.0602	0.0609	**0.1282**	0.0646	0.0612	0.0601	0.0636	**0.1282**
β_5	0.1904	0.1912	0.1819	0.1753	**0.3805**	0.1688	0.1783	0.1846	**0.3805**
β_6	0.1851	0.1791	0.1821	0.1760	0.1913	**0.3263**	0.1773	0.1799	**0.3263**
ϕ_1	0.0880	0.0902	0.0880	0.0880	0.0880	0.0911	**0.0769**	0.0880	**0.0769**
ϕ_2	0.0660	0.0660	0.0665	0.0670	0.0660	0.0660	0.0677	**0.0627**	**0.0627**

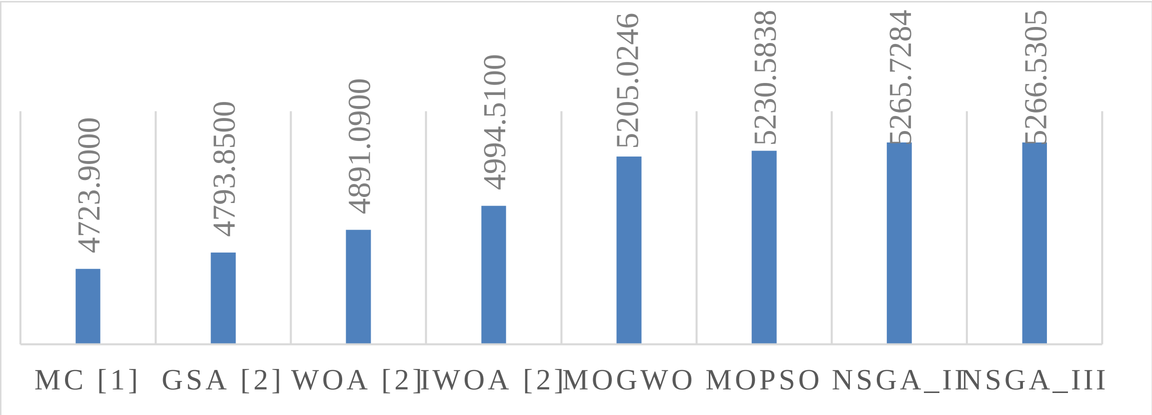

Fig.1. Comparative presentation of the total profit in $

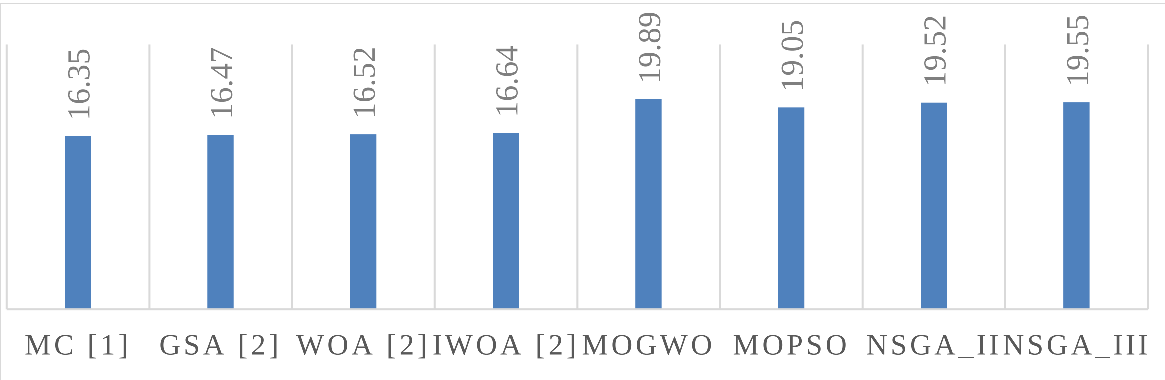

Fig.2. Comparative presentation of the market clearing price in $

Table 4: Comparative presentations of the optimal bidding of the suppliers and buyers as well as their power dispatch, market clearing price and profit:-

		MC [1]	**GSA [2]**	**WOA[2]**	**IWOA [2]**	**MOGWO**
Results Based on Optimal Bidding	MCP	16.35	16.47	16.52	16.64	19.89
	P_1	160.00	160.00	160.00	160.00	160.00
	P_2	89.40	114.20	106.14	107.23	76.62
	P_3	45.70	50.09	49.07	47.97	35.93
	P_4	88.80	88.35	120.00	119.90	79.07
	P_5	43.10	40.15	48.87	49.06	28.61
	P_6	43.10	40.15	48.87	49.06	33.37
	L_1	139.70	149.60	172.77	174.25	131.51
	L_2	112.10	125.70	142.61	141.62	81.51
	ProfitP_1	1368.00	1386.60	1395.30	1416.50	1933.87
	ProfitP_2	572.70	596.20	604.85	618.21	813.23
	ProfitP_3	322.90	329.52	332.39	338.14	429.22
	ProfitP_4	386.40	395.73	447.91	462.72	643.18
	ProfitP_5	177.50	178.85	188.39	194.54	250.10
	ProfitP_6	177.50	178.85	188.39	194.54	279.75
	ProfitL_1	1126.30	1129.40	1134.80	1158.20	638.21
	ProfitL_2	592.60	598.70	599.06	611.66	217.47

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