Double Sided Bidding Strategy in a Day-Ahead Electricity Market

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***Abstract*— A double-sided strategic bidding problem is projected in the developing electricity market as a multi-objective difficulty. The most important aim of this paper is to identify optimal values of bidding coefficients for sellers and buyers of electrical energy to optimize their remuneration in terms of overall profit. When both sellers and buyers of electrical energy are involved in a double-sided bid procedure to maximize their profits, the issue becomes a multi-goal in which two goals are simultaneously optimized. Therefore, in this work, problem of profit maximization of both entities is included as a complex multi-objective problem and solved by a new hybrid solution, it relies on a correspondence to the form of ideal solution (TOPSIS) coupled with a algorithm for gravitational exploration (GSA). The TOPSIS method uses Euclidean geometry to provide a standardized outcome distribution for multi-objective optimization issues and can be used in combination with any recent form of heuristic optimization to choose the best compromising result. The proposed methodology is productively implemented on the system having six electrical energy sellers and two large buyers participating in a single hour trading period. Results obtained using TGSA provide a superior result in terms of higher profits / benefits than other methods like Monte Carlo. The comparison suggests that the TGSA approach is effective and may be a useful tool in multi-objective bidding procedure in day-ahead market for maximizing social welfare.**

Keywords*— *Double-sided strategic bidding, electricity market, gravitational search algorithm, market clearing price, TOPSIS

I. Introduction

Since 1980, worldwide transition of the electricity market into deregulated market structure has been ongoing. It urged innovative technology to establish a competitive market environment for electricity to improve the business economy [1], [2]. Competition is essential in market restructurings; also cost reduction and e□ciency are often preferred. The primary concept of this electricity market transformation is to design a fresh open market structure, a Pool Co model for dynamic power trading in order to obtain greater financial effectiveness. It will result from private entities being carefully regulated and enable them to access the market. It can be introduced solely for the accumulation of new generating capability called competitive bidding in which the existing company is inviting contractors to construct, operate and sell electricity at a specified price to the monopoly. Sealed bids are structured in a POOL based market model, candidates send their offers for selling / purchasing energy from / to the network operator depending on the market clearing rate (MCP). Participants build up their bids in this scenario to exploit their anticipated earnings in term of profits. Unforeseen deviations in the electricity market may result in imperfection in electricity trading. Therefore, participant take benefit from these imperfections in order to improve their profit by bidding [3].

The strategic bidding issue was first discussed for competitive energy providers [4], and the author observed that Rival suppliers' unpredictable bidding actions may affect bidding strategies due to the natural behavior of members playing to maximize their benefits. This may exacerbate the problems in the process of bidding decision. In [5], [6], authors have assumed that the electricity providers are free to charge their marginal production expenses and submit single hour [5] and multi hour [6] linear bidding features, and are paid the MCP once their o□ers have been selected. Moreover, in these works rivals bidding behaviours are presented as a discrete nature. Therefore, a detailed work has been done on the production of strategic bids, taking into account the involvement of the generation side [7], [8], [9], [10], [11], [12], [13], [14], [15]; on the demand side, little work was done. Based on this, [16] proposed a strategic bidding problem together for electricity suppliers and big buyers. Thereafter, [17], [18], [19], [20], [21], [22] attempted and solved the problem of PS and large buyer profit maximization by determining both entities bidding parameters. In an emerging power market, when both entities; suppliers and buyers; participate in double sided bidding for profit maximization, issue becomes a multi-objective issue which simultaneously optimizes two goals. This is because of the nature of the power suppliers and buyers. The energy producers are attempting to increase the MCP by phasing out business efficiency and by changing their power consumption, the big consumers are trying to reduce the MCP. Since these goals are conflicting, it is important to have a clear multi-objective problem model. Several multi-objective approaches have been developed by researchers in the literature to address problems of power system optimization. Remember that the need to solve multi-objective problems cannot be satisfied by a single algorithm. Consequently, the mix optimization methods were introduced and published in precise literature [23]-[29]. By assigning weights [23]-[26] or multiply them by a function of penalty [27], most multi-objective formulations with multiple goals are translated into a single-objective issue. The normally utilized structures for multi-objective formulation may incorporate weighted sum [23]-[26], penalty function [27], goal programming [28], epsilon-constrained [29] based methodologies. However, these techniques have a few restrictions; for example, the ideal arrangement of the weighted sum methodology relies upon choosing weights, pre-specified goals in task scheduling, and setting master and slave goals in epsilon-limited approaches. The above discussed methods su□er from some more limitations which can be overcome by scaling the

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objectives through the di□erent approaches like fuzzification [30], max-min technique [31] and goal programming focused on fuzzy [32], but they may be lacking the inbuilt mechanism to deliver the desired Pareto-front. Therefore, more powerful multi-objective solution approaches are required. Recently, in hybrid optimization category, the new method is TOPSIS and suggested in [28], [29] to provide the best compromise solutions. At some stage of technical iterations, can be paired any heuristic technique with this approach to decide the best compromise result. In general, TOPSIS is now considered one of the new approaches for solving multi-objective troubles. It uses Euclidean geometry to calculate the detachment between outcomes and their most excellent resolution. Compared to other methods used, it generates Pareto front more evenly [28], demonstrating its ability. Nonetheless, some TOPSIS implementations are available for real-world applications. Thus, the energy market problem considers the discovery of its potential using heuristic methods.

Several methodologies depend on heuristic methods have been introduced in the literature [6]-[22] to address the various strategic bidding issues. These heuristic approaches are basically based on the tuning of its parameters and thus the techniques having less tuning parameter results in the most accurate results. A novel heuristic technique is being developed in this regard, Gravitational Search Algorithm (GSA), depend on gravity theory and mass interaction law. Implementation of physics-based algorithm GSA on power system issue provide high quality results as compared to bio-inspired or other algorithms of nature [13], [35]-[37] like GA, PSO, etc. Its most comprehensive function is the gravitational constant adjustment to increase the precision of the search. It provides high-quality results with a quick solution. Therefore, a multi-objective approach for the dynamic double-sided strategic offering difficulties of both sellers and purchasers is formulated in this manuscript to maximize profit and solved using a new methodology based on TOPSIS along with GSA (TGSA).

II. POBLEM FORMULATION

Assume that a arrangement includes ' u ' self-governing energy suppliers, an unified ISO restricted network, a power exchange (PX), an aggregated buyer (load) is not involved in bidding on the demand side, but is flexible in electricity costs, and ' z ' large customers engaging in demand-side bidding. Assume that every supplier / costumer is required to provide PX with a linear, non-decreasing supply / non-increasing demand characteristic, respectively

$$C_n(\mathrm{P}_n) = \alpha_n + \beta_n P_n \,,\; n = 1,2,......,\mathrm{u} \tag{1}$$

$$L_m(\mathrm{D}_m) = \theta_m - \pi_m D_m \,,\qquad m = 1,2,......,\mathrm{z} \tag{2}$$

Where, P_n and D_m are power generation output and load, α_n, β_n, θ_m, π_m are offering parameters, which has to be positive parameters.

The decision maker or an operator of market now selects a generation / demand range that fits and reduces full purchase costs and increases community interests by addressing (3) to (7).

$$\alpha_n + \beta_n P_n = MCP \,,\qquad n = 1,2,......,\mathrm{u} \tag{3}$$

$$\theta_m - \pi_m D_m = MCP \,,\qquad m = 1,2,......,\mathrm{z} \tag{4}$$

$$\sum_{n=1}^{u} P_n = Q(\mathrm{MCP}) + \sum_{m=1}^{z} D_m \tag{5}$$

$$P_{\mathrm{min,n}} \le P_n \le P_{\mathrm{max,n}} \tag{6}$$

$$D_{\mathrm{min,m}} \le D_m \le D_{\mathrm{max,m}} \tag{7}$$

Here, for the n[th] power source, the minimum and maximum active power generation limits are $P_{\mathrm{min,n}}$ and $P_{\mathrm{max,n}}$ respectively. Load expected by the operator of market is $Q(\mathrm{MCP})$. Suppose that $Q(\mathrm{MCP})$ is

$$Q(\mathrm{MCP}) = Q_c - k * MCP \tag{8}$$

Here, Q_c is unvarying and k=5 is non-negative demand cost elasticity. The solution of (3), (4) and (5) when ignoring (6), (7) is

$$MCP = \frac{Q_c + \sum_{n=1}^{u} \frac{\alpha_n}{\beta_n} + \sum_{m=1}^{z} \frac{\theta_m}{\pi_m}}{k + \sum_{n=1}^{u} \frac{1}{\beta_n} + \sum_{m=1}^{z} \frac{1}{\pi_m}} \tag{9}$$

$$P_n = \frac{MCP - \alpha_n}{\beta_n} \tag{10}$$

$$D_m = \frac{\theta_m - MCP}{\pi_m} \tag{11}$$

If the solution of equations (10) and (11) violets limits, then limits are set according the procedure given in [16].

The maximization of supplier / buyer can be described in order to build strategic bidding profit / benefit

Maximize:

$$F(\alpha_n, \beta_n) = MCP * \mathrm{P}_n - C_n(\mathrm{P}_n) \tag{12}$$

$$F(\theta_m, \pi_m) = B_m(\mathrm{D}_m) - MCP * D_m \tag{13}$$

Subject to: equation (9)-(11)

Where, $\mathrm{C}_n(\mathrm{P}_n) = a_n P_n + b_n P_n^2$ is supplier price feature of output, $B_m(\mathrm{D}_m) = e_m D_m - f_m D_m^2$ is buyers cost function, and (a_n , b_n) / (e_m , f_m) are price coefficients. Supplier/buyers are designed to determine α_n / θ_m , β_n / π_m to maximize (12) / (13) subject to the (9)-(11).

In a competitive electricity market with a closed bid, bidding information for the next period is confidential. Therefore, bidders have no details about the bid of other participants. However, data on the last cycle of bidding is available; it is possible to estimate MCP on the basis of this data. Each participant attempts to infer coefficients from other participants, but this is not easy. As a result, for estimating offering parameters, each participant represents their offering parameters by a normal joint distribution with the following probability density (pdf) function.

$$\mathrm{pdf_i}(\alpha_n,\beta_n) = \frac{1}{2\pi\sigma_n^{(\alpha)}\sigma_n^{(\beta)}\sqrt{1-\rho_n^2}} \times \exp\left\{ -\frac{1}{2\left(1-\rho_n^2\right)} \left[\left(\frac{\alpha_n - \mu_n^{(\alpha)}}{\sigma_n^{(\alpha)}}\right)^2 + \left(\frac{\beta_n - \mu_n^{(\beta)}}{\sigma_n^{(\beta)}}\right) - \frac{2\rho_n\left(\alpha_n - \mu_n^{(\alpha)}\right)\left(\beta_n - \mu_n^{(\beta)}\right)}{\sigma_n^{(\alpha)}\sigma_n^{(\beta)}} \right] \right\} \tag{14}$$

May define this equation in the condensed form:

$$(\alpha_n,\beta_n) \sim N\left\{\begin{bmatrix}\mu_n^{(\alpha)}\\ \mu_n^{(\beta)}\end{bmatrix},\begin{bmatrix}(\sigma_n^{(\alpha)})^2 & \rho_n\sigma_n^{(\alpha)}\sigma_n^{(\beta)}\\ \rho_n\sigma_n^{(\alpha)}\sigma_n^{(\beta)} & (\sigma_n^{(\beta)})^2\end{bmatrix}\right\} \quad (15)$$

where, ρ_n is coefficient of correlation among α_n and β_n, $\mu_n^{(\alpha)}$, $\mu_n^{(\beta)}$, $\sigma_n^{(\alpha)}$ and $\sigma_n^{(\beta)}$ is the integrated distribution parameters. The minimal variations of α_n and β_n are with average values standard of $\mu_n^{(\alpha)}$ and $\mu_n^{(\beta)}$, and standard variations $\sigma_n^{(\alpha)}$ and $\sigma_n^{(\beta)}$. Correspondingly, assumed for every bulky purchasers pdf is

$$(\theta_m,\pi_m) \sim N\left\{\begin{bmatrix}\mu_m^{(\theta)}\\ \mu_m^{(\pi)}\end{bmatrix},\begin{bmatrix}(\sigma_m^{(\theta)})^2 & \rho_m\sigma_m^{(\theta)}\sigma_m^{(\pi)}\\ \rho_m\sigma_m^{(\theta)}\sigma_m^{(\pi)} & (\sigma_m^{(\pi)})^2\end{bmatrix}\right\} \quad (16)$$

The meaning of $\mu_m^{(\theta)}$, $\mu_m^{(\pi)}$, $\sigma_m^{(\theta)}$, $\sigma_m^{(\pi)}$, and ρ_m are similar to $\mu_n^{(\alpha)}$, $\mu_n^{(\beta)}$, $\sigma_n^{(\alpha)}$, $\sigma_n^{(\beta)}$ and ρ_n.

These parameters can be calculated on the basis of the historical offer for the previous hour [16]. The integrated sharing of α_n, β_n, θ_m and π_m is characterized by the method of probability distribution, With that goal as given in equation (12)/(13) due to equation (9)-(11) is a stochastic problem of optimization.

III. Multi-Objective Problem Formulation Using TOPSIS Technique

Each and every one offering goals can be described as

Maximize

$$\left[O_1(x),\ O_2(x),..............,O_{n_2}(x)\right] \quad (17)$$

ST: $x \in S$

Here, $O_i(x)$: $R^n \to R$ is i[th] objective, i=1, 2,….., n_2, n_2>1, and S is searching zone.

As described above, the TOPSIS strategy is applied to outline and address the multi-objective double-sided strategic offering difficulty in order to maximize sellers and big purchasers' profits. Euclidean geometry is used in this method, and two reference points such as PIS and NIS are used to find the most excellent solution. Choosing the substitute outcome should therefore be the adjoining Euclidean detachment from PIS and the most distant from NIS. The outcomes should stay focused upon their most excellent solution using this technique. This outcome improves performance of high quality of real multi-objective optimization problems. The following step in the TOPSIS technique is used to work out multi-objective difficulty:

Step I: Build a uniform medium of choice to make over every dimensional function into non-dimensional functions. Matrix variables can be represented by

$$F_{ab} = \frac{O_{ab}}{\sqrt{\sum_{a=1}^{n_1} O_{ab}^2}} \quad \forall\ a \in n_1\ \&\ b \in n_2 \quad (18)$$

where, O_{ab} is the value of b[th] objective for a[th] element and n_1 is element number.

Step II: A subjective uniform choice medium may be built to provide the items with weights if appropriate. The Matrix variables are defined as

$$W_{ab} = w_b \times F_{ab} \quad \forall\ a \in n_1\ \&\ b \in n_2 \quad (19)$$

where, w_b is weight of the b[th] objective and $\sum_{b=1}^{n_2} w_b = 1$.

Step III: PIS and NIS are measured and represented in order to holding the most excellent and most horrible options for all goal.

$$PIS = \left\{W_1^+,\ W_2^+,\ W_3^+,............,\ W_{n2}^+\right\} \quad (20)$$

$$NIS = \left\{W_1^-,\ W_2^-,\ W_3^-,............,\ W_{n2}^-\right\} \quad (21)$$

where,

$$W_b^+ = \begin{cases}\max\langle W_{ab}\rangle & \forall\text{ a; if the goal is a profit}\\ \min\langle W_{ab}\rangle & \forall\text{ a; if the goal is a benefit}\end{cases}$$

$$W_b^- = \begin{cases}\max\langle W_{ab}\rangle & \forall\text{ a; if the goal is a benefit}\\ \min\langle W_{ab}\rangle & \forall\text{ a; if the goal is a profit}\end{cases}$$

Step IV: Euclidean distances db+ and db− are measured and given by; for each occasion from PIS and NIS:

$$d_a^+ = \sqrt{\sum_{b=1}^{n2}\left(W_{ab} - W_b^+\right)^2} \quad \& \quad d_a^- = \sqrt{\sum_{b=1}^{n2}\left(W_{ab} - W_b^-\right)^2} \quad (22)$$

Step V: The relative closeness index (RCI) can be calculated on a case by case basis using the Step IV value.

$$RCI_a^+ = \frac{d_a^+}{d_a^+ + d_a^-} \quad (23)$$

It is possible to select the best compromise results from relative closeness index. Whose alternatives have the highest value of RCI will be considered the most excellent option for solution.

The next section will address the GSA, which is used to work out the above discussed stochastic problem of optimization.

IV. Gravitational Search Algorithm

Authors suggested a GSA in [35] to tackle non-differentiated and non-linear difficulty. Each GSA member supports the issue with an improved outcome. Figure 1 includes a flowchart for the solution process.

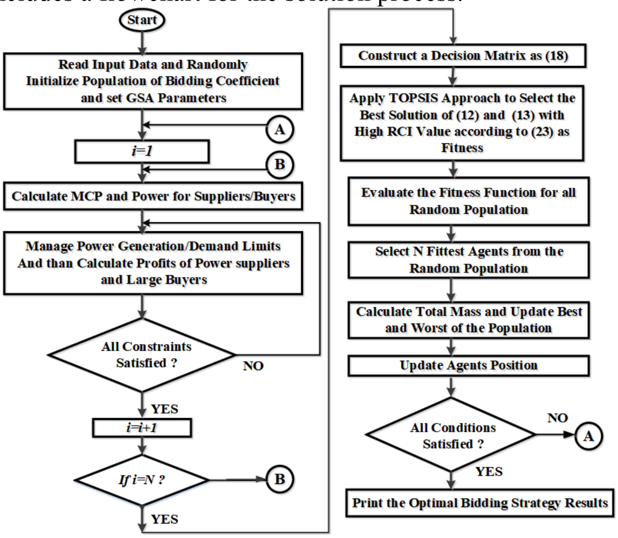

Fig. 1. Flow chart for IGSA

A. Initializationof the Population

Suppose that a scheme including of N representatives (masses) that reflect the kth agent's position

$$\lambda_k = (\lambda_k^1, \ldots\ldots, \lambda_k^D, \ldots\ldots, \lambda_k^M) \quad \text{for} \quad k = 1, 2, \ldots\ldots, N \tag{24}$$

here $\lambda_k^D \in [L_k^D, U_k^D]$, $D = 1, 2 \ldots\ldots, M$, is position of the kth representative in the Dth length and M is the search space length and L_k^D, U_k^D are kth agents lesser and higher limits in the Dth dimension.

B. Evaluationof the Fitness Function

The best solution of the equations (12) and (13) with high RCI Value according to (23) is considered as a fitness function.

C. Acceleration of Representative

The fitness test is used to determine the weight of that agent in GSA. The weight of this agent is measured as follows

$$M_k(i) = \frac{m_k(i)}{\sum_{l=1}^{N} m_l(i)} \tag{25}$$

here, $m_k(i) = \dfrac{fit_k(i) - worst(i)}{best(i) - worst(i)}$

The uniform weight of kth representative at ith iteration is $M_k(i)$. Each representative's, worst and best fitness at ith iterations are $worst(i)$, $best(i)$. Following is the acceleration $a_k^D(i)$ operating on kth representative at ith iteration.

$$a_k^D(i) = \sum_{\substack{l \in Gbest, \\ l \neq k}} rand_l \quad G(i) \frac{M_k(i)}{R_{kl}(i) + E} (\lambda_l^D(i) - \lambda_l^D(i)) \tag{26}$$

Where the first 2% of representatives have the most excellent fitness quality $Gbest$ and a identical number of random intervals between 0 and 1 is the largest mass $rand_l$, $R_{kl}(i)$ is the Euclidean distance among two representatives kth and lth at ith iteration and E is a little constructive constant. This represents the gravitational force G(j)

$$G(i) = G \times \left(1 - \frac{iteration}{Total \quad iteration}\right) \tag{27}$$

here, $$G = c \max_{D \in \{1,2,\ldots\ldots,M\}} \left(|\lambda_U^D - \lambda_L^D|\right)$$

where c is parameter of the search interval.

D. Updates Representative's Velocity and the Position

The following iteration (i+1) measures the representatives ' location and speed as follows.

$$\begin{cases} v_k^D(i+1) = rand_k \times v_k^D(i) + a_k^D(i) \\ \lambda_k^D(i+1) = \lambda_k^D(i) + v_k^D(i+1) \end{cases} \tag{28}$$

where $rand_k$ is a random number between [0, 1], $v_k^D(i)$ is the speed of kth representative at Dth measurement in ith iteration and $\lambda_k^D(i)$ is the location of kth representative at Dth measurement in ith iteration.

V. Result & Discussion

The performance and quality of the proposed IGSA is tested on the IEEE 30-bus network. The suppliers and buyers data are given in Table I. In addition, considered value of Q_c is 300 with demand cost flexibility (k=5 [16]) for aggregate demand at the moment of bidding for 30-bus system. The obtained results using TGSA is compared with MC [16] to prove the potential of TGSA. Table II summarizes the best-tuned parameters for the GSA system and is taken from [35]. In Table II, N is the size of the population; G is the gravity constant of GSA. The simulation tests were performed on a 3.20 GHz, i5 pc, 4 GB RAM PC on MATLAB R2014a.

TABLE I. IEEE 30-bus system Data for Supplier's and large Buyer's

Suppliers	P_{min} (MW)	P_{max} (MW)	a	b
1	40	160	6.0	0.01125
2	30	130	5.25	0.0525
3	20	90	3.0	0.1375
4	20	120	9.75	0.02532
5	20	100	9.0	0.075
6	20	100	9.0	0.075
Buyers	D_{min} (MW)	D_{max} (MW)	e	f
1	00	200	30	0.04
2	00	150	25	0.03

TABLE II. Best tuned parameters for GSA

GSA
N = 50; Generations = 1000; G = 100

The bidding coefficients α_n / θ_m and β_n / π_m can't be considered separately to maximize the suppliers/large buyers profit/benefit. As the coefficients α_n / θ_m and β_n / π_m are feature interdependent [16], here one variable is previously known and the other is defined using an optimization method. Such criteria are used to optimize profit/benefit for the suppliers/large buyers. The suppliers/large buyers determine the value of the bid coefficients in this work, fix the α_n / θ_m and Uses TGSA to calculate the optimal bid coefficients values β_n / π_m To develop a competitive bid. The best values of bidding coefficients β_n / π_m is searched between the intervals b_n / f_m and $M * b_n / M * f_m$, M is put to be 10. The approximation of the bidding coefficient for the rival as described in (14) in a normal joint distribution. It is listed in Table III and taken from [16].

TABLE III. PARAMETERS OF RIVAL'S ESTIMATION

Rival's estimation of suppliers				
$\mu_n^{(\alpha)}$	$\mu_n^{(\beta)}$	$\sigma_n^{(\alpha)}$	$\sigma_n^{(\beta)}$	ρ_n
$1.2\times a_n$	$1.2\times 2\,b_n$	$0.0375\times a_n$	$0.0375\times b_n$	-0.1
Rival's estimation of large buyers				
$\mu_m^{(\theta)}$	$\mu_m^{(\pi)}$	$\sigma_m^{(\theta)}$	$\sigma_m^{(\pi)}$	ρ_m
$0.8\times e_m$	$1.2\times 2 f_m$	$0.5\times e_m$	$0.5\times f_m$	0.1

In view of suppliers and buyers in [16], the bus network IEEE-30 has already been investigated in strategic bidding difficulty. The suggested design is therefore being tested on the IEEE-30 bus system. Taking into account the above discussion in the introduction paragraph, authors are concluded, the considered objectives are contradictory in nature. Therefore, it is going to be necessary for a technique to determine the optimal position of operation taking into account all entities (suppliers and buyers). Then, TOPSIS method is applied to get the best compromising result. It is essentially an efficient multi-objective problem approach which decreases Pareto-set's Euclidean distance from the best outcome for individual objects and provides the best compromise solution. The optimal values of bidding coefficients α_n, β_n, θ_m, and π_m of different suppliers/large buyers for IEEE 30-bus system by TOPSIS along with GSA (TGSA) are presented in Table IV. The evaluated MCP using TGSA is higher than MC [16]. The MCP is proportionally related to profit through revenue. Table V reveals that suppliers' net income is increased by \$60.7 using TGSA relative to MC [16]. In comparison, buyers use TGSA's overall benefit is increased by \$9.2 relative to MC [16]. TGSA offers an ideal MCP to optimize suppliers / buyers' profit / benefit. It also allows all parties to increase power exchange. Table IV shows that, TGSA yields 22.8 MW extra power exchanged than MC [16]. The summation of both entities profits is increased by \$69.9 relative to MC [16], considering double-sided bidding using TGSA. Test for the design of the IEEE 30-bus illustrate that the designed approach of this manuscript is better than MC. The TGSA strategy is therefore found to be useful and shows potential to achieve the better compromise answer for the multi-goal strategic offering difficulty of sellers / big purchasers. Plot between number of iterations and objective function for TGSA is given in figure 2.

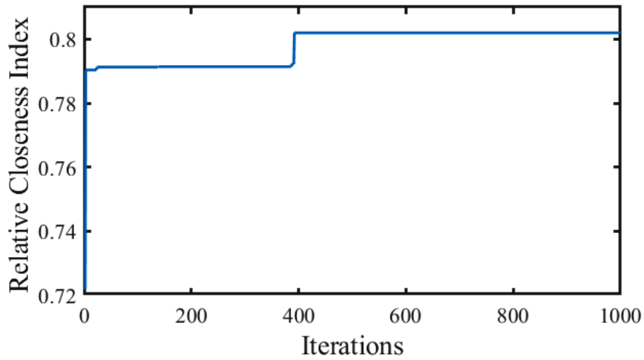

Fig. 2. Number of iterations and objective function of TGSA

TABLE IV. OPTIMAL OFFEREING RESULTS CONSIDERED STRUCTURE USING TOPSIS ALONG WITH GSA

Suppliers	α_n	TGSA			MC [16]		
		β_n	PG (MW)	Profit (\$)	β_n	PG (MW)	Profit (\$)
1	6.0	0.037574	160	1386.6	0.02927	160	1368
2	5.25	0.119268	114.2	596.2	0.12420	89.4	572.7
3	3.0	0.449634	50.09	329.52	0.29231	45.7	322.9
4	9.75	0.098465	88.35	395.73	0.07433	88.8	386.4
5	9.0	0.673058	40.15	178.85	0.17058	43.1	177.5
6	9.0	0.673058	40.15	178.85	0.17058	43.1	177.5
Total			492.9	3065.7		470.1	3005
Buyers	θ_m	π_m	DE (MW)	Benefit (\$)	π_m	DE (MW)	Benefit (\$)
1	30	0.090492	149.6	1129.4	0.09771	139.7	1126.3
2	25	0.067894	125.7	598.7	0.07719	112.1	592.6
Total			275.3	1728.1		251.8	1718.9
MCP		16.47			16.35		
Q(MCP)		217.6			218.3		
Total power traded (MW)		492.9			470.1		
Total (Profit + Benefit) (\$)		4793.8			4723.9		

VI. CONCLUSION

In this work, a GSA along with TOPSIS has been successfully applied to effectively dealing with the problem of multi-objective double-sided competitive tendering. In this problem, suppliers and buyers have been measured in a electricity market for the 30-bus IEEE system. The proposed technique is successful in increasing the trading of power between suppliers and buyers & thus the description value of the goal functions given the double-sided tender has been improved. Moreover, the total power output of suppliers is exactly equal to addition of the buyer's demand and forecasted load demand. The GSA approach retains a proper balance over the iterative process between the discovery and exploitation phenomenon and finishes with the optimal solution. The obtained results shows that the effectiveness of the proposed TGSA technique and could be a useful tool in multi-objective bidding process in day-ahead electricity market for maximizing social welfare.

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