A Solution of Bid-based dynamic economic load dispatch using a hybrid Mutualism based Pathfinder algorithm

Manoranjan Sahoo
Electrical Engineering Department
NIT Rourkela
Rourkela,Odisha
520ee1002@nitrkl.ac.in

Shekha Rai
Department of Electrical Engineering
NIT Rourkela
Rourkela,Odisha
rais@nitrkl.ac.in

Bimal Kumar Dora
Electrical and Electronics Engineering Department
VNIT Nagpur
Nagpur, Maharashtra
dt20eee003@students.vnit.ac.in

Abstract— **This paper introduces a hybrid mutualism based pathfinder algorithm (mPFA) for solving the bid-based dynamic economic load dispatch (BBDED) problem by taking into consideration of various bidding strategies in a deregulated environment. In a deregulated environment BBDED problem is evolved to achieve different goals, such as resource scheduling, maximize social profits, and simultaneously to intend power system security. The IEEE-30 bus test system is considered, which contains 6-power generators and 2-consumers who are supposed to bid in two separate trading periods under various bidding strategies in a day-ahead electricity market. The market co-ordinator known as independent system operator (ISO) matches different bids received from supply and demand side participants and tries to maximize the social profit. In this work, a novel hybrid meta-heuristic algorithm, namely mPFA is proposed, which combines the Pathfinder algorithm (PFA) and the mutualism phase of the Symbiotic Organisms Search (SOS) algorithm. The proposed mPFA scheme avoids the slow and premature convergence of original PFA by exploration with PFA and exploitation with the mutualism phase of SOS. The proposed hybrid scheme was compared to different meta-heuristic algorithms, including Pathfinder algorithm (PFA), Differential Evolution (DE) algorithm, particle swarm optimizer (PSO), and Salp Swarm Algorithm (SSA). The simulation results show that mPFA has the capability and adequacy to solve BBDED.**

***Index Terms*-- Bid-based dynamic economic dispatch, independent system operator, hybrid mutualism based pathfinder algorithm, Pathfinder algorithm, Symbiotic Organisms Search.**

I. INTRODUCTION

In the early days, vertically integrated monopolies provided electric power to customers, in which the responsibility of vertically integrated utilities is to generate electric power, transmit it, and distribute it among the consumers. Due to the global trend towards restructuring in the electric power industry has resulted in creating a competitive environment in the industry as a means of lowering energy prices and increasing access to the network[1]. Deregulation, in general, involves the separation of traditionally monopolized utility systems into three basic components: generation (GENCOs), transmission (TRANSCOs), and distribution (DISCOs) companies [1-2]. The central co-ordinator, known as ISO, maintains the supply-demand balance by ensuring system reliability and security.

The distribution of load among different thermal generating units in a secure and reliable way is called load dispatch. but finding an operating point of these generating units in order to reduce the cost of production is called economic load dispatch (ED). When the ED is used to meet a fixed load demand for a particular time of period, then it is known as static economic dispatch (SED). By incorporating with a dynamic constraint known as ramp rate constraints, the SED is transformed into Dynamic Economic Dispatch (DED) [3]. This constraint is important for maintaining the thermal gradient inside the generator within the limit, so that the lifespan of the generator can be extended.

The DED problem can be analyzed in two ways in the deregulated electricity market: price-based technique and bid-based technique. In a price-based technique, power suppliers use DED to maximize their profits rather than to reduce their generation costs. A new framework is being developed in order to develop an optimal bidding strategy among the competitive generators in [4]. In [5] a fuzzy optimization technique was developed to solve a price-based DED problem by taking into account the energy and reserve market uncertainties. ISO utilizes DED in the bid-based approach to maximize the social benefit by matching various bids obtained via demand-side and supply-side participants. In [6] a differential evolutionary algorithm is being utilized to solve multi-player, multi-period bid based problem taking transmission loss into account. In [7] a predictor corrector Interior-point (IP) quadratic algorithm is being utilized for solving the BBDED problem, which is an improvement of the original IP algorithm.

In [8] monte carlo simulation and genetic algorithm has been utilized to develop a bi-level bidding problem. A comparative study of results of Genetic Algorithm (GA), DE, PSO, and Linear Programming (LP) has been carried out in [9]. An IEEE-30 bus system is being utilized in [6], [7], and [9] to increase the social profit by thinking load price elasticity and different consumer bidding strategies into account.

In this paper presents a new hybrid algorithm called mPFA, wherein the primary focus is to improve the search capability original PFA by incorporating the mutualism phase of SOS in

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it. The exploration ability of PFA and the exploitation capability of SOS make the proposed algorithm a robust and effective one. The proposed algorithm's performance is evaluated by solving a BBDED problem in a day-ahead power market with the motive of maximizing social profit. A variety of case studies have been conducted and the test results of mPFA are compared to those of other approaches.

The rest of the paper is arranged as follows: Section 2 explains the problem formulation, while Section 3 explains about different strategic bidding in the deregulated power market, The methodology of the proposed mPFA scheme has been discussed in Section 4 and the results and discussion are drawn in Section 5, Thereafter the conclusion is drawn in section 6.

II. PROBLEM FORMULATION

The operation mechanism of BBDED is based on the central auction mechanism and with the motto of maximizing the social benefit. In some deregulated electricity markets, ISO receives different bids together with their corresponding constraints from suppliers and customers on a daily and hourly basis. Basically, the bids received from the bidders are increasing and decreasing function of price with quantity. ISO also collects information from the available transmission companies on available transmission capacities. The market clearing price is determined by ISO by utilizing different bids submitted by suppliers and customers. In this case, ISO solves the BBDED problem by maintaining system reliability and security.

A. Objective function

The model of BBDED problem can be developed as follows

$$\text{Maximizing} \quad \sum_{t=1}^{nt}\{\sum_{j=1}^{nd} B_j(D_j^t) - \sum_{i=1}^{ng} C_i(P_i^t)\} \tag{1}$$

Where ng and nd represents the total numbers of generator and customer taking participation in the power market at time t, C_i and B_j are the bid functions of generators and consumers, and for a given time span t, D_j^t and P_i^t are the bid quantity submitted by customers *j and* generator *i*.

B. Equality constraints

1) *Power balance constraints*

The power balance constraint is an equality constraint that ensures a balance between GENCOs' total power generation with total demand of customer, as well as transmission line losses.

$$\sum_{i=1}^{ng} P_i^t = \sum_{j=1}^{nd} D_j^t + Pl^t \tag{2}$$

Where Pl^t is the transmission line loss.

C. Inequality constraints

1) *Generators' bid quantities constraints*

In order to preserve power system stability, every power generator is built to generate its output power within a specific limit, which are considered to be a set of inequality constraints.

$$P_{i\,min}^t \le P_i^t \le P_{i\,max}^t \tag{3}$$

2) *Customers' bid quantities constraints*

Customers' energy demands are restricted by maximum and minimum of real-power output limits, can be expressed as,

$$D_{j\,min}^t \le D_j^t \le D_{j\,max}^t \tag{4}$$

3) *Ramp rate limits constraints*

It is a dynamic constraint that is necessary for keeping the thermal gradients within the generator under control, so that the shortening of life of generators can be avoided [3]. As the turbines of the generating station are connected to a number of steam valves. The sudden increase or decrease in generator output may increase the temperature inside the turbine. So to maintain the temperature inside the turbine within an acceptable value, each generator is permitted to decrease or increase its power output under certain limits. As a result, these limits are thought of as a set of inequality constraints.

$$DR_i \le P_i^t - P_i^{t-1} \le UR_i \tag{5}$$

Where UR_i and $DR_i$are generator-i up and down ramp rate limit constraints for a particular time period t.

III. STRATEGIC BIDDING IN THE DEREGULATED POWER MARKET

The basic motive of restructuring is to lower consumers' energy price. As a result, one of the main challenges for players in the competitive energy market is to develop the best bidding strategy. Based on different restructuring models, It can be divided into two categories: Bilateral market and Mediated market. Buyers and sellers engage directly in a bilateral market. Whereas in mediated market, there exists an intermediary called ISO between them [1].

The mediated market is the most secure and unified form of market, since it is centralized and each participant has to obey specific rules. Here sellers and buyers linked with each other in terms of bidding quantity and bidding price. The social benefit economic notation is used to quantify the market's performance. Which is the difference between the price of the commodity and willingness of the consumer to pay for that benefit [2].

A. Supply side bids

In this scenario, all generating companies are believed to bid at their marginal production cost (pure price takers). In the power market, most of the generating companies sell their capacity as a discretise function of price and quantity, which is further approximated to quadratic in order to minimize the complexity [10].

$$C_i(P_i^t) = a_{pi}(P_i^t)^2 + b_{pi}P_i^t + c_{pi} \tag{6}$$

Where a_{pi}, $b_{pi}$and c_{pi} are taken as the bid price coefficients of the ith supplier.

B. Demand side bids

Often, in the power market, load-serving entities and large consumers also participate in bidding. The bid function is basically decreasing rate of price with quantity, and can be expressed as follows,

$$B_j(D_j^t) = a_{dj}(D_j^t)^2 + b_{dj}D_j^t \tag{7}$$

Where $a_{dj}$and $b_{dj}$are taken as the bid price coefficients of jth customer.

Depending upon different bid price co-efficient of customers, the bidding strategy is classified into different categories such as "bidding low (L)", "bidding medium (M)", and "bidding high (H)", with an equal probability of 1/3. The optimal bidding strategy is one that allows the customers' bid to be accepted and also allow them to maximize their profit in the market. According to the literature [10], the authors concluded that the bid coefficients of consumer for low bidding strategy (a_{dj}) should be $\leq$ 0.01, for medium bidding strategy (a_{dj}) should be in the range 0.05 and for high bidding strategy (a_{dj}) should be≥0.09.

IV. METHODOLOGY OF THE PROPOSED MPFA SCHEME

A. PFA

Now a days the novel meta-heuristic algorithms known as PFA have drawn the attention of researchers due to its simplicity, flexibility, and local optima avoidance property. It is developed by H Yapici and N Cetinkaya in 2019 by observing the collective movement of animal groups and animals' hunting behaviour led by their leader individual while food searching [11]. The member in the group located at the most promising area at any time is considered as the leader, and the leader is treated as the pathfinder in this algorithm.

B. SOS

The symbiosis organisms search (SOS) algorithm is a simple and powerful metaheuristic algorithm. it was first introduced by M Y Cheng and D Prayogo in 2014 [12]. It's a swarm-based algorithm inspired by nature, and it's simulated using the three most common symbiotic relationships found in nature: mutualism, commensalism, and parasitism. In the proposed approach only the mutualism stage of SOS is considered.

Mutualism represents a symbiotic relation between two different types of organisms live in an eco-system and both will get benefits from the synergy, eg. bees and flowers. In SOS, X_{isos} and X_{jsos} are two organisms of ith and jth eco-system respectively. The new candidate solution X_{inew} and X_{jnew} can be developed based on the mutualistic symbiosis between the organism X_{isos} and X_{jsos} , which is presented in equations (10) and (11).

C. mPFA

In general, the characteristic of different meta-heuristic algorithms can be classified into exploration and exploitation. In exploration, the algorithm tries to find out all the possible search areas and in exploitation, the algorithm is shaped around the local search area. According to NFL (No Free lunch) theorem, the performance of the algorithm depends upon the balancing between exploration and exploitation [11]. When the exploration is dominant over exploitation, it results in slow convergence of algorithm due to exploring uninteresting region of search-space. On the other hand, when exploitation is dominant, the algorithm results in premature convergence [13].

In the PFA algorithm, it has been observed that the algorithm often loses the optimum solution as a result of exploring uninteresting search space due to random selection of global and local search. So in this proposed approach, a modified PFA called mPFA is discussed by utilizing the mutualism part of SOS algorithm. The flowchart of mPFA scheme to solve BBDED problem is shown in fig.1. The implementation step of mPFA is given below.

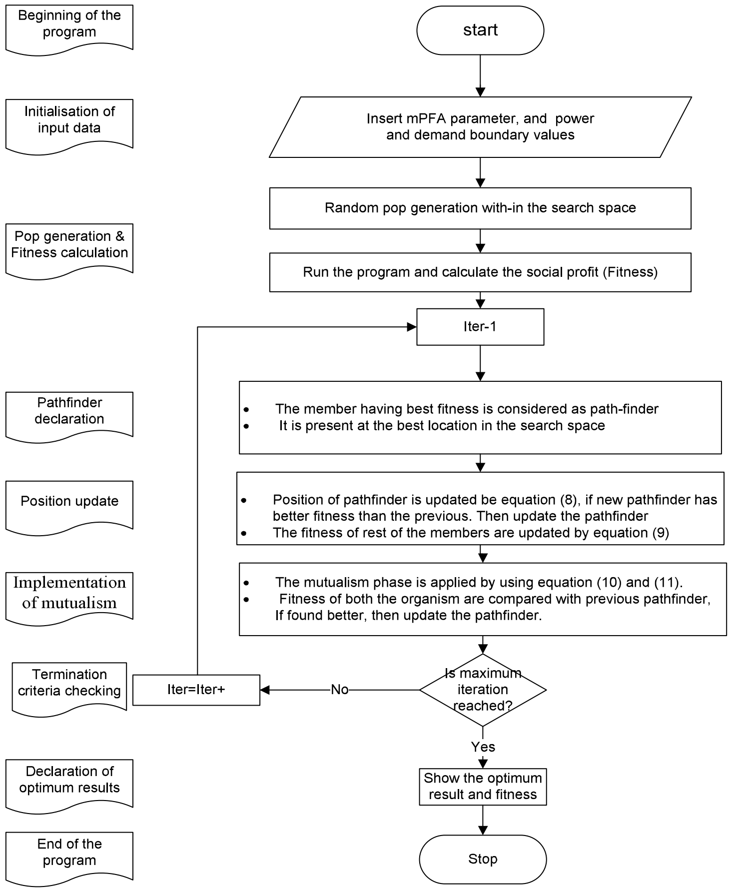

Fig.1 Flowchart of mPFA scheme to solve BBDED problem

Step 1: Initialization

As mPFA is a population-based algorithm, it is necessary to initialize the position of the particle in the swarm. Here the pop are randomly generated by taking upper and lower bound of control variables.

Step 2: Fitness evaluation

In this step fitness of all the members in the swarm is calculated based on their objective.

Step 3: Pathfinder declaration

The member having the best fitness is declared as the pathfinder and its location is assumed as the best location.

Step 4: Position update

The position of the pathfinder is updated by equation (8) and checks all the bounds. If the fitness of the new pathfinder is better than the older one, then update the pathfinder. The position of each member of the group is updated with respect to the pathfinder and other members of the group according to equation(9). So that each member of the group moves together and stays close to their neighbour.

$$X_i^{K+1} = X_i^K + 2r_3 . \left(X_p^k - X_p^{k-1}\right) + u_2 . e^{\frac{-2K}{K_{max}}} \tag{8}$$

$$X_i^{K+1} = X_i^K + R_1 . \left(X_J^K - X_i^K\right) + R_2 . (X_P^K - X_i^K) + \left(1 - \frac{K}{K_{max}}\right) . u_1 . D_{ij}$$

$$D_{ij} = \left\|X_i - X_j\right\| \tag{9}$$

Step 5: Implementation of mutualism

The mutualism phase is applied in this algorithm by taking equation (10), and (11). Both the fitness of the two organisms are compared with the previous pathfinder if found better then update it for the next step.

$$X_{inew} = X_{isos} + rand(0,1) * (X_{best} - Mutual\_\text{Vector} * BF_1) \tag{10}$$

$$X_{jnew} = X_{jsos} + rand(0,1) * (X_{best} - Mutual\_Vector * BF_2) \quad (11)$$

$$Mutua\_Vector = \frac{X_{isos} + X_{jsos}}{2}$$

Where rand(0,1) is a uniformly distributed random number. BF_1 and BF_2 are the benefit factor, which are decided based on the beneficial advantages between two organisms.

Step 6: Stopping criteria

Check if the stopping criterion is satisfied otherwise move to step-2.

Step 7: stop

If the maximum number of iteration reached then stop and show the best result.

V. Result and Discussion

To verify the performance and effectiveness of mPFA for solving BBDED problem, IEEE-30 bus system, which has 6-generators and 41-transmission lines is considered. On the generator side, the cost coefficient of generators (a_{pi}, b_{pi} and c_{pi}) are considered as its bidding data. In the demand side, it has been assumed that two consumers attempt to bid during two separate treading times. Bids on the customer side are divided into three categories: "bid low," "bid medium," and "bid high". The bidding price coefficients of generators and customers and their limits of bidding quantities are listed in Table I and Table II [6]. Taking the bid price and quantity as input data, the BBDED problem has been solved for maximizing the social benefit by using mPFA algorithm.

TABLE I THE GENERATOR'S DATA OF IEEE-30 BUS SYSTEM

Bus No	Gen No	a_{pi} (\$ /MWh^2)	b_{pi} (\$/MWh)	c_{pi} (MWh)	p_{min} (MW)	p_{max} (MW)	UR_i (MW)	DR_i (MW)
1	1	0.00375	2.0	0	50	200	65	85
2	2	0.01750	1.75	0	20	80	12	22
5	3	0.00625	1.00	0	15	50	12	15
8	4	0.00834	3.25	0	10	35	08	16
11	5	0.02500	3.00	0	10	30	06	09
13	6	0.02500	3.00	0	12	40	08	16

TABLE II CUSTOMER'S BID DATA

	Customer-1 L/M/H	***Customer-2*** L/M/H
a_{dj}(\$/MWh^2)	-0.06/0.07/0.1	-0.08/0.05/0.09
b_{dj}(\$/MWh)	20	15
Power demand at hour-1 (Dmin to Dmax)(MW)	100 to 150	50 to 100
Power demand at hour-2 (Dmin to D_max)(MW)	20 to 70	100 to 200

Case-1: low bidding strategy of customers

It is considered that 6-power suppliers and 2-consumers submitted offer and demand bids to the market operator (ISO) on a day-ahead basis. Table I and Table II show the bidding data for power suppliers and consumers respectively. As per low bidding strategy, the bid coefficient (a_d) was set to -0.06 \$/MWh^2 for consumer-1 and -0.08 \$/MWh^2 for consumer-2 respectively [6]. And the electrical energy prices (b_d) have been set at 20 \$/MWh and 15 \$/MWh, respectively.

During the first period, consumer-1 submits a bid quantity ranging from 100MW - 150MW, and consumer-2 submits its bid quantity ranging from 50MW - 100MW. Similarly, in period 2, consumer-1 submits its bid quantity ranging from 20MW - 70MW, and consumer-2 submits its bid quantity ranging from 100MW - 200MW, as shown in Table II.

Optimization is performed via mPFA and the optimum output power to meet consumers' demand pattern, generation cost, consumer benefit, as well as the total social benefit of two different auction periods are presented in Table III. During period 1, power suppliers spent a sum of 505.50 \$ to supply power of 143.12MW and 76.09MW, and during period 2 power suppliers spent a sum of 374.04\$ to supply power of 70MW and 100MW to consumer 1 and 2 respectively.

The optimization of the BBDED problem is carried by the proposed approach for low bidding strategy. Despite of the maximum number of iterations being set to 100, the simulation result of mPFA converges at approximately 15th iteration and 10th iteration by providing an optimum value of 1806.0\$ and at 1432\$ at both the periods respectively.

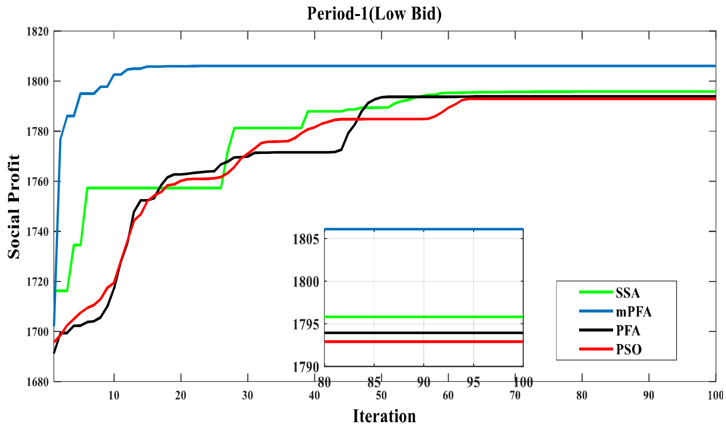

Fig.2. Period-1(Low Bid)

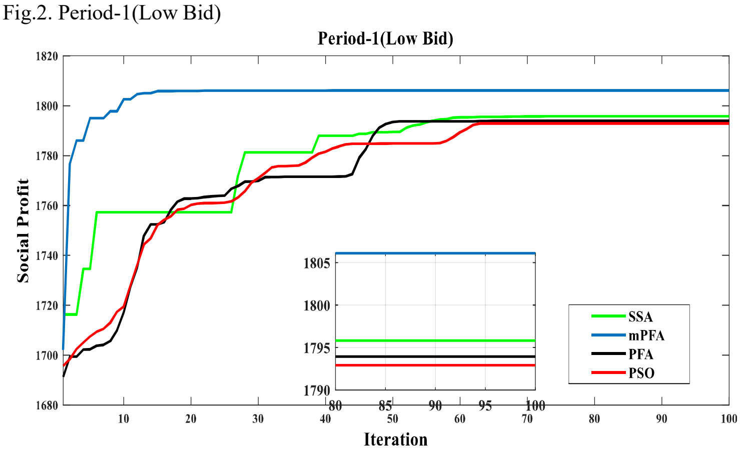

Fig.3. Period-2(Low Bid)

DE's potential to solve various BBDED problems is illustrated in [6]. The author concluded in [9] that PSO has better capability in resolving the BBDED problem than LP, IP, and GA. Thus, the BBDED problem is solved through mPFA in this proposed approach. To demonstrate the potential of mPFA, its simulation results are compared to those of PFA, DE, SSA, and PSO. Table IV shows the comparative statistical study that confirms the effectiveness and robustness of the proposed approach for solving the BBDED problem, and Table V shows the comparative simulation results with other approaches. The parameters for PFA, DE, SSA, and PSO were chosen based on the experimental results carried out in [11], [14]–[16]. The convergence characteristics of mPFA, PFA, SSA, and PSO for low bid strategy for the first and second period have been provided in Fig. 2 and Fig. 3 respectively.

CASE-2 :MEDIUM BIDDING STRATEGY OF CUSTOMERS

As in the prior case, all power supplier's bidding data and consumers' load data are maintained the same. As per medium bidding strategy, the bid coefficient (a_d) was set to 0.07 $\$/MWh^2$ for consumer-1 and 0.05 $\$/MWh^2$ for consumer-2 respectively as given in Table II. The same process has been repeated as the prior case, and the optimized results are shown in Table III. During period 1 and 2 of medium bidding strategy, generators spent a sum total of 595.4$ and 657.02$ to supply power of 250MW and 270MW to both the consumer respectively.

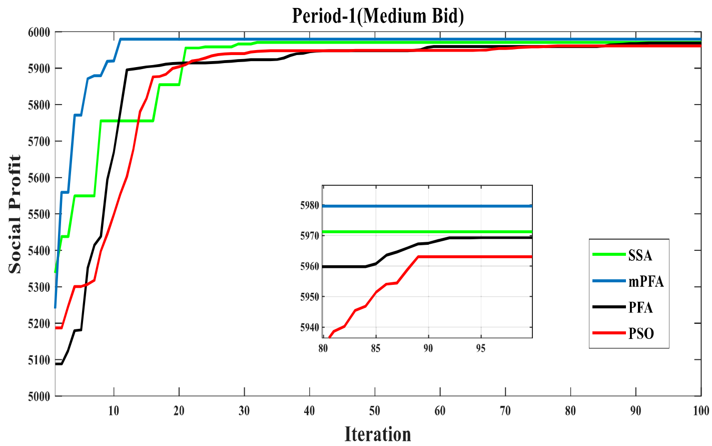

Fig. 4. Period-1(Medium Bid)

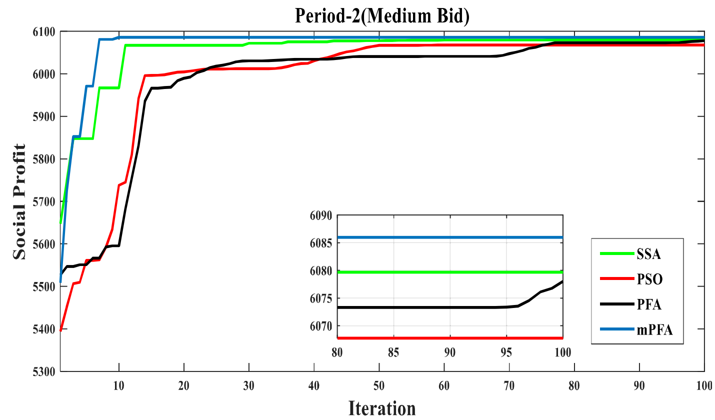

Fig. 5. Period-2(Medium Bid)

The optimization for medium bidding strategy has been performed by mPFA and the optimal value of social profit is achieved at the 11th and 10th iterations in both periods. In this strategy, the consumers get a social benefit of 5979.6$ and 6086.0$ respectively in the corresponding periods. If customers submit a medium bidding strategy rather than low bidding, cost of generation rises in the respective periods, while the customers' benefit rises as well because of the highest allotment of electric power. Which is the reason behind the rise in social benefits.

Table V shows the comparative simulation results with other approaches. The convergence characteristics of mPFA, PFA, SSA, and PSO for medium bid strategy for first and second period have been provided in Fig. 4 and Fig. 5 respectively.

CASE-3 HIGH BIDDING STRATEGY OF CUSTOMERS

Similar to the previous case, all power supplier's bidding data and consumers' load data are maintained the same. As per high bidding strategy, the bid coefficient (a_d) was set to 0.1 $\$/MWh^2$ for consumer-1 and 0.09 $\$/MWh^2$ for consumer-2 respectively as given in Table II. To get the optimal scheduling of generators, the same steps as in the prior case were followed. The optimum value of power suppliers' output power to meet consumer demand pattern, cost of generation, consumer benefit, as well as the total social benefit of two

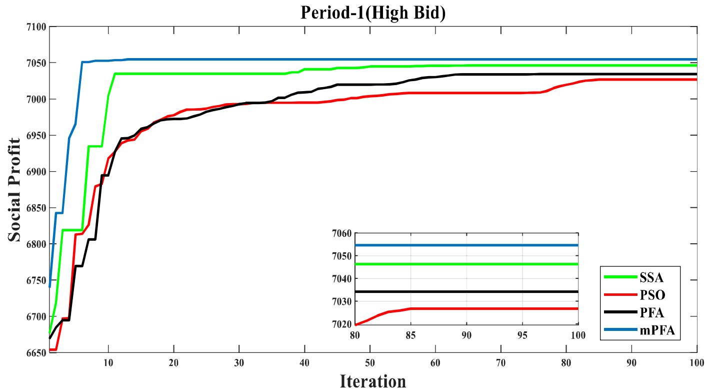

Fig.6. Period-1(High Bid)

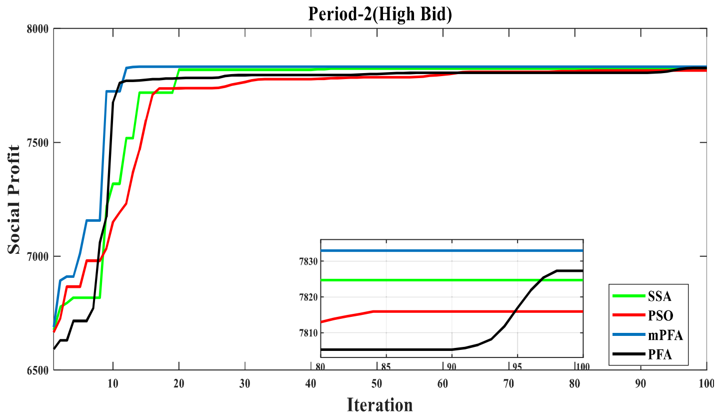

Fig.7. Period-2(High Bid)

different trading periods are presented in Table III. During period 1 and 2 of high bidding strategy, generators spent a sum total of 595.4$ and 657.02$ to supply power of 250MW and 270MW to both the consumer respectively.

The optimization for high bidding strategy has been performed by mPFA and the optimal social benefit is achieved at the 13th and 14th iterations in both periods. In this bidding strategy, the social benefit rises to 7054.6$ and 7833.0$ in respective periods. The generation cost in a high bidding strategy is the same as in a medium bidding strategy, but the social benefit rises because of the high customer bid price. Table V shows the comparative simulation results with other approaches. The convergence characteristics of mPFA, PFA, SSA, and PSO for high bid strategy for first and second period has been provided in Fig. 6 and Fig. 7 respectively.

So from the simulation results, we found that the low bidding strategy has a lower generation cost since the total power allocated to the generator is lower than in the other two bidding strategies. Furthermore, in the low bid strategy, the consumer benefit is low, lowering overall social benefit. So this strategy is not preferable for the power market. In contrast, the generation cost is the same in both the medium and high bidding strategies.

TABLE III RESULT FOR DIFFERENT BIDDING STRATEGY

	Result for low bidding strategy		Result for medium bidding strategy		Result for high bidding strategy	
	Period-1	Period-2	Period-1	Period-2	Period-1	Period-2
P1	109.9544	68.9088	135.6998	152.4639	135.6998	152.4639
P2	30.3386	22.1561	35.4050	38.6771	35.4050	38.6771
P3	50.0000	50.00	50.000	50.00	50.00	50.00
P4	10.00	10.00	10.00	10.00	10.00	10.00
P5	10.00	10.00	10.00	10.00	10.00	10.00
P6	12	12.00	12.00	12.00	12.00	12.00
Total Gen	222.293	173.0649	253.1	273.141	253.1048	273.141
D1	143.1278	70	150	70	150	70
D2	76.0959	100	100	200	100	200
Total Demand	219.2237	170	250	270	250	270
Total Loss	3.0693	3.0648	3.1048	3.141	3.1048	3.141
Total gen cost	505.5055	374.0469	595.4080	657.02	595.4080	657.0200
Total Customer Benefit	2311.6	1806	6575	6743	7650	8490
Social Profit	1806.1	1432.0	5979.6	6086.0	7054.6	7833.0
Total social profit	**3238.1**		**12065.6**		**14887.6**	

TABLE IV STATISTICAL ANALYSIS FOR LOW BIDDING STRATEGY

	Period-1				Period-2			
	Best Value	Worst Value	Mean	Standard Deviation	Best Value	Worst Value	Mean	Standard Deviation
PSO	1792.25	1788.9	1790.1	2.298	1411.2	1405.3	1409.28	1.98
SSA	1795.8	1792.89	1794.4	1.0014	1413.23	1409.7	1412.6	1.2483
PFA	1793.93	1790.01	1792.9	1.4466	1422.2	1417.65	1421.96	1.1789
mPFA	1806.1	1804.1	1805.69	0.3563	1432	1431.2	1431.8	0.2269

TABLE V. THE COMPARATIVE STUDY OF SIMULATION RESULTS OF MPFA WITH DE, PSO, SSA AND PFA

	Low Bid					Medium Bid					High Bid				
	DE	PSO	SSA	PFA	mPFA	DE	PSO	SSA	PFA	mPFA	DE	PSO	SSA	PFA	mPFA
Total generation Cost	989.72	899.3	913.5	905.82	879.5	1431.5	1275.2	1267.0	1270.66	1252.4	1431.5	1298.4	1268.9	1278.54	1252.4
Total Customer Benefit	4101.3	4119.5	4120.8	4122.81	4117.6	13318	13318	13317.2	13318.01	13318	16140	16140	16139	16140.0	16139
Total Social Profit	3111.8	3220.2	3207.3	3216.99	3238.1	11886.5	12042.8	12050.2	12047.35	12065.6	14708.5	14841	14870.1	14861.46	14886.6

However, because of the high bidding price of suppliers, the high bidding strategy consumers' profit is more. As a result, in the high bidding strategy, the social profit is more. In the deregulated electricity market, all generators and consumers send bids to the market co-ordinator (ISO), and which plays a significant part in matching the bid. Hence all of the studies help ISO in matching the bid in order to maximize social benefit.

VI. CONCLUSION

This paper introduces mPFA, a new hybrid algorithm for solving a BBDED problem in a day-ahead deregulated electricity market by matching different bids from the supply and demand sides market. Here the premature convergence of PFA is successfully avoided by incorporating the mutualism phase of SOS algorithm, which enhances the local exploitation of the algorithm in an effective way.

The comparative analysis of simulation results of mPFA with different meta-heuristic algorithms like PFA, DE, SSA, and PSO is carried out. The simulation results indicate that this scheme has a better balancing between exploration and exploitation, resulting in fast convergence and able to avoid the local optima trapping and premature convergence. So the proposed scheme is both effective and robust to solve the BBDED problem.

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