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Profit maximization through bid based dynamic power dispatch using symbiotic organism search

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Abstract. Deregulation of power system has created competition in the power market shifting the focus from cost optimization to profit maximization, which has created different trading mechanisms. The power companies and their customers submit their bids for each trading interval of the next day and the independent system operator (ISO) conducts a bid based dynamic economic dispatch (BBDED) to allocate power to the generating companies and customers in such a manner that the total profit is maximized while all constraints such as power balance, operating limits and ramp rate limits are satisfied. Nature inspired (NI) optimization techniques score over the classical numerical methods for solving such complex practical problems due to (i) their population based random search mechanism and (ii) their non-dependence on initial solution. This paper proposes a symbiotic organisms search (SOS) based solution for solving BBDED problem in the deregulated electricity market. The SOS algorithm depicts the interaction between different species in nature, the three symbiotic relationships. The performance of the proposed approach has been tested on standard power system bench marks from literature having 10 generators, 6 customers and varying power demands over 12 dispatch periods. The results have been validated with published results and SOS is found to be more effective than the other methods for solving the BBDED problem.

Keywords: BBDED; deregulated electricity market; social profit; SOS.

1. Introduction

In a competitive electricity market the dynamic economic dispatch is carried out in a bid-based frame work to maximize the social profit under changing demands and bids. Matching the continuously changing power demand with generation is a complex task for complex power system networks with large number of variables. A competitive bidding mechanism needs to allocate power generation to customers having different demands in such a way that the social profit is maximized and the scheduled generation for two consecutive time periods satisfies the ramp rate constraints. Due to randomly changing load demands and ramping constraints, BBDED is a complicated optimization problem requiring efficient algorithms.

Optimization is a branch of mathematics which means making something better [1][2]. The maximization of profit and minimization of operating cost have to satisfy certain practical operating conditions known as constraints. The most flexible form of energy is electric energy that is used in various applications such as it is used to operate electrical equipment in factories and domestic appliances in houses. Cost of generating the power is very high because in most of the countries power generation depends on fossil fuels. The fossil fuel resources are depleting very fast and therefore their optimal utilization is receiving tremendous research focus. The objective of traditional economic dispatch (ED) is to allocate generation to committed generating units such that the fuel cost is minimized [3, 4]. The demand of electricity is raising day by day ED helps in saving the fuel cost by optimal allocation of generation [5]. Storage of electricity in large amounts is not possible as it is not a true commodity, so it has to be consumed when it is generated [6]. Maintaining a balance between generation and continuously varying load is a very challenging task.

In competitive electricity market there is a paradigm shift as cost minimization objective gets converted to profit maximization, taking into consideration the bids submitted by generating companies as well as by the consumers. Henceforth, the traditional ED problem gets converted to a bid based ED in the competitive market. The ED problem can be solved either as a static problem or as a dynamic problem. The static ED minimizes the generation cost while satisfying the load demand of customers for a single time period [7] assuming the load to be constant. In practice this assumption is not correct [8]. To overcome the difficulty the ED is formulated in a dynamic environment where the power outputs of two consecutive time intervals must satisfy ramp rate constraints. The dynamic ED (DED) is the realistic representation which is solved by dividing all dispatch periods assuming the power demand to be constant in each small interval [9]. In Bid based electricity market there are two types of trading mechanisms, bilateral trading and central auction. In bilateral trading mechanism suppliers and customers submit their bids and the quantities traded are at the discretion of the participants; this mechanism does not involve independent system operator (ISO). In central auction trading mechanism all participant (i.e. suppliers and customers) submit their bids to an ISO who matches the bids and dispatch them in an economic manner based on the price offered by suppliers and load demanded by customers while maintaining the security and reliability of the system [10]-[12]. Traditionally the main goal of ED problem was to minimize the cost; deregulation shifts that goal from cost minimization to maximization of social profit. Therefore BBDED is sometimes also referred to as profit based DED. It is concerned with ensuring high social profit from customer benefit and increasing the competitiveness of the participating parties [13]-[17]. Various mathematical programming methods have been employed in the past decade to solve the ED problem such as quadratic programming [18], dynamic programming [19] etc. Conventional methods include convex, linear and differentiable function which is not easy to handle and do not converge to optimum solution. Solution of large scale ED problem using quadratic programming and GAMES is presented in [20]. ED problem exhibit the nonlinear and non-convex features which is difficult to solve by conventional method. On the other nature inspired (NI) techniques that follow heuristic approaches have been proven to be effective for solution of complex optimization problem. Among NI techniques Genetic Algorithm (GA) [21], Particle swarm optimization (PSO)[3], Biogeography-based optimization (BBO)[22], Invasive Weed Optimization (IWO)[23], Simulated Annealing [24], Flower pollination algorithm(FPA)[25], social spider algorithm [26], applied to solve complex constraints ED problem. A comprehensive study of NI optimization algorithms and their application to ED is presented in [27].

Symbiotic organisms search (SOS) is a new NI algorithm proposed by cheng and prayogo in 2014 [28]. SOS algorithm finds the optimum solution based on the symbiotic interaction behavior of organism. No algorithm specific parameters and fast convergence rate is the main advantage of SOS algorithm [29][30]. For solving engineering field problems SOS found very efficient.

2. Mathematical model of BBDED

A bid consist of load which is demanded by the customers and price offered by generation companies. The mathematical model of BBDED is based on central auction trading mechanism. The operator dispatches the requested transactions if constraints are not violated and sellers/buyers charges for the services. The demand side and supply side bids are matched by operator to maximize the social benefit. Profit maximization for BBDED problem is formulated as:

2.1. Objective function

$$\text{Maximize} \quad PF = \sum_{t=1}^{T}\left[\sum_{j=1}^{N_c} BC_j\left(D_j^t\right) - \sum_{i=1}^{N} BG_i\left(P_i^t\right)\right] \tag{1}$$

$$BC_j\left(D_j^t\right) = a_{dj}\left(D_j^t\right)^2 + b_{dj}D_j^t \tag{2}$$

$$BG_i\left(P_i^t\right) = a_{pi}\left(P_i^t\right)^2 + b_{pi}P_i^t + c_{pi} \tag{3}$$

2.1.1. Power balance constraints: This constraint keeps the power system in equilibrium between total generation of generators and customers demand in electricity market.

$$\sum_{i=1}^{N} P_i^t = \sum_{j=1}^{N_c} D_j^t + P_l^t \qquad t=1, 2, 3 \ldots T \tag{4}$$

2.1.2. Generator bid quantities constraints: Generators related to its generator design have its lower and upper generation limits that is given by

$$P_{i\,min}^t \le P_i^t \le P_{i\,max}^t \tag{5}$$

2.1.3. Customer bid quantities constraints: Customer bid quantities are related to minimum and maximum bid load of user which is presented as:

$$D_{j\,min}^t \le D_j^t \le D_{j\,max}^t \tag{6}$$

2.1.4 Ramp rate limits constraints: The ramp up/down limits or rate of increase/decrease of power is kept within a safe limit to avoid shortening the life of generators.

$$DR_i \le P_i^t - P_i^{t-1} \le UR_i \tag{7}$$

3. Symbiotic organisms search algorithm

Dependency based interaction behavior seen among organisms for sustenance or survival is known as symbiosis. Like other NI algorithm, SOS also shares some common characteristics: it uses population of organisms for obtaining the global solution, it uses random variable. Unlike other NI algorithms which have certain control parameters such as GA has crossover and mutation rates, Differential Evolution has crossover, mutation and selection parameters and PSO has inertia weight, cognitive factor and social factor, SOS does not have such algorithm specific parameters so there is no additional work of tuning the parameters like other algorithms. The population initialization is the first task in any optimization algorithm. SOS algorithm begins with an initial population generated randomly to the search space called the ecosystem. There are three types of symbiotic relationship mutualism, commensalism and parasitism.

3.1. Ecosystem initialization

SOS starts with an initial population consist of certain number of organisms generated randomly is called ecosystem.

$$eco(i,:) = rand(1,n).*(ub - lb) + lb \quad (8)$$

The control variables of SOS algorithm such as population size and number of iterations are also specified. Then calculate the fitness value of the organisms. Identify the best organism which will be the organism with minimum fitness value.

3.2. Mutualism phase

Mutualism is the symbiotic relationship between two distinct organisms in which both organisms gets benefit from the relationship. An example of mutualism is between plants and humans. Human wants oxygen to survive which plants give off and plants need carbon dioxide to survive which human gives off. Human and plants both are getting benefit from the relationship and also they can't live without each other.

In this relationship X_i is the ith organism and X_j is selected randomly from the ecosystem. New candidate solution for X_i and X_j based on mutualistic relationship is given by eq. (9) and (10).

$$X_{inew} = X_i + rand\ (0, 1) * (X_{best} - Mutual\_Vector * BF_1) \quad (9)$$

$$X_{jnew} = X_j + rand\ (0, 1) * (X_{best} - Mutual\_Vector * BF_2) \quad (10)$$

$$Mutual\_Vector = \frac{X_i + X_j}{2} \quad (11)$$

Where rand (0,1) is a vector of random number between 0 and 1. BF_1 and BF_2 are benefit factors related with the benefits organisms are getting from the relationship and their values are selected as either 1 or 2. These factors shows the level of benefit, in the mutualistic relationship as both organisms are getting benefit so there is a possibility that both organisms are not getting equal benefit while one is getting more benefit and other is getting only adequate benefit. (X_{best} − Mutual_Vector*BF_1) is the mutualistic effort of achieving the survival advantage in the ecosystem. X_{best} is the highest degree of adaptation or the target point of fitness increment of both organisms.

Finally we calculate the new candidate solution and their fitness, if the new fitness is better than the pre-interaction fitness then organisms will be updated otherwise keep the previous.

3.3. Commensalism phase

Commensalism is the symbiotic relationship between two distinct organisms in which one is getting benefit while other is unaffected from the relationship. An example of commensalism is between pilot fish and shark. Pilot fish live around shark and eat the leftover food which shark do not eat and also eat the sea turtles and the parasites that live on them. In this relationship pilot fish is getting benefit while shark is unaffected.

In this phase organism X_j which is unaffected from the relationship is randomly selected from the ecosystem to interact with organism X_i which is getting benefit from the interaction. New candidate solution is calculated based on the commensal symbiosis between organisms X_i and X_j which is modeled in eq. (12)

$$X_{inew} = X_i + rand(-1, 1) * (X_{best} - X_j) \quad (12)$$

Where (X_{best} − X_j) is representing the benefit received from organism X_j to help X_i for increasing its survival advantage to the highest degree represented by X_{best}.

If the fitness of the new solution is better than the pre-interaction fitness then organism will be updated otherwise keep the previous.

3.4. Parasitism phase

Parasitism is the symbiotic relationship between two distinct organisms in which one organism gets benefit while other organism is harmed from the relationship. In this relationship organism getting benefit is called parasite and the organism which is harmed is considered as host to the parasite. Parasites harm their host but do not kill them because they rely on them. Examples of parasites are tapeworms, fleas, barnacles etc. An example of parasitism is between fleas and dogs. Fleas harm the dogs by sucking their blood, bite dog's skin and cause itching. In this relationship flea is getting benefit by getting food but dog is harmed.

In this phase organism X_i is given a role similar to Parasite_Vector. Parasite_Vector is created by duplicating X_i organism and then modify its randomly selected dimensions using random numbers. Organism X_j serves as host to the Parasite_Vector and selected randomly from the ecosystem. The fitness of both organisms is then evaluated. If the fitness of Parasite_Vector is better than the host then it will kill the host and take host position in the ecosystem. If the fitness of host X_j is better than Parasite_Vector, then X_j will live in the ecosystem. The computational procedure for BBDED problem using SOS algorithm can be seen from the flowchart shown in Fig. 1.

4. Results and discussion

BBDED problem is solved using SOS algorithm for a system of 10 generators, 6 customers in 12 dispatch periods. The parameters set as: population size-50, maximum number of iteration-100.

4.1. Convergence analysis

Convergence characteristic is plotted between iteration and social profit ($). While doing the convergence and consistency analysis for a system of 10 generators, 6 customers in 12 dispatch periods the value of minimum profit ($), maximum profit ($), mean profit ($), standard deviation (SD) and CPU time (sec) is obtained and given in Table 1 for Load Pattern (LP)-1 and hour-1. From the Table 1 we can say as the population size increased, the social profit increased, standard deviation (SD) decreased and computation time (sec) increased. The value of social profit obtained for population size 10 is always less than the population size 50 as given in Table 1. Population size 50 converges faster than population size 10 as shown in Fig. 2.

Table 1. Effect of population sizes for test case I, LP-1, and hour-1

Pop. size	Min. profit ($)	Max. profit ($)	Mean profit ($)	SD	CPU time (sec)
10	12401.9600	12620.3532	12534.2095	15.1460	7.4451
20	12519.5949	12648.2593	12605.3367	8.7139	15.3987
30	12538.4008	12648.2611	12626.7618	6.7195	23.1757
40	12604.7114	12648.2611	12638.3887	3.1460	27.9261
50	12635.0598	12648.2611	12643.7672	0.8967	38.2745

Table 2. Customer bid data for LP-1

Customers		D1	D2	D3	D4	D5	D6	Demand per period
a_{dj}($/MWh^2)		0.1	0.099	0.097	0.094	0.093	0.09	
a_{dj}($/h)		20	19	17	16	15	12	
Maximum Load Demand Bids at each period	1	300	180	130	200	116	110	1036
	2	190	220	100	200	150	250	1110
	3	208	150	250	300	100	250	1258
	4	270	230	256	200	300	160	1406
	5	300	280	240	260	150	250	1480
	6	400	320	170	230	208	300	1628
	7	250	192	350	300	400	200	1702
	8	370	250	350	406	150	250	1776
	9	320	400	200	350	420	234	1924
	10	472	300	400	350	300	250	2072
	11	500	490	250	240	360	306	2146
	12	410	420	380	350	360	300	2220

4.2. Consistency analysis

Consistency characteristic is plotted between trial and social profit ($). In the consistency analysis the population sizes 10, 20, 30, 40 and 50 is taken. The consistency of population size 50 is more than population sizes 10, 20, 30 and 40 as shown in the Fig. 3, and we can also see the values of SD from Table 1 which is less for population size 50 than the other population sizes. If we increase the population size further there will not be much change in social profit and SD but CPU time will increase. So we can say population size 50 is more appropriate to solve BBDED problem for both the test cases.

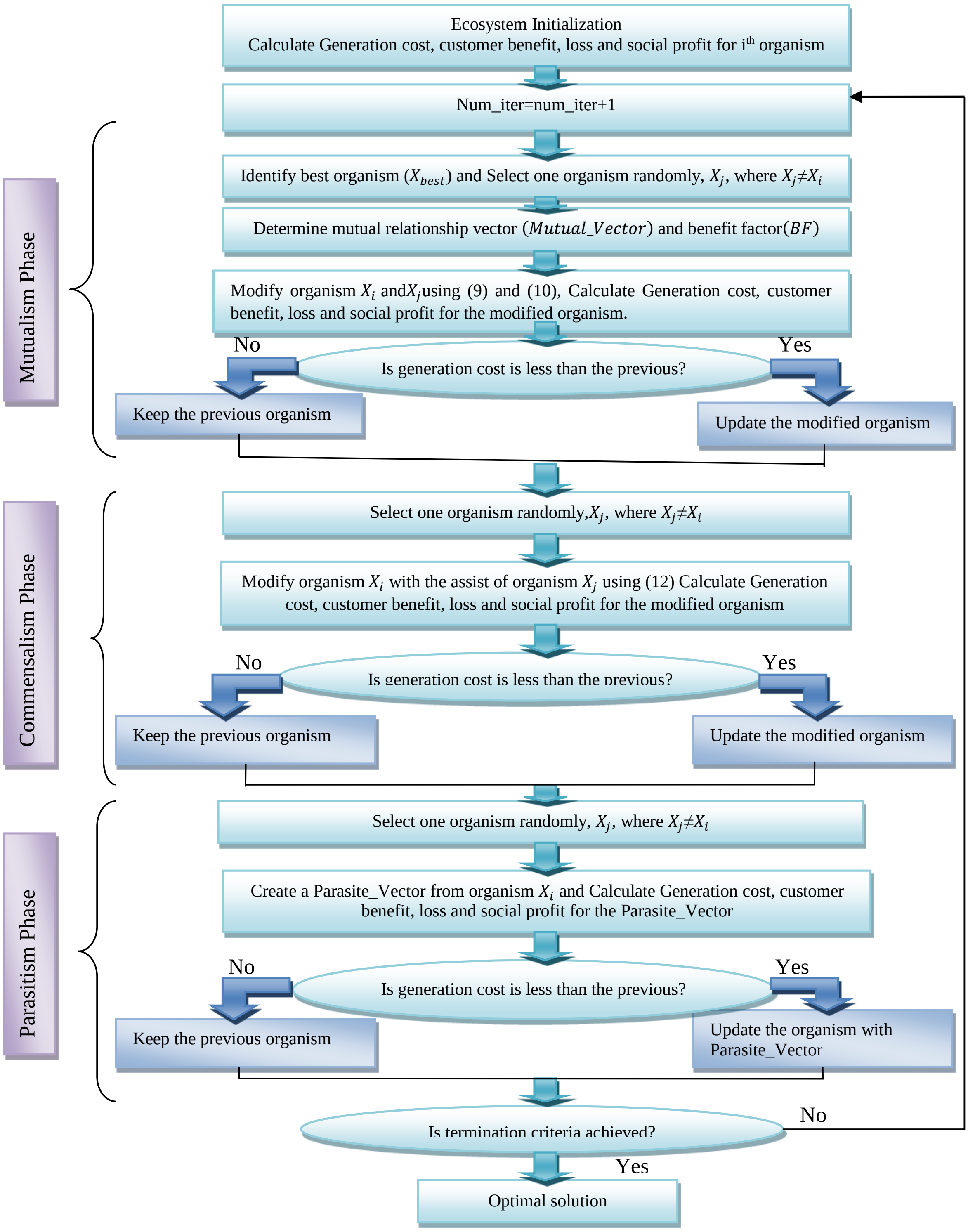

Fig.1. Flowchart for solution of BBDED problem using symbiotic organisms search algorithm

4.3. BBDED results using SOS algorithm for four load patterns

The generator bid data is adopted from [31]. The minimum and maximum limits of generators to generate power are 690 MW and 2358 MW respectively. Customer bid data for LP-1 is given in Table 3 taken from [9]. It can be seen from the Table 3 that the demand per period lies within the minimum and maximum limits of generators for generating power. The total demand in 12 dispatch periods for LP-1 is 19758 MW and the total generation cost ($) and the total social profit ($) obtained are 437659.185 and 476238.265 respectively without losses and 440602.667 and 473294.783 respectively with losses. The customer bid data for LP-2 is given in Table 6. The total demand for LP-2 is 17426 MW which is less than LP-1 but demand per period lies within the minimum and maximum limits of generators. The total generation cost ($) and the total social profit ($) obtained for LP-2 are 380972.293 and 345212.484 respectively without losses and 382577.590 and 343607.187 respectively with losses. The customer bid data for LP-3 is given in Table 7. The total power demand for LP-3 is 18510 MW which is more than LP-2 power demand which is 17426 MW but less than LP-3 power demand which is 19758 MW. The total generation cost ($) and the total social profit ($) obtained for LP-3 are 404594.424 and 396005.214 respectively without losses and 407028.760 and 393570.878 respectively with losses. The customer bid data for LP-4 is given in Table 8. Similarly for LP-4 the total power demand is 17972 MW which is more than LP-2 power demand but less than LP-1 and LP-3 power demand. The total generation cost ($) and the total social profit ($) obtained are 391635.326 and 365960.860 respectively without losses and 393358.250 and 364237.936 respectively with losses for LP-4. The above analysis clearly shows that if the total power demands increases, the generation cost increases and total social profit decreases and if the total power demand decreases, the total generation cost decreases and total social profit increases also the total social profit obtained is always more without losses than with losses. Load curve for four different load patterns is shown in Fig. 4. These simulation results of power output of generators, customers benefit, generation cost and social profit shown in Table 4 are without losses for LP-1. The simulation results of power output of generators, customers benefit, generation cost and social profit for LP-1 given in Table 5 include transmission losses also. The social profit obtained without losses is 476946.256 ($) while social profit obtained with losses is 474002.774 ($), which is less than the profit obtained without losses. The simulation results for the power output of 10 generators, customers benefit, generation cost and social profit for four different load patterns is given in Table 9. We compare the results of SOS algorithm under the high bidding strategy with the results of three variants of smart mutation (SM) – SM1, SM2 and SM3 for a system of 10 generators, 6 customers in 12 dispatch periods. The comparison of total customer benefit, generation cost and social profit obtained by SOS algorithm for LP-1 and the three variants of SM are given in Table 10. The social profit obtained by SOS is more than other three techniques of SM (SM1, SM2 and SM3). The results show the effectiveness of SOS algorithm to solve BBDED problem.

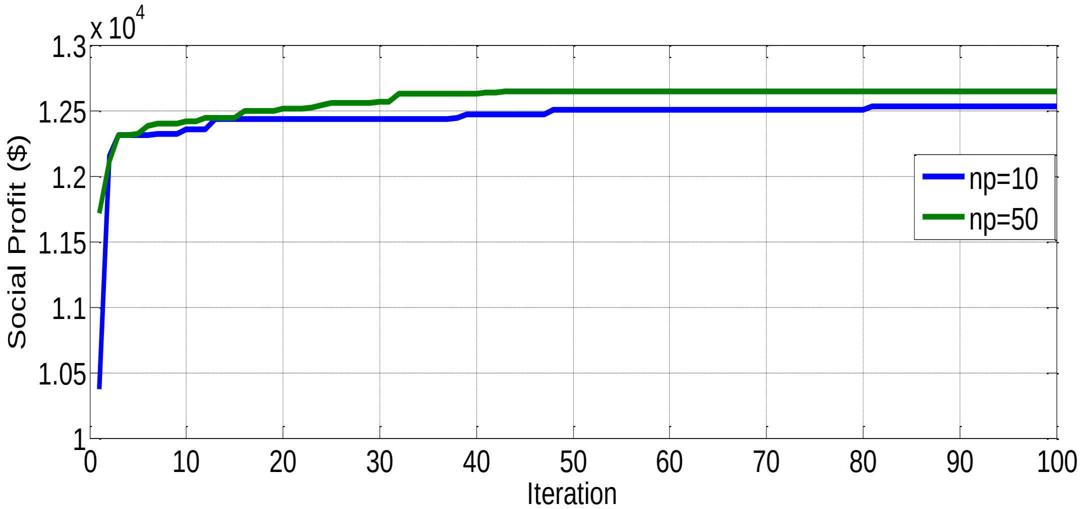

Fig. 2. Convergence characteristic for Test Case-I, LP-1 and Hour-1

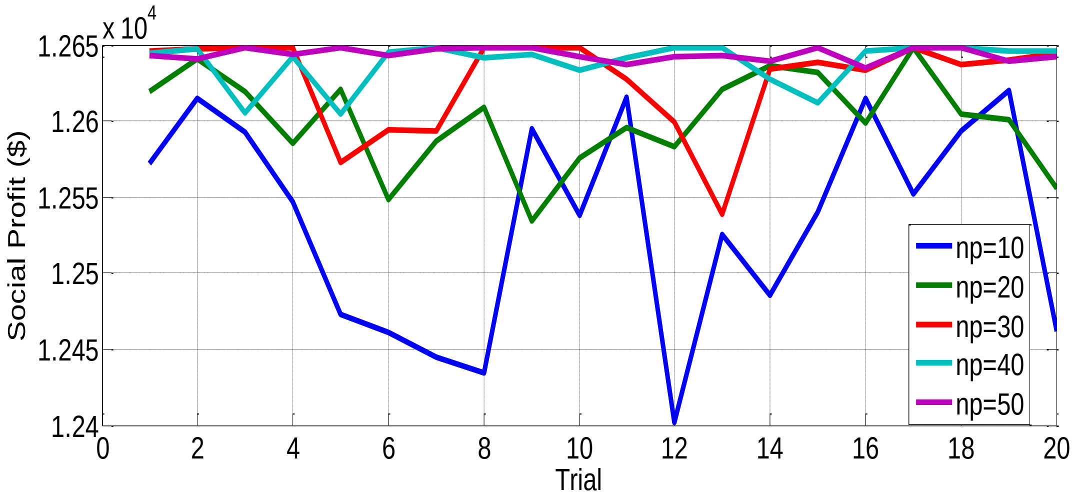

Fig.3. Consistency characteristic for Test Case-I, LP-1 and Hour-1

Table 3. Simulation results without losses for LP-1

Hour	1	2	3	4	5	6	7	8	9	10	11	12
P_1 (MW)	229.604	309.552	230.000	233.171	229.857	238.108	316.925	383.074	437.788	470.000	470.000	470.000
P_2 (MW)	191.152	159.484	154.890	269.439	340.777	459.933	446.389	457.708	460.000	460.000	460.000	460.000
P_3 (MW)	152.620	149.810	313.000	340.000	340.000	331.070	338.656	320.761	340.000	340.000	340.000	340.000
P_4 (MW)	60.000	60.000	60.011	60.000	60.000	60.021	60.000	60.000	60.000	110.000	160.000	209.991
P_5 (MW)	123.000	73.000	105.048	91.408	94.578	126.776	123.936	141.407	212.711	243.000	242.970	243.000
P_6 (MW)	106.657	157.000	158.274	159.949	160.000	160.000	155.909	160.000	160.000	160.000	159.990	160.000
P_7 (MW)	50.000	79.182	110.000	130.000	130.000	130.000	130.000	129.717	129.938	130.000	130.000	130.000
P_8 (MW)	47.000	47.037	47.000	47.065	49.853	47.000	48.350	48.286	48.452	77.058	106.968	120.000
P_9 (MW)	20.948	20.009	24.791	20.000	20.000	20.011	26.763	20.000	20.000	26.814	20.961	31.875
P_{10} (MW)	55.000	55.000	55.000	55.000	55.000	55.000	55.000	55.000	55.000	55.000	55.000	55.000
∑P (MW)	1035.981	1110.074	1258.014	1406.032	1480.065	1627.919	1701.928	1775.953	1923.889	2071.872	2145.889	2219.866
Gen cost ($)	24906.679	25327.175	29150.602	32153.144	33782.786	36887.171	37670.653	38541.116	41165.520	44237.672	46017.001	47819.666
customer benefit ($)	37837.308	38979.100	48191.400	57060.092	61230.700	73407.052	76520.036	84818.084	94916.240	107258.400	117198.840	117188.200
Social profit ($)	12930.628	13651.924	19040.797	24906.947	27447.913	36519.881	38849.382	46276.967	53750.719	63020.727	71181.838	69368.533
Total Social profit ($)	476946.256											

Table 4. Simulation results with losses for LP-1

Hour	1	2	3	4	5	6	7	8	9	10	11	12
P_1 (MW)	229.999	309.636	230.000	233.202	230.000	238.033	316.792	382.808	437.953	470.000	470.000	470.000
P_2 (MW)	184.648	145.269	154.890	287.629	353.782	426.799	412.751	423.390	460.000	460.000	460.000	460.000
P_3 (MW)	153.000	165.775	313.000	340.000	340.000	340.000	337.809	339.821	339.356	340.000	340.000	340.000
P_4 (MW)	60.000	60.000	60.000	60.038	60.000	88.238	60.000	61.459	63.145	110.000	160.000	209.991
P_5 (MW)	113.817	73.000	112.136	79.885	92.586	134.035	168.969	168.327	213.826	243.000	243.000	243.000
P_6 (MW)	107.000	157.000	160.000	159.791	159.989	160.000	159.970	160.000	159.574	160.000	160.000	160.000
P_7 (MW)	50.000	80.000	110.000	129.938	130.000	129.895	130.000	129.802	129.999	130.000	130.000	130.000
P_8 (MW)	65.474	47.000	47.000	47.122	47.000	47.000	50.688	47.000	58.908	77.058	107.058	120.000
P_9 (MW)	20.000	20.000	20.000	20.000	20.000	20.000	20.998	20.000	20.000	42.188	36.889	48.905
P_{10} (MW)	55.000	55.000	55.000	55.000	55.000	55.000	55.000	55.000	55.000	55.000	55.000	55.000
∑P (MW)	1038.938	1112.680	1262.026	1412.605	1488.357	1639.000	1712.977	1787.607	1937.761	2087.246	2161.947	2236.896
Gen cost ($)	25003.049	25372.430	29219.063	32290.510	33952.169	37191.724	37894.505	38793.050	41494.252	44654.954	46433.191	48303.770
customer benefit ($)	37837.308	38979.100	48191.400	57060.092	61230.700	73407.052	76520.036	84818.084	94916.240	107258.400	117198.840	117188.200
P_loss (MW)	3.002	2.664	4.089	6.648	8.374	11.034	10.954	11.550	13.798	15.393	16.089	17.050
Social profit ($)	12834.258	13606.669	18972.337	24769.581	27278.530	36215.327	38625.530	46025.033	53421.987	62603.445	70765.648	68884.429
Total Social profit ($)	474002.774											

Table 5. Customer bid data for LP-2

Customers		**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**Demand per period**
$a_{dj}(\$/MWh^2)$		0.1	0.099	0.097	0.094	0.093	0.09	
$a_{dj}(\$/h)$		20	19	17	16	15	12	
Maximum Load Demand Bids at each period	1	150	110	160	140	90	130	780
	2	180	142	190	160	120	150	942
	3	196	152	210	180	130	160	1028
	4	230	186	240	200	160	170	1186
	5	250	210	260	230	180	220	1350
	6	260	220	280	240	200	240	1440
	7	270	230	300	260	230	250	1540
	8	290	250	320	280	240	272	1652
	9	308	260	330	300	250	282	1730
	10	330	290	368	320	270	310	1888
	11	320	300	370	330	290	300	1910
	12	340	310	380	340	300	310	1980

Table 6. Customer bid data for LP-3

Customers		**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**Demand per period**
$a_{dj}(\$/MWh^2)$		0.1	0.099	0.097	0.094	0.093	0.09	
$a_{dj}(\$/h)$		20	19	17	16	15	12	
Maximum Load Demand Bids at each period	1	160	120	170	150	100	140	840
	2	180	100	200	160	110	150	900
	3	200	140	230	190	140	180	1080
	4	225	160	260	210	190	195	1240
	5	260	230	280	260	210	230	1470
	6	280	240	300	270	230	240	1560
	7	300	260	320	290	250	260	1680
	8	280	300	340	250	270	280	1720
	9	300	320	350	270	290	300	1830
	10	310	330	370	290	310	320	1940
	11	340	350	390	310	330	340	2070
	12	350	380	410	330	350	360	2180

Table 7. Customer bid data for LP-4

Customers		**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**Demand per period**
$a_{dj}(\$/MWh^2)$		0.1	0.099	0.097	0.094	0.093	0.09	
$a_{dj}(\$/h)$		20	19	17	16	15	12	
Maximum Load Demand Bids at each period	1	160	120	180	190	100	150	900
	2	180	140	210	220	120	170	1040
	3	200	160	230	250	150	190	1180
	4	220	180	250	270	170	210	1300
	5	236	190	220	300	180	200	1326
	6	250	210	240	330	200	228	1458
	7	270	230	250	340	220	250	1560
	8	300	240	270	360	240	270	1680
	9	310	250	290	370	260	280	1760
	10	322	280	300	380	270	290	1842
	11	340	300	310	390	280	300	1920
	12	350	326	330	400	290	310	2006

Table 8. Simulation results for LP-1, LP-2, LP-3 and LP-4

Load Pattern	**Total Customer benefit ($)**	**Total Generation cost ($)**	**Total Social profit ($)**
LP-1 Without Losses	913897.45	437659.185	476238.265
LP-1 With Losses	913897.45	440602.667	473294.783
LP-2 Without Losses	726184.777	380972.293	345212.484
LP-2 With Losses	726184.777	382577.590	343607.187
LP-3 Without Losses	800599.638	404594.424	396005.214
LP-3 With Losses	800599.638	407028.760	393570.878
LP-4 Without Losses	757596.186	391635.326	365960.860
LP-4 With Losses	757596.186	393358.250	364237.936

5. Conclusion

Bid Based Dynamic Economic Dispatch problem is solved using symbiotic organisms search algorithm. SOS minimizes the generation cost to maximize the social profit. The results obtained by SOS for LP-1 is found better than the three variants of the smart mutation method SM1, SM2 and SM3 for a system of 10 generators, 6 customers in 12 dispatch period. Four different load patterns are taken with different load demand. The total customer benefit ($), total generation cost ($) and total social profit ($) are obtained for all four LP with and without losses. The total social profit obtained for all four LPs with losses is always less than total social profit obtained without losses. The results obtained show that as the total power demand increases the generation cost increases which reduces the total social profit and if total power demand decreases the generation cost decreases with the increase in the total social profit. These results show that SOS is effective and efficient for solving the different LPs in BBDED problem.

Table 9. Comparison of simulation results

	SOS (LP-1)	SM1[9]	SM2[9]	SM3[9]
Customers Benefits ($)	913897.45	913,897.45	913,897.45	913,897.45
Total Gen. Costs ($)	437659.185	443,122.89	464,119.80	452,111.89
Social Profits ($)	476238.265	470,774.56	449,777.65	461,785.56

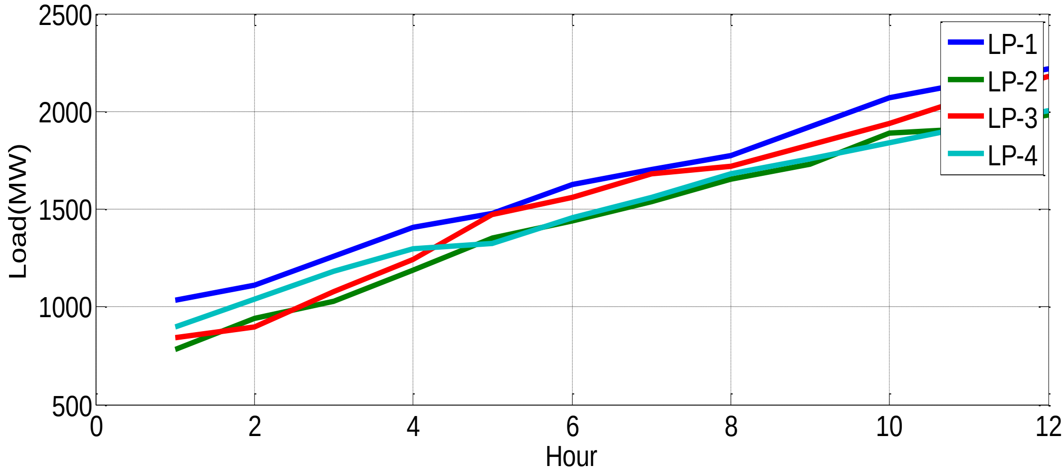

Fig. 4. Load curve for four different load patterns for four different LPs

6. Nomenclature

N_c	Number of customers
N	Number of generators
D_j^t	Bid quantities of customer j at period t
P_i^t	Bid quantities of generator i at period t
BC_j	Bid functions submitted by customers j
BG_i	Bid functions submitted by generators i
a_{dj} , b_{dj}	bid price coefficients of customer j
$a_{pi,}$ b_{pi}, c_{pi}	bid price coefficients of generator i.
P_l^t	Transmission losses in the system
$P_{i\,min}^t$	Minimum power generation limit of generator i at period t
$P_{i\,max}^t$	Maximum power generation limit of generator i at period t
$D_{j\,min}^t$	Minimum bid quantity limit of customer j at period t
$D_{j\,max}^t$	Maximum bid quantity limit of customer j at period t
DR_i	Ramp down limits of generator i
UR_i	Ramp up limits of generator i
P_i^{t-1}	Power generation of generator i ay previous time period
$t \in (1, T)$	Number of time periods in hours
lb	lower bound
ub	upper bound

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