Application of Differential Evolution to Dynamic Economic Dispatch Problem with Transmission Losses under Various Bidding Strategies in Electricity Markets

B. Rampriya[†], K. Mahadevan* and S. Kannan**

Abstract – This paper presents the application of Differential Evolution (DE) algorithm to obtain a solution for Bid Based Dynamic Economic Dispatch (BBDED) problem including the transmission losses and to maximize the social profit in a deregulated power system. The IEEE-30 bus test system with six generators, two customers and two trading periods are considered under various bidding strategies in a day-ahead electricity market. By matching the bids received from supplying and distributing entities, the Independent System Operator (ISO) maximize the social profit, (with the choices available). The simulation results of DE are compared with the results of Particle swarm optimization (PSO). The results demonstrate the potential of DE algorithm and show its effectiveness to solve BBDED.

Keywords: Bid Based Dynamic Economic dispatch (BBDED), Differential Evolution (DE), Generation Companies (GENCOs), Independent System Operator (ISO)

1. Introduction

Dynamic Economic Dispatch (DED) is one of the most important functions for economic operation of power system and control. Dynamic economic dispatch is an extension of the conventional economic dispatch problem that takes into consideration the limits on the ramp rate of the generating units. The DED problem of a deregulated power system can be classified as price based approach and bid based approach [1]. In price based DED, the objective of Generation Companies (GENCO) is to maximize its profit (and not minimizing its own cost). A fuzzy optimization approach to solve price based DED is presented in [2]. In Bid Based Dynamic Economic Dispatch (BBDED), Independent System Operator (ISO) matches the supply and demand side bids (of both supplier and customer) so that the social benefit is maximized [3].

The electricity markets may undergo two distinct trading mechanisms, the central auction and bilateral trading [4]. In a centralized auction trading mechanism, the suppliers and customers submit their bids to a central pool or Power eXchange (PX). The pool operator takes electricity transaction bids and offers from these two entities and dispatches them in an economic manner depending on the price and MW biddings. The customers and suppliers do not directly interact to each other, but only interact through the pool operator. After all bids and offers are received, any of the optimization technique will be used to solve the problem which includes loss allocation.

In bilateral trading, the sellers and buyers submit their bids, where the quantities are traded and the prices are at the discretion of these parties and not a matter of ISO [5]. These transactions are then brought to the ISO with a request that the transmission facilities for the relevant amount of power be provided. If there is no violation of constraints, ISO simply dispatches all requested transactions and charges for service.

An efficient Interior Point (IP) algorithm by extending the pure IP algorithm is used to solve BBDED problem [3]. A comparison of BBDED results by Linear Programming (LP), Genetic algorithm (GA) and Particle Swarm Optimization (PSO) is done in [6]. In [3] and [6], BBDED is solved for a 5- bus network with three generators and two customers submitting bids. In this paper, various bidding strategies of customers based on the market price are explained and their impact on the increase of social profit is proved experimentally for a standard IEEE-30 bus system.

This paper gives a solution for BBDED problem in which the power dispatch contracts are done through central auction mechanism. This paper is organized as follows: Section 2 presents the mathematical model of BBDED, section 3 outlines the various bidding strategies, section 4 deals with application of Differential Evolution (DE) for solving BBDED, section 5 presents the results and discussions, and section 6 concludes.

---

† Corresponding Author: Dept. of Electrical and Electronic Engineering, Sri Krishna College of Eng. and Tech., Coimbatore, India. (rampriyame@gmail.com)
* Dept. of Electrical and Electronic Engineering, PSNA College of Engg and Tech., Dindugal, India.
** Dept. of EEE, Kalasalinagm University, India.

2. Mathematical Model of BBDED

The trading mechanism of suppliers and customers are modeled based on central auction mechanism. These central auctions are identical in function to a simple Economic Dispatch (ED) algorithm [7, pp. 29] and the dispatch is performed based on the bids received from entities and so the model is termed as BBDED [3]. The solution of BBDED problem aims to maximize the social profit.

2.1 Objective function

The problem of BBDED can be modeled as

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

where N_c and N are the number of customers and generators, D_j^t is the bid quantities of customer j at period t, P_i^t is the bid quantities of generator i at period t, BC_j and BG_i are the bid functions submitted by customers and generators.

2.2 Constraints

The three constraints a) Power balance b) Generator & customer bid quantities and c) Ramp rate limits are used.

a) Power balance constraints

The power balance constraint is an equality constraint that reduces the power system to a basic principle of equilibrium, between total generation of GENCO and customers participating in the electricity markets.

$$\sum_{i=1}^{N} P_i^t = \sum_{i=1}^{N_c} D_i^t + P_l^t \qquad t=1,2, \dots T \quad (2)$$

where P_l is the transmission losses in the system.

b) Generator and customer bid quantities constraints

Generation units have lower and upper production limits that are directly related to the generator design. These bounds can be defined as a pair of inequality constraints,

$$P_{i\,\min}^t \le P_i^t \le P_{i\,\max}^t \quad (3)$$

Customer bid quantities are subject to minimum and maximum limits and is given by,

$$D_{j\,\min}^t \le D_j^t \le D_{j\,\max}^t \quad (4)$$

c) Ramp rate limits constraints

In order to keep thermal gradients inside the turbine within safe limits and to avoid shortening the life, the rate of increase/decrease of the power output of generators is limited within a range. These ramp rate constraints can be defined as,

$$DR_i \le P_i^t - P_i^{t-1} \le UR_i \quad (5)$$

where DR_i and UR_i are maximum decrease and maximum increase in the output of i-th generator in a particular hour.

3. Bidding Strategies in deregulated markets

A number of different bidding strategies can be framed by specifying the parameters for the capacities and prices to be bid into the market for the different generation plants in the system [8]. The strategies can be either static or dynamic and they will typically vary by generation technology and need of the customer participating in the competition. In deregulated electricity markets, the market participants submit their bids to an ISO. A bid consists of price offers and the amount of load demanded by the customers, which can be matched by the ISO.

3.1 Representation of supply side bids

The production cost bidding strategy of generators is used to represent the supply side bids. Under this strategy, the GENCO acts as a pure price-taker in the market, and bid according to the marginal production cost of its plants as specified by the heat rate curve [8]. Many generating utilities present their bid function as piecewise linear function [9]. To reduce the number of parameters associated with a bid, the piece-wise linear bidding cost function is approximated by a quadratic function (often done in scheduling problems [10]). Thus the bid price curves of generators are approximated as quadratic function of their bid quantities and given as,

$$BG_i\left(P_i^t\right) = a_{pi}\left(P_i^t\right)^2 + b_{pi}P_i^t + c_{pi} \quad (6)$$

where a_{pi}, b_{pi} and c_{pi} are the bid price coefficients of generator i.

3.2 Representation of demand side bids

The bid function of customers are expressed as,

$$BC_j\left(D_j^t\right) = a_{dj}\left(D_j^t\right)^2 + b_{dj}D_j^t \quad (7)$$

where a_{dj} and b_{dj} are the bid price coefficients of customer j. For customers participating in electricity markets, the

bidding strategies are classified as "bidding high (H)", "bidding low (L)" and "bidding medium (M)" based on the bid price coefficients [9]. The optimization of bidding strategies have been performed and from the literature, the authors have concluded by experiments that the high value of bid coefficient of customer (a_{dj}) is ≥ 0.09, medium value of bid coefficient of customers (a_{dj}) can be in the range of 0.05 and the low value of bid coefficient of customers (a_{dj}) is ≤ 0.01 [9]. The authors also suggested to frame the bid coefficient b_d of the customers as per the equation, $0 < b_d < \lambda_m$, where λ_m is the energy clearing price. Energy clearing price or equilibrium price is the price of energy at which energy supplied is equal to energy demanded.

4. Application of DE to solve BBDED

DE is a new floating point encoded evolutionary algorithm for global optimization proposed by Storn and price [11]. Instead of classical crossover or mutation, DE is owing to a special kind of differential operator to create new offspring from parent chromosomes. DE's advantages are its simple structure, ease of use, speed and robustness [12]. DE algorithm is a population based algorithm using three operators; crossover, mutation and selection. There are three real control parameters in the algorithm, which are differentiation (or mutation) constant F, crossover constant CR, and size of population NP. The rest of the parameters are dimension of problem d that scales the difficulty of the optimization task; maximum number of iterations $MAXGEN$, which may serve as a stopping condition and low & high boundary constraints of variables that limit the feasible area. The DE algorithm is presented in the flowchart and shown in Fig. 1.

A step-by-step procedure of the DE algorithm for solving BBDED problem is as follows:

4.1 Initialization

All the independent variables, bid quantities of generators P_i^t and bid quantities of customer D_j^t have to be generated according to equation,

$$x_{ij}(0) = x_j^L + \left(rand(0,1)\right)\left(x_j^U - x_j^L\right) \qquad (8)$$

Each individual in the population is assigned a value within the minimum and maximum bid quantity limits of generators or customers. This creates parent vectors of independent variables for the first iteration. Since these parent vectors are created within the minimum and maximum limits of bid quantities, they readily satisfy the inequality constraints given in Eqs. (3) and (4). The transmission line losses are calculated using B_{mn}

coefficients. With the bid quantities and network losses, the equality constraint in Eq. (2), is also checked.

4.2 Mutation

In each iteration, a donor vector $V_i(k)$ is created in order to change the population member vector $X_i(k)$. Generally, the method of creating this donor vector is different for various DE schemes. The algorithm outlined here is the seventh strategy of DE (i.e.DE/rand/1/bin). Therefore, the j-th component of $V_i(k)$ can be expressed as,

$$V_{ij}(k+1) = x_{r1j}(k) + F\left(x_{r2j}(k) - x_{r3j}(k)\right) \qquad (9)$$

where x_{r1}, x_{r2} and x_{r3}, are three different members chosen randomly from the current population and not coinciding with the current member x_i, F is a scalar number which is the difference between any two of the chosen members and this scaled difference is added to the third one.

4.3 Crossover

The crossover is performed for each target vector $X_i(k)$ with its noisy vector $V_i(k)$ and creates a trial vector $u_i(k)$. This is done by introducing a crossover operator in which the noisy vector exchanges its components with the current vector $X_i(k)$. Binomial crossover is used. In binomial type, the crossover is performed on all variables as far as a randomly picked number between 0 and 1 is within CR value. The binomial crossover operation which is performed on all variables can be given as,

$$u_{i,j}(k) = \begin{cases} V_{i,j}(k) & if \; rand(0,1) \langle CR \\ X_{i,j}(k) & else \end{cases} \qquad (10)$$

4.4 Selection

The fitness function is calculated according to Eq. (1) with trial and target vectors. The selection process is performed for each target vector, X_i by comparing its fitness function with that of the trial vector, u_i whichever has the maximum fitness function will survive for the next iteration. This process is explained as follows:

$$f\left(u_i(k)\right) > f\left(X_i(k)\right) \text{then} \; X_i(k+1) = u_i(k)$$
$$\text{else} \; X_i(k+1) = X_i(k) \qquad (11)$$

The fitness function is calculated according to Eq. (1) with trial and target vectors. The corresponding vector with maximum fitness is selected for next iteration. The procedure is repeated until maximum iterations are reached.

5. Results and Discussion

The available generator cost coefficients (a_p, b_p and c_p) for the systems are used as generator bid data. The customers bid data are assumed according to various bidding strategies. With these bid data, BBDED is performed using DE algorithm. The best values of DE parameters are chosen by the experiments carried out with different values of parameters [13]. Thus the algorithm parameters are set as: *CR*=0.9, *F*=0.5, *NP*=20, MAXGEN=200. The optimized values of generated power dispatch and customer demand, satisfying the constraints specified for the test system under various bidding strategies are presented.

5.1 IEEE-30 bus system

The DE method is applied to solve BBDED problem for IEEE-30 bus test system with 6 generating units and 41 transmission lines. The supply side bids are represented with the production cost bidding strategy of generators. The customer bids are represented as three bidding strategies. The generator's bid price coefficients, bounds of their bid quantities are given in Table 6 and B_{mn} coefficients are taken from reference [14]. With the generators and customers bid data and B_{mn} coefficients as the input, DE algorithm finds the optimized values of bidding quantities of generator (P_i^t) and customers (D_j^t) and the maximum social profit is calculated.

Case-A: Low bidding strategy of customers

It is assumed that, two customers are participating in the competition together with GENCOs and submitting their demand bids. The bid data of customers has been presented in Table 6. The values of bid coefficient a_d is assumed by choosing Low bidding strategy and kept as -0.016 and -0.087 $/MWh^2 for customer 1 and 2 respectively, for both the periods. The energy price (λ_m) is taken as 20 $/hour (may subject to periodic change based on the current issues in the electricity markets) and, the bid coefficient value b_d is taken as 20 $ and 15 $ for customer 1 and 2 respectively for the periods, i.e, periods 1 and 2.

At period 1, the customer 1 submits MW bidding between 100 to 150 MW; customer 2 submits MW bidding between 50 to100 MW, as shown in Table 7. With their resource allocation, the generators spend fuel cost of 561.708 $ and supplies 140.0379 MW to customer 1 and 73.7784 MW to customer 2. The maximum social profit at this period is 1734.1292 $.

Table 1 shows the dispatch results of BBED under Low bidding strategy. The convergence characteristic of DE algorithm for this test system under Low bidding strategy is shown in Fig. 2. Though the maximum number of iterations are set as 200, the DE algorithm is able to converge an optimum value of 3111.5292 $ within 40 iterations.

Case –B: Medium bidding strategy of customers

The generator bid data and customer demand data is kept same as the previous case. To represent the customer bid, medium values of customer bid coefficient (a_d) are used as given in Table 6. The same procedure is repeated to obtain the dispatch results of generators and customers. The optimum values of generator output powers, customer load, generation cost, customer benefit and social profit for two trading periods are tabulated in Table 2. Fig. 3 shows the convergence characteristics of DE algorithm for this problem under medium strategy. From 50th iteration, DE produces an optimum value of 11886.5 $ as social profit. If the customer submits the bid, based on the medium strategy rather than low bidding strategy, the social profit is increased to 5893.9 $ and 5992.6 $ at periods 1 and 2 respectively. The generators supplies maximum demand (250 MW) of the two customers by spending a fuel cost of 681.1074 $ and 750.3631 $ at periods 1 and 2 which are higher than the fuel cost spent under low bidding strategy. Even though the generators spent cost more in medium bidding strategy, the customer benefit is raised due to allocation of maximum demand which is the main reason for this increase in social profit.

Case –C: High bidding strategy of customers

The generator data and customer demand data is kept same as the previous case. High values of customer bid coefficients (a_d) 0.09 and 0.1 are used as given in Table 6. The same procedure is repeated to obtain the dispatch results of generators and customers. The optimum values of generator output powers, customer load, generation cost, customer benefit and social profit for two trading periods are tabulated in Table 3. Fig. 4 shows the convergence characteristics of DE algorithm for this problem under high strategy. From 50th iteration, DE produces an optimum value of 14708.5 $ as social profit.

In this strategy, the dispatch results, cost for generation remains same as in the case of medium bidding strategy for all trading periods but the social profit is increased to 6968.9 $ and 7739.6 $ at periods 1 and 2. The reason for the increase in social profit under this strategy compared to other strategies is that the customers have benefited 7650 $ and 6743 $ at periods 1 and 2 due to selection of bid coefficient (a_d) of customers to a high value (say > 0.09).

5.2 Result analysis

Fig. 5 shows the values of total generation cost, total customer benefit and total social profit in the various bidding strategies. If the customers submit bid based on low bidding strategy, the generation cost is less than other strategies, but the consumer benefit and social profit is too low. So, ISO matching the generator bids and customers with low bids is not suitable for a deregulated power system. Under medium and high strategies, the generation cost is same and little bit high than the low bid strategy.

With the same generation cost as that of the medium bids, the customers under high bidding strategy receives a higher benefit which leads to maximum social benefit. So, high bidding strategy is suitable in deregulated power system.

The customers submit any type of bid based on market price with an objective to yield higher benefit and GENCOs submit bid to increase their own profit. Both these entities will aim for their individual benefits and not bother about social profit. ISO will play an important role to make regulatory bond between the resources of generators and need of customers. These analyses on various bidding strategies will guide ISO to make decisions while matching the supply bid to demand bid so as to maximize the social profit.

5.3 Comparison of DE results with PSO

In reference [6], the authors have concluded that PSO has proved its excellence in providing better results in finding solution to BBDED problem than IP, LP and GA. In this paper, a DE algorithm is successfully applied to solve BBDED problem. In order to validate the potential of DE algorithm in solving BBDED, the results of DE is compared with PSO and tabulated as given in Table 4.

The search procedure of PSO algorithm for BBDED problem is given in [6]. The PSO parameters are studied and fixed as the following values [15].The PSO parameters are set as: Maximum number of iterations = 500, Population size = 10, acceleration const (C_1) = 2, acceleration const (C_2) = 2, Initial inertia weight = 0.9, Final inertia weight = 0.4, Epoch when inertial weight at final value= 1500.

Under low bidding strategy, PSO produces a dispatch of P_1= 50 MW, P_2=80 MW, P_3=50 MW, P_4=35 MW P_5=30 MW and P_6=40 MW to serve a load of 150 MW to customer1 and 100 MW to customer 2 at trading period 1. Similarly at period 2, the six generators supplies 50MW, 61.76 MW, 50 MW, 35 MW, 30 MW, 40 MW to cusomer1 (70 MW) and customer 2 (185.62 MW). PSO produces a dispatch schedule with generation cost of 1851.0215 $ which is higher than the generation cost of DE (989.7219$) and customer benefit of 3483.8 $ which is lesser than the customer benefit of DE (4101.3$). Similarly for medium and high bidding strategies, DE results are better than PSO. It is evident that the social profit is maximum (which is the objective of DED) in all the three bidding strategies using DE rather than PSO.

6. Useful hints

The figures and tables are given in the sections 6.1 and 6.2 respectively. The flowchart of DE algorithm is shown in Fig. 1. The convergence characteristics of DE algorithm under low, medium and high bidding strategies are shown in Fig. 2, 3 and 4 respectively. Outputs under various bidding strategies are shown in Fig. 5.
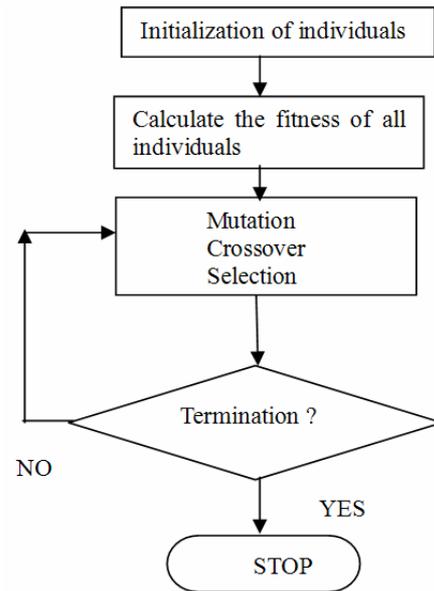
6.1 Figures
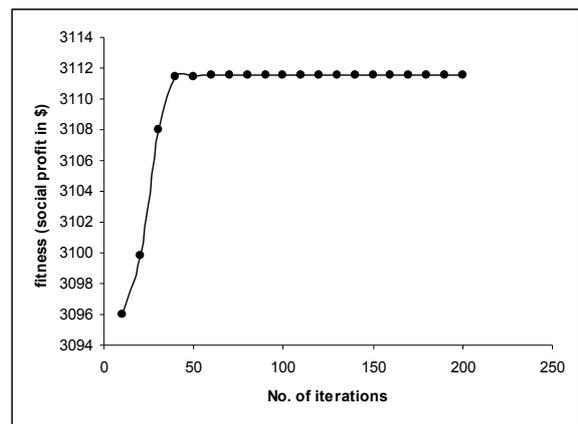

Fig. 1. Flow chart of DE Algorithm

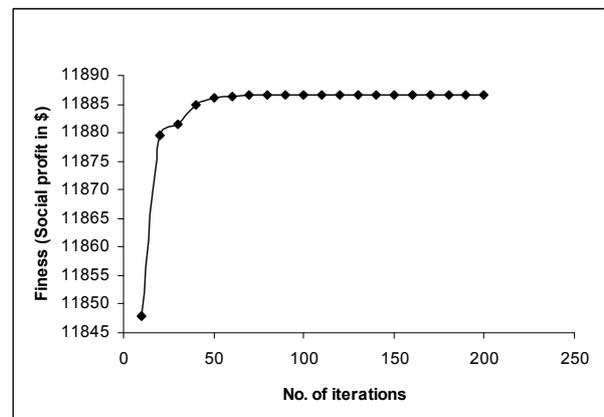**Fig. 2.** Convergence characteristic of DE under low bidding strategy

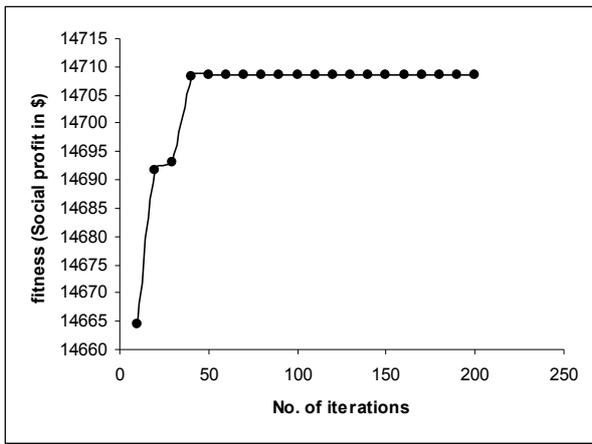**Fig. 3.** Convergence characteristic of DE under medium bidding strategy

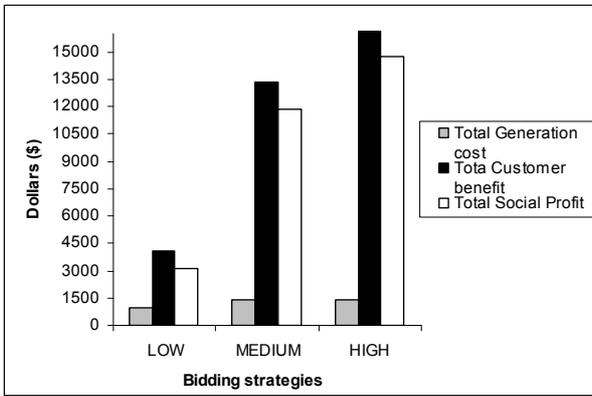**Fig. 4.** Convergence characteristic of DE under high bidding strategy

Fig. 5. Outputs under various bidding strategies

6.2 Tables

Table 1. Dispatch results of BBDED using DE under low bidding strategy

	Period 1	Period 2
P_1 (MW)	131.3014	95.8827
P_2 (MW)	38.3058	29.8440
P_3 (MW)	17.2255	15.0000
P_4 (MW)	10	10.0000
P_5 (MW)	10	10.0000
P_6 (MW)	12	12.0000
Total generation (MW)	218.8327	172.7267
D_1 (MW)	140.0379	70
D_2 (MW)	73.7784	100
Total demand (MW)	213.8163	170
Total losses (MW)	5.0164	2.7267
Total generation cost ($)	561.1708	428.5511
Total customer benefit ($)	2295.3	1806
social profit ($)	1734.1292	1377.4
Total Social profit ($)	3111.5292	

Table 2. Dispatch results of BBDED using DE under medium bidding strategy

	Period 1	Period 2
P_1 (MW)	153.3611	163.5880
P_2(MW)	44.3595	47.4813
P_3(MW)	18.9327	19.7576
P_4(MW)	17.8545	24.3363
P_5(MW)	10	10
P_6(MW)	12	12
Total generation (MW)	256.5078	277.1632
D_1(MW)	150	70
D_2(MW)	100	200
Total demand (MW)	250	270
Total losses (MW)	6.5078	7.1632
Total generation cost ($)	681.1074	750.3631
Total customer benefit ($)	6575	6743
social profit ($)	5893.9	5992.6
Total Social profit ($)	11886.5	

Table 3. Dispatch results of BBDED using DE under high bidding strategy

	Period 1	Period 2
P_1 (MW)	153.3611	163.5880
P_2(MW)	44.3595	47.4813
P_3(MW)	18.9327	19.7576
P_4(MW)	17.8545	24.3363
P_5(MW)	10.0000	10
P_6(MW)	12.0000	12
Total generation (MW)	256.5078	277.1632
D_1(MW)	150	70
D_2(MW)	100	200
Total demand (MW)	250	270
Total losses (MW)	6.5078	7.1632
Total generation cost ($)	681.1074	750.3631
Total customer benefit ($)	7650	8490
social profit ($)	6968.9	7739.6
Total Social profit ($)	14708.5	

Table 4. Comparison of DE results with PSO

	LOW		MEDIUM		HIGH	
	DE	PSO	DE	PSO	DE	PSO
Total Gen cost	989.72	1851.0	1431.5	1928.2	1431.5	1793.1
Total Customer benefit	4101.3	3483.8	13318	12141	16140	15570. 5
Total Social profit	3111.5	1632.8	11886.5	10213	14708.5	13777

Table 5. IEEE 30 bus sytem generator data

Bus No.	Gen No.	a_{pi} ($/MWh^2)	b_{pi} ($/MWh)	C_{pi} ($)	P_{min} (MW)	P_{max} (MW)	UR_i (MW)	DR_i (MW)
1	1	0.00375	2.00	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 6. Customer bid data

	Customer1 Low / Medium/ High	Customer 2 Low / Medium / High
a_{dj}($/MWh^2)	-0.06/ 0.07/ 0.1	-0.08/0.05/ 0.09
b_{dj} ($/MWh)	20	15
Load demand at hour(D_{min} to D_{max}) (MW)	100 to 150	50 to 100
Load demand at hour 2(D_{min} to D_{max}) (MW)	20 to 70	100 to 200

7. Conclusion

This paper presents the solution methodology for the BBDED problem in a day-ahead deregulated power market with known generator and customer bid data. The solution to BBDED problem of matching the supply and demand bids within the acceptable levels of ISO has been achieved. The proposed method can provide optimal solutions for different parameters such as generation cost, customer benefit. Bidding in double side auction mechanism is incorporated and thus several strategies of customer bidding have been demonstrated. The simulation results prove the effectiveness and robustness of the proposed methodology for balancing the power bids submitted by GENCOs and customers taking an account of transmission losses. It is evident that social profit is high, when the ISO matches the bids of GENCOs and customers following the high bidding strategy while submitting their bids. Simulation results show that that the proposed method can be used by ISO wishing to maximize the social profit. The significance of this method is that the customers have a choice to buy power from any GENCOs participating in the competition.

Acknowledgements

References

[1] Xia.X, Elaiw.A.M, Optimal dynamic economic dispatch of generation: A review, Electric power systems research, Vol. 80,2010, pp.975-986.

[2] P.Attaviriyanupap, H.Kita, E.Tanaka, J.Hasegawa, A fuzzy optimization approach to dynamic economic dispatch considering uncertainities, IEEE Trans. on power systems, Vo. 19, No. 3, 2004, pp. 1299-1307.

[3] Whei –Min Lin, Shi –Jaw Chen, Bid based dynamic economic dispatch with an efficient interior point algorithm, International Journal of Electrical power and energy systems, Vol. 24,2002, pp.51-57.

[4] H.Rudnick, R.Varela and W.Hogan, Evaluation of alternatives for power system coordination and pooling in a competitive environment, IEEE Trans. On power systems, Vol. 12, 1997, pp. 605-613

[5] S.N. Singh, Power Systems Restructuring Models, Proceedings of CEP course held at IIT Bombay, 2002.

[6] Bo Zhao, Chuangxin Guo and Yijia Cao, Dyanamic Economic dispatch in Electricity market using Particle swarm optimization algorithm, in IEEE Proceedings of the 5th World Congress on Intelligent control and Automation, pp. 5050-5054, June 2004.

[7] A.J.Wood and Woolenberg, power generation operation and control (John Wiley& Sons).

[8] http://www.dis.anl.gov/publications/articles/ceeesa_ EMCAS_IAEE72005NorwayPaper.pdf

[9] Daoyuan Zhang, Yajun Wang, and Peter B. Luh, Optimization Based Bidding Strategies in the Deregulated Market, IEEE Transactions on Power systems, Vol.15, No.3, 2000.

[10] X. Guan, P. B. Luh, H. Yan, and P. M. Rogan, Optimization-based scheduling of hydrothermal power systems with pumped-storage units, IEEE Trans. on Power Syst., Vol. 9, No. 2, pp. 1023–1031, May 1994.

[11] R.Storn, K.Price, Differential Evolution- A simple and efficient adaptive scheme for global optimization over continuous spaces, in Technical Report TR -95-012, ICSI, 1995.

[12] D.Karaboga, S.Okdem, A simple and global optimization for engineering problems: differential evolution algorithm, Turkish Journal of Electrical Engineering, Vol. 12, No.1, 2004.

[13] Abou. A. A, Abido. M.A, Spea S.R, Differential evolution algorithm for emission constrained economic power dispatch problem, Electric power systems Research, Vol. 80, 2010, pp.1286-1292.

[14] ietd.inflibnet.ac.in/bitstream/1063/1271/18/18_appendix. pdf (Accessed online on 22 March 2011)

[15] Shi, Y., Eberhart, R.C, Parameter selection in particle swarm optimisation, In. EP VII (1998), Lecture Notes in Computer science 1447, Springer pp.591-600.

Mrs. B. Rampriya She received B.E. and M.E. degrees in Electrical and Electronics and Power systems engineering from Manonmaniam Sundaranar University and Anna University in 2000 and 2004, respectively. She is pursuing Ph.D in Kalasalingam University, Krishnankoil. She is currently working as an Assistant Professor in the department of Electrical and Electronics Engineering, Sri Krishna College of Engineering and Technology, Coimbatore. Her area of interest includes Restructured Power Systems, Swarm and Evolutionary Computation techniques.

Dr. K. Mahadevan He was born in Tirumangalam, India, in 1968. He graduated in Electrical and Electronics Engineering and post graduated in Industrial Engineering from Madurai Kamaraj University, India in 1993 and 1997 respectively. He was awarded with Ph.D degree from the same university in the year 2006. He has been a faculty member of Electrical Engineering at P.S.N.A. Engineering College, Dindigul, India. His fields of interest include Power system Operation & Control, Power System Optimization and Evolutionary Computation.

Dr. S. Kannan He received B.E, M.E, and PhD Degrees from Madurai Kamaraj University, India in 1991, 1998 and 2005 respectively. He is Professor and Head of Electrical and Electronics Engineering, Kalasalingam University, Krishnankoil-626190, India, where he has been since July 2000. He was a visiting scholar in Iowa State University, USA (October 2006–September 2007) supported by the Dept. of Science and Technology, Government of India with BOYSCAST Fellowship. His research interests include power system Deregulation and Evolutionary computation.